Anomaly-driven demand

Abstract

We examine whether the supply and demand of anomaly-targeting stock investors have pricing implications. To examine this, we introduce a simple proxy for anomaly-driven demand. Our proxy captures demand and supply arising from rebalancing of anomaly-targeting investors. We find empirically that stock returns are increasing in our proxy and the effect is mainly generated in the begining-of-month. This points to a significant rebalancing effect of anomaly-targeting investors. Our findings imply that by merely targeting the risk premia associated with different anomalies, anomaly-targeting investors impact stock prices.

Keywords: Anomalies, Investor rebalancing, Factor investing

JEL Classification: G11, G12

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1. Introduction

The financial literature has discovered hundreds of different cross-sectional relations between firm characteristics and stock returns. The research on these "anomalies" has impacted the investment industry substantially. A vast array of mutual funds, hedge funds, and ETFs now focus on factor investing, collectively overseeing trillions of dollars under management (see, e.g. Wigglesworth, 2018, Ang, 2019, Choy, Dutt, Garcia-Zarate, Gogoi, and Johnson, 2022). In this paper, we investigate whether the demand and supply of investors who target anomalies have pricing implications on anomaly factors' constituents. To address this question, we introduce a novel proxy for anomaly-driven demand and our empirical findings suggest that anomaly-driven demand has significant pricing impacts. Throughout the paper, we refer to investors who target anomalies as arbitrageurs.

The literature traditionally defines an anomaly factor as a self-financing strategy: long high-characteristic stocks and short low-characteristic stocks (assuming that risk premium is increasing in the characteristic). As these characteristics are updated, stocks will move in and out of the long- and short-legs. An arbitrageur aiming to harvest the risk premium would then need to buy the stocks entering the long-leg or exiting the short-leg while selling those leaving the long-leg or entering the short-leg. Essentially, updates in these characteristics, which are observable to investors, should offer insights into arbitrageurs' demand and supply. Extrapolating this reasoning to the broader cross-section of anomalies, we recognize that all anomaly factors draw from the same stock universe. This allows us to aggregate supply and demand across anomalies. Based on this intuition, we introduce a simple proxy for anomaly-driven demand: for each stock, we measure changes in the number of long- relative to short-leg inclusions across anomalies. An increase in our proxy implies that the stock has entered more long-legs than short-legs, and/or left more short-legs than long-legs. Consequently, the arbitrageurs' aggregate net demand should be increasing in our proxy. Using the dataset of Chen and Zimmermann (2021), we show that monthly stock returns are increasing in anomaly-driven demand with a significant return differential between stocks with high- and low-anomaly-driven demand, which points to a pricing effect arising from the rebalancing of arbitrageurs. In essence, by merely targeting the risk premia associated with different anomalies, arbitrageurs impact stock prices and potentially enhance the ex-post observed risk premia.

By construction, stocks with high (low) anomaly-driven demand will be constituents in many long-legs (short-legs) and thereby have exposure to many anomaly factors. This poses a central challenge for answering our research question: separating the rebalancing effect from the associated factor risk premium. We address this issue in several ways. Initially, we construct our proxy for anomaly-driven demand using only already published anomalies, aligning with the findings of McLean and Pontiff (2016), who demonstrate that factor risk premia significantly decline post-publication. This approach should, therefore, mitigate the influence of the factor risk premium. Second, we control for factor exposure explicitly by employing the Fama and French (2015) five factor model, Carhart (1997) momentum factor, and the principal components from our cross-section of anomalies. Finally, we consider a more implicit control using the return differential between stocks with high- and low number of long relative to short leg inclusions (Engelberg, McLean, and Pontiff, 2018), but with no anomay-driven demand. We thereby capture the risk premium associated with the anomalies cleaned for the anomaly-driven demand effect. We find empirically that none of the considered controls can explain the return differential between low- and high-anomaly-driven demand stocks, suggesting that our results are not driven by factor exposure.

Many investors are restricted from taking short positions in stocks. Thus, we should expect an asymmetric return pattern when comparing anomaly-driven demand derived from long-leg inclusions relative to short-leg inclusions. We document this asymmetry empirically. We find a larger return differential between the high- and low portfolio when sorting on changes in long-leg inclusions relative to sorting on changes in short-leg inclusions. Both return differentials are significant but smaller in magnitude than sorting on the combined anomaly-driven demand proxy. This suggests that information from changes in long-leg inclusions and changes in short-leg inclusion do not substitute each other, but are complements.

Real-life arbitrageurs must update data on stock characteristics before rebalancing their portfolios. Hence, if arbitrageurs update their information set end-of-month, they will trade begining-of-the-month (Ariel, 1987, Ogden, 1990, Etula, Rinne, Suominen, and Vaittinen, 2020). So if our results are driven by a rebalancing effect, one would expect the return differential to concentrate at the beginning of the month, when arbitrageurs update their information set and rebalance their portfolios. We find that the return differential between stocks with low and high anomaly-driven demand is significant only at the beginning of the month, consistent with an arbitrageur rebalancing effect.

The literature has employed two methodologies for constructing factors: the portfolio sort approach (e.g. Bali, Engle, and Murray, 2016) and a rank-based approach (e.g. Asness, Moskowitz, and Pedersen, 2013). A portfolio sort corresponds, in principle, to investors restricting their investment universe to only include stocks in the top and bottom portfolios, while the rank-based holds all assets with portfolio weights increasing in the characteristic. Furthermore, the portfolio sort approach is consistent with the habitat view, i.e., many investors choose only to trade a subset of available securities (Barberis, Shleifer, and Wurgler, 2005). Taking this idea into our context corresponds to arbitrageurs only focusing on the extreme characteristic portfolios: only when a stock enters the long or short leg of a given factor does it become part of the arbitrageurs' habitat. Hence, from the habitat view, we would not expect a proxy of anomaly-driven demand based on the rank-based approach to identify arbitrageurs' supply and demand as precise. We find that the return differential between low- and high-anomaly-driven demand stocks constructed from a rank-based approach is insignificant.

A critique of the existing literature is that anomalies tend to overweight small illiquid stocks (Novy-Marx and Velikov, 2016), making the anomalies unrealistic to implement. Hence, if arbitrageurs actually target anomalies, we would not expect the rebalancing effect to only exist among small illiquid stocks, but also among large liquid stocks. We show that the return differential between stocks with high and low anomaly-driven demand is also significant among the largest and most liquid stocks, even though the return differential is largest among the smallest illiquid stocks.

The studies by Calluzzo, Moneta, and Topaloglu (2019), Gerakos, Linnainmaa, and Morse (2021), Broman and Moneta (2023), Gao and Wang (2023) all affirm that institutional investors trade to exploit stock market anomalies. Furthermore, both McLean and Pontiff (2016) and Chen and Velikov (2022) show that the returns associated with anomalies tend to decline substantially post-publication, indicating that anomaly targeting by arbitrageurs lowers the associated risk premia. Our paper complements these studies by proposing a strategy for identifying the stocks most likely to be bought or sold by arbitrageurs while concurrently demonstrating the significance of arbitrageur rebalancing effects. The stocks with large rebalancing effects are also constitutents in long- or short-legs of anomaly factors. Consequently, an important implication of our findings is that ex-post risk premia estimates are likely to be considerably inflated by the arbitrageur rebalancing effect, particularly when the researcher relies on samples that encompass post-publication periods.

More broadly our study also fits within the extensive literature that explores the pricing impacts of mechanical investment rules, such as the influence of indexing (e.g. Shleifer, 1986, Barberis et al., 2005, Greenwood, 2005, Chang, Hong, and Liskovich, 2015), ETFs (e.g. Shum, Hejazi, Haryanto, and Rodier, 2016, Ben-David, Franzoni, and Moussawi, 2018, Ivanov and Lenkey, 2018), and institutional flows (e.g. Coval and Stafford, 2007, Greenwood and Thesmar, 2011, Lou, 2012, Vayanos and Woolley, 2013, Anton and Polk, 2014, Lou and Polk, 2022). We document the existence of pricing impacts in stocks due to mechanical rebalancing of arbitrageurs.

There has been much recent debate in the literature about whether many of the published anomalies do in fact exist or are simply false discoveries as a result of p-hacking (Harvey, Liu, and Zhu, 2016, Harvey, 2017, Harvey and Liu, 2019, 2020, Chen and Zimmermann, 2020, Jensen, Kelly, and Pedersen, 2023). We completely refrain from this discussion. The sole purpose of our paper is to explore any pricing impacts that arise due to the demand and supply of arbitrageurs who target anomalies. For our research question, the existence of anomalies is irrelevant; only their perceived existence matters.

The rest of the paper is organized as follows: Section 2 presents our hypothesis development, Section 3 our proxy of anomaly-driven demand and data, Section 4 the main empirical analysis, Section 5 some further results, while Section 6 concludes.

2. Hypothesis development

In this section, we develop our main testable hypotheses related to whether the demand and supply of arbitrageurs have pricing implications on the stock constituents of anomaly factors. The focus of our paper is purely empirical, but we sketch the economic mechanism by simple heuristics to establish testable hypotheses.

Consider a one-period economy with N different stocks each with a fixed number of shares outstanding, S. There are two arbitrageurs with a margin requirement implying a limit to arbitrage. The two arbitrageurs invest blindly according to an equal-weighted long-short strategy based on some characteristic, z^j. Additionally, they limit their investment universe to stocks with $z^j > \bar{z}^j$ and $z^j < \underline{z}^j$. This assumption aligns with the habitat view of Barberis et al. (2005). Both arbitrageurs believe that for stocks with

$z^j > \bar{z}^j$ the expected return is constant and equals μ^+, while for stocks with $z^j < \underline{z}^j$ the expected return is again constant but equals μ^-. The arbitrageurs believe that high characteristic stocks have higher expected returns than low, i.e., $\mu^+ > \mu^-$. To have market clearing, we also have a market-maker (M) with mean-variance preferences, and conditional expectation, $\mathbb{E}_M()$. Her relative risk aversion is γ and, for simplicity, she believes that all stocks are uncorrelated with identical volatility. Furthermore, we assume no dividends, implying that only price changes generate returns.

Suppose now that Investor 1 conditions her investment universe based on characteristics z_1. The optimal portfolio weight of Investor 1 for stock j is then:

$$\omega_{1,j} = \begin{cases} \frac{1}{N_1^+}, \text{ if } z_1^j \geq \bar{z}_1 \\ 0 \text{ if } \underline{z}_1 < z_1^j < \bar{z}_1 \\ -\frac{1}{N_1^-}, \text{ if } z_1^j \leq \underline{z}_1, \end{cases} \tag{1}$$

where $N_1^+ = \sum_j \mathbb{1}_{z_{1,j} > \bar{z}_1}$ (the number of stocks with $z_1 > \bar{z}_1$) and $N_1^- = \sum_j \mathbb{1}_{z_{1,j} < \underline{z}_1}$ (the number of stocks with $z_1 < \underline{z}_1$). We note that, since Investor 1's conditional expected return does not depend on the price, her relative weight is independent of price changes. We will assume that Investor 2 is identical to Investor 1 except she conditions her investment universe on a different characteristic, namely z_2.

Next, M, who invests in the entire stock universe, has the following optimal portfolio weights:

$$\omega_{M,j} = \frac{1}{\gamma} \frac{\mathbb{E}_M(P_{j,t+1})}{P_{j,t}} \frac{1}{\sigma^2}, \tag{2}$$

such that the optimal weight of stock j in M's portfolio is decreasing in stock j's price today. For simplicity, we assume that M's expected price is constant across stocks such that $\mathbb{E}_M(P_{j,t+1}) = P_{t+1} \forall j$.

Last, denote the wealth of each investor by $W_{i,t}$. Market clearing implies that:

$$S = \omega_{1,j}\frac{W_1}{P_{j,t}} + \omega_{2,j}\frac{W_2}{P_{j,t}} + \omega_{M,j}\frac{W_M}{P_{j,t}} \ \forall j. \tag{3}$$

Now consider the case for stock j that enters the investment universe of Investor 1, meaning that $z_1^j \geq \bar{z}_1$, but is not included in the investment universe of Investor 2. The equilibrium implies that:

$$S - \left(\frac{1}{\gamma}\frac{P_{t+1}}{P_{t,j}}\frac{1}{\sigma^2}\right)\frac{W_M}{P_{t,j}} = \frac{1}{N_1^+}\frac{W_2}{P_{t,j}}, \tag{4}$$

$$P_{t,j} = \frac{P_{t+1}W_M}{(S - \frac{1}{N_1^+}W_1)\gamma\sigma^2} > \frac{P_{t+1}W_M}{S\gamma\sigma^2}. \tag{5}$$

In words; the equilibrium ensures that the demand of three investors must sum to S. This implies that with high demand from Investor 1, the optimal portfolio weight of M decreases. This can only be accomplished by a price increase such that M's conditional expected return decreases. Translating the intuition into the universe of anomalies: when a stock enters the long-leg for a given anomaly, demand for the stock increases which increases the price.

Suppose now that stock j also enters the long-leg of Investor 2 ($z_2^j > \bar{z}_2$). The equilibrium price for stock j now becomes

$$P_{t,j} = \frac{P_{t+1}W_M}{(S - \frac{1}{N_1^+}W_1 - \frac{1}{N_2^+}W_2)\gamma\sigma^2} > \frac{P_{t+1}W_M}{(S - \frac{1}{N_1^+}W_1)\gamma\sigma^2} > \frac{P_{t+1}W_M}{S\gamma\sigma^2}. \tag{6}$$

So stock j becomes included in the investment universe of both Investor 1 and 2 simultaneously, the prices increase further than if the stock j had only entered the universe for one of the investors. In the context of anomalies: the more anomalies having stock j in their long-legs, the higher the return.

Similarly, if j had entered short-leg, we would have the opposite

$$P_{t,j} = \frac{P_{t+1}W_{M,t}}{(S + \frac{1}{N^-_{1,t}}W_{1,t} + \frac{1}{N^-_{2,t}}W_{2,t})\gamma\sigma^2} < \frac{P_{t+1}W_{M,t}}{(S + \frac{1}{N^-_{1,t}}W_{1,t})\gamma\sigma^2} < \frac{P_{t+1}W_{M,t}}{S\gamma\sigma^2}. \quad (7)$$

The more anomalies having stock j in their short-legs, the lower the return. In sum, stock returns should be increasing in anomaly-driven net demand. This lead to the first testable hypothesis:

Hypothesis 1: Stocks with high anomaly-driven net demand should deliver a higher return relative to stocks with low anomaly-driven net demand.

In a real-world setting, not all investors are allowed to short stocks. For instance, most mutual funds are restricted from holding short positions. This implies that many arbitrageurs can only target the long-leg of the anomaly. So suppose now that Investor 2 cannot short stocks. The optimal weight of investor 2 becomes

$$\omega^t_{2,j} = \begin{cases} \frac{1}{N^+_2}, \text{ if } z^j_2 > \bar{z}_2, \\ 0 \text{ if } z^j_2 \leq \bar{z}_2. \end{cases} \quad (8)$$

In this case, we should expect a larger pricing impact from stocks entering (leaving) long-legs, relative to stocks leaving (entering) short-legs. This leads to our second testable hypothesis.

Hypothesis 2: The return differential between stocks with high- and low anomaly-driven net demand arising from long-leg changes should be larger than the return differential between stocks with high- and low anomaly-driven net demand arising from short-leg changes.

The heuristics above point to a rebalancing effect immediately following a characteristics update. If the return differential between stocks with low and high anomaly-driven demand is driven by a rebalancing effect, one would expect the return differential to concentrate in the immediate period following the characteristic update when arbitrageurs rebalance their portfolio. This leads to our third testable hypothesis.

Hypothesis 3: The return differential between stocks with low and high net anomaly-driven demand is concentrated at the beginning of the holding period.

3. Data and variable construction

3.1. A proxy for anomaly-driven demand

We introduce a proxy for anomaly-driven demand. To illustrate the economic intuition of our proxy, consider the momentum anomaly documented in Jegadeesh and Titman (1993) who find that stocks with high past performance tend to outperform stocks with low past performance. Sorting stocks into portfolios based on past performance, the momentum factor is then the returns from a strategy that is long in past winners and short past losers. An example of the long and short portfolios is illustrated in Panel (a) of Figure 1.

Figure 1 about here

The portfolio of a momentum targeting arbitrageur consists today of a short position in the bottom quintile portfolio ("losers") and a long position in the top quintile portfolio ("winners").[1] Iterating one period forward, the arbitrageur now updates the trading signal, i.e. past performance, and stocks will be reallocated between quintile portfolios, as illustrated in Panel (b). To keep following the anomaly strategy, the arbitrageur must rebalance her portfolio by; 1) buying the new winners (T, G, and O) and previous losers (X, Z, and B), and 2) selling new losers (U, N, and I) and previous winners (U, Q, and J). The key insight is that we can observe the stocks' reshufflement between portfolios and, thereby, predict which stocks a momentum-targetting arbitrageur will buy and sell.

[1] In the original paper of Jegadeesh and Titman (1993) stocks are sorted into decile portfolios. However, here we consider quintile portfolios for the simple illustration

Extrapolating this reasoning to the broader cross-section of observable characteristics, we can aggregate arbitrageurs' supply and demand across anomalies. Based on this intuition, we construct a simple proxy for anomaly-driven demand in three steps:

First, for each anomaly characteristic, we sort all stocks into portfolios. Assuming that arbitrageurs' expected returns are increasing in the characteristic value, we define the "short-leg", as the portfolio containing the stocks with the lowest value of the characteristic and the "long-leg" as the portfolio containing the stocks with the highest characteristic value. We label the short-leg as P^{short}, and the long-leg as P^{long}.

In the second step, following Engelberg et al. (2018), we count the number of times stock j is a constitutent of either P^{short} or P^{long} across all characteristics and calculate the net difference:

$$\text{NET}_{j,t} = \sum_{i=1}^{N_t} \mathbb{1}_{j \in P_{i,t}^{long}} - \mathbb{1}_{j \in P_{i,t}^{short}}, \tag{9}$$

where N_t is the number of published anomalies at time t and $\mathbb{1}$ is the indicator function. In the last step, we utilize the fact that an increase in NET implies either that stock j has entered more long-legs than short-legs and/or left more short-legs than long-legs. In other words, an increase in NET predicts that arbitrageurs, in aggregate, have a positive net demand for the stock, implying that changes in NET should reflect arbitrageurs' demand and supply. Following this intuition, for each stock j we introduce our proxy for anomaly-driven demand, ADD, as changes in $\text{NET}_{j,t}$:

$$\text{ADD}_{j,t} = \text{NET}_{j,t} - \text{NET}_{j,t-1}. \tag{10}$$

Consequently, the arbitrageurs' aggregate net demand for a given stock should be increasing in ADD.

For the practical implementation, we consider quintile portfolios based on breakpoints calculated using NYSE stocks only (see Hou, Xue, and Zhang, 2020) with monthly rebalancing or whenever the characteristic is updated. Section 5.3 shows that the results are similar when only considering rebalancing in accordance with the original papers[2], while Section 5.4 shows that results are similar when considering a different number of portfolios when sorting the stocks. For binary characteristics, we divide all stocks into a buy and a sell portfolio based on the characteristics.[3]

3.2. Stock data

We consider data from the Center for Research in Security Prices (CRSP) monthly security file. We follow the literature and only include US common stocks (shrcd=10 or 11) trading on NYSE, AMEX, and NASDAQ (exchcd=1, 2, or 3).

3.3. Stock anomalies and portfolio constitutes

We obtain data on anomaly characteristics from Chen and Zimmermann (2021) including publication year, in-sample return, and t-statistics from the original study.[4] The dataset contains characteristics for 204 different anomalies signed such that a high (low) characteristic value is a buy (sell) signal. We focus on the post-publication period of the anomalies for two reasons: 1) To ensure that arbitrageurs are aware of the anomaly, and 2) to mitigate the effect of the anomaly risk premium since McLean and Pontiff (2016) find that anomaly risk premia decline significantly after they have been published. This restriction means that our sample starts in January 1990, to ensure a sufficient number of anomalies, and ends in December 2021. Figure 2 shows the number of published anomalies in our dataset over time.

Figure 2 about here

[2]Rebalancing frequencies are obtained from Chen and Zimmermann (2021).
[3]Ignoring the short portfolio for binary variables generates the same conclusions.
[4]We thank the authors for making the data available at https://www.openassetpricing.com/

The number of published anomalies starts at 11 in 1990 and increases to 204 around 2017. In particular, we note the steep increases in published anomalies from 2006 to 2010 aligning with Harvey et al. (2016).

4. Results

This section presents our main results. We show first that high ADD stocks generate higher returns than low ADD stocks, with a significant return differential. We show that the return differential cannot be explained by factor exposure and that the differential is generated in the first days following a characteristics update. Overall, our results point towards a significant pricing effect from arbitrageur rebalacning.

4.1. Anomaly-driven demand and stock returns

We first test Hypothesis 1: stock returns are increasing in anomaly-driven demand. To test the hypothesis, we sort stocks into quintile portfolios based on ADD from Equation (10). Table 1 reports the average excess returns of the five different portfolios and a High minus Low portfolio. The "Low" portfolio contains the stocks with the lowest ADD, and the "High" portfolio contains the stocks with the highest ADD. The portfolios are value-weighted and rebalanced monthly. Both breakpoints are included in the portfolios (see Bali et al., 2016), implying a potential overlap between portfolios due to the discrete nature of the characteristics. The High and Low portfolios are, however, completely non-overlapping.[5]

Table 1 about here

The results align with Hypothesis 1: excess stock returns are monotonically increasing

[5] Redefining the portfolio boundaries such that a portfolio only included a single breakpoint generates similar results but this approach does not guarantee that at least 20% of the NYSE stocks are allocated to each portfolio. Hence, our approach is conservative.

in ADD. The High portfolio generates an annual excess return of 11.17%, compared to 7.30% for the Low portfolio. A long-short (High-Low) strategy that buys the High portfolio and sells the Low portfolio generates an annualized excess return of 3.86% with a t-statistic of 4.00. Stock returns are increasing in our anomaly-driven demand proxy with a significant return differential between low- and high-anomaly-driven demand stocks.

Next, to test Hypothesis 2 we decompose ADD into demand arising from stocks moving in and out of the long-leg and short-leg separately. Excess returns are monotonically increasing in changes in long-leg inclusions and monotonically decreasing in short-leg inclusions. Hence, the more long-legs a stock enters (leaves), the higher (lower) returns. Similarly, the more short-legs a stock enters (leaves), the lower (higher) returns. We note that these effects are not symmetric in magnitude. Changes in long-leg inclusions have a larger effect on future stock returns than changes in short-leg inclusions. This asymmetry is expected if some investors are restricted from short-selling and, thereby, align with Hypothesis 2. None of the two signals, individually, delivers superior portfolios compared to combining the two, meaning that the two signals complement each other.

Figure 3 shows the cumulative returns of the High-Low return differential from sorting on ADD, changes in long-leg inclusions, and changes in short-leg inclusions.

Figure 3 about here

The return differential is consistent over time. Disregarding the period 1999-2000, the cumulative return differentials are steadily increasing over time with little variation, explaining the high t-statistics relative to the annualized returns. The spikes in the series for changes in long-leg- and short-leg inclusions occur during a run-up to the peak of the dot-com bubble in the spring 2000.

4.1.1. Controlling for factor exposure

We have shown that the return differential between stocks with high- and low ADD is significant. Now, we ask whether this differential can be explained by factor exposure. Anomaly-driven demand has two channels; if a stock leaves a short-leg or if a stock enters a long-leg. If anomaly-driven demand i driven by the latter channel, we expect the stock to have high exposure on the underlying anomaly factor. For instance, a stock that enters the long-leg of the momentum factor should have higher expected returns, due to the positive risk premium of momentum. Hence, our main results in Table 1 may be entirely driven by exposure to systematic risk. In the following, we adjust the returns of the High-Low portfolio, based on the ADD-sort, for factor exposure using different control variables. Ideally, we would control for the factor returns of each of the 204 anomalies that we have considered. This, however, is not feasible because of the time differences in publication across anomalies. Instead, we employ the Fama and French (2015) factors (FF5), the Carhart (1997) momentum factor (MOM), and the first three principal components from the cross-section of anomaly factors.[6] Additionally, we consider a more implicit way to control for the factor exposure. We perform a five-by-five conditional bivariate portfolio sort in which we first sort on NET (see Equation (9)) and afterwards the absolute ADD value. Stocks with high NET are constituents in many long-legs relative to short-legs and have large exposure to different anomalies. NET will, however, also capture stocks that have just moved into the long- or short-leg, for which we expect an arbitrageur pricing effect. Hence, to isolate the associated anomaly risk premia from anomaly-driven demand, we add the second sort. We construct our control variables as the "high NET low absolute ADD" portfolio minus the "low NET low absolute ADD" portfolio ($\text{NET}_{\perp \text{ADD}}$). This return differential have high factor exposure,

[6]The first three principal components explains 72% of the total variation. The results are identical using five and 10 principal components.

but no expected anomaly-driven demand. The return differential, thereby, captures the associated risk premium cleaned for anomaly-driven demand. Tabel 2 presents the results from regressing the return differential between High- and Low ADD stocks (cf. Table 1) on the control variables.

TABLE 2 ABOUT HERE

A significant proportion of the return differential between high- and low ADD stocks cannot be explained by the controls: all intercepts are highly significant and align in magnitude with the High-Low return differentials reported earlier. The loading on the market factor is almost zero and insignificant for all specifications and the FF5 and MOM factors are all insignificant at the 5% level. The CMA (investment) factor has the highest loading and is also borderline significant. For the principal components, the first and the third are significant for all specifications. The loadings on $\text{NET}_{\perp\text{ADD}}$ are positive but only significant when included as the only control variable. Overall, these results suggest that the return differential between high- and low anomaly-driven demand stocks is not attributable to systematic factor risk exposure.

4.2. Intra-monthly return pattern

So far we have documented that following a characteristics update, stocks with the most (least) new long (short) leg inclusions have higher returns over the subsequent month than stocks with the most (least) new short (long) leg inclusions. If these results are explained by arbitrageur rebalancing, we should expect that stock returns react shortly after a characteristic update enters the arbitrageurs' information set. From studies on "turn of the month" effects (e.g. Ariel, 1987, Ogden, 1990, Etula et al., 2020) investors typically rebalance portfolios in the beginning of the month. This implies that the return differential between low- and high ADD stocks should be generated during the first days of the month following a characteristic update. Panel (a) of Figure 4 shows the average daily return differential between low- and high ADD stocks from the first trading day to end-month following a characteristics update.

Figure 4 about here

The figure shows a clear clustering of positive returns during the first five trading days following the characteristics update, while for the remainder of the month, the pattern is mixed. To formally examine the difference, Panel (b) shows the return differential over the first week, post-update, relative to the remaining month. Consistent with a rebalancing effect the return differential is highly significant for the first week, while the remaining month is insignificant. However, focusing on the distribution of returns for the first five days, cf. Panel (a), the return differential on the second trading day stands out as the most significant with an average of 15% annualized. This pattern could indicate a small time lag from the update of characteristics to full incorporation in the information set of arbitrageurs. If this is the case, we would expect the return differential on the first trading day of a month should be different if this falls on a Monday, when investors have the weekend to process the information update. Panel (c) shows the average return of the month's first trading day across the five different weekdays (i.e., Monday, Tuesday,...). Mondays clearly stand out as the only weekday with a significant positive return differential. For the remaining weekdays, the return differential is either negative or insignificantly positive. In magnitude, the return differential on Mondays is a factor of 1.66 higher than the second-highest weekday, Wednesdays. This pattern seems consistent with a small time lag from the characteristics update until this is fully reflected in prices.

Overall, the intra-monthly distribution of return differentials between high- and low anomaly-driven demand stocks is consistent with a significant rebalancing effect.

4.3. Anomaly-driven demand and short-interest

Gao and Wang (2023) find that the short positions of alternative mutual funds are consistent with the targeting of anomalies. In similar spirit, we now look at the relation between anomaly-driven demand and aggregated short-interest changes. If arbitrageurs indeed pursue anomalies, and if ADD captures arbitrageurs' demand and supply, changes in short-interest should be decreasing in ADD. Table 4, presents the average change in short-interest, divided by the number of outstanding shares, for the five portfolios sorted on ADD and changes in the number of long- and short-leg inclusions separately. Since end-of-month short-interest data from Compustat is only available from January 2007, the following results are based on data from January 2007 to December 2021.

Table 4 about here

There is a nearly monotonic decrease in average short interest change from the Low to the High portfolio. For the stocks with lowest ADD, the short-interest increases next month, while for the stocks with highest ADD the short interest decreases. Although changes in short interest are statistically insignificant at the portfolio level (also due to our limited sample period), the difference between the Low and High portfolios is significant. This finding highlights that stocks with the highest anomaly-driven demand exhibit fewer new short positions compared to stocks with the lowest anomaly-driven demand, consistent with arbitrageurs pursuing anomalies jointly with ADD capturing arbitrageurs' demand and supply.

4.4. Anomaly driven demand, size, and liqudity

A critique of the existing literature is that anomalies tend to overweight small illiquid stocks (Novy-Marx and Velikov, 2016), making the anomalies unrealistic to implement. Hence, if arbitrageurs actually target anomalies, we would not expect the rebalancing effect to only be concentrated among small illiquid stocks, but also among large liquid stocks. Next, we examine whether the return differential between high- and low ADD stocks is concentrated among small illiquid stocks or whether it also exists among large liquid stocks. To examine this, we consider a bivariate conditional sort based on either the illiquidity measure of Amihud (2002) or size in addition to ADD. We first sort the stocks into quintile portfolios ranked by illiquidity or market capitalization, respectively. Then, within each of these quintile portfolios, we form a second set of quintile portfolios ranked on ADD. This creates a set of portfolios with similar past illiquidity or size characteristics but with spreads in anomaly-driven demand. Table 5 shows the average return of a size- and illiquidity-conditional return differential between High and Low ADD stocks. The different panels present the results of 5x5 conditional sort. The breakpoints are still based on NYSE-listed stocks. The portfolios are value-weighted, rebalanced at the end of each month, and are still only based on post-publication anomalies.

Table 5 about here

The table reveals a striking pattern: the average returns have a skewed U-shaped across both size and liquidity, meaning that the return differential between high- and low ADD stocks is economically strongest among small and illiquid stocks, but is also highly significant among the largest and most liquid stocks. In the mid quintile portfolio results are the weakest. Hence, the arbitrageurs' pricing effect exists both in small illiquid stocks and in large liquid stocks.

5. Further results

In this section, we present supplementary findings that refine and corroborate the previous results.

5.1. Scaled anomaly-driven demand

In the construction of our ADD proxy, all anomalies are weighted equally. However, McLean and Pontiff (2016) find that the post-publication decline in anomaly risk premia is increasing in the t-statistic of the original paper, indicating that performing anomalies attract more investor attention. Consequently, we consider a modification to ADD by scaling the indicator function in Equation (9) with the t-statistic of the original paper. This modification allows us to account for the possibility of investor attention being influenced by the statistical evidence provided in the original publication of the anomaly. Again we sort stocks into quintile portfolios but this time the sort is based on the modified version of ADD, ADD-scaled. Table 8 reports the average excess returns of the five portfolios and a High-Low portfolio. Again, the "Low" portfolio contains the stocks with lowest ADD-scaled, and the "High" portfolio contains the stocks with the highest ADD-scaled.

Table 8 about here

Allowing for a larger weight on anomalies with higher reported t-statistics enhances the results. The economic magnitude of the High-Low portfolio is larger in all cases, ranging between 53 and 120 basis points above, compared to the results in Table 1.

5.2. Alternative investment universe

So far, we have constructed anomaly factors by means of a portfolio sort, as illustrated in Section 3. As an alternative, the literature has proposed a rank-based approach (e.g. Asness et al., 2013) where investors are assumed to hold all assets, with portfolio weights increasing in the anomaly characteristic. This approach, however, is expensive to apply in practice both in terms of transaction costs and attention, making it infeasible to real-world investors (Novy-Marx and Velikov, 2022). Furthermore, the portfolio sort approach is consistent with the habitat view, i.e., many investors choose only to trade a subset of available securities (Barberis et al., 2005). Taking this idea into our context corresponds to arbitrageurs only focusing on the extreme characteristic portfolios and, consequently, using the rank-based approach to proxy anomaly-driven demand should be more noisy. We now modify ADD to a rank-based approach. Specifically, we rank each stock based on its beginning-of-month characteristic values and then sum the ranks over the different characteristics. For binary characteristics, we assign the median rank over the groups. We form quantile portfolios based on changes in the sum over ranks and report the average monthly portfolio returns in Table 3. The "Low"-portfolio contains the stocks with the lowest change in the sum of ranks in the previous month. The "High" portfolio includes stocks with the largest change in sum over ranks in the previous month.

Table 3 about here

The return differential between stocks with high and low anomaly-driven demand is not significant using a rank-based approach and we no longer observe a consistent monotonic increase in returns from the Low to the High portfolio. Consequently, in comparison to our primary findings as presented in Tabel 3, the application of rank-based weights yields weaker results.

5.3. Updating portfolios according to original papers

Previously, we considered monthly (or whenever the charactertic is updated) rebalancing for all anomalies. However, many of the original anomaly studies consider different rebalancing frequencies. For instance, Jegadeesh and Titman (1993) considered quarterly rebalancing for the momentum anomaly even though the signal can be updated monthly. Now, we examine whether our results are sensitive towards to the rebalancing frequency. We do that by updating the anomaly portfolios according to the rebalancing frequency proposed in the original paper. Table 7 presents the result from sorting on ADD based on the original rebalancing frequency.

Table 7 about here

The results are very similar to Table 1.

5.4. Different number of portfolios

As highlighted in Walter, Weber, and Weiss (2022), when conducting a portfolio sort, the number of portfolios that stocks are sorted into may have a substantial impact on the results. Our main results apply portfolio sorts in two stages. In the initial stage, we use portfolio sorting to construct ADD (the ADD sort), and we use the second stage to test for the pricing implications of anomaly-driven demand (the testing sort). All previous results are based on quintile portfolios in both stages. We now investigate the sensitivity of our main result (see Table 1) to variations in the number of portfolios in both stages. Table 6 reports the average return differential between the High and Low portfolio. Along the columns, we vary the number of portfolios in the ADD sort, while along the rows, we vary the number of portfolios in the testing sort. We consider three, five, or ten portfolios.

Table 6 about here

The return differentials remain highly significant both in economic and statistical terms, meaning that our findings are not sensitive to the number of portfolios applied.

6. Conclusion

We introduce a new proxy of anomaly-targeting arbitrageurs' demand and supply. We proxy anomaly-driven demand, for each stock, by tracking changes in the net number of long- and short-inclusions across anomalies. We show empirically that monthly stock returns are increasing in anomaly-driven demand with a significant return differential between high- and low anomaly-driven demand stocks. This difference cannot be explained by anomaly factor exposure, and is contratrate in the begining of the month folllowing an update in arbitrageurs' information set. In sum, our empirical evidence point to a significant rebalancing effect of arbitrageurs, implying that by merely targeting the risk premia associated with different anomalies, arbitrageurs drive stock prices.

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Table 1: Quantile portfolios of stocks sorted by ADD

This table reports average monthly annualized returns on portfolios formed by sorting on anomaly-driven demand (top row), changes in the number of long-leg inclusions (middle row), and changes in short-leg inclusions (bottom row). The "Low" portfolio contains the stocks with the lowest anomaly-driven demand (top row), the lowest number of changes in long-leg inclusions (middle row), or the lowest number of changes in short-leg inclusions (bottom row). Similarly, the "High" portfolio contains the stocks with the highest anomaly-driven demand (top row), the highest number of changes in long-leg inclusions (middle row), or the highest number of changes in short-leg inclusions (bottom row). The column "High-Low" reports the difference in average monthly returns between the High and Low portfolios. Our sample period is January 1990 to December 2021 and *t*-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Low	2	3	4	High	High-Low
ADD	7.3	8.87	9.92	10.01	11.17	3.86
	[2.62]	[3.17]	[3.56]	[3.69]	[4.00]	[4.00]
Long	7.98	8.54	9.03	9.3	10.88	2.9
	[2.96]	[2.97]	[3.17]	[3.34]	[3.91]	[3.28]
Short	10.24	10	9.91	9.04	7.93	-2.31
	[3.65]	[3.62]	[3.75]	[3.3]	[2.82]	[-2.24]

Table 2: Controlling for factor exposure

This table reports the risk-adjusted annualized returns (Intercept) on the High-Low portfolio from sorting on ADD (top row of Table 1), and loadings on several control variables. The control variables are: Fama and French (2015) factors, the Carhart (1997), the first three principal components from our cross-section of anomaly factors, and the return-differential between the "high NET low absolute ADD" and "low NET low absolute ADD" portfolio ($NET_{\perp ADD}$). Our sample period is January 1990 to December 2021 and t-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	4.14	3.13	3.03	3.63	3.08	2.94	2.94
	[4.14]	[2.75]	[3.14]	[3.61]	[2.66]	[3.04]	[2.72]
MKT	-0.03	0.00			0.01		0.05
	[-1.26]	[0.15]			[0.39]		[1.51]
SMB		0.03			0.01		0.06
		[0.56]			[0.26]		[1.22]
HML		-0.02			-0.04		-0.08
		[-0.28]			[-0.62]		[-1.28]
RMW		0.01			-0.01		-0.07
		[0.11]			[-0.08]		[-0.8]
CMA		0.17			0.16		0.03
		[1.93]			[1.74]		[0.27]
MOM		0.04			0.03		-0.05
		[0.92]			[0.82]		[-1.25]
PC1			0.01			0.01	0.03
			[3.69]			[2.86]	[3.22]
PC2			0.00			0.01	0.01
			[0.64]			[0.93]	[0.54]
PC3			-0.03			-0.03	-0.03
			[-3.21]			[-3.02]	[-2.57]
$NET_{\perp ADD}$				0.06	0.05	0.03	0.03
				[2.47]	[1.62]	[1.20]	[1.09]
R^2	0.49	3.69	6.45	1.85	4.32	6.74	8.45

Table 3: Rank based weighting

This table reports average monthly annualized returns on portfolios formed by sorting on changes in the sum of ranks across anomalies. Specifically, each stock is ranked based on its beginning-of-month characteristic and we sum the ranks over the different anomaly-characteristics. The "Low" portfolio contains the stocks with the lowest change in the sum of ranks in the previous month. Similarly, the "High" portfolio contains the stocks with the largest change in the sum of ranks in the previous month. The column "High-Low" reports the difference in average monthly returns between the High and Low portfolios. Our sample period is January 1990 to December 2021 and *t*-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Low	2	3	4	High	High-Low
Change in sum of ranks	9.2	7.75	9.36	9.43	10.99	1.79
	[3.03]	[2.43]	[2.97]	[2.87]	[3.72]	[1.8]

Table 4: Anomaly-driven demand and short interest

This table reports average monthly changes in short interest for portfolios formed by sorting on anomaly-driven demand (top row), changes in the number of long-leg inclusions (middle row), and changes in short-leg inclusions (bottom row). The "Low" portfolio contains the stocks with the lowest anomaly-driven demand (top row), the lowest number of changes in long-leg inclusions (middle row), or the lowest number of changes in short-leg inclusions (bottom row). Similarly, the "High" portfolio contains the stocks with the highest anomaly-driven demand (top row), the highest number of changes in long-leg inclusions (middle row), or the highest number of changes in short-leg inclusions (bottom row). The column "High-Low" reports the difference in average short interest between the High and Low portfolios. Our sample period is January 2007 to December 2021 and *t*-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Low	2	3	4	High	High-Low
			Plain			
ADD	0.71	-1.04	-0.76	-1.14	-1.47	-2.19
	[0.6]	[-0.83]	[-0.66]	[-1.01]	[-1.33]	[-2.61]
Long	-0.34	-0.74	-0.93	-0.76	-1.27	-0.94
	[-0.34]	[-0.59]	[-0.76]	[-0.76]	[-1.16]	[-1.42]
Short	-1.59	-0.96	-0.71	-0.43	-0.53	1.05
	[-1.41]	[-0.79]	[-0.68]	[-0.39]	[-0.35]	[0.77]

Table 5: Anomaly-driven demand across size and liquidity

This table reports the average monthly return annualized differential between the "Low" and "High" from a bivariate sort. We first sort stocks into quintile portfolios based on the market cap (top panel) or the illiquidity measure of Amihud (2002) (bottom panel). Then within each quintile, stocks are sorted into quintile portfolios based on changes in the number of long-leg inclusions (first column), changes in the number of short-leg inclusions (middle column), or anomaly-driven demand (last column) and we report the return differential between the "High" and "Low" portfolios. For example, the combination Micro/ADD means that for the smallest stocks, the return differential between the portfolio containing stocks with high anomaly-driven demand and the portfolio containing the stocks with low anomaly-driven demand is 5.71%. Our sample period is January 1990 to December 2021 and *t*-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Long	Short	ADD
		Market cap/Size	
Micro	5.42	-3.14	5.71
	[4.63]	[-3.03]	[4.77]
2	3.38	-2.77	5.06
	[3.07]	[-2.48]	[4.59]
3	1.49	-1.19	1.55
	[1.19]	[-1.12]	[1.24]
4	2.5	-0.79	2.57
	[2.5]	[-0.69]	[2.19]
Mega	3.02	-2.76	2.73
	[2.8]	[-2.23]	[2.34]
		Illiquidity	
Most liquid	3.00	-2.56	3.47
	[2.53]	[-2.02]	[2.9]
2	2.93	-0.24	2.4
	[2.23]	[-0.22]	[1.8]
3	1.16	-2.45	1.92
	[1.05]	[-2.15]	[1.54]
4	3.23	-1.66	2.56
	[2.68]	[-0.86]	[1.09]
Most illiquid	5.65	-4.49	7.15
	[4.78]	[-3.13]	[4.5]

Table 6: Robustness: number of portfolios in portfolio sorts.

This table reports the average monthly annualized return differential between the portfolios with low and high anomaly-driven demand, using different numbers of portfolios for 1) Constructing our ADD proxy (columns) and 2) Sorting stocks based on their ADD (rows). For example 10 in the column and 3 in the rows means that for each anomaly characteristic stocks are sorted into decile portfolios for counting for calculating ADD. Then subsequently stocks are sorted into tercile portfolios based on ADD for estimating the arbitrageur rebalancing effect. Our sample period is January 1990 to December 2021 and *t*-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	3	5	10
3	3.64	3.16	2.48
	[4.45]	[4.04]	[2.30]
5	4.56	3.86	3.44
	[3.38]	[4.00]	[2.70]
10	4.62	5.45	3.60
	[3.77]	[4.46]	[3.05]

Table 7: Robustness: rebalancing frequency

This table reports average monthly annualized returns on portfolios formed by sorting on anomaly-driven demand (top row), changes in the number of long-leg inclusions (middle row), and changes in short-leg inclusions (bottom row). The "Low" portfolio contains the stocks with the lowest anomaly-driven demand (top row), the lowest number of changes in long-leg inclusions (middle row), or the lowest number of changes in short-leg inclusions (bottom row). Similarly, the "High" portfolio contains the stocks with the highest anomaly-driven demand (top row), the highest number of changes in long-leg inclusions (middle row), or the highest number of changes in short-leg inclusions (bottom row). The column "High-Low" reports the difference in average monthly returns between the High and Low portfolios. For these results, our proxy, ADD, is constructed using the rebalancing frequency of the original papers. Our sample period is January 1990 to December 2021 and t-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Low	2	3	4	High	High-Low
ADD	8.23	8.79	9.01	9.57	11.01	2.78
	[2.96]	[3.22]	[3.28]	[3.39]	[3.82]	[2.88]
Long	7.57	8.52	9.21	9.51	10.69	3.12
	[2.89]	[3.09]	[3.35]	[3.48]	[3.76]	[3.19]
Short	10.51	9.66	9.3	9.13	8.11	-2.41
	[3.66]	[3.44]	[3.33]	[3.35]	[2.90]	[-2.49]

Table 8: Quantile portfolios of stocks sorted by t-statistics scaled ADD

This table reports average monthly annualized returns on portfolios formed by sorting on anomaly-driven demand (top row), changes in the number of long-leg inclusions (middle row), and changes in short-leg inclusions (bottom row). The "Low" portfolio contains the stocks with the lowest anomaly-driven demand (top row), the lowest number of changes in long-leg inclusions (middle row), or the lowest number of changes in short-leg inclusions (bottom row). Similarly, the "High" portfolio contains the stocks with the highest anomaly-driven demand (top row), the highest number of changes in long-leg inclusions (middle row), or the highest number of changes in short-leg inclusions (bottom row). The column "High-Low" reports the difference in average monthly returns between the High and Low portfolios. For these results, our proxy, ADD, has been constructed by scaling the indicator function in Equation (9) with the t-statistic of the original paper. Our sample period is January 1990 to December 2021 and t-statistics calculated using Newey and West (1994) standard errors with six lags are provided in brackets.

	Low	2	3	4	High	High-Low
ADD-scaled	7	8.04	9.89	10.54	11.67	4.67
	[2.44]	[2.71]	[3.6]	[4.01]	[4.12]	[4.11]
Long-scaled	7.18	7.93	9.89	10.06	11.29	4.1
	[2.49]	[2.7]	[3.48]	[3.82]	[4]	[3.7]
Short-scaled	10.26	9.92	10	9.57	7.41	-2.84
	[3.56]	[3.72]	[3.82]	[3.59]	[2.4]	[-2.41]

Figure 1: Past performance portfolio sort

This figure illustrates the portfolio sort for constructing a momentum factor. At rebalancing, stocks are sorted into quintile portfolios based on their pased performance; the bottom quintile contains the stocks with worst past performance ("Losers"), while the top quintile contains the stocks with best past performance ("winners"), shown i Panel (a). At the next rebalancing, as the past performance is updated, stocks will be reallocated between quintile portfolios, shown in Panel (b). The stocks "U", "Q", "J" are no longer in the Winners, while stocks "T", "G", "O" are now in the Winners portfolio. Similarly, the stocks "X", "Z", "B" are no longer in the Losers, while the stocks "U", "N", "I" are now in the losers portfolio.

(a) Quintile portfolios pre-performance update

(b) Quintile portfolios post-performance update

Figure 2: Number of anomalies in dataset

This figure shows the number of anomaly characteristics in our dataset. Our sample period is January 1990 to December 2021 and anomaly characteristics are obtained from Chen and Zimmermann (2021).

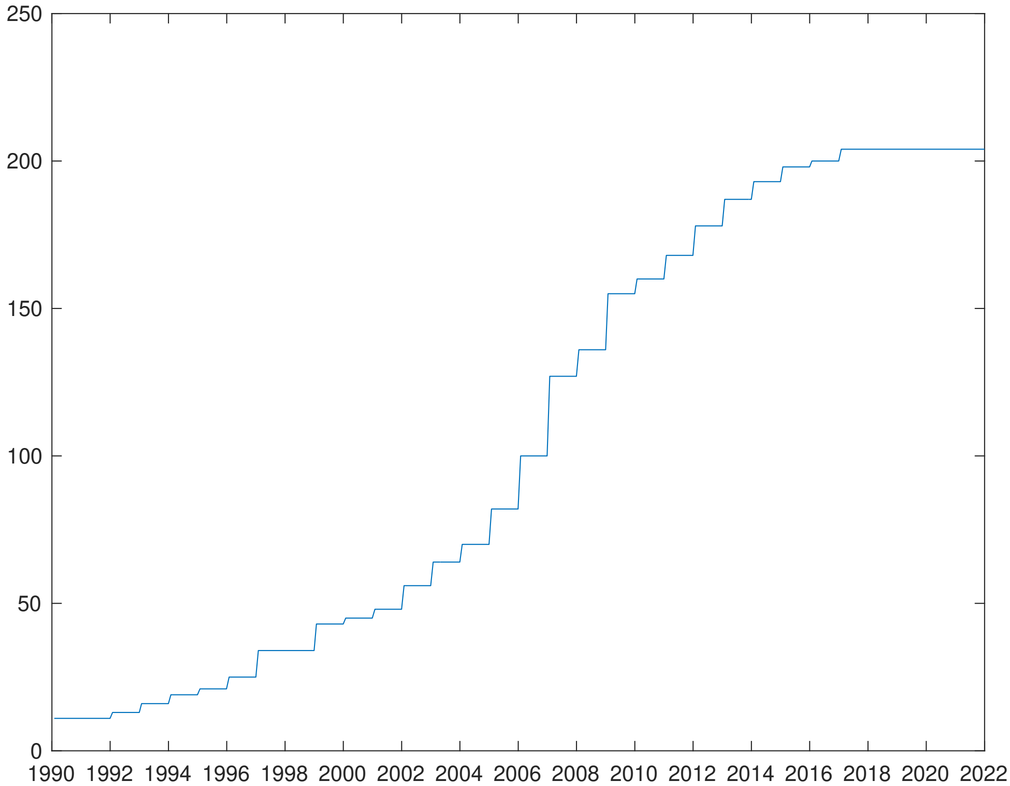


Figure 3: Cumulative return differential between High and Low portfolios.
This figure shows the cumulative annualized return differential betwen the Low and High portfolios from sorting on ADD (blue), changes in the number long-leg inclusions (orange), and changes in the number of short-leg inclusions (green). Our sample period is January 1990 to December 2021.

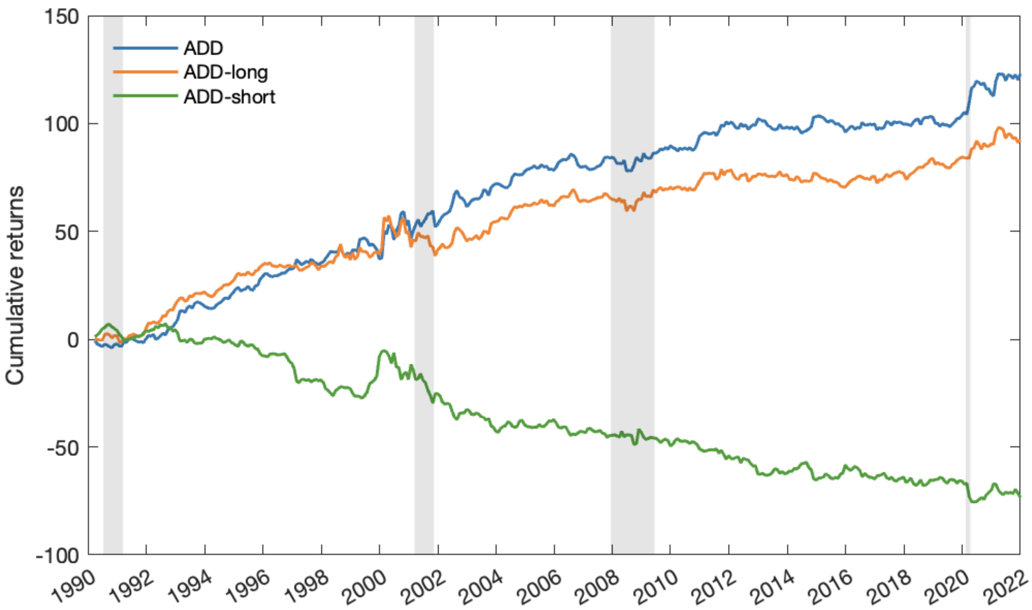
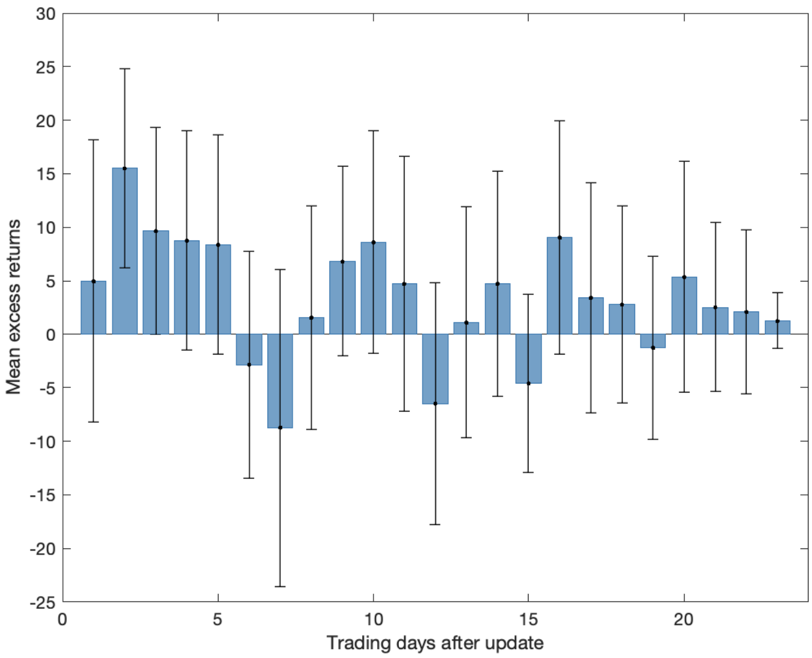


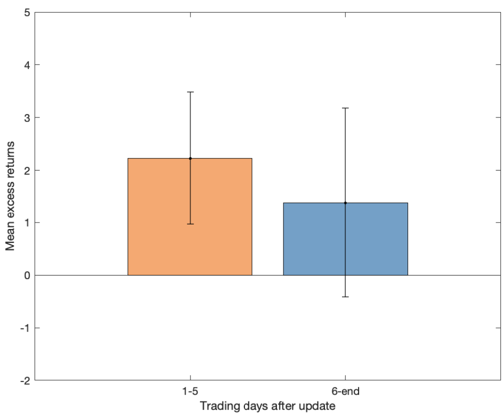
Figure 4: Intra-monthly return pattern of High-Low portfolio.

This figure shows the intra-monthly annualized return differential between low- and high ADD stocks. Panel (a) shows the average daily return differential, Panel (b) shows the return differential over the first week, and the remainder of the month, and Panel (c) shows the average reurn differential of the month's first trading day, following a characteristics update, across the five different weekdays (i.e., Monday, Tuesday, ...). Our sample period is January 1990 to December 2021.

(a) Daily return differential



(b) First week vs. remainder of the month



(c) First trading day