ANOMALY TIME[1]

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ABSTRACT: In this paper, we test the view that anomaly returns are driven by information. We show that anomaly returns are not distributed throughout the year, instead, anomaly returns are earned, almost exclusively, around the release of information. We focus on ten accounting-based anomalies that are inherently tied to an information release and create a dynamic, daily trading strategy that updates based on new information flows related to the anomalies. We find that, based on their original design, several anomalies fail to replicate in a more recent sample period, but that a daily, information-based rebalancing resurrects the returns to those information signals. For example, a daily, information-based rebalanced portfolio of all ten anomalies outperforms an annual buy-and-hold portfolio by 16% per year. Furthermore, we show that stocks that move in and out of anomaly portfolios drive anomaly returns far more than stocks that persistently remain in the portfolios. The results are robust to some robustness considerations, such as market cap. Overall, the results support an information-based explanation for anomaly returns and call into question the infrequently rebalanced buy-and-hold portfolios common in prior research.

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There are now over 400 documented anomalies in the asset pricing literature (Hou, Xue, and Zhang (2017)), yet the source of their abnormal returns remains unclear. Some papers have suggested that anomaly returns can be explained by data mining (e.g., Hou, Xue, and Zhang (2017)), while other papers suggest risk may be the source of anomaly returns (e.g., Kelly, Pruitt and Su (2018)). In this paper, we test the view that anomaly returns are driven by information.

The anomalies in the literature are often rebalanced at relatively low frequencies, which makes it difficult to distinguish risk-based explanations from information-based explanations. In this paper, we attempt to disentangle these explanations by measuring returns around information release dates and comparing them to returns when information is stable. Put differently, we explore the precise timing of anomaly returns to inform the debate about the source of the anomaly returns.

We find that the returns to anomaly strategies are driven largely by information releases. Of course, this idea can be difficult to test because information is constantly evolving, so we focus on a set of anomalies whose portfolio construction is determined solely by information arriving at specific points in time. Our main empirical setting is fairly simple: first, we identify a set of anomalies that have a clear and knowable information release date. Then, using that information release date, we then compare anomaly returns occurring close to that date to anomaly returns that occur when the relevant information is not changing.

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)). We also create a "super" portfolio based on the combined returns to all ten of these anomalies. The sample period covers the 18-year period from 1997 through 2015 as these are the dates during which we can cleanly identify information releases using the dates of SEC-mandated filings (10-Ks).

Our primary innovation is to modify the formation of information-based anomaly portfolios to capture new releases of information. Specifically, we employ the 10-K (i.e., annual report) filing date for each firm as the information release "event" for each accounting variable that underlies a particular anomaly. The 10-K is the first document that, with certainty, contains the full set of financial statements (and supporting footnotes) for a given fiscal year; we can thus be certain that our sorting variables (e.g., accruals, working capital, inventories) are in the public domain on the 10-K filing date. Using this date, we rebalance the portfolio each day based on a new ranking of the anomaly variable using the newly released information. This effectively creates a real-time strategy in which new information (e.g., accruals information contained in the 10-K) triggers a portfolio rebalancing (e.g., shifting a firm into/out of the long leg of the accrual decile) on that date. Since these 10-K dates occur continuously throughout the year, the portfolios are effectively updated in real time.

We begin by replicating these anomalies using the measurement as identified in the original papers and based on annual rebalancing. Perhaps surprisingly, we find that most of these anomalies fail to replicate using equal-weighted anomaly returns (9 out of 10) or value-weighted anomaly returns (7 out of 10), and some anomalies actually generate hedge returns that are the opposite (i.e., negative) of those presented in the original paper. The annualized daily equal-weighted return to the super portfolio of all ten anomalies is -1.27%, which is not statistically different from zero. This finding is consistent with those in Green, Hand, and Zhang (2017) and McLean and Pontiff (2016), who document the decline in the predictability of abnormal returns in more recent sample periods.

The predictability of returns to the ten anomalies we consider is much more striking using our novel information-based rebalancing approach. Specifically, we find that the equal-weighted hedge return using daily information-based rebalancing is statistically greater than the annual (information-less) rebalancing in several anomalies, and that the spread between the super portfolio's annually rebalanced return and its daily information-rebalanced return is 15% annualized. Further, the 250-day return to annual rebalancing yields on average -1.24%, while daily rebalancing yields 15.41%, a difference of 16.64%.

For annually rebalanced portfolios, information grows stale over the one-year holding period. Our evidence suggests that this matters greatly for anomaly return predictability. Specifically, we find that the majority of the spread between the annual portfolio and the daily, information-rebalanced portfolio 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 250 days after June rebalancing, where the annualized difference is 27.58%. During this period, the annual information (from the previous June) has grown quite stale, while the daily information rebalancing approach takes into account new information arising from firms releasing new accounting information, which many firms release during the first three to four months of the year. Overall, this finding supports the intuition that an annual approach is "stuck in a rut" in the face of continuous information flow, which leads to a strong spread in predictable returns between the annual and daily information rebalancing approaches.

We also consider 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 then enters the long or short leg of an anomaly based on its ranking as of the 10-K date. We then accumulate returns for 30, 120, and 250 trading days. Again, these results point to the advantages of timely investing based on the underlying anomaly variable. Across eight 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 days 31 through 120 or days 121 through 250). For example, the abnormal returns to the super portfolio for the first 30 days following the information release date are 8.21% annualized, whereas those for the next two windows ([31,120] and [121,250]) are much more modest at 2.77% and -0.01%, respectively. These results suggest that the anomaly returns manifest primarily in the first month or so after the information release date and diminish thereafter. These results also point to an information-based explanation for the cross-sectional anomalies we have considered. Risk and data mining explanations are not consistent with predictable, decaying returns.

Finally, we generate a new portfolio, the Fast Minus Slow (FMS hereafter) portfolio. This portfolio mimics the experience of a trader who holds stocks included in the daily information rebalancing portfolios and shorts stocks included in the annual rebalancing portfolios. We find that across the sample period, the annualized returns to the strategy for the super portfolio are 14.99%. Moreover, a trader who used this strategy would have never had a losing year, as the super FMS portfolio yields positive returns every year in the sample (the lowest FMS return is in 2001 at 1.32% and the highest FMS return is in 2008 at 46.5%).

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 small stocks. Specifically, the difference in predictable returns for the annual versus daily rebalancing strategy is 16.18% for the subsample of small stocks. Large and micro stocks evidence a positive difference of 1.09% and 4.56%, respectively, but neither of these is statistically different from zero. 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, but the statistical significance for these is somewhat mixed.

We also consider how the results vary based on the "persistence" of a stock's ranking, by which we mean information signals that are consistently high or low every year (e.g., a stock that is persistently in the top decile of asset growth every year). The results suggest that daily information rebalancing outperforms annual rebalancing primarily for non-persistent stocks. The abnormal returns to the super portfolio for non-persistent stocks shows a 15.75% spread between daily and annual rebalancing, while that for persistent stocks is 11.39% for the super portfolio.

We also examine event-time anomaly returns for persistent versus non-persistent stocks. Here again, the outperformance of daily over annual rebalancing is much more stark for the non-persistent subgroup of stocks. In the first 30 days after the information event, the non-persistent super portfolio yields 12.16% annualized, which diminishes to 6.16% annualized between days 31 through 120. On the other hand, the persistent super portfolio yields only 2.53% annualized in the first 30 days and -1.96% in the subsequent days 31 through 120. Taken together, these results indicate that the non-persistent stocks are a stronger source of predictable returns for daily rebalancing. Moreover, these results support an information-based explanation for these anomalies--the predictable returns accrue to the firms for which new information causes the portfolio to rebalance.

To summarize: we find that the information-based anomaly returns are much stronger for portfolios that trade responsively to new information flows relative to those that buy and hold a stock based on a single information point that is likely already stale at portfolio formation. While this finding is somewhat intuitive, it provides evidence related to several important debates in the literature. First, these results are much more consistent with an information-based explanation for these anomalies than with risk or data-mining explanations for certain anomalies. Second, prior research documents a dramatic decline in many anomalies in recent sample periods; our information-based rebalancing approach resurrects those once-dead anomaly returns. Third, our results call into question the simplified buy-and-hold strategy that blindly holds a stock when new information regarding other stocks would re-rank the stock into or out of the long/short end of a hedge strategy. We document severe costs to such a strategy.

We expect this work to be relevant not only to academics, but also to practitioners. This is primarily because information processing for trading is difficult; it requires spending on infrastructure, personnel and data. The results in this paper indicate that sizeable returns can result from reacting quickly to information. In particular, there may be only weakly significant returns on infrequently rebalanced portfolios, but substantial, statistically, and economically meaningful returns to portfolios that respond to information quickly. These results suggest that spending on infrastructure that allows funds to respond quickly may well be worthwhile.

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. We then formalize the hypotheses introduced in the beginning of the paper.

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 process 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.

C. Hypotheses

In order to understand more about the sources of anomaly returns, we rely on a simple assumption: if anomalies are related to delayed information processing, then the returns to each anomaly strategy should be a function of the time elapsed since the information was released. Put differently, we examine the returns to anomalies in event time to understand *when* each strategy earns a profit. By doing so, we are able to distinguish risk-based explanations (which are likely unrelated to timing) from information-based explanations (which directly tie to the time/date of the information release). Formally, our hypothesis seeks to empirically test this view:

$H1_a$: If the profitability of anomaly strategies is due to delayed information processing, then the returns to these strategies should be highest, in event time, immediately following the release of information relevant to the anomaly.

This hypothesis is an alternative to the null hypothesis:

$H1_0$: The expected returns to anomaly strategies are constant through time.

Our null hypothesis is motivated by the idea that, in an efficient market, stock prices should follow a random walk with drift of the form:

$$Y_t = \alpha + Y_{t-1} + \varepsilon_t ,$$

where α is the drift term and represents compensation for systematic risk. In other words, risk-based explanations for anomalies suggests that anomaly returns are due to changes in the drift parameter, which implies a relatively stable change in expected returns over time.

Of course, it is also possible that the returns to anomaly strategies are due to time-varying loadings on systematic risk. In a market-model framework, this would imply that Capital Asset Pricing Model (CAPM) betas are rapidly changing in event time around the release of anomaly information. Similarly, if the information release is a signal of risk, we might expect most of the price adjustment from that risk to be earned around the time of the information release.

II. Methodology

To test the hypothesis discussed above, we combine daily data from the Center for Research in Security Prices (CRSP) and Compustat, as discussed in detail below.

A. Data

Underlying our premise is the notion that information-based anomalies are tied to the release of an information signal. We identify the specific date on which each information signal is released to the public. These signals arise from two primary sources of information--earnings announcements and financial statements--and the former typically precedes the latter. Prior research demonstrates that the earnings announcement typically contains only a fraction of the information needed for several of our anomalies (e.g., asset growth, net working capital), but it can sometimes contain enough information to trade on other anomalies (e.g., gross profits).

In this draft of the paper, 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.[3] 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 function of investors' private information, information asymmetries, or other informational frictions.[4]

B. Anomaly Selection

When studying the impact of information releases on anomaly returns, it is important to choose a setting in which that impact can be measured clearly. 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 hypothesis. For example, McLean and Pontiff's

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

[4] 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).

(2016) first anomaly, E/P (Basu 1977), requires two data points for each stock: earnings and prices. Although earnings has a clear information release date, the price is constantly changing, making it difficult to define an information release date for the ratio E/P.

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)).[5] All of these anomalies have underlying calculations that change at distinct and measureable points in time. 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.

It is worth pointing out that the long and short portfolios 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 then affect the portfolio inclusion of another stock.

In our continuous approach, we update these rankings daily and potentially form a new long and short 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

[5] The calculation of each anomaly variable (i.e., asset growth) is outlined in the appendix.

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 250 days or until their next annual filing.

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, called the filing date. Second, portfolios are formed based on the relative ranks of the resulting calculations. Finally, portfolios are formed using these relative rankings on the portfolio formation date.

We begin by replicating prior anomalies. For many of the accounting-based anomalies below, the original papers rebalance portfolios annually. We follow the annually rebalancing approach in our replication of each anomaly's return. Take asset growth, for example. At the end of June of year *t*, the report of total assets from the most recent 10-K (i.e., the last 10-K filed prior to June 30) 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 on the last day of June provides a measure of asset growth. That measure 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 until June of the following year.

Our primary innovation is to form a continuous version of the anomaly, using data and rankings as soon as they are available. We again use asset growth to illustrate. On any given day, assume that firm ABC files its 10-K on March 15 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 according to asset growth. If stock ABC warrants inclusion in either the long or short leg of the portfolio by being in an extreme decile, then we assume that 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 15. 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 16. Finally, suppose that stock XYZ remained in the long leg after March 15. There would be no adjustment to the holding of XYZ (i.e., no rebalancing).

D. Abnormal Return Calculations

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

III. Results

We start by examining summary statistics in Table I. Our sample coverage includes approximately 6,000 stocks throughout the time period 1996 through 2014. Each anomaly encompasses a varying number of stocks, with a low of approximately 3,038 stocks in the investment anomaly and a high of 5,904 stocks in the return on equity and gross profitability anomalies.

A. Benchmark: Annual Rebalancing

We first replicate the results of the original papers as applied to our sample period. For this exercise, we generally follow the original papers' portfolio formation approach, which leads us to rebalance portfolios once a year, on July 1st. Most of the original papers sorted stocks into deciles; some sorted them into quintiles. Others didn't sort at all according to our anomaly variable. All anomalies in our results here have been sorted into deciles, though we find that our results are qualitatively unchanged when we sort into quintiles. The results from this replication exercise can be found in Table II.

We start by examining the benchmark portfolio formation for our set of anomalies and find considerable variability among them. For example, the benchmark portfolio approach shown in Table II, Panel A gives a positive return for several anomalies, but that result is not consistent. In particular, asset growth and sustainable growth both show positive anomaly returns during our sample period, with annualized returns of 1.65% and 3.82%, respectively. However, the majority of the anomalies show negative returns during our sample time period. In fact, the super portfolio shows a negative overall return for the average of these anomalies. The poorest performing anomalies in our sample are inventory growth, investment, and net working capital, with annualized returns of -5.09%, -4.69%, and -4.73%, respectively.

The fact that some of these anomaly returns are negative or not significantly different from zero is consistent with findings in several recent papers such as Green, Hand, and Zhang (2017), McLean and Pontiff (2016) and Hou, Xue, and Zhang (2017).

Figure 1 presents the time series patterns in these separate anomaly returns over the sample period. The figure shows that the return over time is significantly negative for the majority of anomalies. Figure 1 also highlights the variability across anomalies, and in particular shows relatively strong returns for asset growth and sustainable growth. As Table II suggests, the overall return to the super portfolio during our sample period is significantly negative. It is also worth noting that the profitability of anomalies can change across the sample period. Although the pattern is fairly consistent through time, four anomalies exhibit higher returns at the beginning of our time series. In particular, sustainable growth, net working capital, investment, and accruals all exhibit higher returns at the beginning of the sample period than they do later on in that period.

When we consider the passage of time (in columns 4 - 6 of Panel A, Table II), we find that the anomaly returns are generally better in the first 120 days following portfolio formation, before they decrease during the subsequent 130 days. For example, the super portfolio exhibits a 0.51% percent return after the first 30 days and a positive 1.44% return after the first 120 days. The overall pattern seen in the total annualized return is driven mainly by what occurs between day 120 and day 250. During this period, many anomalies exhibit negative overall returns, with the super portfolio averaging -1.24% after this period. Since the 120-day return is positive but the 250-day return is strongly negative, it stands to reason that most of the negative return occurs after the 120th day following portfolio formation.

In these portfolios, value-weighted anomaly returns tell a different story. Table II, Panel B shows positive returns overall for the anomalies in our sample, with a 13.51% annualized return for the super portfolio. Furthermore, the return is more consistently positive across the three time periods, from 30 days to 250 days. The anomalies with the highest returns are profit margin and ROE, with annualized returns of 25.53% and 16.13%, respectively.

B. Information-Based Rebalancing

In this section we constantly adjust the portfolios to reflect new information. As discussed above, we allow the portfolios to change daily as new information is released. More specifically, on any day on 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 this daily, information-based rebalancing. In particular, the table shows annualized average daily returns from an annual rebalancing strategy in column (1) and from a daily rebalancing strategy in column (2). The results suggest that daily rebalancing outperforms annual rebalancing fairly consistently across the ten anomalies and for the super anomaly. For example, the first anomaly in our set, accruals, shows an annualized return from annual rebalancing of -2.95%, whereas the daily rebalancing yields a positive 3.27% annualized return, resulting in a difference of 6.22% between the two approaches. In column (3) we see generally positive differences, indicating that daily rebalancing outperforms annual rebalancing, with the difference for the super portfolio being 14.99%. The most dramatic difference is in sustainable growth, wherein we find a 3.82% positive return for the annual rebalancing strategy and a 23.48% return for the daily rebalancing strategy, a difference of

19.66%. It is interesting to note that asset growth and sustainable growth are the two anomalies that performed relatively well with the benchmark annual rebalancing, and now we see in Table III that these are the same two anomalies that exhibit the largest differences between annual rebalancing and daily rebalancing.

When we consider the results according to time period in columns 5 through 7, we see positive differences in the 30-day return window, with daily rebalancing of the super portfolio yielding a 1.46% improvement over annual rebalancing. Likewise, daily rebalancing within the 120-day window yields a 3.16% improvement over annual rebalancing (columns 8 through 10). However, by far the most dramatic period is the 250-day return window, in which annual rebalancing yields -1.24% and daily rebalancing yields 15.41%, a difference of 16.64% (columns 11 through 13). The fact that the largest differences are between 120 days and 250 days is indicative of the benchmark approach's inability to take new information into account six months after portfolio formation, while the daily rebalancing approach reflects that new information. Specifically, it is between the 120-day and 250-day windows where the vast majority of firms release their annual reports. Column (13) indicates that quickly conditioning portfolio holdings on information in those reports results in a far superior return.

Figure 2 shows the difference between annual rebalancing and daily rebalancing in the time series, individually for the anomalies 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 accruals, asset growth, inventory growth, and sustainable growth, exhibit consistently higher returns for a daily-rebalanced portfolio as compared with an annually-rebalanced portfolio. However, the opposite is true for gross profitability and ROE. Again, asset growth and sustainable growth show the largest differences between daily and annual rebalancing, and the cumulative return difference exceeds 40%.

Table IV provides a closer examination of time period effects. In particular, this table shows the incremental return during the first 30 days, from 30 to 120 days after formation, and from 120 to 250 days after formation. Table IV shows that the return earned from 30 days to 120 days is fairly consistent across the two portfolio approaches, annual rebalancing and daily rebalancing. The super portfolio difference is only 0.57% annualized over that window. However, if we consider the period from 120 to 250 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 again from asset growth and sustainable growth. Overall, we see that the super portfolio's daily rebalancing outperforms the annual rebalancing with a return difference of 27.58% during that second half of the annual rebalancing period. 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.

C. Event Study Approach

In Table V, we change the perspective. Instead of rebalancing on July 1st, as in previous tables, Table V examines anomaly returns in event time, where the event is the information release date (i.e., annual 10-K date) for every stock in the sample. 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 0.99% for the super portfolio during that first 30 days. Column (2) repeats the exercise for the first 120 days and column (3) repeats the exercise for the first 250 days. Column (2) indicates that the super portfolio has earned 2.17% after 120 days and 1.51% after 250 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, with some exceptions. The super portfolio in columns (1) through (3) has statistically significant positive returns in each event window. Taken together, these results show strong statistical significance for abnormal returns around the information release date.

Columns (4) through (6) show the annualized returns earned within each window. For example, from 31 to 120 days the super portfolio earns an annualized return of 2.77% compared with an annualized return for the 30-day window of 8.21%. This difference indicates that the majority of the returns are earned by the anomalies at the beginning of the window. Similarly, column (6) shows results for the second half of the 250-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. Some individual anomalies exhibit negative returns. This is again consistent with the pattern we noticed in previous tables; as the information becomes stale, the portfolio approach no longer yields positive returns for the anomalies.

In terms of statistical significance, we see that days 1-30 and 31-120 are statistically positive. However, column (6) shows that the second half of the year following the information release date exhibits no strong statistical or economic pattern. Overall, these findings are consistent with the idea that information, as opposed to risk exposure, drives much of the anomalies' returns.

D. Fast Minus Slow

To understand the difference in returns between annual and daily rebalancing, we construct a new portfolio, 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 rebalancing 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 in Table VI. 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 (20.64%) and the sustainable growth anomaly (19.66%). Overall, the super portfolio exhibits an annualized return of 14.99%.

E. Robustness

In Table 7, we examine size effects by splitting the sample into large, small, and micro subsets, using the same empirical approach as in Table III. Panel A shows that large stocks still show a positive difference overall, with the super portfolio exhibiting a 1.09% improvement in annualized returns for daily rebalancing compared with annual rebalancing. However, the difference between the rebalancing frequencies are seldom statistically significant for these large stocks. Giving the overall view, the super portfolio return is positive but not statistically significant.

In contrast, panel B shows the small stock results. For small stocks, three of the individual anomaly differences between annual and daily rebalancing are statistically significant, and the overall view given by the super portfolio return is statistically significant.

Like large stocks, micro stocks do not show significant differences between the rebalancing frequencies. Columns (3) and (4) show that while the differences are usually positive, those differences are not statistically different from zero in any consistent way. The overall view given by the super portfolio shows that the estimate is positive with a 4.56% improvement in the annualized return, but again it is not statistically significant.

Overall, Table VII shows that daily rebalancing yields a positive improvement over annual rebalancing for all size groups, consistent with our previous results. However, the statistical significance is strongest in small stocks, with micro and large stocks showing positive point estimates, but not in a statistically significant sense.

We also show the anomaly returns in event time, similar to the method used in Table V, broken up by size groups. Table VIII, Panel A shows the results for large stocks, which resemble the overall sample. Namely, for the super portfolio, the 30- and 120-day windows are statistically significantly positive. However, the 30 - 120 and 120 - 250 day windows are not statistically significant. In contrast, the small stocks don't show a statistically significant pattern. Even though the point estimates for the super portfolio are positive for all event windows, the positive differences are not statistically significant. The Panel C results for micro stocks are similar to those for small stocks. Taken together, we see that the point estimates are positive for all event windows for each size group. However, statistical significance is mixed, with the strongest statistical significance lying with the large stocks. Overall, these results indicate that the large stocks likely drive the statistical significance of the overall sample.

F. Persistence of Portfolio Inclusion

In our setting, it is important to think about how the long and short portfolios are formed. Since portfolios are rebalanced, or potentially rebalanced, every release of a 10-K for any firm in the sample creates the possibility that the number of the stocks would go in and out of portfolios frequently.[6]

To understand the effect of stocks going in and out of the long and short legs of the portfolios, we construct a set of persistent stocks and a set of non-persistent stocks. To do this, we ask whether a stock has been in the top quintile of rankings in the sample 50% of the time or more. If it has, we consider that stock to be a persistent stock. Similarly, if a stock has been in the top quintile for less than 50% of the time in the sample, we consider that stock to be a non-persistent stock. Since the long and short legs and our experiment are based on deciles, not quintiles, this gives us an approximate sense of the stocks that are consistently likely to be in one

[6]Transactions costs could play a big role in these daily rebalanced portfolios, making them expensive to implement.

leg or another of the portfolio. In Table IX, we repeat the exercise used in Table III and allow stocks to enter the long leg only if they are in the top decile; however, we split the long leg into non-persistent and persistent stocks.

Panel A shows that non-persistent stocks exhibit positive returns to the daily rebalancing versions of the portfolio. The asset growth and sustainable growth anomalies again show the strongest differences between rebalancing periods with a 20.82% and a 20.61% annual difference in returns, respectively. The super portfolio shows that the overall result is also strongly positive, with a 15.75% improvement in return from the daily rebalancing frequency, compared with the annual rebalancing frequency.

Panel B shows very similar results for the persistent stocks. We see a 17.59% difference for asset growth, a 17.53% difference for sustainable growth, and an overall difference of 11.39% for the super portfolio. These results are strongly statistically significant for the non-persistent stocks and less statistically significant for the persistent stocks. For both non-persistent and persistent stocks, the difference in returns between rebalancing frequencies is statistically significant for the super portfolio.

In Table X we replicate the event study approach of Table V, this time splitting by non-persistent and persistent stocks. This table draws a much sharper contrast between the results of non-persistent and persistent stocks. Namely, in Panel A, we see that non-persistent stocks are strongly statistically positive in each of the three event windows. For example, in column (1) we see that the super portfolio has a 1.46% compound return over the first 30 days, which is strongly statistically significant. In contrast, when we look at the persistence stocks in Panel B, we see positive but statistically insignificant results. For example, the super portfolio's

30-day event window return is 0.30%, which is not statistically different from zero. It's also worth noting that the point estimates differ drastically in magnitude between Panel A and Panel B. For example, in column (4) we see that the annualized 30-day return is 12.16% for the non-persistent stock super portfolio but 2.53% for the persistent stock super portfolio. Taken together, these results indicate that the non-persistent stocks are a stronger source of return for the overall effect seen in Table V.

IV. Conclusion

In this paper, we ask whether anomaly returns are driven by information. We find that anomaly returns are not evenly distributed through time, instead they arrive around information arrival. Specifically, we look at portfolios formed on information release dates, and we compare those portfolios to portfolios formed annually. We find that the information-responsive portfolios have large statistically significant returns, and the returns are statistically and economically larger than those from annual rebalancing. For example, a daily, information-based rebalanced portfolio of all ten anomalies outperforms an annual buy-and-hold portfolio by 16% per year.

We take this idea to construct a Fast Minus Slow portfolio which has statistically significant market-adjusted returns of 14.99% percent per year. We expect the Fast Minus Slow idea to broadly applicable. For example, future researchers may understand the source of returns to both trader types and investment types through this lens.

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 consider the underlying information on which these anomalies are based to be trading opportunities, like merger announcements, that happen to repeat annually.

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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 = $(\text{sales}_t - \text{cogs}_t) / \text{total assets}_t$
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 I

Sample Summary Statistics

Table I provides summary statistics for the sample used in this study. The sample uses 10-K filings from 1996 through 2014.

Panel A: Summary of Entire Sample

	Mean	Median	Standard Deviation	1st Percentile	99th Percentile
Daily Returns (bps. & %)	0.33	-8.82	4.45%	-9.95%	11.53%
Market Cap. (thousands)	2,443,084	375,554	11,369,839	13,369	39,203,420

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	0.01	0.00	0.08	-0.23	-0.06	0.08	0.25	30,190	4,416
Asset Growth	0.18	0.06	4.44	-0.50	-0.15	0.46	2.18	30,906	4,497
Gross Profitability	0.32	0.30	0.33	-0.56	0.07	0.66	1.18	38,821	5,904
Inventory Growth	0.01	0.00	0.05	-0.12	-0.02	0.04	0.17	30,507	4,470
Investment	1.08	0.93	1.25	0.07	0.39	1.74	4.22	19,786	3,038
Net Working Capital	0.00	0.00	0.09	-0.25	-0.06	0.07	0.23	30,190	4,416
Operating Leverage	1.00	0.82	0.81	0.08	0.29	1.84	3.95	33,398	5,301
Profit Margin	-2.93	0.35	190.35	-10.13	0.10	0.72	0.91	38,515	5,860
ROE	-0.23	0.07	63.76	-3.45	-0.39	0.24	2.19	38,818	5,904
Sustainable Growth	0.27	0.08	4.67	-0.75	-0.24	0.51	3.59	29,462	4,405

Table II

Replication of Anomaly Returns Using Annual Rebalancing

Table II 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. The results are qualitatively unchanged using quintiles. 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. It is noted that the investment anomaly has limited data due to the variable construction 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 250). Column 3 shows the *p*-value 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 at the 30 trading day mark 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 39% 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	Return in Basis Points	Return in Annualized Percent	*p*-value	30 Day Return (7/1 - 8/15)	120 Day Return (7/1 - 12/31)	250 Day Return (7/1 - 6/30)	Percent of Years 250 Day Return > 0
Accruals	-1.18	-2.95	0.271	-0.07	-0.82	-2.99	39
Asset Growth	0.66	1.65	0.621	0.57	7.72	2.05	50
Gross Profitability	0.79	1.98	0.557	2.38	1.87	3.94	50
Inventory Growth	-2.04	-5.09	0.043	-0.07	0.08	-5.18	17
Investment	-1.87	-4.69	0.104	-0.31	-1.33	-4.75	40
Net Working Capital	-1.89	-4.73	0.084	-0.46	-2.45	-4.93	11
Operating Leverage	-1.36	-3.41	0.235	0.53	2.42	-2.91	39
Profit Margin	-0.21	-0.53	0.906	1.10	-4.42	1.14	50
ROE	0.53	1.34	0.742	0.88	-2.55	2.12	50
Sustainable Growth	1.53	3.82	0.266	-0.05	8.81	4.31	61
Super	-0.51	-1.27	0.292	0.51	1.44	-1.24	39

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	Return in Basis Points	Return in Annualized Percent	*p*-value	30 Day Return (7/1 - 8/15)	120 Day Return (7/1 - 12/31)	250 Day Return (7/1 - 6/30)	Percent of Years 250 Day Return > 0
Accruals	-0.32	-0.81	0.838	0.55	-1.44	-1.13	50
Asset Growth	-0.27	-0.68	0.865	2.25	4.82	-0.92	61
Gross Profitability	5.95	14.87	0.000	3.74	9.23	18.86	72
Inventory Growth	-0.96	-2.39	0.527	1.59	-0.83	-1.52	50
Investment	0.06	0.15	0.974	-0.05	0.11	0.44	53
Net Working Capital	-2.31	-5.76	0.145	-0.02	-3.62	-6.38	28
Operating Leverage	1.34	3.35	0.468	0.42	2.38	1.89	50
Profit Margin	10.21	25.53	0.000	4.99	16.28	32.72	78
ROE	6.45	16.13	0.000	2.94	11.74	19.61	83
Sustain Growth	2.46	6.15	0.113	1.52	4.55	6.28	56
Super	5.40	13.51	0.000	3.79	8.65	15.48	78

Table III

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

Table III replicates the anomalies from their original papers, with one 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 nearly 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 the next day the portfolio is adjusted to reflect the new information. The portfolio adjustment is simple. If, after the new information, a stock warrants addition to a leg of the portfolio, then the stock is purchased or sold short. Likewise, if a stock that has been previously part of the portfolio is no longer in an extreme decile, then the stock is taken out of the portfolio. The portfolio weights, 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. Only the equally-weighted portfolio is shown below. The super anomaly represents an equally-weighted average of the ten anomalies shown below. The sample begins at July 1, 1997, and ends at June 30, 2015. Although it is artificial in this daily rebalancing scheme, we think of 18 portfolio-years as we did in Table II. 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 (from Table II). 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. 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 at the 30 trading day mark over the 18 portfolio-years for the annual and daily rebalanced portfolios while Column 7 shows their difference. Columns 8 through 13 repeat the functions of Columns 5 through 7 for their respective time periods.

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)			250 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)
Accruals	-2.95	3.27	6.22	0.110	-0.07	-0.11	-0.03	-0.82	1.17	1.99	-2.99	3.23	6.21
Asset Growth	1.65	22.29	20.64	0.000	0.57	1.87	1.30	7.72	4.20	-3.52	2.05	25.64	23.59
Gross Profitability	1.98	-0.24	-2.22	0.645	2.38	-0.30	-2.68	1.87	3.44	1.58	3.94	2.44	-1.50
Inventory Growth	-5.09	7.36	12.45	0.001	-0.07	1.08	1.15	0.08	0.39	0.30	-5.18	7.90	13.08
Investment	-4.69	-1.60	3.09	0.491	-0.31	-0.29	0.03	-1.33	-4.40	-3.07	-4.75	-0.83	3.92
Net Working Capital	-4.73	0.55	5.28	0.180	-0.46	0.34	0.80	-2.45	0.69	3.14	-4.93	0.47	5.40
Operating Leverage	-3.41	2.01	5.41	0.184	0.53	1.05	0.53	2.42	1.29	-1.13	-2.91	4.59	7.50
Profit Margin	-0.53	-3.43	-2.90	0.630	1.10	-0.48	-1.57	-4.42	1.98	6.40	1.14	2.73	1.59
ROE	1.34	-8.62	-9.96	0.065	0.88	-0.12	-1.00	-2.55	-1.81	0.75	2.12	-7.16	-9.28
Sustainable Growth	3.82	23.48	19.66	0.000	-0.05	3.49	3.54	8.81	7.38	-1.43	4.31	27.36	23.05
Super	-1.27	13.72	14.99	0.000	0.51	1.97	1.46	1.44	3.16	1.72	-1.24	15.41	16.64

Table IV

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

Table IV compares the returns earned by the annual and daily portfolios during different parts of the portfolio-year (previously defined as July to June). The days are measured from the first of July for each of the 18 years. The returns shown below represent the return earned over the specified period. For instance, Columns 4 and 5 show the return earned from holding the portfolios from day 30 (approximately mid-August) to day 120 (approximately the end of December).

Equally-Weighted Anomaly Portfolios									
	Annualized Return Earned in the First 30 days (7/1 - 8/15)			Annualized Return Earned from 31 to 120 days (8/16 - 12/31)			Annualized Return Earned from 121 to 250 days (1/1 - 6/30)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anomaly	Annual Rebalancing	Daily Rebalancing	Average Difference	Annual Rebalancing	Daily Rebalancing	Average Difference	Annual Rebalancing	Daily Rebalancing	Average Difference
Accruals	-0.61	-0.90	-0.29	-2.53	3.46	5.99	-3.84	3.99	7.83
Asset Growth	4.79	15.62	10.83	19.89	6.31	-13.59	-7.98	39.49	47.47
Gross Profitability	19.84	-2.46	-22.30	-1.23	10.03	11.27	3.50	-4.12	-7.62
Inventory Growth	-0.59	9.02	9.61	0.37	-2.17	-2.54	-9.50	14.74	24.24
Investment	-2.62	-2.38	0.24	-2.59	-11.15	-8.56	-6.65	6.16	12.82
Net Working Capital	-3.87	2.82	6.69	-5.82	0.99	6.81	-4.51	-0.53	3.98
Operating Leverage	4.39	8.78	4.38	4.77	-0.70	-5.48	-9.47	5.20	14.67
Profit Margin	9.13	-3.97	-13.11	-15.52	5.28	20.80	11.87	-4.33	-16.21
ROE	7.31	-1.04	-8.35	-9.79	-5.40	4.39	10.63	-10.74	-21.37
Sustainable Growth	-0.39	29.09	29.48	24.80	10.53	-14.26	-6.28	35.65	41.93
Super	4.22	16.41	12.19	2.66	3.22	0.57	-4.83	22.75	27.58

Table V

Anomaly Returns in Event Time

Table V measures returns to anomalies in event time. 10-K filing dates and returns to stocks for the next 250 days are lined up. If a stock at its 10-K filing date warrants admission to the long or short leg of the anomaly portfolio, then it is bought or sold, with that position held for 250 days. The returns shown below represent the return that could 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 following the 30th day after the release and through the 120th day after.

	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	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	1.47	2.46	0.50	12.25	2.36	-3.07
(*p* -value)	(.000)	(.002)	(.698)	(.000)	(.176)	(.025)
Asset Growth	3.23	10.65	10.55	26.88	19.20	4.29
	(.000)	(.000)	(.000)	(.000)	(.000)	(.004)
Gross Profitability	0.50	-1.59	-1.51	4.20	-4.59	0.11
	(.093)	(.039)	(.124)	(.093)	(.002)	(.926)
Inventory Growth	1.43	4.28	2.12	11.91	6.34	-2.17
	(.000)	(.000)	(.064)	(.000)	(.000)	(.074)
Investment	0.63	1.49	-0.81	5.23	-1.33	-2.17
	(.094)	(.242)	(.601)	(.094)	(.483)	(.113)
Net Working Capital	1.08	1.54	-0.21	8.99	0.30	-3.02
	(.001)	(.059)	(.869)	(.001)	(.867)	(.047)
Operating Leverage	0.74	1.33	0.34	6.13	0.92	2.16
	(.013)	(.030)	(.629)	(.013)	(.485)	(.078)
Profit Margin	-0.32	-1.78	-0.94	-2.68	-2.65	-0.56
	(.296)	(.020)	(.365)	(.296)	(.058)	(.664)
ROE	-1.77	-6.17	-4.77	-14.76	-10.75	0.08
	(.000)	(.000)	(.000)	(.000)	(.000)	(.952)
Sustainable Growth	3.68	12.32	11.51	30.65	21.75	3.43
	(.000)	(.000)	(.000)	(.000)	(.000)	(.023)
Super	0.99	2.17	1.51	8.21	2.77	-0.01
	(.000)	(.000)	(.000)	(.000)	(.000)	(.989)

Table VI

Fast Minus Slow

Table VI 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. The "slow" portfolio is rebalanced annually. 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.

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	21.91	8.59	-5.32	-0.05	0.00	25.25	-7.33	-9.51	-16.16	17.64	4.60
1998	23.57	7.21	15.26	14.91	0.00	22.08	12.28	-4.33	13.54	9.89	15.60
1999	-4.54	30.72	10.59	27.82	0.00	-12.14	-2.42	24.04	6.72	14.03	12.46
2000	17.56	38.69	5.08	35.12	-21.73	12.84	4.09	60.10	16.47	40.38	24.08
2001	-8.76	-2.70	-3.41	3.43	25.46	-20.02	42.53	2.21	6.77	-15.18	1.32
2002	-19.86	17.50	-27.01	8.98	-3.36	-17.83	0.24	-33.53	-23.79	17.40	5.61
2003	5.81	23.99	-4.12	24.72	-2.88	12.68	35.74	-18.08	-27.27	17.83	6.50
2004	18.46	-2.12	-2.47	-4.82	-13.22	8.08	-5.71	18.82	7.35	16.51	6.74
2005	-4.27	19.28	-11.70	10.62	5.69	-2.73	0.00	-18.93	-20.69	13.73	12.09
2006	-0.79	24.95	4.29	5.76	0.62	-1.17	7.23	-2.25	-6.88	24.44	15.95
2007	0.03	6.01	2.19	0.51	0.14	-5.45	-21.63	14.36	-13.68	6.35	2.03
2008	-7.89	52.17	-4.01	17.97	39.55	-2.54	43.37	-38.68	-4.67	56.07	46.46
2009	24.61	28.47	11.40	14.25	-17.86	22.07	-11.36	0.76	-34.66	23.50	8.86
2010	-9.70	18.65	-1.01	-1.27	4.16	-5.18	0.73	-1.24	-1.05	19.70	17.00
2011	18.77	15.90	1.25	24.67	-2.27	19.29	-0.14	6.85	-11.23	6.12	22.85
2012	11.25	9.04	-9.36	5.85	-1.20	9.41	-1.38	-6.04	-26.71	19.01	15.75
2013	13.25	54.88	-23.29	31.24	30.84	13.12	-8.26	-31.53	-21.69	45.21	45.62
2014	12.45	19.83	1.61	4.18	3.04	17.10	10.27	-15.26	-21.61	20.72	6.17
Entire Period	6.22	20.64	-2.22	12.45	3.09	5.28	5.41	-2.90	-9.96	19.66	14.99
p -value	0.11	0.00	0.65	0.00	0.49	0.18	0.18	0.63	0.06	0.00	0.00

Table VII

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

Table VII is similar to the first four columns of 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.

Panel A: Large Stocks (N = 4,506)

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (p-value)
Accruals	-6.54	-3.69	2.85	0.347
Asset Growth	-1.71	15.17	16.88	0.000
Gross Profitability	4.91	4.05	-0.86	0.847
Inventory Growth	-6.57	2.04	8.61	0.004
Investment	-8.00	-5.92	2.07	0.648
Net Working Capital	-7.80	-5.08	2.73	0.364
Operating Leverage	-1.10	1.14	2.25	0.592
Profit Margin	11.88	6.74	-5.14	0.290
ROE	10.29	1.34	-8.95	0.031
Sustainable Growth	1.76	16.98	15.21	0.000
Super	6.98	8.06	1.09	0.626

Panel B: Small Stocks (N = 943)

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (p-value)
Accruals	-2.89	2.65	5.53	0.507
Asset Growth	-4.63	19.28	23.91	0.008
Gross Profitability	-10.08	-7.92	2.16	0.814
Inventory Growth	-10.70	4.20	14.90	0.051
Investment	-3.83	0.29	4.11	0.665
Net Working Capital	-6.48	0.30	6.78	0.409
Operating Leverage	-5.99	-3.89	2.11	0.768
Profit Margin	-2.25	-7.63	-5.38	0.546
ROE	1.39	-9.82	-11.20	0.244
Sustain Growth	-2.19	21.79	23.98	0.008
Super	-6.99	9.18	16.18	0.000

Panel C: Micro Stocks (N = 337)

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (p-value)
Accruals	-17.23	8.22	25.45	0.197
Asset Growth	-3.14	8.14	11.28	0.632
Gross Profitability	4.09	-4.97	-9.05	0.659
Inventory Growth	-5.20	-5.01	0.19	0.983
Investment	-20.36	7.73	28.09	0.237
Net Working Capital	-11.32	10.56	21.88	0.262
Operating Leverage	-6.31	-15.17	-8.86	0.594
Profit Margin	0.61	-19.93	-20.54	0.340
ROE	10.74	-21.09	-31.83	0.132
Sustain Growth	-6.70	12.53	19.23	0.442
Super	-15.25	-10.69	4.56	0.660

Table VIII

Anomaly Returns in Event Time - Size Breaks

Table VIII is similar to Table V. The sample has been split into panels based on size.

Panel A: Large Stocks (N = 4,506)

	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	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	0.79	0.37	-2.16	6.61	-1.26	-4.22
(*p*-value)	(.007)	(.576)	(.013)	(.007)	(.410)	(.003)
Asset Growth	2.15	6.34	5.48	17.93	11.60	0.79
	(.000)	(.000)	(.000)	(.000)	(.000)	(.570)
Gross Profitability	1.01	0.28	-0.11	8.42	-2.26	1.73
	(.001)	(.646)	(.884)	(.001)	(.117)	(.131)
Inventory Growth	1.07	2.00	-0.73	8.90	2.35	-4.27
	(.000)	(.000)	(.353)	(.000)	(.053)	(.000)
Investment	-0.41	-1.82	-2.75	-3.43	-3.96	-1.94
	(.169)	(.006)	(.002)	(.169)	(.021)	(.158)
Net Working Capital	0.60	-0.08	-2.49	4.97	-2.20	-4.56
	(.051)	(.905)	(.004)	(.051)	(.135)	(.001)
Operating Leverage	-0.02	-0.76	1.14	-0.13	-2.58	4.02
	(.951)	(.118)	(.093)	(.951)	(.020)	(.000)
Profit Margin	0.22	-0.40	-0.62	1.87	-1.45	-0.27
	(.438)	(.476)	(.427)	(.438)	(.288)	(.827)
ROE	-0.50	-2.42	-0.32	-4.18	-3.00	3.60
	(.113)	(.000)	(.701)	(.113)	(.044)	(.003)
Sustainable Growth	2.74	7.49	6.42	22.82	13.52	1.07
	(.000)	(.000)	(.000)	(.000)	(.000)	(.429)
Super	0.79	1.16	0.46	6.62	1.07	-0.19
	(.000)	(.000)	(.172)	(.000)	(.062)	(.735)

Panel B: Small Stocks (N = 943)

	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	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	0.65	1.91	-1.78	5.42	6.68	-2.89
(*p*-value)	(.386)	(.283)	(.474)	(.386)	(.150)	(.351)
Asset Growth	0.97	4.76	7.03	8.11	22.53	9.06
	(.233)	(.024)	(.018)	(.233)	(.000)	(.073)
Gross Profitability	-1.34	-7.32	-5.37	-11.14	-10.66	-3.55
	(.166)	(.058)	(.052)	(.166)	(.019)	(.432)
Inventory Growth	0.77	-0.97	1.24	6.39	1.18	1.22
	(.365)	(.567)	(.533)	(.365)	(.763)	(.680)
Investment	2.28	7.16	-2.84	18.99	-0.58	-1.66
	(.074)	(.252)	(.184)	(.074)	(.909)	(.625)
Net Working Capital	0.77	0.95	-1.69	6.45	4.71	-3.38
	(.316)	(.608)	(.490)	(.316)	(.342)	(.290)
Operating Leverage	0.69	2.90	-1.28	5.75	-1.29	-1.40
	(.442)	(.143)	(.600)	(.442)	(.713)	(.679)
Profit Margin	-2.01	-6.06	-1.87	-16.75	-1.08	1.69
	(.030)	(.118)	(.492)	(.030)	(.828)	(.712)
ROE	-1.84	-1.39	-4.33	-15.30	-10.14	-3.16
	(.114)	(.734)	(.110)	(.114)	(.063)	(.454)
Sustainable Growth	2.13	9.02	12.92	17.75	24.18	10.76
	(.049)	(.000)	(.000)	(.049)	(.000)	(.043)
Super	0.15	0.57	0.01	1.28	2.90	0.52
	(.641)	(.470)	(.988)	(.641)	(.171)	(.733)

Panel C: Micro Stocks (N = 337)

	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	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	4.13	7.72	16.38	34.45	-7.46	1.41
(*p*-value)	(.023)	(.093)	(.336)	(.023)	(.490)	(.845)
Asset Growth	1.08	2.44	7.09	8.98	21.86	4.11
	(.492)	(.549)	(.108)	(.492)	(.033)	(.498)
Gross Profitability	2.00	4.93	-7.70	16.71	-9.26	-6.71
	(.403)	(.246)	(.597)	(.403)	(.336)	(.254)
Inventory Growth	1.73	2.06	-3.07	14.45	-2.37	-1.95
	(.205)	(.660)	(.492)	(.205)	(.771)	(.759)
Investment	1.25	-1.35	14.28	10.43	5.81	-6.07
	(.533)	(.780)	(.515)	(.533)	(.686)	(.488)
Net Working Capital	2.67	6.27	14.82	22.25	-11.03	3.38
	(.155)	(.154)	(.391)	(.155)	(.302)	(.636)
Operating Leverage	2.35	2.43	-4.83	19.59	-12.35	-7.60
	(.210)	(.658)	(.396)	(.210)	(.273)	(.348)
Profit Margin	-0.94	5.42	-0.70	-7.81	9.63	9.42
	(.719)	(.274)	(.965)	(.719)	(.298)	(.301)
ROE	-1.29	-14.38	-33.33	-10.76	-40.89	-8.90
	(.543)	(.069)	(.079)	(.543)	(.008)	(.248)
Sustainable Growth	-1.03	2.62	25.27	-8.57	35.94	9.42
	(.545)	(.531)	(.152)	(.545)	(.006)	(.188)
Super	1.21	2.04	2.32	10.09	-1.93	-0.36
	(.125)	(.272)	(.314)	(.125)	(.595)	(.875)

Table IX

Returns from Annual Rebalancing vs. Daily Rebalancing on 10-K Filing Dates - Persistence Breaks

Table IX is similar to Table VII except that the panels below split the sample based on the persistence of the anomaly variable and not on size. At each June 30th the anomaly variable is measured and whether it is in the extreme quintiles is determined. If a stock is in the long quintile over 50% of the time (meaning more than 9 of the 18 years measured), then the stock is persistently long. In Panel A below, if a stock would be in the long leg of the anomaly, but the same stock is persistently long, then that stock is left out. If, however, a stock is persistently short and in a given year would be in the long leg, then that stock is allowed in. Panel B uses the same criteria applied in the opposite direction.

Panel A: Non-Persistent Stocks

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (*p* -value)
Accruals	-2.98	4.09	7.07	0.096
Asset Growth	2.03	22.85	20.82	0.000
Gross Profitability	2.68	5.06	2.38	0.718
Inventory Growth	-2.43	9.87	12.30	0.006
Investment	-4.37	-2.83	1.54	0.719
Net Working Capital	-4.65	1.63	6.28	0.135
Operating Leverage	-8.35	5.85	14.20	0.078
Profit Margin	2.68	-11.57	-14.25	0.052
ROE	2.57	-11.94	-14.51	0.008
Sustainable Growth	4.84	25.45	20.61	0.000
Super	-0.63	15.11	15.75	0.000

Panel B: Persistent Stocks

	Annualized Average Daily Returns in Percent			
	(1)	(2)	(3)	(4)
Anomaly	Annual Rebalancing	Daily Rebalancing	Difference (2 - 1)	Difference (*p* -value)
Accruals	-2.81	-0.33	2.48	0.769
Asset Growth	4.16	21.75	17.59	0.071
Gross Profitability	1.16	-2.79	-3.95	0.497
Inventory Growth	-12.12	-1.69	10.43	0.092
Investment	-9.90	-7.03	2.87	0.796
Net Working Capital	-3.72	-4.51	-0.79	0.929
Operating Leverage	-1.89	0.90	2.80	0.527
Profit Margin	-3.12	-0.56	2.55	0.720
ROE	0.60	-3.71	-4.32	0.601
Sustain Growth	-0.37	17.16	17.53	0.082
Super	-3.41	7.98	11.39	0.008

Table X

Anomaly Returns in Event Time - Persistence Breaks

Table X is similar to Table V. The sample has been split into panels based on size.

Panel A: Non-Persistent Stocks

	Compound Returns over # Days			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	30 Days	120 Days	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	1.62	2.87	0.91	13.47	3.07	-2.82
(p-value)	(.000)	(.002)	(.542)	(.000)	(.114)	(.067)
Asset Growth	3.49	11.24	10.97	29.07	20.04	5.57
	(.000)	(.000)	(.000)	(.000)	(.000)	(.001)
Gross Profitability	0.48	0.39	1.57	3.97	1.19	2.59
	(.434)	(.762)	(.337)	(.434)	(.681)	(.305)
Inventory Growth	2.02	4.82	2.45	16.80	5.98	-1.96
	(.000)	(.000)	(.109)	(.000)	(.001)	(.202)
Investment	0.46	0.90	-1.23	3.80	-0.75	-2.40
	(.225)	(.379)	(.232)	(.225)	(.714)	(.085)
Net Working Capital	1.27	1.91	0.12	10.56	0.67	-2.73
	(.000)	(.037)	(.936)	(.000)	(.732)	(.114)
Operating Leverage	1.05	4.32	2.92	8.78	6.01	1.65
	(.239)	(.015)	(.142)	(.239)	(.151)	(.626)
Profit Margin	-0.12	-0.12	4.99	-0.97	1.43	5.68
	(.878)	(.943)	(.024)	(.878)	(.665)	(.074)
ROE	-2.52	-7.77	-7.30	-21.00	-12.44	-1.17
	(.000)	(.000)	(.000)	(.000)	(.000)	(.530)
Sustainable Growth	3.92	13.58	12.39	32.70	24.36	4.02
	(.000)	(.000)	(.000)	(.000)	(.000)	(.018)
Super	1.46	4.02	3.13	12.16	6.16	0.40
	(.000)	(.000)	(.000)	(.000)	(.000)	(.614)

Panel B: Persistent Stocks

	Compound Returns over # Days			Average Annualized Return Earned Over Span of Days		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	30 Days	120 Days	250 Days	1 - 30 Days	31 - 120 Days	121 - 250 Days
Accruals	0.67	0.33	-1.51	5.62	-1.39	-4.27
(p-value)	(.320)	(.838)	(.471)	(.320)	(.721)	(.139)
Asset Growth	2.08	8.12	8.85	17.33	15.57	-0.91
	(.004)	(.000)	(.045)	(.004)	(.000)	(.777)
Gross Profitability	0.52	-2.35	-2.60	4.30	-6.83	-0.80
	(.130)	(.013)	(.030)	(.130)	(.000)	(.566)
Inventory Growth	-0.07	2.94	1.33	-0.57	7.24	-2.68
	(.883)	(.003)	(.272)	(.883)	(.003)	(.131)
Investment	1.49	4.39	1.21	12.42	-4.15	-1.04
	(.236)	(.432)	(.873)	(.236)	(.368)	(.804)
Net Working Capital	0.00	-0.53	-1.94	-0.01	-1.78	-4.54
	(.999)	(.750)	(.353)	(.999)	(.664)	(.111)
Operating Leverage	0.65	0.64	-0.19	5.46	-0.28	2.27
	(.027)	(.312)	(.804)	(.027)	(.828)	(.079)
Profit Margin	-0.39	-2.28	-2.57	-3.22	-3.89	-2.37
	(.237)	(.008)	(.028)	(.237)	(.011)	(.084)
ROE	-0.90	-4.41	-2.19	-7.53	-8.86	1.40
	(.076)	(.000)	(.229)	(.076)	(.000)	(.445)
Sustainable Growth	2.68	7.28	8.11	22.33	11.28	1.14
	(.001)	(.000)	(.074)	(.001)	(.002)	(.726)
Super	0.30	-0.42	-0.63	2.53	-1.96	-0.55
	(.077)	(.293)	(.162)	(.077)	(.022)	(.456)

Table XI

FMS and the Fama-French (1993) Three Factor Model

This table shows the results from a regression of the daily "fast minus slow" for each anomaly on the three Fama-French (1993) factors.

FMS - Rf = Int + MRP + SMB + HML

	Parameter Estimates (in percent), *P*-values, and *R*-squared				
	(1)	(2)	(3)	(4)	(5)
Anomaly	Intercept	MRP	SMB	HML	*R*-sqr
Accruals	0.016	3.530	-0.786	-1.605	0.002
(*p*-value)	(.319)	(.004)	(.750)	(.493)	
Asset Growth	0.072	-0.146	11.451	10.858	0.006
	(.000)	(.921)	(.000)	(.000)	
Gross Profitability	-0.018	4.706	-8.315	-2.759	0.004
	(.359)	(.002)	(.007)	(.341)	
Inventory Growth	0.040	0.457	3.781	4.961	0.002
	(.007)	(.698)	(.111)	(.027)	
Investment	0.006	-0.515	4.060	-3.342	0.001
	(.736)	(.720)	(.190)	(.223)	
Net Working Capital	0.012	2.139	-3.954	-1.040	0.001
	(.431)	(.086)	(.110)	(.661)	
Operating Leverage	0.016	-7.492	6.343	-12.183	0.015
	(.336)	(.000)	(.014)	(.000)	
Profit Margin	-0.021	2.194	-3.646	5.227	0.001
	(.383)	(.249)	(.341)	(.150)	
ROE	-0.048	3.643	-4.217	-6.595	0.002
	(.025)	(.032)	(.218)	(.042)	
Sustainable Growth	0.070	3.694	-1.513	6.262	0.003
	(.000)	(.013)	(.613)	(.028)	
Super	0.051	1.769	1.602	-0.178	0.002
	(.000)	(.005)	(.203)	(.882)	