# Paper Profits or Real Money? Trading Costs and Stock Market Anomalies in Country ETFs


## Abstract

Are the quantitative equity strategies for country selection robust to implementation costs? To answer this question, we conduct a comprehensive examination of the country-level strategies so far. We review, classify, and replicate 120 equity anomalies within a sample of 42 country equity indices for the years 1996–2017. Next, using ETF price and spread data, we test the effect of real-life conditions and trading costs on the anomaly performance. We also examine three cost-mitigation strategies: infrequent rebalancing, capitalization-based weighting, and focus on low-cost securities. We find that 46% of the long-only monthly rebalanced anomaly portfolios display significant alphas, concentrated strongly among strategies based on value, momentum, and liquidity. The effect of transaction costs proves largely lethal to returns, leaving only a handful of anomalies profitable. Less frequent rebalancing (annually) helps to regain the effectiveness of the strategies, increasing the monthly alphas on the long-only anomaly portfolios to 0.44% on average.



*Keywords*: trading costs, exchange traded funds, country equity indices, quantitative strategies, international investment, return predictability, equity anomalies, cross-section of returns.

*JEL-codes*: G12, G15.

**Paper Profits or Real Money? Trading Costs and Stock Market Anomalies in Country ETFs**

Paper profits are sometimes very difficult to turn into real money, and the story of the self-defeating success of Value Line may serve as a classic example. For decades, this company offered equity investors highly successful stock rankings (Salomon, 1998). The stock-picking system had striking predictive abilities, and even Fischer Black, a strong believer in the efficient market hypothesis, admired the system for its efficiency (Black & Kaplan, 1973).[1] In 1979, Value Line decided to establish a mutual fund that invested in the stocks it was recommending to its readers. Alas, the results were at best disappointing. Not only did the real money portfolio fail to keep pace with the system's paper returns, it did not even outperform the market. In the years 1979–1991, the Value Line paper portfolio delivered an annualized return of 26.2%, but the fund produced only 16.1% per annum (Leinweber, 1995). What went wrong? Admittedly, part of the difference could be attributed to Value Line readers purchasing the same stocks at the same time. But a significant portion of the drag could be explained by trading and implementation costs (Leinweber, 1995; Perold & Salomon, 1991; Salomon, 1998).

Naturally, the markets now are not the same as they were in the 1990s. Among other changes, we have seen a huge proliferation of exchange traded funds (ETFs) and index funds, which have given investors cheap, liquid, and efficient access to international equity markets. Now, more easily than ever before, investors can allocate their money around the world. With just one click of the mouse, they can quickly move capital from one country to another. This index revolution was quickly followed by the development of quantitative country-level investment strategies that could be employed to pick the best performing ETFs and country indices. Recent studies show that well-known return patterns, such as value, momentum, size,

[1] Recently, Zhang. and Alexander (2016) reviewed 60 academic studies on Value Line from the years 1967 to 2015, confirming its forecasting abilities.

and low-risk, are present not only at the stock level, but also at the index level.[2] The academic community has once again delivered an array of strategies, which—at least on paper—work very well. Still, even in the new reality, the old questions remain: can these paper profits be translated into true money? Do they withstand the implementation-shortfall reality check? The main aim of this research is to try to answer these questions. In other words, we would like to find out which of the stock-level anomalies are present in country equity indices tracked by ETFs, and to what extent they can be translated into successful country-picking strategies that survive the effect of trading costs.

Our study aims to contribute in three ways. First, we conduct the most comprehensive test ever done of return patterns in country equity indices tracked by ETFs. We aim to determine which of the stock-level return predictive variables also work at the country level. To this end, we review, classify, and replicate 120 equity anomalies at the country level. We use sorting to form long-only and long-short portfolios, and test their performance within a sample of 42 equity indices for the years 1996–2017. This is by far the broadest examination to date of the cross-sectional return patterns in equity indices; earlier studies focused on a single variable, such as size (Keppler & Traub, 1993), momentum (Balvers & Wu, 2006), or reversal (Spierdijk, Bikker, & van den Hoek, 2012; de Groot, Huij, & Zhou, 2012; Baltussen, van Bekkum, & Da, 2016), or considered only a small number of strategies together (Zaremba, 2016a; Umutlu & Bengitöz, 2017). Our research not only re-examines all the patterns already discovered, but also extends the array of potential return patterns.

Second, we test to what extent these country-level equity anomalies could be translated into profitable true-money strategies using ETFs. Thus, we replicate the anomalies with ETFs, accounting for trading costs and using real market spread data. Subsequently, we evaluate their

[2] See, e.g., for value: Kim (2012); for momentum: Balvers and Wu (2006), Bhojraj and Swaminathan (2006); for size: Keppler and Traub (1993), Keppler and Encinosa (2011); for low-risk: Frazzini and Pedersen (2014), de Boer, Campagna, and Norman (2014), and Umutlu (2015).

post-cost performance. In this aspect, our study is related to the strain of research that aims to assess the effect of trading costs on quantitative equity strategies, including Korajczyk and Sadka (2004), Lesmond, Schill, and Zhou (2004), Frazzini, Israel, and Moskowitz (2012), and Novy-Marx and Velikov (2016). As far as we know, with the exception of the examination of momentum in ETFs (e.g., Andreu, Swinkels, and Tjong-A-Tjoe [2013], and Tse [2015]), this issue has not been comprehensively investigated so far.

Third, we check to what extent the effect of trading costs could be avoided with the use of cost-mitigation strategies. Hence, we test three well-known techniques—less-frequent portfolio rebalancing, capitalization-based weighting, and focusing on low-cost securities—and examine their efficiency for quantitative ETF strategies. Although this question has been researched with regard to anomalies in individual equities (e.g., by Agyei-Ampomah [2007], Lesmond, Shill, and Zhou [2004], Hanna and Ready [2005], Novy-Marx and Velikov [2016], and Chen and Velikov [2017]), it has never come under scrutiny in the universe of single country ETFs or indices. We also compare the practical cost-adjusted efficiency of long-only and long-short portfolios. Thus, we also contribute to the literature discussing whether long-short or long-only implementation is preferable (e.g., Huij, Lansdorp, Blitz, & Van Vliet, 2014; Briere & Szafarz, 2017).

The key findings of this paper can be summarized as follows. First, of the 120 tested anomalies, 55 and 22 could be translated into positive and significant anomalies on long-only and long-short portfolios of country equity indices, respectively. The mean monthly alphas on these strategies amount to 0.41% for long-only portfolios and 0.52% for long-short portfolios. The profitable anomalies concentrate largely in the categories of value, momentum, and liquidity strategies.

Second, the influence of trading costs on the returns from monthly rebalanced anomaly portfolios proves largely lethal. In particular, in the case of high-turnover momentum strategies, the significant gains are forgone and transform into structural and significant losses. In fact, only a few strategies survive the deadly effect of transaction costs—and these include liquidity-driven strategies, which are characterized by very low turnover.

Third, infrequent rebalancing proves the most successful cost mitigation strategy. Reducing the portfolio-reforming frequency from one month to one year dramatically reduces the portfolio turnover and, in consequence, the implementation costs. Hence, as many as 49 of the 55 long-only anomaly portfolios that worked well with equity indices on the pre-cost basis continue to overperform with ETFs, even after accounting for trading costs: the anomalies produce a mean alpha of 0.44% per month. The two other approaches—capitalization-based weighting and discarding the most expensive securities—do not lead to any further improvement in performance.

The remainder of the paper is organized as follows. Section 2 presents the data sources and sample. Section 3 focuses on the replication of the equity anomalies at the country level, and Section 4 examines the impact of trading costs on their performance. Section 5 investigates cost mitigation strategies, and, finally, Section 6 concludes the paper.

## 2. Data

This research is based on stock market and accounting data obtained from the Bloomberg database. We conduct our examinations within two samples: a) 42 MSCI equity indexes calculated and tracked by single country-ETFs, and b) 42 single-country ETFs. We use iShares ETFs managed by BlackRock because they provide the broadest geographical coverage. The study relies on monthly observations, and the sample period runs from April 1996 to April 2017.[3] An MSCI index is included in the sample at month *t* when it is possible to compute all

[3] The sample period of returns is dictated by data availability, including ETF prices and spreads, in particular. Nonetheless, we also use earlier data when it is necessary to calculate some return predicting variables, for instance, historical index returns for price-based strategies (e.g., momentum or reversal).

its returns in month *t*, its stock market capitalization in *t*-1, and when the ETF return is available for the same period. This unification provides consistency between the index and ETF return samples. An overview of the sample is presented in Table A1 in the Appendix.

The initial data on equity indices are collected in their local currencies and subsequently converted to U.S. dollars to obtain a pooled international sample. Analogously, our sample includes ETFs denominated in U.S. dollars. We examine total gross returns that are the returns adjusted for distributions, but not adjusted for taxes on dividends. To ensure consistency with the U.S. dollar approach, the risk-free rate is the one-month Treasury bill rate.[4]

Some of the strategies tested in this paper rely on country-level fundamental variables and financial ratios. To obtain these, we weight the characteristics of individual components according to the index weighting scheme.[5]

## 3. Replicating Anomalies at the Country Level

This study relies on a sample of 120 international equity strategies which replicate stock-level anomalies at the country level. The selection of the anomalies was motivated by previous research studies on cross-sectional return patterns and specifically includes the selections made by Hou, Xue, and Zhang (2017) and Jacobs and Müller (2017). We also apply additional screens. For inclusion, an anomaly has to be computable using accounting and market data from standard databases, such as Bloomberg. The anomaly strategies must be replicable with the use of long-short portfolios based on cross-sectional rankings of securities. Furthermore, they must be implementable using the data, which could be transformed to the country level.[6] Finally, we

[4] We thank Kenneth R. French for providing this data at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5] The index-level ratios are computed by Bloomberg. Furthermore, when a strategy relies on accounting data, to calculate the return in month *t* we use data from month *t*-5 to avoid look-ahead bias.

[6] In a few cases, we have slightly modified the original anomaly computation procedures to overcome the difficulties with data availability in emerging markets. For example, we substituted default Bloomberg credit risk evaluations for the (unavailable) formal agency credit ratings when replicating the strategies of Avramov et al. (2007, 2009). All these cases are clearly described in Table A2 in the Appendix.

test only strategies that can be implemented using portfolios from single-sorts. In other words, we do not consider combinations of our strategies, such as size-enhanced momentum, as these require double-sorts (Hong, Lim, & Stein, 2000).

We classify the 120 strategies into nine categories based on the underlying economic rationales: value versus growth, momentum, quality, investment, liquidity, low-risk, reversal, seasonality, and skewness and extreme risk. The list of the examined anomalies is displayed in Table 1.[7] Furthermore, a detailed description of the strategies along with the basic literature references and portfolio formation procedures is presented in Table A2 in the Appendix.

*[Insert Table 1 here]*

To ensure consistency, all the anomaly portfolios are formed using identical procedures. To obtain a return in month *t*, we rank all the markets on anomaly-related return-predicting variables at the end of *t*-1 and determine the 25th and 75th percentiles as breakpoints. Subsequently, we use all the securities from the top and bottom quartiles of the rankings to form equal-weighted portfolios.[8] Next, we investigate long-only portfolios based on the quartile of assets with the highest expected returns. Additionally, we build zero-investment portfolios, which are essentially classic long-short portfolios. In each case, we assume a long (short) position in the portfolio that should display higher (lower) returns based on the available empirical evidence. This alternative approach is motivated by the arguments of Huij, Lansdorp, Blitz, and van Vliet (2014), who acknowledge that while the long-only portfolios are preferred due to practical issues, the long-short approach might be theoretically superior. Indeed, in the case of some countries or ETFs, short sale availability may be limited, but also the implementation costs might be elevated. Comparing the two approaches might yield additional

[7] It should be noted that the returns on certain anomalies are not fully independent, particularly in cases where we include both the original anomalies as well as their enhancements as proposed in the literature. Nonetheless, the average Pearson's correlation coefficient of excess returns in the portfolios amounts to only 0.04 (equal-weighting quintile approach), implying that the sample captures a diverse set of return phenomena.
[8] In the default approach we use the best and worst 25% of securities (indexes); for robustness, we also examine 20% and 30% breakpoints.

insights, contributing to the literature about whether long-short or long-only implementation is preferred (e.g., Huij, Lansdorp, Blitz, & van Vliet, 2014; Briere & Szafarz, 2017).

We evaluate the performance of the anomaly portfolios with the simple CAPM (Sharpe, 1964), according to which, asset returns depend solely on the market portfolio.[9] The CAPM is based on the following regression:

$$R_{i,t} = \alpha_{CAPM,i} + \beta_{MKT,i} R_{MKT,t} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ and $R_{MKT,t}$ are excess returns in month $t$ on the analyzed asset $i$ and the market portfolio, respectively, and $\alpha_{CAPM,i}$ and $\beta_{MKT,i}$ are regression parameters. The intercept $\alpha_{CAPM,i}$ (Jensen's alpha) measures the average abnormal return, whereas $\beta_{MKT,i}$ is the exposure to stock market risk. The return on the market portfolio is a monthly-rebalanced capitalization-weighted average of returns on all the securities in the universe. When calculating it, we always take the same trading cost approach as for the examined anomalies, i.e., we base the calculations on indexes or ETFs, and adjust for the trading costs (or not) as per the anomaly. In consequence, for each month $t$, we consider three different market portfolios: a) based on all available returns on the MSCI indexes for which the iShares ETF is available in month $t$, b) based on raw ETF returns, and c) based on ETF returns adjusted for trading costs.[10] The procedures for adjusting the market portfolio for the trading costs are identical to those for the ETF strategies, which are detailed in Section 4.

Table 2 reports the performance of the different market portfolios. Whereas the correlation coefficients between the payoffs are very high and the risk characteristics are essentially the same, the mean excess returns differ markedly. The portfolios composed of the

[9] We do not consider any more sophisticated multifactor model for two reasons: 1) we are only interested in the outperformance of the standard capitalization-weighted index, and 2) the cross-sectional multifactor models do not consider any cost drags.

[10] We are aware that since 2008 the iShares MSCI ACWI ETF, which covers a broad range of international equity markets and provides global exposure at low cost, has also been available. Nonetheless, we opt for forming the market portfolios using single country ETFs. We assume that this approach provides better comparability of the examined strategies with the benchmark, particularly given that the iShares MSCI ACWI ETF does not cover all the considered countries for the entire study period.

MSCI country indices tracked by ETFs deliver a mean monthly excess return equaling 0.371%. The market portfolio composed of ETFs exhibits a mean payoff of 0.320% per month. The lower profits of about 0.05% relative to the MSCI indexes tracked by ETFs could be attributable predominantly to ETF management fees consuming part of investors' profits. Finally, a roughly similar amount—slightly less than 0.05%—is lost due to the trading costs of forming and rebalancing the portfolios. In consequence, the trading-cost-adjusted market portfolio of ETFs produces a mean monthly return of 0.274%. To sum up, all the real-life limitations and trading frictions related to implementing the passive ETF strategy reduce the monthly excess returns on the market portfolio by about 28%—from 0.371% to 0.274%.

*[Insert Table 2 here]*

Table 3 reports the performance of the strategies examined in the study.[11] Notably, only a fraction of the anomaly portfolios deliver positive and significant alphas. The group of value strategies (Panel A) is relatively successful; the majority of them prove profitable. Interestingly, the best performance is delivered by the valuation ratios based on broad profitability measures, such as EBITDA or gross profits, and on enterprise value rather than equity value. This index-level observation matches the stock-level findings of Grey and Vogel (2012) and Cakici, Chatterjee, and Tang (2017).

*[Insert Table 3 here]*

Panel B of Table 3 summarizes the momentum strategies. In this group, a number of techniques also prove successful, particularly in the long-only approach. Remarkably, the less sophisticated the strategy is, the better it works; the most effective portfolios are largely based merely on past returns, moving averages, or 52-week highs. Also, the returns on signal momentum (33) turn out to be very good in the long-only approach. On the other hand, the

[11] Table A3 in the Appendix illustrates the monthly returns on the anomaly portfolios based on alternative breakpoints. The results display no major qualitative differences.

abnormal returns on the fancier strategies, such as residual or alpha momentum advocated by Blitz, Hanauer, and Vidojevic (2017) and Hühn and Scholz (2017), as well as numerous long-short strategies, turn out to be rather modest and insignificant.

The profitability of two further groups of anomalies—related to quality and investment (Panels C and D)—are scattered over several different strategies. This includes some techniques based on profitability, accruals, earnings volatility, and indebtedness. Notably, the most prominent strategies—including gross profitability by Novy-Marx (2013) and asset growth by Cooper, Gulen, and Schill (2008)—still prove profitable.

Sorting stocks on liquidity-related variables (Panel E of Table 3) also results in highly lucrative strategies. Nearly all the variables produce significant and positive abnormal returns. It appears that the stock level illiquidity premium (Amihud, Mendelson, & Pedersen, 2005) has its parallel at the index level: the smaller and less liquid markets reward investors with higher profits.[12]

Replication of the remaining categories of anomalies does not produce particularly impressive results. With a few exceptions among long-only portfolios, the low-risk anomalies do not show any significant alphas, consistent with the findings of Umutlu (2015) that the country-level risk-return relationships do not closely follow the stock-level patterns. The profits from the reversal strategy are also generally disappointing. The probable reason is that, although this strategy performed very well in the past (Balvers & Wu, 2006), during the last two decades it has tended to generate losses (Zaremba, 2016b). The payoffs to the strategies based on seasonal effects in the cross-section of returns are somewhat modest, reflecting the findings of Keloharju, Linnainmaa, and Nyberg (2016) that seasonal effects in equity indexes are less significant than in individual equities. In the end, the abnormal returns on skewness-related strategies are limited to total skewness (110), previously documented by Zaremba and Nowak

[12] These observations corroborate earlier findings of Keppler and Traub (1993) and Lee (2011).

(2015), as well as the long-only portfolios formed on downside volatility (116) and kurtosis (118).

Summing up, our calculations show that not more than 50% of the examined anomalies prove profitable at the country level. Precisely 55 of the long-only portfolios and 22 of the long-short portfolios display significant and positive alphas. The successful strategies are concentrated primarily in three groups: value, momentum, and liquidity, with some strategies also scattered across other categories. These return regularities may potentially serve as promising tools for quantitatively-oriented investors, at least until they consider the trading costs.

## 4. Influence of Trading Costs

We continue our study with a reality check: we test these strategies in a universe of transaction-cost adjusted returns on ETFs. In this phase of our study, we limit our attention to the anomalies that delivered significant abnormal returns. Specifically, we test the strategies that displayed positive CAPM alphas that departed significantly from zero at the 10% level.[13] These criteria are met by 55 long-only strategies and 22 long-short portfolios.

To obtain the cost-adjusted returns, we assume that trading costs are a sum of two components: spreads and commissions. For spreads, we use real-life bid-ask spreads, calculated based on the last bid and ask price available on a given day in Bloomberg. Our trading cost approach, i.e., to use the effective bid-ask spread, follows numerous papers in trading costs literature which also relied on bid-ask spreads including Brandt, Santa-Clara, and Valkanov (2009), Hand and Green (2011), Novy-Marx and Velikov (2016), Chen and Velikov (2017), and DeMiguel, Martin-Utrera, Nogales, and Uppal (2017). In addition, our approach is more

[13] We deliberately choose a 10% significance level, which is not very demanding, so as to assure a broader sample of examined strategies within a relatively short study period of 21 years.

accurate because we use real-life bid and ask price data, whereas the indicated studies usually relied on bid-ask spread estimates in the style of Hasbrouck (2009) due to data unavailability. Importantly, for the ETFs which have been available to investors for only about 20 years, the use of quoted spreads still allows for coverage of an entire study sample and does not require any additional estimations.

Closely following Novy-Marx and Velikov (2016), we determine the exact trading costs by tracking portfolio weights and applying the spreads and commissions whenever a trading cost occurs. In line with this approach, each time a position is entered, exited, or rebalanced, we assume both the commission and half of the spread is paid. We proxy the spread component of the cost using half the quoted spread, calculated as the difference between the ask and bid prices divided by the mid-price.[14]

Our measure of transaction costs targets relevance and simplicity. As noted by Novy-Marx and Velikov (2016), it omits any estimation of price impact and shorting costs, which would require making strong assumptions about the trade size and the trader, as in the cost estimation models employed by Keim and Madhavan (1997) or de Groot, Huij, and Zhou (2011), among others. Instead, concentrating exclusively on the bid-ask spread yields a simple interpretation: it is the lower bound for an average trader that uses market orders. Nonetheless, we would like to highlight that the omission of the lending fees is a limitation of this study and could be considered in future research.

For commissions, we assume a flat amount of 0.07% of the value of a trade—a rough and conservative estimate of the average cost of commissions in the U.S. large-cap market during the study period (ITG, 2016). Again, by using this approach, we predominantly aim for simplicity. Percentage fees are the dominant model in many countries, including most of Europe. It is the case that the commissions in North American markets are usually fixed

[14] See, also, Hasbrouck (2009) who concentrates on the effective cost that is equivalent to half of the effective spread.

amounts independent of the value of the trade. However, using an average percentage amount is a simple approach that does not require a stand on the trader, the orders, or the implementation algorithm.

To obtain the aggregate value of trading costs, we multiply the estimate of the costs by the change of weights of various ETFs across all positions in the portfolio. Specifically, we use the following formula:

$$c_t = \sum_{n}^{i=1} \left| w_{i,t_{b+1}} - w_{i,t_e} \right| \left(\frac{1}{2} s_{i,t} + c\right), \tag{2}$$

where $c_t$ is the total trading cost of a portfolio of *n* ETFs, $w_{i,t_e}$ is the actual weight at the end of month *t*, $w_{i,t_{b+1}}$ is the target weight at the beginning of month *t*+1, $s_{i,t}$ is the quoted spread at the end of month *t*, and *c* is the commission equal to 0.07%. Finally, we estimate the monthly cost-adjusted returns as the raw returns minus the trading costs. We also calculate the average monthly portfolio turnover—based on the formula of Chincarini and Kim (2006)—interpreted as the sum of the absolute values of all trades necessary to reform the portfolio.

Table 4 reports the performance of the 55 long-only portfolios that proved profitable in initial tests (Table 3). The adjustment for real-life conditions turns out to be lethal to the success of the strategies. The cost-adjusted alphas of anomaly portfolios of ETFs are disappointing. Among the value strategies (Panel A of Table 4), there is not a single significant and positive alpha. The situation with the momentum strategies is even worse. The long-only momentum portfolios are characterized by a remarkable turnover exceeding, on average, 30% per month, which has a deadly effect on profitability. In consequence, the momentum strategies are not only unprofitable, but most of them actually generate losses. Although the effects of transaction costs on the quality (Panel C) and investment (Panel D) portfolios are not as detrimental, still only three of them deliver a significant alpha: gross profitability (GPA), gross margin (GM), and asset growth (AG). The only group of ETF selection techniques that survives is that of liquidity-based strategies. In this case, thanks to low portfolio turnover (6.49% on average), five return-predicting variables continue to produce significant abnormal profits: turnover (Turn), turnover ratio (TR), their variability (TurnV, TRV), and Amihud's measure (Amih).

*[Insert Table 4 here]*

The performance of the long-short portfolios, reported in Table 5, is actually worse than the long-only portfolios. Importantly, the long-short strategies are more expensive to reconstruct and rebalance. This is because both sides of the trade are burdened with transaction costs, as opposed to the long-only portfolios where the investor has to rebalance only one side. In consequence, only a handful of strategies remain profitable. Again, these include almost exclusively liquidity-based sorts on turnover, turnover ratio variability, and Amihud's measure. These strategies have a very low turnover, amounting to about 13% per month on average.

*[Insert Table 5 here]*

We are also interested in how the dramatically lower profitability of the international strategies implemented with ETFs could be decomposed. Hence, we replicate the 55 long-only and 22 long-short strategies using three different universes that have already been mentioned: a) based on MSCI indexes tracked by iShares ETF in month *t*, b) based on raw ETF returns, and c) based on ETF returns adjusted for trading costs. The average performance statistics of the 55 long-only and 22 long-short strategies within these approaches are exhibited in Table 6.

*[Insert Table 6 here]*

To reiterate, we examine 55 (22) long-only (long-short) portfolios, which work well in the universe of equity indexes tracked by ETFs. As reported in row 1 of Table 6, their average alphas amount to 0.41% for the long-only and 0.52% for the long-short strategies. Replacing the indexes with ETFs (row 2) has a minor effect on the returns—the alphas and their significance fall only marginally, particularly in the case of the long-short portfolios. Nonetheless, adjustment for trading costs proves critical: when we account for these, the profitability of the strategies (i.e., the alphas) falls markedly, and essentially to zero in the long-short approach. To be precise, the average intercept equals only 0.13% (0.02%) for the long-only (long-short) portfolios with corresponding average *t*-statistics of 0.68 (0.15).

The picture conveyed by the results in Table 6 is clear. Although the management fees imposed on ETFs play some role, the death-blow to their profitability is struck by the trading costs. Therefore, the key question for investors is: can this blow be dodged or, at least, cushioned?

## 5. Can We Mitigate the Transaction Costs?

Although the influence of trading costs seems to be fairly depressing, there are still some ways to try to evade them. In this section, we test three popular cost-mitigation strategies that are supported by reasonable rationales.

**Infrequent rebalancing.** Frequent rebalancing translates into high portfolio turnover, which, in turn, induces elevated trading costs. In consequence, reducing the portfolio re-forming frequency should lower the costs. Novy-Marx and Velikov (2016) found this technique very promising when they applied it over a range of anomalies to individual stock returns on the U.S. equity market. On the other hand, infrequent rebalancing may also result in diminished pre-cost payoffs, particularly for strategies with low performance persistence and high variability in the return-predicting variables. To test the effect of infrequent rebalancing, we supplement our basic 1-month portfolio reconstruction period with four other frequencies: every 3, 6, 9, and 12 months.

**Weighting on capitalizations.** In the case of equal-weighting, the weights are independent of past returns. On the other hand, when the value-weighting scheme is used, the changes in target weights closely follow past returns. As a result, there should be fewer portfolio adjustments necessary and a lower turnover. Hence, we also investigate capitalization-based portfolio weights as an alternative to equal weights.

**Focusing on low-cost securities.** The spreads on various ETFs are not equal. They are narrower for the large and developed markets and, simultaneously, wider for low-capitalization and less popular securities. The differences between bid and ask prices vary from a fraction of a percent to a few percent. Therefore, discarding the securities with the highest spreads could potentially improve the cost efficiency. On the other hand, Zaremba (2016a) suggests that the payoffs of some country-selection strategies stem from the least liquid markets. In effect, limiting the investment universe might potentially also affect the raw profitability, making the benefits of this cost mitigation approach highly uncertain. In this study, we test five variants of the technique of concentrating on low-cost assets: each month $t$ we discard 10%, 20%, 30%, 40%, and 50% of the securities with the widest average bid-ask spread during a trailing 12-month period ($t$-12 to $t$-1).

Table 7 exhibits the average performance of the 55 long-only and 22 long-short portfolios with alternative rebalancing frequencies and weighting schemes. Let us first focus on the equally weighted portfolios (Panel A). Reducing the portfolio re-formation frequency leads to a dramatic improvement in the post-cost performance, particularly in the case of the long-only portfolios (left-hand side of Table 7). As a rule, the less often you rebalance the portfolio, the higher payoffs you get. The annually rebalanced long-only portfolios deliver monthly alphas amounting to 0.44% on average, with corresponding average $t$-statistics of 2.34. As many as 49 of the 55 strategies produce significant alphas, and the average turnover is as little as 3.58% per month.

Interestingly, for the long-short portfolios, the improvement in performance is not that spectacular. Admittedly, the turnover declines markedly, and the number of significant CAPM alphas approximately doubles. However, the overall average profitability remains relatively low, amounting to 0.18%.

*[Insert Table 7 here]*

Interestingly, replacing the equal weights with capitalization-based weights (Panel B of Table 7) does not lead to a further reduction in trading costs. The number of significant anomalies and the average alphas are slightly smaller. This phenomenon is driven by two factors. On the one hand, the portfolio turnover of the examined strategies is generated mostly by replacing the old portfolio components with new components, rather than simple rebalancing. In consequence, altering the weighting scheme results, at best, in a minuscule reduction of turnover (for instance, a drop from 3.58% to 3.52% in the case of annually rebalanced long-only portfolios). On the other hand, the value-weighted portfolios overweight the large markets, which are not the main source of the anomaly returns in the inter-market framework. The profits are often generated largely by the small, illiquid, and emerging markets (Zaremba, 2016a), and it is exactly the role of these components that is diminished in the capitalization-weighted portfolios.

Table 8 details the performance of the most cost-effective portfolio construction framework so far—the annually rebalanced long-only equal-weighted portfolios.[15] First, the turnover on all the portfolios is visibly reduced, and in some cases—for example, liquidity-based strategies—it is only 2.32% on average. Most of the strategies in nearly all the groups are characterized by significant alphas. The highest Sharpe ratios are recorded on the value and liquidity strategies, on average amounting to 0.52 and 0.55, respectively. Importantly, even the high-turnover momentum strategies perform very well, with the majority of the portfolios producing positive abnormal returns.

*[Insert Table 8 here]*

Finally, Table 9 shows our last cost-mitigation strategy, which discards the securities with the highest bid-ask spreads. We apply this technique on monthly and annually re-formed

[15] As a robustness check, Table A4 in the Appendix shows the performance on the long-only anomaly portfolios of ETFs with an annual rebalancing frequency based on the alternative breakpoints. The results display no major qualitative differences.

portfolios, following the findings of Novy-Marx and Velikov (2016) that combining the two cost-mitigation techniques—discarding the high-cost securities and reducing the rebalancing frequency—may result in further improvement of the performance.

*[Insert Table 9 here]*

The efficiency of reducing the universe to low-cost securities does not prove to be a particularly impressive approach. For monthly-rebalanced portfolios, hardly any strategy is verified as successful, and for annual rebalancing, only a handful of long-only portfolios display significant alphas. The best combination—forming the annually rebalanced long-only portfolios within the universe of the cheapest 90% of the markets—produces an average abnormal return of only 0.26% per month, with as few as 19 portfolios displaying significant alphas. Interestingly, the greater the number of expensive markets we drop from the sample, the worse is the performance. The explanation to this puzzle lies in the turnover. The ETF spreads are not constant in time. In consequence, discarding the securities with the widest spreads dynamically changes the investable universe, resulting in an elevated portfolio turnover. Therefore, for instance, when we drop the most expensive (spread-wise) 40% of ETFs instead of 10%, the turnover of annually rebalanced portfolios rises from less than 10% to more than 40%. This pattern is detrimental to the profitability of the strategies.

Summing up, of the three cost mitigation strategies—less frequent rebalancing, capitalization weighting, and reducing the universe to low-cost securities—the first proves the most effective, particularly for the long-only portfolios. Reducing the rebalancing frequency to a one-year period allows rescuing most of the abnormal returns. Unfortunately, the cost burden on the long-short portfolios turns out to be high and difficult to mitigate with portfolio construction enhancements.

## 6. Concluding Remarks

Our study examined the performance of equity anomalies at the country level and their robustness to trading costs. Having examined 120 return patterns from the literature on equity investing, we found that 55 (22) of them could be translated into positive and significant alphas on long-only (long-short) portfolios. These anomalies, delivering abnormal returns of 0.41% (0.52%), on average, were mainly concentrated in value, momentum, and liquidity-driven strategies.

The effect of trading costs proved truly detrimental for most of the anomalies, leaving only a handful of liquidity strategies profitable. Luckily, reducing the rebalancing frequency regained the efficiency of the majority of strategies. The two other cost mitigation strategies examined—weighting portfolio components on capitalizations and focusing on low-cost securities—were not as successful.

Our study not only provides new insights into asset pricing in international financial markets, but it also has clear practical applications. The examined strategies could be directly employed by quantitatively-oriented investment managers with an international mandate. In the future, studies on the return patterns researched in this paper could be extended to the universe of sector or industry ETFs to check their potential for implementing profitable quantitative strategies.

Future studies on the topic covered in this paper could be pursued in a few directions. First, by making stronger assumptions about the investor, trade size, and implementation algorithms, one may examine the implementation shortfall in the style of Keim and Madhavan (1997) and de Groot, Huij, and Zhou (2011). This exercise would provide further insights into the appropriateness of the international equity strategies for different types of investors. Second, it would be interesting to examine the implementation of international strategies with some different instruments, such as index futures. Finally, one may also consider the influence of taxes on profits and dividends, their influence on active international equity strategies, and to what extent their impact could be mitigated.

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## Tables

Table 1

*List of Anomaly Strategies Examined in the Study*

This table provides detailed information on the 120 anomalies examined in this study. *No.* is the running number in this table, and *Abbr.* is the symbol of the strategy used in the study. The detailed description of the anomalies, along with the reference literature, is displayed in Table A2 in the Appendix.

| No. | Abbr. | Name | No. | Abbr. | Name |
|---|---|---|---|---|---|
| Group 1: Value | | | Group 3 continued | | |
| 1 | EP | Earnings-to-price ratio | 63 | CFD | Cash flow-to-debt ratio |
| 2 | BM | Book-to-market ratio | 64 | EBTD | EBITDA-to-debt ratio |
| 3 | CFP | Cash flow-to-price ratio | 65 | SG1Y | Sales growth (1 year) |
| 4 | FCFY | Free cash flow yield | 66 | NDM | Net debt-to-capitalization value ratio |
| 5 | SP | Sales-to-price ratio | 67 | BL | Balance sheet leverage |
| 6 | EBEV | EBITDA-to-EV ratio | 68 | PEAD | Earnings surprise |
| 7 | SEV | Sales-to-EV ratio | 69 | REVS | Revenue surprise |
| 8 | EBP | EBITDA-to-price ratio | Group 4: Investment | | |
| 9 | GPEV | Gross profit-to-EV ratio | 70 | AG | Asset growth |
| 10 | GPME | Gross profit-to-market equity ratio | 71 | HR | Hiring rate |
| 11 | AM | Assets-to-market ratio ratio | 72 | CIA | Capital investments |
| 12 | SG5Y | 5-year sales growth | 73 | I1Ch | Investment change (1 year) |
| 13 | DY | Dividend yield | 74 | I2Ch | Investment change (2 years) |
| Group 2: Momentum | | | 75 | I3Ch | Investment change (3 years) |
| 14 | StMom | Short-term momentum | 76 | CEI | Composite equity issuance |
| 15 | LtMom | Long-term momentum | 77 | TECh | Change in common shareholder equity |
| 16 | IntMom | Intermediate momentum | 78 | ACI | Abnormal capital expenditures |
| 17 | MomCons | Return consistency-enhanced momentum | Group 5: Liquidity | | |
| 18 | RALtMom | Risk-adjusted momentum | 79 | Turn | Turnover |
| 19 | Acc | Momentum acceleration | 80 | TR | Turnover ratio |
| 20 | MA6Q | 6-month moving average (ratio) | 81 | TRV | Turnover ratio variability |
| 21 | MA12Q | 12-month moving average (ratio) | 82 | TurnV | Turnover variability |
| 22 | 52HQ | 52-week high (ratio) | 83 | Amih | Amihud measure |
| 23 | 52HQL | Lagged 52-week high (ratio) | 84 | TR12 | Annual turnover |
| 24 | RMOM1F | Residual momentum (CAPM) | 85 | Cap | Total market capitalization |
| 25 | RMOM3F | Residual momentum (three-factor model) | Group 6: Low-Risk | | |
| 26 | RMOM5F | Residual momentum (five-factor model) | 86 | Beta | Beta |
| 27 | VARMOM1F | Volatility-adjusted residual momentum (CAPM) | 87 | SD | Volatilty |
| 28 | VARMOM3F | Volatility-adjusted residual momentum (three-factor model) | 88 | OilBeta | Oil beta |
| 29 | VARMOM5F | Volatility-adjusted residual momentum (five-factor model) | 89 | IvolMKT | Idiosyncratic volatility (CAPM) |
| 30 | AMOM1F | Alpha momentum (CAPM) | 90 | Ivol3F | Idiosyncratic volatility (three-factor model) |
| 31 | AMOM3F | Alpha momentum (three-factor model) | 91 | IVol4F | Idiosyncratic volatility (four-factor model) |
| 32 | AMOM5F | Alpha momentum (five-factor model) | 92 | Ivol5F | Idiosyncratic volatility (five-factor model) |
| 33 | RSM | Returns signal momentum | 93 | IvolMF | Idiosyncratic volatility (model-free) |
| 34 | MomSkew | Skewness-enhanced momentum | 94 | Disp | Dispersion |
| Group 3: Quality | | | 95 | RANGE | Range |
| 35 | DYCh | Change in dividend yield | 96 | SystVol | Systematic volatility |

| | | | | | |
|---|---|---|---|---|---|
| 36 | DCh | Change in absolute dividends | 97 | DownBeta | Downside beta |
| 37 | ROA | Return on assets | 98 | SystIV1F | Exposure to idiosyncratic volatility (CAPM) |
| 38 | ROACh | Change of ROA | 99 | SystIV3F | Exposure to idiosyncratic volatility (three-factor model) |
| 39 | ROE | Return on equity | 100 | SystIVMF | Exposure to idiosyncratic volatility (model free) |
| 40 | ROECh | Change of ROE | 101 | SystDisp | Exposure to dispersion |
| 41 | CFA | Cash flow-to-assets ratio | Group 7: Reversal | | |
| 42 | GPA | Gross profit-to-assets ratio | 102 | LtRev36 | Long-term reversal (36 months) |
| 43 | GM | Gross margin | 103 | LtRev48 | Long-term reversal (48 months) |
| 44 | PM | Profit margin | 104 | LtRev60 | Long-term reversal (60 months) |
| 45 | PMCh | Change in profit margin | 105 | StRev | Short-term reversal |
| 46 | AT | Asset turnover | 106 | RevMonth | Stock-reversal month (*t*-13) to (*t*-18) |
| 47 | ATCh | Change in asset turnover | Group 8: Seasonalities | | |
| 48 | GMGSG | Gross margin growth minus sales growth | 107 | SeasMom5 | Seasonality momentum (5 years) |
| 49 | EarVol | Earnings volatility | 108 | SeasMom20 | Seasonality momentum (20 years) |
| 50 | CfVol | Cash flow volatility | 109 | OtherJan | The other January effect |
| 51 | DM | Leverage | Group 9: Skewness and Extreme Risk | | |
| 52 | LevCh | Change in leverage | 110 | Skew | Total skewness |
| 53 | CH | Cash holdings | 111 | CoSkew | Systematic skewness |
| 54 | SC | Sales-to-cash ratio | 112 | IdSkew1 | Idiosyncratic skewness (CAPM) |
| 55 | CR | Current ratio | 113 | IdSkew3 | Idiosyncratic skewness (three-factor model) |
| 56 | CRCh | Change in current ratio | 114 | IdSkew4 | Idiosyncratic skewness (four-factor model) |
| 57 | OA | Operating accruals | 115 | IdSkew5 | Idiosyncratic skewness (five-factor model) |
| 58 | TA | Total accruals | 116 | DownVol | Downside volatility |
| 59 | POA | Percent operating accruals | 117 | VaR | Value at risk |
| 60 | PTA | Percent total accruals | 118 | Kurt | Kurtosis |
| 61 | NOAg | Net operating assets growth | 119 | MAX | Maximum daily return |
| 62 | NOAc | Net operating assets change | 120 | MIN | Minimum daily return |

Table 2

*Descriptive Statistics of Performance of the Market Portfolios*

This table summarizes the mean excess returns on market portfolios calculated using three different approaches: (a) calculated based on the MSCI indexes representing countries covered by ETFs, (b) calculated based on ETF returns, and (c) calculated based on ETFs with adjustment for trading costs. The means and standard deviations are expressed as percentages. The values in brackets are bootstrap *t*-statistics. Panel A displays basic return characteristics, whereas Panel B shows Pearson pair-wise correlation coefficients.

| | (1) Full sample | (2) ETFs - no costs | (3) ETFs - cost-adjusted |
|---|---|---|---|
| *Panel A: Basic Characteristics* | | | |
| R | 0.371 | 0.320 | 0.274 |
| | *(1.21)* | *(0.99)* | *(0.85)* |
| Vol | 4.54 | 4.70 | 4.70 |
| SR | 0.28 | 0.24 | 0.20 |
| Skew | -0.66 | -0.65 | -0.66 |
| Kurt | 1.56 | 1.68 | 1.68 |
| *Panel B: Correlation coefficients* | | | |
| (1) | | 0.99 | 0.99 |
| (2) | | | 1.00 |

Table 3

*Monthly Returns on the Anomaly Portfolios*

This table reports the monthly returns on the equal-weighted long-only (left side) and long-short (right side) quartile portfolios of MSCI country indexes tracked by ETFs, based on equity anomalies. *No.* is the running number in this table and *Abbr.* is the symbol of the anomaly used in the study. *R* is the mean monthly return and *α* is the alpha from the CAPM model. Asterisks *, **, and *** indicate values that are significantly different from zero at the 10%, 5%, and 1% levels, respectively. The numbers in brackets are bootstrap (for *R*) and Newey-West (1987) adjusted (for *α*) *t*-statistics. The full names of the strategies are provided in Table 1.

| No. | Abbr. | Long-only portfolios | | | | Long-short portfolios | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | R | *t*-stat | α | *t*-stat | R | *t*-stat | α | *t*-stat |
| | | | | *Panel A: Value* | | | | | |
| 1 | EP | 0.87* | *(1.94)* | 0.39* | *(1.87)* | 0.33 | *(1.26)* | 0.23 | *(0.93)* |
| 2 | BM | 0.69 | *(1.58)* | 0.23 | *(1.04)* | 0.10 | *(0.45)* | 0.02 | *(0.06)* |
| 3 | CFP | 0.86** | *(2.15)* | 0.42** | *(2.56)* | 0.40** | *(2.35)* | 0.36* | *(1.94)* |
| 4 | FCFY | 0.87** | *(2.21)* | 0.45*** | *(2.62)* | 0.40** | *(2.21)* | 0.41* | *(1.68)* |
| 5 | SP | 0.60 | *(1.58)* | 0.17 | *(1.27)* | 0.14 | *(0.85)* | 0.08 | *(0.40)* |
| 6 | EBEV | 0.89** | *(2.07)* | 0.41** | *(2.05)* | 0.42** | *(2.22)* | 0.35 | *(1.55)* |
| 7 | SEV | 0.76** | *(2.08)* | 0.34** | *(2.33)* | 0.30 | *(1.60)* | 0.26 | *(1.11)* |
| 8 | EBP | 0.87** | *(2.11)* | 0.41** | *(2.31)* | 0.41** | *(2.13)* | 0.35 | *(1.58)* |
| 9 | GPEV | 1.12** | *(2.43)* | 0.63*** | *(2.77)* | 0.88*** | *(3.47)* | 0.81*** | *(3.12)* |
| 10 | GPME | 0.85** | *(2.08)* | 0.40** | *(2.52)* | 0.68*** | *(2.70)* | 0.61** | *(2.43)* |
| 11 | AM | 0.58 | *(1.45)* | 0.13 | *(0.97)* | 0.02 | *(0.17)* | -0.02 | *(-0.08)* |
| 12 | GSGY | 0.72 | *(1.63)* | 0.31* | *(1.74)* | 0.07 | *(0.34)* | 0.07 | *(0.32)* |
| 13 | DY | 0.59 | *(1.60)* | 0.16 | *(0.80)* | 0.06 | *(0.40)* | 0.01 | *(0.06)* |
| | | | | *Panel B: Momentum* | | | | | |
| 14 | StMom | 0.80** | *(2.30)* | 0.42** | *(2.45)* | 0.32 | *(1.17)* | 0.38 | *(1.28)* |
| 15 | LtMom | 0.82** | *(2.43)* | 0.43** | *(2.34)* | 0.47* | *(1.82)* | 0.54* | *(1.75)* |
| 16 | IntMom | 0.69* | *(1.92)* | 0.28 | *(1.54)* | 0.30 | *(1.21)* | 0.34 | *(1.17)* |
| 17 | MomCons | 0.41 | *(0.98)* | 0.08 | *(0.38)* | -0.38 | *(-1.32)* | -0.33 | *(-0.98)* |
| 18 | RALtMom | 0.64* | *(1.89)* | 0.24 | *(1.37)* | 0.24 | *(1.09)* | 0.29 | *(0.90)* |
| 19 | Acc | 0.65* | *(1.75)* | 0.24 | *(1.39)* | 0.02 | *(0.10)* | 0.04 | *(0.16)* |
| 20 | MA6Q | 0.72** | *(1.98)* | 0.33* | *(1.95)* | 0.36 | *(1.28)* | 0.41* | *(1.65)* |
| 21 | MA12Q | 0.78** | *(2.26)* | 0.40** | *(2.35)* | 0.25 | *(0.90)* | 0.32 | *(1.09)* |
| 22 | 52HQ | 0.77** | *(2.39)* | 0.41*** | *(2.79)* | 0.25 | *(0.95)* | 0.36 | *(1.23)* |
| 23 | 52HQL | 0.60* | *(1.82)* | 0.24 | *(1.42)* | -0.06 | *(-0.29)* | 0.04 | *(0.15)* |
| 24 | RMOM1F | 0.53 | *(1.32)* | 0.16 | *(0.93)* | -0.13 | *(-0.68)* | -0.07 | *(-0.32)* |
| 25 | RMOM3F | 0.56 | *(1.41)* | 0.19 | *(1.27)* | -0.07 | *(-0.27)* | -0.03 | *(-0.12)* |
| 26 | RMOM5F | 0.56 | *(1.38)* | 0.18 | *(1.11)* | -0.12 | *(-0.57)* | -0.08 | *(-0.37)* |
| 27 | ARMOM1F | 0.50 | *(1.24)* | 0.13 | *(0.77)* | -0.15 | *(-0.83)* | -0.10 | *(-0.47)* |
| 28 | ARMOM3F | 0.55 | *(1.39)* | 0.19 | *(1.12)* | -0.05 | *(-0.28)* | -0.01 | *(-0.03)* |
| 29 | ARMOM5F | 0.49 | *(1.26)* | 0.13 | *(0.81)* | -0.10 | *(-0.62)* | -0.07 | *(-0.34)* |
| 30 | AMOM1F | 0.65 | *(1.38)* | 0.25 | *(1.03)* | 0.11 | *(0.37)* | 0.09 | *(0.33)* |
| 31 | AMOM3F | 0.63 | *(1.37)* | 0.22 | *(1.08)* | 0.03 | *(0.03)* | 0.00 | *(0.00)* |
| 32 | AMOM5F | 0.65 | *(1.46)* | 0.27 | *(1.27)* | 0.02 | *(-0.01)* | 0.02 | *(0.07)* |
| 33 | RSM | 0.72** | *(2.08)* | 0.31* | *(1.94)* | 0.21 | *(1.12)* | 0.23 | *(0.85)* |
| 34 | MomSkew | 0.64* | *(1.87)* | 0.25 | *(1.56)* | 0.16 | *(0.62)* | 0.22 | *(0.84)* |
| | | | | *Panel C: Quality* | | | | | |
| 35 | DYCh | 0.58 | *(1.42)* | 0.13 | *(0.72)* | -0.33 | *(-1.52)* | -0.39* | *(-1.67)* |
| 36 | DCh | 0.48 | *(1.37)* | 0.09 | *(0.69)* | -0.19 | *(-1.07)* | -0.15 | *(-0.73)* |
| 37 | ROA | 0.82** | *(2.07)* | 0.37* | *(1.95)* | 0.28 | *(1.41)* | 0.25 | *(1.09)* |
| 38 | ROACh | 0.62 | *(1.62)* | 0.19 | *(1.39)* | -0.02 | *(-0.08)* | -0.01 | *(-0.06)* |
| 39 | ROE | 0.78** | *(2.06)* | 0.35** | *(2.12)* | 0.19 | *(1.04)* | 0.17 | *(0.86)* |
| 40 | ROECh | 0.62* | *(1.69)* | 0.19 | *(1.50)* | 0.04 | *(0.35)* | 0.06 | *(0.33)* |
| 41 | CFA | 0.83** | *(2.07)* | 0.38* | *(1.85)* | 0.42** | *(2.41)* | 0.41** | *(2.01)* |
| 42 | GPA | 1.14*** | *(2.64)* | 0.68*** | *(2.82)* | 0.72*** | *(3.44)* | 0.70*** | *(3.13)* |
| 43 | GM | 0.96** | *(2.47)* | 0.54*** | *(3.04)* | 0.41 | *(1.55)* | 0.43* | *(1.78)* |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 44 | PM | 0.54 | *(1.40)* | 0.12 | *(0.58)* | -0.04 | *(-0.32)* | -0.06 | *(-0.25)* |
| 45 | PMCh | 0.55 | *(1.47)* | 0.12 | *(0.84)* | -0.18 | *(-1.14)* | -0.17 | *(-0.98)* |
| 46 | AT | 0.79** | *(2.09)* | 0.36** | *(2.16)* | 0.29 | *(1.53)* | 0.26 | *(1.25)* |
| 47 | ATCh | 0.66 | *(1.52)* | 0.20 | *(1.13)* | -0.10 | *(-0.59)* | -0.10 | *(-0.41)* |
| 48 | GMGSG | 0.63 | *(1.33)* | 0.19 | *(0.86)* | 0.04 | *(-0.11)* | 0.04 | *(0.13)* |
| 49 | EarVol | 0.89** | *(2.07)* | 0.47** | *(2.38)* | 0.56*** | *(3.19)* | 0.53*** | *(2.65)* |
| 50 | CfVol | 0.92** | *(1.99)* | 0.47** | *(2.14)* | 0.36* | *(1.69)* | 0.26 | *(1.21)* |
| 51 | DM | 0.65* | *(1.67)* | 0.21 | *(1.35)* | 0.00 | *(0.13)* | -0.03 | *(-0.12)* |
| 52 | LevCh | 0.65* | *(1.69)* | 0.22 | *(1.43)* | -0.08 | *(-0.34)* | -0.09 | *(-0.39)* |
| 53 | CH | 0.64* | *(1.71)* | 0.23 | *(1.19)* | -0.05 | *(-0.51)* | -0.04 | *(-0.21)* |
| 54 | SC | 0.66* | *(1.84)* | 0.24 | *(1.51)* | 0.19 | *(1.14)* | 0.15 | *(0.76)* |
| 55 | CR | 0.75** | *(2.10)* | 0.34** | *(2.07)* | 0.01 | *(-0.12)* | 0.05 | *(0.25)* |
| 56 | CRCh | 0.67* | *(1.72)* | 0.23 | *(1.34)* | 0.10 | *(0.61)* | 0.10 | *(0.51)* |
| 57 | OA | 0.85** | *(2.29)* | 0.43*** | *(2.79)* | 0.41** | *(2.38)* | 0.43** | *(2.20)* |
| 58 | TA | 0.70* | *(1.85)* | 0.31** | *(2.57)* | 0.03 | *(0.07)* | 0.10 | *(0.43)* |
| 59 | POA | 0.73** | *(1.97)* | 0.33** | *(2.23)* | 0.32 | *(1.64)* | 0.35* | *(1.65)* |
| 60 | PTA | 0.73* | *(1.93)* | 0.33** | *(2.44)* | 0.16 | *(0.89)* | 0.21 | *(0.94)* |
| 61 | NOAg | 0.43 | *(1.16)* | 0.00 | *(-0.03)* | -0.34* | *(-1.80)* | -0.34* | *(-1.75)* |
| 62 | NOAc | 0.49 | *(1.27)* | 0.05 | *(0.33)* | -0.43* | *(-1.90)* | -0.43** | *(-2.01)* |
| 63 | CFD | 0.92** | *(2.26)* | 0.47* | *(1.83)* | 0.47** | *(2.02)* | 0.45* | *(1.69)* |
| 64 | EBTD | 0.83** | *(1.97)* | 0.38* | *(1.75)* | 0.23 | *(0.88)* | 0.22 | *(0.81)* |
| 65 | SG1Y | 0.77** | *(2.01)* | 0.33* | *(1.88)* | 0.01 | *(-0.15)* | 0.02 | *(0.08)* |
| 66 | NDM | 0.78* | *(1.87)* | 0.32* | *(1.77)* | 0.38* | *(1.75)* | 0.33 | *(1.18)* |
| 67 | BL | 0.76* | *(1.80)* | 0.31 | *(1.27)* | 0.17 | *(0.56)* | 0.14 | *(0.45)* |
| 68 | PEAD | 0.53 | *(1.51)* | 0.10 | *(0.62)* | -0.30 | *(-1.46)* | -0.24 | *(-0.98)* |
| 69 | REVS | 0.51 | *(1.40)* | 0.09 | *(0.57)* | -0.37* | *(-1.69)* | -0.28 | *(-1.25)* |
| | | | | *Panel D: Investment* | | | | | |
| 70 | AG | 0.90** | *(2.19)* | 0.52*** | *(3.02)* | 0.39 | *(1.56)* | 0.44* | *(1.88)* |
| 71 | HR | 0.85** | *(2.40)* | 0.44*** | *(2.77)* | 0.43** | *(2.41)* | 0.46** | *(2.32)* |
| 72 | CIA | 0.41 | *(1.20)* | 0.01 | *(0.06)* | -0.28 | *(-1.23)* | -0.22 | *(-0.92)* |
| 73 | IG | 0.64* | *(1.71)* | 0.20 | *(1.09)* | 0.11 | *(0.68)* | 0.09 | *(0.49)* |
| 74 | I2Ch | 0.47 | *(1.19)* | 0.03 | *(0.14)* | -0.36 | *(-1.53)* | -0.36 | *(-1.52)* |
| 75 | I3Ch | 0.70 | *(1.54)* | 0.26 | *(1.09)* | -0.09 | *(-0.27)* | -0.12 | *(-0.38)* |
| 76 | CEI | 0.58 | *(1.37)* | 0.22* | *(1.71)* | 0.03 | *(0.15)* | 0.05 | *(0.30)* |
| 77 | TECh | 0.66* | *(1.90)* | 0.23 | *(1.53)* | -0.01 | *(0.22)* | 0.00 | *(-0.01)* |
| 78 | ACI | 0.83* | *(1.82)* | 0.40* | *(1.67)* | 0.19 | *(0.57)* | 0.20 | *(0.65)* |
| | | | | *Panel E: Liquidity* | | | | | |
| 79 | Turn | 1.00*** | *(2.66)* | 0.61*** | *(3.42)* | 0.61*** | *(3.39)* | 0.62*** | *(3.60)* |
| 80 | TR | 0.95*** | *(2.82)* | 0.59*** | *(3.24)* | 0.37* | *(1.79)* | 0.46*** | *(2.63)* |
| 81 | TRV | 1.03** | *(2.39)* | 0.59*** | *(2.96)* | 0.78*** | *(3.22)* | 0.79*** | *(3.56)* |
| 82 | TurnV | 0.96** | *(2.55)* | 0.54*** | *(3.10)* | 0.52** | *(2.22)* | 0.61*** | *(3.09)* |
| 83 | Amih | 1.02*** | *(2.64)* | 0.62*** | *(3.48)* | 0.60*** | *(3.09)* | 0.58*** | *(3.64)* |
| 84 | TR12 | 0.79** | *(2.31)* | 0.42** | *(2.28)* | 0.18 | *(0.76)* | 0.26 | *(1.51)* |
| 85 | Cap | 0.90** | *(2.29)* | 0.49** | *(2.53)* | 0.58*** | *(2.72)* | 0.54*** | *(2.66)* |
| | | | | *Panel F: Low-Risk* | | | | | |
| 86 | Beta | 0.53* | *(1.79)* | 0.21 | *(1.28)* | -0.33 | *(-1.23)* | -0.15 | *(-0.59)* |
| 87 | SD | 0.60** | *(2.10)* | 0.27** | *(2.01)* | -0.28 | *(-1.01)* | -0.11 | *(-0.40)* |
| 88 | OilBeta | 0.50 | *(1.41)* | 0.09 | *(0.58)* | -0.40* | *(-1.66)* | -0.36* | *(-1.73)* |
| 89 | IVolMKT | 0.50 | *(1.48)* | 0.10 | *(1.15)* | -0.50* | *(-1.93)* | -0.42* | *(-1.65)* |
| 90 | Ivol3F | 0.57* | *(1.67)* | 0.17** | *(1.97)* | -0.46* | *(-1.84)* | -0.37 | *(-1.52)* |
| 91 | Ivol4F | 0.52 | *(1.50)* | 0.12 | *(1.30)* | -0.49** | *(-1.99)* | -0.41* | *(-1.73)* |
| 92 | Ivol5F | 0.52 | *(1.50)* | 0.12 | *(1.32)* | -0.44* | *(-1.80)* | -0.37 | *(-1.46)* |
| 93 | IvolMF | 0.57* | *(1.68)* | 0.18* | *(1.67)* | -0.28 | *(-1.04)* | -0.21 | *(-0.83)* |
| 94 | Disp | 0.48 | *(1.42)* | 0.09 | *(0.93)* | -0.46* | *(-1.77)* | -0.39 | *(-1.48)* |
| 95 | RANGE | 0.42 | *(1.33)* | 0.08 | *(0.56)* | -0.35 | *(-1.34)* | -0.15 | *(-0.78)* |
| 96 | SystVol | 0.66 | *(1.57)* | 0.22 | *(1.03)* | 0.01 | *(0.13)* | 0.00 | *(-0.01)* |
| 97 | DownBeta | 0.47 | *(1.49)* | 0.13 | *(0.75)* | -0.12 | *(-0.46)* | 0.01 | *(0.05)* |
| 98 | SystIV1F | 0.81** | *(2.19)* | 0.40** | *(1.98)* | 0.21 | *(1.24)* | 0.24 | *(0.98)* |
| 99 | SystIV3F | 0.75** | *(2.00)* | 0.35* | *(1.69)* | 0.24 | *(1.12)* | 0.27 | *(1.16)* |
| 100 | SystIVMF | 0.76** | *(2.03)* | 0.35* | *(1.84)* | 0.24 | *(1.43)* | 0.25 | *(1.28)* |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 101 | SystDisp | 0.73* | *(1.70)* | 0.28 | *(1.41)* | 0.19 | *(0.99)* | 0.17 | *(0.90)* |
| | *Panel G: Reversal* | | | | | | | | |
| 102 | LtRev36 | 0.50 | *(1.37)* | 0.08 | *(0.48)* | -0.21 | *(-0.84)* | -0.20 | *(-0.82)* |
| 103 | LtRev48 | 0.53 | *(1.43)* | 0.11 | *(0.72)* | -0.14 | *(-0.59)* | -0.14 | *(-0.61)* |
| 104 | LtRev60 | 0.59* | *(1.72)* | 0.21 | *(1.42)* | -0.03 | *(-0.01)* | 0.02 | *(0.06)* |
| 105 | StRev | 0.72* | *(1.92)* | 0.29* | *(1.91)* | 0.12 | *(0.50)* | 0.10 | *(0.45)* |
| 106 | RevMonth | 0.74** | *(2.07)* | 0.31* | *(1.65)* | 0.12 | *(0.66)* | 0.10 | *(0.39)* |
| | *Panel H: Seasonality* | | | | | | | | |
| 107 | SeasMom5 | 0.66* | *(1.70)* | 0.24 | *(1.20)* | 0.00 | *(-0.14)* | 0.00 | *(0.01)* |
| 108 | SeasMom20 | 0.69* | *(1.74)* | 0.27 | *(1.42)* | 0.01 | *(-0.06)* | 0.00 | *(0.00)* |
| 109 | OtherJan | 0.76** | *(2.18)* | 0.37** | *(2.09)* | 0.29 | *(1.31)* | 0.34 | *(1.37)* |
| | *Panel I: Skewness and Extreme Risk* | | | | | | | | |
| 110 | Skew | 0.94*** | *(2.58)* | 0.52*** | *(3.53)* | 0.41** | *(2.32)* | 0.42** | *(2.43)* |
| 111 | CoSkew | 0.72* | *(1.76)* | 0.27 | *(1.51)* | -0.03 | *(-0.16)* | -0.04 | *(-0.19)* |
| 112 | IdSkew1 | 0.62 | *(1.61)* | 0.19 | *(1.29)* | 0.18 | *(1.14)* | 0.20 | *(1.19)* |
| 113 | IdSkew3 | 0.67* | *(1.70)* | 0.23 | *(1.57)* | 0.06 | *(0.29)* | 0.06 | *(0.47)* |
| 114 | IdSkew4 | 0.53 | *(1.36)* | 0.10 | *(0.72)* | -0.06 | *(-0.47)* | -0.04 | *(-0.24)* |
| 115 | IdSkew5 | 0.63 | *(1.57)* | 0.20 | *(1.28)* | 0.18 | *(0.94)* | 0.20 | *(1.18)* |
| 116 | DownVol | 0.91** | *(1.98)* | 0.41** | *(2.00)* | 0.34 | *(1.17)* | 0.17 | *(0.66)* |
| 117 | VaR | 0.87* | *(1.93)* | 0.36 | *(1.62)* | 0.33 | *(1.24)* | 0.15 | *(0.52)* |
| 118 | Kurt | 0.78** | *(2.18)* | 0.38** | *(2.23)* | 0.30 | *(1.59)* | 0.30 | *(1.52)* |
| 119 | MAX | 0.50 | *(1.53)* | 0.16 | *(1.07)* | -0.34 | *(-1.38)* | -0.19 | *(-0.85)* |
| 120 | MIN | 0.57* | *(1.66)* | 0.22 | *(1.35)* | -0.25 | *(-0.94)* | -0.08 | *(-0.40)* |

Table 4

*Monthly Alphas on the Long-Only Anomaly Portfolios Adjusted for Trading Costs*

This table reports the monthly returns on the monthly-rebalanced equal-weighted long-only quartile portfolios of single country ETFs. *No.* is the running number in this table and *Abbr.* is the symbol of the anomaly used in the study. $\alpha$ is the alpha from the CAPM model and *Turnover* is the average monthly portfolio turnover. Asterisks *, **, and *** indicate values that are significantly different from zero at the 10%, 5%, and 1% levels, respectively. The numbers in brackets are Newey-West (1987) adjusted *t*-statistics. The full names of the strategies are provided in Table 1.

| No. | Abbr. | α | *t*-stat | Turnover |
|---|---|---|---|---|
| | *Panel A: Value* | | | |
| 1 | EP | 0.01 | *(0.05)* | 14.02 |
| 2 | CFP | 0.13 | *(0.76)* | 13.44 |
| 3 | FCFY | 0.22 | *(1.25)* | 13.28 |
| 4 | EBEV | 0.28 | *(1.33)* | 12.58 |
| 5 | SEV | 0.16 | *(1.06)* | 9.60 |
| 6 | EBP | 0.29 | *(1.45)* | 10.07 |
| 7 | GPEV | 0.37 | *(1.63)* | 12.93 |
| 8 | GPME | 0.24 | *(1.48)* | 10.75 |
| 9 | GSGY | 0.11 | *(0.58)* | 11.86 |
| | **Average** | **0.20** | ***1.07*** | **12.06** |
| | *Panel B: Momentum* | | | |
| 10 | StMom | -0.14 | *(-0.74)* | 29.38 |
| 11 | LtMom | 0.02 | *(0.09)* | 22.21 |
| 12 | MA6Q | -0.31 | *(-1.64)* | 37.64 |
| 13 | MA12Q | -0.09 | *(-0.51)* | 27.07 |
| 14 | 52HQ | -0.28 | *(-1.73)* | 39.66 |
| 15 | RSM | -0.10 | *(-0.60)* | 24.37 |
| | **Average** | **-0.15** | ***-0.85*** | **30.06** |
| | *Panel C: Quality* | | | |
| 16 | ROA | 0.09 | *(0.39)* | 6.47 |
| 17 | ROE | 0.09 | *(0.54)* | 8.50 |
| 18 | CFA | 0.06 | *(0.27)* | 9.77 |
| 19 | GPA | 0.56** | *(2.35)* | 6.89 |
| 20 | GM | 0.40** | *(2.27)* | 7.39 |
| 21 | AT | 0.25 | *(1.53)* | 6.14 |
| 22 | EarVol | 0.28 | *(1.31)* | 6.28 |
| 23 | CfVol | 0.32 | *(1.39)* | 6.43 |
| 24 | CR | 0.15 | *(0.92)* | 9.06 |
| 25 | OA | 0.26 | *(1.32)* | 12.74 |
| 26 | TA | 0.14 | *(0.90)* | 12.12 |
| 27 | POA | 0.21 | *(1.21)* | 11.37 |
| 28 | PTA | 0.05 | *(0.38)* | 12.29 |
| 29 | CFD | 0.11 | *(0.39)* | 10.49 |
| 30 | EBTD | 0.22 | *(1.03)* | 6.93 |
| 31 | SG1Y | -0.14 | *(-0.69)* | 20.26 |

| No. | Strategy | α | *t*-stat | Turnover |
|---|---|---|---|---|
| | *Panel C continued* | | | |
| 32 | NDM | 0.19 | *(0.99)* | 6.24 |
| | **Average** | **0.19** | ***0.97*** | **9.38** |
| | *Panel D: Investment* | | | |
| 33 | AG | 0.32* | *(1.67)* | 10.22 |
| 34 | HR | 0.18 | *(1.03)* | 16.22 |
| 35 | CEI | 0.03 | *(0.21)* | 10.16 |
| 36 | ACI | -0.03 | *(-0.12)* | 13.72 |
| | **Average** | **0.13** | ***0.70*** | **12.58** |
| | *Panel E: Liquidity* | | | |
| 37 | Turn | 0.50** | *(2.49)* | 5.36 |
| 38 | TR | 0.48** | *(2.36)* | 8.45 |
| 39 | TRV | 0.44* | *(1.90)* | 5.61 |
| 40 | TurnV | 0.34* | *(1.82)* | 7.63 |
| 41 | Amih | 0.48** | *(2.40)* | 6.50 |
| 42 | TR12 | 0.29 | *(1.39)* | 5.85 |
| 43 | Cap | 0.27 | *(1.11)* | 6.03 |
| | **Average** | **0.40** | ***1.93*** | **6.49** |
| | *Panel F: Low-Risk* | | | |
| 44 | SD | 0.09 | *(0.72)* | 9.34 |
| 45 | Ivol3F | 0.04 | *(0.45)* | 8.18 |
| 46 | IvolMF | 0.05 | *(0.47)* | 9.46 |
| 47 | SystIV1F | 0.16 | *(0.72)* | 16.08 |
| 48 | SystIV3F | 0.12 | *(0.54)* | 15.77 |
| 49 | SystIVMF | 0.01 | *(0.06)* | 17.36 |
| | **Average** | **0.08** | ***0.49*** | **12.70** |
| | *Panel G: Reversal* | | | |
| 50 | StRev | -0.96 | *(-5.41)* | 58.84 |
| 51 | RevMonth | -0.25 | *(-1.31)* | 29.18 |
| | **Average** | **-0.61** | **-3.36** | **44.01** |
| | *Panel H: Seasonality* | | | |
| 52 | OtherJan | 0.23 | *(1.32)* | 8.46 |
| | *Panel I: Skewness and extreme risk* | | | |
| 53 | Skew | 0.21 | *(1.44)* | 15.31 |
| 54 | DownVol | 0.19 | *(0.95)* | 8.67 |
| 55 | Kurt | 0.07 | *(0.45)* | 15.45 |
| | **Average** | **0.16** | ***0.95*** | **13.14** |

Table 5

*Monthly Alphas on the Long-Short Anomaly Portfolios Adjusted for Trading Costs*

This table reports the monthly returns on the monthly-rebalanced equal-weighted long-short quartile portfolios of single country ETFs. *No.* is the running number in this table and *Abbr.* is the symbol of the anomaly used in the study. $\alpha$ is the alpha from the CAPM model and *Turnover* is the average monthly portfolio turnover. Asterisks *, **, and *** indicate values that are significantly different from zero at the 10%, 5%, and 1% levels, respectively. The numbers in brackets are Newey-West (1987) adjusted *t*-statistics. The full names of the strategies are provided in Table 1.

| No. | Abbr. | α | *t*-stat | Turnover |
|---|---|---|---|---|
| | | *Panel A: Value* | | |
| 1 | CFP | -0.19 | *(-0.98)* | 27.07 |
| 2 | FCFY | -0.03 | *(-0.09)* | 26.57 |
| 3 | GPEV | 0.20 | *(0.73)* | 26.79 |
| 4 | GPME | 0.17 | *(0.61)* | 22.91 |
| | **Average** | **0.04** | ***0.07*** | **25.84** |
| | | *Panel B: Momentum* | | |
| 5 | LtMom | -0.41 | *(-1.25)* | 44.72 |
| 6 | MA6Q | -0.86*** | *(-3.07)* | 73.29 |
| | **Average** | **-0.63** | ***-2.16*** | **59.00** |
| | | *Panel C: Quality* | | |
| 7 | CFA | -0.18 | *(-0.90)* | 21.33 |
| 8 | GPA | 0.35 | *(1.59)* | 17.83 |
| 9 | GM | -0.01 | *(0.26)* | 15.96 |
| 10 | EarVol | -0.01 | *(0.84)* | 12.52 |
| 11 | OA | -0.19 | *(-0.07)* | 25.04 |
| 12 | POA | -0.02 | *(-0.05)* | 23.47 |

| No. | Strategy | α | *t*-stat | Turnover |
|---|---|---|---|---|
| | | *Panel C continued* | | |
| 13 | CFD | -0.08 | *(-0.66)* | 20.03 |
| | **Average** | **0.03** | ***0.14*** | **19.45** |
| | | *Panel D: Investment* | | |
| 14 | AG | 0.38* | *(-0.08)* | 22.91 |
| 15 | HR | 0.18 | *(-0.36)* | 31.44 |
| | **Average** | **-0.05** | ***-0.22*** | **27.18** |
| | | *Panel E: Liquidity* | | |
| 16 | Turn | 0.49** | *(1.96)* | 11.42 |
| 17 | TR | 0.26 | *(0.90)* | 18.25 |
| 18 | TRV | 0.31* | *(2.03)* | 10.45 |
| 19 | TurnV | 0.26 | *(1.35)* | 14.45 |
| 20 | Amih | 0.31* | *(1.66)* | 13.61 |
| 21 | Cap | 0.17 | *(0.69)* | 10.13 |
| | **Average** | **0.30** | ***1.43*** | **13.05** |
| | | *Panel F: Skewness and Extreme Risk* | | |
| 22 | Skew | -0.32* | *(-1.73)* | 32.87 |

Table 6

*Performance of Anomaly Portfolios Formed Using Different Approaches*

This table reports the CAPM alphas on the monthly-rebalanced equal-weighted long-only (Panel A) and long-short (Panel B) quartile portfolios. Portfolios are calculated using various approaches: (1) calculated based on the MSCI indexes representing countries covered by ETFs, (2) calculated based on ETF returns, and (3) calculated based on ETFs with adjustment for trading costs. The table presents average values across all the long-only and long-short anomaly portfolios listed in Tables 4 and 5. $\bar{\alpha}$ is the average alpha from the CAPM model, $\overline{t - stat}$ is the average Newey-West (1987) adjusted $t$-statistic, $\overline{Turn}$ is the average portfolio turnover, and N is the number of anomalies with positive alphas that significantly differ from zero at the 10% level. $\bar{\alpha}$ and $\overline{Turn}$ are expressed as percentages.

| No. | Type of portfolios | Long-only portfolios | | | | Long-short portfolios | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\bar{\alpha}$ | $\overline{t - stat}$ | N | $\overline{Turn}$ | $\bar{\alpha}$ | $\overline{t - stat}$ | N | $\overline{Turn}$ |
| (1) | Full sample | 0.41 | 2.31 | 55 | 13.73 | 0.52 | 2.43 | 22 | 23.80 |
| (2) | ETFs - no costs | 0.37 | 2.01 | 40 | 13.75 | 0.51 | 2.27 | 17 | 23.78 |
| (3) | ETFs - cost-adjusted | 0.13 | 0.68 | 8 | 13.75 | 0.02 | 0.15 | 3 | 23.78 |

Table 7

*Performance of Anomaly Portfolios Formed Using Different Rebalancing Frequencies and Weighting Schemes*

This table reports the CAPM alphas on the long-only (left side) and long-short (right side) equal-weighted (Panel A) and value-weighted (Panel B) quartile anomaly portfolios of ETFs based on different rebalancing frequencies. The table presents average values across all the long-only and long-short anomaly portfolios listed in Tables 4 and 5. $\bar{\alpha}$ is the average alpha from the CAPM model, $\overline{t-stat}$ is the average Newey-West (1987) adjusted *t*-statistic, $\overline{Turn}$ is the average portfolio turnover, and N is the number of anomalies with positive alphas that significantly differ from zero at the 10% level. $\bar{\alpha}$ and $\overline{Turn}$ are expressed as percentages.

| Rebalancing frequency | Long-only portfolios | | | | Long-short portfolios | | | |
|---|---|---|---|---|---|---|---|---|
| | $\bar{\alpha}$ | $\overline{t-stat}$ | N | $\overline{Turn}$ | $\bar{\alpha}$ | $\overline{t-stat}$ | N | $\overline{Turn}$ |
| *Panel A: Equal-weighted portfolios* | | | | | | | | |
| Every 1 month | 0.13 | 0.68 | 8 | 13.75 | 0.02 | 0.15 | 3 | 23.78 |
| Every 3 months | 0.36 | 1.82 | 33 | 7.74 | 0.17 | 0.74 | 5 | 14.70 |
| Every 6 months | 0.42 | 2.17 | 44 | 5.21 | 0.19 | 0.87 | 5 | 10.28 |
| Every 9 months | 0.42 | 2.16 | 44 | 4.29 | 0.23 | 0.94 | 6 | 8.71 |
| Every 12 months | 0.44 | 2.34 | 49 | 3.58 | 0.18 | 0.82 | 5 | 7.79 |
| *Panel B: Capitalization-weighted portfolios* | | | | | | | | |
| Every 1 month | -0.08 | -0.55 | 1 | 15.70 | -0.16 | -0.65 | 1 | 25.83 |
| Every 3 months | 0.15 | 0.79 | 12 | 8.35 | 0.06 | 0.21 | 3 | 14.96 |
| Every 6 months | 0.23 | 1.33 | 22 | 5.43 | 0.15 | 0.59 | 3 | 10.10 |
| Every 9 months | 0.22 | 1.19 | 17 | 4.20 | 0.17 | 0.62 | 4 | 8.11 |
| Every 12 months | 0.26 | 1.53 | 28 | 3.52 | 0.17 | 0.69 | 5 | 7.09 |

Table 8

*Performance on the Long-Only Anomaly Portfolios of ETFs: The Annual Rebalancing Frequency*

This table reports the monthly returns on the annually rebalanced equal-weighted long-only quartile portfolios of single country ETFs presented in Table 5. *No.* is the running number in this table, *Abbr.* is the symbol of the anomaly used in the study, *R* is the mean monthly excess return, *Vol* is the standard deviation of monthly excess returns, *SR* is the annualized Sharpe ratio, $\alpha$ is the alpha from the CAPM model, and *Turnover* is the average monthly portfolio turnover. Asterisks *, **, and *** indicate values that are significantly different from zero at the 10%, 5%, and 1% levels, respectively. The numbers in brackets are bootstrap (for *R*) and Newey-West (1987) adjusted (for $\alpha$) *t*-statistics. The full names of the strategies are provided in Table 1.

| No. | Strategy | R | *t*-stat | Vol | SR | α | *t*-stat | Turnover |
|---|---|---|---|---|---|---|---|---|
| | | | | *Panel A: Value* | | | | |
| 1 | EP | 0.93** | *(2.04)* | 7.13 | 0.45 | 0.56** | *(2.44)* | 3.39 |
| 2 | CFP | 0.98** | *(2.19)* | 6.95 | 0.49 | 0.63*** | *(3.07)* | 4.21 |
| 3 | FCFY | 0.70* | *(1.85)* | 5.65 | 0.43 | 0.39** | *(2.24)* | 4.70 |
| 4 | EBEV | 0.91** | *(2.23)* | 6.22 | 0.51 | 0.57*** | *(2.97)* | 2.68 |
| 5 | SEV | 0.81** | *(2.16)* | 5.69 | 0.49 | 0.49*** | *(3.17)* | 2.44 |
| 6 | EBP | 1.05** | *(2.36)* | 6.95 | 0.52 | 0.69*** | *(3.09)* | 2.31 |
| 7 | GPEV | 0.80* | *(1.81)* | 6.62 | 0.42 | 0.46* | *(1.91)* | 6.18 |
| 8 | GPME | 0.79* | *(1.95)* | 6.02 | 0.46 | 0.47*** | *(2.75)* | 4.95 |
| 9 | GSGY | 0.67 | *(1.95)* | 6.02 | 0.46 | 0.47*** | *(2.75)* | 4.95 |
| | **Average** | **0.85** | ***2.03*** | **6.34** | **0.46** | ***0.52*** | **2.61** | **3.80** |
| | | | | *Panel B: Momentum* | | | | |
| 10 | StMom | 0.60 | *(1.63)* | 5.84 | 0.40 | 0.38* | *(1.87)* | 3.34 |
| 11 | LtMom | 0.65 | *(1.53)* | 5.91 | 0.35 | 0.29 | *(1.35)* | 4.53 |
| 12 | MA6Q | 0.60 | *(1.60)* | 5.86 | 0.38 | 0.33* | *(1.65)* | 4.91 |
| 13 | MA12Q | 0.68* | *(1.53)* | 5.87 | 0.36 | 0.29* | *(1.66)* | 3.92 |
| 14 | 52HQ | 0.78** | *(1.75)* | 5.81 | 0.41 | 0.37* | *(1.85)* | 4.69 |
| 15 | RSM | 0.79** | *(2.21)* | 5.46 | 0.50 | 0.49*** | *(3.07)* | 4.97 |
| | **Average** | **0.68** | ***1.78*** | **5.74** | **0.42** | **0.38** | ***2.11*** | **4.57** |
| | | | | *Panel C: Quality* | | | | |
| 16 | ROA | 0.85* | *(2.09)* | 5.52 | 0.50 | 0.49*** | *(3.10)* | 4.41 |
| 17 | ROE | 0.77* | *(1.94)* | 6.92 | 0.42 | 0.49** | *(2.08)* | 2.05 |
| 18 | CFA | 0.67 | *(1.92)* | 5.94 | 0.45 | 0.44** | *(2.54)* | 2.99 |
| 19 | GPA | 1.12** | *(1.56)* | 6.72 | 0.34 | 0.32 | *(1.27)* | 3.06 |
| 20 | GM | 0.78** | *(2.57)* | 6.67 | 0.58 | 0.78*** | *(3.38)* | 2.78 |
| 21 | AT | 0.85** | *(2.15)* | 6.13 | 0.48 | 0.51*** | *(3.00)* | 2.07 |
| 22 | EarVol | 0.79* | *(1.69)* | 6.50 | 0.42 | 0.45** | *(2.12)* | 2.22 |
| 23 | CfVol | 0.88* | *(1.79)* | 6.69 | 0.46 | 0.52** | *(2.36)* | 2.92 |
| 24 | CR | 0.76** | *(2.10)* | 5.62 | 0.47 | 0.45*** | *(3.14)* | 2.51 |
| 25 | OA | 0.81** | *(2.03)* | 5.91 | 0.47 | 0.49*** | *(2.76)* | 3.98 |
| 26 | TA | 0.58 | *(1.50)* | 5.56 | 0.36 | 0.28* | *(1.74)* | 5.20 |
| 27 | POA | 0.60 | *(1.57)* | 5.56 | 0.37 | 0.30* | *(1.96)* | 4.12 |
| 28 | PTA | 0.58 | *(1.49)* | 5.65 | 0.36 | 0.28* | *(1.79)* | 5.06 |
| 29 | CFD | 0.80* | *(1.85)* | 6.88 | 0.40 | 0.44* | *(1.80)* | 6.53 |
| 30 | EBTD | 0.89** | *(2.10)* | 6.58 | 0.47 | 0.54** | *(2.43)* | 1.99 |
| 31 | SG1Y | 0.73* | *(1.67)* | 6.45 | 0.39 | 0.38* | *(1.80)* | 4.35 |
| 32 | NDM | 0.85** | *(2.03)* | 6.15 | 0.48 | 0.51*** | *(2.91)* | 1.63 |
| | **Average** | **0.78** | ***1.88*** | **6.22** | **0.43** | **0.45** | ***2.32*** | **3.51** |
| | | | | *Panel D: Investment* | | | | |
| 33 | AG | 0.82* | *(1.95)* | 5.64 | 0.50 | 0.54*** | *(2.61)* | 3.00 |
| 34 | HR | 0.76* | *(1.94)* | 5.83 | 0.45 | 0.44*** | *(2.93)* | 5.53 |
| 35 | CEI | 0.66 | *(1.53)* | 5.47 | 0.42 | 0.37*** | *(3.30)* | 2.72 |
| 36 | ACI | 0.88** | *(1.99)* | 6.35 | 0.48 | 0.54** | *(2.51)* | 4.15 |
| | **Average** | **0.78** | ***1.85*** | **5.82** | **0.46** | **0.47** | ***2.84*** | **3.85** |
| | | | | *Panel E: Liquidity* | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 37 | Turn | 0.56*** | *(2.21)* | 5.64 | 0.53 | 0.56*** | *(2.80)* | 1.46 |
| 38 | TR | 0.47** | *(2.19)* | 5.30 | 0.49 | 0.47** | *(2.45)* | 1.83 |
| 39 | TRV | 0.57*** | *(1.90)* | 5.73 | 0.52 | 0.57*** | *(2.64)* | 1.60 |
| 40 | TurnV | 0.42** | *(1.76)* | 5.44 | 0.45 | 0.42** | *(2.05)* | 2.54 |
| 41 | Amih | 0.86** | *(2.17)* | 5.71 | 0.52 | 0.56*** | *(2.90)* | 1.85 |
| 42 | TR12 | 0.54*** | *(2.29)* | 5.47 | 0.53 | 0.54*** | *(2.83)* | 2.24 |
| 43 | Cap | 0.75*** | *(2.43)* | 6.86 | 0.55 | 0.75*** | *(2.90)* | 1.81 |
| | **Average** | **0.85** | ***2.14*** | **5.74** | **0.51** | **0.55** | ***2.65*** | **1.90** |
| | *Panel F: Low-Risk* | | | | | | | |
| 44 | SD | 0.52 | *(1.59)* | 4.77 | 0.38 | 0.25** | *(2.01)* | 2.48 |
| 45 | Ivol3F | 0.47 | *(1.33)* | 5.11 | 0.32 | 0.19** | *(2.02)* | 2.21 |
| 46 | IvolMF | 0.51 | *(1.43)* | 5.25 | 0.34 | 0.21* | *(1.83)* | 2.74 |
| 47 | SystIV1F | 0.58 | *(1.54)* | 5.65 | 0.36 | 0.28 | *(1.38)* | 4.22 |
| 48 | SystIV3F | 0.60 | *(1.60)* | 5.58 | 0.37 | 0.30* | *(1.66)* | 4.08 |
| 49 | SystIVMF | 0.53 | *(1.34)* | 5.82 | 0.31 | 0.22 | *(1.04)* | 4.27 |
| | **Average** | **0.53** | ***1.47*** | **5.36** | **0.35** | **0.24** | ***1.66*** | **3.33** |
| | *Panel G: Reversal* | | | | | | | |
| 50 | StRev | 0.68 | *(1.61)* | 6.56 | 0.36 | 0.33 | *(1.64)* | 5.30 |
| 51 | RevMonth | 0.59 | *(1.51)* | 5.94 | 0.34 | 0.27 | *(1.54)* | 4.74 |
| | **Average** | **0.63** | ***1.56*** | **6.25** | **0.35** | **0.30** | ***1.59*** | **5.02** |
| | *Panel H: Seasonality* | | | | | | | |
| 52 | OtherJan | 0.70* | *(1.94)* | 5.65 | 0.43 | 0.40** | *(2.12)* | 5.13 |
| | *Panel I: Skewness and extreme risk* | | | | | | | |
| 53 | Skew | 0.84** | *(2.14)* | 5.99 | 0.49 | 0.51*** | *(2.99)* | 4.15 |
| 54 | DownVol | 0.90* | *(1.94)* | 7.09 | 0.44 | 0.51** | *(2.42)* | 2.74 |
| 55 | Kurt | 0.75** | (1.99) | 5.80 | 0.45 | 0.43*** | (2.59) | 4.60 |
| | **Average** | **0.83** | ***2.02*** | **6.30** | **0.46** | **0.48** | ***2.67*** | **3.83** |

Table 9

*Performance of Anomaly Portfolios: Discarding the Most Expensive Markets*

This table reports the CAPM alphas on the long-short (left side) and long-only (right side) equal-weighted monthly (Panel A) and annually (Panel B) rebalanced quartile anomaly portfolios formed within a filtered ETF: 10%–50% of the instruments with the broadest bid-ask spreads were discarded. The table presents average values across all of the long-only and long-short anomaly portfolios listed in Tables 4 and 5. $\bar{\alpha}$ is the average alpha from the CAPM model, $\overline{t - stat}$ is the average Newey-West (1987) adjusted *t*-statistic, $\overline{Turn}$ is the average portfolio turnover, and N is the number of anomalies with positive alphas that significantly differ from zero at the 10% level. $\bar{\alpha}$ and $\overline{Turn}$ are expressed as percentages.

| Fraction of the discarded markets | Long-only portfolios | | | | Long-short portfolios | | | |
|---|---|---|---|---|---|---|---|---|
| | $\bar{\alpha}$ | $\overline{t - stat}$ | N | $\overline{Turn}$ | $\bar{\alpha}$ | $\overline{t - stat}$ | N | $\overline{Turn}$ |
| *Monthly rebalance portfolios* | | | | | | | | |
| 10% most expensive | 0.03 | 0.10 | 1 | 15.54 | -0.17 | -0.71 | 0 | 27.72 |
| 20% most expensive | 0.05 | 0.17 | 1 | 16.68 | -0.17 | -0.72 | 0 | 30.61 |
| 30% most expensive | 0.06 | 0.25 | 1 | 17.15 | -0.14 | -0.61 | 0 | 31.39 |
| 40% most expensive | 0.02 | 0.05 | 0 | 18.40 | -0.21 | -0.83 | 0 | 33.73 |
| 50% most expensive | 0.00 | -0.10 | 0 | 17.97 | -0.13 | -0.47 | 0 | 33.22 |
| *Annually rebalanced portfolios* | | | | | | | | |
| 10% most expensive | 0.26 | 1.40 | 19 | 9.60 | -0.08 | -0.33 | 0 | 19.92 |
| 20% most expensive | 0.22 | 1.18 | 12 | 12.23 | -0.11 | -0.41 | 0 | 25.45 |
| 30% most expensive | 0.20 | 1.00 | 10 | 13.75 | -0.11 | -0.45 | 0 | 29.98 |
| 40% most expensive | 0.10 | 0.46 | 4 | 16.73 | -0.20 | -0.83 | 0 | 35.69 |
| 50% most expensive | 0.12 | 0.57 | 5 | 15.77 | -0.04 | -0.15 | 3 | 33.27 |