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An Accounting-Based Measure of Valuation Uncertainty

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ABSTRACT: Existing measures of valuation uncertainty are indirect or available for limited samples. We use an accounting-based valuation model to estimate a set of hypothetical intrinsic equity values and measure uncertainty by their spread. We show that our measure reflects both cash flow and discount rate uncertainty, explains price ranges in IPO prospectuses and M&A fairness opinions, and incrementally predicts various future outcomes indicative of uncertainty. An application of our measure to a popular asset pricing context yields new insights into the properties of the value premium. Overall, our paper demonstrates how accounting information can be used to summarize uncertainty about intrinsic equity value.

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I. INTRODUCTION

The main purpose of financial reporting is to aid investors in forming economic decisions (SFAC No. 8; FASB 2021). Such decisions often require estimating not only expected equity values but also their likely ranges—valuations are inherently uncertain. The accounting literature has focused primarily on the former task, producing accounting-based valuation models in which financial statement information is used to estimate expected equity values (e.g., Ohlson 1995; Feltham and Ohlson 1995). This literature has also studied the role of various accounting items in explaining observed equity prices (e.g., Barth, Beaver, Hand, and Landsman 1999; Collins, Maydew, and Weiss 1997) and, to a lesser extent, explaining market-based measures of risk, such as return volatility (e.g., Sridharan 2015;

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Heflin, Kolev, and Whipple 2024). In this paper, we adopt the perspective of an investor concerned with uncertainty about intrinsic equity value. Measurement of such uncertainty is of particular interest to long-term fundamental investors dealing with both public and private equities. Valuation uncertainty is also key to many theoretical models.[1]

To date, the empirical measurement of valuation uncertainty has relied on various proxies, including firm size, asset tangibility, return volatility, option-implied volatility, and analysts' forecast dispersion. The indirect nature or restricted availability of these proxies can stand in the way of well specified tests of the associated models' predictions. For instance, measures of option-implied volatility and analysts' forecast dispersion restrict the sample to smaller sizes, whereas return volatility is backward-looking and requires firms to be listed. In this paper, we use an accounting-based valuation framework to develop a theoretically motivated empirical measure of equity valuation uncertainty that is available for large samples and can be obtained even for private firms. Having established the validity of this new measure, we apply it to a popular asset pricing context. This particular analysis yields novel insights into the nature of the value premium.

We consider a setup in which investors face uncertainty about the distribution of future cash flows and the applicable discount rate, both resolved at some intermediate stage. In that framework, current stock price derives from possible future state-contingent valuations. The dispersion of those values is what we call valuation uncertainty, and our core innovation is the methodology for obtaining such hypothetical valuations. To value firms, we build on the work of Rhodes-Kropf, Robinson, and Viswanathan (2005), who map stock prices into accounting fundamentals to obtain industry-year valuation multiples rooted in the residual income valuation model. We refine that approach in a number of ways and incorporate intangible capital in light of its rising importance (see, e.g., Barth, Li, and McClure 2023). To obtain a *range* of hypothetical fundamental values of a given firm, we model after Konstantinidi and Pope (2016), who use quantile regressions to forecast risk in corporate earnings. We estimate quantile regressions of equity values on accounting fundamentals by industry-year and use the valuation multiples of high- and low-valued peers to generate a range of hypothetical state-contingent values for a given firm. We measure valuation uncertainty as the (scaled) range between valuations implied by the 25th and 75th percentiles of peer valuations.[2]

We validate our measure of valuation uncertainty using a variety of approaches. Theoretically, valuation uncertainty stems from uncertainty about cash flows and discount rates. We show that our measure is indeed related to several *ex ante* firm characteristics linked to such uncertainty. For instance, our measure is higher for firms with more volatile earnings, higher accruals, lower quality earnings, and lower earnings smoothness. It is also higher for firms with more volatile market betas and for firms with higher beta estimation uncertainty (standard error of beta estimates). We then show that our measure is predictive of future or contemporaneous outcomes indicative of cash flow, discount rate, and overall valuation uncertainties. In particular, our measure predicts future stock return volatility and contemporaneous option-implied volatility. It also predicts dispersion in analysts' earnings and long-term growth forecasts, cash flow news volatility, future beta volatility, and the standard error of future beta estimates. Finally, we validate our measure against firm-specific valuation spreads from valuation experts in two contexts. Specifically, we show that our measure explains the width of the proposed price range in IPO prospectuses and the range of fair values of M&A targets in fairness opinions.

Although possible applications of our new measure are numerous, we demonstrate its power through an application to cross-sectional asset pricing. In particular, we test the hypothesis that valuation uncertainty is conducive to valuation mistakes. This prediction obtains in models with heterogeneous investor beliefs and trading frictions (e.g., Miller 1977; Hong, Scheinkman, and Xiong 2006), in models of Bayesian learning (e.g., Lewellen and Shanken 2002), as well as in models with biased investor beliefs (e.g., Daniel, Hirshleifer, and Subrahmanyam 1998).[3] We proxy for valuation mistakes (both under- and overvaluation) with deviations of stock prices from expected fundamental values (i.e., price-to-value ratio), given the same empirical valuation model that we use to derive valuation uncertainty. We refer to low (high) price-to-value stocks as "value" ("growth"). Our analysis here follows Golubov and Konstantinidi (2019), who find that price-to-value is responsible for the entire value premium. We present two novel findings.

First, the long-short strategy formed on price-to-value generates significantly greater returns and Sharpe ratios as valuation uncertainty increases. The average returns of the high-valuation uncertainty "growth" stocks are particularly

[1] Valuation uncertainty is central in models of disclosure (e.g., Lambert, Leuz, and Verrecchia 2007), security issuance (e.g., Myers and Majluf 1984; Benveniste and Spindt 1989), market microstructure (e.g., Glosten and Milgrom 1985; Bessembinder, Hao, and Zheng 2015), and Bayesian learning (e.g., Pástor and Veronesi 2009).

[2] Although, in this paper, we focus on valuation uncertainty due to its central role in accounting and finance, our approach can be used to measure other aspects of the implied distribution of intrinsic values—such as skewness, kurtosis, or value-at-risk (VaR).

[3] Given these different frameworks, our use of the terms "valuation mistakes" and "mispricing" should not be taken to imply investor irrationality. Deviations of prices from fundamental values can occur even when investors are fully rational and use all available information. See Brav and Heaton (2002) for in-depth analysis of this point.

low—as low as the risk-free rate. Second, valuation uncertainty shapes the sensitivity of "value" and "growth" stocks to investor sentiment. Among low-valuation uncertainty stocks, low investor sentiment does not raise the returns of "value" firms and high investor sentiment does not lower the returns of "growth" firms. In contrast, for high-valuation uncertainty stocks, sentiment matters: buying "value" stocks is especially profitable following episodes of low sentiment, whereas shorting "growth" stocks is particularly profitable following high-sentiment periods (when these stocks actually exhibit *negative* average returns).

Overall, these findings are consistent with the hypothesis that valuation uncertainty promotes valuation mistakes and provide some further indirect validation of our measure.[4] As an interesting by-product, this analysis also provides some suggestive evidence on the potential reasons behind the recent "disappearance" of the value premium. First, we show that the profitability of our price-to-value strategy is concentrated in periods of extreme sentiment. Moderate sentiment is not conducive to the buildup of mispricing. Incidentally, sentiment in the recent period was moderate. Second, we show that much of the recent losses produced by the *conventional* value strategy is due to implicit sorting on the ratio of estimated fundamental value to book value and especially among high-valuation uncertainty stocks. We document some preliminary evidence that this may be linked to a duration effect, given the low interest rate environment of the recent years.

Our paper makes two distinct contributions. First, it introduces and validates a novel measure of equity valuation uncertainty that relies on accounting numbers. Unlike existing proxies, the unique advantage of our measure is its direct link to the corresponding theoretical construct and its availability for a large cross-section of firms—including private companies. This part of our work is related to Joos, Piotroski, and Srinivasan (2016); Joos and Piotroski (2017); and Bochkay and Joos (2021), who use the spread of scenario-based analysts' valuations as a measure of valuation uncertainty, as well as to Aleczczyk, Vasvari, and Vyas (2023), who use ranges of asset liquidation values from bankruptcy filings as a proxy for uncertainty about asset recovery values. More broadly, the methodological part of our paper contributes to the literature on the "risk-relevance" of accounting information (e.g., Beaver, Kettler, and Scholes 1970; Baginski and Wahlen 2003; Nekrasov and Shroff 2009; Sridharan 2015; Heflin et al. 2024). Second, our application of the measure yields novel insights into the cross-sectional and time-series properties of the value premium and related anomalies. Hence, our findings add to the literature on the economic origins of the book-to-market effect in stock returns. This part of our paper is related to the work of Gonçalves and Leonard (2023); Golubov and Konstantinidi (2019); Piotroski and So (2012); Frankel and Lee (1998); and La Porta, Lakonishok, Shleifer, and Vishny (1997).

The paper proceeds as follows. We discuss our measurement framework in Section II. We describe data processing, estimation, and the properties of our new measure in Section III. Validation tests are presented in Section IV. In Section V, we use our measure to test the hypothesis that valuation uncertainty promotes valuation mistakes. Section VI concludes with a discussion of potential applications and extensions. The Online Appendix contains supplementary material. Our valuation uncertainty measure, as well as the valuation model coefficients for out-of-sample prediction of the measure, can be accessed by downloading data file GK_VU_data.xlsx.

II. FRAMEWORK AND METHODOLOGY

Valuation Uncertainty

We start from the classic asset pricing equation $P = E(x)/R_f + \mathrm{cov}(m, x)$, where P is today's ($t = 0$) price, x is the future payoff, R_f is the gross risk-free rate, and m is the stochastic discount factor (SDF).[5] Implicit here is an assumption that $E(x)$ and $\mathrm{cov}(m, x)$ are known at $t = 0$. However, $E(x)$ and $\mathrm{cov}(m, x)$ are rarely known with certainty, giving rise to what we call valuation uncertainty. Consider the following setup. A firm is developing a project that will generate some risky future cash flow. The distribution governing this cash flow depends on the outcome of an intermediate stage, revealed at $t+i$: the project either yields a "success" (state H) or a "disappointment" (state L). In the event of success (e.g., product takes off), future cash flows come from a distribution with a high expected value $E(x^H)$. In the case of disappointment, future cash flows are expected to be modest, coming from a distribution with a lower expected value $E(x^L)$.

[4] Some of these results are also in line with a risk premium interpretation, whereby high-valuation uncertainty "value" stocks are especially risky and high-valuation uncertainty "growth" stocks are particularly low risk. However, certain aspects of our findings are hard to square with a risk premium view alone. First, the magnitude of the value premium among high-valuation uncertainty stocks appears too large—the Sharpe ratio is double that of the market portfolio. Second, the average return of high-valuation uncertainty "growth" stocks matches that of T-bills—as if it was a risk-free asset. This seems unlikely, given the *negative* returns of these stocks following periods of high investor sentiment. Nevertheless, our evidence should be seen as *consistent* with valuation mistakes, not a proof thereof.

[5] Note that, for risky assets, covariances with the SDF are negative (i.e., $\mathrm{cov}(m, x) < 0$), with lower values corresponding to higher procyclicality (e.g., higher betas with the market).

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Cash flows in both states are uncertain and have their own covariances with the SDF, cov(m, x^H) and cov(m, x^L). Conditional on the success state, the $t+i$ state-contingent value of the payoff is $P^H = E(x^H) / R_f + \text{cov}(m, x^H)$. Similarly, the $t+i$ state-contingent value in the disappointment case is $P^L = E(x^L) / R_f + \text{cov}(m, x^L)$. Without loss of generality, we assume that state realization (H or L) is uncorrelated with the SDF (i.e., state realization risk requires no compensation) and that the time increment i is negligibly small (i.e., no need to discount P^H and P^L from $t+i$ to $t = 0$[6]). The price of this stock at $t = 0$ is then:

$$P = P^H * prob + P^L * (1 - prob) \tag{1}$$

where $0 < prob < 1$ is the probability of success. As Equation (1) shows, today's valuation of the stock derives from the distribution of (future) state-contingent values P^H and P^L. We define valuation uncertainty (VU) as the spread of this distribution[7]:

$$VU = P^H - P^L = \left[E(x^H)/R_f + cov(m, x^H)\right] - \left[E(x^L)/R_f + cov(m, x^L)\right] \tag{2}$$

$$VU = 1/R_f * \left[E(x^H) - E(x^L)\right] + \left[cov(m, x^H) - cov(m, x^L)\right] \tag{3}$$

Equation (3) shows that valuation uncertainty rises with uncertainty about future cash flows (how much $E(x^H)$ differs from $E(x^L)$) and discount rates (how much cov(m, x^H) differs from cov(m, x^L)). However, measuring valuation uncertainty is a challenge: we observe stock prices P, but not P^H, P^L, or the underlying expectations and covariances. We propose to recover P^H and P^L from high- and low-valued peers—our window into states H and L—and infer the associated discount rates and growth rates from market prices and accounting fundamentals. To that end, we use an adaptation of the residual income valuation model in Rhodes-Kropf et al. (2005) (RRV hereafter) and Golubov and Konstantinidi (2019) (GK hereafter) along with quantile regression estimation.

Valuation Model

The starting point of our empirical valuation model is the residual income valuation equation[8] (e.g., Ohlson 1995; Feltham and Ohlson 1995; Francis, Olsson, and Oswald 2000):

$$V = B_0 + \sum_{t=1}^{\infty} \frac{(ROE_t - r)B_{t-1}}{(1 + r)^t} = B_0 + \sum_{t=1}^{\infty} \frac{RI_t}{(1 + r)^t} \tag{4}$$

The residual income valuation model states that equity value (V) is equal to current book value (B_0) plus the present value of the stream of future residual income (RI_t). Book value represents the value of (net) assets in place. Residual income represents expected future earnings above the level that is required by the cost of equity capital. Under the assumptions that (1) residual income is a constant fraction (d) of net income (NI_t) and (2) net income grows at a constant rate g in perpetuity (where $r > g$), the present value of the stream of residual income can be expressed as $NI_0 * (1 + g) * d / (r - g)$. That is, the second term in Equation (4) can be expressed as a multiple of current net income. RRV propose to infer this multiple from stock prices and accounting fundamentals of all firms in the same industry-year by running a cross-sectional regression of market value of equity on book value and net income. The actual regression run by RRV is of the following form:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt}|ni_{it}| + \alpha_{3jt} I_{NI<0} \times |ni_{it}| + \alpha_{4jt} LEV_{it} + \varepsilon_{it}, \tag{5}$$

6 Alternatively, one can assume that the time increment i is more substantial but that the risk-free rate is 0.

7 We require that $P^H > P^L$, which is equivalent to $\left(E(x^H) / R_f - E(x^L) / R_f\right) > \left(\text{cov}(m, x^L) - \text{cov}(m, x^H)\right)$. This is a realistic assumption. For instance, if the success state were simply a scaled-up version of the disappointment case, where $x^H = k * x^L$ with $k > 1$, then $E(x^H) / E(x^L) = k$, $\text{cov}(m, x^H) / \text{cov}(m, x^L) = k$, and $P^H = k * P^L > P^L$. Here, H and L have *identical* systematic risk, as measured by market beta in the more familiar returns representation (since scaling the payoff scales the price proportionally, producing identical returns). More generally, the success state may have *lower* systematic risk than the disappointment state, in addition to higher cash flows. For example, if a firm's product gains necessity status, its cash flows become less sensitive to the state of the economy and cov(m, x^H) is less negative than cov(m, x^L), all else equal. This reduces the right-hand side of the inequality $\left(\text{cov}(m, x^L) - \text{cov}(m, x^H)\right)$, reinforcing that $P^H > P^L$. Although it is possible for the success state to have higher systematic risk, it is rarely enough to overturn the ordering $P^H > P^L$ since the magnitude of the expected payoff $E(x)/R_f$ tends to dominate that of the risk adjustment cov(m, x).

8 The residual income model is equivalent to the dividend discount model under clean-surplus accounting.

where m_{it} is log market value of equity, b_{it} is log book value of equity, $|ni_{it}|$ is log of absolute net income, $I_{NI<0}$ is an indicator for loss-making firms, and LEV_{it} is book leverage. The regression is estimated in logs, which has two appealing theoretical features. First, the linear relation between log market values and log book values/earnings is convex in their levels, which corresponds to the functional form predicted by Burgstahler and Dichev (1997). Second, this specification ensures that predicted market values are not negative, consistent with limited liability. Since the natural logarithm of net income is not defined for loss-making firms, RRV use the absolute value of net income and estimate a separate multiple for loss-making firms via the interaction term (thus also accounting for the differential relation between market values and earnings in the loss domain (see, e.g., Collins, Pincus, and Xie 1999)). The leverage term acts as a parsimonious adjustment for the possibility that multiples (i.e., cost of equity capital and growth rates) may differ across firms with different capital structures. Overall, the coefficients $\alpha_{0jt} - \alpha_{4jt}$ represent industry-year valuation multiples rooted in the residual income valuation model.[9] The fitted value from Equation (5) estimated using OLS is the expected log market equity, denoted as v.

We make one modification to the valuation model in Equation (5), motivated by the rise in the importance of intangible assets over the last decades (see, e.g., Collins et al. 1997; Barth et al. 2023). It is well understood that accounting book values exclude value-relevant intangible assets, such as R&D capital. At the same time, immediate expensing of R&D depresses the reported earnings of R&D-intensive firms, which further distorts comparability of accounting fundamentals. To enhance cross-firm comparability of book values and earnings, we include capitalized R&D as an additional valuation model predictor and adjust earnings accordingly. We do not combine book equity and R&D capital into one item, to allow for the possibility that the two types of assets attract different multiples.[10] To compute the value of R&D capital, we follow the approach in Chan, Lakonishok, and Sougiannis (2001). In particular, we capitalize yearly R&D expenditures under the assumption of a five-year useful life and a straight-line amortization rate of 20 percent.[11] We adjust earnings by adding back the R&D expense and subtracting amortization applicable to that particular year. The valuation model we estimate is therefore:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt}|earn_{it}| + \alpha_{3jt} I_{EARN<0} \times |earn_{it}| + \alpha_{4jt} LEV_{it} + \alpha_{5jt} rd_{it} + \varepsilon_{it}, \tag{6}$$

where $|earn_{it}|$ is the log of absolute adjusted earnings, rd_{it} is the log of capitalized R&D (equal to 0 for firms with no R&D capital), and all other variables are as defined above.[12] We make a number of additional refinements to our measurement of the valuation model inputs relative to RRV and GK, discussed further below. Detailed variable definitions are in Appendix A.

Quantile Regressions

Our innovation is to treat within-industry variability in valuation multiples as indicative of *potential* variability in the value of a given firm in that industry. That is, we view high- and low-valued industry peers as proxies for the success (H) and disappointment (L) states and their valuation multiples as reflecting $E(x^H)$ and $\text{cov}(m, x^H)$ and $E(x^L)$ and $\text{cov}(m, x^L)$, respectively. This allows us to recover the *unobservable* distribution of possible equity values $[P^H, P^L]$ for a given firm from the *observable* distribution of equity values across industry peers.[13] To obtain P^H and P^L, we use quantile regression estimates of the valuation model in Equation (6). Recall that the coefficients in our valuation model represent industry-year valuation multiples. Therefore, coefficients from quantile regressions targeting different parts of

[9] The canonical Ohlson (1995) model implies no intercept and a coefficient on book equity equal to unity. We do not impose these constraints in our estimation for three reasons. First, these constraints pertain to the model estimated in raw dollars, whereas we estimate a log specification. Second, even in the canonical raw dollar specification, conservative accounting can cause the coefficient on book equity to be greater than 1. Third, differences in accounting conservatism across industries can result in different book equity coefficients across industries. For example, Barth et al. (1999) find book equity coefficients to range from 0.99 to 2.91.

[10] Note that our ultimate use of the valuation model is to estimate uncertainty about fundamental value rather than fundamental value *per se*. Kothari, Laguerre, and Leone (2002) find that R&D investments contribute to uncertainty. In contrast, book equity acts as a measure of size and we expect large firms to have less uncertain valuations.

[11] Our R&D capitalization approach requires five years' worth of observations on R&D expenses. When such history is available, any missing values are set to zero. For newly listed firms without such history, we impute their R&D capital (and corresponding amortization) using industry multiples: we use all firms in an industry-year with sufficient prior data to compute R&D capital and express it as a multiple of current year R&D expense. We then apply this multiple to the current R&D expense of firms lacking the history of R&D expenses. Amortization is imputed similarly.

[12] We note that the R&D adjustment is not critical for our analysis and our conclusions. The valuation uncertainty measures estimated with and without adjustment for R&D have a correlation of 0.93.

[13] If prices of industry peers vary for nonfundamental reasons, namely, expectation errors, then the degree of dispersion in valuations within industry reflects not only plausible ranges of expected growth rates and discount rates but also the severity of expectation errors. To the extent that expectation errors occur when uncertainty is high—a common prediction of several theoretical setups discussed below—the variation in industry multiples is once again indicative of valuation uncertainty. Therefore, our approach to extracting valuation uncertainty from the distribution of valuations of industry peers is valid under both (1) efficient pricing and (2) pricing subject to expectation errors.

the observed distribution of equity values reflect differences in valuation multiples within an industry-year, whereas fitted values from those regressions represent hypothetical valuations implied by those multiples.[14]

Denote a given conditional quantile prediction as q_{100x}, where x is the targeted quantile. Accordingly, $q_{75} - q_{25}$ is the difference between the 75th and the 25th quantile regression predictions for the same firm or simply the fitted value from the *inter*quartile regression of Equation (6):

$$\begin{aligned} q_{75} - q_{25} &= \boldsymbol{\alpha_{75jt}} \boldsymbol{X_{it}} - \boldsymbol{\alpha_{25jt}} \boldsymbol{X_{it}} \\ &= (\boldsymbol{\alpha_{75jt}} - \boldsymbol{\alpha_{25jt}}) \boldsymbol{X_{it}}, \end{aligned} \tag{7}$$

where $\boldsymbol{\alpha_{75jt}}$ and $\boldsymbol{\alpha_{25jt}}$ are vectors of quantile regression coefficients estimated at the 75th and the 25th percentiles, respectively, and $\boldsymbol{X_{it}}$ is a vector of our valuation model predictors. If we treat the 75th and 25th percentiles of industry valuations as proxies for success and disappointment states, Equation (7) becomes a direct empirical counterpart to our construct of valuation uncertainty in Equation (2). To see this, consider the dividend discount model version of Equation (2), where D is next period dividend, r is the discount rate, g is the perpetual dividend growth rate, and superscripts H and L denote states:

$$VU = P^H - P^L = D/(r^H - g^H) - D/(r^L - g^L) \tag{8}$$

$$VU = \left(1/(r^H - g^H) - 1/(r^L - g^L)\right) * D \tag{9}$$

Here, $1 / (r^H - g^H)$ and $1 / (r^L - g^L)$ are valuation multiples that scale the only fundamental relevant in this framework, namely the level of D. As we have shown above, we can rewrite Equations (8) and (9) in terms of current book value and a growing stream of future residual income and then replace the latter as a multiple of current net income by imposing further assumptions. In that case, VU becomes a linear combination of *current* accounting fundamentals and differences in the valuation multiples associated with them. This is exactly what Equation (7) implements.

Ultimately, we work with exponentiated predicted equity values, denoted by uppercase Q_{25} and Q_{75}, and define our measure of valuation uncertainty VU as a scaled interquartile range:

$$VU = \frac{Q_{75} - Q_{25}}{(Q_{75} + Q_{25})/2} \tag{10}$$

Compared with $q_{75} - q_{25}$, the measure in Equation (10) has more desirable statistical properties (i.e., skewness and kurtosis closer to normality). Scaling by the midpoint between the two exponentiated quantiles ensures comparability across firms of different size. This definition follows Joos et al. (2016), who use the spread in scenario-based analysts' valuations as a measure of valuation uncertainty.

III. DATA SOURCES AND ESTIMATION RESULTS

Sample Selection

We start with the intersection of CRSP and Compustat databases over the period 1974–2022, although we use Compustat data from as far back as 1970 to obtain lagged observations of R&D expenses. Starting our sample period in 1974 ensures that we have at least 20 firms in our industry-level estimation in every sample year. We keep firms that have their common stock (CRSP share codes 10 and 11) listed on NYSE, American Stock Exchange (AMEX), and NASDAQ (CRSP exchange codes 1, 2, 3). We exclude all financial firms (SIC codes 6000–6999), because their financial statement information is not comparable with industrial firms and because they are subject to capital regulation. Following RRV and GK, we further drop firms with June 30 market capitalizations below \$10 million, as illiquidity frictions can prevent efficient and informative pricing of these firms' shares.

Given our task of mapping stock prices into accounting fundamentals, we take extra care to eliminate firms with multiple classes of common stock (dual-class firms). The vast majority of dual-class companies do not have their secondary class publicly traded (Gompers, Ishii, and Metrick 2010), meaning that the market capitalization from CRSP

[14] Linear quantile regressions aim to best explain a particular quantile of the dependent variable's distribution. Some notable applications of quantile regressions in accounting include Konstantinidi and Pope (2016); Correia, Kang, and Richardson (2018); and Chang, Monahan, Ouazad, and Vasvari (2021).

does not reflect the entire equity capital of dual-class firms. At the same time, book value of common equity from Compustat reflects value that is attributable to holders of all classes of common stock, resulting in a mismatch. We eliminate dual-class firms using a four-step process similar to that in Gompers et al. (2010).[15] This eliminates 7.85 percent of unique firms that account for 9.77 percent of firm-year observations.

Next, we drop observations with missing valuation model inputs. Finally, we treat outliers in the valuation model predictors by dropping observations with book-to-market ratios outside the range [0.01, 100], book leverage outside the range [0, 1], ROE outside the range [–1, 1], as well as observations in the top and bottom 1 percent of R&D capital to assets. The remaining sample of 129,074 firm-year observations over the period 1974–2022 forms the basis of our valuation model estimation. Table A1 of the Online Appendix presents descriptive statistics for this sample.

Since valuing firms using pricing information from industry peers is at the core of our analysis, we take three steps to increase the comparability of market values and accounting fundamentals. First, we add back to the market value of equity the dollar amount of dividends paid since the balance sheet date.[16] Second, we account for differences in expected ownership dilution across firms by using the fully diluted number of shares outstanding when computing the market value of equity. This has the effect of increasing the measured market value of equity of firms with dilutive securities outstanding.[17] Third, we purge earnings used in Equation (6) from one-off items. All adjustments are detailed in variable definitions in Appendix A.

Estimation Results

Table 1 presents the results from estimating our valuation model using OLS and quantile regressions. For brevity, these estimation results are shown for three representative Fama-French (FF) 12 industries: manufacturing, business equipment, and utilities. Output for remaining industries can be found in Table A2 of the Online Appendix. The reported coefficients and R^2s are time-series averages across 48 sample years. For quantile regressions, we report results for the 25th and 75th percentiles, which are the two quantiles that feed into the valuation uncertainty measure. We also report the difference between the corresponding coefficients in the two quantile regressions (75th − 25th), labeled as IQR for interquartile range. Applying the IQR coefficients to the valuation model inputs reproduces the interquartile range of the predicted distribution of log fundamental value, $q_{75} - q_{25}$, as in Equation (7). These coefficients show the impact of the valuation model predictors on the spread of the resulting distribution, which is our concept of valuation uncertainty (note that $q_{75} - q_{25} = log(Q_{75} / Q_{25})$ and $VU = (Q_{75} - Q_{25}) / \left((Q_{75} + Q_{25}) / 2\right)$; the two quantities are collinear).

First, consider the OLS coefficients. The intercept—which captures the expected log market equity of a firm with \$1 million in net assets, \$1 million of earnings, zero R&D capital, and zero leverage—can be loosely interpreted as the average value (in logs) of unrecognized intangible capital within an industry. In line with this interpretation, we find that the intercept is the lowest for utilities and the highest for the business equipment industry (the latter is dominated by high-tech firms). The coefficient on capitalized R&D follows the same pattern: R&D capital contributes positively to a firm's market equity in manufacturing and business equipment industries, but the effect is virtually zero for utilities firms. Book value of equity and earnings attract multiples that are similar across the three industries. Interestingly, we find that the coefficient on the loss dummy interaction is negative and highly statistically significant in manufacturing and business equipment industries, but not for utilities. This suggests that investors view losses in the utilities industry

[15] First, we eliminate all firms listed as dual class according to RiskMetrics (formerly Investor Responsibility Research Center (IRRC)); this screen is targeted at large and established firms. Second, we eliminate all firms that went public with a dual-class structure since 1975 according to the IPO dataset from Jay Ritter's website; this screen is targeted at smaller and more recent firms. Third, we eliminate firms whose Compustat GVKEYs are associated with more than one CRSP PERMNO. And fourth, we eliminate all firms for which the number of shares outstanding as of the fiscal year-end differs between CRSP and Compustat by more than 20 percent.

[16] This ensures that market values and book values are both "*cum dividend*." In principle, one may also want to account for other post-balance sheet date events that can create a mismatch between observed book values and market values, such as stock buybacks and issuance. We choose not to do so, because measuring the associated impacts is challenging and may add noise (e.g., we cannot accurately infer prices at which shares are issued or repurchased).

[17] To illustrate the distortions arising from dilutive securities, consider two firms, A and B, with the same accounting fundamentals (book value, earnings, etc.) and the same number of shares outstanding trading at the same prices. Consider also that Firm A has no dilutive securities outstanding (e.g., employee stock options, securities convertible into common stock), whereas Firm B does. The fact that B's shareholders are willing to pay the same price per share—despite expecting dilution of their claims to the firm's net assets and earnings—implies a higher per-share valuation multiple of the fully diluted fundamentals. That is, despite the same observed stock prices, Firm B is trading at a higher effective valuation multiple. Using fully diluted shares outstanding to compute market capitalizations captures this difference. Our adjustment is consistent with Barth, Hodder, and Stubben (2013), who argue that stock options—the most common type of dilutive securities—should be viewed as a type of equity.

TABLE 1

Valuation Model Estimation

	FF 12 Industry: Manufacturing				FF 12 Industry: Business Equipment				FF 12 Industry: Utilities			
	OLS	25%	75%	IQR	OLS	25%	75%	IQR	OLS	25%	75%	IQR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	1.535	1.066	2.028	0.961	1.854	1.287	2.421	1.134	1.461	1.480	1.657	0.176
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.088)
b	0.565	0.569	0.524	−0.046	0.541	0.555	0.501	−0.054	0.584	0.494	0.558	0.064
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.134)
$\lvert earn\rvert$	0.346	0.403	0.369	−0.034	0.328	0.369	0.355	−0.013	0.349	0.458	0.373	−0.084
	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.382)	(0.000)	(0.000)	(0.000)	(0.043)
$\lvert earn\rvert \times I_{EARN<0}$	−0.219	−0.283	−0.162	0.121	−0.259	−0.316	−0.235	0.081	−0.123	−0.132	−0.081	0.051
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.232)	(0.267)	(0.355)	(0.194)
LEV	0.074	0.005	0.067	0.062	0.001	−0.035	−0.006	0.029	0.235	0.146	0.319	0.173
	(0.371)	(0.947)	(0.444)	(0.119)	(0.988)	(0.619)	(0.958)	(0.678)	(0.179)	(0.234)	(0.090)	(0.200)
rd	0.094	0.071	0.089	0.018	0.101	0.082	0.100	0.018	0.066	−0.056	−0.017	0.039
	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.038)	(0.232)	(0.397)	(0.581)	(0.342)
Adjusted R^2 [Pseudo R^2]	0.892	[0.690]	[0.694]		0.833	[0.579]	[0.607]		0.957	[0.841]	[0.805]	

This table reports results from estimating the valuation model in Equation (6) using annual cross-sectional regressions (Fama-MacBeth style) for three representative industries in the FF 12 industries classification: manufacturing, business equipment, and utilities. Columns (1), (5), and (9) report the OLS estimation results. Columns (2), (6), and (10) report estimation results from quantile regressions estimated at the 25th percentile. Columns (3), (7), and (11) report estimation results from quantile regressions estimated at the 75th percentile. Columns (4), (8), and (12) report the so-called IQR coefficients, which equal the difference in coefficients on the same regressor between quantile regressions estimated at the 75th and 25th percentiles. The regression model is:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt}|earn_{it}| + \alpha_{3jt} I_{EARN<0} \times |earn_{it}| + \alpha_{4jt} LEV_{it} + \alpha_{5jt} rd_{it} + \varepsilon_{it},$$

where m_{it} is log (modified) market value of equity, b_{it} is log book value of equity, $|earn_{it}|$ is log absolute adjusted earnings, $I_{EARN<0}$ is an indicator for firms with negative adjusted earnings, LEV_{it} is book leverage, rd_{it} is log(1 + capitalized R&D), and ε_{it} is an error term. The estimation sample includes 129,074 firm-year observations. The sample period runs from 1975 to 2022 (48 years).
Detailed variable definitions are provided in Appendix A.

as more transitory. The coefficient on leverage is insignificant for all three industries. One possible interpretation of this result is that, on average, firms operate at their optimal capital structure.

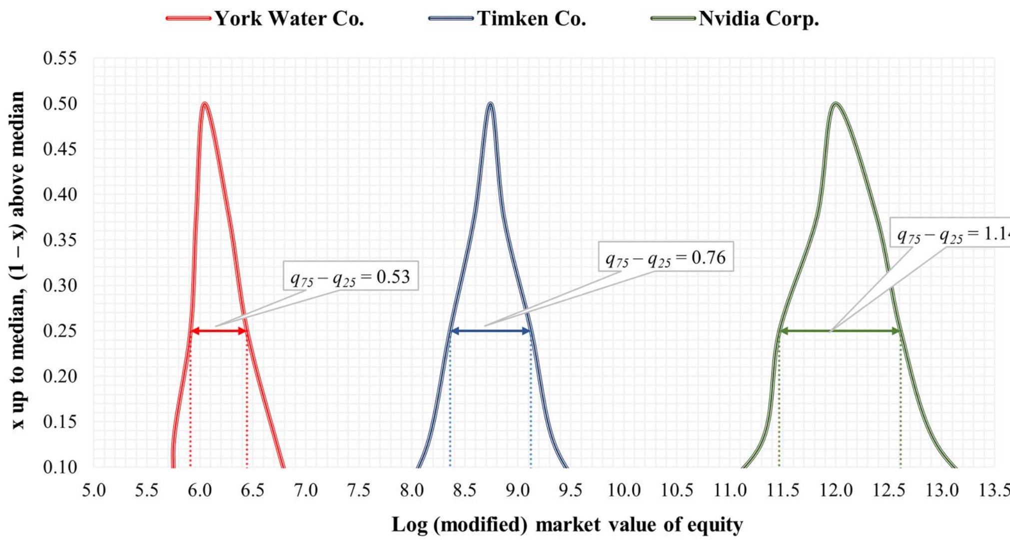
We now turn to the results from quantile regressions. Here, it is most informative to focus on the IQR coefficients, as these coefficients indicate the impact of fundamentals in our valuation model on valuation uncertainty (VU). In fact, the variation in VU comes from two sources: (1) the variation in fundamentals across firms and (2) the variation in IQR coefficients across industry-years. The results indicate that book value of equity—a measure of size—has a negative impact on valuation uncertainty in manufacturing and business equipment industries. Interestingly, the same effect is positive in the utilities industry, albeit not statistically significant. Firms with larger earnings are associated with lower valuation uncertainty in utilities and manufacturing industries, but the effect is insignificant for business equipment firms. The coefficient on negative earnings is positive for all three industries but statistically significant only for manufacturing and business equipment firms: the size of losses does not contribute to valuation uncertainty in the utilities industry. The value of R&D capital positively contributes to the spread of the distribution of estimated fundamental values in manufacturing and business equipment industries, but not in the utilities industry.[18] The effect of leverage is insignificant throughout. Finally, firms in the utilities industry have the lowest "base" level of valuation uncertainty, as evidenced by the intercept.

Figure 1 illustrates the core of our measurement framework using estimates for three sample firms as of the most recent year of our data (June 30, 2022). The three firms—NVidia Corp., Timken Co., and York Water Co.—come from the three industries discussed above, namely, business equipment, manufacturing, and utilities, respectively. For

[18] The finding of R&D contributing to uncertainty is consistent with the results in Kothari et al. (2002).

FIGURE 1

Illustrative Example of Valuation Uncertainty Estimation for Three Sample Firms



This figure plots the predicted quantiles q_{100x} of log (modified) market equity (q_5, $q_{12.5}$, q_{25}, $q_{37.5}$, q_{50}, $q_{62.5}$, q_{75}, $q_{87.5}$, and q_{95}) for three representative firms as of the most recent sample year (June 30, 2022). The horizontal axis is the estimated log (modified) market value of equity. The vertical axis is the quantile of the distribution: x up to the 50th percentile and $(1 - x)$ above the 50th percentile. The red line depicts the estimates for The York Water Company (FF12 industry—utilities). The blue line depicts the estimates for The Timken Company (FF12 industry—manufacturing). The green line depicts the estimates for NVidia Corporation (FF12 industry—business equipment).
(The full-color version is available online.)

each firm, we plot the predicted value of log market equity for various quantiles (from Equation (6)) on the horizontal axis and the corresponding quantile x on the vertical axis. Quantiles above the 50th percentile are inverted as $(1 - x)$, resulting in a visual presentation that resembles the density function. The spread of the resulting distribution is summarized by its interquartile range $q_{75} - q_{25}$. Note that the logarithmic scale of the horizontal axis implies that $q_{75} - q_{25}$ is comparable across firms of different size. The figure shows that the predicted equity values of NVidia Corp. are more spread out than those of Timken Co., whereas the predicted equity values of Timken Co. are more dispersed than those of York Water Co. Therefore, NVidia is subject to greater valuation uncertainty than Timken, whereas York Water exhibits the lowest valuation uncertainty of the three firms. Figure 1 also demonstrates the pitfalls of using indirect proxies for valuation uncertainty. In particular, note that the horizontal axis reflects firm size—a commonly used (inverse) measure. According to firm size, NVidia is the least uncertain firm and York Water is the most uncertain—exactly opposite to our inference.

In our analysis below, we work with exponentiated values of predicted quantiles and compute our valuation uncertainty measure VU as the interquartile range scaled by the midpoint, as shown in Equation (10). Prior to computing VU, we ensure that the distributions of implied fundamental value are well behaved. Specifically, we require that $Q_{12.5} < Q_{25} < Q_{37.5} < Q_{50} < Q_{62.5} < Q_{75} < Q_{87.5}$ and that the difference in predicted values for each of these increments is at least 1 percent. Our resulting sample contains 120,183 firm-year observations for 13,952 unique firms over the period 1974–2022.[19] Table A3 of the Online Appendix presents descriptive statistics of VU for the overall sample and by industry. On average, the sample mean of VU is 0.777, which implies that the range between the 75th and 25th percentiles of implied equity values equals 77.7 percent of their midpoint. VU exhibits meaningful variability, with a standard deviation of 0.239—and the variation across industries is intuitive. For instance, VU is lowest for utilities and highest for the "business equipment" industry (dominated by tech companies) and the medical industry (dominated by

[19] Having obtained the necessary coefficients, one can generate our measure of valuation uncertainty for firms that are not part of the estimation—by means of out-of-sample prediction. It is even possible to do this for private firms, which may be of interest in studies of IPO underpricing, among others (e.g., Barth, Landsman, and Taylor 2017).

biotech firms). Thus, our measure aligns with subjective assessments of relative valuation uncertainty based on industry affiliation and common wisdom.

As a final element of descriptive statistics, we examine the extent to which our measure is explained by industry-, firm-, and time-specific factors—as reflected in the R^2 of full-sample regressions of *VU* on various sets of fixed effects (Table A4 of the Online Appendix). Year fixed effects (48 year-dummies) account for a nontrivial 22.8 percent of the variation in our measure. Dummies for Fama-French 48 industries (of which 44 are represented) explain 33.2 percent of the variation in *VU*—somewhat expected, given that we exploit the dispersion of valuations within industries in its construction. Together, year and industry fixed effects explain 49 percent of the variation. With half of the variation in *VU unexplained* by industry and year effects, our measure appears well suited for studies that wish to isolate within-industry and within-year variation. Time-invariant firm-specific factors, i.e., firm fixed effects (13,952 unique firms) explain 59.4 percent of the variation in our measure, leaving the remaining 40.6 percent available to researchers wishing to exploit within-firm variation over time. Finally, firm and year fixed effects jointly account for 68.8 percent of the variation in *VU*. Researchers wishing to control for time-invariant firm-specific heterogeneity *and* for year-specific effects are left with 31.2 percent of the variation in our measure. It appears that *VU* is best suited for cross-sectional studies—both cross-industry and cross-firm—and perhaps less so for studies requiring within-firm temporal variation *beyond* common trends. Pairwise correlations between *VU* and key variables used in the paper are reported in Table A5 of the Online Appendix.

IV. VALIDATION TESTS

Validation Using *Ex Ante* Characteristics

As Equation (3) shows, valuation uncertainty stems from the uncertainty about valuation inputs: cash flows and discount rates. Therefore, as our first validation analysis, we relate our measure to *ex ante* characteristics that have been linked to such uncertainties. Table 2 reports these tests using Fama-MacBeth cross-sectional regressions.

In column (1), we relate *VU* to earnings volatility—perhaps the most direct proxy for cash flow uncertainty. Earnings volatility is defined as the standard deviation of ROA over the most recent five years. We find that firms with more volatile earnings have higher valuation uncertainty according to our measure. The explanatory power of earnings volatility for *VU* is high, with an adjusted R^2 of 13 percent. In column (2), we consider the role of earnings persistence, measured as the slope coefficient from a firm-specific AR(1) regression of current ROA on lagged ROA (e.g., Dechow, Ge, and Schrand 2010). The coefficient on earnings persistence is negative, meaning that firms with more persistent earnings tend to have lower values of *VU*. However, the explanatory power is low, with an R^2 of only 0.2 percent. In column (3), we consider a related measure of earnings predictability, defined as the R^2 from the AR(1) model for ROA. The results here mirror those for earnings persistence: higher predictability of (scaled) earnings by their lagged values is associated with lower valuation uncertainty according to our measure, although the explanatory power is low.

In columns (4)–(6), we consider three further earnings characteristics. In column (4), we regress *VU* on absolute accruals scaled by average total assets, with accruals defined using the balance sheet approach as in Hribar and Collins (2002). We find that firms with a greater accrual component in their earnings tend to have higher valuation uncertainty according to our measure. The explanatory variable in column (5) is earnings quality, defined following Francis, LaFond, Olsson, and Schipper (2005), with higher values indicating lower quality. As could be expected, firms with lower earnings quality have higher valuation uncertainty according to our measure. The explanatory power of earnings quality for *VU* is high, with an adjusted R^2 of 13 percent. The final earnings characteristic that we consider is earnings smoothness, defined as the ratio of earnings volatility to cash flow volatility following Francis, LaFond, Olsson, and Schipper (2004). One could expect firms whose earnings are relatively more volatile than their cash flows to have more uncertain valuations. This expectation is borne out in the data according to our *VU* measure.

In the penultimate two columns of Table 2, we relate *VU* to two proxies for discount rate uncertainty. In column (7), we regress *VU* on beta volatility, defined as the standard deviation of five market betas estimated over each of the last five years. As expected, we find that *VU* tends to be higher for firms whose betas are more volatile. Beta volatility explains about 10 percent of the cross-sectional variation in *VU*. Finally, in column (8), we regress *VU* on the standard error of the firm's market beta estimated over the past year. The standard error of the beta indicates the degree of its estimation uncertainty (Fama and French 1997; Armstrong, Banerjee, and Corona 2013). Interestingly, we find that

TABLE 2

Validation of *VU* Using *Ex Ante* Proxies

	Expected Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept		0.679***	0.736***	0.736***	0.727***	0.632***	0.691***	0.626***	0.572***	0.468***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\sigma\ (ROA)^{PRE}$	(+)	1.346***								0.363***
		(0.000)								(0.000)
$\beta\ [AR(1)]$	(–)		−0.012**							
			(0.041)							
$R^2\ [AR(1)]$	(–)			−0.020**						0.032***
				(0.035)						(0.000)
$\|ACC\|$	(+)				0.665***					0.173***
					(0.000)					(0.000)
EarnQual	(+)					3.106***				1.248***
						(0.000)				(0.000)
$\sigma\ (ROA)^{PRE}/\sigma\ (CFO)^{PRE}$	(+)						0.082***			0.014***
							(0.000)			(0.000)
$\sigma\ (Beta)^{PRE}$	(+)							0.386***		0.059***
								(0.000)		(0.003)
$SE(Beta)^{PRE}$	(+)								0.971***	0.895***
									(0.000)	(0.000)
Adjusted R^2		0.130	0.002	0.002	0.038	0.130	0.034	0.104	0.240	0.286
n		91,385	74,175	74,175	115,469	64,602	88,249	91,664	120,144	55,415

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

This table reports estimation results from annual Fama-MacBeth regressions of the valuation uncertainty measure (VU) on *ex ante* uncertainty proxies. The proxy in column (1) is earnings volatility ($\sigma\ (ROA)^{PRE}$), measured as the standard deviation of return on assets over the most recent five years. The proxy in column (2) is the slope coefficient from a firm-level AR(1) regression of return on assets on lagged return on assets $(\beta\ [AR(1)])$ estimated over a period of ten years (minimum of eight years is required). The proxy in column (3) is the R^2 from a firm-level AR(1) regression of return on assets on lagged return on assets $(R^2\ [AR(1)])$ estimated over a period of ten years (minimum of eight years is required). The proxy in column (4) is scaled absolute accruals ($|ACC|$), where accruals is the change in working capital minus depreciation, all scaled by average total assets. The proxy in column (5) is earnings quality (*EarnQual*) measured as in Francis et al. (2005) (a minimum of 20 observations per industry-year is required). The proxy in column (6) is earnings smoothness $(\sigma\ (ROA)^{PRE}/\sigma\ (CFO)^{PRE})$, where $\sigma\ (CFO)^{PRE}$ is the standard deviation of operating cash flows (income before extraordinary items minus accruals, scaled by average total assets) over the most recent five years. The proxy is column (7) is beta volatility $(\sigma\ (Beta)^{PRE})$, measured as the standard deviation of five past market betas. Market betas are calculated over one-year windows using daily returns. The proxy in column (8) is the standard error of market beta $(SE(Beta)^{PRE})$, estimated over the past year using daily returns. All explanatory variables are Winsorized at the 1st and 99th percentiles (for $|ACC|$, Winsorization is performed prior to taking the absolute value). The sample period runs from 1975 to 2022 (48 years). p-values in parentheses correspond to Newey-West standard errors with three lags.

Variable definitions are provided in Appendix A.

TABLE 3

Validation of *VU* Using Spreads in Industry Valuation Multiples

	Expected Sign	(1)	(2)	(3)	(4)
Intercept		0.503***	0.584***	0.559***	0.541***
		(0.000)	(0.000)	(0.000)	(0.000)
IQR(P/B)	(+)	0.130***			
		(0.000)			
IQR(EV/EBITDA)	(+)		0.025***		
			(0.000)		
IQR(P/E)	(+)			0.013***	
				(0.000)	
IQR(Forward P/E)	(+)				0.026***
					(0.000)
R^2		0.235	0.188	0.196	0.211
n		120,183	120,181	120,029	118,226

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports estimation results from annual Fama-MacBeth regressions of the valuation uncertainty measure (*VU*) on spreads in industry-year valuation multiples. The explanatory variable in column (1) is the interquartile range in industry-year price-to-book (*IQR(P/B)*). The explanatory variable in column (2) is the interquartile range in industry-year EV/EBITDA (*IQR(EV/EBITDA)*). The explanatory variable in column (3) is the interquartile range in industry-year trailing price-to-earnings (*IQR(P/E)*). The explanatory variable in column (4) is the interquartile range in industry-year forward price-to-earnings (*IQR(Forward P/E)*). The sample period runs from 1975 to 2022 (48 years). p-values in parentheses correspond to Newey-West standard errors with three lags.
Detailed variable definitions are provided in Appendix A.

such estimation uncertainty is a strong positive predictor of *VU*: it explains as much as 24 percent of the cross-sectional variation in our measure.

In the last column of Table 2, we run a multivariate regression of *VU* on the above characteristics. Despite the significant reduction in sample size, we find that each of the characteristics in the multivariate regression continues to be a significant determinant of *VU*. [20] We view this as a sign of comprehensiveness of our measure. Overall, we conclude that *VU* is related to *ex ante* proxies for cash flow and discount rate uncertainties—as our framework predicts.

Validation Using the Spread of Industry Valuation Multiples

A common practice in market-based valuation is to estimate a range of plausible fundamental values given the upper and lower ends of peer valuations. Intuitively, when peer multiples are more dispersed, the firm's implied valuation is more uncertain. Building on this intuition, we relate *VU* to the industry-year dispersion in valuation multiples as another form of validation. Indeed, as Equation (7) shows, our approach tacitly exploits differences in valuation multiples at the upper and lower ends of valuations within an industry-year. We use four common valuation multiples: enterprise value-to-EBITDA (EV/EBITDA), price-to-book (P/B), trailing price-to-earnings (P/E), and forward price-to-earnings using analysts' forecasts (forward P/E). For consistency with our measure of valuation uncertainty, we use interquartile ranges of these multiples.

Table 3 reports the results. We find that *VU* is positively associated with the dispersion in each of the four valuation multiples. The R^2 in these regressions is on the order of 20 percent, meaning that the dispersion in industry-year valuation multiples explains about 20 percent of the variation in our measure. Thus, although *VU* is clearly related to a simple industry-year benchmark, it contains substantial incremental variation as it varies further within industry-years.[21] In the next section, we explore the predictive power of *VU* over and above this simple benchmark.

[20] Because earnings persistence and earnings predictability are almost collinear, we keep only the latter in the joint regression. Our inferences are unchanged if we pick the former. Interestingly, the coefficient on earnings predictability in the multivariate regression becomes positive as opposed to negative in the univariate regression.

[21] The multivariate nature of our approach allows for more than one source of value and controls for some of the "normal" dispersion in multiples. For example, a given industry-year could be characterized by high dispersion in P/B, but this does not necessarily imply high levels of uncertainty—some of that dispersion could be due to differences in profitability across firms. Our measure accounts for that.

TABLE 4

Validation of *VU* Using Future and Contemporaneous Outcomes

Panel A: Total Valuation Uncertainty

	Expected Sign	$\mathrm{Log}(\sigma(Returns)^{POST})$ (1)	(2)	(3)	$\mathrm{Log}(\sigma(Implied))$ (4)	(5)	(6)	$\mathrm{Log}(1+\sigma(E[TP]))$ (7)	(8)	(9)
Intercept		−4.464***	−4.486***	−1.020***	−1.639***	−1.647***	1.890***	0.040***	0.039***	0.470***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VU	(+)	**1.183*** **	**1.110*** **	**0.112*** **	**1.041*** **	**0.939*** **	**0.031*** **	**0.127*** **	**0.117*** **	**−0.004**
		(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.006)**	**(0.000)**	**(0.000)**	**(0.355)**
IQR(EV/EBITDA)	(+)		0.011***	0.002*		0.007**	0.004***		0.001*	0.000***
			(0.002)	(0.065)		(0.029)	(0.000)		(0.087)	(0.006)
Log(*ME*)	(–)			−0.030***			−0.061***			−0.002**
				(0.000)			(0.000)			(0.013)
Log(*Age*)	(–)			−0.024***			−0.013***			0.001
				(0.000)			(0.000)			(0.387)
$\mathrm{Log}(\sigma\ (Returns)^{PRE})$	(+)			0.667***			0.637***			0.093***
				(0.000)			(0.000)			(0.000)
Intan/Assets	(+)			0.011			−0.048***			−0.008*
				(0.487)			(0.000)			(0.085)
$I_{EARN<0}$	(+)			0.066***			0.072***			0.031***
				(0.000)			(0.000)			(0.000)
$I_{DIV>0}$	(–)			−0.055***			−0.029***			0.008***
				(0.000)			(0.000)			(0.000)
Adjusted R^2		0.268	0.283	0.681	0.274	0.298	0.756	0.085	0.091	0.241
n		118,457	118,455	118,413	32,091	32,089	32,081	32,553	32,551	32,542

(continued on next page)

Validation Using *Ex Post* Outcomes

In our third set of validation tests, we examine the ability of *VU* to explain future or contemporaneous outcomes that are indicative of valuation uncertainty. To assess the incremental power of *VU*, each outcome is predicted using three different specifications: (1) a univariate regression using *VU* only, (2) a regression using *VU* and a simple industry benchmark,[22] and (3) a regression using *VU*, a simple industry benchmark, and a further set of proxies for valuation uncertainty: size, age, past return volatility, asset intangibility, and indicators for dividend-paying firms and loss-making firms. We use the natural logarithm of the outcome variable in all cases. Table 4 reports the results of these tests.

In Panel A, we use three metrics to capture overall valuation uncertainty. In columns (1)–(3), the outcome variable is future realized stock return volatility (estimated over the next year). We find that *VU* has strong explanatory power for future stock return volatility. This is true in the univariate case, in the case of controlling for the spread in industry-year multiples, as well as after including other common proxies for valuation uncertainty. In columns (4)–(6), the outcome variable is contemporaneous option-implied volatility extracted from options with maturities of 30 days. Once again, we observe that *VU* has strong explanatory power: the coefficient on *VU* is positive and statistically significant at the 1 percent level in all three specifications. In columns (7)–(9), the outcome variable is the contemporaneous dispersion in analysts' target prices. Here, we find that *VU* has strong explanatory power both individually and incrementally to a simple industry-year benchmark. However, this is no longer the case after including other common proxies for valuation uncertainty. Thus, for the dispersion in analysts' target prices in particular, the explanatory power of *VU* appears to be subsumed by a set of other proxies.

[22] Since the four industry-year multiples that we consider are highly correlated, with correlation coefficients as high as 0.8–0.9, we pick EV/EBITDA as our go-to benchmark.

TABLE 4 (continued)

Panel B: Uncertainty in Cash Flows

	Expected Sign	$\mathrm{Log}(\sigma(ROA)^{POST})$			$\mathrm{Log}(\sigma(CF\ News)^{POST})$			$\mathrm{Log}(1+\sigma(E[EPS]))$		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Intercept		−5.018***	−5.081***	−0.743***	−3.578***	−3.581***	−1.248***	−0.048***	−0.045***	0.464***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VU	**(+)**	**2.259******	**1.933******	**0.538******	**0.920******	**0.810******	**0.345******	**0.235******	**0.259******	**0.030****
		(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.014)**
IQR(EV/EBITDA)	(+)		0.039***	0.023***		0.010***	0.002		−0.002**	−0.001**
			(0.000)	(0.000)		(0.002)	(0.108)		(0.019)	(0.048)
Log(*ME*)	(–)			−0.012			0.041***			−0.012***
				(0.137)			(0.000)			(0.000)
Log(*Age*)	(–)			−0.072***			−0.039***			0.006***
				(0.000)			(0.000)			(0.002)
$\mathrm{Log}(\sigma(Returns)^{PRE})$	(+)			0.794***			0.558***			0.085***
				(0.000)			(0.000)			(0.000)
Intan/Assets	(+)			−0.276*			−0.177***			−0.067***
				(0.067)			(0.004)			(0.000)
$I_{EARN<0}$	(+)			0.361***			0.193***			0.194***
				(0.000)			(0.000)			(0.000)
$I_{DIV>0}$	(–)			−0.139***			0.022			0.001
				(0.000)			(0.355)			(0.851)
Adjusted R^2		0.200	0.222	0.364	0.080	0.087	0.174	0.058	0.063	0.175
n		80,404	80,404	80,379	49,441	49,440	49,436	70,137	70,135	70,124

(continued on next page)

In Panel B, we consider a range of measures of future cash flow uncertainty. In columns (1)–(3), the outcome variable is the volatility of future earnings (standard deviation of ROA over the next five years). In columns (4)–(6), the outcome variable is the volatility of cash flow news, with cash flow news computed similar to Da and Warachka (2009). In columns (7)–(9), the outcome variable is the dispersion in analysts' one-year-ahead earnings forecasts. For each of these measures, we find that *VU* has explanatory power on its own, over and above an industry-year benchmark, as well as after controlling for other *ex ante* proxies for valuation uncertainty.

Finally, in Panel C, we consider the ability of *VU* to explain measures of uncertainty about future growth rates and discount rates. In columns (1)–(3), the outcome variable is the dispersion in analysts' forecasted long-term growth. In columns (4)–(6), the outcome variable is the volatility of future market betas (standard deviation of betas estimated in each of the subsequent five years). And in columns (7)–(9), the outcome variable is the standard error of the future market beta (estimated over the next year), i.e., beta estimation uncertainty. For all three outcomes and regardless of the set of controls, we find a positive and statistically significant coefficient on *VU*.

Overall, we conclude that our measure of valuation uncertainty is predictive of cash flow uncertainty, discount rate uncertainty, and total valuation uncertainty measured *ex post* or contemporaneously utilizing the perceptions of market participants and analysts. The predictive power of our new measure is incremental to a simple benchmark of dispersion in industry-year valuation multiples and to other *ex ante* proxies for valuation uncertainty.

Validation Using Price Ranges from IPO Prospectuses

Our measure is supposed to reflect the spread of likely fundamental equity values. Although we do not observe such spreads quoted in financial markets, there are instances in which valuation experts do provide them. One such instance is the case of IPOs. As part of the IPO process, the issuer furnishes a prospectus containing a preliminary price range—the range in which the stock is expected to be priced in the offering. This price range is the result of extensive valuation analysis by the issuing firm in close co-operation with its lead underwriter. Wider price ranges indicate greater uncertainty about the ultimate offer price. We posit that the width of this price range maps perfectly into our definition of valuation uncertainty, making it a credible validation benchmark.

TABLE 4 (continued)

Panel C: Uncertainty in Growth Rates and Discount Rates

	Expected Sign	Log(1 + $\sigma(E[LTG])$)			Log($\sigma(Beta)^{POST}$)			Log($SE(Beta)^{POST}$)		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept		0.938***	0.916***	3.443***	−1.995***	−2.025***	0.586***	−2.662***	−2.682***	1.041***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VU	(+)	**0.718*** **	**0.577*** **	**0.134** **	**0.994*** **	**0.873*** **	**0.123** **	**1.308*** **	**1.252*** **	**0.116*** **
		(0.000)	**(0.000)**	**(0.012)**	**(0.000)**	**(0.000)**	**(0.015)**	**(0.000)**	**(0.000)**	**(0.000)**
IQR(EV/EBITDA)	(+)		0.014***	0.003		0.020***	0.008**		0.009***	0.001
			(0.001)	(0.210)		(0.005)	(0.036)		(0.008)	(0.241)
Log(*ME*)	(–)			0.064***			−0.005			−0.058***
				(0.000)			(0.660)			(0.000)
Log(*Age*)	(–)			−0.060***			−0.040***			−0.033***
				(0.000)			(0.000)			(0.000)
Log($\sigma\ (Returns)^{PRE}$)	(+)			0.613***			0.480***			0.660***
				(0.000)			(0.000)			(0.000)
Intan/Assets	(+)			−0.303***			−0.074			0.017
				(0.001)			(0.111)			(0.436)
$I_{EARN<0}$	(+)			0.125**			0.058***			0.073***
				(0.013)			(0.001)			(0.000)
$I_{DIV>0}$	(–)			−0.047***			−0.107***			−0.056***
				(0.000)			(0.000)			(0.000)
Adjusted R^2		0.048	0.062	0.159	0.129	0.149	0.315	0.278	0.290	0.688
n		39,687	39,686	39,680	83,464	83,464	83,440	118,457	118,455	118,413

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports estimation results from annual Fama-MacBeth regressions of future/contemporaneous uncertainty outcomes on our valuation uncertainty measure (*VU*). Panel A reports regressions using measures of total valuation uncertainty. The outcome in columns (1)–(3) is the log of future stock return volatility $\left(\sigma\ (Returns)^{POST}\right)$. The outcome in columns (4)–(6) is the log of option-implied volatility $(\sigma(Implied))$. The outcome in columns (7)–(9) is the log of one plus the dispersion of analysts' target prices $(\sigma(E[TP]))$. Panel B reports regressions using measures of cash flow uncertainty. The outcome in columns (1)–(3) is the log of future ROA volatility $\left(\sigma(ROA)^{POST}\right)$. The outcome in columns (4)–(6) is the log of future cash flow news volatility $\left(\sigma(CF\ News)^{POST}\right)$, where cash flow news is constructed in the spirit of Da and Warachka (2009). The outcome in columns (7)–(9) is the log of one plus dispersion of analysts' one-year-ahead earnings forecasts $(\sigma\ (E[EPS]))$. Panel C reports regressions using measures of growth rate and discount rate uncertainty. The outcome in columns (1)–(3) is the log of one plus the standard deviation of analysts' long-term growth forecasts $(\sigma(E[LTG]))$. The outcome in columns (4)–(6) is the log of the volatility of future market betas $\left(\sigma(Beta)^{POST}\right)$. The outcome in columns (7)–(9) is the log of the standard error of future market beta $\left(SE(Beta)^{POST}\right)$. p-values in parentheses correspond to Newey-West standard errors with three lags. Continuous variables except *VU*, *IQR(EV/EBITDA)*, market equity (*ME*), and firm age (*Age*) are Winsorized at the 1st and 99th percentiles.
Variable definitions are provided in Appendix A.

To that end, we collect a sample of IPOs during our sample period from Refinitiv Workspace (formerly Thomson Reuters SDC). We apply the following selection criteria common in the IPO literature: (1) issue type is "IPO"; (2) transaction status is "Live" or "Cancelled"; (3) issuer nation is "United States"; (4) issuer stock exchange is "New York Stock Exchange," "NASDAQ," or "American"; and (5) security type is common/ordinary stock. For our purposes, we further require the offer price range to be nonmissing and nonzero. We match the resulting sample with Compustat fundamentals using issuer CUSIPs such that the fiscal year-end is within 365 days of the IPO filing date. Finally, we require nonmissing valuation model inputs in order to obtain *VU* by means of out-of-sample prediction using the quantile regression coefficients for the corresponding industry-year. Similar to our *VU* measure, we define *IPO Price Spread* as the difference between the high and low filing prices, scaled by their midpoint. Our final sample contains 1,539 IPOs with usable observations on both *IPO Price Spread* and *VU*. The mean *IPO Price Spread* is 0.169, with a standard deviation of 0.053. The mean *VU* for the IPO sample is 0.858—somewhat higher than the mean *VU* in our main sample, consistent with IPO firms being riskier than the average firm.

We use pooled OLS regressions for this test and report our estimates in Table 5, Panel A. In column (1), we regress the log(*IPO Price Spread*) on *VU* with year fixed effects and standard errors clustered by year. The coefficient on *VU* is

TABLE 5

Validation of *VU* Using Professional Valuations

Panel A: IPO Pricing Ranges from Prospectuses

	Expected Sign	(1)	(2)
VU	**(+)**	**0.234*****	**0.176*****
		(0.000)	**(0.002)**
Log(*ME*)	(–)		−0.016***
			(0.002)
Log(*Age*)	(–)		−0.025**
			(0.034)
Intan/Assets	(+)		−0.129**
			(0.022)
$I_{EARN<0}$	(+)		0.001
			(0.977)
$I_{DIV>0}$	(–)		0.008
			(0.624)
Adjusted R^2		0.058	0.073
n		1,539	1,442

Panel B: Target Value Ranges from M&A Fairness Opinions

	Expected Sign	(1)	(2)
VU	**(+)**	**0.475*****	**0.211****
		(0.000)	**(0.027)**
Log(*ME*)	(–)		−0.017
			(0.256)
Log(*Age*)	(–)		0.013
			(0.652)
$\text{Log}(\sigma\,(Returns)^{PRE})$	(+)		0.248***
			(0.000)
Intan/Assets	(+)		0.167*
			(0.086)
$I_{EARN<0}$	(–)		0.037
			(0.411)
$I_{DIV>0}$			−0.034
			(0.555)
Adjusted R^2		0.085	0.114
n		1,224	1,207

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports estimation results from pooled OLS regressions of price ranges from valuation professionals on our valuation uncertainty measure (*VU*) and a set of controls. In Panel A, the dependent variable is log(*IPO Price Spread*), which is the log of IPO price range (scaled by the midpoint) from IPO prospectuses. In Panel B, the dependent variable is log(*M&A FO Spread*), which is the log of fair value range (scaled by the midpoint) from fairness opinions (FO) for takeover targets. Multiple price ranges in a given FO (if any) are averaged across methods and then averaged across banks in case of multiple FOs. *VU* is obtained by means of out-of-sample prediction using the IQR coefficients from corresponding industry-years and the fundamentals of IPO/takeover target firms. *Intan/Assets* and $\sigma(Returns)^{PRE}$ are Winsorized at the 1st and 99th percentiles. Regressions include year fixed effects and the standard errors are clustered by year.
Variable definitions are provided in Appendix A.

positive and highly statistically significant. That is, firms subject to higher valuation uncertainty according to our measure tend to have wider pricing ranges in their IPO prospectuses. We add our usual set of control variables in column (2), except that prior stock return volatility is omitted because it is not available for newly listed firms. In this multivariate regression, *VU* continues to be a strong predictor of the IPO filing range, with a positive coefficient that is significant at the 1 percent level. We conclude that our measure reflects valuation uncertainty manifested in IPO filing ranges.

Validation Using Price Ranges from M&A Fairness Opinions

Another instance in which valuation experts provide a range of likely fair values for the firm's equity is the case of M&A fairness opinions. When a public firm becomes the target of a takeover deal, its board will typically seek a so-called fairness opinion from its investment bank advisor and sometimes even several fairness opinions from multiple advisors (DeAngelo 1990; Liu 2020). The purpose of the fairness opinion is to suggest that the acquisition price is "fair to the target shareholders from the financial point of view." To that end, investment bankers conduct extensive valuation analysis culminating in a range of likely fundamental values of the target's stock. We argue that the width of the resulting range maps perfectly into our notion of valuation uncertainty and that we can therefore use it as a benchmark against which to validate our measure.

We collect a sample of public firm takeovers from Refinitiv Workspace (formerly Thomson Reuters SDC) taking place during our sample period. We apply the following selection criteria standard in the M&A literature: (1) the target is a U.S. public firm listed on NYSE, NASDAQ, or American Stock Exchange; (2) deal status is completed or withdrawn; (3) the acquiror holds less than 20 percent of the target prior to the deal and seeks to own 100 percent; and (4) deal value is at least U.S. $1 million. For our purposes, we further require that Refinitiv reports at least one fairness opinion associated with the deal. We match the resulting sample to Compustat fundamentals using target CUSIPs such that the fiscal year-end precedes the announcement date of the deal by no more than 365 days. We require nonmissing valuation model inputs to estimate *VU* by means of out-of-sample prediction using the quantile regression coefficients for the target's industry-year.

Refinitiv reports a separate valuation range for each of the three valuation approaches commonly found in fairness opinions: discounted cash flows (DCFs), multiples based on traded peers, and multiples based on precedent M&A transactions. A given bank may use one or more approaches in its fairness opinion, and the target may seek one or more fairness opinions. For a given valuation approach in a given fairness opinion, we compute the *M&A FO Spread* as the high minus low estimated price, scaled by their midpoint.[23] When a bank uses multiple approaches in its opinion, we average the spreads from each approach to obtain a single bank-level valuation spread. If a target retains multiple banks, we further average across the bank-level spreads. Our final sample contains 1,224 M&A targets with usable observations on *M&A FO Spread* and *VU*. The mean *M&A FO Spread* is 0.449, with a standard deviation of 0.317. The mean *VU* of M&A targets is 0.827, which is higher than in our main sample but lower than in our IPO sample.

We continue using pooled OLS regressions in this validation test, with estimates reported in Table 5, Panel B. In column (1), we regress log(*M&A FO Spread*) on *VU* with year fixed effects and standard errors clustered by year. *VU* obtains a positive coefficient that is statistically significant at the 1 percent level. In other words, firms characterized by higher valuation uncertainty according to our measure tend to have wider ranges of fundamental value estimated by investment bankers. In column (2), we add our usual set of control variables, this time also including prior stock return volatility (since the targets are listed firms). *VU* continues to have a positive and statistically significant coefficient in this multivariate regression. We conclude that our measure reflects the uncertainty about intrinsic value manifested in valuation ranges prepared by experts.

V. APPLICATION: VALUATION UNCERTAINTY AND VALUATION MISTAKES

As a form of indirect validation of our measure, we apply it to cross-sectional asset pricing. We test the hypothesis that valuation uncertainty promotes valuation mistakes, defined as deviations of prices from fundamental values. This prediction arises in at least three settings.

Hypothesis Development and Empirical Predictions

First, consider a market with heterogeneous investors and trading frictions, such as in Miller (1977). In Miller's words, "the very concept of uncertainty implies that reasonable men may differ in their forecasts" (Miller 1977, 1151). That is, different market participants are likely to arrive at different estimates of a security's fundamental value. Even if investors' forecasts are *un*biased on average, differences of opinion can result in mispricing. This occurs when a group

[23] In a handful of cases, Refinitiv reports a "high" price that is lower than the "low" price. We investigate each instance by reading the original fairness opinion on EDGAR. All of these cases represent data entry errors (e.g., mixing up the high and low or misplacing the decimal point). We manually correct them.

of investors holding specific beliefs is prevented from impounding them into prices due to trading frictions (e.g., short-sale constraints for pessimists, leverage constraints for optimists). Greater valuation uncertainty should be associated with greater mispricing, because truncating the left or right tail of a more dispersed distribution shifts the mean of represented opinions to a greater extent.

Second, consider a setting with parameter uncertainty and learning, as in Lewellen and Shanken (2002). In this setup, investors are uncertain about the true value of the firm and form expectations based on their prior beliefs and noisy signals. If investors' prior is equal to the true (unknown) value, any noisy signal pushes their belief away from the truth, generating mispricing and subsequent corrections. If, on the other hand, investors' prior is already away from the true value and the signal distorts expectations even further, mispricing is exacerbated. Both of these effects intensify when prior uncertainty is higher, as per Bayesian decision making.[24] In this setup, pricing mistakes arise despite investors acting rationally and using all available information.

Finally, a similar prediction regarding the effect of valuation uncertainty on the propensity of valuation mistakes can be obtained in a framework with sentiment traders (those with biased beliefs) and limits to arbitrage, as in Daniel et al. (1998). First, stocks with more uncertain valuations are more prone to speculation. For instance, Baker and Wurgler (2006, 1648) suggest that "the lack of an earnings history combined with the presence of apparently unlimited growth opportunities allows unsophisticated investors to defend, with equal plausibility, a wide spectrum of valuations, from much too low to much too high, as suits their sentiment." Hence, holding limits to arbitrage constant, one can expect greater uninformed demand shocks when valuation uncertainty is high, leading to greater price dislocations. Second, valuation uncertainty is related to the so-called noise-trader risk, whereby informed arbitrageurs, whose actions keep prices in check, fear further price dislocations and limit their trading. For instance, Pontiff (2006) argues that securities with greater idiosyncratic volatility are costlier to arbitrage. Therefore, higher valuation uncertainty can result in larger pricing mistakes via greater limits to arbitrage, holding speculative demand constant. For these reasons, Baker and Wurgler (2006) argue that aggregate sentiment effects should be strongest for stocks that are difficult to value.

Note that valuation uncertainty is conducive to pricing errors of either type—both overvaluation and undervaluation. Instead of assuming that one type of trading friction dominates empirically (e.g., short-sale constraints are more binding than leverage constraints, as in Diether, Malloy, and Scherbina 2002 and Stambaugh, Yu, and Yuan 2015), we propose to sort assets on a directional measure of presumed valuation mistakes, namely, the price-to-intrinsic-value-estimate ratio (price-to-value hereafter). *Price-to-value* is the residual from the valuation model in Equation (6) when estimated with OLS (i.e., $\varepsilon_{it} = m_{it} - v_{it}$) and thus represents deviations of (log) market equity from expected (log) fundamental equity value.[25] *Price-to-value* is analogous to the priced component of market to book ("firm-specific error") in Golubov and Konstantinidi (2019), except for our valuation model refinements discussed above. If valuation uncertainty is conducive to valuation mistakes, then we expect the following:

H1: Long-short returns on the *price-to-value* strategy are higher among high-valuation uncertainty stocks.

To the extent that valuation mistakes get resolved over time, subsequent stock returns partly reflect resolution of mispricing. The magnitude of such resolution is therefore informative about the magnitude or likelihood of initial mistakes. This suggests that trading on *price-to-value* should be more profitable when valuation uncertainty is high, as per H1.

H2: Returns to long (short) positions in "value" ("growth") stocks are higher following periods of low (high) investor sentiment—and particularly so for high-valuation uncertainty stocks.

Put differently, if valuation mistakes arise due to uninformed demand/supply from speculators, then the subsequent returns of the affected stocks should be predictable by investor sentiment. Moreover, if sentiment is more likely to affect high-valuation uncertainty stocks (Baker and Wurgler 2006), then the ability of sentiment to time the returns of such stocks should be higher.[26]

We recognize the joint-hypothesis problem inherent in some of the foregoing discussion. In particular, our tests should be viewed as a test of the joint hypothesis that (1) valuation uncertainty promotes valuation mistakes and (2) our sorting variable, *price-to-value*, identifies valuation mistakes at least to some extent. Although we cannot fully

[24] In the case where prior belief is away from the true value but the signal moves investors' perceptions toward it, pricing mistakes moderate—and more so when uncertainty is high.
[25] If investors applied the same valuation model as we do, there would be no differences between prices and expected fundamental values. Thus, our implicit assumption is that investors do not necessarily apply the same model—or if they do, various market frictions create room for deviations of prices from fundamental values.
[26] Unlike H1, prediction H2 is uniquely associated with models of sentiment traders (i.e., biased investor beliefs).

overcome this joint-hypothesis problem, we will appeal to economic theory to limit the validity of alternative interpretations (e.g., theory constrains the signs and/or magnitudes of certain parameters, such as risk premia).

Analysis Sample

We implement our tests of the above predictions using our main universe over the period 1974–2022 but after excluding megacaps, defined as firms whose June 30 market capitalizations are above the top quartile (75th percentile) of market capitalization of NYSE firms. This requirement is not onerous on the data: it eliminates 10.65 percent of firm-years (12,796) and only 2.24 percent (312) of unique firms, for a sample of 107,387 observations. We impose this filter for two reasons.

First, it is well known that the profitability of value-like strategies is coming primarily from small stocks. For instance, Fama and French (2021) show that the value premium among large stocks over the last 30 years (1991–2019) is virtually zero. Similarly, using data from as far back as 1926, Asness, Frazzini, Israel, and Moskowitz (2015) show that the value premium among large stocks existed only during the 1963–1981 period. Both studies define small (large) firms as firms whose market capitalizations are below (above) the 50th percentile of NYSE firms. Our filter, which is set at the 75th percentile, is less restrictive.

Second, the rise of superstar firms over the last decade (e.g., Autor, Dorn, Katz, Patterson, and Van Reenen 2020) poses a measurement challenge for asset pricing tests: firms with market capitalizations in the trillions of dollars generate excessive concentration in value-weighted portfolios. For instance, in our double-sorted portfolios with megacaps included, the largest stock in a portfolio has an *average* weight of 15.6 percent and can be as high as 84.1 percent. Such concentration may result in unrepresentative inferences. By eliminating megacaps, we reduce the weight of the largest stock per portfolio to 6.1 percent on average, and it never exceeds 44.5 percent. An alternative solution is to use the full sample but cap the weights of the largest stocks (see Jensen, Kelly, and Pedersen 2023). Our results are robust to using the full universe and capping the weights in value-weighted portfolios at a conservatively chosen 85th percentile of market capitalization in our sample.

Double-Sorting on Valuation Uncertainty and *price-to-value*

We now turn to testing H1, which predicts that the long-short strategy exploiting presumed valuation mistakes captured by *price-to-value* should be particularly profitable among high-valuation uncertainty stocks. To that end, we form 4×4 portfolios sorted on VU and *price-to-value*.[27] We use conditional sorts, whereby we first sort stocks into four quartiles based on VU and then further sort on *price-to-value* within each VU quartile. This ensures that our 4×4 portfolios are well populated.[28] The sorts are performed on June 30 of every year, in line with our estimation of the valuation model. Table 6 presents average portfolio returns over the subsequent 12 months.

It is worth commenting on our portfolio return calculation, in light of our specific hypothesis. If the returns to our long-short strategies capture the unwinding of valuation mistakes, then value-weighted portfolio returns tell us whether (and by how much) the average *dollar* invested in the portfolio is mispriced. In contrast, equal-weighted portfolio returns capture valuation mistakes experienced by an average *firm*. Conceptually, valuation mistakes occur at the level of a firm, not the level of a dollar of its market capitalization. Therefore, whether valuation mistakes occur on average is a question about the average firm and not the average dollar invested—making the equal-weighted portfolio return a more appropriate way to test our hypothesis. However, equal-weighted portfolio returns suffer from microstructure-induced measurement biases (e.g., the bid-ask bounce), as shown by Asparouhova, Bessembinder, and Kalcheva (2013). As a solution to this problem, Asparouhova et al. (2013) recommend using prior-period gross return weighted (RW) or value-weighted (VW) portfolios. We report our results using both RW and VW portfolios, although we focus our discussion of the results on the RW portfolios given the arguments above.[29]

Panel A reports the RW returns of double-sorted portfolios. Focusing on low VU in the left-most column, we find that value stocks earn an average return of 1.27 percent per month, whereas growth stocks earn an average return of 0.96 percent. The difference between the two is 0.31 percent per month, significant at the 1 percent level. Moving across the columns to the right, we find that the returns of value stocks increase, from 1.27 percent to 1.51 percent per month, as VU goes up. At the same time, the returns of growth stocks decline with VU, from 0.96 percent to as low as 0.38

[27] To ensure that our tests do not simply pick up the well-known fact that value-like strategies are stronger among small stocks, we repeat the analysis below after orthogonalizing VU with respect to size. All our inferences hold.

[28] Toward the same goal of well-populated portfolios, we compute the breakpoints of valuation uncertainty and *price-to-value* over the whole sample and not over NYSE-listed stocks only. Our conclusions are not sensitive to this choice.

[29] Another reason to focus on portfolios that put roughly equal weight on all stocks is the fact that our estimation of the valuation model in Equation (6) places equal weight on each stock-level observation within an industry-year.

TABLE 6

***price-to-value* Sorts Conditional on Valuation Uncertainty**

Panel A: RW Portfolios

		VU					
price-to-value	**Expected Sign**	**Low**	**2**	**3**	**High**	**High − Low**	**p-value**
Low		1.267	1.319	1.492	1.510	0.244	(0.286)
2		1.272	1.227	1.220	1.236	−0.035	(0.884)
3		1.141	0.958	0.950	0.873	−0.268	(0.283)
High		0.957	0.786	0.695	0.376	−0.580***	(0.007)
Low – High	(+)	0.310***	0.533***	0.797***	1.134***	0.824***	(0.000)
p-value		(0.003)	(0.000)	(0.000)	(0.000)		
Volatility (Std. Dev.)		2.480	3.163	3.821	4.064		
Annualized Sharpe ratio		0.433	0.584	0.723	0.966		

Panel B: VW Portfolios

		VU					
price-to-value	**Expected Sign**	**Low**	**2**	**3**	**High**	**High – Low**	**p-value**
Low		1.264	1.537	1.604	1.558	0.294	(0.224)
2		1.257	1.281	1.342	1.382	0.124	(0.605)
3		1.152	1.102	1.137	1.084	−0.068	(0.776)
High		1.026	0.961	1.016	0.722	−0.304	(0.215)
Low – High	(+)	0.238**	0.576***	0.588***	0.837***	0.598***	(0.003)
p-value		(0.021)	(0.000)	(0.002)	(0.000)		
Volatility (Std. Dev.)		2.564	3.475	4.322	5.041		
Annualized Sharpe ratio		0.322	0.574	0.471	0.575		

***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports average monthly returns of portfolios formed on the basis of *price-to-value*, conditional on valuation uncertainty. Portfolio sorts are formed sequentially—first on valuation uncertainty and then on *price-to-value*—every June 30. The universe excludes megacaps, defined as stocks with market capitalizations above the 75th percentile of market capitalization of NYSE firms. The sample period runs from July 1975 to June 2023 (576 months). Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B. p−values in parentheses correspond to Newey-West standard errors with three lags.
Detailed variable definitions are provided in Appendix A.

percent. As a result, the long-short return is monotonically increasing with *VU*, from 0.31 percent per month to 1.13 percent per month. The difference in long-short returns between high- and low-*VU* stocks is 0.82 percent, significant at the 1 percent level. The volatility of long-short returns also increases with *VU*, but this increase is modest, resulting in a substantially higher Sharpe ratio of the long-short strategy among high-*VU* stocks (0.97) as compared with the same strategy among low-*VU* stocks (0.43).

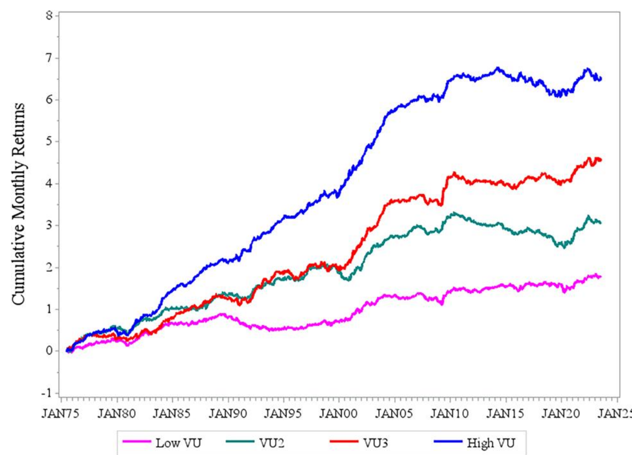
Panel B repeats the analysis using VW portfolio returns. All of the patterns described above continue to hold. The average long-short return among low-*VU* stocks is 0.24 percent per month, growing monotonically as *VU* increases, reaching 0.84 percent for high-*VU* stocks. The difference in hedge returns between extreme quartiles of *VU* is 0.60 percent per month, with a p-value of 0.003. The somewhat lower magnitude of the differential hedge return using VW portfolios is consistent with the existing literature that finds value-like return premia to be less pronounced among large stocks.

Figure 2 reports the cumulative returns to our long-short strategies over the 48-year sample period. Panel A depicts the performance of the RW strategies. An investor in the long-short strategy among high-*VU* stocks would have earned a cumulative return of 653 percent, as compared with only 179 percent for the same strategy among low-*VU* stocks. In Panel B, we turn to the VW strategies. Here, trading on *price-to-value* among high-*VU* stocks would have earned a cumulative return of 482 percent, versus only 137 percent if the strategy was implemented among low-*VU* stocks.

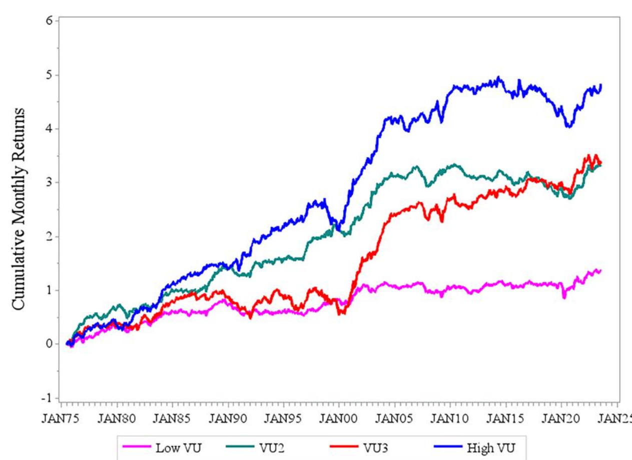
FIGURE 2

Cumulative Performance of *price-to-value* Strategies Conditional on Valuation Uncertainty

Panel A: RW Portfolios



Panel B: VW Portfolios



This figure depicts the cumulative return of long-short trading strategies formed on the basis of *price-to-value*, conditional on valuation uncertainty (*VU*). One unit on the y-scale corresponds to 100 percent. The strategies are long all stocks in the bottom quartile of *price-to-value* and short all stocks in the top quartile of *price-to-value*, within each valuation uncertainty quartile. Portfolio sorts are performed sequentially—first on valuation uncertainty and then on *price-to-value*—every June 30. The universe excludes megacaps, defined as stocks with market capitalizations above the 75th percentile of market capitalization of NYSE firms. The sample period runs from July 1975 to June 2023. Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B.
(The full-color version is available online.)

Overall, the results reported in this section support H1. The long-short strategy that exploits deviations of stock prices from fundamental value is more profitable among high-VU stocks, which is consistent with our overarching hypothesis that valuation uncertainty promotes valuation mistakes. Nevertheless, a risk premium interpretation of our findings here is also possible. In particular, it is possible that sorts on *price-to-value* are picking up a value-relevant characteristic—omitted from our empirical valuation model—that represents a priced source of risk. If so, conditioning on high VU intensifies differences in risk between "value" and "growth."

Note that, for our purposes, it is *not* necessary to rule out differences in risk between value and growth across VU portfolios. Instead, it is sufficient to demonstrate that differences in risk *alone* cannot account for the entire return premium we document. Our results provide two indications of this. First, consider the magnitude of the return on high-

VU "growth" stocks. On average, they earn a monthly return of 0.38 percent (Table 6, Panel A). For comparison, the return on the one-month T-bill over our sample period is 0.35 percent.[30] In other words, high-valuation uncertainty growth stocks have delivered average returns that are statistically indistinguishable from those on the risk-free asset. If the returns we document are determined purely by risk premia, then our portfolio of high-VU "growth" stocks must be risk-free. We view this as unlikely. More plausibly, the average returns on these stocks are low because they contain corrections of overvaluation.

The second aspect of our results that speaks against risk premium being the sole explanation for the return differential we document is the magnitude of the Sharpe ratio. Among high-VU stocks, the Sharpe ratio is as high as 0.97. For comparison, the market risk premium (excess market return) over our sample period is 0.67 percent per month, with a Sharpe ratio of 0.51. In other words, the compensation demanded by investors for bearing the risk in our value-like strategy is almost twice as high as that for bearing overall market risk. Although this is not entirely impossible, a more realistic explanation is that the return premium among high-VU stocks is at least partially due to resolution of mispricing. Our tests of H2 below further support this interpretation.

Timing Long and Short Returns with Investor Sentiment

Our next test builds on the work of Stambaugh, Yu, and Yuan (2012), who show that stocks in the short leg of 11 prominent anomaly strategies earn significantly lower returns following periods of high investor sentiment. The authors interpret their results as consistent with investor sentiment and short-sale constraints, resulting in temporary overvaluation. Interestingly, they do *not* find such results for the conventional value strategy formed on the book-to-market ratio.

If our results so far stem from valuation mistakes due to sentiment traders, then we expect high *price*-*to*-*value* stocks to exhibit particularly low returns following periods of high investor sentiment. Similarly, we expect low *price*-*to*-*value* stocks to exhibit particularly high returns following periods of low sentiment. Moreover, since investor sentiment is more likely to affect difficult-to-value stocks (Baker and Wurgler 2006), we expect these patterns to be strongest for high-valuation uncertainty stocks, as per H2 above. To test this prediction, we classify each month of our sample as low, medium, or high investor sentiment period, using terciles of the investor sentiment index ($SENT^{\perp}$) from Baker and Wurgler (2006, 2007).[31] Table 7 presents the returns of our double-sorted portfolios, conditional on beginning-of-month investor sentiment. For the sake of exposition, we present only the extreme quartiles of *price*-*to*-*value* and VU, i.e., the long and the short legs of the value strategy for stocks with the highest and lowest valuation uncertainty.

We find that the returns of stocks in the short leg ("growth" stocks) are consistently lower following periods of high investor sentiment, and this difference increases with valuation uncertainty. For instance, using RW portfolios, the difference in the returns of low-VU "growth" stocks between low- and high-sentiment periods is 0.76 percent per month and increases to 3.10 percent per month for high-VU "growth" stocks. For VW portfolios, the difference across periods for low-VU growth stocks is 0.49 percent (not statistically significant) and reaches a highly significant difference of 2.51 percent per month for the most uncertain "growth" stocks. The opposite results obtain for the stocks in the long leg, whereby the returns on value stocks are particularly high following periods of low investor sentiment, and this difference is more pronounced among high-VU stocks.

Finally, note the magnitude of the returns on high-VU "growth" stocks following periods of high investor sentiment. Using RW portfolios, which puts roughly equal weight on all stocks in the portfolio, the average return is −1.31 percent, which is significantly different from zero at the 5 percent level. When portfolios are value-weighted, the average return is −0.75 percent, although not significantly different from zero. Recall that these same stocks exhibit an average return over the sample period that is indistinguishable from the risk-free rate. If these stocks were a surrogate for a risk-free asset, an investor in such riskless security would have lost money during at least one-third of our sample period. Although this is not entirely inconceivable in a risk-return framework, the fact that negative returns follow periods of high investor sentiment is suggestive of corrections of overvaluation.

Insights on the "Disappearance" of the Value Premium

Before concluding the paper, we use our methodological tools to shed some light on one of the recent puzzles regarding the value premium: the fact that value-minus-growth strategies have not performed well over the last couple

[30] Data from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[31] We thank Jeffrey Wurgler for making these data available on his website: http://people.stern.nyu.edu/jwurgler/

TABLE 7

Timing Returns with Investor Sentiment

Panel A: RW Portfolios

VU		Low $SENT^{\perp}$	Medium $SENT^{\perp}$	High $SENT^{\perp}$	Expected Sign	High – Low	t-stat	p-value
Low	Low *price-to-value*	1.874***	0.686	1.220***	(−)	−0.654	−1.045	(0.296)
		(0.000)	(0.135)	(0.001)				
	High *price-to-value*	1.394***	0.805**	0.632*	(−)	−0.762	−1.394	(0.164)
		(0.001)	(0.047)	(0.085)				
	Low − High	0.480**	−0.119	0.588***		0.109	0.422	(0.673)
		(0.011)	(0.495)	(0.001)				
High	Low *price-to-value*	2.705***	1.265**	0.712	(–)	−1.993**	−2.242	(0.025)
		(0.000)	(0.032)	(0.203)				
	High *price-to-value*	1.788***	0.632	−1.313**	(–)	−3.102***	−3.834	(0.000)
		(0.002)	(0.264)	(0.028)				
	Low − High	0.917***	0.633**	2.025***		1.108***	2.687	(0.007)
		(0.006)	(0.011)	(0.000)				

Panel B: VW Portfolios

VU		Low $SENT^{\perp}$	Medium $SENT^{\perp}$	High $SENT^{\perp}$	Expected Sign	High – Low	t-stat	p-value
Low	Low *price-to-value*	1.686***	0.807*	1.237***	(−)	−0.448	−0.783	(0.434)
		(0.000)	(0.073)	(0.001)				
	High *price-to-value*	1.329***	0.861**	0.842**	(−)	−0.487	−0.928	(0.354)
		(0.001)	(0.023)	(0.019)				
	Hedge	0.356**	−0.054	0.395**		0.039	0.152	(0.879)
		(0.035)	(0.789)	(0.045)				
High	Low *price-to-value*	2.511***	1.149*	0.957*	(–)	−1.554*	−1.767	(0.078)
		(0.000)	(0.056)	(0.092)				
	High *price-to-value*	1.759***	1.098*	−0.748	(–)	−2.506***	−3.122	(0.002)
		(0.000)	(0.056)	(0.243)				
	Hedge	0.753*	0.051	1.705***		0.952*	1.820	(0.069)
		(0.068)	(0.888)	(0.000)				

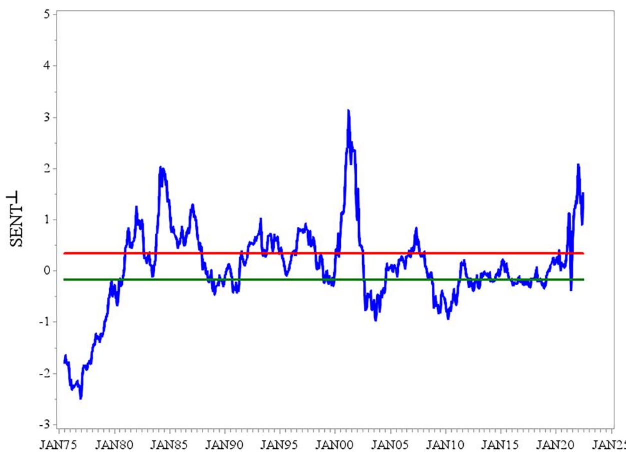
***, **, * Indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
This table reports average monthly returns of portfolios formed on the basis of *price-to-value*, conditional on valuation uncertainty, with the sample split into three periods according to prior month investor sentiment. Only the bottom quartile (low) and top quartile (high) of *price-to-value*, as well as the low-high (hedge) portfolios, are reported. Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006) ($SENT^{\perp}$). Portfolio sorts are formed sequentially—first on valuation uncertainty and then on *price-to-value*—every June 30. The universe excludes megacaps, defined as stocks with market capitalizations above the 75th percentile of market capitalization of NYSE firms. The sample period runs from July 1975 to June 2022 (564 months). Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B. p-values in parentheses correspond to Newey-West standard errors with three lags.
Detailed variable definitions are provided in Appendix A.

of decades. Indeed, the conventional value strategy exemplified by the Fama-French's High Minus Low (HML) factor has delivered negative returns in 11 out of 17 most recent years up to 2023. What is behind the apparent "disappearance" of the value premium?

Our first insight has to do with the evolution of investor sentiment. In the previous section, we have shown that buying high-*VU* "value" stocks is particularly profitable following periods of low investor sentiment and shorting high-*VU* "growth" stocks is particularly profitable following periods of low investor sentiment. In fact, Table 7 shows that periods of moderate investor sentiment are *not* associated with significant hedge returns to our strategy. In other words, extreme sentiment (excessively high or low) is conducive to the buildup of mispricing, whereas moderate sentiment is not. Could it be that the recent period has been characterized by moderate sentiment? Figure 3 plots investor sentiment over our sample period. The two horizontal lines correspond to the 33rd and 66th percentiles of sentiment—our cutoffs

FIGURE 3

Evolution of Investor Sentiment



This figure depicts the evolution of prior month investor sentiment over the period from July 1975 to June 2022 (564 months). Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006) ($SENT^{\perp}$). The sample is divided into three periods according to prior month investor sentiment—low, medium, and high. The three-period split is depicted by the red and green horizonal lines: the red line corresponds to a prior month sentiment value of 0.343 and the green line corresponds to a prior month sentiment value of −0.167. Sentiment values between [−0.167, 0.343] indicate periods of medium sentiment. Sentiment values above 0.343 indicate periods of high sentiment, and sentiment values below −0.167 indicate periods of low sentiment.
(The full-color version is available online.)

for high and low periods. Much of the period between 2005 and 2020 is indeed characterized by moderate sentiment.[32] Interestingly, extreme values of sentiment rebound from about 2020 onward, which coincides with a certain revival in the performance of our *price-to-value* strategy, especially among high-VU stocks.

Second, note that our value-like strategy exploits the price-to-value ratio, not the conventional price-to-book. Figure 4, Panel A shows the performance of the conventional *price-to-book* strategy. Comparing Figure 4 with Figure 2 reveals that the conventional value strategy has fared significantly worse during the recent period than our *price-to-value* strategy, especially on a VW basis. It follows that the outperformance of conventional growth over value in recent years is largely due to stocks characterized by high ratios of fundamental value to book.[33] Figure 4, Panel B confirms this insight. Moreover, it shows that the recent outperformance of high *value-to-book* stocks is driven by high-VU stocks, especially in VW portfolios. In the Online Appendix, we show that *value-to-book* sorts may be picking up differences in duration, with these differences amplified by VU. And since the outperformance of growth over value coincides with an era of declining interest rates, we speculate that duration effects may have confounded value strategies. Incidentally, van Binsbergen and Ma (2025) show that a duration-neutral HML factor outperforms the conventional one.

VI. CONCLUDING REMARKS AND FUTURE RESEARCH

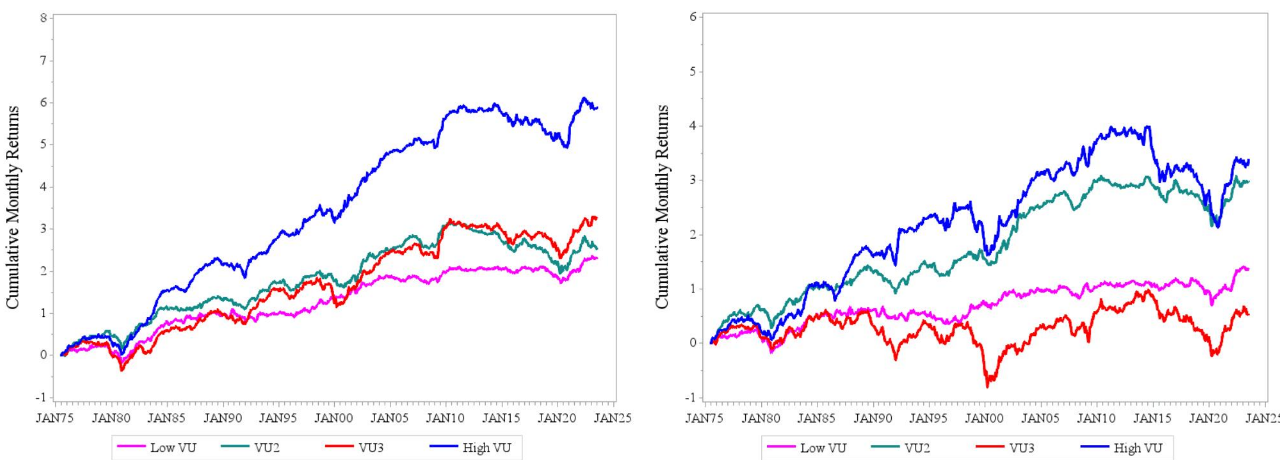
We develop a purpose-made, theoretically grounded measure of valuation uncertainty with large-sample availability. Our approach relies on mapping stock prices to accounting fundamentals via quantile regressions across industry peers. The resulting measure performs well in validation tests: it is related to cash flow and discount rate uncertainty, it explains price ranges in IPO prospectuses and M&A fairness opinions, and it incrementally predicts future outcomes indicative of uncertainty. As indirect validation, we use our measure to test the hypothesis that valuation uncertainty promotes valuation mistakes. The returns of a long-short price-to-value strategy increase with valuation uncertainty,

[32] To substantiate the visual evidence, we regress an indicator variable taking the value of 1 for medium sentiment and 0 otherwise on a year-counter variable that increments by one every year. The year-counter obtains a positive coefficient with a t-statistic of 6.54.
[33] In logs, the price-to-book ratio is just the sum of price-to-value and value-to-book ratios.

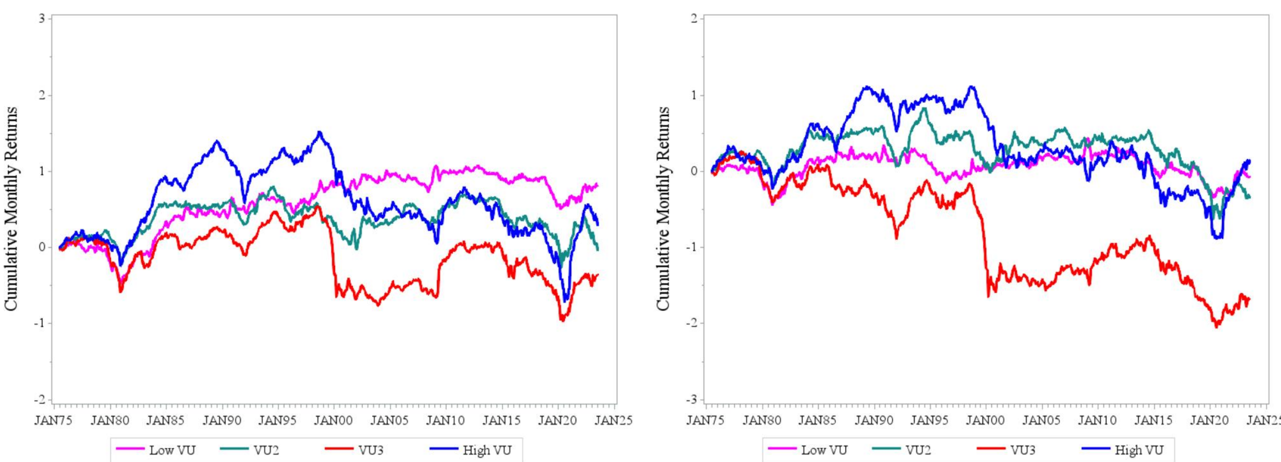
FIGURE 4

Cumulative Performance of *price-to-book* and *value-to-book* Strategies Conditional on Valuation Uncertainty

Panel A: Price-to-Book RW (Left) and VW (Right) Portfolios



Panel B: Value-to-Book RW (Left) and VW (Right) Portfolios



This figure depicts the cumulative return of long-short trading strategies formed on the basis of *price-to-book* (Panel A) or *value-to-book* (Panel B) conditional on valuation uncertainty (*VU*). One unit on the *y*-scale corresponds to 100 percent. The strategies are long all stocks in the bottom quartile of *price-to-book* (*value-to-book*) and short all stocks in the top quartile of *price-to-book* (*value-to-book*) within each valuation uncertainty quartile. Portfolio sorts are performed sequentially—first on valuation uncertainty and then on *price-to-book* (*value-to-book*)—every June 30. The universe excludes megacaps, defined as stocks with market capitalizations above the 75th percentile of market capitalization of NYSE firms. The sample period runs from July 1975 to June 2023. Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B.
(The full-color version is available online.)

and the returns of high-valuation uncertainty "growth" and "value" stocks are predictable by investor sentiment. Our application offers insights into why the conventional value premium has seemingly "disappeared" in recent years: the evolution of investor sentiment and interest rates emerge as plausible culprits deserving further study.

Other natural applications of our measure include tests of asymmetric information models in which uncertainty about intrinsic value drives key outcomes. Examples include IPO underpricing, bid-ask spreads, discounts in seasoned equity offerings, and the use of contingent payments (e.g., stock or earnouts) in M&A. Our measure can also sharpen the interpretation of earnings response coefficients in studies of disclosure quality and the informational content of news: in Bayesian learning frameworks, holding signal quality constant, the response to news intensifies with prior valuation uncertainty—while holding such uncertainty constant, stronger responses imply more credible signals. We note that our measure of valuation uncertainty incorporates variation from a whole range of commonly used proxies (e.g., firm size and age, stock return volatility, asset tangibility), making a case for its use as a single, multifaceted metric.

As any proxy for an unobservable construct, our valuation uncertainty measure has its limitations. We highlight two. First, it relies on a particular implementation of a given valuation model. This includes fixing a set of value-relevant fundamentals, imposing a particular functional form of the relationship between those fundamentals and value, assuming this relationship is constant within industry-years, and adopting a particular set of industry peers. That said, our measurement framework allows for flexibility/improvements in these choices. Second, annual frequency and limited time-series variation of our measure might not suit applications that require high-frequency, within-firm measurements. It is, however, possible to generate a version of our measure that is more frequently updated, e.g., using quarterly fundamentals and stock prices.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors indicate that no generative AI tools or AI-assisted technologies were used at any stage of the research process or in the preparation, writing, or editing of this manuscript.

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APPENDIX A

Variables Definitions

Variable	Definition
VU	Valuation uncertainty, computed as $(Q_{75} - Q_{25})/((Q_{75} - Q_{25})/2)$. Q_{25} and Q_{75} denote the exponentiated values of q_{25} and q_{75}, which are the conditional 25th and 75th percentiles of log (modified) market equity, respectively. The modification of market equity is decribed below.
price-to-value	Deviation of (modified) market value from expected fundamental value, defined as the residual from estimating the valuation model in Equation (6) using OLS regressions by industry-year.
price-to-book	Ratio of (modified) market value of equity (ME) to book value of equity (BE), both as defined below.
value-to-book	Ratio of expected fundamental value of equity, defined as the fitted value from estimating the valuation model in Equation (6) using OLS regressions by industry-year, to book value of equity (BE).
ME	Market value of equity as of June 30 from CRSP, computed as the closing stock price (CRSP item *prc*) multiplied by the number of shares outstanding (CRSP item *shrout*). *Nota Bene* (NB): When estimating the valuation model in Equation (6), we modify this definition in two ways. First, we use the fully-diluted number of shares outstanding, defined as the number of shares outstanding as of June 30 from CRSP (item *shrout*) divided by the ratio of primary shares (item *cshpri*) to fully diluted shares (item *cshfd*) as of fiscal year-end from Compustat. The ratio is capped at 0.5 from below and at 1.0 from above. Second, we add back the dollar value of dividends paid in the period between the fiscal year-end and June 30 (computed using CRSP items *ret* and *retx*).
BE	Book value of common equity (Compustat item *ceq*) plus balance sheet deferred taxes (Compustat item *txdb*) as of fiscal year-end. Observations with negative *BE* are excluded.
RD	Capitalized value of R&D expenditures (based on Compustat item *xrd*) as of the fiscal year-end, assuming a five-year useful life and straight-line amortization of 20 percent (Chan et al. 2001). Specifically, $RD = xrd_t + 0.8 \times xrd_{t-1} + 0.6 \times xrd_{t-2} + 0.4 \times xrd_{t-3} + 0.2 \times xrd_{t-4}$. NB: Missing values of *xrd* are set to 0. For newly listed firms without sufficient reporting history, *RD* is imputed as current *xrd* times the mean ratio of *RD* to current *xrd* in the same industry-year.
EARN	Adjusted earnings as of the fiscal year-end, defined as income before extraordinary items attributable to common shareholders (Compustat item *ibcom*) minus special items (Compustat item *spi*) plus R&D expenditure (Compustat item *xrd*) minus R&D amortization. R&D amortization $= 0.2 \times (xrd_{t-1} + xrd_{t-2} + xrd_{t-3} + xrd_{t-4} + xrd_{t-5})$. NB: Missing values of *xrd* are set to 0. For newly listed firms without sufficient reporting history, R&D amortization is imputed as *RD* times the mean ratio of current R&D amortization to *RD* in the same industry-year.
LEV	Book leverage, defined as long-term debt (Compustat item *dltt*) plus debt in short-term liabilities (Compustat item *dlc*) divided by total assets (Compustat item *at*), all as of the fiscal year-end.
m	Natural logarithm of (modified) *ME* as defined above.
b	Natural logarithm of *BE* as defined above.
|earn|	Natural logarithm of the absolute value of *EARN* as defined above.
rd	Natural logarithm of 1 + *RD* as defined above.
IQR(P/B)	Interquartile range of the price-to-book multiple in a given Fama-French 12 industries-year. Price is *ME* as defined above. Book is *BE* as defined above.
IQR(EV/EBITDA)	Interquartile range of the enterprise value-to-EBITDA multiple in a given Fama-French 12 industries-year. Enterprise value is *ME* defined above plus short-term debt (Compustat item *dlc*) plus long-term debt (Compustat item *dltt*) plus preferred stock (Compustat item *pstk*) minus preferred stock in treasury (Compustat item *tstkp*) plus preferred dividends in arrears (Compustat item *dvpa*). EBITDA is operating income before depreciation (Compustat item *oibdp*). Only firms with positive EBITDA are considered.
IQR(P/E)	Interquartile range of the trailing price-to-earnings multiple in a given Fama-French 12 industries-year. Price is *ME* as defined above. Earnings are defined as income before extraordinary items (Compustat item *ib*). Only firms with positive earnings are considered.

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APPENDIX A (continued)

Variable	Definition
IQR(Forward P/E)	Interquartile range of the forward price-to-earnings multiple in a given Fama-French 12 industries-year. Forward earnings are defined as the most recent consensus EPS forecast from the I/B/E/S unadjusted summary file. Price is the closing stock price (CRSP item *prc*) as of the analyst forecast date. Only firms with positive forward earnings are considered.
$\sigma(ROA)^{PRE/POST}$	Standard deviation of ROA over the years *t* to *t*–4 (^{PRE}) or *t*+1 to *t*+5 (^{POST}). ROA is income before extraordinary items (Compustat item *ib*) scaled by average total assets (Compustat item *at*).
β *[AR(1)]*	AR(1) coefficient from a regression of return on assets on its lag, estimated firm-by-firm over the most recent ten years (min. of eight obs.) Return on assets is defined as in $\sigma(\mathrm{ROA})^{\mathrm{PRE/POST}}$ above.
R^2 *[AR(1)]*	Similar to β *[AR(1)]* above, except that the R^2 coefficient from the same regression is used.
$\lvert ACC \rvert$	Absolute accruals scaled by average total assets (Compustat item *at*). Accruals is the *change* in working capital minus depreciation (Compustat item *dp*). Working capital is current assets (Compustat item *act*) minus cash and cash equivalent (Compustat item *che*) minus current liabilities (Compustat item *lct*) plus short-term debt (Compustat item *dlc*).
EarnQual	Standard deviation of residuals from the following regression: $Accruals_t = \delta_0 + \delta_1 \Delta REV_t + \delta_2 GPPE_t + \delta_3 CashFlows_{t-1} + \delta_4 CashFlows_t + \delta_5 CashFlows_{t+1} + \varepsilon_t$. The regression is estimated by Fama-French 12 industries-years (min. 20 obs.) The standard deviation of residuals is calculated over a period of five years. *GPPE* is gross property, plant, and equipment (Compustat item *ppegt*). ΔREV is the change in revenue (Compustat item *sale*). *Accruals* is the change in working capital plus change in total tax payable (using Compustat item *txp*). Change in working capital is defined the same way as for $\lvert ACC \rvert$ above. *CashFlows* is EBITDA (Compustat item *oibdp*) minus *Accruals*. All items are scaled by average total assets (Compustat item *at*).
$\sigma(ROA)^{PRE}/\sigma(CFO)^{PRE}$	Ratio of $\sigma(ROA)^{PRE}$, as defined above, and the standard deviation of total operating cash flow scaled by average total assets (Compustat item *at*). Total operating cash flow is income before extraordinary items (Compustat item *ib*) minus accruals, defined the same way as for $\lvert ACC \rvert$ above.
$\sigma(Beta)^{PRE/POST}$	Standard deviation of market betas over the years *t* to *t*–4 (^{PRE}) or *t*+1 to *t*+5 (^{POST}). Each year, beta is estimated using daily stock returns against the value-weighted CRSP index (min. 60 obs.).
$SE(Beta)^{PRE/POST}$	Standard error of market beta estimated over the most recent year (^{PRE}) or the subsequent year (^{POST}). Beta is estimated using daily stock returns against the value-weighted CRSP index (min. 60 obs.).
$\sigma(Returns)^{PRE/POST}$	Standard deviation of daily stock returns over the most recent year (^{PRE}) or the subsequent year (^{POST}) (min. 60 obs.).
$\sigma(CF\ News)^{POST}$	Standard deviation of cash flow news computed in the spirit of Da and Warachka (2009) over the subsequent 12 months. We utilize analysts' return on equity (ROE) forecasts (EPS/Book per share) up to Year 5 and allow ROE of Year 5 to fade over the next six years to a long-run ROE equal to *g* / (1 − dividend payout). Dividend payout is set to our sample mean of 22 percent.
$\sigma(Implied)$	Option-implied volatility on the last trading day of June. We use the average implied volatility of the 30-day at-the-money-forward puts and calls from the OptionMetrics standardized options file.
$\sigma(E[TP])$	Standard deviation of analysts' target prices (I/B/E/S item *stdev*) scaled by the mean price target (I/B/E/S item *meanptg*). We use the unadjusted I/B/E/S summary file.
$\sigma(E[EPS])$	Standard deviation of one-year-ahead analysts' EPS forecasts (I/B/E/S item *stdev* when "measure" = *EPS*, "fiscalp" = *ANN*, *fpi* = 1) scaled by the absolute value of mean consensus EPS forecast (I/B/E/S item *meanest*). We use the unadjusted I/B/E/S summary file.
$\sigma(E[LTG])$	Standard deviation of analysts' long-term growth forecasts (I/B/E/S item *stdev* when "measure" = *EPS*, "fiscalp" = *LTG*, *fpi* = 0). We use the unadjusted I/B/E/S summary file.
IPO Price Spread	Difference between the high and low IPO filing prices, scaled by their midpoint, all from Refinitiv Workspace.
M&A FO Spread	Difference between the high and low fair values for the target stock, scaled by their midpoint, all from Refinitiv Workspace. Multiple price ranges in a given FO (if any) are averaged across valuation methods and then averaged across banks in case of multiple FOs.

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APPENDIX A (continued)

Variable	**Definition**
Age	Number of years from foundation in Jay Ritter's IPO database. When this is unavailable, number of years from foundation in Capital IQ. When neither of the two is available, number of years since the first observation in CRSP.
Intan/Assets	Intangible assets (Compustat item *intan*) scaled by total assets (Compustat item *at*).
$I_{DIV>0}$	Indicator: 1 if common stock dividends are positive (Compustat item *dvc*) and 0 otherwise.
$I_{EARN<0}$	Indicator: 1 if *EARN* defined above is negative and 0 otherwise.
$SENT^{\perp}$	Sentiment index orthogonalized to macroeconomic fundamentals from Baker and Wurgler (2006).