The Factor Multiverse: The Role of Interest Rates in Factor Discovery

Jules H. van Binsbergen, Liang Ma, and Michael Schwert*

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Abstract

We examine how the 40-year decline in interest rates impacted the discovery of asset pricing anomalies. We investigate 153 discovered anomalies and 1,395 potential undiscovered anomalies. We find that absent the decline in interest rates, the literature would likely entertain a different set of anomalies today. As the decline in interest rates is unlikely to reoccur, a reevaluation of relevant anomalies going forward is warranted. Accordingly, we use a duration-based interest rate adjustment to classify anomalies as robust, false positives, or false negatives. Our analysis highlights the sensitivity of the factor discovery process to this specific economic time period.

Keywords: anomalies, factor zoo, interest rates, false positives, false negatives.

JEL classification: G12, G14

*van Binsbergen is at the Wharton School, University of Pennsylvania, NBER, and CEPR: julesv@wharton.upenn.edu. Ma is at the Darla Moore School of Business, University of South Carolina: liang.ma@moore.sc.edu. Schwert is with AQR Arbitrage, LLC: mschwert@aqrarbitrage.com. AQR Capital Management is a global investment management firm, which may or may not apply similar investment techniques or methods of analysis as described herein. The views expressed here are those of the authors and not necessarily those of AQR.

1 Introduction

Over the past several decades, a very large number of asset pricing anomalies have emerged in the literature, also sometimes termed the "factor zoo." These deviations from expected return patterns relative to standard asset pricing models have prompted both the empirical and theoretical literature to consider different sources of risk, as well as potential sources of mispricing. Recently, several attempts have been made to separate spurious discoveries from relevant asset pricing facts. For example, one could use the statistical robustness of the return patterns by adjusting the inference for multiple testing (Harvey et al. (2016)). Alternatively, one could look for common patterns across different anomalies through data reduction techniques, such as principal component type analyses (Connor and Korajczyk (1986, 1988); Kelly et al. (2019); Kozak et al. (2020); Lettau and Pelger (2020); Cooper et al. (2021)).

In this paper, we take a different tack and employ a specific, yet undoubtedly relevant source of randomness, and evaluate its impact on the discovery process of asset pricing anomalies over time. In particular, we use the unexpected secular decline in interest rates and evaluate whether, absent this trend, a different set of anomalies would have been discovered. We find that the answer to this question is yes: many currently-accepted anomalies would likely not have been discovered, and several anomalies not identified in the literature would have been.

To illustrate why it is so important to correct for long-term interest rate declines, Figure 1 plots the yields on zero-coupon Treasury bonds at maturities of one, 10, and 30 years from 1962 to 2020, a period that encompasses the sample used in many studies of anomaly returns. Since the early 1980s, long-term interest rates have been trending steadily downward, despite the fact that the slope of the term structure was positive for most of this period. Interest rates bottomed out by 2021 and have started increasing since. This implies that the anomalous return patterns that are driven by the secular decline over the previous 40 years will likely not repeat themselves.

We correct for the effect of the decline in interest rates by constructing a duration-matched fixed income portfolio for each long or short portfolio in each portfolio sort. The duration matching is performed on a dividend-strip-by-dividend-strip basis following Binsbergen (2021) and Binsbergen and Schwert (2022). That is, we use the current dividend yield for each long or short portfolio in each month to fit a Gordon growth model, and use the implied difference between the expected return and the growth rate to construct a weighting scheme that is then utilized to build a duration-matched fixed income portfolio. We calculate the return spread between the fixed income portfolio for the long portfolio and that for the short portfolio, and refer to it as the fixed income return spread. We then obtain the counterfactual anomaly return, which represents the anomaly return that would have been observed if there was no interest rate decline, as the difference between the raw anomaly return and the fixed income return spread.[1]

In terms of the sorting variables we consider, our starting point for discovered anomalies is the set of 153 anomalies in the replication data set of Jensen et al. (2022). In addition to these well-known return patterns, we also construct a set of hypothetical portfolio sorts based on 233 accounting variables available in Compustat with sufficient data coverage, each scaled by one of the following six variables: the market value of the firm's assets and equity, the book value of the firm's assets, equity, and debt, and finally firm sales. This results in an additional 1,395 potential sorting variables for which we evaluate whether the portfolio sort resulted in an anomaly return pattern with and without adjusting for the effect of interest rate changes.[2]

We find that adjusting for interest rate changes has an important effect on a substantial

[1]In other words, we use the counterfactual fixed income portfolio return as the benchmark to calculate the portfolio excess return. In the traditional approach of calculating anomaly return spreads by taking the simple difference between long and short portfolio returns, researchers implicitly use the return on short-term Treasury bills as the reference to calculate the portfolio excess return.

[2]For one accounting variable, sufficient data are available only for three out of the six financial ratios, which leads to $232 \times 6 + 3 = 1,395$ financial ratios in total as sorting variables.

fraction of both discovered and undiscovered anomalies. First, we evaluate the 153 discovered anomalies over the sample periods presented in the original papers that discovered them. We find that 63 of them are robust with t-statistics higher than 1.96 with or without the adjustment for interest rate changes. In contrast, 21 of them can be classified as false positives (raw original t-statistic higher than 1.96 and adjusted t-statistic lower than 1.96) or false negatives (raw t-statistic lower than 1.96 and adjusted t-statistic higher than 1.96).[3] Defining false positives or negatives as false discoveries and robust anomalies as true discoveries, we find the false-to-true ratio (i.e., the ratio between false and true discoveries) is one-third.

Second, we consider the portfolio sorts that would be plausible candidates considering the research process historically employed by the asset pricing literature, as described above. That is, we consider the entire universe of Compustat variables and use them to construct financial ratios that serve as inputs to the portfolio sorts. We find that the ratio between false and true discoveries is 1.35 for the full sample period of July 1963 to December 2020. Furthermore, we calculate the false-to-true ratio for rolling windows beginning in 1963 and ending in years from 1983 to 2020, and we find that the ratio is stable over time with an average close to one. This implies that over the sample period where most of the asset pricing anomalies are discovered, the rate of false discoveries induced by the interest rate decline is similar to that of true discoveries.

Finally, we underscore the effect of the interest rate decline by relating the likelihood of false positive and false negative discoveries to the interest exposure of each long-short portfolio in the cross-section of discovered and potential undiscovered anomalies. We find that false positive discoveries due to the secular decline in interest rates are more likely for long-short portfolios with a more negative dividend yield differential, which corresponds to a higher duration differential and a more positive impact of interest rate declines on long-

[3] The rest (69) of the 153 anomalies are non-robust anomalies that register a t-statistic lower than 1.96 both with and without adjusting for the effect of interest rate changes. This rate of non-replication is largely consistent with Hou et al. (2020) because we also use NYSE breakpoints for portfolio sorts and value-weighted portfolio returns for all anomalies.

short returns. Similarly, we find that false negatives, which may have been discovered in an alternative "universe" without a trend in interest rates, are more likely for portfolios with a more positive dividend yield differential, which reduces the long-short returns realized in a declining rate environment.

The main analysis of the set of published anomalies uses the sample periods used in the original studies. Given the steady decline in interest rates up until very recently, we expect that the effect of interest rate declines extends to the post-publication period of all discovered anomalies in this paper, i.e., the duration-matched fixed income return spreads do not change significantly after publication. On the other hand, McLean and Pontiff (2016) show that raw anomaly returns—the sum of duration-matched fixed income return spreads and counterfactual anomaly returns—decrease after publication on average. Therefore, we hypothesize that this decline stems from counterfactual anomaly returns instead of duration-matched fixed income return spreads. To test this hypothesis, we adopt McLean and Pontiff (2016)'s approach and conduct three sets of analyses, using the raw anomaly return and its two components as dependent variables. We find that there is a post-publication decline in raw anomaly returns for our sample of anomalies, similar in magnitude and significance to that in McLean and Pontiff (2016). Furthermore, this effect indeed mainly comes from counterfactual anomaly returns instead of duration-matched fixed income return spreads, indicating that the interest rate effects we study are largely orthogonal to the publication effect.

Our results raise important questions regarding the research process that has been employed by the asset pricing literature in recent decades. Simply by changing the excess return definition to account for the role of duration-matched (long-term) fixed income returns, a different set of anomalies emerges. This further adds to the concerns raised previously that many potential anomalies could have been the result of data mining (see, e.g., Harvey et al. (2016) and Chordia et al. (2020)).

Furthermore, in an attempt to strengthen the statistical evidence of many discovered anomalies, it has become quite common to test whether these anomalous return patterns are also present in other developed stock markets (e.g., Fama and French (2012), Asness et al. (2013), Amihud et al. (2015), and Asness et al. (2019)). Papers that employ this strategy implicitly assume that such independent verification should alleviate any data mining concerns. However, as many of those geographical areas have shared the same downward trend in interest rates as the one observed in the U.S., the question arises whether those analyses are really providing much independent evidence to establish robust cross-sectional return patterns.

Our findings are also useful to researchers and practitioners who are trying to establish which anomalous return patterns are likely to repeat themselves in the future. After all, as the downward trend in interest rates has reversed, the valuation windfalls that have resulted from the secular declining rate environment are unlikely to happen again, suggesting that those anomalies that are robustly present regardless of the excess return definition are arguably more likely to persist in the future.

Our paper contributes to the recent literature debating whether and to what extent the anomaly discoveries made by academics represent meaningful asset pricing facts or spurious findings resulting from data mining. On the one hand, Harvey et al. (2016) and Chordia et al. (2020), among others, highlight the role of p-hacking or data mining in anomaly discoveries and call for higher significance hurdles that account for multiple hypothesis testing. On the other hand, Chen and Zimmermann (2020) and Chen (2021) argue that p-hacking and publication bias are limited to account for anomaly discoveries. Relatedly, Hou et al. (2020) and Jensen et al. (2022) offer different perspectives on the replicability of existing anomalies. Our paper offers a new perspective on this debate and show that the secular decline in interest rates itself has had a significant impact on the discovery process of asset pricing anomalies over time, further fueling concerns about data mining.

The rest of the paper is organized as follows. Section 2 describes data and sample. Section 3 presents the methodology for adjusting anomaly returns using duration-matched government bond returns. Section 4 reports empirical results. Section 5 concludes.

2 Data and Sample

In our main analysis involving discovered anomalies, we use the replication data set of Jensen et al. (2022) that contains 153 anomaly variables. Table 1 provides the list of these anomalies and the original sample periods in their corresponding publications.

All anomaly variables are signed such that a higher anomaly variable value corresponds to higher average subsequent returns according to the original studies. Since our focus is to examine the role of the interest rate decline in factor discovery, we use the original sample periods in the publications of these anomalies whenever possible. If the original sample period starts before February 1962, we use the sample period from February 1962 to the original sample ending date.[4] The reason is that the term structure data for government bonds, which are needed to calculate counterfactual returns for anomalies, are only available from February 1962.

We merge the data set of 153 anomaly variables with the stock sample consisting of all common stocks traded on NYSE, Amex, and NASDAQ. Stock return data are from CRSP, and we adjust delisting returns following Shumway and Warther (1999). We use NYSE breakpoints for portfolio sorts to mitigate the influence of microcap stocks. We form value-weighted portfolios and rebalance portfolios monthly. For 151 continuous anomaly variables, we sort stocks into deciles and form long and short portfolios using the top and bottom deciles. For two discrete anomaly variables (f_score and ni_inc8q), we sort stocks into terciles and form long and short portfolios using the top and bottom terciles.

To construct zero coupon government bond strips, we use the updated term structure data provided by the Federal Reserve following the approach developed by Gürkaynak et al.

[4] For 22 out of the 153 anomalies, the original sample period starts before 1962. They include $beta\_60m$, $beta\_dimson\_21d$, $betabab\_1260d$, $bidaskhl\_21d$, $corr\_1260d$, $debt\_me$, $div12m\_me$, $iskew\_ff3\_21d$, $market\_equity$, prc, qmj, qmj_growth, qmj_prof, qmj_safety, $rd5\_at$, $resff3\_12\_1$, $resff3\_6\_1$, ret_12_7, ret_1_0, ret_60_12, $rmax5\_rvol\_21d$, $rskew\_21d$.

(2007). Table 2 presents the means and standard deviations of monthly returns on zero coupon government bonds for maturities ranging from one year to thirty years, over the sample period of February 1962 to December 2020. The mean return for a 30-year zero coupon government bond is 1.67% per month, while that for a one-year zero coupon government bond is 0.44% per month, suggesting a large return spread between long- and short-maturity government bonds over this sample period. This result serves as the empirical foundation for the effect of interest rate decline on anomaly returns that we document.

3 Methodology for Adjusting Anomaly Returns

An anomaly strategy involves buying stocks in the long leg and shorting stocks in the short leg. We denote the long portfolio by l, the short portfolio by s, and the raw long-short anomaly return in month $t+1$ by r_{t+1}. To the extent that stocks in the long and short legs have different durations, the secular interest rate decline observed in the past decades itself can lead to a return spread between the two portfolios. To correct for this effect of interest rate decline, we construct counterfactual fixed income (government bond) portfolios that match the duration for the long and short portfolios, respectively. The duration matching is performed on a dividend-strip-by-dividend-strip basis following Binsbergen (2021) and Binsbergen and Schwert (2022). We then take the difference in returns between these two fixed income portfolios and refer to it as the duration-matched fixed income return spread, denoted by r^{fi}_{t+1}.

We apply the Gordon growth equation for a long or short portfolio i in continuous time. Let the continuously compounded expected return and dividend growth rate on the portfolio i be μ^i and g^i, respectively. Denote the dividend of portfolio i at time t by D^i_t. The Gordon growth equation expresses the value of portfolio i as follows:

$$S^i_t = D^i_t \int_0^{\infty} e^{(g^i-\mu^i)\tau} \mathrm{d}\tau = \frac{D^i_t}{\mu^i - g^i},\ \forall i = l, s. \tag{1}$$

We can rearrange equation (1) to show that the dividend yield for portfolio i is equal to the difference between its expected return and dividend growth rate:

$$\frac{D_t^i}{S_t^i} = \mu^i - g^i, \ \forall i = l, s. \tag{2}$$

The present value of the m-th dividend strip for portfolio i is given by:

$$\mathcal{P}_{t,m}^i = D_t^i e^{(g^i - \mu^i)m}, \ \forall i = l, s. \tag{3}$$

This implies a weighting scheme for the m-th dividend strip value for portfolio i as

$$w_{t,m}^i = \frac{\mathcal{P}_{t,m}^i}{S_t^i} = (\mu^i - g^i)e^{(g^i - \mu^i)m}, \ \forall i = l, s. \tag{4}$$

Following Binsbergen (2021), we use the concept of Macaulay Duration (Dur) to characterize the duration of portfolio i:

$$\begin{aligned} Dur_t^i &= \int_0^\infty w_{t,m}^i m \mathrm{d}m, \\ &= \int_0^\infty (\mu^i - g^i)e^{(g^i - \mu^i)m} m \mathrm{d}m \\ &= \frac{1}{\mu^i - g^i}, \ \forall i = l, s, \end{aligned} \tag{5}$$

which shows that under the Gordon growth assumptions the duration for portfolio i is equal to the inverse of its dividend yield $\mu^i - g^i$.

Given our focus on monthly anomaly portfolio returns, we need a monthly weighting scheme. To this end, we convert the continuous-time weighting scheme in equation (4) to a monthly weighting scheme as follows:

$$
\begin{aligned}
w_{t,n}^i &= \int_{n-1}^{n} w_{t,m}^i \mathrm{d}m, \\
&= \int_{n-1}^{n} (\mu^i - g^i) e^{(g^i - \mu^i)m} \mathrm{d}m \\
&= e^{(g^i - \mu^i)(n-1)} - e^{(g^i - \mu^i)n}, \ \forall i = l, s,
\end{aligned} \tag{6}
$$

which gives the weighting scheme for a n-th monthly dividend strip for portfolio i.

We use the updated term structure data provided by the Federal Reserve following the approach developed by Gürkaynak et al. (2007) to construct monthly zero coupon government bond strips. Denoting the yield at month t for the n-th month zero coupon government bond as $y_{t,n}$, the next-month return on this government bond is given by:

$$
r_{t+1,n}^b = \frac{exp(-(n-1)y_{t+1,n-1})}{exp(-ny_{t,n})} - 1. \tag{7}
$$

The duration-matched fixed income return spread r_{t+1}^{fi} can be calculated as:

$$
r_{t+1}^{fi} = \sum_{n=1}^{\infty} w_{t,n}^l r_{t+1,n}^b - \sum_{n=1}^{\infty} w_{t,n}^s r_{t+1,n}^b, \tag{8}
$$

where the weights are calculated using equation (6).

As in Binsbergen (2021), we use a time-varying weighting scheme. Specifically, for each long or short portfolio $i = l, s$ in each month, we calculate its current dividend yield as the value-weighted average of dividend yields (measured over the past twelve months) across all stocks in the portfolio. We then use this current dividend yield as the input for $\mu^i - g^i$ in equation (6) to obtain the weights. We employ a cutoff of 30 years (360 months) for the term structure data of government bonds and assign the residual weight to the terminal period, following Binsbergen (2021). For example, if 40% of the portfolio value comes from dividends paid in year 30 and beyond, then the 30-year Treasury strip receives a weight of

40% in the counterfactual portfolio.

Once we obtain duration-matched fixed income return spread, r^{fi}_{t+1}, from equation (8), we calculate the counterfactual anomaly return after adjustment for interest rate changes as

$$r^{counter}_{t+1} = r_{t+1} - r^{fi}_{t+1}, \tag{9}$$

which reflects the "real" anomaly strength absent the interest rate decline.

4 Empirical Results

4.1 Results from Discovered Anomalies

We first analyze the effect of interest rate decline on the discovery of anomalies that are already discovered by published research. For this purpose, we use the 153 anomaly variables contained in the data set of Jensen et al. (2022).

As shown by equation (5), the durations of the long and short portfolios are equal to the inverse of their dividend yields. Accordingly, the magnitude of the duration-matched counterfactual returns would depend on the difference in dividend yields between long and short portfolios, or the dividend yield spread. The more positive the dividend yield spread, the more negative the counterfactual anomaly return spread, and vice versa.

Table 3 reports the value-weighted average annual dividend yields for the long and short portfolios and the average dividend yield spread for the 153 anomalies, over the original sample periods. For each stock in a given month, the annual dividend yield is calculated as its dividends paid over the past 12 months divided by its stock price at the end of the prior month. The average dividend yield spread shows remarkable variations across anomalies, ranging from −4.06% to 6.60%. This suggests that the interest rate decline would affect the return spread for a large number of anomalies. Furthermore, the effect would be positive for some anomalies and negative for others, which implies that after duration-matched adjustment for interest rate changes, some anomalies will become stronger while others will become weaker.

Figure 2 shows the scatter plots of the mean raw return (Panel A), the mean counterfactual return (Panel B), and the duration-matched fixed income return spread (Panel C) as a function of the mean dividend yield spread for the 153 anomalies. It is evident that adjusting for the interest rate decline has a significant effect on long-short returns for a large number of anomalies. Panel C shows that the duration-matched fixed income return spread declines with the dividend yield spread, or equivalently increases with the duration spread between long and short portfolios. This is consistent with the results in Table 2 that long-maturity bonds outperform short-maturity bonds in our sample period.

To quantify the effect of the interest rate decline, for each anomaly, we calculate the t-statistic for its raw return r_{t+1}, referred to as the raw t-statistic, and that for its counterfactual return $r_{t+1}^{counter}$, referred to as the adjusted t-statistic. We then classify the 153 anomalies into four groups. The first group contains robust anomalies, for which both raw and adjusted t-statistics are greater than 1.96. The second group contains false positives, for which the raw t-statistic is greater than 1.96 and the adjusted t-statistic is less than 1.96. The third group contains false negatives, for which the raw t-statistic is less than 1.96 and the adjusted t-statistic is greater than 1.96. The fourth group contains non-robust anomalies, for which both raw and adjusted t-statistics are less than 1.96.

Out of the 153 anomalies, 63 are robust anomalies, 14 are false positives, 7 are false negatives, and 69 are non-robust anomalies. The rate of non-replicated anomalies (false negatives and non-robust anomalies) is approximately 50%. This lower rate is expected due to our use of NYSE breakpoints for portfolio sorts and value-weighted portfolio returns (Hou et al. (2020)).

It is interesting to examine how the interest rate decline tilts the discovery of false versus true anomalies. To this end, we define a ratio $\frac{False}{True}$, which is the number of false positives and false negatives divided by the number of robust anomalies. The $\frac{False}{True}$ ratio for the discovered anomalies is $\frac{21}{63} = \frac{1}{3}$. False positives and robust anomalies together represent the set of anomalies that would be discovered in our current universe, while false negatives and robust anomalies together represent the set of anomalies that would be discovered in a parallel universe in which the interest rate did not decline. These three groups of anomalies (84 in total) together, therefore, represent the union set of anomalies that would be discovered in either universe. The ratio of false positives, false negatives, and robust anomalies to this union set of discovered anomalies is 0.17, 0.08, and 0.75, respectively.

The top panel of Figure 3 shows the scatter plot of the raw and adjusted t-statistics for false positives, false negatives, robust anomalies, and non-robust anomalies. The vertical and horizontal dashed lines represent t-statistic = 1.96. They divide the graph into four quadrants, where the first quadrant corresponds to robust anomalies, the second quadrant corresponds to false negatives, the third quadrant corresponds to non-robust anomalies, and the fourth quadrant corresponds to false positives. To show false positives and false negatives more clearly, the bottom panel of Figure 3 shows the same scatter plot but only for these two groups of anomalies.

Table 4 lists the individual members of the four groups of anomalies. From Panel A of Table 4 and the bottom panel of Figure 3, it is interesting that several prominent anomalies belong to the group of false positives and negatives. They include the gross profitability premium gp_at (Novy-Marx (2013)), return on assets niq_at (Balakrishnan et al. (2010)), the performance-based mispricing $mispricing\_perf$ (Stambaugh and Yuan (2017)), quality-minus-junk qmj (Asness et al. (2019)), short-term reversal ret_1_0 (Jegadeesh (1990)), max daily return $rmax1\_21d$ (Bali et al. (2011)), and return volatility $rvol\_21d$ (Ang et al. (2006)).

4.2 Results from Potential Undiscovered Anomalies

Given that the interest rate decline can lead to both false positives and false negatives, we extend our analysis to a set of potential undiscovered anomalies. To this end, we evaluate a large number of portfolio sorts that would be plausible candidates given the research process historically employed by researchers evident from the asset pricing literature. Specifically, we consider the entire universe of Compustat variables and use them to construct financial ratios that serve as inputs to the portfolio sorts.

We start with all annual accounting variables on the merged CRSP-Compustat file. For this, we collect all data items that exist on the balance sheet, the income statement, and the cash flow statement, for the years between 1962 and 1963. We choose 1962 as the beginning year because our portfolio sorts for this analysis start in July 1963 following Fama and French (1992) to avoid the backfilling bias in Compustat.

For each accounting variable, we scale it by six common deflators, including total assets (Compustat item *at*), book debt (Compustat item *lt*), market capitalization (*mktcap*, Compustat items $abs(prcc\_f) \times csho$), sales (Compustat item *sale*), book equity (Compustat item *ceq*), quasi-market asset value (*qta*) which equals to market capitalization plus book debt, to create six signal variables. For each signal variable, we sort stocks into deciles using NYSE breakpoints, form value-weighted long and short portfolios, and rebalance these portfolios monthly. For each signal variable, we require that at least 500 firms have valid data for a given year and that portfolio returns based on the signal variable have at least 20 years of data. In total, we have 233 Compustat accounting items as the numerators of these ratios.[5] For one of them, *acominc*, sufficient data are only available for three out of the six ratios. Therefore, we have $232 \times 6 + 3 = 1,395$ signal variables in the final sample.

We merge data of these Compustat signal variables with CRSP stock return data and leave a minimum of six months between accounting information and stock returns as standard in the literature. We include only common stocks traded on NYSE, Amex, and NASDAQ. For each of the 1,395 signal variables, we sort stocks into deciles using NYSE breakpoints and form value-weighted portfolios that are rebalanced monthly. We then calculate the raw and counterfactual anomaly returns and their t-statistics over the full sample period of July

[5] We exclude Compustat items used as deflators (*at*, *lt*, *sale*, and *ceq*) from the list of numerator variables.

1963 to December 2020. Similar to Section 4.1, we classify the 1,395 potential anomalies into four groups. The first group contains robust anomalies, for which the absolute values of both raw and adjusted t-statistics are greater than 1.96. The second group contains false positives, for which the raw $|t\text{-statistic}|$ is greater than 1.96 and the adjusted $|t\text{-statistic}|$ is less than 1.96. The third group contains false negatives, for which the raw $|t\text{-statistic}|$ is less than 1.96 and the adjusted $|t\text{-statistic}|$ is greater than 1.96. The fourth group contains non-robust anomalies, for which the absolute values of both raw and adjusted t-statistics are less than 1.96. Note that for this set of potential undiscovered anomalies, the sign between anomaly variables and future returns is unclear a priori. We therefore use the absolute value of t-statistic (instead of t-statistic) as the criterion for anomaly discovery in this analysis.

Out of the 1,395 potential anomalies, we find 108 robust anomalies, 100 false positives, and 46 false negatives. Table A1 lists the 146 false positives and false negatives. The $\frac{False}{True}$ ratio that represents the ratio of false positives and negatives to robust anomalies is 1.35. In other words, the rate of false positives and false negatives induced by the secular interest rate decline is 1.35 times as high as the rate of true discovery.

One might be interested in the effect of interest rates on the false-to-true ratio for researchers that used Compustat ratios to discover anomalies at some point in time. To this end, we also investigate the dynamics of the false-to-true ratio $\frac{False}{True}$ over time. We repeat the same analysis for each year from 1983 (leaving an initial window of 20 years from July 1963) to 2020. At the end of each year, we calculate the $\frac{False}{True}$ ratio using the data available for the Compustat ratios from July 1963 to the end of that year. Figure 4 plots the time-series of the $\frac{False}{True}$ ratio, which has been stable over time with an average of 0.97. This suggests that over the sample period where most of the asset pricing anomalies are discovered, the rate of false positives and false negatives induced by the secular interest rate decline is similar to the rate of true discovery.

Overall, the results here support the notion that the secular decline in interest rates has played an important role in factor discovery, given that the number of false discoveries due to the interest rate decline is comparable to the number of true discoveries that are robust to the decline. Put differently, if we consider the realized "universe" with the interest rate decline and the counterfactual "universe" without the decline, the common set of anomalies discovered in both "universes" is only half of the union set.

4.3 Regression Analysis

As discussed in Section 3, the average duration-matched fixed income return spread, r^{fi}_{t+1}, decreases with the average dividend yield differential between the long and short anomaly portfolios. Therefore, the average counterfactual anomaly return should tend to be higher (lower) than the average raw anomaly return for anomalies with a more positive (negative) average dividend yield differential. Accordingly, we have two testable hypotheses.

Hypothesis 1: *The likelihood of an anomaly being false positive is negatively associated with the average dividend yield differential.*

Hypothesis 2: *The likelihood of an anomaly being false negative is positively associated with the average dividend yield differential.*

In this subsection, we provide a formal test of these two hypotheses using both the samples of discovered anomalies and potential undiscovered anomalies. The sample periods for discovered anomalies are those in the original publications (Column 3 of Table 1), and the sample period for potential undiscovered anomalies is the full sample period from July 1963 to December 2020. For each anomaly, we construct an indicator FP that equals one if an anomaly is classified as a false positive and zero otherwise. Similarly, we construct an indicator FN that equals one if an anomaly is classified as a false negative and zero otherwise.

We then regress these two indicators on the average dividend yield differential $\Delta DivY$ (measured over the corresponding sample periods):

$$FP_a = \beta_0^+ + \beta_1^+ \Delta DivY_a + \epsilon_t, \tag{10}$$

and

$$FN_a = \beta_0^- + \beta_1^- \Delta DivY_a + \epsilon_t. \tag{11}$$

The unit of observation, a, in these regressions is an anomaly, and we estimate the two regressions for the samples of discovered and potential undiscovered anomalies separately. For the potential undiscovered anomalies, we cluster standard errors by the numerator accounting variable to account for correlation across the portfolio sorts.

Hypotheses 1 and 2 predict that $\beta_1^+ < 0$ and $\beta_1^- > 0$, respectively. Table 5 reports the regression estimates. For the sample of discovered anomalies, the estimated β_1^+ and β_1^- are -0.05 ($t = -3.60$) and 0.03 ($t = 2.26$), respectively. For the sample of potential undiscovered anomalies, the estimated β_1^+ and β_1^- are -0.07 ($t = -8.18$) and 0.03 ($t = 4.30$), respectively.

These results support Hypotheses 1 and 2 and tighten the connection between the effect of interest rate changes and the likelihood of discovering an asset pricing anomaly. We find that false positive discoveries due to the secular decline in interest rates are more likely for long-short portfolios with a more negative dividend yield differential, which corresponds to a stronger tailwind from interest rate declines. Likewise, we find that false negative discoveries, which may have been uncovered in an alternative "universe" without a steady decline in long-term rates, are more likely for long-short portfolios with a more positive dividend yield differential, which created a headwind in the realized "universe."

4.4 Pre- versus Post-Publication Periods

For the set of discovered (published) anomalies, our main analysis uses the sample periods used in the original publications. Given the steady decrease in interest rates up until very recently, we anticipate the impact of interest rate declines would persistent in the post-publication period for all discovered anomalies analyzed in this paper. In other words, the duration-matched fixed income return spreads are unlikely to change significantly on average after publication. On the other hand, McLean and Pontiff (2016) show that, on average, the raw anomaly returns—which can be decomposed into the duration-matched fixed income return spreads and the counterfactual anomaly returns (see equation (9))—decline after publications.[6] Therefore, we hypothesize that the post-publication decline in anomaly returns stems from the counterfactual anomaly returns instead of the duration-matched fixed income return spreads.

HYPOTHESIS 3: *The decline in raw anomaly returns after publication primarily originates from the counterfactual anomaly returns rather than the duration-matched fixed-income return spreads.*

To test this hypothesis, we use the sample of the 153 discovered anomalies and repeat the main exercise of McLean and Pontiff (2016) using r_{t+1}, r_{t+1}^{fi}, and $r_{t+1}^{counter}$, respectively, as dependent variables. The sample period for this analysis is the beginning of the sample periods in the original publication for each anomaly to December 2020, and we have a panel of monthly returns for the 153 anomalies. For r_{t+1}, we run the following regression (equation (1) of McLean and Pontiff (2016)):

$$r_{i,t+1} = \alpha_i + \beta_1 PostSampleDummy_{i,t+1} + \beta_2 PostPublicationDummy_{i,t+1} + \epsilon_{i,t+1}, \quad (12)$$

where the post-sample dummy equals one if month $t+1$ is after the end of the original

[6] They attribute this effect to investor learning about anomaly mispricing from academic publications and arbitraging away anomaly returns post-publication.

sample but still pre-publication and zero otherwise, and the post-publication dummy equals one if month $t+1$ is post-publication and zero otherwise. We include anomaly (predictor) fixed effects α_i and cluster standard errors by month to account for contemporaneous cross-sectional correlation across portfolio return residuals. We also run similar regressions for r^{fi}_{t+1} and $r^{counter}_{t+1}$:

$$r^{fi}_{i,t+1} = \alpha_i + \beta_1 PostSampleDummy_{i,t+1} + \beta_2 PostPublicationDummy_{i,t+1} + \epsilon_{i,t+1}, \quad (13)$$

and

$$r^{counter}_{i,t+1} = \alpha_i + \beta_1 PostSampleDummy_{i,t+1} + \beta_2 PostPublicationDummy_{i,t+1} + \epsilon_{i,t+1}. \quad (14)$$

The coefficient of interest in these regressions is the post-publication coefficients β_2. Table 6 presents the estimation results. Column 1 shows that the estimate of β_2 is -0.32% and statistically significant for raw returns. The estimate is close to that of McLean and Pontiff (2016) in both magnitude and significance and confirms the post-publication decline for our sample of anomalies. Columns 2 and 3 show that the estimate of β_2 is 0.07% ($t = 0.70$) for the duration-matched fixed-income return spread and -0.39% ($t = -2.97$) for the counterfactual return. This clearly indicates that there is a post-publication decline for the counterfactual anomaly return, similar to that for the raw anomaly return, while the component attributed to interest rate changes does not significantly contribute to the post-publication decline. These results are consistent with Hypothesis 3 and also support the notion that investor learning and post-publication arbitraging play an important role in weakening anomalies after discoveries. In summary, the interest rate effects that we study in this paper are largely orthogonal to the publication effect in McLean and Pontiff (2016).

5 Conclusion

The past five decades have witnessed the discovery of a very large number of asset pricing anomalies, sometimes referred to as the "factor zoo." Over this same sample period, there has been a long-term decline in interest rates. We study the importance of this decline in the discovery of asset pricing anomalies. We investigate 153 discovered anomalies as well as 1,395 potential undiscovered anomalies and find that absent the interest-rate decline, the asset pricing literature would likely entertain a different set of anomalies today. As such, our analysis highlights the sensitivity of the factor discovery process to this specific observed non-stationary economic time period.

Our paper raises broader questions regarding the importance of secularly declining economic variables for the robustness of anomaly returns. The secular decline in economic growth rates and population growth numbers are important candidates to consider. Given that some of these variables have been declining for centuries, the recent out-of-sample evidence on anomaly patterns that only go back further by a number of decades may not be sufficient.

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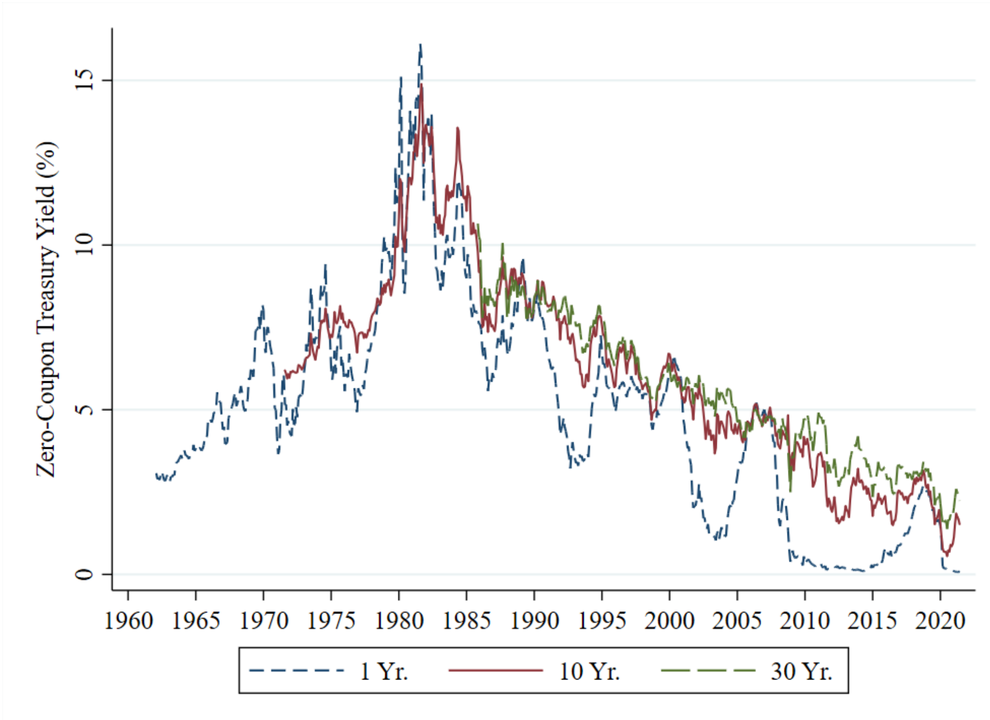


Figure 1. Time-Series of Zero-Coupon Treasury Yields. This figure illustrates the decline in long-term risk-free interest rates over the sample period of February 1962 to December 2020. The plot contains the time series of zero-coupon Treasury yields at maturities of one year, ten years, and 30 years. Zero-coupon yields are from the updated term structure data provided by the Federal Reserve following the approach in Gürkaynak et al. (2007).

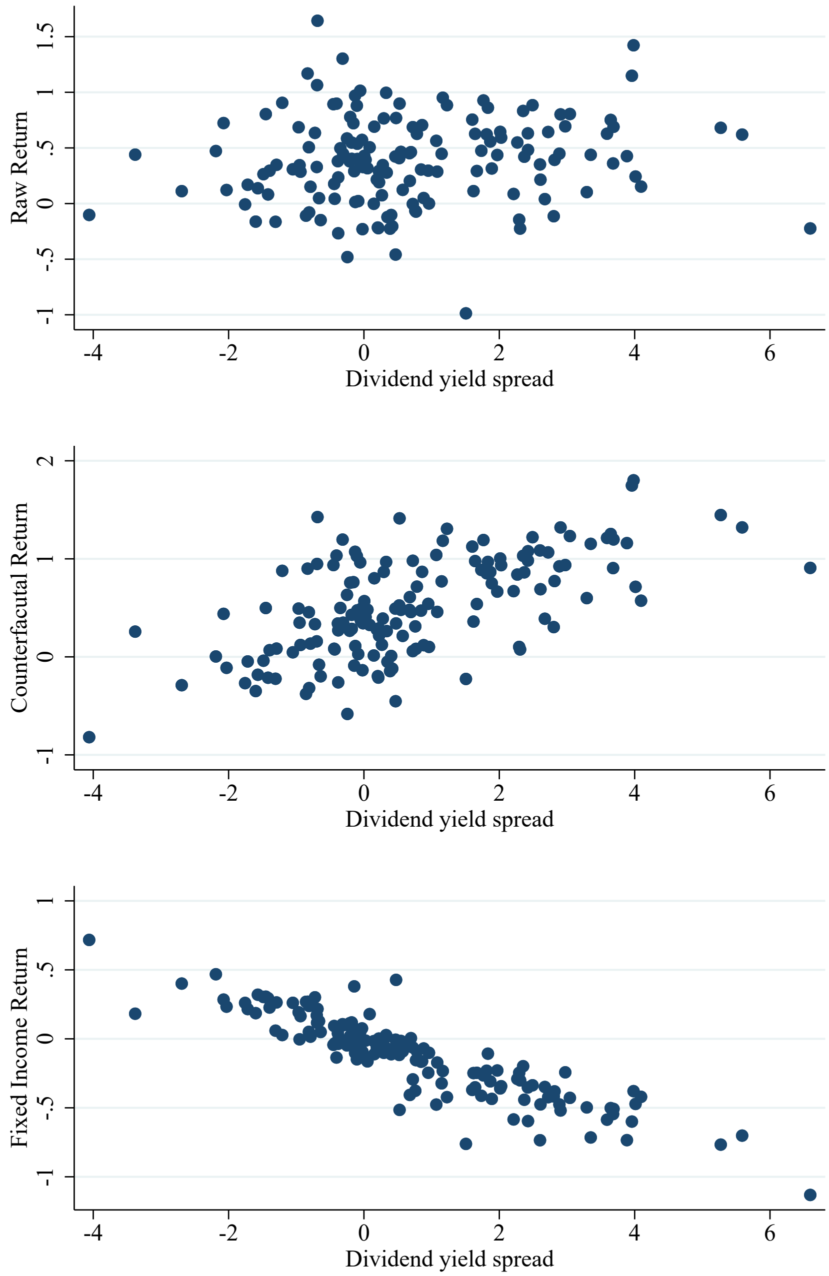
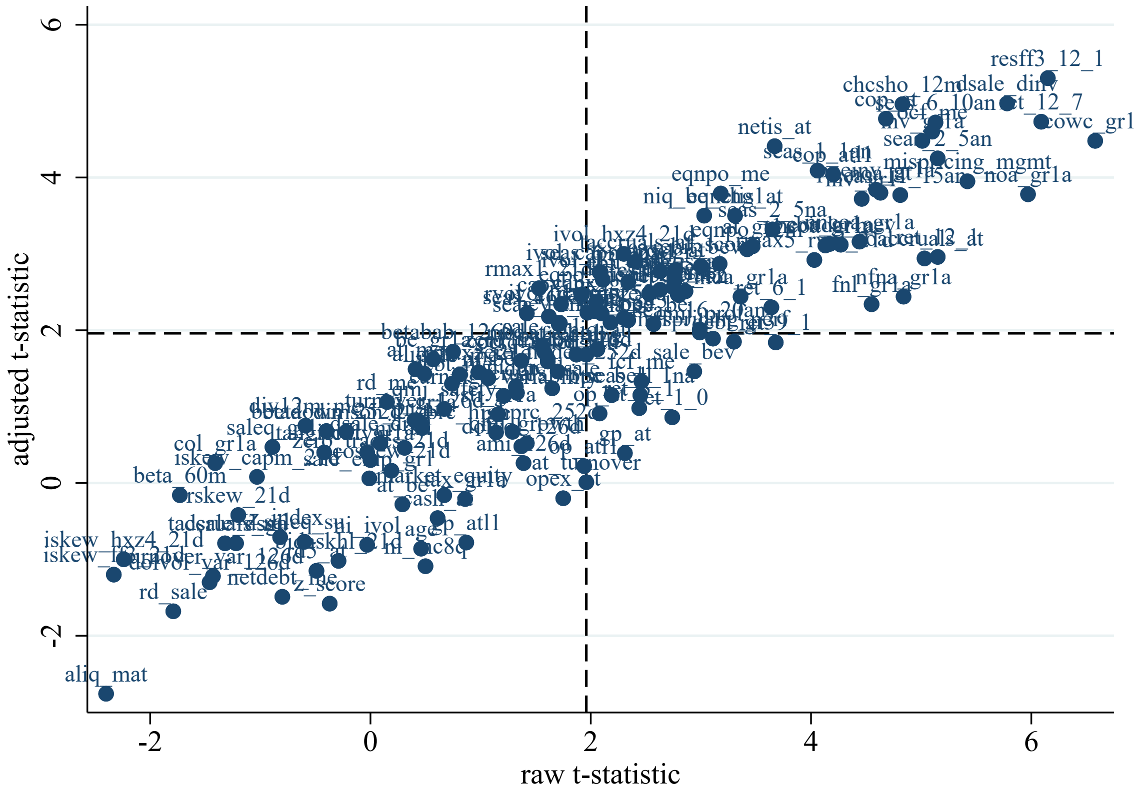


Figure 2. Mean returns as a function of the mean dividend yield spread. This figure plots the mean raw return (top panel), the mean counterfactual return after adjustment for interest rate changes (middle panel), and the mean duration-matched fixed income return spread, as a function of the mean dividend yield spread for the 153 anomalies. Mean returns and mean dividend yield spreads are in percentage terms.



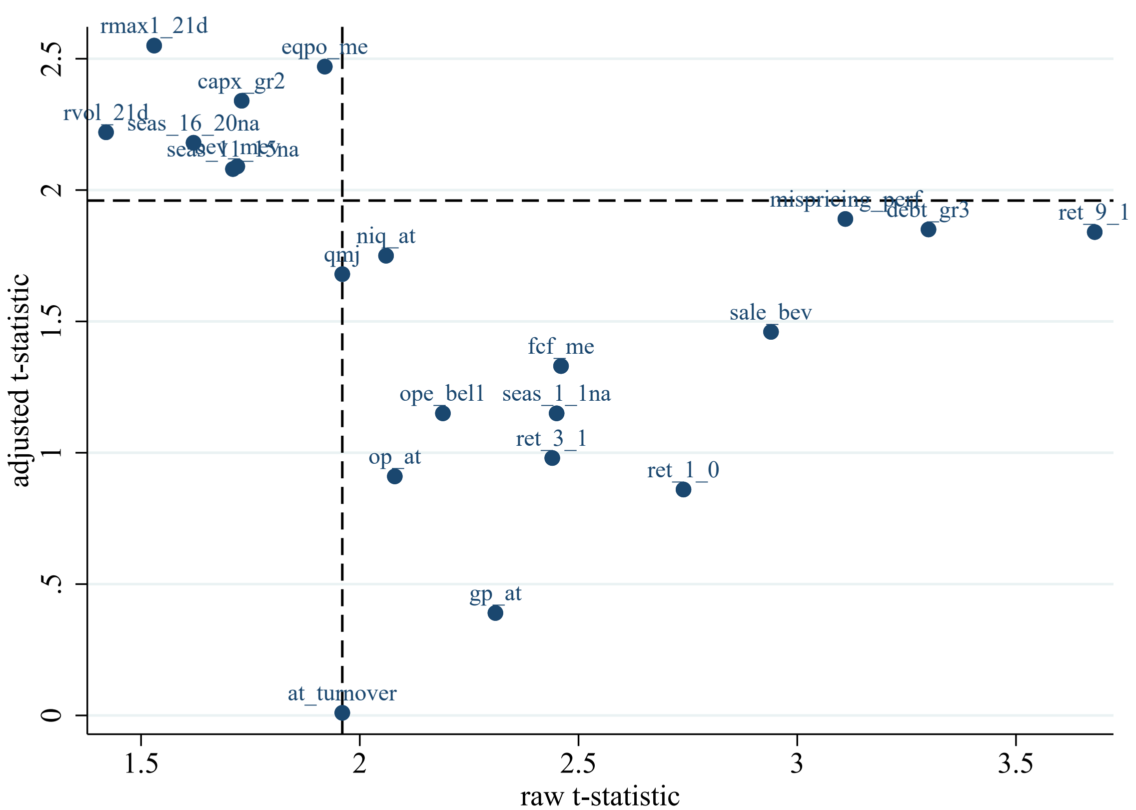


Figure 3. (Caption next page.)

Figure 3. Scatter plot of t-statistics for false positives, false negatives, and robust anomalies. We classify the 153 anomalies into four groups: false positives, false negatives, robust anomalies, and non-robust anomalies. The top panel shows the scatter plot of the raw and adjusted t-statistics for these four groups. The bottom panel shows the scatter plot of the raw and adjusted t-statistics for false positives and false negatives only. The vertical and horizontal dashed lines represent t-statistic=1.96. Anomalies that fall into the first, second, third, and fourth quadrants are robust anomalies, false negatives, non-robust anomalies, and false positives, respectively.

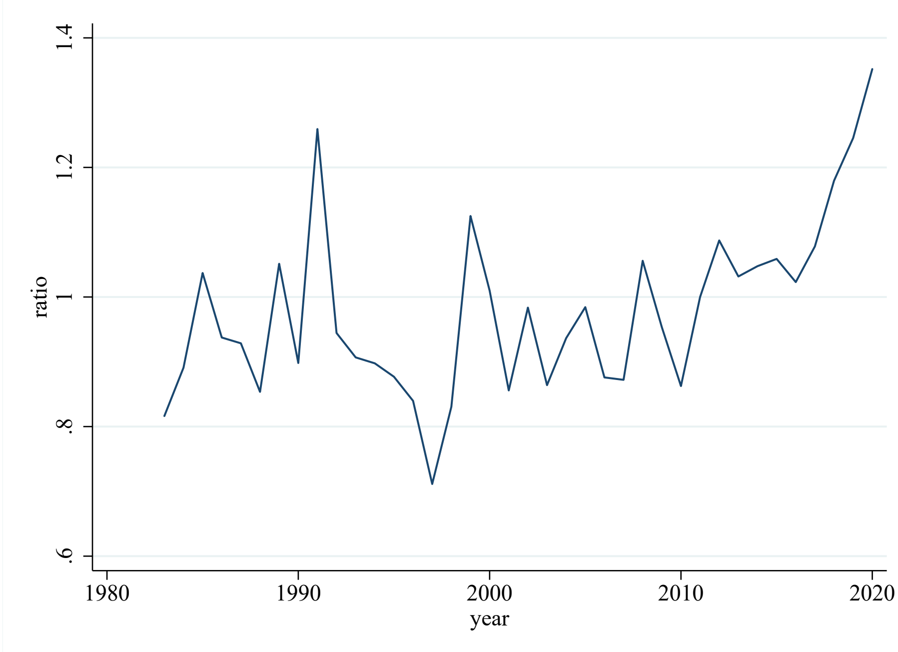


Figure 4. The ratio of $\frac{False}{True}$ over time for a large set of Compustat ratios. For each year from 1983 to 2020, we calculate the $\frac{False}{True}$ ratio using all data available for the Compustat ratios from July 1963 to the end of that year.

Table 1. List of Anomalies

This table lists the acronym, firm characteristic, and original sample period for the 153 anomalies.

Acronym	Firm Characteristic	Original Sample
age	Firm age	1965-2001
aliq_at	Liquidity of book assets	1984-2006
aliq_mat	Liquidity of market assets	1984-2006
ami_126d	Amihud Measure	1964-1997
at_be	Book leverage	1963-1990
at_gr1	Asset Growth	1968-2003
at_me	Assets-to-market	1963-1990
at_turnover	Capital turnover	1979-1993
be_gr1a	Change in common equity	1962-2001
be_me	Book-to-market equity	1973-1984
beta_60m	Market Beta	1935-1968
beta_dimson_21d	Dimson beta	1955-1974
betabab_1260d	Frazzini-Pedersen market beta	1926-2012
betadown_252d	Downside beta	1963-2001
bev_mev	Book-to-market enterprise value	1962-2001
bidaskhl_21d	The high-low bid-ask spread	1927-2006
capex_abn	Abnormal corporate investment	1973-1996
capx_gr1	CAPEX growth (1 year)	1971-1992
capx_gr2	CAPEX growth (2 years)	1976-1998
capx_gr3	CAPEX growth (3 years)	1976-1998
cash_at	Cash-to-assets	1972-2009
chcsho_12m	Net stock issues	1970-2003
coa_gr1a	Change in current operating assets	1962-2001
col_gr1a	Change in current operating liabilities	1962-2001
cop_at	Cash-based operating profits-to-book assets	1967-2016
cop_atl1	Cash-based operating profits-to-lagged book assets	1963-2014
corr_1260d	Market correlation	1925-2015
coskew_21d	Coskewness	1963-1993
cowc_gr1a	Change in current operating working capital	1962-2001
dbnetis_at	Net debt issuance	1971-2000
debt_gr3	Growth in book debt (3 years)	1970-2005
debt_me	Debt-to-market	1948-1979
dgp_dsale	Change gross margin minus change sales	1974-1988
div12m_me	Dividend yield	1940-1980
dolvol_126d	Dollar trading volume	1966-1995
dolvol_var_126d	Coefficient of variation for dollar trading volume	1966-1995
dsale_dinv	Change sales minus change Inventory	1974-1988
dsale_drec	Change sales minus change receivables	1974-1988
dsale_dsga	Change sales minus change SG&A	1974-1988
earnings_variability	Earnings variability	1975-2001
ebit_bev	Return on net operating assets	1984-2002
ebit_sale	Profit margin	1984-2002
ebitda_mev	Ebitda-to-market enterprise value	1963-2009
emp_gr1	Hiring rate	1965-2010
eq_dur	Equity duration	1962-1998

Table 1—*Continued*

Acronym	Firm Characteristic	Original Sample
eqnetis_at	Net equity issuance	1971-2000
eqnpo_12m	Equity net payout	1968-2003
eqnpo_me	Net payout yield	1984-2003
eqpo_me	Payout yield	1984-2003
f_score	Pitroski F-score	1976-1996
fcf_me	Free cash flow-to-price	1963-1990
fnl_gr1a	Change in financial liabilities	1962-2001
gp_at	Gross profits-to-assets	1963-2010
gp_atl1	Gross profits-to-lagged assets	1967-2016
inv_gr1	Inventory growth	1965-2009
inv_gr1a	Inventory change	1970-1997
iskew_capm_21d	Idiosyncratic skewness from the CAPM	1967-2016
iskew_ff3_21d	Idiosyncratic skewness from the Fama-French 3-factor model	1925-2012
iskew_hxz4_21d	Idiosyncratic skewness from the q-factor model	1967-2016
ival_me	Intrinsic value-to-market	1975-1993
ivol_capm_21d	Idiosyncratic volatility from the CAPM (21 days)	1967-2016
ivol_capm_252d	Idiosyncratic volatility from the CAPM (252 days)	1976-1997
ivol_ff3_21d	Idiosyncratic volatility from the Fama-French 3-factor model	1963-2000
ivol_hxz4_21d	Idiosyncratic volatility from the q-factor model	1967-2016
kz_index	Kaplan-Zingales index	1968-1995
lnoa_gr1a	Change in long-term net operating assets	1964-1993
lti_gr1a	Change in long-term investments	1962-2001
market_equity	Market Equity	1926-1975
mispricing_mgmt	Mispricing factor: Management	1967-2013
mispricing_perf	Mispricing factor: Performance	1967-2013
ncoa_gr1a	Change in noncurrent operating assets	1962-2001
ncol_gr1a	Change in noncurrent operating liabilities	1962-2001
netdebt_me	Net debt-to-price	1962-2001
netis_at	Net total issuance	1971-2000
nfna_gr1a	Change in net financial assets	1962-2001
ni_ar1	Earnings persistence	1975-2001
ni_be	Return on equity	1979-1993
ni_inc8q	Number of consecutive quarters with earnings increases	1982-1992
ni_ivol	Earnings volatility	1975-2001
ni_me	Earnings-to-price	1963-1979
niq_at	Quarterly return on assets	1976-2005
niq_at_chg1	Change in quarterly return on assets	1972-2016
niq_be	Quarterly return on equity	1972-2012
niq_be_chg1	Change in quarterly return on equity	1967-2016
niq_su	Standardized earnings surprise	1974-1981
nncoa_gr1a	Change in net noncurrent operating assets	1962-2001
noa_at	Net operating assets	1964-2002
noa_gr1a	Change in net operating assets	1964-2002
o_score	Ohlson O-score	1981-1995
oaccruals_at	Operating accruals	1962-1991
oaccruals_ni	Percent operating accruals	1989-2008
ocf_at	Operating cash flow to assets	1990-2015

Table 1—*Continued*

Acronym	Firm Characteristic	Original Sample
ocf_at_chg1	Change in operating cash flow to assets	1990-2015
ocf_me	Operating cash flow-to-market	1973-1997
ocfq_saleq_std	Cash flow volatility	1980-2004
op_at	Operating profits-to-book assets	1963-2013
op_atl1	Operating profits-to-lagged book assets	1963-2014
ope_be	Operating profits-to-book equity	1963-2013
ope_bel1	Operating profits-to-lagged book equity	1967-2016
opex_at	Operating leverage	1963-2008
pi_nix	Taxable income-to-book income	1973-2000
ppeinv_gr1a	Change PPE and Inventory	1970-2005
prc	Price per share	1940-1978
prc_highprc_252d	Current price to high price over last year	1963-2001
qmj	Quality minus Junk: Composite	1957-2016
qmj_growth	Quality minus Junk: Growth	1957-2016
qmj_prof	Quality minus Junk: Profitability	1957-2016
qmj_safety	Quality minus Junk: Safety	1957-2016
rd_me	R&D-to-market	1975-1995
rd_sale	R&D-to-sales	1975-1995
rd5_at	R&D capital-to-book assets	1952-2004
resff3_12_1	Residual momentum t-12 to t-1	1930-2009
resff3_6_1	Residual momentum t-6 to t-1	1930-2009
ret_1_0	Short-term reversal	1929-1982
ret_12_1	Price momentum t-12 to t-1	1965-1989
ret_12_7	Price momentum t-12 to t-7	1925-2010
ret_3_1	Price momentum t-3 to t-1	1965-1989
ret_6_1	Price momentum t-6 to t-1	1965-1989
ret_60_12	Long-term reversal	1926-1982
ret_9_1	Price momentum t-9 to t-1	1965-1989
rmax1_21d	Maximum daily return	1962-2005
rmax5_21d	Highest 5 days of return	1993-2012
rmax5_rvol_21d	Highest 5 days of return scaled by volatility	1925-2015
rskew_21d	Total skewness	1925-2012
rvol_21d	Return volatility	1963-2000
sale_bev	Assets turnover	1984-2002
sale_emp_gr1	Labor force efficiency	1974-1988
sale_gr1	Sales Growth (1 year)	1968-1989
sale_gr3	Sales Growth (3 years)	1968-1989
sale_me	Sales-to-market	1979-1991
saleq_gr1	Sales growth (1 quarter)	1967-2016
saleq_su	Standardized Revenue surprise	1987-2003
seas_1_1an	Year 1-lagged return, annual	1965-2002
seas_1_1na	Year 1-lagged return, nonannual	1965-2002
seas_11_15an	Years 11-15 lagged returns, annual	1965-2002
seas_11_15na	Years 11-15 lagged returns, nonannual	1965-2002
seas_16_20an	Years 16-20 lagged returns, annual	1965-2002
seas_16_20na	Years 16-20 lagged returns, nonannual	1965-2002
seas_2_5an	Years 2-5 lagged returns, annual	1965-2002

Table 1—*Continued*

Acronym	Firm Characteristic	Original Sample
seas_2_5na	Years 2-5 lagged returns, nonannual	1965-2002
seas_6_10an	Years 6-10 lagged returns, annual	1965-2002
seas_6_10na	Years 6-10 lagged returns, nonannual	1965-2002
sti_gr1a	Change in short-term investments	1962-2001
taccruals_at	Total accruals	1962-2001
taccruals_ni	Percent total accruals	1989-2008
tangibility	Asset tangibility	1973-2001
tax_gr1a	Tax expense surprise	1977-2006
turnover_126d	Share turnover	1963-1991
turnover_var_126d	Coefficient of variation for share turnover	1966-1995
z_score	Altman Z-score	1981-1995
zero_trades_126d	Number of zero trades with turnover as tiebreaker (6 months)	1963-2003
zero_trades_21d	Number of zero trades with turnover as tiebreaker (1 month)	1963-2003
zero_trades_252d	Number of zero trades with turnover as tiebreaker (12 months)	1963-2003

Table 2. Monthly Returns on Constant Maturity Nominal Zero Coupon Bonds

This table reports the means and standard deviations of monthly returns on constant maturity nominal zero coupon government bonds. Both means and standard deviations are in percentage terms. The sample period is February 1962 to December 2020.

Maturity (years)	1	2	3	4	5	10	15	20	25	30
Mean	0.44	0.48	0.51	0.54	0.56	0.65	0.73	0.86	1.12	1.67
St. Dev.	0.51	0.85	1.16	1.45	1.72	3.13	4.77	7.01	10.63	16.97

Table 3. Dividend Yield Spread for 153 Anomalies

This table reports the value-weighted average annual dividend yields (in percentage terms) for the long and short portfolios and the difference between them (dividend yield spread). The anomalies are ranked by average dividend yield spread (from low to high). For each stock in a given month, the annual dividend yield is calculated as its dividends paid over the past 12 months divided by its stock price at the end of the prior month.

Acronym	Short	Long	L-S	Acronym	Short	Long	L-S
z_score	5.91	1.85	-4.06	rskew_21d	2.97	3.32	0.35
prc_highprc_252d	6.34	2.96	-3.38	iskew_ff3_21d	2.96	3.35	0.39
age	4.24	1.54	-2.69	iskew_capm_21d	2.67	3.07	0.40
at_turnover	4.78	2.59	-2.19	iskew_hxz4_21d	2.66	3.08	0.42
sale_bev	3.79	1.72	-2.07	zero_trades_252d	2.07	2.53	0.46
cash_at	3.95	1.92	-2.03	ret_1_0	2.93	3.41	0.47
ni_ivol	4.26	2.51	-1.76	rd_sale	1.80	2.27	0.47
tax_gr1a	3.78	2.06	-1.72	zero_trades_126d	2.01	2.53	0.52
netdebt_me	4.45	2.85	-1.60	ret_60_12	2.60	3.13	0.53
gp_atl1	3.28	1.71	-1.57	ope_be	2.25	2.80	0.55
opex_at	3.69	2.21	-1.48	qmj_safety	1.99	2.56	0.57
seas_1_1na	3.42	1.97	-1.45	ocfq_saleq_std	2.75	3.43	0.67
ni_inc8q	4.73	3.32	-1.42	debt_me	3.55	4.23	0.68
ami_126d	3.79	2.40	-1.39	fnl_gr1a	2.70	3.39	0.69
kz_index	3.29	1.98	-1.31	netis_at	2.30	3.02	0.72
gp_at	3.33	2.04	-1.29	ncol_gr1a	3.20	3.92	0.72
niq_su	5.12	3.91	-1.21	beta_dimson_21d	2.52	3.28	0.76
op_atl1	3.05	2.00	-1.05	tangibility	2.93	3.69	0.77
mispricing_perf	3.02	2.05	-0.97	noa_at	2.35	3.13	0.78
dgp_dsale	4.70	3.75	-0.95	seas_11_15na	2.48	3.33	0.84
dolvol_126d	3.83	2.89	-0.94	eqnetis_at	2.64	3.50	0.86
rd5_at	2.76	1.91	-0.86	lti_gr1a	2.97	3.85	0.88
ret_9_1	3.45	2.61	-0.83	capx_gr1	2.41	3.36	0.95
niq_at	2.94	2.12	-0.81	zero_trades_21d	1.83	2.79	0.96
bidaskhl_21d	3.27	2.46	-0.81	o_score	2.53	3.60	1.07
sti_gr1a	3.22	2.43	-0.79	seas_16_20na	2.74	3.82	1.08
ret_3_1	3.32	2.60	-0.72	seas_6_10na	2.00	3.15	1.15
op_at	2.97	2.28	-0.70	cowc_gr1a	2.26	3.43	1.17
ret_12_1	3.28	2.59	-0.69	seas_2_5na	1.67	2.89	1.23
ret_6_1	3.32	2.63	-0.69	beta_60m	2.85	4.36	1.51
at_be	3.56	2.90	-0.66	oaccruals_at	2.37	3.97	1.60
saleq_su	2.71	2.07	-0.64	turnover_126d	2.40	4.02	1.62
seas_2_5an	2.75	2.30	-0.45	inv_gr1	2.37	4.01	1.64
qmj_growth	2.92	2.48	-0.44	capx_gr2	1.94	3.61	1.67
ni_ar1	4.03	3.60	-0.43	lnoa_gr1a	2.30	4.03	1.73
seas_6_10an	2.99	2.59	-0.41	ebit_sale	1.56	3.32	1.77
qmj	2.90	2.52	-0.39	nncoa_gr1a	2.25	4.06	1.81
niq_at_chg1	2.81	2.43	-0.38	ocf_me	3.99	5.82	1.83

Table 3—*Continued*

dsale_dsga	3.95	3.57	-0.38	rmax5_21d	1.16	3.02	1.87
niq_be	2.70	2.35	-0.35	taccruals_at	1.99	3.88	1.89
ret_12_7	2.73	2.42	-0.32	capx_gr3	1.92	3.89	1.97
qmj_prof	2.93	2.62	-0.31	ivol_hxz4_21d	1.65	3.67	2.01
cop_atl1	2.46	2.21	-0.25	ivol_capm_21d	1.66	3.69	2.03
aliq_mat	2.25	2.01	-0.24	at_me	2.14	4.35	2.21
ope_bel1	2.35	2.14	-0.21	ncoa_gr1a	2.28	4.55	2.27
seas_11_15an	3.18	2.97	-0.20	saleq_gr1	1.82	4.11	2.29
seas_16_20an	3.40	3.22	-0.18	col_gr1a	2.11	4.42	2.31
debt_gr3	2.50	2.32	-0.18	inv_gr1a	1.87	4.23	2.35
ocf_at	2.10	1.94	-0.16	rmax1_21d	1.81	4.18	2.37
market_equity	3.44	3.29	-0.14	sale_gr3	2.23	4.66	2.42
dsale_drec	3.69	3.56	-0.13	ivol_ff3_21d	1.69	4.11	2.42
dsale_dinv	3.98	3.84	-0.13	noa_gr1a	1.74	4.23	2.49
seas_1_1an	2.49	2.39	-0.10	sale_gr1	2.27	4.88	2.60
resff3_6_1	3.32	3.22	-0.10	betabab_1260d	2.22	4.83	2.61
rmax5_rvol_21d	3.31	3.21	-0.10	rd_me	1.80	4.47	2.67
coskew_21d	3.76	3.67	-0.08	coa_gr1a	1.75	4.47	2.72
resff3_12_1	3.24	3.19	-0.06	betadown_252d	1.59	4.39	2.80
fcf_me	4.70	4.65	-0.04	emp_gr1	1.63	4.45	2.82
nfna_gr1a	3.03	3.01	-0.03	rvol_21d	1.63	4.52	2.89
taccruals_ni	2.58	2.56	-0.02	ebitda_mev	1.63	4.53	2.91
f_score	3.95	3.93	-0.01	ppeinv_gr1a	1.62	4.60	2.98
niq_be_chg1	2.80	2.80	0.01	mispricing_mgmt	1.87	4.91	3.04
capex_abn	3.15	3.17	0.02	be_gr1a	1.44	4.73	3.29
ni_be	3.07	3.12	0.05	ni_me	1.32	4.67	3.35
prc	3.06	3.14	0.08	at_gr1	1.69	5.29	3.59
cop_at	2.36	2.52	0.15	ival_me	2.56	6.20	3.65
sale_emp_gr1	3.70	3.84	0.15	bev_mev	1.91	5.59	3.68
corr_1260d	3.14	3.34	0.19	ivol_capm_252d	1.38	5.07	3.69
dolvol_var_126d	3.64	3.85	0.21	eq_dur	1.80	5.69	3.89
turnover_var_126d	3.65	3.86	0.21	eqnpo_me	1.61	5.57	3.96
ocf_at_chg1	1.90	2.12	0.22	be_me	2.29	6.27	3.98
earnings_variability	3.64	3.86	0.22	sale_me	2.42	6.43	4.01
pi_nix	4.05	4.31	0.27	aliq_at	1.08	5.18	4.10
dbnetis_at	2.70	2.98	0.28	eqpo_me	0.54	5.82	5.27
chcsho_12m	3.46	3.75	0.29	eqnpo_12m	2.17	7.76	5.59
ebit_bev	1.62	1.95	0.33	div12m_me	0.60	7.20	6.60
oaccruals_ni	2.35	2.69	0.34				

Table 4. Raw and Counterfactual Returns for 153 anomalies

This table reports the average monthly raw (long-short) return, the average monthly duration-matched fixed income return spread, and the average monthly counterfactual return after adjustment for interest rate changes, for the 153 anomalies. The *t*-statistics are reported in parentheses. The duration-matched fixed income return spread is calculated using equation (8) with the cutoff for term structure data of government bonds set as 30 years. The sample periods are the original sample periods used in the publications corresponding to these anomalies or from February 1962 to the original ending date if the original starting date is before February 1962. Panel A contains false positives (negatives), for which the *t-statistic* associated with the raw return is above (below) 1.96 while that associated with the counterfactual return is below (above) 1.96. Panel B contains robust anomalies, for which *t-statistics* associated with the raw return and the counterfactual return are both above 1.96. Panel C contains non-robust anomalies, for which *t-statistics* associated with the raw return and the counterfactual return are both below 1.96. All returns are in percentage terms.

Panel A: False Positives and False Negatives

Anomaly	Raw		Fixed Income		Counterfactual	
at_turnover	0.47	(1.96)	0.47	(1.71)	0.00	(0.01)
bev_mev	0.36	(1.72)	-0.54	(-1.39)	0.91	(2.09)
capx_gr2	0.29	(1.73)	-0.25	(-1.57)	0.54	(2.34)
debt_gr3	0.40	(3.30)	0.12	(1.26)	0.29	(1.85)
eqpo_me	0.68	(1.92)	-0.77	(-1.69)	1.45	(2.47)
fcf_me	0.36	(2.46)	-0.01	(-0.03)	0.37	(1.33)
gp_at	0.35	(2.31)	0.26	(1.73)	0.08	(0.39)
mispricing_perf	0.69	(3.11)	0.19	(1.35)	0.49	(1.89)
niq_at	0.51	(2.06)	0.05	(0.59)	0.46	(1.75)
op_at	0.33	(2.08)	0.17	(2.37)	0.16	(0.91)
ope_bel1	0.38	(2.19)	0.11	(0.72)	0.27	(1.15)
qmj	0.38	(1.96)	0.04	(0.68)	0.34	(1.68)
ret_1_0	0.77	(2.74)	0.43	(1.41)	0.34	(0.86)
ret_3_1	0.63	(2.44)	0.30	(1.19)	0.33	(0.98)
ret_9_1	1.17	(3.68)	0.27	(0.70)	0.90	(1.84)
rmax1_21d	0.42	(1.53)	-0.44	(-2.27)	0.86	(2.55)
rvol_21d	0.45	(1.42)	-0.48	(-1.75)	0.92	(2.22)
sale_bev	0.72	(2.94)	0.28	(1.71)	0.44	(1.46)
seas_11_15na	0.31	(1.71)	-0.17	(-1.06)	0.47	(2.08)
seas_16_20na	0.29	(1.62)	-0.17	(-1.51)	0.46	(2.18)
seas_1_1na	0.80	(2.45)	0.31	(1.03)	0.50	(1.15)

Panel B: Robust Anomalies

Anomaly	Raw		Fixed Income		Counterfactual	
at_gr1	0.63	(3.47)	-0.59	(-1.63)	1.21	(3.10)
be_me	1.42	(2.86)	-0.38	(-0.66)	1.80	(2.51)
capex_abn	0.39	(2.79)	-0.01	(-0.16)	0.41	(2.47)
capx_gr1	0.30	(2.05)	-0.25	(-1.42)	0.54	(2.37)
capx_gr3	0.44	(2.63)	-0.23	(-1.33)	0.67	(2.77)

Table 4—*Continued*

chcsho_12m	0.77	(4.83)	-0.10	(-1.17)	0.87	(4.96)
coa_gr1a	0.64	(4.17)	-0.42	(-1.36)	1.07	(3.13)
cop_at	0.69	(4.68)	-0.11	(-1.29)	0.80	(4.77)
cop_atl1	0.59	(4.20)	-0.05	(-0.67)	0.63	(4.04)
cowc_gr1a	0.95	(6.58)	-0.23	(-1.06)	1.18	(4.48)
dbnetis_at	0.35	(2.76)	-0.04	(-0.57)	0.39	(2.65)
dsale_dinv	0.97	(5.78)	-0.10	(-0.66)	1.07	(4.97)
ebit_bev	1.00	(3.00)	0.03	(0.33)	0.97	(2.84)
ebit_sale	0.93	(2.34)	-0.27	(-1.29)	1.19	(2.63)
ebitda_mev	0.80	(4.27)	-0.52	(-1.35)	1.32	(3.12)
emp_gr1	0.39	(2.75)	-0.38	(-1.43)	0.77	(2.56)
eq_dur	0.43	(2.04)	-0.73	(-1.54)	1.16	(2.25)
eqnetis_at	0.71	(3.31)	-0.16	(-1.28)	0.87	(3.50)
eqnpo_12m	0.62	(3.42)	-0.70	(-1.72)	1.32	(3.06)
eqnpo_me	1.15	(3.18)	-0.60	(-2.08)	1.75	(3.79)
f_score	0.33	(3.17)	-0.01	(-0.25)	0.34	(2.87)
fnl_gr1a	0.46	(4.55)	0.01	(0.03)	0.46	(2.34)
inv_gr1	0.63	(4.46)	-0.35	(-1.61)	0.98	(3.72)
inv_gr1a	0.83	(5.01)	-0.20	(-1.15)	1.03	(4.48)
ival_me	0.75	(2.53)	-0.50	(-1.20)	1.25	(2.48)
ivol_capm_21d	0.59	(2.08)	-0.34	(-1.91)	0.94	(2.76)
ivol_capm_252d	0.69	(1.97)	-0.51	(-1.29)	1.20	(2.23)
ivol_ff3_21d	0.63	(2.11)	-0.35	(-1.64)	0.98	(2.66)
ivol_hxz4_21d	0.64	(2.30)	-0.36	(-1.98)	1.00	(3.00)
lnoa_gr1a	0.47	(3.36)	-0.41	(-1.19)	0.89	(2.44)
mispricing_mgmt	0.80	(5.42)	-0.43	(-1.52)	1.23	(3.95)
ncoa_gr1a	0.55	(4.13)	-0.29	(-1.22)	0.84	(3.11)
netis_at	0.69	(3.67)	-0.29	(-2.38)	0.98	(4.41)
nfna_gr1a	0.57	(4.84)	0.08	(0.48)	0.50	(2.44)
niq_be	0.50	(2.18)	-0.00	(-0.03)	0.50	(2.10)
niq_be_chg1	0.43	(3.03)	-0.14	(-1.51)	0.57	(3.50)
niq_su	0.91	(2.30)	0.03	(0.09)	0.88	(2.16)
nncoa_gr1a	0.62	(4.44)	-0.23	(-0.99)	0.85	(3.16)
noa_at	0.63	(4.63)	-0.09	(-0.67)	0.72	(3.80)
noa_gr1a	0.88	(5.97)	-0.34	(-1.15)	1.22	(3.78)
o_score	0.56	(2.10)	-0.48	(-1.24)	1.04	(2.22)
oaccruals_at	0.75	(5.03)	-0.37	(-1.03)	1.12	(2.94)
ocf_at	0.72	(2.77)	-0.04	(-0.63)	0.76	(2.79)
ocf_me	0.86	(5.10)	-0.11	(-0.81)	0.97	(4.60)
ope_be	0.46	(2.57)	-0.02	(-0.11)	0.48	(2.08)
ppeinv_gr1a	0.69	(4.59)	-0.24	(-1.27)	0.94	(3.84)
qmj_prof	0.45	(2.99)	0.10	(1.02)	0.35	(1.97)
resff3_12_1	1.01	(6.15)	0.05	(0.63)	0.96	(5.30)
resff3_6_1	0.40	(2.63)	-0.03	(-0.32)	0.43	(2.53)
ret_12_1	1.64	(5.15)	0.22	(0.57)	1.43	(2.96)

Table 4—*Continued*

ret_12_7	1.30	(6.09)	0.11	(0.74)	1.20	(4.73)
ret_60_12	0.90	(2.80)	-0.51	(-1.04)	1.41	(2.46)
ret_6_1	1.06	(3.64)	0.12	(0.39)	0.95	(2.30)
rmax5_rvol_21d	0.54	(4.03)	0.06	(0.68)	0.47	(2.92)
sale_gr3	0.48	(2.34)	-0.60	(-1.22)	1.08	(2.13)
seas_11_15an	0.78	(4.81)	0.02	(0.16)	0.76	(3.77)
seas_16_20an	0.55	(2.99)	0.12	(1.06)	0.43	(2.01)
seas_1_1an	0.88	(4.06)	-0.15	(-1.13)	1.03	(4.09)
seas_2_5an	0.89	(5.15)	-0.04	(-0.33)	0.94	(4.25)
seas_2_5na	0.88	(3.65)	-0.42	(-1.29)	1.31	(3.32)
seas_6_10an	0.90	(5.13)	-0.14	(-1.06)	1.03	(4.72)
seas_6_10na	0.45	(2.09)	-0.32	(-1.76)	0.77	(2.76)
taccruals_at	0.32	(2.41)	-0.44	(-1.82)	0.75	(2.90)
Panel C: Non-robust Anomalies						
Anomaly	Raw		Fixed Income		Counterfactual	
age	0.11	(0.46)	0.40	(1.70)	-0.29	(-0.86)
aliq_at	0.15	(0.49)	-0.42	(-1.68)	0.57	(1.43)
aliq_mat	-0.48	(-2.40)	0.10	(1.43)	-0.58	(-2.76)
ami_126d	0.30	(1.39)	0.23	(1.70)	0.07	(0.26)
at_be	0.05	(0.29)	0.13	(0.62)	-0.08	(-0.28)
at_me	0.09	(0.41)	-0.58	(-1.48)	0.67	(1.49)
be_gr1a	0.10	(0.57)	-0.50	(-1.51)	0.60	(1.62)
beta_60m	-0.99	(-1.73)	-0.76	(-0.55)	-0.23	(-0.16)
beta_dimson_21d	-0.06	(-0.22)	-0.38	(-0.96)	0.31	(0.67)
betabab_1260d	0.21	(0.75)	-0.48	(-1.68)	0.69	(1.72)
betadown_252d	-0.11	(-0.40)	-0.42	(-1.16)	0.30	(0.68)
bidaskhl_21d	-0.08	(-0.29)	0.24	(1.77)	-0.32	(-1.02)
cash_at	0.12	(0.61)	0.23	(1.69)	-0.11	(-0.46)
col_gr1a	-0.23	(-1.41)	-0.30	(-1.19)	0.08	(0.26)
corr_1260d	0.22	(1.37)	-0.06	(-0.88)	0.28	(1.60)
coskew_21d	0.02	(0.19)	-0.01	(-0.05)	0.03	(0.16)
debt_me	0.20	(0.74)	-0.41	(-1.03)	0.61	(1.30)
dgp_dsale	0.35	(1.65)	-0.00	(-0.02)	0.35	(1.24)
div12m_me	-0.22	(-0.59)	-1.13	(-0.94)	0.91	(0.75)
dolvol_126d	0.29	(1.37)	0.16	(1.29)	0.12	(0.48)
dolvol_var_126d	-0.22	(-1.46)	-0.01	(-0.15)	-0.21	(-1.30)
dsale_drec	0.01	(0.09)	-0.10	(-0.70)	0.11	(0.52)
dsale_dsga	-0.27	(-1.22)	-0.01	(-0.03)	-0.26	(-0.79)
earnings_variability	0.19	(1.21)	-0.03	(-0.26)	0.22	(1.14)
gp_atl1	0.14	(0.87)	0.32	(1.85)	-0.18	(-0.78)
iskew_capm_21d	-0.10	(-1.03)	-0.11	(-1.79)	0.01	(0.08)
iskew_ff3_21d	-0.23	(-2.33)	-0.08	(-1.06)	-0.15	(-1.20)
iskew_hxz4_21d	-0.20	(-2.24)	-0.08	(-1.11)	-0.12	(-1.00)
kz_index	-0.16	(-0.82)	0.06	(0.23)	-0.22	(-0.71)
lti_gr1a	0.05	(0.45)	-0.07	(-0.67)	0.12	(0.80)

Table 4—*Continued*

market_equity	0.29	(0.67)	0.38	(1.02)	-0.09	(-0.16)
ncol_gr1a	-0.00	(-0.03)	-0.06	(-0.64)	0.06	(0.40)
netdebt_me	-0.16	(-0.80)	0.19	(1.56)	-0.35	(-1.49)
ni_ar1	0.04	(0.31)	-0.03	(-0.32)	0.08	(0.46)
ni_be	0.32	(1.07)	-0.16	(-0.93)	0.48	(1.37)
ni_inc8q	0.08	(0.50)	0.29	(1.98)	-0.21	(-1.09)
ni_ivol	-0.01	(-0.03)	0.26	(1.62)	-0.27	(-0.81)
ni_me	0.44	(1.32)	-0.71	(-0.82)	1.15	(1.26)
niq_at_chg1	0.23	(1.58)	-0.04	(-0.50)	0.27	(1.71)
oaccruals_ni	0.28	(1.33)	0.02	(0.24)	0.26	(1.18)
ocf_at_chg1	0.29	(1.87)	0.00	(0.02)	0.29	(1.68)
ocfq_saleq_std	0.45	(1.61)	-0.03	(-0.19)	0.48	(1.59)
op_atl1	0.31	(1.94)	0.26	(1.93)	0.05	(0.22)
opex_at	0.26	(1.75)	0.30	(2.53)	-0.04	(-0.20)
pi_nix	0.07	(0.47)	-0.05	(-0.53)	0.12	(0.72)
prc	0.51	(1.14)	0.18	(0.93)	0.33	(0.66)
prc_highprc_252d	0.44	(1.29)	0.18	(1.02)	0.26	(0.67)
qmj_growth	0.18	(1.42)	0.09	(0.96)	0.08	(0.52)
qmj_safety	0.12	(0.67)	-0.09	(-0.73)	0.21	(0.97)
rd5_at	-0.11	(-0.49)	0.27	(1.03)	-0.38	(-1.15)
rd_me	0.04	(0.15)	-0.35	(-1.31)	0.39	(1.06)
rd_sale	-0.46	(-1.79)	-0.01	(-0.06)	-0.45	(-1.68)
rmax5_21d	0.56	(0.98)	-0.31	(-2.57)	0.87	(1.45)
rskew_21d	-0.12	(-1.20)	-0.07	(-1.25)	-0.05	(-0.42)
sale_emp_gr1	-0.00	(-0.01)	-0.02	(-0.13)	0.01	(0.06)
sale_gr1	0.35	(1.56)	-0.73	(-1.28)	1.09	(1.79)
sale_me	0.24	(0.81)	-0.47	(-1.14)	0.71	(1.42)
saleq_gr1	-0.14	(-0.89)	-0.25	(-1.57)	0.10	(0.47)
saleq_su	-0.15	(-0.60)	0.05	(0.89)	-0.20	(-0.77)
sti_gr1a	0.15	(1.16)	0.02	(0.20)	0.14	(0.90)
taccruals_ni	-0.23	(-1.32)	-0.09	(-1.22)	-0.14	(-0.79)
tangibility	-0.07	(-0.42)	-0.15	(-1.19)	0.08	(0.40)
tax_gr1a	0.17	(0.86)	0.22	(1.80)	-0.05	(-0.21)
turnover_126d	0.11	(0.40)	-0.25	(-0.69)	0.36	(0.82)
turnover_var_126d	-0.22	(-1.43)	-0.02	(-0.30)	-0.20	(-1.22)
z_score	-0.10	(-0.37)	0.72	(1.66)	-0.82	(-1.58)
zero_trades_126d	0.41	(1.61)	-0.12	(-0.55)	0.52	(1.62)
zero_trades_21d	0.00	(0.00)	-0.10	(-0.44)	0.10	(0.30)
zero_trades_252d	0.42	(1.70)	-0.07	(-0.30)	0.49	(1.46)

Table 5. Regression Analysis

This table reports results from regressing indicators for false positive (FP) and false negative (FN) discoveries on the average dividend yield differential $\Delta DivY$ for each potential anomaly. Columns (1) and (2) present results for the 153 discovered anomalies and Columns (3) and (4) present results for the 1,395 potential discovered anomalies. The average dividend yield differential, $\Delta DivY$, is annualized and in percentage terms. t-statistics based on heteroskedasticity-consistent standard errors are presented in parentheses below the coefficient estimates. For the 1,395 potential undiscovered anomalies based on Compustat ratios, we cluster standard errors by the accounting variable in the numerator. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) FP Discovered	(2) FN Discovered	(3) FP Undiscovered	(4) FN Undiscovered
$\Delta DivY$	-0.05***	0.03**	-0.07***	0.03***
	(-3.60)	(2.26)	(-8.18)	(4.30)
Constant	0.12***	0.03**	0.10***	0.02***
	(4.08)	(2.28)	(8.97)	(4.95)
No. of Observations	153	153	1,395	1,395
Adjusted R-squared	0.073	0.051	0.092	0.031

Table 6. Pre- versus Post-Publication Periods

This table reports results from regressing anomaly returns onto dummy variables associated with post-sample and post-publication. The dependent variables are the raw long-short anomaly return (Column 1), duration-matched fixed-income return spread (Column 2), and counterfactual return after adjustment for interest rate changes (Column 3). *Post-Sample* equals one if the return month is after the sample period in the original study but still pre-publication and zero otherwise. *Post-Publication* equals one if the return month is after the official publication date of the original study and zero otherwise. t-statistics based on heteroskedasticity-consistent standard errors are presented in parentheses below the coefficient estimates. We cluster standard errors by month to account for contemporaneous cross-sectional correlation across portfolio return residuals. All returns are in percentage terms. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Raw	(2) Fixed Income	(3) Counterfactual
Post-Sample	-0.08	0.05	-0.13
	(-1.15)	(0.65)	(-1.27)
Post-Publication	-0.32***	0.07	-0.39***
	(-3.84)	(0.70)	(-2.97)
Observations	95,883	95,883	95,883
Predictor FE	Yes	Yes	Yes
Predictors	153	153	153

Table A1. List of False Positives and False Negatives from a Large Set of Compustat Ratios
This table presents false positives and false negatives from the sample of 1,395 potential undiscovered anomalies constructed using Compustat ratios. The sample period is July 1963 to December 2020. For false positives, the $|t\text{-statistic}|$ associated with the raw return is above 1.96, while that associated with the counterfactual return is below 1.96. For false negatives, the $|t\text{-statistic}|$ associated with the raw return is below 1.96 while that associated with the counterfactual return is above 1.96. Anomalies are ranked by raw $|t\text{-statistic}|$ from low to high. All returns are in percentage terms.

Anomaly	Raw		Fixed Income		Counterfactual	
txw/ceq	0.12	(0.65)	-0.33	(-2.58)	0.45	(2.02)
dpact/qta	0.13	(0.73)	-0.43	(-1.92)	0.56	(2.00)
ppeveb/qta	0.16	(0.80)	-0.37	(-1.97)	0.54	(2.00)
dpact/ceq	0.13	(0.83)	-0.30	(-1.98)	0.43	(2.03)
dcvt/sale	-0.09	(-0.87)	0.18	(2.13)	-0.27	(-1.97)
dm/lt	-0.13	(-0.98)	0.20	(2.37)	-0.33	(-2.04)
txdb/mktcap	0.14	(0.99)	-0.23	(-2.29)	0.37	(2.08)
dvpa/ceq	-0.30	(-1.04)	0.60	(2.08)	-0.90	(-2.18)
ppeveb/mktcap	0.21	(1.06)	-0.28	(-1.71)	0.49	(1.98)
dpvieb/qta	0.21	(1.07)	-0.33	(-1.98)	0.54	(2.18)
sstk/lt	-0.22	(-1.23)	0.19	(2.15)	-0.40	(-2.01)
cstkcv/at	-0.18	(-1.24)	0.15	(1.96)	-0.33	(-1.96)
dpvieb/ceq	0.21	(1.28)	-0.21	(-2.08)	0.42	(2.22)
capx/mktcap	0.21	(1.29)	-0.30	(-1.88)	0.50	(2.31)
dpvieb/mktcap	0.28	(1.31)	-0.19	(-1.61)	0.48	(2.01)
dcvt/lt	-0.14	(-1.33)	0.16	(1.80)	-0.30	(-2.21)
dpact/mktcap	0.24	(1.34)	-0.34	(-1.66)	0.58	(2.19)
dcvsub/at	-0.15	(-1.34)	0.17	(1.75)	-0.33	(-2.17)
sstk/at	-0.23	(-1.34)	0.16	(2.15)	-0.39	(-2.04)
dcvsub/sale	-0.15	(-1.36)	0.17	(1.91)	-0.32	(-2.26)
aqs/lt	-0.15	(-1.38)	0.09	(2.02)	-0.24	(-2.00)
dfxa/ceq	0.25	(1.41)	-0.17	(-1.88)	0.42	(2.09)
dpvir/mktcap	0.33	(1.43)	-0.45	(-1.73)	0.78	(2.37)
cstkcv/lt	-0.22	(-1.43)	0.16	(1.95)	-0.37	(-2.10)
xpr/mktcap	0.22	(1.49)	-0.19	(-1.27)	0.41	(2.01)
dp/mktcap	0.26	(1.49)	-0.30	(-1.83)	0.56	(2.46)
oancf/mktcap	0.38	(1.52)	-0.12	(-1.82)	0.50	(1.97)
xido/lt	0.12	(1.54)	-0.07	(-1.19)	0.19	(2.00)
dcvsub/lt	-0.19	(-1.64)	0.16	(1.75)	-0.34	(-2.37)
dp/qta	0.26	(1.64)	-0.32	(-1.81)	0.57	(2.57)
dm/sale	-0.22	(-1.65)	0.13	(2.37)	-0.35	(-2.37)
recco/qta	0.17	(1.66)	-0.12	(-1.37)	0.29	(2.22)
dpc/mktcap	0.32	(1.70)	-0.21	(-1.75)	0.53	(2.48)

Table A1—*Continued*

ppenme/mktcap	0.48	(1.74)	-0.23	(-1.35)	0.71	(2.21)
invrm/ceq	0.28	(1.74)	-0.08	(-1.01)	0.36	(2.04)
re/qta	0.29	(1.74)	-0.34	(-1.76)	0.64	(2.49)
pidom/sale	0.39	(1.78)	-0.07	(-1.09)	0.46	(2.01)
dpc/qta	0.31	(1.78)	-0.26	(-1.89)	0.57	(2.69)
dltis/lt	-0.19	(-1.78)	0.06	(0.98)	-0.25	(-2.08)
dltis/at	-0.19	(-1.82)	0.07	(1.17)	-0.27	(-2.25)
txpd/ceq	0.39	(1.83)	-0.09	(-1.46)	0.48	(2.09)
ppenb/qta	0.34	(1.84)	-0.15	(-0.79)	0.49	(2.07)
txp/qta	0.24	(1.87)	-0.35	(-1.45)	0.59	(2.21)
oancf/qta	0.51	(1.88)	-0.09	(-1.36)	0.59	(2.11)
txpd/at	0.35	(1.90)	-0.06	(-1.16)	0.42	(2.08)
ppevbb/qta	0.47	(1.93)	-0.58	(-1.64)	1.05	(2.59)
pstk/lt	-0.20	(-1.96)	-0.14	(-1.58)	-0.06	(-0.40)
dltt/sale	-0.31	(-1.96)	-0.30	(-2.27)	-0.01	(-0.05)
cld3/mktcap	0.32	(1.96)	0.10	(1.70)	0.22	(1.30)
dlc/sale	-0.27	(-1.96)	-0.13	(-1.66)	-0.14	(-0.89)
ppeveb/sale	-0.32	(-2.00)	-0.27	(-1.85)	-0.05	(-0.25)
lcox/qta	0.18	(2.00)	0.07	(1.17)	0.11	(1.02)
dvp/sale	-0.22	(-2.01)	-0.15	(-1.60)	-0.07	(-0.52)
txdc/ceq	-0.25	(-2.01)	-0.13	(-1.40)	-0.13	(-0.82)
dltt/lt	-0.23	(-2.02)	-0.15	(-1.69)	-0.08	(-0.55)
aco/qta	0.24	(2.03)	0.09	(1.19)	0.15	(1.11)
prstkc/at	0.19	(2.04)	0.03	(0.67)	0.16	(1.61)
txdfed/lt	-0.33	(-2.04)	-0.21	(-2.43)	-0.13	(-0.68)
acox/lt	0.24	(2.04)	0.19	(1.71)	0.05	(0.29)
che/qta	0.28	(2.05)	-0.03	(-0.32)	0.31	(1.86)
xsga/sale	0.33	(2.06)	0.30	(1.57)	0.04	(0.15)
prstkc/ceq	0.20	(2.08)	0.02	(0.48)	0.18	(1.73)
xad/mktcap	0.42	(2.08)	0.02	(0.21)	0.40	(1.88)
fca/qta	-0.35	(-2.09)	-0.04	(-0.58)	-0.31	(-1.77)
invo/sale	-0.35	(-2.10)	-0.03	(-0.74)	-0.32	(-1.89)
txndbl/sale	-0.54	(-2.10)	-0.14	(-1.65)	-0.40	(-1.42)
xintd/sale	-0.64	(-2.11)	-0.36	(-1.99)	-0.28	(-0.79)
mrct/qta	0.35	(2.11)	0.12	(1.79)	0.22	(1.27)
lct/sale	-0.21	(-2.12)	-0.13	(-1.71)	-0.09	(-0.67)
xpp/sale	-0.19	(-2.12)	0.03	(0.39)	-0.22	(-1.88)
wcap/mktcap	0.38	(2.13)	0.21	(1.77)	0.17	(0.77)
txfed/at	0.29	(2.13)	0.16	(2.51)	0.13	(0.88)
prstkc/lt	0.20	(2.14)	0.05	(1.12)	0.15	(1.49)
dclo/qta	0.21	(2.15)	0.05	(0.89)	0.16	(1.48)
dxd4/sale	-0.44	(-2.16)	-0.18	(-1.96)	-0.26	(-1.17)
mrct/ceq	0.33	(2.17)	0.16	(2.07)	0.17	(1.00)
ppent/sale	-0.32	(-2.17)	-0.26	(-1.96)	-0.06	(-0.30)
act/ceq	0.33	(2.17)	0.28	(1.59)	0.05	(0.23)

Table A1—*Continued*

optprcey/qta	0.51	(2.17)	0.14	(1.72)	0.36	(1.40)
lco/qta	0.30	(2.18)	0.11	(1.24)	0.19	(1.20)
sppiv/mktcap	0.35	(2.18)	0.06	(1.26)	0.29	(1.72)
txndb/lt	0.49	(2.19)	0.08	(1.35)	0.41	(1.76)
bkvlps/at	0.32	(2.19)	0.29	(2.14)	0.03	(0.15)
ppegt/sale	-0.34	(-2.19)	-0.32	(-1.99)	-0.02	(-0.09)
txdi/lt	-0.24	(-2.21)	-0.07	(-1.23)	-0.17	(-1.38)
ceqt/sale	-0.32	(-2.21)	-0.20	(-1.41)	-0.12	(-0.58)
ch/qta	0.36	(2.23)	0.10	(1.70)	0.26	(1.47)
txdfed/ceq	-0.34	(-2.23)	-0.10	(-2.08)	-0.24	(-1.49)
xint/sale	-0.31	(-2.23)	-0.21	(-2.11)	-0.10	(-0.57)
txc/sale	0.34	(2.25)	0.04	(0.74)	0.30	(1.83)
epsfi/sale	0.39	(2.26)	0.07	(0.46)	0.32	(1.44)
epsfi/at	0.40	(2.26)	0.21	(1.14)	0.19	(0.74)
optprcey/mktcap	0.58	(2.27)	0.13	(1.95)	0.46	(1.67)
dxd5/sale	-0.42	(-2.27)	-0.04	(-0.63)	-0.37	(-1.92)
gp/at	0.32	(2.27)	0.23	(1.85)	0.09	(0.47)
cogs/at	0.29	(2.28)	0.18	(1.76)	0.10	(0.63)
sppiv/ceq	0.36	(2.29)	0.08	(1.73)	0.28	(1.70)
xad/qta	0.38	(2.30)	0.04	(0.56)	0.34	(1.91)
xrent/qta	0.34	(2.31)	0.12	(1.75)	0.21	(1.33)
wcap/qta	0.39	(2.31)	0.22	(2.11)	0.17	(0.83)
invfg/sale	-0.29	(-2.31)	-0.08	(-1.56)	-0.21	(-1.58)
dp/sale	-0.32	(-2.31)	-0.19	(-2.05)	-0.13	(-0.78)
fate/sale	-0.41	(-2.32)	-0.16	(-1.81)	-0.25	(-1.33)
ivaeq/sale	-0.21	(-2.34)	-0.19	(-2.07)	-0.02	(-0.17)
sppiv/lt	0.41	(2.37)	0.10	(1.80)	0.30	(1.65)
acox/qta	0.24	(2.38)	0.13	(1.67)	0.12	(0.92)
txdi/sale	-0.27	(-2.38)	-0.14	(-1.77)	-0.14	(-0.96)
capx/sale	-0.37	(-2.41)	-0.15	(-1.60)	-0.22	(-1.27)
caps/sale	-0.33	(-2.42)	-0.03	(-0.38)	-0.30	(-1.91)
bkvlps/ceq	0.32	(2.42)	0.27	(2.04)	0.05	(0.26)
aco/mktcap	0.31	(2.44)	0.04	(0.48)	0.27	(1.89)
xopr/at	0.35	(2.44)	0.22	(2.20)	0.13	(0.74)
mrc2/qta	0.41	(2.44)	0.12	(1.77)	0.29	(1.62)
lco/mktcap	0.37	(2.49)	0.04	(0.46)	0.32	(1.92)
xrent/at	0.35	(2.49)	0.29	(2.07)	0.06	(0.29)
txc/at	0.38	(2.49)	0.07	(1.45)	0.31	(1.92)
dltis/sale	-0.30	(-2.50)	-0.07	(-1.30)	-0.23	(-1.74)
txc/lt	0.37	(2.52)	0.14	(2.26)	0.23	(1.45)
intc/sale	-0.34	(-2.56)	-0.25	(-2.00)	-0.09	(-0.48)
mrc2/ceq	0.41	(2.56)	0.23	(2.17)	0.18	(0.96)
cogs/ceq	0.32	(2.57)	0.07	(1.12)	0.25	(1.83)
epsfx/ceq	0.50	(2.59)	0.16	(1.15)	0.34	(1.45)
acox/at	0.24	(2.59)	0.19	(1.70)	0.05	(0.35)

Table A1—*Continued*

epsfi/lt	0.41	(2.62)	0.16	(1.08)	0.24	(1.16)
txdi/ceq	-0.28	(-2.64)	-0.01	(-0.07)	-0.28	(-1.95)
mrc1/ceq	0.42	(2.65)	0.12	(1.48)	0.30	(1.70)
epsfx/at	0.48	(2.68)	0.11	(0.76)	0.37	(1.68)
xsga/at	0.41	(2.68)	0.24	(1.82)	0.18	(0.90)
epsfx/lt	0.43	(2.73)	0.10	(0.74)	0.33	(1.71)
capxv/sale	-0.40	(-2.78)	-0.20	(-1.75)	-0.21	(-1.17)
lct/ceq	0.37	(2.78)	0.06	(0.45)	0.31	(1.69)
xacc/qta	0.44	(2.84)	0.13	(1.64)	0.31	(1.88)
cstk/sale	-0.45	(-2.86)	-0.29	(-1.79)	-0.16	(-0.71)
nopio/lt	-0.28	(-2.89)	-0.14	(-1.72)	-0.14	(-1.16)
epspi/ceq	0.55	(2.94)	0.10	(0.73)	0.44	(1.95)
lct/at	0.39	(2.99)	0.21	(1.59)	0.17	(0.94)
bkvlps/qta	0.41	(3.10)	0.18	(2.14)	0.23	(1.44)
acox/mktcap	0.33	(3.10)	0.09	(1.26)	0.24	(1.93)
xacc/ceq	0.42	(3.12)	0.12	(1.42)	0.30	(1.95)
epspi/at	0.52	(3.12)	0.13	(0.95)	0.38	(1.80)
xrent/ceq	0.45	(3.14)	0.23	(1.72)	0.22	(1.13)
seq/sale	-0.45	(-3.21)	-0.21	(-1.48)	-0.24	(-1.23)
xopr/ceq	0.45	(3.23)	0.21	(1.59)	0.23	(1.25)
ceql/sale	-0.46	(-3.57)	-0.21	(-1.50)	-0.25	(-1.34)
icapt/sale	-0.54	(-3.69)	-0.22	(-1.82)	-0.32	(-1.76)
gp/ceq	0.48	(3.89)	0.16	(1.16)	0.33	(1.80)