Anomaly Time*

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Abstract

We examine when anomaly returns occur. We use a powerful database that contains the precise date on which accounting information is first made public. Despite recent findings to the contrary, once timing is considered, anomalies exist in the data. Anomaly returns are concentrated in the first 30 days after information announcements and all of the return occurs within the first 120 days. In recent years, anomaly returns are concentrated in the first five days after the announcement date. Moreover, hedge funds' reaction speed predicts their future performance. These results suggest that anomalies are real yet they are rapidly arbitraged away.

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1 Introduction

A large literature documents evidence of asset pricing anomalies: the idea that firm-level characteristics can predict future stock returns. Researchers have put forward a number of possible explanations for these apparent violations of market efficiency. Several recent papers find evidence that anomaly returns appear to get weaker in more recent periods (McLean and Pontiff (2016), Green et al. (2017)), and a growing body of literature argues that the existence of anomalies is the result of widespread data mining (e.g., Harvey et al. (2016), Hou et al. (2017)), suggesting the original evidence for the presence of anomalies was spurious.[1] We look at the question differently. We use an approach that allows us to precisely examine the timing of anomaly returns in order to learn whether they are real. Put differently, we examine *when* anomaly returns occur in order to understand *if* they exist.

We find that, once timing is considered, anomalies do exist in the data. To show this, we use an event study methodology combined with a novel database that measures the precise date of the first release of key financial data. This approach allows us to examine when anomaly returns occur based on portfolios that are created promptly after information is released. We find that anomaly returns exist, but their profitability is concentrated in the days immediately following information releases. Further, this pattern of return concentration has increased over our sample period. In other words, speed is crucial to measuring, and capturing, anomaly returns.

Over the past three decades, a convention in the literature has taken hold to form portfolios annually, typically in June, to ensure that all financial statement information has been publicly released.[2] A byproduct of this convention is that it ignores the precise timing of information signals. Anomaly signals are often released at different times for different firms. Furthermore, even for the same firm, different data items that can drive portfolio formation

[1] Hou et al. (2017) state that "The anomalies literature is infested with widespread p-hacking."

[2] Fama and French (1992) state, "To ensure that the accounting variables are known before the returns they are used to explain, we match the accounting data for all fiscal year-ends in calendar year t-1 with the returns for July of year t to June of t+1."

are released at different points in time (e.g., total assets vs. earnings).[3] In other words, while standard databases provide earnings announcement dates, these dates do not necessarily correspond to the dates on which key pieces of information are first publicly released.

We overcome these issues by using a powerful, but relatively unknown database, the Compustat Snapshot database. The Snapshot database contains the precise date on which accounting items were first made publicly available, on a data-item by data-item basis, allowing us to identify the exact date on which each data item is first reported. We are then able to capture the relation between returns and the release of information for each firm.

We begin by considering an event-time strategy for a set of nine anomalies whose calculations change at distinct and measurable points in time.[4] We line up stock returns for these anomalies in event time according to the precise release of their annual financial information. A stock enters the long or short leg of an anomaly portfolio based on its ranking as of the date of its information release, as precisely identified in the Snapshot database. We then accumulate returns for the subsequent 30, 120, and 240 trading days.

Across eight of the nine anomalies, an event-time portfolio generates predictable returns that are statistically positive in the first 30 days. Importantly, these returns diminish dramatically in subsequent trading periods. For example, annualized abnormal returns to a "super portfolio" comprised of all nine anomalies, are 7.87% over the first 30 days following an information release, whereas returns over the next two windows ([31,120] days and [121,240] days) are more modest at 3.31% and 0.37%, respectively. These results suggest that anomaly returns are the result of mispricing. We find that profits to trading against the mispricing manifest primarily in the first month or so after the information release date, diminishing thereafter.

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

[4]We use McLean and Pontiff's (2016) list of anomalies, and identify those with clear information release timing, including accruals (Sloan (1996)), asset growth (Cooper, Gulen, and Schill (2008)), gross profitability (Novy-Marx (2013)), growth in inventory (Thomas and Zhang (2002)), net working capital changes (Soliman (2008)), operating leverage (Novy-Marx (2010)), profit margin (Soliman (2008)), return on equity (Haugen and Baker (1996)), and sustainable growth (Lockwood and Prombutr (2010)).

Moreover, the return pattern changes over our sample period. We find anomaly returns are increasingly concentrated in the first five days after the announcement date. Specifically, in the early years of our sample, one tenth of the super portfolio's 30-day return is earned in the first five days, whereas in the latter years of the sample, one third of the portfolio return is earned in that period. The results are consistent with the idea that anomaly returns are being arbitraged away more quickly, and there are significant returns for traders who respond quickly to information.

To gauge the economic significance of these anomaly portfolios, we analyze this result in a framework that is plausibly implementable for an investor by examining a calendar-time approach that rebalances on information release dates instead of once a year, as is common in the literature. We find that returns earned by a daily rebalancing hedge portfolio are statistically greater than the returns earned by an annual rebalancing portfolio. The spread between the super portfolio's daily rebalanced return and the annually rebalanced return is 6.92% annualized when anomaly portfolios are equally weighted. Further, on average, the 240-day return to annual rebalancing is only 1.67%, while daily rebalancing yields 8.52%.[5]

For annually rebalanced portfolios, the simple reality is that information grows stale over the one-year holding period. Our evidence suggests that this staleness matters for anomaly return predictability. Specifically, we find that the majority of the spread between the annually rebalanced and the daily rebalanced portfolios lies in the first six months of the calendar year, when the majority of firms release their annual financial information. However, the question naturally follows as to whether the increased return predictability is a function of the continuous arrival of general news[6] or whether it relates to information signals that specifically drive portfolio assignment. To examine this, we use RavenPack to identify news days and non-news days. We find that immediately following the release of portfolio-

[5]In Section 4.2.1, we show that turnover from our daily rebalancing strategy is only 1.65 times higher than the annual rebalancing strategy so it is unlikely that transaction costs would negate all of the benefit from this strategy.

[6]A number of papers have documented evidence that asset returns are significantly larger around information releases. See, for example, Lucca and Moench (2015), Savor and Wilson (2014, 2016), Ben-Rephael et al. (2017), Engelberg et al. (2018), and Cieslak et al. (2018).

specific information, news days have no higher return than non-news days. Put differently, it is not news, per se, that drives anomaly returns, but news containing information specific to the anomaly.

We also place our findings in the context of investors using hedge fund performance as a gauge of economic significance. Specifically, we generate a new portfolio, the Fast-Minus-Slow portfolio (hereafter FMS), which is equivalent to buying the daily rebalanced portfolio and selling the annually rebalanced portfolio. Then, taking a database of hedge fund returns, we measure the covariation between fund returns and the FMS return as a measure of how quickly funds react to new information. We find that funds that react faster to information earn higher returns on average. Specifically, a one standard deviation increase in fund speed is associated with a 40 basis point increase in future annual abnormal returns. These findings are consistent with our prior results suggesting that anomalies are real and that speed is key to capturing the abnormal returns.

Our results show strong anomaly returns following the release of information. While some recent papers argue that anomaly returns are spurious, our results suggest anomalies are real. To further differentiate between the two explanations, we turn to the notion of arbitrage risk. If anomalies are real, then the magnitude of anomaly returns could be related to arbitrage risk, whereas if the results are spurious, there is no reason to expect such a relation. Accordingly, we construct a measure of arbitrage risk as in Wurgler and Zhuravskaya (2002), and find that anomaly returns are indeed higher when arbitrage risk is high. Furthermore, we find that the rate of information incorporation is faster when arbitrage risk is low, again indicating arbitrage risk contributes to the slow incorporation of information. The results suggest anomalies are real.

In additional analyses, we consider partitions of the sample based on size using NYSE breakpoints (i.e., large, small, and micro stocks based on Fama and French (2012)). The results suggest that the gains to a daily rebalancing strategy are present across large, small, and micro stocks. Specifically, the difference in predictable returns for the daily versus annual rebalancing strategy is 6.18% for the subsample of large stocks. Small and micro stocks evidence a positive difference of 2.28% and 8.91%, respectively, where the difference for micro stocks is statistically significant. We also examine the anomaly returns in event time broken out by size groups. In these analyses, the event-time returns for large, small, and micro stocks demonstrate strong, positive abnormal returns earned in the first 30 days after the information release, with returns diminishing over time. Similarly, we look at these results on a value-weighted basis, and, although somewhat weaker, our conclusions still hold. In sum, all of our findings point to the same conclusion: Anomalies are real.

Our study contributes to the literature by demonstrating that anomalies are still profitable once timing is considered. In other words, by examining *when*, we learn something about *why*. We employ a powerful but relatively unknown database, Snapshot, to pinpoint the timing of information releases and examine how that timing relates to anomaly returns. We have four main sets of results. First, we find that most anomalies have statistically and economically profitable returns in the first 30 days after the information release. Second, using a calendar-time portfolio approach, we find that daily rebalancing leads to a dramatic increases in anomaly returns relative to the traditional approach of annual rebalancing. Third, we find anomaly returns on non-news days are at least as strong as returns on news days immediately following rebalancing. Finally, we extend our findings to the context of hedge funds and show that funds that react faster to information earn higher returns.

Overall, our results provide support for the idea that, as suggested by McLean and Pontiff (2016), returns to anomaly portfolios are the result of trading against real mispricing. Our findings are consistent with under-reaction to portfolio-generating signals, which leads to predictable subsequent returns, even after accounting for other news releases. In summary, taking into account the timing of information, as well as the continuous flow of information, we find that anomalies are indeed real, but that they depend heavily on the the reaction speed of arbitrageurs.

2 Background

Over the past four decades, academic research has uncovered hundreds of asset pricing anomalies.[7] More recently, researchers have examined whether these anomalies have a robust presence in the data after accounting for different samples, time periods, and methodological choices. Green et al. (2017) find that most anomalies cannot be replicated over recent time periods, which the authors argue results from diminished arbitrage costs. Similarly, McLean and Pontiff (2016) provide evidence that this decay in predictability is associated with post-publication arbitrage, consistent with the idea that academic research inspires trading that eliminates anomaly returns. Hou et al. (2017) find that most anomalies cannot be replicated when micro-cap stocks are excluded from the sample. Using recursive out-of-sample methods to examine whether anomalies generate returns using only ex-ante information, Cooper et al. (2005) note that most academic research suffers from a hindsight bias. They find that existing academic evidence likely overstates the performance of anomaly variables and a real-time strategy would have performed relatively poorly.

While the results discussed above call into question the validity and existence of anomaly results, in general there is evidence that some anomaly strategies are valid. For example, Green et al. (2017) find that twelve different firm characteristics reliably predict abnormal returns over their sample. Lu et al. (2017) examine nine anomalies from the academic literature and find consistent abnormal returns across six different countries, suggesting these anomalies are truly present in the data. Finally, Han et al. (2018) find that a dynamic anomaly strategy that rebalances monthly using the recent performance of each stock as a conditioning variable produces significant abnormal returns. In a sense, their strategy combines individual anomalies with a momentum-type strategy in order to supercharge portfolio returns.

In light of these findings, another literature endeavors to understand the economic source of anomaly returns. Several possible explanations have been posited in the literature, in-

[7] Hou et al. (2017) report 447 variables related to anomaly returns.

cluding (i) delayed information processing and/or limited attention, (ii) limits to arbitrage, (iii) exposure to systematic risk, and (iv) time-varying risk aversion. Of course, these explanations are not exhaustive, nor are they mutually exclusive. To distinguish among these various explanations, several recent papers have examined whether anomaly strategies, as a group, have a common component that can provide information about the underlying causes of abnormal returns. For example, Tetlock (2011) finds that investors react to previously released news, suggesting that investors may not process information correctly. Lochstoer and Tetlock (2018) examine five well-known anomalies and build on the present value decomposition of Campbell and Shiller (1988) to examine the sources anomaly returns. They find that cash flow shocks drive much of the variation in anomaly returns. Lu et al. (2017) examine anomalies across six different countries and find that the returns to anomalies are stronger when idiosyncratic volatility is high, consistent with the idea that anomalies represent mispricing due to arbitrage risk. More recently, Kelly et al. (2017) use an instrumental principal components analysis to identify exposures to latent factors that may drive anomaly returns. They argue that much of the variation in returns is due to exposure to risk.

In addition, a number of papers have found that return patterns appear to be related to information releases. Lucca and Moench (2015) and Savor and Wilson (2014; 2016) examine the returns to anomaly strategies on days with news releases relative to days without news releases. They find that returns to anomalies are highest on news days, suggesting that anomaly returns are at least partly driven by biased expectations about information.

In summary, the related literature takes a number of different approaches relating to anomaly returns. Arguably, the papers could be categorized into two groups: some papers argue anomaly returns are spurious, while some papers argue anomaly returns are real. Our goal is to understand the existence of anomaly returns through the lens of timing.

3 Data and Methodology

3.1 Data

Underlying all of our tests is the notion that anomaly returns are tied to the release of an information signal that leads to a long-short portfolio assignment. Thus, it is imperative that we identify the specific date on which these information signals are first publicly released. These signals arise primarily from two sources, earnings announcements and the filing of financial statements with the SEC, with the former typically preceding the latter. Even though anomaly signals come from this small set of accounting releases, there is considerable heterogeneity around the ability to form rankings: both across anomalies and within the time series of a given anomaly, the timing of information releases can vary substantially.

Fortunately, the Compustat Snapshot database allows us to address this issue by consistently providing the precise timing of each signal. The Snapshot database "creates a historical investment environment by showing the information that was available at that time in history."[8] For each financial statement variable, Snapshot identifies the first date on which each variable was reported. For example, if an earnings announcement on March 1st provided only total revenue and net income, Snapshot updates these two variables on March 1st, and no other variables are updated. If the rest of the line items from the income statement and balance sheet are released with the firm's 10-K filing on March 25th, Snapshot recognizes that all other variables are updated on this date. As a counterexample, if the earnings release on March 1st contained a full, detailed income statement and balance sheet, the variables from these statements would all be recognized by Snapshot as being updated on March 1st. Thus, by employing the Snapshot database, we identify the precise date on which each variable in the calculation of an anomaly is first made publicly available.

Snapshot indicates that from 1997 through 2017, 53% of earnings announcements include the amount of total assets, implying that the 10-K filing (which by mandate, includes

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

a full balance sheet) contains the total assets for the other 47%. Firms average 23 days between their annual earnings announcement and their 10-K filing, which means that portfolio assignment and abnormal returns to an asset growth strategy could contain substantial measurement error if the wrong portfolio assignment date is chosen. Moreover, the potential for measurement error in portfolio assignment has evolved substantially over time. First, beginning around 2008, firms increasingly include total assets as part of the complete balance sheet 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 report has decreased over time (Arif et al. (2018)). Taken together, these facts imply that it would often be inaccurate to assume total assets (and likely many other anomaly signals) were first reported in a 10-K report; similarly, forming portfolios only in June would likely introduce substantial delays into the portfolio formation signal.

We combine the Snapshot data with information from the Center for Research in Security Prices (CRSP), Compustat, Ravenpack, and the Morningstar CISDM database. We use CRSP to get stock returns[9] and Compustat for firm-level financial statement data. We use Ravenpack for news release data for each firm and date (see Section 4.3). We use the Morningstar CISDM database to measure hedge fund performance. We focus on approximately 2,500 funds operating from 1998 through 2017. We limit our sample to funds denominated in U.S. Dollars and with strategy types that reflect trading U.S. equities (see Section 4.5).[10]

3.2 Anomaly Calculation

We choose a setting in which we can clearly measure the timing of returns in relation to information releases. Our starting point is the set of 93 anomalies covered by McLean and Pontiff

[9]We include stocks with CRSP share codes of 10 or 11 and we drop stocks with a stock price less than $5.

[10]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.

(2016). However, the constantly changing nature of some underlying data (primarily price- or market-based data) used to generate the core measurements for the majority of these anomalies makes it difficult to establish a clean experimental setting to test our anomaly timing hypotheses.[11] As a result, we confine ourselves to those anomalies on McLean and Pontiff's (2016) list that have clear information release dates, including: accruals, (Sloan (1996)), asset growth (Cooper et al. (2008)), gross profitability (Novy-Marx (2013)), growth in inventory (Thomas and Zhang (2002)), net working capital (Soliman (2008)), operating leverage (Novy-Marx (2010)), profit margin Soliman (2008)), return on equity (Haugen and Baker (1996)), and sustainable growth (Lockwood and Prombutr (2010)). All of these anomalies have underlying calculations that change at distinct and observable points in time.

Each anomaly variable is calculated following the same basic steps. First, a calculation is made using data as of a certain date, the information release date, as indicated by Snapshot. Second, each stock is ranked according to the calculation of its anomaly variable (e.g., for asset growth we calculate the annual percentage change in total assets). Finally, portfolios are formed using these relative rankings. A stock enters the long or short leg of an anomaly portfolio based on its ranking as of the information release date.

The long and short portfolios in all of these anomalies are based on relative rankings. For example, in Cooper et al. (2008), the long portfolio is formed by selecting the bottom 10% of stocks based on their asset growth ratio. Since these rankings are relative, if one stock's asset growth ratio changes, it 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 during the usual reporting season. If these stocks' returns are driving our main results, then it will be difficult to interpret our findings and difficult for a trader to implement. To address this potential issue, in some of our tests, we calculate portfolios following a rule that stocks cannot jump in and out of the portfolio

[11] For example, the first anomaly examined in McLean and Pontiff (2016), the earnings-to-price ratio (Basu (1977)), requires two data points for each stock: earnings and price. While earnings has a clear information release date, prices are constantly changing, making it difficult to define an information release date for the earnings-to-price anomaly.

based on the release of future information on other stocks. Instead, stocks that enter the portfolio remain for 240 days or until their next annual filing. We also compute returns for a *super* portfolio, which is generated as an equally-weighted combination of the nine anomalies listed above. In other words, the super portfolio is an equally-weighted portfolio of the nine anomaly portfolios.

Many of the original papers describing anomalies rebalance portfolios annually. We follow the annual rebalancing approach in our replication of each anomaly. Asset growth is used here as an example. At the end of June, the value of total assets from the most recent annual report is used to calculate asset growth. Each stock in the sample has a measure of asset growth on the last day of June. That value is then used to rank the sample on that date, and the stock is included in the portfolio starting the next trading day (so there is no look ahead bias). A stock in the bottom decile will be in the long leg of the anomaly portfolio and the stock will remain in the portfolio for one year.[12]

We then examine a continuous version of the anomaly portfolio, using data and rankings in real time as soon as they come available. We again use asset growth to illustrate. Assume that the information release date for firm ABC is March 15th. Thus, firm ABC has an updated asset growth value on this date. On the following day, the asset growth variable is calculated for this firm and the entire sample of firms is ranked by asset growth. If stock ABC warrants inclusion in either the long or short leg of the portfolio by being in an extreme decile, then stock ABC is bought or sold at the beginning of the next day. Further, suppose that stock XYZ was in the long leg of the portfolio prior to March 15th. Suppose now that stock ABC should be included in the long leg and stock XYZ should be excluded. In this continuous approach, stock XYZ drops out of the portfolio at the end of trading on March 16th.

Each stock in the sample has daily abnormal returns calculated from the three-factor model (Fama and French (1993)). The abnormal return is calculated using one year's worth

[12]Detailed information about the calculation of the other anomaly variables used in this study (including a reference to the original paper) are outlined in Table A2 of the appendix.

of past daily returns to derive factor loadings, and we use these loadings to estimate future abnormal returns.[13]

4 Results

Table 1 provides summary statistics for the sample. Our sample includes over 8,000 stocks over the 20 year period from 1997 through 2017. Panel A displays firm-level characteristics, while Panel B displays provides summary statistics for each of the nine anomalies discussed previously.

4.1 Anomaly Returns in Event Time

Our first set of analyses examine the returns to anomaly portfolios in event time, for which the event date is the annual information release date for each anomaly variable and for each stock in the sample. In this approach, a given stock's assignment to the long or short legs of an anomaly portfolio is determined by when Snapshot indicates that the information signal pertaining to the anomaly (e.g., total assets for the asset growth anomaly) is made publicly available, as discussed above in Section 3. To assess statistical significance, we calculate standard errors clustered by firm using each stock's event-time compound returns.

Table 2 reports the results, which provide strong evidence for positive abnormal returns following information release dates. Column 1 shows the return earned through the first 30 days after the information release date, Columns 2 and 3 repeat the exercise through the first 120 and 240 days, respectively. Columns 1 through 3 generally show statistically significant positive returns for the nine anomalies and for the super portfolio. Specifically, the super portfolio generates a positive return of 0.98% for the first 30 days subsequent to the portfolio formation date, and earns 2.13% through 120 days and 1.97% through 240 days after portfolio formation dates–nearly half of the 240-day return to the super portfolio is generated in the

[13] Our results are robust to alternate models of abnormal returns.

first 30-day period following portfolio generation. The implication of these findings is that anomaly returns are largely earned in the first month after the portfolio-generating signal becomes public and diminish substantially thereafter.

Columns 4 through 6 show the annualized returns earned within the first 30 days, the next 90 days (days 31-120), and the subsequent 120 days (days 121-240). For example, Column 4 shows that the super portfolio earns an annualized return in the first 30 days of 7.87%, which is more than twice the return of 3.31% earned from day 31 through day 120 by the super portfolio. This difference indicates that the majority of anomaly returns are earned soon after information releases. Similarly, Column 6 shows that the super portfolio do not generate abnormal returns from days 121 - 140. In other words, in the first half of the year following information releases, the super anomaly portfolio earns large and predictably positive returns but after 121 days, the super anomaly portfolio no longer exhibits return predictability. Figures 1 and 2 show this result visually–the return path is steep and rising in the first half of the year following portfolio generation, but it effectively levels off thereafter. The figures are consistent with the notion that as information becomes stale, anomaly portfolios no longer yield positive returns. Overall, the results suggest that anomaly returns are real, but they are concentrated in the window immediately following information release dates.

4.1.1 Trends in Anomaly Timing

We next perform two additional analyses to provide insights on anomaly timing: (1) we examine more refined time windows and (2) we examine for time trends in the pattern of return concentration following information releases over our sample period. Table 3 details anomaly returns earned the first day, the first week, and the first month after information releases. Further, we examine subsamples split on the first half versus the second half of our overall sample period (1998-2007 vs. 2008-2016), which allows us to evaluate whether event-time anomaly returns have changed over time. We find that they have.

Table 3 suggests that anomaly returns earned in the first month have dropped slightly over time: the 30-day return is generally larger in our earlier sub-sample. Specifically, after 30 days the super portfolio earned 1.08% in the early period, but only earned 0.72% in the later period. Most notable from Table 3, however, is *when* the anomaly returns are earned. Columns 4 and 5 (early sub-sample) and 9 and 10 (late sub-sample) show the percent of the total 30-day return that is earned in the first 1 and 5 days, respectively, after information is released. In the first half of the sample period, the super portfolio earned about 3% of the total 30-day return in the first day and about 11% in the first five days. By contrast, in the latter half of the sample period the super portfolio earned almost 10% of the 30-day return in the first day and 32% in the first five days. This finding suggests that the returns to trading quickly on information have trended upwards over time.

4.2 Calendar-Time Returns: Annual vs. Daily Rebalancing

In this section, we examine the economic significance of our findings by comparing the returns for an implementable version of our event-time strategy to those of a traditional strategy that uses annual rebalancing. Specifically, we form an implementable, calendar-time version of our event-time approach using continuously-adjusting anomaly portfolios designed to incorporate new information as it arrives to the market. We allow portfolios to change daily as new information is released; there is a chance that the portfolio will be rebalanced on any day on which Snapshot indicates that a portfolio-generating signal is released for any stock in the sample. Importantly, this strategy is implementable in that we are now examining returns in calendar time instead of event time, as in the previous section. Moreover, this approach does not contain a look-ahead bias: at each point in time we only condition on information that was publicly available.[14]

[14]More specifically, if information about a stock arrives today, that stock will be rebalanced in the portfolio starting tomorrow, such that the strategy does not suffer from a look-ahead bias.

Table 4 shows the results from the daily rebalancing approach compared with the annual approach.[15] The results consistently show that daily rebalancing outperforms annual rebalancing across the nine anomalies and for the super portfolio. For example, consider the inventory growth anomaly, which shows an annualized return from annual rebalancing of -3.22% (Column 1), whereas daily rebalancing yields an annualized return of 3.26% (Column 2), resulting in a statistically and economically significant difference between the two approaches of 6.48% (Column 3). Looking down Column 3, we see only positive differences, indicating that daily rebalancing outperforms annual rebalancing across all nine anomalies, with a substantial 6.92% difference for the super portfolio. The most dramatic difference is in the asset growth anomaly, where the daily rebalancing approach earns a return that is 11.05% greater than annually rebalancing.

Columns 5 through 13 consider the results broken out by time period. For the super portfolio, we find increasing return differences between the annual rebalancing and daily rebalancing approaches as we shift the time period away from the dates when information is released. Recall that the annual rebalancing occurs at the end of June, which is within a few months of when most firms release anomaly information. This is when we would expect the annual rebalancing approach to most accurately reflect information, and as a result, the returns to daily rebalancing are the smallest. As we move away from the information release dates and the information grows more stale, the returns to daily rebalancing should improve relative to the returns from annual rebalancing. The results confirm this. Specifically, daily rebalancing of the super portfolio yields a 0.11% return improvement over annual rebalancing in the 30-day window (Column 6) and a larger improvement of 0.89% in the 120-day window (Column 9). However, by far the most dramatic result is the 240-day return window, in which annual rebalancing yields 1.67% (Column 10) and daily rebalancing yields 8.52% (Column 11), a difference of 6.84% (Column 12). The fact that the largest difference between the two approaches comes during the first half of the calendar year is indicative

[15]More detailed results specific to annual rebalancing are presented in Table A3 of the Appendix.

of the calendar-time approach's inability to take into account new information, while the daily-rebalancing approach quickly reflects new information.[16] Specifically, it is between the 120-day and 240-day windows where the vast majority of firms release their annual earnings and financial reports, which can alter portfolio assignment. Column 12 indicates that conditioning portfolio holdings on the information in these reports leads to significantly superior returns.

Figures 3 and 4 show the difference between annual rebalancing and daily rebalancing in the time series for each anomaly in our set. As suggested by Table 4, we see that daily rebalancing consistently outperforms annual rebalancing. The super portfolio shows daily rebalancing returns dominating those of annual rebalancing over our sample period.

Table 5 provides a closer examination of time period effects when large amounts of accounting information arrive to the market. In particular, we rely on the idea that information arrives in bunches (e.g., earnings season).[17] Importantly, earnings season tends to occur between days 120 and 240 of an annual rebalancing strategy–during these days, a daily rebalancing strategy should strongly outperform an annual strategy. We find that it does.

Table 5 shows the incremental return earned during the first 30 days of portfolio formation, from 30 to 120 days after formation, and from 120 to 240 days after formation.[18] Table 5 shows that the returns earned in the first 30 days and from 30 to 120 days are fairly consistent across the two portfolio approaches, with daily rebalancing showing a slight improvement over annual rebalancing in these windows. The super portfolio differences are respectively only 1.76% and 1.73% annualized. However, if we consider the period from 120 to 240 days after rebalancing, we see a dramatic difference. Column 7 shows the annualized return over that period for the annual rebalancing strategy while Column 8 shows the annu-

[16] In unreported results, we conduct the same analysis dividing stocks into two subsets based on whether they have Dec. 31st fiscal year ends or a different fiscal year end. The results are qualitatively similar to Table 4; the daily-rebalancing approach is especially profitable around the time when firms release their annual financial statements

[17] For example, Hirshleifer et al. (2009) demonstrate the effects of the clustering of earnings announcements that tend to occur during earnings season.

[18] "30 days after portfolio formation" means the first 30 days after June 30th for both annual and daily rebalanced portfolios, even though the daily rebalancing portfolio is rebalanced every day.

alized return over that period for the daily rebalancing strategy. The differences in Column 9 are generally large and positive, with the largest differences coming from asset growth and sustainable growth. Overall, we see that the super portfolio's daily rebalancing approach outperforms annual rebalancing with an annualized return difference of 10.64% during that first half of the calendar year. This is further evidence that predictable returns to these anomalies are strongly related to the elapsed time between the information release and the date of portfolio formation.[19]

4.2.1 Portfolio Turnover

While the daily rebalanced portfolio is technically implementable, one concern is that it may be practically infeasible due to transactions costs associated with portfolio turnover. However, in untabulated results, we find that portfolio turnover is not dramatically different for the daily rebalancing strategy. Across the nine anomalies we consider, portfolio turnover is only 1.65 times higher than the annually rebalanced strategy. On average, 87% of the annually rebalanced portfolio is turned over on the rebalancing date. For the daily rebalanced portfolio, turnover is 146%, with over half of the transactions occurring during the first quarter of the calendar year. In terms of additions to the portfolios, the annually rebalanced portfolio averages 198 additions at the rebalancing date, while the daily rebalanced portfolio averages 327 additions over the span of a year. Given these figures, the daily rebalanced portfolio is able to enhance returns by quickly updating portfolios without suffering a large increase in portfolio turnover. The results suggest that anomaly returns are not simply a result of transaction costs that render rebalancing infeasible.

4.3 News and Anomaly Returns

So far, our results show strong evidence that incorporating newly-released information about portfolio assignment is crucial to earning anomaly returns. At first glance, these findings

[19]Table A4 and Table A5 in the Appendix display results using value-weighted anomaly portfolios; all of our conclusions remain unchanged.

may seem similar to Engelberg et al. (2018), who show that anomaly returns tend to be higher on news release dates. Importantly, we show that our results are distinct from these findings. To do this, we focus on a key distinction: some news drives portfolio assignment, other news does not. In this setting, we take full advantage of our two approaches, event time vs. calendar time, to identify news that is directly relevant for portfolio assignment and news that is not. We find that information about portfolio assignment leads to higher anomaly returns, but corporate news *in general* does not.

In the spirit of Engelberg et al. (2018), we implement a regression approach to test whether, after considering the impact of information that affects portfolio assignment, news days have different returns than non-news days. We split returns into "news days" (i.e., days in which a stock has at least one news article in the Dow Jones Newswire or the Wall Street Journal, as per RavenPack) and "non-news days" (i.e., all other days). Specifically, we examine OLS panel regression models of the form:

$$\begin{aligned} Return_{it} = \alpha &+ \delta_1 NewsDay_{it} + \delta_2 WithinXDays_{it} \\ &+ \delta_3 WithinXDays_{it} \times NewsDay_{it} + \epsilon_{it}, \end{aligned} \tag{1}$$

where $Return_{it}$ is the daily abnormal return, in percent, on stock i in the anomaly portfolio on day t. $NewsDay$ is an indicator variable that takes the value one when stock i has corporate news on date t, and zero otherwise. $WithinXDays$ is an indicator for whether the return for stock i on a given day is within an X day period following an information release, where X is either 30, 60, 90, or 120 days. The sample includes all stocks in the super portfolio and we include year fixed effects in all models to account for time-varying aggregate heterogeneity.

Table 6 reports the regression estimates with standard errors, clustered by stock, shown below the estimates in parentheses. Of primary interest are the parameter estimates for $WithinXDays$ and the interactive effect of $WithinXDays \times NewsDay$. Given the results presented thus far, we expect the estimate for $WithinXDays$ to be positive and significant, indicating that anomalies earn higher returns soon after an information release that is related to portfolio assignment. Indeed, Table 6 provides strong support for our previous finding that anomaly returns are earned early in event time. The joint effect of $NewsDay$ and $WithinXDays \times NewsDay$ ($\delta_1 + \delta_3$) demonstrates whether news-days earn higher returns than non-news days within the early period. The results show that while news days overall earn higher returns than non-news days ($\delta_1 > 0$), returns to news days are not significantly different than returns to non-news days in the first 30 days.

In additional analyses, we consider the effects of news days when taken in the context of the event-time and calendar-time approaches presented in Sections 4.1 and 4.2. First, we take an event-time approach, similar to the methodology described in Section 4.1, and we split returns into days with news and days without news. To select anomaly returns for news days, we use the following approach: if a stock receives news coverage on a given day, that stock's return is included in the news day anomaly return and in the super portfolio return on that day. If a stock is not covered in the news on a given day, that stock contributes a zero return to the news days anomaly return and zero to the super portfolio return on that day. To be clear, this approach is not implementable, but is the analog of an investor who is able to know which stocks will have news on the following day and which stocks will not. If the stock is covered in the news, the investor holds the stock, but if not, the investor instead holds cash.

The results are reported in Table A6 of the Appendix and indicate that in the first 30 days after an information release, news days and non-news days both provide statistically significant and positive returns. In fact, we find that for the super portfolio, non-news days actually outperform news days in this window. Specifically, the average abnormal return is 0.60% on non-news days while only 0.40% on news days. The difference between news days and non-news days over the first 30 days is 0.21% and is statistically significant. We also find that news days become more and more important as the window is lengthened. Column

2 indicates that 120 days after an information release, there is a smaller and less significant difference between abnormal returns to news days and non-news days. We also find that news days outperform non-news days in the latter part of the event window. Specifically, Column 6 shows that between days 121 and 240, news days are significantly more important for driving returns than non-news days. Similarly, Figure 5 depicts the relative contributions of news days and non-news days to the return of the super portfolio in event time.

Finally, we return to the implementable calendar-time approach (described in Section 4.2) and again split returns into days with news and days without news. The results are reported in Table 7. Our baseline is Column 2, which shows returns earned by the daily rebalancing portfolio, regardless of news days. Columns 3 and 4 then present results from decomposing returns into news days and non-news days. The baseline approach shows that, after taking all days into account, the equally-weighted super portfolio yields an annualized daily return of 7.28% on average. Of this return, Column 3 shows that 3.97% comes from news days. This is similar to, but larger than, the portion of the return that comes from non-news days. The fact that the return is larger on news days is consistent with results presented in Engelberg et al. (2018). Indeed, we find that news is very important for driving anomaly returns. Additionally, it is worth pointing out that our research setting is significantly different from Engelberg et al. (2018) in that we are not analyzing stock returns as much as we are focused on portfolio returns. Further, we necessarily have a smaller subset of the anomalies in this paper. However, for our purposes, the key point from Table 7 is that in this calendar-time approach, we are including both news that drives portfolio assignment as well as corporate news in general. Our results show that news, in general, cannot explain our results; instead, after controlling for the release of corporate news, we continue to find predictable returns to speed.

4.4 Arbitrage Risk and Anomaly Returns

Our results so far show strong evidence that anomaly returns are real, yet a number of papers argue that anomaly returns are spurious and/or the result of data mining. To further examine data mining as a potential explanation, we turn to the notion of arbitrage risk. Specifically, if anomalies are real, then anomaly returns could be related to arbitrage risk, whereas if the results are spurious, there is no reason to expect a relation. To this end, we compare the event-time returns of stocks with high and low levels of arbitrage risk.

Following an approach similar to Wurgler and Zhuravskaya (2002), we measure a stock's level of arbitrage risk by measuring the closeness of substitutes for that stock. The intuition is simple. To correct a mispricing an arbitrageur requires a close substitute stock as a hedge in order to construct a long-short pairs trade. Our arbitrage risk variable measures the closeness of each stock's best substitutes by comparing each stock's returns with the returns of potential substitutes.

Specifically, each stock's arbitrage risk is measured as follows: First, we use the Fama and French (1997) 48 industry classification to identify a set of possible substitutes. We then select 20 stocks within the same industry and with the closest market capitalization, and we also select 20 stocks within the same industry and with the closest book-to-market value. Then, using this list of up to 40 potential substitutes, the best substitute stocks are found using the following regression model using one year of daily return data:

$$(R_{it} - R_{ft}) = \beta(R_{mt} - R_{ft}) + \delta(R_{jt} - R_{ft}) + \epsilon_{it}, \tag{2}$$

where R_{it} is stock i's return on day t, R_{ft} is the risk-free rate, R_{mt} is the return on the market, and R_{jt} contains the returns of the potential substitutes. A stepwise-selection method is used to select the stocks that provide the best substitute for stock i.[20] Finally, to capture the

[20] Using the stepwise-selection method to find the best substitutes marks an improvement from Wurgler and Zhuravskaya (2002). In our approach, we use regression techniques to identify the best substitutes from a list of up to 40 potential substitutes. In Wurgler and Zhuravskaya (2002), the best substitutes are simply the three closest firms by market capitalization and book-to-market. The stepwise-selection method

distance from a stock to its substitutes, the residual variance from this regression is defined as stock i's arbitrage risk. In other words, the greater the residual variance, the less stock j serves as a close substitute for stock i and therefore, the higher the risk for an arbitrageur.

To compare the anomaly returns between stocks with low and high levels of arbitrage risk, we follow the same process as in Section 4.1, with one exception, the super anomaly portfolio is divided into three sub-portfolios according to arbitrage risk. Stocks in tercile 1 have the lowest arbitrage risk, while stocks in tercile 3 have the highest arbitrage risk.

If anomaly returns are spurious, we expect to find no relation between anomaly return magnitude and arbitrage risk. Yet, we find strong evidence of a relation. Table 8 shows that stocks with low levels of arbitrage risk earn lower anomaly returns overall, and a large portion of the return is earned in the first 30 days following information releases. Specifically, in the first 120 days following an information release, low risk stocks earn a return of 0.72%. Further, three-quarters of that return, or 0.55%, is earned in the first 30 days. By contrast, high risk stocks earn 2.79% in the first 120 days, but less than half of that return, or 1.25%, is earned in the first 30 days. Put differently, low risk stocks earn lower returns, and arbitrageurs are able to correct mispricing more quickly.

These results are consistent with the idea that arbitrage risk is a contributing factor to the slow incorporation of information; the results are inconsistent with the idea that anomaly returns are spurious.

4.5 Hedge Fund Speed and Performance

To further examine the relation between anomaly returns and the speed of information incorporation, we construct a portfolio that captures the return difference between our daily rebalancing strategy and an annual rebalancing strategy. We then use that return differential

is a combination of the forward-selection method and the backward-selection method. First, regressors are added one by one to the model based on their level of statistical significance (p-value < 0.20). After a regressor is added, regressors that are no longer significant are removed (remove if p-value > 0.15). The stock returns that are the best substitutes are identified when no other regressors should be added to the model and when none should be removed. We use multiple different p-values controlling entry and exit and results are robust.

to gauge hedge fund speed, and we ask whether hedge fund speed is related to hedge fund performance. We find that it is.

4.5.1 Fast Minus Slow

We start by building a portfolio that captures the difference in returns between annual and daily rebalancing, the "Fast Minus Slow" (FMS) portfolio. This portfolio mimics the experience of a trader who is long the daily rebalancing portfolios and is short the annual rebalancing portfolios. This portfolio approach is meant to capture the differential return earned by the fast portfolios over the slow portfolios. Put another way, the FMS portfolio has positive exposure to the daily updating anomaly portfolios and negative exposure to the annually rebalanced portfolios.

The returns to this portfolio are presented in Table 9. Most of the anomalies exhibit a positive return to the FMS portfolio. In other words, positive exposure to the fast version of the anomaly and negative exposure to the slow version of the anomaly yields strong positive results for most anomalies. Consistent with our previous results, we see that the strongest two FMS returns are to the asset growth anomaly (11.64%) and the sustainable growth anomaly (9.44%). Overall, the FMS portfolio across all nine anomalies exhibits a large and statistically significant annualized return of 7.13%.

4.5.2 Fund Speed and Performance

We then examine whether the returns to speed, as measured by FMS, can explain the performance of hedge funds. We focus on hedge funds with fund types related to U.S. equities and based in U.S. Dollars; we use Morningstar data to measure monthly returns for each fund. For each fund j we calculate hedge fund speed as the slope parameter estimate (β) from the following regression:

$$Return_{jt} = \alpha + \beta_{jt}(FMS_t) + \epsilon_{jt}, \tag{3}$$

where $Return_{jt}$ is the return on hedge fund j at date t and FMS_t is the return on the "Fast Minus Slow" portfolio on each date. This regression allows us to capture any possible changes in a fund's speed, and it opens the possibility of pinning down speed changes within a fund. The regression is run in a rolling fashion for each fund, j. We limit the data in the regression to the previous 36 months. In other words, a fund's speed at month t is the parameter estimate from the above regression using fund and FMS returns from month $t-36$ to month $t-1$. The result is a monthly measure of a fund's speed. Thus, the analysis results in a panel of fund-months where an observation is a fund's speed over the last three years.

To examine the implications of the panel of fund speed measures, we construct a similar panel of fund performance to allow for fund performance to change over time. For a given month we measure a fund's compound abnormal return looking forward 12 months. The result is that each fund-month in the panel has a value for the future one-year abnormal return. We link this monthly measure of fund performance with our historical monthly measure of fund speed. We then examine the relation between fund speed and future 12 month performance using panel regressions of the form:

$$AbnReturn_{j,t+1:t+12} = \gamma_0 + \gamma_1 \beta_{jt} + \epsilon_{j,t+1:t+12}, \tag{4}$$

where *AbnReturn* is the abnormal return on fund j over the next 12 months as measured by the Carhart (1997) four-factor alpha. The results are shown in Table 10.

We examine the relation between fund speed and future performance using a variety of specifications. Across all specifications, the result is the same: a fund's 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. In column 3, with all fixed effects, we see that a one standard deviation increase in speed leads to an annual performance increase of 40 basis points (of abnormal returns). It is worth noting here that the fund fixed effect allows us to examine this relation on a fund-by-fund basis. Indeed, as a given fund increases its speed, we find an increase in future performance. Overall we find robust evidence that fund speed relates to fund performance. In other words, funds that react more quickly to information about anomaly portfolio assignments earn higher returns. The results again suggest that anomalies are real and speed is key to capturing anomaly returns.

4.6 Size Effects

Finally, we examine the relation between firm size and the returns to anomaly strategies. Hou et al. (2017) show that anomaly returns 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 daily rebalancing approaches used in Tables 2 and 4, respectively, except we split the sample into terciles based on firm size. The results are reported in Table 11. Panel A shows that anomaly returns to stocks in each size group display the same general pattern as we found in Table 2. That is, returns are most prominent immediately following the release of information, with returns to anomalies diminishing as information becomes stale, and this result occurs for stocks of all size (large, small, and micro-cap). Panel B supports the primary conclusion from Table 4, that regardless of size, returns to daily rebalancing dominate those of annually rebalancing. The results indicate that our main findings in Tables 2 and 4 are not driven by small or micro-cap stocks.[21] In sum, we find that anomaly returns are real once timing is considered, and the results are robust across a wide variety of methodologies and samples.

[21] In the appendix, we show that all of our main conclusions remain unchanged when we examine value-weighted returns, instead of equal-weighted returns.

5 Conclusion

We examine *when* anomaly returns occur using a powerful database that contains the precise date on which accounting information is first made public. In contrast to recent literature arguing that anomalies are spurious and the result of data mining, we find evidence that anomaly returns are real but they are rapidly arbitraged away. Most of the abnormal returns to anomalies occur in the first 30 days following the release of accounting information, and all of the returns occur within the first 120 days. The results suggest that speed is key to capturing and measuring anomaly returns. Moreover, we find that the returns to speed change over our sample period. In the early years of our sample, one-tenth of our super portfolio's 30-day return is earned in the first five days, whereas in the latter years of the sample, one-third of the portfolio return is earned in that period. In other words, we find that anomaly returns are being arbitraged away more quickly in recent years.

For investors, our findings suggest that speed is crucial to profiting from anomaly information. To test this idea, we form a measure of how quickly hedge funds react to new information, and we find that hedge funds that react faster to information earn higher returns. We also show that our findings are robust to a wide-variety of samples and methodological choices. Overall, our results suggest that anomaly returns are real but speed is the key to capturing and measuring them.

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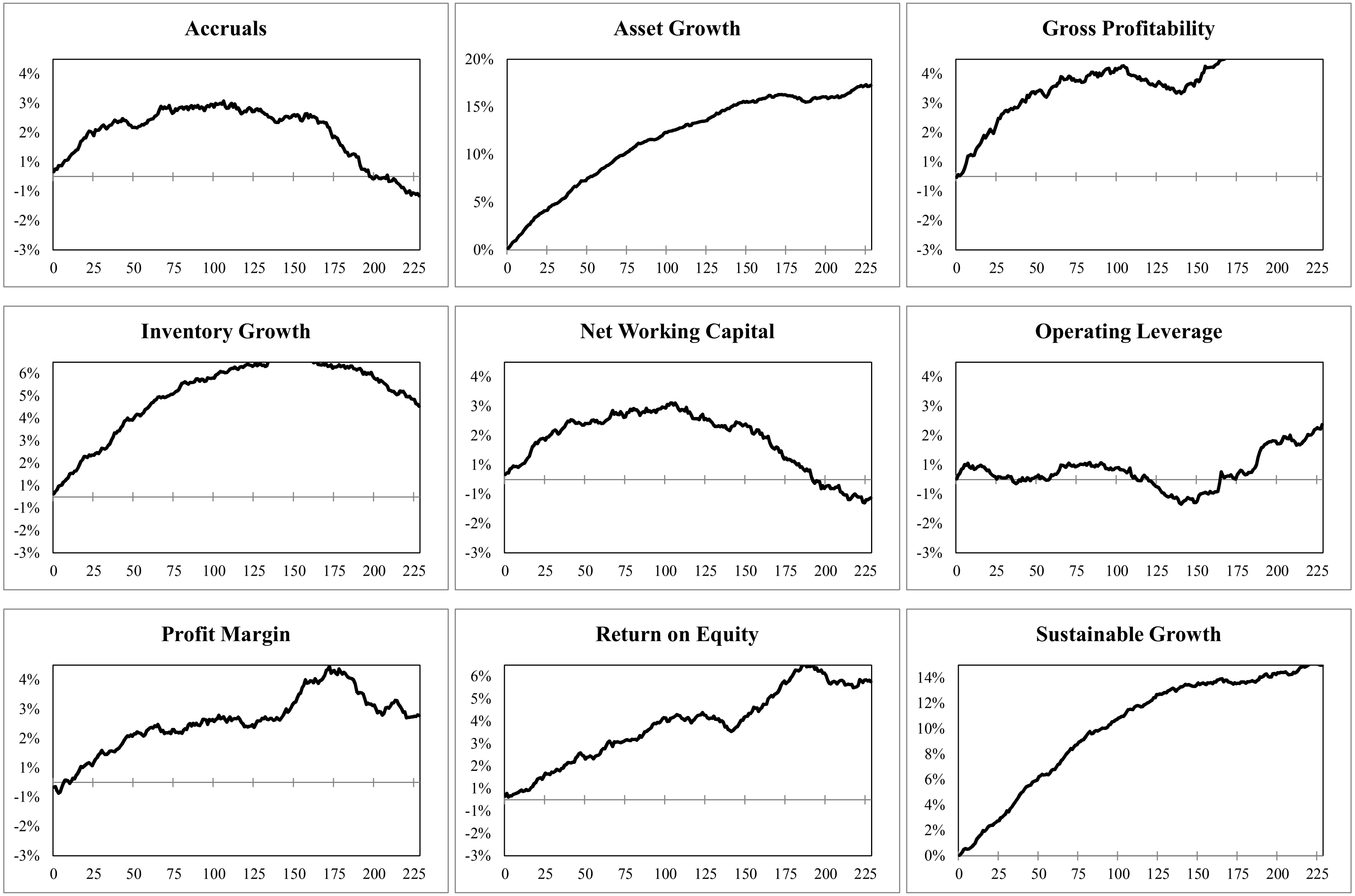

Figure 1: Anomaly Returns in Event Time using Information Release Dates

The figure shows returns in event time for each of the nine anomaly variables. Abnormal returns for each anomaly are lined up in event time; 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 are calculated using the 3-factor model (Fama and French, 1993). The cumulative abnormal return (on the vertical axis) is displayed for 0 to 225 trading days after the event.

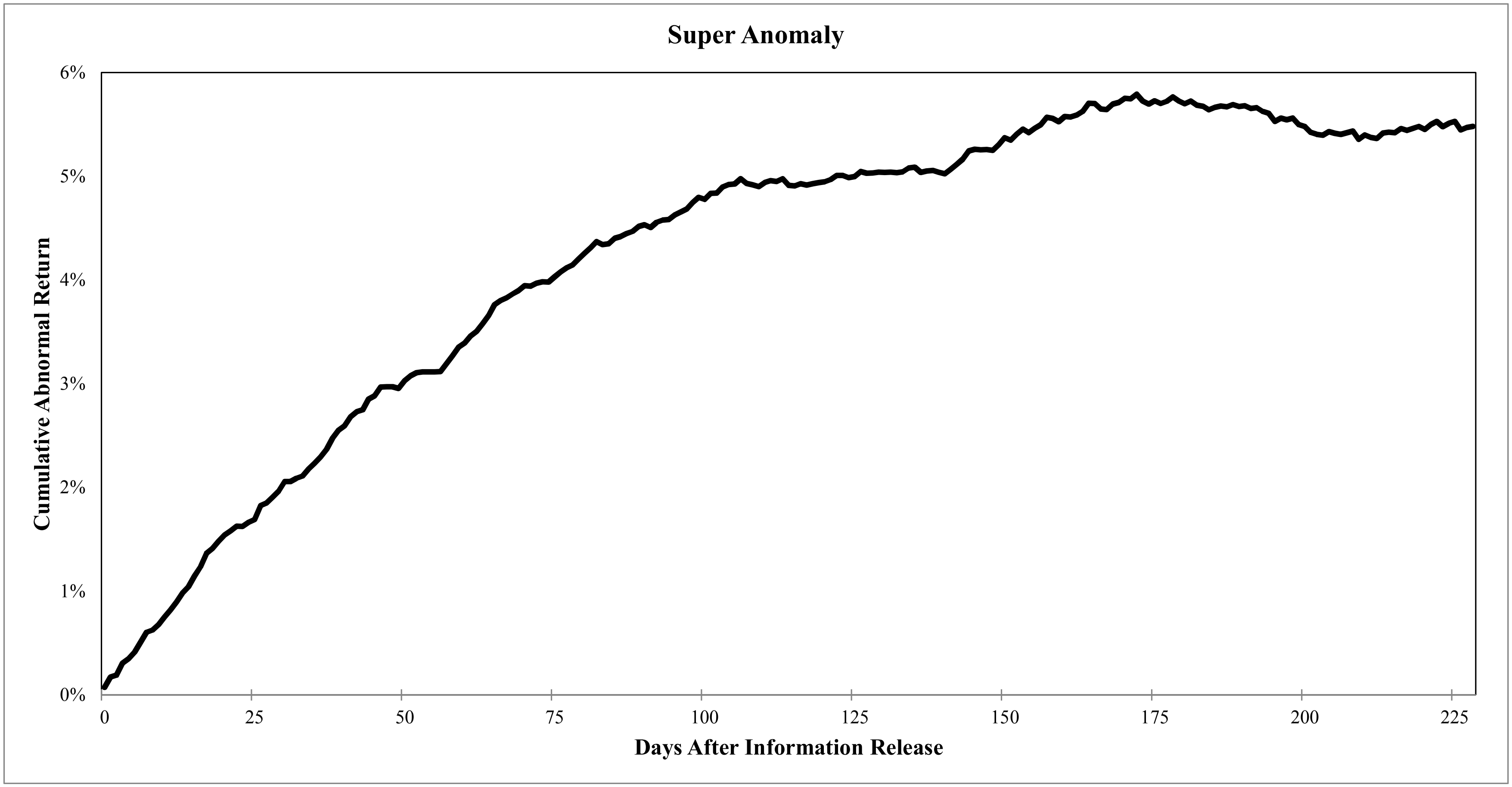

Figure 2: Super Anomaly Portfolio Returns in Event Time using Information Release Dates

The figure shows returns in event time for the super portfolio, which is constructed as the equally-weighted average return across the nine individual anomaly portfolios. Abnormal returns for each anomaly are lined up in event time; 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 are calculated using the 3-factor model (Fama and French, 1993). The cumulative abnormal return (on the vertical axis) is displayed for 0 to 225 trading days after the event.

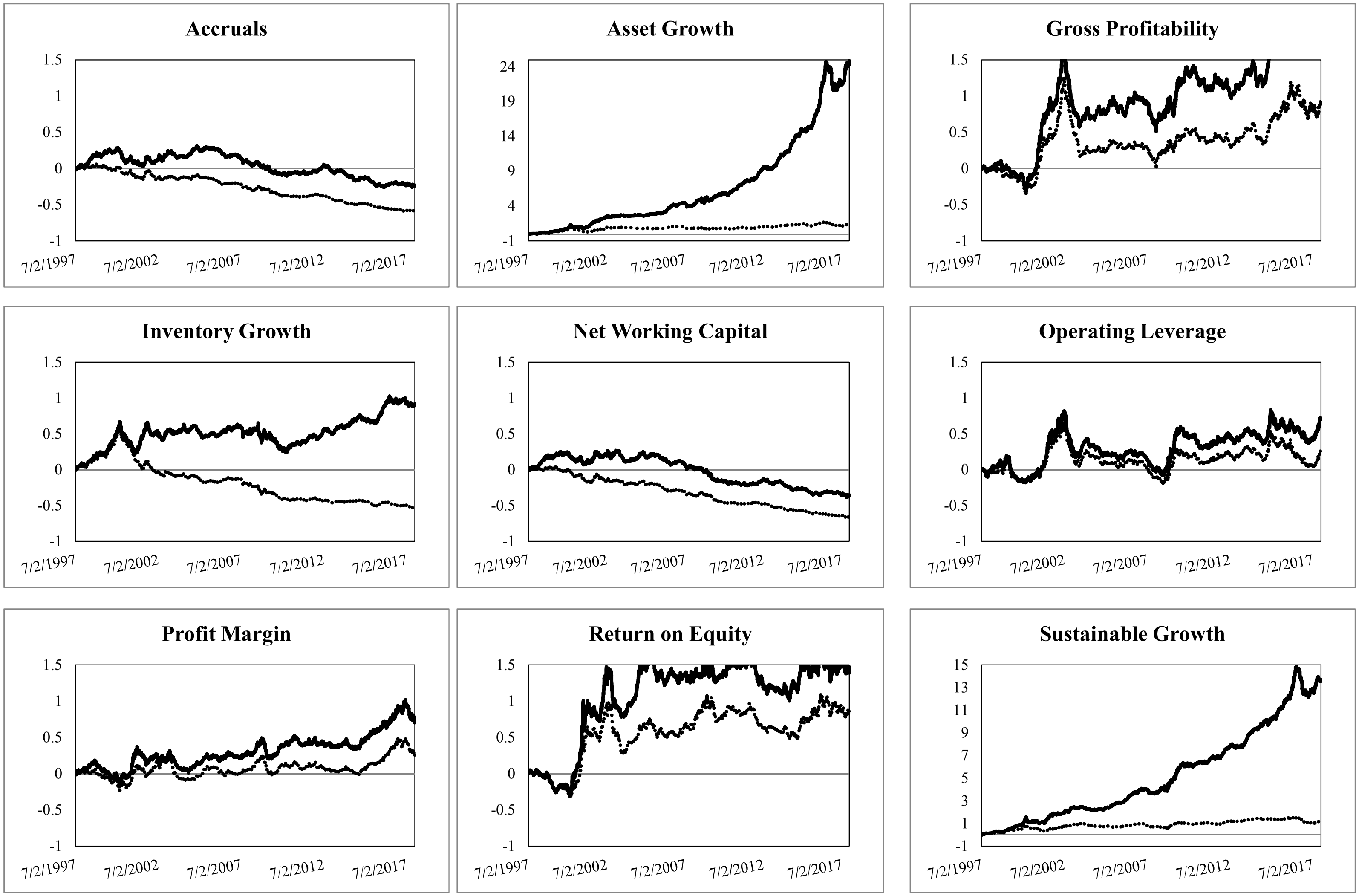

Figure 3: Return Path of Anomalies Using Annual vs. Daily Rebalancing (1997 - 2017)

This figure compares the cumulative abnormal returns (vertical axis) earned by the daily-rebalancing portfolio (solid line) with the annual-rebalancing portfolio (dashed line) for the nine anomalies considered. The daily-rebalancing portfolio is potentially adjusted daily as annual financial information is released. The annual-rebalancing portfolio is adjusted once per year at the end of June.

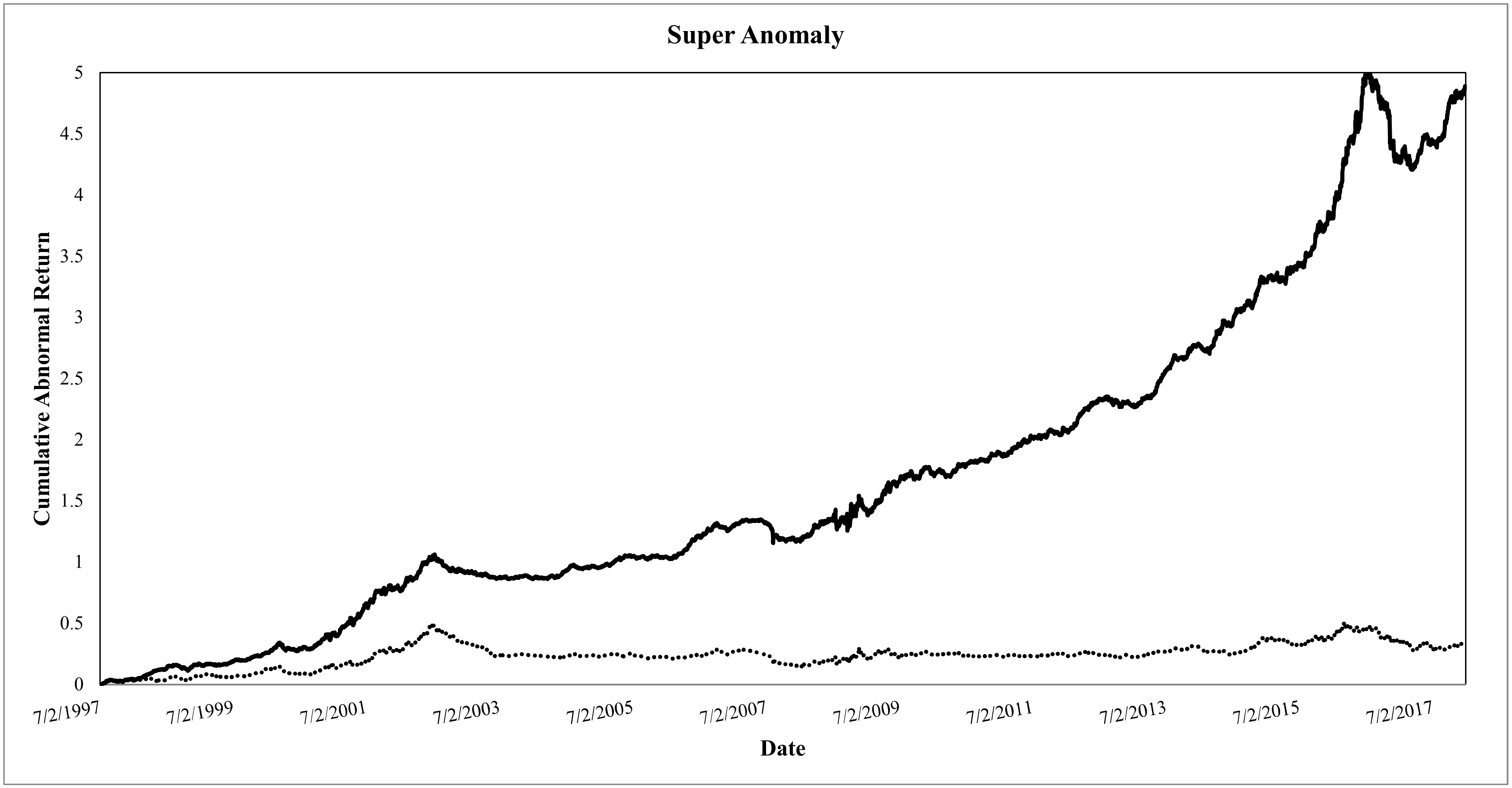

Figure 4: Return Path of Super Anomaly Portfolio Using Annual vs. Daily Rebalancing (1997 - 2017)
This figure compares the cumulative abnormal returns (vertical axis) earned by the daily-rebalancing portfolio with (solid line) the annual-rebalancing portfolio (dashed line) for the super portfolio. The daily-rebalancing portfolio is potentially adjusted daily as annual financial information is released. The annual-rebalancing portfolio is adjusted once per year at the end of June.

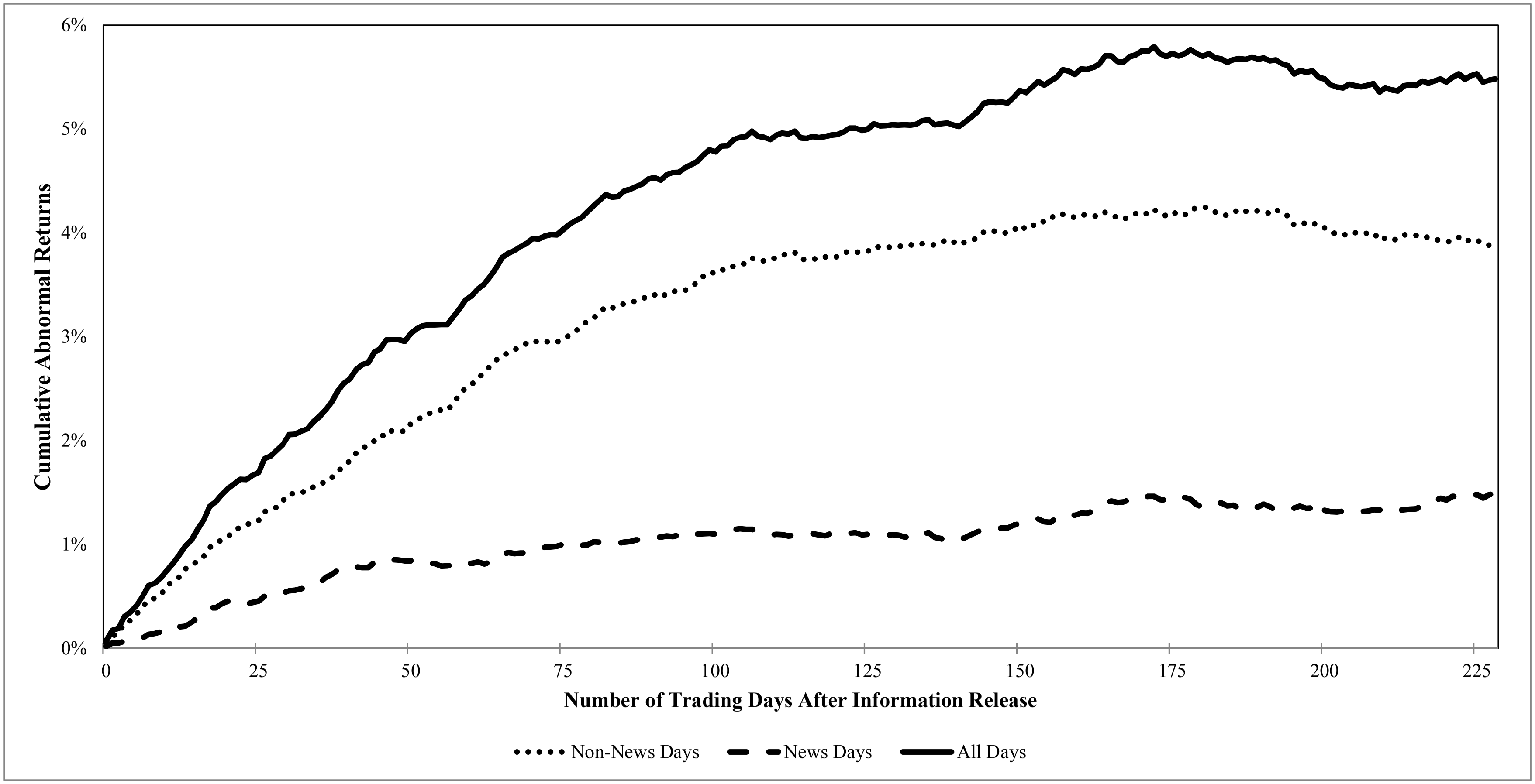

Figure 5: Return Path of Super Anomaly Portfolio in Event Time: News Days vs. Non-News Days

This figure shows cumulative abnormal returns (vertical axis) in event time to the super portfolio for all days, for news days only, and for non-news days only. This figure is produced as follows: for the news days return, if the stocks in the super portfolio experience news on a given day, the return to those stocks is attributed to the super portfolio. If, however, some stocks do not experience news that day, they contribute a return of zero. The same holds for the non-news days return. The news-days return is equivalent to a trading strategy where at the beginning of each day an investor knew which stocks in his portfolio were not going to have news and traded out of his positions on those stocks, earning essentially a zero return on that portion of his portfolio. The non-news days return is the opposite case.

Table 1: Summary Statistics

The table provides summary statistics for the sample which covers the period 1997 through 2017, with approximately 8,350 unique stocks included at some point during the 20-year period. Panel A provides summary statistics for returns and market capitalization across all stocks in our sample. Panel B provides summary statistics for each of the nine anomaly variables we consider. See the Appendix for detailed variable definitions.

	Mean	Median	Standard Deviation	1st Percentile	99th Percentile
Panel A: Firm-level Characteristics					
Daily Returns	5.64 bps	0.00 bps	3.55%	-9.21%	10.46%
Market Cap. (thousands of USD)	2,214,007	300,069	11,253,944	10,661	35,875,402
Panel B: Distribution of Anomaly Variables					
Accruals	0.01	0.01	1.36	-0.21	0.27
Asset Growth	0.22	0.08	1.33	-0.38	2.66
Gross Profitability	0.34	0.31	0.34	-0.43	1.18
Inventory Growth	0.01	0.00	0.05	-0.11	0.21
Net Working Capital	0.01	0.01	1.06	-0.22	0.23
Operating Leverage	1.09	0.91	0.87	0.07	3.99
Profit Margin	-1.59	0.34	132.50	-6.45	0.89
ROE	0.05	0.10	6.16	-1.94	1.21
Sustainable Growth	0.25	0.09	11.63	-1.48	4.21

Table 2: Anomaly Returns in Event Time

The table displays anomaly returns in event time for each of the nine anomaly portfolios, as well as the super anomaly portfolio. 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. Abnormal returns are calculated using the 3-factor model (Fama and French, 1993). The super portfolio is constructed as the equally-weighted average return across the nine individual anomaly portfolios. Column 1 shows the return on an equally-weighted portfolio over the first 30 days (in event time) following the release of financial information used to form the anomaly portfolio, Column 2 shows the return on an equally-weighted portfolio over the first 120 days (in event time), and column 3 shows the return on an equally-weighted portfolio over the first 240 days (in event time). Columns 5 through 6 show annualized returns over sub-sample horizons to examine *when* the returns are earned. For example, column 5 shows the annualized return earned from the 31st day after the information release through the 120th day (and the return is annualized so that columns 4, 5, and 6 are all expressed in the same units). P-values, calculated using standard errors clustered by stock, are shown below the returns in parentheses.

	Compound Returns Earned After Release of Information			Mean Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
	30	120	240	1 - 30	31 - 120	121 - 240
Anomaly	Days	Days	Days	Days	Days	Days
Super	0.98	2.13	1.97	7.87	3.31	0.37
	(.000)	(.000)	(.000)	(.000)	(.000)	(.328)
Accruals	0.79	0.65	-0.55	6.30	-0.60	-2.57
	(.000)	(.085)	(.306)	(.000)	(.496)	(.003)
Asset Growth	2.29	5.56	6.13	18.28	9.53	2.45
	(.000)	(.000)	(.000)	(.000)	(.000)	(.005)
Gross Profitability	1.04	1.60	1.42	8.29	1.86	1.24
	(.000)	(.000)	(.006)	(.000)	(.031)	(.117)
Inventory Growth	1.10	2.78	1.88	8.76	4.47	-1.35
	(.000)	(.000)	(.000)	(.000)	(.000)	(.081)
Net Working Capital	0.76	0.73	-0.10	6.10	-0.10	-2.53
	(.000)	(.048)	(.854)	(.000)	(.910)	(.005)
Operating Leverage	0.05	0.01	0.41	0.43	-0.05	1.59
	(.731)	(.985)	(.415)	(.731)	(.948)	(.049)
Profit Margin	0.36	0.66	0.05	2.89	0.96	0.01
	(.038)	(.066)	(.919)	(.038)	(.240)	(.986)
ROE	0.66	1.39	2.07	5.26	2.71	1.75
	(.000)	(.000)	(.000)	(.000)	(.002)	(.041)
Sustainable Growth	1.59	5.07	5.72	12.71	9.61	2.43
	(.000)	(.000)	(.000)	(.000)	(.000)	(.007)

Table 3: Trends in Anomaly Returns

The table examines trends in anomaly timing by partitioning the sample into two sub-periods, 1998-2007 and 2008-2017, for each of the nine anomaly portfolios as well as the super anomaly portfolio. The super portfolio is constructed as the equally-weighted average return across the nine 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 1, 5, and 30 days, respectively, while the last two columns display the percent of the total 30-day return earned over the 1 and 5 day horizons, respectively. P-values, calculated using standard errors clustered by firm, are shown below the returns in parentheses.

	Sub-period: 1998-2007					Sub-period: 2008-2017				
	Compound Returns Earned After Release of Financial Information			Percent of 30-Day Return Earned Over Span of Days		Compound Returns Earned After Release of Financial Information			Percent of 30-Day Return Earned Over Span of Days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Anomaly	1 Day	5 Days	30 Days	1 Day	5 Days	1 Day	5 Days	30 Days	1 Day	5 Days
Super	0.03	0.12	1.08	2.78	11.11	0.07	0.23	0.72	9.72	31.94
	(.245)	(.017)	(.000)			(.001)	(.000)	(.000)		
Accruals	0.01	0.14	0.75	1.33	18.67	0.15	0.28	0.69	21.74	40.58
	(.899)	(.276)	(.021)			(.002)	(.008)	(.008)		
Asset Growth	0.17	0.46	2.55	6.67	18.04	0.15	0.62	1.94	7.73	31.96
	(.003)	(.000)	(.000)			(.015)	(.000)	(.000)		
Gross Profitability	-0.05	-0.05	1.30	-3.85	-3.85	0.01	0.05	0.70	1.43	7.14
	(.456)	(.726)	(.000)			(.846)	(.682)	(.004)		
Inventory Growth	0.11	0.22	1.02	10.78	21.57	0.14	0.46	1.07	13.08	42.99
	(.034)	(.047)	(.001)			(.006)	(.000)	(.000)		
Net Working Capital	0.05	0.15	0.55	9.09	27.27	0.18	0.39	0.80	22.50	48.75
	(.414)	(.235)	(.087)			(.002)	(.001)	(.002)		
Operating Leverage	0.01	0.06	-0.32	-3.13	-18.75	0.09	0.29	0.04	225	725
	(.889)	(.603)	(.243)			(.077)	(.003)	(.869)		
Profit Margin	-0.08	-0.49	0.43	-19	-114	-0.09	-0.14	0.00	-900	-1400
	(.199)	(.000)	(.179)			(.102)	(.195)	(.987)		
ROE	0.00	0.39	1.53	0.00	25.49	-0.02	-0.15	0.23	-8.70	-65.22
	(.965)	(.002)	(.000)			(.767)	(.227)	(.381)		
Sustainable Growth	0.07	0.27	1.77	3.95	15.25	0.08	0.36	1.06	7.55	33.96
	(.312)	(.047)	(.000)			(.153)	(.001)	(.000)		

Table 4: Calendar-Time Portfolio Returns: Annual versus Daily Rebalancing on Information Release Dates

The table shows returns to calendar-time portfolios formed for each of the nine anomaly portfolios as well as the super anomaly portfolio. The super portfolio is constructed as the equally-weighted average return across the nine individual anomaly portfolios. We examine two portfolio formation strategies: (1) annual rebalancing and (2) daily rebalancing. The annual rebalancing strategy mirrors the strategies from the original published papers and each portfolio is rebalanced one time per year at the end of June. The daily rebalancing strategy updates the portfolio each day to account for new financial information about the anomaly variable using the Snapshot database to determine the precise date on which information was first publicly released. Column 1 shows annualized mean daily returns (in percent) for annually rebalanced portfolios. Column 2 shows annualized mean daily returns (in percent) for daily rebalanced portfolios. Column 3 shows the difference between column 1 and 2. Columns 4 through 12 examine timing to see when the returns are earned, relative to the annual portfolio formation date (July 1). Columns 4 and 5 examine the returns to the annual and daily rebalancing strategy in the first 30 days after the annual rebalance date, columns 7 and 8 examine the returns to the annual and daily rebalancing strategy in the first 120 days after the annual rebalance date, and columns 10 and 11 examine the returns to the annual and daily rebalancing strategy in the 240 day period after the annual rebalance date. Columns 6, 9, and 12 show the difference between the annual and daily strategies.

				Mean Compound Returns over the X day period following July 1								
	Annualized Mean Daily Returns			X = 30 Days (7/1 - 8/15)			X = 120 Days (7/1 - 12/31)			X = 240 Days (7/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			Diff			Diff			Diff			Diff
Anomaly	Annual	Daily	(2 - 1)	Annual	Daily	(6 - 5)	Annual	Daily	(9 - 8)	Annual	Daily	(12-11)
Super	1.44	8.37	6.92	0.65	0.76	0.11	1.57	2.46	0.89	1.67	8.52	6.84
Accruals	-3.87	-1.02	2.85	-0.52	-0.43	0.09	-1.34	-0.57	0.76	-3.82	-1.27	2.55
Asset Growth	4.43	15.48	11.05	0.85	0.86	0.02	3.09	4.29	1.21	4.94	16.33	11.39
Gross Profit.	3.51	6.17	2.66	0.57	0.54	-0.03	2.45	2.67	0.23	6.28	8.87	2.59
Invt. Growth	-3.22	3.26	6.48	-0.20	-0.03	0.17	-0.09	0.70	0.79	-2.38	3.17	5.54
Net W.C.	-4.76	-1.85	2.92	-0.55	-0.44	0.11	-1.92	-1.13	0.79	-4.67	-1.97	2.69
Op. Leverage	1.66	3.08	1.42	0.90	0.80	-0.10	1.89	1.65	-0.23	1.61	3.61	2.00
Profit Margin	1.42	2.83	1.41	-0.31	-0.29	0.02	1.96	2.29	0.33	2.25	3.85	1.60
ROE	3.22	4.53	1.31	1.78	1.67	-0.10	4.09	3.73	-0.35	4.60	6.30	1.70
Sust. Growth	3.80	12.78	8.97	1.65	1.79	0.15	3.06	4.14	1.08	4.72	13.29	8.57

Table 5: Calendar-Time Portfolio Returns: Annual versus Daily Portfolios over Different Parts of the Year

The table shows returns to calendar-time portfolios formed for each of the nine anomaly portfolios as well as the super anomaly portfolio. The super portfolio is constructed as the equally-weighted average return across the nine individual anomaly portfolios. To examine the timing of when returns are earned, the table displays compound returns over different holding horizons, relative to the annual portfolio formation date on July. We examine two implementable portfolio formation strategies: (1) annual rebalancing and (2) daily rebalancing. The annual rebalancing strategy mirrors the strategies from the original published papers and each portfolio is rebalanced one time per year. The daily rebalancing strategy updates the portfolio each day to account for new financial information about the anomaly variable using the Snapshot database to determine the precise date on which information was first publicly released. Columns 1 through 3 compare annual and daily rebalancing over the 30 days immediately following July 1; columns 4 through 6 compare annual and daily rebalancing starting 31 days after July 1 and holding for 120 days (until approximately Dec. 31); columns 7 through 9 compare annual and daily rebalancing starting 121 days after July 1 and holding for 240 days (until approximately June of the next year). To facilitate comparison across columns, all returns are annualized and shown in percent.

	Annualized Compound Return Earned:								
	in the first 30 days (7/1 - 8/15)			from 31 to 120 days (8/16 - 12/31)			from 121 to 240 days (1/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			Diff			Diff			Diff
Anomaly	Annual	Daily	(2 - 1)	Annual	Daily	(5 - 4)	Annual	Daily	(8 - 7)
Super	4.96	6.71	1.76	2.89	4.62	1.73	0.04	10.68	10.64
Accruals	-2.84	-2.11	0.74	-1.69	0.09	1.78	-4.96	-1.72	3.23
Asset Growth	8.07	8.01	-0.06	5.52	8.60	3.09	3.54	22.40	18.86
Gross Profitability	0.88	0.87	-0.01	5.36	6.25	0.89	5.38	9.41	4.04
Inventory Growth	-0.27	0.89	1.16	0.40	1.55	1.15	-5.93	3.85	9.77
Net Working Capital	-2.35	-1.80	0.55	-3.39	-1.49	1.91	-6.00	-2.22	3.78
Operating Leverage	5.71	4.87	-0.84	1.10	0.78	-0.32	2.50	5.79	3.29
Profit Margin	-3.18	-2.86	0.32	6.24	7.18	0.94	-1.91	0.84	2.75
ROE	13.38	12.39	-0.99	7.41	6.92	-0.49	-0.69	3.96	4.65
Sustainable Growth	15.70	16.80	1.10	5.01	7.24	2.23	3.20	17.04	13.84

Table 6: Regression Analysis of Super Anomaly Returns on News Days vs. Non-News Days
The table reports regression results testing the effect of news days on anomaly returns in event time using regressions of the form:

$$Return_{it} = \alpha + \delta_1 NewsDay_{it} + \delta_2 WithinXDays_{it} + \delta_3 WithinXDays_{it} \times NewsDay_{it} + \epsilon_{it},$$

where *Return* is the daily abnormal return, in percent, of stock i on day t. The sample includes all stocks in the super portfolio. $NewsDay$ is an indicator variable that takes the value one when a stock has a news day and zero otherwise. $WithinXDays$ is an indicator for whether the return on a given day is within an X day period following an information release, where X is either 30, 60, 90, or 120 days. We include year fixed effects in all models. Standard errors clustered by firm are shown below the estimates in parentheses.

	Dependent Variable = daily abnormal return				
Explanatory Variable	(1)	(2)	(3)	(4)	(5)
News Day	.003	.004	.006*	.007*	.009**
	(.003)	(.003)	(.003)	(.003)	(.004)
Within 30 Days		.029***			
		(.004)			
Within 30 Days × News Day		-.004			
		(.007)			
Within 60 Days			.026***		
			(.003)		
Within 60 Days × News Day			-.010*		
			(.005)		
Within 90 Days				.024***	
				(.003)	
Within 90 Days × News Day				-.009*	
				(.005)	
Within 120 Days					.020***
					(.003)
Within 120 Days × News Day					-.011**
					(.005)
$\delta_1 + \delta_3$		.000	-.004	-.002	-.002
(p-value)		(.976)	(.342)	(.574)	(.489)
N (in thousands)	17,506	17,506	17,506	17,506	17,506

Table 7: Anomaly Returns from Daily Rebalancing: News Days vs. Non-News Days

The table shows returns to the super anomaly portfolio using (i) annual rebalancing and (ii) daily rebalncing, on news days versus non-news days. The super portfolio is constructed as the equally-weighted average return across the nine individual anomaly portfolios. Column 1 summarizes the return to the super anomaly portfolio using annual rebalancing. Column 2 summarizes the return to the super portfolio using daily rebalancing. Columns 3 and 4 separate the return earned to the daily rebalancing portfolio by splitting the portfolio into news days (column 3) versus non-news days (column 4). Across the entire sample, approximately 40% of all days are news days.

Return (in percent)	Annual Rebalancing All Days (1)	Daily Rebalancing All Days (2)	Daily Rebalancing News Days (3)	Daily Rebalancing Non-News Days (4)
Annualized Average Daily Return	1.36	7.28	3.97	3.88
(p-value)	(.257)	(.000)	(.000)	(.000)
30-Day Return (7/1 - 8/15)	0.43	0.56	0.45	0.21
120-Day Return (7/1 - 12/31)	1.22	2.14	1.20	1.64
240-Day Return (7/1 - 6/30)	2.05	7.77	4.02	3.99
Ann. Ret. First 30 days (7/1 - 8/15)	3.45	4.47	3.57	1.69
Ann. Ret. 31 to 120 days (8/16 - 12/31)	2.00	4.08	2.02	3.72
Ann. Ret. 121 to 240 days (1/1 - 6/30)	0.97	11.06	5.87	4.57

Table 8: Super Anomaly Returns in Event Time: Arbitrage Risk

The table reports returns to the super anomaly in event time using our daily rebalancing strategy, split into terciles based on a measure of arbitrage risk. The super portfolio is constructed as the equally-weighted average return across the nine individual anomaly portfolios. Arbitrage risk is defined using a regression model (see equation (2)) of daily stock returns to identify close substitute stocks as those with highly correlated return movements (similar to Wurgler and Zhuravskaya (2002)). The super anomaly portfolios are then split based on the whether stocks in the long and short legs of the anomaly portfolio have arbitrage risk in the lowest, middle, or highest tercile. *Low Risk* stocks are those for which the best fitting model using similar stocks' returns yields a variance of residuals in the lowest tercile, suggesting that the stock of interest has close substitutes and is easily hedged. Similarly, *High Risk* stocks are those for which the best fitting model using similar stocks' returns yields a variance of residuals in the highest tercile, suggesting that the stock of interest does not have close substitutes and is not easily hedged. Column 1 shows the compound return in the 30 days immediately following the release of information, column 2 shows the compound return in the 120 days immediately following the release of information, and column 3 compare how much of the 120-day return was earned in the first 30 days following information releases. P-values, calculated using standard errors clustered by firm, are shown below the estimates in parentheses.

	Compound Returns Earned After Release of Information		
	(1)	(2)	(3)
Arbitrage Risk	30 Days	120 Days	(1)÷(2)
Low Risk	0.55	0.72	0.76
	(.000)	(.001)	
Medium Risk	0.82	1.39	0.59
	(.000)	(.000)	
High Risk	1.25	2.79	0.45
	(.000)	(.000)	

Table 9: Speed of Reaction: Returns to Fast Minus Slow (FMS)

The table shows the annualized average daily differential return between the "fast" anomaly portfolio and the "slow" anomaly portfolio. Specifically, each period we hold a long position in the "fast" portfolio which is defined as the portfolio with daily rebalancing as information becomes available (as in Table 4) and we hold a short position in the the "slow" portfolio which is defined using the traditional annual rebalancing strategy. The table shows the long-short differential for each portfolio year (in rows) and for each anomaly variable (in columns); the second to last row shows results across the entire sample period with the p-value shown below in parentheses.

	Annualized Long-Short Spread from Fast Minus Slow									
Year	Accruals	Asset Growth	Gross Profitability	Inventory Growth	Net Working Capital	Operating Leverage	Profit Margin	ROE	Sustainable Growth	Super
1997	12.61	7.70	8.63	3.45	13.95	5.93	10.53	2.13	8.68	8.24
1998	9.59	1.55	-3.92	0.54	7.73	-4.09	-4.21	1.05	9.78	2.71
1999	-4.95	13.27	12.26	-0.57	-0.54	-0.09	8.32	17.20	12.66	6.72
2000	1.42	37.59	7.91	33.37	7.75	7.03	2.11	-2.73	26.69	14.51
2001	9.80	-0.92	-7.89	7.06	6.22	0.03	-11.35	4.64	-4.23	-0.04
2002	2.85	4.82	15.95	7.46	-0.95	4.14	8.57	11.65	0.10	9.13
2003	3.19	7.02	1.99	4.90	3.79	-2.36	1.77	6.44	7.64	4.03
2004	4.35	7.06	-1.10	0.80	2.86	0.10	-3.49	1.88	16.91	4.50
2005	-0.49	11.17	6.66	1.05	0.52	-0.55	9.50	0.43	10.56	7.65
2006	-0.37	10.35	-1.96	3.04	2.20	1.29	-3.61	-7.68	11.06	4.73
2007	-2.31	17.55	-3.31	12.50	-3.92	2.35	-1.01	-10.80	11.34	4.73
2008	-0.62	11.79	7.61	1.70	0.49	8.17	4.66	4.44	13.36	10.34
2009	6.07	12.28	0.08	7.83	0.89	-4.79	5.07	0.77	4.27	4.42
2010	-0.26	14.87	-0.24	7.72	-0.99	0.19	-2.16	-0.54	8.18	7.61
2011	9.74	7.13	-0.25	9.26	8.79	0.75	3.18	1.60	0.75	8.73
2012	4.20	8.26	-1.66	5.13	6.44	-1.30	-0.05	-0.32	5.11	4.73
2013	-4.16	12.57	6.65	5.06	-2.96	0.90	2.74	7.10	6.94	12.68
2014	-0.43	16.82	-2.15	10.07	0.45	-0.59	1.94	-8.71	13.98	4.97
2015	8.38	24.29	1.73	11.66	8.03	8.75	-6.19	-5.26	17.49	20.32
2016	1.02	7.39	11.03	3.04	-0.03	4.96	3.91	6.37	7.14	1.62
Overall	2.97	11.64	2.92	6.75	3.03	1.54	1.53	1.49	9.44	7.13
p-value	(.007)	(.000)	(.000)	(.000)	(.006)	(.039)	(.057)	(.170)	(.000)	(.000)

Table 10: Hedge Fund Speed and Future Performance

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

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

where *AbnReturn* is the Carhart (1997) four-factor alpha and *Speed* is a monthly measure of the relation between historical fund returns and the return on the Fast Minus Slow portfolio (see Table 9 and equation (3)). We include fund and/or month-year fixed effects as indicated in the table. Standard errors clustered by firm are shown below the coefficient estimates in parentheses.

	Dependent Variable = future alpha		
	(1)	(2)	(3)
Speed	0.632***	0.885***	0.832***
	(.139)	(.150)	(.187)
Fund FE	No	Yes	Yes
Month-Year FE	No	No	Yes
R-squared	.002	.163	.327
N	218,737	218,737	218,737

Table 11: Super Anomaly Returns: Size Breaks

The table examines 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 equally-weighted average return across the nine individual anomaly portfolios. Large stocks are stocks with market capitalization greater than or equal to the 50th percentile of NYSE breakpoints from Kenneth French's website, Small stocks are those with market capitalization greater than or equal to the 20th percentile but less than the 50th percentile, and Micro stocks are those with market capitalization below the 20th percentile. Panel A shows returns in event time across a variety of horizons (columns) and size portfolios (rows), with p-values shown below the returns in parentheses. Panel B shows returns in calendar time for portfolios split by size; column 1 shows returns to an annual rebalancing strategy, column 2 shows returns to a daily rebalancing strategy, column 3 shows the difference between the two approaches and column 4 displays the p-value from a t-test of differences.

Panel A: Returns in Event Time

	Compound Returns Earned After Release of Annual Information			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Size	30 Days	120 Days	240 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days
All	0.98	2.13	1.97	7.87	3.31	0.37
	(.000)	(.000)	(.000)	(.000)	(.000)	(.328)
Large	0.53	0.91	0.89	4.24	3.41	2.01
	(.000)	(.000)	(.005)	(.000)	(.000)	(.000)
Small	0.85	1.27	0.66	6.78	3.09	0.75
	(.000)	(.000)	(.134)	(.000)	(.000)	(.336)
Micro	0.95	1.63	0.69	7.60	2.71	-1.07
	(.000)	(.000)	(.093)	(.000)	(.000)	(.085)

Panel B: Returns in Calendar Time

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Size	Annual Rebalancing	Daily Rebalancing	Difference (2-1)	p-value
All	1.44	8.37	6.92	.000
Large	4.77	10.95	6.18	.002
Small	5.32	7.60	2.28	.300
Micro	-1.95	6.96	8.91	.000