Rewriting Expected Returns*

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Abstract

We develop a novel, equilibrium-based framework that systematically measures how investor flows can "rewrite returns" by re-pricing the cross-section of stocks. Our methodology enforces market clearing while providing a near-closed-form, economically intuitive approximation of how flows—both where they originate and where they land—ultimately shape asset returns. To illustrate its application, we apply our method to the classic value and momentum anomalies, showing that sufficiently large reallocations from growth to value funds could wipe out the value premium while substantially boosting momentum. In contrast, similarly sized inflows from a more diversified source—such as households, who hold both growth and value stocks—induce less extreme effects. In practice, extreme reallocation scenarios far exceed typical fund flow levels, explaining why certain anomalies persist despite their theoretical fragility. The transparent nature of our approximation provides a computationally efficient tool for "what-if" experiments and can assist researchers, policymakers, and practitioners in gaining clearer insights into how capital flows affect asset prices.

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1 Introduction

Flows of capital across investors are often credited with reshaping asset prices, especially in markets that are not perfectly elastic. A broad literature—sometimes referred to as the "price pressure" or "flow-performance" literature—investigates this link by regressing future returns on flow-based variables. These variables may include raw inflows/outflows or more refined measures that weight each fund's flow by its ownership in a particular stock (for example, FIT from Lou (2012) or MFFlow from Edmans et al. (2012)). In the prototypical case,

$$R_{i,t+1} = \alpha + \beta\, \text{FlowMeasure}_{i,t} + \varepsilon_{i,t+1},$$

a significant β is typically interpreted as evidence that flows affect subsequent returns. Over the past two decades, this approach has yielded important evidence of how moderate reallocation moves prices, and it remains a valuable workhorse model.

Despite these advances, and aside from concerns about identification or measurement (e.g., Wardlaw, 2020), a further limitation arises when we consider larger or more systematic shifts in capital. The flow-return regressions depend on historically observed flows and returns. As soon as we ask, "What if the market reallocates 10% (or 50%) of a certain investor's capital to another investor?," we leave the comfort zone of observed data. Linear extrapolation from regression coefficients may fail if the relationship becomes nonlinear under larger flow magnitudes or if the liquidity environment changes. Moreover, short-run price changes revealed in the data do not necessarily map one-to-one into changes in *expected returns*. If inflows drive up a stock's price today, the longer-horizon expected return may fall due to the higher purchase valuation.

To handle these "what-if" scenarios, we propose a method that re-solves equilibrium prices and explicitly connects them to expected returns. We enforce two constraints absent in partial regressions: *(i)* an *asset-management equilibrium*, ensuring that outflows from one group must reappear as inflows to another, and *(ii)* a *stock-market equilibrium*, guaranteeing

that forced selling and buying lead to a new clearing price rather than simply netting out at the old price. Built on the demand-based logic of Koijen and Yogo (2019), our approach yields a transparent, computationally straightforward formula for how capital shifts among investor groups reshape individual stock prices. Crucially, it also includes a flexible "pass-through" mechanism to convert those price changes into changes in expected returns—allowing for heterogeneity across portfolios or single stocks. Together, these features provide a new, intuitive "stress test" for how flows can fundamentally reprice the cross section of returns, beyond either partial-flow regressions or purely numerical demand-system solutions.

The first layer of our method is the near-closed-form approximation of stock prices that follows a hypothetical reallocation. While one could, in principle, solve the entire demand system exactly, that process often proves cumbersome and opaque. Instead, we derive an explicit formula expressing each stock's price change in terms of *(i)* its baseline ownership by each investor, *(ii)* the investor's price elasticity of demand, and *(iii)* the counterfactual change in that investor's capital. Empirically, we find that this simpler approximation tracks the fully solved demand system almost perfectly, with 90–95% correlations at the stock level under our reallocation scenarios. The result is both precise and unbiased, offering a clear lens on how different inflows and outflows translate into new equilibrium prices.

Building on this price-level innovation, the second layer of our framework converts price shifts into expected returns, following a log-linearization approach inspired by Campbell and Shiller (1988) and related work (e.g., Cochrane, 2008). Intuitively, if capital inflows elevate a stock's price, its subsequent expected return declines because investors effectively "buy in" at a richer valuation. By coupling our equilibrium price-change approximation with a single pass-through parameter, we can systematically "rewrite" each stock's expected return—illustrating that large inflows do more than deliver a short-run boost in realized returns; they also reshape the longer-run compensation investors anticipate. Our approach handles multiple investor or stock types and can simulate anything from modest capital shifts to major reallocations of ownership, revealing not only whether flows matter but also

by how much and under which conditions they reshape the market.[1]

Our empirical analysis illustrates our framework by applying it to two canonical anomalies—value and momentum—demonstrating how large-scale capital reallocations can reshape expected returns. These anomalies have long intrigued researchers: the value premium of Fama and French (1992) remains a prime focus, while the momentum premium of Jegadeesh and Titman (1993) continues to challenge classical views on market efficiency. By examining how investor flows propagate through the cross-section of prices, we offer one illustrative example of how our approach clarifies the durability and interplay of these excess returns under different patterns of fund behavior and various reallocation scales.

Our model simulates hypothetical capital reallocations—first from growth funds to value funds and then from households to value funds—and computes the resulting risk-adjusted expected returns. Our empirical results converge on three core findings. First, substantial reallocations can erode the value premium, yet the "capacity" required to fully eliminate it is strikingly large. In principle, if all capital were diverted exclusively from growth funds to value, the high-minus-low (H–L) return would approach zero. However, such extreme inflows—often exceeding 100 of growth-fund AUM—vastly exceed historical fund-flow levels. Consequently, while the value premium is theoretically fragile, it practically endures because flows of that scale remain improbable.[2]

Second, this same reallocation can boost momentum—an illustration of "cross-capacity."

[1] Koijen et al. (2023) conclude by noting how changes in log market-to-book equity might be linked to expected returns assuming an autoregressive structure for returns—drawing on a single market-level estimate of $1 - \rho\phi$ from earlier research (e.g., van Binsbergen and Koijen, 2010). In contrast, our framework adopts a Campbell–Shiller decomposition at the stock or portfolio level, allowing us to estimate pass-through parameters that differ across anomalies. Hence, whereas Koijen et al. (2023) primarily outline this step conceptually, our method implements a more granular approach that quantifies how large reallocations reshape each portfolio's future returns.

[2] Although growth funds predominantly hold growth stocks and value funds tilt heavily toward value stocks, there is still some overlap. For instance, our data show that value funds hold about 4.43% of top-decile (value) stocks and 1.03% of bottom-decile (growth) stocks, while growth funds hold roughly 5.54% of the bottom-decile and 1.48% of the top-decile. Our stock-level demand approach automatically accounts for these partial overlaps, ensuring we capture both inflows and outflows in each stock from different investor types.

Because momentum's winner leg overlaps heavily with growth stocks (Jegadeesh and Titman, 1993; Asness, 1994), pulling capital from growth depresses winners less than losers, widening the H–L spread and momentum alpha. This dynamic underscores how style-based flows, aimed at undermining one anomaly, may inadvertently amplify another (Barberis et al., 1998). Our novel quantification of this effect echos broader debates on factor crowding and style migration—when capital chases an arbitrage opportunity in one segment of the market, another anomaly may strengthen if it relies on stocks or positions that complement or oppose the targeted trade.

Third, the source of capital proves critical. Even an equal-sized inflow of dollars to value can generate distinctly different outcomes depending on who sells. When reallocation originates with growth funds, the impact on growth stocks—and by extension momentum winners—is sharp and targeted, leading to a pronounced price response. By contrast, the same nominal shift from households, who hold both growth and value exposures, results in a more diffuse outflow that leaves growth portfolios less depleted and momentum winners less affected. This distinction underscores that not all flows are created equal: which investors lose assets can matter as much as where those assets land, because the composition of their portfolios governs how systematically prices get driven up or down. Our findings thus refine the conventional "flow-performance" narrative, highlighting investor identity as a key channel for style-based revaluation.

Taken together, our findings highlight how investor-level demand shifts can, in theory, "rewrite" anomalies—a perspective consistent with recent demand-based asset pricing research. In practice, however, the scale of flows required to fully dismantle something like the value premium is typically beyond real-world fund-flow levels, and depends heavily on which investor type is the source of capital. This duality—theoretically fragile, empirically persistent—underscores that while large, coordinated outflows can indeed erode anomalies, real-world constraints such as institutional mandates, diversification requirements, and investor inertia keep most flows too modest or diffuse to have major market-wide impact.

At the same time, these findings neither rule out a risk-based nor a mispricing-based view of anomalies. For instance, one can interpret a large flow reallocation as signaling a shift in investors' risk preferences—if enough capital becomes willing to hold the "riskier" leg (e.g., value stocks) at lower expected returns, the premium may compress or vanish. Conversely, if investors maintain high risk aversion or such inflows never scale up, the premium endures. Our framework does not resolve why investors tilt toward certain stocks—whether due to risk aversion or behavioral biases—but rather demonstrates that, once such a tilt exists, a sufficiently large reallocation can reshape equilibrium prices and destroy an anomaly's alpha, irrespective of its original root cause.

One caveat is that we treat each investor's demand schedule as given, without modeling the possibility that other investors might strategically respond to large flow shifts (Haddad et al., 2025). In practice, market participants could notice emerging reallocation and adjust their behavior, partly offsetting the price impact. Our equilibrium results should thus be viewed as an upper bound—or "worst-case" scenario—in which no such mitigating trades arise.

Pavlova and Sikorskaya (2023) investigate how fund managers reallocate across stocks in response to benchmark inclusion or exclusion, showing a short-term price boost and a lower subsequent expected return for newly included stocks. In contrast, our framework focuses on how capital reallocation across managers (rather than across stocks) can re-solve the market equilibrium. Both perspectives underscore inelastic demand, but Pavlova and Sikorskaya (2023) emphasize benchmark-driven stock-level shifts, while we highlight how large-scale, multi-investor flows systematically alter expected returns throughout the cross section.

2 Methodology

We begin by outlining the basics of the Koijen and Yogo (2019) (KY) demand system. Next, we introduce a simple equilibrium price approximation that brings clarity to our

counterfactual experiments. We then describe how to compute counterfactual expected returns and alphas once prices shift. Finally, we propose a straightforward way to measure a strategy's capacity.

2.1 Investor Demand

Let $Q^d_{i,j,t}$ represent the number of shares of asset i held by investor j at time t. Let $P_{i,t}$ be the per-share price of asset i, $w_{i,j,t}$ the portfolio weight that investor j allocates to i, and $A_{j,t}$ the investor's total assets under management (AUM). We can then write investor j's demand for stock i as:

$$Q^d_{i,j,t} = \frac{w_{i,j,t} A_{j,t}}{P_{i,t}}. \tag{1}$$

Building on KY, we assume that if an investor places a positive weight on an asset, that weight follows:

$$w_{i,j,t} = \frac{\delta_{i,j,t}}{1 + \sum_n \delta_{n,j,t}},$$
$$\text{where } \delta_{i,j,t} = \exp\Big(\beta_{0,j,t} + p_{i,t} + \sum_{k=1}^{K} X_{i,k,t}\beta_{k,j,t} + \epsilon_{i,j,t}\Big),$$

and $p_{i,t} \equiv \log P_{i,t}$. The β coefficients capture how the asset characteristics $X_{i,k,t}$ affect portfolio weights, while the latent demand term $\epsilon_{i,j,t}$ capture the portion of investor demand unexplained by the characteristics. We include a constant characteristic to allow for an intercept.

To determine prices, we impose the standard market-clearing condition:

$$Q^d_{i,t} \equiv \sum_j Q^d_{i,j,t} \;=\; Q^s_{i,t}, \tag{2}$$

where $Q^s_{i,t}$ is the total supply of shares of asset i. In other words, prices must adjust until

the total number of shares demanded equals the number of shares issued.

2.2 Equilibrium Price Approximation

Below, we introduce a streamlined approximation for the equilibrium price in the Koijen-Yogo (KY) framework. Since the exact solution to Equation (2) is analytically intractable (Koijen and Yogo, 2019), we follow Davis (2024) in showing that KY demand can be closely approximated by an isoelastic form, thereby making counterfactual experiments both transparent and computationally straightforward.

Specifically, for each investor j, the KY demand system can be approximated by:

$$w_{i,j,t} = \exp\left((1-\eta_{j,t})p_{i,t} + \sum_{k=1}^{K} X_{i,k,t}\beta_{k,j,t} + \epsilon_{i,j,t}\right) = P_{i,t}^{1-\eta_{j,t}} \exp(k_{i,j,t}), \tag{3}$$

where $\eta_{j,t}$ is investor j's demand elasticity and

$$k_{i,j,t} = \sum_{k=1}^{K} X_{i,k,t}\beta_{k,j,t} + \epsilon_{i,j,t}. \tag{4}$$

Defining $q_{i,t}^d = \log Q_{i,t}^d$ as the log of total demand for asset i and $q_{i,t}^s = \log Q_{i,t}^s$ as the log of total supply, we can write:

$$q_{i,t}^d = \log\left(\sum_j P_{i,t}^{-\eta_{j,t}} \exp(k_{i,j,t}) A_{j,t}\right). \tag{5}$$

Taking a first-order approximation of (5) gives:

$$\begin{aligned} q_{i,t}^d &\approx c_{i,t} + \sum_j s_{i,j,t} \log\left(P_{i,t}^{-\eta_{j,t}} \exp(k_{i,j,t}) A_{j,t}\right) \\ &= c_{i,t} + \sum_j s_{i,j,t}\left(-\eta_{j,t} p_{i,t} + k_{i,j,t} + a_{j,t}\right), \end{aligned} \tag{6}$$

where $c_{i,t}$ is a constant, $a_{j,t} = \log A_{j,t}$, and $s_{i,j,t} \equiv Q^d_{i,j,t}/Q^s_{i,t}$ is the fraction of shares of asset i held by investor j.

Finally, we define the *aggregate elasticity* of asset i as

$$\eta_{i,t} \equiv \sum_j s_{i,j,t}\eta_{j,t} \quad \text{and} \quad m_{i,t} = \frac{1}{\eta_{i,t}}, \tag{7}$$

where $m_{i,t}$ is the corresponding *price multiplier*. A lower $\eta_{i,t}$ (more inelastic demand) means a larger $m_{i,t}$, amplifying the effect of capital reallocations on the asset's price.

Below we state a key result that links shifts in investor AUM directly to equilibrium price changes. For counterfactuals, we denote changes in a variable x by $\Delta x \equiv x^{CF} - x$, where x^{CF} is the counterfactual value. All the proofs are in Appendix B.1.

Proposition 1 *Assume Equation (6) holds exactly. Then the price change, relative to the original price, that satisfies the market-clearing condition (2) can be written as:*

$$\begin{aligned}\Delta p_{i,t} = \underbrace{m_{i,t}\Big(\sum_j s_{i,j,t}\,\Delta a_{j,t}\Big)}_{\textit{Direct Effect}} + \underbrace{m_{i,t}\sum_j \Delta s_{i,j,t}\Big(\Delta a_{j,t} + a_{j,t} + \kappa_{i,j,t}\Big)}_{\textit{Between-Investor Share Changes}} \\ + \underbrace{\Delta m_{i,t}\Big[c_{i,t} - q^s_{i,t} + \sum_j \big(\Delta s_{i,j,t} + s_{i,j,t}\big)\big(k_{i,j,t} + \Delta a_{j,t} + a_{j,t}\big)\Big]}_{\textit{Change in Price Multiplier}}.\end{aligned} \tag{8}$$

If the last two terms are negligible, we obtain the simpler approximation:

$$\Delta p_{i,t} \;\approx\; m_{i,t}\sum_j s_{i,j,t}\,\Delta a_{j,t}, \tag{9}$$

where $\Delta p_{i,t} = p^{CF}_{i,t} - p_{i,t}$ *and* $\Delta a_{j,t} = a^{CF}_{j,t} - a_{j,t}$.

Proposition 1 shows that reallocations can affect prices through three channels: the *direct effect* (how inflows or outflows among current holders of asset i move its price),

re-composition of ownership shares ($\Delta s_{i,j,t}$), and changes in the price multiplier ($\Delta m_{i,t}$). Although all three channels matter in principle, our empirical checks reveal that share re-composition and multiplier changes remain modest for the scenarios we analyze. Consequently, focusing on the direct effect alone still yields an excellent approximation to the fully solved demand system, enabling us to use Equation (9) as a near-closed-form expression for $\Delta p_{i,t}$.

In implementing our approximation, we also focus exclusively on exogenous shifts in an investor's AUM—such as external inflows or outflows—while deliberately ignoring any endogenous changes in AUM caused by the investor's own portfolio gains or losses. In other words, we only sum over "who receives (or loses) capital," rather than re-scaling ownership based on performance-driven fluctuations.

We assess the approximation's accuracy later in our empirical analysis by comparing its counterfactual price changes to those generated under the Koijen et al. (2023) approach (see Appendix C.1 for details). The Koijen et al. (2023) method iteratively solves a fixed-point problem, reflecting how reallocating capital away from some institutions—and toward others—feeds back into prices, institutional AUM, and so forth. Despite this more complex procedure, our simpler closed-form approximation which —which focuses only on the direct effect and omits endogenous changes in AUM— remains remarkably accurate, matching the iterative solution's results nearly one-to-one.[3]

Consequently, Equation (9) provides a straightforward lens on how the market adjusts to an investor's capital shock. For instance, if the price multiplier is 1.2 (implying an aggregate elasticity of 0.83), and 40% of investors each lose half of their AUM, the asset's price should

[3]The direct effect refers to how each investor scales its portfolio when inflows or outflows arrive, spreading any new capital across existing positions in roughly the same internal proportions $w_{i,j,t}$. This "near-proportional" allocation ensures the fund's internal weights do not shift drastically, a practice documented by Coval and Stafford (2007), Lou (2012), and Edmans et al. (2012). However, an investor's ownership share $s_{i,j,t}$ of a given stock can still change if other investors buy or sell differently at the same time. In other words, each fund scales its own portfolio proportionally, yet the fraction of total market shares it holds may move as the rest of the market trades. These trades are captured through the second channel: the re-composition effect. Empirically, the direct effect alone remains a strong approximation to the overall price impact.

fall by roughly 24% ($1.2 \times 0.4 \times (-0.5)$). In essence, the less elastic the market, the bigger the price impact from a given reallocation. Investors that own a larger share of the asset wield greater influence, and large capital shocks amplify this effect—even if fractional ownership remains nearly constant.

2.3 From Price Changes to Expected Returns

As Davis et al. (2024) point out, a 1% decline in price does not necessarily imply a 1% increase in expected returns. For instance, a one-year zero-coupon bond does exhibit a one-for-one mapping between price drops and yield rises, but stocks—being long-lived assets—show a more muted pass-through from price changes to expected returns. In this section, we present a Campbell and Shiller (1988)-style formula that illustrates how changes in stock prices translate into shifts in expected returns.

Let r_{t+1} denote the log return. By the Campbell-Shiller decomposition,

$$r_{i,t+1} = \kappa_i + (1 - \rho_i)\, d_{i,t+1} \;+\; \rho_i\, p_{i,t+1} \;-\; p_{i,t}, \tag{10}$$

where $d_{i,t}$ is the log dividend, κ_i is a constant (the linearization intercept), and ρ_i is the price-to-(price+dividend) ratio following Cochrane (2008). Define the persistence parameter ψ_i as

$$\psi_i \;\equiv\; \frac{\partial\, \mathbb{E}_t\left[\, p_{i,t+1} \,\right]}{\partial p_{i,t}}, \tag{11}$$

which measures the degree to which a price change today carries forward into next period's price. A ψ_i of 1 implies full persistence, while $\psi_i = 0$ indicates immediate mean reversion. Let $\mu_{i,t} \equiv \mathbb{E}_t\left[\, r_{i,t+1} \,\right]$. Under the assumption that a price change does not forecast a change in expected dividends, we have:

Proposition 2 *The pass-through from prices to expected returns is given by*

$$\theta_i \;\equiv\; -\frac{\partial \mu_{i,t}}{\partial p_{i,t}} \;=\; 1-\rho_i\,\psi_i,$$

which implies

$$\Delta\mu_{i,t} \;\approx\; -\,\theta_i\,\Delta p_{i,t}. \tag{12}$$

This result implies that if dividends are large relative to price ($\rho_i \approx 1$) and price changes exhibit high persistence ($\psi_i \approx 1$), then a 1% drop in price barely raises expected returns. Conversely, if dividends are small ($\rho_i \approx 0$) or price changes revert quickly ($\psi_i \approx 0$), a 1% drop in price can translate almost one-for-one into higher expected returns. For a one-year zero-coupon bond, $\rho_i = 0$, so a 1% price drop lifts the expected return by 1%. In typical equities, where $\rho_i > 0$ and $\psi_i > 0$, the pass-through is more muted: if it is 0.1 on an annual horizon, then a 1% price decline boosts expected returns by only 0.1%.[4]

While Proposition 1 clarifies the economic mechanisms behind counterfactual price changes, Proposition 2 is methodologically crucial, establishing that the pass-through from prices to expected returns must lie between 0 and 1. Hence, when prices rise (fall), expected returns should decrease (increase). A naive approach might simply reassign capital among investors, compute counterfactual returns from realized price changes, and compare these with actual returns. Yet if capital flows into value stocks, pushing up their prices, a purely mechanical calculation could mistakenly conclude that expected returns have gone *up*. In fact, Proposition 2 demonstrates that this is precisely when expected returns should go *down*.

By combining Propositions 1 and 2, we obtain a concise expression for how flows reshape

[4] To show this formally, one takes the conditional expectation of Equation (10), then differentiates with respect to $p_{i,t}$. Using Equation (11)—along with the assumption that an exogenous price change does not predict future dividends $\left(\frac{\partial \mathbb{E}_t[\,d_{i,t+1}\,]}{\partial \log p_{i,t}} = 0\right)$—yields the result stated in Proposition 2.

expected returns in equilibrium:

$$\Delta\mu_{i,t} \;\approx\; -\,\theta_i\, m_{i,t} \sum_j s_{i,j,t}\, \Delta a_{j,t}. \tag{13}$$

This expression is the real workhorse for our method. It pinpoints the key economic drivers—demand elasticities, ownership shares, the pass-through and the magnitude of capital shifts—and shows exactly how a single dollar of reallocation can cascade through to expected returns.

2.4 Application to Asset Pricing Anomalies

Below we describe how we apply our framework to study how reallocation of capital reshapes the alphas of well-known anomalies such as value and momentum. We illustrate the approach using two counterfactual experiments: (i) reallocating a fraction γ of growth fund AUM into value funds, and (ii) reallocating γ from households into value funds. Our goal is to see how these shifts in investor capital flow through to expected returns—and ultimately to alpha—within a single, coherent equilibrium.

2.4.1 Defining the Counterfactual Reallocation

We start by specifying how much capital moves, and from which investors. For the growth-to-value experiment, each growth fund j loses a fraction γ of its AUM, so

$$\Delta a_{j,t} = -\,\gamma, \quad \text{for growth funds } j. \tag{14}$$

That same capital is redistributed to value funds. Because growth and value funds may differ in total size, the inflow each value fund receives is scaled by $\frac{A_G}{A_V}$, where A_G and A_V are the aggregate AUMs of growth and value, respectively:

$$\Delta a_{j,t} = \gamma \frac{A_G}{A_V}, \quad \text{for value funds } j. \tag{15}$$

In the second scenario, we reallocate from households to value funds but still interpret γ as a fraction of *growth* fund capital. This means households lose $\gamma \frac{A_G}{A_{HH}}$ (where A_{HH} is total household wealth in stocks), and value funds each gain $\gamma \frac{A_G}{A_V}$. By construction, the magnitude of these shifts is comparable to the first experiment, but the source of outflows changes.

2.4.2 Calculating the Counterfactual Alphas

We next illustrate how to convert price changes into alpha for a generic long–short anomaly portfolio, denoted by P. Suppose this portfolio has two legs: a long leg L and a short leg S. Let $w_{i,L,t}$ and $w_{i,S,t}$ be the portfolio weights on stock i in these respective legs. Let θ_i^L and θ_i^S denote the pass-through parameters governing how a price change affects expected returns in each leg.[5]

Portfolio-Level Returns. Define the (gross) expected returns on the long and short legs as:

$$\mu_{L,t} = \sum_i w_{i,L,t}\, \mu_{i,t} \quad \text{and} \quad \mu_{S,t} = \sum_i w_{i,S,t}\, \mu_{i,t}. \tag{16}$$

Using Proposition 2, we can decompose the change in the long leg's expected return:

$$\begin{aligned} \Delta\mu_{L,t} &= \sum_i w_{i,L,t}\, \Delta\mu_{i,t} + \sum_i \Delta w_{i,L,t}\, \mu_{i,t} + \sum_i \Delta w_{i,L,t}\, \Delta\mu_{i,t} \\ &= \underbrace{-\sum_i w_{i,L,t}\, \theta_i^L\, \Delta p_{i,t}}_{\text{Direct Price-Change Effect}} + \underbrace{\sum_i \Delta w_{i,L,t}\, \mu_{i,t} - \sum_i \Delta w_{i,L,t}\, \theta_i^L\, \Delta p_{i,t}}_{\text{Indirect Weight-Adjustment Effect}}, \end{aligned} \tag{17}$$

[5] Different legs can, in principle, exhibit distinct price dynamics or persistence; hence, we allow for separate pass-throughs θ_i^L and θ_i^S. We will elaborate on this issue later, when we detail our empirical estimation of the pass-through parameters.

and an analogous expression holds for $\Delta\mu_{S,t}$. Note that because the counterfactual and observed portfolio weights both sum to one, we have $\sum_i \Delta w_{i,L,t} = 0$.

This condition helps explain why the indirect weight-adjustment effect remains small; it merely captures how rebalancing within the portfolio modifies expected returns. In Appendix C.2, we show that these terms contribute little to the overall change in $\mu_{L,t}$ or in the portfolio's alpha, so we safely ignore them in our main analysis.

Thus, the changes in these leg-level expected returns can be approximated via the price changes of portfolio stocks from Equation (12):

$$\Delta\mu_{L,t} \;\approx\; -\sum_i w_{i,L,t}\,\theta_i^L\,\Delta p_{i,t}, \quad \Delta\mu_{S,t} \;\approx\; -\sum_i w_{i,S,t}\,\theta_i^S\,\Delta p_{i,t}. \tag{18}$$

Hence, the counterfactual change in the long–short portfolio's expected return is:

$$\Delta\mu_{P,t} \;=\; \Delta\mu_{L,t} \;-\; \Delta\mu_{S,t} \;\approx\; -\sum_i \Big[\, w_{i,L,t}\,\theta_i^L \;-\; w_{i,S,t}\,\theta_i^S \,\Big]\Delta p_{i,t}. \tag{19}$$

Alpha Computation. Let $\mu_{M,t}$ be the expected return on the market, and assume the portfolio P has a constant beta β with respect to that market. We define the portfolio's alpha as

$$\alpha_{P,t} \;=\; \mu_{P,t} \;-\; \beta\,\mu_{M,t}. \tag{20}$$

Using Equation (19) alongside the analogous expression for $\Delta\mu_{M,t} \approx -\sum_i w_{i,M,t}\,\theta_i^M\,\Delta p_{i,t}$, it follows that

$$\Delta\alpha_{P,t} \;\approx\; -\sum_i w_{i,L,t}\,\theta_i^L\,\Delta p_{i,t} \;+\; \sum_i w_{i,S,t}\,\theta_i^S\,\Delta p_{i,t} \;+\; \beta\sum_i w_{i,M,t}\,\theta_i^M\,\Delta p_{i,t}. \tag{21}$$

Combining this with the approximate price change from Equation (9) yields a near-closed-

form formula for how capital flows $\Delta a_{j,t}$ reshape $\alpha_{P,t}$. Concretely,

$$\Delta\alpha_{P,t} \approx -\sum_i w_{i,L,t}\,\theta_i^L\,m_{i,t}\Big(\sum_j s_{i,j,t}\,\Delta a_{j,t}\Big) \;+\; \sum_i w_{i,S,t}\,\theta_i^S\,m_{i,t}\Big(\sum_j s_{i,j,t}\,\Delta a_{j,t}\Big) \\ +\; \beta\sum_i w_{i,M,t}\,\theta_i^M\,m_{i,t}\Big(\sum_j s_{i,j,t}\,\Delta a_{j,t}\Big). \tag{22}$$

This expression pinpoints all the key terms: the price multiplier $m_{i,t}$, the ownership shares $s_{i,j,t}$, the size of capital shifts $\Delta a_{j,t}$, the leg-specific pass-through θ_i^L or θ_i^S, the market pass-through θ_i^M, and the portfolio weights $w_{i,L,t}, w_{i,S,t}, w_{i,M,t}$. In essence, large inflows to the investors who hold a given asset (in either the long or short leg) will move its price and, correspondingly, the portfolio's alpha.

Equation (22) highlights how expected alphas in long–short anomaly portfolios respond to capital reallocations. If the source of capital (the investor type losing assets) heavily overlaps with the short leg's stocks, for instance, then those stocks may decline when the investor is forced to sell them — reducing the portfolio's overall future alpha. Conversely, reallocation from investors primarily holding the long leg reduces the price of those stocks and thereby boosts future expected returns (and alpha). This unified framework makes it transparent why who loses and who gains capital can materially alter an anomaly's profitability.

A further simplification arises because, in many practical settings, no single investor type holds a large portion of the entire market. As a result, the aggregate flow into or out of *all* market-weighted stocks tends to be small in percentage terms, so changes in the market portfolio's expected return are often negligible. For the anomalies we study, this means that while reallocations can meaningfully move individual legs of the portfolio (and thus its alpha), the overall market barely shifts.

Finally, our approach relies on estimating or calibrating only a small handful of parameters, chiefly: (i) investor elasticities, which determine the price multiplier $m_{i,t}$, (ii) the pass-through parameters θ_i (or θ_i^L and θ_i^S for the long and short legs), and (iii) the portfolio

beta β. Each of these is grounded in either known estimates (e.g., from existing demand-elasticity studies) or straightforward regressions (e.g., for the pass-through and portfolio beta). Consequently, the framework remains transparent and parsimonious, minimizing reliance on unobserved quantities and allowing researchers to plug in credible values from the literature.

2.4.3 Measuring "Capacity"

Our framework also lets us define the *capacity* of an anomaly: the amount of reallocated capital required to eliminate its alpha. Suppose we want to drive a portfolio's alpha from $\bar{\alpha}$ down to zero by shifting a total of C dollars from one investor group to another. Substituting $\Delta\alpha = -\bar{\alpha}$ and the corresponding $\Delta a_{j,t}$ terms into our alpha-change Equation (22) yields a closed-form solution for C. For instance, in a growth-to-value experiment, the capacity is:

$$C^* = \frac{\bar{\alpha}}{\sum_i \left(w_{i,P,t} - \beta\, w_{i,M,t}\right) \theta_i\, m_{i,t} \left(\sum_{j \in G} s_{i,j,t} \left(-\frac{1}{A_G}\right) + \sum_{j \in V} s_{i,j,t} \frac{1}{A_V} \right)}. \tag{23}$$

Overall, high capacity arises if the anomaly's alpha is large, investors have relatively elastic demand ($m_{i,t}$ is small), the pass-through is weak (θ_i is small), or if the relevant investor types do not own much of the stocks that drive the anomaly. Likewise, if the group being depleted (e.g., growth) heavily overlaps with the anomaly's short leg, smaller outflows can suffice to erode alpha. These formulas thus neatly capture how a strategy's "fragility" depends on both its baseline profitability and the structure of investor demand. See Appendix B.2 for the full derivation and parallel results for other reallocation scenarios.

3 Empirical Analyses

3.1 Data Description

Sample Construction. We obtain monthly stock prices and returns from the Center for Research in Security Prices (CRSP) for all common stocks (share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ between January 1981 and December 2019. Firm-level accounting variables, including book equity, come from Compustat. For mutual funds, we rely on the CRSP Survivor-Bias-Free Mutual Fund Database for characteristics such as expense ratios and turnover.

Mutual Fund Selection and Classification. Following Kacperczyk et al. (2008) and Evans (2010), we first screen the CRSP mutual fund data to identify domestic equity mutual funds, merging multiple share classes (CRSP_FUNDNO) into single-fund entities (WFICN) using the MFLINKS file from Wharton Research Data Services. We exclude funds that, on average, invest less than 80% of their assets in equity, as well as those whose total net assets remain below $15 million. To isolate actively managed equity funds, we remove index funds following the procedure of Dannhauser and Pontiff (2024), which identifies index-tracking portfolios by searching the CRSP fund names for key strings.[6]

We then merge these active funds with their Morningstar Direct style categories, narrowing our focus to nine widely studied Morningstar styles defined by size (small, mid, large) and style tilt (value, blend, growth). This classification scheme mirrors that in Han et al. (2021) and ensures consistency in style-based holdings analysis.

Other Investor Types. In addition to these nine Morningstar-based active mutual fund groups, we classify all remaining equity investors into one of several categories: index mutual funds, banks, insurance companies, investment advisors, pension funds, university

[6] An index fund is identified if its CRSP fund name contains "SP," "DOW," "Dow," "DJ," or if the name (in lowercase) contains any of the following: "index," "idx," "indx," "ind_," "composite," "russell," "s&p," "s and p," "s & p," "msci," "Bloomberg," "kbw," "nasdaq," "nyse," "stoxx," "ftse," "wilshire," "Morningstar," or numeric labels such as "100," "400," "500," "600," "900," "1000," "1500," "2000," "3000," or "5000."

endowments and foundations, or households. Appendix A details the classification procedure, closely following KY.

Holdings Data. We obtain the mutual fund holdings data from Thomson Reuters mutual fund holdings (s12 files), and use Thomson Reuters institutional holdings (s34 files) to capture other institutional investors. Note that the s34 files aggregate all mutual fund holdings at the family level, so to avoid double counting, we merge the s12 type5 files with s34 records, and exclude any duplicated mutual fund positions. We then follow KY by defining household holdings for a given stock as the remainder of shares outstanding once we subtract the combined holdings of all mutual funds and other institutional investors. Under this definition, smaller institutions (with AUM below $100 million and thus not required to file with the SEC) are commingled with households, as they are unobserved in the institutional holdings files.

3.2 Estimating Demand Elasticity

In our characteristic-based demand system, each investor's demand depends on market equity, firm characteristics, and a latent demand component. Following KY, we structurally estimate these demand curves by investor type. Specifically, we subdivide active mutual funds into nine Morningstar categories based on size (small, mid, large) and style tilt (value, blend, growth). For all other investor types—such as institutional investors, index mutual funds, and households—we aggregate their holdings within each broad category. We then estimate the demand coefficients for each of these pooled groups, allowing us to capture how different investor types respond to firm characteristics in their portfolio choices.

We estimate the demand curve separately for each investor group j using the following log formulation whenever $w_{i,j,t} > 0$:

$$\ln\left(\frac{w_{i,j,t}}{w_{j,t}(0)}\right) \;=\; \beta_{0,j,t} \;+\; \lambda_{j,t}\,\mathrm{me}_{j,t} \;+\; \sum_{k=1}^{K} X_{i,k,t}\,\beta_{k,j,t} \;+\; \ln\epsilon_{i,j,t}, \tag{24}$$

where $X_{i,k,t}$ represents stock characteristics including the log of book equity, profitability, investment, and beta.[7] The term $w_{j,t}(0)$ is the portfolio weight on the outside asset, defined as

$$w_{j,t}(0) \;=\; \tfrac{1}{1+\sum_n \delta_{n,j,t}}.$$

Following KY, we treat only stocks with non-missing values for these characteristics and returns as inside assets, further requiring that each inside asset's closing price exceed \$5 to limit the influence of micro-cap stocks.

Our primary focus is the parameter $\lambda_{j,t} = (1 - \eta_{j,t})$. Substituting $\lambda_{j,t}$ into Equation (7) gives the *aggregate elasticity* of stock i:

$$\eta_{i,t} \;=\; \sum_j s_{i,j,t}\,\big(1 - \lambda_{j,t}\big).$$

A central identification challenge, as highlighted by Koijen and Yogo (2019), is that observed asset prices are endogenous to investor demand, making them potentially correlated with the latent demand terms $\epsilon_{i,j,t}$. Consequently, OLS estimation of the demand curve would be inconsistent. We require an instrument that affects the price of stock j but is orthogonal to its unobserved characteristics driving $\epsilon_{i,j,t}$. Formally, we impose

$$\mathbb{E}\big[\ln \epsilon_{i,j,t} \,\big|\, \widehat{me}_{j,t},\, \mathbf{x}_{j,t}\big] \;=\; 0,$$

where $\widehat{me}_{j,t}$ is the instrument influencing stock j's price but not its latent demand.

To address the endogeneity between latent demand and prices, we follow Koijen and

[7] Book equity follows Fama and French (1993). Profitability is the ratio of operating profit to book equity. Investment is the annual log growth rate of assets. Beta is estimated by regressing the monthly excess return of the stock on the contemporaneous and lagged market excess return, as in Liu et al. (2018). We winsorize profitability and investment at the one-percent level to remove outliers. Unlike KY, we exclude dividend payout: over 60% of annual dividends (Compustat item *DVC*) in our sample are zero, and existing research (e.g., Fama and French (2015), Hou et al. (2015)) finds little evidence that dividend yield adds explanatory power once other characteristics, such as book-to-market, are included.

Yogo (2019) and exploit exogenous variation in investors' investment mandates as a source of exogenous demand shifts. The exclusion condition holds because these mandates are typically exogenous to the stock's unobserved characteristics, while the relevance condition holds because a stock's price tends to be higher when it is included in more investors' mandates.

Concretely, for investor i, we construct the instrument for $\text{me}_{j,t}$ as:

$$\widehat{\text{me}}_{j,t} = \log\Big(\sum_{j \neq i} A_i \frac{\mathbb{1}_{i,j}}{1 + \sum_{m=1}^{N} \mathbb{1}_{m,j}}\Big),$$

where A_i is investor i's AUM, and $\mathbb{1}_{i,j}$ is an indicator equal to 1 if stock j lies within i's investment universe. Following Koijen and Yogo (2019), we define the investment universe as the set of stocks that the investor currently holds or has ever held in the past eleven quarters.

3.3 Estimating Key Parameters

We begin by estimating the key parameters of the value portfolio. We construct decile portfolios based on firms' book-to-market (B/M) ratios at the end of each June, following the standard methodology in Fama and French (1992). We then compute the annual returns on each decile over the subsequent year. To estimate the market beta and alpha, we run the following regression annually for each decile:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\big(R_{m,t} - R_{f,t}\big) + \varepsilon_{i,t}, \tag{25}$$

where $R_{i,t}$ is the decile portfolio's return, $R_{f,t}$ is the risk-free rate, and $R_{m,t}$ is the market return. The estimated intercept α_i is the alpha, while β_i is the market beta.

Panel A of Table 1 summarizes the average annual return, alpha, and beta for each B/M decile. We see a return spread of approximately 4.8% per year between the highest

(value) and lowest (growth) B/M portfolios. The difference in alpha—roughly 5.6% for the high-minus-low (H–L) strategy—reflects the somewhat higher market beta for growth stocks compared to value stocks. Thus, as in much of the literature, a classic "value premium" emerges, even when adjusting for standard market risk.

We next outline how we estimate the parameters ρ_m (the price-to-price-plus-dividend ratio), ψ_m (the persistence of price changes), and the pass-through θ_m for each portfolio m. We sort stocks into portfolios by book-to-market deciles, then treat ρ_m and ψ_m as common to all stocks within portfolio m. We first define

$$\rho_m \;=\; \frac{\overline{P}_m}{\overline{P}_m + \overline{D}_m},$$

where $\overline{P}_m$ and $\overline{D}_m$ are the average price and dividend for portfolio m. Intuitively, higher ρ_m implies that dividends constitute a smaller fraction of the portfolio's overall value, making its expected returns more sensitive to price changes.

To estimate the persistence of price changes, ψ_m, we run the following annual time-series regression for each portfolio m:

$$p_{m,t} - p_{m,t-1} \;=\; a \;+\; b_0\big(p_{m,t-1} - p_{m,t-2}\big) \;+\; b_1\big(p_{m,t-1} - b_{m,t-1}\big) \;+\; \sum_{k=2}^{K} b_k X_{m,k,t-1} \;+\; \nu_{m,t}. \quad (26)$$

Here, $p_{m,t}$ denotes the log price (excluding dividends), $b_{m,t-1}$ is the log book value, and $X_{m,k,t-1}$ is a set of additional controls - investment-to-asset ratio, profitability, and market beta – consistent with the variables used in our demand-curve estimations. We then set $\psi_m = 1 + b_0 + b_1$, so that larger b_0 and b_1 imply greater persistence of price shocks.

Finally, combining ρ_m and ψ_m gives us the pass-through parameter, $\theta_m = 1 \;-\; \rho_m\,\psi_m$. A smaller θ_m means that even a sizable price move leads to only a modest shift in the portfolio's future returns.

Panel B of Table 1 reports these parameters for our portfolios. The annual autoregressive

coefficients (ψ_m) hover around 0.8, indicating a slow decay of price shocks. The average dividend-price ratio ($\overline{DP}_m$) translates into $\rho_m = 1/\big(1 + \overline{DP}_m\big)$. As expected, ρ_m decreases when $\overline{DP}_m$ is larger, showing that higher dividends dampen the effect of price changes on expected returns. Finally, the implied pass-through, $1 - \rho_m\psi_m$, ranges from roughly 0.18 to 0.35, aligning closely with the 0.16 reported by Davis et al. (2024) and demonstrating the robustness of our estimates across methodologies.

We next examine momentum portfolios, constructed following the standard Jegadeesh and Titman (1993) approach: we sort stocks by their past returns (e.g., over 12 months) and invest in the top decile (*winners*) while shorting the bottom decile (*losers*). Table 2 summarizes their annualized returns, alphas, and market betas.

In Panel A we report a momentum premium of approximately 13.6% per year. The short-leg (losers) has a higher beta of 1.63 compared to the long-leg (winners) at 1.21, creating a 0.42 difference in market exposure. This beta gap partly explains the strategy's relatively large alpha, since losers are more sensitive to overall market fluctuations.

Panel B reports the parameters used to compute the pass-through from price changes into expected returns, namely ψ, $\overline{DP}$, and ρ. Notably, momentum portfolios display a higher pass-through—spanning 0.3 to 0.5—than their book-to-market counterparts. One key reason is the lower annual persistence of returns for extreme momentum deciles, often below 0.7, which makes price changes translate more directly into shifts in expected returns. In contrast, many book-to-market portfolios exhibit higher persistence (above 0.7), resulting in more muted pass-through. These findings highlight that momentum's dynamics differ substantially from value's, suggesting the two anomalies will respond differently to capital reallocation.

3.4 Growth-to-Value Reallocation

Investors routinely move capital between growth- and value-oriented funds, making "growth-to-value" reallocations a realistic channel for examining how style-based flows can impact asset prices. In practice, Morningstar classifications help us (and investors) distinguish growth and value funds: growth funds are typically those seeking high-expected-growth stocks (often with low or zero dividends), whereas value funds focus on "cheap" stocks with higher book-to-market ratios or richer dividend yields. This distinction not only shapes the holdings profiles of each fund type but also means that when investors rotate from growth to value funds, they can plausibly exert price pressure on the underlying stocks in a predictable, style-linked manner.

Figure 1 illustrates this alignment by plotting time-series of holdings-value-weighted book-to-market (B/M) ratios for Morningstar-style funds. Across small, mid, and large size categories, funds labeled as value indeed hold portfolios with higher B/M ratios compared to their growth counterparts, confirming the strong link between Morningstar classifications and conventional value metrics. Interestingly, this pattern remains stable despite the existence of alternative "value" definitions (e.g., earnings-to-price or sales-to-price). In other words, whether a fund is labeled "value" or "growth" in Morningstar strongly correlates with the actual B/M ratio of the stocks it holds—making it a natural setting to study how growth-to-value reallocations might reprice a classic anomaly like the value premium.

Although growth funds predominantly hold growth-oriented stocks and value funds largely emphasize high book-to-market shares, these categories are not perfectly disjoint. In our data, value funds hold a modest 4.43% of top-decile (value) stocks and 1.03% of bottom-decile (growth) stocks, while growth funds hold 5.54% of the bottom-decile and 1.48% of the top-decile. This partial overlap implies that even in a "growth-to-value" capital shift, value stocks may see some outflows from the growth funds that hold them, and growth stocks may receive inflows from value funds. Our stock-level demand framework naturally accom-

modates these crisscross flows, as each reallocation scenario tracks ownership down to the individual stock. Consequently, no artificial assumption of perfectly segregated style boxes is required: we simply let the data's observed holdings guide how inflows and outflows net out at the stock level.

Beyond the direct implications for value stocks, our framework also highlights the potential *cross-anomaly* impact of growth-to-value reallocations on momentum. Figure 2 reveals that growth funds (dashed lines) tend to hold recent winner stocks, while value funds (solid lines) favor recent loser stocks. Since the momentum anomaly hinges on going long winners and short losers, an inflow that boosts value funds' capital can reduce expected returns for those losers (value stocks) but simultaneously increase expected returns for momentum's winner leg (growth stocks). Thus, style-based shifts not only reshape returns in the targeted anomaly (value) but also reverberate through other anomalies (momentum) via overlapping holdings and correlated exposures.[8]

3.4.1 Effects on Stock Prices

Cross-Sectional Perspective. Below we present two sets of figures—first for portfolios sorted by book-to-market (B/M), then for portfolios sorted by momentum—that visualize how our approximation for price changes compares with a "full repricing" solution from the Koijen-Yogo demand system under varying degrees of capital reallocation.

Figure 3 shows the results for book-to-market portfolios. In the top panel, we show the full equilibrium repricing when a fraction of AUM (from 10% up to 100%) is shifted from growth to value funds of the same size category (e.g., small-growth to small-value). This ensures that the reallocation reflects a preference shift towards value without altering size preferences. The horizontal axis lists the B/M deciles, with growth stocks on the left (lower B/M) and value stocks on the right (higher B/M). As more capital flows to value, growth

[8] In our sample, the correlation between the top-minus-bottom decile value and momentum portfolios is -0.203.

stocks depreciate while value stocks appreciate, producing a smooth, concave pattern of price changes across deciles. When the reallocation reaches 100%—a large and arguably extreme scenario—the top decile value portfolios gain around 9%, whereas the bottom decile growth portfolios lose about 10%.

The bottom panel depicts our approximate repricing, which tracks the fully solved model quite closely. For instance, high-B/M deciles appreciate by almost the same magnitude as in the full repricing, and low-B/M deciles depreciate in a similarly concave manner. The minimal gap between the two lines across most deciles underscores both the accuracy and robustness of our simplified formula. Even in the largest reallocation scenarios (e.g., 100% of growth assets to value), the discrepancy between the approximate and the full approach remains small—on the order of one to two percentage points in some deciles.

Turning to portfolios sorted by momentum deciles in Figure 4, the top panel shows the full Koijen-Yogo repricing under the same growth-to-value reallocation. Now, because winners often overlap with growth stocks, additional capital flowing to value funds tends to drive down winner-stock prices while boosting some of the loser deciles. This creates a pronounced negative slope in the right-hand part of the figure: winners depreciate by as much as 12-13%, while losers appreciate by a less than 1%, crossing around the midpoint (deciles 7–8) where the net effect is near zero.

As in the B/M case, the bottom panel compares our approximate solution, and once again, the overall shape tracks closely with the full repricing curve: winners experience a significant price drop, while losers post more modest gains. For instance, in the highest-momentum decile, our approximation suggests a roughly -10% price impact, whereas the first decile's increase comes in at about +1.8%. The close alignment between the two curves reaffirms that our simpler approximation captures the main variation in price changes, even for momentum-sorted portfolios. In practice, researchers can apply our direct formula for large-scale reallocation experiments, confident they are sacrificing little accuracy relative to a fully solved equilibrium solution.

Time-Series Perspective. We now pivot from average cross-sectional results to a quarter-by-quarter view of how growth-to-value reallocations—ranging in size from 10% to 100% of growth fund assets—affect the difference in price impacts between the highest and lowest B/M deciles. As shown in the top panel of Figure 5, this difference can exceed 50% when we consider a 100% reallocation during the dot-com bubble of the late 1990s and early 2000s. In that era, surging inflows into growth funds inflated their valuations, so redirecting that capital exerts substantial price pressure on both "overweighted" growth stocks and the newly favored value stocks. Even in the mid-1990s—though less extreme than the tech mania—heavy flows into high-flying growth names still produce a smaller but significant gap in repricing.

From an economic standpoint, these wide swings reflect the underlying determinants in our approximation. First, ownership fractions $s_{i,j,t}$ can vary significantly over time, magnifying or dampening the "direct effect" of a reallocation. For instance, when growth funds hold a larger overall share of the market (as they did around 2000), a shock to their AUM produces a bigger ripple. Second, demand elasticities $\eta_{j,t}$ may shift cyclically as investor sentiment and liquidity conditions evolve, altering the price multiplier $m_{i,t} = 1/\eta_{i,t}$. Periods of exuberance for growth stocks can make the market less elastic in those segments, so a reallocation away from them has outsized repercussions.

Finally, while these flows are hypothetical, the bottom panel shows our simplified approximation remains highly accurate relative to the full Koijen-Yogo repricing—even in historically volatile eras. In other words, the same core mechanics (ownership fractions, demand elasticities, and dividend-pass-through parameters) drive price changes consistently over time, allowing our method to capture large swings in investor behavior without losing predictive power.

Turning to momentum, Figure 6 presents the quarterly evolution of the repricing gap between "winner" and "loser" portfolios, using the same 10% to 100% reallocation scenarios from Growth to Value funds. Panel (a) reflects the fully solved demand system, while

Panel (b) applies our approximation. In both panels, larger reallocations typically deepen the price discount for "winner" stocks relative to "losers," especially around periods of market turbulence (e.g., mid-1990s, early 2000s). Despite these more pronounced swings, the approximate solution closely tracks the fully solved system's time-varying path, suggesting that even for momentum portfolios—often overlapping with growth—our near-closed-form approach captures the key repricing dynamics.

Regression-Based Validation of Our Approximation. We now compare our approximate price changes to the fully solved Koijen-Yogo (KY) solution. In Table 3, we regress the full price change on our approximation, including time fixed effects. The table is divided into three panels that examine reallocation effects at different levels of aggregation—individual stocks (Panel A), book-to-market deciles (Panel B), and momentum deciles (Panel C)—under two scenarios: shifting capital from growth to value funds, and shifting from households to value funds (the latter scenario will be discussed in depth later).

Across all panels, the approximation explains the bulk of the variation in the KY-based "full" repricing. Even at the stock level (Panel A), where idiosyncratic factors could dominate, the R^2 values remain above 0.88 for the growth-to-value scenario and nearly 0.95 for the households-to-value case. For style-sorted portfolios—book-to-market (Panel B) and momentum (Panel C)—the fit is even stronger, often exceeding 0.97. Moreover, in most panels, the coefficient on the approximated price change lies close to 1.0, indicating a near one-to-one relationship with the fully solved model. Although some estimates (e.g., 1.283 in Panel C for the growth-to-value scenario) exceed unity slightly, these deviations are modest, suggesting our approach may mildly amplify the effect but does not distort the overall price impact.

Overall, these regressions confirm that our approximation offers a remarkably accurate yet transparent way to assess counterfactual price movements, without incurring the computational demands of solving the complete KY system. Whether we look at individual stocks

or at style portfolios—value or momentum—the simplified method reliably captures both the direction and scale of large capital reallocations on equilibrium prices.

3.4.2 Effects on Expected Returns

Strategy Performance. We next focus on the effects of reallocations on expected returns. Table 4 reports how hypothetical reallocations of capital from growth to value funds—ranging from 10% to a full 100%—affect annual expected returns for two strategies: value (H–L in book-to-market) and momentum (H–L in past returns). In the value strategy, H corresponds to high-B/M (value) stocks (top decile) and L corresponds to low-B/M (growth) stocks (bottom decile); in the momentum strategy, H is recent winners and L is recent losers.

Focusing first on the value strategy (left columns), we see that as reallocation scales from 10% to 100%, the H–L expected return (i.e., the value premium) decreases from about 4.33% to nearly 0.01%. Meanwhile, the H–L alpha falls from just above 5% to below 1%. These declines mirror our earlier price-impact findings: when capital floods high-B/M stocks, their prices rise and subsequent returns diminish, eroding the value premium. Furthermore, $\beta_{H-L} \approx 0$ and $R^{Mkt,CF} \approx R^{Mkt}$ imply that the decline in α closely matches the deline in the value premium, indicating no major offset by the broader market.[9]

Turning to the momentum strategy (right columns), the H–L spread and alpha *increase* with the growth-to-value flow. As we move from 10% to 100% reallocation, the expected-return difference grows from roughly 14% to over 18%, while momentum's alpha rises from about 17% to above 21%. This pattern stems from the strong overlap of growth stocks with winners: when growth funds lose capital, winner stocks lose demand, whereas momentum losers (often overlapping with value) receive inflows. As before, the lack of a net market effect is evident, since the difference between α^{CF} and $E\left[R^{H-L,CF}\right]$ remains constant, implying

[9] The fourth column reports $\alpha^{CF} = E\left[R^{H-L,CF}\right] - \beta_{H-L} E\left[R^{Mkt,CF}\right]$. Since the annual equity premium is roughly 8 percentage points in our sample, the difference between the fourth and the third columns is given by $\beta_{H-L} E\left[R^{Mkt,CF}\right] \approx -0.1 \times 8 = 0.8$, and it remains constant across our reallocations.

negligible repricing for the overall market.

Overall, these results indicate that large style-based reallocations substantially reduce the value premium yet amplify the momentum premium. At the 100% level, the value anomaly's alpha nearly vanishes, while momentum's alpha surpasses 21%. From a broader perspective, such flows can profoundly reshape anomalies, even as the market as a whole remains relatively unaffected.

Capacity. We can apply Equation (23) to calculate the amount of capital needed to erase the alpha of the value strategy. Panel (a) of Figure 7 shows that, in recent years, this figure has approached $1 trillion—often exceeding 100% of growth funds' total AUM. In certain years, the required reallocation was nearly on par with the combined assets of all nine Morningstar style categories.

How realistic is such a massive reallocation? To put this scenario into context, Panel (b) compares the time series of actual quarterly flows into value and growth mutual funds against the ratio of our "capacity" metric to each style's AUM. While observed flows typically range between 2% and 6% of fund AUM, the capacity metric for eliminating the value premium can reach 100%–200%, placing it well beyond typical historical reallocations. This result aligns with Li et al. (2024), who demonstrate that realized flows account for only a modest share of the variation in anomaly returns.

Our results show that, although the capacity constraint is finite in principle, it remains well above the scale of flows typically observed in the market. Even if the value premium partly reflects genuine risk, a sufficiently large shift in investor demand—driven by changes in risk preferences—could theoretically compress it. In practice, however, frictions like institutional mandates, diversification requirements, and investor inertia make such major, coordinated reallocations exceedingly rare. Thus, value remains robust not because it is categorically immune to flows, but simply because the volume of capital needed to erase its alpha—regardless of whether that alpha is risk-based or mispricing-driven—rarely material-

izes under real-world conditions.

3.5 Households-to-Value Reallocation

In this section, we explore a different set of reallocations shifting capital from households to value funds. Households represent a sizeable yet distinct source of equity capital, often holding stocks across the style spectrum rather than concentrating in a particular niche such as "growth" or "value." This makes a potential shift of household money into value funds a substantially different scenario than the growth-to-value reallocation. In particular, the household investor base may include both growth and value stocks in their holdings, implying that reallocated dollars come not just from "pure" growth assets but from a wider cross-section of the market. Examining a "households-to-value" flow therefore sheds light on how the origin of capital can drive heterogeneous effects on expected returns—and whether the same value- or momentum-related patterns emerge when the inflows are drawn from more broadly held positions.

3.5.1 Effects on Prices

Figure 8 illustrates how reallocations from households to value funds affect prices for decile portfolios sorted by book-to-market (top panel) and past returns (bottom panel). To compare with the earlier growth-to-value scenario, we define a "10% reallocation" as taking household capital equal to 10% of growth funds' total AUM and transferring it to value funds, scaling up to a full 100% shift.

In the book-to-market panel (top), decile 10 (high B/M) still registers a notable appreciation of roughly 5–6% under the 100% reallocation—similar to the rise observed when capital flowed from growth. Mid-range deciles (6–8) see an even larger boost of about 3–4%, while deciles 1–2 (low B/M) remain near zero or post small positive changes. This stands in contrast to the growth-to-value case, where low-B/M (growth) portfolios dipped more markedly.

The key difference is that households hold a broader mix of stocks, so capital outflows draw from a more diverse set of holdings rather than specifically targeting "growth." As a result, high-B/M stocks are still favored by the inflow, but traditional "growth" segments experience less direct selling pressure. This highlights that who loses assets can be just as important as where they ultimately end up when style-based flows reshape the cross-section of prices.

Turning to the momentum panel (bottom), we see a similar pattern of less concentrated selling in the winner portfolios. Losers (often overlapping with high B/M) still benefit from added demand, climbing by around 2–3%—a slightly higher gain than before. Meanwhile, winners face only modest depreciation, or even remain flat for smaller reallocation fractions. This much weaker effect reflects the absence of a purely "winner-heavy" outflow: because households are more diversified, the outflow is not squarely pinned to stocks classified as momentum winners. Consequently, the cross-capacity impact on momentum is noticeably weaker than when growth funds lost capital.

3.5.2 Effects on Expected Returns

Table 4 shows how reallocating capital from households to value funds—scaled from 10% to 100% of what growth funds hold —affects annual expected returns. Focusing on the value strategy (left columns), a full 100% reallocation reduces the H–L expected return to about 1.82%, considerably less of a drop than the 0.01% observed in the growth-to-value case. Likewise, the alpha falls from roughly 5% to around 2.6%, rather than approaching zero. This more moderate erosion is consistent with the evidence from price changes. Because households do not predominantly hold growth stocks, while some household-owned growth assets are sold, many other types of holdings are reduced as well. As a result, the decline in H-L expected return and alpha is comparatively weaker.

On the momentum strategy side (right columns), the H–L spread and alpha rise only marginally. For instance, under a 100% reallocation, momentum's expected return differen-

tial reaches about 14%, lifting its alpha from about 17% to around 17.4%. This increment is negligible in comparison to the 4–5% jump observed in the growth-to-value scenario, reflecting the fact that the outflow is not concentrated among momentum winners. As a result, the overall cross-capacity effect on momentum is diminished relative to the more "winner-heavy" growth-fund outflows.

In summary, large inflows into value from households still curtail the value premium and slightly boost momentum, but the magnitude of these changes is more muted than when growth-fund assets are the source. This illustrates that the origin of capital, not just its volume, plays a critical role in determining how style-based flows reshape returns across different anomalies.

4 Conclusions

Our analysis highlights how a generalized, equilibrium-based methodology can systematically track investor demand shifts and "rewrite" the return landscape. By clarifying exactly how capital flows—both modest and large—redistribute ownership and re-price stocks, this framework goes beyond local or partial regressions, offering a transparent way to simulate capital reallocations.

To illustrate this potential, we focused on two canonical anomalies—value and momentum—demonstrating how major reallocations between growth funds and value funds can nearly eliminate the value premium while boosting momentum, whereas flows from a more diffuse source (households) have milder effects. This exercise shows that an anomaly's apparent "capacity" depends crucially on whether its long or short leg overlaps with the investors losing assets. Yet the equilibrium lens we propose can easily be applied to other settings. Future studies might explore how hedge funds, pension plans, or sovereign wealth funds reshuffle capital across various equity or even multi-asset markets—offering deeper insight into how newer "hot" anomalies can emerge and older ones might wither under sustained

trading pressure.

From a broader standpoint, these results hold valuable lessons for policy and regulatory discussions. If large-scale style shifts are triggered by, for instance, changes in retirement allocations or new household saving patterns, regulators and industry practitioners may benefit from scenario analyses that anticipate potential "style shocks." Our framework provides exactly that—a practical blueprint for stress-testing how diverse flow sources could propagate through the cross-section of prices. By better understanding investor-level shifts, both policymakers and asset managers can navigate the complex interplay of flows, prices, and strategic responses with greater confidence.

References

Asness, Clifford S., 1994, *Variables That Explain Stock Returns*, Ph.D. thesis, University of Chicago, Ph.D. Dissertation.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Campbell, John Y., and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *The Review of Financial Studies* 1, 195–228.

Cochrane, John H., 2008, The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21, 1533–1575.

Coval, Joshua D., and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Dannhauser, Caitlin D, and Jeffrey Pontiff, 2024, Flow, *Available at SSRN 3428702* .

Davis, Carter, 2024, Elasticity of quantitative investment, *Review of Financial Studies, Forthcoming* .

Davis, Carter, Mahyar Kargar, and Jiacui Li, 2024, Why is stock-level demand inelastic? a portfolio choice approach.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *The Journal of Finance* 67, 933–971.

Evans, Richard B, 2010, Mutual fund incubation, *Journal of Finance* 65, 1581–1611.

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

Fama, E.F., and K.R. French, 2015, A five-factor asset pricing model 116, 1–22.

Fama, Eugene F, and Kenneth R French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427–465.

Haddad, Valentin, Paul Huebner, and Erik Loualiche, 2025, How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing, *American Economic Review* Forthcoming.

Han, Xiao, Nikolai L Roussanov, and Hongxun Ruan, 2021, Mutual fund risk shifting and risk anomalies, *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper* .

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *The Review of Financial Studies* 28, 650–705.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *The Review of Financial Studies* 21, 2379–2416.

Koijen, Ralph S. J., and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Koijen, Ralph SJ, Robert J Richmond, and Motohiro Yogo, 2023, Which investors matter for equity valuations and expected returns?, *Review of Economic Studies* 1–38.

Li, Yizhang, Stanislav Sokolinski, and Andrea Tamoni, 2024, Which investors drive anomaly returns and how?, *SSRN Electronic Journal* .

Liu, Jianan, Robert F Stambaugh, and Yu Yuan, 2018, Absolving beta of volatility's effects, *Journal of Financial Economics* 128, 1–15.

Lou, Dong, 2012, A flow-based explanation for return predictability, *The Review of Financial Studies* 25, 3457–3489.

Pavlova, Anna, and Taisiya Sikorskaya, 2023, Benchmarking intensity, *The Review of Financial Studies* 36, 859–903.

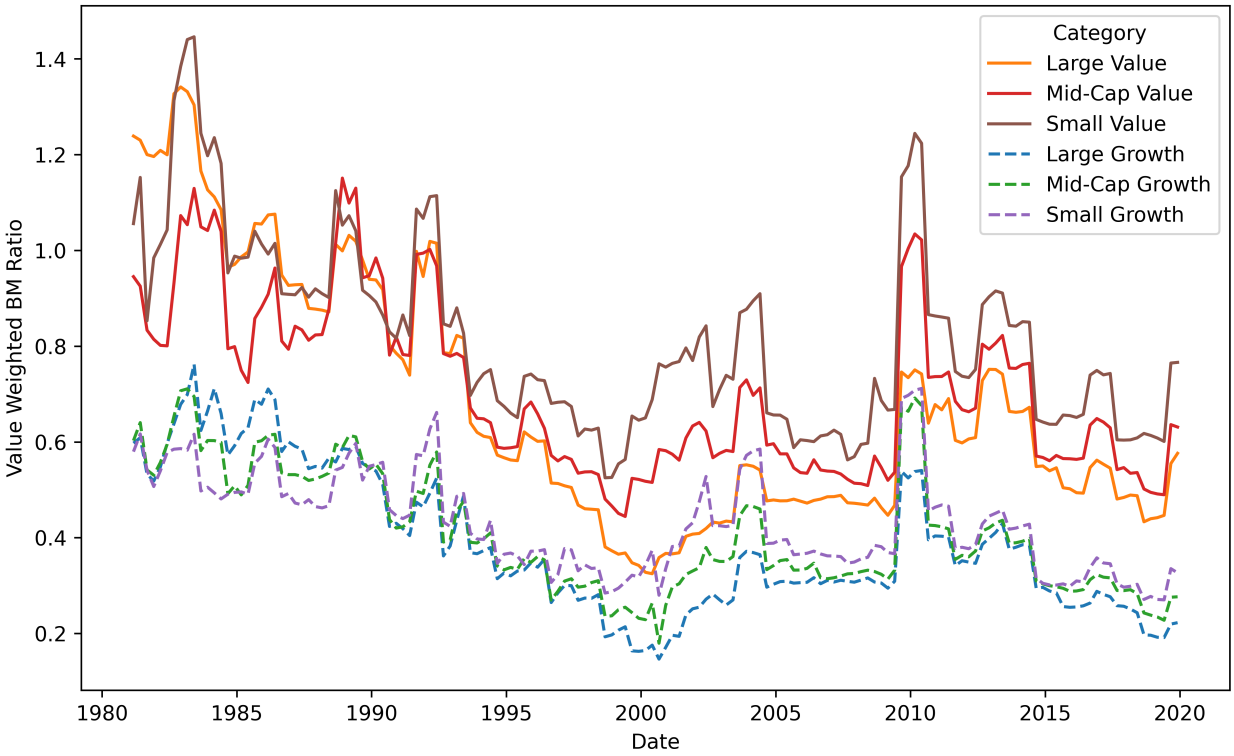
van Binsbergen, Jules H., and Ralph S.J. Koijen, 2010, Predictive regressions: A present-value approach, *The Journal of Finance* 65, 1439–1471.

Wardlaw, Malcolm, 2020, Measuring mutual fund flow pressure as shock to stock returns, *The Journal of Finance* 75, 3221–3243.

Watson, Towers, 2015, The world's 300 largest pension funds: Year end 2014.

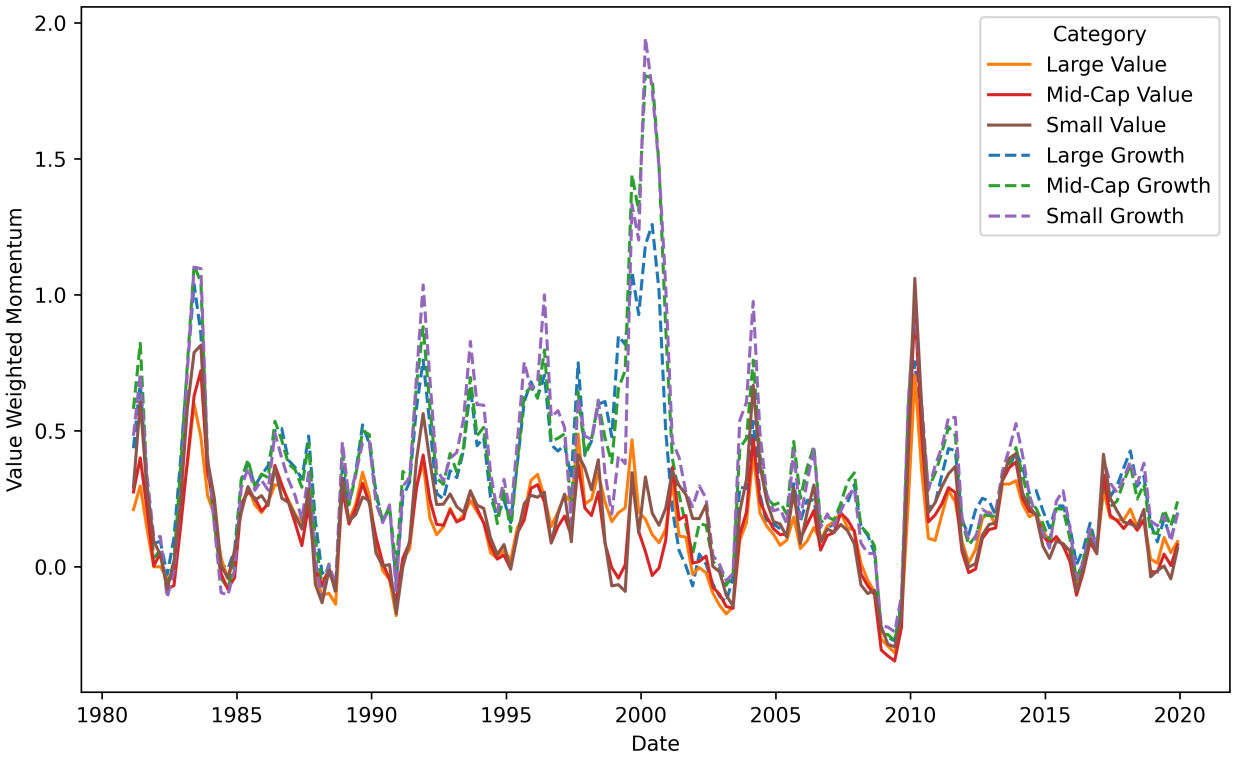
Tables and Figures

Figure 1: Time-Series of Book-to-Market Ratios by Style and Size



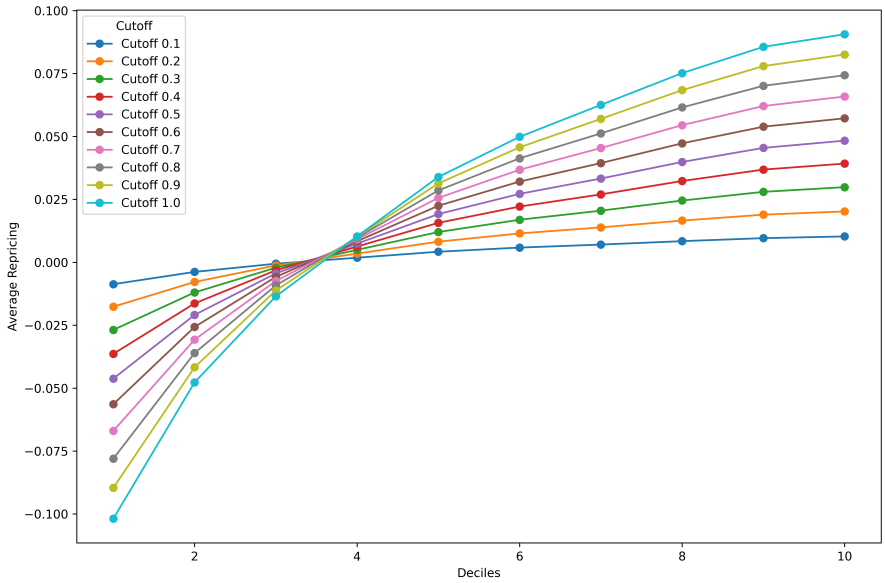
This figure presents the time series of holdings-weighted average book-to-market ratios for six categories of mutual funds: Small-Value, Mid-Cap-Value, Large-Value, Small-Growth, Mid-Cap-Growth, and Large-Growth. The weights are based on each fund's portfolio holdings, reflecting how size (small vs. large) and style (value vs. growth) jointly determine the average B/M ratio in each group over time.

Figure 2: Time-Series of Holdings-Weighted Momentum Scores by Style and Size

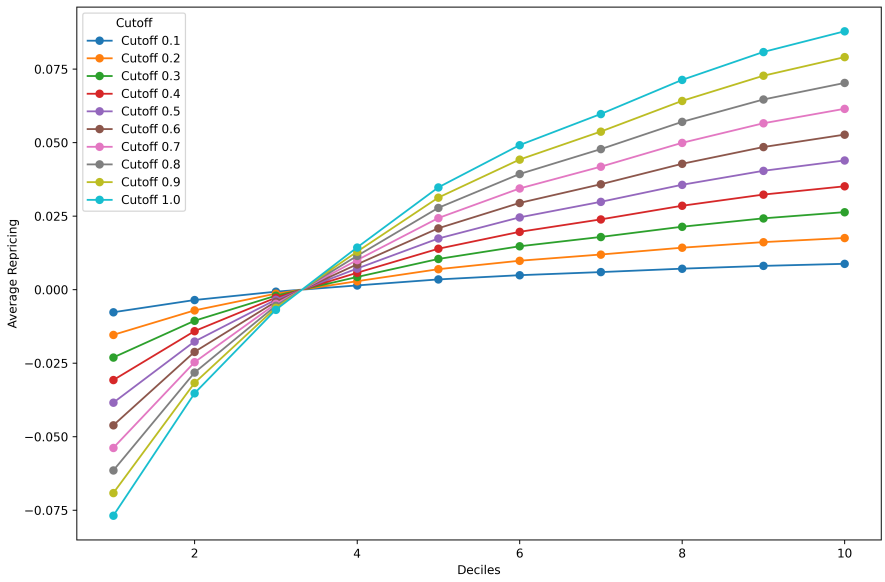


This figure displays the time-series of holdings-weighted average momentum (cumulative returns over the past 12 to two months) for six groups of funds: Small-Value, Mid-Cap-Value, Large-Value, Small-Growth, Mid-Cap-Growth, and Large-Growth. The weights are computed based on each fund's portfolio holdings, illustrating how size and style classifications affect the average momentum profiles.

Figure 3: Average Repricing by Book-to-Market Deciles Under Growth-to-Value Reallocations



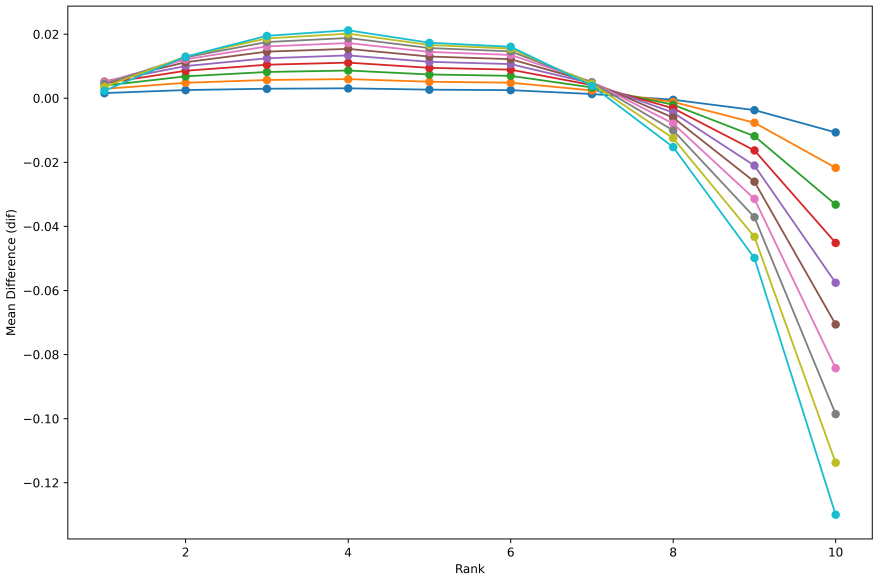
(a) Full Repricing



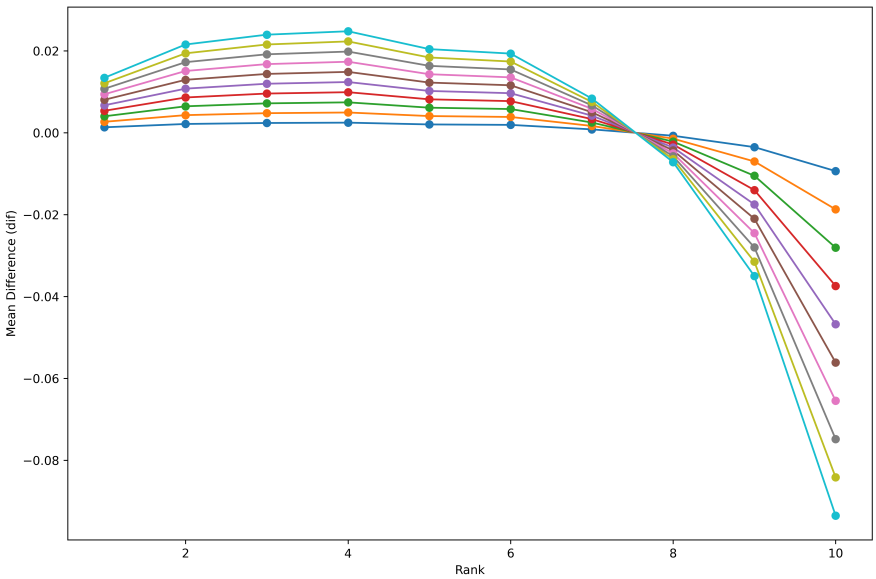
(b) Approximation

This figure presents average repricing statistics for decile portfolios sorted by book-to-market ratio. Repricing is defined as the value-weighted mean log difference between each portfolio's counterfactual and actual stock prices. The panels depict varying reallocations of Growth funds' AUM to Value funds (N = 10% to 100%). Panel (a) shows results from the fully solved demand system, while Panel (b) applies our approximation. The sample spans 1981–2019.

Figure 4: Average Repricing by Momentum Deciles Under Growth-to-Value Reallocations



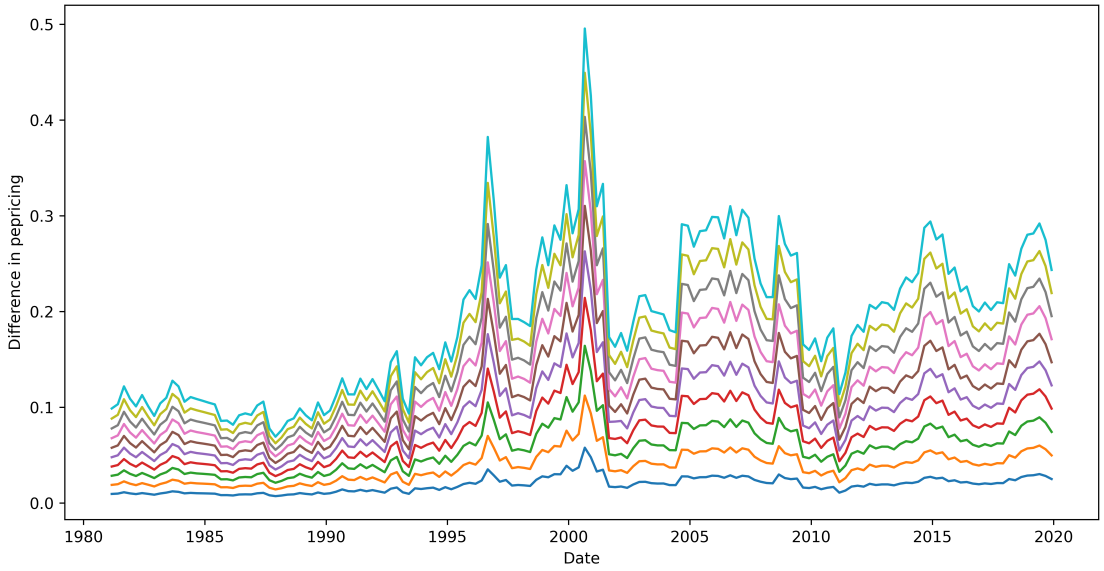
(a) Full Repricing



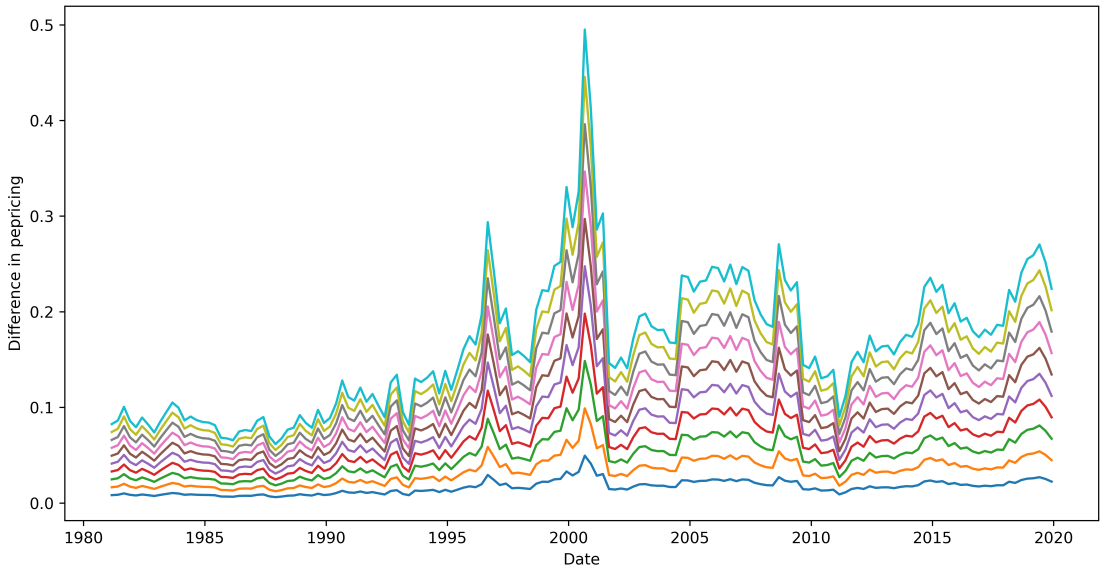
(b) Approximation

This figure presents average repricing statistics for decile portfolios sorted by a momentum variable (cumulative returns over the past 12 to two months). Repricing is defined as the value-weighted mean log difference between each portfolio's counterfactual and actual stock prices. The panels depict varying reallocations of Growth funds' AUM to Value funds (N = 10% to 100%). Panel (a) shows results from the fully solved demand system, while Panel (b) applies our approximation. The sample spans 1981–2019.

Figure 5: Time-Varying Repricing Difference for High vs. Low Book-to-Market Portfolios



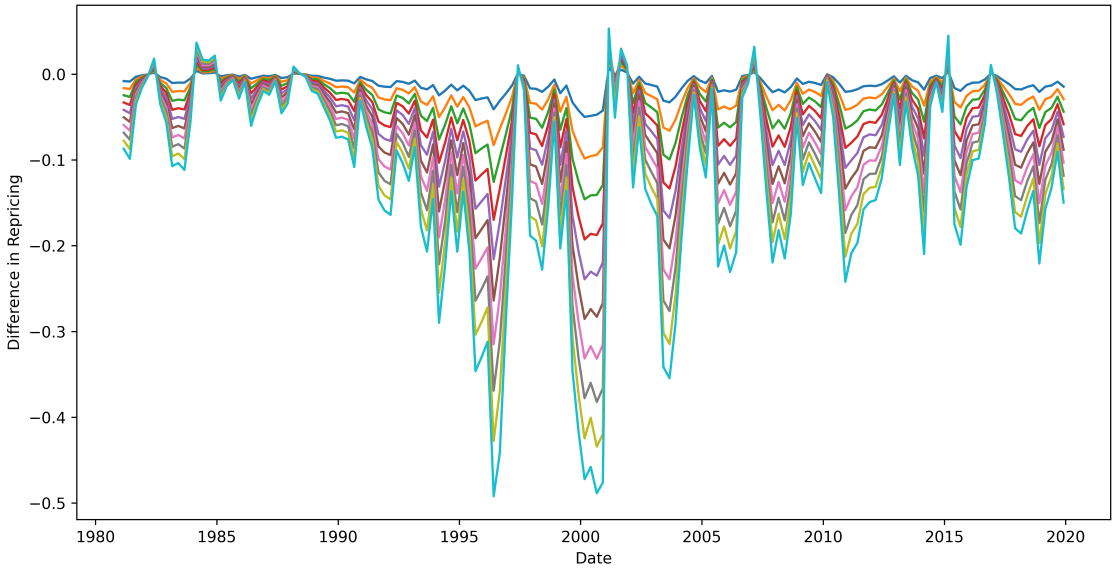
(a) Full Repricing



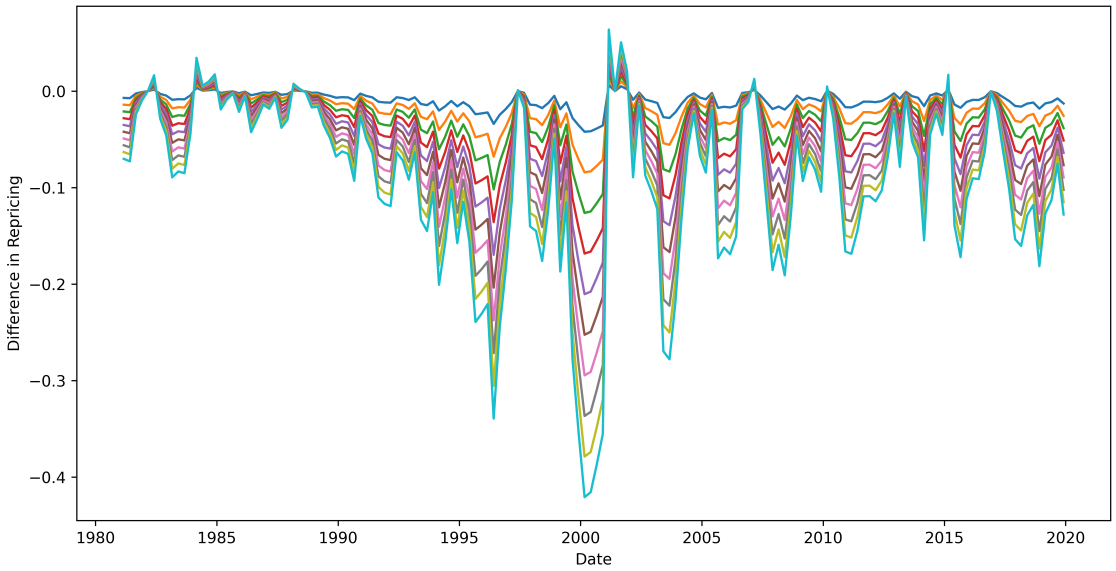
(b) Approximation

This figure shows the quarterly evolution of the repricing difference between the top and bottom book-to-market portfolios. Repricing is defined as the value-weighted mean log difference between each portfolio's counterfactual and actual stock prices. The panels depict varying reallocations of Growth funds' AUM to Value funds (N = 10% to 100%). Panel (a) shows results from the fully solved demand system, while Panel (b) applies our approximation. The sample spans 1981–2019.

Figure 6: Time-Varying Repricing Difference for High vs. Low Momentum Portfolios



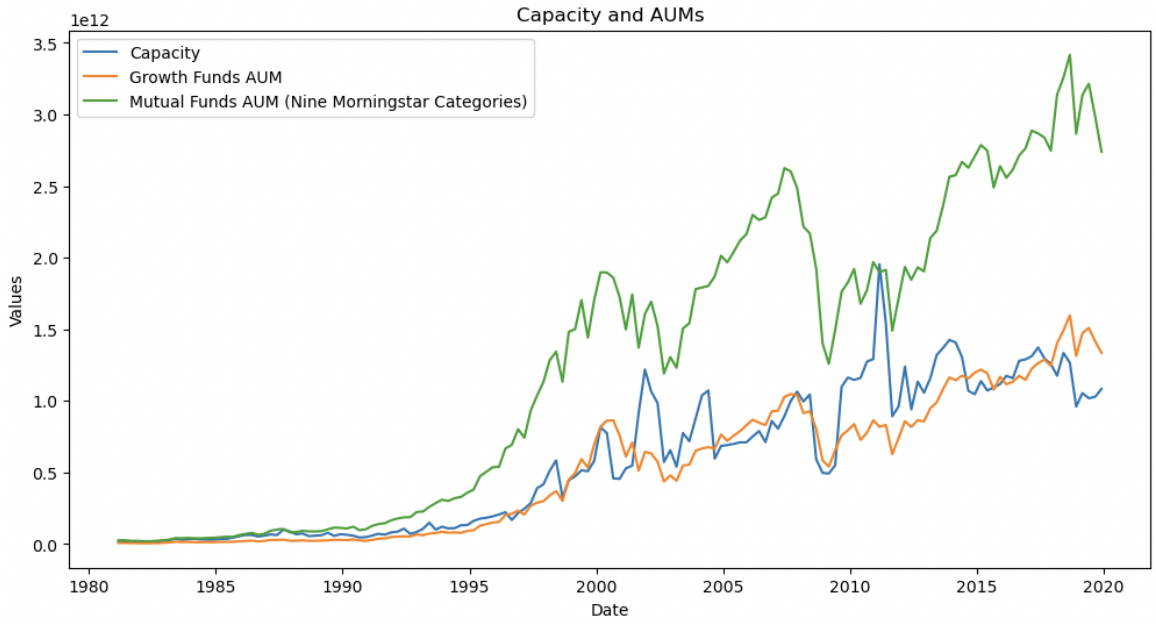
(a) Full Repricing



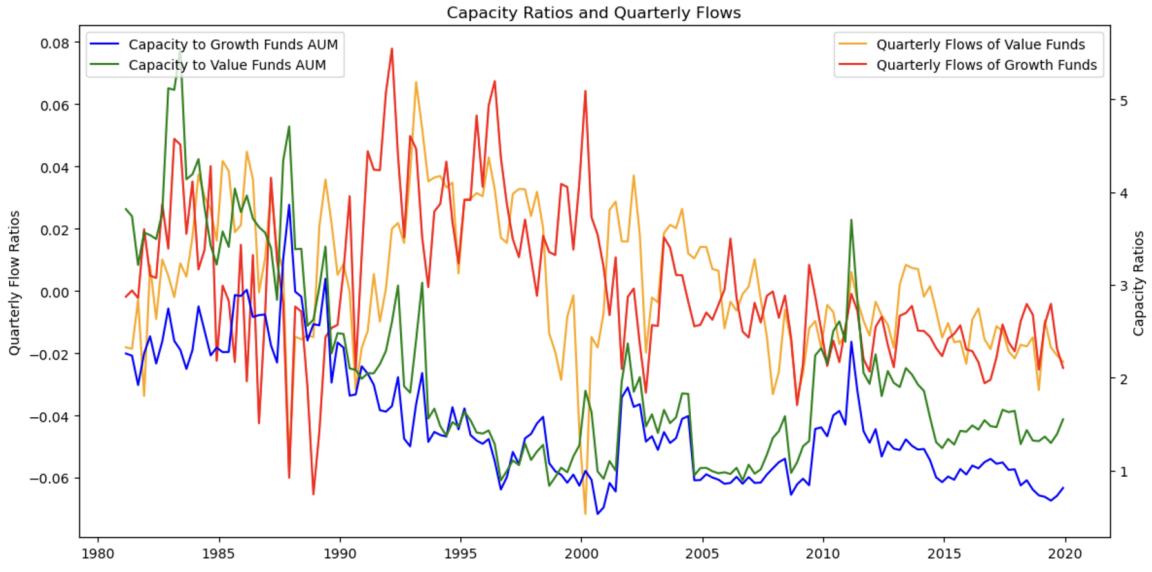
(b) Approximation

This figure shows the quarterly evolution of the repricing difference between the top and bottom portfolios, sorted by a momentum variable (cumulative returns over the past 12 to two months). Repricing is defined as the value-weighted mean log difference between each portfolio's counterfactual and actual stock prices. The panels depict varying reallocations of Growth funds' AUM to Value funds (N = 10% to 100%). Panel (a) shows results from the fully solved demand system, while Panel (b) applies our approximation. The sample spans 1981–2019.

Figure 7: Time-Series of Value Anomaly Capacity



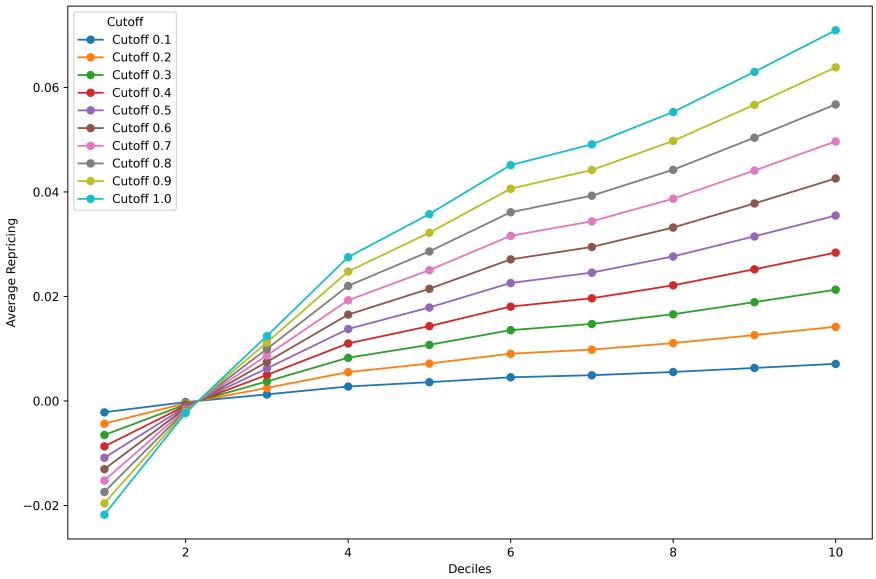
(a) Capacity vs. Fund AUM



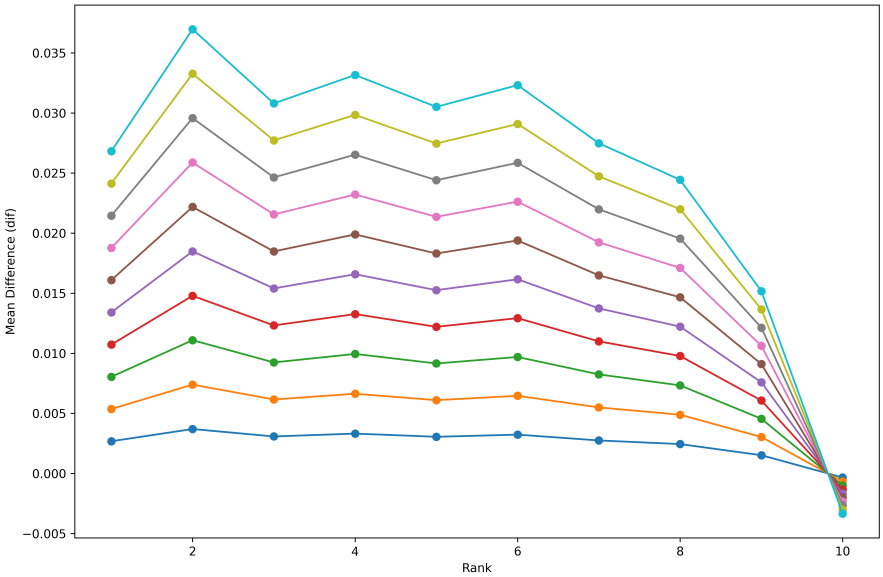
(b) Capacity vs. Fund Flows

This figure presents the time series of the capital required to reallocate from Growth to Value funds in order to drive the Value anomaly's alpha to zero ("capacity"). Panel (a) shows capacity in dollar terms, juxtaposing it against the total AUM of Growth funds and the combined AUM in three Morningstar style boxes. Panel (b) presents the capacity measures as ratios to the same AUM benchmarks along with the actual fund flows into value and growth funds. The sample covers 1981–2019.

Figure 8: Household-to-Value Reallocation: Average Repricing for B/M- and Momentum-Sorted Portfolios



(a) Portfolios Sorted by Book-to-Market



(b) Portfolios Sorted by Momentum

This figure plots the time-series average repricing statistics for decile portfolios sorted by either book-to-market or momentum (cumulative returns over the past 12 to two months). Repricing is defined as the value-weighted log difference between each portfolio's counterfactual and actual stock prices, computed using our approximation. The panels show hypothetical reallocations of N% of Growth funds' AUM (originating from the Household sector) to Value funds (N = 10%–100%). The sample period spans 1981–2019.

Table 1: Summary Statistics for Portfolios Sorted by Book-to-Market

This table reports key statistics for decile portfolios sorted by book-to-market ratios over 1981–2019. Panel A presents annualized average returns, CAPM alphas (in percent), and market betas, all estimated via a market model. Panel B shows each portfolio's average dividend-price ratio $\overline{DP}_{i,t}$, the ratio ρ_i, the persistence parameter ψ_i, and the annual pass-through $\theta = 1 - \rho_i \psi_i$. Parentheses contain t-statistics based on White (1980) heteroskedasticity-consistent standard errors.

Panel A: Average Returns, Alpha and Market Beta

	L	2	3	4	5	6	7	8	9	H	H-L
Mean	7.704	6.960	8.424	7.524	8.604	8.736	8.904	8.220	9.552	12.516	4.812
	[2.63]	[2.7]	[3.4]	[2.96]	[3.4]	[3.57]	[3.65]	[3.22]	[3.81]	[4.04]	[1.81]
Alpha	-1.020	-0.948	0.780	-0.240	1.044	1.488	1.956	1.176	2.676	4.572	5.592
	[-0.86]	[-1.1]	[0.99]	[-0.28]	[1.02]	[1.4]	[1.54]	[0.8]	[1.85]	[2.28]	[2.0]
Beta	1.113	1.009	0.976	0.991	0.965	0.924	0.886	0.899	0.876	1.013	-0.100

Panel B: Portfolio Characteristics Summary

	L	2	3	4	5	6	7	8	9	H
ψ	0.787	0.802	0.734	0.684	0.806	0.749	0.859	0.749	0.779	0.695
$\overline{DP}_{i,t}$	0.009	0.008	0.016	0.018	0.023	0.031	0.049	0.051	0.078	0.076
ρ	0.991	0.992	0.984	0.983	0.978	0.970	0.953	0.951	0.927	0.929
$\theta = 1 - \rho\psi$	0.220	0.205	0.279	0.327	0.212	0.273	0.181	0.287	0.278	0.354

Table 2: Summary Statistics for Portfolios Sorted by Momentum

This table reports key statistics for decile portfolios sorted by momentum (cumulative returns over the past 12 to two months) over 1981–2019. Panel A presents annualized average returns, CAPM alphas (in percent), and market betas, all estimated via a market model. Panel B shows each portfolio's average dividend-price ratio $\overline{DP}_{i,t}$, the ratio ρ_i, the persistence parameter ψ_i, and the annual pass-through $\theta = 1 - \rho_i \psi_i$. Parentheses contain t-statistics based on White (1980) heteroskedasticity-consistent standard errors.

Panel A: Average Returns, Alpha and Market Beta

	L	2	3	4	5	6	7	8	9	H	H-L
Mean	-0.996	4.620	6.396	8.376	7.596	6.936	8.220	8.436	8.904	12.624	13.608
	[-0.19]	[1.22]	[1.98]	[3.08]	[3.05]	[2.94]	[3.57]	[3.51]	[3.36]	[3.43]	[2.99]
Alpha	-13.788	-5.184	-2.388	0.624	0.300	-0.108	1.332	1.272	1.284	3.108	16.896
	[-4.36]	[-2.25]	[-1.32]	[0.47]	[0.28]	[-0.12]	[1.47]	[1.35]	[1.0]	[1.39]	[3.92]
Beta	1.633	1.251	1.120	0.988	0.931	0.899	0.879	0.914	0.973	1.213	-0.420

Panel B: Portfolio Characteristics Summary

	L	2	3	4	5	6	7	8	9	H
ψ	0.698	0.759	0.632	0.741	0.819	0.807	0.959	0.863	0.629	0.503
$\overline{DP}_{i,t}$	0.033	0.049	0.031	0.028	0.032	0.030	0.036	0.028	0.021	0.036
ρ	0.968	0.953	0.970	0.973	0.969	0.970	0.965	0.973	0.980	0.965
$\theta = 1 - \rho\psi$	0.325	0.276	0.388	0.280	0.207	0.216	0.074	0.161	0.384	0.514

Table 3: Validating Our Approximation Against the Fully Solved Demand System

This table presents panel OLS regressions of the fully solved price change on our approximate price change, $\Delta \log p_{i,t} \approx m_{i,t} \sum_j s_{i,j,t} \Delta a_{j,t}$, including time fixed effects. We separately consider Growth-to-Value and Households-to-Value reallocations. Panel A reports results at the individual stock level. Panels B and C show analogous regressions at the portfolio level for book-to-market-sorted and momentum-sorted portfolios, respectively. Parentheses display t-statistics based on standard errors clustered by quarters and stocks (or portfolios).

y = Full Price Change		
Panel A: Stock-Level		
	Growth-to-Value	Household-to-Value
Approximated Price Change	1.024	0.881
	[42.577]	[62.905]
R-squared	0.883	0.948
Observations	565502	565502
Panel B: Book-to-Market Portfolios		
	Growth-to-Value	Household-to-Value
Approximated Price Change	1.150	0.980
	[47.56]	[71.427]
R-squared	0.991	0.992
Observations	1560	1560
Panel C: Momentum Portfolios		
	Growth-to-Value	Household-to-Value
Approximated Price Change	1.283	1.000
	[29.849]	[86.348]
R-squared	0.974	0.987
Observations	1560	1560

Table 4: Counterfactual Expected Returns and Alphas Under Growth-to-Value Reallocations

This table presents the average annual expected returns and alphas for decile portfolios sorted on book-to-market or momentum (cumulative returns over the past 12 to two months), under hypothetical reallocations from Growth to Value funds. H denotes the top decile (value stocks or winner stocks), L denotes the bottom decile, and H–L is the long–short portfolio. We simulate 10 reallocation scenarios, each shifting N% of Growth funds' AUM to Value funds. Parentheses contain t-statistics based on White (1980) heteroskedasticity-consistent standard errors. The sample covers 1981–2019.

	Value				Momentum			
N%	L: E(R)	H: E(R)	H–L: E(R)	H–L: α	L: E(R)	H: E(R)	H–L: E(R)	H–L: α
0.1	7.872	12.204	4.332	5.112	-1.044	13.032	14.076	17.364
	[2.69]	[3.94]	[1.63]	[1.93]	[-0.20]	[3.55]	[3.09]	[3.91]
0.2	8.040	11.892	3.852	4.632	-1.080	13.452	14.532	17.832
	[2.75]	[3.84]	[1.45]	[1.75]	[-0.21]	[3.66]	[3.19]	[4.02]
0.3	8.208	11.580	3.372	4.152	-1.128	13.872	15.000	18.288
	[2.81]	[3.74]	[1.27]	[1.57]	[-0.22]	[3.77]	[3.29]	[4.12]
0.4	8.376	11.268	2.892	3.672	-1.176	14.280	15.456	18.744
	[2.87]	[3.64]	[1.09]	[1.39]	[-0.23]	[3.88]	[3.39]	[4.22]
0.5	8.544	10.956	2.412	3.192	-1.224	14.700	15.924	19.212
	[2.92]	[3.53]	[0.91]	[1.21]	[-0.24]	[3.99]	[3.49]	[4.32]
0.6	8.712	10.644	1.932	2.712	-1.260	15.120	16.380	19.668
	[2.98]	[3.43]	[0.73]	[1.03]	[-0.25]	[4.11]	[3.59]	[4.42]
0.7	8.880	10.344	1.452	2.232	-1.308	15.540	16.848	20.136
	[3.04]	[3.33]	[0.55]	[0.84]	[-0.26]	[4.22]	[3.69]	[4.53]
0.8	9.060	10.032	0.972	1.752	-1.356	15.948	17.304	20.592
	[3.10]	[3.23]	[0.37]	[0.66]	[-0.27]	[4.33]	[3.79]	[4.63]
0.9	9.228	9.720	0.492	1.272	-1.404	16.368	17.772	21.060
	[3.16]	[3.13]	[0.19]	[0.48]	[-0.27]	[4.44]	[3.89]	[4.73]
1.0	9.396	9.408	0.012	0.792	-1.440	16.788	18.228	21.516
	[3.21]	[3.03]	[0.00]	[0.30]	[-0.28]	[4.55]	[3.99]	[4.83]

Table 5: Counterfactual Expected Returns and Alphas Under Household-to-Value Reallocations

This table presents the average annual expected returns and alphas for decile portfolios sorted on book-to-market or momentum (cumulative returns over the past 12 to two months), under hypothetical reallocations from Households to Value funds. H denotes the top decile (value stocks or winner stocks), L denotes the bottom decile, and H–L is the long–short portfolio. We simulate 10 reallocation scenarios, each shifting N% of Growth funds' AUM from Households to Value funds. Parentheses contain t-statistics based on White (1980) heteroskedasticity-consistent standard errors. The sample covers 1981–2019.

	Value				Momentum			
N%	L: E(R)	H: E(R)	H-L: E(R)	H-L: α	L: E(R)	H: E(R)	H-L: E(R)	H-L: α
0.1	7.752	12.264	4.512	5.292	-1.068	12.612	13.680	16.956
	[2.65]	[3.96]	[1.70]	[2.0]	[-0.21]	[3.43]	[3.01]	[3.82]
0.2	7.800	12.012	4.212	4.992	-1.128	12.612	13.752	17.004
	[2.67]	[3.88]	[1.59]	[1.89]	[-0.22]	[3.43]	[3.02]	[3.83]
0.3	7.848	11.760	3.912	4.692	-1.200	12.612	13.812	17.064
	[2.68]	[3.79]	[1.47]	[1.77]	[-0.24]	[3.43]	[3.03]	[3.84]
0.4	7.896	11.508	3.612	4.392	-1.272	12.612	13.884	17.112
	[2.70]	[3.71]	[1.36]	[1.66]	[-0.25]	[3.43]	[3.05]	[3.85]
0.5	7.944	11.256	3.324	4.080	-1.344	12.612	13.956	17.160
	[2.72]	[3.63]	[1.25]	[1.54]	[-0.26]	[3.43]	[3.06]	[3.86]
0.6	7.992	11.004	3.024	3.780	-1.416	12.612	14.016	17.220
	[2.73]	[3.55]	[1.14]	[1.43]	[-0.28]	[3.43]	[3.08]	[3.87]
0.7	8.040	10.764	2.724	3.480	-1.476	12.612	14.088	17.268
	[2.75]	[3.47]	[1.02]	[1.31]	[-0.29]	[3.43]	[3.09]	[3.88]
0.8	8.088	10.512	2.424	3.180	-1.548	12.612	14.160	17.316
	[2.77]	[3.39]	[0.91]	[1.20]	[-0.30]	[3.42]	[3.10]	[3.90]
0.9	8.136	10.260	2.124	2.868	-1.620	12.600	14.220	17.376
	[2.78]	[3.31]	[0.80]	[1.09]	[-0.32]	[3.42]	[3.12]	[3.91]
1.0	8.184	10.008	1.824	2.568	-1.692	12.600	14.292	17.424
	[2.80]	[3.22]	[0.69]	[0.97]	[-0.33]	[3.42]	[3.13]	[3.92]

Online Appendix

A Classification of Institution Types

In this appendix, we detail the process used to classify different types of institutional investors based on the data extracted from Thomson Reuters databases. Thomson Reuters Institutional Holdings Database (s34 file) assigns each manager to a type code (Variable Name TYPECODE),

1. Bank,
2. Insurance companies,
3. Investment company and their managers,
4. Investment advisors, and
5. All other (i.e., pension funds, university endowments, and foundations).

Unfortunately, the TYPECODE variable is not reliable from 1998 and beyond, when many institutions were and are improperly classified as type 5 (endowments and others).[10] We correct the type codes through the following steps:

1. If a managers' first type code is not 5, we replace the incorrect type code of 5 in the subsequent periods with the first type code.
2. Following KY, we assign type codes 3 through 5 to pension funds using the list of top 300 pension funds (Watson (2015)).

[10](See the user's guide provided by Wharton Research Data Services in 2008)

3. As in KY, we construct a database of investment advisors based on the historical archives of Securities and Exchange Commission Form ADV since June 2006. We use the Fuzzy Matching function in Python to match manager names to primary business names in the investment advisor database. If a valid match is found, we reclassify type code 5 to type 4.

B Proofs and Other Derivations

B.1 Proof of Proposition 1

Proof. Step 1: Taking logs and applying the demand approximation.

From Equation (2), equilibrium requires:

$$q_{i,t}^d = q_{i,t}^s.$$

Substituting the demand approximation in Equation (6), we obtain:

$$c_{i,t} \; + \; \sum_j s_{i,j,t}\Big(- \eta_{j,t}\, p_{i,t} \; + \; k_{i,j,t} \; + \; a_{j,t} \Big) = q_{i,t}^s.$$

We can then solve for $p_{i,t}$:

$$p_{i,t} = m_{i,t}\Big(c_{i,t} \; - \; q_{i,t}^s \; + \; \sum_j s_{i,j,t}\big(k_{i,j,t} + a_{j,t}\big) \Big). \tag{B.1}$$

Step 2: Counterfactual prices.

A parallel derivation for the counterfactual scenario $(\cdot)^{CF}$ yields:

$$p_{i,t}^{CF} = m_{i,t}^{CF}\Big(c_{i,t} \;-\; q_{i,t}^{s} \;+\; \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big), \tag{B.2}$$

where $c_{i,t}$, $k_{i,j,t}$, and $q_{i,t}^{s}$ remain constant across both the observed and counterfactual equilibria.

Step 3: Taking the difference to obtain $\Delta p_{i,t}$.

Subtracting Equation (B.1) from Equation (B.2):

$$\begin{aligned}
\Delta p_{i,t} &= p_{i,t}^{CF} - p_{i,t} \\
&= m_{i,t}^{CF}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big) \;-\; m_{i,t}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}\big(k_{i,j,t} + a_{j,t}\big)\Big).
\end{aligned}$$

Step 4: Expanding and rearranging.

We expand and group like terms:

$$\begin{aligned}
\Delta p_{i,t} &= m_{i,t}^{CF}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big) \;-\; m_{i,t}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}\big(k_{i,j,t} + a_{j,t}\big)\Big) \\
&= m_{i,t}\sum_{j}\Big(s_{i,j,t}^{CF}\,a_{j,t}^{CF} - s_{i,j,t}\,a_{j,t} + s_{i,j,t}^{CF}\,\kappa_{i,j,t} - s_{i,j,t}\,\kappa_{i,j,t}\Big) \;+\; m_{i,t}^{CF}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big) \\
&\quad - \; m_{i,t}\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big) \\
&= m_{i,t}\sum_{j}\big(s_{i,j,t}\,a_{j,t}^{CF} - s_{i,j,t}\,a_{j,t}\big) \;+\; m_{i,t}\sum_{j}\Big(s_{i,j,t}^{CF}\,a_{j,t} - s_{i,j,t}\,a_{j,t} + s_{i,j,t}^{CF}\,a_{j,t}^{CF} - s_{i,j,t}^{CF}\,a_{j,t}\Big) \\
&\quad + \; m_{i,t}\sum_{j}\Big(-s_{i,j,t}\,a_{j,t}^{CF} + s_{i,j,t}\,a_{j,t}\Big) \\
&\quad + \; m_{i,t}\sum_{j}\big(s_{i,j,t}^{CF}\,\kappa_{i,j,t} - s_{i,j,t}\,\kappa_{i,j,t}\big) \;+\; \big(m_{i,t}^{CF} - m_{i,t}\big)\Big(c_{i,t} - q_{i,t}^{s} + \sum_{j} s_{i,j,t}^{CF}\big(k_{i,j,t} + a_{j,t}^{CF}\big)\Big).
\end{aligned} \tag{B.3}$$

Step 5: Final rearrangement into $\Delta p_{i,t}$.

We can reorganize (B.3) into three key terms, yielding:

$$\Delta p_{i,t} = m_{i,t}\Big(\sum_j s_{i,j,t}\,\Delta a_{j,t}\Big) + m_{i,t}\sum_j \Delta s_{i,j,t}\,\Big(a_{j,t} + \Delta a_{j,t} + \kappa_{i,j,t}\Big) + \Delta m_{i,t}\Big(c_{i,t} - q^s_{i,t} + \sum_j s^{CF}_{i,j,t}\big(k_{i,j,t} + a^{CF}_{j,t}\big)\Big),$$

which matches the structure of Equation (8) in Proposition 1. Thus, the approximation for the counterfactual price change follows from grouping these components: the direct effect on AUM for investors already holding the asset, the indirect effect from changing ownership shares, and the effect from any shift in $m_{i,t}$. ■

B.2 Detailed Capacity Computation

Here we provide the full derivation of how to compute the capital C required to achieve a desired change in alpha. For concreteness, consider reallocating a fraction γ of aggregate AUM from "growth" investors (total AUM A_G) to "value" investors (total AUM A_V), so the total reallocated capital is $C = \gamma\, A_G$. If we aim to set the counterfactual alpha, α^{CF}, to zero (or equivalently reduce it by $\bar{\alpha}$), we impose

$$\Delta\alpha_{V,t} = -\,\bar{\alpha},$$

and substitute into our key alpha-change equation (Equation (22)). Growth funds' $\Delta a_{j,t}$ values equal $-C/A_G$ (i.e., $-\gamma$), while value funds receive $+C/A_V$. Solving for C^* then yields:

$$C^* \;=\; \frac{\bar{\alpha}}{\sum_i \left(w_{i,P,t} - \beta\, w_{i,M,t}\right) \theta_i\, m_{i,t} \left(\sum_{j \in G} s_{i,j,t} \left(-\frac{1}{A_G}\right) \;+\; \sum_{j \in V} s_{i,j,t} \frac{1}{A_V}\right)}. \tag{B.4}$$

An analogous formula applies when shifting capital from households HH instead of growth funds. In each case, the result is a straightforward function of four key components:

1. The baseline alpha $\bar{\alpha}$.
2. The price multipliers $m_{i,t}$ and pass-throughs θ_i.
3. The investor ownership shares $s_{i,j,t}$.
4. The ratio of total assets between the losing and gaining investor groups (e.g., $\frac{A_G}{A_V}$ or $\frac{A_G}{A_{HH}}$).

C Other Details

C.1 Calculation of Counterfactual AUM and Prices without the Approximation

To compute counterfactual AUM and prices, we follow the procedure in Koijen et al. (2023), which incorporates the endogeneity between AUM and prices. When reallocating capital away from some investor group, prices adjust, which in turn reshapes each investor's AUM. This feedback loop is captured by an iterative fixed-point solution that ensures market clearing.

Step 1: Select the Investor Group. Identify the group of investors G (for instance, growth funds) whose capital is to be reallocated.

Step 2: Determine the Reallocation Fraction. Let x be the fraction of group G's AUM to transfer to another group (e.g., value funds), where $0 < x \leqslant 1$.

Step 3: Reallocate Assets to the Target Group. Distribute the counterfactual inflow among investors in the target group V according to their relative size:

$$F_{j,t} \;=\; \frac{AUM_{j,t}}{\sum_{i\in V} AUM_{i,t}} \;\times\; x \;\times\; \sum_{k\in G} AUM_{k,t}, \quad j \in V.$$

Step 4: Adjust AUM for the Original Group. Subtract the same total amount from each investor $k \in G$:

$$F_{k,t} \;=\; -\,x \;\times\; AUM_{k,t}.$$

Step 5: Solve for Counterfactual Prices and AUM. Let $P_t^{CF}(n)$ be the counterfactual price of asset n. These prices must clear the market:

$$P_t^{CF}(n) \;=\; \sum_{i=V,G,W,\ldots,I} AUM_{i,t}^{CF}\big(P_t^{CF}\big)\; w_{i,t}^{CF}\big(n; P_t^{CF}\big),$$

where $w_{i,t}^{CF}(n; P_t^{CF})$ is the portfolio weight of investor i in asset n under the new prices. Each investor's counterfactual AUM is then updated:

$$AUM_{i,t}^{CF}\big(P_t^{CF}\big) = AUM_{i,t}\Big(w_{i,t}(0) \;+\; \sum_{n\in N_{i,t}} \frac{P_t^{CF}(n)}{P_t(n)}\, w_{i,t}(n)\Big) \;+\; F_{i,t}.$$

By iterating these updates until prices and AUM converge, we obtain a fixed-point solution that consistently incorporates the feedback between reallocated capital, revised prices, and

changes in each investor's asset value.

C.2 Floating-Weight Portfolios and the Indirect Weight-Change Effect

In Section 2, we focus primarily on the direct price-change effect. Here, we show that when portfolio weights are allowed to float with prices, there is also an indirect weight-change effect. In most scenarios we analyze, however, that indirect term proves small and can be safely ignored.

C.2.1 Indirect Weight Changes in Portfolio Returns

Equation (17) decomposes the change in the long leg's expected return into direct and indirect components:

$$\begin{aligned}\Delta\mu_{L,t} &= \sum_i w_{i,L,t}\,\Delta\mu_{i,t} + \sum_i \Delta w_{i,L,t}\,\mu_{i,t} + \sum_i \Delta w_{i,L,t}\,\Delta\mu_{i,t} \\ &= \underbrace{-\sum_i w_{i,L,t}\,\theta_i^L\,\Delta p_{i,t}}_{\text{Direct Price-Change Effect}} + \underbrace{\sum_i \Delta w_{i,L,t}\,\mu_{i,t} - \sum_i \Delta w_{i,L,t}\,\theta_i^L\,\Delta p_{i,t}}_{\text{Indirect Weight-Change Effect}}. \end{aligned} \tag{C.1}$$

For a portfolio with **fixed** weights (e.g., an equal-weighted fund that actively rebalances to maintain equal shares), we have $\Delta w_{i,L,t} = 0$, so the indirect effect vanishes. But if weights are free to float as prices move, then $\Delta w_{i,L,t} \neq 0$ in general.

C.2.2 Weights Floating with Price Changes

To approximate how weights $w_{i,L,t}$ shift with price changes, assume

$$w_{i,L,t}^{CF} \;\approx\; \frac{w_{i,L,t}\,\big(1+\Delta p_{i,t}\big)}{\sum_i w_{i,L,t}\,\big(1+\Delta p_{i,t}\big)}, \tag{C.2}$$

where $\Delta p_{i,t}$ is the price change for asset i. Because $\sum_i w_{i,L,t} = 1$, we can rewrite the denominator and apply a first-order approximation for small $\Delta p_{i,t}$. Tracing through the algebra yields:

$$\Delta w_{i,L,t} \;\approx\; w_{i,L,t}\Big(\,\Delta p_{i,t} \;-\; \sum_n w_{n,L,t}\,\Delta p_{n,t} \;-\; \Delta p_{i,t}\sum_n w_{n,L,t}\,\Delta p_{n,t}\Big). \tag{C.3}$$

Substituting this into (17) yields an expanded expression for $\Delta\mu_{L,t}$, which we simplify by defining:

$$\Delta\bar{p}_{L,t} \;=\; \sum_i w_{i,L,t}\,\Delta p_{i,t}, \quad \Delta\overline{p^2_{L,t}} \;=\; \sum_i w_{i,L,t}\,\Delta p^2_{i,t}, \quad \Delta\overline{p_{L,t}\,\mu_{L,t}} \;=\; \sum_i w_{i,L,t}\,\mu_{i,t}\,\Delta p_{i,t}.$$

For constant θ_i^L across all stocks in the long leg, we obtain:

$$\Delta\mu_{L,t} \;\approx\; \underbrace{-\,\theta^L\,\Delta\bar{p}_{L,t}}_{\text{Direct Effect}} \;+\; \underbrace{\big(1-\Delta\bar{p}_{L,t}\big)\,\big(\Delta\overline{p_{L,t}\,\mu_{L,t}} - \theta^L\,\Delta\overline{p^2_{L,t}}\big) \;-\; \Delta\bar{p}_{L,t}\big(\mu_{L,t} - \theta^L\,\Delta\bar{p}_{L,t}\big)}_{\text{Weight-Adjustment Effect}}. \tag{C.4}$$

An analogous formula applies for $\Delta\mu_{S,t}$, and taking the difference gives $\Delta\mu_{P,t} = \Delta\mu_{L,t} - \Delta\mu_{S,t}$.

C.2.3 Numerical Calibration

To see how large the weight-adjustment effect can be, we run a simple calibration. From Panel A of Table 1, we use $\mu_{L,t} = 12.5\%$ and $\mu_{S,t} = 7.7\%$. We also take $\theta^L = 0.35$ and

$\theta^S = 0.22$ from Panel B of the same table. Suppose we consider $(\Delta\bar{p}_{L,t}, \Delta\bar{p}_{S,t})$ pairs of $(2.5\%, -2.5\%)$, $(5\%, -5\%)$, and $(7.5\%, -7.5\%)$. Table C.1 summarizes the result. The weight-adjustment effect contributes only a tiny fraction of the total change, reinforcing that we can typically focus on the direct effect alone.

Price Change Pair	Direct Effect	Weight-Adjustment	Combined
(0.025, -0.025)	-0.01425	-0.00002	-0.01427
(0.050, -0.050)	-0.02850	-0.00005	-0.02855
(0.075, -0.075)	-0.04275	-0.00003	-0.04278

Table C.1: Calibrated Effects for Varying Price Changes

C.2.4 One-for-One Floating

If the portfolio fully floats one-for-one with price changes (i.e., $w^{CF}_{i,L,t} \approx w_{i,L,t}\,(1 + \Delta p_{i,t})$, ignoring the denominator correction), the math in (C.4) simplifies further. In that case, the indirect effect becomes slightly larger, though still minor in our simulations. Table C.2 shows the calibration under this simplified assumption.

Price Change Pair	Direct Effect	Simplified WA	Combined
(0.025, -0.025)	-0.01425	0.00497	-0.00928
(0.050, -0.050)	-0.02850	0.00978	-0.01873
(0.075, -0.075)	-0.04275	0.01442	-0.02833

Table C.2: Calibrated Effects with One-for-One Floating

Overall, while weights that float with prices introduce an indirect rebalancing effect, it remains quantitatively small in our scenarios. Hence, focusing on the direct price-change channel is usually enough to capture the portfolio's counterfactual returns with high accuracy.