Which Asset Pricing Model Do Firm Managers Use? A Revealed Preference Approach*

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Abstract

When do firms repurchase shares because they believe the stock is undervalued—and what valuation model guides that belief? We study opportunistic repurchases, defined as unusually large buybacks coinciding with insider purchases, and test which signals best predict them. Expected CAPM alphas consistently outperform multifactor models, but simple heuristics such as the earnings-to-price ratio can explain the opportunistic repurchase decisions better. The evidence suggests that while the CAPM best rationalizes the behavior of firm managers among the risk-based models, firm managers in reality may also rely on more intuitive valuation rules based on price multiples.

JEL classification: G11, G12, G31, G35

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1 Introduction

How do firms value their own stock when deciding whether to pursue an opportunistic share repurchase? Do they rely on risk-adjusted models like the CAPM, or do they fall back on simpler heuristics such as book-to-market or earnings-to-price ratios? We investigate these questions by examining the timing of opportunistic share repurchases and test which valuation signals best explain these decisions.

We build on the revealed preference approach of Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016), which infers economic agents' beliefs by observing their choices. In our setting, when a firm undertakes an opportunistic share repurchase, it implicitly reveals a belief that the present value of future cash flows exceeds the market price—in other words, the repurchase represents a positive-NPV investment. By comparing the timing of repurchases to valuation signals from various asset pricing models, we ask: which model best reflects the valuation logic implicit in managerial actions?

This design builds on extensive evidence that firms systematically time equity repurchases. Brav et al. (2005) report that the leading motive for repurchases, cited by 86% of CFOs, is the belief that the stock is undervalued.[1] To isolate repurchases driven by genuine beliefs about undervaluation, we construct a proxy for opportunistic activity following the approach of Dittmar and Field (2015). Specifically, we classify a firm-quarter repurchase as opportunistic if it exceeds the firm's own 12-quarter moving average and coincides with insider purchases reported in Form 4 filings. This joint condition captures repurchases that are both unusually aggressive and corroborated by insider conviction, filtering out routine payouts and earnings management. We show that such opportunistic trades differ sharply from typical repurchases: they are more likely to occur during market downturns, are countercyclical relative to overall repurchase activity, and are disproportionately executed by firms with high book-to-market ratios and weak prior returns. These patterns suggest that managers engage in such trades when they believe the stock is mispriced—and that they may rely on a combination of backward-looking signals and model-based forecasts to identify

[1] Graham and Harvey (2001) similarly show that perceived overvaluation is a key motive for equity issuance.

undervaluation.

Our key finding is that among standard asset pricing models, the CAPM best explains the timing of opportunistic repurchases. Firms are more likely to repurchase their own shares when they anticipate higher future CAPM alphas. This supports the view that firms behave like long-horizon CAPM investors, consistent with the findings of the prior literature on the mental model of risk of mutual fund investors (Berk and Van Binsbergen, 2016; Barber, Huang, and Odean, 2016) as well as survey and empirical evidence (e.g., Graham and Harvey, 2001; Gormsen and Huber, 2024) showing that firms rely on market beta and other simple risk measures to estimate their cost of capital, while neglecting more complex drivers.

However, CAPM-based risk adjustment offers an incomplete account of how firms make real decisions. We find that simple heuristics—such as price multiples—often perform better than risk-adjusted measures of firm misvaluation. In fact, both CAPM-based misvaluation and simple valuation multiples (e.g., book-to-market and earnings-to-price ratios) remain significant predictors of opportunistic repurchases, suggesting that they contain complementary information about perceived undervaluation. This finding echoes a growing literature documenting the persistent use of valuation heuristics in real-world settings: Dècaire and Graham (2024) show that both growth expectations and subjective discount rates play significant roles in analyst valuations, while Ben-David and Chinco (2024) find that analyst price targets can be mechanically explained by simple market multiples.

Taken together, our results suggest that managers rely on a hybrid valuation approach when acting on perceived misvaluation: a CAPM-like cost of capital framework, supplemented by simple heuristics such as book-to-market or earnings-to-price ratios. In other words, their behavior reflects both forward-looking assessments and backward-looking signals, and they draw on coarse but intuitive indicators—possibly due to cognitive constraints, being less subject to estimation errors, or ease of communication within the firm. By examining the timing of opportunistic repurchases, we shed light on the implicit valuation logic behind real-world financial decisions, contributing to a broader understanding of how economic agents form beliefs and act under uncertainty.

Our paper builds on and extends the literature on firm beliefs and corporate financing behavior. Bruner et al. (1998) and Graham and Harvey (2001) show that managers overwhelmingly rely on the CAPM when estimating the cost of capital for investment and financing decisions. Stein (1996) argues that CAPM-style risk adjustment may be a reasonable model for firms facing market inefficiencies. Beyond capital budgeting, recent work by Dessaint et al. (2021) and Hommel, Landier, and Thesmar (2021) explores how real-world valuations rely more heavily on CAPM-based or comparables-based methods than factor-model-implied discount rates. Finally, our approach builds on a growing body of revealed preference studies—such as Berk and Van Binsbergen (2016), Barber, Huang, and Odean (2016), Blocher and Molyboga (2017), and Agarwal, Green, and Ren (2018)—that use investor or manager actions to back out which asset pricing models are most influential in practice. By adapting this logic to opportunistic repurchases, we help bridge research on asset pricing, behavioral corporate finance, and managerial beliefs.

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework and research design. Section 3 presents the results from the horse race of asset pricing models. Section 4 provides robustness checks and additional analyses. Section 5 discusses the implications of our findings. Section 6 concludes.

2 Theoretical Framework and Research Design

2.1 Identifying opportunistic repurchases

Firms repurchase their own shares for a variety of motives, including distributing excess cash, adjusting capital structure, boosting earnings per share (EPS), countering dilution, or signaling/acting on undervaluation (Brav et al., 2005; Graham, 2022; Bonaimé and Kahle, 2024). Among these, *opportunistic repurchases*—repurchases motivated by perceived undervaluation of shares—are the most common rationale provided by CFOs: "the most popular response for all the repurchase questions on the entire survey is that firms repurchase when their stock is a good value relative to its true value: 86.4% of all firms agree" (p.514 of Brav et al. (2005)). These repurchases are motivated by perceived underpricing and the potential to earn abnormal returns, and they could reflect the firm managesr' internal valuation model or beliefs about their stock prices.

A repurchase typically begins with managerial initiation and requires board of directors' approval. The board typically authorizes a maximum dollar amount or number of shares the firm is allowed to repurchase over a specified period. These authorizations are non-binding and confer significant discretion to managers regarding if and when to execute the repurchase (Bargeron, Kulchania, and Thomas, 2011). While firms can execute repurchases through open market transactions, tender offers, or privately negotiated deals, open market repurchases are by far the most common (Jagannathan, Stephens, and Weisbach, 2000).

Importantly, most plans grant managers considerable flexibility in whether, when, and how aggressively to repurchase shares once authorized. This discretion enables timing behavior—that is, buying more when the stock is perceived as undervalued. Such discretion underlies the notion of opportunism in share repurchases.

Following Dittmar and Field (2015), we construct an empirical proxy for opportunistic repurchases that flags firm-quarter observations as opportunistic when two conditions hold:

1. The firm repurchases shares more aggressively than usual, measured relative to its own historical repurchase activity; and
2. Insiders purchase shares in the same quarter, as disclosed in Form 4 filings.

We assign a firm-quarter as having $OppRP_{i,t} = 1$ if an opportunistic repurchase arises in any of the subsequent two quarters (6 months) and $OppRP_{i,t} = 0$ otherwise.

We define aggressive-than-usual repurchases as the one whose repurchase amount in dollar exceeds the moving average of repurchase amounts in the last 12 quarters. We obtain repurchase amount from the PRSTKCY field in Compustat Quarterly and insider trading data from LSEG insider trading data.

This joint condition filters for firm-quarters where repurchases are likely driven by managerial beliefs about undervaluation. The presence of insider buying reinforces the interpretation that the repurchase reflects a genuine conviction about mispricing, rather than routine payout policy or balance sheet management.

Figure 1 shows that while total repurchases are procyclical, as noted in Jagannathan, Stephens, and Weisbach (2000) and others, opportunistic repurchases tend to be countercyclical, peaking during the Great Recession and then during Covid-19. This is consistent with how firms requiring flexibility tend to pay out cash from excess profits during booms and reduce repurchases during busts when cash and liquidity are important, leading to procyclical total repurchases, whereas firms tend to time undervaluation by repurchasing during market busts, leading to countercyclical opportunistic repurchases.

Table 1 summarizes the cross-sectional characteristics of firms doing non-opportunistic repurchases versus opportunistic repurchases. Taken together, the summary statistics highlight key differences between repurchasing and opportunistically repurchasing firms. Firms that engage in non-opportunistic repurchases tend to be larger, more profitable, and have lower book-to-market ratios, consistent with these firms beings ones with cash from excess profits but wanting the flexibility of paying out that cash through share repurchases rather than higher dividends. In contrast, opportunistic repurchases are more common among firms with higher book-to-market ratios and lower recent stock returns, pointing toward perceived undervaluation as a potential motive.

2.2 A revealed preference test of managerial beliefs

Our revealed preference test closely follows that of Berk and Van Binsbergen (2016) but allows for control variables, which we introduce in some of the later tests. We begin with the following assumption in our empirical implementation.

Assumption 1. *Conditional on stock characteristics X (e.g., size or Tobin's Q bin), the probability of opportunistic repurchases increases with the magnitude of perceived underpricing (θ).*

$$\frac{\partial Pr[OppRP = 1|\delta, X]}{\partial \theta} > 0 \tag{1}$$

Under this assumption, we show how to employ the revealed preference approach to infer the firm managers' mental model of underpricing. We then explain our empirical estimator of θ.

Our goal is to use opportunistic repurchases to infer a signal closest to that used by firm managers to infer share underpricing. When evaluating asset pricing models, we aim to make minimal assumptions about the distribution of estimation errors. Therefore, we compare models based on their ability to accurately rank firms by their signal of underpricing, rather than using the estimated level of the signal itself. This approach makes our analysis robust to potential shifts in the distribution of the signal variable.

Let subscript (i, t) denote firm i at time t. Within each characteristic group X_{it}, sort all firms based on their perceived underpricing into two groups:

$$\Theta_{it} = \begin{cases} 1 & \text{Top half of the firms based on the perceived level of undervaluation } \theta_{i,t}. \\ 0 & \text{Bottom half of the firms based on the perceived level of undervaluation } \theta_{i,t}. \end{cases} \tag{2}$$

The following propositions adapt the BvB framework in a way that applies to the rank of mispprincing and controls for the observable characteristics, if needed.

Proposition 1. *Probability of opportunistic repurchase increases with the rank of perceived underpricing:*

$$Pr[OppRP_{it} = 1|\Theta_{it} = 1, X_{it}] > Pr[OppRP_{it} = 1|\Theta_{it} = 0, X_{it}],$$

Proof of all propositions will come in the appendix.

Proposition 2. *The regression coefficient of the opportunistic repurchase on the rank of perceived underpricing is positive.*

$$\beta = \frac{Cov(OppRP_{it}, \Theta_{it})}{Var(\Theta_{it})} > 0 \tag{3}$$

Equation (A.1) in the appendix shows that β has a clear interpretation as the difference in the probability of a opportunistic repurchase between the firms in the top versus bottom half of the perceived underpricing:

$$\beta = Pr[OppRP_{it} = 1|\Theta_{it} = 1] - Pr[OppRP_{it} = 1|\Theta_{it} = 0] \tag{4}$$

Proposition 2 provides a simple test for proxies of undervaluation perceived by the firm: a proxy for perceived undervaluation must predict the opportunistic repurchase. However, as we will see, several different proxies of perceived undervaluation pass this univariate test.

Next, we develop a test to directly compare the performance of two different proxies of perceived undervaluation. The next three propositions establish the foundations for this test. Before we do so, we make the following assumption made in BVB.

Assumption 2. *In the presence of a true signal of perceived undervaluation, a false signal has no additional explanatory power for the opportunistic repurchase.*

$$Pr[OppRP = 1|\Theta_{it}^T, \Theta_{it}^F, X_{it}] = Pr[OppRP = 1|\Theta_{it}^T, X_{it}] \tag{5}$$

Proposition 3. *The regression coefficient of the opportunistic repurchase on the rank of perceived undervaluation is maximized under the true signal of perceived undervaluation; i.e.,* $\beta^T > \beta^F$*.*

Definition 1. *Define model* c *as a better approximation of the true signal of undervaluation perceived by the firm than model* d *if and only if:*

$$\begin{aligned} &Pr[\Theta_{it} = 1|\Theta_{it}^c = 1] + Pr[\Theta_{it} = 0|\Theta_{it}^c = 0] > \\ &\qquad Pr[\Theta_{it} = 1|\Theta_{it}^d = 1] + Pr[\Theta_{it} = 0|\Theta_{it}^d = 0] \end{aligned} \tag{6}$$

Proposition 4. *Model c is a better approximation of the true signal of perceived undervaluation than model d if and only if* $\beta^c > \beta^d$*.*

Proposition 5 gives us a straightforward way to empirically test competing proxies of perceived undervaluation.

Proposition 5. *Consider an OLS regression of $OppRP_{it}$ on the $\Theta^c_{it} - \Theta^d_{it}$:*

$$OppRP_{it} = \gamma_0 + \gamma_1(\Theta^c_{it} - \Theta^d_{it}) + \xi_{it} \tag{7}$$

Model c is a better approximation of the true signal of undervaluation perceived by the firm than model d if and only if $\gamma_1 > 0$.

Empirical implementations of these tests include time fixed effects and weigh different time periods equally using weighted least squares, which makes the test coefficients identical to those based on Fama-MacBeth regressions. This is in response to Ben-David et al. (2021)'s finding that weighing different time periods equally in a revealed preference test generates results that survive a falsification test. We report the estimated γ_1 coefficients along with the t-statistics based on standard errors double clustered on firm and time. All of our tests have quarterly frequency.

While our main tests do not include control variables, the robustness checks incorporate firm size and Tobin's Q as controls X to account for differences in investment opportunities across firms.

2.3 Ex-ante cumulative abnormal returns and other signals

We first explore how expected long-horizon CARs relative to each candidate asset pricing model affects the decision to repurchase opportunistically. This approach is roughly valid under the assumption that firm managers try to time opportunistic repurchases when they rationally expect to enjoy positive abnormal returns over the next several years. To compute CARs, we consider six alternative candidate asset pricing models: the the Capital Asset Pricing Model (CAPM) (Sharpe (1964); Lintner (1965)), the excess market return model (i.e., taking the return net of the market return as the "risk adjusted" excess return) (Excess Market), the three-factor model of Fama and French (1993) (FF3), the Carhart (1997) four-factor model (Carhart), the five factor model of Fama and French (2015) (FF3), the q-factor model of Hou, Xue, and Zhang (2015) (HXZ).

To construct ex-ante expected long-horizon cumulative abnormal returns (CARs), we model stock-specific alphas, with respect to candidate asset pricing model m, as a linear function of stock characteristics:

$$\alpha_{i,t}^{m} = b_{0,t}^{m} z_{i,t}, \tag{8}$$

where z is a vector of stock characteristics and $\alpha_{i,t}^{m}$ is firm i's one-year alpha with respect to candidate asset pricing model m from time t to $t+1$. Similarly, we model future expected alphas as linear in current stock characteristics:

$$E_t \alpha_{i,t+\ \tau \text{ yr}}^{m} = b_{\tau,t}^{m} z_{i,t}. \tag{9}$$

We estimate the b_{τ}^{m} coefficients for each yearly horizon τ and each candidate asset pricing model m in a 20-year moving panel. For instance, we estimate $b_{2,t}^{CAPM}$ at time t by regressing one-year excess stock returns on the three-year-lagged stock characteristics z and those three-year-lagged stock characteristics interacted with the one-year market excess return from $t-20$ years to t, applying value weighting in the cross-section and equal weighting in the time series. The resulting estimate is used to obtain the real-time ex-ante stock-level CAPM alpha from $t+2$ yr to $t+3$ yr:

$$\widehat{E_t \alpha_{i,t+2 \text{ yr}}^{CAPM}} = \widehat{b_{2,t}^{CAPM}} z_{i,t}. \tag{10}$$

We then construct, for instance, the real-time ex-ante 5-year CAR as follows:

$$CAR_{5yrs,i,t}^{CAPM} \equiv \sum_{\tau=0}^{4 \text{ yr}} \widehat{E_t \alpha_{i,t+\tau \text{ yr}}^{CAPM}} = (\widehat{b_{0,t}^{CAPM}} + ... + \widehat{b_{4,t}^{CAPM}}) z_{i,t} \tag{11}$$

These ex-ante CARs have an interpretation as the firm's next-5-year alphas expected by an econometrician running the panel regression to understand which characteristics matter for the 5-year CAR. An important limitation of these estimated future CARs is that we cannot condition on information that is not revealed through the public signals and is private to the firm. However, as long as firm managers' private information is not extensive, these estimates should provide a reasonable approximation to what a rational firm manager would expect.

We use the cross-sectional ranks of the following characteristics as the z vector: book-to-market equity, gross profitability, market beta, market equity, asset growth, net share issuance, prior 1-month return, prior 1-year return, prior 2-to-1 year return, prior 5-to-1-year return (minimum window of prior 3-to-1-year return for newer stocks). As an example, Table 2 reports the fifth-year alpha coefficients ($\widehat{b^m_{4,t}}$) for the six alternative candidate asset pricing models for the 20-year window ending in 2014m3—the end of the first calendar quarter in 2014.

We also explore how past stock returns and price multiples serve as potential signals (Θ^c) of perceived misvaluation. We consider the following two return signals: prior 1-month return ($-Ret[-1, 0]$) and the prior 1-year return ($-Ret[-12, 0]$). These return signals are signed so that higher recent returns raise perceive undervaluation. We consider the following two price multiples: book-to-market (B/M) and 1-year-smoothed-earnings-to-price (E/P).

2.4 Data sources

We use stock price data from the Center for Research in Security Prices (CRSP) and annual accounting data from Compustat. We take one month treasury bill and factor returns data from Kenneth French's data library. We construct our data in quarterly frequency. Our sample period begins in the first quarter of 1996, when insider trading data become less sparse, and end in the last quarter of 2023.

3 Main Tests: What Predicts Opportunistic Repurchases?

3.1 Risk-adjusting models: CAPM works the best

We begin with the single-model regression results that relate the likelihood of opportunistic repurchases to the ex-ante rank of long-horizon cumulative abnormal returns (CARs) with respect to each candidate asset pricing model. Table 3 reports the estimated coefficients from regressions of the form

$$OppRP_{i,t} = \mu_t + \gamma^c\, \Theta^c_{i,t} + \xi_{i,t},$$

where $\Theta^c_{i,t} \in \{0, 1\}$ indicates whether firm i's expected CAR relative to model c is in the top half of the distribution at time t. The coefficient γ^c thus reflects the change in the probability of an opportunistic repurchase when a firm's rank shifts from the bottom to the top half of the signal distribution.

The CAPM consistently yields positive estimates across all horizons, peaking at two years horizon with $\gamma^{\text{CAPM}} = 1.40$ ($t = 7.99$). This means that a firm in the top half of expected 2-year CAPM alphas is 1.40 percentage points more likely to conduct an opportunistic repurchase in the next two quarters (6 months) than a firm in the bottom half. The "Excess Market" model also performs well, with $\gamma = 0.73$ ($t = 4.28$) for the 3-year CAR horizon. More complex models such as FF3, FF5, and HXZ perform worse, often generating small and insignificant coefficients. Table 2 shows that this striking under-performance of multifactor CARs is likely the result of these multifactor CARs having to bet against the book-to-market signal, which we show in the next subsection strongly and positively predicts opportunistic repurchases.

Notably, for all models the predictive strength of the CAR signal tends to be higher at 2 or 3 years horizon relative to 1 year CAR. This pattern may reflect how firm managers behave like long-term investors—seeking to repurchase shares when they believe the market is underpricing the firm over a multi-year horizon.

Table 4 presents pairwise comparisons across models using the difference in binary ranks. The CAPM significantly outperforms all other risk-based models in predicting opportunistic repurchases. These results suggest that firms are more likely to act on valuation signals derived from simple risk-based models centered on beta-adjusted returns.

3.2 Price multiples: simple heuristics also work well

We next consider whether simple valuation heuristics—past returns and price multiples—predict opportunistic repurchases. Table 5 shows that among price multiples, both book-to-market (B/M) ($\gamma = 1.92$, $t = 8.28$) and earnings-to-price (E/P) ($\gamma = 2.14$, $t = 9.24$) significantly predict opportunistic repurchases. Among return signals, both the prior 1-month return ($-\text{Ret}[-1, 0]$) and the prior 1-year return ($-$Ret$[-12, 0]$) predict opportunistic repurchases with coefficients $\gamma = 0.64$ (4.48) and $\gamma = 0.51$ (3.21) respectively. These coefficients imply economically meaningful effects: a one-unit change in the binary rank from 0 to 1 increases the probability of an opportunistic repurchase by 0.51 to 2.14 percentage points.

Table 6 compares the CAPM-based signal to the heuristic signals in pairwise regressions. We find that the predictive ability of simple market multiples are statistically higher than that of the CAPM-implied signal, while the CAPM wins against past return signals. This result contrasts with the earlier model-based horse race in Table 4, where the CAPM outperforms other formal factor models. This suggests several potential explanations. First, the CAPM CAR measure is constructed using ex-ante forecasts over a 3-year horizon and may suffer from estimation error or attenuation bias, weakening its predictive ability relative to simpler, more stable signals like B/M. Particularly important is that we are measuring CAPM CAR from the perspective of an econometrician observing the public signals and cannot account for unobserved within-firm undervaluation signals that could be important in practice. Second, managers may genuinely rely on coarse but valuation heuristics—such as B/M, E/P, or past returns—because of their transparency and intuitive appeal, especially if such metrics correlate well with deeper fundamentals or investor sentiment.

4 Robustness Checks and Future Work

4.1 Adding controls—size and Tobin's q

Although we take care to isolate opportunistic share repurchases, one potential concern is that the decision to repurchase shares may be influenced by differences in firms' investment opportunities. To address this, we rerun our baseline tests while controlling for variables that are likely to capture such differences—namely, firm equity size and total Tobin's q, as defined by Peters and Taylor (2017). Specifically, each quarter we sort firms into 25 groups based on NYSE size breakpoints and total q. Within each control group, we then rank firms into binary groups based on their forecasted 3-year CAR. Table 7 shows that the results are robust to controlling for these characteristics.

4.2 Comparing risk-adjusting models using the BHO method

Barber, Huang, and Odean (2016) (BHO) develop a similar technique to run horse races among asset pricing models. The advantage of the BHO method is that it allows for model comparison using more granular rankings and includes controls for other characteristics through linear regression—though this added complexity makes the regression coefficients more difficult to interpret.

Following the BHO method, we first sort firms into deciles based on their forecasted 3-year CAR. Next, for each pairwise comparison of asset pricing models, we construct 100 dummy variables based on the decile ranking of estimated mispricing as defined by the two models:

$$D_{jkit} = \begin{cases} 1 & \Delta^c_{it} = j, \Delta^d_{it} = k \qquad \forall j, k = 1, ..., 10 \\ 0 & otherwise \end{cases} \tag{12}$$

Figure 2 in the appendix shows all decile rankings and dummy variables for the comparison of CAPM and the three factor model. Gray cells correspond to firm-quarter observations that have similar mispricing rank based on both models and the black cell is the omitted dummy variable. We regress the sign of equity issuance on the full set of dummy variables, as well as time fixed effects. We then compare off-diagonal coefficients of dummy variables. For example, we compare estimated coefficients on the dummy variable corresponding to decile 4 based on the CAPM and decile 1 based on the three factor model (red cell, b_{41}) to the coefficient of the dummy corresponding to decile 1 based on the CAPM and decile 4 based on the three factor model (green cell, b_{14}). If a firm manager uses the CAPM rather than the three factor model, we expect $b_{41} > b_{14}$. Thus, similar to the BHO, we test the null hypothesis that the sum of the difference between off-diagonal coefficients is equal to zero. We also calculate a binomial test statistic which tests the null hypothesis that the proportion of differences equals 50%.

Table 8 presents the results from pairwise model comparisons. Panel A reports the sum of the differences and the corresponding p-values, where a positive (negative) value indicates that the model in the row (column) of the table wins the race. Panel B shows the percentage of cases in which the first model (row) outperforms the second model (column) across 45 comparisons, along with the p-value of the binomial test. The results indicate that CAPM is favored by an overwhelming majority and significantly outperforms other models. This further supports the notion that CAPM is the closest asset pricing model to what firm managers use to estimate the intrinsic value of the firm.

4.3 Non-opportunistic repurchases

Define non-opportunistic repurchases as any repurchases that we do not categorize as opportunistic. We find that the test results change drastically for non-opportunistic repurchases, reminiscent of the contrast between the procyclicality of total repurchases versus the counter-cyclicality of opportunistic repurchases in the time series of repurchases.

Table 9 shows drastically different results from those based on opportunistic repurchases. Multifactor CARs now tend to explain repurchase decisions better than the CAPM, and this is partly driven by how profitable growth firms with positive multifactor alphas tend to utilize non-opportunistic repurchases more to pay out excess profits in a flexible way. Panel B, which relates non-opportunistic repurchase decisions to heuristic signals, tends to show the opposite sign of the effect compared to non-opportunistic repurchases: low B/M firms with recent run-up in stock prices tend to engage in more non-opportunistic repurchases.

4.4 Using earnings calls to improve identification

While our baseline proxy—flagging quarters with concurrent insider buying and abnormally large repurchases—captures instances where managers are likely acting on perceived mispricing, it inevitably includes noise. Some flagged quarters may still reflect routine payout policy, balance sheet adjustments, or other motives unrelated to valuation beliefs.

To address this limitation, a future draft of the paper will incorporate textual analysis of quarterly earnings call transcripts to directly extract managerial language indicating perceived undervaluation. Specifically, we are developing a natural language processing (NLP) pipeline that scores earnings call transcripts based on whether managers signal that their stock is underpriced.

Our scoring algorithm uses a combination of (i) a custom dictionary of undervaluation-related phrases (e.g., "undervalued," "disconnected from fundamentals," "compelling long-term value"), (ii) context-aware sentence embeddings to capture more subtle or indirect references, and (iii) supervised learning models trained on a hand-labeled set of transcripts where undervaluation tone has been manually verified.

Using these textual signals, we will create a firm-quarter-level indicator for whether the manager expresses undervaluation beliefs on the earnings call. This signal will then be matched to the timing of repurchases. Firm-quarters where managers express undervaluation and execute a repurchase will be reclassified as “text-validated” opportunistic repurchases. We expect this cleaner subset to contain a higher concentration of truly belief-driven trades, thus improving the signal-to-noise ratio in our dependent variable.

This refinement is not merely descriptive: it aims to improve the revealed preference test itself. Our power to detect which asset pricing model best aligns with firms’ perceived cost of capital depends on how sharply we can isolate the subset of decisions most clearly driven by valuation beliefs. By identifying these belief-driven repurchases more precisely, we improve the interpretability and power of our horse-race tests across asset pricing models. In this sense, the integration of textual analysis strengthens the core empirical strategy of the paper and directly advances the literature on revealed preferences and managerial beliefs.

5 Discussion: Managerial Beliefs and the Mental Models Behind Repurchase Decisions

Our findings offer new insights into how firm managers form and act on beliefs about mispricing. Specifically, we show that firms are more likely to engage in opportunistic repurchases when they expect high CAPM alphas going forward, though they also appear to rely heavily on backward-looking heuristics such as book-to-market ratios and past returns. This section situates our results within the growing literature on belief formation in economics and finance, highlighting both consistency and divergence from recent theoretical and empirical advances.

5.1 A hybrid between risk-based models and heuristics

Our results are consistent with the idea that firm managers behave like long-horizon investors, consistent with Stein (1996). In particular, firms tend to prioritize future CAPM alphas over multifactor alphas, consistent with the prior findings from revealed preference tests on investors (Berk and Van Binsbergen, 2016; Barber, Huang, and Odean, 2016; Blocher and Molyboga, 2017; Agarwal, Green, and Ren, 2018) and from survey evidence (Bruner et al., 1998; Graham and Harvey, 2001). Gormsen and Huber (2024) also find that firms neglect some important sources of variation in their cost of capital as they rely on simple models of risk. However, we also find that simple, coarse signals—such as market multiples—can perform better in some specifications and that both have incremental explanatory power for opportunistic repurchases in untabulated multivariate tests.

Indeed, the incremental explanatory power of both risk-based models and simple heuristics suggests that managers may implicitly balance statistical sophistication with intuitive metrics. This echoes the interpretation in Dècaire and Graham (2024) that subjective discount rates and growth expectations—not just risk-based models—play central roles in practical valuation as well as the finding of Ben-David and Chinco (2024) that analyst reports tend to rely heavily on relative valuation using price multiples. The hybrid pattern is also interesting in light of Dessaint et al. (2021) and Hommel, Landier, and Thesmar (2021), who document that the sole reliance on CAPM-based risk adjustment can lead to suboptimal decisions and that relative valuation can improve actual decision-making.

5.2 Contrarian beliefs

Our results indicate that managers initiating opportunistic repurchases tend to act on contrarian valuation signals rather than extrapolative price trends. Specifically, we find that repurchase activity is higher following poor stock performance. Further, book-to-market, often associated with a contrarian strategy, strongly explains opportunistic repurchases. This pattern aligns with the view that firms time repurchases to exploit contrarian valuation opportunities (e.g., Vermaelen (2005)). This view, however, does not necessarily contradict the idea that investors tend to have diagnostic expectations (e.g., Bordalo, Gennaioli, and Shleifer (2018)) and extrapolative beliefs (e.g., Da, Huang, and Jin (2021)), as long as the firm managers have a long investment horizon—even if firms extrapolate based on past returns that their share prices might continue to rise in the near future, they may not opportunistically repurchase their shares if they expect the share prices to eventually come back down.

6 Conclusion

Our analysis of opportunistic repurchase behavior shows that firm managers act in ways broadly consistent with CAPM-style risk adjustment. CAPM-based risk adjustment outperforms those based on multifactor models in predicting when firms repurchase their own shares opportunistically. At the same time, we find that simple heuristics, such as valuation multiples, often perform better than expected risk-adjusted alphas.

Our findings have implications for both asset pricing and corporate finance. On the asset pricing side, we show that real-world actions—such as repurchase timing—can be used as a revealed preference test of what method of risk adjustment best approximates firms' opportunistic trades of their own shares. On the behavioral corporate finance side, our evidence is consistent with the idea that the real decisions of firms are influenced by heuristics and contrarian thinking. More broadly, our results contribute to the literature on beliefs by using real-world actions to infer how firms form beliefs about share undervaluation.

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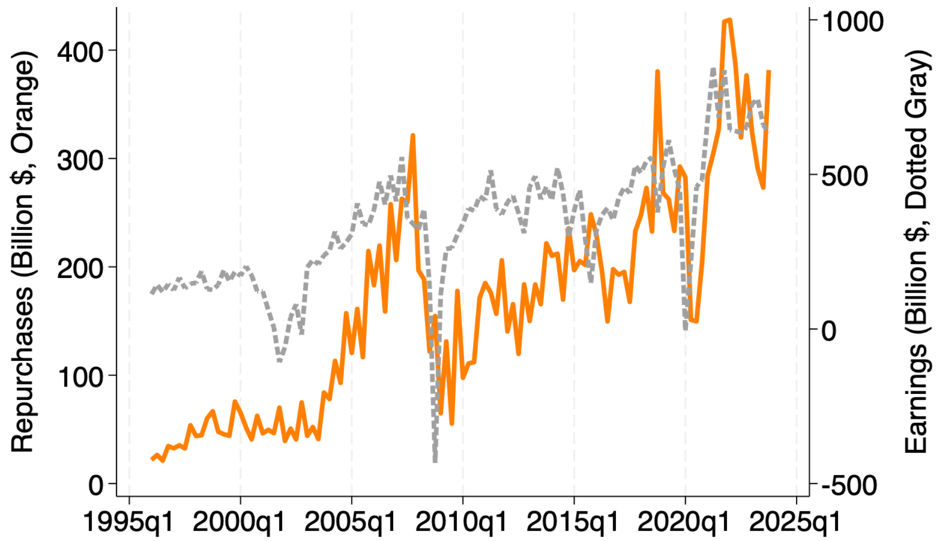

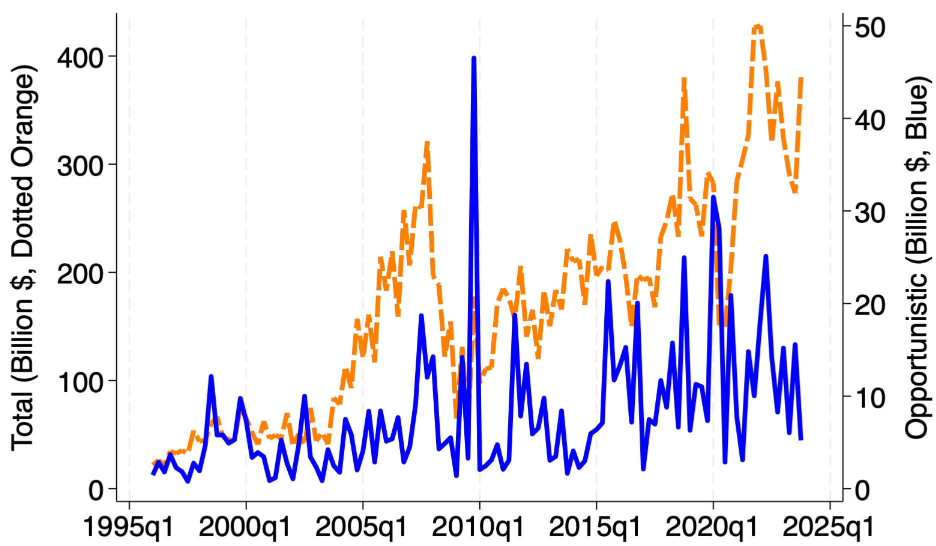

Figure 1: **Repurchase Amount Over Time: Opportunistic versus Total**
The top figure plots the time series of total repurchase amount (in solid orange) along with total earnings (in dotted gray) of public firms in the US. The bottom figure plots the time series of total repurchase amount (in dotted orange) along with total opportunistic repurchases (in solid blue). The data is quarterly from 1996Q1 to 2023Q4.

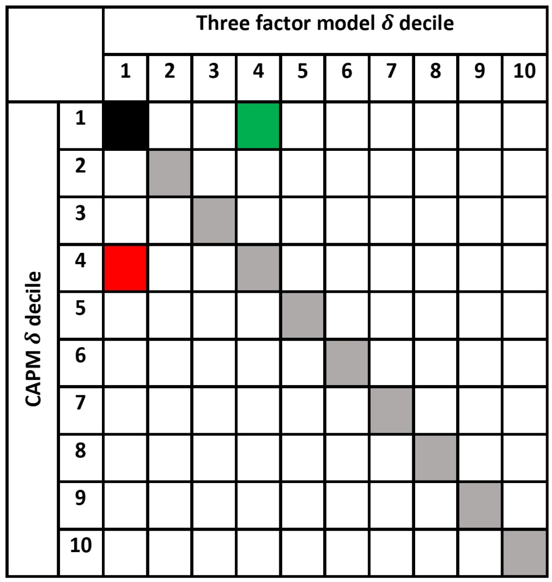

Figure 2: Horse race dummy variables for pairwise comparison (BHO test)

This figure shows 100 possible dummy variables for the regression that compares mispricing with respect to the CAPM versus mispricing with respect to the Fama French three factor model. In the regression, omitted variable is the dummy with the first decile rank for both models. The gray cells represent firms with similar mispricing ranks from both models. The empirical tests compare the coefficients corresponding to 10 upper off-diagonal and 10 lower off-diagonal cells. For example, we compare the coefficient of dummy variable for firms with CAPM mispricing in the forth decile and FF3 mispricing in the first decile (red) to the firms with CAPM mispricing in the first decile and FF3 mispricing in the fifth decile (green). CAPM wins the race if firm's issuance decision is more sensitive to the mispricing with respect to the CAPM, i.e. $b_{4,1} > b_{1,4}$.

Table 1: Summary Statistics: Opportunistic versus Non-Opportunistic Repurchases

	Opportunistic	Non-Opportunistic
Book-to-Market	0.38	-0.24
	(5.77)	(0.94)
Gross Profitability	-0.14	4.91
	(1.82)	(15.87)
Market Beta	0.06	0.62
	(1.16)	(2.17)
Size	-0.04	3.82
	(1.57)	(21.80)
Asset Growth	0.30	0.40
	(6.95)	(3.06)
Net Share Issue	-1.00	-11.32
	(13.45)	(36.38)
Ret[-1,0]	0.13	-0.40
	(3.72)	(4.37)
Ret[-12,0]	-0.33	-0.21
	(6.56)	(1.46)
Number of Repurchases	12,623	183,218

This table summarizes the characteristics of firm-quarter observations engaging in opportunistic versus non-opportunistic repurchases by regressing the dummy variable for the repurchase on a cross-sectional rank of the characteristics in a multivariate panel regression. The data is quarterly from 1996Q1 to 2023Q4. The regressions are equal weighted in the time series. The reported coefficients are in percentage unit through a multiplication by 100. The result shows that opportunistic repurchases are done by firms that tend to have higher B/M and lower profitability. In contrast, the firms engaging in non-opportunistic repurchases tend to be low B/M, high profitability, and large stocks that routinely engage in share repurchases.

Table 2: Determinants of Expected Fifth-Year Buy-and-Hold Alpha for 2014m3

Variable	CAPM	Excess Market	FF3	Carhart	FF5	HXZ
B/M	0.41	1.81	-0.72	-2.08	0.15	-2.12
	(1.22)	(5.43)	(2.76)	(7.92)	(0.56)	(5.82)
Gross Profitability	1.32	1.59	1.68	0.50	2.47	2.30
	(5.45)	(6.06)	(7.96)	(2.16)	(9.32)	(9.33)
Market Beta	-1.50	0.78	-0.87	-0.50	-0.34	0.02
	(5.06)	(1.70)	(3.34)	(1.74)	(1.19)	(0.05)
Market Equity	1.32	-0.47	1.60	1.72	1.46	1.33
	(5.28)	(2.32)	(7.08)	(7.10)	(7.21)	(5.22)
Asset Growth	0.96	0.85	0.33	0.63	0.36	0.07
	(6.08)	(3.67)	(2.80)	(3.29)	(2.60)	(0.45)
Net Share Issuance	-1.00	0.04	-0.81	-0.68	-0.78	-0.34
	(4.88)	(0.18)	(4.45)	(2.77)	(4.50)	(1.56)
Prior 1-Month Return	0.06	0.36	0.01	-0.19	0.08	-0.00
	(0.34)	(1.61)	(0.05)	(0.93)	(0.47)	(0.01)
Prior 1-Year Return	-1.62	-2.11	-0.87	-1.07	-1.68	-0.78
	(6.22)	(6.48)	(3.78)	(2.77)	(8.40)	(2.20)
Prior 2-to-1-Year Return	-1.15	-0.29	-0.29	-1.06	0.03	-0.53
	(4.69)	(0.83)	(1.51)	(4.22)	(0.15)	(2.51)
Prior 5-to-1-Year Return	-0.72	-0.82	-1.36	-1.73	-1.51	-1.77
	(3.22)	(3.25)	(8.45)	(6.87)	(8.41)	(7.58)

This table reports the estimated coefficients $\hat{b}_{m,4,t}$ from cross-sectional regressions of five-year-ahead alpha on firm characteristics, separately for each of six asset pricing models: CAPM, Excess Market, FF3, Carhart, FF5, and q-factor (HXZ). The coefficients are estimated using a 20-year rolling window ending in 2014m3. Alpha is defined relative to each model, and is projected onto a vector of ten standardized stock characteristics: book-to-market, gross profitability, market beta, market equity, asset growth, net share issuance, and returns over four prior windows (1-month, 1-year, 2-to-1 year, and 5-to-1 year). The resulting coefficient vector $\hat{b}_{m,4,t}$ is used as an ingredient to construct ex-ante CAR signals for firm-level misvaluation in our main tests.

Table 3: Single Model Regressions: Expected Multi-Year CAR

Estimated γ^c					
	Cumulative Abnormal Return Horizon				
Factor Model	1 Year	2 Years	3 Years	4 Years	5 Years
CAPM	1.24	1.40	1.28	1.04	0.88
	(7.37)	(7.99)	(7.34)	(6.00)	(4.92)
Excess Market	0.51	0.64	0.73	0.68	0.68
	(3.05)	(3.81)	(4.28)	(3.92)	(4.02)
FF3	0.05	0.16	0.17	0.04	-0.04
	(0.30)	(0.84)	(0.86)	(0.20)	(0.17)
Carhart	0.18	0.21	0.20	0.06	-0.03
	(0.87)	(1.03)	(0.94)	(0.29)	(0.11)
FF5	0.18	0.14	0.13	-0.07	-0.18
	(1.09)	(0.81)	(0.77)	(0.38)	(0.98)
HXZ	-0.78	-0.74	-0.66	-0.74	-0.76
	(4.37)	(3.86)	(3.35)	(3.52)	(3.50)

This table reports the results of the regression of the dummy variable on opportunistic repurchase, $OppRP_{i,t}$, on the binary rank of ex-ante long-horizon CAR relative to a given candidate factor model:

$$OppRP_{i,t} = \mu_t + \gamma^c \Theta^c_{it} + \xi_{it},$$

where Θ^c here represents a long-horizon CAR estimated relative to a particular factor model for a given horizon in years. Each cell represents a separate regression corresponding to a particular model and CAR horizon years. The right-hand variable is the binary, cross-sectional rank of ex-ante (real-time) multi-year CAR relative to model c estimated in a moving window. All regressions include time fixed effects and observations are deflated by the number of firms in each quarter. The *t*-statistics are computed using double-clustered standard errors by firm and quarter.

Table 4: Pairwise Comparisons: Expected 3-Year CAR

Estimated $\gamma^{c,d}$					
	Model d				
Model c	Excess Market	FF3	Carhart	FF5	HXZ
CAPM	0.45	1.02	1.21	0.94	1.28
	(2.95)	(6.50)	(6.31)	(6.63)	(8.56)
Excess Market		0.29	0.30	0.30	0.68
		(2.15)	(1.98)	(2.42)	(5.07)
FF3			-0.07	0.06	1.14
			(0.40)	(0.31)	(6.12)
Carhart				0.09	0.96
				(0.46)	(6.60)
FF5					1.19
					(5.38)

This table reports the coefficients and *t*-statistics associated with $\gamma^{c,d}$ from the test in equation (7):

$$OppRP_{i,t} = \mu_t + \gamma^{c,d}(\Theta^c_{it} - \Theta^d_{it}) + \xi_{it}.$$

The right-hand variable is the difference in the binary rank of ex-ante 3-year CAR Θ with respect to asset pricing model c vs. d. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 5: Single Model Regressions: Price Multiples and Past Returns

	Book to Market Equity (B/M)	Smoothed Earnings to Price (E/P)	Prior 1-month Return $(-Ret[-1,0])$	Prior 1-Year Return $(-Ret[-12,0])$
Estimated γ^c	1.92	2.14	0.64	0.51
	(8.28)	(9.24)	(4.48)	(3.21)

This table reports the results of the regression of the dummy variable on opportunistic repurchase, $OppRP_{i,t}$, on the binary rank of a price multiple or a past return signal:

$$OppRP_{i,t} = \mu_t + \gamma^c \Theta^c_{it} + \epsilon_{it},$$

where Θ^c here represents the firm-level price multiple or past return signal. All regressions include time fixed effects and observations are deflated by the number of firms in each quarter. The *t*-statistics are computed using double-clustered standard errors by firm and quarter.

Table 6: Pairwise Comparisons: CAPM CAR versus Simple Heuristics

Estimated $\gamma^{c,d}$				
	Model d			
Model c	B/M	E/P	$-Ret[-1,0]$	$-Ret[-12,0]$
CAPM 3-Year CAR	-0.46	-0.50	0.32	0.42
	(2.67)	(3.42)	(3.05)	(3.70)

This table reports the coefficients and *t*-statistics associated with $\gamma^{c,d}$ from the test in equation (7):

$$OppRP_{i,t} = \mu_t + \gamma^{c,d}(\Theta^c_{it} - \Theta^d_{it}) + \xi_{it}.$$

The right-hand variable is the difference in the binary rank of Θ, which may be a price multiple (B/M or E/P), prior 1-month or 1-year return or the forecasted 3-year CAR with respect to the CAPM. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 7: Pairwise Comparisons With Control Groups: Expected 3-Year CAR

Estimated $\gamma^{c,d}$					
	Model d				
Model c	Excess Market	FF3	Carhart	FF5	HXZ
CAPM	0.51	0.36	0.27	0.61	0.76
	(4.03)	(2.90)	(2.00)	(5.15)	(6.13)
Excess Market		-0.14	-0.28	0.16	0.41
		(1.26)	(2.30)	(1.56)	(3.58)
FF3			-0.25	0.53	0.91
			(1.59)	(4.05)	(6.41)
Carhart				0.55	0.88
				(4.05)	(6.30)
FF5					0.51
					(3.39)

This table reports the coefficients and *t*-statistics associated with $\gamma^{c,d}$ from the test in equation (7):

$$OppRP_{i,t} = \mu_t + \gamma^{c,d}(\Theta^c_{it} - \Theta^d_{it}) + \xi_{it}.$$

The right-hand variable is the difference in the binary rank of ex-ante 3-year CAR Θ with respect to asset pricing model c vs. d. Binary ranking of firms is done within 25 size and Tobin's q control groups. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 8: Pairwise Model Comparison, BHO Method

Estimated $\gamma^{c,d}$					
	Model d				
Model c	Excess Market	FF3	Carhart	FF5	HXZ
		Sum of differences			
CAPM	0.43	0.64	0.83	0.69	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Excess Market		0.28	0.17	0.26	0.57
		(0.00)	(0.08)	(0.00)	(0.00)
FF3			-0.70	0.30	0.76
			(0.03)	(0.12)	(0.00)
Carhart				0.39	0.95
				(0.59)	(0.00)
FF5					0.72
					(0.00)
		% of differences > 0			
CAPM	84.44	93.33	88.64	93.33	100.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Excess Market		73.33	68.89	77.78	86.67
		(0.00)	(0.02)	(0.00)	(0.00)
FF3			45.95	48.84	87.80
			(0.74)	(1.00)	(0.00)
Carhart				63.64	95.56
				(0.10)	(0.00)
FF5					82.93
					(0.00)

This table presents the results of pairwise horse race between competing risk models using BHO method. We estimate the relation between the opportunistic repurchase dummy (left hand side) and dummy variables denoting the decile ranks of forecasted 3-year CAR with respect to two competing asset pricing models:

$$OppRP_{i,t} = \mu_t + \sum_j \sum_k b_{jk} D_{jkit} + \xi_{i,t}$$

We compare off diagonal coefficients of dummy variables as in Figure 2. Panel A presents sum of the differences of off-diagonal coefficient estimates and their p-values. A positive number indicates that the model in the row wins the race against the model in the column. Panel B shows the percentage of cases in which the first model (row) beats the second model (column) out of the 45 comparisons and the p-value of the binomial test. All observations are deflated by the number of firms in each quarter.

Table 9: Single Model Regressions: Non-Opportunistic Repurchases

Panel A. Risk-Adjusting Models and Excess Market (5-Year CAR)						
	CAPM	Excess Market	FF3	Carhart	FF5	HXZ
Estimated γ^c	15.30	-9.41	24.27	23.03	20.31	17.53
	(16.45)	(12.23)	(28.18)	(30.17)	(24.99)	(17.18)

Panel B. Simple Heuristic Signals				
	B/M	E/P	Prior 1-Mo Ret	Prior 1-Yr Ret
Estimated γ^c	-10.14	16.33	2.22	5.99
	(14.02)	(23.71)	(4.99)	(9.37)

This table reports the results of the regression of the dummy variable on non-opportunistic repurchase, $NonOppRP_{i,t}$, on the binary rank of an undervaluation signal used by firm managers:

$$NonOppRP_{i,t} = \mu_t + \gamma^c \Theta^c_{it} + \epsilon_{it},$$

where Θ^c here represents the firm-level price multiple or past return signal. All regressions include time fixed effects and observations are deflated by the number of firms in each quarter. The *t*-statistics are computed using double-clustered standard errors by firm and quarter.

A Appendix: Proofs

Proof of proposition 1. This proposition directly follows from Assumption 1, considering that the cross-sectional rank of mispricing is increasing in the level of mispricing. ■

Proof of proposition 2. Note that Δ_{it} is equal to 1 for half of the observations and equal to 0 for the other half by construction. Hence, $E[\Delta_{it}] = \frac{1}{2}$ and $Var(\Delta_{it}) = \frac{1}{4}$.

$$\begin{aligned}
\beta = \frac{Cov(\phi(n_{it}), \Delta_{it})}{Var(\Delta_{it})} &= 4 \times (E[\phi(n_{it})\Delta_{it}] - E[\phi(n_{it})]E[\Delta_{it}]) \\
&= 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it} = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it} = 0]) \\
&= Pr[\phi(n_{it}) = 1|\Delta_{it} = 1] - Pr[\phi(n_{it}) = 1|\Delta_{it} = 0] \qquad \text{(A.1)} \\
&= \sum_{X_{it}} \Big(Pr[\phi(n_{it}) = 1|\Delta_{it} = 1, X_{it}] \frac{Pr[\Delta_{it} = 1|X_{it}]Pr[X_{it}]}{Pr[\Delta_{it} = 1]} \\
&\qquad - Pr[\phi(n_{it}) = 1|\Delta_{it} = 0, X_{it}] \frac{Pr[\Delta_{it} = 0|X_{it}]Pr[X_{it}]}{Pr[\Delta_{it} = 0]} \Big) \\
&= \sum_{X_{it}} Pr[X_{it}] \Big(Pr[\phi(n_{it}) = 1|\Delta_{it} = 1, X_{it}] - Pr[\phi(n_{it}) = 1|\Delta_{it} = 0, X_{it}] \Big) \qquad \text{(A.2)}
\end{aligned}$$

The last line comes from the fact that $Pr[\Delta_{it} = 1|X_{it}] = Pr[\Delta_{it} = 0|X_{it}] = Pr[\Delta_{it}] = \frac{1}{2}$ by construction. Proposition 1 implies that the term in the parenthesis is positive for every X_{it}, hence $\beta > 0$. ■

In order to prove Proposition 3, we use the following lemma:

Lemma 1. *For any two asset pricing models and within each control group:*

$$Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] = Pr[\Delta_{it}^T = 0, \Delta_{it}^F = 1|X_{it}] \qquad \text{(A.3)}$$

Proof of Lemma 1.

$$Pr[\Delta_{it}^T = 1|X_{it}] = \frac{1}{2} = Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 1|X_{it}] + Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] \tag{A.4}$$

$$Pr[\Delta_{it}^F = 1|X_{it}] = \frac{1}{2} = Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 1|X_{it}] + Pr[\Delta_{it}^T = 0, \Delta_{it}^F = 1|X_{it}] \tag{A.5}$$

Comparing above two equations proves the result. ■

Proof of proposition 3. In Proposition 2 we showed that:

$$\beta = 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it} = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it} = 0]) \tag{A.6}$$

We can write β^T and β^F as follows:

$$\begin{aligned}
\beta^T &= 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0]) \\
&= 2 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 1] + Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] \\
&\qquad - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 0] \Big) \qquad \text{(A.7)} \\
\beta^F &= 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it}^F = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^F = 0]) \\
&= 2 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 1] + Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] \\
&\qquad - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 0] \Big) \qquad \text{(A.8)}
\end{aligned}$$

Thus,

$$\begin{aligned}
\beta^T - \beta^F &= 4 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] \Big) \\
&= 4 \sum_{X_{it}} \Big(Pr[\phi(n_{it}) = 1|\Delta_{it}^T = 1, \Delta_{it}^F = 0, X_{it}] Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] Pr[X_{it}] \\
&\qquad - Pr[\phi(n_{it}) = 1|\Delta_{it}^T = -1, \Delta_{it}^F = 1, X_{it}] Pr[\Delta_{it}^T = -1, \Delta_{it}^F = 1|X_{it}] Pr[X_{it}] \Big)
\end{aligned} \tag{A.9}$$

By using Lemma 1, we can simplify above equation:

$$\begin{aligned}\beta^T - \beta^F &= 4\sum_{X_{it}} Pr[\Delta^T_{it}=1, \Delta^F_{it}=0|X_{it}]Pr[X_{it}] \\ &\qquad \times \Big(Pr[\phi(n_{it})=1|\Delta^T_{it}=1,\Delta^F_{it}=0,X_{it}] - Pr[\phi(n_{it})=1|\Delta^T_{it}=0,\Delta^F_{it}=1,X_{it}]\Big) \\ &= 4\sum_{X_{it}} Pr[\Delta^T_{it}=1, \Delta^F_{it}=0|X_{it}]Pr[X_{it}] \\ &\qquad \times \Big(Pr[\phi(n_{it})=1|\Delta^T_{it}=1,X_{it}] - Pr[\phi(n_{it})=1|\Delta^T_{it}=0,X_{it}]\Big)\end{aligned}$$

The last line comes from the fact that $Pr[\phi(n_{it})|\Delta^T_{it},\Delta^F_{it},X_{it}] = Pr[\phi(n_{it})|\Delta^T_{it},X_{it}]$. Proposition 1 implies that the term in the parenthesis is positive for every X_{it}, hence $\beta^T > \beta^F$. ■

Proof of proposition 4. Define:

$$\pi^c = Pr[\Delta_{it}=1|\Delta^c_{it}=1] + Pr[\Delta_{it}=0|\Delta^c_{it}=0] \tag{A.10}$$

By using equation (A.1), we can write:

$$\beta^c = Pr[\phi(n_{it})=1|\Delta^c_{it}=1] - Pr[\phi(n_{it})=1|\Delta^c_{it}=0] \tag{A.11}$$

We can write this as:

$$\begin{aligned}\beta^c =& Pr[\phi(n_{it})=1|\Delta^c_{it}=1,\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=1] \\ &+ Pr[\phi(n_{it})=1|\Delta^c_{it}=1,\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=1] \\ &- Pr[\phi(n_{it})=1|\Delta^c_{it}=0,\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=0] \\ &- Pr[\phi(n_{it})=1|\Delta^c_{it}=0,\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=0] \\ =& Pr[\phi(n_{it})=1|\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=1] + Pr[\phi(n_{it})=1|\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=1] \\ &- Pr[\phi(n_{it})=1|\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=0] - Pr[\phi(n_{it})=1|\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=0] \\ =& \Big(Pr[\phi(n_{it})=1|\Delta_{it}=1] - Pr[\phi(n_{it})=1|\Delta_{it}=0]\Big)(\pi^c - 1)\end{aligned} \tag{A.12}$$

The term in the first parenthesis is positive by Proposition 1, so $\beta^c > \beta^d$ is equivalent to $\pi^c > \pi^d$. ■

Proof of proposition 5.

$$\gamma_1 = \frac{Cov(\phi(n_{it}), \Delta_{it}^c - \Delta_{it}^d)}{Var(\Delta_{it}^c - \Delta_{it}^d)} \tag{A.13}$$

and since $Var(\Delta_{it}^c) = Var(\Delta_{it}^d) = \frac{1}{4}$ by construction:

$$\gamma_1 = \frac{\beta^c - \beta^d}{4 \times Var(\Delta_{it}^c - \Delta_{it}^d)} \tag{A.14}$$

Therefore, $\beta^c > \beta^d$ is equivalent to $\gamma_1 > 0$. ■

Proof that our results are identical to Fama-MacBeth. Let $\dot{\phi}_{i,t}$ and $\dot{\Delta}_{i,t}$ be the cross-sectionally demeaned variables for the direction of net issuance and the binary rank of mispricing. Then, the univariate coefficient from a panel regression with time fixed effects is

$$\frac{4}{TN} \sum_t \sum_i \dot{\phi}_{i,t} \dot{\Delta}_{i,t}, \tag{A.15}$$

where $1/4$ is the sample variance of $\dot{\Delta}_{i,t}$, which is either $-1/2$ or $1/2$. Here, we assume balanced panel. Although in reality our panel data are unbalanced, we use weighted least squares to ensure that different years have the same weight in the regression. Hence, it suffices to analyze the balanced panel case.[2] On the other hand, the Fama-MacBeth coefficient is

$$\frac{1}{T} \sum_t \left(\frac{4}{N} \sum_i \dot{\phi}_{i,t} \dot{\Delta}_{i,t}\right), \tag{A.16}$$

which can be rearranged to be identical to the panel coefficient above. ■

[2]We also ignore the degrees of freedom adjustment in the sample covariance calculation for simplicity.