

7524338-the-capacity-of-equity-anomalies

SUMMARY: This paper measures the capacity of equity anomalies, which refers to how much capital investors can deploy before trading costs eliminate market-hedged returns above cash. The authors use stock-day estimates of spreads, price impact, and liquidity replenishment to compute capacity for 35 anomalies. They find that alpha alone is an incomplete guide to scale, with the highest-alpha long legs supporting less than \$2 billion, while lower-alpha strategies support \$20–33 billion. Price impact is found to drive most cross-strategy dispersion through turnover and stock liquidity. The paper also reports on the capacity of machine-learning strategies and finds that partial adjustment alone can expand the value-weighted strategy from \$177 million to \$19 billion. The authors conclude that capacity cannot be inferred from trading costs measured at a single portfolio size, and that price impact plays a significant role in determining capacity.

METHOD: The authors use high-frequency data from the NYSE Daily TAQ to estimate the execution model of Obizhaeva and Wang (2013) for each stock and trading day. They then map the realized rebalances of 35 characteristic-based strategies into trading costs at alternative levels of assets under management and compound capital through the historical sample. The main object of the paper is portable-alpha capacity, defined as the largest initial allocation for which a strategy, after trading costs and a market hedge, compounds at least as fast as cash. The authors also report dynamic capacity for unhedged long legs and apply the same framework to gradient-boosted-tree strategies based on all 153 characteristics.

KEY FINDINGS:

- Alpha alone is an incomplete guide to scale.
- The highest-alpha long legs support less than \$2 billion.
- Lower-alpha strategies support \$20–33 billion.
- Price impact drives most cross-strategy dispersion.
- Partial adjustment alone can expand the value-weighted strategy from \$177 million to \$19 billion.
- Capacity cannot be inferred from trading costs measured at a single portfolio size.
- Price impact plays a significant role in determining capacity.

IMPLICATION FOR TRADING: The findings suggest that the economic magnitude of return predictability is not solely determined by alpha. Instead, it depends on the capacity of deploying capital before trading costs eliminate market-hedged returns. The paper highlights the importance of considering price impact and liquidity in assessing the economic potential of equity anomalies. Practitioners can use these findings to better understand the economic potential of their strategies and allocate capital more effectively. Additionally, the paper's methodology can be applied to other trading strategies and anomalies, providing a framework for further research and practical use.

The Capacity of Equity Anomalies

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Abstract

This paper measures the capacity of equity anomalies: how much capital investors can deploy before trading costs eliminate market-hedged returns above cash. Using stock-day estimates of spreads, price impact, and liquidity replenishment, we compute capacity for 35 anomalies. Alpha alone is an incomplete guide to scale. The highest-alpha long legs each support less than \$2 billion, while lower-alpha profitability strategies support \$20–33 billion. Price impact drives most cross-strategy dispersion through turnover and stock liquidity. Slower rebalancing changes the economics: median factor capacity rises thirteenfold, and the value-weighted machine-learning strategy expands from \$177 million to \$19 billion through partial adjustment alone.

Keywords: Equity anomalies; Trading capacity; Transaction costs; Price impact; Optimal execution; Liquidity

JEL Classification: G11, G12, G14, G23

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1 Introduction

Empirical asset pricing typically evaluates an investment signal by its return per dollar: alpha, Sharpe ratio, or statistical significance (Cochrane, 2011; Harvey et al., 2016; Hou et al., 2020; Jensen et al., 2023). Yet the economic magnitude of a return opportunity also depends on how much capital can earn that return. A strategy with a high alpha but little room to scale can represent a smaller opportunity than a lower-alpha strategy that can absorb tens of billions of dollars. This paper measures that second dimension. We estimate the capacity of equity anomalies—the amount of capital that can be deployed before trading costs eliminate market-hedged returns above cash—and ask whether the anomaly opportunities that look largest in return space are also the largest in deployable capital.

We answer this question by constructing scale-dependent trading-cost curves from public high-frequency data. Using NYSE Daily TAQ trades and quotes from 2010–2023, we estimate the execution model of Obizhaeva and Wang (2013) separately for each stock and trading day. The estimates capture the bid–ask spread, permanent price impact, temporary price pressure, and the rate at which liquidity replenishes after a trade. We then map the realized rebalances of 35 characteristic-based strategies into trading costs at alternative levels of assets under management and compound capital through the historical sample. Our main object, portable-alpha capacity, is the largest initial allocation for which a strategy, after trading costs and a market hedge, compounds at least as fast as cash. We also report dynamic capacity for unhedged long legs and apply the same framework to gradient-boosted-tree strategies based on all 153 characteristics, following Gu et al. (2020).

Capacity cannot be inferred from trading costs measured at a single portfolio size. Proportional costs can determine whether a strategy remains profitable at small scale, but their cost per dollar does not rise with assets under management. Price impact behaves differently: larger portfolios require larger trades, and those trades place greater demands on available liquidity. The way the portfolio is implemented also matters. Spreading an order through time allows liquidity to replenish and reduces temporary price pressure. Capacity thus depends on the return signal, the securities it trades, the amount of capital being deployed, and how quickly the investor moves toward the target portfolio.

Alpha alone provides an incomplete picture of the economic magnitude of return predictability. The two long legs with the highest gross alphas each support less than \$2 billion of market-hedged capital. Profitability and cash-flow strategies with substantially lower alphas, by contrast, support \$20–33 billion. Profit margin is an extreme case: its alpha is roughly two-fifths that of Highest 5 days of return / volatility, yet its capacity is 97 times larger. Among strategies with positive capacity, the ranking by deployable capital differs

substantially from the ranking by alpha. A high return per dollar need not represent a large aggregate investment opportunity.

The cross-sectional differences in capacity come mainly from price impact. At institutional scale, two features of the portfolio matter: how much it trades and how costly the underlying stocks are to trade. The Amihud Measure strategy turns over only 0.12 times per month, but at \$10 billion it incurs impact costs of 1.2% of capital per month because it trades illiquid stocks. Short-term reversal holds more liquid stocks, but turnover of 1.8 times per month produces impact costs of 1.6% per month. High-capacity strategies tend to avoid both sources of cost: they trade relatively infrequently and concentrate their trades in relatively liquid securities. Proportional costs can eliminate strategies even at small scale; price impact determines how far the remaining strategies can grow.

The same pattern appears for long–short factors. Factors generally deliver more alpha than their long legs, but they also require trading both sides of the portfolio. The two effects offset one another to a considerable degree. Among factors with positive capacity, the median supports \$1.53 billion, compared with \$1.32 billion for the median long leg with positive capacity. For perspective, the median qualifying hedge fund reported net assets of \$1.1 billion at the end of 2025 (U.S. Securities and Exchange Commission, 2026). Price impact begins to matter at scales that are common for institutional portfolios.

Capacity also changes with implementation. We keep each strategy’s target portfolio unchanged and vary only the speed at which the investor moves toward it. Slower adjustment gives up some signal freshness but reduces trade size and price impact. Among factors with positive capacity under full monthly rebalancing, choosing the adjustment rate in sample raises median capacity thirteenfold. A common adjustment rate of 0.05 captures most of this gain without strategy-specific tuning. The same signal can support very different amounts of capital depending on how it is traded.

The machine-learning strategies make the point especially clearly. A gradient-boosted tree produces an equal-weighted factor with a gross alpha of 1.62% per month and a value-weighted factor with an alpha of 0.45%. Under full monthly rebalancing, their capacities are only \$13 million and \$177 million because the forecasts generate intensive trading, particularly in small stocks (Avramov et al., 2023). Partial adjustment raises those capacities to approximately \$1.3 billion and \$19 billion. Flexible prediction methods can produce portfolios that change aggressively from one period to the next, so stronger forecasts do not by themselves imply greater deployable scale.

Capacity also bears on the quantitative importance of trading frictions in explaining predictable returns. If a return opportunity can be pursued only with limited capital, trading costs can help sustain it. If the return remains available when much larger amounts of

capital are deployed, that channel has less quantitative force (Shleifer and Vishny, 1997; Berk and Green, 2004; Pástor et al., 2015). For the most scalable profitability strategies in our sample, the spread and price-impact costs measured here remain too small to absorb the return opportunity at institutionally meaningful scale. We do not use this evidence to choose among the other explanations for those returns. It says something narrower: the trading-cost channel measured here is not sufficient on its own.

Our analysis builds on a substantial literature that establishes the importance of trading costs for investment strategies. Chen et al. (2002) and Korajczyk and Sadka (2004) show that nonlinear price impact limits break-even fund size. Lesmond et al. (2004), Novy-Marx and Velikov (2016), and Chen and Velikov (2023) study the effect of trading costs on anomaly profitability, while Hasbrouck (2009) and Avramov et al. (2006) provide influential empirical measures of trading costs and liquidity. Frazzini et al. (2018) document realized implementation costs using a large proprietary institutional dataset, and Kim and Park (2019) estimate factor capacity under price-impact costs. Fama and French (2018) and Detzel et al. (2023) connect implementation costs to the evaluation of asset-pricing models, while DeMiguel et al. (2020), Patton and Weller (2020), and Beckmeyer et al. (2026) study related implementation questions through signal combination, observed fund returns, and machine-learning strategies.

Our contribution is to put different return signals on the same scale-of-capital footing. We estimate stock-day execution costs from public high-frequency data, map those costs into the realized trades required by each strategy, and follow capital as larger allocations generate larger trades and higher implementation costs. The calculation preserves the differences across anomalies in turnover, stock liquidity, and realized return paths. It also lets us change the implementation while holding the forecasting signal and target portfolio fixed. We can then ask not only whether a return opportunity survives trading costs, but how large the opportunity remains under a given trading rule.

The empirical implementation also links market microstructure to portfolio adjustment. Lo and Hall (2015) estimate order-book resilience using high-frequency data, and Chen et al. (2019) estimate market-impact parameters for a cross-section of NASDAQ stocks. We estimate the Obizhaeva–Wang inputs separately for the stocks and trading days that enter our portfolios from 2010–2023. Gârleanu and Pedersen (2013), Collin-Dufresne et al. (2020), and Jensen et al. (2026) study optimal portfolio adjustment when trading costs matter. In our exercise the return signal and target portfolio remain fixed; only the path toward the target changes. This makes the associated change in capacity an implementation effect rather than a change in the forecasting signal.

The paper proceeds as follows. Section 2 develops the trading-cost and capacity frame-

work. Section 3 describes the data and stock-level cost estimates. Section 4 presents anomaly capacities and their determinants. Section 5 studies long–short factors. Section 6 examines estimation uncertainty, execution assumptions, rebalancing speed, and machine-learning strategies. Section 7 concludes.

2 Trading Costs and Capacity

We obtain capacity by starting from the trades required to reach a target portfolio. The execution model gives the expected cost of each stock-level trade. Aggregating those costs produces a portfolio cost curve, which determines net returns and the evolution of capital as assets under management increase. The largest initial allocation that remains economically viable over the sample is the strategy’s capacity. Following standard practice in institutional asset management, we separate portfolio formation from trade execution (e.g., Bertsimas and Lo, 1998; Almgren and Chriss, 2001), so the return signal itself is held fixed throughout the calculation.

2.1 The Trading Model

We model execution with the framework of Obizhaeva and Wang (2013, hereafter [OW](#)). The trader uses market orders and chooses how to distribute a required quantity through the trading day. This setup is standard in the optimal-execution literature (Bertsimas and Lo, 1998; Almgren and Chriss, 2001; Obizhaeva and Wang, 2013) and keeps the analysis focused on the execution cost of a given portfolio decision. We model two components of that cost: the bid–ask spread and price impact. Exchange fees and rebates are not included.

Price impact has a permanent and a temporary component. Signed order flow can convey information and move the fundamental value of the stock (Kyle, 1985). A large order can also consume available liquidity and move the execution price away from fundamental value. The temporary component decays as the order book replenishes. The execution problem therefore links order size to timing: splitting a trade gives liquidity time to recover and reduces the temporary price pressure carried from one child order to the next.

Appendix B presents the [OW](#) price dynamics and intraday execution problem. The object needed for the capacity analysis is the expected cost of executing a daily order. Let $X_{i,d}$ denote the desired purchase of stock i on day d . Our main implementation completes each monthly rebalance within one trading day.¹ Under the optimized [OW](#) schedule, expected

¹A large institution could spread the same rebalance over several days. Under the model, additional time for liquidity replenishment lowers temporary impact and raises capacity. The one-day horizon therefore provides a common execution convention across strategies.

execution cost is

$$C_{i,d}(X_{i,d}) = \frac{s_{i,d}}{2}X_{i,d} + \left(\frac{\lambda_{i,d}}{2} + \frac{\kappa_{i,d}}{\rho_{i,d}N + 2} \right) X_{i,d}^2, \quad (1)$$

where $s_{i,d}$ is the quoted spread, $\lambda_{i,d}$ is permanent price impact, $\kappa_{i,d}$ measures temporary price pressure, and $\rho_{i,d}$ is the rate at which that pressure decays. We measure time in seconds, so $N = 23,400$ is the number of one-second intervals in the 9:30–16:00 trading session.

For the portfolio analysis it is useful to write Equation (1) as

$$C_{i,d}(X_{i,d}) = b_{i,d}X_{i,d} + a_{i,d}X_{i,d}^2, \quad (2)$$

with

$$b_{i,d} = \frac{s_{i,d}}{2}, \quad (3)$$

and

$$a_{i,d} = \frac{\lambda_{i,d}}{2} + \frac{\kappa_{i,d}}{\rho_{i,d}N + 2}. \quad (4)$$

Equation (3) is the linear cost of crossing the spread. Equation (4) governs how rapidly cost rises with order size. It incorporates permanent impact and the temporary pressure that remains after allowing the book to replenish along the execution schedule. The resulting convexity is what makes capacity finite: larger allocations require larger trades, which raise trading cost per dollar.

Two execution benchmarks help interpret the role of order splitting. If the entire daily order is executed at once, the convex coefficient is

$$a_{i,d}^{\text{no-splitting}} = \frac{\lambda_{i,d} + \kappa_{i,d}}{2}. \quad (5)$$

If the same order is divided evenly through the day without using the optimized [OW](#) schedule, the coefficient is

$$a_{i,d}^{\text{naive}} = \frac{\lambda_{i,d}}{2} + \kappa_{i,d} \frac{\rho_{i,d}N - (1 - e^{-\rho_{i,d}N})}{(\rho_{i,d}N)^2}. \quad (6)$$

Equations (5) and (6) preserve the same linear-plus-convex cost form as Equation (2). They allow us to measure how much capacity comes from giving liquidity time to replenish and how much additional benefit comes from the optimized schedule itself.

2.2 Estimating the [OW](#) Model Inputs

The stock-level cost function requires four inputs: the quoted spread $s_{i,d}$, permanent impact $\lambda_{i,d}$, temporary impact $\kappa_{i,d}$, and refill speed $\rho_{i,d}$. We observe the spread directly and estimate the remaining three quantities separately for each security and trading day. Per-

manent impact is estimated from a regression of five-minute midquote changes on signed order flow. Temporary impact and refill speed are estimated from a one-second regression of the deviation between transaction prices and midquotes on signed order flow and recent trade-induced price pressure.

The two sampling frequencies match the economic objects being measured. Permanent impact concerns price adjustment that persists beyond the immediate trade, for which moderate aggregation reduces very-high-frequency noise (Glosten and Harris, 1988; Holden and Jacobsen, 2014; Holden et al., 2023). Temporary impact and replenishment occur over much shorter horizons, so they require the one-second data. Appendix B gives the specifications, the treatment of inactive intervals, the number of observations entering the daily regressions, and the mapping from the estimated persistence coefficient to $\rho_{i,d}$.

Daily estimates of the cost coefficients are noisy. We therefore smooth $\hat{a}_{i,d}$ and $\hat{b}_{i,d}$ with a daily exponential moving average with a span of 50 trading days and a half-life of about 17 trading days, as specified in Equation (B.13) in Appendix B. The month-end values $\tilde{a}_{i,t}$ and $\tilde{b}_{i,t}$ are the inputs to the next portfolio rebalance. This timing ensures that each capacity calculation uses cost information available by the time the trade is formed. Appendix E.4 reports capacities for shorter and longer smoothing spans.

2.3 Trading Capacity

Aggregating the stock-level costs gives the portfolio cost curve and, from it, the capital path. Our main measure, portable-alpha capacity, is the largest initial investment for which a market-hedged strategy compounds at least as fast as cash after trading costs. We also report dynamic capacity, the largest initial investment for which the unhedged strategy ends the sample with at least its initial capital. Portable-alpha capacity measures the scale of abnormal performance after removing market exposure; dynamic capacity measures the scale at which the strategy preserves capital on its own.

Consider a strategy based on characteristic z . Let $w_{i,t}(z_{i,t})$ be its target weight in security i at the end of month t . The required rebalance depends on the new target and on how the previous holdings drifted with returns. Let $R_{i,t}$ denote the total return on security i from $t-1$ to t , and let $R_{z,t}^{\text{pre}}$ denote the total return on the pre-rebalancing portfolio over the same month. The change in desired portfolio weight after accounting for this drift is

$$\Delta w_{i,t}^* = w_{i,t}(z_{i,t}) - w_{i,t-1}(z_{i,t-1}) \frac{1 + R_{i,t}}{1 + R_{z,t}^{\text{pre}}}. \quad (7)$$

Let A_t^z denote the assets allocated to strategy z immediately before the rebalance and

let $P_{i,t}$ be the stock price at that time. The number of shares traded is

$$X_{i,t} = \Delta w_{i,t}^* \left(\frac{A_t^z}{P_{i,t}} \right). \quad (8)$$

Using the stock-level cost function in Equation (2), the absolute trading cost in security i is

$$C_i(X_{i,t}) = b_{i,t}|X_{i,t}| + a_{i,t}X_{i,t}^2. \quad (9)$$

Dividing by assets gives the cost per dollar of strategy capital,

$$\frac{C_i(X_{i,t})}{A_t^z} = \frac{b_{i,t}}{P_{i,t}}|\Delta w_{i,t}^*| + a_{i,t} \left(\frac{\Delta w_{i,t}^*}{P_{i,t}} \right)^2 A_t^z. \quad (10)$$

Equation (10) shows the source of scale dependence. The spread component depends on the portfolio trade but not on assets under management; the price-impact component rises linearly with assets because the underlying dollar trade is larger.

Summing across the n_z securities in strategy z gives

$$\frac{C_t^z}{A_t^z} = \sum_{i=1}^{n_z} \left[\frac{b_{i,t}}{P_{i,t}}|\Delta w_{i,t}^*| + a_{i,t} \left(\frac{\Delta w_{i,t}^*}{P_{i,t}} \right)^2 A_t^z \right]. \quad (11)$$

Define the portfolio-level proportional and impact coefficients as

$$b_t^z = \sum_{i=1}^{n_z} \frac{b_{i,t}}{P_{i,t}}|\Delta w_{i,t}^*|, \quad (12)$$

and

$$a_t^z = \sum_{i=1}^{n_z} \frac{a_{i,t}}{P_{i,t}^2}(\Delta w_{i,t}^*)^2. \quad (13)$$

Then portfolio trading cost per dollar has the same linear-plus-convex structure as the stock-level cost function:

$$\frac{C_t^z}{A_t^z} = b_t^z + a_t^z A_t^z. \quad (14)$$

Equations (12)–(14) also identify the two portfolio margins that later drive the cross-section of capacity. A strategy is costly when it requires large weight changes, when those trades fall in stocks with high impact coefficients, or both.

For a long–short factor, let H and L denote the high and low characteristic legs. Each dollar of factor capital supports one dollar of long positions and one dollar of short positions.

Because the two legs rebalance separately, their execution costs add:

$$\frac{C_t^{H-L}}{A_t} = \frac{C_t^H}{A_t} + \frac{C_t^L}{A_t} = (b_t^H + b_t^L) + (a_t^H + a_t^L) A_t. \quad (15)$$

Thus, \$1 billion of factor capital corresponds to \$1 billion long and \$1 billion short, for \$2 billion of gross stock exposure. At each rebalance, each leg is reset to the current factor capital. The cost calculation charges the trades induced by changes in portfolio weights but does not assign a separate cost to the notional adjustment required solely to resize a leg as capital changes. Factor capacities include the execution costs in Equation (15) and exclude stock-borrow fees, financing spreads, and margin or collateral requirements. We state these assumptions explicitly because they affect the level of factor capacity; the long-leg estimates do not depend on them.

We next map trading costs into net returns. Let $r_{z,t+1}$ denote the strategy's pre-cost excess return from the rebalance at time t to the next rebalance. For an allocation A , the cost fraction paid at time t is $b_t^z + a_t^z A$, and the net excess return used in our capital recursion is

$$r_{z,t+1}^{Net}(A) = (1 - b_t^z - a_t^z A)(1 + r_{z,t+1}) - 1. \quad (16)$$

The timing convention is that the trading cost is paid when the new position is established, after which the remaining strategy exposure earns the pre-cost excess return over the month. The risk-free return is added separately in the wealth recursion below. The implementation therefore applies the risk-free return to beginning-of-period capital rather than to capital net of the contemporaneous trading cost; the omitted interaction between the risk-free return and the trading cost is quantitatively negligible. The coefficients b_t^z and a_t^z use the smoothed cost estimates and prices available by the rebalance date, so the portfolio-cost input contains no future information.

Following Korajczyk and Sadka (2004), we measure capacity over a fixed historical holding horizon. Capital starts at $A_{z,0} = A_0$ and evolves according to

$$A_{z,t+1} = A_{z,t} \left(1 + r_{f,t+1} + r_{z,t+1}^{Net}(A_{z,t}) \right), \quad (17)$$

where $r_{f,t+1}$ is the risk-free return. The recursion is scale dependent: the capital entering a rebalance determines the dollar trades, those trades determine the cost, and the net return determines the capital available at the next rebalance. The first trade, at $t = 0$, forms the portfolio from cash and is charged in full. If the cost of a rebalance exhausts available capital, the path terminates at zero.

For a realized sequence of returns and cost coefficients, iterating Equation (17) gives

average log growth

$$g_{z,T}(A_0) = \frac{1}{T} \log \left(\frac{A_{z,T}}{A_0} \right) = \frac{1}{T} \sum_{t=0}^{T-1} \log \left(1 + r_{f,t+1} + r_{z,t+1}^{Net}(A_{z,t}) \right). \quad (18)$$

A path that ends with zero capital has $g_{z,T}(A_0) = -\infty$. Dynamic capacity is the largest initial allocation for which this growth rate is non-negative:

$$A_{\log,T}^{\max} = \sup \left\{ A_0 > 0 : g_{z,T}(A_0) \geq 0 \right\}. \quad (19)$$

We locate the zero of $g_{z,T}$ on a grid of initial capital levels and refine it by bisection.

Because capacity is defined over many periods, compounding matters in addition to the average net return. A useful approximation is

$$g_{z,T}(A_0) \approx \mathbb{E}[r_f] + \mathbb{E}[r_z^{Net}(A_0)] - \frac{1}{2} \text{Var}(r_z^{Net}(A_0)). \quad (20)$$

The variance term captures the reduction in compound growth generated by return volatility. Holding average returns and trading costs fixed, greater volatility therefore lowers the capital that can be sustained.

Dynamic capacity includes the payoff from market exposure. Our main measure removes that exposure before evaluating growth. Let β_z be the CAPM beta estimated from the strategy's pre-cost excess returns and let $r_{m,t+1}$ denote the market excess return. For each dollar of strategy capital, we take a market position of $-\beta_z$ dollars using stock-index futures. The hedged net excess return is

$$r_{z,t+1}^{PA}(A) = r_{z,t+1}^{Net}(A) - \beta_z r_{m,t+1}. \quad (21)$$

The corresponding hedged capital evolves as

$$A_{z,t+1}^{PA} = A_{z,t}^{PA} \left(1 + r_{f,t+1} + r_{z,t+1}^{PA}(A_{z,t}^{PA}) \right). \quad (22)$$

We treat the market hedge as available at negligible execution cost and report a real-time hedge-ratio robustness check in Appendix E.3.²

²The full-sample beta uses information unavailable at the time of trading. Appendix Tables 18 and 19 use a 60-month rolling beta lagged one month and produce largely similar capacity estimates.

Portable-alpha growth is the average log growth of the hedged capital relative to cash:

$$g_{z,T}^{PA}(A_0) = \frac{1}{T} \sum_{t=0}^{T-1} \left[\log \left(1 + r_{f,t+1} + r_{z,t+1}^{PA}(A_{z,t}^{PA}) \right) - \log(1 + r_{f,t+1}) \right]. \quad (23)$$

Our main capacity measure is therefore

$$A_{PA,T}^{\max} = \sup \left\{ A_0 > 0 : g_{z,T}^{PA}(A_0) \geq 0 \right\}. \quad (24)$$

Because β_z is estimated from pre-cost returns, the average hedged return before costs equals the gross CAPM alpha. Section 4.3 and Appendix C.2 show how portable-alpha growth can be organized into gross alpha, proportional costs, price-impact costs, and variance drag.

For factor portfolios, gains and losses on the long and short legs change the capital that supports both legs. At each rebalance we resize each leg to the updated factor capital and reset the market hedge to $-\beta_z$ times that capital. Our reported factor capacities do not charge a separate cost for this resizing trade; charging it would lower factor capacity. Positions in stocks that leave the sample are carried at zero return and incur no further trading costs. Turnover, where reported, is the average monthly sum of absolute weight changes after the inception month.

Appendix D reports an additional scale measure based on the point at which net alpha under the CAPM or a six-factor model becomes non-positive. That measure is useful when one wants to control for several factor exposures. Portable-alpha capacity remains our main object because it follows the hedged capital path and therefore incorporates both trading costs and the effect of residual volatility on compound growth.

3 Data

Our empirical design combines return signals with stock-day measures of execution costs. We use NYSE TAQ trades and quotes from WRDS to estimate those costs, CRSP for stock returns and security information, and the open-source firm-characteristics data of Jensen et al. (2023) to construct the anomaly portfolios.³ The CRSP universe consists of common stocks listed on NYSE, Amex, and NASDAQ with share codes 10 and 11. Our main analysis uses 35 characteristics spanning thirteen anomaly families: Value, Investment, Profitability, Low Risk, Low Leverage, Momentum, Profit Growth, Quality, Seasonality, Size, Skewness,

³The data are available at <https://wrds-www.wharton.upenn.edu/pages/get-data/contributed-data-forms/global-factor-data/>; detailed documentation and additional factor portfolio data appear at <https://jpkpfactors.com>.

Accruals, and Debt Issuance. The machine-learning application uses all 153 characteristics.

3.1 TAQ Data

Our intraday analysis uses the NYSE Daily Trade and Quote (DTAQ) dataset, with all trades and quotes for common stocks in the U.S. equity market. TAQ records have millisecond timestamps from 2003 to 2015, microsecond timestamps during 2015–2016, and nanosecond timestamps from late 2016 onward. Our sample runs from January 2010 to December 2023.

DTAQ provides rich high-frequency detail but requires extensive cleaning. We follow standard filtering procedures (see Holden and Jacobsen, 2014; Holden et al., 2023), match each trade to its most recent National Best Bid and Offer quote, and sign trades with the Lee and Ready (1991) algorithm. We also introduce one refinement to standard trade cleaning. The TAQ trade file occasionally double-counts opening and closing auctions by reporting both the individual auction trades and an aggregated auction summary; we remove the aggregate print when individual trades from the same auction precede it. We have shared this fix with the WRDS TAQ team, who plan to incorporate it into future versions of their intraday indicator routines. Appendix A details every filter.

Table 1 summarizes the sample. Our sample contains about 12.5 million firm-day observations, with an average of 7.6 thousand trades, 1.2 million shares, and \$51.4 million in dollar volume per firm-day. Medians are substantially below means: the cross-firm distribution of trading activity is highly right-skewed. The median round-trip cost of trading one share is about four cents. Our estimates imply that, for the median firm, a 1,000-share net order moves the fundamental midpoint permanently by roughly \$4 and pushes the execution price away from it by a further \$6 of transitory impact. The permanent component is informational and unavoidable; the transitory component decays as the limit-order book replenishes, so a trader who works the order gradually rather than all at once pays far less of it.

Table 2 reports correlations across the main transaction-cost components. Firm-days with high quoted spreads have higher transitory price impact (correlation 0.14) and higher permanent price impact (correlation 0.01), but correlations are low overall. No single dimension of trading frictions summarizes implementation costs.

Table 3 reports the scale parameter per dollar traded, a/P , conditional on several firm characteristics. Each month, we sort firms into quartiles by the conditioning variable and average the scale parameter within each quartile across firm-days. The pattern matches prior work (Breen et al., 2002): trading is cheaper for large firms and for firms with high volume, high turnover, and low idiosyncratic volatility.

3.2 Descriptive Statistics: Transaction Cost Parameters

The stock-level [OW](#) parameters determine the level and curvature of implementation costs, and differences across firms in these parameters drive the capacity differences across anomaly strategies. We characterize this variation in two figures. Figure 1 reports the three model parameters: the order-book refill speed, plotted as the half-life $\log(2)/\rho$ in seconds; the temporary price impact κ ; and the permanent price impact λ . Figure 2 reports the two cost components that enter the portfolio-level cost function, the linear half-spread $b_{i,t}$ and the quadratic price-impact component $a_{i,t}$.

[Insert Figure 1 here]

First, the order book refills quickly but unevenly: in Figure 1, the cross-firm median half-life of temporary price impact, $\log(2)/\rho$, is about four-tenths of a second and stable over time, yet more than a quarter of firms have half-lives above half a second and some replenish almost instantaneously. Second, the temporary price-impact parameter κ is stable for the median firm over much of the sample, but cross-firm dispersion is wide and widens further in stressed states. Third, permanent impact represents roughly two-fifths of the total contemporaneous impact $\lambda + \kappa$ for the median firm, while temporary pressure represents roughly three-fifths. This comparison describes the initial price response, not the contribution of each component to optimally executed cost: rapid replenishment allows order splitting to dissipate much of the temporary pressure before later child orders arrive. Microsoft sits at or below the cross-firm median on all three parameters; GameStop’s temporary and permanent impact rise substantially during the 2021 meme-stock episode.

The two cost components in Figure 2 connect the parameter estimates to anomaly-level capacity. The linear component $b_{i,t}$, half the quoted spread in dollars per share, determines implementation cost at small scale. The quadratic component $a_{i,t}$ (which is a function of the parameters in Figure 1) determines how fast cost rises with the square of trade size, and hence with assets under management. Portfolio-level cost has the same linear-plus-quadratic form, so the dispersion of $b_{i,t}$ and $a_{i,t}$ across the stocks in an anomaly portfolio, together with portfolio turnover, determines the anomaly’s capacity.

[Insert Figure 2 here]

Both components are modest and stable for the typical stock. The cross-firm median half-spread $b_{i,t}$ is about 2.6 cents per share, roughly flat after an initial rise over 2010–2014, with a brief jump in 2020. The median quadratic component $a_{i,t}$ is small and trends up only mildly over the sample. But the cross-firm distributions are wide and right-skewed:

the interquartile range of each component spans a several-fold difference. Microsoft stays in the lower part of both distributions; GameStop’s half-spread $b_{i,t}$ and quadratic component $a_{i,t}$ rise substantially during the 2021 meme-stock episode, when large trades in that stock became disproportionately expensive.

3.3 Proportional Costs and the Relevance of the Quadratic Term

Figure 3 compares proportional and quadratic transaction costs. For each anomaly we use the same realized portfolio, drift-adjusted month-end trades, and 2010–2023 sample. The first calculation uses the full **OW** cost function $b_{i,t}|X| + a_{i,t}X^2$; the second sets the quadratic term to zero, so per-dollar cost is independent of assets under management. Because everything else is unchanged, the difference between the two panels comes from the quadratic term. The figure shows the long-leg cost curves for two anomalies from opposite ends of the turnover range: Momentum $t-12$ to $t-1$ and Operating profits-to-book equity.

[Insert Figure 3 here]

Under proportional costs the curves are flat in A_0 by construction and remain low at every scale: Momentum pays about two basis points of invested capital per month, and Operating profits-to-book equity a fifth of a basis point, whether the book runs \$10 million or \$50 billion. Under proportional transaction costs, both anomalies would appear implementable even at institutionally relevant scale. Under the **OW** cost function the same trades produce steeply rising per-dollar costs: Momentum pays 0.20% per month at \$1 billion, 0.90% at \$10 billion, and 1.67% at \$50 billion; Operating profits-to-book equity, with an eighth of Momentum’s turnover, pays 1.5 basis points at \$1 billion and 0.46% at \$50 billion.

4 Anomaly Capacity

Allowing trading costs to depend on scale changes the economic comparison across anomalies. We begin with the pre-cost return benchmark, estimate dynamic and portable-alpha capacity for all 35 long legs, and then examine why capacity differs across strategies.

4.1 Gross Performance

We start with the pre-cost return benchmark. Each month we sort stocks into quintiles on NYSE breakpoints of the characteristic, value-weight within quintiles, and define the long

leg H as the top quintile and the factor $H - L$ as top minus bottom.⁴ The cost estimates start in January 2010, so the first rebalance we price is the one at the end of January 2010, and every capital path runs over the 167 months from February 2010 through December 2023; gross performance is measured over the same months. Table 4 reports gross returns, risk measures, and CAPM estimates for the long leg of each of the 35 sorts. It also reports $\alpha - \frac{1}{2}\sigma_\varepsilon^2$, the approximate market-hedged growth rate before trading costs.

[Insert Table 4 here]

First, most of the long legs' gross excess returns reflect market exposure. These returns range from roughly 0.7% to 1.4% per month, while CAPM alphas rarely exceed 0.25%. The largest alpha is 0.41% for Highest 5 days of return. Only eight sorts have significantly positive alphas at the conventional 5% confidence level, and more than a third have negative estimates, consistent with the decline in anomaly returns documented by Chordia et al. (2014). Second, geometric returns are 6 to 25 basis points per month below arithmetic returns. This difference reflects the variance drag, approximately $\frac{1}{2}\sigma(r)^2$.

Figure 4 shows how growth changes with initial capital for the two anomalies in Figure 3. It plots portable-alpha and total-return log growth, both of which decline as price impact increases. At small scale, price impact is negligible, leaving only proportional trading costs. Operating profits-to-book equity pays 1.5 basis points per month in trading costs at \$1 billion, and its market-hedged growth remains positive up to \$20.7 billion. Momentum reaches zero market-hedged growth at just \$143 million. Other strategies are more expensive to trade: short-term reversal, the Amihud Measure, and Highest 5 days of return / volatility incur monthly costs of 0.4 to 0.6% at \$1 billion. At \$50 billion, no long leg generates positive market-hedged growth. Market exposure lets some unhedged strategies keep growing, while the most expensive strategies exhaust their capital before the sample ends.⁵ Each curve's zero crossing gives the corresponding capacity estimate.

[Insert Figure 4 here]

4.2 Capacity Across Anomalies

Table 5 reports portable-alpha capacity ($A_{PA,T}^{\max}$) and dynamic capacity ($A_{\log,T}^{\max}$) for the long leg of each anomaly, together with the mean gross excess return, gross CAPM alpha, and

⁴We compute NYSE cutoffs ($\text{exchcd} = 1$) at the 20th, 40th, 60th, and 80th percentiles of the characteristic each month, assign every stock to one of the five groups, and drop observations without an assignment; assignment uses only information dated t , and breakpoints and weights update monthly. The machine-learning portfolios in Section 6.3 likewise use NYSE quintile breakpoints on predicted returns and are formed as value- and equal-weighted long-short portfolios.

⁵These cases are denoted by $-\infty$ in Appendix Table 14.

the change in rank from alpha to portable-alpha capacity.

[Insert Table 5 here]

Capacity varies widely across anomalies. Among the 21 long legs with positive portable-alpha capacity, the median is only \$1.32 billion, while the range extends from \$143 million to \$32.6 billion. Thus, even conditional on a positive gross alpha, the amount of capital that can earn abnormal returns differs by more than two orders of magnitude across standard characteristic-sorted portfolios.

Gross alpha is positively related to capacity. Its Spearman rank correlation with portable-alpha capacity is 0.80, while the corresponding correlation for the gross Sharpe ratio is 0.84. These correlations largely reflect the strategies with zero capacity. Fourteen of the 35 long legs have negative market-hedged growth even as capital approaches zero and price impact vanishes. Of these, thirteen have negative gross alphas, while one has a positive alpha that is eliminated by proportional spread costs. None has zero capacity because of variance drag.

Among strategies with positive capacity, rankings by alpha and capacity differ substantially. Highest 5 days of return / volatility earns a gross alpha of 0.27% per month but supports only \$237 million of portable-alpha capital, ranking seventeen places lower on capacity than on alpha. Profit margin earns less than half as much alpha, 0.11% per month, yet supports \$23.1 billion and ranks eighteen places higher. The highest-alpha long leg, Highest 5 days of return, earns 0.41% per month but supports only \$1.79 billion. The examples show why alpha and deployable scale need not rank strategies in the same order.

The largest capacities are concentrated among profitability, cash-flow, and quality strategies. Operating profits-to-book assets supports \$32.6 billion, Profit margin \$23.1 billion, Operating profits-to-book equity \$20.7 billion, Operating cash flow to assets \$20.0 billion, and Quality minus Junk \$14.3 billion. At \$10 billion, these strategies earn 6 to 15 basis points of net alpha per month, while the more trading-intensive anomalies have substantially negative net alphas.

For the high-capacity profitability strategies, total-return capacity is six to twelve times portable-alpha capacity. Profit margin supports \$23.1 billion of portable-alpha capital compared with \$267 billion without the market hedge; the corresponding figures are \$32.6 billion and \$238 billion for Operating profits-to-book assets, and \$20.0 billion and \$148 billion for Operating cash flow to assets. These differences reflect the market exposure of the long legs. The two measures also use different thresholds. Dynamic capacity requires that the unhedged strategy ends with at least its initial capital. Portable-alpha capacity requires that the hedged strategy grows at least as fast as the risk-free rate. The second threshold is slightly higher, but most of the gap comes from the market exposure. Over our sample,

the market premium allows these portfolios to preserve capital at scales where trading costs have already eliminated their abnormal returns.

4.3 What Drives Cross-Anomaly Capacity Differences?

We decompose portable-alpha growth into gross alpha less proportional trading costs, price impact, and variance drag. Appendix C derives the following approximation along the realized capital path:

$$g_{z,T}^{PA}(A_0) \approx \alpha_z^{gross} - PC_{z,T} - IC_{z,T}(A_0) - \frac{1}{2}\sigma_{PA,z,T}^2(A_0). \quad (25)$$

Here, $PC_{z,T}$ denotes proportional trading costs, $IC_{z,T}(A_0)$ denotes price impact costs, both averaged along the hedged capital path, and the final term is the variance drag of the hedged return. Using the full-sample gross beta as the hedge ratio makes the average hedged return before costs equal to gross alpha, so no separate market-exposure term is needed. Appendix C reports the approximation error. We decompose growth rather than capacity itself. Capacity is the initial capital at which $g_{z,T}^{PA}(A_0)$ reaches zero; the terms in Equation (25) contribute to growth, not directly to dollar capacity. To compare their importance across anomalies, we evaluate each term at the same initial capital of \$10 billion.

Figure 5 shows the decomposition for all 35 long legs. Price impact accounts for most of the differences in trading costs across anomalies. At \$10 billion, monthly impact costs are a few tenths of a percent or less for the most scalable strategies, but exceed 1.5% for the least scalable. Proportional costs and variance drag are considerably smaller for most anomalies.

[Insert Figure 5 here]

What a strategy trades and how much it trades explain the variation in price impact. Table 6 illustrates these mechanisms using representative anomalies.

[Insert Table 6 here]

The Amihud strategy turns over the portfolio only 0.12 times per month, yet incurs monthly impact costs of 1.20% at \$10 billion. These costs reflect its holdings of illiquid stocks, consistent with the liquidity measure used to form the portfolio. Weighting each stock's per-dollar impact coefficient $a_{i,t}/P_{i,t}^2$ by the squared trade, the stocks Amihud trades cost 233 basis points of price impact per dollar traded for a \$1 million order, against 1.3 basis points for Operating profits-to-book assets and 2.4 for Short-term reversal. Operating profits-to-book assets also has low turnover, at 0.05, but trades substantially more liquid

stocks and incurs impact costs of only 0.07% per month. Low turnover by itself is not enough to keep trading costs small.

Short-term reversal illustrates the other margin. It turns over the portfolio 1.77 times per month, fifteen times as much as Amihud, and incurs monthly impact costs of 1.56% at \$10 billion. Its holdings are much more liquid—about one percent of Amihud’s per-dollar impact—but the greater trading activity produces similarly high costs. Price impact can be large because the stocks are illiquid or because a liquid portfolio is traded frequently.

5 Factor Capacity

Long–short factors provide a second view of the relation between alpha and scale. They typically deliver higher alpha than the long legs, but they also require trading both sides of the portfolio. Whether the factor supports more capital depends on which effect is larger. As throughout the paper, the estimates include execution costs and exclude financing and stock-borrow fees.

5.1 Factor Gross Alphas and Capacity

Table 7 reports gross performance and portable-alpha capacity for the 35 long–short factors. The factors generally have higher gross alphas than their long legs. Gross CAPM alphas reach 1.17% per month for the Mispricing factor (Performance), while momentum, quality, and several profitability factors earn roughly 0.7–0.9% per month. By comparison, the largest long-leg alpha is 0.41%.

[Insert Table 7 here]

Despite their higher alphas, factors have only slightly higher median capacity than long legs. Twenty-one factors have positive portable-alpha capacity, with a median of \$1.53 billion, compared with \$1.32 billion among long legs with positive capacity.

As with the long legs, gross alpha is positively related to factor capacity, with a Spearman rank correlation of 0.82, but factors with similar alphas can support very different amounts of capital. Operating cash flow to assets and idiosyncratic volatility earn gross alphas of 0.91% and 0.87% per month, but their capacities are \$8.8 billion and \$356 million. Momentum earns 0.74% and supports \$414 million. Highest 5 days of return earns a higher alpha than Operating profits-to-book equity, 1.08% versus 0.80%, yet supports only \$435 million compared with \$6.4 billion.

The gain from adding a short leg depends on whether its contribution to alpha compensates for its trading costs. A short leg that trades frequently or holds illiquid stocks can add substantial alpha without increasing capacity. Thus, the higher alphas of long-short portfolios need not translate into substantially more deployable capital.

5.2 What Drives Factor Capacity?

We apply the portable-alpha growth decomposition from Section 4.3 to the factors. Table 8 reports gross alpha, proportional trading costs, price impact costs, and variance drag at an initial capital of \$10 billion.

[Insert Table 8 here]

Price impact accounts for most trading costs and much of their variation across factors. Operating cash flow to assets and idiosyncratic volatility earn gross alphas of 0.91% and 0.87% per month, but their monthly turnover is 0.22 and 2.21, respectively. At \$10 billion, their monthly impact costs are 0.88% and 2.34%, leaving portable-alpha growth of about -0.06% and -1.76% . Momentum earns a gross alpha of 0.74%, turns over 1.24 times per month, and incurs impact costs of 2.15%, leaving portable-alpha growth of about -1.63% per month.

Profitability and quality factors generally combine high gross alphas with low turnover and relatively low impact costs. Operating profits-to-book assets turns over 0.13 times per month and incurs monthly impact costs of 0.50% at \$10 billion. Short-horizon return strategies trade more heavily. Price momentum $t-6$ to $t-1$ turns over 1.78 times per month and incurs impact costs of 2.18%, while Highest 5 days of return turns over 2.32 times and incurs 2.51%. Proportional costs and variance drag are smaller for most factors and account for less of the variation across them.

Together, the long-leg and factor results add deployable scale to the assessment of anomaly profitability (Cochrane, 2011). Profitability strategies support substantial capital because they combine positive gross alphas with infrequent trading in relatively liquid stocks, whereas several higher-alpha strategies give up much more of their return to price impact. For the most scalable profitability strategies, the spread and price-impact costs measured here remain small enough that substantial market-hedged capital can still be deployed. The remaining returns may reflect risks beyond market exposure (Novy-Marx, 2013), compensation for exposure to illiquidity (Acharya and Pedersen, 2005), or other economic forces. Frequently traded strategies such as short-term reversal may also earn compensation for supplying liquidity (Nagel, 2012). Our estimates are not designed to adjudicate among

these explanations. Their role is to show where the execution-cost channel is quantitatively important and where meaningful returns remain after that channel is accounted for.

6 Additional Analysis

The preceding results use a fixed execution protocol. This section examines uncertainty in the capacity estimates, alternative execution assumptions, and the effect of changing the path toward the same target portfolio.

6.1 Uncertainty in Capacity Estimates

We examine how uncertainty in the trading-cost estimates affects the capacity estimates, holding portfolio weights and realized returns fixed. This separates the sensitivity to costs from the uncertainty about strategy performance. The resulting bands are conditional on the historical return path and on the execution model.

For each stock, we express the daily cost estimates relative to their exponential moving average, center these ratios within stock so that resampling does not shift the level of the costs, and resample them in blocks of 21 trading days. Blocks are drawn independently for each stock, so the bands reflect stock-specific estimation noise and exclude common shocks to trading costs. We smooth the resampled ratios with the main exponential moving average, multiply the original month-end cost coefficients by the result, and reconstruct the monthly portfolio costs from the original trades. Each month-end coefficient is thus perturbed by a factor with mean one whose dispersion is that of a 50-day average of the daily estimation noise. We recompute every capacity for each of 499 draws and report the 5th and 95th percentiles in Appendix E.2. The bands measure how much a capacity estimate moves when the daily cost history is resampled. They hold the return history fixed and do not re-estimate the intraday cost model, so they are not confidence intervals for the cost parameters themselves.

Among strategies with positive capacity, the median width of the 90% band is 5.1% of the estimated capacity for long legs and 4.6% for factors. The Operating profits-to-book assets long leg, with an estimated capacity of \$32.6 billion, has a band of \$31.6–\$33.5 billion; the corresponding factor, at \$15.2 billion, has a band of \$14.3–\$15.8 billion; the Momentum long leg, at \$143 million, has a band of \$141–\$145 million. The bands are narrow because a capacity depends on cost coefficients averaged over 167 months and hundreds of stocks, so the daily estimation noise largely averages out.

These bands hold the return history fixed. A block bootstrap that resamples the monthly

returns and cost coefficients jointly, in blocks of twelve months, gives bands that are about twice as wide as the point estimate at the median, and for 22 of the 42 strategies with positive capacity more than 5% of the draws have zero capacity. The capacity estimates are therefore insensitive to resampling of the daily cost noise given the realized returns and imprecise as forecasts of the capacity a different sample of returns would produce.

6.2 Execution Strategies and Capacity Estimates

The capacity estimates depend on how trades are executed and how price impact is estimated. These choices matter at institutional scales. The median qualifying hedge fund had net assets of \$1.1 billion at the end of 2025 (U.S. Securities and Exchange Commission, 2026), and Koijen and Yogo (2019) report institutional equity holdings of \$5.2 billion at the 90th percentile during 2015–2017. These figures motivate our use of \$10 billion to illustrate the costs of capital following similar signals across several investors. The robustness analysis below evaluates each strategy at its own capacity, rather than at this common benchmark. We recompute capacity under four alternatives: uniform execution across the trading day; a single order for the entire rebalance; and the optimal schedule implemented with one-minute or five-minute child orders instead of continuous trading. The parameter estimates, smoothing procedure, portfolio weights, returns, and proportional costs remain unchanged. Each alternative changes the impact coefficient $a_{i,d}$ that depends on raw parameters and the execution strategy as described in Section 2. Table 9 reports the results for long legs and factors.

[Insert Table 9 here]

Uniform execution across the day produces the same capacities as the optimal schedule to the reported precision. Liquidity replenishes quickly relative to the trading day, so the difference in costs between the two schedules is negligible. Coarser execution steps also have little effect. Executing the schedule in one-minute or five-minute child orders instead of every second raises the median impact coefficient by 0.2% and about 0.8%, respectively, and lowers median capacity by 0.2% and about 0.9%.

Executing the entire rebalance in one order has a much larger effect because liquidity has no time to replenish during execution. The portfolio impact coefficient rises by 67% for the median long leg and 72% for the median factor. Among strategies with positive capacity under full monthly rebalancing, the median capacity reduction is 39% for long legs and 42% for factors. The middle half of long legs retain 59–63% of their main-specification capacity. No strategy with positive capacity falls to zero, and rankings across anomalies remain

similar under all four alternatives. The economically important comparison is therefore between giving the order book time to replenish and demanding the full quantity at once; fine adjustments to the intraday schedule matter much less for our estimates.

Appendix E.4 examines sensitivity to smoothing the daily cost estimates. Table 20 reports capacities after halving and doubling the span of the exponential moving average. The median ratio of alternative to main-specification capacity differs from one by at most 7%, and rank correlations remain above 0.98.

6.3 Rebalancing Speed and Capacity

So far, each strategy has traded fully to its target weights every month. We next keep those targets fixed but allow the investor to approach them gradually. Because the signal does not change, any change in capacity comes from the trading rule. We also add two machine-learning factors following Gu et al. (2020) to see whether stronger return forecasts are necessarily more scalable.

We use gradient-boosted regression trees to predict one-month-ahead stock returns from the 153 characteristics in Jensen et al. (2023). We divide the data into a training sample ending in 1994, a validation sample covering 1995–2009, and a test sample covering 2010–2023. We select the hyperparameters on the validation sample, refit the model on the training and validation samples with those hyperparameters, and evaluate the strategy in the test sample.⁶ Each month, we sort stocks into quintiles of predicted returns using NYSE breakpoints and form value-weighted and equal-weighted long–short portfolios. We refer to these two factors as the machine-learning composites.

Under full rebalancing, portfolio weights equal the target weights $w_{i,t}$ after each rebalance. With partial adjustment, the portfolio retains some of its previous positions, so actual holdings need not equal target weights. Let $h_{i,t}$ denote the weight held in stock i after rebalancing. Each month, the investor trades a fraction τ of the difference between the target weight and the weight carried forward from the previous month:

$$\Delta w_{i,t} = \tau \left(w_{i,t} - h_{i,t-1} \frac{1 + R_{i,t}}{1 + R_{z,t}^h} \right), \quad h_{i,t} = h_{i,t-1} \frac{1 + R_{i,t}}{1 + R_{z,t}^h} + \Delta w_{i,t}, \quad (26)$$

where $R_{i,t}$ is the stock’s total return and $R_{z,t}^h = \sum_i h_{i,t-1} R_{i,t}$ is the total return on the held portfolio before rebalancing.

⁶We fit the trees with XGBoost using a pseudo-Huber loss, 500 trees, and no early stopping. The grid is tree depth $\{1, 3, 5, 7\}$, row subsampling $\{0.25, 0.5\}$, column subsampling $\{0.25, 0.5\}$, and learning rate $\{0.01, 0.001\}$; the validation criterion is the out-of-sample R^2 of Gu et al. (2020). The selected model has depth 5, row subsampling 0.25, column subsampling 0.5, and learning rate 0.01.

When $\tau = 1$, holdings equal target weights after each rebalance, reproducing the full-rebalancing trades in Equation (7). When $\tau < 1$, adjustment is gradual. Positions in stocks that leave the target quintile are reduced over subsequent months rather than closed immediately. For persistent signals, partial adjustment spreads trades over time; for short-lived signals, it limits trades that would soon be reversed. Both can reduce costs, but slower adjustment may also lower gross returns because holdings track the signal less closely. This trade-off motivates the optimal policy in Gârleanu and Pedersen (2013). Our rule is simpler: we trade a fixed fraction toward the characteristic-based target rather than solve for the optimal portfolio dynamically. This channel complements DeMiguel et al. (2020), where combining characteristics can reduce costs through offsetting trades across signals. Here, the target portfolios remain fixed and only the speed of adjustment changes.

We compute returns and costs using the holdings and trades from Equation (26). In the first month the investor buys the target portfolio in full, as under full monthly rebalancing. Partial adjustment starts in the second month. The pre-cost excess return is $r_{z,t+1} = \sum_i h_{i,t} r_{i,t+1}$, including returns on positions retained after stocks leave the target quintile.⁷ We calculate b_t^z and a_t^z in Equations (12) and (13) using $\Delta w_{i,t}$ in place of $\Delta w_{i,t}^*$. For a given gap between current and target weights and a given capital allocation, proportional costs scale with τ and impact costs with τ^2 . Both factor legs follow the adjustment rule separately, each with its own drifted weights, and their costs add as in Equation (15). These returns and cost coefficients enter the net-return formula in Equation (16) and the portable-alpha capacity calculation described in Section 2.3.

For each strategy, we choose the rebalancing speed $\tau \in \{0.05, 0.1, 0.2, 0.35, 0.5, 0.75, 1\}$ that maximizes the average monthly net return before the market hedge at a fixed capital allocation of \$10 billion over 2010–2023. We refer to this choice as the *peak speed*. Holding that speed fixed, we then compute portable-alpha capacity as described in Section 2.3. This exercise measures the gains available from choosing rebalancing speed in sample. Table 10 compares capacity, turnover, and net returns at full monthly rebalancing and at each strategy’s peak speed.

[Insert Table 10]

Among factors with positive capacity, the median rises from \$1.5 billion to \$21 billion, and the median strategy-level increase is thirteenfold. The value-weighted machine-learning composite’s capacity rises from \$177 million to \$19 billion, while the equal-weighted composite’s rises approximately one hundredfold, from \$13 million to \$1.3 billion. Although

⁷As in the full-rebalancing calculations, positions in stocks that leave the sample are carried at zero return and incur no further trading costs.

trading costs can make machine-learning strategies difficult to implement (Avramov et al., 2023), trading more slowly allows the value-weighted composite to support substantial capital, even under our simple partial-adjustment rule, before financing and stock-borrow costs on the short leg. More sophisticated execution may offer further gains, consistent with the low institutional trading costs documented by Frazzini et al. (2018). For these portfolios, the trading rule is part of the economic evaluation of the forecast.

Slower rebalancing also improves net returns at a fixed scale. At \$10 billion, fourteen of the 35 factors earn positive net returns at their peak speed, compared with one at full monthly rebalancing. The value-weighted composite moves from an average monthly net loss of 13% to a small positive return. The equal-weighted composite still loses about half a percent per month: although it trades less, its exposure to small stocks keeps trading costs high.

For 26 of the 35 factors, net returns are highest at the slowest speed considered, $\tau = 0.05$. The median capacity gain from reducing τ from 0.1 to 0.05 is 5%. Gains over this last step are modest, but the results leave open whether still slower adjustment would improve performance. Because the peak speed is chosen on the same sample, we also report a rule that needs no choice: $\tau = 0.05$ for every factor. It gives the same median capacity of \$21 billion among factors with positive capacity under full monthly rebalancing, a median increase of nine times against thirteen at the peak speed, and leaves 18 of the 35 factors with positive capacity against 22 at the peak speed.

Figure 6 shows how slower rebalancing affects capacity rankings and how capacity relates to net returns at \$10 billion. Both panels use each factor’s peak speed. The left panel compares portable-alpha capacity rankings at peak speed with those under full monthly rebalancing. The rank correlation across the 35 factors is 0.93, and profitability and quality factors remain near the top. Idiosyncratic volatility, Highest 5 days of return, and Market correlation rise substantially in rank, while accrual and investment factors fall despite increases in capacity because other factors gain more. The right panel plots portable-alpha capacity against net returns at \$10 billion. Several factors support \$21–\$32 billion of portable-alpha capital yet earn negative net returns at \$10 billion. This difference arises because capacity is measured after hedging market exposure, whereas the plotted net returns exclude the hedge. For these negative-beta factors, the hedge adds a long market position, which earns a positive return over the sample.

[Insert Figure 6 here]

An alternative to partial adjustment is to update portfolio sorts less frequently. Figure 7 compares these approaches for the two machine-learning composites. Re-sorting every three

or six months holds portfolio assignments fixed between sorts, while still rebalancing fully to the prevailing target weights each month. Partial adjustment updates the sorts monthly but trades only part of the way toward the new targets.

At similar turnover, partial adjustment supports substantially more portable-alpha capital. For the value-weighted composite, re-sorting every three months produces monthly turnover of 0.99 and capacity of \$0.9 billion, compared with turnover of 0.90 and capacity of \$2.4 billion at $\tau = 0.35$. At turnover of roughly 0.54, re-sorting every six months supports \$1.2 billion, compared with \$6.5 billion at $\tau = 0.2$. Updating sorts less frequently reduces how often portfolio assignments change, but still requires full adjustment when they do. Partial adjustment spreads those trades over time while continuing to incorporate new information. With quadratic impact costs, turnover alone therefore does not determine capacity: the size and distribution of individual trades also matter.

[Insert Figure 7 here]

Slower rebalancing reduces trade sizes relative to observed market volume. Table 11 reports these comparisons at a fixed capital allocation of \$10 billion, measuring each stock's trade against its average daily volume. Under full monthly rebalancing, 63% of the dollars traded by the Operating profits-to-book assets factor, 87% by Momentum, and 94% by the value-weighted composite are in orders exceeding 10% of daily volume. At their peak speeds, these shares fall to 0.5%, 1.2%, and 1.1%, respectively. Orders exceeding a full day's volume account for 4–14% of trading at full speed and nearly disappear with slower adjustment. The equal-weighted composite remains more demanding: its share of trading above 10% of daily volume falls from 92% to 46%.

These comparisons hold capital fixed at \$10 billion for all strategies. At each strategy's own portable-alpha capacity, slower rebalancing can increase the total dollars traded because it supports a larger portfolio. The second block of Table 11 evaluates selected strategies at their own capacities. For Operating profits-to-book assets, this block reports the long leg rather than the long–short factor. At the long leg's \$32.6 billion capacity under full rebalancing, 73% of the dollars traded are in orders above 10% of daily volume and 15% in orders above a full day's volume; at its \$120 billion capacity at the peak speed, the shares are 42% and 0.1%. The value-weighted composite at its \$19 billion peak-speed capacity places 5% of its dollars in orders above 10% of daily volume and none above a full day's volume. The cost function is estimated from observed order flow and applied at these participation rates without a cap, so the capacities of the largest strategies rest on extrapolating the quadratic cost beyond the order sizes typical in the estimation sample. Slower adjustment therefore

reduces trading demands relative to market volume at a given scale, although large orders remain a concern for some strategies.

[Insert Table 11 here]

7 Conclusion

Alpha does not reveal the size of a return opportunity by itself. In our sample, some of the highest-alpha anomalies support less than \$2 billion of market-hedged capital, while lower-alpha profitability strategies support \$20–33 billion. The difference comes mainly from price impact. Strategies that trade frequently, or trade stocks that absorb large orders poorly, give up much more of their return as capital increases. Profitability and quality strategies tend to avoid both problems. For the most scalable of them, the spread and price-impact costs measured here remain too small to absorb the return opportunity even at substantial scale. This limits what the trading-cost channel studied in this paper can explain without taking a position on the other economic forces behind those returns.

Implementation changes the picture further. Holding the target portfolio fixed, moving toward it more slowly can increase capacity by an order of magnitude or more. Among factors with positive capacity under full monthly rebalancing, choosing the rebalancing speed in sample raises median capacity thirteenfold. The value-weighted machine-learning strategy moves from \$177 million under full rebalancing to \$19 billion with partial adjustment. The signal is the same; the amount of capital that can earn its return is not.

The practical implication is simple. A return estimate says how much a strategy earns per dollar before implementation. It does not say how many dollars can earn that return. Answering the second question requires the trades implied by the portfolio, the liquidity of the stocks being traded, and the way those trades are executed. That is the object our capacity estimates are designed to measure.

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Tables

Table 1: Summary Statistics.

The table presents summary statistics for market-microstructure estimates on the universe of NYSE daily TAQ stocks. Our sample runs from 2010 to 2023. Daily trades is defined as the number of trades in thousands, Quoted spread as the difference between the ask and bid at the end of a five-minute interval, Persistent Price Impact as the slope of a regression of the price midpoint on the net order flow estimated on five-minute intervals. Transitory Price Impact is the immediate effect of order flow on effective spread. Resilience is the persistence of the effect estimated using one-second intervals near trades; ρ is the decay rate per second, and $\exp(-\rho)$ is the share of the transitory impact remaining after one second. Scale refers to the slope of the marginal transaction cost with respect to quantity traded. It is derived from the other parameters assuming optimal execution (OW) and uniform execution during the day (Naive). Order flow is in thousands of shares.

	Mean	Median	Std. Dev.	# Obs
# Daily Trades (th)	7.56	1.97	22.48	12,453,952
Dollar Volume (mill)	51.42	3.80	357.59	12,453,952
Share Volume (mill)	1.23	0.24	5.98	12,453,952
Quoted Spread ($2b$)	0.12	0.04	0.25	1,2453,952
Persistent impact ($1000 \times \lambda$)	33.64	4.36	15584.73	12,453,952
Transitory impact ($1000 \times \kappa$)	98.79	5.91	3573.57	12,453,952
Resilience ($\exp(-\rho)$)	0.25	0.20	0.23	12,192,088
Scale OW ($1000 \times a$)	16.04	2.18	7654.53	12,192,088
Scale Naive	16.04	2.18	7654.65	12,191,713

Table 2: Correlations between the transaction-cost parameters.

The table presents correlations among quoted spreads, permanent price impact, transient price impact and order book resilience across all stock-days in the sample. See Table 1 for variable definitions and sample composition.

	$2b$	$1000 \times \lambda$	$1000 \times \kappa$	$\exp(-\rho)$
Quoted Spread ($2b$)	1.00			
Persistent impact ($1000 \times \lambda$)	0.01	1.00		
Transitory impact ($1000 \times \kappa$)	0.14	0.10	1.00	
Resilience ($\exp(-\rho)$)	0.01	-0.00	-0.01	1.00

Table 3: Average scale parameter conditional on firm characteristics.

The table presents averages of the scale parameters conditional on firm characteristics. Each entry is the mean of $1000 \times a/P$ across firm-days within a quartile, where a is the scale parameter under optimal execution (OW) and P is the closing price; dividing by the price makes the impact of a dollar trade comparable across firms with different price levels. Firms are sorted into quartiles on the conditioning variable each month. Volume and turnover are averaged over the previous 126 trading days. Idiosyncratic volatility is measured relative to the CAPM over the previous 252 trading days.

	Lowest	2	3	Highest
Market Capitalization	1.17	0.63	0.28	0.09
Volume	1.30	0.52	0.23	0.07
Turnover	1.21	0.41	0.25	0.22
Idiosyncratic Vol	0.26	0.48	0.53	0.76

Table 4: Gross performance of the 35 long legs.

The table presents gross performance statistics on the long legs of the 35 strategies we consider. Each long leg is the value-weighted top quintile of a characteristic sort using NYSE breakpoints. Sharpe is the Sharpe ratio of gross excess returns. R and R^{Geo} are the arithmetic and geometric mean gross excess returns, respectively. α and β are the intercept and slope of a regression of gross excess returns on the market excess return, respectively. $t(\alpha)$ is the Newey–West t -statistic of the α estimate with three lags. σ_ϵ is the standard deviation of the regression residuals. The last column, $\alpha - \frac{1}{2}\sigma_\epsilon^2$, approximates the market-hedged growth rate before trading costs. R , R^{Geo} , α , σ_ϵ , and the growth rate are reported in percentage points. Rows are sorted by the Sharpe ratio. The sample covers January 2010–December 2023 (167 monthly returns from February 2010). All statistics are based on data at the monthly frequency.

Anomaly	Sharpe	R (%)	R^{Geo} (%)	α	$t(\alpha)$	β	σ_ϵ	$\alpha - \frac{1}{2}\sigma_\epsilon^2$
Highest 5 days of return	0.34	1.22	1.16	0.41	3.42	0.75	1.41	0.40
Years 16-20 lagged returns, nonannual	0.30	1.17	1.10	0.30	2.32	0.81	1.55	0.29
Operating profits-to-book equity	0.29	1.26	1.17	0.24	2.68	0.94	1.11	0.24
Mispricing factor: Performance	0.29	1.24	1.15	0.24	2.42	0.93	1.20	0.23
Operating profits-to-book assets	0.28	1.27	1.17	0.22	2.07	0.98	1.15	0.22
Operating cash flow to assets	0.28	1.25	1.15	0.21	2.00	0.97	1.18	0.21
Highest 5 days of return / volatility	0.28	1.36	1.25	0.27	1.95	1.02	1.79	0.25
Quality minus Junk: Composite	0.28	1.21	1.12	0.20	1.90	0.94	1.15	0.19
R&D-to-market	0.28	1.38	1.25	0.27	1.96	1.03	2.04	0.25
Idiosyncratic volatility	0.27	1.09	1.01	0.16	2.00	0.86	1.10	0.16
Change in net operating assets	0.27	1.34	1.22	0.21	1.60	1.04	1.63	0.20
Net debt-to-price	0.27	1.33	1.21	0.19	1.33	1.05	1.52	0.18
Percent operating accruals	0.26	1.40	1.26	0.17	1.28	1.14	1.64	0.16
Profit margin	0.26	1.15	1.06	0.11	1.59	0.97	0.84	0.11
CAPEX growth (1 year)	0.26	1.38	1.24	0.18	1.14	1.11	1.87	0.16
Asset Growth	0.26	1.31	1.18	0.17	0.95	1.05	2.09	0.15
Share turnover	0.25	0.91	0.84	0.14	1.16	0.71	1.69	0.13
Market correlation	0.25	0.97	0.89	0.16	1.25	0.75	1.86	0.14
Operating accruals	0.25	1.31	1.18	0.14	0.88	1.09	1.94	0.12
Price momentum t-6 to t-1	0.25	1.18	1.07	0.14	1.03	0.97	2.00	0.12
Standardized earnings surprise	0.24	1.08	0.97	0.00	0.04	1.00	1.07	0.00
Momentum t-12 to t-1	0.24	1.12	1.01	0.07	0.48	0.98	1.92	0.05
Change in operating cash flow to assets	0.23	1.13	1.01	-0.03	-0.31	1.08	1.42	-0.04
Change in net financial assets	0.22	1.11	0.98	-0.07	-0.59	1.09	1.44	-0.08
Price momentum t-12 to t-7	0.22	1.14	1.00	-0.02	-0.13	1.08	2.19	-0.05
Residual momentum t-12 to t-1	0.21	1.00	0.89	-0.08	-0.87	1.01	1.37	-0.09
Growth in book debt (3 years)	0.20	1.02	0.89	-0.13	-1.17	1.07	1.62	-0.15
Earnings volatility	0.19	1.10	0.94	-0.22	-1.56	1.23	1.88	-0.23
Years 2-5 lagged returns, annual	0.19	1.07	0.90	-0.25	-1.75	1.22	1.80	-0.26
Ebitda-to-market enterprise value	0.16	0.93	0.75	-0.33	-1.30	1.17	2.72	-0.37
Book-to-market equity	0.16	1.10	0.85	-0.36	-1.15	1.36	3.61	-0.43
Intrinsic value-to-market	0.16	0.88	0.72	-0.36	-1.51	1.16	2.34	-0.39
Short-term reversal	0.15	1.02	0.80	-0.45	-2.12	1.37	2.70	-0.49
Dollar trading volume	0.15	0.82	0.67	-0.30	-1.30	1.04	2.91	-0.34
Amihud Measure	0.11	0.65	0.47	-0.57	-2.41	1.13	3.29	-0.62

Table 5: Capacity of the 35 long legs.

The table presents returns, alphas, capacities, and ranking differences for the long legs of the 35 strategies we consider. Each long leg is the value-weighted top quintile of a characteristic sort using NYSE breakpoints. R is the arithmetic mean gross excess return. Gross α is the intercept of a regression of gross excess returns on the market excess return. Both are monthly and reported in percentage points. $A_{PA,T}^{\max}$ is the portable-alpha capacity, the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. $A_{\log,T}^{\max}$ is the dynamic capacity, the largest initial capital at which average log growth of the unhedged strategy is non-negative. ΔRank is the rank by gross α minus the rank by portable-alpha capacity and is blank for long legs with zero portable-alpha capacity. The sample covers January 2010–December 2023 (167 monthly returns from February 2010). Rows are sorted by gross α .

Anomaly	R (%)	Gross α	$A_{\log,T}^{\max}$	$A_{PA,T}^{\max}$	Δ Rank
Highest 5 days of return	1.22	0.41	5.36 bn	1.79 bn	-7
Years 16-20 lagged returns, nonannual	1.17	0.30	2.85 bn	565 m	-16
Highest 5 days of return / volatility	1.36	0.27	1.56 bn	237 m	-17
R&D-to-market	1.38	0.27	6.33 bn	1.44 bn	-6
Operating profits-to-book equity	1.26	0.24	123.32 bn	20.67 bn	2
Mispricing factor: Performance	1.24	0.24	33.45 bn	8.63 bn	0
Operating profits-to-book assets	1.27	0.22	238.22 bn	32.58 bn	6
Operating cash flow to assets	1.25	0.21	148.31 bn	19.98 bn	4
Change in net operating assets	1.34	0.21	7.58 bn	1.12 bn	-4
Quality minus Junk: Composite	1.21	0.20	104.59 bn	14.27 bn	5
Net debt-to-price	1.33	0.19	34.64 bn	5.74 bn	4
CAPEX growth (1 year)	1.38	0.18	8.86 bn	1000 m	-2
Percent operating accruals	1.40	0.17	12.23 bn	1.60 bn	4
Asset Growth	1.31	0.17	8.11 bn	957 m	-2
Idiosyncratic volatility	1.09	0.16	3.60 bn	620 m	-2
Market correlation	0.97	0.16	9.43 bn	1.32 bn	5
Share turnover	0.91	0.14	9.26 bn	1.20 bn	5
Operating accruals	1.31	0.14	5.44 bn	1000 m	3
Price momentum t-6 to t-1	1.18	0.14	4.04 bn	311 m	0
Profit margin	1.15	0.11	267.06 bn	23.10 bn	18
Momentum t-12 to t-1	1.12	0.07	5.55 bn	143 m	0
Standardized earnings surprise	1.08	0.00	4.76 bn	0	–
Price momentum t-12 to t-7	1.14	-0.02	3.17 bn	0	–
Change in operating cash flow to assets	1.13	-0.03	6.19 bn	0	–
Change in net financial assets	1.11	-0.07	8.72 bn	0	–
Residual momentum t-12 to t-1	1.00	-0.08	3.98 bn	0	–
Growth in book debt (3 years)	1.02	-0.13	9.80 bn	0	–
Earnings volatility	1.10	-0.22	13.12 bn	0	–
Years 2-5 lagged returns, annual	1.07	-0.25	800 m	0	–
Dollar trading volume	0.82	-0.30	666 m	0	–
Ebitda-to-market enterprise value	0.93	-0.33	6.73 bn	0	–
Intrinsic value-to-market	0.88	-0.36	4.06 bn	0	–
Book-to-market equity	1.10	-0.36	4.00 bn	0	–
Short-term reversal	1.02	-0.45	507 m	0	–
Amihud Measure	0.65	-0.57	449 m	0	–

Table 6: Decomposition of long leg portable-alpha growth at \$10 billion.

The table presents a decomposition of portable alpha growth at a size of \$10 bln for a selection of representative long leg strategies. α^{gross} is the intercept of a regression of gross excess returns on the market excess return. Turnover is the average monthly sum of absolute weight changes, excluding the inception month. PC is the average proportional trading cost. IC is the average price-impact cost. $\frac{1}{2}\sigma_{PA}^2$ is half the variance of the market-hedged net return. g^{PA} is the average log growth of market-hedged capital relative to cash. Costs, variance, and growth are evaluated along the capital path starting from \$10 billion. Gross alpha less proportional costs, price-impact costs, and half the variance approximates g^{PA} . The sample covers January 2010–December 2023 (167 monthly returns from February 2010). All entries except Turnover are reported in percentage points per month.

Anomaly	α^{gross}	Turnover	PC	IC	$\frac{1}{2}\sigma_{PA}^2$	g^{PA}
Operating profits-to-book assets	0.22	0.05	0.00	0.07	0.01	0.14
Operating cash flow to assets	0.21	0.08	0.00	0.11	0.01	0.09
Mispricing factor: Performance	0.24	0.18	0.01	0.25	0.01	-0.03
Idiosyncratic volatility	0.16	0.86	0.02	0.98	0.02	-0.87
Momentum t-12 to t-1	0.07	0.57	0.02	0.88	0.02	-0.87
Highest 5 days of return / volatility	0.27	1.61	0.07	1.63	0.03	-1.49
Amihud Measure	-0.57	0.12	0.04	1.20	0.17	-2.12
Short-term reversal	-0.45	1.77	0.09	1.56	0.06	-2.21

Table 7: Gross performance and capacity of the 35 factors.

The table presents gross performance and capacity estimates for the 35 factor strategies we consider. Each factor is the difference between the value-weighted top and bottom quintiles of a characteristic sort using NYSE breakpoints. Sharpe is the Sharpe ratio of gross excess returns. R is the arithmetic mean gross excess return. α and β are the intercept and slope of a regression of gross excess returns on the market excess return, respectively. $t(\alpha)$ is the Newey–West t -statistic of the α estimate with three lags. σ_ϵ is the standard deviation of the regression residuals. $\alpha - \frac{1}{2}\sigma_\epsilon^2$ approximates the market-hedged growth rate before trading costs. These statistics are monthly; R , α , σ_ϵ , and the growth rate are reported in percentage points. $A_{PA,T}^{\max}$ is the portable-alpha capacity, the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. ΔRank is the rank by α minus the rank by portable-alpha capacity and is blank for factors with zero portable-alpha capacity. Rows are sorted by α . The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Anomaly	Gross performance							At scale	
	Sharpe	R (%)	α	$t(\alpha)$	β	σ_ϵ	$\alpha - \frac{1}{2}\sigma_\epsilon^2$	$A_{PA,T}^{\max}$	ΔRank
Mispricing factor: Performance	0.15	0.70	1.17	3.33	-0.43	4.34	1.07	3.44 bn	-4
Highest 5 days of return	0.05	0.30	1.08	2.93	-0.72	4.65	0.97	435 m	-14
Operating cash flow to assets	0.14	0.56	0.91	3.11	-0.33	3.64	0.84	8.76 bn	1
Idiosyncratic volatility	0.05	0.24	0.87	2.53	-0.58	4.58	0.76	356 m	-15
Quality minus Junk: Composite	0.07	0.32	0.80	2.39	-0.45	3.87	0.73	3.63 bn	1
Operating profits-to-book equity	0.11	0.44	0.80	2.99	-0.33	3.66	0.73	6.40 bn	3
Operating profits-to-book assets	0.11	0.46	0.75	2.31	-0.27	3.93	0.67	15.16 bn	6
Momentum t-12 to t-1	0.04	0.21	0.74	2.02	-0.49	5.16	0.61	414 m	-9
Price momentum t-6 to t-1	0.06	0.27	0.71	2.45	-0.41	4.30	0.62	373 m	-9
Net debt-to-price	0.07	0.27	0.54	1.42	-0.25	3.50	0.48	2.59 bn	2
Years 16-20 lagged returns, nonannual	0.05	0.16	0.54	2.39	-0.35	2.76	0.50	628 m	-4
Percent operating accruals	0.26	0.59	0.50	2.78	0.08	2.21	0.48	2.72 bn	5
Operating accruals	0.16	0.44	0.46	2.03	-0.02	2.82	0.42	2.03 bn	4
CAPEX growth (1 year)	0.14	0.40	0.46	2.05	-0.05	2.80	0.42	1.53 bn	3
Share turnover	-0.07	-0.37	0.38	1.19	-0.70	4.23	0.29	1.59 bn	5
Change in net operating assets	0.12	0.33	0.38	1.52	-0.05	2.77	0.34	1.37 bn	3
Highest 5 days of return / volatility	0.16	0.44	0.37	1.79	0.07	2.84	0.33	129 m	-3
Profit margin	0.00	-0.01	0.35	1.27	-0.34	3.63	0.28	3.10 bn	12
Asset Growth	0.07	0.23	0.34	1.12	-0.11	3.41	0.29	1.41 bn	7
Market correlation	-0.08	-0.25	0.14	0.71	-0.36	2.66	0.11	803 m	6
Price momentum t-12 to t-7	-0.02	-0.10	0.08	0.21	-0.17	5.08	-0.05	0	–
R&D-to-market	0.07	0.22	0.06	0.28	0.15	3.09	0.02	32 m	1
Standardized earnings surprise	-0.01	-0.01	0.04	0.30	-0.05	1.86	0.03	0	–
Change in operating cash flow to assets	-0.01	-0.02	0.02	0.14	-0.04	1.97	0.00	0	–
Residual momentum t-12 to t-1	-0.04	-0.10	-0.06	-0.34	-0.03	2.55	-0.09	0	–
Earnings volatility	0.05	0.17	-0.14	-0.54	0.29	2.96	-0.18	0	–
Growth in book debt (3 years)	-0.08	-0.18	-0.17	-0.83	-0.01	2.30	-0.20	0	–
Change in net financial assets	-0.06	-0.11	-0.17	-1.00	0.06	1.92	-0.19	0	–
Ebitda-to-market enterprise value	-0.04	-0.18	-0.22	-0.48	0.04	4.72	-0.34	0	–
Dollar trading volume	-0.09	-0.28	-0.35	-1.34	0.06	3.23	-0.40	0	–
Years 2-5 lagged returns, annual	-0.04	-0.16	-0.36	-1.29	0.19	3.43	-0.42	0	–
Short-term reversal	0.00	-0.01	-0.46	-1.46	0.41	3.99	-0.54	0	–
Intrinsic value-to-market	-0.11	-0.38	-0.53	-1.51	0.14	3.51	-0.59	0	–
Book-to-market equity	-0.03	-0.13	-0.54	-1.27	0.38	4.67	-0.65	0	–
Amihud Measure	-0.12	-0.45	-0.63	-2.39	0.17	3.64	-0.70	0	–

Table 8: Decomposition of factor portable-alpha growth at \$10 billion.

The table presents a decomposition of portable alpha growth at a size of \$10 bln for a selection of representative factor strategies. α^{gross} is the intercept of a regression of gross excess returns on the market excess return. Turnover is the average monthly sum of absolute weight changes, excluding the inception month. PC is the average proportional trading cost. IC is the average price-impact cost. $\frac{1}{2}\sigma_{PA}^2$ is half the variance of the market-hedged net return. g^{PA} is the average log growth of market-hedged capital relative to cash. Costs, variance, and growth are evaluated along the capital path starting from \$10 billion. Gross alpha less proportional costs, price-impact costs, and half the variance approximates g^{PA} . The sample covers January 2010–December 2023 (167 monthly returns from February 2010). All entries except Turnover are reported in percentage points per month.

Anomaly	α^{gross}	Turnover	PC	IC	$\frac{1}{2}\sigma_{PA}^2$	g^{PA}
Operating profits-to-book assets	0.75	0.13	0.01	0.50	0.08	0.16
Operating cash flow to assets	0.91	0.22	0.01	0.88	0.08	-0.06
Quality minus Junk: Composite	0.80	0.31	0.01	1.18	0.09	-0.48
Mispricing factor: Performance	1.17	0.59	0.04	1.58	0.10	-0.57
Momentum t-12 to t-1	0.74	1.24	0.06	2.15	0.15	-1.63
Highest 5 days of return	1.08	2.32	0.13	2.51	0.15	-1.73
Idiosyncratic volatility	0.87	2.21	0.13	2.34	0.14	-1.76
Price momentum t-6 to t-1	0.71	1.78	0.09	2.18	0.19	-1.77

Table 9: Capacity under alternative execution assumptions.

The table presents capacity estimates under alternative execution assumptions. Each row recomputes portable-alpha capacity for every long leg and factor using an alternative stock-day impact coefficient $a_{i,d}$. Spread costs, smoothing, portfolio weights, and returns are unchanged. The baseline uses the [OW](#) optimal execution schedule. Uniform execution splits the rebalance evenly across the trading day. No splitting executes the entire rebalance in one order, with $a = (\lambda + \kappa)/2$. 1-minute steps and 5-minute steps execute the optimal schedule at one-minute and five-minute intervals instead of one-second intervals, using the same daily parameters. Zero is the number of strategies with zero capacity. Med. cap. is the median capacity among strategies with positive capacity, reported in billions of dollars. Med. ratio and IQR are the median and interquartile range of the ratio of alternative to baseline capacity among strategies with positive baseline capacity. a^{port} ratio is the median across strategies of the ratio of the alternative to baseline portfolio impact coefficient. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Estimator	Zero	Med. cap.	Med. ratio	IQR	a^{port} ratio
Long legs (H)					
Baseline (optimal schedule)	14	1.32	1.00	1.00–1.00	1.00
Uniform execution	14	1.32	1.00	1.00–1.00	1.00
No splitting	14	0.76	0.61	0.59–0.63	1.66
1-minute steps	14	1.32	1.00	1.00–1.00	1.00
5-minute steps	14	1.31	0.99	0.99–0.99	1.01
Long-short factors (H–L)					
Baseline (optimal schedule)	14	1.53	1.00	1.00–1.00	1.00
Uniform execution	14	1.53	1.00	1.00–1.00	1.00
No splitting	14	0.88	0.58	0.55–0.61	1.71
1-minute steps	14	1.52	1.00	1.00–1.00	1.00
5-minute steps	14	1.51	0.99	0.99–0.99	1.01

Table 10: Rebalancing speed and factor capacity.

The table presents performance statistics of the 35 factor strategies we consider for full and peak adjustment speeds. Each factor trades a fraction $\tau \in \{1, 0.75, 0.5, 0.35, 0.2, 0.1, 0.05\}$ of the difference between its target and actual portfolio weights each month. $\tau = 1$ denotes full monthly rebalancing. The peak τ maximizes the average monthly net return before the market hedge at a fixed capital of \$10 billion on the grid for τ . $A_{PA}^{\max}$ is the portable-alpha capacity, the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash, reported at full and peak speed. Turnover is the average monthly sum of absolute weight changes, excluding the inception month. Net is the average monthly net return before the market hedge at a fixed capital of \$1 billion or \$10 billion, reported in percentage points, with monthly losses capped at 100%. The peak τ maximizes the same capped average. The machine-learning composites are value- and equal-weighted long-short portfolios formed from quintiles of predicted returns using NYSE breakpoints. Returns are predicted using gradient-boosted regression trees and 153 firm characteristics. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

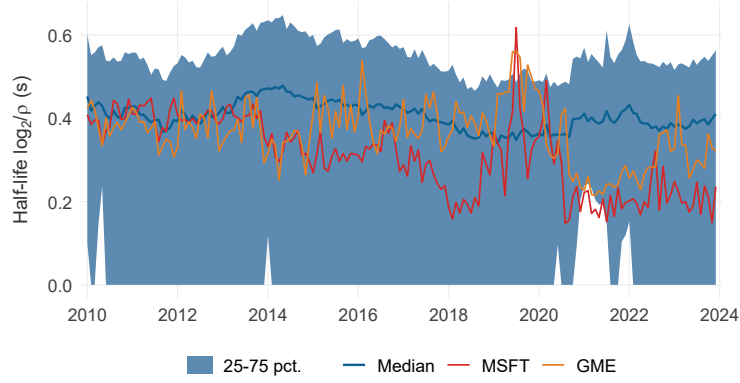
Anomaly	Capacity		Peak	Turnover		Net, $\tau = 1$		Net, peak
	$\tau = 1$	peak	τ	$\tau = 1$	peak	\$1bn	\$10bn	\$10bn
Characteristic sorts								
Operating profits-to-book assets	15.16 bn	69.71 bn	0.05	0.13	0.03	0.42	0.10	0.45
Operating cash flow to assets	8.76 bn	66.00 bn	0.10	0.22	0.08	0.47	-0.26	0.43
Quality minus Junk: Composite	3.63 bn	59.98 bn	0.05	0.31	0.08	0.13	-1.49	0.26
Mispricing factor: Performance	3.44 bn	52.32 bn	0.05	0.59	0.07	0.34	-2.59	0.35
Operating profits-to-book equity	6.40 bn	46.47 bn	0.10	0.21	0.09	0.33	-0.64	0.37
Net debt-to-price	2.59 bn	40.85 bn	0.05	0.27	0.06	0.12	-1.09	0.33
Idiosyncratic volatility	356 m	31.54 bn	0.05	2.21	0.11	-1.40	-15.01	-0.02
Highest 5 days of return	435 m	31.28 bn	0.05	2.32	0.12	-1.31	-14.31	-0.17
Profit margin	3.10 bn	28.32 bn	0.05	0.16	0.05	-0.09	-0.85	-0.03
Market correlation	803 m	27.89 bn	0.05	0.18	0.05	-0.32	-1.05	-0.16
Share turnover	1.59 bn	21.16 bn	0.05	0.37	0.07	-0.51	-1.78	-0.37
Percent operating accruals	2.72 bn	14.96 bn	0.20	0.48	0.26	0.38	-1.21	0.22
Operating accruals	2.03 bn	12.35 bn	0.05	0.43	0.10	0.22	-1.42	0.18
Asset Growth	1.41 bn	11.24 bn	0.10	0.49	0.18	-0.01	-1.88	-0.01
CAPEX growth (1 year)	1.53 bn	8.58 bn	0.10	0.53	0.22	0.14	-1.96	0.06
Change in net operating assets	1.37 bn	7.73 bn	0.05	0.57	0.13	0.06	-2.14	0.01
Price momentum t-6 to t-1	373 m	6.07 bn	0.05	1.78	0.15	-1.01	-10.17	-0.01
Years 2-5 lagged returns, annual	0	5.97 bn	0.05	3.44	0.16	-2.39	-21.06	0.05
Momentum t-12 to t-1	414 m	5.50 bn	0.05	1.24	0.14	-0.71	-8.17	0.00
R&D-to-market	32 m	4.34 bn	0.10	0.26	0.06	0.07	-1.26	0.17
Highest 5 days of return / volatility	129 m	2.93 bn	0.10	3.24	0.32	-1.17	-14.42	-0.06
Years 16-20 lagged returns, nonannual	628 m	2.75 bn	0.10	1.18	0.15	-0.52	-6.32	-0.27
Amihud Measure	0	0	0.05	0.13	0.04	-1.25	-8.07	-0.38
Book-to-market equity	0	0	0.10	0.36	0.08	-0.38	-2.45	-0.23
Growth in book debt (3 years)	0	0	0.05	0.32	0.09	-0.32	-1.34	-0.18
Dollar trading volume	0	0	0.05	0.13	0.04	-1.06	-7.69	-0.27
Ebitda-to-market enterprise value	0	0	0.05	0.45	0.07	-0.35	-1.85	-0.18
Intrinsic value-to-market	0	0	0.05	0.60	0.11	-0.66	-3.13	-0.15
Change in net financial assets	0	0	0.05	0.59	0.12	-0.42	-2.84	-0.04
Earnings volatility	0	0	0.05	0.30	0.06	0.04	-0.90	0.19
Standardized earnings surprise	0	0	0.05	1.00	0.15	-0.39	-3.54	-0.05
Change in operating cash flow to assets	0	0	0.05	0.68	0.14	-0.35	-3.02	-0.05
Residual momentum t-12 to t-1	0	0	0.05	1.49	0.15	-0.68	-5.34	-0.06
Price momentum t-12 to t-7	0	0	0.05	1.79	0.15	-1.15	-9.57	-0.03
Short-term reversal	0	0	0.05	3.47	0.17	-2.24	-20.44	-0.07
Machine-learning composite								
ML composite, value-weighted	177 m	18.93 bn	0.05	2.53	0.15	-1.18	-13.48	0.13
ML composite, equal-weighted	13 m	1.31 bn	0.05	2.01	0.13	-50.31	-100.00	-0.47

Table 11: Trade size relative to daily volume at full speed and at the peak speed.

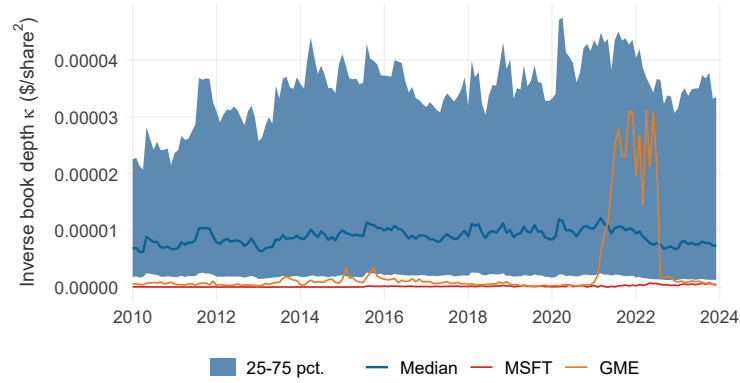
The table presents for a selection of strategies considered statistics on the strategy’s trading volume relative to daily market trading volume at two different implementation scales. The first block evaluates each book at a fixed capital of \$10 billion; the second evaluates it at its own portable-alpha capacity at that speed, reported in the column A in billions of dollars. Participation is the dollar value of a trade divided by the stock’s average daily dollar volume over the previous 126 trading days. The inception month is excluded. Turnover is the average monthly sum of absolute weight changes. Participation (%) reports the median and 90th percentile (P90) across trades, in percentage points. Share of trading above reports the percentage of total dollars traded in orders with participation exceeding 10%, 50%, and 100%. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Book	Leg	τ	A	Turnover	Participation (%)		Share of trading above (%)		
					Median	P90	>10%	>50%	>100%
At a fixed capital of \$10 billion									
ML composite, equal-weighted	H-L	1.00	10.00	2.01	138.17	8086.3	91.7	75.8	66.7
ML composite, equal-weighted	H-L	0.05	10.00	0.13	2.39	148.3	46.4	26.8	19.9
ML composite, value-weighted	H-L	1.00	10.00	2.53	33.79	221.2	94.2	42.6	12.2
ML composite, value-weighted	H-L	0.05	10.00	0.15	0.49	4.4	1.1	0.1	0.0
Operating profits-to-book assets	H	1.00	10.00	0.05	0.12	2.1	57.1	2.7	0.1
Operating profits-to-book assets	H	0.10	10.00	0.02	0.08	1.0	0.1	0.0	0.0
Operating profits-to-book assets	H-L	1.00	10.00	0.13	0.39	8.8	63.4	16.9	4.1
Operating profits-to-book assets	H-L	0.05	10.00	0.03	0.22	2.5	0.5	0.1	0.0
Momentum t-12 to t-1	H-L	1.00	10.00	1.24	11.42	132.8	86.6	38.7	14.2
Momentum t-12 to t-1	H-L	0.05	10.00	0.14	0.45	4.6	1.2	0.1	0.0
At each book's own portable-alpha capacity									
ML composite, equal-weighted	H-L	1.00	0.01	2.01	0.18	10.7	15.8	5.2	2.3
ML composite, equal-weighted	H-L	0.05	1.31	0.13	0.31	19.5	22.5	9.8	5.9
ML composite, value-weighted	H-L	1.00	0.18	2.53	0.60	3.9	0.3	0.0	0.0
ML composite, value-weighted	H-L	0.05	18.93	0.15	0.92	8.4	5.3	0.2	0.0
Operating profits-to-book assets	H	1.00	32.58	0.05	0.40	6.8	72.7	42.6	15.2
Operating profits-to-book assets	H	0.10	119.78	0.02	0.97	12.2	41.5	1.7	0.1
Operating profits-to-book assets	H-L	1.00	15.16	0.13	0.59	13.4	70.2	32.0	10.3
Operating profits-to-book assets	H-L	0.05	69.71	0.03	1.55	17.1	21.7	0.8	0.3
Momentum t-12 to t-1	H-L	1.00	0.41	1.24	0.47	5.5	1.8	0.1	0.0
Momentum t-12 to t-1	H-L	0.05	5.50	0.14	0.25	2.5	0.4	0.0	0.0

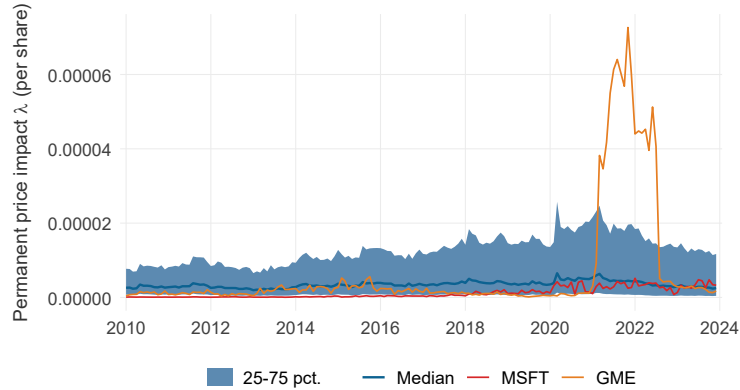
Figures



(a) Order book refill speed (ρ), shown as the half-life $\log(2)/\rho$

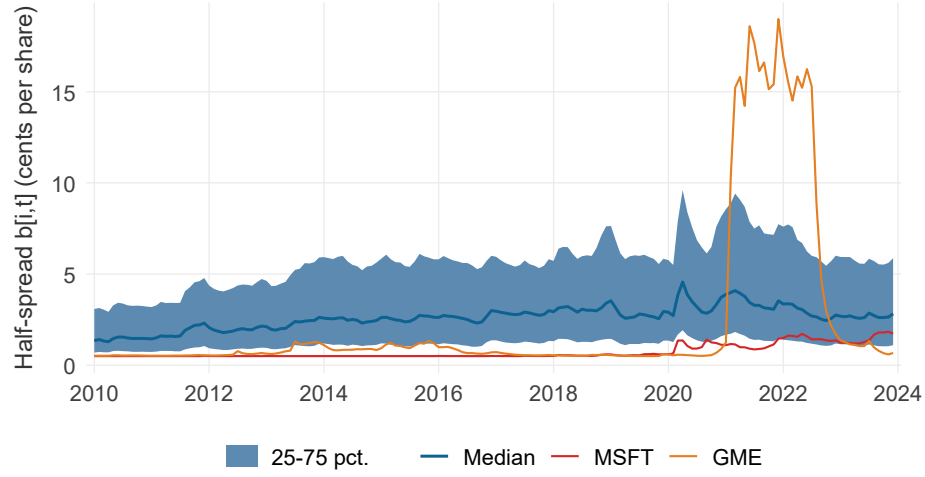


(b) Temporary price impact (κ)

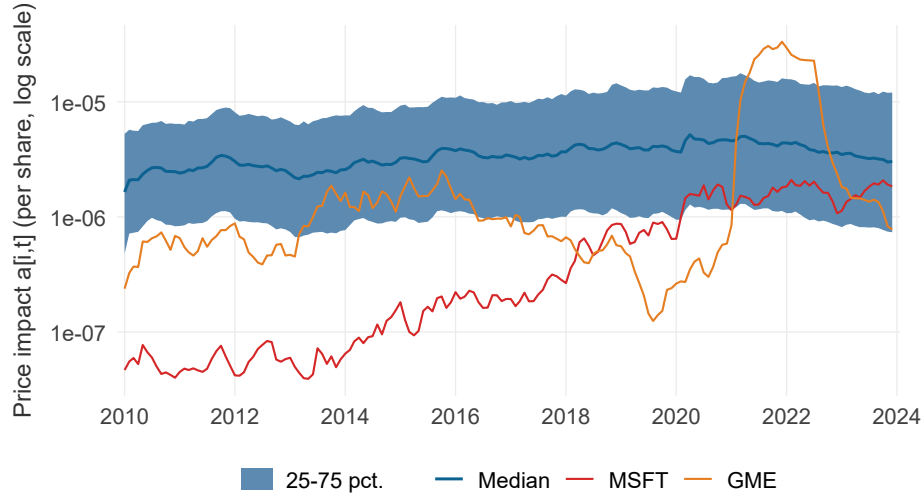


(c) Permanent price impact (λ)

Figure 1: Stock-level OW parameters over time. Each panel shows the monthly cross-sectional distribution of one stock-level OW parameter: the order-book refill speed ρ , reported as the half-life $\log(2)/\rho$ in seconds (panel a); the temporary price impact κ (panel b); and the permanent price impact λ (panel c). We compute a monthly median for each firm, then plot the cross-firm median (line) and the 25th–75th percentile band (shaded) in each month. Microsoft (MSFT) and GameStop (GME) are shown for comparison. The sample is January 2010 to December 2023.

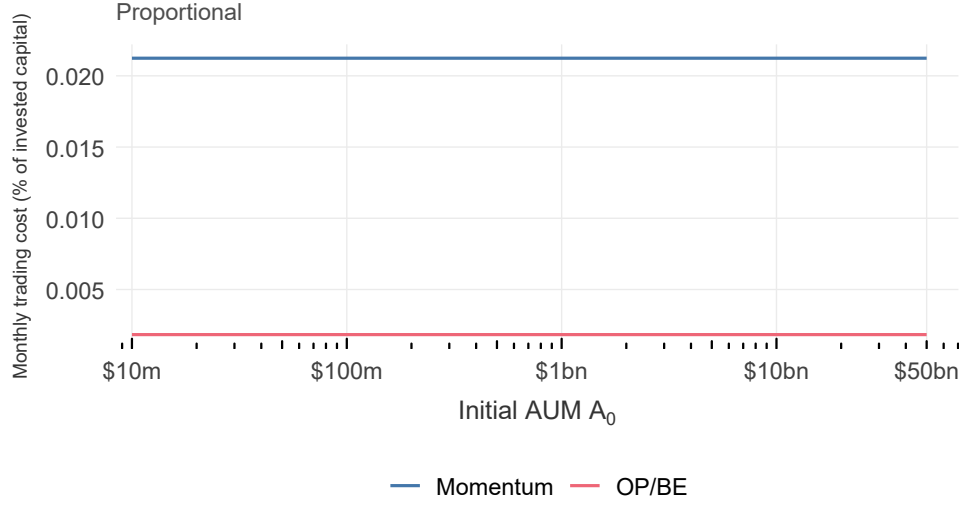


(a) Linear cost component $b_{i,t}$ (half-spread per share)

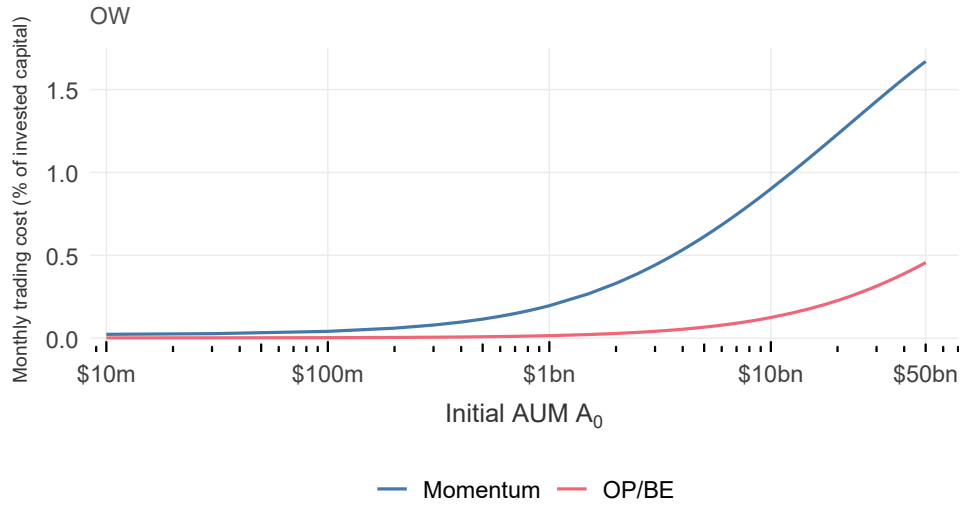


(b) Quadratic cost component $a_{i,t}$ (per share, log scale)

Figure 2: Stock-level cost components over time. Panel (a) plots the linear cost component $b_{i,t}$, half the quoted dollar spread, in cents per share. Panel (b) plots the quadratic cost component $a_{i,t}$ in dollars per share squared on a log scale. In each panel the line is the cross-firm median and the band the 25th–75th percentiles of the monthly firm medians. Microsoft (MSFT) and GameStop (GME) are shown for comparison. The sample is January 2010 to December 2023.

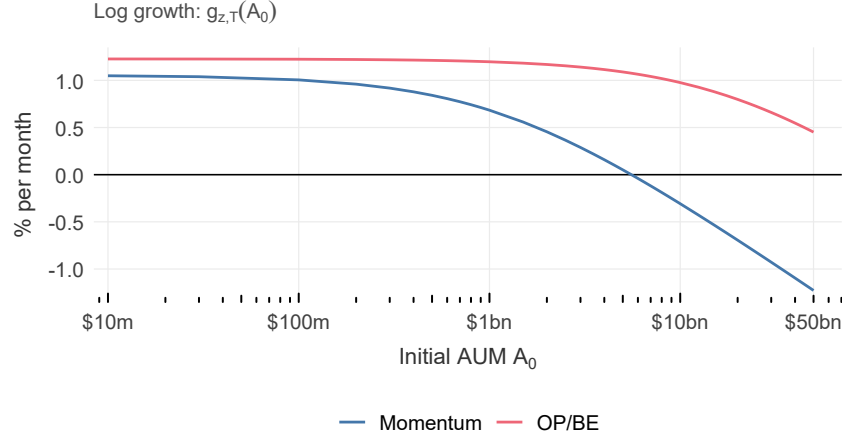


(a) Proportional cost ($a_{i,t} = 0$)

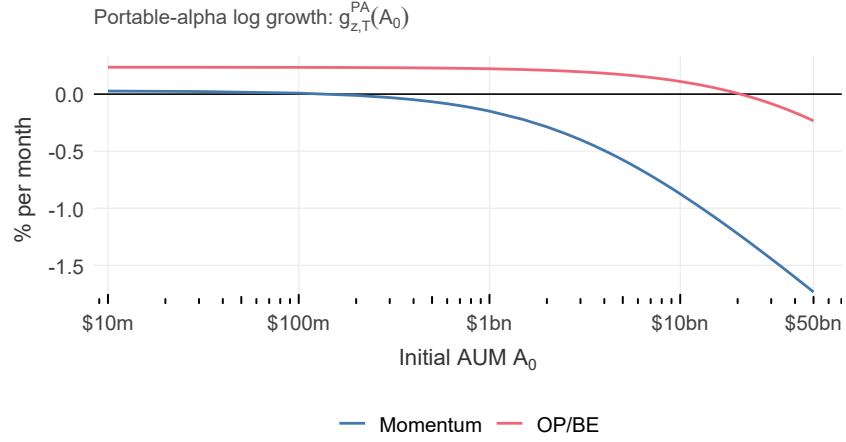


(b) Full OW cost ($b_{i,t}|X| + a_{i,t}X^2$)

Figure 3: Trading-cost curves (long legs). Each panel plots average monthly trading costs as a percentage of invested capital against initial capital A_0 for the long legs of Momentum $t-12$ to $t-1$ (Momentum) and Operating profits-to-book equity (OP/BE). Initial capital ranges from \$10 million to \$50 billion on a logarithmic scale. Panel (a) excludes quadratic costs by setting $a_{i,t} = 0$. Panel (b) uses the full OW cost function $b_{i,t}|X| + a_{i,t}X^2$, where X is the number of shares traded. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).



(a) Average monthly log growth $g_{z,T}(A_0)$



(b) Portable-alpha log growth $g_{z,T}^{PA}(A_0)$

Figure 4: Log growth against initial capital (long legs). Panel (a) plots the average monthly log growth of unhedged capital, $g_{z,T}(A_0)$. Panel (b) plots the average monthly log growth of market-hedged capital relative to cash, $g_{z,T}^{PA}(A_0)$. Both panels show the long legs of Momentum $t-12$ to $t-1$ (Momentum) and Operating profits-to-book equity (OP/BE). Growth is reported in percent per month. Initial capital A_0 ranges from \$10 million to \$50 billion on a logarithmic scale. The capital at which each curve crosses zero is the dynamic capacity in panel (a) and the portable-alpha capacity in panel (b). The sample covers January 2010–December 2023 (167 monthly returns from February 2010).



Figure 5: Decomposition of portable-alpha growth at \$10 billion (long legs). Each bar decomposes portable-alpha growth of the corresponding long leg strategy with an initial capital of \$10 billion into gross CAPM alpha less proportional trading costs, price-impact costs, and half the variance of the market-hedged net return. All components are reported in percent per month. The diamond marks portable-alpha growth g^{PA} , the average log growth of market-hedged capital relative to cash. The decomposition holds up to an approximation error. Bars are ordered by g^{PA} . The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

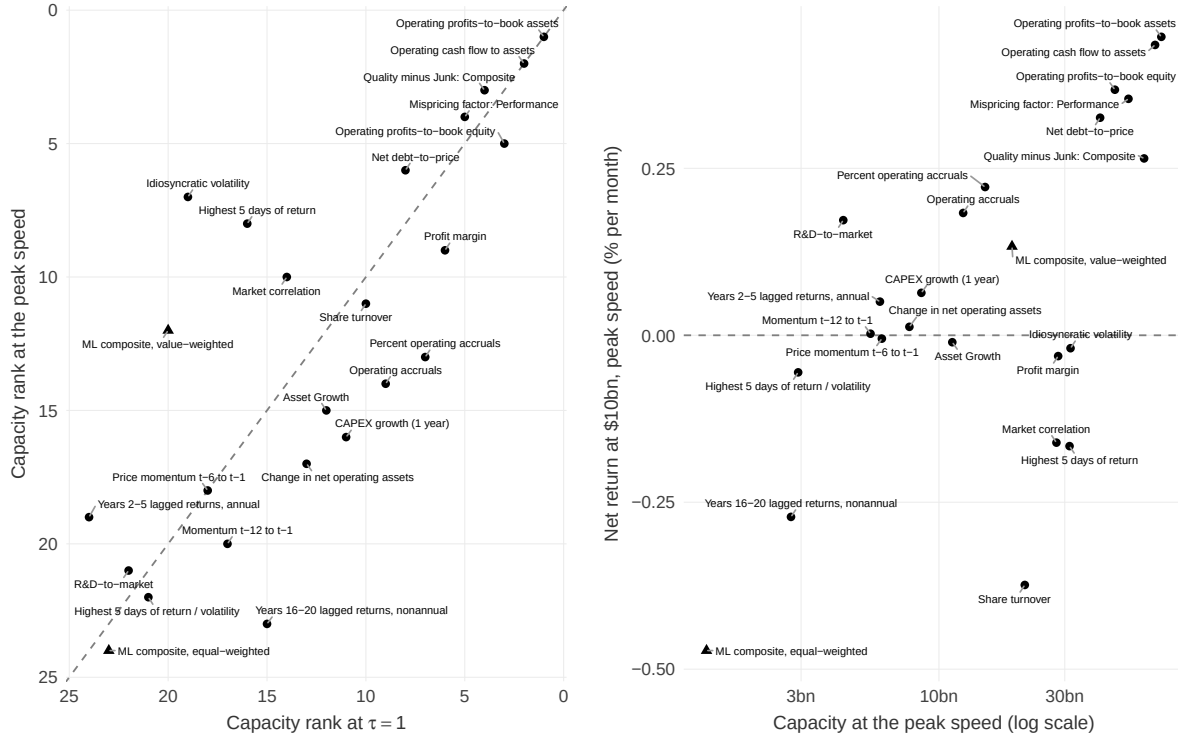


Figure 6: Rebalancing speed and factor capacity. The left panel compares each long–short factor’s portable-alpha capacity rank under full monthly rebalancing ($\tau = 1$) with its rank at the peak speed. The peak speed is the tested rebalancing speed that maximizes the average monthly net return before the market hedge at a fixed capital of \$10 billion. Ranks are computed over the 35 factors and the two composites, with zero-capacity strategies tied at the bottom; only strategies with positive capacity at the peak speed are drawn. The dashed line marks equal ranks. The right panel plots portable-alpha capacity at the peak speed on a logarithmic scale against the average monthly net return before the market hedge at \$10 billion, using the same speed. Portable-alpha capacity is the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Triangles denote the value- and equal-weighted machine-learning composites. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

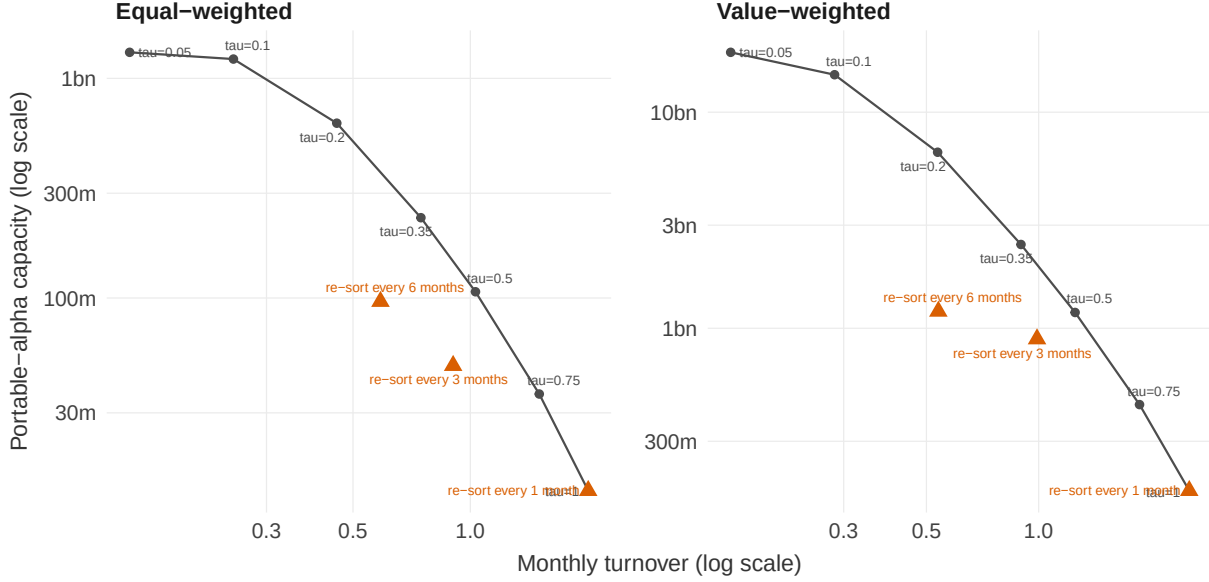


Figure 7: Rebalancing frequency and rebalancing speed. Each panel plots portable-alpha capacity against average monthly turnover for a machine-learning composite, equally-weighted in the left panel and value-weighted in the right panel. Both axes use logarithmic scales. Portable-alpha capacity is the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Circles correspond to partial adjustments toward monthly target weights for $\tau \in \{1, 0.75, 0.5, 0.35, 0.2, 0.1, 0.05\}$, where τ is the fraction of the desired trade executed each month. Triangles correspond to portfolios re-sorted every one, three, or six months, with full monthly rebalancing to the current target weights between sorts. Turnover is the average monthly sum of absolute weight changes, excluding the inception month. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

A TAQ Data Construction

In this section, we outline how we put together our NYSE TAQ dataset that we use for the estimation of the parameters of our transaction cost function. In doing so, we follow the basic steps of Holden and Jacobsen (2014). We begin with the National Best Bid and Offer (NBBO) file from TAQ and remove quotes with missing or negative bid or ask prices or sizes. We retain only quotes with normal quote conditions (codes A, B, H, O, R, and W) and discard cancelled entries. We exclude quotes with bid–ask spreads above \$5 or with midquotes that differ by more than \$2.50 from the previous midquote. The NBBO file omits entries when the best bid and offer are posted at the same exchange, so we supplement it with quote updates from the main quote file.

We obtain trade data for all stocks and trading days, and discard corrected trades and trades with negative prices. As Holden et al. (2023) note, the TAQ trade file can contain duplicate entries from opening and closing auctions. We remove these duplicates by removing the summary prints (with trade condition 'Q' or 'M') if there are one or more corresponding auction trades (with trade condition 'O' or '6') reported on the tape for the same exchange.

The refinement to trade cleaning described in the main text addresses fragmented duplication around auctions: individual trades from an opening or closing auction can appear separately and then be followed a few seconds later by an aggregated auction summary with a different trade-condition code. The total volume in the individual prints need not match the volume in the summary print, so a volume-matching rule need not identify every duplicate. Our procedure removes the aggregation print when individual auction trades from the same auction precede it.⁸

We match each trade to its most recent NBBO quote, where we apply the latency correction of Holden et al. (2023) for the years that these are available. For each stock-day pair (i, d) , the trading day starts at the timestamp of the first trade matched to an NBBO quote, and we discard trades and quotes before that time. We remove all trade and quote records after 16:00. If the last closing auction for a stock occurs before 16:00, we discard all subsequent trades and quotes. We then sign each trade with the algorithm of Lee and Ready (1991), falling back on the tick test in case of ties or when the NBBO is crossed or locked, and aggregate the signed trades into intraday segments of fixed length.

⁸In our records, the individual auction trades precede the summary print in the cases to which this rule is applied.

B The OW Model and Estimation Details

This appendix presents the Obizhaeva and Wang (2013) execution problem and the estimation procedure used to construct the stock-day cost inputs in Section 2.

B.1 The Execution Problem and Price Dynamics

For exposition, consider a buyer; the seller's problem is symmetric. Let i index securities, d trading days, and $j \in \{1, \dots, N\}$ one-second intraday intervals, with $N = 23,400$ seconds from 9:30 to 16:00. Let $x_{i,d,j}$ denote the shares of stock i executed in interval j on day d , $P_{i,d,j}$ the corresponding execution price per share, and $X_{i,d}$ the total quantity to be purchased. The trader chooses the execution schedule $\{x_{i,d,j}\}_{j=1}^N$ to minimize expected dollar expenditure:

$$\min_{x \in \Theta_{i,d}^D} \mathbb{E} \left[\sum_{j=1}^N P_{i,d,j} x_{i,d,j} \right]. \quad (\text{B.1})$$

The feasible set is

$$\Theta_{i,d}^D = \left\{ \{x_{i,d,1}, \dots, x_{i,d,N}\} : x_{i,d,j} \geq 0 \ \forall j, \quad \sum_{j=1}^N x_{i,d,j} = X_{i,d} \right\}. \quad (\text{B.2})$$

The order must be completed by the end of the trading day; the choice variable is how the total quantity is distributed through time.

The OW model separates permanent price adjustment from temporary pressure on the order book. Let $V_{i,t}$ denote fundamental value. A trade of size $x_{i,t}$ changes fundamental value according to

$$\Delta V_{i,t} = \lambda_i x_{i,t} + \varepsilon_{i,t}, \quad (\text{B.3})$$

where $\lambda_i > 0$ is permanent price impact and $\varepsilon_{i,t}$ is a mean-zero innovation. The execution price also reflects finite order-book depth. Under the block-shaped book in OW,

$$P_{i,t}^E - V_{i,t} = \mu_i + \kappa_i \sum_{s \leq t} x_{i,s} e^{-\rho_i(t-s)} + u_{i,t}, \quad (\text{B.4})$$

where μ_i is half the quoted spread, κ_i governs temporary price pressure, and ρ_i is the rate at which that pressure decays. In the block-book representation,

$$\kappa_i = \frac{1}{q_i} - \lambda_i, \quad (\text{B.5})$$

where q_i is order-book depth. Lower depth implies greater temporary price pressure, while a larger ρ_i implies faster replenishment. The combination of linear permanent impact and exponentially decaying transient impact satisfies the no-dynamic-arbitrage condition studied by Gatheral (2010).

B.2 Two-Stage Estimation

For each security i and trading day d , the cost function in Equation (1) requires the quoted spread $s_{i,d}$ and the three estimated inputs $\lambda_{i,d}$, $\kappa_{i,d}$, and $\rho_{i,d}$. We observe the spread directly. We estimate permanent impact at five-minute frequency and temporary impact and refill speed at one-second frequency. This two-stage procedure is designed to retain the sampling frequency most informative about each component while remaining scalable to the full stock-day panel.

Let $m_{i,d,j}^{\text{mid}}$ denote the midquote price of security i at the end of interval j on day d , and let $OF_{i,d,j}$ denote signed order flow over that interval, computed as buyer-initiated minus seller-initiated volume using the Lee and Ready (1991) algorithm. Permanent price impact is estimated from

$$\Delta m_{i,d,j}^{\text{mid}} = \lambda_{i,d} OF_{i,d,j} + \varepsilon_{i,d,j}, \quad (\text{B.6})$$

where

$$\Delta m_{i,d,j}^{\text{mid}} = m_{i,d,j}^{\text{mid}} - m_{i,d,j-1}^{\text{mid}}. \quad (\text{B.7})$$

The coefficient $\lambda_{i,d}$ measures the persistent response of the midpoint to signed order flow. Following Holden and Jacobsen (2014), we use five-minute intervals for this step. The aggregation reduces very-high-frequency noise while preserving the price movement relevant for permanent impact. We omit five-minute intervals without trading, leaving 49 observations per day on average for the median firm.

Temporary price pressure requires finer sampling because it can dissipate within seconds. Define the execution-price deviation

$$ES_{i,d,j} = P_{i,d,j} - m_{i,d,j}^{\text{mid}}, \quad (\text{B.8})$$

where $P_{i,d,j}$ is the last transaction price in interval j . If a security traded in every one-second interval, the [OW](#) dynamics would imply

$$ES_{i,d,j} = \mu_{i,d} + \kappa_{i,d} OF_{i,d,j} + \phi_{i,d} (ES_{i,d,j-1} - \mu_{i,d}), \quad (\text{B.9})$$

with

$$\phi_{i,d} = e^{-\rho_{i,d}}. \quad (\text{B.10})$$

Many securities do not trade every second, and quote revisions during inactive intervals need not represent the decay of trade-induced price pressure. We therefore focus on observations around actual trades and estimate

$$ES_{i,d,j} = \phi_{0,i,d} + \kappa_{i,d} OF_{i,d,j} + \sum_{k=1}^K \phi_{k,i,d} ES_{i,d,j-k} \mathbf{1}\{\text{trade}_{j-k}\}, \quad (\text{B.11})$$

where $\mathbf{1}\{\text{trade}_{j-k}\}$ equals one when a trade occurs in interval $j - k$. We set $K = 5$, covering the previous five seconds of trading activity. The median firm contributes 321 one-second observations per day to this regression.

The coefficient on the most recent lag maps into refill speed. If $\hat{\phi}_{1,i,d} > 0$, we set

$$\rho_{i,d} = -\log(\hat{\phi}_{1,i,d}). \quad (\text{B.12})$$

If $\hat{\phi}_{1,i,d} \leq 0$, we treat the temporary pressure as having dissipated within one second and set $\rho_{i,d} \rightarrow \infty$. If $\hat{\phi}_{1,i,d} > 1$, the implied decay rate is not admissible and we omit that stock-day from the refill-speed calculation. Apart from this mapping needed to obtain a nonnegative refill speed, we do not truncate the daily impact estimates by sign. The quoted half-spread $\mu_{i,d} = s_{i,d}/2$ is observed directly rather than estimated in these regressions.

We combine the daily inputs through Equations (3) and (4) to obtain $\hat{b}_{i,d}$ and $\hat{a}_{i,d}$. Because daily estimates are noisy, the portfolio analysis uses exponentially smoothed coefficients:

$$\tilde{a}_{i,t} = \omega \hat{a}_{i,t} + (1 - \omega) \tilde{a}_{i,t-1}, \quad \tilde{b}_{i,t} = \omega \hat{b}_{i,t} + (1 - \omega) \tilde{b}_{i,t-1}. \quad (\text{B.13})$$

We initialize at $\tilde{a}_{i,0} = \hat{a}_{i,0}$ and $\tilde{b}_{i,0} = \hat{b}_{i,0}$. The half-life $h(\omega) = \log(1/2)/\log(1 - \omega)$ is the number of trading days over which the weight on an innovation falls by one half. We set $\omega = 2/51 \approx 0.04$, corresponding to a span of 50 trading days and a half-life of about 17 trading days. Appendix E.4 reports capacity estimates for spans of 25 and 100 days. The month-end values of $\tilde{a}_{i,t}$ and $\tilde{b}_{i,t}$ price the next portfolio rebalance, preserving the timing convention in Section 2.3.

C Derivation of the Decomposition Identities

Fix initial capital A_0 and the realized returns, portfolio weights, and cost coefficients. We write $\mathbb{E}$ for the time average over the T months and normalize variances and covariances by

T . Costs paid at time t are paired with returns earned from t to $t + 1$. We suppress time subscripts where possible.

The trading cost per dollar of capital is

$$\text{tc}_{z,t}(A) = b_t^z + a_t^z A. \quad (\text{C.1})$$

Equation (16) therefore gives

$$1 + r_{z,t+1}^{\text{Net}}(A) = (1 - \text{tc}_{z,t}(A))(1 + r_{z,t+1}), \quad (\text{C.2})$$

where $r_{z,t+1}$ is the pre-cost excess return. Costs are evaluated along the unhedged capital path for dynamic capacity and net alpha, and along the hedged path for portable-alpha capacity. The decompositions apply to paths on which trading costs remain below available capital and all logarithms have positive arguments.

We approximate average log growth by the mean return less half its variance, neglecting the squared mean and higher-order terms. For growth relative to cash, we also neglect the adjustments from dividing excess returns by the gross risk-free return. We retain an explicit remainder in the portable-alpha decomposition to account for these approximation errors and the cost–return interaction.

C.1 Log-Growth Decomposition

Along the unhedged capital path, define $g_{z,T}^{\text{exc}}(A_0) = \mathbb{E}[\log(1+r_z^{\text{Net}})]$ and $g_{z,T}^{\text{gross}} = \mathbb{E}[\log(1+r_z)]$. Taking logs of the net-return equation gives

$$g_{z,T}^{\text{exc}}(A_0) = g_{z,T}^{\text{gross}} - \text{PC}_{z,T} - \text{IC}_{z,T}(A_0) + \varrho_{z,T}(A_0), \quad (\text{C.3})$$

where $\text{PC}_{z,T} = \mathbb{E}[b^z]$ is the average proportional cost, $\text{IC}_{z,T}(A_0) = \mathbb{E}[a^z A]$ is the average price-impact cost along the unhedged path, and

$$\varrho_{z,T}(A_0) = \mathbb{E}[\log(1 - \text{tc}_z) + \text{tc}_z] \leq 0, \quad (\text{C.4})$$

which is the exact remainder from the logarithm.

Gross returns and proportional costs do not depend on initial capital because the portfolio weight changes are fixed. Initial capital affects growth through price-impact costs and the remainder. Proportional costs remain even as initial capital approaches zero.

The total-return growth used to define dynamic capacity also includes the risk-free return:

$$g_{z,T}(A_0) = \mathbb{E}[\log(1 + r_f + r_z^{Net})] \approx g_{z,T}^{exc}(A_0) + \mathbb{E}[r_f], \quad (\text{C.5})$$

where the approximation neglects interactions between the risk-free rate and net excess returns, and higher-order terms.

Using the approximation stated above, gross log growth is

$$g_{z,T}^{gross} \approx \mathbb{E}[r_z] - \frac{1}{2} \text{Var}(r_z). \quad (\text{C.6})$$

Volatility therefore reduces compound growth even before trading costs. Equation (C.3) separates this effect from proportional and price-impact costs.

C.2 Portable-Alpha Decomposition

Portable-alpha growth measures the average log growth of hedged capital relative to cash. All costs in this subsection are evaluated along the hedged capital path $\{A_{z,t}^{PA}\}$: $\text{PC}_{z,T} = \mathbb{E}[b_t^z]$ and $\text{IC}_{z,T}(A_0) = \mathbb{E}[a_t^z A_{z,t}^{PA}]$. Let $x_{t+1} = r_{z,t+1}^{PA}(A_{z,t}^{PA})$ denote the hedged net excess return. Using the approximation stated above,

$$g_{z,T}^{PA}(A_0) \approx \mathbb{E}[x] - \frac{1}{2} \text{Var}(x) = \bar{r}_{z,T}^{PA}(A_0) - \frac{1}{2} \sigma_{PA,z,T}^2(A_0). \quad (\text{C.7})$$

Because the hedge ratio β_z is the full-sample CAPM beta of gross excess returns, $\mathbb{E}[r_z] - \beta_z \mathbb{E}[r_m] = \alpha_z^{gross}$. Subtracting trading costs gives the exact mean hedged return:

$$\mathbb{E}[x] = \alpha_z^{gross} - \text{PC}_{z,T} - \text{IC}_{z,T}(A_0) - \mathbb{E}[\text{tc}_z r_z]. \quad (\text{C.8})$$

Portable-alpha growth therefore satisfies

$$g_{z,T}^{PA}(A_0) = \alpha_z^{gross} - \text{PC}_{z,T} - \text{IC}_{z,T}(A_0) - \frac{1}{2} \sigma_{PA,z,T}^2(A_0) + R_{z,T}(A_0), \quad (\text{C.9})$$

where the exact remainder is

$$R_{z,T}(A_0) = -\mathbb{E}[\text{tc}_z r_z] + \mathbb{E}\left[\log\left(1 + \frac{x}{1 + r_f}\right)\right] - \mathbb{E}[x] + \frac{1}{2} \text{Var}(x). \quad (\text{C.10})$$

The remainder includes the cost-return interaction, the squared mean, the risk-free-rate adjustments, and higher-order terms in the logarithm. At an initial capital of \$10 billion, its median is 1.5 basis points per month across long legs and 0.8 basis points across factors.

The largest remainder is 13 basis points for the Amihud long leg.

Equation (C.9) separates proportional trading costs, price-impact costs, and the variance of the hedged net return. No separate beta-shift term appears because the hedge uses the gross beta. Trading costs can nevertheless leave the net return with residual market exposure, which is included in x .

As initial capital approaches zero, price-impact costs per dollar vanish, but proportional costs remain. The frictionless benchmark $\alpha_z^{gross} - \frac{1}{2}\sigma_\varepsilon^2$ instead sets both costs to zero, in which case the hedged return has mean α_z^{gross} and variance equal to the gross CAPM residual variance σ_ε^2 . It approximates growth before trading costs, rather than the small-capital limit.

C.3 Net-Alpha Decomposition

For each initial capital A_0 , we estimate the net CAPM alpha and beta from returns along the unhedged capital path. Trading costs are charged to the strategy but not to the market benchmark. Define the change from gross to net beta as $\Delta\beta_{z,T}(A_0) = \beta_{z,T}^{net}(A_0) - \beta_z^{gross}$. Since net returns equal gross returns less $tc_z(1 + r_z)$, the regression intercept satisfies

$$\alpha_{z,T}^{net}(A_0) = \alpha_z^{gross} - \mathbb{E}[tc_z(1 + r_z)] - \Delta\beta_{z,T}(A_0) \mathbb{E}[r_m]. \quad (C.11)$$

Separating proportional and price-impact costs and dropping the cost–return interaction gives

$$\alpha_{z,T}^{net}(A_0) \approx \alpha_z^{gross} - PC_{z,T} - IC_{z,T}(A_0) - \Delta\beta_{z,T}(A_0) \mathbb{E}[r_m], \quad (C.12)$$

where costs are evaluated along the unhedged path. The omitted term is $-\mathbb{E}[tc_z r_z]$.

The beta-shift term appears because net alpha uses the beta estimated from net returns, whereas portable-alpha growth uses a hedge fixed at the gross beta. If trading costs lower beta and the sample market premium is positive, this term raises measured net alpha relative to gross alpha less trading costs. This adjustment reflects the change in the regression benchmark; it is not an additional return earned by the strategy.

D Alpha-Based Capacity

Alpha-based capacity provides a complementary measure of scale. It is the smallest initial capital at which net alpha under a given factor model becomes non-positive. Unlike portable-alpha capacity, it does not account for the effect of residual volatility on compound growth, so a strategy at its alpha-based capacity can still have negative compound growth. Its advantage is that it extends naturally to benchmarks with several risk factors. We therefore

report alpha-based capacity for each anomaly under the CAPM and under a six-factor model.

For each initial capital A_0 , we construct net excess returns along the unhedged capital path described in Section 2.3. We estimate $\alpha_{z,T}^{net}(A_0)$ as the intercept of a regression of these returns on the market excess return and define

$$A_{\alpha,T}^{\max} = \inf \left\{ A_0 \geq 0 : \alpha_{z,T}^{net}(A_0) \leq 0 \right\}. \quad (\text{D.1})$$

At $A_0 = 0$, returns are defined by their limit as initial capital approaches zero, with proportional costs retained. The same definition applies to other factor models by replacing the CAPM intercept with the corresponding regression intercept. We report the CAPM estimate as the main specification and the five Fama and French (2015) factors plus momentum as a comparison.

For negative-beta factors, alpha can be substantially higher than the unhedged excess return. The market excess return averages about 1.05% per month over 2010–2023, so a factor with a beta of -0.5 has an alpha about 0.53 percentage points above its average excess return. Portable-alpha capacity tracks capital after hedging market exposure and paying trading costs along the resulting capital path. It also accounts for the remaining volatility: a positive average hedged excess return may not be enough for capital to compound faster than cash.

Portable-alpha capacity need not be below alpha-based capacity because the two measures use different capital paths and hedge adjustments. Nevertheless, $A_{PA,T}^{\max} \leq A_{\alpha,T}^{\max}$ holds for 69 of the 70 portfolios in our sample. The exception is the Idiosyncratic volatility long leg, where the difference is less than 1%. The two measures produce nearly identical long-leg rankings, with a rank correlation of 0.999. Among long legs with alpha-based capacities above \$1 billion, portable-alpha capacity is 1–28% lower, with a median reduction of 9%. Relative differences are larger when capacity is small and hedged growth changes little with capital.

Table 12 reports the alpha-based capacity under the CAPM benchmark and under the six-factor benchmark (Fama–French five factors plus momentum).

Replacing the CAPM with the six-factor model raises some alpha-based capacities and lowers others. Profitability, cash-flow, and quality long legs retain roughly 20–75% of their CAPM capacities. Momentum has zero capacity for both the long leg and the factor under a benchmark that includes momentum. Some accrual, investment, and R&D strategies gain capacity because their negative exposures to factors with positive sample returns raise measured alpha. Among strategies with positive capacity under both benchmarks, the median ratio of six-factor to CAPM capacity is 0.54 for long legs and 0.59 for factors.

Table 12: Alpha-based capacity under the CAPM and FF6.

The table presents alpha-based capacities for long legs and factors of the 35 strategies considered in the paper. Each entry reports alpha-based capacity, $A_{\alpha,T}^{\max}$, for the long leg (H) or the long-short factor ($H - L$). Alpha-based capacity is the smallest initial capital at which net alpha under the benchmark model becomes non-positive. CAPM uses the market excess return. FF6 uses the Fama–French five factors plus momentum. An entry of 0 indicates non-positive net alpha as initial capital approaches zero, with proportional trading costs retained. Rows are sorted by long-leg CAPM capacity. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Anomaly	Long-only (H)		Long-short ($H - L$)	
	CAPM	FF6	CAPM	FF6
Operating profits-to-book assets	35.44 bn	19.13 bn	18.62 bn	2.23 bn
Profit margin	25.41 bn	18.48 bn	3.97 bn	0
Operating profits-to-book equity	21.75 bn	5.40 bn	7.15 bn	824 m
Operating cash flow to assets	21.71 bn	7.94 bn	10.04 bn	1.74 bn
Quality minus Junk: Composite	15.21 bn	3.32 bn	4.48 bn	641 m
Mispricing factor: Performance	8.75 bn	1.85 bn	4.23 bn	576 m
Net debt-to-price	6.28 bn	12.32 bn	3.50 bn	2.09 bn
Highest 5 days of return	1.86 bn	883 m	531 m	140 m
Market correlation	1.84 bn	408 m	1.30 bn	0
Percent operating accruals	1.84 bn	4.15 bn	3.00 bn	3.85 bn
R&D-to-market	1.83 bn	2.93 bn	386 m	3.82 bn
Share turnover	1.31 bn	0	2.22 bn	0
Change in net operating assets	1.29 bn	1.10 bn	1.63 bn	1.06 bn
CAPEX growth (1 year)	1.21 bn	1.60 bn	1.82 bn	1.66 bn
Asset Growth	1.19 bn	1.39 bn	1.87 bn	1.53 bn
Operating accruals	1.14 bn	1.75 bn	2.25 bn	1.57 bn
Idiosyncratic volatility	618 m	11 m	469 m	93 m
Years 16-20 lagged returns, nonannual	605 m	330 m	703 m	418 m
Price momentum t-6 to t-1	399 m	42 m	620 m	79 m
Highest 5 days of return / volatility	267 m	464 m	153 m	248 m
Momentum t-12 to t-1	249 m	0	628 m	0
Book-to-market equity	0	1.19 bn	0	543 m
Intrinsic value-to-market	0	0	0	0
Ebitda-to-market enterprise value	0	0	0	0
Earnings volatility	0	0	0	0
Residual momentum t-12 to t-1	0	0	0	0
Standardized earnings surprise	0	0	19 m	0
Price momentum t-12 to t-7	0	0	0	0
Change in operating cash flow to assets	0	33 m	0	0
Years 2-5 lagged returns, annual	0	0	0	0
Amihud Measure	0	0	0	0
Dollar trading volume	0	34 m	0	22 m
Short-term reversal	0	0	0	0
Growth in book debt (3 years)	0	0	0	0
Change in net financial assets	0	0	0	0

These comparisons charge trading costs to the strategies but use benchmark factor returns before costs. Accounting for the factors’ own trading costs could change the estimated alphas and capacities (Detzel et al., 2023). Several benchmark factors also use characteristics

represented in our anomaly portfolios, so the comparison partly measures how much of each strategy’s return these factors explain.

E Additional Tables and Robustness

E.1 Net Performance at Scale for All 35 Anomalies

Tables 13 and 14 report net performance for all 35 long legs. Tables 15 and 16 report the corresponding statistics for factors. At initial capital of \$1 billion, \$10 billion, and \$50 billion, we report average monthly trading costs, net CAPM alpha and beta, residual volatility, portable-alpha log growth, and total-return log growth. Rows are ordered by the gross geometric mean return. Entries of $-\infty$ indicate that the corresponding capital path reaches zero before the sample ends; the other statistics of those rows are blank, because the months after capital reaches zero have no investment interpretation.

Table 13: Net performance at fixed capital for long legs 1–18 of 35 (Part 1 of 2).

The table presents net performance statistics and its components for long legs of the 35 strategies considered at various investment scales. Each portfolio is evaluated at initial capital of \$1 billion, \$10 billion, and \$50 billion. Avg. TC is the average trading cost as a percentage of capital. Gross α is the intercept of a regression of gross excess returns on the market excess return. Net α and Net β are the intercept and slope of the corresponding regression using net excess returns along the unhedged capital path. σ_ϵ is the standard deviation of that regression's residuals. Total log growth is the average log growth of unhedged capital. PA log growth is the average log growth of market-hedged capital relative to cash. Trading costs, alphas, residual volatility, and growth rates are reported in percent. An entry of $-\infty$ indicates that the corresponding capital path reaches zero before the sample ends. Trading costs, net alpha, net beta, and residual volatility are blank for those paths because the months after capital reaches zero have no investment interpretation. Rows are ordered by the gross geometric mean return. The sample covers January 2010–December 2023 (167 monthly returns from February 2010). All statistics are monthly.

Anomaly	Gross α	A_0	Avg. TC	Net α	Net β	σ_ϵ	Total log growth	PA log growth
Percent operating accruals	0.17	1bn	0.11	0.07	1.14	1.69	1.03	0.05
		10bn	0.62	-0.44	1.13	2.17	0.11	-0.47
		50bn	1.34	-1.16	1.12	3.66	-0.80	-1.26
R&D-to-market	0.27	1bn	0.18	0.10	1.01	1.97	0.84	0.06
		10bn	0.87	-0.54	0.94	2.26	-0.25	-0.66
		50bn	1.64	-1.25	0.87	3.82	-1.19	-1.53
Highest 5 days of return / volatility		1bn	0.62	-0.34	1.00	1.77	0.23	-0.37
		10bn	1.70	-1.41	0.97	2.36	-1.05	-1.49
		50bn	2.49	-2.17	0.92	4.69	-2.00	-2.43
CAPEX growth (1 year)	0.18	1bn	0.16	0.03	1.10	1.83	0.93	0.00
		10bn	0.80	-0.59	1.07	2.12	-0.07	-0.66
		50bn	1.53	-1.32	1.05	4.19	-0.99	-1.51
Change in net operating assets	0.21	1bn	0.18	0.04	1.03	1.58	0.88	0.02
		10bn	0.87	-0.64	1.02	2.14	-0.15	-0.70
		50bn	1.61	-1.41	1.04	4.69	-1.08	-1.56
Net debt-to-price	0.19	1bn	0.04	0.15	1.05	1.52	1.16	0.14
		10bn	0.28	-0.09	1.05	1.59	0.60	-0.10
		50bn	0.81	-0.62	1.04	2.28	-0.20	-0.66
Operating accruals	0.14	1bn	0.12	0.02	1.09	1.89	0.88	0.00
		10bn	0.69	-0.57	1.10	2.79	-0.47	-0.61
		50bn	1.41	-1.30	1.09	4.96	-1.71	-1.47
Asset Growth	0.17	1bn	0.15	0.03	1.04	2.02	0.88	-0.01
		10bn	0.79	-0.60	1.02	2.39	-0.11	-0.66
		50bn	1.50	-1.32	1.02	4.86	-1.04	-1.52
Operating profits-to-book assets	0.22	1bn	0.01	0.21	0.98	1.15	1.22	0.21
		10bn	0.07	0.15	0.97	1.18	1.10	0.14
		50bn	0.30	-0.07	0.97	1.57	0.74	-0.09
Operating profits-to-book equity	0.24	1bn	0.02	0.23	0.94	1.11	1.20	0.22
		10bn	0.12	0.12	0.94	1.15	0.98	0.11
		50bn	0.46	-0.21	0.94	1.77	0.45	-0.23
Highest 5 days of return	0.41	1bn	0.26	0.15	0.75	1.40	0.73	0.14
		10bn	1.07	-0.67	0.75	1.46	-0.34	-0.69
		50bn	1.92	-1.50	0.72	2.13	-1.26	-1.57
Operating cash flow to assets	0.21	1bn	0.01	0.20	0.96	1.18	1.19	0.19
		10bn	0.11	0.10	0.96	1.22	1.01	0.09
		50bn	0.41	-0.19	0.95	1.84	0.54	-0.22
Mispricing factor: Performance	0.24	1bn	0.04	0.20	0.93	1.21	1.13	0.19
		10bn	0.26	-0.03	0.94	1.44	0.63	-0.03
		50bn	0.77	-0.55	0.94	2.35	-0.25	-0.57
Quality minus Junk: Composite	0.20	1bn	0.02	0.18	0.94	1.15	1.14	0.18
		10bn	0.14	0.06	0.93	1.17	0.91	0.05
		50bn	0.50	-0.30	0.93	1.57	0.36	-0.32
Years 16-20 lagged returns, nonannual	0.30	1bn	0.43	-0.13	0.81	1.61	0.49	-0.15
		10bn	1.41	-1.10	0.78	2.73	-0.69	-1.18
		50bn	—	—	—	—	$-\infty$	$-\infty$
Price momentum t-6 to t-1	0.14	1bn	0.27	-0.13	0.97	2.01	0.61	-0.16
		10bn	1.09	-0.94	0.95	2.37	-0.49	-1.00
		50bn	1.85	-1.68	0.91	4.57	-1.42	-1.89
Profit margin	0.11	1bn	0.01	0.10	0.97	0.84	1.11	0.10
		10bn	0.05	0.06	0.97	0.90	1.04	0.06
		50bn	0.20	-0.09	0.96	1.42	0.78	-0.11
Momentum t-12 to t-1	0.07	1bn	0.20	-0.12	0.97	1.90	0.68	-0.15
		10bn	0.90	-0.81	0.94	2.04	-0.31	-0.87
		50bn	1.67	-1.56	0.91	3.72	-1.23	-1.73

Table 14: Net performance at fixed capital for long legs (continued).

Anomaly	Gross α	A_0	Avg. TC	Net α	Net β	σ_ϵ	Total log growth	PA log growth
Idiosyncratic volatility	0.16	1bn	0.23	-0.07	0.87	1.20	0.56	-0.07
		10bn	1.00	-0.87	0.89	1.92	-0.56	-0.87
		50bn	1.84	-1.71	0.88	2.66	-1.50	-1.74
Change in operating cash flow to assets	-0.03	1bn	0.15	-0.18	1.08	1.45	0.72	-0.19
		10bn	0.77	-0.81	1.08	1.94	-0.25	-0.83
		50bn	1.50	-1.56	1.10	4.14	-1.17	-1.66
Price momentum t-12 to t-7	-0.02	1bn	0.29	-0.31	1.07	2.20	0.50	-0.34
		10bn	1.13	-1.14	1.05	2.53	-0.62	-1.21
		50bn	1.90	-1.89	1.00	4.45	-1.55	-2.10
Change in net financial assets	-0.07	1bn	0.11	-0.18	1.09	1.45	0.78	-0.19
		10bn	0.62	-0.69	1.08	1.76	-0.07	-0.71
		50bn	1.35	-1.43	1.10	3.16	-0.96	-1.49
Standardized earnings surprise	0.00	1bn	0.17	-0.17	1.00	1.13	0.64	-0.17
		10bn	0.84	-0.87	1.03	1.86	-0.40	-0.85
		50bn	1.62	-1.70	1.07	3.62	-1.34	-1.70
Earnings volatility	-0.22	1bn	0.07	-0.29	1.23	1.88	0.83	-0.30
		10bn	0.45	-0.66	1.22	2.04	0.13	-0.69
		50bn	1.05	-1.27	1.21	4.03	-0.73	-1.40
Years 2-5 lagged returns, annual	-0.25	1bn	0.54	-0.78	1.21	1.82	-0.11	-0.81
		10bn	1.58	-1.79	1.17	2.55	-1.39	-1.90
		50bn	2.34	-2.50	1.10	5.09	-2.34	-2.83
Market correlation	0.16	1bn	0.11	0.06	0.74	1.86	0.76	0.03
		10bn	0.62	-0.40	0.67	2.44	-0.03	-0.52
		50bn	1.35	-1.08	0.62	3.96	-0.93	-1.33
Residual momentum t-12 to t-1	-0.08	1bn	0.21	-0.29	1.00	1.37	0.54	-0.31
		10bn	0.94	-1.00	0.98	1.70	-0.47	-1.06
		50bn	1.72	-1.76	0.93	3.53	-1.40	-1.92
Growth in book debt (3 years)	-0.13	1bn	0.09	-0.22	1.07	1.62	0.75	-0.24
		10bn	0.53	-0.66	1.06	1.86	-0.01	-0.69
		50bn	1.19	-1.31	1.05	3.90	-0.88	-1.45
Book-to-market equity	-0.36	1bn	0.13	-0.49	1.35	3.61	0.53	-0.57
		10bn	0.70	-1.04	1.32	3.77	-0.47	-1.16
		50bn	1.37	-1.67	1.27	5.54	-1.39	-1.98
Share turnover	0.14	1bn	0.11	0.03	0.71	1.69	0.71	0.02
		10bn	0.63	-0.50	0.71	2.05	-0.04	-0.51
		50bn	1.30	-1.15	0.69	4.45	-0.91	-1.31
Short-term reversal	-0.45	1bn	0.60	-1.04	1.34	2.68	-0.32	-1.11
		10bn	1.65	-2.05	1.29	3.40	-1.61	-2.21
		50bn	2.41	-2.76	1.23	5.73	-2.57	-3.15
Ebitda-to-market enterprise value	-0.33	1bn	0.09	-0.42	1.17	2.74	0.60	-0.47
		10bn	0.56	-0.86	1.14	2.88	-0.19	-0.95
		50bn	1.23	-1.50	1.09	4.15	-1.06	-1.70
Intrinsic value-to-market	-0.36	1bn	0.13	-0.49	1.15	2.36	0.48	-0.52
		10bn	0.69	-1.03	1.13	2.68	-0.44	-1.10
		50bn	1.29	-1.61	1.10	5.52	-1.35	-1.94
Dollar trading volume	-0.30	1bn	0.47	-0.76	1.03	2.97	-0.18	-0.82
		10bn	1.34	-1.60	0.98	5.58	-1.44	-1.91
		50bn	—	—	—	—	— ∞	— ∞
Amihud Measure	-0.57	1bn	0.42	-0.99	1.13	3.31	-0.32	-1.05
		10bn	1.24	-1.78	1.08	5.87	-1.57	-2.12
		50bn	—	—	—	—	— ∞	— ∞

Table 15: Net performance at fixed capital for long–short factors 1–18 of 35 (Part 1 of 2).

The table presents net performance statistics and its components for factors based on the 35 strategies considered at various investment scales. Each long–short factor is evaluated at initial capital of \$1 billion, \$10 billion, and \$50 billion. Avg. TC is the average trading cost as a percentage of capital. Gross α is the intercept of a regression of gross excess returns on the market excess return. Net α and Net β are the intercept and slope of the corresponding regression using net excess returns along the unhedged capital path. σ_ϵ is the standard deviation of that regression’s residuals. Total log growth is the average log growth of unhedged capital. PA log growth is the average log growth of market-hedged capital relative to cash. Trading costs, alphas, residual volatility, and growth rates are reported in percent. An entry of $-\infty$ indicates that the corresponding capital path reaches zero before the sample ends. Trading costs, net alpha, net beta, and residual volatility are blank for those paths because the months after capital reaches zero have no investment interpretation. Rows are ordered by the gross geometric mean return. The sample covers January 2010–December 2023 (167 monthly returns from February 2010). All statistics are monthly.

Anomaly	Gross α	A_0	Avg. TC	Net α	Net β	σ_ϵ	Total log growth	PA log growth
Mispricing factor: Performance	1.17	1bn	0.54	0.62	-0.43	4.35	0.27	0.53
		10bn	1.62	-0.45	-0.44	4.54	-0.71	-0.57
		50bn	2.37	-1.18	-0.47	6.42	-1.63	-1.51
Percent operating accruals	0.50	1bn	0.23	0.28	0.08	2.28	0.39	0.25
		10bn	1.00	-0.50	0.08	2.84	-0.43	-0.54
		50bn	1.77	-1.28	0.09	4.77	-1.31	-1.42
Operating cash flow to assets	0.91	1bn	0.18	0.72	-0.33	3.64	0.42	0.66
		10bn	0.89	0.00	-0.32	3.89	-0.17	-0.06
		50bn	1.64	-0.75	-0.32	5.53	-0.99	-0.93
Highest 5 days of return / volatility	0.37	1bn	0.97	-0.60	0.07	2.87	-0.54	-0.65
		10bn	2.16	-1.78	0.05	3.65	-1.78	-1.88
		50bn	2.88	-2.46	0.00	6.28	-2.74	-2.84
Operating accruals	0.46	1bn	0.24	0.21	-0.02	2.75	0.23	0.17
		10bn	1.05	-0.63	0.00	3.36	-0.60	-0.67
		50bn	1.71	-1.29	-0.01	6.09	-1.52	-1.58
Operating profits-to-book assets	0.75	1bn	0.08	0.66	-0.27	3.94	0.38	0.59
		10bn	0.51	0.24	-0.26	4.09	0.03	0.16
		50bn	1.15	-0.40	-0.27	5.51	-0.66	-0.59
CAPEX growth (1 year)	0.46	1bn	0.31	0.16	-0.06	2.78	0.14	0.11
		10bn	1.18	-0.71	-0.07	3.19	-0.74	-0.79
		50bn	1.86	-1.38	-0.09	5.90	-1.66	-1.70
Operating profits-to-book equity	0.80	1bn	0.19	0.60	-0.33	3.70	0.29	0.53
		10bn	0.92	-0.15	-0.30	4.01	-0.34	-0.20
		50bn	1.57	-0.79	-0.32	6.41	-1.20	-1.09
Change in net operating assets	0.38	1bn	0.27	0.11	-0.05	2.77	0.10	0.07
		10bn	1.09	-0.72	-0.04	3.36	-0.73	-0.78
		50bn	1.76	-1.40	-0.03	6.19	-1.64	-1.69
Quality minus Junk: Composite	0.80	1bn	0.30	0.51	-0.46	3.88	0.08	0.42
		10bn	1.19	-0.39	-0.46	4.22	-0.69	-0.48
		50bn	1.94	-1.17	-0.44	6.14	-1.58	-1.40
Net debt-to-price	0.54	1bn	0.24	0.32	-0.26	3.53	0.09	0.24
		10bn	1.03	-0.43	-0.31	3.81	-0.63	-0.57
		50bn	1.76	-1.11	-0.35	5.79	-1.51	-1.46
R&D-to-market	0.06	1bn	0.15	-0.07	0.13	3.04	0.07	-0.13
		10bn	0.77	-0.65	0.08	3.33	-0.63	-0.78
		50bn	1.03	-0.86	0.04	7.52	-1.67	-1.85
Asset Growth	0.34	1bn	0.22	0.13	-0.12	3.38	0.04	0.07
		10bn	0.98	-0.62	-0.12	3.76	-0.70	-0.71
		50bn	1.66	-1.31	-0.12	6.21	-1.59	-1.60
Price momentum t-6 to t-1	0.71	1bn	1.03	-0.20	-0.50	5.19	-0.58	-0.44
		10bn	2.27	-1.36	-0.56	6.09	-1.81	-1.77
		50bn	2.94	-1.97	-0.61	8.13	-2.77	-2.73
Highest 5 days of return	1.08	1bn	1.37	-0.32	-0.70	4.88	-0.74	-0.41
		10bn	2.65	-1.56	-0.72	5.49	-1.97	-1.73
		50bn	3.30	-2.14	-0.78	7.90	-2.93	-2.69
Earnings volatility	-0.14	1bn	0.10	-0.24	0.29	2.95	0.07	-0.28
		10bn	0.57	-0.72	0.29	3.10	-0.48	-0.77
		50bn	1.17	-1.29	0.27	5.64	-1.31	-1.57
Years 16-20 lagged returns, nonannual	0.54	1bn	0.66	-0.13	-0.35	2.84	-0.37	-0.17
		10bn	1.78	-1.22	-0.38	3.68	-1.47	-1.33
		50bn	–	–	–	–	$-\infty$	$-\infty$
Idiosyncratic volatility	0.87	1bn	1.23	-0.35	-0.59	4.68	-0.75	-0.47
		10bn	2.48	-1.56	-0.62	5.31	-1.97	-1.76
		50bn	6.69	-2.10	-0.67	7.86	-2.93	-2.72

Table 16: Net performance at fixed capital for long-short factors (continued).

Anomaly	Gross α	A_0	Avg. TC	Net α	Net β	σ_ϵ	Total log growth	PA log growth
Momentum t-12 to t-1	0.74	1bn	0.98	-0.20	-0.51	5.33	-0.61	-0.37
		10bn	2.21	-1.42	-0.52	5.49	-1.79	-1.63
		50bn	2.98	-2.19	-0.56	7.00	-2.74	-2.58
Standardized earnings surprise	0.04	1bn	0.34	-0.31	-0.03	2.02	-0.28	-0.31
		10bn	1.24	-1.27	0.02	3.01	-1.20	-1.25
		50bn	2.00	-2.08	0.07	5.44	-2.12	-2.17
Change in operating cash flow to assets	0.02	1bn	0.28	-0.26	-0.04	2.04	-0.25	-0.28
		10bn	1.12	-1.12	-0.02	2.68	-1.09	-1.14
		50bn	1.82	-1.83	-0.01	5.52	-2.00	-2.05
Profit margin	0.35	1bn	0.11	0.23	-0.33	3.64	-0.11	0.17
		10bn	0.64	-0.30	-0.32	3.90	-0.56	-0.36
		50bn	1.29	-0.95	-0.32	5.93	-1.34	-1.17
Short-term reversal	-0.46	1bn	0.82	-1.26	0.40	3.99	-1.02	-1.37
		10bn	1.93	-2.34	0.37	4.90	-2.25	-2.55
		50bn	2.58	-2.93	0.31	7.52	-3.21	-3.50
Change in net financial assets	-0.17	1bn	0.25	-0.43	0.07	2.10	-0.32	-0.44
		10bn	1.05	-1.28	0.12	3.41	-1.20	-1.29
		50bn	1.83	-2.09	0.15	5.47	-2.12	-2.20
Residual momentum t-12 to t-1	-0.06	1bn	0.40	-0.46	-0.04	2.55	-0.46	-0.50
		10bn	1.36	-1.39	-0.06	2.96	-1.42	-1.47
		50bn	2.13	-2.13	-0.10	5.26	-2.34	-2.40
Growth in book debt (3 years)	-0.17	1bn	0.12	-0.29	-0.01	2.30	-0.25	-0.32
		10bn	0.66	-0.83	-0.01	2.57	-0.80	-0.86
		50bn	1.27	-1.42	-0.03	5.42	-1.63	-1.70
Years 2-5 lagged returns, annual	-0.36	1bn	0.81	-1.16	0.18	3.50	-1.04	-1.24
		10bn	1.93	-2.24	0.15	4.53	-2.25	-2.42
		50bn	2.60	-2.84	0.08	7.23	-3.20	-3.38
Price momentum t-12 to t-7	0.08	1bn	0.75	-0.66	-0.17	5.07	-0.86	-0.81
		10bn	1.89	-1.80	-0.19	5.32	-2.02	-1.99
		50bn	2.64	-2.52	-0.22	7.14	-2.96	-2.94
Book-to-market equity	-0.54	1bn	0.13	-0.67	0.37	4.68	-0.36	-0.78
		10bn	0.69	-1.20	0.35	4.83	-1.03	-1.35
		50bn	1.30	-1.76	0.30	6.79	-1.90	-2.19
Ebitda-to-market enterprise value	-0.22	1bn	0.15	-0.37	0.04	4.73	-0.37	-0.49
		10bn	0.75	-0.95	0.02	4.88	-1.00	-1.10
		50bn	1.38	-1.53	-0.02	6.85	-1.85	-1.95
Market correlation	0.14	1bn	0.13	0.03	-0.38	2.65	-0.32	-0.02
		10bn	0.72	-0.50	-0.44	3.04	-0.82	-0.62
		50bn	1.43	-1.14	-0.48	5.08	-1.61	-1.46
Dollar trading volume	-0.35	1bn	0.46	-0.80	0.06	3.27	-0.74	-0.86
		10bn	1.34	-1.64	0.02	5.70	-1.84	-1.95
		50bn	—	—	—	—	— ∞	— ∞
Intrinsic value-to-market	-0.53	1bn	0.17	-0.70	0.14	3.52	-0.56	-0.77
		10bn	0.83	-1.35	0.14	3.95	-1.27	-1.44
		50bn	1.04	-1.49	0.09	7.83	-2.34	-2.54
Share turnover	0.38	1bn	0.20	0.17	-0.69	4.23	-0.56	0.09
		10bn	0.93	-0.56	-0.68	4.45	-1.11	-0.65
		50bn	1.60	-1.19	-0.71	6.59	-1.94	-1.53
Amihud Measure	-0.63	1bn	0.41	-1.04	0.17	3.64	-0.91	-1.12
		10bn	1.24	-1.83	0.13	6.02	-1.99	-2.17
		50bn	—	—	—	—	— ∞	— ∞

E.2 Bootstrap Bands for the Capacity Estimates

Table 17 reports 90% bootstrap bands for portable-alpha capacity that account for estimation error in transaction cost parameter estimates. The bootstrap holds the realized return path fixed and resamples the daily cost estimates, as described in Section 6.1. Among strategies with positive capacity, the median band width is 5.1% of the point estimate for long legs and 4.6% for factors. Every point estimate lies within its band. Strategies with zero estimated capacity have bands of $[0, 0]$ because their capacity remains zero in every bootstrap draw. These bands measure variation from resampling costs, conditional on the realized returns and the execution model.

Table 17: Bootstrap bands for the portable-alpha capacity.

The table presents bootstrap bands for the portable-alpha capacity that reflects measurement error variance in transaction cost model parameter estimates. Each row reports portable-alpha capacity for the long leg (H) and the long-short factor ($H - L$), with a 90% percentile band from 499 bootstrap draws. Portable-alpha capacity is the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Each draw holds portfolio weights and realized returns fixed. For each stock, daily cost estimates divided by their exponential moving average are resampled in blocks of 21 trading days. Blocks are drawn independently for each stock, so the bands reflect stock-specific estimation noise and exclude common shocks to trading costs; the same draws are used for every strategy. The resampled ratios are smoothed using the same moving average and multiplied by the month-end cost coefficients before capacity is recomputed. The band endpoints are the 5th and 95th percentiles of the bootstrap capacities. An entry of 0 indicates that no positive initial capital produces non-negative hedged growth relative to cash. Rows are sorted by long-leg capacity. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Anomaly	$A_{PA}^{\max}(H)$	90% band (H)	$A_{PA}^{\max}(H - L)$	90% band ($H - L$)
Operating profits-to-book assets	32.58 bn	[31.62 bn, 33.47 bn]	15.16 bn	[14.29 bn, 15.81 bn]
Profit margin	23.10 bn	[22.33 bn, 23.92 bn]	3.10 bn	[2.91 bn, 3.23 bn]
Operating profits-to-book equity	20.67 bn	[20.16 bn, 21.17 bn]	6.40 bn	[6.05 bn, 6.67 bn]
Operating cash flow to assets	19.98 bn	[19.53 bn, 20.45 bn]	8.76 bn	[8.52 bn, 8.98 bn]
Quality minus Junk: Composite	14.27 bn	[14.07 bn, 14.50 bn]	3.63 bn	[3.55 bn, 3.69 bn]
Mispricing factor: Performance	8.63 bn	[8.25 bn, 9.29 bn]	3.44 bn	[3.41 bn, 3.49 bn]
Net debt-to-price	5.74 bn	[5.66 bn, 5.83 bn]	2.59 bn	[2.55 bn, 2.62 bn]
Highest 5 days of return	1.79 bn	[1.78 bn, 1.81 bn]	435 m	[420 m, 462 m]
Percent operating accruals	1.60 bn	[1.55 bn, 1.67 bn]	2.72 bn	[2.66 bn, 2.80 bn]
R&D-to-market	1.44 bn	[1.41 bn, 1.48 bn]	32 m	[31 m, 33 m]
Market correlation	1.32 bn	[1.28 bn, 1.35 bn]	803 m	[783 m, 821 m]
Share turnover	1.20 bn	[1.16 bn, 1.23 bn]	1.59 bn	[1.56 bn, 1.63 bn]
Change in net operating assets	1.12 bn	[1.09 bn, 1.15 bn]	1.37 bn	[1.35 bn, 1.39 bn]
CAPEX growth (1 year)	1000 m	[974 m, 1.03 bn]	1.53 bn	[1.50 bn, 1.55 bn]
Operating accruals	1000 m	[983 m, 1.01 bn]	2.03 bn	[2.00 bn, 2.05 bn]
Asset Growth	957 m	[932 m, 984 m]	1.41 bn	[1.37 bn, 1.44 bn]
Idiosyncratic volatility	620 m	[600 m, 645 m]	356 m	[353 m, 360 m]
Years 16-20 lagged returns, nonannual	565 m	[555 m, 578 m]	628 m	[614 m, 643 m]
Price momentum t-6 to t-1	311 m	[308 m, 313 m]	373 m	[347 m, 420 m]
Highest 5 days of return / volatility	237 m	[236 m, 238 m]	129 m	[128 m, 130 m]
Momentum t-12 to t-1	143 m	[141 m, 145 m]	414 m	[409 m, 418 m]
Book-to-market equity	0	[0, 0]	0	[0, 0]
Intrinsic value-to-market	0	[0, 0]	0	[0, 0]
Ebitda-to-market enterprise value	0	[0, 0]	0	[0, 0]
Earnings volatility	0	[0, 0]	0	[0, 0]
Residual momentum t-12 to t-1	0	[0, 0]	0	[0, 0]
Standardized earnings surprise	0	[0, 0]	0	[0, 0]
Price momentum t-12 to t-7	0	[0, 0]	0	[0, 0]
Change in operating cash flow to assets	0	[0, 0]	0	[0, 0]
Years 2-5 lagged returns, annual	0	[0, 0]	0	[0, 0]
Amihud Measure	0	[0, 0]	0	[0, 0]
Dollar trading volume	0	[0, 0]	0	[0, 0]
Short-term reversal	0	[0, 0]	0	[0, 0]
Growth in book debt (3 years)	0	[0, 0]	0	[0, 0]
Change in net financial assets	0	[0, 0]	0	[0, 0]

E.3 Capacity with a Real-Time Hedge Ratio

The main portable-alpha calculation uses a hedge that depends on the strategy's full-sample gross beta, which is unavailable to an investor at the time of trading. Tables 18 and 19 recompute capacity using a 60-month rolling beta estimated from gross excess returns and lagged one month, with all other assumptions unchanged. For the first months of the sample the window extends back to January 2005, before the cost data begin, using the gross returns of the same value-weighted quintile portfolios, so the hedge in every month uses only returns observed before that month. Capacity falls by 22% for the median long leg and rises by 3% for the median factor. No long leg changes between zero and positive capacity; one factor moves from positive to zero and one from zero to positive. Rankings remain nearly unchanged, with rank correlations of 0.99 for long legs and 0.98 for factors.

Table 18: Portable-alpha capacity with a rolling hedge ratio (long legs).

The table presents portable-alpha capacities for long legs with a full sample and rolling hedge ratio. β_z is the full-sample CAPM beta estimated from gross excess returns. $\bar{\beta}_{z,t}$ is the time-series mean of the 60-month rolling beta, lagged one month. The rolling window uses the 60 months ending in the previous month; for the first months of the sample it extends back to January 2005, before the cost data begin, using the gross returns of the same value-weighted quintile portfolios. The capacity columns report portable-alpha capacity under each hedge ratio, defined as the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Ratio is rolling-beta capacity divided by full-sample-beta capacity and is blank when the full-sample-beta capacity is zero. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Anomaly	β_z (full sample)	$\bar{\beta}_{z,t}$ (rolling)	$A_{PA}^{\max}$, full-sample β	$A_{PA}^{\max}$, rolling β	Ratio
Operating profits-to-book assets	0.98	0.95	32.58 bn	39.73 bn	1.22
Profit margin	0.97	0.98	23.10 bn	21.11 bn	0.91
Operating profits-to-book equity	0.94	0.93	20.67 bn	23.09 bn	1.12
Operating cash flow to assets	0.97	0.94	19.98 bn	24.30 bn	1.22
Quality minus Junk: Composite	0.94	0.91	14.27 bn	17.66 bn	1.24
Mispricing factor: Performance	0.93	0.91	8.63 bn	10.30 bn	1.19
Net debt-to-price	1.05	1.05	5.74 bn	6.45 bn	1.12
Highest 5 days of return	0.75	0.76	1.79 bn	1.70 bn	0.95
Percent operating accruals	1.14	1.19	1.60 bn	762 m	0.48
R&D-to-market	1.03	1.11	1.44 bn	911 m	0.63
Market correlation	0.75	0.79	1.32 bn	829 m	0.63
Share turnover	0.71	0.78	1.20 bn	481 m	0.40
Change in net operating assets	1.04	1.09	1.12 bn	817 m	0.73
CAPEX growth (1 year)	1.11	1.14	1000 m	709 m	0.71
Operating accruals	1.09	1.11	1000 m	863 m	0.86
Asset Growth	1.05	1.14	957 m	233 m	0.24
Idiosyncratic volatility	0.86	0.85	620 m	659 m	1.06
Years 16-20 lagged returns, nonannual	0.81	0.87	565 m	432 m	0.76
Price momentum t-6 to t-1	0.97	0.99	311 m	236 m	0.76
Highest 5 days of return / volatility	1.02	1.04	237 m	186 m	0.78
Momentum t-12 to t-1	0.98	0.99	143 m	102 m	0.72
Book-to-market equity	1.36	1.51	0	0	–
Intrinsic value-to-market	1.16	1.21	0	0	–
Ebitda-to-market enterprise value	1.17	1.20	0	0	–
Earnings volatility	1.23	1.25	0	0	–
Residual momentum t-12 to t-1	1.01	0.98	0	0	–
Standardized earnings surprise	1.00	1.01	0	0	–
Price momentum t-12 to t-7	1.08	1.08	0	0	–
Change in operating cash flow to assets	1.08	1.09	0	0	–
Years 2-5 lagged returns, annual	1.22	1.16	0	0	–
Amihud Measure	1.13	1.20	0	0	–
Dollar trading volume	1.04	1.11	0	0	–
Short-term reversal	1.37	1.38	0	0	–
Growth in book debt (3 years)	1.07	1.09	0	0	–
Change in net financial assets	1.09	1.10	0	0	–

Table 19: Portable-alpha capacity with a rolling hedge ratio (factors).

The table presents portable-alpha capacities for factors with a full sample and rolling hedge ratio. β_z is the full-sample CAPM beta estimated from gross excess returns. $\bar{\beta}_{z,t}$ is the time-series mean of the 60-month rolling beta, lagged one month. The rolling window uses the 60 months ending in the previous month; for the first months of the sample it extends back to January 2005, before the cost data begin, using the gross returns of the same value-weighted quintile portfolios. The capacity columns report portable-alpha capacity under each hedge ratio, defined as the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Ratio is rolling-beta capacity divided by full-sample-beta capacity and is blank when the full-sample-beta capacity is zero. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Anomaly	β_z (full sample)	$\bar{\beta}_{z,t}$ (rolling)	$A_{PA}^{\max}$, full-sample β	$A_{PA}^{\max}$, rolling β	Ratio
Operating profits-to-book assets	-0.27	-0.37	15.16 bn	17.74 bn	1.17
Operating cash flow to assets	-0.33	-0.40	8.76 bn	9.57 bn	1.09
Operating profits-to-book equity	-0.33	-0.38	6.40 bn	6.68 bn	1.04
Quality minus Junk: Composite	-0.45	-0.55	3.63 bn	4.21 bn	1.16
Mispricing factor: Performance	-0.43	-0.56	3.44 bn	3.90 bn	1.13
Profit margin	-0.34	-0.36	3.10 bn	3.46 bn	1.12
Percent operating accruals	0.08	0.14	2.72 bn	2.33 bn	0.86
Net debt-to-price	-0.25	-0.35	2.59 bn	3.63 bn	1.40
Operating accruals	-0.02	0.00	2.03 bn	2.00 bn	0.99
Share turnover	-0.70	-0.59	1.59 bn	1.02 bn	0.64
CAPEX growth (1 year)	-0.05	-0.00	1.53 bn	1.31 bn	0.86
Asset Growth	-0.11	0.02	1.41 bn	557 m	0.40
Change in net operating assets	-0.05	0.01	1.37 bn	1.07 bn	0.78
Market correlation	-0.36	-0.37	803 m	828 m	1.03
Years 16-20 lagged returns, nonannual	-0.35	-0.23	628 m	448 m	0.71
Highest 5 days of return	-0.72	-0.73	435 m	422 m	0.97
Momentum t-12 to t-1	-0.49	-0.55	414 m	515 m	1.25
Price momentum t-6 to t-1	-0.41	-0.45	373 m	402 m	1.08
Idiosyncratic volatility	-0.58	-0.63	356 m	385 m	1.08
Highest 5 days of return / volatility	0.07	0.05	129 m	131 m	1.02
R&D-to-market	0.15	0.22	32 m	0	0.00
Book-to-market equity	0.38	0.56	0	0	–
Intrinsic value-to-market	0.14	0.22	0	0	–
Ebitda-to-market enterprise value	0.04	0.08	0	0	–
Earnings volatility	0.29	0.26	0	0	–
Residual momentum t-12 to t-1	-0.03	-0.11	0	0	–
Standardized earnings surprise	-0.05	-0.07	0	63 m	–
Price momentum t-12 to t-7	-0.17	-0.20	0	0	–
Change in operating cash flow to assets	-0.04	-0.03	0	0	–
Years 2-5 lagged returns, annual	0.19	0.06	0	0	–
Amihud Measure	0.17	0.24	0	0	–
Dollar trading volume	0.06	0.14	0	0	–
Short-term reversal	0.41	0.41	0	0	–
Growth in book debt (3 years)	-0.01	0.04	0	0	–
Change in net financial assets	0.06	0.05	0	0	–

E.4 Capacity under Alternative Smoothing of the Cost Estimates

For the main results, we smooth daily cost estimates using exponential moving averages with a span of 50 trading days. Table 20 recomputes both cost coefficients with spans of 25 and 100 trading days and recalculates portable-alpha capacity, holding all other inputs fixed. For the median long leg, capacity is 0.3% higher with the 25-day span and 1.6% lower with the 100-day span; for the median factor, it is 3.6% higher and 7.3% lower. The median capacity among strategies with positive capacity moves more, from \$1.32 billion to \$1.04 billion for long legs under the 100-day span, because a few mid-ranked legs change places. No strategy moves between zero and positive capacity, and rank correlations with the main specification are at least 0.98.

Table 20: Capacity under alternative smoothing of the cost estimates.

The table presents capacities and capacity-related statistics under alternative smoothing assumptions of transaction cost parameter estimates. Each row recomputes portable-alpha capacity after smoothing the daily spread and impact coefficients with an exponential moving average of the stated span, holding all other inputs fixed. The baseline span is 50 trading days. Portable-alpha capacity is the largest initial capital at which compound growth after hedging market exposure matches or exceeds the return on cash. Span is measured in trading days. Zero is the number of strategies with zero capacity. Med. cap. is the median capacity among strategies with positive capacity, reported in billions of dollars. Med. ratio and IQR are the median and interquartile range of the ratio of alternative to baseline capacity among strategies with positive baseline capacity. Spearman is the rank correlation between alternative and baseline capacities. Δ rank is the largest absolute change in capacity rank. H denotes long legs and $H - L$ long-short factors. The sample covers January 2010–December 2023 (167 monthly returns from February 2010).

Span	Zero	Med. cap.	Med. ratio	IQR	Spearman	Δ rank
Long legs (H)						
25	14	1.26	1.003	0.989–1.059	0.999	1
50	14	1.32	1.000	1.000–1.000	1.000	0
100	14	1.04	0.984	0.932–1.014	0.985	6
Long-short factors (H–L)						
25	14	1.60	1.036	1.009–1.057	1.000	1
50	14	1.53	1.000	1.000–1.000	1.000	0
100	14	1.41	0.927	0.876–0.957	0.997	2