ANOMALY TIME[1]

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ABSTRACT: We show that it is not news, per se, that drives anomaly returns. Instead, we present evidence showing that anomaly returns are driven by the specific information on which long-short equity portfolios are based. We show that anomaly returns are earned almost exclusively following the release of portfolio assignment information, and we show that abnormal returns to anomalies in the first 30 days following an information release are more than 6 and 20 times larger than returns in the following 90 and 120 days, respectively. Building on this, we hypothesize that reacting to information quickly is an important part of capturing anomaly returns. We test this using a sample of hedge funds and find that the speed with which funds react to information is a significant predictor of their abnormal returns. Specifically, a one standard deviation increase in the speed at which a fund reacts to information is associated with a 27 basis point increase in future abnormal returns.

JEL classification: G12, G14

Keywords: asset pricing anomalies, information release, daily rebalancing, hedge funds

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A number of recent papers have shown that anomaly returns are stronger around the release of information. We posit that there is a key distinction missing in these papers: some information drives anomaly long-short portfolio assignment while other information does not. In other words, only a portion of new information is relevant for anomaly portfolio assignment. In this paper, we make a distinction between all news and the news that drives anomaly portfolio assignment.

Of course, this distinction can be difficult to make as information is constantly evolving, particularly information regarding portfolio assignment. To solve this problem, we focus on a set of anomalies whose portfolio construction (i.e., stock assignment to long and short legs) is determined solely by information arriving at specific points in time. This enables us to employ an event-time approach that captures the information signal relevant for portfolio assignment, as well as the timing of returns earned around the signal. We use this event-time approach as a tool to better understand *what* information matters for anomaly returns and *when* that information matters. Furthermore, this approach enables us to measure the speed with which hedge funds react to information, and how their reaction speed relates to their performance.

Our main empirical setting is straightforward. First, we identify a set of ten anomalies that have a clear and observable date on which the information relevant for portfolio assignment is released.[3] We also create a "super" portfolio based on the combined returns to all ten of these anomalies. Then, we couple the relevant information dates with the release of other forms of

[3] We start with 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)), investment (Titman, Wei, and Xie (2004)), net working capital changes (Soliman (2008)), operating leverage (Novy-Marx (2010)), profit margin (Soliman (2008)), return on equity (Haugen and Baker (1998)), and sustainable growth (Lockwood and Prombutr (2010)).

news, as in Engelberg et al (2018), around which prior research shows anomaly returns tend to cluster.

Our analyses can be combined into two groups; examining both *when* and *what* information influences return predictability for the anomalies we consider. The first group of analyses (hereafter, the "timing tests") considers the *when* question by examining the performance differences of dynamic portfolio formation relative to the static portfolio formation approach often employed in prior research (i.e., portfolios are formed once a year on June 30th). The second group of analyses (hereafter the "news tests") considers the *what* question by drawing a distinction between the information signal underlying anomaly portfolio assignment and other general news related to the firm. Both of these sources of information are continuously arriving to the market, but only the former directly affects portfolio assignment.

In the timing tests, we begin by considering an event-time strategy for the ten anomalies, in which the returns are lined up in event-time according to the 10-K filing date. A stock enters the long or short leg of an anomaly portfolio based on its ranking as of the 10-K date. We then accumulate returns for 30, 120, and 240 trading days. These results point to the advantages of timely investing based on the underlying anomaly variable. Across six of the ten anomalies, an event-time portfolio generates predictable returns that are statistically positive in the first 30 days. Importantly, these returns diminish dramatically in the subsequent trading periods (i.e., from day 31 through 120). For example, abnormal returns to the super portfolio for the first 30 days following the 10-K release date are 6.52% annualized, whereas returns over the next two windows ([31,120] and [121,240]) are much more modest at 1.03% and 0.28%, respectively.

These results suggest that anomaly returns manifest primarily in the first month or so after the 10-K release date, diminishing thereafter.

To analyze this result in a framework that is plausibly implementable for an investor, we consider a calendar-time approach that simply rebalances on 10-K release dates instead of once a year. We find that daily equal-weighted hedge returns using daily rebalancing are statistically greater than annual rebalancing returns for several anomalies. The spread between the super portfolio's daily rebalanced return and its annually rebalanced return is 4.44% annualized. Further, on average, the 240-day return to annual rebalancing is 1.53%, while daily rebalancing yields 5.65%.

For annually-rebalanced portfolios, information grows stale over the one-year holding period. Our evidence suggests that this 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 last six months of the annual time period (i.e., during the first six months of the calendar year). Indeed, the differences between annual and daily rebalancing returns are largest in the time period from 121 days to 240 days after June rebalancing, where the annualized difference is 6.53%. It is important to note that it is during this time period (the first half of the calendar year) when the majority of firms release their 10-K reports.[4] The daily rebalancing portfolios react to the new information in these 10-K reports by rebalancing in real-time. Portfolios that rebalance annually in June, however, are unable to react to the new information. Overall, finding that the daily rebalanced portfolio dominates the annually rebalanced portfolio in this time period supports the intuition that the annual approach is "stuck in a rut" in the face of

[4] In unreported results, we conducted the same analysis on a subset of stocks that report the annual results within the first three months of the year. The results from this analysis are consistent with our reported results.

continuous information flow, which leads to the strong spread in predictable returns between the annual and daily rebalancing approaches. However, the question naturally follows as to whether the increased return predictability is a function of the continuous arrival of general news or whether it relates to information signals that drive portfolio assignment. We turn to this question next.

In our second group of tests, the news tests, we decompose news effects. We finds that immediately following portfolio formation, news days have no more return than non-news days. In fact, when analyzing compound returns, we find that in the 30 days following a 10-K release, non-news days matter at least as much as news days, consistent with the idea of portfolio assignment information slowly diffusing into prices. Further, using regression techniques we again find that news days provide no more return than non-news days in the first 30 to 120 days following a 10-K release.

When looking at an implementable calendar time approach, our results are similar to Engelberg, McLean and Pontiff (2017) in that news days earn higher returns than non news days. Specifically, returns on news days are 2.99%, while returns on non-news days are 2.17%. It is important to notice that news days, in this empirical context, comprise both portfolio formation information as well as other information. Also of note is that during the first half of the calendar year non-news days actually earn more, on an annualized basis, than news days.

In the context of investors, these findings suggest that faster reactions to key information will lead to larger returns. To test this implication, we generate a new portfolio, the Fast Minus Slow (hereafter FMS) portfolio. This portfolio mimics the experience of a trader who buys the daily rebalanced portfolio and shorts the annually rebalanced portfolio. Then, taking a database of hedge fund returns, we measure the covariation between fund returns and the FMS return. We interpret the covariation as a measure of how quickly funds react to new information, and we call it fund speed.

We find that funds which react faster to information earn higher returns on average. Specifically, looking at overall performance throughout our sample period, we find a cross-sectional relationship indicating that a one standard deviation increase in fund speed is associated with a 48 bps increase in annual abnormal returns. To account for the possibility that a given fund's reaction speed may change through time, we look at this relationship in a panel framework. We find that an increase in a fund's speed in given month predicts the next 12 months' average alpha. Specifically, a one standard deviation increase in fund speed is associated with a 27 basis point increase in future annual alpha. In other words, we find that fund speed measured today can predict the abnormal performance of that fund in the future.

In additional analyses, we consider partitions of the sample based on size using the NYSE breakpoints (i.e., large, small, and micro based on Fama and French (2012)). The results suggest that the gains to a daily rebalancing strategy are strongest in large stocks. Specifically, the difference in predictable returns for the daily versus annual rebalancing strategy is 8.15% for the subsample of large stocks. Small and micro stocks evidence a positive difference of 3.18% and 3.50%, respectively, which are statistically different from zero, though not as strong as for the large stocks. We also examine the anomaly returns in event time broken up by size groups. In these analyses, the event-time returns for large stocks lead out, and continue to demonstrate strong, positive abnormal returns earned in the first 30 days after the information release, with returns diminishing over time. The returns for small and micro stocks generally follow this same pattern.

The rest of this paper proceeds as follows: Section I briefly describes the existing literature, Section II describes the data used in this study, Section III characterizes our findings, and Section IV concludes.

I. Background

Our paper is related to an extensive literature on asset pricing anomalies. In this section, we briefly discuss existing work concerning anomalies and their possible origins.

A. Replication of Anomalies

Over the past four decades, academic research has uncovered hundreds of asset pricing anomalies. More recently, a growing literature has examined whether these anomalies have a robust presence in the data after accounting for different samples, time periods, and methodological choices. Green, Hand, and Zhang (2017) find that, " [I]n 2003 there is a sharp kink downward in the magnitude of the hedge portfolio returns to characteristics-based predictability, especially in non-microcap stocks." In other words, they find that most anomalies do not replicate over recent time periods, which the authors argue results from the diminished costs of arbitrage. 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 leads to trading that eliminates anomaly returns. Hou, Xue, and Zhang (2017) find that most anomalies cannot be replicated if you exclude micro-cap stocks from the sample. They argue that many anomalies are not truly in the data, but rather they are the result of data mining. Cooper, Gutierrez, and Marcum (2005) also provide evidence on this point. They note that most academic research suffers from a hindsight bias, and they use recursive out-of-sample methods to examine whether anomalies generate returns using only ex-ante information. They find that existing academic evidence likely overstates the performance of anomaly variables and a real-time strategy would have performed relatively poorly.

B. Possible Explanations for Anomaly Returns

While the results discussed above call into question the validity of anomaly strategies, in general there is strong evidence that *some* anomaly strategies are valid. For example, Green, Hand, and Zhang (2017) find that 12 different firm characteristics reliably predict abnormal returns over their sample. In addition, Lu, Stambaugh, and Yuan (2017) examine nine anomalies from the academic literature and find that they consistently produce abnormal returns across six different countries, which suggests they are truly present in the data. Finally, Han, Huang, and Zhou (2017) find that a dynamic anomaly strategy that rebalances monthly to account for the recent performance of each stock in the anomaly portfolio 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, including (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, Lochstoer and Tetlock (2017) examine five well-known anomalies and they build on the present-value decomposition of Campbell and Shiller (1988) to examine the driver of anomaly returns. They find that cash flow shocks drive much of the variation in anomaly returns. Engelberg, McLean, and Pontiff (2017) 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, which suggests that anomaly returns are at least partly driven by biased expectations about information. Lu, Stambaugh, and Yuan (2017) examine anomalies across six different countries and they find that the returns to anomalies are stronger when idiosyncratic volatility is high, consistent with the idea that anomalies represent mis-pricing due to arbitrage risk. Finally, Kelly, Pruitt, and Su (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. However, their approach is based on the assumption that firm characteristics lineup with mean returns *because* they are proxies for loadings on latent risk factors. As such, their results can be viewed as a joint test of risk-based explanations and the assumption that firm characteristics contain information about loadings on latent risk factors.

II. Methodology

A. Data

Underlying our premise is the notion that anomaly returns are tied to the release of an information signal regarding portfolio assignment. We identify the specific date on which each information signal is released to the public. These signals arise primarily from two sources, earnings announcements and financial statements, with the former typically preceding the latter. Prior research demonstrates that earnings announcements typically contain only a fraction of the information needed for several of our anomalies (e.g., asset growth and net working capital), but they can sometimes contain enough information to trade on other anomalies (e.g., gross profitability).

In this draft, we focus primarily on the public release of financial statements, which occurs when the company files Form 10-K (i.e., its annual report) with the Securities and Exchange Commission. By choosing the 10-K filing date, we can ensure that *all* financial statement data needed for all of our anomalies -- including revenues, profits, accruals, working capital, capital investments, total assets, inventories, equity issuances, etc. -- are definitively in the public domain. There are two advantages to using the 10-K filing date as our information release date. First, this date is easy to measure and identify for all public companies.[5] Second, on this date, we know with certainty that the information signals are available to all investors, and they are effectively costless to access, which ensures that predictable returns are not a

[5] We thank Bill McDonald for providing the 10-K filing dates for all public companies on his website: https://www3.nd.edu/~mcdonald/.

function of investors' private information, information asymmetries, or other informational frictions.[6]

When looking at fund performance, we employ the Morningstar CISDM database of hedge fund returns. We focus on approximately 2,500 funds operating from 1998 through 2014. We limit our sample of funds to those based in U.S. Dollars and with strategy types that reflect trading U.S. equities.[7] We also utilize data from the Center for Research in Security Prices (CRSP), Compustat, and Ravenpack.

B. Anomaly Selection

When studying the timing of anomaly returns, it is important to choose a setting in which the timing of returns in relation to information releases can be clearly measured. Our starting point is the set of 93 anomalies covered by McLean and Pontiff (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. For example, McLean and Pontiff's (2016) first anomaly, E/P (Basu 1977), requires two data points for each stock: earnings and price. Although earnings has a clear information release date, the price is constantly changing, making it difficult to define an information release date for the E/P anomaly.

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[6] All these information signals are freely available to the investing public on the 10-K filing date via the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. For example, Cisco's most recent 10-K was filed on September 7, 2017, and can be accessed at https://tinyurl.com/yavdbes4. This document contains all the information signals needed for the accounting-based anomalies we examine in this study. This document is freely available to the public almost instantaneously; prior research documents that many investors acquire the 10-K almost immediately after it is posted to EDGAR (Drake, Roulstone and Thornock 2015).

[7] Specifically, fund types included in our study are: 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.

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, Gulen, and Schill (2008)), gross profitability (Novy-Marx (2013)), growth in inventory (Thomas and Zhang (2002)), investment (Titman, Wei, and Xie (2004)), net working capital (Soliman (2008)), operating leverage (Novy-Marx (2010)), profit margin (Soliman (2008)), return on equity (Haugen and Baker (1998)), and sustainable growth (Lockwood and Prombutr (2010)).[8] All of these anomalies have underlying calculations that change at distinct and observable points in time.[9]

The long and short portfolio legs in all of these anomalies are based on relative rankings. For example, in Cooper, Gulen, and Schill (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 changes its asset growth ratio, it may affect the portfolio inclusion of another stock.

In our continuous approach, we update these rankings daily and potentially form new long and short legs of the portfolio at the end of each day. 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 stock's returns are driving our main results, then it will be difficult to interpret our findings. To address this potential issue, we recalculate portfolios following a rule stating that stocks cannot jump in and out of the portfolio 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.

[8] The calculation of each anomaly variable is outlined in the appendix.
[9] It is worth noting that a few more anomalies share this property, such as short interest, etc. In future drafts, we expect to include these anomalies in our analysis.

C. Anomaly Calculations

All of the following anomaly calculations share some basic concepts. First, a calculation is done with data as of a certain date, the 10-K filing date. Second, each stock is ranked according to the calculation of its anomaly variable (i.e., asset growth). Finally, portfolios are formed using these relative rankings.

We form anomaly portfolios in event time. For this approach, a stock enters the long or short leg of an anomaly portfolio based on its ranking as of the 10-K date. Returns to stocks that make it into the long or short legs are then lined up in event time, with date zero being the 10-K date for these stocks.

Many of the original papers describing anomalies rebalance portfolios annually. We follow the annually rebalancing approach in our replication of each anomaly's return. Asset growth is used here as an example. At the end of June of year *t*, the report of total assets from the most recent 10-K is used to calculate asset growth. Asset growth is measured as the change in assets over the prior year divided by the prior year's total assets. 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. A stock in the bottom decile will be in the long leg of the anomaly portfolio. The stock will remain in the portfolio for one year.

We also form a continuous version of the anomaly portfolio, using data and rankings as soon as they are available. We again use asset growth to illustrate. Assume that firm ABC files its 10-K on March 15th and thus has an updated asset growth value. 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 portfolio, stock XYZ drops out of the portfolio at the end of trading on March 16th. Finally, suppose that stock XYZ remained in the long leg after March 15th. There would be no adjustment to the holding of XYZ.

Each stock in the sample has a daily abnormal return calculated from the 3-factor model (Fama and French (1993)). Where the predicted return is based on the 3-factor model using one year's worth of daily returns ended three months prior to the day for which the abnormal return is calculated.

D. Fund Speed Calculations

We begin by identifying over 2,500 hedge funds with fund types related to U.S. equity and based in U.S. Dollars. The Morningstar data provides monthly returns for funds. We label the differential between the daily-rebalanced and annually-rebalanced super portfolio the "Fast minus Slow" (FMS) return. Using the entire sample period, each fund is given a speed using the following regression:

$$Return_{it} = \alpha + \beta FMS_{it} + \varepsilon_{it}$$

This regression is run by fund. The coefficient on FMS for each fund is called that fund's "speed" over the entire sample.

We also measure a fund's speed in a rolling fashion. To do this we use the past three years of monthly returns for a fund to run the above regression again. The coefficient on FMS for a given fund is that fund's speed for the next month. In other words, we use the past 36 months of returns to measure a fund's speed over the last 36 months.

Coupled with monthly fund speed, we also measure forward looking abnormal returns for a fund each month. These are the 12 month compound alphas for a fund, looking ahead 12 months.[10] Thus, we have a panel of fund-months, where an observation is the speed measured on 36 months of past returns, and a future performance measured with the next 12 months of abnormal returns.

E. "Surprising" 10-K Releases

We label the 10-K release for a stock for a given anomaly as "surprising" or "unsurprising." A surprising stock-filing is one for which the information released in the 10-K surprisingly places the stock in one of the legs of the anomaly portfolio. The definition of an unsurprising stock-filing is one for which the stock is expected to be near one of the legs of the anomaly portfolio, and the 10-K reveals that the stock is indeed in the expected leg.

We utilize a simple prediction model to predict a firm's anomaly value (e.g., asset growth) using the anomaly value from the most recent third quarter 10-Q filing and the anomaly value from the last 10-K. The prediction model is estimated using data from 1965 up to the year preceding the year in which we want to make a prediction. The model is run for each industry and contains a firm fixed effect. For example, asset growth is calculated as the change in total

[10] Fund alphas are calculated from the 4-factor model.

assets divided by the previous total assets. The prediction model is for asset growth is as follows:

$$AG_{4ijt} = \alpha_i + \beta_j AG_{4ijt-1} + \gamma_j AG_{3ijt}$$

The explanatory variables on the right-hand side are the annual asset growth from the previous year (AG_4) and the year-to-date asset growth measured from the third quarter 10-Q (AG_3). The model is run for each industry, j, and a firm fixed effect is computed for each firm, i. The parameter estimates change each year as the prediction model rolls another year into the estimation period.

III. Results

Table I provides summary statistics for the sample we use in this study. Our sample coverage includes approximately 7,000 stocks from 1996 through 2014. Each anomaly encompasses a varying number of stocks, with a low of approximately 4,399 stocks in the investment anomaly and a high of 6,963 stocks in the return on equity anomaly.[11]

A. Anomaly Returns in Event Time

In our first set of analyses, we examine the returns to anomaly portfolios in event time where the event is the annual 10-K filing date for every stock in the sample. In this approach, a given stock's assignment to the long or short legs of an anomaly portfolio is determined at the

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[11] Per the original paper, the investments anomaly requires 3 years of data, hence the sample for this anomaly is reduced.

date of that stock's 10-K release, as discussed above in Section II. Table II reports the results. For example, column 1 shows the return earned in the first 30 days after the 10-K date for stocks in the sample. Column 1 indicates that there is a positive return of 0.81% for the super portfolio during that first 30 days. Columns 2 and 3 repeat the exercise for the first 120 and 240 days, respectively. They indicate that the super portfolio earns 1.19% after 120 days and 0.98% after 240 days.

To judge statistical significance, we cluster by firm and calculate standard errors based on the individual stock's event time compound returns. Columns 1 through 3 generally show statistically significant positive returns for the ten anomalies, with some exceptions. The super portfolio has statistically significant positive returns in each event window. Taken together, these results show strong statistical significance for abnormal returns following the information release date.

Columns 4 through 6 show the annualized returns earned within each window. For example, column 5 shows that from day 31 through day 120 the super portfolio earns an annualized return of 1.03% compared with an annualized return in the first 30 days of 6.52%. This difference indicates that the majority of anomaly returns are earned immediately following 10-K releases. Similarly, column 6 shows results for the second half of the 240-day window, during which time the super portfolio's return is essentially zero. In other words, the first half of the event-year exhibits positive returns and the second half of the event-year exhibits zero returns.

Figure 1 shows this result clearly. And although some individual anomalies exhibit negative returns, overall the results are consistent with the idea that as information becomes stale, anomaly portfolios no longer yield positive returns.

B. Anomaly Returns in Calendar Time

In this section, we attempt to form an implementable version of the event time approach by continuously adjusting anomaly portfolios to reflect new information. As discussed in Section II, we allow the portfolios to change daily as new information is released. More specifically, on any day in which a 10-K comes out for any stock in the sample, there is a chance that the portfolio will be rebalanced.

Table III shows the results from the daily rebalancing approach compared to the annual approach.[12] The results suggest that daily rebalancing outperforms annual rebalancing fairly consistently across the ten anomalies and for the super anomaly. For example, one anomaly in our set, inventory growth, shows an annualized, equally-weighted return from annual rebalancing of -3.63%, whereas daily rebalancing yields an annualized return of 1.78%, resulting in a statistically significant difference of 5.41% between the two approaches. Looking down column 3 we see generally positive differences, indicating that daily rebalancing outperforms annual rebalancing, with the difference for the equally-weighted super portfolio being 4.44%. The most dramatic difference is in the asset growth anomaly, where the daily rebalancing approach earns a return that is 11.39% greater than annually rebalancing.

[12] More detailed results specific to annual rebalancing are presented in the appendix Table A1.

Columns 5 through 13 consider the results according to time period. We find both positive and negative differences in the 30-day and 120-day return windows, with daily rebalancing of the super portfolio yielding a 0.43% return improvement over annual rebalancing in the 30-day window and a 0.82% improvement in the 120-day window. However, by far the most dramatic period is the 240-day return window, in which annual rebalancing yields 1.53% and daily rebalancing yields 5.63%, a difference of 4.12%. The fact that the largest difference between the two approaches comes during the first half of the calendar year is indicative of the benchmark approach's inability to take new information into account, while the daily rebalancing approach reflects new information. Specifically, it is between the 120-day and 240-day windows where the vast majority of firms release their 10-K reports.[13] Column 13 indicates that quickly conditioning portfolio holdings on the information in these reports results in a far superior return.

Figure 2 shows the difference between annual rebalancing and daily rebalancing in the time series for each anomaly in our set. As suggested by Table III, we generally see that daily rebalancing outperforms annual rebalancing; however, the result is not consistent either through time or across anomalies. Several anomalies, such as asset growth, gross profitability, inventory growth, profit margin, and sustainable growth, exhibit consistently higher returns for the daily-rebalanced portfolio as compared with an annually-rebalanced portfolio. However, the opposite is true for return on equity. The super portfolio shows daily rebalancing returns dominating those of annual rebalancing over our sample period.

[13] In unreported results we have conducted the same analysis dividing stocks between the subset of firms that have Dec. 31st fiscal year end and those that have a different fiscal year end. The results were qualitatively similar to Table III, the daily rebalancing approach is especially profitable around the time of year where firms report their annual financial statements.

Table IV provides a closer examination of time period effects. In particular, this table 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.[14] Table IV shows that the return earned from 30 to 120 days is fairly consistent across the two portfolio approaches, with daily rebalancing returns showing a slight improvement over annual rebalancing returns in this window. The super portfolio difference is only 1.04% annualized over that window. However, if we consider the period from 120 to 240 days after rebalancing, we see a dramatic difference among the anomalies. Column 7 shows the annualized return over that period for the annual rebalancing strategy and column 8 shows the annualized return over that period for the daily rebalancing strategy. The differences 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 a return difference of 6.53% during that first half of the calendar year. This is further evidence that the annual rebalancing approach is unable to include value-relevant information in the second half of the annual rebalancing period, supporting the results from Table II.

C. News and Returns

To analyze the impact of news on returns, 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, calendar and event time, to draw a distinction between news that is directly relevant for portfolio assignment and news that is not.

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[14] "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.

In Table V, we take an event time approach, similar to Table II, and split returns into days with news (hereafter, "news days") and days without news (hereafter, "non-news days").[15] Selecting anomaly returns using only news days is as follows: if a stock experiences a news day, that stock's return is included in the news days anomaly return and in the super portfolio return on that day. If a stock does not have 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. This approach 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 has news, the investor holds the stock, but if the stock does not have news, the investor instead holds cash. (Decomposing the all days return into the non-news days return is equivalent, *mutatis mutandis*.)

Table V indicates that in the first 30 days after a 10-K filing, news days and non-news days both have statistically significant and positive returns. In fact, we find that non-news days are actually more important than news days in this post-filing window. Specifically, the average abnormal return is 0.52% on non-news days while it is only 0.31% on news days. The annualized difference between news days and non-news days over the first 30 days is 1.67%, which is statistically significant.

Consistent with the idea of the value of information fading over time, we find that news days become more and more important as the window is lengthened. Column 2 indicates that 120 days after a 10-K release, there is no difference between news days and non-news days, as indicated by the insignificant differential return of 0.15%. We also find that news days become significantly more important than non-news days in the later part of the event window.

[15] News days are defined as a day in which a stock has at least one news article hit the Dow Jones News Wire or the Wall Street Journal.

Specifically, column 6 shows that between days 121 and 240, news days are significantly more important for driving returns than non-news days.

Figure 3 depicts the relative contributions of news days and non-news days to the return of the super portfolio in event time. As demonstrated in Table V, in the first month after a 10-K release, non-news days returns are larger than returns on news days. However, this relationship is reversed as the 10-K filing date is further in the past, as news days returns are larger than non-news days after 150 or so days.

In Table VI, we use regression techniques to analyze returns to news versus non-news days in event time. Following the findings outlined in Table V and Figure 3, we test whether the effect of news days on anomaly returns is different between days immediately following a 10-K release and days further away. We utilize the following regression model:

$$Return_{it} = \alpha + \delta_1 NewsDay_{it} + \delta_2 Under\#Days_{it} + \delta_3 Under\#DaysXNewsDays_{it} + \varepsilon_{it}$$

where the return on the left-hand side is the daily abnormal return, in percent, to a given stock, *i*, on a given day, *t*, following its 10-K release. We include all stocks in the super portfolio. *NewsDay* is an indicator for whether a stock has a news day. *Under#Days* is an indicator for whether the return on a given day is within a certain number of days following a 10-K release. *Under#DaysXNewsDays* is an indicator for whether a given day is both a news day and within the early time period following a 10-K release. We use 30, 60, 90, and 120 days as the number of days and find consistent results.

In this regression setup, we are particularly interested in δ_1 and δ_3. A positive δ_1 would indicate that, on average, news days yield higher returns than non-news days. However, if $\delta_1 + \delta_3 = 0$, then the impact of news days within the earlier time period would be no different than the impact of non-news days. Our results confirm these findings. Column 5 of Table VI shows that, unconditionally, returns are higher on news days $(\delta_1 > 0)$ and returns are higher when they occur nearer the 10-K release $(\delta_2 > 0)$. However, consistent with our findings from Table V, returns on news days within the early period are no different than returns to non-news days during the early period $(\delta_1 + \delta_3 = 0)$.

In Table VII, we take a calendar time approach, similar to Tables III and IV, and again split returns into days with news and days without news. Our baseline is column 2, which is equivalent to column 2 in Table III.[16] Table VII then presents results from decomposing returns into news days and non-news days. Column 3 shows the return to the super portfolio on news days while column 4 shows the return from non-news days, as described above when discussing Table V. Column 2 shows that when taking into account all days, the equally-weighted super portfolio yields an annualized daily return of 4.84% on average. Of this return, column 3 shows that 2.99% 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 Engelberg et al. Indeed, we find that news is very important for driving anomaly returns. Additionally, it is worth pointing out that our statistical setting is significantly different from Engelberg et al. in that we are not analyzing stock returns, per se, as much as we are focused on portfolio returns. Further, we necessarily have a relatively small subset of the anomalies in that

[16] Note that the numbers are slightly different in Table VI. This is because we are using a slightly different sample period, beginning in 2000 instead of 1997, to match news data provided by Ravenpack.

paper. However, for our purposes, the key point from Table VII is that in this calendar time approach, we are including both news that drives portfolio assignment as well as other news.

D. Hedge Fund Speed and Performance.

In what follows, we construct a portfolio that captures the return difference between the daily rebalancing strategy and annual rebalancing. We then use that return differential to gauge hedge fund speed, and we ask whether hedge fund speed is related to hedge fund performance.

D.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 hedge portfolios and is short the annual rebalancing hedge portfolios. This portfolio approach is meant to capture the differential return earned by the fast, daily-rebalanced portfolios over the slow, annually-rebalancing portfolios. Put another way, the FMS portfolio has positive exposure to the daily updating version of anomaly returns and negative exposure to the original, annually-rebalanced portfolios.

We see the returns to this portfolio are presented in the appendix, Table A2. 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 returns for most anomalies. Consistent with our previous results, we see that the strongest two FMS returns are to the asset growth anomaly (11.87%) and the sustainable growth anomaly (9.31%). Overall, the super portfolio exhibits an annualized return of 4.63%.

D.2. Fund Speed

We calculate hedge fund speed in two ways. First, we calculate a fixed estimate of fund speed which is simply the parameter estimate from the following regression:

$$Return_{it} = \alpha + \beta FMS_{it} + \varepsilon_{it}$$

This regression is a time-series regression over the entire sample for each fund, and thus an average sensitivity of a given fund's return to the FMS portfolio.

Our second approach is similar, except it 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. This approach is run on a rolling basis. Namely, we estimate a fund's speed in month *t* as the parameter estimate from the same regression presented above. However, 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, we have a panel of fund-months where an observation is a fund's speed over the last three years.

D.3. Fund Performance

Just as fund speed was calculated using two approaches, we have also calculated fund performance in two similar ways. The first approach is simply the time series average of a fund's monthly abnormal returns over their entire time in the sample. Thus, each fund in our sample has one measure of performance, which we link to the fund's one measure of speed over the entire sample.

The second measure of fund performance allows for changes in performance through time. For a given month we measure a fund's compound alpha looking forward 12 months. The result is that each fund-month in the panel has a value for the future one-year alpha. We link this monthly measure of fund performance with our monthly measure of fund speed.

D.4. Speed and Performance

We examine the relationship between fund speed and performance in three different empirical settings: in the cross-section of funds, in panel regressions, and using a fama-macbeth approach.

Our first setting is fairly simple: we estimate each fund's speed over the entire sample, and we ask how that speed is correlated with performance over the entire sample. In panel A of Table VIII, we find that this purely cross-sectional relationship is fairly strong. In particular, the positive coefficient estimate of 0.14 indicates that funds with higher speeds earn higher returns. Specifically, this regression implies that a one standard deviation increase in fund speed leads to an increased performance of 48 basis points annually.

Our next empirical setting is a panel regression in which a fund's monthly estimate of speed is used to predict its future performance over the next 12 months. In this regression, we see again that a fund's speed is positively related to its future performance. Specifically, in column 1, the positive and statistically significant coefficient estimate of 1.15 indicates that a one standard deviation increase in a fund's speed leads to a 44 basis point increase in annual future performance. Columns 2 and 3 are similar, but they allow us to control for fund fixed effects and fund and month-year fixed effects, respectively. In the most conservative empirical setting, with all fixed effects, we see that a one standard deviation increase in speed leads to an annual performance increase of 27 basis points. It's worth noting here that the fund fixed effect allows us to think about this relationship on a fund by fund basis.

Our final empirical setting is a Fama Macbeth regression. The first step is to measure all funds' speed at a given month, *t*, using our rolling approach. Then, taking the cross section of funds at month *t*, we estimate how speed relates to future fund performance. This gives us a single coefficient estimate per month. We then take the average of these coefficients over the time series to gauge the effect of speed on performance. Here again, we find that as speed increases so does performance. More specifically, the positive and statistically significant coefficient estimate of 0.51 can be interpreted to mean that a one standard deviation increase in fund speed for an average fund leads to a 21 basis point increase in future annual performance.

Overall we find a robust result. In a variety of empirical settings, we are able to show that fund speed relates to fund performance; funds that react more quickly to information earn higher excess returns.

E. Surprising Portfolio Inclusion

Thus far, our results have indicated that anomaly returns are at least in part driven by information. We construct another test of this idea by comparing anomaly returns using stock-filings for which the 10-K releases “surprising” information with anomaly returns using stock-filings for which the information in the 10-K was “unsurprising.” If it is truly information that is driving anomaly returns then we expect that the returns to the subset of "surprising" stocks will be higher.

Table IX is similar to Table II and provides results comparing the event time anomaly returns between surprising and unsurprising stock-filings. Panel A shows that surprising stocks earn significant positive returns in the first 30 days following a 10-K filing, and earn lower returns in the 31-120 and 121-240 day windows. Specifically, the super portfolio for surprising stocks yields 8.12% annualized in the first 30 days after the 10-K release, while over the next two periods the portfolio earns 2.29% and 0.69% respectively. Further, this general pattern can be observed for almost every anomaly.

Similarly, in panel B the unsurprising super portfolio shows the same general pattern of high earnings in the early period, with lower or negative earnings in the later periods. However, it can easily be seen that the super portfolio of surprising stocks has a higher 30-day return than that of the unsurprising. Further, for almost every anomaly the return in the 30-day window is much higher for the surprising subset than for the unsurprising.

The results of Table IX can been seen pictorially in Figure 4. Figure 4 shows that the return to surprising stocks dominates that of unsurprising stocks. One notable exception is the return on equity anomaly. Taken together, these results indicate that the surprising stocks are a stronger source of return for the overall effect seen in Table II.

F. Robustness

In Table X, we examine size effects by splitting the sample into large, small, and micro subsets and following the same empirical approach as in Tables II and III. Panel A shows that anomaly returns to stocks in each size group display the same general pattern as was shown in Table II. That is, returns are most prominent immediately following the release of 10-K information, with returns to anomalies diminishing as information becomes stale. Panel B supports a primary conclusion from Table III, that regardless of size, returns to daily rebalancing dominate those of annually rebalancing. Overall, these results indicate that the results presented in Tables II and III are not driven by any one of the three size groups of stocks.

IV. Conclusion

In this paper, we make a distinction between all news and the news that drives anomaly portfolio assignment, and we find that anomaly returns are not evenly distributed through time. Instead, we find returns are concentrated immediately after the release of information that drives portfolio assignment.

When we consider an event-time strategy for anomalies, we find that anomaly returns manifest primarily in the first month or so after the 10-K release date, diminishing thereafter. In a framework that is plausibly implementable for an investor, we find that returns are statistically greater when the investor reforms portfolios on the information release dates. Furthermore, we find that immediately following portfolio formation, news days have no more return than non-news days.

In the context of investors, these findings suggest that faster reactions to key portfolio information will lead to larger returns. We form a measure of how quickly funds react to new information, and we find that funds that react faster to information earn higher returns.

If we take a step back, it is worth asking: Why do we think of anomalies as buy-and-hold portfolios anyway? Our results show, for a specific set of anomalies at least, returns are not distributed throughout the year, instead, there are earned, almost exclusively, around the release of information. This suggests that we may consider the information on which these anomaly portfolios are based to be trading opportunities, like merger announcements, that happen to repeat regularly.

REFERENCES

Ball, Ray, and Philip Brown,1968), An empirical evaluation of accounting income numbers, *Journal of Accounting Research*, 159-178.

Basu, Sanjoy, 1977, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663-682.

Bernard, Victor L., and Jacob K. Thomas,1989, Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research*, 1-36.

Bernard, Victor L., and Jacob K. Thomas,1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13(4), 305-340.

Campbell, John Y. and Robert J. Shiller, 1988, Stock Prices, Earnings, and Expected Dividends, *Journal of Finance* 43, 661-676.

Chan, Konan, Louis K. C. Chan, Narasimhan Jegadeesh, and Josef Lakonishok, 2006, Earnings quality and stock returns, *Journal of Business* 79 (3), 1041–1082.

Cooper, Michael J., Robert C. Gutierrez, Jr., and Bill Marcum, 2005, On the predictability of stock returns in real time, *Journal of Business* 78, 469-499.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross section of asset returns, *Journal of Finance* 63,1609-51.

Drake, Michael, Darren T. Roulstone, and Jake Thornock, 2015, The determinants and consequences of information acquisition via EDGAR, *Contemporary Accounting Research* 32 (3), 1128-61.

Engelberg, Joseph, R. David McLean, and Jeffrey Pontiff, 2017, Anomalies and news, *Journal of Finance*, forthcoming.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Foster, George, Chris Olsen, and Terry Shevlin,1984, Earnings releases, anomalies, and the behavior of security returns, *The Accounting Review*, 574-603.

Green, Jeremiah, John R. Hand, and X. Frank Zhang, 2017, The characteristics that provide independent information about average U.S. monthly stock returns, forthcoming in *Review of Financial Studies*.

Han, Yufeng, Dayong Huang, and Guofu Zhou, 2017, Anomalies enhanced: A dynamic trading strategy Working paper.

Haugen, Robert A., and Nardin L. Baker,1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41(3), 401-439.

Hou, Kewei, Chen Xue, and Lu Zhang, 2017, Replicating anomalies, Working paper.

Kelly, Bryan T., Seth Pruitt, and Yinan Su, Some characteristics are risk exposures, and the rest are irrelevant, Working paper, University of Chicago.

Kothari, S. P., 2001, Capital markets research in accounting, *Journal of Accounting and Economics* 31(1), 105-231.

Lochstoer, Lars A. and Paul C. Tetlock, 2017, What drives anomaly returns? Working paper.

Lockwood, Larry, and Wikrom Prombutr, 2010, Sustainable growth and stock returns, Journal of Financial Research 33, 519-538.

Lu, Xiaomeng, Robert F. Stambaugh, and Yu Yuan, 2017, Anomalies abroad: beyond data mining, Working paper.

McLean, R. David and Jeffrey Pontiff, 2016, Does academic publication destroy stock return predictability? *Journal of Finance* 71, 5-32.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108,1–28.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and A. Irem Tuna,2005, Accrual reliability, earnings persistence and stock prices, *Journal of Accounting and Economics* 39(3), 437-485.

Sloan, Richard G., 1996, Do stock prices fully reflect information for accruals and cash flows about future earnings? *The Accounting Review* 71(3), 289-315.

Soliman, Mark T. (2008), The use of DuPont analysis by market participants, *The Accounting Review* 83(3), 823-853.

Thomas, Jacob K., and Huai Zhang,2002, Inventory changes and future returns, *Review of Accounting Studies* 7(2), 163-187.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39 (4), 677-700.

Xie, Hong, 2001, The mispricing of abnormal accruals, *The Accounting Review* 76(3), 357-373.

Appendix: Anomaly Variable Construction

Anomaly	Paper	Original Paper Rebalancing	Our Calculation
Accruals	Sloan (AR 1996)	Ranked into deciles annually. Return calculations begin four months following fiscal year end.	Accruals = $(WC_t – WC_{t-1}) / ((TA_t + TA_{t-1}) / 2)$ WC = (current assets - cash) - (current liabilities - debt in current liabilities - income taxes payable) - depreciation
Asset Growth	Cooper *et al.* (JF 2008)	Ranked into deciles at the end of June.	Asset Growth = $(TA_t - TA_{t-1}) / TA_{t-1}$ TA = total assets
Gross Profitability	Novy-Marx (JFE 2013)	Ranked into quintiles at the end of June.	GP = $(sales_t – cogs_t) / total\ assets_t$
Inventory Growth	Thomas & Zhang (RAS 2002)	Ranked into deciles annually. Return calculations begin four months following fiscal year end.	Inventory Growth = Change in inventory scaled by average total assets (average of current year and last year assets)
Investment	Titman, Wei, and Xie (JFQA 2004)	Ranked into quintiles at the end of June.	Capital Expenditures divided by Sales. Scaled by average Capex/Sales over the last 3 years.
Net Working Capital Changes	Soliman (AR 2008)	Measures control variables from FYE_{t-1}. Starts calculating monthly returns during the first month of the fiscal year.	Change in working capital scaled by total assets. Working capital is defined as (current assets - cash and short term equivalents) - (current liabilities - debt in current liabilities).
Operating Leverage	Novy-Marx (ROF 2010)	Ranked into quintiles at the end of June.	COGS + SG&A / total assets
Profit Margin	Soliman (AR 2008)	Measures control variables from FYE_{t-1}. Starts calculating monthly returns during the first month of the fiscal year.	(sales - cogs) / sales
Return on Equity	Haugen and Baker (JFE 1996)	"We assume a reporting lag of 3 months." We take this to mean the start 3 months after the FYE.	Net income scaled by book value of equity.
Sustainable Growth	Lockwood and Prombutr (JFR 2010)	Ranked into deciles or quintiles at the end of June.	BE = common equity + balance sheet deferred taxes. Sustain Growth = (BEt / BEt-1) - 1

Table A1

Replication of Anomaly Returns Using Annual Rebalancing

This table replicates the anomalies from their original papers. Each anomaly portfolio is constructed as follows. On the last day of June for every year the data from the most recent 10-K filing is used to calculate the value of an anomaly variable for each stock. At the end of the last day of June each stock is classified as either in the long leg of the portfolio, the short leg, or neither. For all anomalies below, the legs of the portfolio are based on whether a stock has an anomaly value in the extreme deciles. In the equally-weighted portfolio (Panel A) an equally-weighted portfolio is purchased after close on the last day of June and held until the last day of June the following year. In the value-weighted portfolio (Panel B) a value-weighted portfolio is purchased after close on the last day of June and held until the last day of June the following year. There is no other rebalancing. The super anomaly represents an equally-weighted portfolio of the ten anomalies. The sample begins at July 1, 1997, and ends at June 30, 2015. Thus, there are 18 unique portfolios created, one for each year. The investment anomaly has limited data, due to the construction of the investment variable, until July 1, 2000. Column 1 shows the average daily return on the portfolios over the entire period, shown in basis points. Column 2 shows the annualized average daily return (daily return times 240) in percent. Column 3 shows the *p*-value from testing whether the daily returns over the approximately 4,500 days of the sample are different from zero. Column 4 shows the average compound return earned after 30 trading days over the 18 portfolio-years. Columns 5 and 6 are similar to Column 4. Column 6 shows the average annual return from holding these anomaly portfolios for 18 years. Column 7 is percentage of the 18 years that have a positive annual return. For instance, the equally weighted accruals anomaly provides a postive annual return in 22% of the 18 years observed.

Panel A: Equally-Weighted Anomaly Portfolios

	Average Daily Returns			Average Compound Returns Across 18 Portfolios-Years in Percent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Anomaly	Daily Return in Basis Points	Return in Annualized Percent	*p*-value	30 Day Return (7/1 - 8/15)	120 Day Return (7/1 - 12/31)	240 Day Return (7/1 - 6/30)	Percent of Years 240 Day Return > 0
Super	0.46	1.11	.261	0.30	0.87	1.53	56
Accruals	-1.64	-3.94	.017	-0.44	-1.57	-4.11	22
Asset Growth	-0.12	-0.29	.888	0.74	0.81	1.27	50
Gross Profitability	2.38	5.71	.025	0.45	3.70	9.19	56
Inventory Growth	-1.51	-3.63	.038	0.28	-0.23	-3.14	39
Investment	-2.82	-6.78	.001	-1.56	-3.70	-6.52	7
Net Working Capital	-1.83	-4.38	.008	-0.72	-1.86	-4.54	17
Operating Leverage	-1.44	-3.45	.181	0.73	0.90	-1.56	44
Profit Margin	1.30	3.11	.170	-0.66	2.25	3.39	61
ROE	2.79	6.70	.003	0.50	2.29	8.57	61
Sustainable Growth	1.21	2.91	.143	1.82	2.72	4.09	61

Panel B: Value-Weighted Anomaly Portfolios

	Average Daily Returns			Average Compound Returns Across 18 Portfolios-Years in Percent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Anomaly	Daily Return in Basis Points	Return in Annualized Percent	*p*-value	30 Day Return (7/1 - 8/15)	120 Day Return (7/1 - 12/31)	240 Day Return (7/1 - 6/30)	Percent of Years 240 Day Return > 0
Super	2.30	5.53	.001	1.01	4.29	5.83	83
Accruals	-0.52	-1.25	.713	0.86	0.54	-1.46	39
Asset Growth	2.73	6.55	.039	2.45	8.75	7.45	78
Gross Profitability	3.38	8.12	.025	-0.27	3.15	13.31	44
Inventory Growth	1.06	2.53	.437	2.38	5.15	2.55	50
Investment	-0.49	-1.18	.746	-0.63	-1.76	-1.00	53
Net Working Capital	-0.85	-2.03	.564	0.31	0.99	-2.70	39
Operating Leverage	1.06	2.55	.557	-0.76	0.95	2.92	50
Profit Margin	3.30	7.91	.014	-0.05	3.30	8.53	67
ROE	5.28	12.68	.000	1.80	7.77	14.74	72
Sustain Growth	2.99	7.16	.016	2.40	8.14	8.18	56

Table A2

Fast Minus Slow

This table shows the annualized average daily differential return between the "fast" anomaly portfolio and the "slow" anomaly portfolio. The "fast" portfolio is the portfolio with daily updating when 10-K reports are filed (see Table III). The "slow" portfolio is rebalanced annually (see Table A1). The differential is shown for each portfolio year and for the entire period. The p-value for the entire period is based on the daily differential from July 1997 through June 2015 being different from zero.

Panel A: Equally-Weighted Anomaly Portfolios

	Annualized Average Daily Returns for Each Anomaly										
Portfolio-Year	Accruals	Asset Growth	Gross Profitability	Inventory Growth	Investment	Net Working Capital	Operating Leverage	Profit Margin	ROE	Sustainable Growth	Super
1997	9.25	2.00	6.69	3.43		9.04	-0.50	8.39	-9.88	4.28	3.80
1998	5.11	3.62	-6.63	9.67		4.31	-3.00	-3.27	-6.09	22.35	4.96
1999	-20.79	8.15	28.12	0.29		-20.50	4.45	30.02	8.78	19.91	5.10
2000	6.83	28.49	5.41	24.08	-10.98	5.53	9.06	0.40	-2.36	27.40	11.73
2001	5.92	5.39	-3.16	2.95	3.80	5.33	7.11	-9.67	-4.93	-11.62	0.58
2002	-4.28	7.12	10.36	3.74	-16.65	-7.88	6.23	13.30	10.20	-3.00	5.22
2003	6.43	5.33	4.44	7.44	-10.83	2.45	-2.64	-2.28	-2.62	-0.33	-0.38
2004	5.37	8.02	-4.52	1.26	-3.96	0.90	-3.12	1.34	-5.62	14.27	2.96
2005	-0.17	10.72	0.61	1.96	-3.53	0.63	1.16	7.79	-1.76	6.98	6.48
2006	-3.84	9.61	-5.00	-0.57	-3.32	-3.75	1.05	-4.25	-8.68	10.66	2.50
2007	8.19	15.65	-1.81	10.80	2.51	6.86	2.78	-4.06	-15.06	14.11	4.43
2008	-2.10	19.46	12.95	5.70	-15.69	-2.41	7.86	-3.14	-0.35	11.52	7.65
2009	4.13	12.92	4.58	6.66	-12.83	2.90	0.10	2.87	3.05	0.72	2.50
2010	-2.07	16.74	-2.74	4.50	4.27	-4.18	-1.24	1.06	-3.03	10.09	6.25
2011	10.16	10.56	-2.86	9.47	3.20	9.24	2.16	0.35	-2.30	-0.51	9.46
2012	3.07	15.64	-6.48	7.97	5.76	3.03	-1.40	-3.02	-8.92	9.00	2.23
2013	-2.13	16.89	12.23	7.70	-6.65	-1.18	1.37	4.33	7.71	16.51	12.33
2014	3.74	17.33	-5.20	-5.62	5.59	1.51	4.78	-7.27	-10.00	14.80	-4.62
Entire Period	1.81	11.87	2.64	5.63	-3.99	0.64	2.01	1.86	-2.87	9.31	4.63
p-value	.230	.000	.038	.000	.014	.673	.084	.128	.070	.000	.000

Panel B: Value-Weighted Anomaly Portfolios

	Annualized Average Daily Returns for Each Anomaly										
Portfolio-Year	Accruals	Asset Growth	Gross Profitability	Inventory Growth	Investment	Net Working Capital	Operating Leverage	Profit Margin	ROE	Sustainable Growth	Super
1997	-3.84	14.91	4.48	27.15		-3.88	-9.82	0.71	-11.64	8.73	3.57
1998	19.43	35.60	11.88	19.28		20.90	9.38	0.79	15.80	30.15	20.90
1999	-0.22	37.33	21.54	21.02		7.23	4.29	15.74	13.35	9.28	15.16
2000	-24.60	-1.49	-4.67	28.68	1.25	-0.98	10.47	1.58	12.01	4.50	-1.23
2001	2.43	3.70	-14.74	8.48	0.25	1.90	7.79	-27.85	-4.49	0.56	-3.93
2002	-6.78	18.36	9.40	-11.35	-14.26	-21.06	2.43	21.21	8.32	0.49	9.10
2003	16.72	-1.09	-0.25	4.20	-15.69	7.27	10.70	1.80	6.25	-10.35	0.54
2004	8.06	10.67	-5.44	4.54	0.15	5.09	1.21	-1.86	-2.97	16.98	3.85
2005	-1.19	15.80	2.81	3.97	-0.02	1.34	-8.69	0.13	-6.95	12.27	6.54
2006	4.44	9.17	-1.81	2.89	-1.25	5.11	-2.82	0.97	0.22	5.84	3.41
2007	-13.33	20.51	-4.36	-2.26	-3.78	-12.80	4.58	0.10	-12.82	14.88	-0.87
2008	-4.22	9.73	4.15	28.00	-24.69	2.68	9.99	2.53	-13.36	6.33	6.44
2009	-5.45	1.93	2.12	-3.79	-13.26	-6.82	-4.69	5.90	20.51	-7.23	7.39
2010	2.69	17.44	-7.61	12.60	-0.33	4.67	1.84	-3.98	-10.64	18.85	8.79
2011	-1.68	2.47	-2.33	-4.74	0.85	0.64	-0.85	3.64	1.39	-7.85	0.29
2012	-1.25	14.20	-0.83	6.34	4.47	3.77	1.74	-5.65	-6.53	1.69	1.00
2013	13.60	9.00	3.26	-1.12	-5.72	16.21	0.03	-0.35	-3.08	11.64	7.68
2014	3.39	1.09	3.25	1.12	-2.88	2.28	-7.70	1.86	-0.77	2.66	-2.02
Entire Period	0.46	12.21	1.19	8.06	-5.21	1.87	1.66	1.00	0.26	6.65	4.83
p-value	.879	.000	.557	.001	.038	.569	.264	.454	.902	.002	.000

Figure 1

Return Path of Anomalies in Event Time

Figure 1
Return Path of Anomalies in Event Time

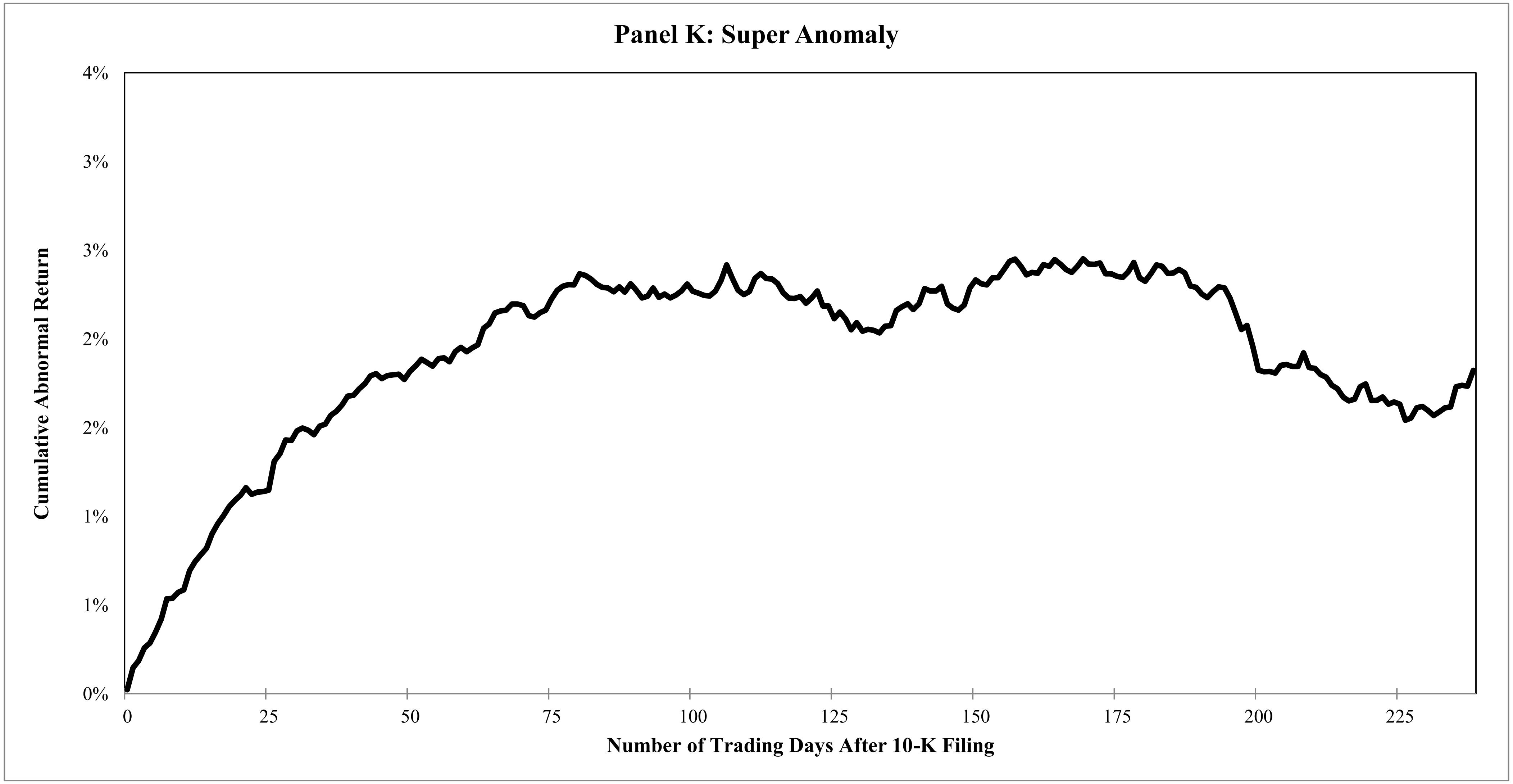

Figure 2

Return Path of Anomalies Using Annual versus Daily Rebalancing from July 1997 through June 2015

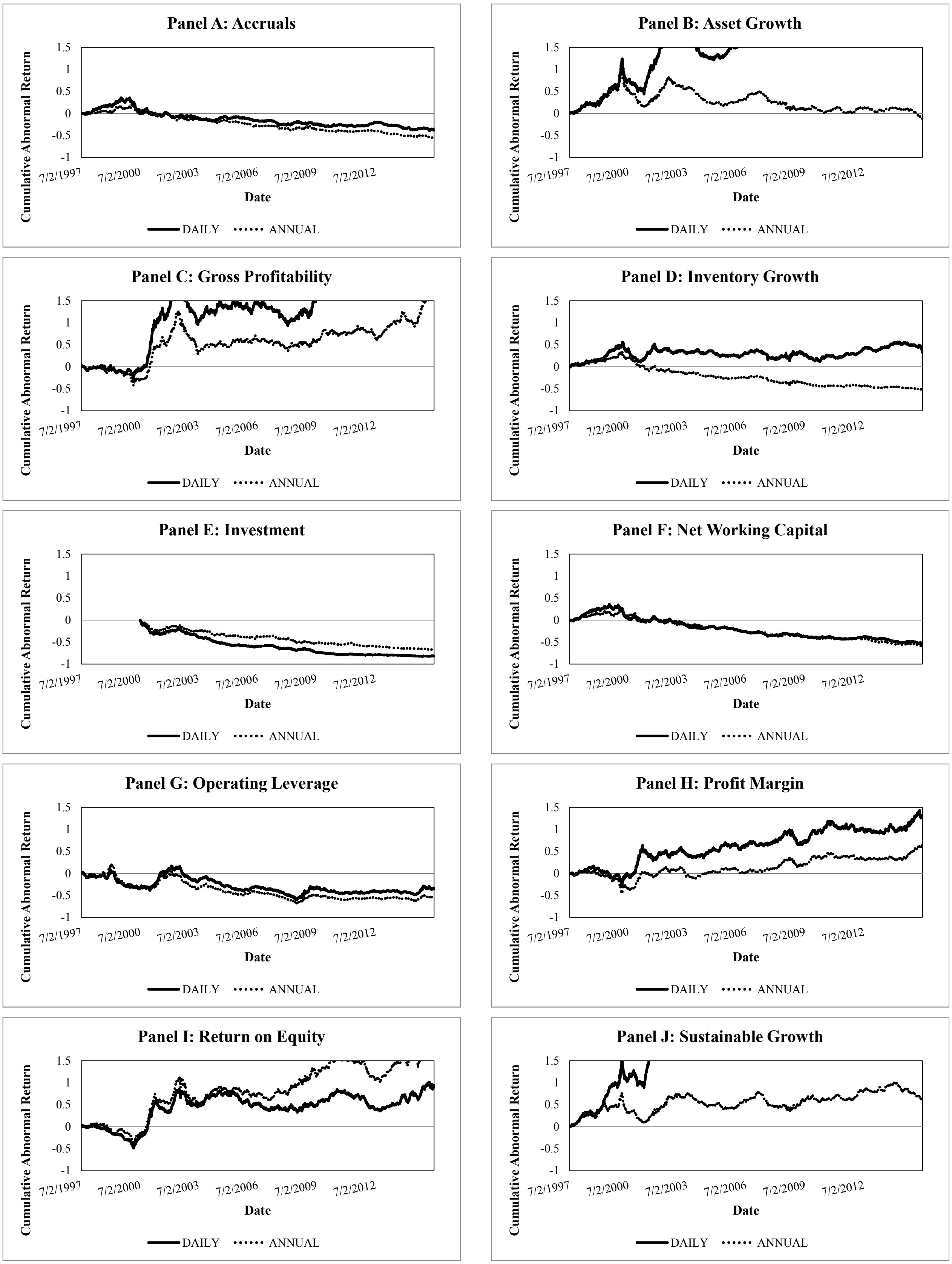

Figure 2
Return Path of Anomalies Using Annual versus Daily Rebalancing from July 1997 through June 2015

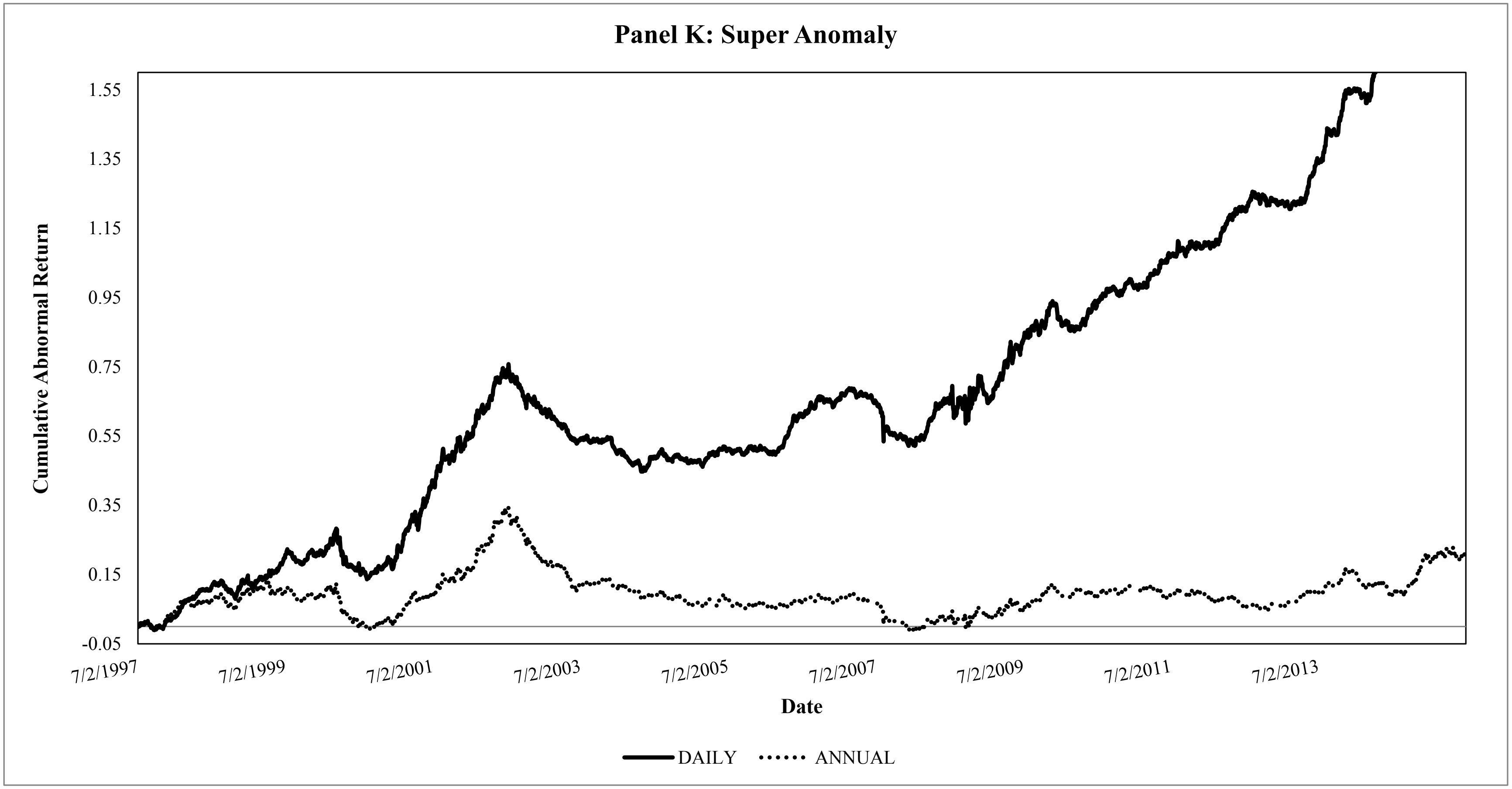

Figure 3
Return Path of Super Portfolio in Event Time - News Days v. Non-News Days

Figure 4

Return Path of Anomalies in Event Time - Surprising versus Unsurprising

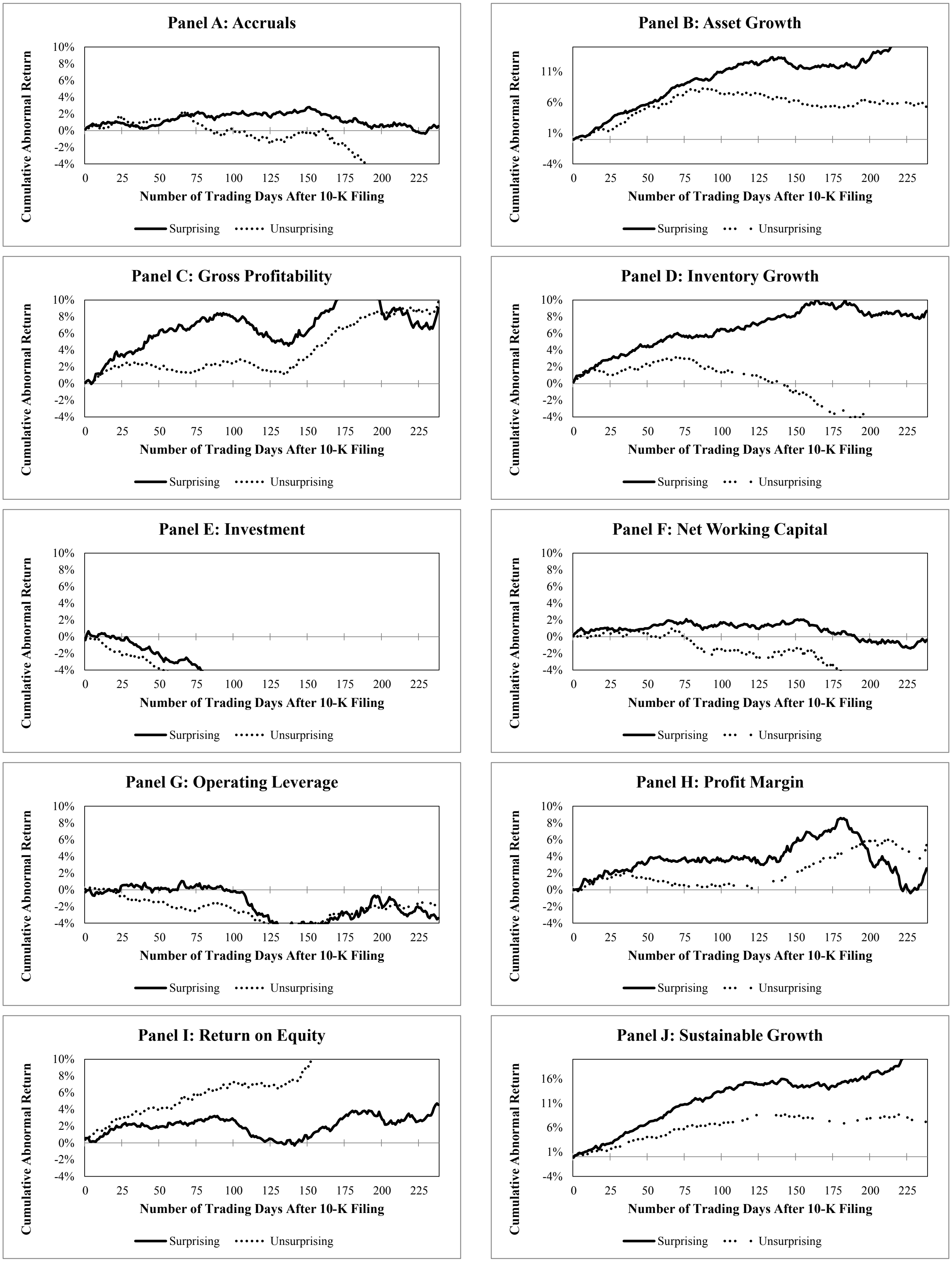

Figure 4

Return Path of Anomalies in Event Time - Surprising versus Unsurprising

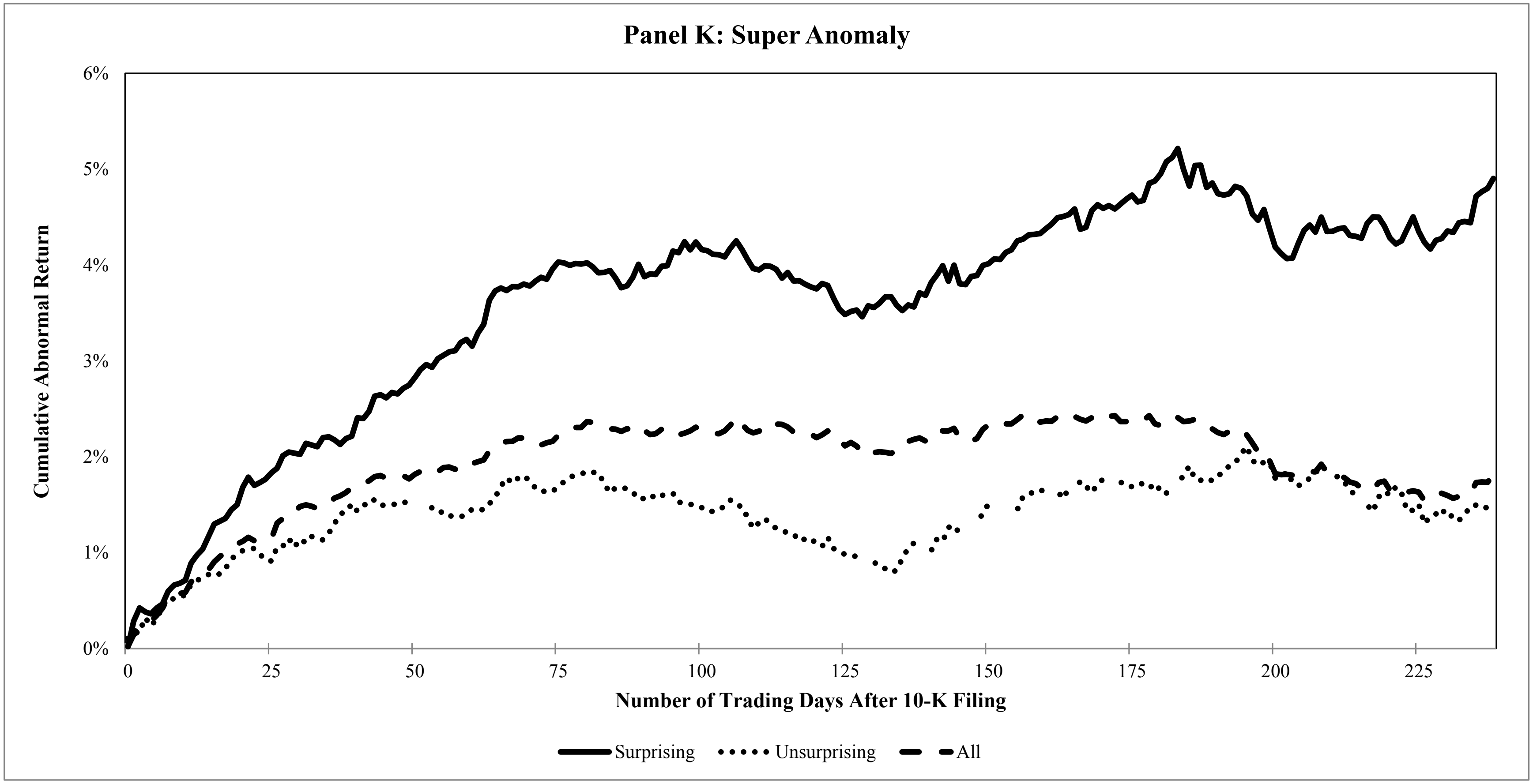

Table I

Sample Summary Statistics

This table provides summary statistics for the sample used in this study. The sample uses 10-K filings from 1996 through 2014. The sample covers approximately 7,000 unique stocks over the 18 year period. Panel A provides a summary of the stocks in the sample. Panel B describes the ten anomaly variables we use.

Panel A: Summary of Entire Sample

	Mean	Median	Standard Deviation	1st Percentile	99th Percentile
Daily Returns (bps. & %)	5.41	0.00	3.59%	-9.38%	10.64%
Market Cap. (thousands)	2,426,192	351,954	11,503,848	13,860	40,595,934

Panel B: Summary of Each Anomaly

Anomaly	Mean	Median	Standard Deviation	1st Percentile	10th Percentile	90th Percentile	99th Percentile	No. 10-K Filings	No. Stocks
Accruals	0.00	0.00	0.10	-0.28	-0.08	0.09	0.27	46,197	6,627
Asset Growth	0.16	0.05	0.83	-0.58	-0.20	0.48	2.46	47,474	6,792
Gross Profitability	0.31	0.29	0.38	-0.80	0.03	0.67	1.22	45,385	6,724
Inventory Growth	0.01	0.00	0.05	-0.15	-0.03	0.05	0.18	46,910	6,743
Investment	1.10	0.90	2.00	0.05	0.32	1.81	4.79	28,026	4,399
Net Working Capital	0.01	0.00	1.14	-0.32	-0.08	0.08	0.25	46,195	6,627
Operating Leverage	1.04	0.85	1.02	0.07	0.29	1.95	4.22	38,306	5,954
Profit Margin	-3.73	0.35	183.57	-22.10	0.07	0.72	0.91	44,822	6,665
ROE	-0.49	0.06	94.44	-6.37	-0.75	0.27	3.84	46,549	6,963
Sustainable Growth	0.16	0.06	6.53	-2.67	-0.39	0.54	4.43	47,461	6,792

Table II

Anomaly Returns in Event Time

This table reports anomaly returns in event time. 10-K filing dates and returns to stocks for the next 240 days are lined up. If a stock at its 10-K filing date warrants admission to the long or short leg of an anomaly portfolio, then it is bought or sold, with that position held for 240 days. The returns shown below represent the return that would be earned on this hypothetical portfolio given the number of days after 10-K filings are released. For instance, Column 1 shows the return on an equally-weighted portfolio from all 10-K announcements over the first 30 days after a firm releases its 10-K. Column 5 shows the return earned from the 31st day after the release of the 10-K through the 120th day post 10-K release. The super anomaly represents an equally-weighted average of the ten anomalies.

Equally-Weighted Anomaly Portfolios						
	Compound Returns Earned After Release of 10-K Report			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	30 Days	120 Days	240 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days
Super	0.81	1.19	0.98	6.52	1.03	0.28
(*p* -value)	(.000)	(.000)	(.001)	(.000)	(.028)	(.571)
Accruals	0.72	0.74	-0.64	5.76	-0.54	-2.54
	(.003)	(.137)	(.352)	(.003)	(.639)	(.024)
Asset Growth	1.86	4.88	4.56	14.90	8.30	1.48
	(.000)	(.000)	(.000)	(.000)	(.000)	(.194)
Gross Profitability	1.13	0.80	1.58	9.05	-0.33	3.26
	(.000)	(.110)	(.020)	(.000)	(.773)	(.002)
Inventory Growth	1.07	2.19	0.96	8.57	2.51	-2.01
	(.000)	(.000)	(.107)	(.000)	(.017)	(.041)
Investment	-0.58	-3.27	-3.50	-4.67	-7.53	-1.98
	(.028)	(.000)	(.000)	(.028)	(.000)	(.086)
Net Working Capital	0.58	0.17	-1.16	4.62	-1.54	-2.78
	(.015)	(.722)	(.083)	(.015)	(.164)	(.013)
Operating Leverage	0.25	-0.59	0.17	2.01	-2.03	2.02
	(.256)	(.195)	(.789)	(.256)	(.055)	(.061)
Profit Margin	0.32	-0.01	0.27	2.56	-0.41	0.57
	(.188)	(.976)	(.692)	(.188)	(.703)	(.595)
ROE	0.33	-0.74	0.02	2.61	-2.25	1.88
	(.198)	(.159)	(.980)	(.198)	(.058)	(.100)
Sustainable Growth	1.71	5.22	5.35	13.67	9.32	2.37
	(.000)	(.000)	(.000)	(.000)	(.000)	(.045)

Table III

Returns from Annually Rebalancing vs. Daily Rebalancing on 10-K Filing Dates

This table replicates the anomalies from their original papers, with an important modification. When information becomes available on a stock through the release of a 10-K report, the anomaly variable of this stock is calculated and all stocks are ranked on the anomaly variable again. This is essentially using real-time information to update the portfolio instead of using data only once per year (i.e., on June 30th). At the end of trading of the day after the 10-K release the portfolio is adjusted to reflect the new information. If a stock warrants addition to a leg of the portfolio, then the stock is purchased or sold short. Likewise, if a stock that has previously been a part of the portfolio is no longer in an extreme decile, then the stock is taken out of the portfolio. The portfolio weights when equally weighting, however, are not readjusted when this realignment takes place. Instead, if on this new date a stock remains in place in the long leg of the portfolio, then nothing is done to the holdings of that stock. Thus, this represents a buy and hold strategy where once a stock is put into the portfolio it is not adjusted until it comes out of the portfolio. For the value-weighted portfolio, the portfolio is rebalanced whenever there is a change to the holdings. The super anomaly represents an equally-weighted average of the ten anomalies. The sample begins at July 1, 1997, and ends at June 30, 2015. Although it is artificial in the daily rebalancing scheme, we think of 18 portfolio-years, as if the portfolios were rebalanced annually. Each portfolio-year is from July to June. Column 1 shows the annualized average daily return on the annually rebalanced portfolios over the entire period in percent (see Appendix Table 1). Column 2 shows the annualized average daily return on the daily rebalanced portfolio. Column 3 shows the difference between the annualized return of the daily updating portfolio and the annual portfolio. A positive difference indicates that the returns earned to the daily portfolio are superior, on average, to the returns earned to the annual portfolio. Column 4 shows a *p*-value from testing whether the daily difference between the two portfolios is different from zero. Columns 5 and 6 show the average compound returns earned after 30 trading days over the 18 portfolio-years for the annual and daily rebalanced portfolios. Column 7 shows their difference. Columns 8 through 13 repeat the functions of Columns 5 through 7 for their respective time periods.

Panel A: Equally-Weighted Anomaly Portfolios

	Annualized Average Daily Returns in Percent				Average Compound Returns Across 18 Portfolios/Years in Percent								
					30 Day Return (7/1 - 8/15)			120 Day Return (7/1 - 12/31)			240 Day Return (7/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (*p*-value)	Annual Rebalancing	Daily Rebalancing	Difference (6 - 5)	Annual Rebalancing	Daily Rebalancing	Difference (9 - 8)	Annual Rebalancing	Daily Rebalancing	Difference (12 - 11)
Super	1.11	5.55	4.44	.002	0.30	0.73	0.43	0.87	1.68	0.82	1.53	5.65	4.12
Accruals	-3.94	-2.21	1.74	.457	-0.44	-0.40	0.04	-1.57	-1.22	0.35	-4.11	-2.38	1.74
Asset Growth	-0.29	11.10	11.39	.000	0.74	1.08	0.35	0.81	1.81	1.00	1.27	11.38	10.11
Gross Profitability	5.71	8.24	2.53	.482	0.45	1.03	0.58	3.70	4.89	1.19	9.19	11.57	2.39
Inventory Growth	-3.63	1.78	5.41	.029	0.28	-0.06	-0.34	-0.23	0.01	0.24	-3.14	1.58	4.73
Investment	-6.78	-10.61	-3.83	.177	-1.56	-1.61	-0.05	-3.70	-4.27	-0.57	-6.52	-9.44	-2.92
Net Working Capital	-4.38	-3.77	0.61	.792	-0.72	-0.98	-0.25	-1.86	-1.66	0.19	-4.54	-3.82	0.72
Operating Leverage	-3.45	-1.52	1.93	.606	0.73	0.58	-0.15	0.90	0.33	-0.57	-1.56	0.15	1.71
Profit Margin	3.11	4.90	1.79	.577	-0.66	-0.18	0.48	2.25	3.64	1.39	3.39	5.35	1.96
ROE	6.70	3.94	-2.75	.389	0.50	0.37	-0.13	2.29	2.51	0.22	8.57	5.64	-2.93
Sustainable Growth	2.91	11.85	8.94	.001	1.82	2.51	0.69	2.72	4.10	1.38	4.09	12.01	7.92

Panel B: Value-Weighted Anomaly Portfolios

	Annualized Average Daily Returns in Percent				Average Compound Returns Across 18 Portfolios/Years in Percent								
					30 Day Return (7/1 - 8/15)			120 Day Return (7/1 - 12/31)			240 Day Return (7/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (*p*-value)	Annual Rebalancing	Daily Rebalancing	Difference (6 - 5)	Annual Rebalancing	Daily Rebalancing	Difference (9 - 8)	Annual Rebalancing	Daily Rebalancing	Difference (12 - 11)
Super	5.53	10.17	4.64	.049	1.01	1.21	0.21	4.29	5.36	1.07	5.83	10.29	4.46
Accruals	-1.25	-0.81	0.44	.928	0.86	0.76	-0.10	0.54	1.14	0.60	-1.46	-2.01	-0.55
Asset Growth	6.55	18.27	11.72	.010	2.45	1.91	-0.53	8.75	8.76	0.01	7.45	20.02	12.57
Gross Profitability	8.12	9.26	1.14	.826	-0.27	-0.24	0.03	3.15	3.09	-0.06	13.31	12.76	-0.55
Inventory Growth	2.53	10.27	7.74	.095	2.38	2.52	0.14	5.15	6.51	1.36	2.55	9.58	7.04
Investment	-1.18	-6.18	-5.00	.344	-0.63	-0.86	-0.22	-1.76	-3.03	-1.27	-1.00	-4.89	-3.89
Net Working Capital	-2.03	-0.24	1.79	.724	0.31	0.15	-0.16	0.99	2.26	1.27	-2.70	-0.69	2.00
Operating Leverage	2.55	4.14	1.59	.794	-0.76	-0.65	0.10	0.95	1.11	0.17	2.92	4.71	1.78
Profit Margin	7.91	8.87	0.96	.832	-0.05	0.21	0.26	3.30	4.00	0.70	8.53	8.94	0.41
ROE	12.68	12.93	0.25	.954	1.80	1.79	-0.01	7.77	8.21	0.44	14.74	16.23	1.49
Sustainable Growth	7.16	13.55	6.39	.127	2.40	2.42	0.02	8.14	7.30	-0.84	8.18	13.12	4.94

Table IV

Returns to Annual and Daily Portfolios During Different Parts of the Year

This table compares the returns earned by the annual and daily rebalancing methods during different parts of the portfolio-year (see Table III description). The days are counted from the first of July for each of the 18 years. The returns shown below represent the return earned over the specified time period. For example, Column 4 and Column 5 show the return earned from holding the portfolios from day 31 (approximately mid-August) to day 120 (approximately the end of December).

Panel A: Equally-Weighted Anomaly Portfolios

	Annualized Compound Return Earned in the First 30 days (7/1 - 8/15)			Annualized Compound Return Earned from 31 to 120 days (8/16 - 12/31)			Annualized Compound Return Earned from 121 to 240 days (1/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference	Annual Rebalancing	Daily Rebalancing	Difference	Annual Rebalancing	Daily Rebalancing	Difference
Super	2.40	5.81	3.40	1.42	2.46	1.04	1.15	7.68	6.53
Accruals	-3.50	-3.22	0.28	-2.97	-2.15	0.81	-5.09	-2.32	2.77
Asset Growth	5.90	8.66	2.77	-0.17	1.60	1.77	0.07	18.43	18.36
Gross Profitability	3.62	8.26	4.64	8.13	9.70	1.56	7.77	10.01	2.24
Inventory Growth	2.26	-0.45	-2.71	-1.52	0.06	1.58	-5.94	3.47	9.41
Investment	-12.51	-12.92	-0.41	-5.96	-7.53	-1.57	-5.97	-11.01	-5.04
Net Working Capital	-5.78	-7.81	-2.03	-3.00	-1.80	1.20	-5.43	-4.44	0.98
Operating Leverage	5.87	4.68	-1.19	-0.63	-1.67	-1.04	-5.27	-1.33	3.94
Profit Margin	-5.31	-1.46	3.85	7.97	10.37	2.40	1.43	2.77	1.34
ROE	4.01	2.95	-1.06	4.22	5.16	0.94	10.75	5.00	-5.75
Sustainable Growth	14.54	20.07	5.53	2.19	3.90	1.72	2.12	15.37	13.26

Panel B: Value-Weighted Anomaly Portfolios

	Annualized Compound Return Earned in the First 30 days (7/1 - 8/15)			Annualized Compound Return Earned from 31 to 120 days (8/16 - 12/31)			Annualized Compound Return Earned from 121 to 240 days (1/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference	Annual Rebalancing	Daily Rebalancing	Difference	Annual Rebalancing	Daily Rebalancing	Difference
Super	8.08	9.72	1.64	8.66	10.89	2.24	2.62	9.40	6.77
Accruals	6.88	6.08	-0.80	-1.17	0.91	2.08	-4.87	-5.76	-0.89
Asset Growth	19.60	15.32	-4.28	15.54	17.05	1.51	-1.83	20.50	22.33
Gross Profitability	-2.17	-1.89	0.28	8.54	8.19	-0.35	13.92	14.65	0.72
Inventory Growth	19.07	20.19	1.12	6.78	9.77	2.99	-4.08	6.96	11.04
Investment	-5.07	-6.87	-1.80	-3.61	-6.41	-2.79	0.92	-4.44	-5.36
Net Working Capital	2.47	1.22	-1.25	1.29	5.13	3.83	-7.49	-5.27	2.22
Operating Leverage	-6.06	-5.23	0.83	4.12	4.27	0.14	3.60	6.53	2.93
Profit Margin	-0.43	1.64	2.07	8.86	9.94	1.08	7.99	7.40	-0.59
ROE	14.38	14.33	-0.05	16.04	17.09	1.04	11.55	12.42	0.88
Sustainable Growth	19.19	19.33	0.13	14.80	12.68	-2.12	-0.10	10.85	10.95

Table V

Super Anomaly Returns in Event Time - News Days v. Non-News Days

This table is similar to Table II. The return to the super anomaly is described in event time, with the return separated between news days and non-news days. Column 1 shows the return to the average anomalous stock 30 days after the release of its 10-K. The last two rows show the difference between returns earned on news days versus non-news days. Columns 4 through 6 look at the annualized return earned within a period of days after the 10-K. For example, the non-news days driven return earned between 31 and 120 days after a 10-K release is 0.57% annualized. Further, in the first 30 days after a 10-K release, non-news days yield an annualized return on 1.67% more than on news days.

Equally-Weighted Anomaly Portfolios							
	Compound Returns Earned After Release of 10-K Report			Average Annualized Return Earned Over Span of Days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subset of Days	30 Days	120 Days	240 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days	Pct. of All Days
All Days	0.83	1.37	1.10	6.63	1.34	0.30	100%
(*p* -value)	(.000)	(.000)	(.000)	(.000)	(.007)	(.550)	
News Days Only	0.31	0.59	0.89	2.46	0.80	1.06	41%
	(.000)	(.000)	(.000)	(.000)	(.021)	(.004)	
Non-News Days Only	0.52	0.74	0.22	4.13	0.57	-0.76	59%
	(.000)	(.000)	(.371)	(.000)	(.129)	(.045)	
Non-News Days minus News Days	0.21	0.15	-0.67	1.67	-0.23	-1.82	
	(.016)	(.400)	(.008)	(.016)	(.562)	(.000)	

Table VI

Super Anomaly Returns - News Days v. Non-News Days in Regression

This table reports regression results testing the effect of news days on anomaly returns in event time. We utilize the following regression model:

$$Return_{it} = \alpha + \delta_1 NewsDay_{it} + \delta_2 Under\#Days_{it} + \delta_3 Under\#DaysXNewsDay_{it} + \epsilon_{it}$$

Return on the left-hand side is the daily abnormal return, in percent, to a given stock, i, on a given day, t, following its 10-K release. We include all stocks in the super portfolio. *NewsDay* is an indicator for whether a stock has a news day. *Under#Days* is an indicator for whether the return on a given day is within a certain number of days following a 10-K release. *Under#DaysXNewsDays* is an indicator for whether a given day is both a news day and within the early time period following a 10-K release. We use 30, 60, 90, and 120 days as the number of days and find consistent results. We control for year fixed effects and cluster standard errors by stock.

	(1)	(2)	(3)	(4)	(5)
Intercept	.028	.023	.020	.020	.020
(p-value)	(.042)	(.095)	(.143)	(.160)	(.164)
News Day	.008	.009	.012	.011	.013
	(.024)	(.010)	(.002)	(.012)	(.007)
Under30		.029			
		(.000)			
Under30 x News Day		-.011			
		(.234)			
Under60			.023		
			(.000)		
Under60 x News Day			-.018		
			(.009)		
Under90				.017	
				(.000)	
Under90 x News Day				-.008	
				(.171)	
Under120					.014
					(.000)
Under120 x News Day					-.011
					(.077)
$\delta_1 + \delta_3$		-.001	-.006	.003	.002
(p-value)		(.872)	(.329)	(.577)	(.564)
Observations	11,557,319	11,557,319	11,557,319	11,557,319	11,557,319
R-squared	.000	.000	.000	.000	.000
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered SE by Stock	Yes	Yes	Yes	Yes	Yes

Table VII

Super Anomaly Returns from Daily Rebalancing - News Days v. Non-News Days

This table is similar to Table III and Table IV. Super anomaly portfolio returns are summarized. Column 1 summarizes the return to the super anomaly portfolio using annual rebalancing. Column 2 summarizes the return to the super portfolio using daily (continuous) rebalancing. Columns 3 and 4 separate the return earned to the daily rebalancing portfolio by accounting for returns on news versus no-news days. In Column 3, if a stock in the long leg of an anomaly is not having a news day, that stock is treated as if it had no return that day. By contrast, in Column 4, if a stock in the long leg of an anomaly is having a news day, that stock is treated as if it had no return that day. The effect of this is to be able to see how the news and non-news days contribute to the total return of the portfolio. Approximatley 40% of all days are news days.

Panel A: Equally-Weighted Anomaly Portfolios

	Rebalancing Method and Subset of Days Included in Portfolio Return			
	Annual Rebalancing All Days	Daily Rebalancing All Days	Daily Rebalancing News Days	Daily Rebalancing Non-News Days
Return (in percent)	(1)	(2)	(3)	(4)
Annualized Average Daily Return	0.25	4.84	2.99	2.17
(p-value)	(.822)	(.000)	(.000)	(.003)
30 Day Return (7/1 - 8/15)	0.48	0.46	0.64	-0.33
120 Day Return (7/1 - 12/31)	0.50	1.27	1.39	0.06
240 Day Return (7/1 - 6/30)	0.58	5.35	3.14	2.40
Annualized Return Earned in First 30 days (7/1 - 8/15)	3.82	3.65	5.12	-2.61
Annualized Return Earned from 31 to 120 days (8/16 - 12/31)	0.06	2.15	1.98	1.03
Annualized Return Earned from 121 to 240 days (1/1 - 6/30)	0.16	8.06	3.45	4.68

Panel B: Value-Weighted Anomaly Portfolios

	Rebalancing Method and Subset of Days Included in Portfolio Return			
	Annual Rebalancing All Days	Daily Rebalancing All Days	Daily Rebalancing News Days	Daily Rebalancing Non-News Days
Return (in percent)	(1)	(2)	(3)	(4)
Annualized Average Daily Return	1.97	8.07	4.83	3.33
(p-value)	(.202)	(.000)	(.001)	(.000)
30 Day Return (7/1 - 8/15)	0.51	0.69	0.48	0.05
120 Day Return (7/1 - 12/31)	2.18	4.33	3.01	1.31
240 Day Return (7/1 - 6/30)	2.45	8.70	4.89	3.48
Annualized Return Earned in First 30 days (7/1 - 8/15)	4.09	5.48	3.85	0.39
Annualized Return Earned from 31 to 120 days (8/16 - 12/31)	4.42	9.65	6.71	3.36
Annualized Return Earned from 121 to 240 days (1/1 - 6/30)	0.53	8.38	3.65	4.28

Table VIII

Fund Speed and Performance

This table reports results from regressions of fund speed on fund performance. In Panel A, each fund has a speed measure over the entire sample and monthly returns are averaged for each firm over the sample. In Panel B, each fund has a speed measure every month. Further, returns for each fund-month are the forward looking one-year alpha that the fund earns. In Panel C, the panel of speed and forward looking alphas are used to run Fama-Macbeth Regressions. A cross-sectional regressions is run every month, and the parameter estimates are averaged. The regression results reported in panel A are from the following regression:

$$Performance_i = \alpha + Speed_i + \epsilon_{\mathrm{i}}$$

The regression results reported in panels B and C are from the following:

$$Performance_{it} = \alpha + Speed_{it} + \epsilon_{it}$$

Panel A: Performance in the Cross Section

	(1) Performance
Speed	0.14
(p-value)	(.009)
R-squared	.005
Observations	3,774

Panel B: Performance in the Panel

	(1) Performance	(2) Performance	(3) Performance
Speed	1.15	1.56	0.71
(p-value)	(.000)	(.000)	(.001)
Fund FE	No	Yes	Yes
Month-Year FE	No	No	Yes
Clustered Std. Errors	Yes	Yes	Yes
R-squared	.005	.175	.340
No. of Funds	2,627	2,627	2,627
No. of Months	162	162	162
Observations	192,978	192,978	192,978

Panel C: Performance from a Fama-MacBeth Approach

	(1) Performance
Avg. Speed Parameter Est.	0.51
(p-value)	(.004)
Avg. R-squared	.018
Observations	162

Table IX

Anomaly Returns in Event Time - Surprising v. Unsurprsing

This table is similar to Table II. The sample has been split into panels based on whether the information revealed at the 10-K announcement was surprising or not. A surprising announcement is defined as one where the information announced places a given stock into the long (short) leg of the portfolio, however, when using a prediction model and data from the third quarter financial statements, the stock was not expected to be near the long (short) leg. Conversely, an unsurprising stock announcement is one where a stock is expected to be long and is actually long when the 10-K is released. The prediction model is discussed in the body of the paper.

Panel A: Surprising Stocks

	Compound Returns over # Days			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	30 Days	120 Days	240 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days
Accruals	0.20	0.55	-0.94	1.56	0.30	-3.49
(p-value)	(.570)	(.463)	(.356)	(.570)	(.860)	(.035)
Asset Growth	1.65	4.99	6.07	13.24	8.93	5.96
	(.000)	(.000)	(.000)	(.000)	(.000)	(.004)
Gross Profitability	2.46	4.16	6.47	19.69	4.82	5.32
	(.000)	(.000)	(.000)	(.000)	(.068)	(.056)
Inventory Growth	1.56	2.56	1.32	12.46	1.85	-1.19
	(.000)	(.001)	(.177)	(.000)	(.262)	(.477)
Investment	-0.03	-3.40	-3.06	-0.26	-8.12	-0.68
	(.950)	(.001)	(.019)	(.950)	(.000)	(.768)
Net Working Capital	0.27	0.20	-1.12	2.15	-0.69	-3.65
	(.428)	(.781)	(.269)	(.428)	(.671)	(.027)
Operating Leverage	0.41	-0.03	3.00	3.31	-2.60	3.88
	(.439)	(.976)	(.065)	(.439)	(.290)	(.133)
Profit Margin	1.29	2.15	1.80	10.30	2.78	-1.10
	(.015)	(.044)	(.262)	(.015)	(.250)	(.693)
ROE	1.09	-0.24	0.41	8.71	-2.16	0.70
	(.008)	(.780)	(.765)	(.008)	(.275)	(.758)
Sustainable Growth	1.54	6.43	8.36	12.31	12.88	6.14
	(.000)	(.000)	(.000)	(.000)	(.000)	(.006)
Super	1.01	1.91	2.05	8.12	2.29	0.69
	(.000)	(.000)	(.000)	(.000)	(.006)	(.441)

Panel B: Unsurprising Stocks

	Compound Returns over # Days			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	30 Days	120 Days	240 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days
Accruals	0.88	0.79	1.02	7.06	-0.41	-0.06
(p-value)	(.054)	(.412)	(.453)	(.054)	(.850)	(.978)
Asset Growth	1.20	3.51	3.39	9.58	5.93	0.83
	(.002)	(.000)	(.002)	(.002)	(.001)	(.665)
Gross Profitability	1.05	-0.34	0.84	8.41	-2.93	4.41
	(.002)	(.617)	(.368)	(.002)	(.059)	(.002)
Inventory Growth	0.77	2.02	1.39	6.15	3.08	-2.18
	(.033)	(.005)	(.175)	(.033)	(.057)	(.200)
Investment	-0.83	-2.93	-3.48	-6.64	-6.26	-1.93
	(.022)	(.000)	(.001)	(.022)	(.000)	(.258)
Net Working Capital	0.59	0.34	0.46	4.73	-1.50	-0.06
	(.198)	(.722)	(.731)	(.198)	(.484)	(.980)
Operating Leverage	-0.23	-2.02	-0.79	-1.86	-4.32	3.59
	(.426)	(.001)	(.355)	(.426)	(.003)	(.009)
Profit Margin	0.69	-0.45	-0.09	5.53	-2.61	1.07
	(.052)	(.515)	(.922)	(.052)	(.080)	(.481)
ROE	1.88	3.38	6.27	15.02	4.81	6.73
	(.000)	(.000)	(.000)	(.000)	(.017)	(.000)
Sustainable Growth	0.91	3.63	4.13	7.24	6.71	2.92
	(.013)	(.000)	(.000)	(.013)	(.000)	(.115)
Super	0.73	0.84	1.41	5.87	0.35	1.85
	(.000)	(.004)	(.001)	(.000)	(.595)	(.018)

Table X

Super Anomaly Returns - Size Breaks

This table is similar to Table II and Table III. In this table, the sample has been split by size based on the NYSE size breakpoints from data on Kenneth French's website. Large stocks are stocks with market capitalization greater than or equal to the 50th percentile. Small stocks are those with market capitalization greater than or equal to the 20th percentile but less than the 50th percentile. Micro stocks are those with market capitalization below the 20th percentile. Returns are shown only for the super anomaly.

Panel A: Returns in Event Time

	Compound Returns Earned After Release of 10-K Report			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Size	30 Days	120 Days	250 Days	1 - 30 Days	31 - 120 Days	121 - 240 Days
All	0.81	1.19	0.98	6.52	1.03	0.28
(*p* -value)	(.000)	(.000)	(.001)	(.000)	(.028)	(.571)
Large	0.51	0.92	0.68	4.07	3.09	0.92
	(.000)	(.001)	(.078)	(.000)	(.000)	(.166)
Small	0.42	-0.19	-0.13	3.38	0.27	1.51
	(.021)	(.636)	(.816)	(.021)	(.762)	(.121)
Micro	0.58	0.41	-0.56	4.61	-0.22	-0.79
	(.002)	(.288)	(.312)	(.002)	(.784)	(.341)

Panel B: Returns in Calendar Time

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Size	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (p-value)
All	1.11	5.55	4.44	.002
Large	3.97	12.12	8.15	.000
Small	3.03	6.20	3.18	.062
Micro	-1.49	2.02	3.50	.023