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-duration cash flows, our approach avoids the discount-rate sensitivity that undermines DCF and uncovers fundamental variation missed by leading methods. Applying our estimates, we find that private equity funds appear to 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. Furthermore, biased beliefs embedded in analyst estimates appear to be an important driver of model-implied price distortions. However, despite these pockets of misvaluation, firm equity values are "almost efficient" by Black's (1986) definition.

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

JEL classification: G12, G14, G32

What is the fundamental value of a stock, that is, the value based solely on its stream of future cash flows? This question moves billions of dollars in the stock market each day and drives acquisitions, share issuance, and real investment.[1]

However, despite its importance, estimating fundamental value relies on highly imperfect methods—discounted cash flow (DCF) and price multiples—with well-documented shortcomings. DCF is sensitive to stock-level cost of equity estimates that are "distressingly imprecise" (Fama and French, 1997), while low price multiples may simply reflect low future profitability and/or high future risk rather than an underpriced stock (Cohen, Polk, and Vuolteenaho, 2003, 2009).

These weaknesses with existing methods call for an entirely new approach to valuation—one that is both theoretically coherent and empirically tractable. We answer that call by introducing *discounted alpha*, a novel valuation framework for individual stocks that exploits the predictive structure of a stock's future abnormal returns (alphas). Rather than valuing a stock via projected cash flows and discount rates, our approach values it simply as the current price plus the present value of all future (buy-and-hold) alphas:

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

The weights, X_τ, that are applied to alphas are based on a simple intuitive formula; they are always positive and shrink to zero as $\tau \to \infty$.

Equation (1) is a mathematical identity, not a model assumption. If a stock's fundamental value (V_0) exceeds its price (P_0), a long-term buy-and-hold investor should expect to recover the difference through (mostly) positive future buy-and-hold alphas (α_τ), where V and α are measured relative to the same candidate asset pricing model (e.g., the CAPM).[2] Importantly, the identity does not require V and P to converge at any point in the future.

[1] Discretionary buy-and-hold managers (e.g., Berkshire Hathaway and Capital Group) and equity analysts prioritize fundamental value over short-term returns. Numerous studies link corporate actions to firm (mis)valuation: 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, Olivier, Otto, and Thesmar (2021).

[2] In the spirit of 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.

Cho and Polk (2024) first derived this intuitive identity and used it to estimate the average time-series misvaluation of a buy-and-hold portfolio. Our contribution is to provide a novel way to operationalize this identity to estimate, in real time, the fundamental value of an individual stock relative to any asset pricing model, addressing the long-standing question of how to value individual stocks. Specifically, we first model short-horizon alphas, capital gains, and the evolution of characteristics as functions of stock-level characteristics. We then estimate how those same characteristics map to fundamental value in a way that is internally consistent with the structure of the identity, ensuring that the resulting characteristic-based fundamental value estimates align with both return dynamics and forward-looking information. Estimating this mapping in a moving window yields real-time, out-of-sample measures of fundamental value.

Discounted-alpha valuation offers three key advantages over DCF. First, it values stocks by "correcting" the price rather than building up the entire value from scratch. This "correction" approach is far less sensitive to discount rates because alphas are much less persistent than cash flows, giving the estimator a much shorter effective horizon. Second, because alphas are already risk-adjusted, it is less reliant on noisy, stock-specific discount rates. Third, by casting fundamental valuation as a problem of predicting one-period alpha and the evolution of the characteristics that forecast it, the approach allows us to leverage the extensive evidence on how alpha relates to observed stock characteristics—the central focus of asset pricing research over the past three decades.

Applying discounted alpha, we estimate real-time fundamental values for approximately 2.6 million stock-month observations from 1953m6 to 2024m12. As the first test of validation, we show that real-time estimates based solely on ex-ante information produce large and persistent differences in post-formation alphas with respect to the same asset-pricing model. We further confirm the validity of our estimates through a novel short-horizon consistency test, which shows that realized short-horizon alphas are offset by contemporaneous changes in estimated misvaluation, as implied by the discounted-alpha identity. As further validation, our real-time estimates 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).

We use these fundamental value estimates 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 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 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.

3. Traditional DCF-based estimates (Morningstar fair values, sell-side targets) fail to identify underpricing. Moreover, biased expectations embedded in analyst price targets appear to be an important driver of distortions in stock price levels.

4. Private equity funds exploit CAPM misvaluation, acquiring stocks at roughly 13% below fundamental value and exiting at about 17% above. 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

Recent work documents pervasive limitations in the current practice of fundamental valuation—particularly DCF—renewing interest in viable alternatives. Décaire and Graham (2024) find that subjective discount rates and growth expectations strongly shape analyst valuations. Décaire, Sosyura, and Wittry (2024) find substantial ambiguity in estimating equity betas and discount rates, while Hommel, Landier, and Thesmar (2022) show that discount rates derived from factor models underperform simple heuristics in DCF settings. Ben-David and Chinco (2024) find that analysts often set price targets mechanically by multiplying EPS by trailing P/E ratios, while Gormsen and Huber (2024) and Gormsen and Huber (2025) both show that firms also often rely on coarse rules-of-thumb and imperfect risk adjustment. Delao, Han, and Myers (2024) show that biased earnings-growth expectations enter into professional valuations.

Within the DCF paradigm, a large literature has proposed refinements, including the residual income approach: Ohlson (1995), Frankel and Lee (1998), Dechow, Hutton, and Sloan (1999), and Lee, Myers, and Swaminathan (1999). Recently, Gonçalves and Leonard (2023) use a regression-based approach to forecast cash flows, while imposing a single discount rate across firms to reduce sensitivity to discount-rate assumptions. van Binsbergen et al. (2023) apply DCF to estimate average misvaluations of characteristic-sorted portfolios and map these to stock-level overpricing via portfolio weights.[3] However, these methods inherit DCF's core weakness—sensitivity to assumed discount rates. Because stock-level costs of equity are notoriously difficult to estimate (Fama and French, 1997), most studies impose a single market-wide or industry-wide discount rate. On a related note, Stambaugh and Yuan (2017), Bartram and Grinblatt (2018), Gerakos and Linnainmaa (2018), and Golubov and Konstantinidi (2019) generate stock-level misvaluation scores based on composite signals, "agnostic" regressions, or decompositions of the book-to-market ratio.

Despite these efforts, financial economics has yet to develop a better framework for valuing individual stocks—even though equity valuation underpins everyday market decisions: fundamental investors selecting stocks, investment bankers pricing equity for M&A or IPOs, analysts issuing recommendations, and corporate CFOs timing repurchases or issuances. Our approach fills this gap by formally linking fundamental value to alpha through an identity, thereby connecting equity valuation to the vast literature on the cross-section of average short-run returns.

[3] They find that the DCF-based portfolio misvaluation estimates contain potentially large biases arising from DCF's discount-rate sensitivity. For example, they report that applying DCF to the 15-year roll-over strategy on the 1-month Treasury bill implies about a 50% overpricing relative to the CAPM and propose correcting for these biases with a bootstrap. Discounted alpha avoids these biases (Cho and Polk, 2024).

1 Equity Valuation with Discounted Alpha

1.1 Asset pricing environment and definition

An asset generates a stream of cash flows (dividends), $\{D_{i,t+\tau}\}_{\tau=1}^{\infty}$, where i and t index asset and time, respectively. $\{\widetilde{M}_{t,t+\tau}\}_{\tau=1}^{\infty}$ is a candidate cumulative stochastic discount factor (candidate SDF). Define *fundamental value* as the buy-and-hold value of the asset's cash flows, discounted according to the candidate asset pricing model.

Definition 1 (Fundamental value). 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 SDF:

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

Here, the candidate SDF is a pricing model an econometrician uses to evaluate asset prices in the sense of Hansen and Jagannathan (1991, 1997) and may not be the true SDF.

We emphasize three aspects of fundamental value. First, it is the asset's buy-and-hold cash-flow value, not a buy-and-sell value tied to resale price—that is, it reflects the perspective of a long-term buy-and-hold investor rather than a short-term trader.[4] Second, like abnormal returns (alphas), it is subject to the joint-hypothesis problem (Fama, 1970): deviations from price may reflect model misspecification or genuine misvaluation. Thus, fundamental value, like alpha, differs across different asset-pricing models. Third, fundamental value is specific to the econometrician's information set, which we assume to include all historical data on returns and a chosen set of stock characteristics up to that point.

1.2 Fundamental value = price + discounted alphas

An exact identity from Cho and Polk (2024) shows that one arrives at the fundamental value of the asset by simply "correcting" the price with discounted future alphas.

Lemma 1 (Discounted alpha valuation). *Suppose* $\lim_{\tau\to\infty} E_t[\widetilde{M}_{t\to t+\tau} P_{i,t+\tau}] = 0$ *such*

[4] $V_{i,t}^{ST} \equiv E_t \left[\widetilde{M}_{t,t+1}(D_{i,t+1} + P_{i,t+1}) \right]$, where $V_{i,t} \neq V_{i,t}^{ST}$ if the candidate SDF is not the true SDF. Fundamental value is "fundamental" in that it values future cash flows, not a future selling price.

that the price is not explosive relative to $\widetilde{M}$. Then, as an exact mathematical identity, fundamental value is the price plus the discounted sum of subsequent abnormal returns (alphas), with both the fundamental value and the alphas defined relative to the same $\widetilde{M}$:

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

with P denoting the price and α the $\widetilde{M}$-implied conditional alpha.

Proof. Appendix C in the Internet Appendix provides a formal proof. For intuition, the net present value (NPV) of buying and holding the stock ($V_0 - P_0$) is the present value (PV) of all abnormal payoffs: $V_0 - P_0 = \sum_{\tau=1}^{\infty} E_0 \left[\widetilde{M}_{0\to\tau} Y_\tau^{Abnormal} \right]$. Abnormal payoff at τ is the abnormal return from $\tau - 1$ to τ ($\alpha_{\tau-1}$) times the price on which the alpha is earned ($P_{\tau-1}$): $Y_\tau^{Abnormal} = P_{\tau-1}\alpha_{\tau-1}$. Plugging in, $V_0 - P_0 = \sum_{\tau=0}^{\infty} E_t[X_\tau \, \alpha_\tau]$ with $X_\tau = \widetilde{M}_{0\to\tau+1} P_\tau$, where the discount factor X_τ serves as a *stochastic duration* that measures how much today's market price depends on future cash flows starting at τ. □

The discounted-alpha identity in equation (3) states that the "stock" of underpricing, $V_{i,t} - P_{i,t}$, equals the discounted sum of the "flow" of future alphas, $\{\alpha_{i,t+\tau-1}\}_{\tau=1}^{\infty}$, as illustrated in Figure 1. Each term in this sum represents the abnormal return to be earned by a buy-and-hold investor in a future period, weighted by $M_{t\to t+\tau} P_{i,t+\tau-1}$, which acts as a stochastic *duration* factor. This duration term measures the value of dividends from time $t+\tau$ onward—the dividends to which the abnormal discount rate $\alpha_{i,t+\tau-1}$ applies. The bigger the cash-flow duration, the greater the alpha's contribution to today's underpricing. Hence, the extent of underpricing depends on the magnitude, persistence, and importance of the alphas that will eventually be realized.[5]

Example 1.1 (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

[5] Alphas are more important if they occur sooner, in more valuable states, or after relatively large capital gains.

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,

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

Example 1.1 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.

1.3 Why discounted alpha valuation?

Discounted alpha focuses on estimating the gap between price and value rather than building up the entire value from scratch. By targeting the difference rather than the whole, this approach can substantially reduce estimator variance. In addition, lower duration and automatic risk adjustment are two additional features of discounted alpha that make it a potentially superior valuation method.

A. A "correction" approach

Discounted-alpha valuation recasts DCF valuation in terms of *correcting the price* rather than reconstructing value from cash-flow forecasts and discount rates. This formulation directly addresses the main weakness of DCF: cash flows have high duration, since dividends grow geometrically, leading to extreme sensitivity to discount-rate estimation error. Since any discount-rate estimates inevitably contain estimation errors, discount-rate noise translates into large valuation errors. Discounted-alpha valuation sharply reduces this sensitivity because much of an asset's cash flow duration is contained in the *price*, which is observed without error. The simple example below highlights this benefit.

Consider a perpetuity with $D = \$1$ and $R = 4\%$. DCF valuation gives

$$\begin{aligned} \hat{V_0}^{DCF}|_{\hat{R}=5\%} &= \quad \tfrac{D}{R+1\%} = \tfrac{1}{0.05} \times 1 \quad = 20. \\ \hat{V_0}^{DCF}|_{\hat{R}=4\%} &= \quad \tfrac{D}{R} = \tfrac{1}{0.04} \times 1 \quad = 25. \\ \hat{V_0}^{DCF}|_{\hat{R}=3\%} &= \quad \tfrac{D}{R-1\%} = \tfrac{1}{0.03} \times 1 \quad = 33.3. \end{aligned}$$

If the price is \$20 (20% underpriced), then discounted alpha valuation gives

$$\begin{aligned} \hat{V_0}^{DA}|_{\hat{R}=5\%} &= \quad P_0 + \tfrac{1}{R+1\%} \times P_0 \times \alpha = 20 + \tfrac{1}{0.05} \times 20 \times 1\% \quad = 24. \\ \hat{V_0}^{DA}|_{\hat{R}=5\%} &= \quad P_0 + \tfrac{1}{R} \times P_0 \times \alpha = 20 + \tfrac{1}{0.04} \times 20 \times 1\% \quad = 25. \\ \hat{V_0}^{DA}|_{\hat{R}=3\%} &= \quad P_0 + \tfrac{1}{R-1\%} \times P_0 \times \alpha = 20 + \tfrac{1}{0.03} \times 20 \times 1\% \quad = 26.7. \end{aligned}$$

Hence, if the discount rate is mismeasured by ± 1 percentage point, DCF valuations range from 20 to 33.3 (an error exceeding 50%), whereas discounted-alpha valuations move only from 24 to 26.7 (an error below 11%). Thus, correcting price through discounted alphas is five times as precise. Appendix C.2 in the Internet Appendix show that this benefit continues to be true when cash flows and alphas are also estimated with noise.

B. Lower duration

The above advantage of discounted alpha relative to DCF increases in more realistic settings where alphas decay over time. Indeed, since alphas tend to be transitory, the effective horizon of the valuation problem shrinks dramatically. That is, one would expect that the "discounted alpha" component of fundamental value would have much lower duration:

$$\underbrace{V}_{\text{high duration}} = \underbrace{P}_{\text{high duration}} + \underbrace{\text{discounted alphas}}_{\text{low duration}}. \tag{4}$$

The duration of discounted alphas is zero for stocks with zero future alphas, and it likely remains relatively low for mispriced stocks as well because alphas typically decay quickly. This aspect of our method results in estimates of fundamental value that are less dominated by discount-rate mismeasurement—an issue that has long plagued empirical valuation work (Fama and French, 1997).

For example, consider a stock with a constant dividend-price ratio $\overline{DP}$ and a fixed $\widetilde{M}_{0\to\tau}\frac{P_\tau}{P_0} = \rho^\tau = 0.97^\tau$ as in Campbell and Shiller (1988). Its current alpha $\alpha_0/(1+R_{f,0})$ will decay at the known annual rate $\phi_\alpha < 1$. Then, DCF valuation requires a duration factor of $1/(1-\rho) = 1/0.03 \approx 33$ years:

$$V_0^{DCF} = P_0 \sum_{\tau=1}^{\infty} E_0\left[\widetilde{M}_{0\to\tau}\frac{P_\tau}{P_0}\right]\overline{DP} \;=\; P_0\frac{1}{1-\rho}\overline{DP} \;=\; P_0 \times \underbrace{33 \text{ yrs}}_{\text{duration}} \times \overline{DP}.$$

In contrast, discounted alpha has a much shorter duration of $1/(1-\rho\,\phi)$:

$$V_0 = P_0 + P_0 \sum_{\tau=0}^{\infty} E_0\left[\widetilde{M}_{0\to\tau}\frac{P_\tau}{P_0}\frac{\alpha_\tau}{1+R_{f,\tau}}\right] \;=\; P_0 + P_0 \times \underbrace{\frac{1}{1-\rho\phi_\alpha}}_{\text{duration}} \times \frac{\alpha_0}{1+R_{f,0}}.$$

The duration in discounted alpha is zero when there is zero alpha and underpricing; 3 years for mildly persistent alpha ($\phi_\alpha = 0.7$; half-life 2 years); and 7.8 years for highly persistent alpha ($\phi_\alpha = 0.9$; half-life 6.6 years).

That is, the transitory nature of alphas reduces the duration of the problem from $\frac{1}{1-\rho}$ to $\frac{1}{1-\rho\phi_\alpha}$ as we switch from DCF to discounted alpha. In this way, discounted alpha can cut duration by over tenfold to 3 years when the autoregressive (AR) coefficient of alpha is 0.7, and by more than fourfold to 7.8 years when the coefficient is 0.9. Appendix C.3 repeats the analysis in a more general setting.

C. Automatic risk adjustment

The DCF's discount rate must vary across stocks to perform two distinct economic functions at once: adjusting expected dividends for contemporaneous risk and discounting them through time.[6] Having to encode both contemporaneous risk adjustment and intertemporal discounting in the discount rate makes it especially susceptible to measurement error leading to both bias and lower efficiency.[7] This source of error exacerbates the already large estimation error in DCF-based value estimates due to their sensitivity to discount-rate measurement. In contrast, discounted alpha simplifies risk adjustment, as alphas are already contemporaneously risk-adjusted.

D. Other non-DCF approaches

Our critique applies to all DCF approaches, including modified ones such as the residual income approach (Sloan, 1996). Furthermore, an approach that simply estimates fundamental value as $P_0 + P_0 \sum_{\tau=0}^{\infty} \rho^\tau \alpha_\tau$ leads to less accurate estimates, as it ignores the state-dependent nature of conditional α.[8]

E. Stock-level alphas

A potential reservation about our method could be that it utilizes stock-level estimates of alpha. Part of this objection may derive from the (correct) notion that stock-level returns are extremely noisy, making forecasted return an extremely low-R^2 predictor of realized stock-level return. However, the extent of firm-level return predictability is an incorrect benchmark: What matters for discounted alpha valuation is not how much of *realized* returns we explain—but how much of the *true expected return (or alpha)* we explain. A simple analysis shows that a large panel regression of the sort we run can recover a large share of the true expected return even if realized stock-level returns are noisy (Figure A1 and Appendix C.5 in the Internet Appendix). Indeed, Lewellen (2015) makes a similar point about his Fama-MacBeth regression for forecasting expected returns on individual stocks.[9]

[6] Cochrane (2009) explain that being able to abstract away from the time discount to focus on contemporaneous risk adjustment is the main reason why we use excess returns rather than gross returns when estimating abnormal returns in the expected return framework (p.9).

[7] See Appendix C.4 in the Internet Appendix for more detail.

[8] Table A2 in the Internet Appendix evaluates this approach (in Column 3), first developed and implemented in Cohen et al. (2009).

[9] "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).

Still, if one of our objections to DCF is that stock-level *discount rates* are imprecise, would this not automatically make our approach based on *alphas* an hopeless endeavor? Two reasons make our approach based on stock-level alphas more promising—yielding likely narrower confidence intervals around the estimated model-implied fundamental values. First, alpha likely has lower variance than the discount rate because it strips out the component of expected returns driven by benchmark risk factors. For example, uncertainty about the market risk premium or the market beta affects estimates of stock-level discount rates but not stock-level CAPM or multifactor alphas. Second, and more importantly, uncertainty in discount rates is amplified in DCF estimates by a factor proportional to the long cash-flow duration, whereas the shorter-horizon nature of discounted alphas makes any remaining uncertainty in alphas far less consequential relative to the overall magnitude of the discounted-alpha estimate of fundamental value, which is dominated by the stock's price rather than the discounted-alpha component.

1.4 Discounted alpha valuation with one-period alpha

We show how to value individual stocks without a long-horizon forecast of future alphas but with information on (i) how current characteristics relate to the immediate one-year alpha and (ii) how those characteristics are expected to evolve over the next year. The focus on one-period (short-horizon) alpha means that the large asset-pricing literature on short-horizon return anomalies—which, over the last four decades, has carefully studied hundreds of characteristics—can now directly be used to estimate the fundamental value of a stock. The focus on one-period alpha also avoids the need to specify multi-period risk factors or impose an exponentially linear model of the SDF.

To value stocks with one-period alpha, we restate the discounted alpha identity in equation (3) to show that one-period alpha is the payout from the stock of underpricing. To see this, discounted alpha at times 0 and 1 roughly says,

$$\begin{aligned} underpricing_0 &= \alpha_0 + E_0[X_1\alpha_1] + .. \\ underpricing_1 &= \alpha_1 + E_1[X_2\alpha_2] + .. \end{aligned}$$

So, one-period alpha is the duration-adjusted *decay* in underpricing:[10]

$$\alpha_0 = \mathit{underpricing}_0 - E_0[X_1 \ \mathit{underpricing}_1].$$

Remark 1 states this formally.

Assumption 1 (Candidate SDF explains the risk-free rate). From hereon, we assume that the candidate SDF explains the one-period risk-free rate:

$$E_t\left[\widetilde{M}_{t+1}\right] = \frac{1}{1+R_{f,t}}. \tag{5}$$

Remark 1 (Alpha as a payout from underpricing). *The discounted alpha identity in equation (3) implies that the flow of one-period alpha equals the expected duration-adjusted decline in the stock of (model-specific) underpricing:*

$$\frac{\alpha_{i,t}}{1+R_{f,t}} \ = \ vp_{i,t} \ - \ E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\ vp_{i,t+1}\right], \quad vp_{i,t} \equiv \underbrace{\frac{V_{i,t}}{P_{i,t}} - 1}_{\mathit{underpricing}}, \tag{6}$$

The duration adjustment $\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}$*, whose expected value is typically below one, means that a positive alpha can arise even when underpricing is constant over time,* $vp_{i,t+1} = vp_{i,t} = \overline{vp}$*, as was the case for the consol bond in Example 1.1.*

How does equation (6) help? To illustrate, suppose that underpricing decays deterministically at rate ϕ_{vp} and that $E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\right] = \rho$, the duration parameter in Campbell and Shiller (1988). Then, equation (6) simplifies to

$$\underbrace{\frac{\alpha_{i,t}}{1+R_{f,t}}}_{\text{alpha payout}} = \underbrace{(1-\rho\phi_{vp})}_{\text{payout ratio}} \times \underbrace{\left(\frac{V_{i,t}}{P_{i,t}} - 1\right)}_{\text{underpricing}}. \tag{7}$$

In such a case, the "stock" of underpricing can be estimated as the likely payout ratio,

[10] Multiply both sides of the second equation by X_1, take time-0 expectations, and subtract it from the first equation.

$1 - \rho\phi_{vp}$, times the estimated one-period alpha:[11]

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \frac{1}{1 - \rho\phi_{vp}} \times \frac{\alpha_{i,t}}{1 + R_{f,t}}. \tag{8}$$

In reality, however, the underpricing decay ϕ_{vp} is unobserved. We circumvent this problem by writing underpricing as a projection on stock characteristics:

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \gamma_V z_{i,t} + u_{i,t}, \tag{9}$$

where z is a vector of stock characteristics, γ_V is the mapping from stock characteristics to underpricing, and u is a projection error. This approach allows us to link the alpha payout to the decay in stock characteristics observed in the data.

Lemma 2 (Alpha as a payout from characteristics times γ_V). *Equations (6) and (9) imply that the alpha payout equals the duration-adjusted decay in stock characteristics times γ_V, the mapping from stock characteristics to underpricing:*

$$\frac{\alpha_{i,t}}{1 + R_{f,t}} \;=\; \gamma_V \left(I - \rho_{i,t}\phi_{z,i,t} - \frac{\Gamma_{G,z,i,t}}{1 + R_{f,t}} \right) z_{i,t} + \widetilde{u}^*_{i,t}, \tag{10}$$

where $\rho_{i,t} \equiv E_t[\widetilde{M}_{t+1}(1 + G_{i,t+1})]$ is cash-flow duration, $\phi_{z,i,t} \equiv E_t[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}} \frac{z_{i,t+1}}{z_{i,t}}]$ is the risk-adjusted characteristic persistence, $\Gamma_{G,z,i,t} \equiv Cov_t(G_{i,t+1}, \frac{z_{i,t+1}}{z_{i,t}})$ corrects the persistence for its covariance with capital gain, and $\widetilde{u}^*$ includes projection errors and higher-order terms.

Proof. See Appendix A. Here, the covariance term $\Gamma_{G,z,i,t}$ accounts for how—in the context of the discounted alpha identity in equation (3)—future alphas in high-price states matter more for today's model-implied fundamental value. □

Simply put, the lemma says,

$$\begin{aligned} alpha_{i,t} \;&=\; [\text{duration-adjusted decay in underpricing}]_{i,t} \\ &=\; \gamma_V \times [\text{duration-adjusted decay in characteristics}]_{i,t} + \widetilde{u}_{i,t}. \end{aligned}$$

[11] Example C.1 in the Internet Appendix contains a numerical example and a figure that provide further intuition.

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 mapping from stock characteristics to model-specific underpricing. Estimated $\widehat{\gamma}_V$ using data up to time T provides a model of real-time fundamental value at time T:

$$\widehat{V}_{i,T} = (1 + \widehat{\gamma}_V z_{i,T}) P_{i,T}. \tag{11}$$

The standard error on $\widehat{\gamma}_V$ allows us to put a confidence interval around the estimated fundamental value.

1.5 Implementation with linear regressions

Estimating the process for return, capital gain, and the evolution of characteristics in panel regressions allows us to estimate the conditional moments in equation (10) in the data. We can then run a second-stage regression to estimate γ_V.

Without loss of generality, write stock return (R), capital gain (G), and stock characteristics (z) as having stock-specific intercepts and factor exposures:

$$\begin{aligned} R_{i,t+1} &= R_{f,t} + \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1}, && (12) \\ 1 + G_{i,t+1} \equiv \frac{P_{i,t+1}}{P_{i,t}} &= (1 + R_{f,t})\rho_{i,t} + \beta_{G,i,t} f_{t+1} + \epsilon_{G,i,t+1} && (13) \\ z_{i,t+1} &= \phi_z \, z_{i,t} + \beta_{z,i,t} f_{t+1} + \epsilon_{z,i,t+1}, && (14) \end{aligned}$$

where $R_f + \alpha$, ρ, and $\phi_z z$ are the stock-time-specific intercepts, β the factor exposure, f the candidate risk factor(s) underlying $\widetilde{M}$, and ϵ a mean-zero projection error orthogonal to f.

In the spirit of Fama and MacBeth (1973) and Shanken (1990), we specify the intercepts and factor exposures in equations (12), (13), and (14) to depend on stock characteristics:[12]

$$\begin{aligned} \alpha_{i,t} &= \gamma_R \, z_{i,t}, & \beta'_{i,t} &= \Gamma_R \, z_{i,t}, \\ (1+R_{f,t})(\rho_{i,t}-1) &= \gamma_G \, z_{i,t}, & \beta'_{G,i,t} &= \Gamma_G \, z_{i,t}, \\ \beta'_{z,i,t} &= \begin{pmatrix} \beta'_{z,1,i,t} & \dots & \beta'_{z,L,i,t} \end{pmatrix}, & \beta'_{z,l,i,t} &= \Gamma_{z,l} \, z_{i,t}. \end{aligned} \tag{15}$$

We also allow $\sigma_{G,z,i,t} \equiv E_t[\epsilon_{G,i,t+1}\epsilon_{z,i,t+1}]$ to be nonzero and assume it follows

$$\sigma_{G,z,i,t} = \Gamma_{G,z} z_{i,t} + \epsilon_{G,z,i,t}. \tag{16}$$

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.[13] With these estimates in hand, we can then run a simple regression model of valuation.

Lemma 3 (A linear regression model of discounted alpha valuation). *The model of return, capital gain, and evolution of characteristics allows us to rewrite the valuation regression in equation (10) as*

$$\frac{\alpha_{i,t}}{1+R_{f,t}} \;=\; \gamma_V \left(I - (1 + \frac{\gamma_V}{1+R_{f,t}} z_{i,t})\phi_z - \frac{\Gamma_{G,z}}{1+R_{f,t}} \right) z_{i,t} + \widetilde{u}_{i,t}, \tag{17}$$

which is a linear regression model for estimating γ_V, the mapping from characteristics to underpricing. The error term $\widetilde{u}$ now also includes the covariance between G and z due to systematic factors.[14]

Proof. See Appendix A. □

For the regression in equation (17) to be valid, one should estimate the alpha on the

[12]Fama and MacBeth (1973) and Shanken (1990) model expected returns and factor loadings, respectively, as a function of characteristics. Lewellen (2015) and Kelly, Pruitt, and Su (2019) are recent examples of such an approach.

[13]If z and f are the L-column and K-column vectors of characteristics (including a constant) and candidate risk factors, respectively, β and β_G are K-row vectors, and β_z is an L-by-K matrix. To match these dimensions, γ_R and γ_G are L-row vectors, ϕ_z and $\Gamma_{G,z}$ are L-by-L matrices, and Γ_R and Γ_G are K-by-L matrices. $\Gamma_{z,l}$ is also a K-by-L matrix for each $l = 1, ..., L$.

[14]In this regard, it differs slightly from $\widetilde{u}^*_{i,t}$ in equation (10).

left-hand side with the same information used to estimate the right-hand side quantities. For instance, if alpha is high because of stronger arbitrage on the asset that period, z should include the measure of arbitrage intensity which—through the matrix ϕ_z—would predict a faster decline in characteristics associated with underpricing. For the error term $\widetilde{u}_{i,t}$ to be uncorrelated with the regressors, we recommend that a price multiple (e.g., book-to-market) and past return be included in the characteristic vector z (see Appendix A).

Given these specifications, we estimate γ_V, and hence stock-level $V_{i,t}$, in two steps:

(i) Estimate equations (12), (13), and (14) by regressing the left-hand side on the intercept, characteristics, and factors interacted with characteristics, as specified in equation (15), in a stock-time panel. Based on the residuals from these regressions, regress $\widehat{\epsilon}_{G,i,t+1}\widehat{\epsilon}_{z,l,i,t+1}$ on $z_{i,t}$ for each characteristic $l = 1, ..., L$ to estimate $\Gamma_{G,z}$ in equation (16).

(ii) As the second-step panel regression, regress $\widehat{\gamma}_R z_{i,t}/(1 + R_{f,t})$ on time fixed effects and the L-vector of regressors,

$$\left[I - (1 + \frac{\widehat{\gamma}_G}{1 + R_{f,t}} z_{i,t})\widehat{\phi}_z - \frac{1}{1 + R_{f,t}}\widehat{\Gamma}_{G,z} \right] z_{i,t}, \tag{18}$$

to estimate γ_V, where $\widehat{\gamma}_R$, $\widehat{\gamma}_G$, $\widehat{\phi}_z$, and $\widehat{\Gamma}_{G,z}$ are from the first step.[15] Use the resulting $\widehat{\gamma}_V$ to obtain the fundamental values of individual stocks in equation (11).

We use one year as the interval of time between t and $t + 1$ in equations (12), (13), and (14) but estimate all regressions using overlapping monthly observations.[16] We use value-weight least squares panel regressions to prevent small stocks with outlier values of some characteristics from driving the results.[17] We provide bootstrap t-statistics and confidence

[15]The l'th regressor in the L-vector of regressors equals $(1 + R_{f,t})(z_{l,i,t} - \widehat{\alpha}_{z,l,i,t}) - \widehat{\alpha}_{G,i,t}\widehat{\alpha}_{z,l,i,t} - \widehat{\sigma}_{G,z,l,i,t}$. The constant ($l = 1$) gets absorbed by the time fixed effects.

[16]There is some discretion over what time interval one uses as one period (t). Monthly is too short to capture how accounting-based characteristics evolve over time, but using a time interval that is too long results in an inaccurate estimation of alpha, since over such a long period, a significant part of the return comes from dividends that are paid out at different points in time. We measure one period to be a year and use annual data to estimate the first- and second-stage coefficients. Two-year or three-year intervals could also be reasonable alternatives if one wants to capture longer-horizon dynamics of characteristics.

[17]In particular, we use $\widetilde{w}_{i,t} = \frac{1}{1+R_{f,t}} \frac{MktCap_{i,t}}{\sum_j MktCap_{j,t}}$ as the weight on asset i at time t. The risk-free rate adjustment here is quantitatively unimportant but ensures that our regression minimizes the weighted sum

intervals that correct for cross-sectional and time-series correlation in the residuals as well as the two-stage nature of our estimation approach.

Our approach is flexible: it accommodates nonlinear projections, subsets of stocks (e.g., industries or size groups), large information sets that may call for shrinkage methods, and extensions that extract factor models of price levels as in Kelly et al. (2019). The linearity we assume, however, is not particularly restrictive, since it can include the polynomials of the variables as well as their interactions. Allowing stocks in different industries to follow different processes is a potentially interesting extension. By postulating the same process across different industries, we are assuming that the characteristics of different firms are expected to converge to the same steady state. Note that our approach also allows orthogonal information from other fundamental value measures (e.g., DCF-based or composite metrics) to be incorporated by adding them to the characteristic vector.

2 Data and Variables

The monthly stock-level dataset combines CRSP monthly stock prices, annual accounting data from CRSP/Compustat Merged (CCM), and pre-Compustat book equity data from Davis, Fama, and French (2000). Factor returns are from Kenneth French's data library. The one-month Treasury bill rate proxies for the risk-free rate, and the annual risk-free rate is constructed by compounding monthly bill rates over the year.

Our analysis uses eight standard stock-level characteristics to proxy for the econometrician's information set used in stock valuation. Book-to-market (*BM*), profitability (*Prof*), and market beta (*Beta*) capture different components of a firm-level present-value identity (Vuolteenaho, 2002). Investment (*Inv*) and net issuance (*NetIss*) may indicate overpricing if managers time these decisions based on perceived mispricing. Liquidity is proxied by the Amihud (2002) liquidity measure (*Liq*), which is highly correlated with size (market equity) but avoids the potentially unstable dynamics of size itself.[18] Past 1-year return (*Ret*) and past 2-to-1-year return (*LagRet*) may signal misvaluation if driven by price changes

of squared u rather than $\widetilde{u}$.

[18] A VAR process that includes the rank of market equity can be unstable due to the high persistence of market equity. The correlation between liquidity rank and market equity rank exceeds 90%.

unsynchronized with changes in value. While future work may expand the information set with additional characteristics, this parsimonious set highlights our methodology—the paper's main contribution—without relying on information unavailable at the time of real-time estimation.

Similar to Kelly, Pruitt, and Su (2020), we use cross-sectional ranks of the characteristics, except for the two return signals, which are simply demeaned cross-sectionally.[19] All variables are then cross-sectionally standardized using value weights. Table 1 reports their autocorrelations.

Our real-time, out-of-sample estimates are based on panel regressions using a 40-year moving window (minimum of 15 years). Fundamental value reflects how stock characteristics relate to a firm's long-term prospects, so conservative estimates require a longer window than typical short-horizon analyses. Shorter windows generate stronger validation results but also imply larger recent misvaluations.[20]

Our full stock-month panel runs from June 1939 to December 2024, with lagged characteristics starting in June 1938.[21] This setup yields approximately 2.6 million stock-month observations with real-time fundamental values from June 1953 to December 2024. For comparison, we also present in-sample estimates for the same period.

We consider three alternative factor models: the CAPM, the three-factor model of Fama and French (1993) (FF3), and the five-factor model of Fama and French (2015) (FF5). CAPM fundamental values are especially interesting because most DCF forecasts are made relative to that model (e.g., Morningstar, Value Line), and surveys of CFOs indicate that the CAPM remains the most widely used framework in firms' capital budgeting decisions (Graham and Harvey, 2001).[22] Accordingly, our interpretation often focuses on the CAPM.

[19]By not ranking past returns, we hope to better capture potentially large price changes that might not be reflected in rank changes.

[20]Table A1 in the Internet Appendix compares the strength of the out-of-sample signals across alternative window lengths as well as an exponential weighted moving average approach that downweights older data. An extension of our method could use cross-validation to select the optimal window length and exponential weighted moving average parameter.

[21]We start in 1938 because, as Cohen et al. (2003) argue, accounting practices before then had not yet converged to full compliance with the reporting requirements of the 1934 Securities Exchange Act.

[22]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

3 Valuing Individual Stocks with Discounted Alpha

We present stock-level fundamental values estimated via the two-step discounted-alpha valuation described in Section 1.5. Section 3.1 examines how stock characteristics incrementally predict underpricing relative to the CAPM and other factor models, both in-sample and out-of-sample. Section 3.2 then validates the resulting model-implied fundamental value estimates.

3.1 Incremental predictors of stock underpricing

Prior to studying moving-window estimates, we study full-sample estimates of γ_V that map the vector stock characteristics, $z_{i,t}$, to model-implied underpricing, $V_{i,t}/P_{i,t} - 1$:

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \gamma_V \, z_{i,t} + u_{i,t}. \tag{9}$$

Table 2 reports the estimated coefficients, with and without the lagged past return signal.

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 fundamental value.[23] A one-standard-deviation increase in the rank of these characteristics predicts shifts in fundamental value relative 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),

Fama and French (2015) or the four-factor model of Hou, Xue, and Zhang (2015) are more recent and likely less relevant for decision makers over most of our sample period, they may nonetheless capture forces present throughout the 20th century. We report results for the five-factor model to illustrate how refinements affect fundamental value estimates.

[23]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. 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.

profitable, and low-risk is likely underpriced.[24] Profitability and beta continue to predict fundamental value 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 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 behaving 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. This 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 is a significant predictor of overpricing (and the inclusion of this long-run reversal signal makes BM borderline statistically insignificant), whereas past return is not a significant predictor of mispricing under the CAPM or FF3. Under FF5, by contrast, momentum stocks appear underpriced. 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).

[24] 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.

D. Role of alpha conditionality

The discounted alpha regression in Lemma 2 accounts for cross-stock differences in the cash-flow duration (measured by $\rho_{i,t}$) as well as the conditionality of alphas (measured by $\Gamma_{G,z}$). Not accounting for the conditionality of alphas by setting $\Gamma_{G,z} = 0$ leads us to over-estimate the importance of the Liq characteristic (and B/M to some extent) for CAPM underpricing. In the context of the discounted alpha identity in equation (3), the CAPM alphas of illiquid (small) stocks tend to occur in states when the future price falls, which are the states that the identity discounts more heavily. This fact dampens the CAPM underpricing of small stocks, and setting $\Gamma_{G,z} = 0$ ignores this potentially important covariance effect.[25] Setting $\rho_{i,t}$ to be the same across stocks, however, does not meaningfully affect the estimates—with the performance judged by the Cho-Polk p-value dropping as opposed to rising. This is consistent with our claim that the short-horizon nature of discounted alpha makes it less susceptible to misspecifying the duration parameter (discount rate) and suggests a potential way to simplify discounted alpha valuation further. However, a simple ρ-discounted sum of alphas, which ignores both the alpha conditionality and the $\rho_{i,t}$ heterogeneity, leads to a substantial drop in accuracy. These results are summarized as Table A2 in the Internet Appendix.

E. Moving-window estimates

The moving-window estimates of γ_V in Figure 2 illustrate how full-sample results translate to specific periods. 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 today. Third, coefficients on profitability, investment, and net issuance have increased, contributing to greater CAPM misvaluations in recent years.

[25] Although the opposite is true for the large (liquid) stock effect—the negative CAPM alphas of large stocks occurring when the price rises—the substantially higher idiosyncratic volatility of small stocks compared to large stocks means that the effect from small stocks dominates the size effect on underpricing.

3.2 Fundamental value and validation

Our model of stock-level underpricing immediately generates stock-level estimates of fundamental value: $\widehat{V}_{i,t} = (1 + \widehat{\gamma}_V z_{i,t}) \, P_{i,t}$. We plot this for the biggest stocks in Dec 2024 as Figure 3. Relative to the CAPM, Tesla and Broadcom appear overpriced, whereas Apple, Eli Lilly, and Walmart appear underpriced.[26] 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.

How can one validate real-time estimates of fundamental value? Theory offers concrete guidance, which we translate into empirical tests below. These same tests can also be applied to estimates produced in future research, helping to discipline subsequent estimates of fundamental value.

A. Post-formation alphas

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

$$\underbrace{\frac{V_{i,t}}{P_{i,t}} - 1}_{\text{Underpricing}} = \sum_{\tau=0}^{\infty} E_t \left[\frac{\widetilde{M}_{t \to t+\tau+1} P_{i,t+\tau}}{P_{i,t}} \alpha_{i,t+\tau} \right], \tag{19}$$

has an expected value 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 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.

Figure 4 and Panel A of Table 3 show that sorting stocks on real-time fundamental value-to-price generates persistent differences in alphas and large 5-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.

[26] Our estimate that Apple is underpriced is interesting in light of Warren Buffett's concentrated holding of that firm since 2018.

B. A short-horizon test of valuation-return consistency

To complement our long-horizon evidence, we develop a novel test of short-horizon consistency based on the discounted-alphas identity.

Define the *valuation residual* as the deviation from the identity, given a value estimator $\widehat{V}_{i,t}$:

$$\eta^V_{i,t+1} = \underbrace{R^e_{i,t+1}}_{\text{Excess Return}} + \underbrace{\frac{\widehat{V}_{i,t+1} - P_{i,t+1} - (1 + R_{f,t})(\widehat{V}_{i,t} - P_{i,t})}{P_{i,t}}}_{\Delta\,\text{Underpricing}}. \tag{20}$$

If $\widehat{V}_{i,t}$ is accurate, the discounted alpha identity (equation (3)) implies that the valuation residual should be orthogonal to the factor(s) driving the candidate SDF:

$$E_t\left[\widetilde{M}_{t+1}\, \eta^V_{i,t+1}\right] = 0. \tag{21}$$

Intuitively, this tests whether ex-post one-month alpha is offset by the contemporaneous change in underpricing, as implied by the discounted-alphas identity. For example, if our underpricing estimate is correct, both today and next period, a large alpha should coincide with a large decline in estimated underpricing.

We implement this test by sorting stocks on $\frac{\widehat{V}}{P}$, constructing long-short portfolios, and regressing the long-short valuation residual on the factor(s) in the candidate SDF:

$$\eta^V_{t+1,LS} = \phi + \beta' f_{t+1} + \nu_{t+1}. \tag{22}$$

Under the null, $\phi = 0$. Unlike the post-formation alpha test, this procedure evaluates the *accuracy* of the valuation measure's magnitude rather than its predictive power.

Panel B of Table 3 presents the result for the long and short quintile portfolios separately and then for the long-short portfolio. The table also reports the decomposition of the intercept coefficient from the long-short portfolio regression into its excess return and "Δ underpricing" components. We find no significant intercept associated with these model-based valuation residuals, indicating that we cannot reject the null hypothesis that our estimates of fundamental value are accurate.

C. Sample-average mispricing

Though we have shown that V/P generates spread in post-formation alphas, an important question remains. In particular, the Cho-Polk identity that links mispricing to subsequent alphas makes specific predictions about the way those alphas should be aggregated into a price-level measure. Those predictions are implicit in both this paper's ex-ante conditional measure of firm-level V/P and in Cho-Polk's ex-post measure of average portfolio-level mispricing. Our tests so far, that only examine alphas by each horizon separately (Figure 4) or simply apply equal weights to accumulate alphas (Panel A of Table 3), have not confirmed that the weights implicit in our ex-ante V/P measure are accurate.

A concern might be that though our firm-level V/P estimates do generate persistent differences in future model-specific abnormal returns, the predicted price-level distortions are only useful in an ordinal sense. In other words, our model's output may be relatively inaccurate and thus unreliable in applications where the cardinal nature of the prediction is crucial.[27]

To show that our method's outputs of predicted price-level distortions line up well with subsequent realized price-level outcomes, we plot Cho-Polk's ex-post portfolio V/P against the value-weight average ex-ante firm-level V/P of our portfolios sorted by this measure. Figure 5 shows that the resulting estimates of ex-post realized V/P are monotonically increasing and line up well with our ex-ante predicted V/Ps, as observations fall close to the 45-degree line. Indeed, we cannot reject the null hypothesis that the forecasted V/Ps we estimate are equal to the realized V/P we measure after the sort, not only individually for each estimate, but also jointly across the quintiles. This failure to reject is not because of lack of power as we are able to reject that the ex-post realized V/P estimates are different from zero for the extreme quintile portfolios.

Table 3 Panel C reports the associated ex-post V/P for each quintile that we plot in Figure 5 as well as the difference between the extreme quintile portfolios. That difference is economically large (43.67%) and statistically significant (p value of 0.017). The table also

[27]For example, both a buy-and-hold portfolio manager and a CEO who caters to mispricing would presumably want to size their investments according to the specific magnitude of V/P that they estimate.

measures the difference (ΔHi-Lo) between that estimate and the underlying ex-ante measures on which firms were sorted. That difference (-14.35%) is not statistically significant (p value of 0.434).

We find similar results for FF3-based estimates in terms of how well the ex-post estimates line up with our ex-ante predictions.[28] Indeed, the difference between these two, summarized by ΔHi-Lo, not only remains statistically insignificant but is also much smaller for the FF3-based estimate (only -6.15%) compared to the CAPM version. Indeed, our method generates more spread in fundamental value relative to price when we measure systematic risk using those three factors instead of simply the market.

D. Russell index classification

To further validate our estimates, we test whether our CAPM-based underpricing measure captures the well-known price distortions at the Russell 1000/2000 cutoff. Because of benchmarking concerns, stocks just inside the Russell 1000 receive disproportionately less capital, while those just inside the Russell 2000 receive disproportionately more (Chang et al., 2015).

Table 4 shows that the stocks at the bottom of the Russell 1000 are 7.8% more underpriced relative to the rest of the Russell 1000, while the stocks at the top of the Russell 2000 are 13.3% more overpriced relative to the rest of the Russell 2000. Overall, a small *increase* in the market capitalization that moves a stock out of the 2000 to the 1000 index can make the stock more *underpriced* relative to the CAPM by 8.6% points on average. This finding confirms that our real-time estimates detect this well-known demand-driven, non-fundamental component of stock prices.

4 Empirical Comparisons to DCF

4.1 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

[28] The limited FF5 sample prevents reliable estimation of portfolio-average $\frac{V}{P}$.

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).

A. Distribution and ex-post performance

Figure 6 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 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 et al., 2024; and Bordalo, Gennaioli, 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.

B. Sources of errors in DCF valuation

Figure 7 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 with 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 from 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 under-apply discount rates, 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 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.

4.2 Other misvaluation metrics can add incremental information

A. Goncalves-Leonard FE/ME (DCF, no risk adjustment)

Gonçalves and Leonard (2023) forecast future cash flows using a Vector Autoregressive (VAR) model of firm-level variables to obtain a firm-level ratio of fundamental value to price, which they call the fundamental-to-market ratio (FE/ME). They avoid the problem of having to estimate stock-specific costs of equity by applying the same discount rate to all stocks, namely, the rate that equates the market's long-term average fundamental-value-to-book and price-to-book.

Table 5 shows strong evidence that this dividend-based measure contains incremental information about the deviation of CAPM fundamental value from prices. *FE/ME* carries an economically large coefficient of 8.0 that is also highly statistically significant; i.e., controlling for the other characteristics, a one-standard-deviation increase in the rank of *FE/ME* is associated with a 8.0% point rise in CAPM-implied underpricing. Comparing the coefficients on the other characteristics in the first column to those from the second column of Table 2, we find that the incremental explanatory power of this measure draws partly from driving out the explanatory power of gross profitability, investment, and lagged return (long-term reversal) characteristics. However, this fact does not seem to explain the large magnitude of its coefficient, which means that dividend-based measures of value-to-price, when carefully estimated, likely contain information orthogonal to our baseline fundamental value estimates.

These results point to a complementary relationship between discounted-alphas and traditional DCF approaches, and suggest that expanding the set of characteristics included in our analysis can help capture additional variation in model-implied underpricing. For example, adding the rank of *FE/ME* to our existing model generates more precise estimates of fundamental value. Indeed, the ability to incorporate other misvaluation signals as additional elements in the characteristic vector is an important advantage of our framework.

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

Stambaugh and Yuan (2017) and Asness et al. (2019) take a different approach to generate a stock-level signal of misvaluation, combining several characteristics likely to proxy for mispricing into a composite signal. Stambaugh and Yuan (2017) generate two "mispricing" factors, management (*Mgmt*) and performance (*Perf*), whereas Asness et al. (2019) generate quality (*Quality*).

Columns 2 and 3 of Table 5 show that these signals also contain incremental information about mispricing. The mispricing factors of Stambaugh and Yuan appear to drive out the explanatory power of investment and net issuance, which is to be expected, since *Mgmt* contains measures of investment, although we also find that *Perf* contains information about mispricing as well. *Quality* also contains incremental information about CAPM fundamental values and seems to do so without substantially weakening the coefficients on other characteristics. Hence, although Cho and Polk (2024) find *Quality* to be a weak univariate signal of price-level mispricing, this result shows that it may work in a multivariate setting that controls for the effect of other characteristics on prices.

van Binsbergen et al. (2023) employ DCF to estimate portfolio mispricing relative to the CAPM in sample and extract the principal components to compute firm-level "price wedges."[29] Column 4 of Table 5 show that these in-sample estimates generate incremental information about CAPM underpricing, but can be significantly improved using information about profitability, beta, net issuance, and lagged one-year return within the discounted alpha framework.

Unlike Gonçalves and Leonard, which provides a real-time (out-of-sample) measure, the signals of Stambaugh–Yuan, Asness et al., and van Binsbergen et al. are constructed in-sample and thus subject to potential look-ahead bias, giving them an inherent advantage relative to our real-time estimates. Nevertheless, when evaluated using post-formation alphas, these in-sample signals perform worse: beyond two years, only the Stambaugh–Yuan management signal continues to predict statistically significant alphas, while alphas based on the other measures lose all predictive power (Figure A3).

5 Applications

We apply our framework to examine how biased investor beliefs, as reflected in analyst expectations, contribute to stock price distortions. We further use our estimates to study the investment behavior of private equity funds and discretionary buy-and-hold managers.

5.1 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 6 suggests this possibility. We re-estimate the valuation regression (γ_V) over the

[29] Relative to the firm-level estimates in Cho and Polk (2020), vBBOT differ in that they utilize DCF-based portfolio estimates. We thank Andrea Tamoni for generously sending us their data.

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 statistically highly 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.

Including analyst targets as a control also alters the role of other characteristics. In particular, the magnitude of the coefficient on book-to-market increases once analyst targets are added. This fact suggests that analysts tend to assign especially favorable targets to low-price-multiple firms, which weakens book-to-market as a clean signal of underpricing. Once this bias is accounted for, book-to-market's importance as a valuation signal is restored.

Taken together, these results provide direct price-level evidence on the view that analyst expectations are not merely noisy forecasts but a systematic source of price-level distortions (e.g., La Porta, 1996; Bordalo et al., 2019; Engelberg, McLean, and Pontiff, 2020; Delao and Myers, 2021; Bordalo et al., 2024; Delao et al., 2024). One interpretation is that biased expectations held by a broad set of investors in the market, which tend to make the affected stocks over- or undervalued, also shape the expectations of analysts. 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.

5.2 Long-term buy-and-hold investors

A. Private equity funds

An interesting question is the way that private equity (PE) funds trade equity shares—particularly relevant in light of our fundamental value estimates, since PE funds are often viewed as canonical sophisticated, long-term investors.

Table 7 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.

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 buy-and-hold 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 8 shows that stocks held by these fundamental investors tend to be significantly underpriced (Panel A). A typical Berkshire holding is about 14.2% underpriced relative to the CAPM (value-weight estimate of 7.9%), while the average across the broader group is 3.6% underpriced (value-weight estimate of 5.7%). 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 taken alone generate a positive but modest annualized one-month value-weight alpha that is not statistically significant. This apparent disparity reflects contrarian behavior: these investors tend to hold stocks with negative momentum characteristics, which tend to hurt 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.

5.3 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 et al. (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):

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

where *top* and *bottom* are the top and bottom third of stocks by B/M within the subset of stocks that remove all microcaps.[30] Analogous spreads are constructed for other characteristics. This adds richer time-series dynamics to stock-level V/P without materially altering cross-sectional variation or the γ_V estimates.[31]

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

Figure 8 plots the dispersion in CAPM-implied mispricing over time measured by the share of total market capitalization estimated to be more than 50% mispriced.[32] 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,

[30]We define microcaps here as the ones with the rank of liquidity below −1. We find that the estimation accounting for cross-sectional dispersion depends importantly on how we compute the characteristic spread. We do not think that the NYSE-based spread does the right job here, since some misvaluation phenomena such as the dot-com were driven primarily by NASDAQ stocks.

[31]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.

[32]To be precise, the 50% benchmark corresponds to a V/P between 0.5 and 2 rather than 0.5 to 1.5 we use. However, a V/P above 2 is extremely rare in our estimate, making it less interesting to analyze.

there are episodic surges in valuation dispersion that encompass a large portion of the market.

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 the level of prices 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 8 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 valuation levels toward the outer edge of Black's bounds (within 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 8 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 9 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 less 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 8 coincides with a steady rise in the persistence of mispricing (Panel C of Figure 9). 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, reminiscent of the argument in Summers (1986).[33]

To summarize this point in the context of the discounted alpha identity, equation (6) says that one-period alpha is the "payout" from existing mispricing adjusted by duration. Rearranging this expressions result 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 higher persistent 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

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

that remain significant even in an “almost efficient” market.

6 Conclusion

We develop a novel way to estimate stock-level 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 come up with bespoke but rigorous estimates of fundamental value, not only for stocks but also for other assets.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Asness, Clifford, 2024, The less-efficient-market hypothesis, *Journal of Portfolio Management* 51.

Asness, Clifford S., Andrea Frazzini, and Lasse Heje Pedersen, 2019, Quality minus junk, *Review of Accounting Studies* 24, 34–112.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245–282.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969–1005.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–32.

Bartram, Söhnke M, and Mark Grinblatt, 2018, Agnostic fundamental analysis works, *Journal of Financial Economics* 128, 125–147.

Ben-David, Itzhak, and Alex Chinco, 2024, Expected EPS × trailing P/E, working paper, Working paper.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 528–543.

Bordalo, Fedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2019, Diagnostic expectations and stock returns, *Journal of Finance* 74.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2024, Belief overreaction and stock market puzzles, *Journal of Political Economy* 132, 1450–1484.

Brav, Alon, John R. Graham, Campbell R. Harvey, and Roni Michaely, 2005, Payout policy in the 21st century, *Journal of Financial Economics* 77, 483–527.

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

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, Regression discontinuity and the price effects of stock market indexing, *Review of Financial Studies* 28, 212–246.

Cho, Thummim, 2020, Turning alphas into betas: Arbitrage and endogenous risk, *Journal of Financial Economics* 137, 550–570.

Cho, Thummim, and Christopher Polk, 2020, Asset pricing with price levels, https://marriott.byu.edu/upload/event/event_767/_doc/chopolk_pricelevel_20200831_c.pdf.

Cho, Thummim, and Christopher Polk, 2024, Putting the price in asset pricing, *Journal of Finance* 79, 3943–3984.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41–58.

Cochrane, John, 2009, *Asset pricing: Revised edition* (Princeton University Press, Princeton, NJ).

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2009, The price is (almost) right, *Journal of Finance* 64, 2739–2782.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Décaire, Paul, and John R Graham, 2024, Valuation fundamentals, working paper.

Décaire, Paul, Denis Sosyura, and Michael D. Wittry, 2024, Resolving estimation ambiguity, working paper.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 1999, An empirical assessment of the residual income valuation model, *Journal of Accounting and Economics* 26, 1–34.

Dechow, Patricia M., and Richard G. Sloan, 1997, Returns to contrarian investment strategies: Tests of naive expectations hypotheses, *Journal of Financial Economics* 43, 3–27.

Delao, Ricardo, Xiao Han, and Sean Myers, 2024, The cross-section of subjective expectations: Understanding prices and anomalies, working paper.

Delao, Ricardo, and Sean Myers, 2021, Subjective cash flow and discount rate expectations, *Journal of Finance* 76, 1339–1387.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2019, Noisy stock prices and corporate investment, *The Review of Financial Studies* 32, 2625–2672.

Dessaint, Olivier, Jacques Olivier, Clemens A Otto, and David Thesmar, 2021, Capm-based company (mis) valuations, *Review of Financial Studies* 34, 1–66.

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

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2020, Analysts and anomalies, *Journal* *of Accounting and Economics* 69, 101249.

Fama, Eugene F., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383–417.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Frankel, Richard, and Charles MC Lee, 1998, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283–319.

Gerakos, J., and J. T. Linnainmaa, 2018, Decomposing value, *Review of Financial Studies* 31, 1825–1854.

Golubov, Andrey, and Theodosia Konstantinidi, 2019, Where is the risk in value? evidence from a market-to-book decomposition, *Journal of Finance* 74, 3135–3186.

Gonçalves, Andrei S., and Gregory Leonard, 2023, The fundamental-to-market ratio and the value premium decline, *Journal of Financial Economics* 147, 382–405.

Gormsen, Niels Joachim, and Kilian Huber, 2024, Firms' perceived cost of capital, working paper.

Gormsen, Niels Joachim, and Kilian Huber, 2025, Corporate discount rates, *American Economic Review* 115, 2001–2049.

Graham, John R., and Campbell R. Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.

Hansen, Lars Peter, and Ravi Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99, 225–262.

Hansen, Lars Peter, and Ravi Jagannathan, 1997, Assessing specification errors in stochastic discount factor models, *Journal of Finance* 52, 557–590.

Hommel, Nicolas, Augustin Landier, and David Thesmar, 2022, Corporate valuation: An empirical comparison of discounting methods, working paper.

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

Kelly, Bryan T, Seth Pruitt, and Yinan Su, 2019, Characteristics are covariances: A unified model of risk and return, *Journal of Financial Economics* 134, 501–524.

Kelly, Bryan T, Seth Pruitt, and Yinan Su, 2020, Instrumented principal component analysis, working paper, Working paper.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *Journal of Finance* 51, 1715–1742.

Lee, Charles M.C., James Myers, and Bhaskaran Swaminathan, 1999, What is the intrinsic value of the dow?, *Journal of Finance* 54, 1693–1741.

Lewellen, Jonathan, 2015, The cross section of expected stock returns, *Critical Finance Review* 4, 1–44.

Martin, Ian W.R., and Stefan Nagel, 2022, Market efficiency in the age of big data, *Journal of Financial Economics* 145, 154–177.

McLean, R David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.

Morningstar, Inc., 2022, Master equity research methodology, Technical report, Morningstar, Inc., Accessed: September 27, 2025.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Ohlson, James A., 1995, Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661–687.

Polk, Christopher, and Paola Sapienza, 2009, The stock market and corporate investment: A test of catering theory, *Review of Financial Studies* 22, 187–217.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921–945.

Shanken, Jay, 1990, Intertemporal asset pricing: An empirical investigation, *Journal of Econometrics* 45, 99–120.

Shumway, Tyler, 1997, The delisting bias in crsp data, *Journal of Finance* 52, 327–340.

Shumway, Tyler, and Vincent A. Warther, 1999, The delisting bias in crsp's nasdaq data and its implications for the size effect, *Journal of Finance* 54, 2361–2379.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

Stafford, Erik, 2022, Replicating private equity with value investing, homemade leverage, and hold-to-maturity accounting, *Review of Financial Studies* 35, 299–342.

Stambaugh, Robert F, and Yu Yuan, 2017, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Summers, Lawrence H., 1986, Does the stock market rationally reflect fundamental values?, *Journal of Finance* 41, 591–601.

van Binsbergen, Jules H., Martijn Boons, Christian C. Opp, and Andrea Tamoni, 2023, Dynamic asset (mis) pricing: Build-up versus resolution anomalies, *Journal of Financial Economics* 147, 406–431.

Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, *Journal of Finance* 57, 233–264.

Table 1: **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. 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 2: **Incremental Predictors of Equity Underpricing (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 $V_{i,t} \equiv \sum_{\tau=1}^{\infty} E_t \left[\widetilde{M}_{t,t+\tau} D_{i,t+\tau} \right]$ is the fundamental cash-flow value of stock i at time t, $\widetilde{M}_{t,t+\tau}$ 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. 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	7.01	9.36	-5.18	-3.60	1.46	1.40
	(1.72)	(2.17)	(2.36)	(1.66)	(0.52)	(0.53)
Prof	12.71	12.82	19.43	19.71	19.60	19.69
	(2.95)	(2.89)	(5.04)	(5.03)	(4.58)	(4.55)
Beta	-13.48	-14.23	-8.94	-9.51	1.99	2.17
	(2.70)	(2.74)	(1.88)	(1.94)	(0.37)	(0.40)
Inv	-1.81	-2.04	-1.94	-2.17	-0.67	-0.67
	(3.63)	(3.89)	(3.72)	(3.99)	(1.42)	(1.32)
NetIss	-2.88	-3.10	-1.97	-2.16	-0.50	-0.49
	(5.02)	(4.96)	(4.00)	(4.03)	(0.97)	(0.94)
Liq	-0.09	-0.48	-1.13	-1.42	-5.09	-5.09
	(0.02)	(0.11)	(0.44)	(0.54)	(2.60)	(2.53)
Ret	-0.08	0.93	0.56	1.44	3.15	3.03
	(0.11)	(1.64)	(0.73)	(2.43)	(3.27)	(3.50)
LagRet	-1.05		-0.93		0.07	
	(2.86)		(2.44)		(0.15)	

Table 3: **Validating Fundamental Value Estimates with Ex-Post Performance**

We report five-year model-specific cumulative abnormal returns (CARs), a short-horizon test described in Section 3.2, and post-formation model-specific Cho–Polk portfolio-level $\frac{V}{P}$ (all in percentage units) for extreme quintiles sorted on real-time model-specific underpricing. The coefficients in Panel B are annualized percentages. Wec ompute both CARs and Cho–Polk underpricing in calendar time: the CAR equals the sum of contemporaneous alphas from underpricing-sorted portfolios formed in each of the prior 60 months. Panel C omits FF5 V/P results because the short sample prevents estimating the cumulative model-specific SDF as in Cho–Polk. ΔHi-Lo in Panel C refers to the difference between the value-weight average of the real-time underpricing estimate and the Cho-Polk portfolio underpricing estimate. We bold the diagonal elements in Panel A, as these estimates are expected to be economically and statistically strong. We report bootstrap t statistics in parentheses and p values in brackets.

Panel A. Ex-Post Five-year Cumulative Abnormal Returns (CAR)

Ex-ante Sorting Variable	CAPM CAR	FF3 CAR	FF5 CAR
CAPM Underpricing	**27.39 (4.43)**	22.31 (3.51)	9.56 (1.41)
FF3 Underpricing	20.76 (3.68)	**26.84 (4.82)**	17.53 (2.97)
FF5 Underpricing	4.35 (0.49)	13.15 (2.52)	**16.13 (3.07)**

Panel B. Short-Horizon Test of Valuation-Return Consistency

	Intercept Coefficient [p-value]				
	Long	Short	Long-Short		
	X^L	X^S	Excess return	Δ Underpricing	X^{LS}
CAPM	1.93 [0.147]	0.06 [0.955]	7.91 [0.000]	-6.04 [0.000]	1.87 [0.390]
FF3	1.69 [0.206]	-1.14 [0.270]	7.44 [0.000]	-4.61 [0.000]	2.83 [0.191]
FF5	-0.50 [0.517]	-0.50 [0.517]	5.63 [0.006]	-5.96 [0.000]	-0.33 [0.909]

Panel C. Cho-Polk Portfolio Underpricing

	Portfolio Underpricing Based on Ex-Post Returns						
Ex-ante Sorting Variable	Low	2	3	4	High	Hi-Lo	ΔHi-Lo
CAPM Underpricing	-17.55	1.52	16.82	23.98	26.11	43.67	-14.35
[p-value]	[0.016]	[0.781]	[0.006]	[0.021]	[0.034]	[0.017]	[0.434]
FF3 Underpricing	-31.91	-11.92	6.42	20.73	23.91	55.83	-6.15
[p-value]	[0.012]	[0.032]	[0.274]	[0.003]	[0.017]	[0.011]	[0.779]

Table 4: **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 dummy indicator variables for the bottom of Russell 1000 (bottom 150 stocks in the index), the top of Russell 2000 (top 150 stocks in the index), the Russell 1000, and the Russell 2000. The last column shows that the estimated CAPM-implied underpricing increases by 8.6 percentage points as a stock moves from the top of the Russell 2000 to the bottom of the Russell 1000, consistent with the notion that the bottom (top) of the Russell 1000 (Russell 2000) is underpriced (overpriced) because of the way benchmarking concerns drive fund capital allocation (Chang et al. (2015)). We report *t*-statistics based on standard errors that are robust to both time and stock-level clustering. The sample period is 1987 to 2019.

	Dependent Variable: CAPM Underpricing			
Bottom of Russell 1000	7.81		7.83	8.59
	(3.48)		(3.49)	(6.18)
Top of Russell 2000		-13.25	-13.26	
		(11.44)	(11.43)	
Russell 1000	-2.89		-0.32	
	(1.26)		(0.17)	
Russell 2000		7.24	7.03	
		(3.23)	(5.81)	
Sample	All	All	All	1000/2000 Border

Table 5: **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 (an) existing measure(s) of misvaluation: the fundamental-to-market ratio (*FE/ME*) (1973m6–2018m12) of Gonçalves and Leonard (2023), 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	11.65	9.86	9.00	9.02
	(2.05)	(2.53)	(2.18)	(2.13)
Prof	10.39	12.00	13.72	10.59
	(1.57)	(2.48)	(2.35)	(2.19)
Beta	-15.69	-11.92	-11.83	-19.91
	(2.37)	(2.42)	(2.49)	(4.18)
Inv	-1.06	-0.38	-1.68	-1.06
	(1.50)	(0.83)	(3.28)	(1.76)
NetIss	-2.92	-0.84	-2.71	-2.84
	(4.23)	(1.12)	(4.96)	(4.37)
Liq	-0.56	-0.41	-2.46	3.49
	(0.13)	(0.10)	(0.54)	(0.76)
Ret	-0.44	-1.07	0.45	-0.53
	(0.44)	(1.36)	(0.57)	(0.54)
LagRet	-0.46	-1.02	-0.94	-1.01
	(0.81)	(2.66)	(2.42)	(2.13)
FE/ME	7.96			
	(3.31)			
Mgmt		3.10		
		(4.29)		
Perf		4.00		
		(3.34)		
Quality			2.43	
			(2.61)	
PW				-6.56
				(2.51)

Table 6: **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 include 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 sub-sample. 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	5.66	2.54	6.70	-1.03	-5.69	4.50
	(0.90)	(0.82)	(1.46)	(0.15)	(1.37)	(0.94)
Prof	21.49	23.15	19.71	31.30	35.11	22.95
	(3.13)	(4.10)	(2.80)	(3.16)	(4.54)	(2.55)
Beta	-5.97	-0.93	-4.23	-9.92	-4.94	-7.21
	(0.64)	(0.12)	(0.52)	(0.93)	(0.57)	(0.75)
Inv	-3.07	-2.86	-1.47	-4.16	-4.16	-1.59
	(4.33)	(4.17)	(1.97)	(5.05)	(5.20)	(1.63)
NetIss	-3.60	-2.77	-0.33	-4.08	-3.40	-0.53
	(3.04)	(2.74)	(0.31)	(3.71)	(3.66)	(0.54)
Liq	-9.49	-11.18	-15.45	-4.98	-5.15	-12.45
	(1.60)	(2.95)	(3.13)	(0.64)	(0.85)	(2.17)
Ret	-1.28	-1.40	-0.21	0.79	0.94	1.57
	(0.90)	(1.15)	(0.15)	(0.52)	(0.74)	(1.09)
LagRet	0.11	0.40	1.04	-0.08	0.16	1.18
	(0.15)	(0.73)	(1.83)	(0.11)	(0.26)	(1.90)
Price Target	-10.81	-11.33	-7.18			
	(4.28)	(4.70)	(3.35)			

Table 7: **Private Equity Funds Buy Low and Sell High**

We show that stocks delisted because of private equity buyout 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. Interestingly, the characteristics private equity funds look for when buying or selling coincide with the characteristics our model shows predict CAPM misvaluation. We report t-statistics based on standard errors that are robust to both time and stock-level clustering. The sample period is 1986 to 2024.

	Dependent Variable: CAPM Underpricing					
PE buyout	10.71	12.32			12.28	12.52
	(3.56)	(5.27)			(5.26)	(5.00)
PE IPO			-15.03	-18.33	-18.33	-17.06
			(19.69)	(26.41)	(26.41)	(17.68)
Delisting						-1.28
						(1.56)
IPO						-0.24
						(0.29)
Sample	Delisting stocks	All	IPO stocks	All	All	All

Table 8: **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 1-month alpha (Panel B; annualized). Panel B uses Fama-MacBeth style regressions, and all regressions control for the rank of liquidity based on Amihud (2002). Panel B scales 1-month alphas to be annualized. All numbers are in percentages. 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. We report t-statistics based on standard errors that are robust to both time and stock-level clustering. The sample period is 1981 to 2024.

Panel A. CAPM Underpricing

Buffett	14.19		12.15	7.94		6.88
	(4.94)		(4.22)	(2.11)		(1.83)
Fundamental		3.56	2.87		5.66	4.75
		(5.11)	(4.19)		(4.66)	(4.46)
Weight	EW	EW	EW	VW	VW	VW

Panel B. CAPM Alpha (annualized)

Buffett	5.62		3.80	1.71		1.28
	(3.31)		(2.39)	(0.88)		(0.66)
Fundamental		2.76	2.56		2.08	1.94
		(3.33)	(3.06)		(3.03)	(2.90)
Weight	EW	EW	EW	VW	VW	VW

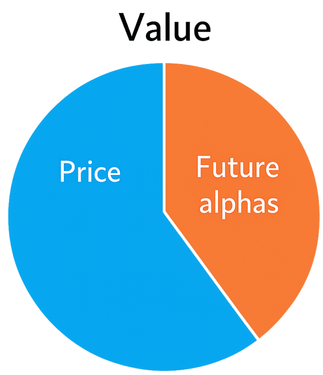


Figure 1: **Discounted Alpha Valuation**

The figure illustrates the intuition behind the discounted-alpha valuation formula. 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:

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

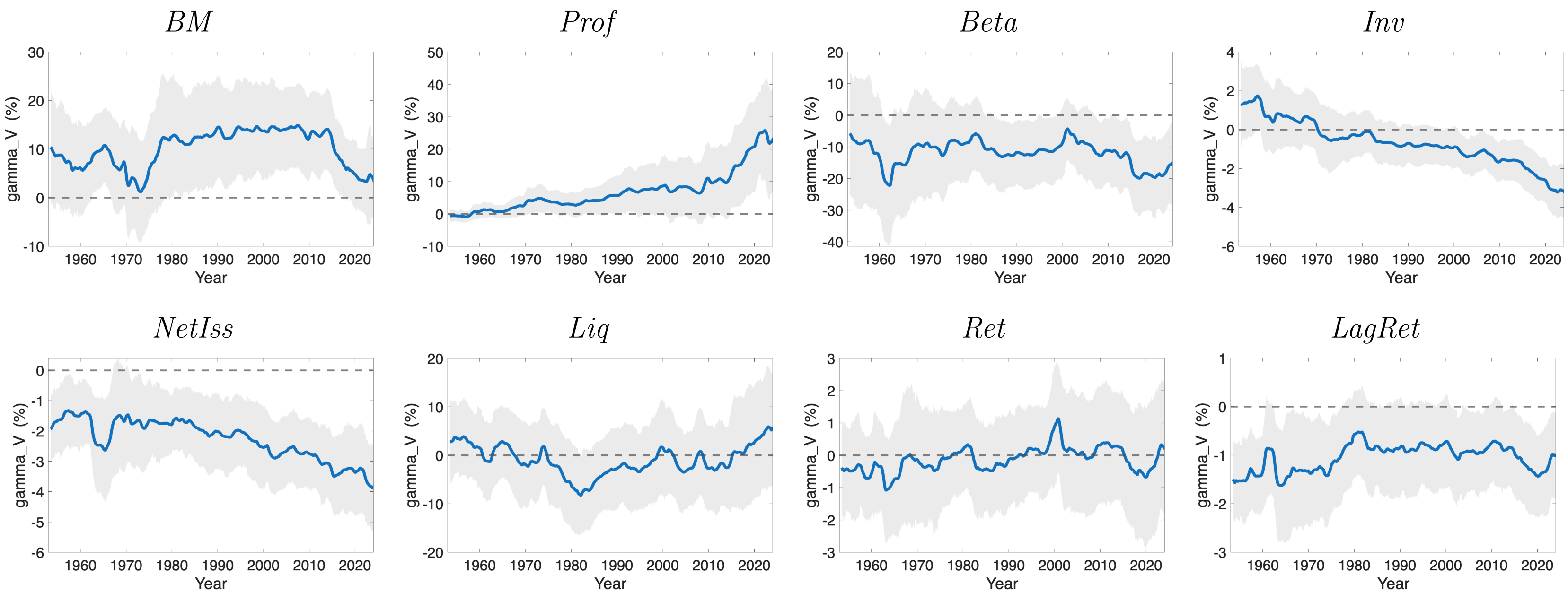


Figure 2: **Moving-Window Multivariate Coefficients of CAPM Underpricing on Stock Characteristics**

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 rolling windows that cover 40 years (with 15 years as a minimum window size at the beginning of the sample period) over the period 1953m6–2024m12. The shaded area represents the 95% bootstrap confidence interval.

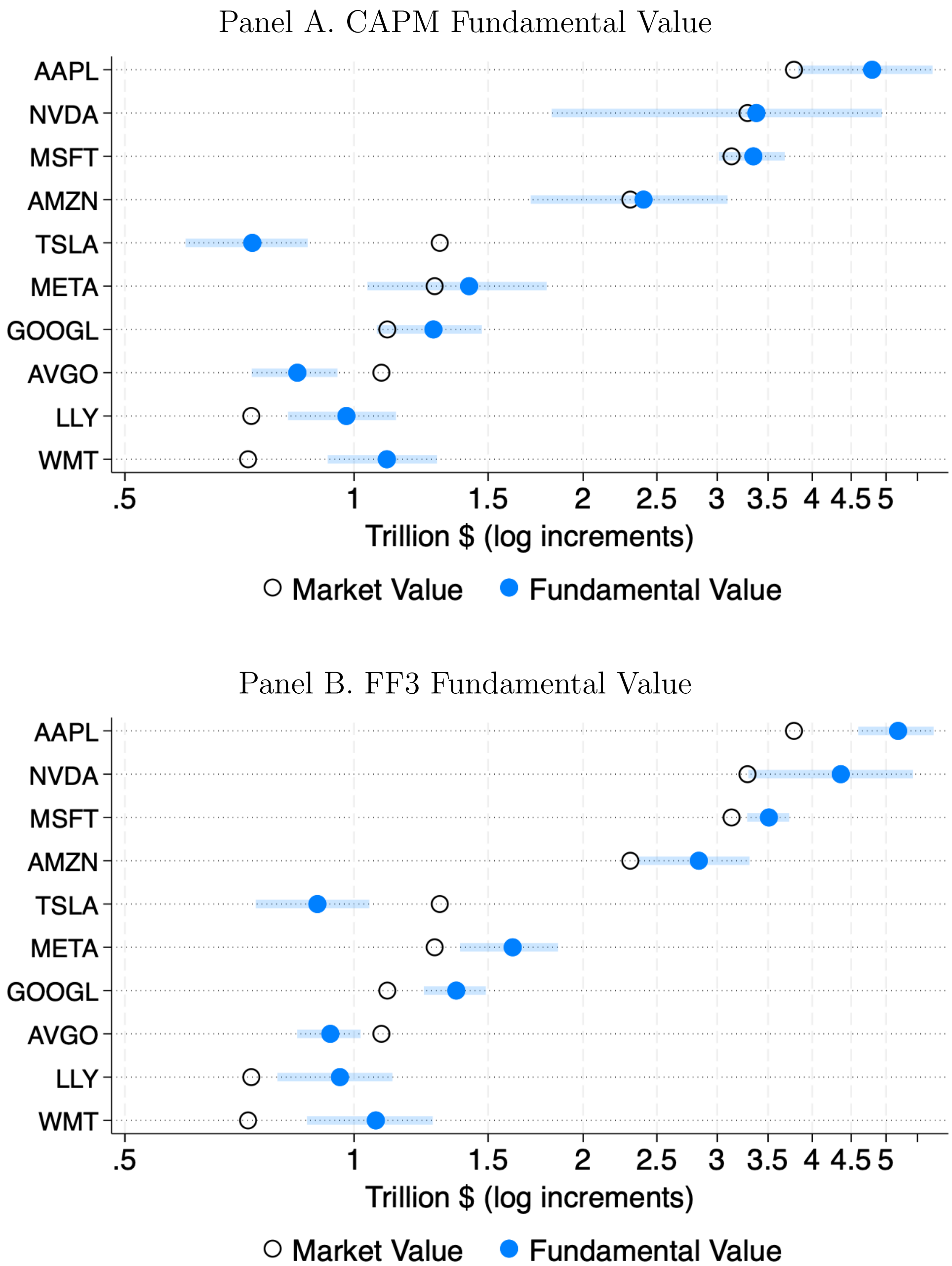


Figure 3: **Fundamental Equity Values of Largest Companies (December 2024)**

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. We show the associated 95% confidence interval in light blue.

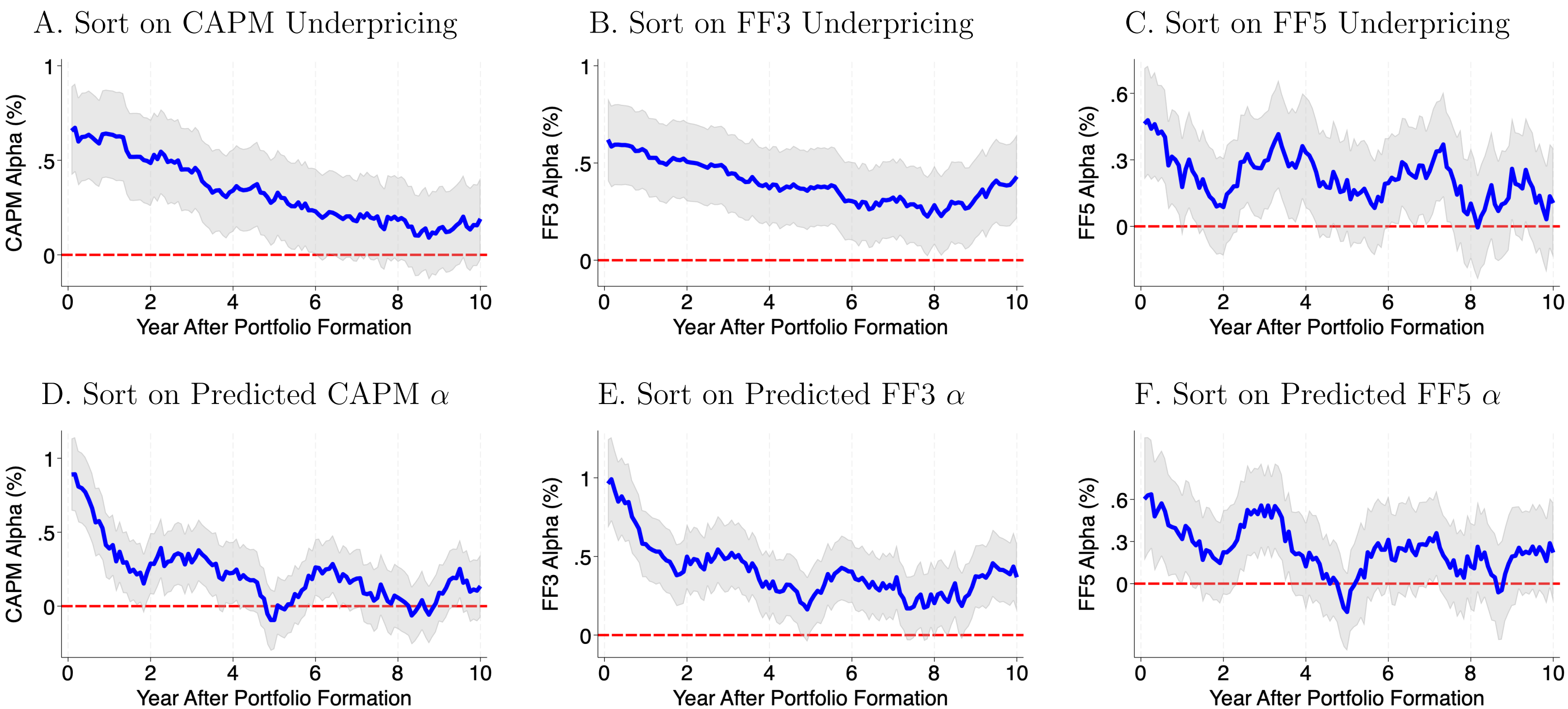


Figure 4: **Out-of-Sample Alphas on Portfolios Sorted on Real-time Underpricing**

We plot the evolution of alpha on long-short quintile portfolios formed by sorting on out-of-sample model-specific 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.

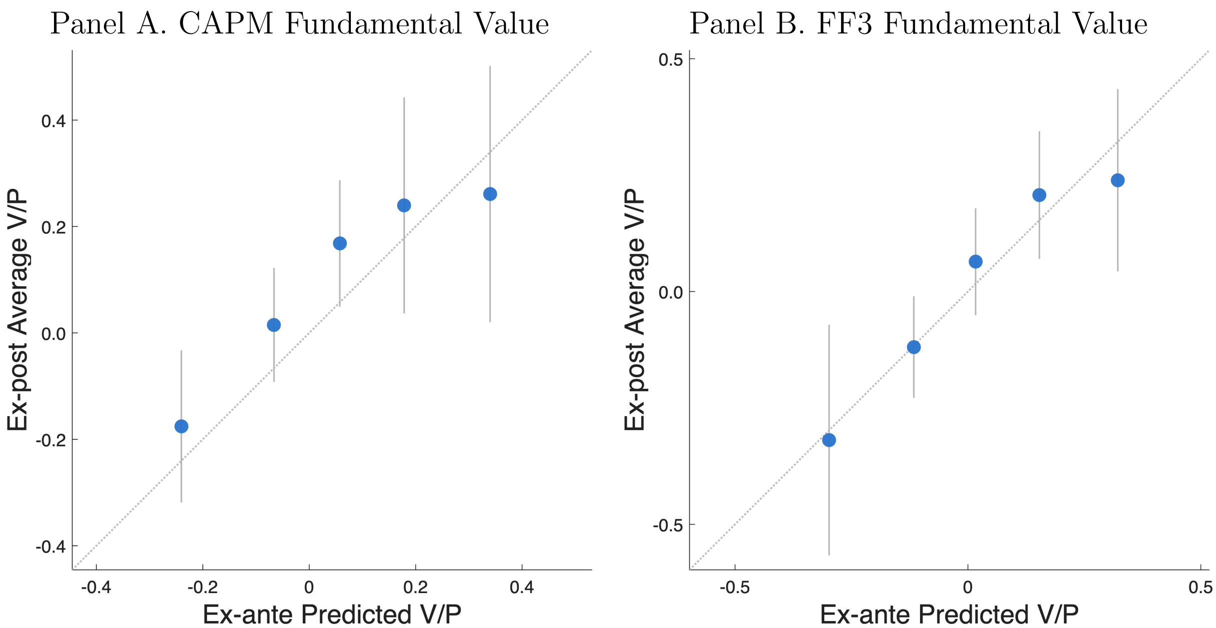


Figure 5: **Ex-Ante Predicted vs. Ex-Post Realized Fundamental Value**

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/Ps 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, as observations should line up in that manner if our ex-ante predicted V/P ratios are accurate.

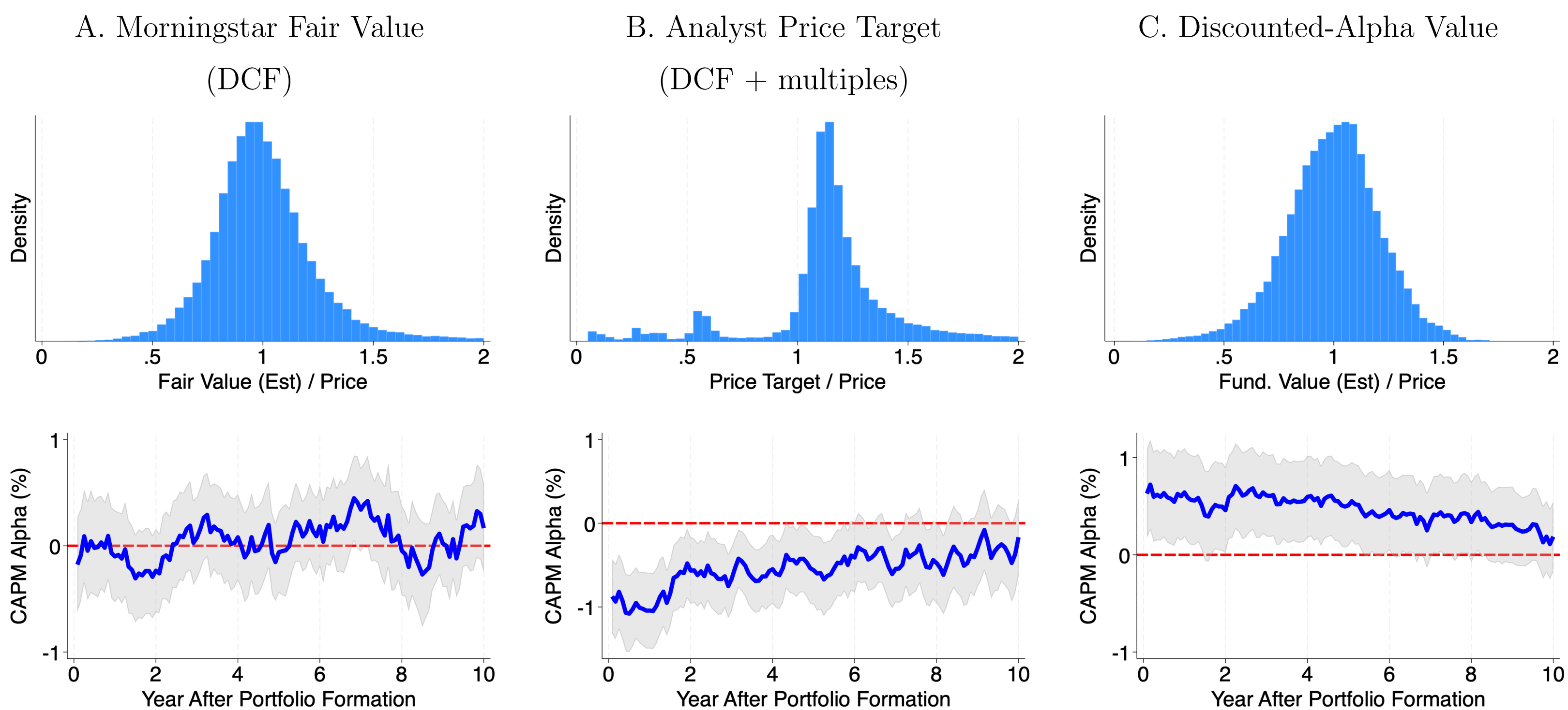


Figure 6: **Distribution and Performance of DCF-based Valuation Estimates (2001m6–2024m12)**

The first-row figures plot the distribution of fundamental value estimates to price for the stocks with market equity greater than the value-weight average market equity each month—i.e., average firm from the perspective of invested capital. The second-row figures report the out-of-sample alphas of long-short quintile portfolios sorted on estimates of fundamental value to price. The sample period is 2001m6–2024m12, for which Morningstar DCF estimates are available.

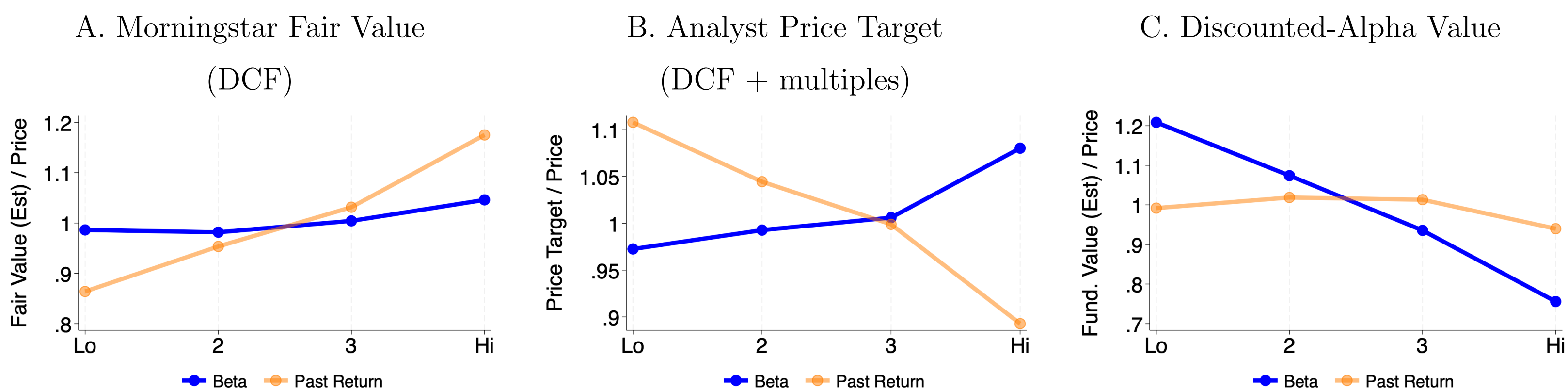


Figure 7: **Which Stock Characteristics Drive DCF-based Valuation Estimates? (2001m6–2024m12)**

We plot value-weight averages of value to price estimates for each of four rank-characteristic-sorted bins (cross-sectional 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 analyst's 1-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 return. 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.

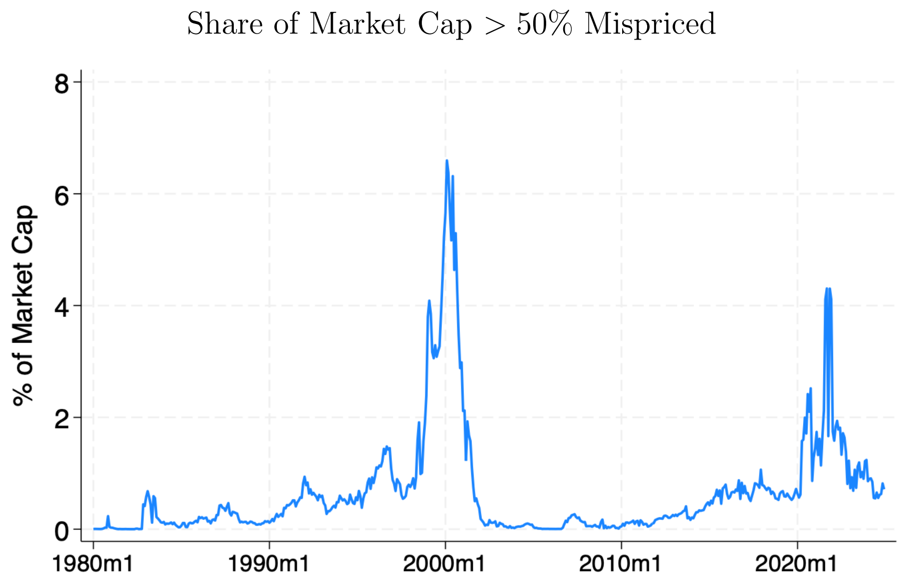


Figure 8: **CAPM-Implied Mispriced Market Share Over Time**

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.

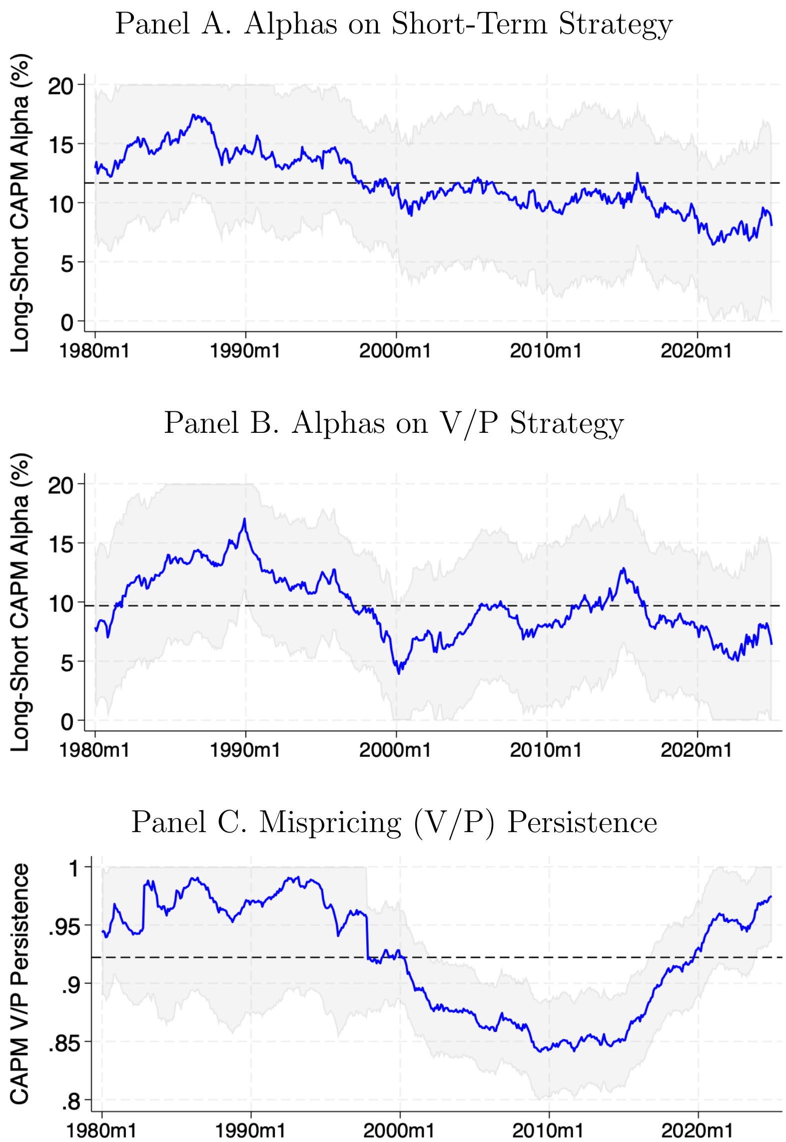


Figure 9: **Alpha Decay—Not the Whole Story**

Panel A plots the annualized monthly long–short alpha from quintile portfolios sorted on ex-ante one-month alpha, estimated by projecting alphas on the eight baseline characteristics. Panel B plots the corresponding long–short alpha from quintile portfolios sorted on estimated ex-ante 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 mispricing, defined as the ratio of next-month value-to-price to this-month value-to-price for the extreme quintile portfolios, value-weighted within each quintile. In all figures, the dash line denotes the average value over the sample. All figures are based on a 15-year trailing moving window with the end month from January 1980 to December 2024.

A Appendix: Proof of Lemma 2 and Lemma 3

Begin with the one-period discounted alpha identity in equation (6):

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = vp_{i,t} - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\ vp_{i,t+1}\right], \quad vp_{i,t} \equiv \underbrace{\frac{V_{i,t}}{P_{i,t}} - 1}_{\text{underpricing}}. \tag{6}$$

Applying the projection in equation (9),

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V z_{i,t} + u_{i,t} - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\ \gamma_V z_{i,t+1}\right] - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\ u_{i,t+1}\right]. \tag{23}$$

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

$$\begin{aligned}\frac{\alpha_{i,t}}{1+R_{f,t}} &= \gamma_V z_{i,t} + u_{i,t} - \gamma_V\, E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\right] E_t\left[z_{i,t+1}\right] \\ &\quad -\gamma_V\, E_t\left[\widetilde{M}_{t+1}\right] Cov_t\left(G_{i,t+1}, z_{i,t+1}\right) - \gamma_V\, E_t\left[1+G_{i,t+1}\right] Cov_t\left(\widetilde{M}_{t+1}, z_{i,t+1}\right) \\ &\quad -\gamma_V\, \sigma_{\widetilde{M},G,z,i,t} - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\ u_{i,t+1}\right],\end{aligned} \tag{24}$$

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 (24) becomes

$$\begin{aligned}\frac{\alpha_{i,t}}{1+R_{f,t}} &= \gamma_V z_{i,t} + u_{i,t} - \gamma_V\, E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\right] E_t\left[\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}} z_{i,t+1}\right] \\ &\quad -\gamma_V\, E_t\left[\widetilde{M}_{t+1}\right] Cov_t\left(G_{i,t+1}, z_{i,t+1}\right) + \gamma_V\, Cov_t\left(\widetilde{M}_{t+1}, G_{i,t+1}\right) Cov_t\left(\frac{\widetilde{M}_{t+1}}{E_t\widetilde{M}_{t+1}}, z_{i,t+1}\right) \\ &\quad -\gamma_V\, \sigma_{\widetilde{M},G,z,i,t} - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\ u_{i,t+1}\right].\end{aligned} \tag{25}$$

Rewriting, we obtain the result in Lemma 2:

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V \left(I - \rho_{i,t}\phi_{z,i,t} - \frac{\Gamma_{G,z,i,t}}{1+R_{f,t}} \right) z_{i,t} + \widetilde{u}^*_{i,t} \tag{10}$$

where

$$\rho_{i,t} \equiv E_t \left[\widetilde{M}_{t+1} \left(1 + G_{i,t+1}\right) \right] \tag{26}$$

$$\phi_{z,i,t} \equiv E_t \left[\frac{\widetilde{M}_{t+1}}{E_t \widetilde{M}_{t+1}} \frac{z_{i,t+1}}{z_{i,t}} \right] \tag{27}$$

$$\Gamma_{G,z,i,t} \equiv Cov_t \left(G_{i,t+1}, \frac{z_{i,t+1}}{z_{i,t}} \right) \tag{28}$$

$$\begin{aligned} \widetilde{u}^*_{i,t} \equiv\ & u_{i,t} - E_t \left[\widetilde{M}_{t+1} \left(1 + G_{i,t+1}\right)\, u_{i,t+1} \right] \\ & + \gamma_V\, Cov_t \left(\widetilde{M}_{t+1}, G_{i,t+1} \right) Cov_t \left(\frac{\widetilde{M}_{t+1}}{E_t \widetilde{M}_{t+1}}, z_{i,t+1} \right) - \gamma_V\, \sigma_{\widetilde{M},G,z,i,t}. \end{aligned} \tag{29}$$

Note that the error term $\widetilde{u}^*_{i,t}$ 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 explains the returns on 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 (15) and (16), the usual asset-pricing algebra implies

$$\phi_{z,i,t}\, z_{i,t} = E_t \left[\frac{\widetilde{M}_{t+1}}{E_t \widetilde{M}_{t+1}} z_{i,t+1} \right] = E_t \left[\frac{\widetilde{M}_{t+1}}{E_t \widetilde{M}_{t+1}} \left(\phi_z z_{i,t} + \beta_{z,i,t} f_{t+1} + \epsilon_{z,i,t+1} \right) \right] = \phi_z z_{i,t} \tag{30}$$

$$\Gamma_{G,z,i,t}\, z_{i,t} = \beta_{z,i,t} \Sigma_t \beta'_{G,i,t} + \Gamma_{G,z} z_{i,t} + \epsilon_{G,z,i,t} \tag{31}$$

$$Cov_t \left(\widetilde{M}_{t+1}, G_{i,t+1} \right) Cov_t \left(\frac{\widetilde{M}_{t+1}}{E_t \widetilde{M}_{t+1}}, z_{i,t+1} \right) = \beta_{z,i,t} \lambda_t \lambda'_t \beta'_{G,i,t}, \tag{32}$$

where $\lambda_t \equiv E_t \left[f_{t+1} \right]$. Therefore, equation (10) becomes

$$\frac{\alpha_{i,t}}{1+R_{f,t}} = \gamma_V \left(I - \left(1 + \frac{\gamma_V}{1+R_{f,t}} z_{i,t}\right) \phi_z - \frac{\Gamma_{G,z}}{1+R_{f,t}} \right) z_{i,t} + \widetilde{u}_{i,t}, \tag{17}$$

where

$$\widetilde{u}_{i,t} = \underbrace{u_{i,t} - E_t\left[\widetilde{M}_{t+1}\left(1+G_{i,t+1}\right)\, u_{i,t+1}\right] - \gamma_V \frac{\epsilon_{G,z,i,t}}{1+R_{f,t}}}_{\text{projection error}}$$

$$-\gamma_V \left(\underbrace{\frac{1}{1+R_{f,t}} \beta_{z,i,t}\left(\Gamma_t - \lambda_t \lambda_t'\right) \beta_{G,i,t}'}_{\text{second moment terms}} + \underbrace{\sigma_{\widetilde{M},G,z,i,t}}_{\text{third moment}} \right). \tag{33}$$

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 (10), 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.

B Additional Tables and Figures (Internet Appendix)

Table A1: **Comparison of Cho-Polk t statistics Across Estimation Windows**

The table shows how the t-statistic of the portfolio average underpricing measure of Cho and Polk (2024) changes across different ways of estimating a real-time stock-level fundamental value. 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).

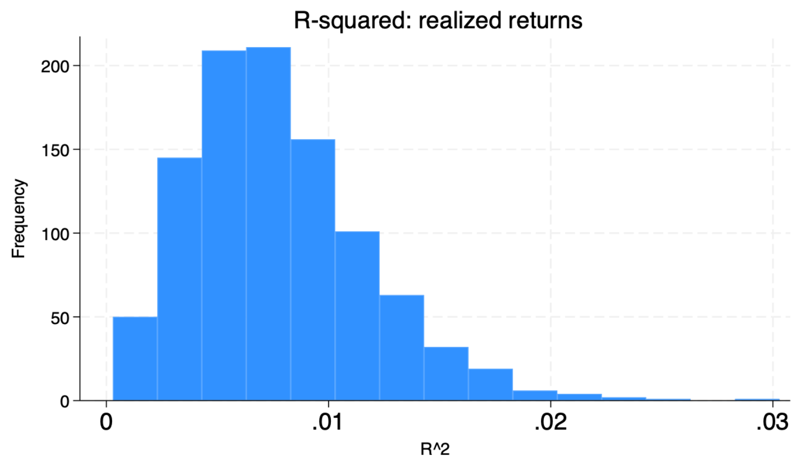
Exponential	CAPM Estimates					FF3 Estimates				
	Moving Window Length									
Weight Factor	60yrs	50yrs	40yrs	30yrs	20yrs	60yrs	50yrs	40yrs	30yrs	20yrs
1.00	2.22	2.31	2.38	2.40	3.00	3.06	2.93	2.54	2.55	2.19
0.99	2.34	2.43	2.48	2.47	2.95	2.91	2.77	2.52	2.47	2.15
0.98	2.44	2.54	2.52	2.52	2.88	2.84	2.66	2.49	2.42	2.11
0.97	2.54	2.59	2.58	2.60	2.80	2.67	2.58	2.40	2.35	2.06

Table A2: **Not Accounting for Alpha Conditionality**

This table shows that not accounting for the conditionality of alpha by setting $\Gamma_{G,z} = 0$ substantially reduces the accuracy of the fundamental value estimates as judged by the drop in the Cho-Polk portfolio misvaluation p-value in the long-short portfolio formed by real-time CAPM underpricing. In contrast, setting $\rho_{i,t} = 0.97$ such that the cash-flow duration is assumed to be uniform across stocks does not affect the estimator's accuracy, consistent with the notion that the short-horizon nature of discounted alpha valuation makes it less susceptible to misspecifying the discount rate. Finally, using a simple ρ-discounted alpha to proxy for misvaluation by setting both $\Gamma_{G,z} = 0$ and $\rho_{i,t} = 0.97$ leads to further decline in accuracy. The bottom two rows are based on real-time estimates based on the simplified method, and the rows above are based on full-sample estimates based on the simplified method.

	CAPM γ_V		
Assumption:	$\Gamma_{G,z} = 0$	$\rho_{i,t} = \rho = 0.97$	$\Gamma_{G,z} = 0$ and $\rho_{i,t} = \rho = 0.97$
BM	8.67	6.61	8.36
Prof	12.57	14.18	13.85
Beta	-11.68	-15.10	-13.00
Inv	-1.70	-1.97	-1.83
NetIss	-2.65	-3.00	-2.73
Liq	-4.31	0.85	-4.65
Ret	-0.03	-0.02	-0.03
LagRet	-0.89	-1.24	-1.02
Cho-Polk V/P	42.52	44.47	38.08
p-value	0.045	0.014	0.077

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 Appendix C.5. 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.

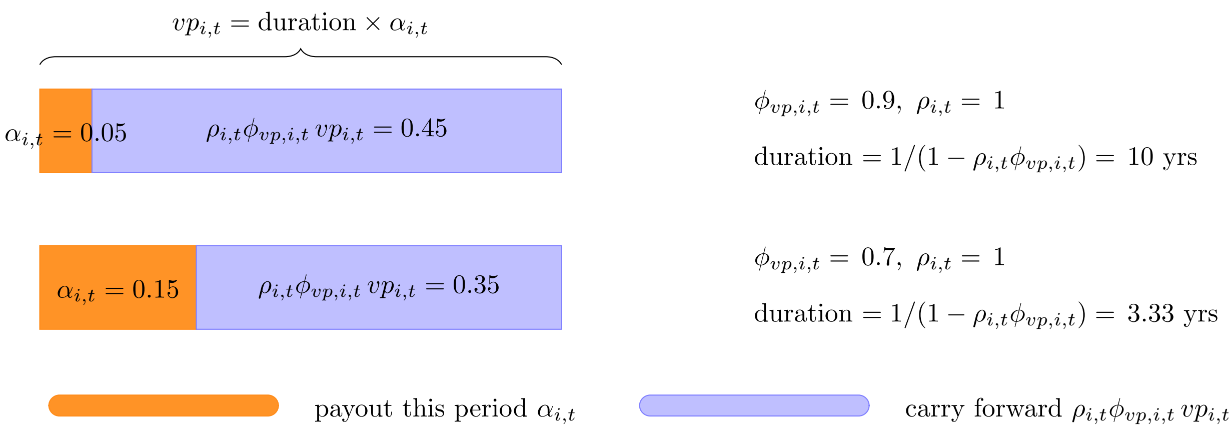


Figure A2: **Valuation with One-Period Alpha and Known Underpricing Decay**

This figure illustrates that, under simplifying assumptions, underpricing $vp_{i,t} \equiv \frac{V_{i,t}}{P_{i,t}} - 1$ is simply a duration term $(1/[1-\rho_{i,t}\phi_{vp,i,t}])$ times the one-period alpha (Example C.1). The two cases considered here (top and bottom) assume the same underpricing of $vp_{i,t} = 50\%$ today (bar length), same current cash-flow duration $\rho_{i,t} = 1$, but different current payout ratios $\phi_{vp,i,t} \in \{\text{top: } 0.9, \text{bottom: } 0.7\}$. No future ρ, ϕ_{vp} is assumed; today's inversion is $vp_{i,t} = \alpha_{i,t}/(1-\rho_{i,t}\phi_{vp,i,t})$. The risk-free rate is assumed to be zero.

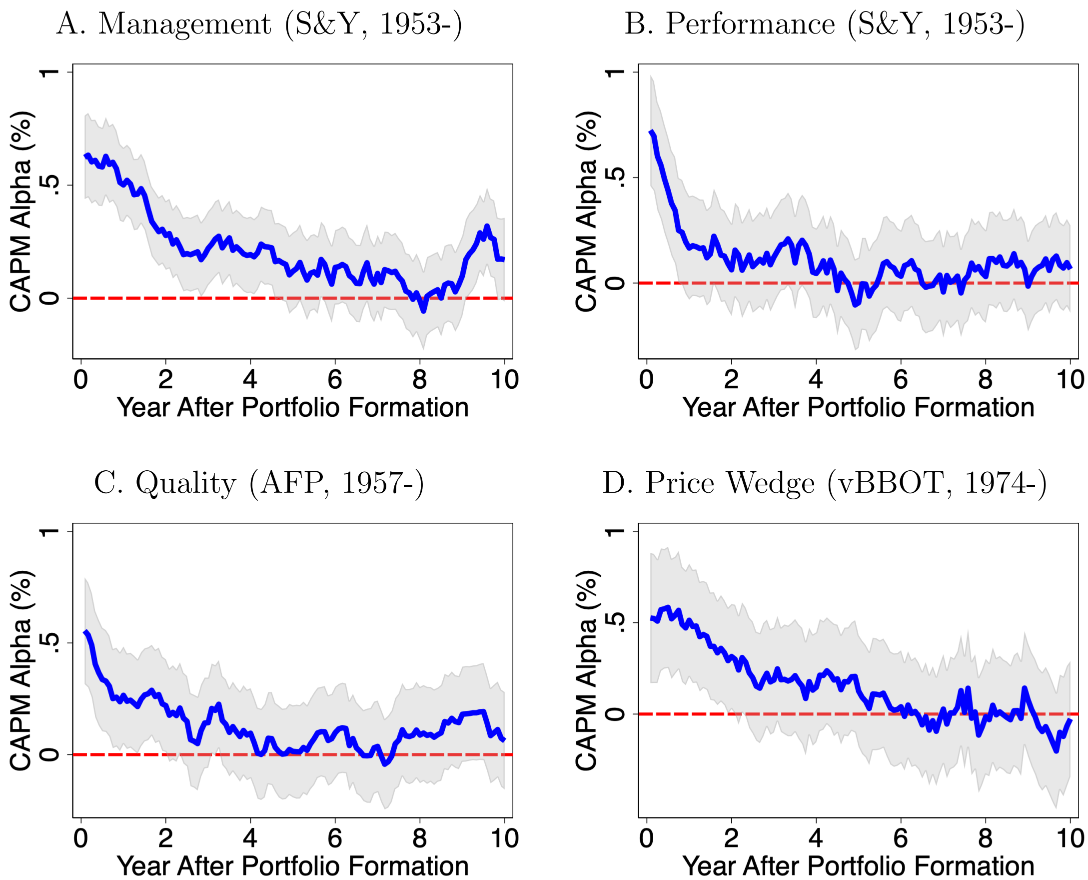


Figure A3: **Ex-Post Performance of Other Misvaluation Signals (CAPM Alphas)**

The figure reports the ex-post alphas of long-short quintile portfolios sorted on 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), 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. These figures show that these signals tend to predict shorter-term alphas well but tend not to predict statistically significant alphas beyond the two-year horizon, with the exception of the management signal of S&Y.

C Theory Internet Appendix

C.1 The discounted alpha identity (Lemma 1)

This identity is a variant of the mispricing identity derived in Cho and Polk (2024) and is therefore relegated to this internet appendix. The definition of $V_{i,t}$ in equation (2) (Definition 1) and the law of iterated expectations imply that the fundamental asset pricing equation holds for $V_{i,t}$ with respect to $\widetilde{M}$:

$$V_{i,t} = E_t\left[\widetilde{M}_{t+1}\left(D_{i,t+1} + V_{i,t+1}\right)\right], \tag{34}$$

where $\widetilde{M}_{t+1}$ is the one-period candidate SDF. Dividing both sides by $P_{i,t}$ and adding and subtracting appropriately results in

$$\frac{V_{i,t}}{P_{i,t}} = E_t\left[\widetilde{M}_{t+1}(\frac{D_{i,t+1}}{P_{i,t}} + \frac{P_{i,t+1}}{P_{i,t}} - \frac{P_{i,t+1}}{P_{i,t}} + \frac{V_{i,t+1}}{P_{i,t}}\right] + \underbrace{1 - E_t\left[\widetilde{M}_{t+1}(1+R_{f,t})\right]}_{=0 \text{ if } \widetilde{M} \text{ explains the risk-free rate}} \tag{35}$$

Next, rearrange the terms to get the law of motion for $\frac{V}{P}$:

$$\frac{V_{i,t}}{P_{i,t}} - 1 = \underbrace{\frac{\alpha_{i,t}}{1+R_{f,t}}}_{=E_t\left[\widetilde{M}_{t+1}R^e_{i,t+1}\right]} + E_t\left[\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}\left(\frac{V_{i,t+1}}{P_{i,t+1}} - 1\right)\right], \tag{6}$$

which is the expression we use in estimation. To get to the discounted alpha expression, simply multiply both sides by $P_{i,t}$, iterate forward, and apply the no-explosive-bubble condition that $\lim_{\tau\to\infty}\widetilde{M}_{t\to t+\tau}P_{i,t+\tau} = 0$ to get

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

C.2 A "correction" approach

Our discounted-alpha valuation approach exploits the fact that the fundamental value of an asset is the current price plus the discounted sum of all future alpha flow:

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

Note that V_0, like α, is always *relative to an asset pricing model.*[34]

A. Key point

The above is a mathematical identity derived from DCF. This recasting sharply reduces the core problem of fundamental valuation—sensitivity to discount-rate error—yielding much more reliable estimates, since even the "best" available discount-rate estimates inevitably contain estimation errors.[35] The simple example below shows this.

Consider a perpetuity where $D = \$1$ and $R = 4\%$. Then, DCF valuation:

$$V_0^{DCF} = \frac{1}{R} \times D = \frac{1}{0.04} \times \$1 = \underbrace{25}_{CF\, duration} \times \$1 = \$25.$$

Suppose that the price is always 20 so that the stock is 20% underpriced. If so, alphas are also a perpetuity.

Then, *discounted alpha* valuation:

$$V_0^{DA} = P_0 + \frac{1}{R} P_0 \, \alpha = \$20 + \underbrace{25}_{\alpha\, duration} \times \$20 \times 1\% = \$25.$$

To illustrate how the discounted alpha approach is less sensitive to noisy discount rates, consider the effects of using a discount rate that is off by one percentage point, either too

[34]Thus, any analysis of V_0 is always subject to the joint-hypothesis interpretation (Fama, 1970): deviations from price may reflect model misspecification or genuine misvaluation. In our analysis, we primarily measure α and thus V_0 with respect to the CAPM. We also plan to benchmark prices against influential behavioral models such as the expectations-based returns approach of Bordalo, Gennaioli, La Porta, and Shleifer (2024).

[35]See, for example, Fama and French (1997) who show that estimates of discount rates are "distressingly imprecise."

high or too low. Using DCF, we find that the resulting estimates range from 20 to 33.3. This large swing in estimated valuation represents more than 50% of the true fundamental value of 25.

$$\hat{V}_0^{DCF}|_{\hat{R}=5\%} = \frac{1}{0.05} \times 1 = 20 \times 1 = 20.$$

$$\hat{V}_0^{DCF}|_{\hat{R}=3\%} = \frac{1}{0.03} \times 1 = 33.3 \times 1 = 33.3$$

However, our novel approach is much less sensitive to this noisy discount rate issue. The resulting discounted alpha estimates, based on the same variation in discount rates (3% to 5%) are only 24 to 26.7. This much smaller swing in estimated valuation is less than 11% of the true fundamental value of 25.

$$\hat{V}^{DA}|_{\hat{R}_f=5\%} = 20 + \frac{1}{0.05} \times 20 \times 1\% = 20 + 4 = 24.$$

$$\hat{V}^{DA}|_{\hat{R}_f=3\%} = 20 + \frac{1}{0.03} \times 20 \times 1\% = 20 + 6.7 = 26.7$$

Intuitively, as illustrated in the pie chart, our approach measures only the "discounted alpha" slice of fundamental value and adjusts the price accordingly, rather than rebuilding the entire pie from scratch. Indeed, the benefits are directly proportional to the relative size of the discounted alpha slice, namely $1 - (26.7 - 24)/(33.3 - 20) = 80\%$ more precise.

Thus, the above analysis confirms that our novel valuation approach, despite being a reformulation of the standard technique, brings significant improvement in the precision of valuation estimates, an issue that has long plagued the work of both practitioners and academics. Figure 3 plots real-time CAPM-implied values of the top-10 stocks in December 2024. The tight confidence intervals around the estimates (light blue) are thanks to discounted alpha valuation's high precision.

B. The lower duration of alphas reinforces this point

Moreover, this improvement is larger in more realistic examples where alphas are not perpetual but instead decay over time. That more realistic assumption is important as a stock's fundamental value likely has high duration, since dividends grow geometrically. In contrast, alphas are usually much less persistent than the firm's underlying cash flows, given market forces should eventually correct mispricing.

In other words, most of a stock's duration is contained in the "price," which is observed without error, rather than the "discounted alpha" component of fundamental value:

$$\underbrace{V}_{\text{high duration}} = \underbrace{P}_{\text{high duration}} + \underbrace{\text{discounted alphas}}_{\text{low duration}}.$$

Indeed, the duration of discounted alphas is zero for stocks with zero future alphas, and it likely remains relatively low for mispriced stocks as well, since alphas typically decay quickly. This aspect of our method results in estimates of fundamental value that are even less dominated by discount-rate mismeasurement than in the above stylized perpetual alpha example.

C. More than just a clever estimator, also an important new perspective

Recasting DCF as discounted alpha is much more than just addressing discount-rate noise. It redirects the focus of valuation from cash-flow forecasts to expected returns, allowing practitioners and academics to discipline valuation by capitalizing on key findings in the literature that identify which types of stocks are more prone to the sentiment and bias that cause price to deviate from fundamental value (e.g., Lakonishok, Shleifer, and Vishny 1994; Barberis, Shleifer, and Vishny 1998).

Indeed, having generated state-of-the-art real-time fundamental values of individual stocks from 1953 to 2024, we will distribute our estimates to allow others to revisit important corporate finance and asset pricing topics that depend on fundamental value and its deviation from price.

D. Uncertainty in estimates of alphas and dividends

One might worry that the assumption that alpha is measured without error makes our analysis misleading. Of course, dividends (or more generally, a company's underlying free cash flow) are also measured with error. Below, we repeat the above analysis, with estimates of all future alphas or dividends off by 10% (namely we scale estimates either up by 1.1 or down by 0.9) starting two periods from now.[36] At the correct discount rate, those estimates are as follows:

$$\hat{V}^{DCF}|_{\hat{R}_f=4\%,\hat{D}=0.9*D} = \frac{1}{1.04} \times [1 + \frac{1}{0.04} \times 0.9] = 22.6$$

$$\hat{V}^{DCF}|_{\hat{R}_f=4\%,\hat{D}=1.1*D} = \frac{1}{1.04} \times [1 + \frac{1}{0.04} \times 1.1] = 27.4$$

and

$$\hat{V}^{DA}|_{\hat{R}_f=4\%,\hat{\alpha}=0.9*\alpha} = 20 + \frac{1}{1.04} \times [20 \times 1\% + \frac{1}{0.04} \times 20 \times 0.9\%] = 24.5$$

$$\hat{V}^{DA}|_{\hat{R}_f=4\%,\hat{\alpha}=1.1*\alpha} = 20 + \frac{1}{1.04} \times [20 \times 1\% + \frac{1}{0.04} \times 20 \times 1.1\%] = 25.5$$

One can immediately see that our discounted alpha estimates are less sensitive to uncertainty in the "flow" that is being estimated, again leveraging the fact that the method only needs to measure a slice of fundamental value rather than the whole pie.[37] Of course, the extent to which estimates of fundamentals or alphas are noisier is an empirical question. However, we note that a large literature emphasizes the difficulty investors have in estimating future cash flows, in particular long-term growth rates (e.g., Bordalo, Gennaioli, La Porta, and Shleifer 2019, 2024).

E. Noisy discount rates and uncertain alphas/dividends

We repeat the above analysis where we have both discount rates off by one percentage point *and* future dividends and alpha off by a 10% scaling factor.

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[36] We have the uncertainty in both alphas and dividends start in two periods, since in textbook valuation models are typically assumed to be known one period in advance (and we are modeling cash flows as perpetuities starting one period from now).

[37] Again, the benefits are proportional to the size of the slice, 1-(25.5-24.5)/(27.4-22.6)=80% more precise.

$$\hat{V}^{DCF}|_{\hat{R}_f=5\%,\hat{D}=0.9*D} = \frac{1}{1.05} \times [1 + \frac{1}{0.05} \times 0.9] = 18.1$$

$$\hat{V}^{DCF}|_{\hat{R}_f=5\%,\hat{D}=1.1*D} = \frac{1}{1.05} \times [1 + \frac{1}{0.05} \times 1.1] = 21.9$$

$$\hat{V}^{DCF}|_{\hat{R}_f=3\%,\hat{D}=0.9*D} = \frac{1}{1.03} \times [1 + \frac{1}{0.03} \times 0.9] = 30.1$$

$$\hat{V}^{DCF}|_{\hat{R}_f=3\%,\hat{D}=1.1*D} = \frac{1}{1.03} \times [1 + \frac{1}{0.03} \times 1.1] = 36.6$$

and

$$\hat{V}^{DA}|_{\hat{R}_f=5\%,\hat{\alpha}=0.9*\alpha} = 20 + \frac{1}{1.05} \times [20 \times 1\% + \frac{1}{0.05} \times 20 \times 0.9\%] = 23.6$$

$$\hat{V}^{DA}|_{\hat{R}_f=5\%,\hat{\alpha}=1.1*\alpha} = 20 + \frac{1}{1.05} \times [20 \times 1\% + \frac{1}{0.05} \times 20 \times 1.1\%] = 24.4$$

$$\hat{V}^{DA}|_{\hat{R}_f=3\%,\hat{\alpha}=0.9*\alpha} = 20 + \frac{1}{1.03} \times [20 \times 1\% + \frac{1}{0.03} \times 20 \times 0.9\%] = 26.0$$

$$\hat{V}^{DA}|_{\hat{R}_f=3\%,\hat{\alpha}=1.1*\alpha} = 20 + \frac{1}{1.03} \times [20 \times 1\% + \frac{1}{0.03} \times 20 \times 1.1\%] = 27.3$$

As with our simpler example, where there was no uncertainty regarding the amount of flow, we find that the range in estimates of value based on discounted alpha (23.6 to 27.3, less than 15% of true fundamental value) is smaller than the range of estimates of value based on DCF (18.1 to 36.6, more than 73% of true fundamental value). The range across discounted alphas estimates is again 80% smaller than that of DCF, highlighting once more the usefulness of correcting the price.

Moreover, as mentioned above, in a more realistic example where alphas are less persistent than fundamentals, the above takeaways are amplified, with the effect of uncertainty having less impact for the lower-duration alpha slice than the entire high-duration fundamental pie.

C.3 An analysis of duration in DCF versus discounted alpha

A. Definitions

Define

$$VP_t \equiv \frac{V_t}{P_t} = \sum_{h=1}^{\infty} E_t \left[\widetilde{M}_{t \to t+h} \frac{D_{t+h}}{P_t} \right].$$

The discounted alphas identity shows that

$$VP_t - 1 = \sum_{h=1}^{\infty} E_t \left[\widetilde{M}_{t \to t+h} \frac{P_{t+h-1}}{P_t} \alpha_{t+h-1} \right].$$

We compare the duration of the two discounted sums. First, the cash-flow duration is defined

$$Dur_t^{CF} \equiv \sum_{h=1}^{\infty} \frac{E_t \left[\widetilde{M}_{t \to t+h} \frac{D_{t+h}}{P_t} \right]}{VP_t} h.$$

The alpha duration is defined

$$Dur_t^{\alpha} \equiv \sum_{h=1}^{\infty} \frac{E_t \left[\widetilde{M}_{t \to t+h} \frac{P_{t+h-1}}{P_t} \alpha_{t+h-1} \right]}{VP_t - 1} h.$$

B. An iteration method for computing durations

Rewrite cash-flow duration as

$$Dur_t^{CF} = \sum_{h=1}^{\infty} \frac{E_t \left[\widetilde{M}_{t+1} \frac{D_{t+1}}{P_t} \right]}{VP_t} + \sum_{h=2}^{\infty} \frac{E_t \left[\widetilde{M}_{t+1} \frac{P_{t+1}}{P_t} \widetilde{M}_{t+1 \to t+h} \frac{D_{t+h}}{P_{t+1}} \right]}{VP_t} (h-1)$$

$$= 1 + \frac{E_t \left[\widetilde{M}_{t+1} \frac{P_{t+1}}{P_t} \sum_{h=1}^{\infty} E_{t+1} \left[\widetilde{M}_{t+1 \to t+1+h} \frac{D_{t+1+h}}{P_{t+1}} \right] h \right]}{VP_t}.$$

Hence,

$$Dur_t^{CF} = 1 + E_t \left[\widetilde{M}_{t+1} \frac{P_{t+1}}{P_t} \frac{VP_{t+1}}{VP_t} Dur_{t+1}^{CF} \right].$$

Iterating forward,

$$Dur_t^{CF} = 1 + E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}\frac{VP_{t+1}}{VP_t}\right] + E_t\left[\widetilde{M}_{t\to t+2}\frac{P_{t+2}}{P_t}\frac{VP_{t+2}}{VP_t}\right] + ...$$

Similarly, rewrite alpha duration as

$$Dur_t^{\alpha} = \sum_{h=1}^{\infty}\frac{E_t\left[\widetilde{M}_{t\to t+h}\frac{P_{t+h-1}}{P_t}\alpha_{t+h-1}\right]}{VP_t - 1} + \sum_{h=2}^{\infty}\frac{E_t\left[\widetilde{M}_{t\to t+h}\frac{P_{t+h-1}}{P_t}\alpha_{t+h-1}\right]}{VP_t - 1}(h-1)$$

$$= 1 + \frac{E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}\sum_{h=1}^{\infty}E_{t+1}\left[\widetilde{M}_{t+1\to t+1+h}\frac{P_{t+h-1}}{P_{t+1}}\alpha_{t+1+h-1}\right]h\right]}{VP_t - 1}$$

So,

$$Dur_t^{\alpha} = 1 + E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}\frac{VP_{t+1} - 1}{VP_t - 1}Dur_{t+1}^{\alpha}\right].$$

Iterating forward,

$$Dur_t^{\alpha} = 1 + E_t\left[\widetilde{M}_{t+1}\frac{P_{t+1}}{P_t}\frac{VP_{t+1} - 1}{VP_t - 1}\right] + E_t\left[\widetilde{M}_{t\to t+2}\frac{P_{t+2}}{P_t}\frac{VP_{t+2} - 1}{VP_t - 1}\right] + ...$$

C. Analysis

Use the approximation $\widetilde{M}_{t+h}\frac{P_{t+h}}{P_{t+h-1}} \approx \rho = 0.97$ throughout. Then, when $VP_t = 1$:

- Cash-flow duration: $Dur_t^{CF} = 1 + \rho + \rho^2 + ... = \frac{1}{1-\rho} = 33$ years.
- Alpha duration: $Dur_t^{\alpha} = 0$ year, trivially.

Next, if $VP_{t+h} = VP \neq 1$ forever, we get the benchmark result that the cash-flow duration equals the alpha duration in the case with a constant perpetual alpha, as Alexi derived:

- Cash-flow duration: $Dur_t^{CF} = \frac{1}{1-\rho} = 33$ years.
- Alpha duration: $Dur_t^{\alpha} = \frac{1}{1-\rho} = 33$ years.

Finally, suppose we model the VP process as a deterministic $AR(1)$ process with a coefficient of ϕ. Then,

- Cash-flow duration: $Dur_t^{CF} = \frac{1}{1-\rho} = 33$ years.
- Alpha duration: $Dur_t^{\alpha} = 1 + \rho\phi + \rho^2\phi^2 + ... = \frac{1}{1-\rho\phi}$
  - Hence, Dur_t^{α} equals 3 years if $\phi = 0.7$ (half life around 2 years; mildly persistent stock-level alphas).
  - Also, Dur_t^{α} equals 7.8 years if $\phi = 0.9$ (half life around 6.5 years; very persistent stock-level alphas).

So, even when stock-level alphas are very persistent, we find that using the discounted alpha method instead of the DCF reduces the required duration from 33 to 7.8 years, which would greatly reduce the noise generated by the measurement errors in the discount rate.

C.4 Conceptual comparisons to alternative valuation approaches

We review alternative approaches to estimating fundamental values and highlight the advantages of our proposed method. Importantly, our proposal is not to discard existing methods entirely, but rather to adopt discounted alpha as the primary valuation framework, while allowing complementary approaches to contribute additional signals where informative.

A. Discounted cash flow (DCF)

Along with valuation based on price multiples, discounted cash flow (DCF) is the most commonly used method of stock-level valuation. Our approach has two key advantages over DCF.

First, we avoid the need for stock-specific cost of equity estimates by working directly with risk-adjusted abnormal returns. Estimating firm-specific costs of capital is a central challenge of DCF (Fama and French, 1997). Most academic implementations sidestep this issue by assuming constant discount rates across all stocks or within industries (e.g. Ohlson, 1995; Frankel and Lee, 1998; Dechow et al., 1999; Lee et al., 1999; Gonçalves and Leonard, 2023). Our approach allows discount rates to vary flexibly across firms.

Second, our method corrects the price to arrive at fundamental value, rather than building up the entire stock of value from accounting variables. While DCF requires forecasting cash flows over long horizons, discounted alpha rely on near-term alphas and discount rates. Appendix D.2 shows that scaling by book value rather than price yields only a 50% correlation with our price-scaled estimates, and the associated t-statistics in predicting the mispricing measure of Cho and Polk (2024) are half as large.

B. Using stochastically-discounted dividends

A variant of the DCF approach is to take the definition of fundamental value as $\widetilde{M}$-discounted dividends directly to the data:

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

Nevertheless, our discounted alpha methodology retains the same two key advantages over this approach.

It is easier to see the distinction by noting that discounted alpha correct the price, whereas the $\widetilde{M}$-discounted dividends formulation attempts to build the entire value from the ground up. The latter is still subject to large estimation errors stemming from discount rates. Consider a stock that is perfectly priced by the CAPM ($V_t = P_t$) and whose future dividends and alphas (which are zero) are known for all time and states. Defining the DCF-based estimate of fundamental value as

$$\widehat{V}_{i,t}^{\widetilde{M}\text{-DCF}} \equiv \sum_{\tau=1}^{\infty} E_t \left[\widehat{\widetilde{M}}_{t\to t+\tau} D_{i,t+\tau} \right],$$

where $\widehat{\widetilde{M}}_{t\to t+\tau}$ is an estimate of $\widetilde{M}_{t\to t+\tau}$, we obtain

$$\widehat{V}_{i,t}^{\widetilde{M}\text{-DCF}} - V_{i,t} = \sum_{\tau=1}^{\infty} E_t \left[\widehat{\widetilde{M}}_{t\to t+\tau} - \widetilde{M}_{t\to t+\tau} \right] E_t[D_{i,t+\tau}] + \sum_{\tau=1}^{\infty} Cov_t \left(\widehat{\widetilde{M}}_{t\to t+\tau} - \widetilde{M}_{t\to t+\tau}, D_{i,t+\tau} \right).$$

Thus, even with the entire dividend process $\{D_{i,t+\tau}\}$ known, measurement errors in either the intertemporal mean discount (the E_t term) or the model-specific risk discount (the Cov_t

term) generate both bias and low estimator efficiency.[38]

By contrast, in the discounted alpha approach, mismeasuring the intertemporal discount component of $\widetilde{M}$ is less problematic as long as contemporaneous risk adjustment is done correctly. Letting $\widetilde{\Lambda}_{t+\tau} \equiv \frac{\widetilde{M}_{t+\tau}}{E_{t+\tau-1}\widetilde{M}_{t+\tau}}$ denote the contemporaneous risk adjustment (the Radon–Nikodym derivative), which can be estimated with relatively little error, the discounted alpha formulation yields

$$\widehat{V}_{i,t} = P_{i,t} + \sum_{\tau=1}^{\infty} E_t\left[\widehat{\widetilde{M}}_{t\to t+\tau}\frac{P_{i,t+\tau-1}}{P_{i,t}}\alpha_{i,t+\tau-1}\right].$$

Since

$$E_{t+\tau-1}\left[\widehat{\widetilde{\Lambda}}_{t+\tau}R^e_{i,t+\tau}\right] = 0,$$

the expression collapses to

$$\widehat{V}_{i,t} = P_{i,t} \quad\implies\quad \widehat{V}_{i,t} - V_{i,t} = 0.$$

Thus, in this example, our discounted alpha approach correctly estimates fundamental value, while the $\widetilde{M}$-discounted dividends formulation remains vulnerable to large estimation error. The stark contrast arises because our method applies contemporaneous risk adjustment directly to excess returns before intertemporal discounting—something infeasible with dividends unless they are restated in terms of returns and alphas to recover the discounted alpha identity.

[38] For illustration, suppose the intertemporal covariance component is zero and the time components are serially uncorrelated. Then

$$Var_t\Big(\widehat{V}^{\widetilde{M}\text{-DCF}}_{i,t} - V_{i,t}\Big) = \sum_{\tau=1}^{\infty}(E_t[D_{i,t+\tau}])^2\, Var_t\left(E_t\left[\widehat{\widetilde{M}}_{t\to t+\tau} - \widetilde{M}_{t\to t+\tau}\right]\right),$$

so even if $\widehat{\widetilde{M}}_{t\to t+\tau}$ is an unbiased estimate of $\widetilde{M}_{t\to t+\tau}$, estimation error in $\widetilde{M}$ can lead to large variance (low efficiency).

C. Restating stochastically-discounted dividends as discounted alphas

Lemma 1 shows that the $\widetilde{M}$-discounted dividends identity can be restated as the discounted alpha identity, which is empirically much easier to implement. Our argument is not that one should estimate fundamental value directly from $\widetilde{M}$-discounted dividends, but rather that it should first be expressed as discounted alphas, ensuring that risk adjustment is handled explicitly.

D. Naive rho-discounted alphas

A simpler class of approaches replaces the stochastic discounting of alphas with the simple geometric discounting of future alphas using the constant ρ from Campbell and Shiller (1988), which we call the ρ-discounted alpha approach. However, as seen in Table A2, this approach results in significant loss of accuracy. In particular, it places undue weight on liquidity (size), which does not reliably predict long-horizon CAPM alphas. Our baseline approach corrects for this by explicitly accounting for the covariance between characteristics and capital gains.

E. A method using loglinear variables

Another 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.

F. Portfolio abnormal prices

Finally, one could estimate portfolio abnormal prices as in Cho and Polk (2024) and then project these onto firm characteristics, as done in an earlier draft of Cho and Polk and in van Binsbergen et al. (2023).[39] While feasible in long samples, this approach performs poorly out of sample when historical data are limited, since it relies on precise portfolio-level estimates. Furthermore, our empirical analysis of the firm-level price wedge metric of van Binsbergen et al. shows that this approach can miss important sources of variation in CAPM underpricing

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

(Figure A3).

In summary, our discounted alpha framework addresses key limitations of competing methods while remaining flexible enough to incorporate complementary signals.

C.5 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 $i = 1, \ldots, N$:

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

with standardized characteristics $z_{i,t}$, $Var(\varepsilon_{i,t+1}) = \sigma_\varepsilon^2$, and $\mu_{i,t} \perp \epsilon_{i,t+1}$. 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—i.e., 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 $\sigma_\epsilon = 0.25$ 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 Appendix B) 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).

C.6 A numerical example illustrating Remark 1

Example C.1 (Valuation with one-period alpha and known underpricing decay). Suppose $vp_{i,t+1} = \phi_{vp,i,t} vp_{i,t} + \epsilon_{vp,i,t+1}$ with $\phi_{vp,i,t}$ known and $Cov_t\left(\widetilde{M}_{t+1}\frac{P_{i,t+1}}{P_{i,t}}, \epsilon_{vp,i,t+1}\right) = 0$. Then, equation (6) implies that one can value that stock based on its flow of one-period alpha:

$$vp_{i,t} = \underbrace{\frac{1}{1 - \rho_{i,t}\phi_{vp,i,t}}}_{\text{duration}} \times \frac{\alpha_{i,t}}{1 + R_{f,t}}, \quad V_{i,t} = (1 + vp_{i,t})\, P_{i,t}, \tag{36}$$

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 ($vp_{i,t} = 0.5$), 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 the underpricing will decay deterministically at the rate $\phi_{i,t} = 0.9$ to $vp_{i,t+1} = 0.45$, equation (6) shows today's one-year alpha must be $\alpha_{i,t} = 0.50 - 0.45 = 5\%$. Hence,

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

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

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

In both cases, we recover the current underpricing from the flow of one-year alpha and the current decay rate of underpricing.

At first glance, it may seem surprising that a valuation formula resembling the one under time-invariant ρ and ϕ_α in equation (8) still applies when $\rho_{i,t}$ and $\phi_{vp,i,t}$ can vary.[40] But the key intuition comes from viewing the stock of underpricing as fixed and view alpha as the 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.

[40] These formulas from those involving ϕ_α in Section 1.3, which measures the persistence of alpha. In contrast, $\phi_{vp,i,t}$ measures the persistence of underpricing. The two concepts are related, but expressing the formula in terms of the persistence of underpricing, vp, clarifies how the "stock" of underpricing is the more primitive variable than the "flow" of alpha, which is a payout from the underpricing.

D Empirical Internet Appendix

D.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 et al. (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). If quarterly data are missing (prior to 1971m6 for quarterly book-to-market and quarterly asset growth and prior to 1976m6 for quarterly gross profitability to allow for sufficient cross-section), 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 over 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 3-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.