Transaction Costs of Factor Investing Strategies

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Abstract: Although hidden, implicit market impact costs of factor investing strategies may substantially erode the strategies' expected excess returns. The authors explain these market impacts costs and model them using rebalancing data of a suite of large and long-standing factor investing indices. They introduce a framework to assess the costs of rebalancing activities, and attribute these costs to characteristics such as rate of turnover and the concentration of turnover, which intuitively describe the strategies' demands on liquidity. The authors evaluate a number of popular factor-investing strategy implementations and identify how index construction methods, when thoughtfully designed, can reduce market impact costs.

Key Words: Factor investing, smart beta, transactions costs, implementation costs, implicit market impact cost, market impact cost model, capacity

Factor investing strategies have become increasingly popular. With transparent investment processes, low management fees, and the potential for above-average performance, they have diverted a large amount of assets from traditional active management. According to data from Morningstar Direct, assets under management (AUM) in factor investing ETFs and mutual funds across global markets increased from just below US$75 billion in 2005 to more than US$800 billion by the end of 2016. Further,

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1 Some academic journal articles use the term “factor investing” more broadly to include strategies that buy one and short another portfolio of companies with distinctively different characteristics. We refer, however, to factor investing as commercially available, long-only alternative indexing with transparent rules for security selection and weighting. These strategies that systematically target exposure to alternative factors beyond the market are often referred to as smart beta.
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this figure likely understates the size of this space because it does not include strategies pursued by institutional investors. The trend in AUM growth is likely to persist given that factor investing is a hot topic in industry and academic journals and is commonly covered at industry conferences. Large investment consultants also recommend that clients diversify their passive allocations to include factor investing strategies (Kahn and Lemmon [2016]).

With the substantial increase in AUM, however, the risks related to factor investing demand attention. Berk and Green (2004) demonstrated that fund size is inversely related to performance. It stands to reason that excess returns grow scarcer as AUM rises: managers must buy more of the stocks in their opportunity set, creating upward price pressure that inexorably lowers the expected return. Conversely, when they exit existing positions, their trading generally pushes prices down, reducing the realized return. Factor investing indices are not immune to the return-dampening effect of trading costs, even though these costs are not easily observable.

In practice, when a provider rebalances an index, most managers tracking it execute the necessary transactions near the close of the rebalancing day in order to minimize their portfolio’s tracking error. The fund managers may appear to be perfectly tracking the index; in another words, minimizing implementation shortfall, which is the aggregate difference between the average traded price and the closing price of each of the index's underlying securities on the rebalancing day. Thus, the total implementation cost of an index fund could be perceived as merely the sum of the explicit costs associated with trading, such as commissions, taxes, ticker charges, and so forth. This notion misses the propagating market impact that trading has on the index’s value. The large volume of buy
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and sell orders for the same securities, executed at the same time, can result in securities prices moving against the managers, producing losses for both the index and the fund investors. This implicit cost is often overlooked because it is not visible when comparing a fund’s net asset value (NAV) and the index’s value; it can, however, be overwhelmingly large relative to the explicit costs for strategies with massive AUM. This article focuses on unmasking the market impact costs that arise from synchronous buying and selling.²

New factor indexing strategies are marketed with backtests in lieu of live history. Impressive backtest returns may be achieved by holding concentrated portfolios with high turnover rates, and strategies that require specific selection criteria can exhibit these characteristics.³ A backtest is not an accurate representation of an investor’s experience because it only simulates the history of a strategy and does not incur actual asset-related trading activity and associated costs. In the presence of real trading, how many assets can a strategy attract before alpha erosion sets in?

Cost and capacity are two sides of the same coin for evaluating the excess return potential of a strategy. Our study lays out a framework to address this concern from a cost perspective because the definition of capacity is ambiguous. We analyze the behavior of stocks that were traded during the rebalancing of 49 FTSE RAFITM Indices (henceforth, “the indices”).⁴ This suite of indices includes some of the longest live index histories, and represents approximate total AUM of $8 billion in 2009 to $74 billion in 2016 (henceforth,

² Other risks of factor investing exist. Specifically, overfitting or data mining in historical backtests may lead investment managers to overestimate their prospects of future performance of factor investing strategies that only have short-term track records (or none at all) (Harvey, Liu, and Zhu, 2016). Our study mitigates part of the data-mining risk by quantifying realizable returns net of market impact costs.
³ For example, the MSCI USA Quality Index, MSCI USA Momentum Index, and the S&P 500 Low Volatility Index cover only about 20% of their parent indices, and their reported turnover rates are 20%, 96%, and 53%, respectively. See MSCI (2017a and 2017b) and PowerShares (2017).
⁴ The indices are described at http://www.ftse.com/products/indices/rafi.
all amounts are in US dollars), which provides sufficient transaction data around rebalancing dates to be analyzed. We find significant evidence of market impact on the rebalancing day and a subsequent price reversal over the next four days. We find that the magnitude of price impact is predictable, because it is directly related to the security’s liquidity and the size of the trade. Specifically, we identify that a fund incurs approximately 30 basis points (bps) of trading costs due to market impact for every 10% of a stock’s average daily volume (ADV) traded in aggregate by the factor investing index–tracking funds.

The hidden costs of traditional passive indexing have been studied extensively by Petajisto (2011) and Chen, Noronha, and Singal (2006), who present costs as abnormal returns due to additions and deletions to index compositions from the announcement day through the effective day. Despite promising growth, the level of indexing of factor investing strategies is low relative to traditional benchmarks; trades in the indices in our study are unlikely to garner attention from arbitrageurs given the relatively low absolute dollar amounts. Unlike previous studies on traditional benchmarks, we attribute the observed presence of market impact and its relationship to the percent of ADV traded to the microstructure aspect of the rebalancing returns: costs induced by the orders of the indexers. As a result, our study focuses on contrasting implementation methods and the liquidity profiles of the required trades.

Our simple relationship of market impact versus the security’s liquidity and the size of the trade can be used to estimate the implicit transaction costs of rebalancing trades. We apply our model and evaluate the costs of an extended list of popular strategies with various turnover rates, trade sizes, levels of security liquidity, and number of rebalances. We find
that, at a modest level of AUM, and assuming all rebalancing trades occur near the end of the rebalancing date, the expected transaction costs can significantly erode the expected alpha as indicated by long-term historical backtests. Specifically, with as little as $10 billion in AUM, momentum indexing strategies can have trading costs of 200 bps or more. At the same level of assets, income strategies’ costs are in the 60–80 bps range, and quality strategies’ costs fall below 40 bps. We report the capacities, defined as AUM when expected costs reach a high and fixed level (50 bps a year), of these strategies. We also present an attribution model to relate costs to strategy characteristics and explain in detail how certain styles of investing—for instance, those that trade frequently and those that trade completely in and out of a few illiquid positions—require higher costs than others.

No commonly accepted definition of capacity exists. The research of Chen, Stanzl, and Watanabe (2002), Frazzini, Israel, and Moskowitz (2012), and Novy-Marx and Velikov (2016), for example, attempted to identify capacities of alternative equity factors, and their calculations varied widely based on the assumptions they made. Despite the increasing popularity of investible long-only factor investing strategies, very little work has been published on their related capacities. Ang, Miranda, and Ratcliffe (2017), using a proprietary transaction-cost model developed by BlackRock, Inc., estimated capacities of six MSCI factor indices in the United States. They used a carefully calibrated cost model which causes their analyses to not be easily extendable beyond the United States and the six strategies they studied.

Our research enhances the market microstructure literature by demonstrating the market impact made collectively by indexers, even for strategies that have not attracted nearly as many assets as traditional benchmarks. In addition, our research makes far more
significant advancement in understanding the costs and capacities of factor investing. Previous studies identified capacities of certain factor investing methods. Our simple market impact cost model and standardized comparisons of cost-sensitive strategy characteristics can be easily and broadly applied to all systematic strategies that can be backtested. Our work not only includes cost estimations for a broad set of strategies across factors, styles, and regions, it also explains how strategies with certain characteristics will reach capacity sooner than others. In addition, our illustration of the cause of costs as related to strategy characteristics, and our cross-sectional comparisons of implementation methods, are especially useful to practitioners by helping investors and providers assess the validity of historical backtested performance and conduct a sensible trade-off between desired portfolio attributes and expected realized return, as well as to make rational strategy selections and design decisions.

**Review of the Research Landscape**

The extant literature does not offer a consensus on how to define capacity, but three versions of capacity advanced by Vangelisti (2006) are cited most often. Vangelisti’s preference is *threshold capacity*, the maximum AUM at which the strategy can still achieve its stated objective. This definition, however, is not useful in comparing factor investing strategies with different objectives such as earning market-like returns at reduced volatility or steadily providing high dividend yields. *Wealth-maximizing capacity* is the level of AUM that adds the most value to a fund’s investors, but it cannot be estimated without

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5 The literature on cost and investment capacity is large and diverse and our review of past contributions is limited. For a more comprehensive review, see O’Neill and Warren (2016) for an excellent survey of many more articles related to all aspects of investment capacity.
accurate predictions of a strategy’s excess returns. Finally, terminal capacity, the AUM that reduces a strategy’s net excess return to zero, seems unduly stringent because investors are not rewarded at that level of AUM for bearing tracking error risk.

Other researchers suggest analyses that are sensible and straightforward to compute, such as the number of days required to liquidate a portfolio (IML [2012]) or to trade portfolio positions back to benchmark weights (Scobie [2013]). Index providers S&P Dow Jones (S&P [2013]) and EDHEC (Shirbini [2015]) use a “maximum ownership” rule (holdings cannot exceed some percentage of market cap) and a “cost proportional to turnover” limit (for instance, 20 bps per 100% one-way turnover), respectively. These pragmatic measures simply provide factual descriptions of the portfolios under investigation; they do not establish a connection between the level of AUM and alpha erosion due to trading costs.6

Under any definition, an analysis of capacity is challenging because capacity by its very nature is dynamic. Research on the subject justly assumes that a portfolio manager’s decisions will vary as circumstances change, and the optimal level of AUM fluctuates accordingly. Managers may respond to increasing AUM in different ways; for example, they may defer or forgo trades and they may accept implementation shortfall (Perold [1988], Bertsimas and Lo [1998], Almgren and Chriss [2000], Almgren et al. [2005], and Huberman and Stanzl [2005]).

Alternately, fund managers may adjust the optimal level of turnover (Kahn and Shaffer [2005]) or take on higher tracking-error risk (Frazzini, Israel, and Moskowitz [2012]) in exchange for reduced implementation costs. Because we are studying the cost

6 Additionally, it is perhaps too simple to assume cost is directly proportional to turnover. Trading the same amount of a mega-cap company versus a micro-cap company will certainly result in different costs.
of investment strategies implemented by managers whose mandate is to track indices as closely as possible, we focus on the immediate market impact and assume no strategic scheduling of trades beyond those occasioned by index rebalancing.

Multiple studies have attempted to explain the price response to pre-announced additions and deletions to traditional benchmark indices. Petajisto (2011) measured an index premium from the announcement day through the effective day of additions and deletions to index compositions from 1990 through 2005, and identified average costs of 21–28 bps for the S&P 500 and 38–77 bps for the Russell 2000 (the two benchmarks with the highest amount of indexed assets). Chen, Noronha, and Singal (2006) reported higher average costs for the same benchmarks using shorter-sample data. They attribute the abnormal return to front running by arbitrageurs. Our study makes the observation that market impact cost is also significant and relevant for indices with far fewer indexed assets.

More closely related to our study is research investigating the capacity of investment strategies that target the common return anomalies also targeted by factor investing strategies. These studies make various assumptions, and accordingly, arrive at widely different estimates. Table 1 presents the disparities in their assumptions and results.

Chen, Stanzl, and Watanabe (2002) defined capacity as the AUM when a trade reaches 1%, or a holding reaches 5%, of a company’s market capitalization. They find the capacities of long–short size, value, and momentum factor portfolios range from $0.4 billion to $4.6 billion.

In contrast, Frazzini, Israel, and Moskowitz (2012) defined capacity on the basis of trading costs rather than ownership limits, with a tolerance for tracking error against underlying indices. They estimated the breakeven AUM for the same size, value, and
momentum factors to be one-to-two orders of magnitude higher than the estimates published by Chen, Stanzl, and Watanabe. Novy-Marx and Velikov (2016) computed factor breakeven capacities without imposing ownership caps, but used stringent requirements to limit turnover due to trading into new positions. They reported a much higher capacity for size and a much lower capacity for momentum than Frazzini, Israel, and Moskowitz.

Similar to the objective of our study, which is to assess the costs and capacities of commercially available factor investing indices rather than of academic factor strategies, Ang, Miranda, and Ratcliffe (2017) estimated the cost of six MSCI factor strategies using the trading-cost model developed by BlackRock, Inc. They defined capacities of these strategies as the AUM at which each of their historical single-index model alphas were negated by cost, and found them to range from $65 billion (for the momentum strategy) to $5 trillion (for the size strategy) in the US market.

Our study differs in a couple of ways: First, our cost model is simpler with one parameter, which is calibrated once, rather than three that are re-calibrated daily. Our cost model may not be as current and accurate, yet it can be intuitively and simply applied to any systematic rebalancing strategies including and beyond those in the US market, and it produces stable estimates and consistent comparisons of strategies amid noisy daily market activities. Second, we assume a fixed high cost (50 bps a year) when the capacity is reached, so that our analyses are not subjected to the choice of sample period or to the model classification. Finally, and most significantly, we attribute the costs of a broad number of popular, professionally managed strategies to the characteristics which are

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7 For instance, low beta (or low volatility) strategies can have different alphas depending on which factor model is used.
directly related to the expected market impact costs, and thoroughly compare and contrast them.

Even though most market impact models use relative trade size as a key determinant of cost, no clear consensus exists on the functional form most appropriate for cost modeling. Barclay and Warner (1993) offered a theoretical argument, and Almgren et al. (2005) provided an empirical model in support of a concave relationship between market impact cost and relative trade size. Gabaix et al. (2006) suggested that a concave relationship is appropriate for very large trades (50% ADV or greater). Others, such as Berkowitz, Logue, and Noser (1988), Keim and Madhavan (1997), Jones and Lipson (2001), and Chiyachantana et al. (2004) used linear functions for this relationship. In our study, we assume that the market impact cost is linearly related to relative trade size; therefore, in addition to simplicity, our assumption allows us to follow Aked and Moroz (2015) in attributing costs to various strategy characteristics such as turnover and portfolio concentration.

**Trade Data**

We obtain daily returns of traded securities from Bloomberg. Our trade data contain end-of-day AUM and security-level weights for each index, as of the rebalancing dates. The dollars traded in each stock in each index are the product of the AUM tracking the index and the weight change of the stock from the close on the rebalancing day (pre-rebalance weight) to the open on the next trading day (post-rebalance weight). Because the same stock can be traded by multiple indices, we aggregate the dollars traded for each stock across all indices to determine the total net dollars traded. The majority of our aggregations
are summing trades of the same direction (i.e., all purchases or all sales) of the same component stocks, which often arise when the companies being held are traded all at once by the global parent index (e.g., All World) and the regional index (e.g., Europe). Trading is assumed to occur on the rebalancing date.\textsuperscript{8} These data reflect the aggregate trading, necessitated by changes in index weights, of all fund managers tracking the indices.

Our dataset consists of 49,867 aggregated trades,\textsuperscript{9} with a total amount of $56.6 billion from 2009 to 2016. Table 2 describes the AUM size breakpoints as of rebalancing dates of the underlying indices, all of which are rebalanced annually in March. More than half of our trade data is drawn from rebalancing of indices that are tracked by more than $500 million assets, which indicates the significance of the source of our trading data. The largest rebalancing are of US indices, for which 95% represent indices with AUM greater than $92.9 million. In contrast, the smallest rebalancings are of other single-country strategies, for which the median AUM is less than one-third of the indices in the United States. Less than 10\% of our rebalancings are restricted to emerging markets only or small-size companies only, however, they are represented by indices with substantial AUM (medians at $1.3 billion and $202.4 million, respectively) given the size of these markets. Note that these AUM also include institutional investment which is not included in the Morningstar Direct ETFs and mutual funds database.

\textsuperscript{8} We also looked at the market behavior before the rebalancing for indications of front running. Some evidence of front running on the day before the rebalancing (buys have positive, and sells negative, market impact on the day before the trade) exists, but they are statistically insignificant and on a very small scale relative to the impact registered on the actual rebalancing date.

\textsuperscript{9} We exclude 1,131 outlying observations (~2.2\% of our sample) in order to arrive at this final dataset. Specifically, we exclude all observations in which the dollars traded are greater than two-thirds of the volume on the trade date, because the stated assumption of all trading occurring on the rebalancing day likely fails for these trades. Additionally, we exclude those with large abnormal returns (±15\%) on the rebalancing day or any of the four subsequent days, because these returns are likely related to firm-specific events beyond the rebalancing of indices, and only serve to add noise to our analysis.
Table 3 summarizes the distribution of relative trade size, defined as the dollar amount traded as a percentage of the stock’s trading volume on the trade day, of our trades. Geographically, roughly 17% of the trades we observe take place in the emerging markets; the rest come evenly from the United States and other developed markets. Approximately 50% of the trades consume less than 1.7% of the volume of the underlying security, while about 10% of the trades consume 13% or more. Consistent with the existing literature on microstructure, this ratio strongly predicts market impact cost.\textsuperscript{10}

**Single-Security Trading Cost Model**

We quantify the market impact from trading as the abnormal price movement that remains after adjusting for the traded stock’s corresponding regional market and industry returns

\[
(r_{\text{regional}, t}, r_{\text{industry}, t}).^{11,12}
\]

\[
r_{i,t} = \alpha_i + \beta_{i,\text{regional}} r_{\text{regional}, t} + \beta_{i,\text{industry}} r_{\text{industry}, t} + r_{\text{risk adjusted}, i,t} \tag{1}
\]

We assume a stock’s excess return is predominantly driven by its correlations with the corresponding market and industry. The returns unexplained by Equation (1), namely, \( r_{\text{risk adjusted}, i,t} \), are then driven by an event common to all companies—they are all traded

\textsuperscript{10} Prior studies on costs of front-running activities to investors of passive indexing, such as Petajisto (2011) and Chen, Noronha, and Singal (2006), describe indices’ demand of liquidity with level of indexing. This measure is helpful for estimating aggregate costs to all investors of a traditional passive benchmark which incurs turnover primarily when stocks are added or deleted from the composition. However, as factor investing strategies require many more trades beyond additions and deletions to compositions, the relative trade size of the component securities is the more relevant characteristics of our subject in study.

\textsuperscript{11} Sensitivities to regional and industry markets for each stock \( (\beta_{i,\text{regional}}, \beta_{i,\text{industry}}) \) are estimated with 1.5 years of daily returns centered on the trade day. We find that estimation periods other than 1.5 years made no material difference to our analyses.

\textsuperscript{12} We also experiment with controlling for other common equity factors, namely, size, value, and momentum, and find they generally do not enhance regression fit.
heavily on the index rebalancing date—as well as other events that are idiosyncratic to each company. Thus, we define mark impact \((market \ impact_{i,t})\) as \(r^{risk \ adjusted}_{i,t}\) for all purchases and negative of \(r^{risk \ adjusted}_{i,t}\) for all sales; flipping the sign of \(r^{risk \ adjusted}_{i,t}\) for stocks that are sold ensures market impact is always presented as a return against the trade.

To demonstrate the linearity of the relationship between market impact and relative trade size, we group our unmodeled trade data into bins and display in Figure 1 each bin’s average market impact and average trade size.\(^{13}\) (The subsequent reversal is also shown, and will be discussed shortly.)

Next, we formally identify the trade factor, the excess return that is linearly related to relative trade size, in the following regression:\(^{14}\)

\[
market \ impact_{i,t} = k_t \cdot \frac{Dollar \ traded_i}{Dollar \ volume_i} + \varepsilon_i
\]

\[
= k_t \cdot relative \ trade \ size_i + \varepsilon_i
\]

where \(Dollar \ traded_i\) is the net dollar amount of security \(i\) traded by our set of indices on the rebalancing day; \(Dollar \ volume_i\) is the total dollar trading volume for security \(i\) on that same rebalancing day.

\(^{13}\) Barclay and Warner (1993) hypothesized that informed traders who break trades into certain sizes that are neither too big nor too small are the primary causes of stock price movement, which implies market impact will have a concave relationship to relative trade size. We observe no empirical evidence to support or reject this “stealth-trading hypothesis.” We prefer the linear approach for its simplicity.

\(^{14}\) Relative trade size as a key determinant has been adopted in a few others in microstructure literature, for example Chiyachantana et al. (2004). We also expand Equation (2) to include other control variables commonly thought to be related to trading costs (market capitalization, return volatility, and return momentum at various horizons). We find, however, that the market impact cost depends primarily on relative trade size. Because the inclusion of other variables does not statistically or economically change the results, we do not report those findings here.
The trade-day *market impact factor*, \( k_0 \) (where \( t = 0 \) denotes the trade day), is used to estimate the market impact for a trade of given size on that day. The trade-day market impact represents the adverse return that the manager experiences when placing the trade. In other words, an abnormal return occurs on the underlying stock against the trade direction. The magnitude is expected to be the market impact factor \( k \) times relative trade size.\(^{15}\)

We apply Equation (2) as a panel regression, using all of the trades and present robust standard errors clustered on firm and rebalance year; see Petersen (2009). Results are presented in Figure 2. As robustness checks, we also look at US, developed ex US, and emerging market trades separately, as well as at purchases and sales separately. Interestingly, we find no statistically significant evidence of a different impact across the three regions or of different trade directions for the same relative trade size.\(^ {16,17}\) Figure 2 also shows the reversal impact we measure using the regression set forth in Equation (2), with cumulative market impact over four subsequent days after the trade as the dependent variable.\(^ {18}\) The reversal impact factor, \( k_{+4} \), stands for the regression coefficient. The linearity of the reversal impact with respect to trade size is illustrated in Figure 1.

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\(^{15}\) We force the intercept through zero for clearer interpretation: no trading = no impact.

\(^{16}\) This is in conflict with Domowitz, Glen, and Madhavan (2001) and Chiyachantana et al. (2004), who reported the market impact cost to be higher in the emerging markets after controlling for determinants such as market capitalization and return volatility. A potential explanation is that the emerging markets no longer warrant higher market impact costs because they have become more liberal and have established stronger shareholder protections since the early 2000s.

\(^{17}\) The implicit cost of selling is on par with buying. Our analyses do not fully represent the cost of short selling, which requires an additional cost of borrowing shares.

\(^{18}\) We also look for evidence of reversal up to 20 days after the trade. We find, however, that the reversal effect is concentrated in the first four days following a trade. Note that we observe slightly stronger and significantly faster price reversal than Petajisto (2011), who studied constituent changes to the S&P 500 and the Russell 2000 from 1990 to 2005.
We estimate the trade-day market impact factor is 4.27% and the reversal impact factor is −2.42%. Our results suggest that for every 10% of volume traded, the price of the underlying stock changes 43 bps, on average, against the trade on the trade day, and that 24 bps of the rise in price is expected to be reversed in the subsequent four days.

The findings presented in Figure 2 are crucial. Existing studies, for example, Petajisto (2011) and Chen, Noronha, and Singal (2006), have analyzed the market impact costs of changes to benchmark indices, such as the S&P 500 and the Russell 2000. Changes to these indices are informative because they represent very large and easily anticipated trades by the index funds. Chen, Noronha, and Singal (2006) highlighted the adoption of “Rarely Used Indices” as one way index investors can mitigate losses to arbitrageurs who attempt to front run the index changes. By their definition, factor investing indices are classified as “rarely used” based on the low level of assets that track them relative to a traditional benchmark. Our observations indicate, however, that market impact, in the absence of front running, can still be a significant cost to investors.

We use a hypothetical example to illustrate how the market impact occurs as a trading cost to investors: A trader executes a round-trip trade (buy, hold, and sell) of a stock with a market value of $100 per share at a trade size equivalent to 10% of daily trading volume. He observes a price level of $100 and is able to buy the stock at an average price of $100.43. After a few days, the value of the stock depreciates by 24 cents, on average, to $100.19. At this point, the trader places a sell order on the stock and its price falls by 43 cents, on average. He sells at $99.76. The trader’s total loss is 67 cents per share, on average ($100.43 minus $99.76), or 67 bps for the round trip. A few days after the sale, the price of the stock reverts 24 cents to $100, producing no long-term impact on the stock price.
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from the trading activity. The index’s value is equivalent to the prices of the shares it holds. Under the influence of rebalancing, the index’s value as well as the returns to the index fund move in parallel. The implementation shortfall appears to be minimized, but fund investors still suffer an implicit market impact cost.

For simplicity, the hypothetical example shows the implicit cost of trading a single security. But in order to mitigate noise in estimations, we recommend using this cost model with aggregate trades rather than for forecasting the cost of a single trade. In the next section, we demonstrate how to apply our model to baskets of trades induced by the rebalancing of broadly diversified indices.

Application

We use the market impact cost model we have described to estimate the costs associated with implementing a comprehensive list of factor investing strategies, including value, income, low beta (or low volatility\textsuperscript{19}), quality, momentum, and multi-factor funds. Some can be characterized as core-market indices with style tilts, while others appear to be satellites that focus on a small subset of the entire universe. Using our index construction methodologies, we conduct backtests on strategies that are reasonably similar to commercially available funds. (Their security selection and weighting protocols are summarized in Appendix A\textsuperscript{20}.) We simulate the resulting indices’ performance using data

\textsuperscript{19} The low beta anomaly advanced by Frazzini and Pedersen (2014) is the relevant factor, but we extend our analysis to include the broader low volatility anomaly, so that we also include popular strategies with relatively long live records, such as minimum volatility.

\textsuperscript{20} To allow for apples-to-apples comparisons, we modify the methodologies slightly to have consistent starting universes, regional definitions, and rebalancing dates. We include South Korea in emerging markets despite conflicting classifications by popular index providers. All annual rebalances occur at the end of June, semi-annual rebalances at the end of June and December, and quarterly rebalances at the end of March, June, September, and December.
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from Compustat and CRSP for US strategies, and from Worldscope and Datastream for international strategies.

We compute the expected market impact cost of all trades using Equation (2) and our estimated market impact factor, \( \bar{k} = 0.03 \).\(^{21}\) We then calculate the index-level market impact cost by aggregating the costs of all individual trades. The implicit cost of rebalancing a strategy equals the sum of the costs of all its underlying stocks’ trades, as follows:

\[
\text{Dollar Cost of Each Trade} = E[\text{market impact}_i] \cdot \Delta \omega_i \cdot AUM
\]

\[
= \bar{k} \cdot \frac{\text{Dollar traded}_i}{\text{Dollar volume}_i} \cdot \Delta \omega_i \cdot AUM = \bar{k} \cdot \frac{(\Delta \omega_i \cdot AUM)^2}{\text{Dollar volume}_i} \quad (3)
\]

\[
\text{Dollar Cost of Strategy} = \sum_i \left[ \bar{k} \cdot \frac{(\Delta \omega_i \cdot AUM)^2}{\text{Dollar volume}_i} \right]
\]

\[
\text{Cost of Strategy} = \frac{\text{Dollar Cost}}{AUM} = \bar{k} \cdot AUM \cdot \sum_i \left[ \frac{(\Delta \omega_i)^2}{\text{Dollar volume}_i} \right] \quad (4)
\]

where

- \( \bar{k} \) is the estimated trade-day impact, \( \bar{k} = 0.03 \);
- \( \Delta \omega_i \) is the change in weight to stock \( i \) for a given rebalancing of the strategy;
- \( \text{Dollar volume}_i \) is the short-term median dollar volume observed on trade day for stock \( i \); and
- \( AUM \) is assets under management of the strategy.

\(^{21}\) We estimate the cost of two-way turnover to be 6.7 bps for each 1% of volume traded, and we round the impact factor of a one-way trade to 3 bps (0.03%). Readers who are interested in estimating the implementation cost of a factor investing strategy assuming a different impact level can simply scale the cost estimates we present in Table 4.
Because we are estimating the *expected* cost of managing strategies without perfect foresight of trade-day volume of future rebalancing, dollar volume for this equation, as well as for the strategy characteristics throughout the “Application” section, is defined as the higher of 90-day median and 30-day median number of shares traded multiplied by the share price at current rebalancing.  

This model can be applied for calculating both the cost and the capacity of the various strategies. For calculating cost, we assume AUM equal to $10 billion for all of our simulated US and international strategies, and AUM equal to $1 billion for all emerging market strategies. To establish a uniform basis for comparing capacity, we set a fixed cost for all strategies at 50 bps a year and compute the corresponding AUM, effectively defining capacity as the largest amount of assets a strategy can hold without incurring more than 50 bps of market impact cost a year. The choice of 50 bps as the upper threshold is admittedly arbitrary, but we believe this approach is superior to estimating breakeven costs, because excess returns are highly sensitive to the sample period.

The cost and capacity estimates of factor investing strategies are more meaningful if we understand the drivers of high cost and of low capacity. For this purpose, we follow the approximation proposed by Aked and Moroz to attribute implementation costs to strategy characteristics:

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22 The 90-day horizon captures a robust estimate of the median number of shares traded, and the 30-day horizon captures a sudden spike (if any) in number of shares traded; the current share price is the best estimate of share price at the upcoming rebalancing.
Cost of Strategy

\[
\approx \bar{k} \cdot AUM \cdot \Phi \cdot \frac{1}{\text{Portfolio Volume}} \cdot \text{Tilt} \cdot \text{Turnover}
\]

\cdot \text{Turnover Concentration}

where

- \( \text{Tilt} = \sum_i \omega_i \cdot \frac{\omega_i}{v_i} \);

- \( \text{Turnover Concentration} \)

\[
= \frac{2}{T_{\text{replace}} + T_{\text{reweight}}} \left( T_{\text{replace}} + \frac{2}{2 - T_{\text{replace}}} \cdot \Psi \cdot T_{\text{reweight}}^2 \right);
\]

- \( v_i = \) Daily trading-volume weight of stock \( i \);

- \( T_{\text{replace}} = \) Average turnover due to adding and removing securities;

- \( T_{\text{reweight}} = \) Average turnover due to reweighting existing securities;

and

- \( \Psi = \frac{E^\omega[\delta^2_i]}{(E^\omega[|\delta_i|])}; E^\omega[x_i] = \sum_{i \in \text{reweight}} \omega_i x_i; \delta_i = \frac{\Delta \omega_i}{\omega_i}. \)

- \( \Phi = \frac{1}{\text{Number of days over which the trade is executed}} \)

The strategy’s cost is inversely proportional to its portfolio volume, defined as the aggregate of median daily trade volume, in dollars, of all the stocks in the portfolio. This reflects the inverse relationship of cost to trading volume, as expressed in Equation (2). All else equal, a small-cap portfolio would cost twice as much to implement as a large-cap portfolio, if it has half the latter’s aggregate volume.

Tilt, in this context, is the degree to which the portfolio-holding weights deviate from a volume-weighted portfolio, which is the most liquid combination of a given set of
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stocks. (In respect to purchases made by the portfolio, if a trade’s expected cost is defined by Equation (2), then the lowest-cost combination would be to weight stocks by their daily volume.) The volume-weighted portfolio has a tilt of 1; holding all else equal, a portfolio with a tilt of 2 would experience twice as much market impact cost. Tilt and portfolio volume are complementary measures: portfolio volume measures the liquidity of the selection of stocks, and tilt measures the liquidity of the weighting method applied to the selection. An investment strategy with a weighting methodology highly correlated with trading volume—for example, cap-weighting—will tend to have a low cost.

The strategy’s annualized one-way turnover is another key determinant of cost; a strategy that requires a higher rate of trading is more costly to implement. Alone, however, one-way turnover is an inadequate indicator of cost. Consider two rebalancings with the same turnover rate. One requires buying $100 million of the shares of a single large-cap company, while the other requires buying $10 million of the shares of each of 10 large-cap companies. Intuitively, we understand that the two portfolios would not incur the same costs: highly concentrated trades are more costly to execute.

The turnover concentration metric captures the degree to which costs are reduced by spreading trades across the portfolio. Factor strategies that invest in small subsets of the market—momentum is a good example—tend to have high turnover concentration because they routinely require that the manager completely eliminate a few existing positions and buy into new positions. In contrast, broad market indices that reweight constituents back to predetermined and stable weights tend to have lower turnover concentration. Additionally, strategies that rebalance more frequently, such as quarterly versus annually, will tend to have lower turnover concentration.
The number of days over which a single trade is executed also affects cost. (Ang, Miranda, and Ratcliffe [2017] also discussed this point.) Consider two trades of the same amount. One requires buying $100 million of a large-cap company today, whereas the other buys $50 million today, and buys another $50 million at a later date. Assuming the volume is the same for both trading days, the cost of the trade would be reduced by one-half, according to Equation (2). More formally, cost can be reduced by \( N \) times if all of the trades for one rebalancing are executed over \( N \) distinct periods (\( \Phi = \frac{1}{N} \) in Equation (5)), which is set to 1 for our study. But an index implementer who is less concerned with tracking error might choose to spread trades over multiple days, which should reduce implementation costs. Note that this describes the execution of a strategy, rather than a characteristic, and is different from rebalancing frequency (e.g., annually versus quarterly).

Table 4 displays the expected costs, as defined in Equation (4), and capacities at a hypothetical cost of 50 bps a year, of an array of popular US factor investing indices, along with their simulated performance from 1968 to 2016.\(^{23}\) The table also shows strategy characteristics that are helpful in explaining differences in implementation costs. We relegate descriptions of these factor investing simulations to Appendix A. We limit the following discussion to US strategies, but present similar results for international developed and emerging markets in Appendix B.

The two momentum strategies stand out as the most costly to implement. At $10 billion in AUM, the Sharpe momentum and standard momentum strategies are estimated to incur annual market impact costs of 2.0% and 2.7%, respectively, more than offsetting

\(^{23}\) The costs are estimated with five years of rebalancing and the market volume through the end of 2016. In reality the expected costs are time varying; estimations across all strategies, as indicated by Equation (3), shall be higher during times when liquidity is systematically low; see Huberman and Halka (2001).
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their simulated excess return. At 50 bps of annual cost they can manage only $2.4 billion and $1.8 billion, respectively, in total assets. The momentum strategies have high turnover rates (108.5% and 155.8%, respectively), high turnover concentrations (88.4% and 90.2%, respectively), and low portfolio volumes ($35.7 billion and $37.9 billion, respectively) relative to strategies of other styles. Collectively, these characteristics imply they have concentrated or illiquid holdings, completely trade out of and into a few positions, and do so at a fast pace. All of these traits contribute to their high cost of implementation. In contrast, they have the lowest tilt at 1.3, which suggests their weighting by market capitalization (or a variant) mitigates some of the trading challenges.

Dividend strategies also incur noticeably high costs. At the assumed level of $10 billion in assets, the high dividend and dividend growth strategies have annual costs of 61 bps and 76 bps, respectively. Their turnover rates are much lower than momentum strategies because they both use stringent banding rules. The main causes of their high costs are their low portfolio volumes of $13.4 billion and $26.0 billion, respectively, and their high tilts of 9.3 and 4.5, respectively, likely the result of investing in a small number of the highest-yielding companies and weighting their positions by yield. Investors who seek steady streams of healthy dividends pay a hidden price in the form of market impact costs.

At the other extreme, the Fundamental Index is the least expensive to implement. At $10 billion in AUM, it has the lowest annual market impact cost (2 bps), and at the annual cost ceiling of 50 bps, has the highest capacity ($291 billion). The Fundamental Index is a broad market index, as evidenced by its very high portfolio volume of $97 billion.

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Practitioners such as Beck et al. (2016) argued against using momentum as a stand-alone factor investing strategy.
Distributed over four quarters, its turnover primarily consists of restoring existing constituents to their fundamental weights; accordingly, both its turnover rate (11.4%) and turnover concentration (21.9%) are the lowest among the factor investing strategies in our sample. The tilt of the Fundamental Index is also low (on a par with cap-weighted strategies), indicating that fundamental size is highly correlated with trading volume. In contrast, the concentrated value strategy has significantly lower capacity. A strong bet on a target factor may have higher expected return, but the trade-off is higher implementation cost as well as more risk.

The low beta (or low volatility) group offers the most interesting observations. Although the strategies in this category have distinctive methodologies and characteristics, they all achieve their primary investment objective—respectable returns with lower risk. They have strikingly different costs, however, ranging from 1.9% for the low volatility strategy (almost as high as momentum) to 5 bps for the fundamental low-vol strategy and 7 bps for the defensive strategy (almost as low as fundamental indexation). The extended high–low range underlines the importance of index design. The low volatility strategy has the simplest methodology: select the 20% of stocks with the lowest volatility and weight them by the inverse of volatility. Empirically, these straightforward selection and weighting rules have the further merit of producing the lowest simulated volatility. Nevertheless, a 185 bp difference in expected implementation costs seems too great to overlook.

The multi-factor strategies, which can be viewed as mixtures of single-factor portfolios, have moderate costs despite their added complexity. Their capacities are well above those of the minimum volatility and quality strategies, which constitute two-thirds
of the quality/value/low-vol strategy. Mixing multiple single-factor portfolios tends to lower costs because the constituent strategies find liquidity in different subsets of the market. (Witness the multi-factor strategies’ high portfolio volumes, ranging from $52.6 billion to $99.9 billion.) Interestingly, the mathematical beta 6 and dynamic multi-factor strategies do not have higher costs despite their investments in momentum stocks. Mixing factors together diversifies the holdings and reduces turnover concentration. Recall that the two momentum strategies in our analysis had portfolio volumes of $35.7 billion and $37.9 billion and turnover concentrations of 88.4% and 90.2%, respectively. With multiple factor exposures that include momentum, the portfolio volume measures jump to $96.7 billion for the dynamic multi-factor strategy and $99.9 billion for the mathematical beta 6 strategy—as high as the portfolio volume of the Fundamental Index strategy—and turnover concentration drops to the 48–60% level.

Understanding implementation costs in relation to strategy characteristics may allow providers to offer, and investors to select, factor investing funds with better long-term net-of-cost returns. Given a strategy’s specific investment objective, some undesirable characteristics are admittedly unavoidable. For example, momentum strategies inherently come with high turnover rates, and dividend-yield strategies entail high concentrations. Still, refined design techniques—such as spreading rebalances over multiple distinct periods, constraining stock selection rules to limit turnover, and weighting selections by a metric correlated with a stock’s trading volume—should be considered whenever possible.

25 The first and second techniques, staggered rebalancing and applying asymmetric rules for establishing or maintaining positions, are also proposed by Novy-Marx and Velikov (2016).
Limitations of Our Research

All models are imperfect, and ours has at least two weaknesses. First, our market impact model potentially overestimates the cost of very large changes in positions, because we assume all portfolio managers rebalance a given indexing strategy on the same trade day. Experienced managers who care about trading costs are unlikely, however, to place orders on an exchange for multiples of the underlying security’s average daily volume. Moreover, our model undoubtedly misestimates the cost of very large trades that the market anticipates, such as S&P 500 Index reconstitutions. In these cases, arbitrageurs may step up to provide liquidity around the trade day (e.g., Petajisto [2011]). To the extent that very large trades are predictable, the market impact relative to trade size should be recalibrated.

Second, we acknowledge a related and possibly more important limitation: users of our model cannot precisely estimate relative trade sizes in advance of rebalancing a particular strategy. Other investment strategies of similar or opposite style might rebalance on the same day, competing for liquidity from, or providing liquidity to, one another. In addition, sophisticated managers may turn to off-exchange facilities such as crossing networks or dark pools.

For these reasons, we provide our framework, results, and discussion merely to illuminate the less-obvious challenges involved in designing and selecting factor investing strategies. The model enables market participants to gauge the relative implementation costs of different strategies and to compare their capacities on a fair basis. We contend that the model we use captures salient factors, but we do not claim it definitively quantifies or accurately predicts actual market impact costs.
Conclusion

Assets have been flowing steadily from actively managed funds to factor investing strategies over the past decade. The significant growth in factor investing leads to potential capital erosion when trading volume affects security prices: investors don’t get the price they see, but the price they pay. Transaction costs, including implicit market impact costs, are a key element in determining the returns that investors actually earn. An index fund’s NAV moving in parallel with the index return creates the illusion that the portfolio has no market impact cost. Nonetheless, the cost is reflected implicitly in both the index and the tracking funds, whose values change simultaneously with the prices of their holdings. The returns of both are lower than they would have been in the absence of trading.

Our study uncovers the implicit cost of market impact by studying the rebalancing information of a suite of live factor-investing indices. Extending our observations to a cost model, we analyze the trading costs of the most common and popular factor-investing strategies. In contrast to traditional benchmarks, these strategies use various stock selection and weighting methods to target exposures to similar (or the same) factors, resulting in dramatically different liquidity profiles and trading patterns among these indices. Knowing what drives costs is perhaps more important than the cost estimations themselves. Therefore, we present a cost attribution framework to contrast the characteristics of strategies and relate them to the specific cost estimates.

We find that strategies with low portfolio volume, high turnover rates, high concentration of turnover, and strong tilts away from volume-weighted benchmarks tend to experience high trading costs. This learning is helpful for investors in their evaluation of the feasibility of investment objectives and for providers in their making of sensible
design decisions. Momentum strategies are generally costly because they require a high rate and a high concentration of turnover. Income strategies are also generally costly, because they hold concentrated sets of, and tilt weights toward, the highest yielding stocks.

In other types of factor investing, we show that strategies which offer similar factor exposures, such as value and low beta, can have vastly different expected costs. Our cost attribution framework sheds light on how practitioners can make an appropriate trade-off between expected net-of-cost return and strategy characteristics.
Appendix A. Strategy Simulation Methodologies

1. Concentrated Value: The semi-annually rebalanced strategy selects the top 20% from the large- and mid-cap universe based on a value score calculated using the ratios of price to book value, price to earnings, and enterprise value to cash flow from operations. It weights selections by market capitalization times value score.

2. Fundamental Index: The strategy selects and weights companies according to four fundamental measures of company size: book value, cash flow, dividends plus buyback, and adjusted sales. It is implemented in four annually rebalanced tranches such that trades are spread over four quarters.

3. High Dividend: After screening for dividend growth and dividend coverage, the annually rebalanced strategy selects 100 stocks by dividend yield from the large-, mid-, and small-cap universe, and weights selections by indicated dividend yield.

4. Dividend Growth: For US market simulations, the strategy rebalances quarterly, selecting companies from the top 1,500 by market cap that had stable or increasing dividends in the last 20 years. For developed-market simulations, stocks with stable or increasing dividends in the last 10 years are selected from the large-, mid-, and small-cap universe, and weighted by indicated dividend yield. In emerging-market simulations, stock selections are made based on growing earnings and high dividend yields, and weighted by annual dividend yield. Both developed and emerging markets are rebalanced semi-annually.

5. Minimum Volatility: The strategy minimizes the volatility of a large- and mid-cap portfolio by means of a constrained optimization. Constraints include maximum single-
holding weight, country and sector active weights, and turnover limits. The optimization is recomputed semi-annually.

6. Low Volatility: The quarterly rebalanced strategy selects the 20% lowest-volatility stocks from the parent universe and weights them by 1/volatility.

7. Defensive: The strategy reweights stocks from the parent universe according to a stability score, which captures low volatility, low earnings variability, low leverage, and high return on assets. The portfolio is rebalanced annually.

8. Fundamental Low Volatility: The strategy selects companies from each sector and region of the parent universe with low valuations and low systemic risk, and weights selections by their fundamental size. It is implemented in four annual rebalancing tranches such that trades are spread over four quarters.

9. Quality: The semi-annually rebalanced strategy selects companies from the large- and mid-cap parent universe based on a quality score that combines high return on equity, low debt to equity, and low earnings variability, and weights selections by market capitalization times quality score.

10. Conservative Profitable: The strategy selects the top 25% of large companies with high profitability and low investment, and weights selections by fundamental size. It is implemented in four annual rebalancing tranches such that trades are spread over four quarters.

11. Sharpe Momentum: The strategy selects companies from the large- and mid-cap parent universe based on a momentum score reflecting prior 6-month and 12-month Sharpe ratios, and weights selections by market capitalization times momentum score. It is
rebalanced semi-annually, with additional ad hoc rebalances triggered by volatility spikes.

12. Standard Momentum: The quarterly rebalanced strategy selects the top third of companies from the large- and mid-cap parent universe by momentum, defined as prior-year return, skipping the most recent month, and weights selections by market capitalization.

13. Mathematical Beta 6: The quarterly rebalanced strategy equally weights six factor indices: value, momentum, mid-cap, low volatility, profitability, and investment. Each factor is constructed by selecting half the companies from regional large-cap universes by characteristics, and weights the selections via five diversification methods.

14. Quality/Value/Low Vol: The fund equally weights quality, low volatility, and a value strategy that reweights the large- and mid-cap parent universe by fundamental size.

15. Dynamic Multi-Factor: At every quarter, the strategy dynamically weights five factor indices—value, low volatility, quality, momentum, and size—based on long-term reversal and short-term momentum. The large-size factor is constructed by selecting the top 25% of large- and mid-cap company universes (50% for momentum), and weighting selections by fundamental size (market capitalization for momentum). The small-size factor is constructed by equally weighting the other four factors constructed within the small-company universe.

16. Equal Weight: The quarterly rebalanced strategy equally weights all stocks in the parent universe.
Transaction Costs of Factor Investing Strategies, 31

References

Aked, Michael, and Max Moroz. 2015. “The Market Impact of Passive Trading.” *Journal of Trading*, vol. 10, no. 3 (Summer):1–8.

Almgren, Robert, and Neil Chriss. 2000. “Optimal Execution of Portfolio Transactions.” *Journal of Risk*, vol. 3, no. 2 (Winter):5–40.

Almgren, Robert, Chee Thum, Emmanuel Hauptmann, and Hong Li. 2005. “Direct Estimation of Equity Market Impact.” *Risk*, vol. 18, no. 7 (July): 58–62.

Ang, Andrew, Paolo Miranda, and Ronald Ratcliffe. 2017. “Capacity of Smart Beta Strategies: A Transaction Cost Perspective.” *Journal of Index Investing*, vol. 8, no. 3 (Winter):39–50.

Barclay, Michael, and Jerold Warner. 1993. “Stealth Trading and Volatility: Which Trades Move Prices?” *Journal of Financial Economics*, vol. 34, no. 3 (December):281–305.

Beck, Noah, Jason Hsu, Vitali Kalesnik, and Helga Kostka. 2016. “Will Your Factor Deliver? An Examination of Factor Robustness and Implementation Costs.” *Financial Analysts Journal*, vol. 72, no. 5 (September/October):58–82.

Berk, Jonathan, and Richard Green. 2004. “Mutual Fund Flows and Performance in Rational Markets.” *Journal of Political Economy*, vol. 112, no. 6 (December):1269–1295.

Berkowitz, Stephen, Dennis Logue, and Eugene Noser. 1988. “The Total Cost of Transactions on the NYSE.” *Journal of Finance*, vol. 43, no. 1 (March): 97–112.

Bertsimas, Dimitris, and Andrew Lo. 1998. “Optimal Control of Execution Costs.” *Journal of Financial Markets*, vol. 1, no. 1 (April): 1–50.

Chen, Honghui, Gregory Noronha, and Vijay Singal. 2006. “Index Changes and Losses to Index Fund Investors.” *Financial Analysts Journal*, vol. 62, no. 4: 31–47.

Chen, Zhiwu, Werner Stanzl, and Masahiro Watanabe. 2002. “Price Impact Costs and the Limit of Arbitrage.” EFA 2002 Berlin Meetings Presented Paper (February 26); Yale ICF Working Paper No. 00-66. Available at SSRN: [https://ssrn.com/abstract=302065](https://ssrn.com/abstract=302065).

Chiyachantana, Chiraphol, Pankaj Jain, Christine Jiang, and Robert Wood. 2004. “International Evidence on Institutional Trading Behavior and Price Impact.” *Journal of Finance*, vol. 59 no. 2 (April): 869–898.

Domowitz, Ian, Jack Glen, and Ananth Madhavan. 2001. “Liquidity, Volatility, and Equity Trading Costs Across Countries and Over Time.” *International Finance*, vol. 4, no. 2 (Summer): 221–255.
Transaction Costs of Factor Investing Strategies, 32

Frazzini, Andrea, Ronen Israel, and Tobias Moskowitz. 2012. “Trading Costs of Asset Pricing Anomalies.” Fama–Miller Working Paper, Chicago Booth Research Paper No. 14-05 (December 5). Available at SSRN: https://ssrn.com/abstract=2294498.

Frazzini, Andrea, and Lasse Pedersen, 2014. “Betting Against Beta.” Journal of Financial Economics, vol. 111, no. 1(January): 1–25.

Gabaix, Xavier, Parameswaran Gopikrishnan, Vasiliki Plerou, and Eugene Stanley. 2006. “Institutional Investors and Stock Market Volatility.” Quarterly Journal of Economics, vol. 212, no. 2 (May): 461–504.

Harvey, Campbell, Yan Liu, and Heqing Zhu. 2016. “…and the Cross-Section of Expected Returns.” Review of Financial Studies, vol. 29, no. 1 (January): 5–68.

Huberman, Gur, and Dominika Halka. 2001. “Systematic Liquidity.” Journal of Financial Research, vol. 24, no. 2 (Summer):161–178.

Huberman, Gur, and Werner Stanzl. 2005. “Optimal Liquidity Trading.” Review of Finance, vol. 9, no. 2 (June): 165–200.

IML. 2012. “Analysis of Institutional Fund Capacity: Implications for Investment and Execution.” Investors Mutual Limited, White paper.

Jones, Charles, and Mark Lipson. 2001. “Sixteenths: Direct Evidence on Institutional Execution Costs.” Journal of Financial Economics, vol. 59, no. 2: 253–278.

Kahn, Ronald, and Michael Lemmon. 2016. “The Asset Manager’s Dilemma: How Smart Beta Is Disrupting the Investment Management Industry.” Financial Analysts Journal, vol. 72, no.1: 15–20.

Kahn, Ronald, and Scott Shaffer. 2005. “The Surprisingly Small Impact of Asset Growth on Expected Alpha.” Journal of Portfolio Management, vol. 32, no. 1 (Fall): 49–60.

Keim, Donald, and Ananth Madhavan. 1997. “Transactions Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades.” Journal of Financial Economics, vol. 46, no. 3: 265–292.

MSCI. 2017a. “MSCI USA Quality Index (USD) Factsheet.” (April 28).

———. 2017b. “MSCI USA Momentum Index (USD) Factsheet.” (April 28).

Novy-Marx, Robert, and Mihail Velikov. 2016. “A Taxonomy of Anomalies and Their Trading Costs.” Review of Financial Studies, vol. 29, no. 1 (January):104–147.
Transaction Costs of Factor Investing Strategies, 33

O’Neill, Michael, and Geoffrey Warren. 2016 “Evaluating Fund Capacity: Issues and Methods.” CIFR Paper No. 124/2016 (September 27). Available at SSRN: https://ssrn.com/abstract=2844532.

Perold, André. 1988. “The Implementation Shortfall: Paper versus Reality.” Journal of Portfolio Management, vol. 14, no. 3 (Spring):4–9.

Petajisto, Antti. 2011. “The Index Premium and Its Hidden Cost for Index Funds.” Journal of Empirical Finance, vol. 18, no. 2: 271–288.

Petersen, Mitchell. 2009. “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches.” Review of Financial Studies, vol. 22, no. 1 (January):435–480.

PowerShares. 2017. “PowerShares S&P 500® Low Volatility Portfolio Prospectus.” (February 24).

S&P Dow Jones Indices. 2013. “10 Years Later: Where in the World Is Equal Weight Indexing Now?” (April 22).

Scobie, David. 2013. “Keep Your Eyes on the Size: Fund Manager Capacity and Why It Matters.” Mercer, White paper (March).

Shirbini, Eric. 2015. “Implementation of Multi-Smart Factor Indices.” Presentation to CFA Society Netherlands (March 12). Available at https://www.cfasociety.org/netherlands/Documents/Slides_CFA_Implementation_of_Multi_Smart_Factor_Indices.pdf.

Vangelisti, Marco. 2006. “The Capacity of an Equity Strategy.” Journal of Portfolio Management, vol. 32, no. 2 (Winter):44–50.
Table 1. Literature in Capacities of Factor Investing

| Study | Factor Definition | Maximum Capacities Reported | Key Assumptions |
|-------|-------------------|-----------------------------|-----------------|
| Chen, Stanzl, and Watanabe (2002) | Long–short arbitrage strategies formed in the larger half of the US market | $0.4, $5 and $2 billion for size, value, and momentum factors. | 1) Trade size cannot exceed 1% of market cap. 2) Expected market impact erodes historical excess returns entirely. |
| Frazzini, Israel, and Moskowitz (2012) | Long–short arbitrage strategies across developed markets countries | $2,735, $2,755, and $159 billion for size, value, and momentum factors in the US; $0, $753, and $50 billion for size, value, and momentum factors in the international markets. | 1) Restrict trading to no more than 5% of daily volume, and allow up to 2% of tracking error against intended strategies. 2) Expected market impact erodes historical excess returns entirely. |
| Novy-Marx and Velikov (2016) | Long–short arbitrage strategies in the US | $0.7 to $131 billion for low-turnover factors, which includes size and value at $20 and $21 billion, respectively; $1 to $12 billion for mid-turnover factors, which includes momentum at $5 billion. | 1) Apply trade restriction based on factor signal ranking to lower turnover. 2) Effective bid–ask spread and expected market impact erodes historical excess returns entirely. |
| Ang, Miranda, and Ratcliffe (2017) | Six MSCI factor strategies in the US | $25,435, $1,765, $324, $6,765, $1,437, and $1,579 billion for size, value, momentum, low vol, quality, and multi-factor strategies, respectively. | 1) Trading over 5 days. 2) Explicit cost and market impact erodes historical excess returns entirely. |
| Our Study | Popular factor investing strategies in US, developed, and emerging markets | $291, $2, $108, $45, $8, and $41 billion for value, momentum, low vol, quality, income, and multi-factor strategies in the US; $357, $4, $104, $54, $7, and $36 billion for value, momentum, low vol, quality, income, and multi-factor strategies in developed markets, respectively. | 1) Trading near the close of rebalancing dates. 2) Expected market impact reaches 50 bps. |

Table 2. Distribution of Asset Levels ($ millions) on Rebalancing Dates of the Underlying Indices

| Underlying Indices | No. Re-balancings | 5th | 25th | 50th | 75th | 95th |
|--------------------|-------------------|-----|-----|------|------|------|
| US Only            | 35                | 92.9| 647.6| 1123.2| 4504.2| 9698.7|
| Other Single-Country | 62 | 5.8 | 114.4 | 149.6 | 1603.8 | 9563.7 |
| Developed Markets Multi-Country | 78 | 59.5 | 248.9 | 727.1 | 1727.4 | 9180.1 |
| Emerging Markets Multi-Country | 19 | 65.9 | 583.4 | 1289.2 | 1685.8 | 3709.7 |
| Benchmarked to Large Cap or All Cap | 178 | 22.3 | 156.1 | 540.1 | 1745.9 | 9571.6 |
|Benchmarked to Small Cap | 16 | N/A | 112.6 | 202.4 | 1032.1 | N/A |
| Benchmarked to Large Cap or All Cap | 75 | 5.3 | 153.7 | 464.2 | 524.2 | 5184.7 |
|Benchmarked to Small Cap | 119 | 29.5 | 167.4 | 751.4 | 1801.6 | 10241.0 |
| All | 194 | 24.6 | 153.7 | 520.3 | 1643.2 | 9563.6 |

Source: Research Affiliates, LLC, using data from Bloomberg. Note: Asset levels in $ millions as of rebalancing dates.

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Table 3. Distribution of Relative Trade Size

| Region            | Obs. | Avg. Market Cap ($US Millions) | 1st | 5th | 10th | 25th | 50th | 75th | 90th | 95th | 99th |
|-------------------|------|-------------------------------|-----|-----|------|------|------|------|------|------|------|
| United States     | 20,462 | $6,900 | 0.007% | 0.056% | 0.140% | 0.503% | 1.62% | 4.63% | 12.4% | 21.0% | 42.5% |
| Developed x US    | 20,405 | $7,895 | 0.008% | 0.050% | 0.108% | 0.411% | 1.57% | 4.99% | 12.8% | 21.4% | 43.4% |
| Emerging          | 8,788 | $5,524 | 0.002% | 0.021% | 0.084% | 0.471% | 2.14% | 7.30% | 17.6% | 27.9% | 51.4% |
| All               | 49,655 | $7,066 | 0.005% | 0.046% | 0.116% | 0.458% | 1.67% | 5.16% | 13.6% | 22.6% | 44.9% |

Source: Research Affiliates, LLC, using data from Bloomberg.
Note: Relative trade size is defined as the trade size in dollars divided by the dollar volume on the trade day.

Figure 1. Average Market Impact by Trade Size

Source: Research Affiliates, LLC, using data from Bloomberg.
Figure 2. Market Impact and Reversal across Different Regions.

|                     | All Trades | United States | Developed ex. US | Emerging Markets | Purchases Only | Sales Only |
|---------------------|------------|---------------|------------------|------------------|----------------|------------|
| Trade Day Impact Factor ($k_0$) | 4.27%      | 4.70%         | 3.83%            | 4.30%            | 4.60%          | 4.16%      |
| $t$-Stat.           | 8.15       | 3.38          | 11.99            | 18.36            | 6.37           | 6.29       |
| Reversal Impact Factor ($k_{+4}$) | -2.42%     | -3.53%        | -1.42%           | -2.34%           | -1.74%         | -3.73%     |
| $t$-Stat.           | -5.67      | -5.53         | -1.74            | -5.76            | -1.25          | -4.43      |

Source: Research Affiliates, LLC, using data from Bloomberg.
# Table 4. Market Impact Costs and Liquidity Characteristics of US Factor Investing Strategies

| Strategy Type          | Return | Volatility | Market Impact Cost | Capacity ($B) | Portfolio Volume ($M) | Turnover | Turnover Concentration | Tilt |
|------------------------|--------|------------|--------------------|---------------|-----------------------|----------|------------------------|------|
| **Value Strategies**   |        |            |                    |               |                       |          |                        |      |
| Concentrated Value     | 11.6%  | 16.1%      | 0.28%              | 17.7          | 39,299                | 25.1%    | 77.2%                  | 1.5  |
| Fundamental Index      | 11.6%  | 14.8%      | 0.02%              | 290.7         | 96,651                | 11.4%    | 21.9%                  | 1.6  |
| **Income Strategies**  |        |            |                    |               |                       |          |                        |      |
| High Dividend          | 12.1%  | 14.4%      | 0.61%              | 8.2           | 13,464                | 20.1%    | 67.5%                  | 9.3  |
| Dividend Growth        | 12.1%  | 14.1%      | 0.76%              | 6.6           | 26,016                | 37.5%    | 49.5%                  | 4.5  |
| **Low Volatility**     |        |            |                    |               |                       |          |                        |      |
| Minimum Volatility     | 11.2%  | 13.3%      | 0.39%              | 12.9          | 34,290                | 24.8%    | 73.3%                  | 2.3  |
| Low Volatility         | 11.1%  | 12.6%      | 1.90%              | 2.6           | 21,382                | 71.6%    | 84.3%                  | 2.1  |
| Defensive              | 10.6%  | 13.2%      | 0.07%              | 72.7          | 68,539                | 14.1%    | 83.6%                  | 1.5  |
| Fundamental Low Volatility | 12.5%  | 13.4%      | 0.05%              | 107.8         | 42,257                | 23.1%    | 44.9%                  | 1.5  |
| **Quality Strategies** |        |            |                    |               |                       |          |                        |      |
| Quality                | 11.1%  | 15.7%      | 0.37%              | 13.5          | 35,029                | 23.8%    | 71.9%                  | 1.3  |
| Conservative Profitable| 11.5%  | 14.2%      | 0.11%              | 44.6          | 35,794                | 19.1%    | 38.4%                  | 1.5  |
| **Momentum Strategies**|        |            |                    |               |                       |          |                        |      |
| Sharpe Momentum        | 11.9%  | 17.3%      | 2.05%              | 2.4           | 35,797                | 108.5%   | 88.4%                  | 1.3  |
| Standard Momentum      | 11.9%  | 17.7%      | 2.72%              | 1.8           | 37,928                | 155.8%   | 90.2%                  | 1.3  |
| **Multi-Factor Strategies** |    |            |                    |               |                       |          |                        |      |
| Quality/Value/Low Vol | 11.2%  | 14.1%      | 0.22%              | 22.6          | 52,410                | 23.4%    | 71.2%                  | 1.6  |
| Mathematical Beta 6    | 11.5%  | 14.9%      | 0.12%              | 40.6          | 99,997                | 36.8%    | 47.9%                  | 2.3  |
| Dynamic Multi-Factor   | 12.6%  | 14.8%      | 0.23%              | 21.3          | 96,739                | 51.6%    | 60.0%                  | 1.8  |
| **Other**              |        |            |                    |               |                       |          |                        |      |
| Equal Weight           | 10.8%  | 17.1%      | 0.20%              | 25.0          | 109,263               | 29.8%    | 47.6%                  | 2.0  |

Source: Research Affiliates, LLC, using data from Worldscope and Datastream.

Note: Return, volatility, and turnover are averaged over the period 1968–2016. Other characteristics are based on the most recent rebalancing up to the end of 2016. Market impact costs assume $10 billion in AUM and are averaged over the most recent five years, with the cost of each trade capped at 2%.26 Capacity is the estimated AUM at which the strategy is expected to have 50 bps of market impact cost.

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26 This would imply a trade that consumes 66% of daily volume. Many practitioners would be unwilling to trade more than this or would stop trading upon incurring a cost of 2%. This limit also reduces the incidence of volume data outliers.

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### Table B1. Estimated Market Impact Cost and Liquidity Characteristics of Developed Market Factor Investing Strategies

| Developed ex US | Return | Volatility | Market Impact Cost | Capacity (US$B) | Portfolio Volume (US$M) | Turnover | Turnover Concentration | Tilt |
|-----------------|--------|------------|--------------------|-----------------|------------------------|----------|------------------------|------|
| **Value Strategies** |        |            |                    |                 |                        |          |                        |      |
| Concentrated Value | 10.9%  | 15.0%      | 0.27%              | 18.8            | 75,180                 | 25.7%    | 82.5%                  | 1.7  |
| Fundamental Index  | 9.7%   | 14.3%      | 0.01%              | 357.1           | 179,395                | 12.7%    | 20.8%                  | 1.6  |
| **Income Strategies** |        |            |                    |                 |                        |          |                        |      |
| High Dividend     | 10.3%  | 16.1%      | 0.71%              | 7.0             | 14,059                 | 24.5%    | 74.9%                  | 11.0 |
| Dividend Growth   | 11.1%  | 15.1%      | 2.81%              | 1.8             | 13,136                 | 85.9%    | 90.9%                  | 6.2  |
| **Low Volatility Strategies** |        |            |                    |                 |                        |          |                        |      |
| Minimum Volatility | 7.4%   | 11.4%      | 0.40%              | 12.6            | 33,785                 | 27.6%    | 74.8%                  | 3.3  |
| Low Volatility    | 9.8%   | 9.8%       | 1.87%              | 2.7             | 29,089                 | 70.2%    | 82.4%                  | 10.4 |
| Defensive         | 8.1%   | 12.9%      | 0.09%              | 52.7            | 109,626                | 16.5%    | 87.7%                  | 2.0  |
| Fundamental Low Volatility | 10.7%  | 11.6%      | 0.05%              | 104.2           | 63,346                 | 24.0%    | 45.9%                  | 1.6  |
| **Quality Strategies** |        |            |                    |                 |                        |          |                        |      |
| Quality           | 10.4%  | 14.0%      | 0.16%              | 31.2            | 60,972                 | 20.2%    | 74.6%                  | 1.3  |
| Conservative Profitable | 10.1%  | 12.8%      | 0.09%              | 53.9            | 58,131                 | 22.4%    | 38.3%                  | 1.6  |
| **Momentum Strategies** |        |            |                    |                 |                        |          |                        |      |
| Sharpe Momentum   | 9.1%   | 16.1%      | 1.15%              | 4.3             | 62,052                 | 105.1%   | 87.7%                  | 1.4  |
| Standard Momentum | 8.7%   | 15.9%      | 1.46%              | 3.4             | 65,601                 | 145.5%   | 92.0%                  | 1.3  |
| **Multi-Factor Strategies** |        |            |                    |                 |                        |          |                        |      |
| Quality/Value/Low Vol | 9.0%   | 12.1%      | 0.18%              | 27.8            | 81,922                 | 23.1%    | 73.3%                  | 2.6  |
| Mathematical Beta 6 | 8.9%   | 14.1%      | 0.14%              | 36.4            | 173,570                | 39.6%    | 48.7%                  | 3.0  |
| Dynamic Multi-Factor | 10.3%  | 13.2%      | 0.16%              | 31.8            | 172,078                | 49.7%    | 60.6%                  | 1.9  |
| **Other**         |        |            |                    |                 |                        |          |                        |      |
| Equal Weight      | 7.8%   | 15.7%      | 0.31%              | 16.1            | 194,900                | 34.0%    | 48.7%                  | 8.3  |

**Source:** Research Affiliates, LLC, using data from Worldscope and Datastream.

**Note:** Return, volatility, and turnover are averaged over the period 1989–2016. Other characteristics are based on the most recent rebalancing date up to the end of 2016. Market impact costs assume $10 billion in AUM and are averaged over the most recent five years, with the cost of each trade capped at 2% to mitigate the impact of outlying volume data. Capacity is the estimated AUM at which the strategy is expected to have 50 bps of market impact cost.
Table B2. Estimated Market Impact Cost and Liquidity Characteristics of Emerging-Market Factor Investing Strategies

| Emerging Markets          | Return | Volatility | Market Impact Cost | Capacity (US$B) | Portfolio Volume (US$M) | Turnover | Turnover Concentration | Tilt |
|---------------------------|--------|------------|--------------------|----------------|------------------------|----------|------------------------|------|
| **Value Strategies**      |        |            |                    |                |                        |          |                        |      |
| Concentrated Value        | 13.9%  | 23.1%      | 0.38%              | 1.3            | 6,417                  | 30.2%    | 78.0%                  | 3.4  |
| Fundamental Index         | 14.2%  | 23.6%      | 0.02%              | 25.0           | 14,901                 | 18.1%    | 23.3%                  | 1.9  |
| **Income Strategies**     |        |            |                    |                |                        |          |                        |      |
| High Dividend             | 15.3%  | 20.4%      | 1.78%              | 0.3            | 1,449                  | 51.5%    | 91.1%                  | 5.2  |
| Dividend Growth           | 14.0%  | 21.6%      | 1.98%              | 0.3            | 2,136                  | 61.5%    | 81.1%                  | 2.2  |
| **Low Volatility Strategies** |      |            |                    |                |                        |          |                        |      |
| Minimum Volatility        | 13.2%  | 17.6%      | 0.64%              | 0.8            | 2,087                  | 30.4%    | 79.7%                  | 3.8  |
| Low Volatility            | 12.6%  | 16.8%      | 2.16%              | 1.2            | 15,029                 | 82.3%    | 63.5%                  | 15.8 |
| Defensive                 | 12.8%  | 21.1%      | 0.17%              | 2.9            | 10,108                 | 22.0%    | 90.3%                  | 2.7  |
| Fundamental Low Vol       | 15.7%  | 18.4%      | 0.17%              | 2.9            | 10,108                 | 29.8%    | 44.1%                  | 1.8  |
| **Quality Strategies**    |        |            |                    |                |                        |          |                        |      |
| Quality                   | 11.8%  | 20.7%      | 0.28%              | 1.8            | 5,138                  | 31.5%    | 77.6%                  | 1.6  |
| Conservative Profitable   | 13.6%  | 22.5%      | 0.13%              | 3.7            | 3,822                  | 25.6%    | 40.6%                  | 2.0  |
| **Momentum Strategies**   |        |            |                    |                |                        |          |                        |      |
| Sharpe Momentum           | 11.9%  | 23.6%      | 1.34%              | 0.4            | 5,773                  | 101.6%   | 88.6%                  | 1.6  |
| Standard Momentum         | 12.3%  | 23.3%      | 1.95%              | 0.3            | 8,105                  | 144.7%   | 90.5%                  | 1.6  |
| **Multi-Factor Strategies** |      |            |                    |                |                        |          |                        |      |
| Quality/Value/Low Vol     | 12.6%  | 18.9%      | 0.34%              | 1.5            | 6,486                  | 29.9%    | 77.4%                  | 4.0  |
| Mathematical Beta 6       | 13.0%  | 21.5%      | 0.31%              | 1.6            | 14,452                 | 50.7%    | 56.4%                  | 4.6  |
| Dynamic Multi-Factor      | 14.6%  | 22.2%      | 0.19%              | 2.6            | 11,674                 | 52.0%    | 61.0%                  | 2.1  |
| **Other**                 |        |            |                    |                |                        |          |                        |      |
| Equal Weight              | 12.1%  | 22.7%      | 0.38%              | 1.3            | 17,280                 | 39.4%    | 50.4%                  | 7.3  |

Source: Research Affiliates, LLC, using data from Worldscope and Datastream.
Note: Return, volatility, and turnover averaged over the period 2002–2016. Other characteristics are based on the most recent rebalancing date up to the end of 2016. Market impact costs assume $10 billion in AUM and are averaged over the most recent five years, with the cost of each trade capped at 2% to mitigate the impact of outlying volume data. Capacity is the estimated AUM at which the strategy is expected to have 50 bps of market impact cost.

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