NBER WORKING PAPER SERIES

A TAXONOMY OF ANOMALIES AND THEIR TRADING COSTS

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Working Paper 20721
http://www.nber.org/papers/w20721

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2014

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NBER Working Paper No. 20721
December 2014
JEL No. G12,G14

ABSTRACT

This paper studies the performance of a large number of anomalies after accounting for transaction costs, and the effectiveness of several transaction cost mitigation strategies. It finds that introducing a buy/hold spread, which allows investors to continue to hold stocks that they would not actively trade into, is the single most effective simple cost mitigation strategy. Most of the anomalies that we consider with one-sided monthly turnover lower than 50% continue to generate statistically significant net spreads, at least when designed to mitigate transaction costs. Few of the strategies with higher turnover do. In all cases transaction costs reduce the strategies' profitability and its associated statistical significance, increasing concerns related to data snooping.

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1. Introduction

This paper provides a taxonomy of the most important anomalies, and calculates the cost of trading each strategy. It also studies several simple transaction cost mitigation techniques, and shows that while transaction costs dramatically reduce the profitability of many anomalies, especially those with high turnover, designing strategies to minimize transaction costs significantly reduces these costs. It also shows that equal-weighted portfolio results, popular in the academic literature because they frequently provide stronger results than value-weighted results, are misleading and should be viewed skeptically. Because equal-weighted strategies are more expensive to trade, equal-weighting often results in a deterioration of net performance.

Over the last 30 years academic researchers have documented hundreds of cross-sectional “anomalies," a term which has come to mean size, value, momentum, and any other strategy that generates a significant positive alpha relative to a four-factor model that accounts for these first three. The incentives to find these strategies are high both within academia (publications and tenure) and on the street (a marketable story and a bigger paycheck). This raises significant data snooping concerns. Harvey et al. (2014) argue on econometric grounds that three should be the new two for t-stats, and conclude that “most claimed research findings in financial economics are likely false.” This paper ignores transaction costs, however, meaning that even the spreads reported in the literature often dramatically overstate the profitability of attempting to trade these strategies.

McLean and Pontiff (2014) study the post-publication performance of 82 anomalies and find average post-publication performance decay of 35%. They attribute less than a third of this decay to statistical bias, and the rest to price pressure by newly aware investors, arguing that their results are “consistent with costly (limited) arbitrage,” because post-publication return declines are more pronounced for strategies that disproportionately take positions in stocks that are easier to trade.

Limits to arbitrage are important for addressing questions related to market efficiency. Market anomalies are often used as potential evidence against efficiency. We generally believe that markets should be fairly efficient because of the forces of arbitrage, however, and these so called anomalies do not test market efficiency if they should not attract arbitrage capital because they are not actually profitable to trade. In this case they may indicate suboptimal behavior on the part of some individual traders, but they are not suggestive of aggregate mispricing.

Several authors have studied the limits trading costs impose when implementing momentum strategies. Lesmond et al. (2004) argue that while the large gross spreads observed on momentum trades create an "illusion of profit opportunity when, in fact, none exists." Korajczyk and Sadka (2004) consider the price impact of trading momentum, and conclude that it would only be profitable to trade on a very small scale. These papers do not, however, study momentum strategies designed to minimize transaction costs. More recently Frazzini et al. (2014) have argued that "actual trading costs are less than a tenth as large as, and therefore the potential scale of these strategies is more than an order of magnitude larger than, previous studies suggest," and conclude that the strategy is "robust [and] implementable," but their study is conducted using proprietary data that covers a relatively short time-series, limited to larger stocks. No studies provide a comprehensive analysis of the cost of trading more than a few of the known anomalies, especially over longer horizons or using the entire cross-section of stocks.

We consider a large array of well known anomalies, evaluating their after transaction cost performance over long horizons and across different types of stocks. In order to do this we develop a new performance metric. This measure agrees with common notions of alpha when trading is frictionless, but provides unambiguous information about the extent to which an asset improves the investment opportunity set, something about which the common notion of alpha can be misleading in the presence of trading frictions.

We also evaluate three simple strategies for reducing transaction costs: limiting trading to low expected transaction costs stocks, reduced rebalancing frequencies, and the use of a buy/hold spread that lowers turnover by introducing trading hysteresis. We find that for most of the anomalies we consider the buy/hold spread is the most effective cost mitigation technique, though for very high turnover strategies, for which transaction cost mitigation is most important, a combination of all three techniques yields greater performance enhancements.

Round trip transaction costs for typical value-weighted strategies average in excess of 50 bps, and though these have fallen over the last decade they can be significantly higher for strategies that take disproportionately in high transaction cost stocks such as the anomalies based on idiosyncratic volatility or distress. Transaction costs consequently generally reduce realized spreads by more than 1% of the monthly one-sided turnover, i.e., if the long side of a strategy turns over 20% per month, the realized long/short spread will be at least 20 bps per month lower than the gross spread, and the statistical significance of the spread will be reduced proportionately. Transaction costs for equal-weighted strategies are generally two to three times as high, and often less profitable to actually implement. While many of the strategies that we study remain significantly profitable after accounting for transaction costs, only two of the strategies that have more than 50% one-sided monthly turnover have significant net spreads, even when these strategies are designed with trading costs mitigation in mind. In all cases transaction costs significantly reduce the anomalies profitability, and its significance. This greatly increases concerns related to data snooping, as while many of the strategies' net excess returns remain significant at the t-stat greater than two level, far fewer of the strategies generate net excess spreads with t-stats greater than three.

The rest of the paper is organized as follows. Section 2 describes our trading cost model. Section 3 describes our generalized alpha performance metric. Section 4 provides our taxonomy of anomalies, and the cost of trading these. Section 5 considers three simple techniques for transaction cost mitigation, and shows that these can significantly reduce trading costs. Section 6 considers an alternative mitigation technique available to an investor already trading one anomaly: using the turnover generated by that strategy to opportunistically take small positions in another anomaly at negative effective transaction costs. Section 7 investigates anomaly trading costs in different segments of the market by capitalization. Section 8 concludes.

2. Trading Cost Model

When evaluating anomaly performance we calculate transactions costs using the effective bid-ask spread measure proposed by Hasbrouck (2009). These costs are estimated using a Bayesian Gibbs sampler on a generalized Roll (1984) model of stock price dynamics. Roll's model can be formally defined as:

$$\begin{aligned} V_t &= V_{t-1} + \varepsilon_t \\ P_t &= V_t + cQ_t \end{aligned}$$

where V_t is the underlying "efficient value" (the log quote midpoint prevailing prior to trade t), P_t is the observed trade price, Q_t is a random indicator for the direction of the trade that takes the value one (minus one) if the trade took place at the ask (bid), ε_t is a random disturbance reflecting public information about the stock, and c is the effective cost of trading. The previous equations imply that

$$\Delta P_t = c\Delta Q_t + \varepsilon_t,$$

which yields $c = \sqrt{-\mathrm{Cov}(\Delta P_t, \Delta P_{t+1})}$. Earlier empirical studies used the sample autocovariances of daily price changes to estimate transactions costs but, as noted by Hasbrouck (2009) and discussed in detail by Harris (1990), such an estimation is infeasible due to the relatively high proportion of positive autocoviarances between daily changes in stock prices in the data. Hasbrouck (2009) instead advocates a Bayesian approach to estimating the cost measure. He generalizes the previous equation to include a market return factor,

$$\Delta P_t = c\Delta Q_t + \beta_m r_{mt} + \varepsilon_t,$$

and assumes $\varepsilon_t \sim i.i.d. N(0, \sigma_\varepsilon^2)$. Then, given the history of price data and additional assumptions about initial values and prior distributions for the unknowns $\{c, \sigma_\varepsilon^2, Q_1, ..., Q_T\}$, he draws sequentially the parameter estimates using a Gibbs sampler to characterize the posterior densities. Hasbrouck (2009) shows that effective spreads estimated using this procedure have a 96.5% correlation with the ones estimated from actual trades from the trade and quote (TAQ) dataset.

The effective bid/ask spread has limitations. It does not account for the price impact of large trades, and should thus be interpreted as the costs faced by a small liquidity demander. While it ignores this important concern for large institutional traders it is nevertheless conservative, because it assumes market orders. It is also the appropriate measure for questions related to market efficiency, which depend on the marginal profitability of a strategy for an arbitrageur considering directing capital to the trade.

This measure has other significant advantages. It is easy to estimate for all stocks over the entire sample using publicly available information.[1] This contrasts with estimates from the TAQ data or proprietary trade execution datasets, which are limited in their coverage, difficult to extrapolate due to the nonlinear and time varying nature of transaction costs, and harder to obtain.[2]

Figure 1 shows cross-sectional and time-series variation in trading costs, by looking at the estimated median effective spreads of the largest 2,000 firms by decade. Not surprisingly it shows that smaller cap stock are more expensive to trade. It also shows

[1] Hasbrouck provides SAS code for estimating effective spreads using the procedure at http://people.stern.nyu.edu/jhasbrou/.

[2] Korajczyk and Sadka (2004), Lesmond et al. (2004), and Chen et al. (2005) use TAQ data to estimate spreads and price impacts. Keim and Madhavan (1997), Engle et al. (2012), and Frazzini et al. (2014) use proprietary trade datasets.

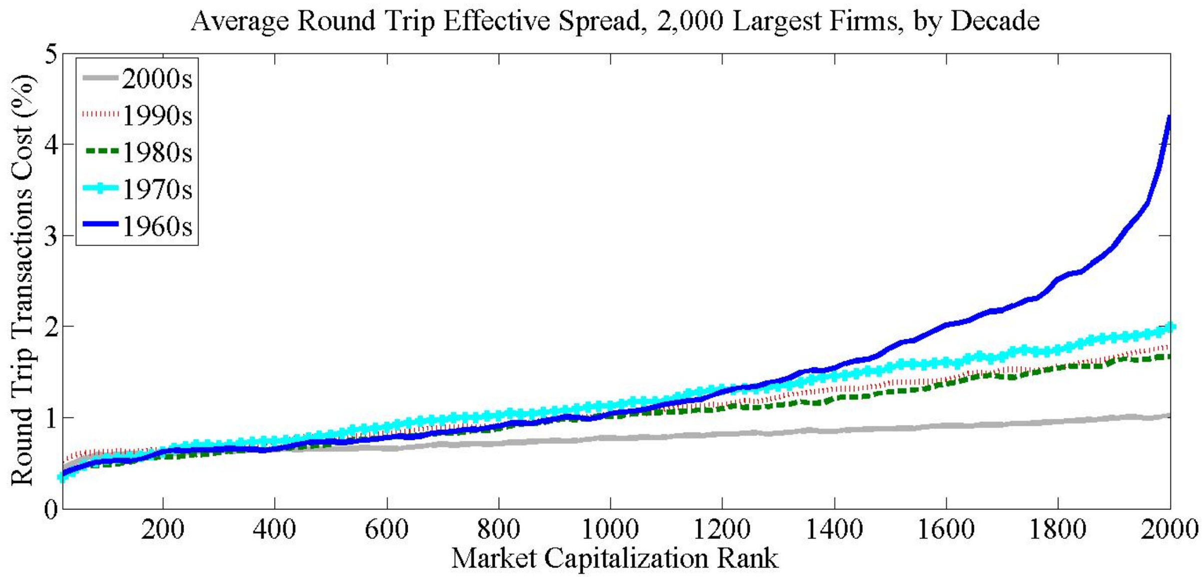


Figure 1: Median effective spreads across market capitalization ranks

a general trend towards lower costs over time, and a dramatic reduction in the cost of trading stocks outside the mega-cap universe over the last decade.

Table 1 examines the transaction cost estimates in greater detail. It reports Fama-MacBeth cross-sectional regressions of the trading costs estimates on firm characteristics. We can see that the trading costs are persistent and significantly positively associated with idiosyncratic volatility. As expected, size is strongly negatively correlated with transaction costs in the cross section, but the effect is non-linear. The coefficient on the squared market cap variable is positive and significant, implying a convex relation between trading costs and size. More generally, nonlinearities make it difficult to parametrically estimate costs accurately using directly observable firm characteristics. Table 14 in Appendix A.2 highlights the danger of extrapolating transaction costs estimated on large, relatively liquid stocks to small stocks using a linear model. It reports results from similar regressions performed on firms with above (panel A) and below (panel B) NYSE median market capitalization, and shows dissimilar parameter estimates for the two groups.

The Bayesian/Gibbs estimation technique requires relatively long strings of re-

Table 1: Determinants of transaction costs

The table reports results from Fama-MacBeth regressions of trading cost estimates on lagged trading costs, market capitalization, and idiosyncratic volatility. The trading costs consist of the effective bid-ask spread measure proposed by Hasbrouck (2009). Idiosyncratic volatility is measured as the standard deviation of residuals of past three months' daily returns on the daily excess market return. Both market capitalization and idiosyncratic volatility use end of July values. The regressions are estimated on an annual frequency and cover 1963 through 2013.

Lagged T-costs	0.96					0.47
	[25.7]					[21.1]
log(ME)/100		-0.41	-1.40		-0.86	-0.59
		[-12.2]	[-12.4]		[-12.6]	[-10.8]
$[\log(ME)]^2/100$			0.10		0.07	0.05
			[12.2]		[13.0]	[10.9]
Idiosyncratic Volatility				0.62	0.43	0.25
				[16.8]	[13.8]	[10.0]
Average $\hat{R}^2$ (%)	62.7	38.3	50.4	55.0	65.0	72.2

ported daily returns, which results, especially in the early part of our sample, in a substantial number of missing monthly and annual observations, the rebalance frequency for most of the trading strategies we consider. We are interested in the cost of trading anomalies, and cannot know ex ante at the time of portfolio formation if the trading cost estimate for any given stock will be missing ex post, and thus cannot limit our trading to stocks for which the direct estimates of trading costs are available. We consequently need a method for estimating trading costs when the direct estimates from the Baysian-Gibbs sampler is unavailable. Because of the the difficulties associated with fitting transaction costs to a linear model observed in Table 1, we use a non-parametric matching method. The high observed cross sectional correlations between transaction costs and size and idiosyncratic volatility lead us to match on these characteristics. Specifically, in each month we rank all firms on market equity and estimated idiosyncratic volatility. Each missing transaction cost observation is then replaced with the estimated cost of trading the nearest match stock for which a direct trading cost estimate is available. The closest match is defined by the shortest Euclidean distance in size and idiosyncratic volatility rank space, i.e., where the distance between firms i and j equals $\sqrt{\left(\text{rankME}_i - \text{rankME}_j\right)^2 + \left(\text{rankIVOL}_i - \text{rankIVOL}_j\right)^2}$. This methodology adds a time series average of 29% to the total number of observations, though these additional observations account on average for less than 4% of market capitalization.

Figure 2 shows the estimated monthly 12-month moving average cost of trading momentum and post earnings announcement drift (PEAD) strategies, using directly estimated transaction costs (solid lines) and transaction costs estimates obtained through the matching procedure (dashed lines), on the sample for which we have direct trading costs estimates.[3] Strategies are long and short the highest and lowest deciles, using NYSE breaks, of sorts on stock market performance over the first eleven

[3] These strategies are not actually implementable, as the direct trading cost estimates require data that are not available at the time of portfolio formation. We restricted the sample here to stocks for which we have direct trading costs estimates in order to facilitate the comparison of the estimates obtained through the matching procedure to those estimated directly.

months of the year prior to portfolio formation (momentum) and the change in earnings per share between the last quarterly earnings announcement and the the earnings announcement one year earlier, scaled by the standard deviation in earnings per share over the last eight quarters (PEAD).

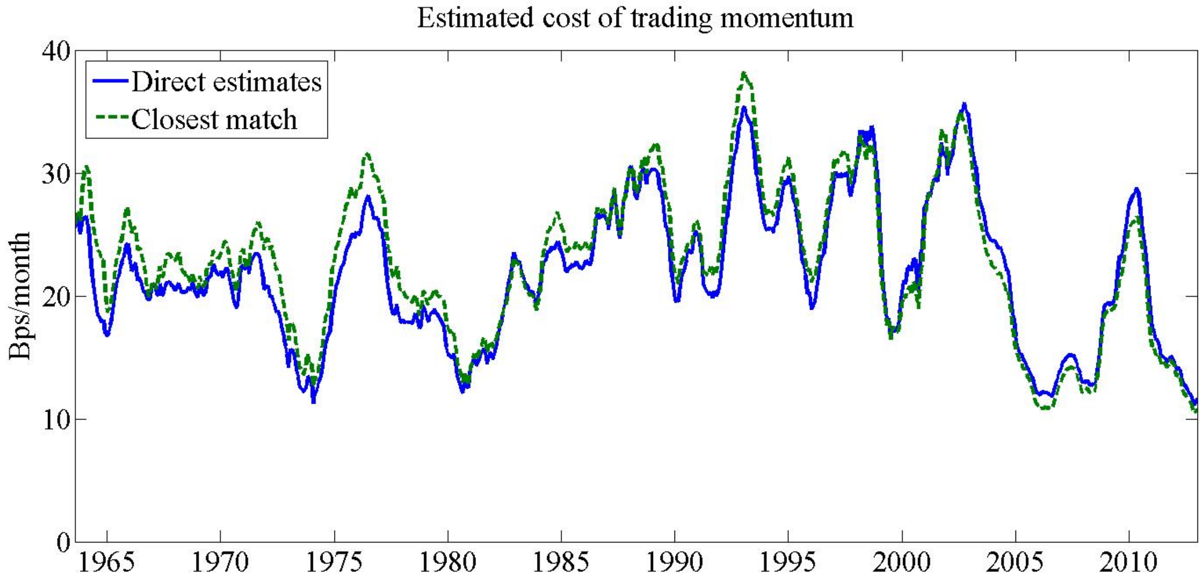
The figure shows that the matching procedure yields similar costs of trading momentum and PEAD as the direct estimates, with no obvious biases in either direction. Both strategies show similar time-series variation in trading costs using estimates obtained through the two different procedures, and in both cases the difference in the estimated monthly transaction costs averages less than one basis point per month. For the remainder of the paper we consequently use the trading costs estimates obtained through the matching procedure to fill the 4% of market capitalization for which we are missing direct estimates.

3. Performance evaluation

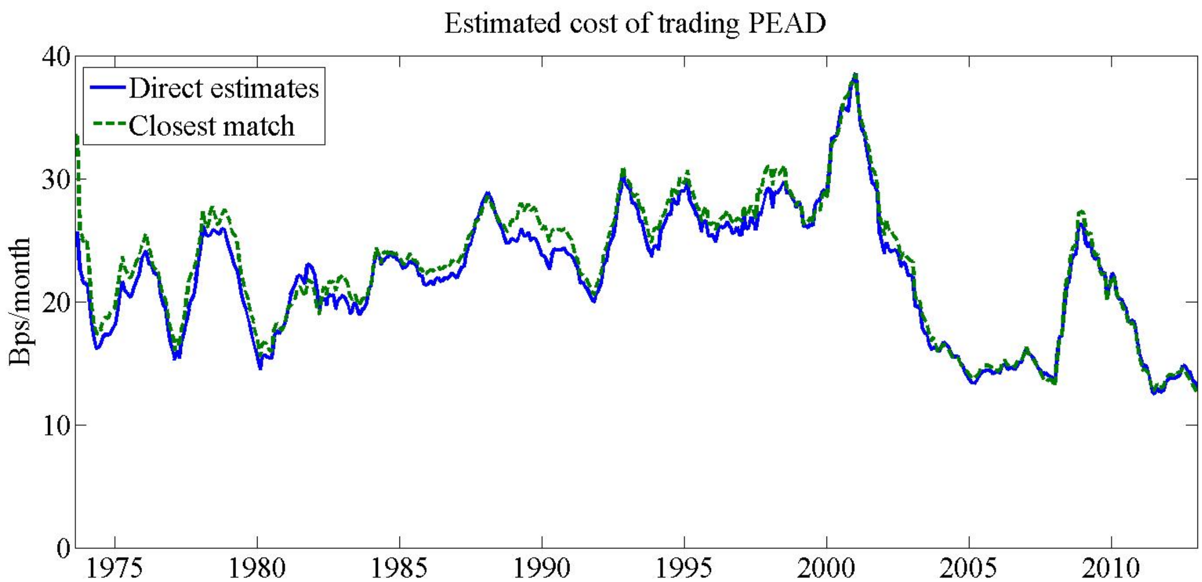
We are interested in whether anomalies documented in the literature are "real," both in the sense that they generate significant excess returns after accounting for transaction costs, and that they are distinct from the most studied anomalies, value and momentum. Indeed, anomalies other than value or momentum are essentially defined as those strategies that have generated significant abnormal returns relative to the Fama-French four-factor model.

In the presence of transaction costs evaluating performance against the standard four-factor model is complicated by two issues. First, the Fama-French factors are gross factors, i.e., do not themselves account for transactions costs. They consequently overstate the returns an investor could have realized, especially in the case of the momentum factor UMD.

The second issue is more subtle, and related to the very notion of performance evaluation. Evaluating anomaly performance against the four-factor pricing model



(a)



(b)

Figure 2: Comparison of transaction cost estimates: direct versus matched

The figure reports estimated monthly 12-month moving average cost of trading momentum and post earnings announcement drift (PEAD) strategies, using directly estimated transaction costs (solid lines) and transaction costs estimates obtained through a matching procedure (dashed lines). For the matching procedure, each trading cost estimate is replaced by its closest match, defined as the shortest Euclidean distance in size and idiosyncratic volatility rank space, i.e., where the distance between firms i and j equals $\sqrt{(\text{rankME}_i - \text{rankME}_j)^2 + (\text{rankIVOL}_i - \text{rankIVOL}_j)^2}$. The sample covers stocks for which we have direct trading costs estimates.

requires a metric of performance. The metric most commonly employed is "alpha," an asset's abnormal returns relative to a set of potential explanatory assets. Alpha is defined as the average return to the part of a test strategy not spanned by the explanatory assets, i.e., the average active return benchmarked against the replicating portfolio of explanatory assets. Alpha, and in particular its significance, is important because it answers, at least in a frictionless world, the question "would the test asset have improved the investment opportunity set of an investor already trading the explanatory assets?"

In the presence of trading costs, however, alpha does not unambiguously answer this question. A strategy can have a significant positive alpha relative to the explanatory assets without significantly improving the investment opportunity set. This is most easily seen by example. Suppose an investor has access to a strategy that generates insignificant excess returns. Now suppose the investor gains access to a new highly correlated strategy that generates slightly higher returns. This new strategy itself generates insignificant excess returns, but will nevertheless have a highly significant alpha relative to the original set strategy. In fact, in a frictionless world the introduction of this asset could theoretically improve the Sharpe ratio available to the investor by a factor of ten, or a hundred–a long position in the higher return asset hedged with a short position in the highly correlated lower return asset could have an extremely high Sharpe ratio. In the real world, however, the introduction of this asset may hardly improve the investment opportunity set. Trading costs can easily exceed the small spread generated by pairs trading the two assets, in which case the investor would just switch out of the old strategy into the new, with essentially no impact on the available Sharpe ratio.

These issues are important here. We are evaluating anomaly performance explicitly accounting for the cost of trading, and many of the anomalies we consider have high correlations with the explanatory factors we employ, particularly with HML and UMD, the Fama and French (1993) value factor and their version of the Carhart (1997) momentum factor. We consequently prefer a generalized notion of alpha, which both agrees with the common notion of alpha when trading is frictionless and unambiguously answers the question "does the test asset improve the investment opportunity set of an investor with access to the explanatory assets?"

3.1. Factor trading costs

Figure 3 shows the estimated 12-month moving average cost of trading the Fama/French size, value and momentum factors (SMB, HML and UMD, respectively) each month, over the period spanning July 1963 through December 2013. SMB and HML incur similar trading costs, because they are constructed using the same two-way cut on size (NYSE median market capitalization) and three-way cut on book-to-market (30 and 70 percentiles using NYSE break points). These factors' underlying portfolios are only rebalanced annually, and both size and book-to-market are fairly persistent, so turnover is fairly low and transaction costs are modest. Over the sample SMB and HML on average only turn over 2.32% and 1.99% and per year. The time-series average cost of trading these factors is 5.66 and 5.45 basis points per month, and the 12-month moving averages are constant over one year periods because the strategies are only rebalanced annually. UMD, which is constructed using the same two-way cut on size and a tertile sort of stock performance over the first eleven months of the prior year, is rebalanced monthly and incurs much higher transaction costs. Over the sample UMD turns over 24.64% per year, and its time-series average cost of trading is 48.39 basis points per month. The figure shows the Sharpe downward trend in trading costs after 2000, and spikes in trading cost over periods of market stress (e.g., OPEC oil crisis in 1973, Nasdaq deflation in 2001, and the great recession in 2008).

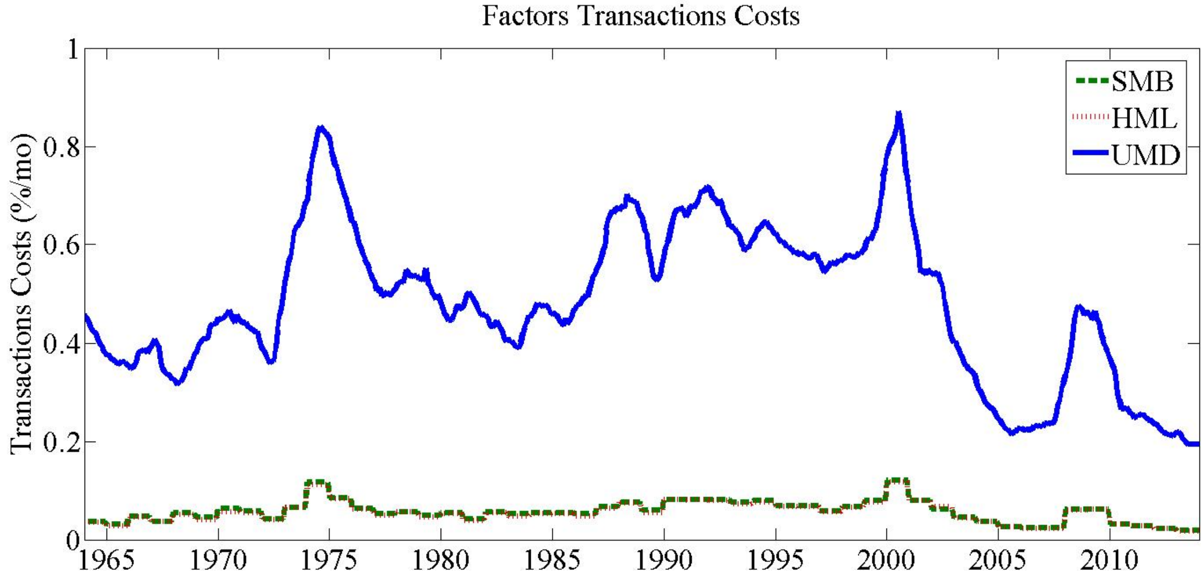


Figure 3: Transactions Costs for Fama-French Factors over Time
The figure reports the estimated 12-month moving average cost of trading the Fama and French (1993) size, value and momentum factors (SMB, HML and UMD, respectively) each month, over the period spanning July 1963 through December 2013.

3.2 Performance metric: a generalized alpha

Our generalized notion of alpha is simplified by letting $y \perp X \equiv y - X(X'X)^{-1}X'y$ denote the part of the test asset y not spanned by the explanatory assets X, MVE_X denote the ex post mean variance efficient portfolio of the assets X, $w_{y,\text{MVE}_{\{X,y\}}}$ be the weight on y in $\text{MVE}_{\{X,y\}}$, and temporarily ignoring transaction costs. Then $\text{MVE}_{\{X,y\perp X\}} = \text{MVE}_{\{X,y\}}$, so

$$\begin{aligned}
\text{MVE}_{\{X,y\}} \perp \text{MVE}_X &= \text{MVE}_{\{X,y\perp X\}} \perp \text{MVE}_X \\
&= \text{MVE}_{\{X,y\perp X\}} \perp X \\
&= \text{MVE}_{\{X,y\}} \perp X \\
&= w_{y,\text{MVE}_{\{X,y\}}}\, y \perp X.
\end{aligned}$$

The first and third equalities follow from the equivalence of $\text{MVE}_{\{X,y\}}$ and $\text{MVE}_{\{X,y\perp X\}}$. The second equality holds because $\text{MVE}_{\{X,y\perp X\}}$ is a convex combination of MVE_X and

$y \perp X$, and X spans MVE_X while $y \perp X$ is orthogonal to X.

Dividing by $w_{y,\text{MVE}_{\{X,y\}}}$ and taking the average yields our generalized notion of α,

$$\alpha^* \equiv w^{-1}_{y,\text{MVE}_{\{X,y\}}} \overline{\text{MVE}_{\{X,y\}} \perp \text{MVE}_X}. \tag{1}$$

When trading is frictionless this reduces to the common definition of α, the average return to the part of the test strategy not spanned by the explanatory strategy. More generally α^* can be interpreted as the average return to the highest Sharpe ratio portfolio of the test asset and the explanatory assets that has a one dollar position in the test asset, beta adjusted for the highest Sharpe ratio portfolio of the explanatory assets. It thus provides information about how much better the investor can do with access to the test strategy, and thus about how the test asset improves the investment opportunity frontier. This interpretation is valid even when trading is costly. Our generalized notion of alpha can yield substantially different inferences than the common notion, particularly when the test asset would not be held either long or short in the MVE portfolio, or when access to the test asset pushes one or more of the explanatory assets out of the MVE portfolio.[4]

[4] The notion employed here is closely related to, but distinct from, that proposed by Grinblatt and Titman (1989) and employed by Hanna and Ready (2005) to evaluate the stock selection strategy proposed by Haugen and Baker (1996). These authors evaluate performance using the average return to the part of the test asset itself that is not spanned by the MVE portfolio of the explanatory assets. To see the relation between this notion and ours, let $y||X \equiv X(X'X)^{-1}X'y$ denote the part of y spanned by X. Then $y = y \perp X + y||X$, so

$$y \perp \text{MVE}_X = y \perp X + (y||X) \perp \text{MVE}_X,$$

where we have used the fact that the part of y that is orthogonal to X is orthogonal to the MVE portfolio of X. The part of y not spanned by the MVE portfolio of X thus differs from the part of y not spanned by X by the part of the projection of y onto X not spanned by the MVE portfolio of X, a mean-zero series uncorrelated with $y \perp X$. This metric, the test asset's average returns not explained by the MVE portfolio of the explanatory assets, thus provides the same alpha estimate as the common methodology. This notion of alpha can again however yield misleading inferences regarding whether the test asset improves the investment opportunity set when the test asset would not be held either long or short in the MVE portfolio, or when access to the test asset pushes one or more of the explanatory assets out of the MVE portfolio.

4. Simple Strategies

Equipped with our transactions costs measures and a generalized notion of alpha, we next study the behavior of popular asset pricing anomalies accounting for costs of trading. Our first goal is to establish a taxonomy of anomalies in the cross-section of expected stock returns. Focusing on the economics of the underlying problems, researchers often compare the behavior of strategies whose implementability differs substantially. For example, Jegadeesh and Titman (1993) study momentum and short-term reversal portfolios rebalanced each month. Fama and French (1993), on the other hand, look at size and value portfolios that are only rebalanced annually. Clearly, size and value are much cheaper to trade. Moreover, even though both momentum and reversals are rebalanced monthly, prior year's performance is far more persistent than prior month's performance, resulting in turnover on the short-term reversal strategy almost three times as high as on momentum.

Table 2 reports the twenty-three anomalies that we examine. In our taxonomy we group trading strategies into three groups, low-, mid-, and high-turnover strategies, corresponding roughly to strategies where each the long and short side on average turnover less than once per year, between one and five times per year, and more than five times per year, respectively. The table includes references to the studies that first document them, brief descriptions of the sorting variable used, the frequency of rebalancing, and the starting year. For additional details on the construction of the signals, see Appendix A.1.

Table 2: The anomalies

All strategies consist of a time-series of value-weighted returns on a long/short self-financing portfolio, constructed using a decile sort on a signal using NYSE breakpoints. Column 2 indicates the relevant reference, column 3 reports the signal used for sorting. The last two columns indicate the frequency of rebalancing and the time-period used (07/1963 - 12/2012 for the full period and 07/1973 to 12/2012 for the recent one). See the appendix and/or the references for further details on the construction.

Panel A: Low Turnover

Anomaly	Reference(s)	Signal	Rebal.	Period
Size	Fama and French (1993)	Market equity	Annual	1963
Gross Profitability	Novy-Marx (2013)	Gross Profitability	Annual	1963
Value	Fama and French (1993)	Book-to-market equity	Annual	1963
ValProf	Novy-Marx (2014)	Sum of firms' ranks in univariate sorts on book-to-market and gross profitability	Annual	1963
Accruals	Sloan (1996)	Accruals	Annual	1963
Asset Growth	Cooper et al. (2008)	Asset Growth	Annual	1963
Investment	Lyandres et al. (2008)	Investment	Annual	1963
Piotroski's F-score	Piotroski (2000)	Piotroski's F-score	Annual	1963

Panel B: Mid Turnover

Anomaly	Reference(s)	Signal	Rebal.	Period
Net Issuance (M)	Fama and French (2008)	Net stock issuance	Monthly	1973
Return-on-book equity	Chen et al. (2010)	Return-on-book equity	Monthly	1973
Failure Probability	Campbell et al. (2008)	Failure Probability	Monthly	1973
ValMomProf	Novy-Marx (2014)	Sum of firms' ranks in univariate sorts on book-to-market, gross profitability, and momentum	Monthly	1963
ValMom	Novy-Marx (2014)	Sum of firms' ranks in univariate sorts on book-to-market and momentum	Monthly	1963
Idiosyncratic Volatility	Ang et al. (2006)	Idiosyncratic volatility, measured as the residuals of regressions of their past three months' daily returns on the daily returns of the Fama-French three factors	Monthly	1963
Momentum	Jegadeesh and Titman (1993)	Prior year's stock performance excluding the most recent month	Monthly	1963
PEAD (SUE)	Foster et al. (1984)	Standardized Unexpected Earnings (SUE)	Monthly	1973
PEAD (CAR3)	Brandt et al. (2008)	Cumulative three-day abnormal return around announcement (days minus one to one)	Monthly	1973

Table 2:
Continued

Panel C: High Turnover

Anomaly	Reference(s)	Signal	Rebal.	Period
Industry Momentum	Moskowitz and Grinblatt (1999)	Industry past month's return	Monthly	1963
Industry Relative Reversals	Da et al. (2014) and Linnainmaa et al. (2014)	Difference between a firm's prior month's return and the prior month's return of their industry	Monthly	1963
High-frequency Combo		Sum of firms' ranks in the univariate sorts on industry relative reversals and industry momentum	Monthly	1963
Short-run Reversals	Jegadeesh and Titman (1993)	Prior month's returns	Monthly	1963
Seasonality	Heston and Sadka (2011)	Average return in the calendar month over the preceding five years	Monthly	1963
Industry Relative Reversals (Low Volatility)	Linnainmaa et al. (2014)	Industry relative reversals, restricted to stocks with idiosyncratic volatility lower than the NYSE median for the month	Monthly	1963

4.1. Basic strategies

Table 3 reports time-series regression results for the twenty-three strategies, constructed using the simple decile sorting procedure popular in the academic literature, split into the three bins, low- (Panel A), mid- (Panel B), and high- (Panel C) turnover. In each panel we report the gross average monthly returns of the strategy (column 1), these returns four-factor alpha (column 2), monthly average turnover of each side of the strategy (column 3) and transactions costs (column 4), net return (column 5), and the generalized alpha described in subsection 3.2 of the net returns relative to the four factors (column 6).

The cost of trading the low turnover strategies is generally quite low, often less than 10 bp per month, primarily because all of them are constructed using annual rebalancing. Because transactions costs generally represent a small fraction of these strategies' gross spreads, we focus on the mid- and high-turnover strategies when we consider transaction cost mitigation techniques.

The mid-turnover strategies on the other hand exhibit sizable transactions costs. These are all rebalanced monthly, and have average turnover on each of the long and the short side of between 14% and 35% per month. Trading costs average between 20 bp and 57 bp per month, often exceeding half the strategies' gross spreads. In fact, only the net issuance, earnings momentum strategy based on cumulative abnormal three day return around the prior earnings announcement, and momentum and its derivative anomalies, achieve net excess returns that are statistically significantly larger than zero. The best performing strategy is the one sorted on the basis of

Table 3: Value-weighted returns
This table presents results for returns on value-weighted long/short self-financing portfolios, constructed using a decile sort on a signal using NYSE breakpoints. Panel A presents results for low turnover strategies, panel B reports the results for mid-turnover strategies, while panel C focuses on the high-turnover strategies. In each panel, the strategies' gross excess return, alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, and the net four-factor alpha are presented. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Panel A: Low turnover strategies

Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$
Size	0.33	-0.14	1.23	0.04	0.28	
	[1.66]	[-1.77]			[1.44]	
Gross Profitability	0.40	0.52	1.96	0.03	0.37	0.51
	[2.94]	[3.83]			[2.74]	[3.77]
Value	0.47	-0.17	2.91	0.05	0.42	-0.02
	[2.68]	[-1.76]			[2.39]	[-0.17]
ValProf	0.82	0.50	2.94	0.06	0.77	0.49
	[5.18]	[4.01]			[4.82]	[3.93]
Accruals	0.27	0.27	5.74	0.09	0.18	0.19
	[2.14]	[2.15]			[1.43]	[1.55]
Asset Growth	0.37	0.07	6.37	0.11	0.26	0.03
	[2.52]	[0.58]			[1.75]	[0.21]
Investment	0.56	0.35	6.40	0.10	0.46	0.31
	[4.44]	[2.90]			[3.60]	[2.62]
Piotroski's F-score	0.20	0.31	7.24	0.11	0.09	0.24
	[1.04]	[1.75]			[0.45]	[1.37]

Table 3: continued

Panel B: Mid turnover strategies						
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$
Net Issuance (M)	0.57	0.58	14.36	0.20	0.37	0.41
	[3.70]	[4.10]			[2.43]	[2.93]
Return-on-book equity	0.71	0.84	22.27	0.38	0.33	0.59
	[2.96]	[4.41]			[1.38]	[3.18]
Failure Probability	0.85	0.94	26.10	0.61	0.24	0.70
	[2.52]	[4.89]			[0.73]	[3.55]
ValMomProf	1.43	0.68	26.81	0.43	0.99	0.68
	[7.41]	[5.52]			[5.18]	[5.22]
ValMom	0.93	-0.12	28.67	0.41	0.51	
	[4.81]	[-1.31]			[2.67]	
Idiosyncratic Volatility	0.63	0.83	24.59	0.52	0.11	0.41
	[2.13]	[5.14]			[0.37]	[2.57]
Momentum	1.33	0.35	34.52	0.65	0.68	0.40
	[4.80]	[3.04]			[2.45]	[3.12]
PEAD (SUE)	0.72	0.58	35.07	0.46	0.26	0.29
	[4.52]	[4.31]			[1.60]	[2.21]
PEAD (CAR3)	0.91	0.87	34.69	0.57	0.34	0.38
	[6.54]	[6.39]			[2.41]	[2.85]

Panel C: High turnover strategies						
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$
Industry Momentum	0.93	0.83	90.13	1.22	-0.29	
	[3.97]	[3.52]			[-1.20]	
Industry Relative Reversals	0.98	1.05	90.28	1.78	-0.80	
	[5.72]	[6.66]			[-4.73]	
High-frequency Combo	1.61	1.48	91.04	1.45	0.16	0.05
	[11.21]	[9.93]			[1.11]	[0.35]
Short-run Reversals	0.37	0.45	90.87	1.65	-1.28	
	[1.71]	[2.22]			[-6.02]	
Seasonality	0.84	0.82	91.12	1.46	-0.62	
	[5.21]	[5.03]			[-3.88]	
Industry Relative Reversals	1.25	1.17	93.99	1.06	0.19	0.07
(Low Volatility)	[9.36]	[8.96]			[1.41]	[0.57]

the combined value, momentum and gross profitability signals. Including the profitability considerations almost doubles the net spread relative to the strategy based on value and momentum signals alone, from 51 to 99 bp per month, with a t-stat of 5.18.

Other popular anomalies including idiosyncratic volatility and the strategy based on predicted failure probability, are only marginally profitable after accounting for transaction costs. With the exception of ValMom, however, all these strategies do have significant generalized alphas relative to the four factor model.

The cost of trading the high-turnover strategies, at least when designed with complete disregard for trading costs, always exceeds 1% per month. Transactions costs significantly exceed the gross spread for all but two of the anomalies we examine, with only the High-frequency Combo and the Low Volatility Industry Relative Reversals strategies achieving positive net excess returns. Given that accounting for the effective bid-ask spread alone eradicates the profits from all but two of these strategies, we contend that there are significant barriers to arbitrage among the high-turnover strategies.

Table 4 shows the ex-post mean-variance efficient tangency portfolio weights and the maximum attainable Sharpe ratios, accounting for transaction costs, using the Fama and French factors and each of the twenty-three anomalies. All of the low-turnover anomalies except for size, and all of the mid-turnover strategies except for ValMom, seem to improve the mean-variance frontier. Only the High-frequency combo and the Low Volatility Industry Relative Reversals get positive weights in the MVE from the high-turnover anomalies and improve the maximum Sharpe ratio by one percentage point to 0.76.

Table 4: Ex post mean variance efficient portfolios
The table reports ex-post mean-variance efficient tangency portfolio weights on the net returns to the Fama/French factors and one of the twenty-three anomalies at a time. Panel A presents results for low turnover strategies, panel B reports the results for mid-turnover strategies, while panel C focuses on the high-turnover strategies. For each anomaly, the weights in the tangency portfolio are reported as well as the maximum attainable Sharpe Ratio. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Anomaly	MKT	SMB	HML	UMD	Strat.	SR
Panel A: Low Turnover Strategies						
Size	25.1	12.9	45.2	16.8		0.75
Gross Profitability	17.9	11.5	37.8	9.7	23.1	0.93
Value	24.8	13.6	47.1	16.5	-2.1	0.75
ValProf	27.3		21.2	18.0	33.6	0.94
Accruals	22.2	14.4	36.5	13.9	13.0	0.79
Asset Growth	25.2	12.5	43.5	16.7	2.1	0.75
Investment	24.6	6.6	31.3	13.6	24.0	0.84
Piotroski's F-score	23.4	15.4	39.4	13.4	8.4	0.78
Panel B: Mid Turnover Strategies						
Net Issuance (M)	22.3	18.0	26.5	9.1	24.1	0.89
Return-on-book equity	21.1	25.7	32.4	2.7	18.0	0.92
Failure Probability	24.5	26.9	33.6		14.9	0.94
ValMomProf	30.9		34.9		34.2	1.04
ValMom	25.1	12.9	45.2	16.8		0.75
Idiosyncratic Volatility	24.1	29.2	25.4	7.4	14.0	0.84
Momentum	26.3	13.6	44.7		15.4	0.85
PEAD (SUE)	21.0	16.8	39.2	2.4	20.6	0.84
PEAD (CAR3)	21.6	12.4	36.2	4.9	24.8	0.89
Panel C: High Turnover Strategies						
Industry Momentum	25.1	12.9	45.2	16.8		0.75
Industry Relative Reversals	25.1	12.9	45.2	16.8		0.75
High-frequency Combo	24.3	12.5	43.9	16.4	2.9	0.76
Short-run Reversals	25.1	12.9	45.2	16.8		0.75
Seasonality	25.1	12.9	45.2	16.8		0.75
Ind. Rel. Rev. (Low Vol.)	23.4	11.3	43.1	16.8	5.3	0.76

5. Transaction Cost Mitigation

The strategies presented in the previous section, constructed using the the high-minus-low decile sort most commonly employed in academic studies, significantly overstate the actual cost of trading these anomalies for at least two reasons. First, even though the effective bid-ask spread measure we use does not account for price impact it assumes market orders for all trades and it does nothing to reduce transactions costs. In practice large institutional investment managers devote entire departments to the sole purpose of reducing the costs of executing trades.

Even more importantly, the strategies were designed ignoring trading costs, and thus generate far more trading and far higher transaction costs than necessary. In this section we propose three simple, rule-based methodologies designed to reduce trading costs. The first of these simply limits trading to the universe of stocks that we expect to be relatively cheap to trade. The other two use strategies that attempt to significantly reduce turnover without significantly reducing exposure to the underlying anomaly. The first of these turnover reduction techniques, staggered partial rebalancing, is considered by Jegadeesh and Titman (1993), though for the purpose of identifying the horizon over which momentum generates the highest gross returns, not as a method for reducing transaction costs. The second of these turnover reduction techniques, the use of a buy-hold spread (i.e., a willingness to hold positions that you would not actively trade into), is largely absent from the academic literature though frequently employed in practice (e.g., Dimensional Fund Advisors employ this strategy in small cap funds, and MSCI has several indices that use it).

We are primarily interested in whether anomalies are real, in the sense that they are attractive to trade in the real world after accounting for transaction costs, and that they are distinct from the best known anomalies, especially value and momentum. In order to determine whether an anomaly truly improves the investment opportunity set of an investor with access to the four factors employed in our asset pricing model, we need to use factors that do not themselves incur unreasonably large trading costs.

In particular, the anomalies should be evaluated relative to a momentum factor that is constructed using transaction cost mitigation techniques to create a fair playing field. Table 5 reports the performance of UMD-like factors, constructed using each of the three trading-cost mitigation techniques. The table reports gross returns, transactions costs, net returns and results from a net-on-net Fama-French four factor model regression.

The table shows that while all three factors generate significant net-on-net four factor alphas, the momentum strategy constructed using a spread between the buy and hold thresholds, has the largest and most significant net alpha relative to the standard four factor model that accounts for transaction costs. This momentum factor is also outside the span of the other two. The ex post mean-variance efficient portfolios, accounting for transaction costs, of the three momentum factors, or the three momentum factors and the three Fama-French factors, put no weight on the momentum factors constructed in the low cost universe and with staggered quarterly rebalancing. The three Fama-French factors and UMD together explain 87.3%, 95.3% and 94.8% of the variation in the three factors. Figure 4 further examines the transactions costs associated with the three momentum factors over time. We can observe that all four factors' trading costs seem to move together, but the level of the ones constructed with trading hysteresis and staggered rebalancing are lower. We will consequently employ the momentum factor constructed using trading hysteresis when evaluating anomaly performance.

5.1. Strategies Formed in the Low Cost Universe

The first transactions cost mitigation technique we examine is limiting the universe of stocks to low trading cost stocks. To this end, we use only stocks that are in the low *lagged* trading cost tertile of each NYSE size decile. Since the effective spread measure is fairly persistent, this procedure helps us identify the low-cost universe without having a look-ahead bias. The conditional double sort is used to avoid a

Table 5: Momentum factor performance net of transaction costs
This table reports the performance of UMD-like factors, constructed using the three trading-cost mitigation techniques. The table reports gross return, transactions costs, net returns and results from a net-on-net Fama-French four factor model regression. The sample covers July 1973 to December 2012.

Cost mitigation strategy	$E[r^e_{\text{gross}}]$	T-costs	$E[r^e_{\text{net}}]$	net-on-net FF4 regression results α	β_{mkt}	β_{smb}	β_{hml}	β_{umd}
Restrict trading to	0.66	0.35	0.31	0.17	-0.04	-0.11	-0.06	0.93
low cost universe	[3.84]		[1.82]	[3.06]	[-3.05]	[-5.97]	[-2.81]	[69.19]
Staggered quarterly	0.62	0.26	0.37	0.19	-0.00	-0.02	-0.04	0.89
rebalancing	[3.98]		[2.34]	[6.62]	[-0.11]	[-1.58]	[-3.64]	[131.33]
Trading Hysteresis	0.77	0.26	0.51	0.33	0.01	-0.05	-0.08	1.01
(buy/hold spread)	[4.29]		[2.87]	[8.81]	[0.69]	[-4.34]	[-5.78]	[114.56]

large caps bias when selecting low trading cost stocks. Table 6 shows the strategies' gross excess returns, gross alpha relative to the four-factor model, average turnover on each side, transactions costs, net returns, the generalized net four-factor alpha, and the generalized net alpha relative to the four factors and the respective simple strategy from table 3.

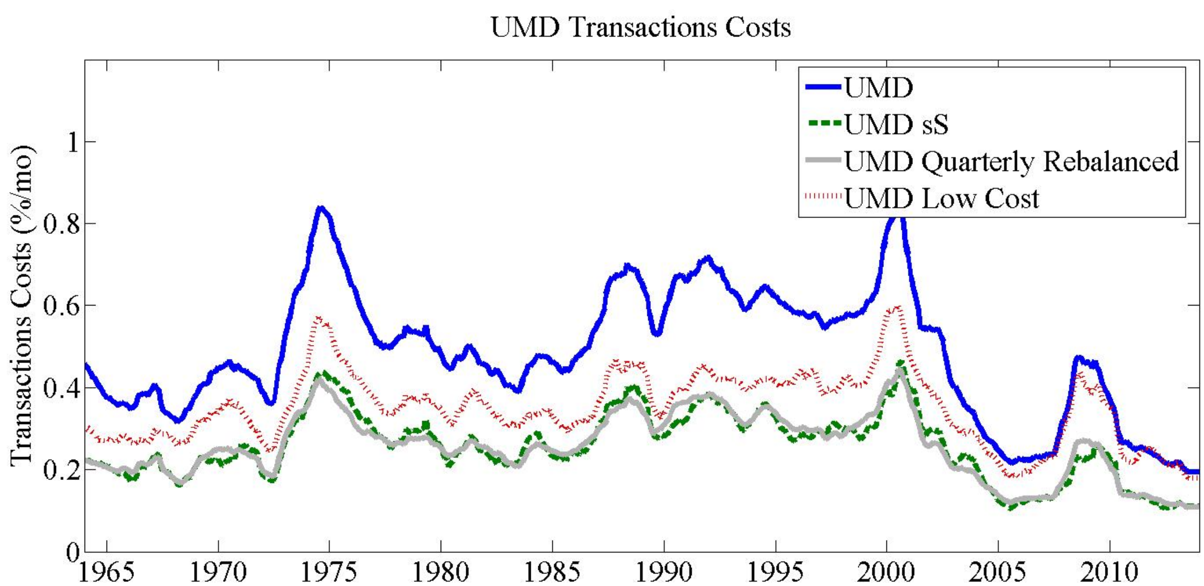


Figure 4: Transactions costs for UMD factor versions over time
This figure reports the transactions costs over time of UMD-like factors, constructed using the three trading-cost mitigation techniques. The sample covers July 1973 to December 2012.

Table 6: Low cost universe

This table presents results for returns on strategies constructed using only stocks that are in the low *lagged* trading cost tertile of each NYSE size decile. Each strategy consists of a value-weighted long/short self-financing portfolio, constructed using a decile sort on a signal using NYSE breakpoints. Panel A examines mid-turnover strategies, while panel B looks at high-turnover strategies. Columns 2-7 reports the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, and net four-factor alpha. The last column indicates the net alpha relative to the four factors and the respective simple strategy from table 3. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Panel A: Mid Turnover Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Net Issuance (M)	0.48	0.45	15.77	0.17	0.31	0.32	
	[2.81]	[2.60]			[1.83]	[1.87]	
Return-on-book equity	0.63	0.68	24.61	0.37	0.25	0.40	
	[2.05]	[2.76]			[0.83]	[1.64]	
Failure Probability	0.88	0.83	24.89	0.62	0.26	0.39	0.07
	[2.18]	[3.34]			[0.65]	[1.62]	[0.35]
ValMomProf	1.41	0.67	29.62	0.41	1.00	0.48	0.16
	[6.66]	[3.75]			[4.74]	[2.72]	[1.06]
ValMom	0.96	-0.09	32.06	0.39	0.57		
	[4.09]	[-0.54]			[2.46]		
Idiosyncratic Volatility	1.07	1.08	26.02	0.65	0.41	0.53	0.29
	[3.21]	[5.26]			[1.25]	[2.63]	[1.79]
Momentum	1.44	0.29	38.17	0.62	0.82	0.07	0.07
	[4.00]	[1.33]			[2.29]	[0.33]	[0.33]
PEAD (SUE)	0.51	0.39	40.03	0.41	0.10	0.05	
	[2.53]	[2.09]			[0.48]	[0.26]	
PEAD (CAR3)	1.20	1.27	41.96	0.58	0.62	0.69	0.42
	[5.73]	[5.84]			[2.97]	[3.22]	[2.34]
Panel B: High Turnover Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Industry Momentum	0.83	0.63	91.58	0.94	-0.11		
	[3.47]	[2.68]			[-0.45]		
Industry Relative Reversals	1.34	1.35	93.79	1.44	-0.10		
	[5.75]	[6.17]			[-0.44]		
High-frequency Combo	1.68	1.55	93.04	1.10	0.58	0.45	0.43
	[9.86]	[8.76]			[3.39]	[2.60]	[2.59]
Short-run Reversals	0.66	0.71	94.36	1.33	-0.67		
	[2.56]	[2.92]			[-2.65]		
Seasonality	1.02	1.00	95.04	1.22	-0.20		
	[5.06]	[4.76]			[-1.01]		
Industry Relative Reversals	1.44	1.36	94.81	0.88	0.56	0.46	0.38
(Low Volatility)	[8.31]	[7.81]			[3.27]	[2.76]	[2.63]

Surprisingly this procedure does not significantly reduce the trading costs for any of the mid-turnover strategies. The average turnover and trading costs are similar to the ones for the strategies, which can be most easily seen in the last column. Only the PEAD (CAR3) anomaly has a positive and statistically significant α_{net}^{FF4+}, and this comes primarily from an increased gross spread, not a reduction in the cost of trading the strategy. Restricting the universe to the low trading cost does not add much over using the traditional decile sort on the entire universe for the mid-turnover anomalies.

For the high-turnover strategies, however, there seems to be a marked reduction in trading costs. While there is not much of a reduction in turnover, the trading costs for this lot decrease by 25% on average. The performances of the High-frequency Combo and the IRR (Low Volatility) benefit the most, as evidenced by the positive and significant net returns and net four-factor alphas.

5.2 Strategies Formed Using Staggered Partial Rebalancing

The second cost mitigation technique we examine is staggered partial rebalancing. This technique reduces turnover by simply lowering the frequency at which a strategy is traded, at the expense of some staleness in the signals on which the strategies are based. The technique is popular among large institutional money-managers. For example, Applied Quantitative Research's (AQR) momentum indices, which are designed to track the Momentum strategy with limited trading costs, are rebalanced quarterly.[5] We consider mid-turnover strategies here similarly rebalanced quarterly. For the high-frequency strategies, which are sorted on signals that are much less persistent, rebalancing quarterly is too infrequent to maintain a large average exposure to the underlying anomaly. We consequently run these strategies twice as fast, with staggered rebalancing at a half-quarterly frequency.

The table shows that a two-thirds reduction in trading frequency generally yields roughly only a one-third reductions in turnover and transaction cost, as more of the portfolio turns over at each rebalance point. For the mid-turnover strategies these cost reductions generally come at the expense of only marginal reductions in the net spreads, however, resulting in significant generalized net alphas relative to the four Fama and French factors and the corresponding simple strategies. The high-frequency strategies, and the highest turnover mid-turnover strategies (the fundamental momentum strategies), see similar proportional trading cost reductions, but suffer larger deterioration in the gross spreads, yielding more modest improvements to these strategies realized performance.

[5] See http://www.aqrindex.com/resources/docs/PDF/News/News_Momentum_Indices.pdf

Table 7: Staggered partial rebalancing

This table presents results for returns on strategies that rebalance one third of the portfolio each month. Each strategy consists of a value-weighted long/short self-financing portfolio, constructed using a decile sort on a signal using NYSE breakpoints. Panel A examines mid-turnover strategies, while panel B looks at high-turnover strategies. Columns 2-7 reports the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, and net four-factor alpha. The last column indicates the net alpha relative to the four factors and the respective simple strategy from table 3. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Panel A: Mid Turnover Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Net Issuance (M)	0.58	0.60	11.33	0.15	0.43	0.46	0.10
	[4.00]	[4.49]			[2.98]	[3.53]	[2.61]
Return-on-book equity	0.52	0.64	14.07	0.29	0.23	0.39	
	[2.23]	[3.46]			[0.99]	[2.14]	
Failure Probability	0.75	0.77	12.82	0.33	0.43	0.59	0.25
	[2.31]	[4.30]			[1.31]	[3.40]	[3.09]
ValMomProf	1.29	0.54	14.62	0.23	1.06	0.54	0.18
	[7.41]	[4.76]			[6.09]	[4.75]	[3.45]
ValMom	0.89	-0.17	15.14	0.22	0.67		
	[4.95]	[-1.97]			[3.72]		
Idiosyncratic Volatility	0.56	0.74	12.74	0.33	0.23	0.43	0.13
	[1.92]	[4.68]			[0.79]	[2.81]	[2.43]
Momentum	1.25	0.20	16.66	0.34	0.91	0.20	0.20
	[4.85]	[2.19]			[3.53]	[2.28]	[2.28]
PEAD (SUE)	0.49	0.30	24.91	0.33	0.17	0.06	
	[3.28]	[2.37]			[1.11]	[0.46]	
PEAD (CAR3)	0.39	0.29	27.67	0.45	-0.06		
	[3.46]	[2.64]			[-0.54]		
Panel B: High Turnover Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Industry Momentum	0.50	0.36	57.89	0.75	-0.26		
	[4.40]	[3.21]			[-2.26]		
Industry Relative Reversals	0.82	0.94	60.39	1.15	-0.33		
	[8.23]	[10.36]			[-3.42]		
High-Frequency Combo	1.14	1.05	61.24	0.96	0.18	0.11	0.10
	[14.68]	[12.90]			[2.40]	[1.35]	[1.34]
Short-run Reversals	0.42	0.58	60.86	1.07	-0.65		
	[3.45]	[5.29]			[-5.44]		
Seasonality	0.23	0.28	60.60	0.95	-0.72		
	[2.63]	[3.17]			[-8.32]		
Industry Relative Reversals	0.80	0.82	61.84	0.72	0.08	0.08	0.04
(Low Volatility)	[10.71]	[11.26]			[1.07]	[1.11]	[0.75]

5.3. Strategies Formed Using a Buy/Hold Spread

The last cost mitigation technique we consider is trading with a buy/hold spread. These strategies follow an sS rule, under which a trader will hold (maintain short positions on) stocks that they own (are short) provided that the sorting variable is in the extreme s%, but will only actively buy (short) a stock that they have no position in when it enters the most extreme S%.[6] For example, a 10%/20% buy/hold rule implies that we only buy (sell short) stocks when they get into the top (bottom) 10%, and hold them by restricting sales (short covers) only for stocks that leave the top (bottom) 20%.

The sS strategies present an easy to implement, rule-based methodology, which doesn't depend on an explicit model for transactions costs or expected returns, such as the one employed in Frazzini et al. (2014). It provides exposure to the sources of excess returns without incurring the high turnover inherent in the traditional decile sorted portfolios. The procedure dramatically reduces turnover by holding (not selling) close substitutes to the stocks you would have bought, since there is not much of a difference in expected returns between stocks in the 75-80% range of the distribution of a given return predictor and those in the 80-85% range.

Figure 5 examines sS momentum strategies in further detail. Panel (a) plots the buy and hold thresholds that yield strategies that hold roughly the same number of names as the standard decile sort, as a function of the difference between the long and the short thresholds, i.e. the sS spread. Panels (b) to (f) show that as spread increases

[6] The term follows Arrow et al. (1951). This paper develops the sS inventory control model, and includes an inaction region when the level of inventory is between s (the lower threshold) and S (the higher threshold). The basic idea is that, in order to minimize the cost of storage and order handling, a firm needs to rebalance its inventory back to S only when it drops below the lower threshold, s. See also Davis and Norman (1990), which introduces proportional transactions costs in a simple continuous-time model of optimal consumption and investment with one risky stock and one money market and find that the optimal policy consists of an inaction region and a return to the closer boundary when rebalancing, and, Abel and Eberly (1996), which studies optimal investment with costly reversibility and show that there is an inaction region for investment/disinvestment when there is a wedge between the purchase and sale prices of capital. Abel and Eberly (1996) also shows that even tiny transaction costs lead to non-trivial inaction regions. Specifically, they show that the size of this region is proportional to the cube-root of the price wedge for small wedges, which makes its derivative with respect to the wedge infinite.

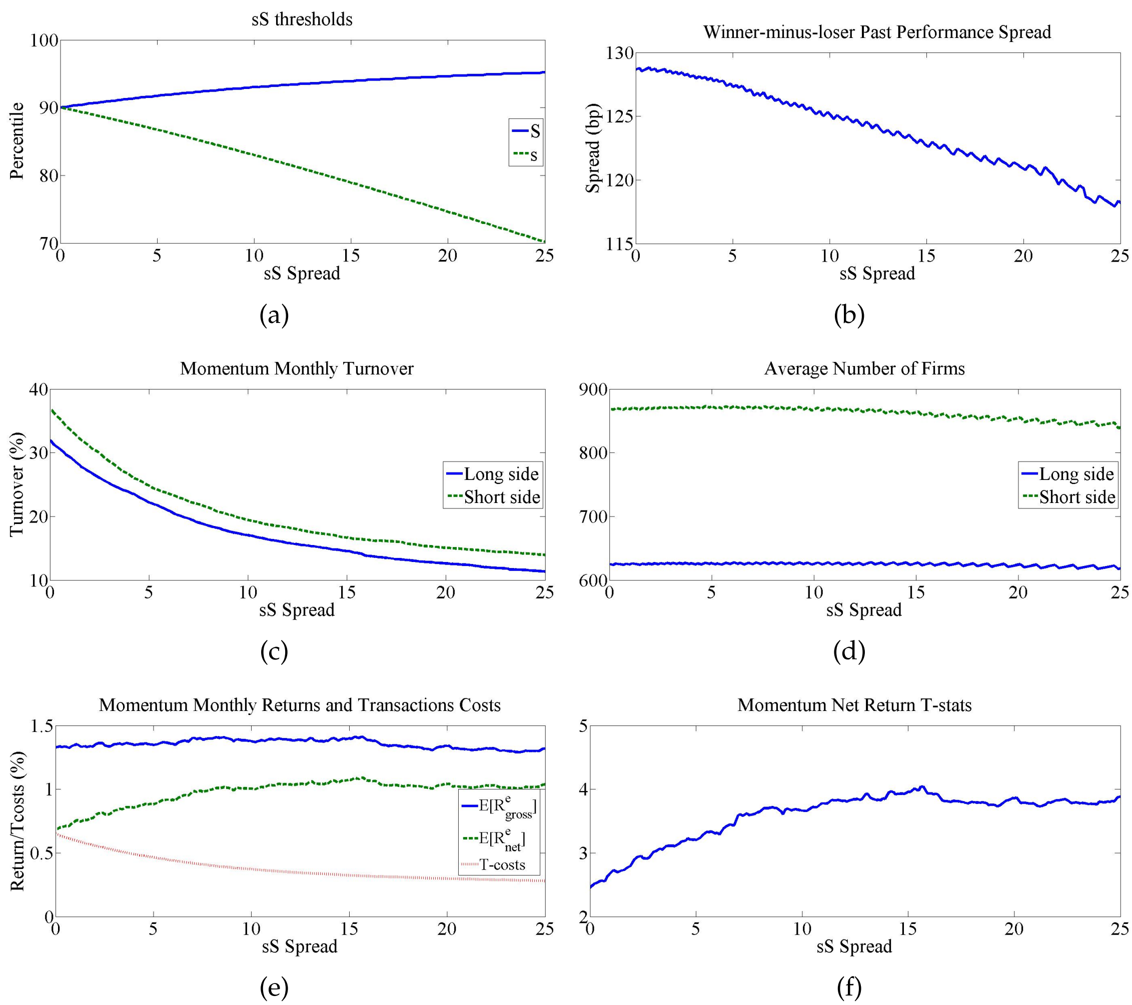


Figure 5: sS momentum strategy
The figure plots various sS Momentum strategy results as a function of the sS spread. Panel (a) plots percentile thresholds, panel (b) plots the spread in returns on the sS strategy, panels (c) and (d) plot the turnover and the average number of firms over the long and short sides of the strategy, panel (e) plots the gross and net returns as well as the trading costs associated with the strategy, and panel (f) plots the net return t-statistics.

the past performance spread between the winners and losers portfolio narrows, but that the turnover and transactions costs reduction is even more dramatic, resulting in increasing net spreads and Sharpe ratios.

Table 8 presents results sS strategies for all the mid- and high-frequency strategies. Panel A looks at 10%/20% mid-turnover strategies, while panel B examines 10%/50% high-turnover strategies. In each panel, we report the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, net four-factor alpha, and the net alpha relative to the four factors and the respective simple strategy from table 3. The sS strategies exhibit slightly lower gross returns but much lower turnover and transactions costs as opposed to their simple counterparts. The average reduction in the turnover for the twenty-three anomalies is 41%, while the transactions costs decrease by 42%. Net returns are consequently higher. The clear winner is the ValMomProf again, with an average monthly return of 1.02%, with a t-stat of 6.19. virtually all of the mid-turnover anomalies also have significant positive generalized net four-factor alphas. Moreover, the sS strategies seem to add to the investment possibilities even after the basic equivalents of the strategies are included in the investment opportunity set, as evidenced by the last column.

There is an improvement in the performance of the high-frequency strategies as well, and the High-frequency Combo and the Low Volatility Industry relative Reversals have positive and statistically significant net returns, and marginally significant net-on-net four and five factor alphas.

Table 8: Trading hysteresis
This table presents results for returns on sS strategies. Panel A contains results for mid-turnover strategies using the 10%/20% buy/hold rule. Panel B contains results for high-turnover strategies using the 10%/50% buy/hold rule. Columns 2-7 reports the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, and net four-factor alpha. The last column indicates the net alpha relative to the four factors and the respective simple strategy from table 3. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Panel A: Mid Turnover 10%/20% Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Net Issuance (M)	0.51	0.54	8.21	0.11	0.40	0.44	0.11
	[3.53]	[4.18]			[2.74]	[3.49]	[2.11]
Return-on-book equity	0.61	0.76	13.82	0.24	0.37	0.55	0.15
	[2.77]	[4.42]			[1.69]	[3.27]	[2.40]
Failure Probability	0.61	0.66	10.32	0.23	0.38	0.57	0.24
	[1.97]	[3.87]			[1.22]	[3.38]	[2.91]
ValMomProf	1.20	0.49	11.57	0.19	1.02	0.52	0.21
	[7.30]	[4.60]			[6.19]	[4.86]	[3.28]
ValMom	0.81	-0.17	13.35	0.19	0.62		
	[4.83]	[-2.12]			[3.67]		
Idiosyncratic Volatility	0.43	0.65	12.41	0.25	0.18	0.41	0.13
	[1.56]	[4.34]			[0.65]	[2.79]	[2.38]
Momentum	1.20	0.13	18.82	0.35	0.85	0.13	0.13
	[4.71]	[1.48]			[3.35]	[1.52]	[1.52]
PEAD (SUE)	0.66	0.47	24.38	0.32	0.35	0.24	0.11
	[4.36]	[3.75]			[2.26]	[1.91]	[1.69]
PEAD (CAR3)	0.82	0.74	28.92	0.47	0.35	0.31	0.03
	[6.11]	[5.73]			[2.58]	[2.43]	[0.81]
Panel B: High Turnover 10%/50% Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Industry Momentum	0.73	0.53	57.36	0.75	-0.02		
	[3.64]	[2.62]			[-0.09]		
Industry Relative Reversals	0.79	0.93	56.96	1.09	-0.31		
	[4.91]	[6.86]			[-1.98]		
High-frequency Combo	1.18	1.05	53.64	0.83	0.35	0.23	0.21
	[9.87]	[8.43]			[2.83]	[1.81]	[1.81]
Short-run Reversals	0.28	0.50	57.09	1.00	-0.72		
	[1.44]	[2.91]			[-3.78]		
Seasonality	0.51	0.53	57.59	0.88	-0.36		
	[3.61]	[3.70]			[-2.56]		
Industry Relative Reversals	0.95	0.94	58.81	0.67	0.28	0.24	0.17
(Low Volatility)	[7.93]	[8.63]			[2.41]	[2.30]	[2.19]

5.4. Cost Mitigation Technique Comparison

Next, we compare the performance of the three trading cost mitigation techniques. Table 9 reports ex-post mean-variance efficient tangency portfolio weights on the net returns to the Fama/French factors and each of the twenty-three anomalies, mitigated using the three mitigation techniques separately. Panel A presents results for basic, non-mitigated low turnover strategies, while panels B and C add to the four factors the mid- and high-turnover strategies, mitigated in three different ways discussed above. For each anomaly, the weights in the tangency portfolio are reported as well as the maximum attainable Sharpe Ratio.

Here, we also use the sS UMD factor, as opposed to the traditional one to better judge the improvement in the investment opportunity set by each strategy. Thus, the maximum attainable Sharpe ratio from the four factors alone is 0.90, which is significantly higher than the 0.75 in table 4 using the regular UMD factor, which is more expensive to trade. The low-turnover strategies used are the basic ones, since turnover for these is low enough that applying the mitigation techniques reduces exposure to the underlying anomaly without significantly reducing trading costs. All the low turnover strategies, with the exception of size and value which are redundant to the Fama and French factors, improve the investment opportunity set.

The more interesting results, however, are with regards to the mid- and high-turnover strategies. All of the mid-turnover strategies, with the exception of ValMom, benefit from trading cost mitigation. The maximum attainable Sharpe ratio for the ValMomProf strategy increases to 1.15, by putting weight on all three mitigated strategies. It is also worth emphasizing that the most weight out of the three types of mitigated strategies seems to be put on the sS ones, suggesting that it is the most useful single simple method for reducing turnover while preserving exposure to the underlying signal. Not surprisingly, the maximum attainable Sharpe ratio is improved on for the High-frequency Combo and the IRR (Low Volatility) out of the high-turnover strategies. For both of them, no weight is put in the tangency portfolio on the staggered rebalanced strategies.

5.5. Strategies that Employ Multiple Cost Mitigation Techniques

While the buy/hold spread seemed to be the single most useful cost mitigation technique for most of the strategies we consider, the other techniques often contribute to marginal performance improvements, and sometimes to significant ones. It is thus natural to ask if these separate improvements can be realized simultaneously using multi-mitigated strategies, which employ all three mitigation techniques simultaneously. The strategies are constructed in the lower lagged trading cost half of each NYSE size decile, using staggered partial rebalancing, with turnover further reduced using a buy hold spread.

Table 10 reports the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, net four-factor alpha, and the net alpha relative to the four factors and the respective simple strategy from table 3. There is a dramatic decrease in turnover (60% on average) and in transactions costs (59% on average) compared to the basic strategies, which is partially offset by decrease in the exposure to signal evidenced by the gross returns. While these strategies do see improved performance relative to the basic strategies, they generally do not improve on the single mitigation technique of the buy/hold spread.

The benefit of multiple mitigation techniques is much greater, however, for the high turnover strategies. This is not surprising, as reducing transaction costs is much more important for the net performance of high transaction cost strategies. The net returns to the High-Frequency Combo and the IRR (Low Volatility) have impressive t-statistics of 5.23 and 4.12, resulting in net Sharpe ratios of 0.74 and 0.58, respectively. Further, even the simple IRR strategy seems to have a positive net four-factor alpha, albeit not statically significant.

Table 9: Ex post mean variance efficient portfolio weights and Sharpe ratios

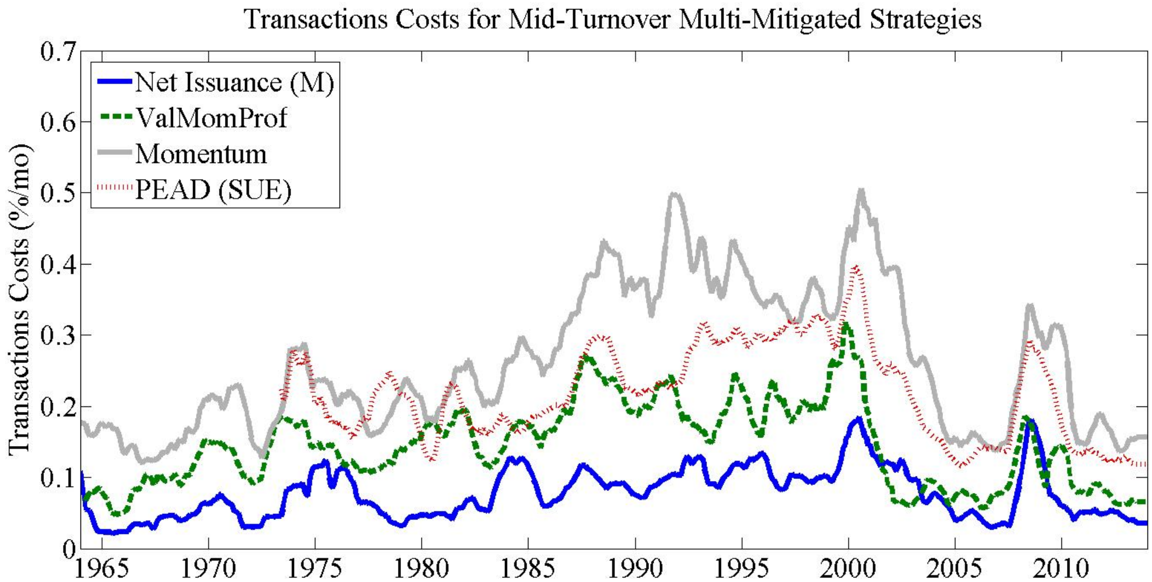
The table reports ex-post mean-variance efficient tangency portfolio weights on the net returns to the Fama/French factors and each of the twenty-three anomalies, mitigated using the three mitigation techniques separately. Panel A presents results for basic, non-mitigated low turnover strategies, while panels B and C add to the four factors the mid- and high-turnover strategies, mitigated in three different ways. For each anomaly, the weights in the tangency portfolio are reported as well as the maximum attainable Sharpe Ratio. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Anomaly	MKT	SMB	HML	UMD_{sS}	Anomaly	SR
Panel A: Low Turnover Strategies						
Size	22.3	11.9	42.3	23.5		0.90
Gross Profitability	20.3	12.6	39.7	20.3	7.1	0.92
Value	22.1	13.3	44.4	23.0	-2.9	0.90
ValProf	24.6		31.6	24.9	18.8	1.00
Accruals	21.5	13.5	38.2	21.0	5.8	0.92
Asset Growth	22.1	11.4	38.8	23.0	4.6	0.91
Investment	21.9	9.1	31.4	18.0	19.6	1.07
Piotroski's F-score	20.0	15.6	38.0	18.8	7.6	0.94

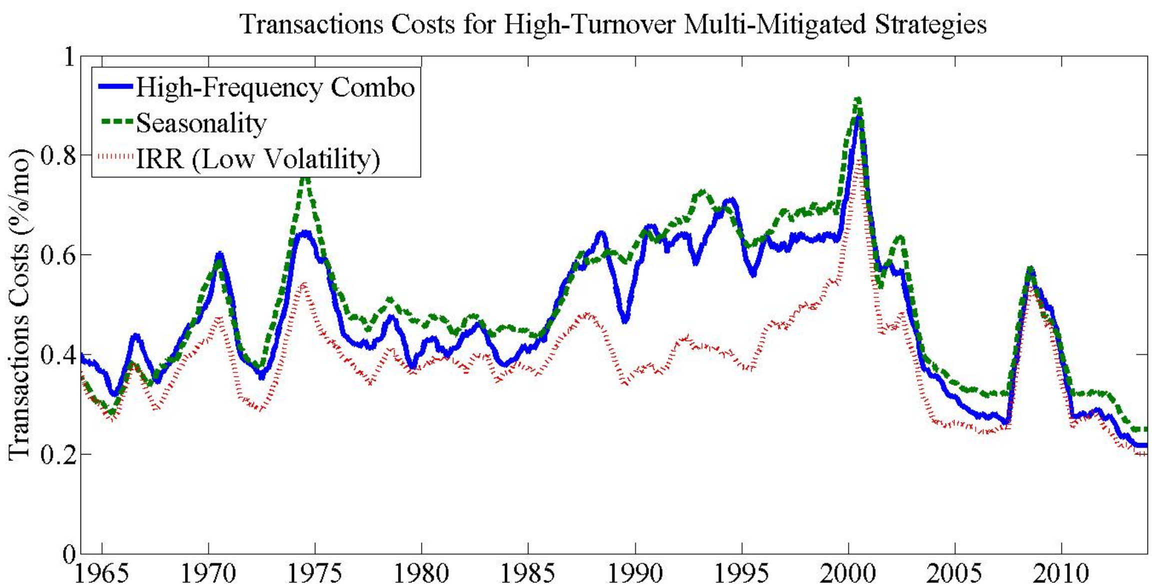
					T-cost mitigation technique used in anomaly construction			
Anomaly	MKT	SMB	HML	UMD_{sS}	LC	QR	sS	SR
Panel B: Mid Turnover Strategies								
Net Issuance (M)	20.4	17.1	23.3	13.3		14.8	11.1	1.06
Return-on-book equity	19.4	23.4	31.5	8.3			17.4	1.04
Failure Probability	23.5	27.5	31.8			9.4	7.8	1.05
ValMomProf	27.7		30.6		3.2	12.5	26.1	1.15
ValMom	22.3	11.9	42.3	23.5				0.90
Idiosyncratic Volatility	21.9	29.3	23.9	10.1	5.5		9.2	1.01
Momentum	24.2	13.6	42.9			19.3		0.96
PEAD (SUE)	19.8	15.4	37.1	11.0			16.7	0.94
PEAD (CAR3)	19.8	12.8	33.2	13.8	12.5		8.0	1.04
Panel C: High Turnover Strategies								
Industry Momentum	22.3	11.9	42.3	23.5				0.90
Industry Relative Reversals	22.3	11.9	42.3	23.5				0.90
High-Frequency Combo	17.2	10.6	35.4	20.2	11.7		4.8	0.98
Short-run Reversals	22.3	11.9	42.3	23.5				0.90
Seasonality	22.3	11.9	42.3	23.5				0.90
Ind. Rel. Rev. (Low Vol.)	15.3	6.0	33.1	23.8	11.1		10.7	1.00

Table 10: Strategies that use multiple cost mitigation techniques
The table reports results for strategies that use all three trading cost mitigation techniques. Panel A examines mid-turnover strategies, while panel B looks at high-turnover strategies. Columns 2-7 reports the strategies' gross excess return, gross alpha relative to the four-factor model, average turnover (average over the long and short side), transactions costs, net returns, and net four-factor alpha. The last column indicates the net alpha relative to the four factors and the respective simple strategy from table 3. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

Panel A: Mid Turnover 10%/20% Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Net Issuance (M)	0.43	0.46	6.18	0.08	0.34	0.41	0.12
	[2.83]	[3.07]			[2.28]	[2.77]	[1.12]
Return-on-book equity	0.44	0.59	5.79	0.19	0.25	0.45	0.03
	[1.51]	[2.58]			[0.87]	[2.03]	[0.18]
Failure Probability	0.31	0.46	3.46	0.23	0.08	0.35	0.10
	[0.85]	[2.35]			[0.22]	[1.82]	[0.67]
ValMomProf	1.11	0.64	9.66	0.14	0.97	0.65	0.39
	[6.22]	[4.05]			[5.41]	[4.21]	[2.83]
ValMom	0.77	-0.12	10.23	0.14	0.63		
	[4.11]	[-0.94]			[3.36]		
Idiosyncratic Volatility	0.81	0.93	2.87	0.34	0.47	0.64	0.41
	[2.52]	[5.14]			[1.45]	[3.60]	[2.97]
Momentum	1.27	0.34	15.48	0.26	1.01	0.42	0.42
	[4.10]	[2.08]			[3.25]	[2.61]	[2.61]
PEAD (SUE)	0.43	0.36	20.14	0.22	0.21	0.21	0.09
	[2.31]	[2.24]			[1.12]	[1.33]	[0.77]
PEAD (CAR3)	0.66	0.64	26.34	0.36	0.30	0.30	0.11
	[3.78]	[3.51]			[1.74]	[1.69]	[0.68]
Panel B: High Turnover 10%/50% Strategies							
Anomaly	$E[r^e_{\text{gross}}]$	$\alpha^{FF4}_{\text{gross}}$	TO	T-costs	$E[r^e_{\text{net}}]$	$\alpha^{FF4}_{\text{net}}$	$\alpha^{FF4+}_{\text{net}}$
Industry Momentum	0.35	0.14	38.21	0.40	-0.05		
	[3.47]	[1.49]			[-0.44]		
Industry Relative Reversals	0.61	0.82	39.61	0.60	0.01	0.14	0.14
	[5.43]	[8.95]			[0.10]	[1.54]	[1.54]
High-Frequency Combo	0.84	0.74	39.21	0.48	0.37	0.28	0.28
	[12.04]	[10.24]			[5.23]	[3.98]	[3.98]
Short-run Reversals	0.38	0.65	41.19	0.54	-0.17		
	[2.85]	[6.35]			[-1.29]		
Seasonality	0.01	0.09	36.81	0.50	-0.49		
	[0.10]	[1.05]			[-5.59]		
Industry Relative Reversals	0.70	0.78	41.09	0.39	0.31	0.35	0.33
(Low Volatility)	[9.10]	[11.75]			[4.12]	[5.50]	[5.44]



(a)



(b)

Figure 6: Transactions costs for multi-mitigated strategies over time

6. Alternative Cost Mitigation Strategies

Next, we focus on an alternative cost mitigation technique that allows investors trading one strategy to opportunistically take small positions in another at effectively negative trading costs. We call this technique trading one strategy on the margin of another, but it is also known in the industry as screens or filters. To examine its effectiveness, we look at how trading Momentum and PEAD on the margin of Size improves performance of the regular Size strategy and how trading the high-frequency combo on the margin of momentum and sS momentum improves the performance of the two momentum strategies.

Table 11 documents results of trading the two mid-turnover strategies on the margin of size. Panel A looks at size screened by momentum, while panel B looks at size screened by PEAD. The screened strategies are enhanced by slowing sales (purchases) and short covers (shorts) when the screening variable is in the top (bottom) x%, where x is indicated by the first column. The third column shows each strategy's turnover in percentages, the fourth one indicates its net excess return over the risk-free rate. The fifth one presents the generalized four factor net α. Finally, the last three columns report the coefficients from the following spanning regression: $R^i_{\text{net}} = \alpha + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{MOM}_{sS,n} + \varepsilon$ for panel A, and $R^i_{\text{net}} = \alpha + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{PEAD}_{sS,n} + \varepsilon$ for panel B.

We can observe that in both cases, as the screen decile cutoff is increased, the turnover decreases and the net returns t-stats increase. The loadings in the last three columns demonstrate the extent to which the exposure to the screening strategy increases. Naturally, the loadings on the size strategy decrease while the loadings on the sS momentum in panel A and sS PEAD in panel B increase. Interestingly, trading momentum on the margin of size does not seem to add much if an investor is already trading size and sS momentum, as evidence by the insignificant alphas in column 5. On the other hand, trading PEAD on the margin of size seems to improve the investment opportunity set, as evidenced by the significant alphas in column 5 of panel B.

What this results implies is that, using this technique, an investor could take a small position in PEAD on top of the size exposure at effectively negative transactions costs.

Similarly, table 12 shows that trading the high-frequency combo on the margin of momentum (panel A) or sS momentum (panel B) also decreases turnover (up to 28% for the 50% momentum screen) and improves the net returns. The spanning regression results in the last three columns of panel B reveal that the sS momentum enhanced high-frequency combo is worth trading even if an investor already has positions in both strategies separately, simply because we are saving the trading costs associated with rebalancing against the high-frequency combo. We can see a similar result in panel A for the basic momentum enhanced combo strategy, but only after the screen is increased to 30% and above.

7. Anomalies Across Size

In this section, we examine the strategies across various size groups. Fama and French (2008) emphasize the point that, when studying anomalies, researchers often use equal-weighted returns of a hedge portfolio, which can be dominated by microcaps (which they define as stocks with market capitalization below the 20$^{\text{th}}$ percentile of the NYSE). These tiny stocks typically account for 60% of the number of firms listed on NYSE, NASDAQ, and AMEX, but they comprise only about 3% of the total market capitalization. Thus, they might be illiquid and accounting for transactions costs for these stocks is important.

In table 13 we present gross and net excess returns for the 23 anomalies across three size bins: micro-, small-, and large-caps. We first sort the universe of firms into three bins. Following Fama and French (2008), we use NYSE 20$^{\text{th}}$ and 50$^{\text{th}}$ percentile breakpoints. Then, in each group, we form each anomalies by slowing down sales (short covers) for stocks leaving the size bins, but which would have otherwise stayed in portfolio 10 (1).

Table 11: Trading momentum and PEAD on the margin of size

This table presents results from trading the momentum and PEAD strategies on the margin of the size strategy. Panel A looks at size screened by momentum, while panel B looks at size screened by PEAD. The screened strategies are enhanced by slowing sales (purchases) and short covers (shorts) when the screening variable is in the top (bottom) x%, where x is indicated by the first column. The third column shows each strategy's turnover in percentages, the fourth one indicates its net excess return over the risk-free rate. The fifth one presents the generalized four factor net α. Finally, the last three columns report the coefficients from the following regression: $R^i_{\text{net}} = \alpha_{\text{simple}} + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{MOM}_{sS,n} + \varepsilon$ for panel A, and $R^i_{\text{net}} = \alpha_{sS} + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{PEAD}_{sS,n} + \varepsilon$ for panel B.

Panel A: Trading momentum on the margin of size

MOM Screen	MOM Accel.	TO	$E[R^e_{\text{net}}]$	α^{FF4}	$R^i_{\text{net}} = \alpha + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{MOM}_{sS,n} + \varepsilon$ α	β_1	β_2
		4.2	0.12	0.15			
			[0.63]	[0.73]			
10%		3.2	0.22	0.19	0.00	0.99	0.11
			[1.12]	[0.95]	[0.11]	[119.19]	[16.36]
30%		2.3	0.31	0.23	0.03	0.97	0.18
			[1.62]	[1.13]	[0.57]	[76.22]	[18.75]
50%		1.5	0.31	0.26	0.00	0.94	0.22
			[1.65]	[1.27]	[0.06]	[63.97]	[19.87]
50%	10%	2.5	0.42	0.24	0.08	0.85	0.28
			[2.27]	[1.17]	[0.80]	[41.55]	[18.00]
50%	20%	3.0	0.43	0.23	0.07	0.82	0.30
			[2.35]	[1.14]	[0.77]	[40.67]	[19.27]

Panel B: Trading PEAD on the margin of size

PEAD Screen	PEAD Accel.	TO	$E[R^e_{\text{net}}]$	α^{FF4}	$R^i_{\text{net}} = \alpha + \beta_1 R^{SIZE}_{\text{net}} + \beta_2 R^{PEAD}_{sS,n} + \varepsilon$ α	β_1	β_2
		4.2	0.12	0.15			
			[0.63]	[0.73]			
10%		3.9	0.16	0.16	0.04	0.99	0.02
			[0.83]	[0.79]	[4.59]	[495.37]	[6.45]
30%		3.2	0.23	0.19	0.10	0.97	0.07
			[1.19]	[0.92]	[2.67]	[114.99]	[6.17]
50%		2.6	0.27	0.21	0.14	0.94	0.11
			[1.45]	[1.04]	[2.45]	[73.15]	[6.56]
50%	10%	3.5	0.41	0.21	0.28	0.79	0.18
			[2.31]	[1.03]	[3.13]	[39.39]	[6.54]
50%	20%	3.8	0.42	0.20	0.29	0.77	0.18
			[2.39]	[1.00]	[3.24]	[37.94]	[6.34]

Table 12: Trading high-frequency combo on the margin of momentum

This table presents results from trading the high-frequency combination strategy on the margin of the momentum and the sS momentum strategies. Panel A looks at momentum screened by the combo, while panel B looks at sS momentum screened by the combo. The screened strategies are enhanced by slowing sales (purchases) and short covers (shorts) when the screening variable is in the top (bottom) x%, where x is indicated by the first column. The third column shows each strategy's turnover in percentages, the fourth one indicates its net excess return over the risk-free rate. The fifth one presents the generalized four factor net α. Finally, the last three columns report the coefficients from the following regression: $R^i_{\text{net}} = \alpha_{sS} + \beta_1 R^{MOM}_{sS,n} + \beta_2 R^{COMBO}_{sS,n} + \varepsilon$.

Panel A: Trading the high-frequency combo on the margin of momentum

COMBO	COMBO				$R^i_{\text{net}} = \alpha + \beta_1 R^{MOM}_{sS,n} + \beta_2 R^{COMBO}_{sS,n} + \varepsilon$		
Screen	Accel.	TO	$E[R^e_{\text{net}}]$	α^{FF4}	α	β_1	β_2
		34.4	0.68	0.70	-0.23	1.06	0.01
			[2.45]	[2.45]	[-3.51]	[103.76]	[0.54]
10%		33.5	0.76	0.72	-0.15	1.05	0.06
			[2.77]	[2.50]	[-2.45]	[105.57]	[2.87]
30%		29.8	1.00	0.78	0.10	1.04	0.06
			[3.69]	[2.71]	[1.58]	[106.94]	[2.84]
50%		24.9	1.05	0.86	0.16	0.99	0.14
			[4.01]	[2.99]	[2.20]	[83.82]	[5.83]
50%	10%	31.9	0.90	0.79	0.08	0.82	0.34
			[3.97]	[2.76]	[1.08]	[69.98]	[14.29]
50%	20%	36.6	0.71	0.78	-0.05	0.75	0.34
			[3.36]	[2.69]	[-0.57]	[59.15]	[13.13]

Panel B: Trading the high-frequency combo on the margin of sS momentum

COMBO	COMBO				$R^i_{\text{net}} = \alpha + \beta_1 R^{MOM}_{sS,n} + \beta_2 R^{COMBO}_{sS,n} + \varepsilon$		
Screen	Accel.	TO	$E[R^e_{\text{net}}]$	α^{FF4}	α	β_1	β_2
		18.7	0.85	0.86			
			[3.35]	[3.27]			
10%		18.6	0.89	0.86	0.04	0.99	0.02
			[3.52]	[3.28]	[2.99]	[507.78]	[5.05]
30%		18.0	0.98	0.87	0.14	0.97	0.02
			[3.93]	[3.32]	[4.72]	[200.89]	[1.93]
50%		16.8	0.97	0.89	0.15	0.93	0.08
			[3.97]	[3.40]	[2.41]	[93.57]	[3.97]
50%	10%	23.2	0.85	0.81	0.08	0.82	0.23
			[3.88]	[3.08]	[1.20]	[77.75]	[10.44]
50%	20%	28.3	0.71	0.77	-0.02	0.76	0.25
			[3.41]	[2.91]	[-0.28]	[66.17]	[10.73]

In panel A, we look at the simple low-turnover strategies. Just like in Fama and French (2008), the micro caps exhibit the highest gross excess returns, followed by the small and the large caps. The transactions costs seem to be immaterial for the low-turnover anomalies, even for the micro caps. The only exception to this rule are the micro caps Size, Accruals, and Piotroski's F-score strategies, whose net excess returns seem to drop to insignificant levels.

Not surprisingly, accounting for the cost of trading seems to matter a lot more for mid- and high-turnover strategies. An interesting pattern emerges in panel B, which looks at mid-turnover strategies. Again, just as in Fama and French (2008), the microcaps exhibit the highest gross returns. However, the differences in the net excess returns between the three size bins seem to be much smaller. For example, the ValMomProf anomaly has gross excess returns of 1.67%, 1.42%, and 1.09% per month for the micro-, small-, and large-caps, respectively, while the corresponding net returns for this strategy are 1.27%, 1.14%, and 0.83%. This is not surprising, because firm size is negatively correlated with transactions costs, and as long as there is sufficient trading we should expect to see smaller stocks being disproportionately affected.

In this context, the net returns are even more affected by the effective spread in the high-turnover strategies, as evidenced by panel C. The extremely high gross returns across the microcaps turn severely negative once we account for transactions costs. For example, the High-frequency Combo micro-cap strategy has a gross excess return of 1.77% per month with a t-stat of 13.94. However, the net return for the same strategy is -0.66% with a t-stat of -5.12. In fact, the net returns are not significantly positive for all but two of the strategies. The high-frequency combo strategy achieves a monthly return of 30 bp with a t-stat of 2.26 in the large caps and 35 bp and a t-stat of 3.40 in the small caps. The low volatility industry relative reversals earns 31 bp with a t-stat of 2.73 in the large caps and 28 bp with a t-stat of 1.96 in the small caps.

Figure 7 presents the same effects by plotting the Sharpe ratios for all the strategies across the three size bins discussed above. A simple visual inspection shows that the net and gross excess returns are not very different for the the low-turnover strategies. Moreover, the larger differences across the three size bins in the gross returns seem to be mitigated in the net returns for the mid-turnover strategies, and only a couple of large-cap high-turnover strategies seem to survive transactions costs.

8. Conclusion

This paper studies the performance of a large number of anomalies after accounting for transaction costs, and the effectiveness of several transaction cost mitigation strate-

Table 13: Value-weighted excess returns on sS strategies by size
This table presents results for returns on value-weighted long/short self-financing portfolios, constructed using a decile sort on a signal using NYSE breakpoints. For each strategy, gross and net returns after transactions costs are presented across size bins, along with their t-stats in brackets. For each strategy, sales (short covers) are slowed down for stocks leaving the size bins, but which would have otherwise stayed in portfolio 10 (1). The breakpoints used for the size sorts are 20^{th} and 50^{th} percentile of all NYSE stocks. In panel A, low turnover strategies are presented. In Panel B, mid-turnover 10%/20% sS strategies are presented. In Panel C, high-turnover 10%/50% sS strategies are reported. In all panels firms are first screened on *size*, and then sorted by the *signal*

Panel A: Low turnover strategies

	Gross Returns			Net Returns		
Anomaly	Micro	Small	Large	Micro	Small	Large
Size	0.32	0.10	0.20	0.05	-0.03	0.15
	[1.63]	[0.76]	[1.64]	[0.24]	[-0.27]	[1.20]
Gross Profitability	0.74	0.75	0.46	0.66	0.71	0.44
	[3.16]	[3.85]	[2.81]	[2.81]	[3.62]	[2.66]
Value	1.02	0.56	0.29	0.89	0.49	0.26
	[4.94]	[2.64]	[1.57]	[4.25]	[2.31]	[1.39]
ValProf	1.10	0.78	0.59	1.00	0.71	0.55
	[4.74]	[3.42]	[3.56]	[4.26]	[3.11]	[3.32]
Accruals	0.42	0.62	0.26	0.14	0.49	0.20
	[3.04]	[4.54]	[1.94]	[0.99]	[3.60]	[1.46]
Asset Growth	0.84	0.80	0.35	0.53	0.66	0.27
	[4.83]	[4.59]	[2.09]	[2.96]	[3.78]	[1.63]
Investment	0.98	0.76	0.40	0.70	0.64	0.33
	[5.49]	[4.74]	[3.12]	[3.76]	[3.91]	[2.53]
Piotroski's F-score	0.71	0.52	0.21	0.40	0.36	0.13
	[3.24]	[2.84]	[1.33]	[1.76]	[1.99]	[0.83]

Table 13: Continued

Panel B: Mid Turnover Strategies

Anomaly	Gross Returns Micro	Gross Returns Small	Gross Returns Large	Net Returns Micro	Net Returns Small	Net Returns Large
Net Issuance (rebal.:M)	1.06	0.78	0.37	0.74	0.61	0.27
	[5.22]	[4.28]	[2.57]	[3.63]	[3.34]	[1.89]
Return-on-book equity	1.72	1.06	0.45	1.24	0.77	0.24
	[6.57]	[4.34]	[2.18]	[4.75]	[3.13]	[1.16]
Failure Probability	1.34	0.97	0.38	0.74	0.58	0.13
	[4.17]	[3.08]	[1.41]	[2.31]	[1.83]	[0.48]
ValMomProf	1.67	1.42	1.09	1.27	1.14	0.83
	[8.02]	[7.43]	[5.90]	[6.14]	[6.00]	[4.52]
ValMom	1.86	1.32	0.57	1.29	0.99	0.35
	[8.28]	[6.29]	[3.14]	[5.80]	[4.76]	[1.94]
Idiosyncratic Volatility	1.63	1.18	0.41	0.86	0.62	0.10
	[4.81]	[3.54]	[1.44]	[2.55]	[1.87]	[0.35]
Momentum	1.91	1.40	0.90	1.15	0.94	0.57
	[6.42]	[5.13]	[3.45]	[3.88]	[3.44]	[2.16]
PEAD (SUE)	2.11	1.28	0.54	1.10	0.81	0.26
	[12.67]	[7.39]	[3.52]	[6.56]	[4.67]	[1.67]
PEAD (CAR3)	1.98	1.25	0.60	0.73	0.60	0.20
	[15.78]	[9.68]	[4.29]	[5.77]	[4.67]	[1.44]

Panel C: High Turnover Strategies

Anomaly	Gross Returns Micro	Gross Returns Small	Gross Returns Large	Net Returns Micro	Net Returns Small	Net Returns Large
Industry Momentum	1.64	1.32	0.60	-0.87	0.08	-0.03
	[9.49]	[6.70]	[2.88]	[-4.45]	[0.39]	[-0.16]
Industry Relative Reversals	1.54	0.89	0.61	-1.42	-0.37	-0.12
	[6.55]	[4.73]	[4.08]	[-6.22]	[-2.01]	[-0.85]
High-frequency Combo	1.77	1.50	0.92	-0.66	0.35	0.30
	[13.94]	[14.19]	[7.13]	[-5.12]	[3.40]	[2.26]
Short-run Reversals	1.05	0.41	0.18	-1.90	-0.84	-0.51
	[4.22]	[1.92]	[0.88]	[-7.86]	[-3.97]	[-2.54]
Seasonality	0.49	0.41	0.43	-2.30	-0.84	-0.24
	[3.97]	[3.38]	[2.91]	[-17.70]	[-6.92]	[-1.61]
Industry Relative Reversals (Low Volatility)	0.89	1.17	0.92	-0.86	0.28	0.31
	[5.45]	[8.07]	[7.83]	[-5.36]	[1.96]	[2.73]

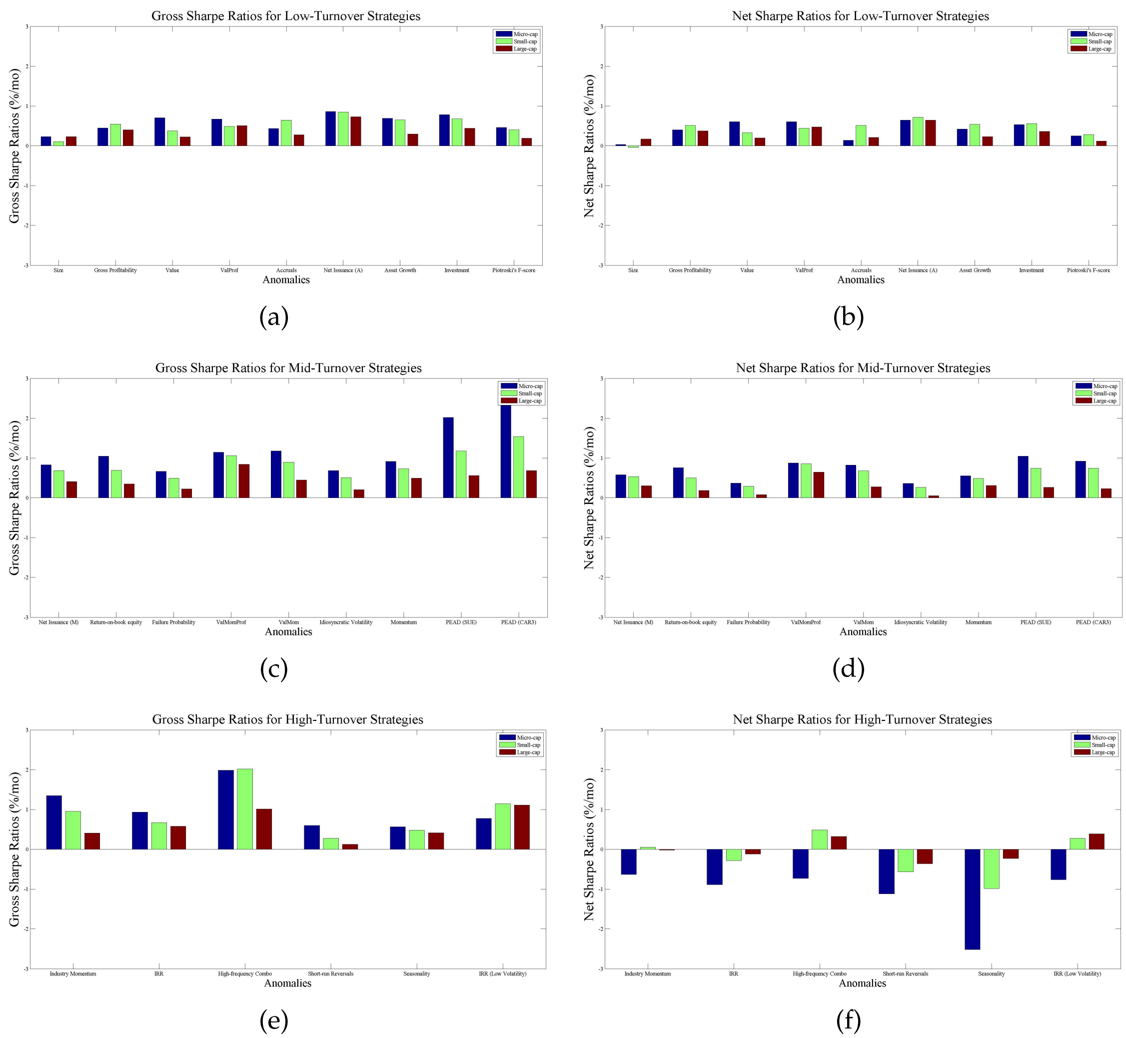


Figure 7: Gross and net Sharpe ratios for anomalies across size terciles

This figure presents results for returns on value-weighted long/short self-financing portfolios, constructed using a decile sort on a signal using NYSE breakpoints. For each strategy, gross and net Sharpe ratios are presented across size bins. For each strategy, sales (short covers) are slowed down for stocks leaving the size bins, but which would have otherwise stayed in portfolio 10 (1). The breakpoints used for the size sorts are 20^{th} and 50^{th} percentile of all NYSE stocks. In panel (a) and (b), low turnover strategies are presented. In panels (c) and (d), mid-turnover 10%/20% sS strategies are presented. In panel (e) and (f), high-turnover 10%/50% sS strategies are reported. In all panels firms are first screened on *size*, and then sorted by the *signal* gies. It finds that introducing a buy/hold spread, which allows investors to continue to hold stocks that they would not actively buy, is the single most effective simple cost mitigation strategy. Most of the anomalies that we consider with one-sided monthly turnover lower than 50% continue to generate statistically significant spreads after accounting for transaction costs, at least when designed to mitigate transaction costs. Few of the strategies with higher turnover do. In all cases transaction costs reduce the strategies' profitability and its associated statistical significance, increasing concerns related to data snooping.

A Appendix

A.1. Anomaly Construction

All strategies consist of a time-series of value-weighted returns on a long/short self-financing portfolio, constructed using a decile sort on a signal using NYSE break-points. The period examined is between July 1963 and December 2012 (full period) for the anomalies using the annual files and between July 1973 and December 2012 (recent period) for the anomalies using the quarterly files. For the strategies using the annual files, accounting data for fiscal-year end of year t is matched with stock returns data from July of year t+1 until June of year t+2 to avoid look-ahead bias. For the ones that use the quarterly files, the accounting data for a given quarter are matched to the end of the month in which they were reported.

All strategies are constructed using data downloaded from the merged CRSP and COMPUSTAT industrial database. We start with all domestic common shares trading on NYSE, AMEX, and NASDAQ with available accounting data and returns. Book equity of firms is calculated by adding the deferred taxes and investment tax credits where available, and preferred stock values were incorporated in the following order of availability - redemption value, liquidation value, or par value of preferred stock. Book-to-market equity is calculated using the December of year t - 1 value for market equity. Stock returns are adjusted for delisting where applicable. For further details on the construction of the strategies, please see the referenced papers.

A.1.1 Low turnover Strategies

- **Size** - follows Fama and French (1993). The portfolios are constructed at the end of each June using the CRSP end of June price times shares outstanding. Rebalanced annually, uses the full period.

- **Gross Profitability** - follows Novy-Marx (2013). Gross Profitability = GP/AT, where GP is gross profits and AT is total assets. Financial firms (those with SIC codes between 6000 and 6999) are excluded. Rebalanced annually, uses the full period.

- **Value** - follows Fama and French (1993). At the end of June of each year, we use book equity from the previous fiscal year and market equity from December of the previous year. Rebalanced annually, uses the full period.

- **ValProf** - follows Novy-Marx (2014). Firms are sorted into deciles based on the sum of their ranks in univariate sorts on book-to-market and profitability. Annual book-to-market and profitability values are used for the entire year. Rebalanced annually, uses the full period.

- **Accruals** - follows Sloan (1996). Accruals $= \frac{\Delta\text{ACT}-\Delta\text{CHE}-\Delta\text{LCT}+\Delta\text{DLC}+\Delta\text{TXP}-\text{DP}}{(\text{AT}+\text{AT}_{-12})/2}$, where ΔACT is the annual change in total current assets, ΔCHE is the annual change in total cash and short-term investments, ΔLCT is the annual change in current liabilities, ΔDLC is the annual change in debt in current liabilities, ΔTXP is the annual change in income taxes payable, ΔDP is the annual change in depreciation and amortization, and $(\text{AT} + \text{AT}_{-12})/2$ is average total assets over the last two years. Rebalanced annually, uses the full period.

- **Asset Growth** - follows Cooper et al. (2008). Asset Growth=$\text{AT}/\text{AT}_{-12}$ Rebalanced annually, uses the full period.

- **Investment** - follows Lyandres et al. (2008) and Chen et al. (2010). Investment $=$ $(\Delta\text{PPEGT} + \Delta\text{INVT})/\text{AT}_{-12}$, where ΔPPEGT is the annual change in gross total property, plant, and equipment, ΔINVT is the annual change in total inventories, and AT_{-12} is lagged total assets. Rebalanced annually, uses the full period.

- **Piotroski's F-score** - based on Piotroski (2000). Piotroski's F-score $= \mathbb{1}_{IB>0} + \mathbb{1}_{\Delta ROA>0} + \mathbb{1}_{CFO>0} + \mathbb{1}_{CFO>IB} + \mathbb{1}_{\Delta DTA<0|DLTT=0|DLTT_{-12}=0} + \mathbb{1}_{\Delta ATL>0} + \mathbb{1}_{EqIss\leq 0} +$

$\mathbb{1}_{\Delta GM>0} + \mathbb{1}_{\Delta ATO>0}$, where IB is income before extraordinary items, ROA is income before extraordinary items scaled by lagged total assets, CFO is cash flow from operations, DTA is total long-term debt scaled by total assets, DLTT is total long-term debt, ATL is total current assets scaled by total current liabilities, EqIss is the difference between sales of of common stock and purchases of common stock recorded on the cash flow statement, GM equals one minus the ratio of cost of goods sold and total revenues, and ATO equals total revenues, scaled by total assets. Rebalanced annualy, uses the full period.

A.1.2 Medium Turnover Strategies

- **Net Issuance (M)** - follows Fama and French (2008). Net issuance is the year-over-year change in adjusted shares outstanding, ADJEXQ $\times$ CSHOQ, where ADJEXQ is the quarterly COMPUSTAT split adjustment factor and CSHOQ is common shares outstanding. Rebalanced monthly, uses the recent period.

- **Return-on-book equity** - follows Chen et al. (2010). Return-on-book equity $=$ IBQ/BEQ$_{-3}$, where IBQ is income before extraordinary items (updated quarterly), and BEQ is book value of equity. Rebalanced monthly, uses the recent period.

- **Failure Probability** - follows Campbell et al. (2008). Also used in Chen et al. (2010). Failure Probability $= -9.164 - 20.264\text{NIMTAAVG} + 1.416\text{TLMTA} - 7.129$ EXRETAVG $+ 1.411\text{SIGMA} - 0.045\text{RSIZE} - 2.132\text{CASHMTA} + 0.075\text{MB} - 0.058$ PRICE, where NIMTAAVG $= \frac{1-\phi^3}{1-\phi^{12}}(\text{NIMTA}_{-1,-3} + ... + \phi^9\text{NIMTA}_{-10,-12})$, EXRETAVG $= \frac{1-\phi^3}{1-\phi^{12}}(\text{EXRET}_{-1} + ... + \phi^{11}\text{EXRET}_{-12})$, NIMTA is net income (updated quarterly) divided by the sum of market equity (price times shares outstanding from CRSP) and total liabilities (updated quarterly), EXRET$= log\left(\frac{1+r_{it}}{1+r_{S\&P500it}}\right)$, TLMTA is the ratio of total liabilities (updated quarterly) scaled by the sum of market equity and total liabilities, SIGMA $= \sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$ in which

r_k^2 is firm's daily return and N is the number of trading days in the three-month period, RSIZE is the relative size of each firm measured as the log of its market equity to that of the S&P500, CASHMTA is the ratio of cash and short-term investments (updated quarterly) to the sum of market equity and total liabilities, MB is the the market-to-book ratio, and PRICE is each firm's log price per share, truncated above at $15. Rebalanced monthly, uses the recent period.

- **ValMomProf** - follows Novy-Marx (2014). Firms are sorted based on the sum of their ranks in univariate sorts on book-to-market, profitability, and momentum. Annual book-to-market and profitability values are used for the entire year. Rebalanced monthly, uses the full period.

- **ValMom** - follows Novy-Marx (2014). Firms are sorted based on the sum of their ranks in univariate sorts on book-to-market and momentum. Annual book-to-market values are used for the entire year. Rebalanced monthly, uses the full period.

- **Idiosyncratic Volatility** - follows Ang et al. (2006). In each month, firms are sorted based on the standard deviation of the residuals of regressions of their past three months' daily returns on the daily returns of the Fama-French three factors. Rebalanced monthly, uses the full period.

- **Momentum** - follows Jegadeesh and Titman (1993). In each month, firms are sorted based on their cumulated past performance in the previous year by skipping the most recent month. Rebalanced monthly, uses the full period.

- **PEAD (SUE)** - follows Foster et al. (1984). Earnings surprises are measured by Standardized Unexpected Earnings (SUE), which is the change in the most recently announced quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters. SUE $= \frac{\text{IBQ}-\text{IBQ}_{-12}}{\sigma_{\text{IBQ}_{-24}:\text{IBQ}_{-3}}}$, where IBQ is income before extraordinary items (updated quarterly), and $\sigma_{\text{IBQ}_{-24}:\text{IBQ}_{-3}}$ is the standard deviation of IBQ in the past two years skipping the most recent quarter. Rebalanced monthly, uses the recent period.

- **PEAD (CAR3)** - follows Brandt et al. (2008). Earnings surprised are measured by the cumulative three-day abnormal return around the announcement (days minus one to one). Rebalanced monthly, uses the recent period.

A.1.3 High Turnover Strategies

- **Industry Momentum** - follows Moskowitz and Grinblatt (1999). In each month, the Fama and French 49 industries are sorted on their value-weighted past month's performance and assigned to 10 industry deciles. Then, all firms in decile 10 (from the 5 winner industries) form the value-weighted long portfolio and all firms in decile 1 (the 5 loser industries) form the short portfolio. Rebalanced monthly, uses the full period.

- **Industry Relative Reversals** - follows Da et al. (2014) and Linnainmaa et al. (2014). In each month, firms are sorted based on the difference between their prior month's return and the prior month's return of their industry (based on the Fama and French 49 industries). Updated monthly, uses the full period.

- **High-Frequency Combo** In each month, firms are sorted based on sum of their ranks in the univariate sorts on industry relative reversals and industry momentum. Rebalanced monthly, uses the full period.

- **Short-term reversals** - follows Jegadeesh and Titman (1993) . In each month, firms are sorted based on their prior month's returns. Rebalanced monthly, uses the full period.

- **Seasonality** - follows Heston and Sadka (2011). At the end of each month firms are sorted based on their average return in the coming calendar month over the preceding five years. Rebalanced monthly, uses the full period.

- **Industry Relative Reversals (Low Volatility)** - follows Linnainmaa et al. (2014). In each month, firms are sorted based on the difference between their prior month's return and the prior month's return of their industry (based on the Fama and French 49 industries). Only stocks with idiosyncratic volatility lower than the NYSE median for month are included in the sorts. Updated monthly, uses the full period.

A.2. Fama-MacBeth regressions by size

Table 14: Determinants of transaction costs
The table reports results from Fama-MacBeth regressions of trading cost estimates on lagged trading costs, market capitalization, and idiosyncratic volatility. The trading costs consist of the effective bid-ask spread measure proposed by Hasbrouck (2009). Idiosyncratic volatility is measured as the standard deviation of residuals of past three months' daily returns on the daily excess market return. Both market capitalization and idiosyncratic volatility use end of July values. The regressions are estimated on an annual frequency and cover 1963 through 2013. In panel A (B), only stocks with market capitalization higher (lower) than the NYSE median are used.

Panel A: Large cap stocks						
Lagged T-costs	0.54					0.35
	[29.6]					[12.4]
log(ME)/100		-0.07	-0.18		-0.12	-0.05
		[-14.1]	[-5.71]		[-4.13]	[-2.38]
$[\log(ME)]^2/100$			0.01		0.01	0.00
			[4.22]		[3.38]	[1.87]
Idiosyncratic Volatility				0.19	0.16	0.10
				[23.0]	[23.2]	[18.3]
Average $\hat{R}^2$ (%)	32.0	9.26	9.47	28.1	30.8	42.4
Panel B: Small cap stocks						
Lagged T-costs	0.93					0.45
	[25.7]					[20.7]
log(ME)/100		-0.65	-1.93		-1.28	-0.97
		[-12.7]	[-13.1]		[-13.9]	[-11.9]
$[\log(ME)]^2/100$			0.18		0.13	0.10
			[13.1]		[14.5]	[12.2]
Idiosyncratic Volatility				0.63	0.44	0.26
				[16.7]	[13.6]	[10.3]
Average $\hat{R}^2$ (%)	59.5	39.8	46.1	50.9	62.7	70.0

A.3. Strategies Across Transactions Costs Tertiles

Table 15: Strategy returns across trading cost tertiles

This table presents results for returns on strategies constructed within lagged transactions costs tertiles. In each period, a conditional ten by three sort is conducted on market cap and lagged transactions costs. Then, for each tertile, and across all ten size bins, firms are sorted into deciles based on the signals. For each strategy, sales (short covers) are slowed down for stocks leaving the t-costs quintile, but which would have otherwise stayed in portfolio 10 (1).

Panel A: Mid turnover strategies

	Gross Returns			Net Returns		
Anomaly	Low	Mid	High	Low	Mid	High
Net Issuance (rebal.:M)	0.54	0.77	0.68	0.39	0.58	0.42
	[3.69]	[5.70]	[3.84]	[2.67]	[4.29]	[2.40]
Return-on-book equity	0.68	0.83	0.69	0.30	0.38	0.08
	[2.26]	[2.89]	[2.28]	[1.01]	[1.33]	[0.27]
Failure Probability	0.97	1.28	1.27	0.35	0.42	0.22
	[2.46]	[3.26]	[2.94]	[0.89]	[1.08]	[0.50]
ValMomProf	1.41	1.53	1.84	1.00	1.02	1.15
	[6.66]	[6.76]	[6.68]	[4.74]	[4.53]	[4.20]
ValMom	0.96	1.30	1.50	0.57	0.83	0.87
	[4.09]	[5.37]	[5.79]	[2.46]	[3.45]	[3.36]
Idiosyncratic Volatility	1.04	1.21	1.47	0.35	0.18	0.24
	[2.67]	[2.90]	[3.10]	[0.89]	[0.45]	[0.52]
Momentum	1.44	1.63	1.91	0.82	0.85	0.70
	[4.00]	[4.67]	[5.18]	[2.29]	[2.44]	[1.89]
PEAD (SUE)	0.58	0.84	0.92	0.17	0.31	0.19
	[2.91]	[4.30]	[4.47]	[0.85]	[1.58]	[0.91]
PEAD (CAR3)	1.19	1.00	1.28	0.62	0.30	0.29
	[5.85]	[5.50]	[5.52]	[3.03]	[1.62]	[1.23]

Panel B: High turnover strategies

	Gross Returns			Net Returns		
Anomaly	Low	Mid	High	Low	Mid	High
Industry Momentum	0.55	0.80	0.57	-0.40	-0.39	-1.09
	[1.97]	[2.74]	[1.85]	[-1.40]	[-1.31]	[-3.46]
Industry Relative Reversals	1.34	0.88	1.04	-0.17	-1.07	-1.99
	[4.83]	[3.18]	[2.80]	[-0.61]	[-3.94]	[-5.50]
High-frequency Combo	1.48	1.67	1.43	0.35	0.19	-0.64
	[7.42]	[7.67]	[5.80]	[1.77]	[0.88]	[-2.61]
Short-run Reversals	0.66	0.62	0.51	-0.67	-1.10	-2.24
	[2.56]	[2.19]	[1.44]	[-2.65]	[-3.90]	[-6.50]
Seasonality	1.02	1.15	1.05	-0.20	-0.43	-1.47
	[5.06]	[5.43]	[4.24]	[-1.01]	[-2.02]	[-5.98]
Industry Relative Reversals	1.44	1.24	1.55	0.56	0.20	0.16
(Low Volatility)	[8.31]	[7.44]	[7.56]	[3.27]	[1.24]	[0.82]

A.4. Cost Mitigation Technique Comparison

Table 16: Ex post mean variance efficient portfolio weights and Sharpe ratios
The table reports ex-post mean-variance efficient tangency portfolio weights on the net returns to the Fama/French factors and each of the twenty-three anomalies, mitigated using the three mitigation techniques separately and the multi-mitigation technique. Panel B presents results for mid-turnover strategies, while panel B focuses on the high-turnover ones. For each anomaly, the weights in the tangency portfolio are reported as well as the maximum attainable Sharpe Ratio. See table 2 and/or Appendix A.1 for further details on the construction of the signals.

					T-cost mitigation technique used in anomaly construction				
Anomaly	MKT	SMB	HML	UMD_{SS}	LC	QR	sS	M	SR
Panel A: Mid Turnover Strategies									
FF3 and UMD_{SS}	22.3	11.9	42.3	23.5					0.90
Net Issuance (rebal.:M)	20.3	16.5	24.0	12.7		12.5	10.3	3.7	1.07
Return-on-book equity	19.4	23.4	31.5	8.3			17.4		1.04
Failure Probability	23.5	27.5	31.8			9.4	7.8		1.05
ValMomProf	27.2		29.7			3.3	24.8	15.0	1.18
ValMom	22.3	11.9	42.3	23.5					0.90
Idiosyncratic Volatility	20.6	32.6	23.2	8.1			4.2	11.4	1.05
Momentum	23.8	17.5	40.8			6.5		11.4	0.99
PEAD (SUE)	19.8	15.4	37.1	11.0			16.7		0.94
PEAD (CAR3)	19.8	12.8	33.2	13.8	12.5		8.0		1.04
Panel B: High Turnover Strategies									
Industry Momentum	22.3	11.9	42.3	23.5					0.90
Industry Relative Reversals	16.8	7.7	36.7	24.1				14.6	0.93
High-Frequency Combo	12.8	7.2	27.3	13.6	4.0			35.1	1.08
Short-run Reversals	22.3	11.9	42.3	23.5					0.90
Seasonality	22.3	11.9	42.3	23.5					0.90
Ind. Rel. Rev. (Low Vol.)	8.0	1.0	23.1	21.4	2.2			44.3	1.21

References

Abel, A. B., Eberly, J. C. 1996. Optimal investment with costly reversibility. Review of Economic Studies, 63, 581–593.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X. 2006. The cross-section of volatility and expected returns. Journal of Finance, 61, 259–299.

Arrow, K. J., Harris, T., Marschak, J. 1951. Optimal inventory policy. Econometrica, 19, 250–272.

Brandt, M. W., Kishore, R., Santa-Clara, P., Venkatachalam, M. 2008. Earnings announcements are full of surprises. Working paper.

Campbell, J. Y., Hilscher, J., Szilagyi, J. 2008. In search of distress risk. Journal of Finance, 63, 2899–2939.

Carhart, M. M. 1997. On the persistence in mutual fund performance. Journal of Finance, 52, 57–82.

Chen, L., Novy-Marx, R., Zhang, L. 2010. An alternative three-factor model. Working paper.

Chen, Z., Watanabe, M., Stanzl, W. 2005. Price impact costs and the limit of arbitrage. Working paper.

Cooper, M. J., Gulen, H., Schill, M. J. 2008. Asset growth and the cross-section of stock returns. Journal of Finance, 63, 1609–1651.

Da, Z., Liu, Q., Schaumurg, E. 2014. A closer look at the short-term reversal. Management Science, 60, 658–674.

Davis, M., Norman, A. 1990. Portfolio selection with transaction costs. Mathematics of Operations Research, 15, 676–713.

Engle, R., Festenberg, R., Russel, J. 2012. Measuring and modeling execution cost and risk. Journal of Portfolio Management, 38, 14–28.

Fama, E. F., French, K. R. 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3–56.

Fama, E. F., French, K. R. 2008. Dissecting anomalies. Journal of Finance, 63, 1653–1678.

Foster, G., Olsen, C., Shevlin, T. 1984. Earnings releases, anomalies, and the behavior of security returns. The Accounting Review, 59, 574–603.

Frazzini, A., Israel, R., Moskowitz, T. 2014. Trading costs of asset pricing anomalies. Working paper.

Grinblatt, M., Titman, S. 1989. Portfolio performance evaluation: old issues and new insights. Review of Financial Studies, 2, 393–416.

Hanna, J. D., Ready, M. J. 2005. Profitable predictability in the cross section of stock returns. Journal of Financial Economics, 78, 463–505.

Harris, L. E. 1990. Statistical properties of the roll serial covariance bid/ask spread estimatior. Journal of Finance, 45, 579–590.

Harvey, C., Liu, Y., Zhu, H. 2014. ... and the cross-section of expected returns. Working Paper.

Hasbrouck, J. 2009. Trading costs and returns for u.s. equities: estimating effective costs from daily data. Journal of Finance, 64, 1446–1477.

Haugen, R. A., Baker, N. L. 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics, 41, 401–440.

Heston, S. L., Sadka, R. 2011. Seasonality in the cross-section of stock returns. Journal of Financial Economics, 87, 418–445.

Jegadeesh, N., Titman, S. 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance, 48, 65–91.

Keim, D. B., Madhavan, A. 1997. Execution costs and investment style: an interexchange analysis of instituitional equity trades. Journal of Financial Economics, 46, 265–292.

Korajczyk, R. A., Sadka, R. 2004. Are momentum profits robust to trading costs? Journal of Finance, 59, 1039–1082.

Lesmond, D. A., Schill, M. J., Zhou, C. 2004. The illusory nature of momentum profits. Journal of Financial Economics, 71, 349–380.

Linnainmaa, J., Novy-Marx, R., Tetlock, P. C. 2014. .... Working paper.

Lyandres, E., Sun, L., Zhang, L. 2008. Investment-based underperformance following seasoned equity offerings. Review of Financial Studies, 21, 2825–2855.

McLean, D., Pontiff, J. 2014. Does academic research destroy return predictability. Working paper.

Moskowitz, T., Grinblatt, M. 1999. Do industries explain momenum? Journal of Finance, 54, 1249–1290.

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

Novy-Marx, R. 2014. The quality dimension of value investing. Working paper.

Piotroski, J. 2000. Value investing: the use of historical financial statement information to separate winners from losers. Journal of Accounting Research, 38, 1–41.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. Journal of Finance, 39, 1127–1139.

Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review, 71, 289–315.