The Factor Multiverse: The Role of Interest Rates in Factor Return Measurement and Discovery

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Abstract

We study the equity factor zoo using an alternative excess return definition that measures factor performance in excess of a duration-matched government bond portfolio. Our approach quantifies the realized return premium that investors have received for investing in a stream of risky cash flows relative to a fixed cash flow counterfactual. We document different average excess returns than the ones previously reported in the literature, even for the most commonly-used factors. Further, our approach results in a different correlation structure among asset pricing factors. Finally, using a sample of 153 discovered and 1,395 potential undiscovered anomalies, we find that our excess return definition would have resulted in the discovery of several different asset pricing anomalies, highlighting the sensitivity of the discovery process to the excess return definition and (potentially) the sample period used.

Keywords: anomalies, factor zoo, duration, excess returns, interest rates.

JEL classification: G12, G14

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1 Introduction

We study stock return anomalies using a novel excess return definition that adjusts for duration. Contrary to the usual practice of comparing the performance of long-duration risky assets to that of a short-duration fixed-income instrument, we compute portfolio returns in excess of a duration-matched riskless fixed-income counterfactual. To construct this counterfactual, strip-by-strip we replace a stock portfolio's claim to the risky cash flow at each horizon with an equivalent investment in a zero-coupon government bond of the same maturity.[1] We define each anomaly's fixed-income return spread as the difference between the matched fixed-income portfolio returns of the long and short legs of the anomaly. We then obtain our novel measure of anomaly excess returns as the difference between the raw anomaly return spread and the fixed-income return spread. Using this novel definition, we document different average excess returns than the ones previously reported in the literature, even for the most commonly-used factors such as the market, size, value and investment factors. Further, our approach results in a different correlation structure among factors.

To illustrate the intuition for our approach, consider the problem of measuring the excess return of a risky corporate bond with five years to maturity. What is the appropriate risk-free counterfactual return for this asset? One approach is to gauge the investment horizon of its investors and use that horizon to select the risk-free counterfactual. However, investment horizons are hard to observe and may exhibit large cross-sectional variation across investors. The common practice in the literature today is to align the maturity of the risk-free return with the frequency at which returns are calculated, which in most cases implies defining excess returns relative to the 1-month, 3-month, or 1-year T-bill return.

We argue that it is unclear why this common excess return definition should be preferred over alternative approaches. In fact, the downside of computing excess returns this way is that the ex post realized term premium and compensation for fundamental risk (i.e., credit and illiquidity in the case of corporate bonds) are both present and their respective impacts are difficult to disentangle. If, instead, a duration-matched risk-free bond portfolio is used to compute excess returns, a clean measurement of the compensation for fundamental risk is achieved. The pricing of interest rate risk can then be left to the government bond term structure literature, allowing a clearer focus on the pricing of *risky* cash flows. Indeed, this

[1] See Binsbergen (2021) and Binsbergen et al. (2023) who apply this idea to the aggregate stock market and corporate bonds respectively.

seems like a natural approach in the context of pricing risky fixed-income securities, but it should also apply for other claims on long-term risky cash flows.[2]

In this paper, we apply the duration-adjusted excess return definition to the cross-section of stock returns. The key advantage in this setting is that our excess return definition separates the effect of (and potential compensation for) long-duration interest rate movements from the other sources of randomness that affect stock returns: time variation in (expected) growth rates and risk premia. This also helps isolate the impact on stock valuations of the low-frequency movements in interest rates that have been observed in the past few decades (see Figure 1).

There are several reasons why this exercise should offer valuable insights. Investors can easily bet on interest rate movements across maturities through the government bond market. Stock investments are distinct from fixed-income bets because they allow investors to bet on variation in (expected) growth and risk premia across firms. Therefore, it is important to separate the returns on fixed-income exposure from the returns directly attributable to owning risky cash flows. In this context, it is also important to note that many traditional asset pricing models generate substantial stock risk premia as the required compensation for growth and/or volatility risk, while the risk premium on bonds is quite small or even zero.[3] Further, many behavioral models focus on errors in growth expectations in the cross-section of returns, not errors in interest rate exposures. Adjusting for the effect of interest rates on stock valuations may thus also be useful in that context.

Before proceeding, we should note that our approach is different from simply regressing anomaly returns on a government bond factor, a potential alternative method of duration adjustment, for at least three reasons. First and foremost, the regression loading on the government bond factor may be affected by correlation between risk premia and risk-free interest rates, thereby complicating the measurement of risk premia. This is clear in the context of corporate bonds, where credit spreads are negatively correlated with risk-free rates, but may also matter in the stock market setting. Second, the government bond factors considered in the literature are usually based on a small set of maturities, while our approach matches risky securities strip-by-strip across all maturities. Third and finally, the regression approach requires one to estimate betas over a particular time window and using

[2] Binsbergen et al. (2023) use this approach to study the cross-section of corporate bond returns, finding that investors received relatively little compensation for credit and liquidity risk over the sample studied, and that the duration-adjusted excess return definition resolves the CAPM's failure to price corporate bonds.

[3] See Rietz (1988), Campbell and Cochrane (1999), Bansal and Yaron (2004), and Barro (2006).

a particular data frequency (daily, weekly, monthly, or annual data), whereas our duration adjustment does not require such assumptions.

To construct a sample of stock return anomalies (sorting variables) for our empirical analysis, our starting point for *discovered* anomalies is the set of 153 factors 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 results in an anomaly return pattern under both excess return definitions.[4]

We find that using this alternative excess return definition has an effect on a substantial fraction of both discovered and undiscovered anomalies. Starting with first moments, we document different return premia than the ones previously reported in the literature. As a first example, consider the equity risk premium. While under the traditional definition of excess returns the equity risk premium is large, under the duration-adjusted definition the equity risk premium is much smaller and not statistically different from zero (Binsbergen (2021)). Other examples include the size premium, the value premium and the investment premium. Like the equity risk premium, the size premium is weaker after adjusting for duration, while the value and investment premia become stronger.

Our approach also results in a different correlation structure among commonly-used asset pricing factors. First, the correlations of the duration-adjusted excess return series with their traditional counterparts are substantially below 1 for many factors. For example, the commonly-used market factor (i.e. the aggregate market return in excess of the one-month T-bill rate) has a correlation with its duration-adjusted counterpart under 0.5. For cross-sectional return factors, these correlations vary between 0.5 and 1. Given that stocks are all relatively long-duration investments, their individual duration-matched fixed-income counterparts are also long-duration, leading to substantial excess return adjustments. However, once stocks are sorted into portfolios, the long-short duration-matched fixed-income portfolio return depends on the relative duration of the long and short legs of the factor. If the duration is roughly the same across the long and short legs, then the fixed-income return

[4] 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.

spread is close to 0 and the correlation between the return series under the traditional and duration-adjusted excess return definitions is close to 1. Second, we find that the correlations among the factors in the Fama and French (2015) 5-factor model plus momentum change when we use our duration-adjusted definition of excess returns.

We further evaluate the 153 discovered anomalies over the sample periods used in the original papers that discovered them, with a focus on the effect of using our alternative excess return definition on factor discovery. We find that 66 of them are robust, with a t-statistic higher than 1.96 for both the traditional and duration-adjusted excess return definitions. In contrast, 20 of them can be classified as false positives (traditional t-statistic higher than 1.96 and duration-adjusted t-statistic lower than 1.96) or false negatives (traditional t-statistic lower than 1.96 and duration-adjusted t-statistic higher than 1.96).[5] 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 0.30.

To arrive at a plausible set of potential undiscovered anomalies, 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 of false discoveries to true discoveries is 1.03 for the full sample period from 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 explore the potential effect of low-frequency interest rate movements by relating the likelihood of false positive and false negative discoveries to the fixed-income return spread of each long-short portfolio in the cross-section of discovered and potential undiscovered anomalies. Not surprisingly, we find that false positive discoveries are more likely for long-short portfolios with a more negative dividend yield differential, which corresponds to a higher duration differential. Similarly, we find that false negatives, which may have been discovered if our novel excess return definition had been used, are more likely for portfolios with a more positive dividend yield differential, which reduces the long-short returns realized in sample given the observed path of interest rates.

[5] The rest (67) of the 153 anomalies are non-robust anomalies that register a t-statistic lower than 1.96 with both traditional and duration-adjusted excess return definitions. 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.

The analysis of the set of published anomalies focusing on factor discovery uses the sample periods from the original studies. Given the steady decline in interest rates up until last year, 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 the approach in McLean and Pontiff (2016) 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 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 shows that the excess return definition used, in combination with the observed path of interest rates, has had a significant impact on the discovery of asset pricing anomalies over time.

Our findings can thus be 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 decline in rates are unlikely to happen again. This suggests that those anomalies that are present regardless of the excess return definition used are arguably more robust.

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. Sections 4 and 5 report empirical results on factor return measurement and factor discovery, respectively. Section 6 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. For the analysis in Section 4, we use sample periods from the beginning of the original sample periods in the publications of these anomalies to December 2020. For the analysis in Section 5, due to our focus on the role of interest rates in factor discovery, we use the original sample periods in the publications of these anomalies whenever possible. For all analyses, if the original sample period starts before February 1962, we use the sample period from February 1962 to the original sample ending date.[6] 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.

[6] 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.

3 Method

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 $t+1$ under the traditional definition of excess returns by $r_{t+1}^{traditional}$. To the extent that stocks in the long and short legs have different durations, the observed path of interest rates will lead to a return spread between the two portfolios. 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 et al. (2023). 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_{t+1}^{fi}.

The strip-by-strip matching is based on 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_t^i. The Gordon growth equation expresses the value of portfolio i as follows:

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

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:

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

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

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

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

$$w^i_{t,m} = \frac{\mathcal{P}^i_{t,m}}{S^i_t} = (\mu^i - g^i)e^{(g^i-\mu^i)m}. \tag{4}$$

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

$$\begin{aligned} Dur^i_t &= \int_0^\infty w^i_{t,m} m \mathrm{d}m, \\ &= \int_0^\infty (\mu^i - g^i)e^{(g^i-\mu^i)m} m \mathrm{d}m \\ &= \frac{1}{\mu^i - g^i}, \end{aligned} \tag{5}$$

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:

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

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:

$$r^b_{t+1,n} = \frac{e^{-(n-1)y_{t+1,n-1}}}{e^{-n y_{t,n}}} - 1. \tag{7}$$

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. Based on equation (2), we use this current dividend yield as the input for $\mu^i - g^i$ in equation (6) to obtain the weights.[7] 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 a duration-matched fixed-income return spread, r_{t+1}^{fi}, from equation (8), we can calculate the counterfactual anomaly return using our duration-adjusted excess return definition:

$$r_{t+1}^{duradj} = r_{t+1}^{traditional} - r_{t+1}^{fi}. \tag{9}$$

4 Results on Factor Return Measurement

In this section we analyze factor returns using our duration-adjusted excess return definition. We start by focusing on the most commonly-used factors, such as the market factor and the other factors in the Fama and French (2015) 5-factor model and then study the larger set of 153 anomalies.

4.1 The Market Factor

Before studying equity factors in the cross-section of returns, we first analyze the market return factor. This market factor is most often used as the first explanatory factor in asset pricing studies (the CAPM). The most common way in which the market factor is constructed is to take the difference between the monthly return on the value-weighted portfolio of all

[7]In the Appendix, we show that our main results are robust to using the net payout yield, which takes into account stock repurchases and issues, as the input for $\mu^i - g^i$ in equation (6) to obtain the weights.

stocks traded on the NYSE, NASDAQ and Amex and the 1-month T-bill rate, where the latter is used as the proxy for the risk-free rate. The monthly average of this excess return over our sample period of February 1962 to December 2020 equals 0.53% (6.41% annualized) with a monthly standard deviation of 4.47% (15.50% annualized).

If instead of the 1-month risk-free rate, we use a duration-matched government bond portfolio in the excess return definition (r_{t+1}^{duradj}), a very different picture emerges (Binsbergen (2021)). The monthly average excess return now equals −0.20% (−2.42% annualized) with a monthly standard deviation that is double that of the usual market factor: 9.60% at a monthly level (33.25% annualized). Furthermore, the correlation between the traditional market factor and this duration-adjusted market factor is below 0.5. We can conclude that the basic properties of the most commonly-used factor (the market) change materially from considering a different excess return definition.

4.2 Cross-Sectional Factors

We now turn our attention to a large set of cross-sectional factors represented by the 153 anomaly variables contained in the data set of Jensen et al. (2022). The sample periods for this analysis are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020.

We begin our analysis with several prominent anomalies that are associated with the remaining factors of the widely-used Fama and French (2015) 5-factor model plus momentum. These include *market_equity*, *be_me*, *ope_be*, *at_gr*1, and *ret*_12_1, which correspond to the size, value, profitability, investment, and momentum factors, respectively.[8] The results are summarized in Table 3. The table shows that for several of these prominent anomalies, the return spread materially changes. For example, the investment and value anomalies both are substantially larger under the duration-adjusted excess return definition compared to the traditional one, whereas the size anomaly becomes substantially smaller. Not surprisingly, there are no large duration differences between loser and winner stocks over the past year (Momentum), leading to very small return differences. The profitability factor also does not seem to be much affected by adjusting for duration differences.

Next, we analyze the correlation structure among these commonly-used factors under both excess return definitions. The results are summarized in Table 4, which shows important changes in this correlation structure. For example, whereas under the traditional

[8]Fama and French (2015) measure investment using growth in total assets.

excess return definition the market factor and the investment factor have a small negative correlation of -0.25, under the duration-adjusted excess return definition, this correlation becomes much more negative at -0.69. The value factor was somewhat positively correlated with the market portfolio under the traditional definition, but under the duration-adjusted definition this correlation switches signs.

After studying these commonly-used factors, we next extend our analysis to the broad set of 153 anomalies. To structure the analysis, we use the dividend yield spread as the guiding variable. 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 difference in anomaly returns under the traditional and duration-adjusted definitions of excess 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 positive the mean of $r_{t+1}^{duradj} - r_{t+1}^{traditional}$, and vice versa.

Table 5 reports the value-weighted average annual dividend yields for the long and short portfolios and the average dividend yield spread for the 153 anomalies. For each stock in a given month, the annual dividend yield is calculated as its total dividends paid over the past 12 months divided by its stock price at the end of the prior month. As in Boudoukh et al. (2007) and Jensen et al. (2022), we calculate monthly dividends by taking the difference in cum- and ex-dividend returns using CRSP data. The average dividend yield spread shows large variation across anomalies, ranging from -2.27% to 7.35%. This suggests that using our novel excess return definition affects the return spread for a large number of anomalies. Furthermore, the effect can be positive for some anomalies and negative for others, which implies that after adjusting for duration some anomalies will become stronger while others will become weaker.

The results are presented in Figure 2, which shows the scatter plot of the difference in mean return spreads under the traditional and duration-adjusted definitions of excess returns, as a function of the mean dividend yield spread for the 153 anomalies. It is evident that using the duration-adjusted definition of excess returns has a significant effect on long-short return measurement for a large number of anomalies. As predicted, the effect increases with the dividend yield spread, or equivalently decreases with the duration spread between long and short portfolios. This is consistent with the results in Table 2 showing that long-maturity bonds have strongly outperformed short-maturity bonds in our sample period.

Figure 3 reports the correlations between anomaly returns under traditional and duration-adjusted definitions of excess returns as a function of the average dividend yield spread. The figure shows that for anomalies where the dividend yield spread on average is close to 0, the factor returns under both definitions are highly correlated. After all, the durations of the long and the short portfolios are so similar that the duration-matched fixed-income adjustment does not have much of an effect. However, as the yield spread deviates from zero (in either direction) the duration-adjusted excess return definition produces meaningfully different factor returns that have correlations that can be substantially below 1. Not surprisingly, the correlation is the lowest for the anomaly portfolio that sorts on dividend yields directly.

Table 6 reports the average monthly long-short returns under the traditional versus duration-adjusted excess return definitions, and their difference and time-series correlation, for the 153 anomalies individually, complementing the results presented in Figures 2 and 3.

5 Results on Factor Discovery

In this section we explore how a different excess return definition would have affected the anomaly discovery process in the literature. While the analysis in the previous sections used the full sample period of anomaly returns, we now focus our attention on the sample periods presented in the original papers that discovered each anomaly.

5.1 Results from Discovered Anomalies

For each of the 153 anomalies, we calculate the t-statistic for the long-short return spread under the traditional definition of excess returns, $r_{t+1}^{traditional}$, referred to as the traditional t-statistic, and that for the return spread under the duration-adjusted definition of excess returns, r_{t+1}^{duradj}, referred to as the duration-adjusted t-statistic. We then classify the 153 anomalies into four groups. The first group contains "robust" anomalies, for which both the traditional and the duration-adjusted t-statistics are greater than 1.96. The second group contains false positives, for which the traditional t-statistic is greater than 1.96 and the duration-adjusted t-statistic is less than 1.96. The third group contains false negatives, for which the traditional t-statistic is less than 1.96 and the duration-adjusted t-statistic is greater than 1.96. The fourth group contains non-robust anomalies, for which both traditional and duration-adjusted t-statistics are less than 1.96.

Out of the 153 anomalies, 66 are robust anomalies, 11 are false positives, 9 are false negatives, and 67 are non-robust anomalies. The rate of non-significant 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 observed path of interest rates (i.e., the 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 $\frac{20}{66} = 0.30$. 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 discovery was based on our alternative excess return definition and/or a universe where interest rates had not declined, while keeping all other variables unaffected (c.p.). These three groups of anomalies (86 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 0.13, 0.08, and 0.77, respectively.

The top panel of Figure 4 shows the scatter plot of the traditional and duration-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 4 shows the same scatter plot but only for these two groups of anomalies.

Table A3 lists the individual members of the four groups of anomalies. From Panel A of Table A3 and the bottom panel of Figure 4, 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)), quality-minus-junk *qmj* (Asness et al. (2019)), short-term reversal *ret*_1_0 (Jegadeesh (1990)), max daily return *rmax*1_21*d* (Bali et al. (2011)), and return volatility *rvol*_21*d* (Ang et al. (2006)).

5.2 Results from Potential Undiscovered Anomalies

Given that the use of our novel excess return definition 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, as of or after 1962. 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 the vairable 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.[9] 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 anomaly returns under traditional and duration-adjusted excess return definitions and their t-statistics over the full sample period of July 1963 to December 2020. Similar to Section 5.1, we classify the 1,395 potential anomalies into four groups. The first group contains robust anomalies, for which the absolute values of both traditional and duration-adjusted t-statistics

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

are greater than 1.96. The second group contains false positives, for which the traditional $|t\text{-statistic}|$ is greater than 1.96 and the duration-adjusted $|t\text{-statistic}|$ is less than 1.96. The third group contains false negatives, for which the traditional $|t\text{-statistic}|$ is less than 1.96 and the duration-adjusted $|t\text{-statistic}|$ is greater than 1.96. The fourth group contains non-robust anomalies, for which the absolute values of both traditional and duration-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 125 robust anomalies, 81 false positives, and 48 false negatives. Table A4 lists the 129 false positives and false negatives. The $\frac{False}{True}$ ratio that represents the ratio of false positives and negatives to robust anomalies is 1.03. In other words, the rate of false positives and false negatives induced by the secular interest rate decline is 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 5 plots the time-series of the $\frac{False}{True}$ ratio, which has been stable over time with an average of 0.94. 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 low-frequency interest rate movements is similar to the rate of true discovery.

Overall, the results here support the notion that low-frequency interest rate movements have 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 and the counterfactual "universe" without low-frequency interest rate movements, the common set of anomalies discovered in both "universes" is only half of the union set.

5.3 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 anomaly return under the duration-adjusted excess return definition should tend to be higher (lower) than the average anomaly return under the traditional excess return definition 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 7 reports the regression estimates. For the sample of discovered anomalies, the estimated β_1^+ and β_1^- are

-0.04 ($t = -2.99$) and 0.04 ($t = 2.67$), respectively. For the sample of potential undiscovered anomalies, the estimated β_1^+ and β_1^- are -0.06 ($t = -7.64$) and 0.03 ($t = 4.25$), respectively.

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

5.4 Pre- versus Post-Publication Periods

For the set of discovered (published) anomalies, our analysis in this section 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 persist 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.[10] 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 $r_{t+1}^{traditional}$, r_{t+1}^{fi}, and r_{t+1}^{duradj}, 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

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

of monthly returns for the 153 anomalies. For $r_{t+1}^{traditional}$, we run the following regression (equation (1) of McLean and Pontiff (2016)):

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

where the post-sample dummy equals one if month $t+1$ is after the end of the original 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_{t+1}^{fi} and r_{t+1}^{duradj}:

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

and

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

The coefficient of interest in these regressions is the post-publication coefficients β_2. Table 8 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 0.09% ($t = 1.08$) for the duration-matched fixed-income return spread and -0.41% ($t = -3.45$) 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).

6 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 have also been pronounced low-frequency movements in long-term interest rates. In this paper, we study the so-called equity factor zoo using an alternative excess return definition that measures factor performance in excess of a duration-matched government bond strategy. Our approach quantifies the realized return premium that investors have received for investing in a stream of risky cash flows relative to a fixed cash flow counterfactual.

Our paper shows that this different excess return definition results in substantially different average excess returns than the ones previously reported in the literature even for the most commonly-used factors. For example, while the realized equity premium is much smaller under the duration-adjusted definition, the value and investment factors have much higher average returns. In addition, our approach results in a materially different correlation structure among asset pricing factors.

We investigate 153 discovered anomalies as well as 1,395 potential undiscovered anomalies and find that the asset pricing literature would likely entertain a different set of anomalies today if it had used our novel excess return definition. As such, our analysis highlights the sensitivity of the factor discovery process to this specific definition in combination with the observed low-frequency movements in interest rates.

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. We consider this an important area for future research.

References

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Asness, Clifford S, Andrea Frazzini, and Lasse Heje Pedersen, 2019, Quality minus junk, *Review of Accounting Studies* 24, 34–112.

Balakrishnan, Karthik, Eli Bartov, and Lucile Faurel, 2010, Post loss/profit announcement drift, *Journal of Accounting and Economics* 50, 20–41.

Bali, Turan G, Nusret Cakici, and Robert F Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Barro, Robert J, 2006, Rare disasters and asset markets in the twentieth century, *The Quarterly Journal of Economics* 121, 823–866.

Binsbergen, Jules H. van, 2021, Duration-based stock valuation: Reassessing stock market performance and volatility, *Working Paper, University of Pennsylvania* .

Binsbergen, Jules H. van, Yoshio Nozawa, and Michael Schwert, 2023, Duration-based valuation of corporate bonds, *Working Paper, University of Pennsylvania* .

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael R Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *Journal of Finance* 62, 877–915.

Campbell, John Y, and John H Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

Chen, Andrew Y, 2021, The limits of p-hacking: Some thought experiments, *Journal of Finance* 76, 2447–2480.

Chen, Andrew Y, and Tom Zimmermann, 2020, Publication bias and the cross-section of stock returns, *Review of Asset Pricing Studies* 10, 249–289.

Chordia, Tarun, Amit Goyal, and Alessio Saretto, 2020, Anomalies and false rejections, *Review of Financial Studies* 33, 2134–2179.

Fama, Eugene F, and Kenneth R French, 1992, The cross-section of expected stock returns, *Journal of Finance* 427–465.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of financial economics* 116, 1–22.

Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright, 2007, The U.S. Treasury yield curve: 1961 to the present, *Journal of Monetary Economics* 54, 2291–2304.

Harvey, Campbell R, Yan Liu, and Heqing Zhu, 2016, … and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

Hou, Kewei, Chen Xue, and Lu Zhang, 2020, Replicating anomalies, *Review of Financial Studies* 33, 2019–2133.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

Jensen, Theis Ingerslev, Bryan T Kelly, and Lasse Heje Pedersen, 2022, Is there a replication crisis in finance?, *Journal of Finance, Forthcoming* .

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

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

Rietz, Thomas A, 1988, The equity risk premium a solution, *Journal of Monetary Economics* 22, 117–131.

Shumway, Tyler, and Vincent A Warther, 1999, The delisting bias in crsp's nasdaq data and its implications for the size effect, *Journal of Finance* 54, 2361–2379.

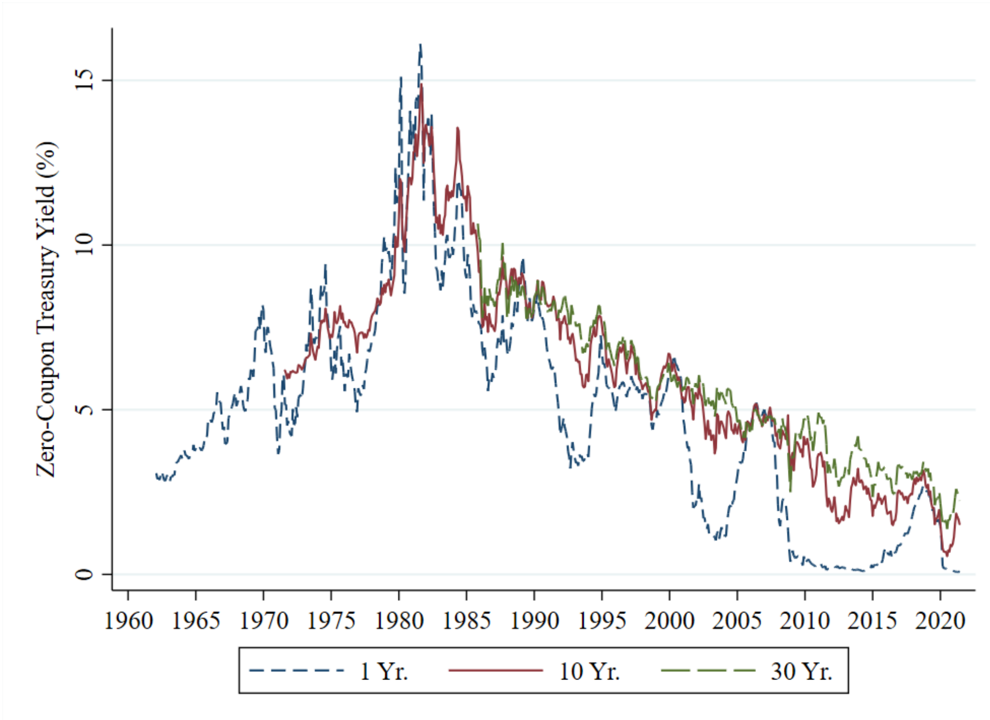

Figure 1. Time-Series of Zero-Coupon Treasury Yields. This figure illustrates the decline in long-term risk-free interest rates over the sample period of February 1962 to December 2020. The plot contains the time series of zero-coupon Treasury yields at maturities of one year, ten years, and 30 years.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

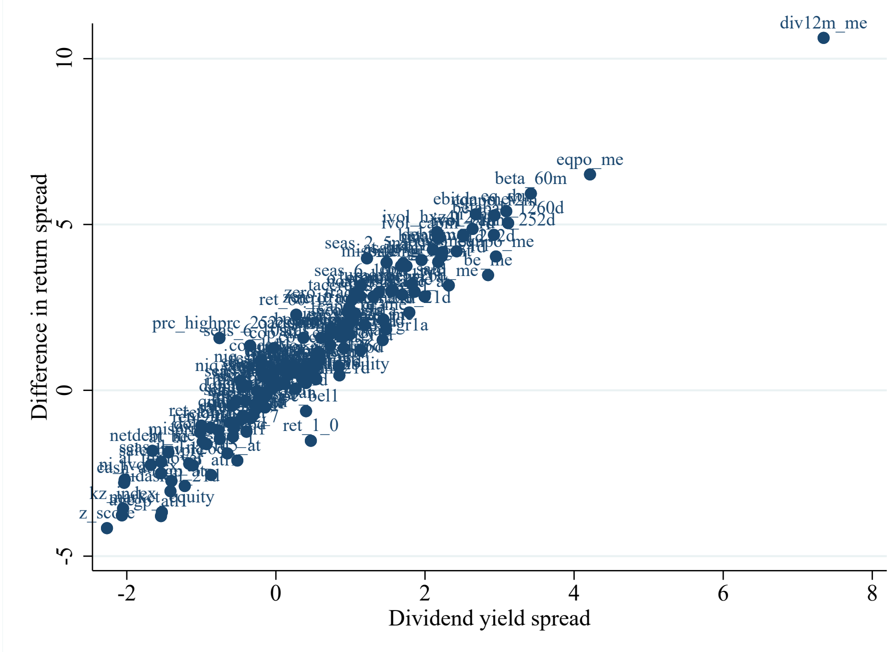

Figure 2. Difference in mean return spread as a function of the mean dividend yield spread. For each of the 153 anomalies, we calculate its mean long-short return spread under the traditional and duration-adjusted definitions of excess returns and take the corresponding difference. This figure plots the difference in mean return spread as a function of the mean annual dividend yield. The sample periods are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020. 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. Return spreads are annualized by multiplying monthly return spreads by 12. Both return spreads and dividend yields are in percentage terms.

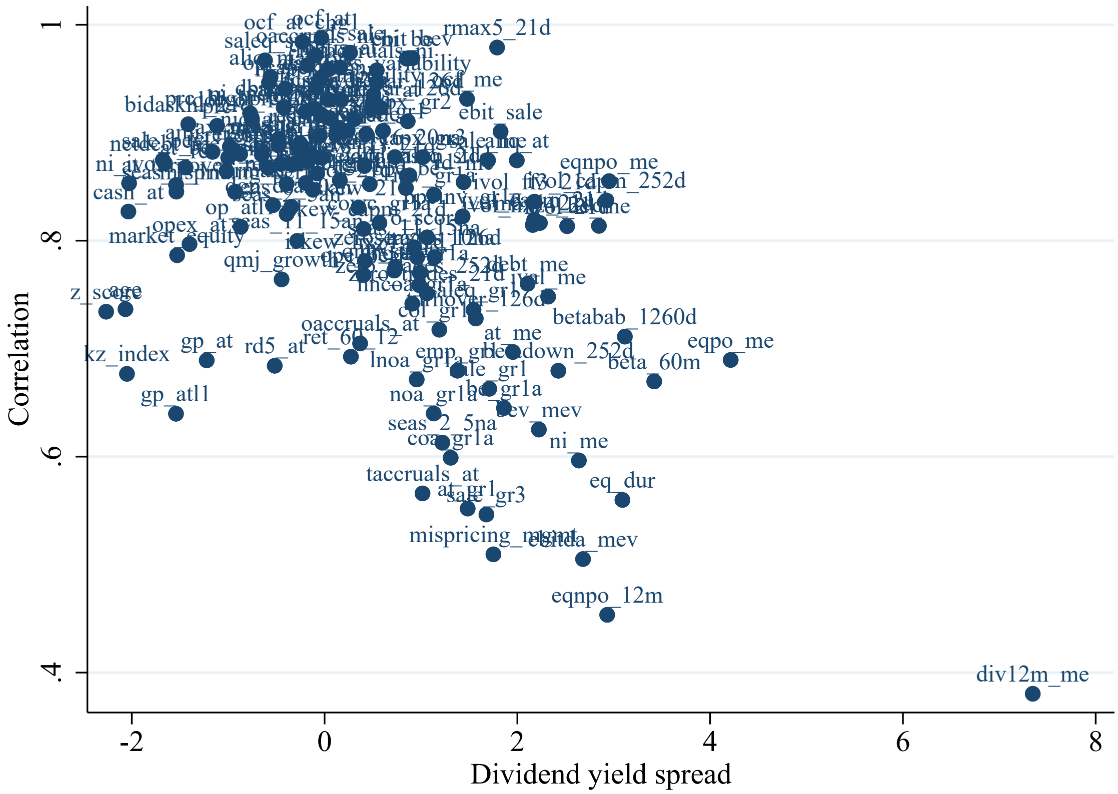

Figure 3. Correlation between anomaly returns under traditional and duration-adjusted definitions of excess Returns as a function of the mean dividend yield spread. For each of the 153 anomalies, we calculate the time-series correlation between long-short return spreads under the traditional and duration-adjusted definitions of excess returns. This figure plots the resulting correlation as a function of the mean annual dividend yield. The sample periods are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020. Dividend yields are in percentage terms.

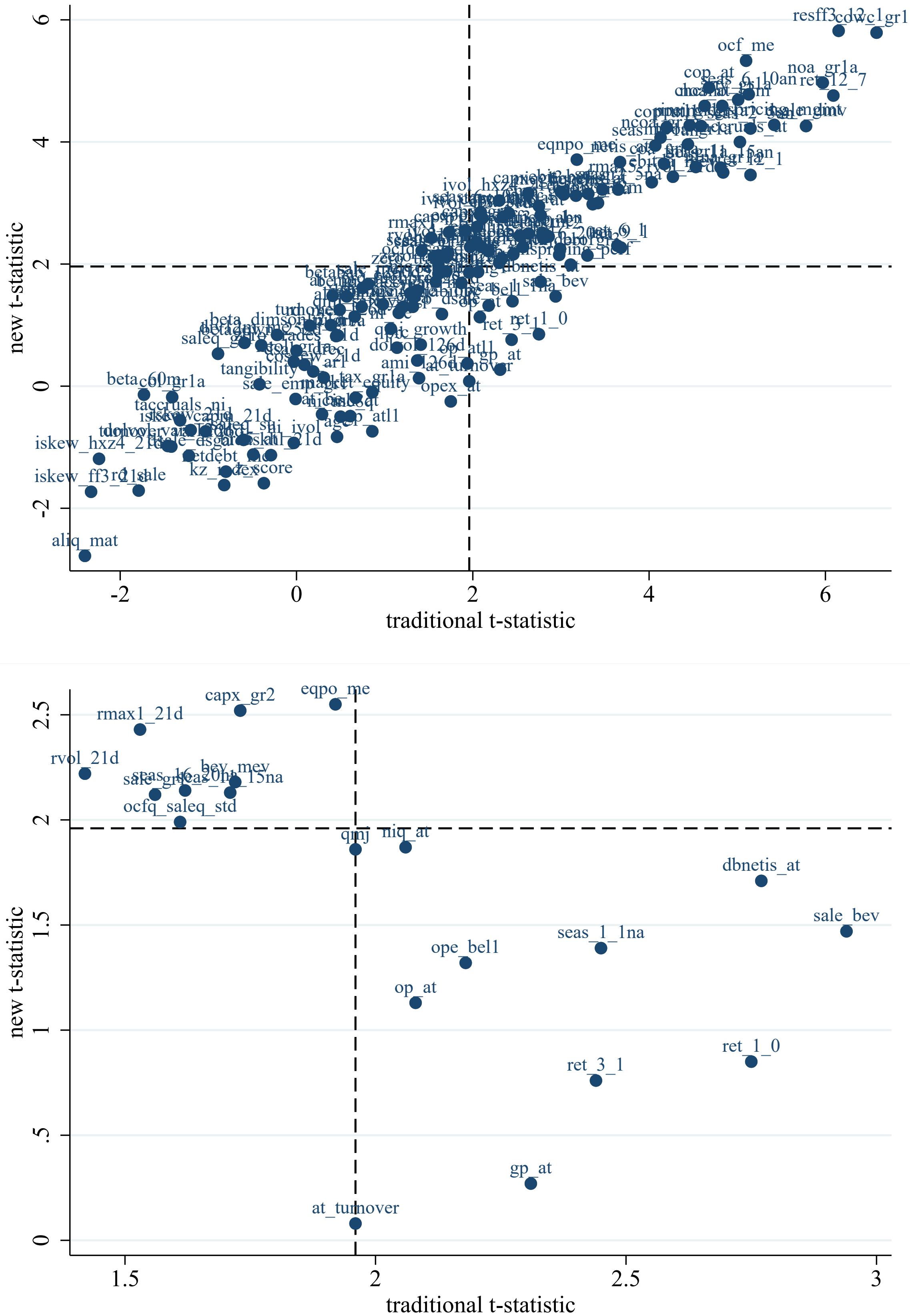

Figure 4. (Caption next page.)

Figure 4. 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 traditional and duration-adjusted t-statistics for these four groups. The bottom panel shows the scatter plot of the traditional and duration-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.

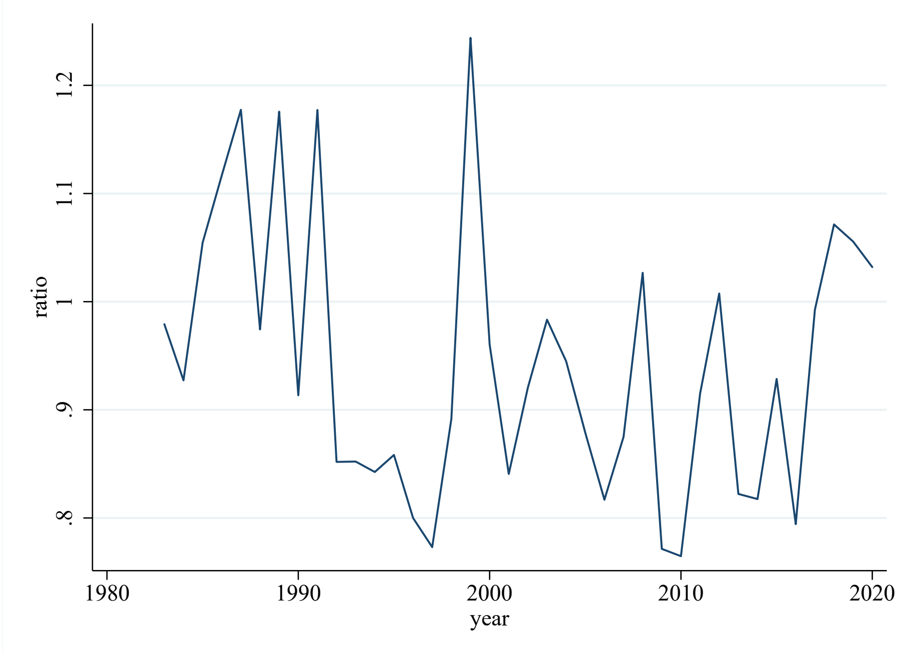

Figure 5. The ratio of $\frac{False}{True}$ over time for a large set of Compustat ratios. For each year from 1983 to 2020, we calculate the $\frac{False}{True}$ ratio using all data available for the Compustat ratios from July 1963 to the end of that year.

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. Results for Prominent Cross-Sectional Factors: Mean Returns

This table reports the average monthly raw long-short returns under the traditional versus duration-adjusted definitions of excess returns, and their difference, for the market factor and five anomalies associated with the Fama and French (2015) 5-factor plus momentum factor model. The t-statistics are reported in parentheses. The sample periods are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020. All returns are in percentage terms.

Anomaly	Traditional		Duration-Adjusted		Difference	
Investment (at_gr1)	0.41	(2.84)	0.73	(3.12)	0.32	(1.65)
Value (be_me)	0.42	(1.57)	0.71	(2.26)	0.29	(1.59)
Size (market_equity)	0.19	(1.04)	-0.12	(-0.52)	-0.31	(-2.12)
Profitability (ope_be)	0.39	(2.29)	0.45	(2.22)	0.06	(0.55)
Momentum (ret_12_1)	1.23	(4.45)	1.14	(3.74)	-0.09	(-0.60)

Table 4. Results for Prominent Cross-Sectional Factors: Return Correlations

This table reports the pairwise correlation between monthly factor returns under the traditional and duration-adjusted definitions of excess returns, for the market factor and five anomalies associated with the Fama and French (2015) 5-factor plus momentum factor model. For each anomaly factor, the sample period is from the beginning date of the original sample periods used in its original publication to December 2020. For the market factor, the sample period is February 1962 to December 2020.

	Market	Inv.	Value	Profit.	Size	Mom.	Market*	Inv.*	Value*	Profit.*	Size*	Mom.*
Market	1.00											
Inv.	-0.25	1.00										
Value	0.17	0.43	1.00									
Profit.	-0.38	-0.01	-0.33	1.00								
Size	0.23	0.15	0.52	-0.54	1.00							
Mom.	-0.22	-0.19	-0.68	0.25	-0.32	1.00						
Market*	0.40	-0.04	0.20	-0.23	0.18	-0.18	1.00					
Inv.*	-0.09	0.55	0.31	0.03	0.06	-0.06	-0.69	1.00				
Value*	0.21	0.31	0.81	-0.23	0.38	-0.52	-0.16	0.51	1.00			
Prof.*	-0.33	0.00	-0.32	0.85	-0.49	0.21	-0.02	-0.25	-0.16	1.00		
Size*	0.11	0.15	0.44	-0.44	0.79	-0.27	0.61	-0.38	0.04	-0.31	1.00	
Mom.*	-0.20	-0.15	-0.65	0.22	-0.30	0.88	0.16	-0.36	-0.59	0.35	-0.05	1.00

Table 5. 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	3.40	1.14	-2.27	oaccruals_at	1.90	2.26	0.37
age	3.57	1.50	-2.07	ope_bel1	1.72	2.13	0.40
kz_index	2.83	0.78	-2.05	iskew_capm_21d	2.43	2.83	0.40
cash_at	3.67	1.64	-2.04	iskew_ff3_21d	2.47	2.89	0.41
ni_ivol	3.55	1.52	-2.03	iskew_hxz4_21d	2.42	2.84	0.42
sale_bev	3.05	1.38	-1.68	fcf_me	2.98	3.41	0.43
netdebt_me	4.03	2.37	-1.66	ret_1_0	1.92	2.39	0.47
gp_atl1	3.20	1.66	-1.54	eqnetis_at	2.05	2.54	0.49
at_turnover	3.12	1.58	-1.54	tangibility	2.16	2.67	0.51
seas_1_1na	2.92	1.38	-1.54	turnover_var_126d	2.55	3.06	0.51
market_equity	3.01	1.48	-1.53	taccruals_ni	1.56	2.10	0.54
at_be	3.09	1.64	-1.44	earnings_variability	2.58	3.13	0.54
bidaskhl_21d	2.88	1.47	-1.41	cowc_gr1a	1.76	2.33	0.57
opex_at	3.47	2.07	-1.40	dolvol_var_126d	2.49	3.07	0.58
gp_at	3.17	1.95	-1.22	capx_gr1	1.48	2.09	0.61
ami_126d	3.00	1.83	-1.16	qmj_safety	1.63	2.35	0.72
prc	2.41	1.30	-1.12	seas_16_20na	2.17	2.90	0.73
ret_9_1	2.60	1.58	-1.02	inv_gr1	2.21	2.95	0.73
ret_12_1	2.55	1.55	-1.00	ope_be	1.74	2.58	0.84
tax_gr1a	2.81	1.83	-0.98	beta_dimson_21d	1.86	2.71	0.85
mispricing_perf	2.85	1.92	-0.93	ni_be	1.38	2.23	0.85
ret_6_1	2.55	1.67	-0.88	capx_gr2	1.33	2.19	0.86
op_atl1	2.82	1.95	-0.87	ocfq_saleq_std	1.92	2.80	0.88
ni_inc8q	2.77	1.99	-0.77	nncoa_gr1a	1.90	2.81	0.91
prc_highprc_252d	3.30	2.54	-0.76	ebit_bev	0.88	1.79	0.91
dolvol_126d	2.91	2.15	-0.75	seas_11_15na	1.88	2.81	0.93
ret_3_1	2.42	1.77	-0.65	lnoa_gr1a	1.80	2.75	0.96
saleq_su	2.34	1.72	-0.62	zero_trades_126d	1.36	2.32	0.96
niq_su	2.97	2.38	-0.59	zero_trades_252d	1.35	2.33	0.98
op_at	2.76	2.18	-0.58	ncoa_gr1a	1.94	2.92	0.99
aliq_mat	2.05	1.48	-0.56	taccruals_at	1.53	2.54	1.02
dgp_dsale	2.84	2.31	-0.54	capx_gr3	1.26	2.28	1.02
rd5_at	2.26	1.75	-0.52	zero_trades_21d	1.43	2.49	1.06
nfna_gr1a	2.36	1.88	-0.48	o_score	1.22	2.28	1.06
niq_at_chg1	2.46	1.98	-0.48	noa_gr1a	1.48	2.61	1.13
sti_gr1a	2.41	1.96	-0.45	inv_gr1a	1.50	2.63	1.14
qmj_growth	2.57	2.13	-0.45	seas_6_10na	1.54	2.68	1.14
dbnetis_at	2.29	1.87	-0.42	col_gr1a	1.74	2.93	1.19

Table 5—*Continued*

ni_ar1	3.09	2.68	-0.41	seas_2_5na	1.26	2.49	1.22
ret_12_7	2.19	1.79	-0.39	coa_gr1a	1.55	2.86	1.31
seas_2_5an	2.20	1.81	-0.39	emp_gr1	1.44	2.82	1.38
seas_6_10an	2.37	2.02	-0.35	ppeinv_gr1a	1.43	2.87	1.43
qmj_prof	2.58	2.24	-0.33	rd_me	1.37	2.81	1.44
debt_gr3	2.00	1.70	-0.30	ocf_me	2.51	3.99	1.48
seas_11_15an	2.57	2.29	-0.28	at_gr1	1.45	2.94	1.48
dsale_dsga	2.34	2.08	-0.27	saleq_gr1	1.63	3.18	1.55
dsale_dinv	2.71	2.46	-0.25	turnover_126d	1.35	2.92	1.57
ocf_at_chg1	1.45	1.22	-0.23	sale_gr3	1.36	3.04	1.68
cop_atl1	2.30	2.10	-0.20	sale_me	1.41	3.11	1.70
fnl_gr1a	2.33	2.13	-0.20	sale_gr1	1.45	3.16	1.71
niq_be_chg1	2.50	2.31	-0.20	mispricing_mgmt	1.87	3.62	1.75
qmj	2.46	2.28	-0.18	rmax5_21d	0.83	2.62	1.79
seas_1_1an	2.04	1.87	-0.17	ebit_sale	0.81	2.64	1.83
seas_16_20an	2.72	2.57	-0.15	be_gr1a	1.19	3.05	1.86
rmax5_rvol_21d	2.82	2.70	-0.12	at_me	1.54	3.49	1.95
sale_emp_gr1	2.35	2.25	-0.10	aliq_at	0.89	2.89	1.99
oaccruals_ni	1.99	1.89	-0.09	debt_me	1.67	3.78	2.11
capex_abn	2.10	2.01	-0.09	ivol_hxz4_21d	1.33	3.49	2.16
coskew_21d	2.84	2.77	-0.08	ivol_capm_21d	1.35	3.52	2.18
resff3_6_1	2.81	2.76	-0.05	ivol_ff3_21d	1.33	3.51	2.18
f_score	2.66	2.62	-0.04	bev_mev	1.62	3.85	2.22
ocf_at	1.50	1.47	-0.03	rmax1_21d	1.51	3.75	2.23
cop_at	2.29	2.26	-0.03	ival_me	1.41	3.73	2.32
resff3_12_1	2.76	2.73	-0.03	betadown_252d	1.36	3.79	2.43
niq_at	1.92	1.96	0.04	rvol_21d	1.32	3.84	2.52
chcsho_12m	2.81	2.85	0.04	ni_me	1.55	4.19	2.64
pi_nix	2.97	3.02	0.06	ebitda_mev	1.15	3.83	2.68
dsale_drec	2.12	2.24	0.12	be_me	1.58	4.43	2.85
corr_1260d	2.78	2.93	0.15	ivol_capm_252d	0.86	3.79	2.92
ncol_gr1a	2.68	2.84	0.16	eqnpo_12m	1.97	4.90	2.93
netis_at	1.82	1.98	0.16	eqnpo_me	1.10	4.05	2.95
niq_be	2.05	2.22	0.17	eq_dur	1.22	4.31	3.09
noa_at	2.07	2.31	0.24	betabab_1260d	1.51	4.62	3.12
rd_sale	1.38	1.65	0.26	beta_60m	1.07	4.49	3.42
ret_60_12	1.52	1.79	0.27	eqpo_me	0.06	4.28	4.21
lti_gr1a	2.49	2.79	0.31	div12m_me	0.00	7.35	7.35
rskew_21d	2.55	2.90	0.35				

Table 6. Anomaly Returns Under Traditional versus Duration-Adjusted Definitions of Excess Returns

This table reports the average monthly raw long-short returns under the traditional versus duration-adjusted definitions of excess returns, and their difference and time-series correlation, for the 153 anomalies. The t-statistics are reported in parentheses. The sample periods are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020. Anomalies are ranked from low to high by their mean dividend yield spread DYS (obtained from Table 5) presented in the second column. All returns are in percentage terms.

Anomaly	DYS	Traditional		Duration-Adjusted		Difference		Corr.
z_score	-2.27	0.08	(0.42)	-0.26	(-1.02)	-0.35	(-1.97)	0.73
age	-2.07	0.25	(1.37)	-0.07	(-0.27)	-0.31	(-1.92)	0.74
kz_index	-2.05	0.01	(0.06)	-0.29	(-1.26)	-0.30	(-1.76)	0.68
cash_at	-2.04	0.27	(1.61)	0.04	(0.19)	-0.23	(-1.99)	0.83
ni_ivol	-2.03	0.04	(0.18)	-0.19	(-0.75)	-0.22	(-1.72)	0.85
sale_bev	-1.68	0.79	(4.48)	0.60	(2.96)	-0.19	(-1.91)	0.87
netdebt_me	-1.66	0.12	(0.70)	-0.04	(-0.19)	-0.15	(-1.65)	0.87
gp_atl1	-1.54	0.23	(1.44)	-0.09	(-0.37)	-0.32	(-1.70)	0.64
at_turnover	-1.54	0.39	(2.20)	0.18	(0.85)	-0.21	(-1.89)	0.85
seas_1_1na	-1.54	0.70	(2.41)	0.52	(1.57)	-0.18	(-1.02)	0.85
market_equity	-1.53	0.19	(1.04)	-0.12	(-0.52)	-0.31	(-2.12)	0.79
at_be	-1.44	0.03	(0.15)	-0.13	(-0.63)	-0.16	(-1.52)	0.87
bidaskhl_21d	-1.41	-0.13	(-0.53)	-0.38	(-1.37)	-0.25	(-2.14)	0.91
opex_at	-1.40	0.28	(1.99)	0.05	(0.29)	-0.23	(-2.08)	0.80
gp_at	-1.22	0.37	(2.62)	0.13	(0.64)	-0.24	(-1.60)	0.69
ami_126d	-1.16	0.23	(1.43)	0.04	(0.22)	-0.18	(-2.11)	0.88
prc	-1.12	-0.04	(-0.16)	-0.23	(-0.81)	-0.19	(-1.57)	0.91
ret_9_1	-1.02	0.88	(3.35)	0.78	(2.64)	-0.11	(-0.71)	0.86
ret_12_1	-1.00	1.23	(4.45)	1.14	(3.74)	-0.09	(-0.60)	0.88
tax_gr1a	-0.98	0.06	(0.40)	-0.07	(-0.41)	-0.13	(-1.69)	0.89
mispricing_perf	-0.93	0.68	(3.29)	0.54	(2.24)	-0.14	(-1.05)	0.85
ret_6_1	-0.88	0.74	(3.01)	0.65	(2.38)	-0.09	(-0.73)	0.88
op_atl1	-0.87	0.32	(2.09)	0.11	(0.57)	-0.21	(-1.91)	0.81
ni_inc8q	-0.77	0.08	(0.89)	-0.02	(-0.19)	-0.10	(-2.59)	0.92
prc_highprc_252d	-0.76	0.21	(0.66)	0.35	(0.98)	0.13	(0.92)	0.91
dolvol_126d	-0.75	0.22	(1.51)	0.10	(0.58)	-0.12	(-1.81)	0.91
ret_3_1	-0.65	0.61	(2.81)	0.45	(1.87)	-0.16	(-1.38)	0.88
saleq_su	-0.62	0.18	(1.12)	0.10	(0.59)	-0.08	(-1.94)	0.97
niq_su	-0.59	0.22	(1.84)	0.19	(1.42)	-0.04	(-0.58)	0.87
op_at	-0.58	0.34	(2.24)	0.22	(1.38)	-0.12	(-2.23)	0.95
aliq_mat	-0.56	-0.02	(-0.09)	-0.11	(-0.56)	-0.09	(-1.51)	0.95
dgp_dsale	-0.54	0.22	(1.80)	0.19	(1.36)	-0.03	(-0.34)	0.83
rd5_at	-0.52	0.00	(0.02)	-0.17	(-0.74)	-0.18	(-1.03)	0.68
nfna_gr1a	-0.48	0.44	(4.74)	0.37	(3.40)	-0.07	(-1.50)	0.89
niq_at_chg1	-0.48	0.24	(1.69)	0.26	(1.76)	0.02	(0.36)	0.89
sti_gr1a	-0.45	0.08	(0.87)	0.09	(0.85)	0.01	(0.16)	0.87

Table 6—*Continued*

qmj_growth	-0.45	0.17	(1.44)	0.11	(0.68)	-0.07	(-0.65)	0.76
dbnetis_at	-0.42	0.23	(2.25)	0.16	(1.40)	-0.07	(-1.52)	0.92
ni_ar1	-0.41	0.10	(0.93)	0.07	(0.64)	-0.03	(-0.68)	0.94
ret_12_7	-0.39	1.05	(5.29)	0.95	(4.08)	-0.10	(-0.86)	0.85
seas_2_5an	-0.39	0.64	(4.51)	0.65	(3.70)	0.01	(0.11)	0.82
seas_6_10an	-0.35	0.77	(5.54)	0.88	(5.23)	0.11	(1.20)	0.83
qmj_prof	-0.33	0.49	(3.31)	0.42	(2.48)	-0.07	(-0.84)	0.87
debt_gr3	-0.30	0.19	(1.89)	0.13	(1.10)	-0.06	(-1.07)	0.87
seas_11_15an	-0.28	0.56	(4.37)	0.53	(3.42)	-0.04	(-0.39)	0.80
dsale_dsga	-0.27	-0.16	(-1.21)	-0.21	(-1.33)	-0.05	(-0.63)	0.89
dsale_dinv	-0.25	0.44	(3.82)	0.44	(3.44)	-0.00	(-0.03)	0.89
ocf_at_chg1	-0.23	0.22	(1.58)	0.20	(1.42)	-0.02	(-0.83)	0.98
cop_atl1	-0.20	0.61	(4.50)	0.68	(4.51)	0.07	(1.05)	0.88
fnl_gr1a	-0.20	0.31	(3.62)	0.28	(2.91)	-0.03	(-0.81)	0.92
niq_be_chg1	-0.20	0.43	(3.26)	0.48	(3.30)	0.05	(0.61)	0.85
qmj	-0.18	0.43	(2.24)	0.42	(2.13)	-0.01	(-0.13)	0.96
seas_1_1an	-0.17	0.52	(3.04)	0.56	(2.84)	0.03	(0.36)	0.87
seas_16_20an	-0.15	0.44	(3.07)	0.40	(2.45)	-0.04	(-0.56)	0.88
rmax5_rvol_21d	-0.12	0.57	(4.46)	0.56	(3.72)	-0.01	(-0.15)	0.85
sale_emp_gr1	-0.10	0.01	(0.12)	0.01	(0.10)	-0.00	(-0.02)	0.92
oaccruals_ni	-0.09	0.40	(2.52)	0.44	(2.59)	0.03	(0.77)	0.97
capex_abn	-0.09	0.32	(2.53)	0.34	(2.55)	0.03	(0.58)	0.94
coskew_21d	-0.08	0.09	(0.79)	0.12	(0.85)	0.02	(0.35)	0.86
resff3_6_1	-0.05	0.30	(2.31)	0.32	(2.20)	0.02	(0.27)	0.90
f_score	-0.04	0.19	(2.15)	0.19	(2.12)	0.01	(0.21)	0.95
ocf_at	-0.03	0.69	(2.88)	0.72	(2.94)	0.03	(0.76)	0.99
cop_at	-0.03	0.73	(5.10)	0.84	(5.24)	0.11	(1.37)	0.88
resff3_12_1	-0.03	0.77	(5.33)	0.81	(5.16)	0.04	(0.69)	0.92
niq_at	0.04	0.44	(2.28)	0.45	(2.22)	0.01	(0.23)	0.96
chcsho_12m	0.04	0.52	(3.93)	0.54	(3.88)	0.02	(0.35)	0.93
pi_nix	0.06	0.16	(1.36)	0.22	(1.74)	0.05	(1.06)	0.91
dsale_drec	0.12	-0.02	(-0.18)	-0.00	(-0.02)	0.02	(0.31)	0.90
corr_1260d	0.15	0.20	(1.31)	0.26	(1.55)	0.06	(0.86)	0.90
ncol_gr1a	0.16	-0.01	(-0.05)	0.05	(0.41)	0.05	(0.88)	0.86
netis_at	0.16	0.48	(3.48)	0.52	(3.60)	0.04	(0.96)	0.96
niq_be	0.17	0.44	(2.19)	0.49	(2.32)	0.05	(0.64)	0.93
noa_at	0.24	0.62	(5.72)	0.66	(5.54)	0.04	(0.87)	0.90
rd_sale	0.26	-0.16	(-0.83)	-0.16	(-0.79)	0.00	(0.10)	0.97
ret_60_12	0.27	0.30	(1.57)	0.49	(1.79)	0.19	(0.96)	0.69
lti_gr1a	0.31	0.08	(0.84)	0.13	(1.32)	0.05	(1.31)	0.91
rskew_21d	0.35	-0.10	(-1.08)	-0.07	(-0.64)	0.03	(0.48)	0.83
oaccruals_at	0.37	0.80	(6.44)	0.93	(5.45)	0.13	(1.09)	0.70
ope_bel1	0.40	0.31	(1.88)	0.26	(1.21)	-0.05	(-0.38)	0.77
iskew_capm_21d	0.40	-0.10	(-1.02)	-0.08	(-0.70)	0.02	(0.28)	0.81
iskew_ff3_21d	0.41	-0.17	(-1.91)	-0.13	(-1.36)	0.03	(0.70)	0.87

Table 6—*Continued*

iskew_hxz4_21d	0.42	-0.23	(-2.62)	-0.17	(-1.49)	0.06	(0.85)	0.78
fcf_me	0.43	0.49	(3.50)	0.54	(3.39)	0.05	(0.76)	0.90
ret_1_0	0.47	0.39	(1.89)	0.26	(1.09)	-0.13	(-1.02)	0.85
eqnetis_at	0.49	0.50	(3.14)	0.57	(3.25)	0.07	(0.98)	0.92
tangibility	0.51	0.01	(0.06)	0.05	(0.32)	0.04	(0.74)	0.93
turnover_var_126d	0.51	-0.11	(-0.93)	-0.04	(-0.33)	0.07	(1.49)	0.93
taccruals_ni	0.54	-0.08	(-0.48)	-0.02	(-0.09)	0.06	(1.26)	0.96
earnings_variability	0.54	0.07	(0.58)	0.10	(0.76)	0.03	(0.66)	0.95
cowc_gr1a	0.57	0.76	(6.64)	0.85	(6.04)	0.10	(1.17)	0.82
dolvol_var_126d	0.58	-0.13	(-1.06)	-0.06	(-0.43)	0.07	(1.45)	0.92
capx_gr1	0.61	0.38	(2.94)	0.51	(3.49)	0.13	(2.08)	0.90
qmj_safety	0.72	0.11	(0.62)	0.25	(1.11)	0.14	(0.97)	0.77
seas_16_20na	0.73	0.24	(1.67)	0.35	(2.19)	0.11	(1.48)	0.88
inv_gr1	0.73	0.49	(3.93)	0.65	(3.96)	0.15	(1.50)	0.78
ope_be	0.84	0.39	(2.29)	0.45	(2.22)	0.06	(0.55)	0.85
beta_dimson_21d	0.85	-0.03	(-0.15)	0.11	(0.48)	0.14	(1.20)	0.86
ni_be	0.85	0.38	(1.58)	0.42	(1.65)	0.04	(0.60)	0.97
capx_gr2	0.86	0.33	(2.19)	0.48	(2.92)	0.15	(2.23)	0.91
ocfq_saleq_std	0.88	0.36	(1.77)	0.50	(2.12)	0.13	(1.13)	0.86
nncoa_gr1a	0.91	0.46	(4.01)	0.60	(3.94)	0.14	(1.36)	0.74
ebit_bev	0.91	0.60	(2.64)	0.71	(2.96)	0.11	(1.79)	0.97
seas_11_15na	0.93	0.18	(1.23)	0.32	(1.83)	0.14	(1.30)	0.79
lnoa_gr1a	0.96	0.45	(3.93)	0.62	(3.81)	0.16	(1.36)	0.67
zero_trades_126d	0.96	0.15	(0.70)	0.35	(1.29)	0.20	(1.18)	0.78
zero_trades_252d	0.98	0.18	(0.86)	0.39	(1.41)	0.21	(1.16)	0.76
ncoa_gr1a	0.99	0.43	(3.85)	0.57	(4.05)	0.14	(1.56)	0.77
taccruals_at	1.02	0.29	(2.80)	0.52	(3.13)	0.23	(1.67)	0.57
capx_gr3	1.02	0.37	(2.53)	0.54	(3.27)	0.17	(2.20)	0.88
zero_trades_21d	1.06	-0.16	(-0.77)	0.03	(0.10)	0.19	(1.05)	0.75
o_score	1.06	0.35	(1.76)	0.60	(2.38)	0.24	(1.63)	0.80
noa_gr1a	1.13	0.64	(5.43)	0.88	(4.99)	0.24	(1.75)	0.64
inv_gr1a	1.14	0.58	(4.28)	0.68	(4.39)	0.10	(1.21)	0.84
seas_6_10na	1.14	0.41	(2.54)	0.68	(3.23)	0.26	(2.03)	0.78
col_gr1a	1.19	-0.22	(-1.78)	-0.06	(-0.36)	0.16	(1.38)	0.72
seas_2_5na	1.22	0.35	(1.80)	0.69	(2.28)	0.33	(1.39)	0.61
coa_gr1a	1.31	0.42	(3.34)	0.65	(3.32)	0.24	(1.49)	0.60
emp_gr1	1.38	0.23	(1.77)	0.47	(2.49)	0.25	(1.76)	0.68
ppeinv_gr1a	1.43	0.47	(3.62)	0.60	(3.68)	0.13	(1.36)	0.82
rd_me	1.44	0.31	(1.51)	0.49	(2.07)	0.18	(1.45)	0.85
ocf_me	1.48	0.59	(3.18)	0.75	(3.78)	0.15	(2.12)	0.93
at_gr1	1.48	0.41	(2.84)	0.73	(3.12)	0.32	(1.65)	0.55
saleq_gr1	1.55	-0.19	(-1.22)	0.06	(0.28)	0.25	(1.84)	0.74
turnover_126d	1.57	-0.05	(-0.20)	0.21	(0.66)	0.25	(1.19)	0.73
sale_gr3	1.68	0.10	(0.72)	0.41	(1.71)	0.31	(1.54)	0.55

Table A3—*Continued*

sale_me	1.70	0.43	(1.87)	0.67	(2.64)	0.24	(1.94)	0.87
sale_gr1	1.71	0.12	(0.74)	0.44	(1.90)	0.32	(1.86)	0.66
mispricing_mgmt	1.75	0.76	(5.63)	1.07	(4.52)	0.31	(1.53)	0.51
rmax5_21d	1.79	0.36	(0.80)	0.55	(1.18)	0.20	(2.03)	0.98
ebit_sale	1.83	0.34	(1.37)	0.61	(2.11)	0.27	(2.12)	0.90
be_gr1a	1.86	0.13	(0.92)	0.38	(1.78)	0.25	(1.53)	0.65
at_me	1.95	0.11	(0.60)	0.44	(1.65)	0.33	(1.71)	0.70
aliq_at	1.99	-0.04	(-0.17)	0.20	(0.77)	0.24	(1.88)	0.87
debt_me	2.11	0.06	(0.33)	0.42	(1.69)	0.35	(2.21)	0.76
ivol_hxz4_21d	2.16	0.59	(2.21)	0.99	(2.98)	0.40	(2.07)	0.81
ivol_capm_21d	2.18	0.57	(2.09)	0.95	(2.84)	0.38	(2.00)	0.82
ivol_ff3_21d	2.18	0.46	(1.82)	0.78	(2.58)	0.32	(1.94)	0.84
bev_mev	2.22	0.07	(0.37)	0.41	(1.43)	0.34	(1.51)	0.63
rmax1_21d	2.23	0.38	(1.62)	0.73	(2.53)	0.35	(2.10)	0.82
ival_me	2.32	0.36	(1.83)	0.63	(2.41)	0.26	(1.53)	0.75
betadown_252d	2.43	-0.16	(-0.64)	0.19	(0.54)	0.35	(1.34)	0.68
rvol_21d	2.52	0.36	(1.27)	0.75	(2.14)	0.39	(1.91)	0.81
ni_me	2.64	0.57	(2.80)	0.98	(2.94)	0.41	(1.52)	0.60
ebitda_mev	2.68	0.51	(2.92)	0.95	(2.99)	0.44	(1.62)	0.51
be_me	2.85	0.42	(1.57)	0.71	(2.26)	0.29	(1.59)	0.81
ivol_capm_252d	2.92	0.38	(1.15)	0.77	(1.91)	0.39	(1.77)	0.84
eqnpo_12m	2.93	0.38	(2.63)	0.82	(2.85)	0.44	(1.71)	0.45
eqnpo_me	2.95	0.59	(2.51)	0.93	(3.29)	0.34	(2.31)	0.86
eq_dur	3.09	0.24	(1.32)	0.69	(2.15)	0.45	(1.68)	0.56
betabab_1260d	3.12	0.19	(0.71)	0.61	(1.62)	0.42	(1.58)	0.71
beta_60m	3.42	-0.18	(-0.68)	0.31	(0.81)	0.49	(1.72)	0.67
eqpo_me	4.21	0.16	(0.69)	0.70	(1.99)	0.54	(2.12)	0.69
div12m_me	7.35	-0.03	(-0.13)	0.86	(1.64)	0.89	(1.83)	0.38

Table 7. Factor Discovery: 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
$\Delta DivY$	-0.04***	0.04***	-0.06***	0.03***
	(-2.99)	(2.67)	(-7.64)	(4.25)
Constant	0.09***	0.04***	0.08***	0.02***
	(3.53)	(2.77)	(8.15)	(5.67)
No. of Observations	153	153	1,395	1,395
Adjusted R-squared	0.051	0.069	0.090	0.028

Table 8. Factor Discovery: 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 traditional long-short anomaly return (Column 1), duration-matched fixed-income return spread (Column 2), and anomaly return under the duration-adjusted excess return definition (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) Traditional	(2) Fixed Income	(3) Duration-Adjusted
Post-Sample	-0.08	0.05	-0.14
	(-1.16)	(0.88)	(-1.46)
Post-Publication	-0.32***	0.09	-0.41***
	(-3.84)	(1.08)	(-3.45)
Observations	95,883	95,883	95,883
Predictor FE	Yes	Yes	Yes
Predictors	153	153	153

A Robustness Check: Net Payout Yield

In the main text, we use dividend yield as the proxy for $\mu^i - g^i$ to obtain weights for the series of dividend strips. In this appendix, we explore the use of net payout yield as the proxy for $\mu^i - g^i$. Following Boudoukh et al. (2007), we use CRSP data and calculate net equity issuance for firm i in month t as

$$(shrout_t \times cfacshr_t - shrout_{t-1} \times cfacshr_{t-1}) \times (prc_t/cfacpr_t + prc_{t-1}/cfacpr_{t-1})/2, \quad (15)$$

where *shrout* is the number of shares outstanding, *prc* is the share price, and $cfacshr$ and $cfacpr$ represent the cumulative factors to adjust shares and price, respectively.

For each stock in a given month, we calculate net equity issuance yield as the sum of net equity issued over the past 12 months divided by its market equity at the end of the prior month. We then calculate net payout yield as the difference between dividend yield and net equity issuance yield.

For each long or short portfolio $i = l, s$ in each month, we calculate its current net payout yield as the value-weighted average of net payout yield (measured over the past twelve months) across all stocks in the portfolio.

We then repeat the main analysis using the portfolio-level net equity issuance yield as the proxy for $\mu^i - g^i$ in equation (6). When net equity issuance yield takes negative values, we assign the entire weight of one to the terminal period, i.e., the 30-year Treasury strip receives a weight of 100% in the counterfactual portfolio.

Tables A1 and A2 present robustness checks on the results in Tables 3 and 4. These tables reaffirm our main findings. Specifically, we observe significant changes in the mean return spreads of commonly-used asset pricing factors and the correlation structure between them, under the duration-adjusted excess return definition.

For instance, similar to the findings in Table 3, Table A1 demonstrates considerably larger investment and value anomalies under the duration-adjusted excess return definition, whereas the size anomaly diminishes significantly compared to the traditional definition.

Similar to Table 4, in Table A2, we also observe a much more negative correlation (-0.76) between the market factor and the investment factor under the duration-adjusted excess return definition. Furthermore, the correlation between the value factor and the market factor also changes signs under the duration-adjusted versus traditional definitions of excess returns.

Table A1. Robustness Check for Mean Returns of Prominent Cross-Sectional Factors
This table reports the average monthly raw long-short returns under the traditional versus duration-adjusted definitions of excess returns, and their difference, for the market factor and five anomalies associated with the Fama and French (2015) 5-factor plus momentum factor model. The t-statistics are reported in parentheses. The sample periods are from the beginning date of the original sample periods used in the publications corresponding to these anomalies to December 2020. All returns are in percentage terms.

Anomaly	Traditional		Duration-Adjusted		Difference	
Investment (at_gr1)	0.41	(2.84)	1.04	(2.72)	0.63	(1.73)
Value (be_me)	0.42	(1.57)	0.78	(2.14)	0.37	(1.38)
Size (market_equity)	0.19	(1.05)	-0.23	(-0.85)	-0.42	(-2.17)
Profitability (ope_be)	0.39	(2.29)	0.71	(3.07)	0.32	(2.24)
Momentum (ret_12_1)	1.23	(4.45)	1.32	(4.23)	0.09	(0.64)

Table A2. Robustness Check for Return Correlations of Prominent Cross-Sectional Factors

This table reports the pairwise correlation between monthly factor returns under the traditional and duration-adjusted definitions of excess returns, for the market factor and five anomalies associated with the Fama and French (2015) 5-factor plus momentum factor model. For each anomaly factor, the sample period is from the beginning date of the original sample periods used in its original publication to December 2020. For the market factor, the sample period is February 1962 to December 2020.

	Market	Inv.	Value	Profit.	Size	Mom.	Market*	Inv.*	Value*	Profit.*	Size*	Mom.*
Market	1.00											
Inv.	-0.25	1.00										
Value	0.17	0.43	1.00									
Profit.	-0.38	-0.01	-0.33	1.00								
Size	0.23	0.15	0.52	-0.54	1.00							
Mom.	-0.22	-0.19	-0.68	0.25	-0.32	1.00						
Market*	0.40	-0.04	0.20	-0.23	0.18	-0.18	1.00					
Inv.*	-0.01	0.31	0.14	0.04	0.02	0.00	-0.76	1.00				
Value*	0.23	0.26	0.69	-0.20	0.34	-0.46	-0.19	0.65	1.00			
Profit.*	-0.29	-0.04	-0.30	0.79	-0.48	0.24	-0.41	0.21	0.01	1.00		
Size*	0.10	0.16	0.40	-0.41	0.71	-0.26	0.64	-0.56	-0.13	-0.62	1.00	
Mom.*	-0.19	-0.16	-0.61	0.23	-0.32	0.90	-0.14	-0.04	-0.50	0.28	-0.24	1.00

Table A3. Factor Discovery Revisited: Results for 153 anomalies

This table reports the average monthly long-short anomaly return under the traditional versus duration-adjusted excess return definitions and their difference 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 traditional *t-statistic* is above (below) 1.96 while the duration-adjusted *t-statistic* is below (above) 1.96. Panel B contains robust anomalies, for which both traditional and duration-adjusted *t-statistics* are above 1.96. Panel C contains non-robust anomalies, for which both traditional and duration-adjusted *t-statistics* associated are below 1.96. All returns are in percentage terms.

Panel A: False Positives and False Negatives						
Anomaly	Traditional		Duration-Adjusted		Difference	
at_turnover	0.47	(1.96)	0.03	(0.08)	0.44	(1.55)
bev_mev	0.36	(1.72)	0.83	(2.18)	-0.47	(-1.43)
capx_gr2	0.29	(1.73)	0.53	(2.52)	-0.23	(-1.93)
dbnetis_at	0.35	(2.77)	0.25	(1.71)	0.09	(1.37)
eqpo_me	0.68	(1.92)	1.48	(2.55)	-0.80	(-1.80)
gp_at	0.35	(2.31)	0.06	(0.27)	0.28	(1.57)
niq_at	0.51	(2.06)	0.49	(1.87)	0.02	(0.26)
ocfq_saleq_std	0.45	(1.61)	0.66	(1.99)	-0.21	(-1.12)
op_at	0.33	(2.08)	0.19	(1.13)	0.13	(2.28)
ope_bel1	0.38	(2.18)	0.30	(1.32)	0.08	(0.52)
qmj	0.38	(1.96)	0.37	(1.86)	0.01	(0.12)
ret_1_0	0.77	(2.75)	0.35	(0.85)	0.42	(1.30)
ret_3_1	0.64	(2.44)	0.26	(0.76)	0.37	(1.50)
rmax1_21d	0.42	(1.53)	0.85	(2.43)	-0.43	(-1.97)
rvol_21d	0.45	(1.42)	0.97	(2.22)	-0.52	(-1.71)
sale_bev	0.72	(2.94)	0.45	(1.47)	0.28	(1.61)
sale_gr1	0.35	(1.56)	0.94	(2.12)	-0.59	(-1.48)
seas_11_15na	0.31	(1.71)	0.48	(2.13)	-0.17	(-1.11)
seas_16_20na	0.29	(1.62)	0.44	(2.14)	-0.16	(-1.41)
seas_1_1na	0.80	(2.45)	0.56	(1.39)	0.24	(0.95)
Panel B: Robust Anomalies						
Anomaly	Traditional		Duration-Adjusted		Difference	
at_gr1	0.63	(3.47)	1.04	(3.22)	-0.41	(-1.45)
be_me	1.42	(2.86)	1.81	(2.45)	-0.38	(-0.64)
capex_abn	0.39	(2.79)	0.41	(2.51)	-0.02	(-0.20)
capx_gr1	0.30	(2.05)	0.52	(2.61)	-0.22	(-1.69)
capx_gr3	0.44	(2.63)	0.68	(3.16)	-0.25	(-1.73)
chcsho_12m	0.77	(4.83)	0.77	(4.59)	-0.01	(-0.09)
coa_gr1a	0.64	(4.17)	0.98	(3.64)	-0.34	(-1.46)
cop_at	0.69	(4.68)	0.81	(4.89)	-0.12	(-1.49)
cop_atl1	0.59	(4.20)	0.68	(4.24)	-0.09	(-1.18)

Table A3—*Continued*

cowc_gr1a	0.95	(6.58)	1.09	(5.79)	-0.14	(-1.16)
debt_gr3	0.40	(3.30)	0.32	(2.14)	0.09	(1.08)
dsale_dinv	0.97	(5.78)	0.97	(4.26)	0.00	(0.02)
ebit_bev	1.00	(3.00)	1.12	(3.18)	-0.12	(-1.25)
ebit_sale	0.93	(2.34)	1.31	(2.77)	-0.38	(-1.65)
ebitda_mev	0.80	(4.27)	1.30	(3.43)	-0.49	(-1.47)
emp_gr1	0.39	(2.75)	0.65	(2.95)	-0.26	(-1.54)
eq_dur	0.43	(2.04)	1.11	(2.36)	-0.68	(-1.60)
eqnetis_at	0.71	(3.31)	0.76	(3.15)	-0.05	(-0.49)
eqnpo_12m	0.62	(3.42)	1.21	(3.00)	-0.59	(-1.57)
eqnpo_me	1.15	(3.18)	1.65	(3.71)	-0.50	(-1.96)
f_score	0.33	(3.17)	0.37	(3.12)	-0.04	(-0.69)
fcf_me	0.36	(2.46)	0.44	(2.16)	-0.08	(-0.59)
fnl_gr1a	0.46	(4.53)	0.42	(3.59)	0.04	(0.68)
inv_gr1	0.63	(4.46)	0.82	(4.27)	-0.19	(-1.48)
inv_gr1a	0.83	(5.01)	0.97	(4.69)	-0.14	(-0.97)
ival_me	0.75	(2.53)	1.23	(2.46)	-0.48	(-1.18)
ivol_capm_21d	0.59	(2.08)	1.00	(2.81)	-0.40	(-1.95)
ivol_capm_252d	0.69	(1.97)	1.30	(2.28)	-0.61	(-1.39)
ivol_ff3_21d	0.63	(2.11)	1.07	(2.75)	-0.44	(-1.78)
ivol_hxz4_21d	0.64	(2.30)	1.07	(3.04)	-0.42	(-2.03)
lnoa_gr1a	0.47	(3.36)	0.75	(2.98)	-0.28	(-1.24)
mispricing_mgmt	0.80	(5.42)	1.15	(4.28)	-0.34	(-1.46)
mispricing_perf	0.69	(3.11)	0.53	(1.99)	0.16	(1.07)
ncoa_gr1a	0.55	(4.13)	0.73	(4.07)	-0.18	(-1.42)
netis_at	0.69	(3.67)	0.73	(3.67)	-0.04	(-0.65)
nfna_gr1a	0.57	(4.84)	0.49	(3.50)	0.08	(1.19)
niq_be	0.50	(2.18)	0.53	(2.21)	-0.03	(-0.37)
niq_be_chg1	0.43	(3.03)	0.49	(3.14)	-0.06	(-0.71)
niq_su	0.91	(2.30)	0.90	(2.02)	0.01	(0.02)
nncoa_gr1a	0.62	(4.44)	0.79	(3.96)	-0.17	(-1.15)
noa_at	0.63	(4.63)	0.70	(4.59)	-0.07	(-1.00)
noa_gr1a	0.88	(5.97)	1.19	(4.97)	-0.30	(-1.55)
o_score	0.56	(2.10)	1.08	(2.28)	-0.51	(-1.31)
oaccruals_at	0.75	(5.03)	1.08	(4.00)	-0.33	(-1.41)
ocf_at	0.72	(2.77)	0.75	(2.80)	-0.03	(-0.60)
ocf_me	0.86	(5.10)	1.08	(5.33)	-0.22	(-1.85)
ope_be	0.46	(2.57)	0.50	(2.28)	-0.03	(-0.28)
ppeinv_gr1a	0.69	(4.59)	0.84	(4.26)	-0.14	(-1.13)
qmj_prof	0.45	(2.98)	0.37	(2.15)	0.07	(0.83)
resff3_12_1	1.01	(6.15)	1.05	(5.82)	-0.04	(-0.54)
resff3_6_1	0.40	(2.63)	0.43	(2.50)	-0.03	(-0.32)
ret_12_1	1.64	(5.15)	1.50	(3.46)	0.14	(0.44)
ret_12_7	1.30	(6.09)	1.21	(4.76)	0.09	(0.66)
ret_60_12	0.90	(2.80)	1.48	(2.42)	-0.58	(-1.08)

Table A3—*Continued*

ret_6_1	1.07	(3.64)	0.92	(2.30)	0.14	(0.52)
ret_9_1	1.17	(3.68)	0.99	(2.27)	0.18	(0.56)
rmax5_rvol_21d	0.54	(4.03)	0.53	(3.34)	0.01	(0.08)
sale_gr3	0.48	(2.33)	1.04	(2.09)	-0.56	(-1.18)
seas_11_15an	0.78	(4.81)	0.72	(3.58)	0.06	(0.42)
seas_16_20an	0.55	(2.99)	0.48	(2.25)	0.07	(0.62)
seas_1_1an	0.88	(4.07)	1.00	(3.94)	-0.12	(-0.89)
seas_2_5an	0.89	(5.15)	0.96	(4.22)	-0.06	(-0.44)
seas_2_5na	0.88	(3.65)	1.33	(3.22)	-0.44	(-1.27)
seas_6_10an	0.90	(5.13)	1.06	(4.78)	-0.16	(-1.16)
seas_6_10na	0.45	(2.09)	0.80	(2.85)	-0.36	(-1.91)
taccruals_at	0.31	(2.41)	0.65	(2.83)	-0.33	(-1.66)

Panel C: Non-robust Anomalies

Anomaly	Traditional		Duration-Adjusted		Difference	
age	0.11	(0.46)	0.39	(1.61)	-0.28	(-0.83)
aliq_at	0.15	(0.49)	-0.30	(-1.61)	0.46	(1.25)
aliq_mat	-0.48	(-2.40)	0.12	(1.46)	-0.60	(-2.78)
ami_126d	0.29	(1.39)	0.26	(1.80)	0.03	(0.13)
at_be	0.05	(0.29)	0.17	(0.90)	-0.13	(-0.46)
at_me	0.09	(0.41)	-0.57	(-1.48)	0.66	(1.48)
be_gr1a	0.10	(0.57)	-0.32	(-1.38)	0.43	(1.47)
beta_60m	-0.99	(-1.73)	-0.78	(-0.54)	-0.21	(-0.14)
beta_dimson_21d	-0.06	(-0.22)	-0.50	(-1.08)	0.44	(0.84)
betabab_1260d	0.21	(0.75)	-0.46	(-1.49)	0.67	(1.61)
betadown_252d	-0.11	(-0.40)	-0.42	(-1.10)	0.31	(0.67)
bidaskhl_21d	-0.08	(-0.29)	0.28	(1.86)	-0.36	(-1.13)
cash_at	0.12	(0.61)	0.24	(1.66)	-0.12	(-0.49)
col_gr1a	-0.22	(-1.41)	-0.18	(-1.07)	-0.04	(-0.18)
corr_1260d	0.22	(1.37)	-0.06	(-0.79)	0.28	(1.57)
coskew_21d	0.02	(0.19)	-0.02	(-0.16)	0.04	(0.24)
debt_me	0.20	(0.74)	-0.44	(-1.04)	0.65	(1.30)
dgp_dsale	0.35	(1.65)	0.00	(0.00)	0.34	(1.18)
div12m_me	-0.22	(-0.59)	-1.16	(-0.88)	0.94	(0.71)
dolvol_126d	0.28	(1.37)	0.18	(1.47)	0.10	(0.42)
dolvol_var_126d	-0.22	(-1.46)	-0.05	(-0.64)	-0.17	(-0.98)
dsale_drec	0.01	(0.09)	-0.06	(-0.42)	0.08	(0.35)
dsale_dsga	-0.27	(-1.22)	0.10	(0.45)	-0.36	(-1.14)
earnings_variability	0.19	(1.21)	-0.03	(-0.49)	0.22	(1.30)
gp_atl1	0.14	(0.86)	0.33	(1.63)	-0.19	(-0.74)
iskew_capm_21d	-0.10	(-1.03)	-0.01	(-0.20)	-0.09	(-0.74)
iskew_ff3_21d	-0.23	(-2.33)	-0.04	(-0.66)	-0.19	(-1.73)
iskew_hxz4_21d	-0.20	(-2.24)	-0.06	(-0.81)	-0.14	(-1.19)
kz_index	-0.16	(-0.82)	0.42	(1.37)	-0.58	(-1.62)
lti_gr1a	0.05	(0.45)	-0.05	(-0.91)	0.10	(0.82)
market_equity	0.29	(0.67)	0.41	(0.95)	-0.12	(-0.19)

Table A3—*Continued*

ncol_gr1a	-0.00	(-0.03)	-0.06	(-0.74)	0.06	(0.40)
netdebt_me	-0.16	(-0.80)	0.17	(1.38)	-0.33	(-1.40)
ni_ar1	0.04	(0.31)	0.02	(0.35)	0.02	(0.14)
ni_be	0.32	(1.07)	0.01	(0.06)	0.31	(0.94)
ni_inc8q	0.08	(0.50)	0.18	(1.66)	-0.09	(-0.50)
ni_ivol	-0.01	(-0.03)	0.33	(1.56)	-0.34	(-0.93)
ni_me	0.44	(1.32)	-0.62	(-0.81)	1.06	(1.30)
niq_at_chg1	0.23	(1.58)	-0.03	(-0.48)	0.27	(1.71)
oaccruals_ni	0.28	(1.33)	-0.04	(-0.69)	0.32	(1.45)
ocf_at_chg1	0.29	(1.87)	0.03	(0.96)	0.27	(1.69)
op_atl1	0.31	(1.94)	0.23	(1.87)	0.08	(0.37)
opex_at	0.26	(1.75)	0.32	(2.31)	-0.05	(-0.25)
pi_nix	0.07	(0.47)	-0.07	(-0.79)	0.14	(0.83)
prc	0.50	(1.14)	0.19	(0.90)	0.31	(0.63)
prc_highprc_252d	0.44	(1.29)	-0.17	(-0.81)	0.61	(1.52)
qmj_growth	0.18	(1.41)	0.06	(0.60)	0.11	(0.68)
qmj_safety	0.12	(0.66)	-0.15	(-0.95)	0.27	(1.14)
rd5_at	-0.11	(-0.49)	0.24	(1.01)	-0.35	(-1.12)
rd_me	0.04	(0.15)	-0.32	(-1.22)	0.36	(0.99)
rd_sale	-0.46	(-1.79)	0.00	(0.03)	-0.46	(-1.71)
rmax5_21d	0.56	(0.98)	-0.25	(-1.93)	0.80	(1.34)
rskew_21d	-0.12	(-1.20)	-0.03	(-0.48)	-0.09	(-0.72)
sale_emp_gr1	-0.00	(-0.01)	0.05	(0.34)	-0.05	(-0.21)
sale_me	0.24	(0.81)	-0.55	(-1.44)	0.79	(1.67)
saleq_gr1	-0.14	(-0.89)	-0.26	(-1.75)	0.11	(0.53)
saleq_su	-0.15	(-0.60)	0.08	(1.29)	-0.23	(-0.88)
sti_gr1a	0.15	(1.16)	-0.03	(-0.38)	0.18	(1.20)
taccruals_ni	-0.23	(-1.32)	-0.13	(-1.98)	-0.10	(-0.56)
tangibility	-0.07	(-0.42)	-0.08	(-0.92)	0.01	(0.03)
tax_gr1a	0.17	(0.86)	0.19	(1.75)	-0.02	(-0.10)
turnover_126d	0.11	(0.39)	-0.37	(-0.89)	0.48	(1.00)
turnover_var_126d	-0.21	(-1.42)	-0.05	(-0.64)	-0.16	(-0.99)
z_score	-0.10	(-0.37)	0.76	(1.66)	-0.86	(-1.59)
zero_trades_126d	0.41	(1.61)	-0.22	(-0.93)	0.63	(1.84)
zero_trades_21d	0.00	(0.00)	-0.21	(-0.81)	0.21	(0.58)
zero_trades_252d	0.42	(1.70)	-0.23	(-0.92)	0.65	(1.88)

Table A4. 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 traditional $|t$-statistic$|$ is above 1.96, while the duration-adjusted $|t$-statistic$|$ is below 1.96. For false negatives, the traditional $|t$-statistic$|$ is below 1.96 while the duration-adjusted $|t$-statistic$|$ is above 1.96. Anomalies are ranked by traditional $|t$-statistic$|$ from low to high. All returns are in percentage terms.

Anomaly	Traditional		Duration-Adjusted		Difference	
caps/lt	-0.11	(-0.72)	-0.45	(-2.14)	0.34	(2.60)
dpact/qta	0.13	(0.73)	0.54	(1.99)	-0.41	(-1.91)
reuna/mktcap	0.19	(0.77)	0.61	(1.97)	-0.42	(-2.31)
dpact/ceq	0.13	(0.83)	0.44	(2.08)	-0.31	(-2.06)
icapt/mktcap	0.15	(0.88)	0.55	(2.01)	-0.39	(-1.82)
dm/lt	-0.13	(-0.97)	-0.36	(-2.17)	0.22	(2.52)
txdb/mktcap	0.14	(0.99)	0.37	(2.12)	-0.23	(-2.46)
aox/sale	-0.11	(-1.05)	-0.25	(-1.96)	0.14	(1.96)
caps/at	-0.18	(-1.06)	-0.44	(-2.03)	0.26	(2.05)
dpvieb/qta	0.21	(1.07)	0.49	(2.08)	-0.28	(-1.92)
dpvir/qta	0.24	(1.07)	0.71	(1.96)	-0.47	(-1.53)
ppeveb/mktcap	0.22	(1.08)	0.51	(1.97)	-0.29	(-1.65)
reunr/mktcap	0.25	(1.09)	0.58	(2.00)	-0.33	(-1.77)
xint/qta	0.19	(1.25)	0.36	(2.03)	-0.18	(-1.73)
dpvieb/ceq	0.21	(1.26)	0.41	(2.17)	-0.20	(-2.07)
capx/mktcap	0.21	(1.28)	0.51	(2.35)	-0.30	(-1.92)
dpvieb/mktcap	0.28	(1.31)	0.53	(2.23)	-0.25	(-1.99)
dpact/mktcap	0.24	(1.32)	0.63	(2.37)	-0.39	(-1.90)
dcvt/lt	-0.14	(-1.33)	-0.27	(-1.99)	0.13	(1.44)
dcvsub/sale	-0.15	(-1.36)	-0.28	(-1.99)	0.12	(1.49)
dpvir/mktcap	0.33	(1.43)	0.78	(2.36)	-0.45	(-1.70)
cstkcv/lt	-0.22	(-1.43)	-0.36	(-2.02)	0.14	(1.78)
dp/mktcap	0.26	(1.49)	0.56	(2.50)	-0.31	(-1.91)
xpr/mktcap	0.22	(1.49)	0.43	(2.13)	-0.21	(-1.42)
invt/mktcap	0.24	(1.51)	0.36	(2.08)	-0.12	(-1.46)
xpr/qta	0.19	(1.54)	0.37	(2.04)	-0.18	(-1.25)
mrc5/mktcap	0.29	(1.59)	0.38	(2.02)	-0.09	(-1.73)
dp/qta	0.26	(1.64)	0.52	(2.49)	-0.27	(-1.69)
dcvsub/lt	-0.19	(-1.64)	-0.29	(-2.08)	0.11	(1.27)
dm/sale	-0.22	(-1.65)	-0.36	(-2.40)	0.13	(2.12)
recco/qta	0.17	(1.66)	0.29	(2.19)	-0.12	(-1.34)
spi/qta	-0.18	(-1.66)	-0.24	(-2.07)	0.06	(1.30)
exre/mktcap	-0.22	(-1.68)	-0.28	(-1.99)	0.05	(1.68)
dpc/mktcap	0.32	(1.69)	0.55	(2.58)	-0.23	(-1.99)
invrm/ceq	0.28	(1.74)	0.40	(2.36)	-0.12	(-2.07)
ppenme/mktcap	0.48	(1.74)	0.73	(2.25)	-0.25	(-1.40)
re/qta	0.30	(1.75)	0.64	(2.56)	-0.34	(-1.85)

Table A4—*Continued*

dpc/qta	0.31	(1.77)	0.52	(2.54)	-0.21	(-1.67)
pidom/sale	0.39	(1.78)	0.44	(1.97)	-0.05	(-0.94)
txpd/ceq	0.39	(1.83)	0.46	(2.05)	-0.07	(-1.52)
ppenb/qta	0.34	(1.84)	0.52	(2.15)	-0.18	(-0.91)
oancf/qta	0.50	(1.87)	0.61	(2.18)	-0.10	(-1.82)
xrent/mktcap	0.32	(1.87)	0.35	(2.01)	-0.03	(-0.69)
txp/qta	0.24	(1.87)	0.60	(2.25)	-0.36	(-1.50)
acominc/ceq	-0.38	(-1.88)	-0.43	(-2.13)	0.05	(0.97)
txpd/at	0.35	(1.89)	0.39	(2.00)	-0.03	(-1.05)
ppevbb/qta	0.47	(1.93)	0.91	(2.31)	-0.44	(-1.30)
seq/mktcap	0.36	(1.95)	0.77	(2.60)	-0.41	(-1.73)
pstk/lt	-0.20	(-1.96)	-0.02	(-0.11)	-0.18	(-1.70)
dlc/sale	-0.27	(-1.96)	-0.13	(-0.81)	-0.14	(-1.92)
xintd/lt	-0.50	(-1.98)	-0.24	(-0.77)	-0.27	(-1.72)
lcox/qta	0.18	(2.00)	0.10	(0.84)	0.09	(1.37)
ppeveb/sale	-0.32	(-2.00)	-0.06	(-0.29)	-0.26	(-1.71)
txdc/ceq	-0.25	(-2.01)	-0.13	(-0.86)	-0.12	(-1.57)
dvp/sale	-0.22	(-2.01)	-0.02	(-0.10)	-0.20	(-1.77)
dltt/lt	-0.23	(-2.01)	-0.10	(-0.70)	-0.13	(-1.44)
che/qta	0.28	(2.04)	0.28	(1.71)	-0.00	(-0.05)
txdfed/lt	-0.33	(-2.04)	-0.30	(-1.77)	-0.04	(-0.99)
acox/lt	0.24	(2.04)	0.05	(0.34)	0.18	(1.65)
aco/qta	0.24	(2.04)	0.19	(1.39)	0.05	(0.71)
xsga/sale	0.33	(2.07)	0.04	(0.15)	0.29	(1.44)
fca/qta	-0.35	(-2.09)	-0.29	(-1.63)	-0.06	(-0.82)
lct/sale	-0.21	(-2.09)	-0.12	(-0.97)	-0.09	(-1.59)
txndbl/sale	-0.54	(-2.09)	-0.43	(-1.52)	-0.12	(-1.61)
xintd/sale	-0.63	(-2.10)	-0.25	(-0.69)	-0.38	(-2.00)
mrct/qta	0.35	(2.10)	0.29	(1.67)	0.06	(1.12)
txfed/at	0.29	(2.12)	0.17	(1.16)	0.12	(2.25)
xpp/sale	-0.19	(-2.12)	-0.22	(-1.84)	0.03	(0.37)
wcap/mktcap	0.38	(2.13)	0.16	(0.69)	0.23	(1.81)
dxd4/sale	-0.44	(-2.15)	-0.37	(-1.76)	-0.07	(-1.37)
dclo/qta	0.21	(2.15)	0.18	(1.64)	0.03	(0.57)
mrct/ceq	0.33	(2.17)	0.22	(1.27)	0.12	(1.59)
ppent/sale	-0.32	(-2.17)	-0.04	(-0.20)	-0.28	(-1.88)
optprcey/qta	0.51	(2.17)	0.40	(1.58)	0.11	(1.71)
act/ceq	0.33	(2.18)	0.05	(0.21)	0.28	(1.52)
ppegt/sale	-0.34	(-2.19)	-0.00	(-0.02)	-0.33	(-1.94)
txndb/lt	0.49	(2.19)	0.41	(1.80)	0.07	(1.45)
bkvlps/at	0.32	(2.19)	0.02	(0.09)	0.30	(2.12)
lco/qta	0.30	(2.19)	0.24	(1.55)	0.05	(0.70)
txdfed/ceq	-0.33	(-2.22)	-0.26	(-1.62)	-0.08	(-2.02)
ceqt/sale	-0.32	(-2.23)	-0.11	(-0.55)	-0.20	(-1.34)
xint/sale	-0.31	(-2.23)	-0.13	(-0.72)	-0.19	(-1.89)

Table A4—*Continued*

ch/qta	0.36	(2.23)	0.28	(1.61)	0.08	(1.49)
txc/sale	0.34	(2.24)	0.28	(1.68)	0.07	(1.09)
sstk/mktcap	-0.35	(-2.26)	-0.31	(-1.74)	-0.05	(-0.63)
cogs/at	0.28	(2.27)	0.12	(0.75)	0.16	(1.51)
epsfi/at	0.40	(2.27)	0.22	(0.84)	0.19	(0.98)
gp/at	0.32	(2.27)	0.09	(0.42)	0.24	(1.59)
optprcey/mktcap	0.58	(2.27)	0.49	(1.83)	0.10	(2.12)
epsfi/sale	0.39	(2.27)	0.28	(1.20)	0.11	(0.70)
wcap/qta	0.39	(2.30)	0.17	(0.80)	0.22	(2.00)
invfg/sale	-0.28	(-2.31)	-0.19	(-1.48)	-0.09	(-2.29)
xrent/qta	0.34	(2.32)	0.21	(1.30)	0.13	(1.69)
dp/sale	-0.32	(-2.32)	-0.15	(-0.98)	-0.16	(-1.91)
fate/sale	-0.41	(-2.33)	-0.25	(-1.34)	-0.16	(-1.97)
ivaeq/sale	-0.21	(-2.34)	-0.06	(-0.50)	-0.15	(-1.84)
txdi/sale	-0.27	(-2.36)	-0.15	(-1.14)	-0.12	(-1.77)
acox/qta	0.24	(2.38)	0.16	(1.29)	0.08	(1.17)
capx/sale	-0.37	(-2.41)	-0.22	(-1.28)	-0.15	(-1.56)
bkvlps/ceq	0.32	(2.43)	0.05	(0.27)	0.27	(1.94)
xopr/at	0.35	(2.44)	0.14	(0.74)	0.21	(1.90)
dltis/sale	-0.29	(-2.47)	-0.23	(-1.71)	-0.06	(-1.08)
txc/at	0.38	(2.48)	0.31	(1.89)	0.07	(1.45)
xrent/at	0.35	(2.48)	0.05	(0.22)	0.30	(1.91)
txc/lt	0.37	(2.54)	0.25	(1.61)	0.12	(2.05)
mrc2/ceq	0.41	(2.56)	0.29	(1.62)	0.12	(1.54)
cogs/ceq	0.31	(2.57)	0.23	(1.64)	0.09	(1.28)
acox/at	0.24	(2.58)	0.08	(0.58)	0.15	(1.38)
epsfx/ceq	0.50	(2.59)	0.34	(1.43)	0.16	(1.07)
intc/sale	-0.34	(-2.59)	-0.09	(-0.49)	-0.25	(-1.94)
epsfi/lt	0.41	(2.63)	0.27	(1.25)	0.14	(0.94)
mrc1/ceq	0.42	(2.63)	0.32	(1.82)	0.10	(1.22)
epsfx/at	0.48	(2.67)	0.39	(1.73)	0.08	(0.56)
xsga/at	0.41	(2.67)	0.20	(1.01)	0.22	(1.72)
epsfx/lt	0.43	(2.74)	0.36	(1.77)	0.07	(0.55)
capxv/sale	-0.40	(-2.78)	-0.21	(-1.15)	-0.19	(-1.65)
lct/ceq	0.37	(2.79)	0.33	(1.85)	0.04	(0.31)
cstk/sale	-0.45	(-2.86)	-0.13	(-0.55)	-0.32	(-1.85)
nopio/lt	-0.28	(-2.88)	-0.16	(-1.26)	-0.13	(-1.55)
epspi/ceq	0.55	(2.93)	0.46	(1.95)	0.09	(0.59)
lct/at	0.39	(3.00)	0.16	(0.83)	0.23	(1.62)
bkvlps/qta	0.41	(3.10)	0.23	(1.44)	0.18	(2.08)
epspi/at	0.52	(3.13)	0.40	(1.80)	0.12	(0.81)
xrent/ceq	0.45	(3.13)	0.21	(1.01)	0.24	(1.66)
seq/sale	-0.45	(-3.21)	-0.22	(-1.07)	-0.23	(-1.45)
xopr/ceq	0.45	(3.23)	0.23	(1.17)	0.22	(1.52)
ceql/sale	-0.46	(-3.57)	-0.24	(-1.27)	-0.22	(-1.44)

Table A4—*Continued*

icapt/sale	-0.54	(-3.69)	-0.31	(-1.59)	-0.23	(-1.74)
gp/ceq	0.48	(3.88)	0.34	(1.82)	0.14	(1.01)