Equity Valuation Without DCF*

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Abstract

We introduce *discounted alpha*—a novel framework for equity valuation. By correcting market prices rather than discounting long-horizon cash flows, our approach delivers lower-variance, better-performing estimates of a stock's value. Our real-time estimates indicate that private equity funds capture substantial CAPM misvaluation, both initially at buyout and subsequently at exit, and that fundamental buy-and-hold funds tilt toward characteristics that predict underpricing but not short-term alphas. Although firm equity values are "almost efficient" relative to the CAPM benchmark by Black's (1986) definition, these misvaluations have trended upward since 2000, even as cross-sectional alphas have declined, reflecting greater persistence in price-level inefficiencies.

Keywords: equity valuation, fundamental value, DCF, market efficiency, discretionary investing, private equity, analyst expectations, CAPM

JEL classification: G12, G14, G32

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What is the fundamental value of a stock—the value of its cash-flow claim under a specified asset-pricing model? Measuring this value is a central problem in economics as valuation affects portfolio choice, acquisitions, equity issuance, real investment, and tests of market efficiency. However, the two workhorse approaches to stock-level valuation remain fragile. Discounted cash flow (DCF) requires long-horizon cash-flow forecasts and stock-specific cost-of-equity estimates, while price multiples confound low prices with low expected profitability or high risk.[1]

We introduce *discounted alpha*, a valuation framework that estimates an individual stock's model-implied fundamental value by correcting its observed price. The starting point is the identity

$$V_0 \quad = \quad P_0 + \sum_{\tau=0}^{\infty} E_0 \left[X_\tau \, \alpha_\tau \right], \tag{1}$$

which expresses value as price plus the present value of future buy-and-hold alphas (model-implied abnormal returns), with value and alpha measured relative to the same candidate asset-pricing model.[2] The weights X_τ are positive, economically interpretable, and shrink to zero at long horizons.

Cho and Polk (2024) derive this identity and apply it to infer average historical model-implied misvaluation of a diversified portfolio from realized buy-and-hold returns. Nevertheless, their work leaves the central valuation problem unresolved: How does one use their identity to assign a real-time value to each stock using ex ante information?

This paper provides that real-time valuation framework. Our key observation is that one-period alpha is the payout from the current stock of model-implied underpricing (V/P). Hence, a stock-time-specific alpha payout rate should allow us to convert the alpha payout into the stock of underpricing. We estimate how characteristics forecast alpha, risk-adjusted capital gains, and their own future evolution, and use the discounted-alpha identity to map those forecasts into real-time estimates of individual stocks' V/P. The result is a new cardinal estimator of model-implied value for a specified asset-pricing model.

Discounted-alpha valuation offers two key advantages over DCF. First, it values stocks by "correcting" the price rather than building value from long-horizon forecasts. Because prices already embed much of the long-horizon cash-flow information, this approach shortens the required forecasting horizon. Second, it imposes valid asset-pricing restrictions from the outset, thereby reducing finite-sample noise, much as working with excess rather than gross returns sharpens the estimation

[1] See Fama and French (1997) and Cohen, Polk, and Vuolteenaho (2003, 2009).

[2] As in Hansen and Jagannathan (1991, 1997), this candidate asset-pricing model does not have to be the one that sets $V = P$ and $\alpha = 0$ for all stocks at all points in time.

of short-horizon alphas (Cochrane, 2009). As a result, discounted-alpha valuation outperforms a variety of industry and academic valuations, as well as a like-for-like DCF-type measure. A limitation of discounted-alpha valuation is that it requires an observed market price, so its extension to settings such as private-firm valuation or post-M&A valuation remains for future work. Our current implementation also normalizes the market portfolio's model-implied mispricing to zero, analogous to an alpha model that normalizes the market portfolio's alpha to zero.

Applying discounted alpha, we value approximately 2.6 million stock-month observations, in real time, from June 1953 to December 2024. We focus primarily on CAPM-implied fundamental value because the CAPM remains the standard model for estimating stock-level costs of equity, making it the natural benchmark for comparison with conventional DCF valuation.[3] We provide two tests of cardinality: (i) The magnitudes of these real-time fundamental value estimates are consistent with the discounted value of subsequent long-horizon dividends, and (ii) they satisfy a novel short-horizon time-series cardinality test in which value-based excess returns constructed from dividends and changes in estimated fundamental value have zero alpha with respect to the candidate SDF, as they must if estimated value equals true model-implied value. In terms of tests of ordinality, these real-time estimates also predict large and persistent post-formation alphas with respect to the same asset-pricing model and detect the relative underpricing (overpricing) of stocks at the bottom (top) of the Russell 1000 large-cap (Russell 2000 small-cap) index (Chang, Hong, and Liskovich, 2015).

A superficial view of discounted-alpha valuation is that it merely combines several alpha-predicting signals into a composite alpha signal. That view misses the central measurement problem: valuation requires a level, not a ranking. Discounted-alpha valuation provides a simple but rigorous way to convert those signals, in real time, into the correct *magnitude* of a stock's model-implied valuation gap, V/P. Indeed, the conversion from alpha signals to valuation levels is far from obvious; Section 3.2.A and Table A5 show that simply scaling predicted alphas by their persistence fails the cardinality tests by a large margin.

We use our novel estimates of fundamental value to document five new empirical findings:

1. Profitable, low-beta, high book-to-market firms tend to be the most undervalued relative to the CAPM, consistent with the present-value identity of Vuolteenaho (2002) and the *adjusted value* metric of Cho and Polk (2024). This variation in CAPM-implied fundamental value is not captured by leading DCF methods such as Gonçalves and Leonard (2023).

2. However, measures of misvaluation such as Gonçalves and Leonard (2023), Stambaugh and

[3] See Graham and Harvey (2001), Dessaint, Olivier, Otto, and Thesmar (2021), Gormsen and Huber (2025), and Décaire and Graham (2024).

Yuan (2017), Asness, Frazzini, and Pedersen (2019), and van Binsbergen, Boons, Opp, and Tamoni (2023) do add incremental information about CAPM-implied value beyond the parsimonious set of our baseline characteristics, suggesting complementary roles for discounted-alpha and alternative approaches to valuation.

3. Traditional DCF-based estimates (Morningstar fair values, sell-side targets) fail to identify CAPM-implied mispricing. Moreover, biased expectations embedded in analyst price targets appear to be an important driver of distortions in stock price levels not explained by the market or other candidate risk factors.

4. Private equity funds exploit CAPM misvaluation, acquiring stocks at roughly 12% below CAPM fundamental value and exiting at about 17% above CAPM fundamental value. Discretionary buy-and-hold funds also tilt toward underpriced stocks, and focusing only on their short-horizon performance understates the extent to which these investors contribute to price correction by holding undervalued stocks.

5. Overall, CAPM-implied misvaluations have, on average, remained a small fraction of the market, consistent with Black (1986)'s view that markets are "almost efficient." However, these misvaluations have trended upward since 2000, even as cross-sectional alphas have declined, reflecting greater persistence in price-level inefficiencies.

Related literature

Our proposed approach is partly motivated by the recent literature documenting practical challenges in implementing DCF, particularly in the estimation of discount rates. Firm discount rates are often driven by coarse rules of thumb (Gormsen and Huber, 2024, 2025) and idiosyncratic analyst-specific effects (Décaire, Sosyura, and Wittry, 2024). Discount rate calculations based on asset-pricing models often fare worse than simpler heuristics (Hommel, Landier, and Thesmar, 2022). In practice, analysts often forgo DCF analysis and rely on simple multiples-based heuristics (Ben-David and Chinco, 2024).

Our methodology differs from academic DCF-based approaches to equity valuation. Gonçalves and Leonard (2023) represents the most recent and complete application of DCF to value individual stocks on a forward-looking basis. Earlier work includes Ohlson (1995); Frankel and Lee (1998); Dechow, Hutton, and Sloan (1999); Lee, Myers, and Swaminathan (1999). Because firm-level discount rates are difficult to estimate (Fama and French, 1997), these studies all impose a single market-wide or industry-wide discount rate, and thus do not calculate value relative to a given asset-pricing model in the way this paper does. van Binsbergen et al. (2023) use DCF to compute historical average misvaluation of characteristic-sorted portfolios, and map these misvaluations to individual stocks via portfolio weights. Our approach is inherently different in that it uses short-horizon alpha forecasts to estimate fundamental value. More broadly, we view discounted alpha and DCF as complementary approaches whose joint use can improve valuation and, in turn, asset-price efficiency.

Other non-DCF approaches to valuation include Stambaugh and Yuan (2017), Bartram and Grinblatt (2018), Gerakos and Linnainmaa (2018), and Golubov and Konstantinidi (2019), which generate stock-level misvaluation scores based on composite signals, "agnostic" regressions, or decompositions of the book-to-market ratio.

A large literature argues stock (mis)valuation affects corporate actions, highlighting the need for a better economic framework for valuing individual stocks in real time. A partial list of such studies includes Graham and Harvey (2001), Baker and Wurgler (2002), Baker, Stein, and Wurgler (2003), Brav, Graham, Harvey, and Michaely (2005), Polk and Sapienza (2009), Edmans, Goldstein, and Jiang (2012), Dessaint, Foucault, Frésard, and Matray (2019), and Dessaint et al. (2021).

Paper overview

The remainder of the paper is arranged as follows: Section 1 presents the discounted-alpha approach and its advantages over DCF. Section 2 describes our implementation. Section 3 presents and validates the stock-level valuation results. Section 4 applies the framework to buy-and-hold investor holdings, analyst expectations, and market efficiency. Section 5 concludes.

1 The discounted-alpha approach to equity valuation

This section first defines the discounted-alpha approach to equity valuation, and shows why it offers important advantages over the standard discounted cash flow approach.

1.1 Defining discounted alpha and discounted cash flow

Both the discounted cash flow and discounted-alpha approaches aim to estimate the model-implied *fundamental value* of a stock, defined as the value of its cash-flow claim under a specified asset-pricing model.

Definition 1 (Model-implied fundamental value). Model-implied fundamental value of asset i at time t, denoted $V_{i,t}$, is the buy-and-hold value of all future cash flows discounted with the candidate asset-pricing model:

$$V_{i,t} \equiv \sum_{\tau=1}^{\infty} E_t \left[\widetilde{M}_{t\to t+\tau} D_{i,t+\tau} \right]. \tag{2}$$

where $D_{i,t+\tau}$ represents dividends paid by stock i at time $t+\tau$, and $\widetilde{M}_{t\to t+\tau}$ is a candidate cumulative stochastic discount factor (SDF).

Model-implied fundamental value—like short-horizon abnormal return (alpha)—is defined relative to an assumed *asset-pricing model* $\widetilde{M}$ (e.g., the CAPM). But this model dependence does not make the object uninteresting. Discounted cash flow valuation is similarly model-dependent, yet the resulting model-implied value guides real financial decisions.[4] Our contribution is not to defend any particular factor model, but to show that, once a model is specified, its implied value can be estimated more precisely. Model-implied fundamental value is also specific to the conditioning information set $E_t[\,]$: our baseline estimate uses eight stock characteristics that summarize a broad range of characteristic styles. Of course, one can potentially augment this set with additional characteristics, with the goal of better describing patterns in the cross-section of stock prices.

A. DCF

The discounted cash flow (DCF) approach estimates $V_{i,t}$ by forecasting expected cash flows, i.e., $E_t(D_{i,t+\tau})$, and estimating or assuming the covariance of $\widetilde{M}_{t\to t+\tau}$ and $D_{i,t+\tau}$. For example, industry practitioners often assume a constant discount rate r, implying the assumption that $E_t\left[\widetilde{M}_{t\to t+\tau} D_{i,t+\tau}\right] = E_t[D_{i,t+\tau}]/(1+r)^{\tau}$.

B. Discounted alpha

The *discounted-alpha* approach instead forecasts the stock's alphas and risk-adjusted capital gains to compute discounted expected alphas. These quantities are then used to "correct" the price to calculate value. The connection between alpha and price is given by the discounted-alpha identity from Cho and Polk (2024), which states that value is equal to price plus discounted alphas.

Lemma 1 (Discounted-alpha valuation). *Suppose (a) the price of asset i is not explosive relative to $\widetilde{M}$, i.e., $\lim_{\tau\to\infty} E_t[\widetilde{M}_{t\to t+\tau} P_{i,t+\tau}] = 0$, and (b) there is some base asset b (e.g. the risk-free asset) that is always correctly priced, i.e., $E_t[\widetilde{M}_{t\to t+1}(1+R_{b,t+1})] = 1$. Then, as an exact mathematical identity, the fundamental value of i is its price plus the discounted sum of its subsequent abnormal returns (alphas). Both fundamental value and alphas are defined relative to*

[4]For instance, Graham and Harvey (2001) and Dessaint et al. (2021) show that firms' capital budgeting and M&A decisions, respectively, are shaped by CAPM-implied estimates of value.

the same $\widetilde{M}$*:*

$$V_{i,t} = P_{i,t} + \sum_{\tau=0}^{\infty} E_t \left[\widetilde{M}_{t\to t+\tau} P_{i,t+\tau} \frac{\alpha_{i,t+\tau}}{1+R_{f,t+\tau}} \right] \tag{3}$$

where P *is the price,*

$$\alpha_{i,t+\tau} \equiv E_{t+\tau} \left[\frac{\widetilde{M}_{t+\tau+1}}{E_{t+\tau}\widetilde{M}_{t+\tau+1}} R^e_{i,t+\tau+1} \right] \tag{4}$$

is the conditional alpha, $\widetilde{M}_{t+\tau+1}$ *is the one-period model-implied SDF,* R^e *is excess return above the base-asset return (e.g., the risk-free rate or the market return), and* R_f *is the risk-free rate.*

Proof. See Section B.2. For intuition, the net present value (NPV) at time $t = 0$ of buying and holding the stock ($V_0 - P_0$) is the present value (PV) of all abnormal payoffs: $V_0 - P_0 = \sum_{\tau=0}^{\infty} E_0 \left[\widetilde{M}_{0\to\tau} Y_\tau^{Abnormal} \right]$. Abnormal payoff at τ is the abnormal return from τ to $\tau+1$ discounted back to τ by the risk-free rate and then multiplied by the price on which the alpha is earned: $Y_\tau^{Abnormal} = P_\tau \frac{1}{1+R_{f,\tau}} \alpha_\tau$. Plugging in, $V_0 - P_0 = \sum_{\tau=0}^{\infty} E_0[X_\tau\, \alpha_\tau]$ with $X_\tau = \widetilde{M}_{0\to\tau} P_\tau \dfrac{1}{1+R_{f,\tau}}$. □

Lemma 1 states that model-implied underpricing, $V_{i,t} - P_{i,t}$, equals the discounted sum of future alphas, $\{\alpha_{i,t+\tau}\}_{\tau=0}^{\infty}$, as illustrated in Figure 1. Crucially, equation (3) is a mathematical identity, not a model assumption. It shows that abnormal returns contain price-level information: If a stock's model-implied fundamental value exceeds its price, a buy-and-hold investor should expect to recover the gap through future alphas, with value and alpha measured relative to the same candidate asset-pricing model. Perhaps surprisingly, the identity does not require V and P to converge at any point in the future, as Section B.3 illustrates for a consol bond.

1.2 Why discounted-alpha valuation?

A. A "correction" approach

The approach values a stock by correcting the observed price by the discounted sum of future alphas:

$$\underbrace{V}_{\text{large}} = \underbrace{P}_{\text{large}} + \underbrace{\text{discounted alphas}}_{\text{small}} \tag{5}$$

This correction term is small relative to model-implied value unless the candidate asset-pricing model is severely misspecified.[5] Since price is already observed, the sampling uncertainty in V comes only from estimating this small correction term. This aspect of our estimator allows discounted-alpha valuation to deliver a tight confidence interval around $\hat{V}$.

A natural concern is that stock-level returns are noisy, so stock-level alpha may also seem too

[5]Empirically, our estimated CAPM misvaluations lie primarily within a ±50% range.

noisy to be useful. But the relevant benchmark is not what percentage (R^2) of ex-post *realized* return or realized alpha we explain, but what percentage of ex-ante conditional alpha—a component of *expected* return—we explain. Indeed, Section B.6 and Figure A1 provide a simple analytical decomposition and simulation to show why a Fama-MacBeth-style regression in a large stock-time panel can estimate stock-level alphas with high precision, even if the realized-return R^2 remains close to zero. Lewellen (2015) makes a similar point about forecasting expected returns on individual stocks: "FM regressions provide an effective way to combine many firm characteristics into a composite forecast of a stock's expected return in real time ..." (p. 18).

To demonstrate the benefits of our correction approach more formally, in Section B.1, we specify processes where the discounted-alpha approach yields a closed-form solution for V/P, and a DCF-style valuation based purely on accounting variables yields a closed-form solution for value-to-book (V/B). We show that if V/P is reasonably close to unity, then the discounted-alpha approach will be less sensitive to small errors in parameter estimation. Applying empirical moments to this model suggests that the sample variance of the discounted-alpha estimator of value will be 40× smaller (standard error 6.5× smaller) than that of the DCF estimator.

For a more practical illustration, we also implement a book-based approach to estimate V/B that closely resembles our main discounted-alpha implementation. Section 3.3 shows that the risk-adjusted payouts measured by the book-based approach are much larger and more persistent: The value-weight standard deviation of alpha is only 0.03, whereas the standard deviation of the analogous book-based excess-payout term is 0.51. As a result, the book-based approach yields less precise fundamental-value estimates that perform substantially worse out of sample.

B. Valid population-level restrictions reduce estimator variance

From an econometric perspective, discounted-alpha valuation can have lower finite-sample variance because it uses valid population-level restrictions to remove population-zero components from the outset. Consider a simple, one-period-lived asset with price 1. In this case, the standard DCF identity (2) and discounted-alpha identity (3) reduce to:

$$\textbf{DA:} \quad V_t^{DA} = 1 + \frac{\alpha_t}{1+R_{f,t}} \tag{6}$$

$$\textbf{DCF:} \quad V_t^{DCF} = E_t\left[\widetilde{M}_{t+1}(1+R_{t+1})\right] = \left(E_t\left[\widetilde{M}_{t+1}(1+R_{f,t})\right]-1\right) + V_t^{DA} \tag{7}$$

The difference between these two valuation equations is that the discounted-alpha (DA) identity already imposes correct pricing of the risk-free rate (or another base asset) under $\widetilde{M}$, i.e., $E_t[\widetilde{M}_{t+1}(1+R_{f,t})] = 1$. By contrast, DCF valuation inherits sampling variation both from the discounted-alpha term and from estimation error in $\widetilde{M}_{t+1}(1+R_{f,t})$. Because alphas are typically estimated from excess returns independently of the risk-free-rate process, these two DCF components are unlikely to exhibit enough negative sampling covariance to offset this additional noise. DCF valuation therefore typically has higher finite-sample variance.[6]

One might be tempted, based on the one-period example in equation (7), to conclude that a DCF implementation using an $\widetilde{M}$ that prices the current yield curve is equivalent to equation (6). That logic does not extend to the valuation of multi-period cash flows $\{D_{t+\tau}\}_{\tau=1}^{\infty}$ (see Section B.2). For the DCF estimator to reduce to the DA estimator, $\widetilde{M}$ must satisfy the stronger requirement of conditionally pricing all future short rates, date by date and state by state, not merely matching the term structure observed at time t. Pricing the current yield curve only restricts date-t marginal moments of the cumulative SDF. It does not determine the full future conditional pricing kernel. Even ex post, observing realized short rates reveals only one realized path of rates, not whether the model SDF would have correctly priced future short rates in every state. By contrast, the discounted-alpha estimator removes these population-zero base-asset-pricing components from the outset.

2 Discounted-alpha valuation of individual stocks

This section explains how we turn the discounted-alpha identity in equation (3) into an estimator of stock-level fundamental value. Our key innovation is to work with *one-period* alpha. Doing so lets us apply the large empirical literature on short-horizon return predictability while avoiding the need to model long-horizon factor dynamics or impose a fully specified dynamic term-structure model.

The logic has three steps. First, we show that one-period alpha is the payout from the current stock of underpricing (equation 10). Second, because underpricing itself is latent, we project it onto observable stock characteristics (equation 14). Third, we estimate from the data how those same characteristics forecast (i) next-period alpha, (ii) risk-adjusted capital gains, and (iii) their own future evolution. Combining these objects yields a simple two-stage panel estimator of fundamental value (equation 26).

2.1 From one-period alpha to current underpricing

We begin with the one-period version of the discounted-alpha identity.

[6] See also the analysis in Section III of Cho and Polk (2024).

Assumption 1. The candidate SDF prices the one-period risk-free asset:

$$E_t\left[\widetilde{M}_{t+1}\right] = \frac{1}{1+R_{f,t}}. \tag{8}$$

Remark 1 (One-period alpha is the payout from underpricing). *Define model-implied underpricing as*

$$\nu_{i,t} \equiv \frac{V_{i,t}}{P_{i,t}} - 1. \tag{9}$$

Then the discounted-alpha identity implies

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \nu_{i,t} - E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\,\nu_{i,t+1}\right]. \tag{10}$$

Equation (10) is our central economic relation. One-period alpha is the *payout* from the "stock" of underpricing after adjusting for how much underpricing is expected to remain next period and for the fact that future underpricing realized in high-SDF, high-price states receives more weight in today's valuation. Example 2.1 shows how to use equation (10) directly to value a stock in a useful special case.

Example 2.1. *Suppose underpricing decays deterministically at rate ϕ_ν and*

$$E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\right] = \rho,$$

where ρ is the duration parameter in Campbell and Shiller (1988). Then equation (10) reduces to

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = (1-\rho\phi_\nu)\left(\frac{V_{i,t}}{P_{i,t}} - 1\right). \tag{11}$$

Hence,

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \frac{1}{1-\rho\phi_\nu}\frac{\alpha_{i,t}}{1+R_{f,t}}, \tag{12}$$

or

$$V_{i,t} = \left(1 + \frac{1}{1-\rho\phi_\nu}\frac{\alpha_{i,t}}{1+R_{f,t}}\right)P_{i,t}. \tag{13}$$

This special case shows how one-period alpha can be used to value a stock. If underpricing is more persistent ($\phi_\nu \uparrow$), or if the stock has longer duration ($\rho \uparrow$), then today's alpha is a smaller payout from a given stock of underpricing. In this case, holding fixed the level of alpha ($\frac{\alpha_{i,t}}{1+R_{f,t}}$), today's model-implied value must be a larger positive correction ($\frac{1}{1-\rho\phi_\nu} \uparrow$) of today's price. Example B.2 shows that the same logic extends when the alpha payout ratio $1-\rho_{i,t}\phi_{\nu,i,t}$ varies over time: Current underpricing is still pinned down by current alpha together with the current payout ratio, whose dynamics we later infer from stock characteristics.

Of course, an empirical challenge is that the decay of underpricing is not directly observed. Our strategy is to infer it from the dynamics of stock characteristics.

2.2 Valuation as a simple regression problem

Let $z_{i,t}$ denote a vector of stock characteristics observed at time t. We write the latent stock of underpricing as a projection on those characteristics:

$$\nu_{i,t} = \frac{V_{i,t}}{P_{i,t}} - 1 = \gamma_V z_{i,t} + u_{i,t}, \tag{14}$$

where γ_V is the mapping from characteristics to underpricing and $u_{i,t}$ is the projection error.

This projection is the bridge from the valuation identity to an empirically estimable object. Substituting (14) into (10) shows that current alpha is linked not to the level of characteristics per se, but to their *duration-adjusted expected decay.*

Lemma 2 (**Alpha as a payout from characteristic-based underpricing**). *Equations* (10) *and* (14) *imply*

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V\, x_{i,t} + \varepsilon_{i,t}, \tag{15}$$

where

$$x_{i,t} \equiv \left(I - \rho_{i,t}\phi_{z,i,t} - \frac{\Gamma_{G,z,i,t}}{1+R_{f,t}}\right) z_{i,t} \tag{16}$$

$$\rho_{i,t} \equiv E_t\left[\widetilde{M}_{t+1}(1+G_{i,t+1})\right], \tag{17}$$

$$\phi_{z,i,t} z_{i,t} \equiv E_t\left[\frac{\widetilde{M}_{t+1}}{E_t[\widetilde{M}_{t+1}]} z_{i,t+1}\right], \tag{18}$$

$$\Gamma_{G,z,i,t} z_{i,t} \equiv Cov_t(G_{i,t+1}, z_{i,t+1}), \tag{19}$$

and $\varepsilon_{i,t}$ collects projection-error and higher-order terms.

Proof. See Section A.1. □

Equation (15) is the key insight of this section: Our focus on one-period alpha turns valuation into a simple regression problem. The left-hand side is the one-period alpha payout. The regressor $x_{i,t}$ is not the raw characteristics $z_{i,t}$, but their duration-adjusted expected decay.

Each subcomponent of $x_{i,t}$ has a natural interpretation. The term $\rho_{i,t}$ is a duration object: Holding characteristics fixed, a high-duration stock spreads the correction of underpricing over more future states, so the current payout is smaller. The matrix $\phi_{z,i,t}$ captures how slowly the valuation-relevant characteristics decay. The covariance term $\Gamma_{G,z,i,t}$ appears because future alpha realized in high-price states receives more weight in the discounted-alpha identity than future alpha realized in low-price states.

In words, we go from equation (10) to equation (15) as follows:

$$
\begin{aligned}
alpha_{i,t} = \ & [\text{duration-adjusted decay in underpricing}]_{i,t} && (10^*) \\
= \ & \gamma_V \times [\text{duration-adjusted decay in characteristics}]_{i,t} + \varepsilon_{i,t}, && (15^*)
\end{aligned}
$$

where γ_V is the mapping from characteristics to underpricing. This characteristic-based transformation reduces the problem of estimating latent stock-specific underpricing to estimating γ_V, the mapping from characteristics to model-implied underpricing. The model-implied value of a stock is then obtained by multiplying γ_V by the stock's observed characteristic vector.

Both alpha and (duration-adjusted) characteristic decay can be estimated in the data with stock-time panel regressions. We can then regress the estimated alpha on estimated characteristic decay in the stock-time panel to find γ_V. The resulting γ_V instructs us how to correct the observed price to arrive at model-implied value at time T:

$$V_{i,T} = (1 + \gamma_V z_{i,T})\, P_{i,T}. \tag{20}$$

2.3 Implementation with panel regressions

We now specify processes for return, capital gain, and characteristic evolution that allow the left-hand ($\frac{\alpha_{i,t}}{1+R_{f,t}}$) and right-hand ($x_{i,t}$) objects of the regression in Lemma 2 to be estimated from a stock-time panel.

Write return (R), capital gain (G), and characteristics (z) as

$$R_{i,t+1} = R_{f,t} + \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}, \tag{21}$$

$$1 + G_{i,t+1} \equiv \frac{P_{i,t+1}}{P_{i,t}} = (1 + R_{f,t})\rho_{i,t} + \beta_{G,i,t} f_{t+1} + \epsilon_{G,i,t+1}, \tag{22}$$

$$z_{i,t+1} = \phi_z z_{i,t} + \beta_{z,i,t} f_{t+1} + \epsilon_{z,i,t+1}, \tag{23}$$

where f_{t+1} denotes the candidate factor excess returns, and the residuals are orthogonal to f_{t+1}.

Following the Fama-MacBeth/Shanken tradition, we allow the intercepts and factor loadings to vary with characteristics:[7]

$$\begin{aligned} \alpha_{i,t} &= \gamma_R \, z_{i,t}, & \beta'_{i,t} &= \Gamma_R \, z_{i,t}, \\ (1+R_{f,t})(\rho_{i,t}-1) &= \gamma_G \, z_{i,t}, & \beta'_{G,i,t} &= \Gamma_G \, z_{i,t}, \\ \beta'_{z,i,t} &= \begin{pmatrix} \beta'_{z,1,i,t} & \dots & \beta'_{z,L,i,t} \end{pmatrix}, & \beta'_{z,l,i,t} &= \Gamma_{z,l} \, z_{i,t}. \end{aligned} \tag{24}$$

We also allow the covariance between capital-gain and characteristic shocks to depend on characteristics:[8]

$$\sigma_{G,z,i,t} \equiv E_t[\varepsilon_{G,i,t+1}\varepsilon_{z,i,t+1}] = \Gamma_{G,z} z_{i,t} + \epsilon_{G,z,i,t}. \tag{25}$$

Under these specifications, we obtain a data-ready version of the regression model in Lemma 2.

Lemma 3 (**The regression model of discounted-alpha valuation**). *The processes* (21)–(25) *imply*

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V \, x^*_{i,t} + \varepsilon^*_{i,t} \tag{26}$$

where

$$x^*_{i,t} \equiv \left[I - \left(1 + \frac{\gamma_G z_{i,t}}{1+R_{f,t}}\right)\phi_z - \frac{\Gamma_{G,z}}{1+R_{f,t}} \right] z_{i,t} \tag{27}$$

and $\varepsilon^*_{i,t}$ *collects the remaining projection and higher-order terms.*

For this second-stage regression to be well specified, the information used to construct the left- and right-hand sides must be aligned. If, for example, alpha ($\hat{\alpha}_{i,t}$) is temporarily high because arbitrage capital is especially strong in that period, then the same information should enter $\hat{x}_{i,t}$ so that characteristic dynamics imply a faster decay of underpricing. We recommend that $z_{i,t}$ include a price multiple and past return. These variables absorb the covariance between capital gains and omitted determinants of underpricing and help make the second-stage error orthogonal to the regressors.

We note that the discounted-alpha valuation model in Lemma 3 suggests a simplified version of our discounted-alpha approach based on persistence-weighted alphas.

Remark 2 (**Valuation with persistence-weighted alphas**). *Further simplifying equation* (27)

[7] See Fama and MacBeth (1973) and Shanken (1990) as well as the recent examples of such an approach in Lewellen (2015) and Kelly, Pruitt, and Su (2019).

[8] As for dimensions, α and ρ are scalars; $\beta_{z,i,t}$ is a matrix, the other β objects are conformable vectors; and γ, ϕ_z, and Γ are sized to match the characteristics and factors. If we define L and K as the length of the characteristic vector z and factor vector f, respectively, then β and β_G are $1 \times K$ vectors, and β_z is an $L \times K$ matrix. To match these dimensions, γ_R and γ_G are $1 \times L$, ϕ_z and $\Gamma_{G,z}$ are L-by-L, and Γ_R and Γ_G are K-by-L. $\Gamma_{z,l}$ is also a K-by-L matrix for each $l = 1, ..., L$.

using $\frac{\alpha_{i,t}}{1+R_{f,t}} \approx \alpha_{i,t}$, $1 + \frac{\gamma_G z_{i,t}}{1+R_{f,t}} \approx \rho$, $\phi_z \approx \phi_z^{auto}$, *and* $\frac{\Gamma_{G,z}}{1+R_{f,t}} \approx 0$ *suggests using*

$$\gamma_V \approx \gamma_R \left(I - \rho\, \phi_z^{auto}\right)^{-1} \tag{28}$$

where ρ *is the Campbell and Shiller (1988) parameter that is close to one, and* ϕ_z^{auto} *is the auto-correlation matrix of characteristics that does not account for their factor exposures.*

However, as we show later in our validation exercise in Section 3.2.A, this simplification destroys the cardinal aspect of the baseline discounted-alpha estimator in Lemma 3, although it continues to be a reasonable ordinal signal of model-implied V/P.

2.4 Estimation procedure

Estimation proceeds in two steps.

First, we estimate the return, capital-gain, and characteristic processes (21)–(25) in the stock-time panel. This yields estimates $\hat{\gamma}_R$, $\hat{\gamma}_G$, $\hat{\phi}_z$, and $\hat{\Gamma}_{G,z}$.

Second, we construct the transformed regressor

$$\hat{x}^*_{i,t} \equiv \left[I - \left(1 + \frac{\hat{\gamma}_G z_{i,t}}{1+R_{f,t}}\right) \hat{\phi}_z - \frac{\hat{\Gamma}_{G,z}}{1+R_{f,t}} \right] z_{i,t}, \tag{29}$$

and estimate γ_V from the panel regression

$$\frac{\hat{\gamma}_R z_{i,t}}{1+R_{f,t}} = \gamma_V\, \hat{x}^*_{i,t} + \text{time fixed effects} + \text{error}. \tag{30}$$

The resulting estimate of stock-level fundamental value is

$$\hat{V}_{i,T} = (1 + \hat{\gamma}_V z_{i,T})\, P_{i,T}. \tag{31}$$

This estimate is a real-time estimate of the fundamental value of stock i at time T when equation (30) and all of its inputs are estimated using only data available through time T. Standard errors for $\hat{\gamma}_V$ immediately translate into confidence intervals for $\hat{V}_{i,T}$.

This two-step structure makes clear why the methodology is tractable. We never need to forecast a full path of firm-level cash flows and discount rates. Instead, we estimate how current characteristics forecast the next alpha payout and how quickly those same characteristics unwind. That is enough to recover a price-level estimate of value. Section B.6 and Figure A1 show why low stock-level realized-return predictability does not imply imprecise estimation of the conditional expected-return objects needed here.

The baseline implementation is deliberately simple, but the approach is not tied to this exact linear specification. It can accommodate nonlinear projections, subsets of stocks such as industries or size groups, larger information sets that may call for shrinkage, and additional orthogonal signals from other valuation measures. The linear form is mainly a transparent starting point that makes the economics of our novel estimator easy to see.

2.5 Empirical design choices

We let one period correspond to one year, with overlapping monthly observations.[9] All panel regressions are estimated by value-weight least squares so that small stocks with extreme characteristic realizations do not dominate the estimates. We report bootstrap t-statistics and confidence intervals that account for both cross-sectional and time-series dependence, as well as for the two-stage nature of the estimator.[10]

Our baseline information set contains eight stock characteristics: book-to-market (BM), gross profitability ($Prof$), market beta ($Beta$), investment (Inv), net issuance ($NetIss$), Amihud illiquidity (Liq), past one-year return (Ret), and past two-to-one-year return ($LagRet$). This set is deliberately parsimonious. It spans the main characteristic styles emphasized in the asset-pricing literature while preserving the paper's focus on methodology rather than on maximizing predictive fit through an expansive signal zoo. Table A1 reports the autocorrelations of our eight characteristics.

With the exception of the two return variables, which we demean cross-sectionally, we use cross-sectional ranks of the characteristics and then standardize them using value weights. As a result, our measure is inherently *cross-sectional*, capturing relative mispricing across stocks rather than time-series variation in aggregate valuation. This transformation also makes the characteristic vector stable over time and keeps the second-stage coefficients comparable across predictors.

Our real-time estimates are obtained from moving-window panel regressions using a 40-year window, expanding from a minimum of 15 years at the start of the sample. Because fundamental value is a long-horizon object, conservative estimation calls for a substantially longer window than

[9] A monthly horizon is too short to capture the dynamics of accounting-based characteristics.

[10] In each bootstrap replication, we assign a common resampling weight to all observations for a given stock and a common block weight to all observations in a June–May year block. The bootstrap regression weight is the product of these resampling weights and the original value weight. We then re-estimate the first-stage return, capital-gain, and characteristic-dynamics regressions, reconstruct the generated regressor $\hat{x}^*_{i,t}$, and re-estimate the second-stage valuation regression. The resulting distribution of $\hat{\gamma}_V$ therefore reflects both cross-sectional and time-series dependence, as well as uncertainty from the generated regressors.

is typical in short-horizon return forecasting.[11] We implement the procedure under three candidate pricing models—the CAPM, FF3, and FF5—with particular emphasis on the CAPM, both because it remains the benchmark most commonly used in practice and because it provides the most direct comparison with standard DCF-based valuation.[12]

Our full stock-month panel runs from June 1939 to December 2024, with lagged characteristics beginning in June 1938. This setup yields approximately 2.6 million stock-month observations, with real-time fundamental-value estimates available from June 1953 to December 2024. For comparison, we also report in-sample estimates over the same period.

3 Empirical performance of discounted-alpha valuation

This section presents the stock-level fundamental values estimated via the two-step discounted-alpha valuation described in Section 2. We first examine which characteristics incrementally explain underpricing. We then validate the fundamental-value estimates out of sample, both as ordinal and cardinal measures of model-implied value. Finally, we show that our approach performs better than DCF approaches and other signals of misvaluation.

3.1 Incremental predictors of fundamental value

Table 1 presents the full-sample estimates of the relation between characteristics and mispricing. That is, the estimates of γ_V from the relation:

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \gamma_V \, z_{i,t} + u_{i,t}. \tag{14}$$

This subsection briefly describes the key results and characteristics.

A. Book-to-market, profitability, and beta

For the CAPM, three characteristics—book-to-market, profitability, and beta—predict the largest percentage differences between price and CAPM-implied fundamental value. A one-standard-deviation increase in the rank of these characteristics predicts shifts in fundamental value relative

[11] Our results are consistent and robust across different estimation windows and alternative weighting of samples (Table A4); however, using both a short moving window (20 years) and exponentially down-weighting observations that appear earlier in that window can result in estimates that (barely) do not pass our cardinality test.

[12] Both Morningstar and Value Line use the CAPM in DCF valuation, and surveys of CFOs indicate that the CAPM remains the most widely used framework (Graham and Harvey, 2001). Recent evidence also shows that size and value exposures affect the costs of capital firms report in earnings announcements (Gormsen and Huber, 2024). While refinements such as the five-factor model of Fama and French (2015) or the four-factor model of Hou, Xue, and Zhang (2015) are more recent and perhaps less relevant for decision makers over most of our sample period, they may nonetheless capture economic forces present throughout the 20th century. Thus, we also report results for the five-factor model to illustrate how that refinement affects fundamental-value estimates.

to price of roughly 7 to 9, 13, and −13 to −14 percentage points, respectively. The prominence of these three characteristics for CAPM underpricing is consistent with the present-value identity of Vuolteenaho (2002): Equity that is cheap (high book-to-market), profitable, and low-risk is likely underpriced.[13] Profitability and beta continue to predict fundamental-value deviations relative to the three-factor model. Moreover, our profitability measure—gross profitability (Novy-Marx, 2013)—remains relevant even relative to the five-factor model, which includes a factor based on operating profitability (RMW). The fact that the estimates of γ_V change as we vary the benchmark factor model is precisely what one should expect and reflects the strength of our approach: It confirms that our method is responsive to the underlying discount-rate model and thus behaves as it should.

B. Investment and net issuance

Both investment and net equity issuance predict overpricing relative to the CAPM and FF3, though the effect is weaker under FF5. Based on t-statistics, these two variables provide the strongest statistical evidence that CAPM fundamental value differs from market price. The first pattern is consistent with managers catering to mispricing (as in Polk and Sapienza, 2009), while the second pattern is consistent with managers repurchasing or issuing shares opportunistically when perceived CAPM value deviates from market price (as in Baker and Wurgler, 2002).

C. Liquidity and past returns

Although liquidity is the most persistent characteristic, it adds little incremental information about CAPM or FF3 fundamental value. Under the five-factor model, however, liquid (large) stocks appear overpriced. Lagged past return (i.e., two-year to one-year return) is a significant predictor of overpricing and the inclusion of this long-run reversal signal makes BM borderline statistically insignificant when estimating CAPM-implied underpricing in column (1). In contrast, past one-year return (i.e. momentum) is not a significant predictor of mispricing under the CAPM, in either columns (1) or (2). However, it predicts FF3 underpricing in column (4) and FF5 underpricing in both columns (5) and (6). Thus, our multivariate, stock-level analysis refines the univariate, portfolio-level evidence that momentum reflects investor overreaction (Cho and Polk, 2024; van Binsbergen et al., 2023).[14]

[13] Specifically, the identity implies

$$\log\left(\frac{V_{i,t}}{P_{i,t}}\right) = bm_{i,t} + \sum_{\tau=0}^{\infty} \rho^{\tau} E_t\, roe_{i,t+1+\tau} - \sum_{\tau=0}^{\infty} \rho^{\tau} E_t \widetilde{r}_{i,t+1+\tau},$$

where bm is log book-to-market, roe is log return on equity (profitability), and $\widetilde{r}$ is the log return under the candidate pricing model.

[14] Using characteristic-sorted portfolios, Cho and Polk (2024) and van Binsbergen et al. (2023) link characteristics to CAPM misvaluation in a univariate setting. An earlier draft of Cho–Polk (Table 6 of https://marriott.byu.edu/upload/event/event_767/_doc/chopolk_pricelevel_20200831_c.pdf) and van Binsbergen et al.

D. Real-time estimates from a moving window

In addition to the full-sample estimates, we produce moving-window estimates of γ_V for out-of-sample analysis. Figure 2 illustrates how the moving-window estimates vary over time. First, γ_V coefficients vary meaningfully over time, so the choice of estimation window matters for fundamental-value estimation. Second, book-to-market, beta, and lagged return tend to be important throughout the sample, including recent years. Third, coefficients on profitability, investment, and net issuance have increased, contributing to greater CAPM misvaluations in recent years.[15] These real-time estimates are what we focus on in subsequent analyses.

3.2 Real-time fundamental value and validation

Our model of stock-level underpricing immediately generates stock-level estimates of fundamental value: $\hat{V}_{i,t} = (1 + \hat{\gamma}_V z_{i,t})\, P_{i,t}$. We plot these estimates for the biggest stocks in December 2024 in Figure 3. Relative to the CAPM, Tesla and Broadcom appear overpriced, whereas Apple, Eli Lilly, and Walmart appear underpriced. Relative to the three-factor benchmark, confidence intervals tend to be narrower and most of these large stocks appear underpriced, with the exception of Tesla and Broadcom, which still appear overpriced.

We propose tests to validate the out-of-sample performance of our real-time estimates of fundamental value. We emphasize that the tests of cardinality are particularly important.

A. Do subsequent long-horizon dividends justify $\hat{V}/P$? A cardinality test

We ask whether our real-time model-implied value-to-price ratio is cardinally accurate. To do so, we compare the magnitude of the ex-ante real-time fundamental value estimates to the ex-post realized value of long-horizon dividends.

For each formation date t, we sort stocks into five value-weight portfolios using NYSE breakpoints of the real-time estimate $\widehat{V}_{i,t}/P_{i,t}$. Let $\mathcal{Q}_{q,t}$ denote the set of stocks in quintile q, and let $w_{i,t}$ denote their formation-date value weights. The ex-ante portfolio underpricing is

$$\widehat{v}_{q,t} \equiv \sum_{i \in \mathcal{Q}_{q,t}} w_{i,t} \frac{\widehat{V}_{i,t}}{P_{i,t}}, \tag{32}$$

project their portfolio misvaluations on a vector of stock characteristics. Both analyses highlight the role of book-to-market but do not detect the prominent roles of profitability and beta once book-to-market is controlled for. In contrast, our analysis explicitly measures the incremental effect of each characteristic in a multi-characteristic setting.

[15] One way to measure the importance of our moving-window estimates is to compare our conditional estimate of mispricing to more static ones. Figure A9 plots the time-series of cross-sectional R^2s when we regress our measure on the adjusted value metric of Cho and Polk (2024) and the book-to-market equity ratio.

and its sample average is

$$\bar{v}_q \equiv \frac{1}{T}\sum_{t=1}^{T}\widehat{v}_{q,t}. \tag{33}$$

If $\widehat{v}_{q,t}$ is correctly calibrated, it should equal the conditional present value of the subsequent buy-and-hold dividends of the same portfolio, discounted using the candidate SDF associated with the risk model.

The relevant ex-post benchmark is the value of the subsequent buy-and-hold cash flows of the same portfolio. For a portfolio q formed at date t, let $P^q_{(t),s}$ and $D^q_{(t),s}$ denote, respectively, the market value and cash dividend at date s of the portfolio formed at t. For $J = 180$ months, define the realized long-horizon cash-flow value ratio as

$$v^{CF}_{q,t}(J) \equiv \sum_{\tau=1}^{J}\widetilde{M}_{t\to t+\tau}\frac{D^q_{(t),t+\tau}}{P^q_{(t),t}} + \widetilde{M}_{t,t+J}\frac{P^q_{(t),t+J}}{P^q_{(t),t}}. \tag{34}$$

This measures the realized value, relative to the formation-date price, of the portfolio's subsequent 15-year dividends plus terminal price, discounted using the same candidate risk model.

If our estimates are correctly calibrated, this average ex-ante value ratio should match the unconditional mean of the ex-post cash-flow value ratio:

$$H_{0,q}: \quad \mathbb{E}\big[v^{CF}_{q,t}(J)\big] = \bar{v}_q, \qquad q = 1,\ldots,5. \tag{35}$$

We follow Cho and Polk (2024) to estimate the same long-horizon cash-flow value using an equivalent buy-and-hold return representation, which avoids the severe overlapping-window problems from directly discounting dividends and other bias issues. Let v^{CP}_q denote this ex-post realized V/P estimate. The empirical cardinality test is therefore

$$H_{0,q}: \quad v^{CP}_q - \bar{v}_q = 0, \qquad q = 1,\ldots,5, \tag{36}$$

and we also report the same test for the high-minus-low spread.

Figure 4 shows that the ex-post realized V/P estimates are monotonically increasing across the ex-ante $\widehat{V}/P$ quintiles and lie close to the 45-degree line. Thus, portfolios that we classify in real time as more underpriced are also more underpriced based on their subsequent long-horizon cash flows, with similar magnitudes.

Table 2 Panel A reports the corresponding tests. For the CAPM, the ex-post high-minus-low spread in realized V/P is 43.6 percentage points and statistically significant ($p = 0.017$), showing that the sort identifies large ex-post differences in cash-flow value. The cardinality test compares this realized spread with the ex-ante spread of 58.0 percentage points. The difference is −14.4 percentage points and is not statistically significant ($p = 0.433$), indicating that the ex-ante valuation spread has approximately the right magnitude but slightly over-estimates the true extent of the spread in model-implied fundamental value.[16] In contrast, Figure A4 shows that the real-time DCF-based valuation measures of Gonçalves and Leonard (2023) and of Morningstar (see Section 3.3) fail our cardinality test, confirming that this test is a demanding one.[17]

The FF3 results are similar. The ex-post high-minus-low spread is 55.7 percentage points and statistically significant ($p = 0.011$), while the difference between the ex-post and ex-ante spreads is only −6.3 percentage points and statistically insignificant ($p = 0.773$).[18]

Finally, Table A5 shows why these cardinality tests are useful. A natural simpler implementation of discounted-alpha valuation discussed as Remark 2 is to scale characteristic-predicted alphas by their persistence. These persistence-weighted alpha measures perform well as ordinal measures: stocks they classify as more underpriced earn higher ex-post realized underpricing. But they perform poorly as cardinal measures, often implying ex-ante valuation spreads that are far too large relative to the ex-post realized V/P spreads. Thus, the challenge is not simply to rank stocks by persistent alpha predictability, but to combine those signals so that the resulting valuation levels have the right scale. Our baseline implementation delivers accurate measures of fundamental value through a series of simple panel regressions that appropriately reflect *all* the aspects of the Cho and Polk (2024) identity.

B. Are short-horizon dividends consistent with $\hat{V}/P$? Time series cardinality

The long-horizon cardinality test asks whether the average level of $\hat{V}/P$ across portfolios is consistent with their realized long-run cash flows. As a complementary check of cardinality, we can also ask whether the time-series of $\hat{V}_{i,t}$ is consistent with dividends and risk-factor exposures realized at short horizons. Intuitively, the test asks whether there would be any alpha if investors bought and sold at the measured $\hat{V}_{i,t}$ instead of the real-world price.

Define $R^e_{V,i,t}$ as the "value-based excess return," that is, the excess return that would be achieved

[16] Shrinkage or cross-validation on short-horizon alpha estimates would be some natural ways to further reduce over-fitting.

[17] Note, however, that the FE/ME measure of Gonçalves and Leonard (2023) is not meant to be a CAPM-implied measure; thus, the upward sloping pattern that we find is promising. In contrast, the Morningstar fair value measure does not show clear monotonicity despite it explicitly being a CAPM-implied measure.

[18] The limited FF5 sample prevents reliable estimation of portfolio-average V/P using the Cho–Polk long-horizon estimator.

by an investor who can only buy and sell the stock at a price equal to the true value, $V_{i,t}$:

$$R^e_{V,i,t+1} = \frac{D_{i,t+1} + V_{i,t+1}}{V_{i,t}} - (1 + R_{f,t}) \tag{37}$$

By the basic definition of V and the SDF, the discounted value of these returns must be 0:[19]

$$0 = E_t[\widetilde{M}_{t+1} R^e_{V,i,t+1}] \tag{38}$$

Under the null that measured value is correct and $\hat{V} = V$, the same condition must hold for $\hat{V}$ and $\hat{R}^e_{V,i,t}$. We therefore implement this test by sorting stocks into quintiles on $\hat{V}/P$, aggregating to portfolio-level $\hat{R}^e_{V,q,t+1}$ using $\hat{V}$-weights,[20] and regressing on the factors in the candidate SDF:

$$\hat{R}^e_{V,q,t+1} \; = \; \alpha^V_q + \beta'_q f_{t+1} + \nu_{q,t+1}. \tag{39}$$

Under the null that $\hat{V} = V$, $\alpha^V_q = 0$ for every q.

Table 2 Panel B shows the results of this test. We are unable to reject the model with any portfolio. This finding contrasts with simple monthly alpha regressions where the null of zero alpha is readily rejected (see Internet Appendix Table A2).

Intuitively, the test asks us to consider a "value world" where stocks were actually always priced at our measured $\hat{V}_t$. Would there be any alpha in this world? We find that when we sort stocks by $\hat{V}/P$ the answer is no—in other words, "real world" price would not be a valuable signal in "value world."

C. Post-formation alphas

Rearranging the discounted-alpha identity in equation (3) to have underpricing on the left-hand side,

$$\underbrace{\frac{V_{i,t}}{P_{i,t}} - 1}_{\text{Underpricing}} \; = \; \sum_{\tau=0}^{\infty} E_t \left[\frac{\widetilde{M}_{t \to t+\tau+1} P_{i,t+\tau}}{P_{i,t}} \alpha_{i,t+\tau} \right], \tag{40}$$

where $\frac{\widetilde{M}_{t \to t+\tau+1} P_{i,t+\tau}}{P_{i,t}}$ has an expected value that is near one when τ is small but converges toward zero as τ grows, reflecting the no-explosive-bubble condition. In short, the identity implies that underpriced stocks today must, on average, deliver positive future alphas. Hence, we sort stocks

[19]This identity can also be derived from Equation (2) by dividing both sides by $V_{i,t}$ and substituting in $V_{i,t+1}$ to express the relationship as a one-period law of motion.

[20]We use $\hat{V}$-weights rather than market-cap weights because $\hat{R}^e_V$ is naturally the return on a value-based investment, so portfolio aggregation should weight by the size of that investment.

by our estimated model-implied underpricing ($\frac{\widehat{V}}{P}$) and test whether this sorting generates large and persistent differences in realized alphas with respect to the same risk model ex post. One might worry that this test is mechanical, since our estimator is constructed from expected future alphas. But this is precisely the implication of the identity: stocks classified *ex-ante* as underpriced relative to an asset-pricing model should earn positive *ex-post* buy-and-hold alphas relative to the same model.

Figure A3 and Table 2 Panel C show that sorting stocks on real-time fundamental value-to-price generates persistent differences in alphas and large five-year cumulative abnormal returns (CARs) with respect to the same risk model, whereas sorting on stock-level real-time one-month alphas produces faster-decaying post-formation returns. Results are similar for FF3 and FF5.

The ex-post long-horizon alpha performance is reassuring, but it remains an ordinal and relatively low-hurdle test, since the estimator projects on characteristics already known to predict alphas, and, of course, some forecast alphas over long horizons. The stronger test is whether the valuation levels have the right magnitude, as done in the two cardinality tests above.

D. Russell index classification

As a further validation exercise, we test whether our real-time CAPM-implied underpricing measure detects the well-known price distortion at the Russell 1000/2000 cutoff. This test complements the post-formation-alpha validation above: Rather than asking whether our estimates predict future returns, it asks whether they identify a prominent, externally documented non-fundamental distortion in the level of stock prices. Because investors benchmarked to the Russell indices need not hold the entire market, index assignment creates discontinuous demand at the Russell 1000/2000 boundary: stocks just inside the Russell 1000 receive disproportionately less capital, while those just inside the Russell 2000 receive disproportionately more (Chang et al., 2015).

Figure 5 shows that our real-time estimates pick up this pattern sharply. Plotting CAPM-implied underpricing by market-equity rank and index membership reveals a clear kink: the smallest stocks in the Russell 1000 are underpriced relative to the largest stocks in the Russell 2000. Table A6 reports the corresponding regression evidence.[21] The results show that this discontinuity is economically large. With respect to the CAPM, stocks at the top of the Russell 2000 are 5%–6% more

[21] Following the Russell reconstitution literature, we focus on stocks close to the rank-1000 cutoff and regress the real-time June estimate of V/P on June Russell 2000 assignment, controlling flexibly for market capitalization. The specification follows the approach of Appel, Gormley, and Keim (2016, 2024), who use Russell index inclusion to estimate the effect of passive ownership. We make two modifications to their approach. First, we define the local bandwidth using measured May market capitalization rather than June Russell index weights, following the concern in Glossner (2024) that the latter can introduce sample-selection bias. Second, we measure May market capitalization using the Ben-David, Franzoni, and Moussawi (2019) procedure, which combines CRSP and Compustat data to better match Russell's index-assignment criteria.

overpriced relative to stocks at the bottom of the Russell 1000. We report the estimates for the full pre-2007 sample, 1989–2006, and for the shorter 1999–2006 sample, where measured market capitalization more closely matches Russell's realized index classifications (Ben-David et al., 2019). We stop in 2006 because Russell changed its index methodology after that year (Appel, Gormley, and Keim, 2019).

3.3 Empirical comparisons to DCF and other approaches

To demonstrate that the discounted-alpha approach performs better and adds information relative to existing valuation approaches, we compare our results to three benchmarks: (A) valuations produced by professional analysts, (B) DCF estimates created using an analogous procedure to our main discounted-alpha estimates, and (C) other valuation signals from the literature.

A. Analyst DCF estimates

We compare our discounted-alpha estimates to two prominent sources of real-time discounted cash flow (DCF) valuations: Morningstar's fair value estimates and sell-side analyst price targets. Morningstar employs roughly 150 equity analysts to produce DCF-based, CAPM-implied fundamental values for each firm. Their methodology relies on detailed cash-flow projections, staged fade-to-perpetuity assumptions, and explicit discounting at the CAPM-implied weighted average cost of capital to arrive at a fair value per share (Morningstar, 2022). Sell-side analyst targets typically combine DCF with relative valuation based on price multiples, as documented in Dechow and Sloan (1997), Asquith, Mikhail, and Au (2005), and Décaire and Graham (2024).

Distribution and ex-post performance

Figure A5 shows that both Morningstar fair value estimates and our discounted-alpha valuations are well centered around one, suggesting balance between stocks priced above and below estimated value. Furthermore, model-specific mispricing greater than 50% in magnitude is extremely rare, especially for discounted-alpha value estimates. In contrast, sell-side one-year price targets are uniformly skewed upward, with a median implied return of about 15% and an average near 20%, and typically exhibit a large deviation from the current price. This pattern suggests systematic optimism—arising either from analysts' cash-flow forecasts or their discounting assumptions—and highlights how current practice leaves ample room for discretion.

Turning to performance, the bottom row of Figure A5 shows that the post-formation alpha evidence is stark. Morningstar's DCF-based fair values fail to identify underpriced stocks during 2001–2024. Even more striking, sell-side price targets generate the opposite of what they should: Stocks with the most optimistic targets subsequently turn out to be the most overpriced. This result echoes prior findings that analysts' forecasts often reflect biased expectations, leading them to systematically overestimate future performance and misprice stocks (Dechow and Sloan, 1997; La Porta, 1996; Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Delao and Myers, 2021; Delao, Han, and Myers, 2024; and Bordalo, Gennaioli, La Porta, and Shleifer, 2024). In contrast, over the same sample, discounted-alpha valuations reliably identify underpriced stocks, highlighting their robustness relative to traditional DCF approaches.

Sources of errors in analyst DCF valuation

Figure 6 helps reveal where DCF-based approaches go wrong. Morningstar's fair values exhibit strong extrapolation from past one-year returns: firms with high prior returns not only receive proportionally higher fair values, but the adjustments are exaggerated, making these stocks appear underpriced. For example, firms in the top past-return group imply nearly 20% CAPM underpricing, while firms in the bottom group imply over 10% overpricing.

A second bias seems to arise from improper discount-rate adjustment. Both Morningstar and sell-side valuations systematically portray high-beta stocks as underpriced and low-beta stocks as overpriced. Their portrayal stands in sharp contrast to that of our discounted-alpha framework, which finds that high-beta stocks are actually overpriced relative to the CAPM. This evidence confirms our conjecture about DCF difficulties: because DCF valuations hinge on long-duration cash flows, they are highly sensitive to discount-rate errors. The empirical patterns imply that analysts systematically underestimate discount rate variation, whether by assuming risk premia that are too low or failing to scale discount rates with long-term beta.

Sell-side targets, however, lean less on past-return extrapolation than Morningstar fair values. Because price targets are one-year forecasts and are often cross-checked against multiples, they instead tend to be contrarian relative to past returns. Nevertheless, their treatment of beta still embeds the same fundamental discount-rate misapplication.

B. DCF approach analogous to our discounted-alpha framework

Section 1.2 argues that one key advantage of the discounted-alpha approach is that it uses price-based ratios (e.g. alphas) instead of pure accounting ratios (e.g. dividend-to-book). To demonstrate the importance of this difference, this section develops a "book-based" approach that is identical to our main implementation from Section 2, except that it uses ratios to book equity instead of price. We then show that this book-based approach requires forecasting larger payouts that decay more slowly, necessitating longer forecast horizons. An implementation of this approach does not significantly predict out-of-sample mispricing.

Method

The main discounted-alpha implementation starts from a law of motion for deviations of an asset's V/P from 1, as shown in Remark 1. For the book-based measure, we start from the equivalent expression for deviations of an asset's value-to-book (V/B) from market value-to-book. Since we assume the market is correctly priced, the market's V/B is equal to its price-to-book (P/B), and hence we can express the V/B deviations as:

$$\nu_{i,t}^b \equiv \frac{V_{i,t}}{B_{i,t}} - \overline{P/B}_t \tag{41}$$

where $\overline{P/B}_t$ represents the ratio of the price of the market to its total book value. We write the relationship in terms of deviations instead of raw V/B in order to put the book-based estimator on equal footing with our discounted-alpha implementation which imposes zero average mispricing.

The same steps used to derive Remark 1 then yield a law of motion given below.

Remark 3 (Value-to-book law of motion).

$$E_t[\widetilde{M}_{t+1}\ EP_{i,t+1}] = \nu_{i,t}^b \ - \ E_t\left[\widetilde{M}_{t+1}\frac{B_{i,t+1}}{B_{i,t}}\ \nu_{i,t+1}^b\right] \tag{42}$$

where EP is the book-based excess payout ratio—the equivalent of excess returns from the discounted-alpha approach:

$$EP_{i,t+1} \equiv \frac{D_{i,t+1}}{B_{i,t}} + \overline{P/B}_{t+1}\frac{B_{i,t+1}}{B_{i,t}} - \overline{P/B}_t(1+R_{f,t})$$

Proof. See Internet Appendix B.4. □

Note that if the market price-to-book is equal to 1, then the excess payout ratio will be the ratio of earnings (measured as dividends plus equity growth) to book equity minus the risk-free rate.

This law of motion mirrors the law of motion provided for $V/P-1$ in Remark 1 in form. Hence we can estimate $\nu_{i,t}^b$ by repeating the same steps described in Section 2 to estimate $\nu_{i,t} = \frac{V_{i,t}}{P_{i,t}} - 1$— i.e., forecast alphas and regress forecasts onto characteristics— replacing returns with excess payout and capital gains with book equity:

$$R_{i,t+1}^e \to EP_{i,t+1}; \quad \frac{P_{i,t+1}}{P_{i,t}} \to \frac{B_{i,t+1}}{B_{i,t}} \tag{43}$$

Estimates of $\nu_{i,t}^b$ can then be converted into value-to-price by adding the market P/B and multiplying by the stock's book-to-price ratio, using the relationship $V_{i,t}/P_{i,t} = (\nu_{i,t}^b + \overline{P/B}_t) \times (B_{i,t}/P_{i,t})$.

Results

The book-based estimator performs substantially worse out-of-sample than the discounted-alpha estimator. Estimating the ex-post realized CAPM V/P leads to an average top-minus-bottom spread of 26%, with a p-value of 0.38, compared with 44% and 0.02 for the main discounted-alpha approach in Panel A of Table 2. Furthermore, as shown in Table 4, the ex-ante book-based spread in estimated CAPM V/P is over 100 ppt greater than the ex-post spread, and we can reject their equality with a p-value $< 0.1\%$. Similarly, the short-horizon dividend-based cardinality test also allows us to reject the book-based measure but not our discounted alpha approach.[22]

This weaker performance is consistent with the fact that the book-based approach must forecast a much larger and more persistent payout object. Table 4 summarizes the key comparison. The value-weight standard deviation of alpha is only 0.03, as compared to 0.51 for the analogous book-based excess-payout term. The implied payout ratio is also substantially smaller under the book-based approach. Under discounted alpha, the value-weight average duration is 0.97 (the Campbell and Shiller, 1988, constant) and the weighted average autocorrelation of estimated alphas is 0.63, implying an average payout ratio of $1 - 0.97 \times 0.63 = 0.38$. Under the book-based approach, the corresponding values are 1.11 and 0.72, implying a payout ratio of just $1 - 1.11 \times 0.72 = 0.20$, approximately half as large.

A smaller payout ratio means that a given valuation gap is paid out more slowly, increasing reliance on distant forecasts. To make this difference concrete, suppose duration and autocorrelation are constant at these average values. For a stock with a one-standard-deviation-above-average valuation gap, the contribution of future payouts falls below 1 percentage point after only a few years under discounted alpha, but only after more than a decade under the book-based approach:

$$\begin{aligned} \text{DA horizon:} \quad & \min\{T \in \mathbb{N}: \quad 0.03 \times (1 - 0.38)^T < 0.01\} = 3, \\ \text{Book-based horizon:} \quad & \min\{T \in \mathbb{N}: \quad 0.51 \times (1 - 0.20)^T < 0.01\} = 18, \end{aligned}$$

The book-based estimator therefore requires economically important forecasts much farther into the future. Discounting and aggregating such long-horizon forecasts into an estimate of value-to-book is not straightforward—DCF implementations generally use constant discount rates (e.g. Gonçalves and Leonard, 2023). More importantly, this longer horizon is not just a theoretical inconvenience: it appears to materially degrade out-of-sample performance in the data.

[22]For the short horizon test, we winsorize the book based $\hat{V}/P$ at 0.1 and 10 to avoid negative or extreme portfolio weights.

C. Other academic valuation approaches

Gonçalves–Leonard FE/ME (DCF, real-time, no risk adjustment)

Gonçalves and Leonard (2023) conduct a DCF valuation of all CRSP/Compustat stocks using a constant discount rate across time and stocks, and call the implied value-to-price ratio the "fundamental-to-market ratio" (*FE/ME*). Table 3 shows the results of adding *FE/ME* as an additional characteristic in our full-sample valuation approach. The large and significant coefficient on *FE/ME* shows that it contains incremental information about valuation: controlling for the other characteristics, a one-standard-deviation increase in the rank of *FE/ME* is associated with an 8.0 percentage-point rise in CAPM-implied underpricing. This finding points to a complementary relation between discounted-alpha and traditional DCF approaches, while also illustrating an important advantage of our framework: other misvaluation signals can be incorporated directly as additional elements of the characteristic vector.

In terms of ex-post performance, the *FE/ME* measure of Gonçalves and Leonard (2023) significantly predicts ex-post CAPM alphas up to four years (Figure A6), although the performance tails out beyond the four-year horizon. Note, however, that the *FE/ME* measure applies a homogeneous discount rate to all stocks, so that measure is explicitly not meant to capture CAPM-implied misvaluation. Perhaps the weaker performance relative to the discounted-alpha approach is the result of that choice.

In-sample signals of Stambaugh and Yuan (2017), Asness et al. (2019), and van Binsbergen et al. (2023)

We also consider the in-sample signals of mispricing from Stambaugh and Yuan (2017), Asness et al. (2019), and van Binsbergen et al. (2023).[23] Columns 2, 3, and 4 of Table 3 show that these signals also contain incremental information about mispricing, although they can be significantly improved using information from other characteristics.

When evaluated using post-formation alphas, these in-sample signals remain informative, but their predictive power is less persistent than that of our main discounted-alpha implementation. Beyond three years, only the Stambaugh–Yuan management signal continues to predict statistically significant alphas, while the predictive content of the other measures attenuates (Figure A7).

A direct horse race based on independent double sorts leads to the same conclusion. When we form discounted-alpha portfolios that are neutralized with respect to a competing signal, post-

[23]We thank Andrea Tamoni and his coauthors for generously sending us their estimates.

formation alphas remain positive and persistent. By contrast, when we form portfolios on that competing signal that are neutralized with respect to discounted alpha, resulting alphas are generally smaller and less persistent, although several of the signals still contain useful incremental information (Figure A8).

Overall, these results suggest that existing valuation signals capture meaningful variation in CAPM mispricing, but that the discounted-alpha approach more reliably isolates the component associated with persistent CAPM-implied underpricing.

4 Applications

We use our estimates to study the investment behavior of private equity funds and discretionary buy-and-hold managers. We also apply our framework to examine how biased investor beliefs, as reflected in analyst expectations, contribute to stock price distortions and to ask whether stock price levels have become more efficient relative to the CAPM benchmark.

4.1 Long-term buy-and-hold investors

A. Private equity funds

PE funds are often viewed as the canonical sophisticated, long-term investor. How do they trade equity shares in light of our fundamental-value estimates?

Table 5 shows that PE funds buy stocks that are about 10.7%–12.5% cheaper than other stocks from the perspective of the CAPM and sell at prices 15.0%–18.3% higher than other stocks. Holding fundamental CAPM value fixed, PE transactions appear to raise the market value of portfolio firms by almost 30 percentage points (last column). Moreover, we find that the characteristics that predict PE buyouts—previously documented in Stafford (2022)—align exactly with those associated with CAPM underpricing, while the characteristics of PE sales exhibit the opposite pattern. Of course, unlike Stafford (2022), our novel discounted-alpha approach delivers the magnitude of the CAPM-implied revaluation associated with PE activity.

Taken together, these results suggest that PE funds act as sophisticated buy-and-hold arbitrageurs of valuation levels. Independent of their ability to improve the fundamentals of their portfolio firms, PE funds appear to systematically buy undervalued stocks and sell overvalued ones.

B. Fundamental investors

Discretionary buy-and-hold ("fundamental") investors approach security selection from a long-term perspective. Their objective is to identify stocks that are meaningfully underpriced, even if those positions do not generate the highest short-term alpha. We ask whether the holdings of four of the most prominent discretionary investors in our sample—Berkshire Hathaway (Warren Buffett), Tiger Management (Julian Robertson), Capital Group, and Dodge & Cox—reflect this philosophy.

Table 6 shows that stocks held by these fundamental investors tend to be significantly underpriced (Panel A). A typical Berkshire holding is about 17% underpriced relative to the CAPM (value-weight estimate of 7.8%), while the average across the broader group is 3.5% underpriced (value-weight estimate of 5.6%). This pattern is not representative of institutional investors as a whole; we find that institutions on average have held slightly overpriced stocks.

At the same time, these fundamental portfolios do not necessarily deliver high short-run alphas (Panel B). For example, Berkshire's holdings in isolation generate a modest and statistically insignificant value-weight alpha. This apparent disparity reflects contrarian behavior: these investors tend to hold negative-momentum stocks, dragging down their short-term alpha performance.

The broader implication is that short-term alpha may be a poor measure of the welfare contribution of discretionary funds. By systematically identifying and holding underpriced stocks, these investors promote long-term price discovery and more efficient capital allocation.

4.2 Analyst expectations and stock price distortions

So far, we have shown that analyst price targets are systematically biased. We now take a more aggressive step and ask whether these biased expectations might account for a meaningful share of the price-level distortions observed in the stock market.

Table 7 suggests this possibility. We re-estimate the valuation regression (γ_V) over the 2001–2024 sample, adding the median analyst price-target-to-price ratio as an additional predictor of model-specific underpricing. The coefficient on price targets is economically large and highly statistically significant, indicating that stocks viewed most favorably by analysts are precisely those most overpriced relative to their fundamental cash-flow value. Importantly, this relation is present across benchmarks and does not disappear even when the five-factor model is applied, underscoring that this finding is not an artifact of a particular pricing specification.

Taken together, these results provide direct price-level evidence on the view that analyst expectations are a systematic source of price-level distortions (e.g., La Porta, 1996; Bordalo et al., 2019; Delao and Myers, 2021; Bordalo et al., 2024; Delao et al., 2024), going beyond prior evidence that betting against analyst price targets generates short-horizon alpha (Engelberg, McLean, and Pontiff, 2020). One interpretation is that a broad set of investors hold biased expectations that tend to make certain stocks over- or undervalued, and that these same biases also shape analyst expectations. A more aggressive interpretation is that analyst targets directly embed optimistic narratives into the market's pricing of stocks, amplifying cross-sectional noise in equity prices.

4.3 Price-level perspective on market efficiency

A. Allowing for time-varying dispersions

So far, we have used characteristic ranks as the characteristic vector z_t. Using ranks—rather than levels—(i) accommodates different definitions of profitability and investment across the pre- and post-Compustat eras, (ii) mitigates outliers, and (iii) aligns with the literature on alphas (e.g., Kelly, Pruitt, and Su, 2020). A limitation is that this approach restricts time variation in the spread of value-to-price ratios needed for the analysis in this subsection.

We address this by interacting characteristic ranks with time-varying spreads. For book-to-market, for example, we multiply the rank by the log "value spread" from Cohen et al. (2003):

$$\text{value spread} = \log\left(BE/ME^{top}\right) - \log\left(BE/ME^{bottom}\right),$$

where *top* and *bottom* are the top and bottom third of stocks by B/M within the subset of non-microcap stocks.[24] Analogous spreads are constructed for other characteristics. This modified approach adds richer time-series dynamics to stock-level V/P while still using characteristic ranks in the procedure.[25]

B. Black's (1986) "almost efficient" benchmark

Figure 7 plots the dispersion in CAPM-implied mispricing over time, measured by the share of total market capitalization estimated to be more than 50% mispriced.[26] Dispersion is generally modest but widens sharply during two distinct periods—the late-1990s dot-com boom and the post-COVID years. Hence, while price-level deviations are typically contained, there are episodic surges in valuation dispersion that encompass a large portion of the market.

[24] We define microcaps here as the stocks with liquidity rank below −1, after normalizing the rank to have value-weight mean and standard deviation 1. The spread-interacted estimates depend importantly on how the characteristic spread is computed. An alternative approach would be to use the NYSE-only spread, but we believe this is likely to ignore some misvaluation phenomena that were driven by NASDAQ stocks, such as the dot-com boom.

[25] Since cross-sectional variation in $\frac{\widehat{V}}{P}$ is not materially affected by these interactions, the resulting estimates perform similarly well in our various validation tests.

[26] To be precise, the factor-of-two benchmark corresponds to a V/P between 0.5 and 2 rather than the 0.5-to-1.5 range we use. However, a V/P above 2 is extremely rare in our estimate, making it less interesting to analyze.

To interpret these patterns with more context, recall that Fama (1970) defines an efficient capital market as one in which firms and investors can make optimal decisions based on the *level* of prices that "fully reflect all available information." Yet Fama's empirical tests operationalize efficiency in terms of *changes* in prices—short-horizon returns—rather than in price levels themselves. Fischer Black (1986), in contrast, defines a testable benchmark for efficiency directly in terms of price levels: an "almost efficient" market is one in which prices are within a factor of two of fundamental value for more than 90% of the market. Although this factor-of-two range may seem generous, it provides a concrete, empirically measurable standard for price-level efficiency that Fama's return-based framework leaves implicit.

Viewed through this lens, Figure 7 suggests that equity markets have indeed been "almost efficient" for most of the past half-century. Typical deviations—roughly 30% between the top and bottom V/P terciles—fall comfortably within Black's tolerance, and only about 0.9% of aggregate market capitalization appears more than 50% mispriced. Yet the same evidence shows that "almost efficiency" can come under pressure: both the dot-com and post-COVID periods pushed the share of the market more than 50% mispriced toward the outer edge of Black's bounds (10% of the market), with even the largest firms trading at prices far from their CAPM-implied values. These rare but broad departures highlight how markets may remain "almost efficient" most of the time, but occasionally only just so.

C. Alpha decay—not the whole story

Figure 7 shows that CAPM-implied misvaluations have trended upward since around 2000. In contrast, a long literature documents that cross-sectional alphas have declined sharply since the early 2000s (e.g., Chordia, Subrahmanyam, and Tong 2014; McLean and Pontiff 2016; Cho 2020; Martin and Nagel 2022), a pattern often interpreted as evidence of increasing market efficiency. How, then, can we reconcile the apparent rise in price-level misvaluations with the simultaneous decline in measured alphas?

Figure 8 helps clarify this divergence. Panel A shows that alphas have indeed fallen noticeably for the short-horizon trading strategy that maximizes ex-ante expected one-month alpha. That is, alpha decay is especially pronounced for short-term, easy-to-arbitrage signals that were historically the most profitable. Panel B shows that alphas on the fundamental strategy that bets on real-time ex-ante V/P—which would require patient capital and hence would be harder to exploit—tend to be somewhat lower after 2000 than before but to a noticeably lesser extent than the pattern in Panel A. What stands out is that the sharp rise in CAPM-implied misvaluation in recent years seen in Figure 7 coincides with a steady rise in the persistence of mispricing (Panel C of Figure 8).

Put differently, the lower alphas in recent years can, at least in part, be attributed to mispricing correcting more slowly, rather than prices being more tightly anchored to CAPM-implied fundamental value. This finding resembles the arguments in Summers (1986) and Atkeson, Perri, and Heathcote (2026), which emphasize in an aggregate setting that weaker short-run predictability need not imply smaller price-level distortions or disagreements when long-run expected-return components become more persistent.[27]

To summarize this point in the context of the discounted-alpha identity, equation (10) says that one-period alpha is the "payout" from existing mispricing adjusted by duration. Rearranging this expression results in the following:

$$\text{mispricing}_{i,t} = \text{alpha}_{i,t} + E_t\left[\text{duration adjustment} \times \text{mispricing}_{i,t+1}\right],$$

which highlights that a lower alpha payout can coexist with persistent, high mispricing. When persistence ($E_t \text{mispricing}_{i,t+1}/\text{mispricing}_{i,t}$) rises, mispricing levels can increase even as short-term alphas shrink.

This interpretation carries broader implications. If arbitrage capital has migrated toward shorter-horizon, capacity-constrained signals, the resulting decline in short-term alpha may have left longer-duration inefficiencies underexploited. A reallocation of institutional capital toward strategies that target long-term underpricing—such as those implied by our V/P estimates—could therefore serve a dual purpose: offering investors more stable sources of alpha while promoting a more efficient allocation of capital over time. Of course, these implications are model-implied rather than normative, but they highlight that the apparent "alpha decay" of recent decades need not mean that markets have become more fundamentally efficient. Rather, it may reflect a structural shift toward slower-moving mispricing dynamics that remain significant even in an "almost efficient" market.

5 Conclusion

We develop a novel way to estimate stock-level model-specific fundamental values by simply estimating linear regressions. The flexible nature of our methodology allows researchers to use their own inputs and favorite asset-pricing model to construct bespoke but rigorous estimates of fundamental value, not only for stocks but also for other assets.

[27] Relatedly, Asness (2024) argues that the rise in the value spread indicates that stock prices have become less informationally efficient.

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Table 1: **Incremental Predictors of Fundamental Value (γ_V): Full Sample**

We report estimates, in percentage units, of the coefficients (γ_V) linking stock characteristics (z) to underpricing ($\frac{V}{P} - 1$):

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \gamma_V \, z_{i,t} + u_{i,t},$$

where $V_{i,t} \equiv \sum_{\tau=1}^{\infty} E_t \left[\widetilde{M}_{t \to t+\tau} D_{i,t+\tau} \right]$ is the fundamental cash-flow value of stock i at time t, $\widetilde{M}_{t \to t+\tau}$ is a candidate cumulative discount factor that depends on the factor model of risk, $P_{i,t}$ is the market price, and $u_{i,t}$ is a projection error. Estimates vary across each column based on either the factor model assumed to drive $\widetilde{M}$ (the CAPM, the three-factor model of Fama and French (1993), or the five-factor model of Fama and French (2015)) or the set of characteristics assumed to capture mispricing (including or excluding two-to-one-year lagged returns). We report bootstrap absolute t-statistics in parentheses. Estimates are based on value-weight stock-level panel regressions over the full sample period of 1953m6–2024m12.

	CAPM γ_V		Three-factor γ_V		Five-factor γ_V	
Characteristic	(1)	(2)	(3)	(4)	(5)	(6)
BM	6.92	9.24	-5.18	-3.61	1.43	1.37
	(1.73)	(2.19)	(2.43)	(1.70)	(0.51)	(0.52)
Prof	12.69	12.79	19.41	19.69	19.51	19.60
	(2.96)	(2.90)	(5.02)	(5.01)	(4.56)	(4.53)
Beta	-13.49	-14.24	-8.95	-9.52	1.95	2.12
	(2.76)	(2.80)	(1.92)	(1.98)	(0.37)	(0.39)
Inv	-1.81	-2.03	-1.93	-2.17	-0.66	-0.66
	(3.61)	(3.87)	(3.71)	(3.97)	(1.45)	(1.35)
NetIss	-2.88	-3.10	-1.97	-2.16	-0.49	-0.49
	(4.87)	(4.82)	(3.91)	(3.95)	(0.96)	(0.93)
Liq	-0.10	-0.49	-1.11	-1.40	-5.05	-5.05
	(0.02)	(0.11)	(0.42)	(0.52)	(2.46)	(2.40)
Ret	-0.08	0.92	0.56	1.45	3.14	3.02
	(0.11)	(1.68)	(0.73)	(2.51)	(3.33)	(3.59)
LagRet	-1.04		-0.94		0.07	
	(2.80)		(2.40)		(0.15)	

Table 2: **Validating Fundamental-Value Estimates**

Panels A and B report two cardinality tests for real-time model-implied $\widehat{V}/P$. Panel A compares the value-weight average ex-ante $\widehat{V}/P$ of each quintile portfolio with its ex-post realized V/P, estimated using the Cho and Polk (2024) return-based estimator. "Diff" is ex-post realized V/P minus ex-ante estimated $\widehat{V}/P$; the associated p-values test whether this difference equals zero. The column [p(Hi-Lo = 0)] tests whether the ex-post realized high-minus-low spread in V/P is zero. Panel B reports the short-horizon time-series cardinality test that value-based excess returns constructed from dividends and changes in estimated fundamental value have zero alpha with respect to the candidate SDF, as they must if estimated value equals true fundamental value. The quintile columns report the resulting value-implied alphas, while the high-minus-low column reports that for the high-minus-low quintile portfolio. We report the coefficients in Panel B in annualized percentage points. Panel C reports five-year model-specific cumulative abnormal returns (CARs), in percentage units, for high-minus-low quintile portfolios, sorted on real-time model-specific underpricing. We compute CARs in calendar time: the CAR equals the sum of contemporaneous alphas from underpricing-sorted portfolios formed in each of the prior 60 months. We bold the diagonal elements as these estimates are expected to be economically and statistically strong. We report p-values in brackets and t-statistics in parentheses.

Panel A. Do Subsequent Long-horizon Dividends Justify $\hat{V}/P$? A Cardinality Test

	Low	2	3	4	High	Hi-Lo	[p(Hi-Lo = 0)]
CAPM							
Ex-ante estimated V/P	0.760	0.934	1.058	1.178	1.340	0.580	
Ex-post realized V/P	0.825	1.015	1.169	1.239	1.261	0.436	[0.017]
Diff	0.065	0.081	0.111	0.061	-0.079	-0.144	
[p-value]	[0.372]	[0.139]	[0.069]	[0.557]	[0.521]	[0.433]	
FF3							
Ex-ante estimated V/P	0.702	0.884	1.016	1.153	1.321	0.620	
Ex-post realized V/P	0.682	0.881	1.065	1.206	1.238	0.557	[0.011]
Diff	-0.020	-0.003	0.049	0.053	-0.083	-0.063	
[p-value]	[0.872]	[0.957]	[0.408]	[0.442]	[0.403]	[0.773]	

Panel B. Are Short-Horizon Dividends Consistent with $\hat{V}/P$? A Time-Series Cardinality Test

	Low	2	3	4	High	Hi-Lo
Real-time V/P	α^V_{Lo}	α^V_2	α^V_3	α^V_4	α^V_{Hi}	$\alpha^V_{\text{Hi-Lo}}$
CAPM $\hat{V}/P$	1.801	1.318	0.668	0.971	1.602	-0.484
	[0.415]	[0.189]	[0.447]	[0.207]	[0.078]	[0.862]
FF3 $\hat{V}/P$	-1.510	1.168	-1.438	0.179	1.218	2.677
	[0.350]	[0.241]	[0.090]	[0.817]	[0.111]	[0.241]
FF5 $\hat{V}/P$	-0.818	-0.581	-1.321	0.612	1.953	0.237
	[0.377]	[0.734]	[0.069]	[0.509]	[0.227]	[0.921]

Panel C. Ex-Post Return Performance of Real-Time $\hat{V}/P$: A Test of Ordinality

	Ex-post 5-Year CAR		
Ex-ante Sorting Variable	CAPM *CAR*	FF3 *CAR*	FF5 *CAR*
CAPM $\hat{V}/P$	**27.36 (4.43)**	22.28 (3.50)	9.52 (1.41)
FF3 $\hat{V}/P$	20.80 (3.68)	**26.90 (4.83)**	17.55 (2.97)
FF5 $\hat{V}/P$	4.45 (0.50)	13.32 (2.53)	**16.28 (3.08)**

Table 3: **Incremental Information in Misvaluation Measures**

We report estimates of coefficients (γ_V, in percentage units) linking stock characteristics (z) to CAPM-implied underpricing ($\frac{V}{P}-1$), where the z vector includes existing measures of misvaluation: the fundamental-to-market ratio (FE/ME) of Gonçalves and Leonard (2023) (1973m6–2018m12), the composite management ($Mgmt$) and performance ($Perf$) signals of Stambaugh and Yuan (2017) (1953m6–2024m12), the quality metric ($Quality$) of Asness et al. (2019) (AFP) (1957m6–2024m12), and the price wedge (PW) metric of van Binsbergen et al. (2023) (1974m6–2017m12), with the sample period indicated in parentheses. We report bootstrap absolute t-statistics in parentheses.

	Goncalves-Leonard	Stambaugh-Yuan	AFP	vBBOT
BM	11.59	9.83	8.97	8.95
	(2.04)	(2.52)	(2.17)	(2.12)
Prof	10.37	11.98	13.69	10.58
	(1.57)	(2.48)	(2.35)	(2.21)
Beta	-15.66	-11.90	-11.81	-19.81
	(2.37)	(2.42)	(2.49)	(4.17)
Inv	-1.06	-0.37	-1.68	-1.05
	(1.50)	(0.83)	(3.28)	(1.76)
NetIss	-2.92	-0.84	-2.71	-2.84
	(4.22)	(1.11)	(4.96)	(4.38)
Liq	-0.67	-0.42	-2.48	3.34
	(0.15)	(0.10)	(0.55)	(0.72)
Ret	-0.44	-1.06	0.46	-0.53
	(0.44)	(1.35)	(0.57)	(0.54)
LagRet	-0.45	-1.02	-0.94	-1.01
	(0.81)	(2.65)	(2.41)	(2.12)
FE/ME	7.94			
	(3.31)			
Mgmt		3.10		
		(4.29)		
Perf		3.99		
		(3.35)		
Quality			2.42	
			(2.61)	
PW				-6.54
				(2.51)

Table 4: **Size and Persistence of Discounted Alpha vs. Analogous DCF Estimation**

We report summary statistics comparing our discounted-alpha implementation to an equivalent DCF implementation that uses book equity in place of market prices. Both estimates are with respect to the CAPM. The "book-based" DCF approach shows greater cross-sectional variance in payouts and dependence on distant forecast horizons. A description of the "book-based" estimator is provided in Section 3.3. Duration is calculated as the weighted average risk-adjusted excess capital gain or book-equity growth $\left(\frac{1+\gamma_G z_{i,t}}{1+R_{f,t}}\right)$. Long- and short-horizon dividend cardinality tests are calculated as described in Section 3.2 and shown in Table 2. All stock-level regressions and summary statistics are based on value-weight calculations.

	Discounted Alpha	DCF
Payout size		
Std deviation of risk-adjusted payout (alpha or earnings)	0.03	0.51
Payout persistence		
Average duration (ρ)	0.97	1.11
Autocorrelation of alpha or risk-adjusted earnings (ϕ)	0.63	0.72
Average payout ratio ($1 - \phi\rho$)	0.38	0.20
Long-horizon dividend cardinality test (CAPM)		
Diff between ex-post & ex-ante Hi-Lo V/P	-0.14	-1.77
[p-value]	[0.43]	[0.00]
Short-horizon time-series cardinality test (CAPM)		
$\alpha^V_{\text{Hi-Lo}}$	-0.48	-43.65
[p-value]	[0.86]	[0.01]

Table 5: **Private Equity Funds Buy Low and Sell High**

We report coefficients from a regression of real-time CAPM-implied $\hat{V}/P$ onto stock×month-level dummies for acquisition by a private equity firm (Columns 1 and 2), public listing from a private equity fund (Columns 3 and 4) or both (Columns 5 and 6). Stocks delisted because of private equity buyouts tend to be significantly underpriced (relative to the CAPM), whereas those sold publicly by private equity funds tend to be significantly overpriced according to our estimates. All specifications include time fixed effects, and all t-statistics are robust to both time and stock-level clustering. The delisting dummy is one for the last monthly observation in CRSP of a stock delisted, and the IPO dummy is one for the first observation of a newly listed stock on CRSP. The sample includes monthly data 1986 to 2024 for all stocks (Columns 2 & 4–6) just delisting stocks (Column 1) or just newly listed stocks (Column 3). PE buyouts and PE IPOs are identified from SDC Platinum.

	Dependent Variable: CAPM $\hat{V}/P$ (ppt)					
	(1)	(2)	(3)	(4)	(5)	(6)
PE buyout	10.71	12.32			12.29	12.52
	(3.56)	(5.27)			(5.26)	(5.01)
PE IPO			-15.02	-18.31	-18.31	-17.05
			(19.70)	(26.40)	(26.40)	(17.70)
Delisting						-1.26
						(1.55)
IPO						-0.24
						(0.29)
Sample	Delisting stocks	All	IPO stocks	All	All	All

Table 6: **Fundamental Investors: Underpricing versus Alpha**

We show that stocks held by Warren Buffett (Berkshire Hathaway) or other well-known fundamental investors tend to be significantly underpriced (Panel A; relative to the CAPM) to an extent that may not be captured by their one-month alpha (Panel B; annualized). Panel A reports coefficients form an equal-weight or value-weight regression of real-time estimated $\hat{V}/P$ onto dummies for the relevant portfolio holdings. Panel B estimates portfolio alphas using Fama-MacBeth-style regressions. All regressions control for the rank of liquidity based on Amihud (2002) and time fixed effects, and all t-statistics are robust to time and stock-level clustering. All numbers are in percentage points. The Buffett indicator equals one if the stock is held by Berkshire Hathaway and zero otherwise. The Fundamental indicator equals one if the stock is held by Berkshire Hathaway, Tiger Management, Capital Group, or Dodge & Cox and zero otherwise. The sample period is 1981 to 2024.

Panel A. Dependent Variable: CAPM $\hat{V}/P$ (ppt)

Buffett	17.09		15.20	7.77		6.76
	(5.89)		(5.22)	(2.08)		(1.81)
Fundamental		3.45	2.65		5.59	4.75
		(4.93)	(3.84)		(4.83)	(4.55)
Weight	EW	EW	EW	VW	VW	VW

Panel B. Dependent Variable: CAPM Alpha (annualized ppt)

Buffett	5.62		3.82	1.28		0.87
	(3.13)		(2.25)	(0.69)		(0.47)
Fundamental		2.70	2.54		1.84	1.91
		(3.22)	(3.00)		(2.54)	(2.79)
Weight	EW	EW	EW	VW	VW	VW

Table 7: **Biased Expectations as a Potential Driver of Price Distortions**

We report estimates of coefficients (γ_V, in percentage units) linking stock characteristics (z) to model-implied underpricing ($\frac{V}{P}-1$), where the z vector in the first three columns includes the ratio of median analyst price target to price (*Price Target*). For comparison, the last three columns re-estimate our baseline specification using the same subsample. We report bootstrap absolute t-statistics in parentheses. The sample period is 2001m6–2024m12.

	Analyst Price Target			Baseline Specification		
Characteristic	CAPM	FF3	FF5	CAPM	FF3	FF5
BM	5.36	2.53	6.43	-1.09	-5.69	4.18
	(0.81)	(0.77)	(1.29)	(0.15)	(1.35)	(0.79)
Prof	21.92	23.09	21.03	30.65	33.96	24.37
	(2.90)	(3.86)	(2.88)	(2.88)	(4.14)	(2.65)
Beta	-6.60	-1.70	-3.87	-10.61	-5.77	-5.91
	(0.69)	(0.22)	(0.45)	(0.98)	(0.65)	(0.61)
Inv	-2.82	-2.63	-1.17	-3.83	-3.82	-1.33
	(3.49)	(3.38)	(1.63)	(4.45)	(4.66)	(1.54)
NetIss	-3.57	-2.74	-0.20	-3.78	-3.07	-0.10
	(3.04)	(2.82)	(0.18)	(3.35)	(3.35)	(0.10)
Liq	-9.14	-11.23	-15.75	-4.55	-5.43	-12.26
	(1.46)	(2.90)	(3.25)	(0.59)	(0.91)	(2.19)
Ret	-1.12	-1.28	0.02	0.76	0.82	1.64
	(0.76)	(0.98)	(0.01)	(0.48)	(0.60)	(1.12)
LagRet	0.05	0.34	0.95	-0.16	0.06	1.08
	(0.08)	(0.60)	(1.67)	(0.21)	(0.10)	(1.78)
Price Target	-9.94	-10.47	-6.10			
	(4.09)	(4.54)	(3.06)			

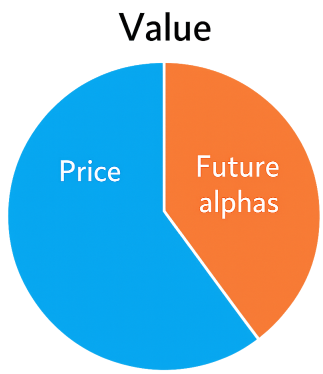


Figure 1: **Discounted-Alpha Valuation**

The figure illustrates the intuition behind the discounted-alpha valuation formula for an underpriced stock. From the perspective of a buy-and-hold investor, the stock of underpricing $(V_0 - P_0)$ equals the discounted sum of future flows of alphas, leading to the discounted-alpha valuation identity:

$$V_0 = P_0 + \sum_{\tau=0}^{\infty} E_0[X_\tau \, \alpha_\tau].$$

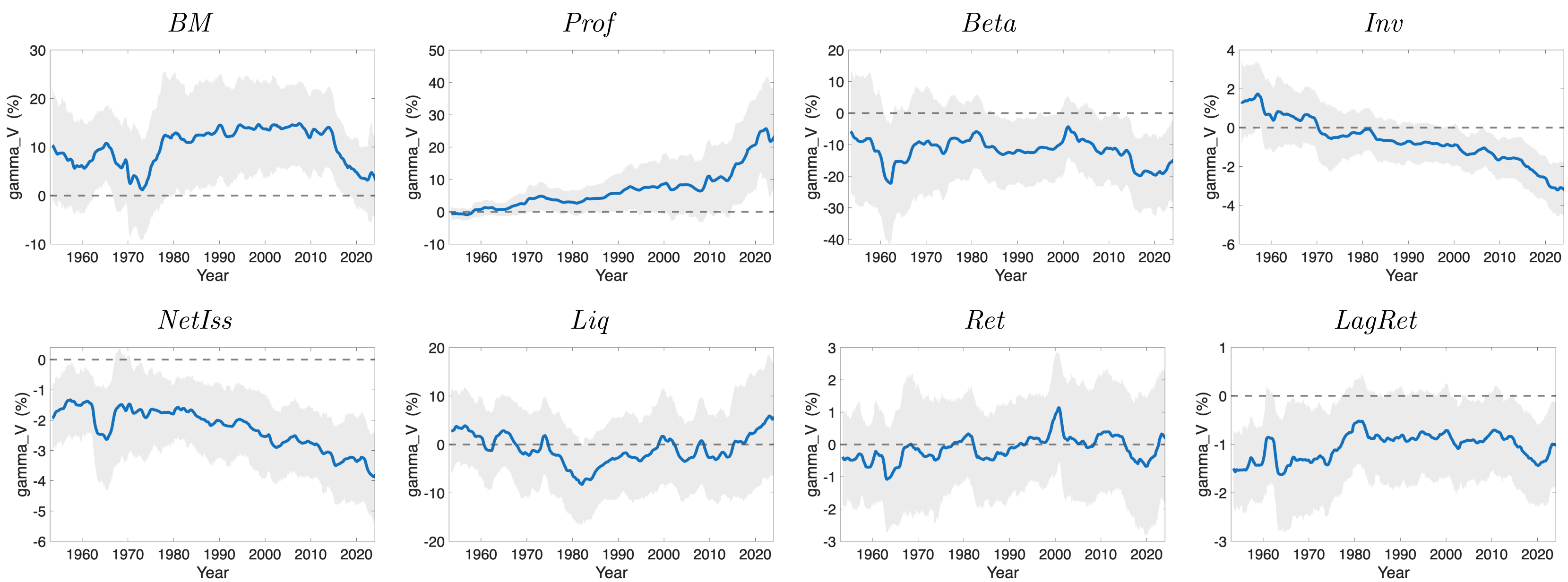


Figure 2: **Moving-Window Multivariate Coefficients of CAPM Underpricing on Stock Characteristics**

We plot the multivariate projection coefficients, γ_V, linking stock-level CAPM underpricing $(\frac{V}{P} - 1)$ to stock characteristics. We estimate these coefficients in 40-year rolling windows over 1953m6–2024m12, expanding from a 15-year minimum at the start of the sample. The shaded area represents the 95% bootstrap confidence interval. Coefficients are plotted in percentage points by window end date.

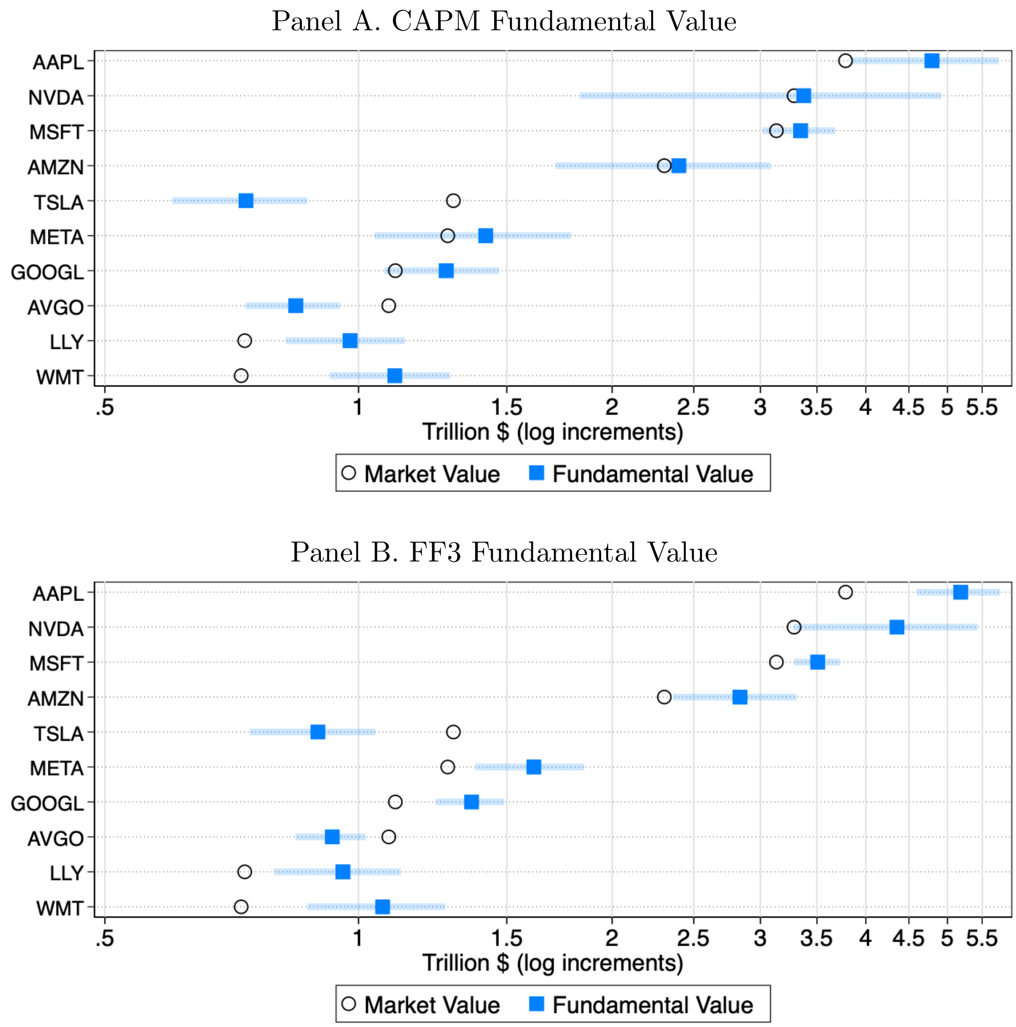


Figure 3: **Fundamental Equity Values of Largest Companies (December 2024)**
This figure compares the market value of the 10 largest US stocks as of the end of December 2024 to their estimated fundamental value implied by either the CAPM (Panel A) or the Fama and French (1993) three-factor model (Panel B). We show the associated bootstrap 95% confidence interval in light blue.

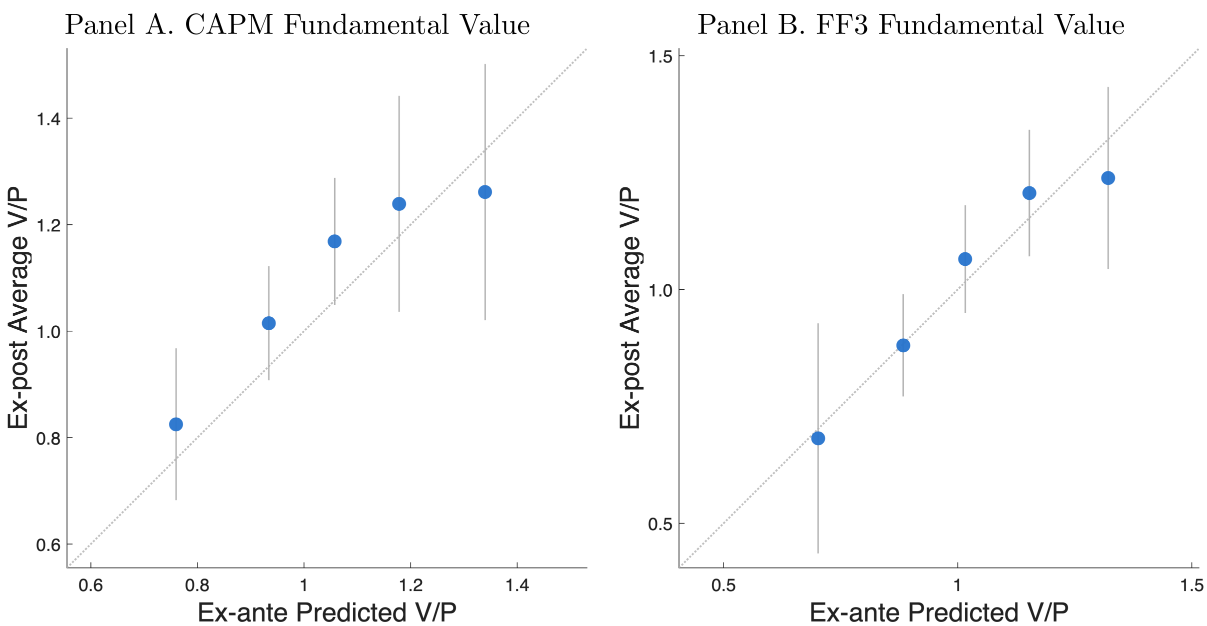


Figure 4: **Ex-Ante Predicted vs. Ex-Post Realized Fundamental Value**

We plot ex-post realized V/P ratios against ex-ante predicted V/P ratios for five quintiles sorted on predicted V/P based on NYSE breakpoints. We estimate ex-post realized value-weight portfolio V/P ratios and the associated 95% confidence intervals using the post-formation-return approach of Cho and Polk (2024), which assigns the exact weight to the post-formation buy-and-hold returns of each portfolio needed in order to correctly estimate formation-period model-specific V/P. We value-weight the ex-ante V/P ratios within each portfolio. We also plot a 45-degree dotted line, since observations should line up along this line if the ex-ante predicted V/P ratios are accurate.

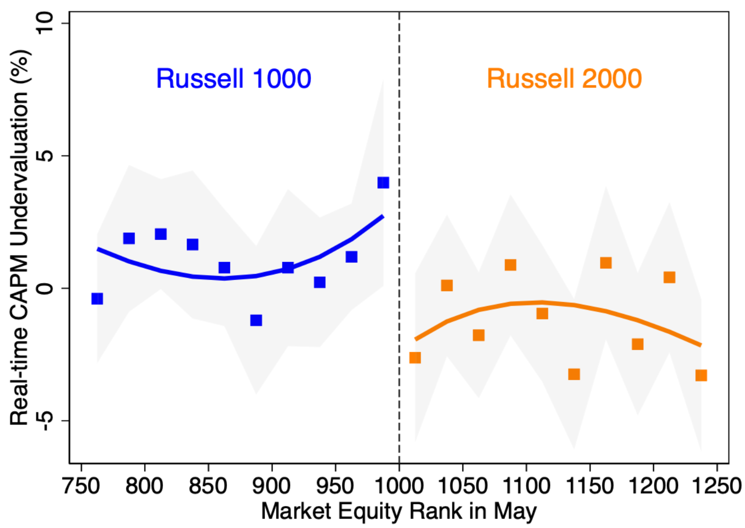


Figure 5: **Real-Time CAPM Underpricing Reveals the Russell Price Distortion**

The figure plots point estimates of June real-time CAPM-implied underpricing, $\hat{V}_{i,t}/P_{i,t} - 1$, regressed onto May market-equity-rank bin dummies (of 25 rank positions) for each index. The pattern lines up with the Russell 1000/2000 evidence in Table A6: stocks near the bottom of the Russell 1000 appear underpriced relative to stocks near the top of the Russell 2000. Russell 1000 stocks whose measured market-cap rank falls below 1000 are assigned to the bottom bin (ranks 975–1000); symmetrically, Russell 2000 stocks whose measured rank falls above 1000 are assigned to the top bin (ranks 1000–1025). Estimates are from a value-weight regression with time fixed effects; vertical bars report double-clustered standard errors by stock and time. The regression includes a third order polynomial of log market cap as well as the log of June float-adjusted market value as additional controls. The sample period is from 1989 to 2006. We end the sample before 2007, when the banding rule was introduced to the Russell 1000/2000 assignment.

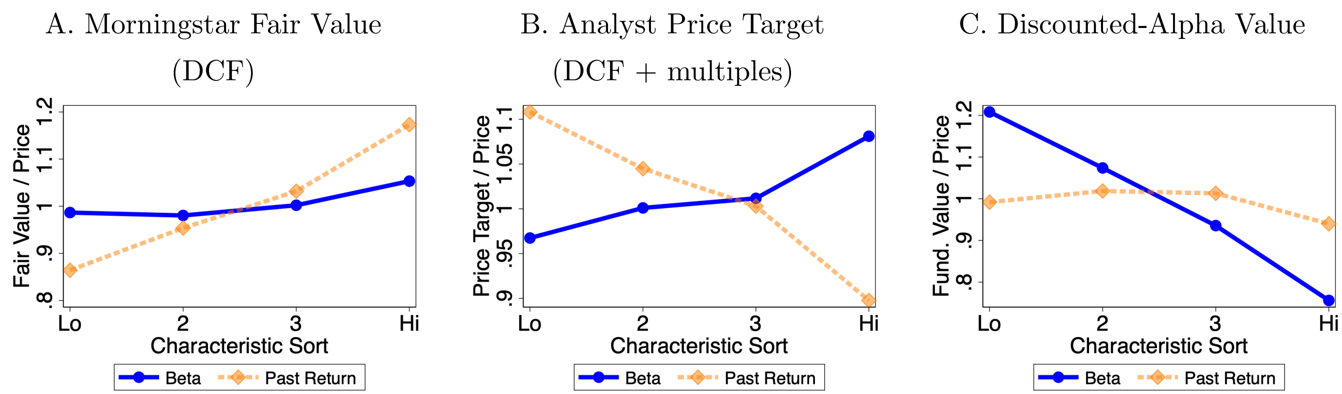


Figure 6: **Which Stock Characteristics Drive Industry DCF-based Value Estimates? (2001m6–2024m12)**

We plot value-weight averages of value-to-price estimates for each of four rank-characteristic-sorted bins (cross-sectional standardized rank of −1 or lower; −1 to 0; 0 to 1; and 1 or higher). Panel A shows that Morningstar's DCF-based fair value estimates tend to rise with market beta, suggesting issues with their discount-rate adjustment. Their estimates also strongly increase with past returns, consistent with analysts systematically extrapolating from past performance. Panel B shows that analysts' one-year target prices strongly increase with market beta, again suggesting problems with their discount-rate adjustment. However, these one-year target prices tend to bet against past one-year returns. Panel C shows that our real-time CAPM-based discounted-alpha estimates of fundamental value strongly decrease with market beta but only weakly decrease with past returns.

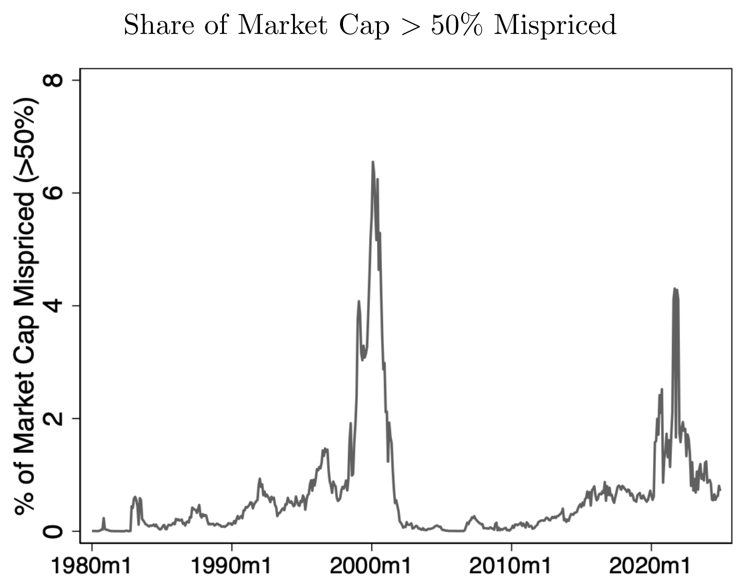
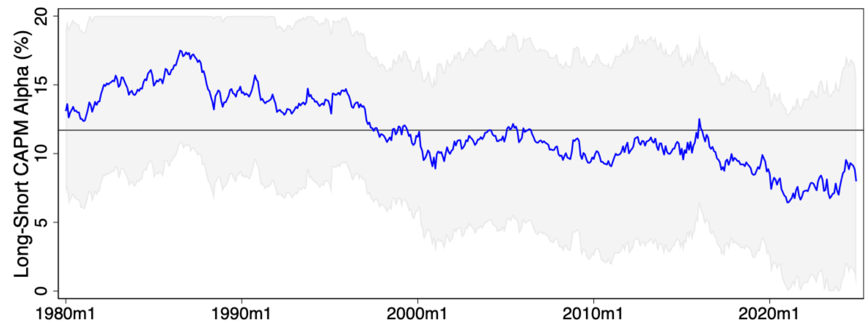
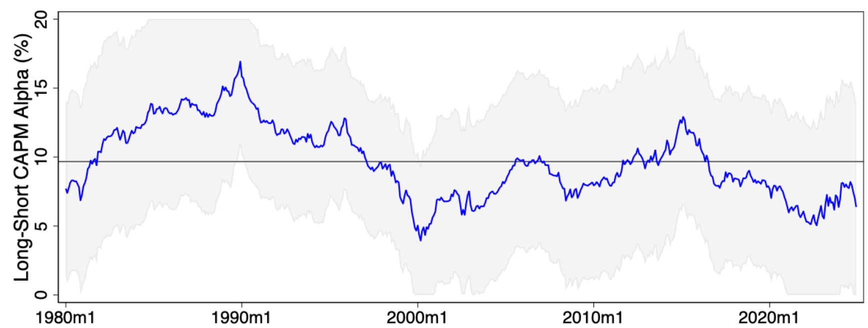


Figure 7: **Share of Market Cap with CAPM-Implied Mispricing Greater than 50%**
The figure plots the percentage of market capitalization that is more than 50% mispriced, i.e., where the V/P ratio is outside the range of 0.5 to 1.5. It illustrates periods of high CAPM-implied mispricing during the dot-com bubble and after Covid-19.

Panel A. CAPM Alphas on Short-Term Strategy



Panel B. CAPM Alphas on V/P Strategy



Panel C. CAPM Mispricing (V/P) Persistence

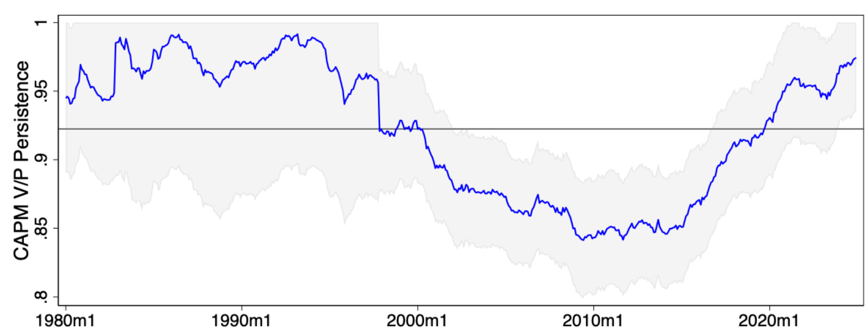


Figure 8: **Alpha Decay—Not the Whole Story**

Panel A plots the annualized monthly long–short CAPM alpha from quintile portfolios sorted on ex-ante one-month alpha, estimated by projecting alphas onto the eight baseline characteristics. Panel B plots the corresponding long–short CAPM alpha from quintile portfolios sorted on estimated ex-ante CAPM value-to-price ratios, where value-to-price is constructed from the same characteristics interacted with their time-varying spreads. Panel C plots the persistence of CAPM mispricing, defined as the ratio of next-month value-to-price to this-month value-to-price for the extreme quintile portfolios, value-weight within each quintile. In all figures, the horizontal line denotes the average value over the sample. All figures are based on a 15-year trailing moving window with the window's end month from January 1980 to December 2024.

A Main Paper Appendix

A.1 Proof of Lemma 2 and Lemma 3

Begin with the one-period discounted-alpha identity in equation (10):

$$\frac{\alpha_{i,t}}{1+R_{f,t}} \;=\; \nu_{i,t} \;-\; E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\;\nu_{i,t+1}\right], \quad \nu_{i,t} \equiv \underbrace{\frac{V_{i,t}}{P_{i,t}}-1}_{\text{underpricing}}\;. \tag{10}$$

Applying the projection in equation (14),

$$\frac{\alpha_{i,t}}{1+R_{f,t}} \;=\; \gamma_V z_{i,t} + u_{i,t} \;-\; E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\;\gamma_V z_{i,t+1}\right] - E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\;u_{i,t+1}\right]. \tag{44}$$

Since $E[XYZ] = E[XY]E[Z] + E[X]Cov(Y,Z) + E[Y]Cov(X,Z) + E[(X-E[X])(Y-E[Y])(Z-E[Z])]$,

$$\begin{aligned}
\frac{\alpha_{i,t}}{1+R_{f,t}} \;=\;& \gamma_V z_{i,t} + u_{i,t} \;-\; \gamma_V\, E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\right]\; E_t\left[z_{i,t+1}\right] \\
& -\gamma_V\, E_t\left[\widetilde{M}_{t+1}\right]\; Cov_t\left(G_{i,t+1}, z_{i,t+1}\right) - \gamma_V\, E_t\left[1+G_{i,t+1}\right] Cov_t\left(\widetilde{M}_{t+1}, z_{i,t+1}\right) \\
& -\gamma_V\, \sigma_{\widetilde{M},G,z,i,t} - E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\;u_{i,t+1}\right],
\end{aligned} \tag{45}$$

where $\sigma_{\widetilde{M},G,z,i,t} \equiv E_t\left[\left(\widetilde{M}_{t+1} - E_t\widetilde{M}_{t+1}\right)\left(G_{i,t+1} - E_tG_{i,t+1}\right)\left(z_{i,t+1} - E_tz_{i,t+1}\right)\right]$ measures coskewness. Since $E_t[z_{i,t+1}] = \frac{E_t[\widetilde{M}_{t+1}z_{i,t+1}] - Cov_t(\widetilde{M}_{t+1}, z_{i,t+1})}{E_t\widetilde{M}_{t+1}}$ and $E_t\left[1+G_{i,t+1}\right] = \frac{E_t[\widetilde{M}_{t+1}(1+G_{i,t+1})] - Cov_t(\widetilde{M}_{t+1}, G_{i,t+1})}{E_t\widetilde{M}_{t+1}}$, equation (45) becomes

$$\begin{aligned}
\frac{\alpha_{i,t}}{1+R_{f,t}} \;=\;& \gamma_V z_{i,t} + u_{i,t} \;-\; \gamma_V\, E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\right]\; E_t\left[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}} z_{i,t+1}\right] \\
& -\gamma_V\, E_t\left[\widetilde{M}_{t+1}\right]\; Cov_t\left(G_{i,t+1}, z_{i,t+1}\right) + \gamma_V\, Cov_t\left(\widetilde{M}_{t+1}, G_{i,t+1}\right) Cov_t\left(\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}}, z_{i,t+1}\right) \\
& -\gamma_V\, \sigma_{\widetilde{M},G,z,i,t} - E_t\left[\widetilde{M}_{t+1}\,(1+G_{i,t+1})\;u_{i,t+1}\right].
\end{aligned} \tag{46}$$

Rewriting, we obtain the result in Lemma 2:

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V\left(I - \rho_{i,t}\phi_{z,i,t} - \frac{\Gamma_{G,z,i,t}}{1+R_{f,t}}\right) z_{i,t} + \varepsilon_{i,t} \tag{15}$$

where

$$\rho_{i,t} \equiv E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\right] \tag{47}$$

$$\phi_{z,i,t}z_{i,t} \equiv E_t\left[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}}z_{i,t+1}\right] \tag{48}$$

$$\Gamma_{G,z,i,t}z_{i,t} \equiv Cov_t\left(G_{i,t+1},z_{i,t+1}\right) \tag{49}$$

$$\begin{aligned}\varepsilon_{i,t} \equiv\; & u_{i,t}-E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)u_{i,t+1}\right] \\ & +\gamma_V\, Cov_t\left(\widetilde{M}_{t+1},G_{i,t+1}\right)Cov_t\left(\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}},z_{i,t+1}\right)-\gamma_V\,\sigma_{\widetilde{M},G,z,i,t}.\end{aligned} \tag{50}$$

Note that the error term $\varepsilon_{i,t}$ contains the projection errors and the third- and fourth-order terms, which are empirically small.

To get the result in Lemma 3, we further assume that the candidate SDF correctly prices its own factors: $Cov_t\left(\widetilde{M}_{t+1},f_{t+1}\right)=-\frac{1}{1+R_{f,t}}E_t\left[f_{t+1}\right]$. Given the specification in equations (24) and (25), the usual asset-pricing algebra implies

$$\phi_{z,i,t}\,z_{i,t}=E_t\left[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}}z_{i,t+1}\right]=E_t\left[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}}\left(\phi_z z_{i,t}+\beta_{z,i,t}f_{t+1}+\epsilon_{z,i,t+1}\right)\right]=\phi_z z_{i,t} \tag{51}$$

$$\Gamma_{G,z,i,t}\,z_{i,t}=\beta_{z,i,t}\Sigma_t\beta_{G,i,t}'+\Gamma_{G,z}z_{i,t}+\epsilon_{G,z,i,t} \tag{52}$$

$$Cov_t\left(\widetilde{M}_{t+1},G_{i,t+1}\right)Cov_t\left(\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}},z_{i,t+1}\right)=\frac{1}{1+R_{f,t}}\beta_{z,i,t}\lambda_t\lambda_t'\beta_{G,i,t}', \tag{53}$$

where $\lambda_t \equiv E_t\left[f_{t+1}\right]$. Therefore, equation (15) becomes

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V\left(I-(1+\frac{\gamma_G}{1+R_{f,t}}z_{i,t})\phi_z-\frac{\Gamma_{G,z}}{1+R_{f,t}}\right)z_{i,t}+\varepsilon_{i,t}^{*}, \tag{26}$$

where

$$\begin{aligned}\varepsilon_{i,t}^{*} =\; & \underbrace{u_{i,t}-E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)u_{i,t+1}\right]-\gamma_V\frac{\epsilon_{G,z,i,t}}{1+R_{f,t}}}_{\text{projection error}} \\ & -\gamma_V\left(\underbrace{\frac{1}{1+R_{f,t}}\beta_{z,i,t}\left(\Sigma_t-\lambda_t\lambda_t'\right)\beta_{G,i,t}'}_{\text{second moment terms}}+\underbrace{\sigma_{\widetilde{M},G,z,i,t}}_{\text{third moment}}\right).\end{aligned} \tag{54}$$

First-moment terms involving $\beta_{G,i,t}$ cancel out in the "duration" part of the formula, since duration reflects *risk-adjusted* capital gain. A large expected capital gain due to higher risk does not raise duration, since riskier future cash flows are discounted more heavily. We place the second- and third-moment terms—which tend to be small—in the error term. We find that explicitly including second-moment terms makes little difference to estimates of γ_V.

For the term $E_t\left[\widetilde{M}_{t+1}(1+G_{i,t+1})u_{i,t+1}\right]$ in the projection error to be uncorrelated with the regressors in equation (26), it is important to include a price multiple (e.g., book-to-market) and past return in the characteristic vector z. Since these characteristics covary with capital gain, omitting them can cause $E_t\left[\widetilde{M}_{t+1}(1+G_{i,t+1})u_{i,t+1}\right]$ to be nonzero and potentially covary with the regressors.

Internet Appendix to "Equity Valuation Without DCF"

B Theory Internet Appendix

B.1 Variance of discounted-alpha vs DCF estimators with closed-form solutions

This section specifies a process for earnings and returns that result in value-to-book (V/B) and value-to-price (V/P) being linear in characteristics. The parameters for V/B can be recovered from regressions of earnings and book growth on predictors, akin to DCF, while the parameters for V/P can be recovered from alpha and capital gains regressions, akin to the discounted-alpha approach. We show that the sample variance of these estimators is increasing in the persistence and cross-sectional variance of risk-adjusted dividend growth (for DCF) and alphas (for discounted alpha). Using empirical values for these persistence and variance numbers yields a sample variance that is $> 100\times$ higher for the DCF estimator than the discounted-alpha estimator.

A. Processes

For simplicity, we will assume that true V/B is linear in a single characteristic $x_{i,t}$ and V/P is linear in a single characteristic $y_{i,t}$. This assumption is possible if risk-adjusted earnings and returns are linear in x and y, respectively, and if $x_{i,t}$ and $y_{i,t}$ each follow a particular sort of "twisted" AR1 process, similar to the processes in Gabaix (2007).

Define earnings-to-book as dividends plus book equity growth (per share), and excess earnings-to-book as earnings-to-book minus the gross risk-free rate

$$E_{i,t+1} = \frac{B_{i,t+1} + D_{i,t+1}}{B_{i,t}}$$

$$E^e_{i,t+1} = E_{i,t+1} - (1 + R_{f,t})$$

Let excess earnings and returns be linear in x or y after adjusting for (potentially time-varying) factor loadings. Here we will assume a single-factor CAPM model where the SDF is linear in $R^e_{m,t+1}$.

$$\frac{E^e_{i,t+1}}{1 + R_{f,t}} = \gamma_{E,0} + \gamma_{E,1} x_{i,t} + \beta_{E,i,t} R^e_{m,t+1} + \varepsilon_{E,i,t+1} \quad (55)$$

$$\frac{R^e_{i,t+1}}{1 + R_{f,t}} = \gamma_{R,0} + \gamma_{R,1} y_{i,t} + \beta_{R,i,t} R^e_{m,t+1} + \varepsilon_{R,i,t+1} \quad (56)$$

Given the single-factor model, these equations imply that alphas and risk-adjusted excess earnings $\left(E_t\left[\widetilde{M}_{t+1} E^e_{i,t+1}\right]\right)$ are linear in $y_{i,t}$ and $x_{i,t}$, respectively.

In order to deliver a linear V/P or V/B, we must specify that $x_{i,t}$ and $y_{i,t}$ follow a "book-growth-and-risk-adjusted" or "capital-gains-and-risk-adjusted" AR1 process (a "twisted" AR1 in the language of Gabaix, 2007).[28]

$$x_{t+1}\frac{B_{t+1}/B_t}{1+R_{f,t}} = \gamma_{x,0} + \gamma_{x,1}x_t + \beta_x R^e_{m,t+1} + \varepsilon_{x,t+1} \tag{57}$$

$$y_{t+1}\frac{P_{t+1}/P_t}{1+R_{f,t}} = \gamma_{y,0} + \gamma_{y,1}y_t + \beta_y R^e_{m,t+1} + \varepsilon_{y,t+1} \tag{58}$$

These equations imply that $E_t\left[\widetilde{M}_{t+1}\frac{B_{t+1}}{B_t}x_{t+1}\right]$ and $E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}y_{t+1}\right]$ are linear in $x_{i,t}$ and $y_{i,t}$, respectively.

To keep the form of the resulting estimator simple, we will also assume that the expected risk-adjusted book growth and capital gains are constant:

$$E_t\left[\widetilde{M}_{t+1}\frac{B_{t+1}}{B_t}\right] = \rho_B$$

$$E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}\right] = \rho_P$$

Loosening this assumption to allow risk-adjusted book growth and capital gains to be linear in x_t and y_t yields similar results, although with a slightly more complicated expression for the variance of the value estimator.

B. Values

Plugging these processes into Equation (10) for V/P, and into the equivalent identity for V/B yields the following expressions for value.

Remark 4 (Linear V/B and V/P). *Given the processes specified in Equations (55) to (58), and a CAPM SDF, firm value is given by:*

$$\frac{V_t}{B_t} - 1 = \gamma_{vb,0} + \gamma_{vb,1}x_t$$

$$\frac{V_t}{P_t} - 1 = \gamma_{vp,0} + \gamma_{vp,1}y_t$$

[28] Note that these processes differ from the ones we estimate in the main part of the paper. We make them here only to help simplify our discussion of the relative magnitudes of the two different types of estimators.

with parameters given by:

$$\gamma_{vb,0} = \left(\gamma_{E,0} + \frac{\gamma_{x,0}\gamma_{E,1}}{1-\gamma_{x,1}}\right)/(1-\rho_B); \qquad \gamma_{vb,1} = \frac{\gamma_{E,1}}{1-\gamma_{x,1}}$$
$$\gamma_{vp,0} = \left(\gamma_{R,0} + \frac{\gamma_{y,0}\gamma_{R,1}}{1-\gamma_{y,1}}\right)/(1-\rho_P); \qquad \gamma_{vp,1} = \frac{\gamma_{R,1}}{1-\gamma_{y,1}}$$

C. Sensitivity of estimators

The coefficients $\gamma_{vb,1}$ and $\gamma_{vp,1}$ represent the effect of characteristic x or y on V/B or V/P. If we assume, without loss of generality, that x and y have unit variance, then they also represent the cross-sectional standard deviation of valuation ratios.

Consider an econometrician estimating these values by estimating the parameters of the underlying processes for E, R, x, and y from Equations (55) to (58). The sensitivity of valuation estimates to small errors in the estimation of the underlying parameters would be given by the gradients of the value parameters:

$$\frac{\partial\hat{\gamma}_{vb,1}}{\partial\hat{\gamma}_{E,1}} = \frac{\hat{\gamma}_{vb,1}}{\hat{\gamma}_{E,1}}; \quad \frac{\partial\hat{\gamma}_{vb,1}}{\partial\hat{\gamma}_{x,1}} = \frac{\hat{\gamma}_{vb,1}}{(1-\hat{\gamma}_{x,1})}$$
$$\frac{\partial\hat{\gamma}_{vp,1}}{\partial\hat{\gamma}_{R,1}} = \frac{\hat{\gamma}_{vp,1}}{\hat{\gamma}_{R,1}}; \quad \frac{\partial\hat{\gamma}_{vp,1}}{\partial\hat{\gamma}_{y,1}} = \frac{\hat{\gamma}_{vp,1}}{(1-\hat{\gamma}_{y,1})}$$

From this form we can clearly see that the V/B ("DCF") estimator will be more sensitive to small errors if the cross-sectional variation of V/B, measured by $\hat{\gamma}_{vb,1}$, is sufficiently greater than that of V/P, measured by $\hat{\gamma}_{vp,1}$—i.e., if the price is not too far from the model-implied value.

In this sense, we can say that the discounted-alpha estimator is less sensitive to discount-rate estimation than the DCF estimator. If we attribute higher earnings from firms with high levels of characteristic x to risk-adjusted growth instead of higher discount rates (i.e., we over-estimate $\gamma_{E,1}$), such an error will lead to a larger mistake than if we over-estimate the alpha associated with characteristic y, i.e., $\gamma_{R,1}$. Note that a mistake in the constant term of the process for either earnings ($\gamma_{E,0}$) or alphas ($\gamma_{R,0}$) will have approximately the same effect on the value estimator. However, errors in the constant term are not relevant for our main analysis where we impose that cross-sectional and steady state alphas and mispricings are both 0.

D. Sample variance of value estimators

Suppose an econometrician estimates Equations (55) to (58) by value-weight least squares and then uses those parameters to estimate $\gamma_{vb,1}$ and $\gamma_{vp,1}$. Applying the delta method, the sample variances will be given by:

$$
\begin{aligned}
Var\left(\hat{\gamma}_{vb,1}\right) &\approx \hat{\gamma}_{vb,1}^2 \left(\frac{Var(\hat{\gamma}_{E,1})}{\hat{\gamma}_{E,1}^2} + \frac{Var(\hat{\gamma}_{x,1})}{\left(1-\hat{\gamma}_{x,1}\right)^2} + 2\frac{Cov(\hat{\gamma}_{E,1},\hat{\gamma}_{x,1})}{\hat{\gamma}_{E,1}\left(1-\hat{\gamma}_{x,1}\right)} \right) \\
Var\left(\hat{\gamma}_{vp,1}\right) &\approx \hat{\gamma}_{vp,1}^2 \left(\frac{Var\left(\hat{\gamma}_{R,1}\right)}{\hat{\gamma}_{R,1}^2} + \frac{Var\left(\hat{\gamma}_{y,1}\right)}{\left(1-\hat{\gamma}_{y,1}\right)^2} + 2\frac{Cov\left(\hat{\gamma}_{R,1},\hat{\gamma}_{y,1}\right)}{\hat{\gamma}_{R,1}\left(1-\hat{\gamma}_{y,1}\right)} \right)
\end{aligned}
$$

If we consider cross-sectional variation in valuation and ignore the constant terms $\gamma_{vb,0}$ and $\gamma_{vp,0}$, then for any given stock, the variance of its estimated value is given by either of:

$$
\begin{aligned}
Var\left(\hat{V}_{i,t}^{DCF}\right) &= B_t^2 x_t^2 Var\left(\hat{\gamma}_{vb,1}\right) \\
Var\left(\hat{V}_{i,t}^{DA}\right) &= P_t^2 y_t^2 Var\left(\hat{\gamma}_{vp,1}\right)
\end{aligned}
$$

Here we can see that the sample variance of the DCF estimator is going to be larger than that of the discounted-alpha estimator if $\gamma_{vp,1}$, the cross-sectional standard deviation in V/P, is sufficiently small. The DCF estimator may instead have lower sample variance if $\gamma_{vb,1}$ is smaller than $\gamma_{vp,1}$ or if the sample variance of the risk-adjusted earnings coefficient, $\gamma_{E,1}$, is sufficiently smaller than that of the alpha coefficient, $\gamma_{R,1}$.

E. Empirical estimation of sample variance

To quantify the size of the difference in sample variance, we run the linear regressions implied by Equations (55) to (58) using annual observations of the full value-weight panel of stock data from 1953 onwards.

To create empirical counterparts to the earnings-predictor characteristic x and the alpha-predictor characteristic y, we first run the regressions from Equations (55) and (56) using the full vector of demeaned firm characteristics z used in our main analysis as explanatory variables. We then combine these characteristics according to their coefficient weights into a single x and y characteristic and standardize to unit variance. These composite characteristics should capture the persistence of the signals that predict earnings and alphas. Betas are estimated by letting beta be linear in characteristics z, as in our main approach.

The resulting estimates and standard errors are shown in Table A3. Point estimates for the DCF coefficient $\gamma_{vb,1}$ are approximately 9× higher than those for $\gamma_{vp,1}$. As a result, after clustering by year, the sample variance of the DCF coefficient, $\hat{\gamma}_{vb,1}$, is approximately 100× higher (standard error over 10× higher) than that of the discounted-alpha coefficient, $\hat{\gamma}_{vp,1}$.

The value-weight average book-to-price ratio during our sample period is 0.6. Thus, for a stock with a unit value of characteristic x or y and an average level of price to book, the DCF sample variance will be 40× higher (standard error 6× higher) than that of discounted alpha.

Note that the standard errors for both approaches are underestimated in this exercise. We have created characteristics x and y by running a first-stage regression on a longer list of characteristics z and not accounted for this first stage in the sample variance. Nonetheless, the ratio between the sample variance of the two approaches illustrates that there can be large differences between the power of the discounted-alpha and DCF approaches.

B.2 Discounted alpha = population-level restrictions on DCF

If discounted alpha (DA) is simply a rewriting of DCF, how could it exhibit less sampling noise? Indeed, DA and DCF coincide in the population, equaling model-implied value. However, the benefit of DA as an *estimator* arises from removing population-zero components from the DCF representation, obviating the need to estimate these quantities in the data.

To see where DA imposes restrictions, start with DCF and manipulate the expression by adding and subtracting accordingly.

$$
\begin{aligned}
\textbf{DCF:}\quad V_{i,t} &= \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, D_{i,t+\tau}\right] && (2)\\
&= \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau-1}\,(1+R_{i,t+\tau})\right] - \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau}\right]\\
&= P_{i,t} + \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau-1}\,(1+R_{i,t+\tau})\right] - \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau-1}\, P_{i,t+\tau-1}\right]\\
&= P_{i,t} + \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau-1}\widetilde{M}_{t+\tau}\, P_{i,t+\tau-1}\,((1+R_{i,t+\tau})-(1+R_{b,t+\tau}))\right] + \varepsilon_{i,t}^{base} + \varepsilon_{i,t}^{cumul}\\
&= P_{i,t} + \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau-1}\, P_{i,t+\tau-1} E_{t+\tau-1}\left[\widetilde{M}_{t+\tau} R^e_{i,t+\tau}\right]\right] + \varepsilon_{i,t}^{base} + \varepsilon_{i,t}^{cumul}\\
&= P_{i,t} + \sum_{\tau=0}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau}\frac{\alpha_{i,t+\tau}}{1+R_{f,t+\tau}}\right] + \varepsilon_{i,t}^{f} + \varepsilon_{i,t}^{base} + \varepsilon_{i,t}^{cumul}, && (59)
\end{aligned}
$$

where the second-to-last step uses the law of iterated expectations, $R^e_{i,t+\tau} \equiv R_{i,t+\tau} - R_{b,t+\tau}$ is excess return above the base-asset return, and ε^f, ε^{base}, and ε^{cumul} are errors arising from conditionally pricing the risk-free asset and the base asset, and from accumulating the model SDF:

$$\varepsilon_{i,t}^{f} = \sum_{\tau=0}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau}\left(E_{t+\tau}\left[\widetilde{M}_{t+\tau+1} R_{i,t+\tau+1}^{e}\right] - \frac{\alpha_{i,t+\tau}}{1+R_{f,t+\tau}}\right)\right] \tag{60}$$

$$\varepsilon_{i,t}^{base} = \sum_{\tau=1}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau-1}\, P_{i,t+\tau-1}\left(E_{t+\tau-1}\left[\widetilde{M}_{t+\tau}(1+R_{b,t+\tau})\right] - 1\right)\right] \tag{61}$$

$$\varepsilon_{i,t}^{cumul} = \sum_{\tau=1}^{\infty} E_t\left[\left(\widetilde{M}_{t\to t+\tau} - \widetilde{M}_{t\to t+\tau-1}\widetilde{M}_{t+\tau}\right) P_{i,t+\tau-1}(1+R_{i,t+\tau})\right]. \tag{62}$$

However, $\varepsilon_{i,t}^{f}$, $\varepsilon_{i,t}^{base}$, and $\varepsilon_{i,t}^{cumul}$ must all be zero under the mild conditions that the model SDF conditionally prices the risk-free asset and the base asset, and is time-consistent.

(i) **Conditional pricing of base assets.** The model-implied SDF conditionally prices the risk-free asset and the base asset (b), which could be the risk-free asset (making equations (63) and (64) identical) or the market portfolio:

$$\frac{1}{1+R_{f,\tau}} = E_{t+\tau}\left[\widetilde{M}_{t+\tau+1}\right] \qquad \text{for all } \tau \geq 0 \tag{63}$$

$$1 = E_{t+\tau-1}\left[\widetilde{M}_{t+\tau}\,(1+R_{b,t+\tau})\right] \qquad \text{for all } \tau \geq 1. \tag{64}$$

(ii) **Time consistency.** The model-implied SDF satisfies

$$\widetilde{M}_{t\to t+\tau} = \widetilde{M}_{t\to t+u}\,\widetilde{M}_{t+u\to t+\tau} \qquad \text{a.s. for all } u < \tau. \tag{65}$$

Discounted alpha (DA) applies these asset-pricing restrictions $\varepsilon_{i,t}^{f} = \varepsilon_{i,t}^{base} = \varepsilon_{i,t}^{cumul} = 0$ prior to estimation rather than attempting to estimate those quantities in sample.[29]

DA:

$$V_{i,t}^{DA} = P_{i,t} + \sum_{\tau=0}^{\infty} E_t\left[\widetilde{M}_{t\to t+\tau}\, P_{i,t+\tau}\frac{\alpha_{i,t+\tau}}{1+R_{f,t+\tau}}\right], \tag{66}$$

The efficiency gain arises because DA imposes valid asset-pricing restrictions on the DCF representation; an estimator that imposes correct theoretical restrictions generally offers higher efficiency (lower variance) than an unrestricted one.

This analysis also suggests how to improve DCF estimation if one wished to stay within the cash-flow framework. Theoretically, adding moment conditions $\hat{\varepsilon}_{i,t}^{f} = \hat{\varepsilon}_{i,t}^{base} = \hat{\varepsilon}_{i,t}^{cumul} = 0$ along with an optimal weighting matrix in a GMM implementation of the DCF estimator should achieve the

[29] To get equation (3) from equation (66), note that $\alpha_{i,t+\tau-1} \equiv E_{t+\tau-1}[\frac{\widetilde{M}_{t+\tau}}{E_{t+\tau-1}\widetilde{M}_{t+\tau}} R_{i,t+\tau}^{e}]$ and $\widetilde{M}_{t+\tau}$ are orthogonal and apply time consistency again.

same asymptotic variance as the discounted-alpha estimator, which applies those conditions at the population level. In finite samples, however, sampling error can enter into the moment conditions as well as the weighting matrix, raising finite-sample variance.

Furthermore, estimating DCF with a model-implied SDF that prices the current term structure of interest rates is not equivalent to imposing conditional risk-free-rate pricing in population. Matching the observed term structure at date t amounts to imposing

$$E_t\left[\widetilde{M}_{t\to t+\tau}\right] = \frac{1}{\left(1 + R^f_{t\to t+\tau}\right)^{\tau}}, \qquad \tau = 1, 2, \ldots, \tag{67}$$

where $R^f_{t\to t+\tau}$ is the observed yield on a τ-period zero-coupon bond. These are restrictions on the *unconditional* (from date t's perspective) marginal moments of the cumulative SDF.

By contrast, the conditions required for DA above (equations (63) and (64)) are *conditional* restrictions at every *future* date. And one cannot ex-ante specify a model SDF that will conditionally price all future short rates $\{R_{f,t+\tau}(\omega_{t+\tau})\}_{\tau=1}^{\infty}$ in every state ω. For instance, suppose one proposes calibrating the model SDF to match all observed *forward* rates, thereby constraining the conditional expectations more tightly. However, forward rates reflect risk-neutral expectations, $E^Q_t[R_{f,t+\tau}]$, not physical conditional expectations. Matching forward rates constrains the Q-measure dynamics of the short rate but does not enforce the P-measure conditional pricing restriction state by state. Bridging this gap requires specifying a complete dynamic model of the market price of interest-rate risk—exactly the kind of additional modeling layer that DA avoids.

B.3 Valuing a consol bond with discounted alpha

Example B.1 (**Valuing a consol**). *A consol paying* \$1 *perpetually has a constant market price of* $P = \$10$*. What is its fundamental value relative to the constant risk-free model if the risk-free rate is* $R_f = 5\%$*? Using DCF, one finds*

$$V_0^{DCF} \;=\; \frac{1}{1.05} + \frac{1}{1.05^2} + ... \;=\; \frac{1}{0.05} \;=\; \$20.$$

To instead apply discounted alpha, note that $\alpha = \frac{1}{P} - R_f = 0.10 - 0.05 = 0.05$*, since return equals the dividend yield. Hence,*

$$\begin{aligned} V_0^{DA} &= P_0 + \widetilde{M}_{0\to 0} P_0 \frac{1}{1+R_f}\alpha + \widetilde{M}_{0\to 1} P_1 \frac{1}{1+R_f}\alpha + ... \\ &= 10 + \frac{1}{1.05} 10 \times 0.05 + \frac{1}{1.05^2} 10 \times 0.05 + ... \;=\; 10 + \frac{1}{0.05} 0.5 \;=\; \$20. \end{aligned}$$

Example B.1 shows that discounted-alpha valuation works even without price convergence to fundamental value. Permanently depressed prices raise future dividend yields, generating abnormally high alphas that reveal the initial underpricing. Discounted-alpha valuation works under other price dynamics: if prices rise to correct underpricing, abnormal capital gains signal initial underpricing; if prices fall further, abnormal returns are realized as higher dividend yields offset weak capital gains, again signaling initial underpricing.

Indeed, the no-explosive-bubble condition in Lemma 1 is not restrictive: discounted-alpha valuation remains valid under most price deviations from value, including no convergence or even a permanent, non-explosive divergence.

B.4 Proof of Remark 3

First rearrange the definition of fundamental value in Definition 1 as a one-period law of motion:

$$V_{i,t} = E_t\left[\widetilde{M}_{t+1} D_{i,t+1}\right] + E_t\left[\widetilde{M}_{t+1} V_{i,t+1}\right]$$

Then divide by time-t book value (B) and subtract the market-average price-to-book at time t:

$$\frac{V_{i,t}}{B_{i,t}} - \overline{\frac{P_t}{B_t}} = E_t\left[\widetilde{M}_{t+1}\frac{D_{i,t+1}}{B_{i,t}}\right] + E_t\left[\widetilde{M}_{t+1}\frac{B_{i,t+1}}{B_{i,t}}\left(\frac{V_{i,t+1}}{B_{i,t+1}} - \overline{\frac{P_{t+1}}{B_{t+1}}} + \overline{\frac{P_{t+1}}{B_{t+1}}}\right)\right] - \overline{\frac{P_t}{B_t}}$$

Rearranging in terms of excess payout and the change in the deviation of value-to-book from market-average price-to-book yields:

$$E_t\left[\widetilde{M}_{t+1}\left(\frac{D_{i,t+1}}{B_{i,t}} + \frac{B_{i,t+1}}{B_{i,t}}\overline{\frac{P_{t+1}}{B_{t+1}}}\right)\right] - \overline{\frac{P_t}{B_t}} \ = \frac{V_{i,t}}{B_{i,t}} - \overline{\frac{P_t}{B_t}} - E_t\left[\widetilde{M}_{t+1}\frac{B_{i,t+1}}{B_{i,t}}\left(\frac{V_{i,t+1}}{B_{i,t+1}} - \overline{\frac{P_{t+1}}{B_{t+1}}}\right)\right]$$

And using the assumption that the risk free asset is correctly priced $\left(E_t[\widetilde{M}_{t+1}] = \frac{1}{1+R_{f,t}}\right)$:

$$E_t\left[\widetilde{M}_{t+1}\left(\frac{D_{i,t+1}}{B_{i,t}} + \overline{\frac{P_{t+1}}{B_{t+1}}}\frac{B_{i,t+1}}{B_{i,t}} - \overline{\frac{P_t}{B_t}}(1+R_{f,t})\right)\right] \ = \frac{V_{i,t}}{B_{i,t}} - \overline{\frac{P_t}{B_t}} - E_t\left[\widetilde{M}_{t+1}\frac{B_{i,t+1}}{B_{i,t}}\left(\frac{V_{i,t+1}}{B_{i,t+1}} - \overline{\frac{P_{t+1}}{B_{t+1}}}\right)\right]$$

This can be written in terms of the excess payout and value-to-book as:

$$E_t[\widetilde{M}_{t+1}\ EP_{i,t+1}] \ = \nu^b_{i,t} \ - \ E_t\left[\widetilde{M}_{t+1}\frac{B_{i,t+1}}{B_{i,t}}\ \nu^b_{i,t+1}\right]$$

where:

$$\nu^b_{i,t} \equiv \frac{V_{i,t}}{B_{i,t}} - \overline{\frac{P_t}{B_t}}$$

$$EP_{i,t+1} \equiv \frac{D_{i,t+1}}{B_{i,t}} + \overline{\frac{P_{t+1}}{B_{t+1}}} \frac{B_{i,t+1}}{B_{i,t}} - \overline{\frac{P_t}{B_t}}(1 + R_{f,t})$$

B.5 Conceptual comparisons to other valuation approaches

We review alternative approaches to estimating fundamental values—other than the firm-level real-time DCF (e.g., Gonçalves and Leonard, 2023 and our V/B implementation) analyzed conceptually in Section 3.3—and highlight the advantages of our proposed method.

A. A method using loglinear variables

One alternative is to start from the identity of Campbell and Shiller (1988) involving log-linear variables. However, this method faces difficulties: risk-adjusting expected log returns requires a Jensen's correction of unknown size, and both dividend growth and value-to-dividend ratios are undefined for firms with zero dividends. These issues make it less practical than our discounted-alpha framework. See Cho and Polk (2024) for more details.

B. Composite characteristic-based mispricing scores

Another class of approaches, including Stambaugh and Yuan (2017) and Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), combines characteristics that are *a priori* thought to be related to mispricing into a composite stock-level score. Such measures can be useful as auxiliary signals of likely underpricing or overpricing, but they are not naturally *cardinal* estimators of stock-level misvaluation.

The reason is that the scale of these composite scores is determined by design choices—which signals enter, how they are signed, standardized, and weighted—rather than by a valuation identity linking the score to the magnitude of $V_{i,t}/P_{i,t} - 1$. As a result, they are best suited to ordinal comparisons, i.e., ranking stocks from relatively more likely underpriced to relatively more likely overpriced, rather than measuring how far price is from model-implied value in percentage terms. By contrast, our approach is constructed to estimate precisely that cardinal object.

C. Projecting portfolio-level misvaluation on characteristics

Yet another alternative is to estimate time-series average misvaluation at the portfolio level—for example, for characteristic-sorted portfolios—and then project those portfolio estimates onto firm characteristics, as in an earlier draft of Cho and Polk (2024) and in van Binsbergen et al. (2023).[30] This, however, is a suboptimal way to recover *stock-level* fundamental values.

[30] See Table 6: https://marriott.byu.edu/upload/event/event_767/_doc/chopolk_pricelevel_20200831_c.pdf.

The main reason is that the object delivered by such a procedure is a historical time-series *average* misvaluation for a portfolio, which is then mapped back to firms. But the relevant object for valuation is the *conditional* mapping from a firm's current characteristics to its current underpricing. In our framework, the coefficients linking characteristics to underpricing vary meaningfully over time. A portfolio-level approach therefore averages across periods in which the same characteristic can imply very different misvaluation, and may also be less well suited to capturing incremental effects that arise only in a multivariate setting. Our procedure, by contrast, is multivariate from the outset.

A further limitation is that, when the portfolio-level abnormal prices are estimated using a DCF-style procedure, any imprecision in those first-stage estimates may naturally carry over to the second-stage projection onto characteristics. Our approach instead estimates the stock-level conditional mapping directly in a way that is internally consistent with the discounted-alpha identity.

B.6 Stock-level alphas: realized-return vs. true-expected-return benchmark

Discounted-alpha valuation requires stock-level alphas as an input. A concern could be that the R^2 for estimating the expected return on an individual stock is extremely low relative to the large variance of realized returns. However, this is an incorrect benchmark: what matters for discounted alpha is how much of the *true expected return (or alpha)* we capture, not how much of realized returns we explain.

Low realized-return R^2 simply reflects the dominance of idiosyncratic shocks (ε), not the imprecision of the expected-return estimates. Indeed, a simple analysis shows how the expected-return R^2—the fraction of cross-sectional variation in *true* expected returns recovered—can exceed 60% even when realized-return R^2 is below 1%. That is, characteristics can recover a large share of the true expected return even if realized stock-level returns are noisy. This is because, in a very large cross-section or panel, the idiosyncratic noise in realized returns averages out, allowing the regression to identify how characteristics relate to true expected returns, even when individual stocks are dominated by noise. Lewellen (2015) makes a similar point about his Fama-MacBeth regression for forecasting expected returns on individual stocks.

A simple annual data-generating process illustrates this point. For stocks $i = 1, \dots, N$:

$$\mu_{i,t} = \gamma^\top z_{i,t} + u_{i,t},$$
$$R_{i,t+1} = \mu_{i,t} + \varepsilon_{i,t+1},$$

with standardized characteristics $z_{i,t}$, $Var(\varepsilon_{i,t+1}) = \sigma_\varepsilon^2$, and $\mu_{i,t} \perp \varepsilon_{i,t+1}$. Suppose we estimate a cross-sectional regression

$$R_{i,t+1} = a_t + b_t^\top z_{i,t} + \eta_{i,t+1}, \qquad \hat{\mu}_{i,t} = \hat{a}_t + \hat{b}_t^\top z_{i,t}.$$

We contrast (i) realized-return $R^2_{realized} = Var(\hat{\mu}_{i,t})/(Var(\mu_{i,t}) + \sigma^2_\varepsilon)$, which is small when noise dominates, with (ii) expected-return $R^2_\mu = Var(\hat{\mu}_{i,t})/Var(\mu_{i,t})$, which is large when

$$\rho^2_\mu = \frac{Var(\gamma^\top z_{i,t})}{Var(\mu_{i,t})}$$

is high. Indeed, if γ is estimated consistently, R^2_μ converges in probability to ρ^2_μ (the fraction of the true expected return driven by the chosen characteristics z) as the sample size gets arbitrarily large. How much larger is R^2_μ than $R^2_{realized}$? Note that

$$\frac{R^2_\mu}{R^2_{realized}} = \frac{Var(\mu_{i,t}) + \sigma^2_\varepsilon}{Var(\mu_{i,t})} = 157$$

when $\sigma_\varepsilon = 0.25$ and $\sqrt{Var(\mu_{i,t})} = 0.02$.

Simulation. With $(N, K) = (1500, 4)$, $\sigma_\mu = 0.02$, $\sigma_\varepsilon = 0.25$, and $\rho^2_\mu = 0.8$, across 1,000 simulations we obtain a median R^2_{realized} of only 0.7%, but a median R^2_μ of 61%. Figure A1 (Internet Section D) plots the distribution. The lesson is that alphas can look imprecise under realized-return benchmarks even if they are in fact well estimated for our purposes (i.e., with respect to the "true-alpha" benchmark).

B.7 A numerical example illustrating Remark 1

Example B.2 (Valuation with one-period alpha when alpha payout varies over time). *Let* $\nu_{i,t} \equiv \frac{V_{i,t}}{P_{i,t}} - 1$ *and suppose* $\nu_{i,t+1} = \phi_{\nu,i,t}\nu_{i,t} + \epsilon_{\nu,i,t+1}$ *where* $Cov_t\left(\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}, \epsilon_{\nu,i,t+1}\right) = 0$. *Then, equation (10) implies that one can value that stock based on its flow of one-period alpha:*

$$\nu_{i,t} = \underbrace{\frac{1}{1 - \rho_{i,t}\phi_{\nu,i,t}}}_{\text{alpha payout ratio}} \times \frac{\alpha_{i,t}}{1 + R_{f,t}}, \quad V_{i,t} = (1 + \nu_{i,t})\, P_{i,t}, \tag{68}$$

where $\rho_{i,t} = E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\right]$ *measures the stock's current cash-flow duration. As an example, consider a stock that is currently 50% underpriced* ($\nu_{i,t} = 0.50$)*, a value we hold fixed in this example, whereas the flow of one-year alpha will adjust depending on how fast underpricing decays by next year. We set* $\rho_{i,t} = 1$ *and* $R_{f,t} = 0$.

1. *If underpricing will decay slowly at the rate* $\phi_{i,t} = 0.9$ *to* $\nu_{i,t+1} = 0.45$*, equation* (10) *shows today's one-year alpha must be* $\alpha_{i,t} = 0.50 - 0.45 = 5\%$*. Hence,*

$$\nu_{i,t} \;=\; \frac{1}{1 - \rho_{i,t}\phi_{\nu,i,t}} \frac{\alpha_{i,t}}{1 + R_{f,t}} \;=\; \frac{1}{1 - 0.9} \times 5\% \;=\; 50\%.$$

2. *If, on the other hand, underpricing will decay quickly at the rate* $\phi_{i,t} = 0.7$ *to* $\nu_{i,t+1} = 0.35$*, today's one-year alpha must be* $\alpha_{i,t} = 15\%$*. Hence,*

$$\nu_{i,t} \;=\; \frac{1}{1 - \rho_{i,t}\phi_{\nu,i,t}} \frac{\alpha_{i,t}}{1 + R_{f,t}} \;=\; \frac{1}{1 - 0.7} \times 15\% \;=\; 50\%.$$

In both cases, we recover today's underpricing from today's flow of one-year alpha and today's underpricing decay rate.

At first glance, it may seem surprising that a valuation formula resembling the one under time-invariant ρ and ϕ_ν in Example 2.1 still applies when $\rho_{i,t}$ and $\phi_{\nu,i,t}$ vary over time. The key intuition comes from viewing the stock of underpricing as fixed and viewing alpha as variable. As Figure A2 illustrates, holding underpricing fixed, alpha and the underpricing payout ratio are inversely related, and their product—current alpha times the payout-dependent duration term—recovers today's underpricing.

C Empirical Internet Appendix

C.1 Details on data and variables

A. Data sources and basic adjustments

We use domestic common stocks (CRSP share code *SHRCD* 10 or 11) listed on the three major exchanges (CRSP exchange code *EXCHCD* 1, 2, or 3). Missing prices are replaced with the average bid–ask price when available, and we drop observations with missing share or price information in the previous month. Missing returns are coded as zero, and delisting returns are added to returns. If delisting returns (*DLRET*) are missing but the CRSP delisting code (*DLSTCD*) is 500 or between 520 and 584, we assign −35% (−55%) as the delisting return for NYSE/AMEX (NASDAQ) stocks (Shumway, 1997; Shumway and Warther, 1999). We compute capital gains *RETX* from CRSP.

To compute stock characteristics, we use Compustat Quarterly, Compustat Annual, and the book equity data of Davis, Fama, and French (2000), in that order of preference. For Compustat, we use the CRSP/Compustat Merged Database. Quarterly Compustat data are assumed available four months after the quarter-end date (*DATADATE*). Annual Compustat data for fiscal year y are assumed available at the end of June in calendar year $y+1$. We exclude stocks with fewer than two years of data to allow construction of characteristics that require accounting information or past returns.

B. Stock-level characteristics

Our goal is to estimate real-time stock-level $\frac{V}{P}$. We therefore use the most up-to-date accounting information available. Annual quantities are constructed from quarterly data when possible (e.g., annual gross profits as the sum of the last four quarters).

In the pre-Compustat period, we rely on book equity from Davis et al. (2000) instead of assets when computing profitability and investment, and we assume comparability between equity-based pre-Compustat ranks and asset-based post-Compustat ranks.

Book-to-Market (BM). *BM* is the monthly log of book equity from the most recent quarter divided by current market value. Quarterly book equity equals stockholders' equity (*SEQQ*, or *ATQ*–*LTQ* if missing), plus deferred taxes and investment tax credits (*TXDITCQ* if available, zero otherwise), minus preferred stock (*PSTKQ* if available, zero otherwise). Quarterly data are treated as available beginning 1971m6 for book-to-market and asset growth, and 1976m6 for gross profitability (later in the latter case, to ensure a sufficient cross-section). When quarterly data are unavailable, *BM* as of June in year y is computed as book equity from fiscal year $y-1$ divided by current market value. Annual book equity is defined as $SEQ + TXDITC - BPSTK$, where preferred stock $BPSTK$ equals $PSTKRV$, $PSTKL$, $PSTK$, or zero, depending on availability. If SEQ is missing, it is set to $AT - LT$. Negative or zero book equity values are treated as missing.

Following Fama and French (2015), we adjust book equity for share growth between the reporting date and the market value date by deflating market equity accordingly. This reduces extreme BM outliers due to mismatched share counts. We also adjust for firms with multiple equity share classes to prevent inflated BM values at the share-class level.

Profitability (Prof). Prof is the monthly cross-sectional rank of gross profitability-to-assets, based on the trailing four quarters. Quarterly gross profitability equals sales minus cost of goods sold, scaled by assets in the most recent quarter. If quarterly data are unavailable, we use annual gross profitability as of June in year y, defined as sales minus cost of goods sold in fiscal year $y - 1$ divided by assets in fiscal year $y - 1$. When both quarterly and annual data are unavailable, as in the pre-Compustat period, we use the rank of return on equity, constructed from Compustat or Davis et al. (2000).

Market Beta (Beta). Beta is the trailing four-year (minimum two years) market beta, estimated with overlapping three-day returns. We winsorize at the 1st and 99th percentiles cross-sectionally.

Liquidity (Liq). Liq is the monthly liquidity measure of Amihud (2002).

Investment (Inv). Inv is the cross-sectional rank of asset growth when available (quarterly Compustat preferred, annual otherwise). If missing, we use book equity growth, based on Compustat or Davis et al. (2000).

Net Issuance (NetIss). NetIss is the average of the z-scores of two measures: 12-month share growth (Pontiff and Woodgate, 2008) and 12-month equity net payout (Daniel and Titman, 2006).

Returns (Ret and LagRet). Ret is the cumulative gross return over the past 12 months. LagRet is the cumulative gross return from months -24 to -12.

C.2 Correlation of second-stage regressors with projection errors

One potential problem with the two-stage regression methodology described in Section 2 is that regressors in the second stage could be correlated with the projection errors of $\nu_{i,t}$ onto $z_{i,t}$. Such correlation would bias the estimated values for γ_V. This appendix describes this issue and a potential solution to it. We then demonstrate that the issue is immaterial for the rank ordering of value-to-price in our main implementation, although it may cause us to modestly underestimate the scale of underpricing. Problems may be more significant for the book-based "DCF" estimator described in Section 3.3.

Lemma 3 proposes that we estimate the mispricing coefficients γ_V from the regression:

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V \, x^*_{i,t} + \varepsilon^*_{i,t}$$

Where $\varepsilon^*_{i,t}$ collects projection errors and higher-order terms, including the projection error $u_{i,t}$ defined by the projection of value-to-price onto characteristics:

$$\nu_{i,t} = \gamma_V z_{i,t} + u_{i,t}; \quad E[u_{i,t} z_{i,t}] = 0$$

One potential concern could be that this projection error is not orthogonal to $x_{i,t}$, leading to bias in the linear regression (i.e., $E[u_{i,t} x_{i,t}] \neq 0$).

By construction, this will not be the case if regressor $x_{i,t}$ is linear in $z_{i,t}$. Since $u_{i,t}$ is orthogonal to $z_{i,t}$, it will be orthogonal to any linear combination of $z_{i,t}$. In our main implementation, this is very nearly the case. The R^2 of the second-stage regression is 0.97, demonstrating that $\alpha_{i,t} = \gamma_R z_{i,t}$ is almost a linear combination of $x_{i,t}$.

Nonetheless, $x_{i,t}$ is not exactly linear in $z_{i,t}$. To demonstrate that the bias created is small, we can employ an instrumental variables approach. The characteristics themselves, $z_{i,t}$, are by definition orthogonal to $u_{i,t}$, and are in practice highly correlated with the regressors $x_{i,t}$. Hence, to check the importance of this source of bias, we can simply estimate our second-stage regression using two-stage least squares with $z_{i,t}$ as an instrument for $x_{i,t}$.

Table A7 summarizes the differences in instrumented vs. non-instrumented estimates, using a CAPM factor model. Estimated firm-level value-to-price ($\nu_{i,t}$) has a value-weight correlation of $> 99.9\%$ between the two methods. The relative ordering of underpricing across firms is essentially unchanged. However, the estimated scale of underpricing is 7% higher using the instrumental variables approach.

By contrast, results differ fundamentally for the book-based estimator described in Section 3.3. The instrumented results are nearly non-stationary, with implied standard deviation of V/B over $100\times$ greater than the non-instrumented results; indeed, the estimated V/B is often less than zero. The correlation between the two sets of estimates is under 30%. These different results underscore the challenges of discount-rate estimation using DCF approaches. Expected book-equity growth differs widely by firm, so expected book-equity-growth-adjusted characteristics ($x_{i,t}$) can be highly non-linear. As a result, the second stage has large errors that are correlated with the projection errors for V/B.

D Additional Tables and Figures (Internet Appendix)

Table A1: **Autocorrelations in Characteristics**

We report the autocorrelation matrix for the eight stock characteristics used in the paper. We first cross-sectionally rank-transform the first six characteristics and then standardize all variables by their cross-sectional value-weight standard deviation. Entry (r,c) is the value-weight correlation between characteristic r at t and characteristic c at $t+12$. The sample period is 1953m6–2024m12.

	12-Month Lag							
	BM	*Prof*	*Beta*	*Inv*	*NetIss*	*Liq*	*Ret*	*LagRet*
BM	0.83	-0.03	-0.01	0.05	0.01	-0.00	0.02	0.01
Prof	-0.05	0.90	0.00	-0.06	-0.01	-0.01	0.02	-0.01
Beta	-0.01	-0.01	0.90	0.01	0.04	0.02	0.03	0.02
Inv	-0.21	0.03	-0.05	0.17	0.09	0.03	0.14	0.06
NetIss	-0.12	-0.07	0.10	0.00	0.44	-0.09	0.02	-0.00
Liq	-0.04	-0.01	0.01	-0.02	-0.02	0.97	0.15	-0.02
Ret	0.11	0.08	-0.01	-0.06	-0.08	-0.01	0.04	0.00
LagRet	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.97	-0.00

Table A2: **Comparison of V/P versus One-Month Alpha Coefficients (CAPM)**

This table compares the coefficients from a simple CAPM alpha regression, γ_α^{1mo}, to the estimated CAPM V/P coefficients, γ_V. Alpha coefficients are expressed in annualized percentage points and retrieved from a regression of monthly excess returns on characteristics and characteristics interacted with market returns:

$$R^e_{i,t+1} = \gamma_\alpha^{1mo} z_{i,t} + \Gamma_\beta z_{i,t} R^e_{mkt,t+1} + \varepsilon_{i,t+1}$$

V/P coefficients are expressed in percentage points and as described and presented in Table 1. Estimates are based on value-weight stock-level panel regressions over the full sample period of 1953m6–2024m12. We report t-statistics based on standard errors that are clustered by date and firm for γ_α^{1mo} and bootstrapped for γ_V.

Characteristic	One-month alpha (γ_α^{1mo})	CAPM-implied $V/P - 1$ (γ_V)
BM	1.88	6.92
	(4.04)	(1.73)
Prof	2.32	12.69
	(5.39)	(2.96)
Beta	-1.80	-13.49
	(-3.22)	(-2.76)
Inv	-0.29	-1.81
	(-1.08)	(-3.61)
NetIss	-1.20	-2.88
	(-3.56)	(-4.87)
Liq	-0.43	-0.10
	(-1.08)	(-0.02)
Ret	2.92	-0.08
	(4.95)	(-0.11)
LagRet	0.02	-1.04
	(0.04)	(-2.80)

Table A3: **Closed-Form Model DCF and Discounted-Alpha Parameter Estimates**

Parameter estimates from DCF and discounted-alpha approaches to valuation in a model with linear closed-form V/B and V/P. Details of the closed-form model are described in Internet Appendix B.1. Coefficients are expressed for annual observations in whole numbers. Sample period is 1953–2024. All regressions are value-weight and standard errors are clustered by date

DCF		DA	
Risk-adjusted earnings ($\gamma_{E,1}$)	0.264	Alpha ($\gamma_{R,1}$)	0.048
	(0.069)		(0.007)
Characteristic persistence ($\gamma_{x,1}$)	0.719	Characteristic persistence ($\gamma_{y,1}$)	0.562
	(0.023)		(0.018)
Value-to-book ($\gamma_{vb,1}$)	0.941	Value-to-price ($\gamma_{vp,1}$)	0.110
	(0.204)		(0.019)

Table A4: **Robustness of Cardinality and Ordinality Across Estimation Windows**

The table shows how the p-values associated with the cardinality test (i.e., difference between ex-ante estimated V/P and ex-post V/P based on realized dividends of the long-short quintile portfolio formed on ex-ante V/P) change with the method used to estimate real-time stock-level fundamental value. As a sanity check on ordinal aspects of the estimates, Panel B reports the p-values associated with the spread in ex-post V/P between the extreme quintile portfolios. Our baseline method is to use a moving window of 40 years and no exponential weighting (i.e., an exponential weight factor of 1.00).

Panel A. Cross-sectional Cardinality: Ex-ante minus Ex-post V/P (p-value, null of zero)

	CAPM Estimates					FF3 Estimates				
Exponential	Moving Window Length									
Weight Factor	60yrs	50yrs	40yrs	30yrs	20yrs	60yrs	50yrs	40yrs	30yrs	20yrs
1.00	0.32	0.33	0.43	0.28	0.11	0.91	0.99	0.93	0.92	0.77
0.99	0.28	0.30	0.36	0.21	0.07	0.96	0.97	0.99	0.96	0.72
0.98	0.22	0.25	0.26	0.19	0.03	0.91	0.92	0.94	0.97	0.70
0.97	0.20	0.29	0.23	0.17	0.01	0.84	0.82	0.87	0.90	0.67

Panel B. Ordinality: Ex-post V/P Spread (p-value, null of zero)

	CAPM Estimates					FF3 Estimates				
Exponential	Moving Window Length									
Weight Factor	60yrs	50yrs	40yrs	30yrs	20yrs	60yrs	50yrs	40yrs	30yrs	20yrs
1.00	0.03	0.02	0.02	0.02	0.00	0.00	0.00	0.01	0.01	0.03
0.99	0.02	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.03
0.98	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.02	0.03
0.97	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.04

Table A5: **Simpler Implementations of Discounted-Alpha Valuation**

This table evaluates simpler implementations of discounted-alpha valuation. For each ex-ante V/P model, we sort stocks into value-weight quintile portfolios using NYSE breakpoints. "Ordinal" reports the high-minus-low ex-post realized underpricing spread, estimated using the Cho–Polk return-based estimator, and tests whether it equals zero. "Cardinal" reports the difference between this ex-post spread and the ex-ante high-minus-low V/P spread implied by the model, and tests whether that difference equals zero. ϕ_{zz}^{auto} is a diagonal matrix containing self-autocorrelations, and ϕ_{z}^{auto} is a full matrix of autocorrelations including cross-autocorrelations. We use $\rho = 0.97$, which is within the range of parameter values used in the present-value literature (e.g., Campbell, 1991). Entries are percentage points; p-values are in brackets.

	Ex-post Realized V/P			
	CAPM		FF3	
Ex-ante V/P Model	Ordinal (Diff from 0)	Cardinal (Diff from ex-ante V/P)	Ordinal (Diff from 0)	Cardinal (Diff from ex-ante V/P)
$\gamma_V = \gamma_\alpha(I - \phi_{zz}^{auto})^{-1}$	51.12	-113.55	63.88	-87.97
[p-value]	[0.016]	[0.000]	[0.012]	[0.001]
$\gamma_V = \gamma_\alpha(I - \rho\phi_{zz}^{auto})^{-1}$	51.10	-48.08	64.23	-26.21
[p-value]	[0.015]	[0.023]	[0.011]	[0.297]
$\gamma_V = \gamma_\alpha(I - \phi_{z}^{auto})^{-1}$	47.23	-111.94	37.18	-171.98
[p-value]	[0.004]	[0.000]	[0.057]	[0.000]
$\gamma_V = \gamma_\alpha(I - \rho\phi_{z}^{auto})^{-1}$	53.69	-38.53	47.43	-57.02
[p-value]	[0.009]	[0.060]	[0.039]	[0.013]
$\rho_{i,t} = \rho,\ \Gamma_{G,z} = 0$	38.16	-49.98	47.15	-51.00
[p-value]	[0.076]	[0.020]	[0.004]	[0.002]
$\Gamma_{G,z} = 0$	42.44	-20.64	52.75	-10.27
[p-value]	[0.045]	[0.330]	[0.009]	[0.611]
$\rho_{i,t} = \rho$	44.44	-22.80	53.04	-28.71
[p-value]	[0.014]	[0.207]	[0.014]	[0.184]

Table A6: **Detecting Price Distortions Near the Russell 1000/2000 Border**

We measure whether our estimates of CAPM underpricing detect price distortions near the Russell 1000/2000 border. We regress estimated CAPM underpricing (in percentage points) on a dummy indicator variable for being in the top of the Russell 2000 as opposed to the bottom of the Russell 1000 index in June. The table shows that the estimated CAPM-implied underpricing falls (i.e., CAPM-implied overpricing increases) by around 5.1 to 6.6 percentage points as a stock moves from the bottom of the Russell 1000 to the top of the Russell 2000. This finding is consistent with the notion that the top (bottom) of the Russell 2000 (Russell 1000) is overpriced (underpriced) because of the disproportionate weight received by the top-of-2000 stocks within the Russell 2000 index (Chang et al., 2015). All regressions are as of each June and control for the log of market equity in May as well as the square and cube of the log of market equity. All regressions also control for the log of float-adjusted market capitalization in June. We end the sample in 2006, since the banding rule for Russell 1000/2000 assignment was introduced in 2007. We report t-statistics based on standard errors that are robust to both time and stock-level clustering.

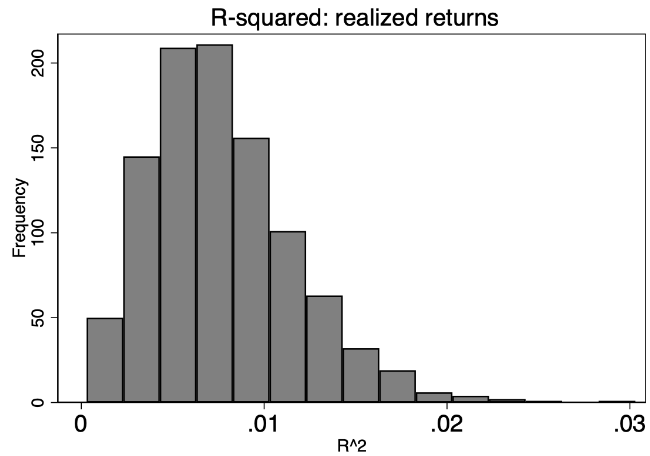
	Dependent Variable: CAPM $\hat{V}/P$			
Russell 2000	-6.61	-6.58	-6.07	-5.07
	(4.05)	(4.97)	(3.95)	(3.20)
Sample	1989-2006	1989-2006	1989-2006	1999-2006
Rank Bandwidth	750–1250	850–1150	650–1350	750–1250

Table A7: **Summary Statistics Comparing Instrumented versus Non-instrumented Estimates of Value-to-Price and Value-to-Book.**

The first row shows the value-weight correlation between the instrumented and non-instrumented estimates of V/P in the first column and of V/B in the second column. The second row displays the ratio of the value-weight standard deviations of the instrumented and non-instrumented estimates of V/P or V/B. The instrumented approach is described in Internet Appendix C.2.

	Main estimator	"Book-based" DCF estimator
Correlation of V/P estimates (or V/B)	1.00	0.21
Ratio of standard dev of estimates	1.07	125.73

Panel A. Simulated Distribution of Realized-Return $R^2_{realized}$



Panel B. Simulated Distribution of True-Expected-Return R^2_μ

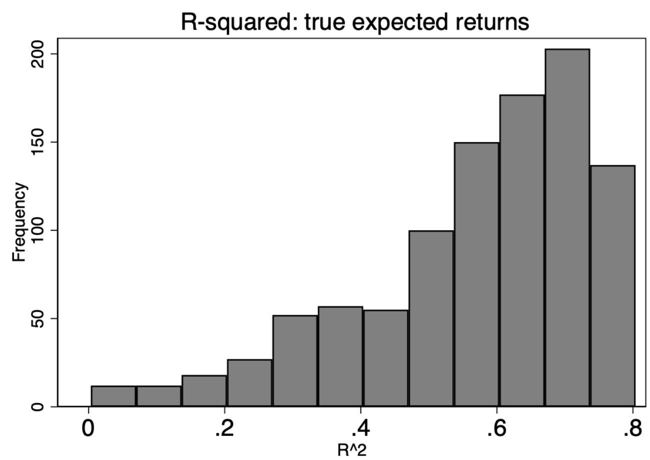


Figure A1: **Comparing R^2 for Forecasting Realized vs. Expected Returns**

This figure reports results from the simulation described in Section B.6. Panel A shows the distribution of realized-return R^2_{realized}, which measures the fraction of realized return variation explained by the fitted values $\hat{\mu}_{i,t}$. Panel B shows the distribution of R^2_μ, which measures the fraction of the cross-sectional variation in *true expected returns* $\mu_{i,t}$ explained by $\hat{\mu}_{i,t}$. The comparison illustrates why realized-return R^2 is close to zero, while R^2_μ can be much larger (often 60–80%), reconciling the apparent discrepancy in the precision of stock-level alpha estimates.

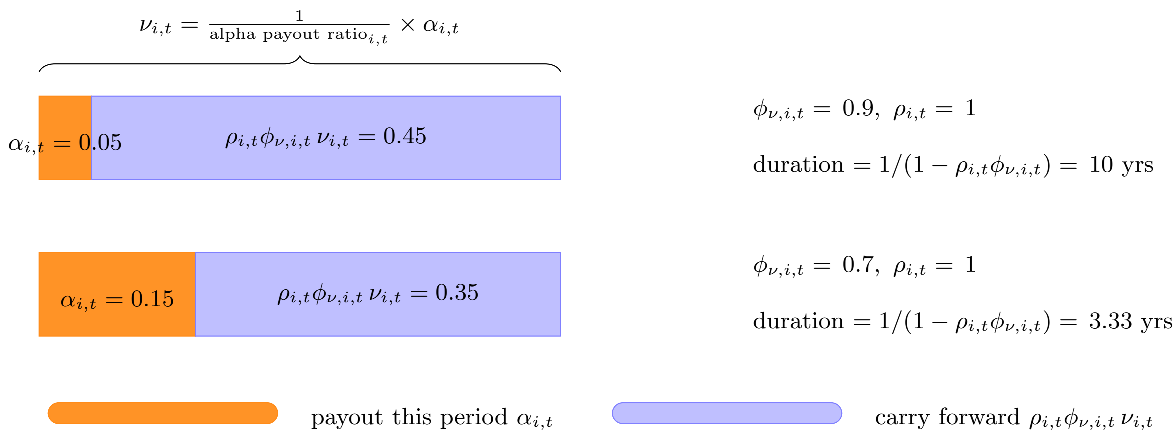


Figure A2: **Valuation with One-Period Alpha When Alpha Payout Varies Over Time**

This figure illustrates that, under simplifying assumptions, today's underpricing $\nu_{i,t} \equiv \frac{V_{i,t}}{P_{i,t}} - 1$ is simply today's one-period alpha divided by the alpha payout ratio: $\nu_{i,t} = \alpha_{i,t}/(1 - \rho_{i,t}\phi_{\nu,i,t})$. The two cases considered here (top and bottom) assume the same underpricing of $\nu_{i,t} = 50\%$ today (bar length), same current cash-flow duration $\rho_{i,t} = 1$, but different current payout ratios $\phi_{\nu,i,t} \in \{\text{top: } 0.9, \text{bottom: } 0.7\}$. No future values of ρ, ϕ_ν are required. The risk-free rate is assumed to be zero.

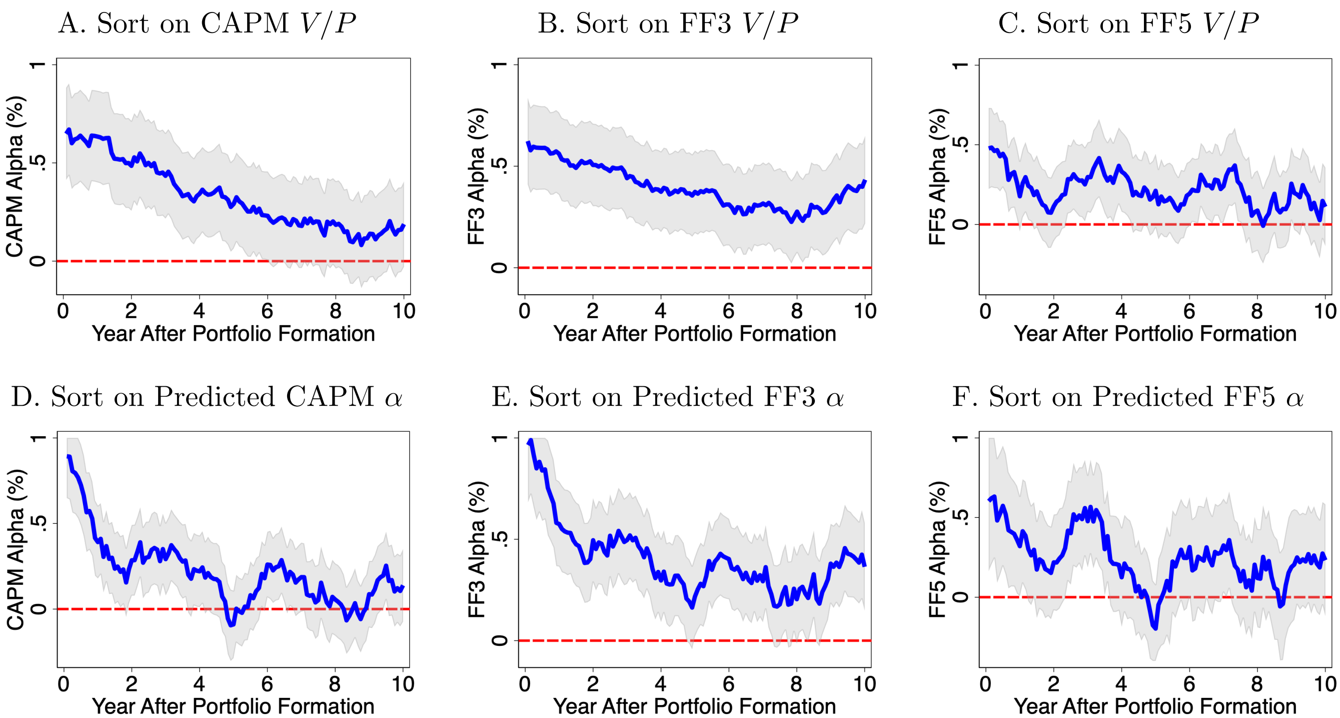


Figure A3: **Out-of-Sample Alphas on Portfolios Sorted on Real-Time V/P**

We plot the evolution of alpha on long-short high-minus-low quintile portfolios formed by sorting on out-of-sample model-implied V/P. The bottom row repeats the analysis using portfolios sorted on the corresponding out-of-sample estimates of one-month α. Across all panels, the gray shaded area represents the 95% bootstrap confidence interval. The sample period is 1953m6–2024m12 for the CAPM and the Fama and French (1993) three-factor model and 1979m6–2024m12 for the Fama and French (2015) five-factor model.

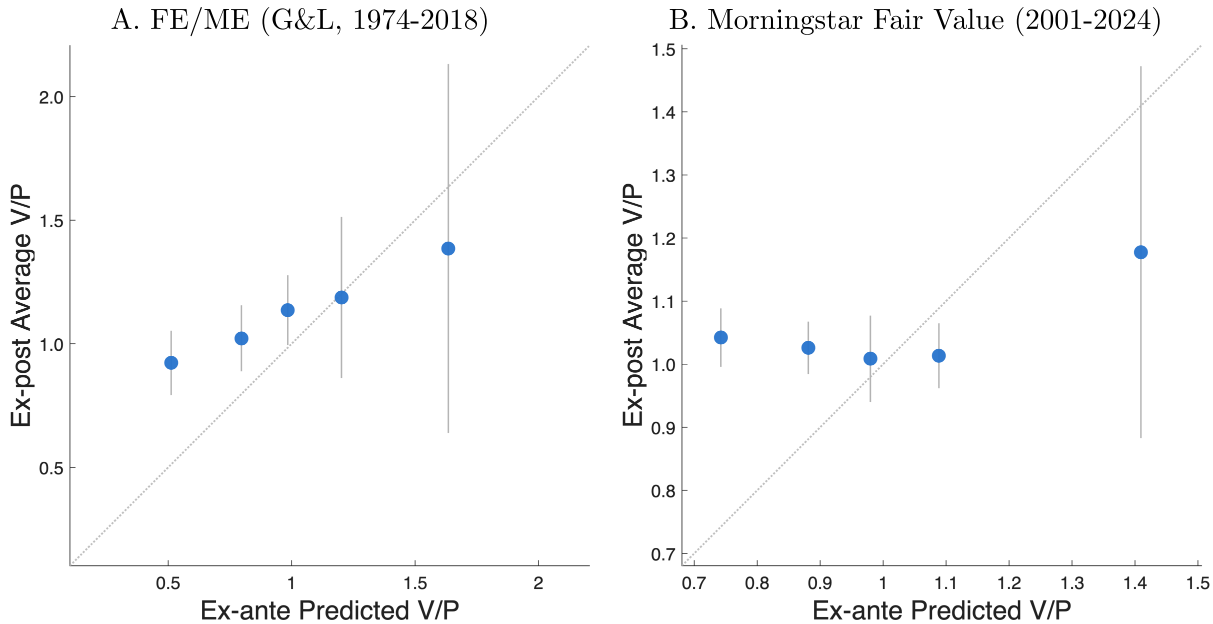


Figure A4: **Cardinality Tests on Real-Time DCF-based Misvaluation Signals**

For the real-time V/P estimates of Gonçalves and Leonard (2023) ("FE/ME", 1974–2018) and of Morningstar ("Fair Value", 2001–2024), we plot ex-post realized CAPM-implied V/P ratios against ex-ante predicted V/P ratios for five quintiles sorted on predicted V/P based on NYSE breakpoints. We estimate ex-post realized value-weight portfolio V/Ps and the associated 95% confidence intervals using the post-formation-return approach of Cho and Polk (2024). This approach assigns the exact weight to the post-formation buy-and-hold returns of each portfolio needed in order to correctly estimate formation-period model-specific V/P. We value-weight the ex-ante V/P ratios within each portfolio. We also plot a 45-degree dotted line, as observations should line up in that manner if our ex-ante predicted V/P ratios are accurate. Note that the ex-ante FE/ME measure uses a single discount rate on all stocks and is not intended to be a CAPM-implied signal.

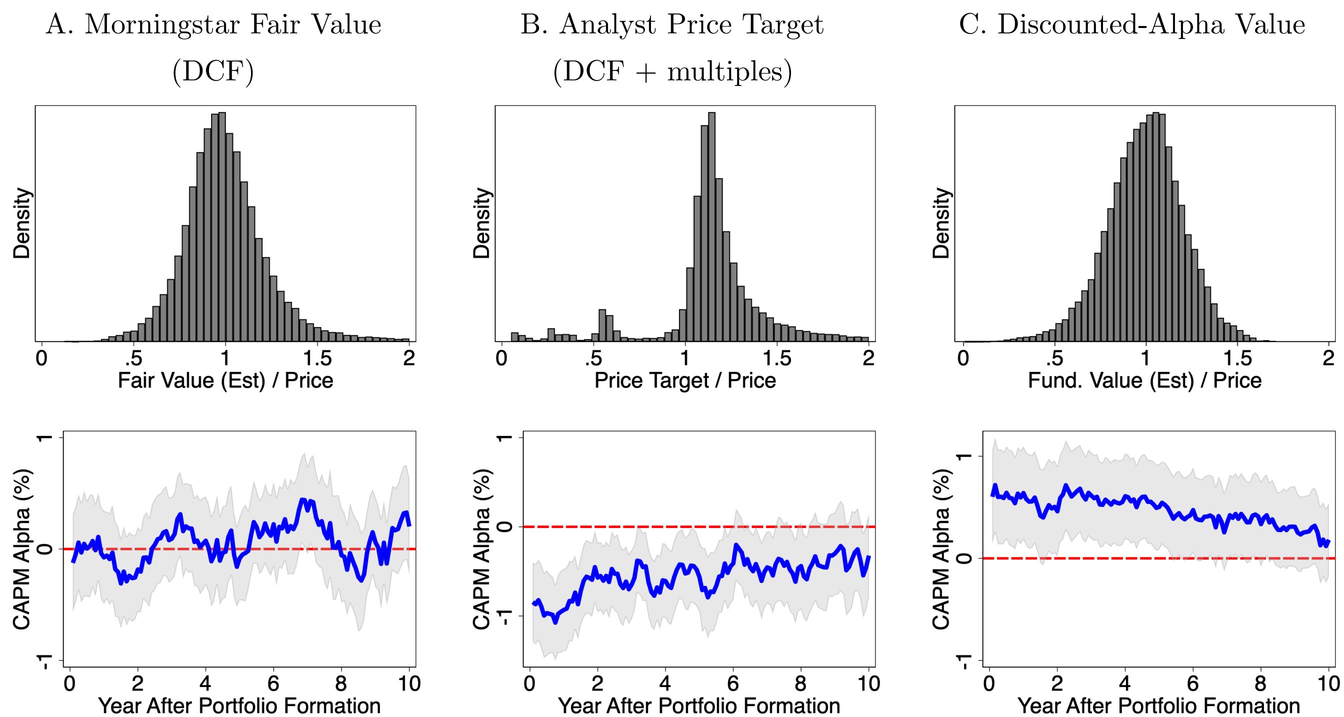


Figure A5: **Distribution and Performance of Industry DCF-based Value Estimates (2001m6–2024m12)**

The first-row figures plot the distribution of estimated fundamental-value-to-price for high market capitalization stocks each month. High market capitalization is defined as stocks above the value-weight average market capitalization. The second-row figures report the out-of-sample alphas of long-short high-minus-low quintile portfolios sorted on estimates of fundamental value-to-price. The sample period is 2001m6–2024m12, for which Morningstar DCF estimates are available.

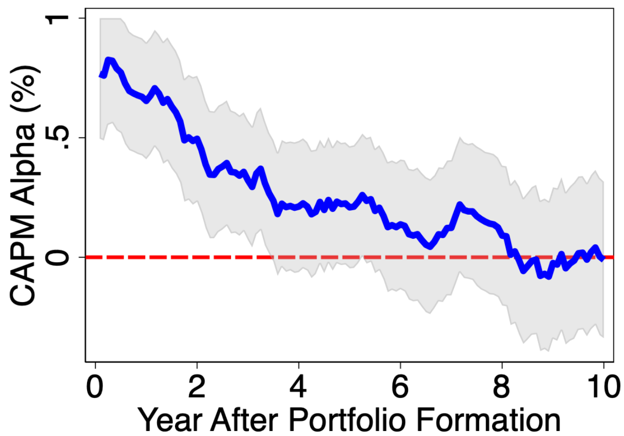


Figure A6: **Ex-Post CAPM Alpha Performance of Gonçalves–Leonard's Real-Time Measure**

The figure reports the ex-post alphas of long-short quintile portfolios sorted on *real-time* signals of stock-level misvaluation proposed in Gonçalves and Leonard (2023). The gray shaded area represents the 95% bootstrap confidence interval. Note that the misvaluation signal of GL uses a single discount rate for all stocks and thus does not adjust for CAPM risk. The sample begins in 1974, the first year the measure is available, and ends in 2018.

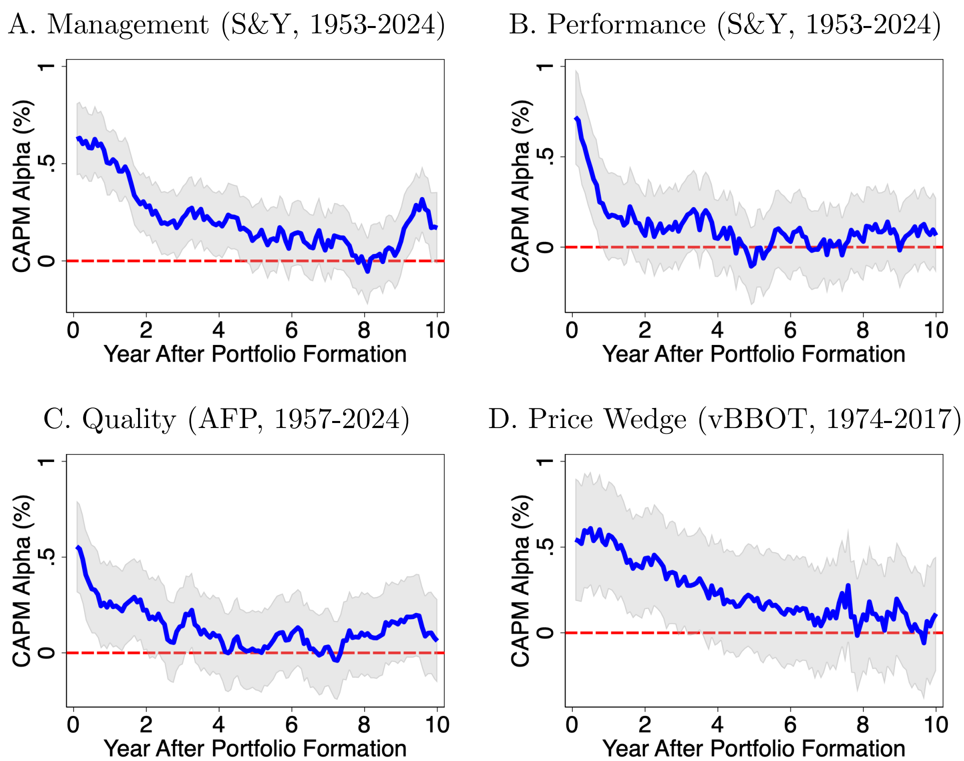


Figure A7: **Ex-Post Performance of In-Sample Misvaluation Signals (CAPM Alphas)**

The figure reports the ex-post alphas of long-short quintile portfolios sorted on in-sample (as opposed to real-time out-of-sample) signals of stock-level misvaluation proposed in the literature: the management and performance signals of Stambaugh and Yuan (2017) (S&Y), the quality signal of Asness et al. (2019) (AFP), and the DCF-based price wedge signal of van Binsbergen et al. (2023) (vBBOT). These signals are intended to be in-sample signals rather than real-time estimates. Across all panels, the gray shaded area represents the 95% bootstrap confidence interval.

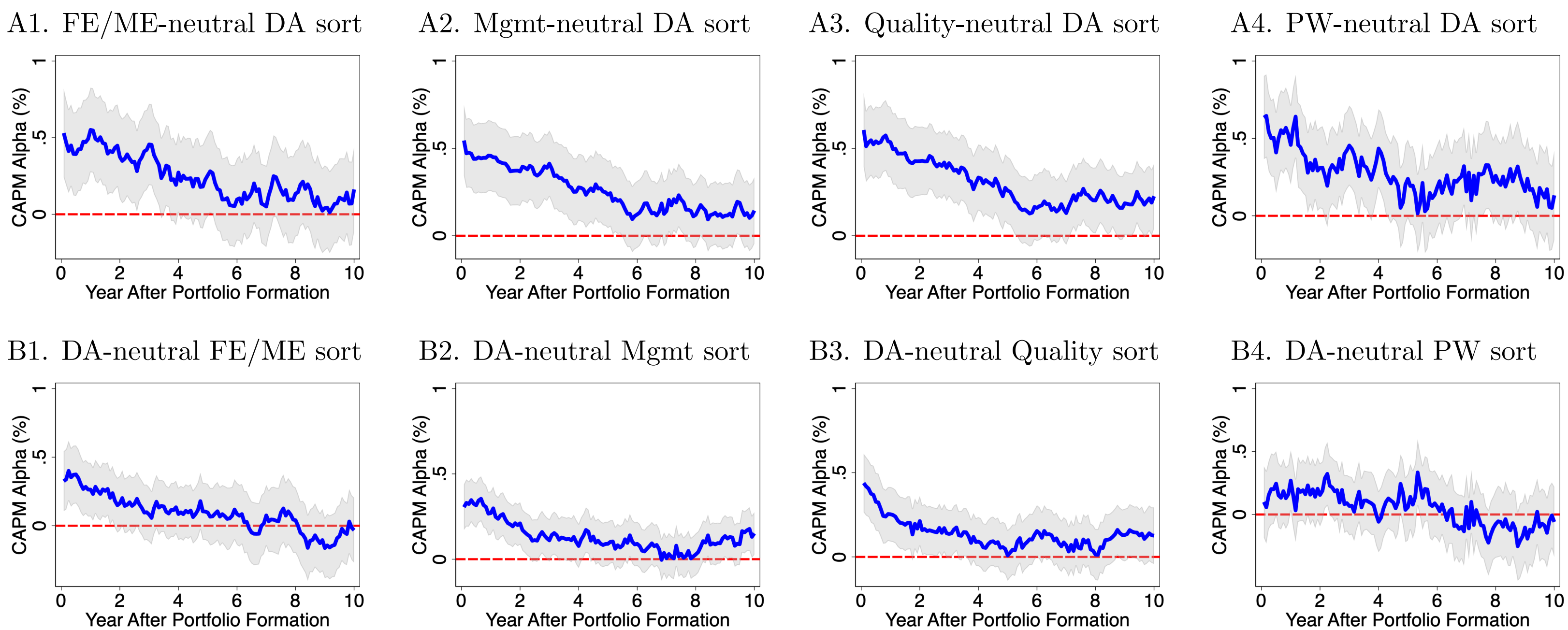


Figure A8: **Ex-Post Performance of Misvaluation Signals: A Horse Race (CAPM Alphas)**

The figure reports the ex-post CAPM alphas of characteristic-neutral long-short portfolios constructed from independent 3×3 sorts. Each year, we independently sort stocks into terciles based on our real-time discounted-alpha valuation signal and one alternative misvaluation signal, using NYSE 30/70 breakpoints. The alternative signals are FE/ME from Gonçalves and Leonard (2023), the management signal of Stambaugh and Yuan (2017), the quality signal of Asness et al. (2019), and the DCF-based price wedge (PW) signal of van Binsbergen et al. (2023). In Panel A, we form portfolios that are long high-DA stocks and short low-DA stocks while neutralizing the alternative signal. That is, if P_{ab} denotes the portfolio in DA tercile a and alternative-signal tercile b, the Panel A portfolio is

$$\frac{1}{3}\left(P_{31} + P_{32} + P_{33}\right) - \frac{1}{3}\left(P_{11} + P_{12} + P_{13}\right).$$

In Panel B, we reverse the exercise and form portfolios that are long high values of the alternative signal and short low values of the alternative signal while neutralizing DA:

$$\frac{1}{3}\left(P_{13} + P_{23} + P_{33}\right) - \frac{1}{3}\left(P_{11} + P_{21} + P_{31}\right).$$

The gray shaded area represents the 95% bootstrap confidence interval. The sample starts in 1974 for FE/ME and the price wedge, in 1953 for the S&Y management signal, and in 1957 for the quality signal.

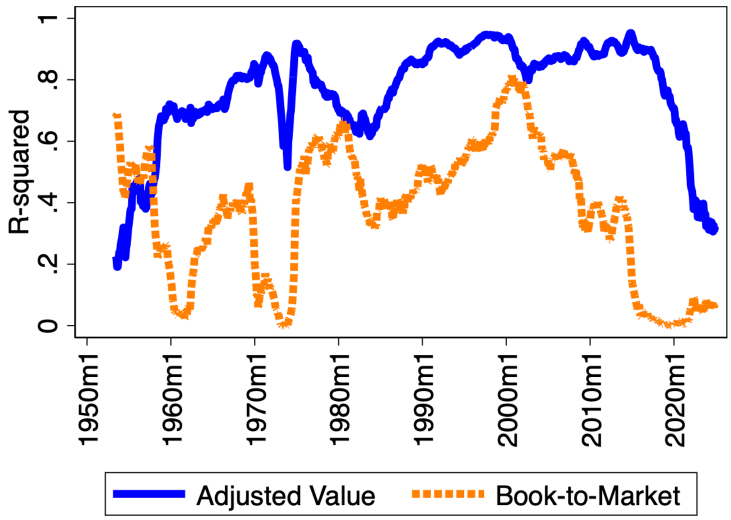


Figure A9: **Explaining CAPM V/P with B/M or Adjusted Value**

The figure shows the extent to which simpler proxies for mispricing (the adjusted value metric of Cho and Polk (2024) and the Book-to-Market equity ratio) explain our measure. In particular, we plot the time series of R^2 values from regressing our measure on either of these simpler proxies.