Valuation uncertainty

Andrey Golubov and Theodosia Konstantinidi*

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Abstract

We develop a firm-specific measure of valuation uncertainty from the distribution of valuations predicted by an empirical multiples-based valuation model. The measure is effective in summarizing the information in existing proxies and offers substantial incremental variation. Among many possible applications, we use our measure to test the hypothesis that valuation uncertainty is conducive to valuation mistakes. A value-like long-short strategy is particularly profitable among high valuation uncertainty stocks. Stocks in the short leg earn average returns indistinguishable from the risk-free rate – turning *negative* following periods of high investor sentiment – and their future earnings disappoint. Insiders trade against the presumed valuation mistakes.

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* Golubov is from the Rotman School of Management, University of Toronto, 105 St. George Street, Toronto, ON, M5S 3E6, Canada (andrey.golubov@rotman.utoronto.ca). Konstantinidi is from Bayes Business School, City, University of London, 106 Bunhill Row, London, EC1Y 8TZ, United Kingdom (sonia.konstantinidi.1@city.ac.uk).
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1. Introduction

Valuation uncertainty is a fundamental concept in virtually all areas of finance. For instance, in corporate finance models with asymmetric information, greater uncertainty about the value of the firm intensifies outcomes such as adverse selection in equity issuance and IPO underpricing (Myers and Majluf (1984), Rock (1986), Benveniste and Spindt (1989)). Similarly, in market microstructure models with informed traders, valuation uncertainty exacerbates market makers' responses such as the bid-ask spread (Glosten and Milgrom (1985)).[1] In asset pricing, valuation uncertainty gives rise to differences of opinion that can affect asset prices in markets with trading frictions (Miller (1977), Hong, Scheinkman, and Xiong (2006)). In models of Bayesian learning, greater uncertainty about fundamental value intensifies agents' response to new information (Pástor and Veronesi (2009)).

While the theoretical notion of valuation uncertainty is well established, empirical measurement of valuation uncertainty in the literature has relied on indirect proxies. These surrogate metrics range from firm size and firm age to asset tangibility and dividend payment. The indirect nature of these proxies, as well as their correlation with extraneous characteristics, stands in the way of well-specified tests of the associated models' predictions. Similarly, inability to adequately control for valuation uncertainty does not allow for establishing new, alternative economic mechanisms.[2] In this paper, we propose a theoretically motivated and direct empirical measure of equity valuation uncertainty that is available for large samples. Having established the validity of this new measure, we demonstrate its power through one specific application to cross-sectional asset pricing. This particular analysis yields novel insights into the nature of the value premium.

Our starting point is the definition of valuation uncertainty. Following the theoretical tradition, we define valuation uncertainty as the dispersion of possible fundamental values, as reflected in the shape of the distribution of potential valuation outcomes. If one were able to observe such distribution, valuation uncertainty would be measured by its spread using quantities

[1] Note the distinction between valuation uncertainty and information asymmetry. Valuation uncertainty is the degree of dispersion of possible fundamental values. Information asymmetry is the extent to which the actual realization of fundamental value is common knowledge (e.g., the ratio of informed to uninformed traders). Valuation uncertainty can be present even when information is fully symmetric, i.e. all agents face the same uncertainty.

[2] Measures such as dispersion in analysts' earnings forecasts or option-implied volatility come closer to the theoretical notion of valuation uncertainty, but they exist only for small and selected samples.

such as standard deviation or interquartile range. This is precisely what we propose. The implementation of this idea requires us to obtain a distribution of predicted fundamental values. To value firms, we build on the work of Rhodes–Kropf, Robinson, and Viswanathan (2005) who map stock prices into accounting fundamentals and obtain time-varying industry-level valuation multiples. We expand that model to better account for the rising importance of intangible assets, and we make a number of further adjustments in our implementation of the model to increase cross-firm and within-firm comparability of market values and fundamentals.

Our main innovation, however, is to use quantile regressions to obtain predicted values of various quantiles of firm-specific fundamental values. This builds on the ideas in Konstantinidi and Pope (2016), who use quantile regressions to forecast risk in corporate earnings. Having obtained a distribution of predicted fundamental values, we define valuation uncertainty as the dispersion of that distribution, and, in particular, its interquartile range. Firms with greater (scaled) interquartile range are subject to higher valuation uncertainty, because their predicted valuations are more spread out. Although in this paper we focus on valuation uncertainty due to its central role in finance theories, our approach can be used to measure other aspects of the distribution of fundamental values – such as skewness, kurtosis, or value-at-risk – via the corresponding quantile predictions.

We first validate our measure of valuation uncertainty using existing proxies. We find that all proxies are associated with our measure with consistent signs, both individually and jointly. Specifically, we confirm that smaller and younger firms are subject to greater valuation uncertainty, as are firms with more intangible assets, higher stock return volatility, higher option-implied volatility, and greater dispersion of analysts' earnings forecasts. We also find that utility firms and dividend-payers, which are characterized by stable and predictable cash flows, have lower valuation uncertainty according to our measure, while the converse is true for firms in high-tech industries and firms reporting losses. Interestingly, all of these characteristics combined explain only 60 percent of the variation in our new measure. We conclude that our measure effectively summarizes the information in existing proxies and offers substantial incremental variation not spanned by existing measures.

While 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] Using the same empirical valuation model that we employ to measure valuation uncertainty, we define potential valuation mistakes as deviations of stock prices from expected fundamental values (price-to-value hereafter). Our analysis here follows Golubov and Konstantinidi (2019), who find that price-to-value is responsible for the entire value premium. We recognize that, a priori, stock price deviations from predicted fundamental values do not necessarily imply valuation mistakes by the market. However, our results that follow are highly suggestive of that interpretation. We present five main findings.

First, the relationship between price-to-value and valuation uncertainty is U-shaped. Stocks in the extreme price-to-value portfolios are characterized by significantly greater valuation uncertainty than stocks in the intermediate portfolios. That is, both "growth" and "value" stocks have more uncertain valuations than moderately priced stocks. Second, we find that 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 low – as low as the risk-free rate. These stocks, however, are far from risk-free, as demonstrated by our third finding. In particular, we show that high valuation uncertainty "growth" stocks exhibit *negative* average returns in one third of our sample period, namely, following episodes of high investor sentiment. Similarly, high valuation uncertainty "value" stocks earn particularly high returns following periods of low investor sentiment. This responsiveness of "value" and "growth" stocks to investor sentiment weakens for low valuation uncertainty stocks. Fourth, we find that investor surprises around earnings announcements are amplified by valuation uncertainty. High valuation uncertainty "value" stocks exhibit significantly positive earnings announcement returns in the four quarters following portfolio formation, while similarly uncertain "growth" stocks exhibit substantially negative earnings announcement returns. Finally, our fifth finding is that insiders trade against price-to-value (presumed valuation mistakes), and this trading also intensifies with valuation uncertainty.

[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 value 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.

Overall, these findings are consistent with the hypothesis that valuation uncertainty promotes valuation mistakes. In principle, 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. This interpretation, however, would require a theory whereby valuation uncertainty increases the covariance of "value" stocks with the stochastic discount factor while *simultaneously* lowering the same covariance for "growth" stocks. Moreover, various aspects of our results are hard to square with a risk premium view alone.

First, the magnitude of the "value" premium conditional on high valuation uncertainty appears too large, with a Sharpe ratio that is twice as high as that of the market portfolio. Second, with high valuation uncertainty "growth" stocks earning a risk-free rate of return, the risk premium interpretation implies that this portfolio is a risk-free asset. We view this as unlikely, especially in light of the negative returns of these stocks around subsequent earnings announcements and following periods of high investor sentiment. Finally, it is not clear why insiders of high valuation uncertainty "value" stocks would find it optimal to increase their exposure to the presumed risk factor, on top of their existing exposure through firm-specific human capital. Nevertheless, despite the foregoing discussion, our evidence should be viewed as being "consistent" with valuation mistakes, not a proof thereof. We also note that valuation mistakes and risk premia are not mutually exclusive (Kozak, Nagel, and Santosh (2018)).

Our paper makes two distinct contributions to the finance literature. First, we propose and validate a novel measure of equity valuation uncertainty that is available for a large cross-section of firms – including, potentially, private companies. Our work is related to that of Joos, Piotroski, and Srinivasan (2016) who use the spread of scenario-based analysts' valuations as a measure of valuation uncertainty. Second, our application of the measure yields novel insights into the properties of the value premium. This is because the sorting variable in this analysis is a component of the conventional market-to-book ratio. 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 Golubov and Konstantinidi (2019), Piotroski and So (2012), La Porta et al. (1997), as well as to the analysis in Rozeff and Zaman (1998) and Jenter (2005) as regards insider trading.

The rest of the paper proceeds as follows. We discuss our measurement framework in Section 2. We describe data processing, estimation, and the properties of our new measure of valuation uncertainty in Section 3. In Section 4, we use our measure to test the hypothesis that valuation mistakes are more likely when valuation uncertainty is high. Section 5 concludes the paper with suggestions of possible future applications of the measure we develop.

2. Framework and Methodology

2.1. Valuation uncertainty

Valuation uncertainty is a key parameter in models with asymmetric information, as well as in models with heterogeneous investor beliefs. Using the former for illustration purposes, the tradition in this literature is to model the value of a project or security as a random variable drawn from a distribution with a given variance (e.g., p. 76 in Glosten and Milgrom (1985)). Under this modeling choice, higher variance of the distribution means greater uncertainty about the value of the project faced by the uninformed party. Similarly, valuation uncertainty is sometimes modeled as a parameter that determines the range between high and low liquidation values known privately by the informed agent (e.g., Table 1 of Bessembinder, Hao, and Zheng (2015)). Regardless of the modeling technique, greater valuation uncertainty implies distributions of possible values that are more dispersed. Thus, a measure of valuation uncertainty that respects the associated theories is a measure of the spread of the distribution of possible fundamental values. Figure 1 provides an illustration. It shows the density functions of two normally distributed variables with the same mean (zero) but different degrees of dispersion: the blue line corresponds to a distribution with a standard deviation of one, whereas the red line corresponds to a distribution with a standard deviation of two. The dashed lines indicate the respective interquartile ranges and demonstrate that the valuation outcomes of the more dispersed distribution cover a wider range of values.

We obtain distributions similar to the ones in Figure 1 by estimating various quantiles of predicted fundamental equity values. To value firms, we use an empirical multiples-based valuation model that builds on the work of Rhodes–Kropf, Robinson, and Viswanathan (2005) (RRV hereafter) and Golubov and Konstantinidi (2019) (GK hereafter). Specifically, we estimate industry-year regressions of market prices on fundamentals to infer discount rates and growth rates in the residual income valuation equation. We use this approach to estimate not only the expected fundamental value, but also its predicted distribution. We then measure the spread of the resultant distribution and generate a firm-specific, time-varying measure of valuation uncertainty. We now discuss the valuation model and quantile regression estimation in turn.

2.2. Valuation model

The starting point of the empirical valuation model we estimate is the well-known residual income valuation[4] equation:

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

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 as reported on a company's balance sheet. Residual income represents expected future earnings above the level that is required by the cost of equity capital. Under the assumptions that i) residual income is a constant fraction (d) of net income (NI_t), and ii) 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 eq. (1) 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:

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

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 to accommodate right skewness in market values and accounting fundamentals; this also ensures that predicted market values are not negative, consistent with limited lability. 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. The leverage term is included 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 α_{0jt} – α_{4jt} represent time-varying industry-level valuation multiples rooted in the residual income valuation model. The fitted value from eq. (2) estimated using OLS is the expected log market equity and is denoted as v.

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

We make one modification to the valuation model in eq. (2), motivated by the rise in the importance of intangible assets over the last decades (see, e.g., Peters and Taylor (2017)). It is well-understood that accounting book values exclude value-relevant intangible assets such as R&D capital. If it were not for the principle of conservative accounting, which does not allow for capitalization of R&D expenditures, past investments in R&D would have contributed to the book value of equity – just as capital expenditures do. 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. 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 5-year useful life and a straight-line amortization rate of 20%.[5] 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:

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

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

2.3. Quantile regressions

While RRV and GK focus on the expected fundamental equity value – the conditional mean forecast – we are interested in the entire distribution of possible fundamental values. In particular,

[5] Note that 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. Specifically, we use all firms in an industry-year with sufficient prior data to compute R&D capital and express the latter as a multiple of current year R&D expense. We then apply this multiple to the current R&D expense of firms that lack the requisite history of R&D expenses. We follow the same approach to impute amortization.

we are interested in the spread of that distribution. To measure this spread, we estimate the valuation model in eq. (3) using quantile regressions and obtain fitted values of various quantiles.[6] Linear quantile regressions express a given quantile of an outcome variable's distribution as a function of predictors. Coefficients in such regressions are obtained by minimizing the sum of weighted absolute residuals, where the weights are equal to the targeted quantile x for positive residuals and $1 - x$ for negative residuals. We denote the conditional quantile prediction as q_{100x}. For example, q_{50} is the fitted value from the quantile regression of the valuation model in eq. (3) estimated at the median ($x = 0.50$) and represents the predicted median fundamental value given the values of the valuation model inputs.

In principle, one can estimate any number of such conditional quantiles. For our purposes, we only need the predictions of the conditional 25th and 75th percentiles, denoted q_{25} and q_{75}, respectively. This is because we define valuation uncertainty as the interquartile range of the distribution of fundamental values. Note that, since the valuation model is estimated in logs, we first exponentiate the predictions (denoted by uppercase Q_{25} and Q_{75}) and then compute our valuation uncertainty measure VU:

$$VU = \frac{Q_{75} - Q_{25}}{(Q_{75} + Q_{25})/2} \tag{4}$$

The interquartile range is scaled by the midpoint between the two quantiles in order to make the measure comparable across firms of different size. This definition is the same as in Joos, Piotroski, and Srinivasan (2016), who use the spread in scenario-based analysts' valuations as a measure of valuation uncertainty. Finally, while we are interested in valuation uncertainty, which corresponds to the dispersion/spread of the distribution of fundamental values, we note that our methodology allows for measuring other aspects of that distribution, such as asymmetry (via quantile skewness), the probability of extreme outcomes (via quantile kurtosis), and value-at-risk.

[6] Some notable applications of quantile regressions to predict outcomes in finance and accounting include Edmans, Goldstein, and Jiang (2012), Konstantinidi and Pope (2016), Correia, Kang, and Richardson (2018), Chang et al. (2021).

3. Data Sources and Estimation Results

3.1. Sample selection

We start with the intersection of CRSP and Compustat databases over the period 1974 to 2018, 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 30 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, 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 to 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 observed market capitalization from CRSP does not reflect the entire market value of equity capital of dual class firms. At the same time, book value of common equity from Compustat reflects the book 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, Ishii, and Metrick (2010). First, we eliminate all firms listed as dual class according to RiskMetrics (formerly 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%. These filters eliminate 7.6% unique firms that account for 9.7% of firm-year observations.[7]

[7] An alternative solution is to keep dual class firms in the sample and compute market capitalization using the number of shares outstanding from Compustat as of the end of the fiscal year. This share count is inclusive of all share classes. However, this creates a timing mismatch between the stock price and the number of shares outstanding, as we wish to use stock prices that are actually observed at the time when accounting information has been made public and observed by market participants.

Next, we drop observations with missing valuation model inputs (book value of equity, earnings, capitalized R&D, and leverage). Finally, we eliminate outliers in terms of 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% of RD capital-to-assets. The remaining sample of 120,405 firm-year observations over the period 1974-2018 forms the basis of our valuation model estimation. Table 1 presents descriptive statistics for this estimation sample.

Since valuing firms using pricing information from industry peers is at the core of our analysis, we take a number of steps to ensure that market values and accounting fundamentals are comparable across firms. First, given the lag between fiscal year-end dates and the measurement of market value of equity, firms that pay out dividends during that period will trade at ex-dividend market values of equity, whereas the associated fiscal year-end accounts are "cum-dividend". We therefore add back to the market value of equity the dollar amount of dividends paid since the balance sheet date. The dollar amount of dividends is computed as the difference between monthly returns with and without dividends, multiplied by the opening market capitalization, cumulated from the fiscal year-end date to June 30.[8]

Second, we account for differences in expected ownership dilution across firms. When dilution is expected, current shareholders will have a claim to less than 100% of the firms' net assets and the associated income stream. Efficient market prices should therefore reflect any expected dilution of the current equity holders' claims to the accounting fundamentals and the value they generate.[9] To account for this in our relative valuations, we use the fully-diluted number of shares outstanding when computing the market value of equity. To compute the fully-diluted

[8] 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).

[9] To illustrate this point, 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. In other words, despite the same observed stock prices, firm B is trading at a higher effective valuation multiple. The market capitalization based on the number of shares currently outstanding fails to account for this difference in valuations.

number of shares, we use the number of shares outstanding from CRSP as of June 30 and divide it by the ratio of basic shares to diluted shares from Compustat (as of the fiscal year end). When the information on basic and diluted shares outstanding is not available in Compustat, we impute the ratio of 1. We winsorize the ratio at [0.5, 1] to reduce the influence of any data errors (the top end is naturally capped at 1). Our use of the diluted number of shares outstanding has the effect of increasing the measured market value of equity of firms with dilutive securities outstanding, thereby restoring cross-firm comparability of valuation multiples.

Finally, while RRV and GK use net income (Compustat item *ni*) for the earnings variable in eq. (3), we use income before extraordinary items attributable to common stockholders adjusted for special items (Compustat item *ibcom* minus Compustat item *spi)*. Purging earnings from one-off items is expected to improve estimation on two dimensions. First, it increases earnings comparability across firms. Second, recurring earnings serve as a better basis for the perpetuity implied by the multiple.

3.2. Estimation results

Table 2 presents the results from estimating our valuation model using OLS and quantile regressions. For brevity, these estimation results are reported for three representative Fama-French 12 industries: manufacturing, business equipment, and utilities. The reported coefficients and R^2s are time-series averages across 44 sample years. For quantile regressions, we report results for the 25^{th} and 75^{th} 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 (75^{th} minus 25^{th}), labelled as IQR. Applying the IQR coefficients to the valuation model inputs reproduces the interquartile range of the predicted distribution of log fundamental value, $q_{75} – q_{25}$. Hence, these coefficients indicate 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 $VU = (Q_{75} – Q_{25})/((Q_{75} + Q_{25})/2)$; the two quantities are collinear).

We start our discussion with 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. Consistent 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 negative earnings is negative and highly statistically significant in manufacturing and business equipment industries, but not for utilities. In other words, utilities are not penalized for the size of their losses, suggesting that investors view negative earnings in that industry as more transitory than in the manufacturing or business equipment industries. 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 discussing the results from quantile regressions. This discussion is most informative when focusing on the IQR coefficients. Recall that these coefficients indicate the impact of fundamentals in our valuation model on valuation uncertainty (*VU*). In fact, the variation in estimated valuation uncertainty *VU* comes from two sources: i) the variation in fundamentals across firms, and ii) the variation in IQR coefficients across industries and over time.[10]

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 negative in the utilities industry. 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. 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 2 illustrates the core of our measurement framework using estimates for three sample firms as of the most recent year of our data (June 30, 2018). The three firms – NVidia Corp., Polaris Inc., and Connecticut Water Services Inc. – come from the three industries discussed

[10] Note that the IQR intercept also varies by industry-year, allowing the "base" level of valuation uncertainty to also vary with industry and time.

above, namely, business equipment, manufacturing, and utilities, respectively. For each firm we plot the predicted value of log market equity for various quantiles (from eq. (3)) 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 Polaris Inc., while the predicted equity values of Polaris Inc. are more dispersed than those of Connecticut Water Services. Therefore, NVidia is subject to greater valuation uncertainty than Polaris, while Connecticut Water Services exhibits the lowest valuation uncertainty of the three firms. Figure 2 also demonstrates the pitfalls of relying on 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 Connecticut 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 eq. (4). Prior to computing our measure *VU*, we ensure that the predicted distributions of 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%. Our resulting sample contains 112,048 firm-year observations for 13,054 unique firms over the period 1974–2018. On average, valuation uncertainty in our sample has a mean of 0.7656, which implies that the range between the 75th and 25th percentiles of predicted fundamental values is equal to 76.56% of their midpoint. There is significant cross-sectional variation in our valuation uncertainty measure, with a standard deviation of 0.2355.

Table 3 exemplifies the results of our measurement using well-known firms from the most recent year of our sample. Specifically, we report our measure of valuation uncertainty *VU* for three representative companies from each of the Fama-French 12 industries, including the three firms used above. Firms are sorted according to *VU* in descending order. Interestingly, technology companies such as eBay Inc. and NCR Corp. are at the top of this list with values of *VU* above 1.0, while utilities firms such as Xcel Energy Inc. and CenterPoint Energy Inc. are at the very bottom of the list with values of *VU* around 0.3. Energy and chemical firms such as ConocoPhillips and

Eastman Chemical Co. rank towards the bottom, as do manufacturers such as Goodyear Tire & Rubber Co and Ingersoll Rand Inc. Telecommunications providers Cable One Inc. and Sprint Corp., as well as healthcare firms FibroGen Inc. and Boston Scientific Corp. rank relatively highly. Overall, these examples suggest that our measure is in agreement with subjective assessments of relative valuation uncertainty based on industry affiliation and common wisdom.

Finally, we note that, having estimated the valuation model and obtained the necessary coefficients, one can measure valuation uncertainty for firms that are not part of the estimation, by means of out-of-sample predictions. For instance, we have excluded dual class firms to ensure that we have an accurate mapping of market values to accounting fundamentals. However, one can still obtain a measure of valuation uncertainty for dual class firms by applying the industry-specific time-varying IQR coefficients to those firms' fundamentals. Moreover, one can also obtain estimates of valuation uncertainty for private firms, which may be of interest, for example, in studies of IPO underpricing.

3.3. Validation tests

The literature so far has relied on a range of indirect proxies for valuation uncertainty, such as firm size and firm age, asset tangibility, stock return volatility, dispersion in analysts' earnings forecasts, as well as industry affiliation (e.g., technology firms).[11] In this section, we examine the association of our new measure of valuation uncertainty with these existing proxies using univariate and multivariate regressions. These tests serve two purposes. First, using existing proxies as benchmarks, we aim to validate our new measure. Second, reversing the logic and taking our new measure as the benchmark, we assess whether existing proxies adequately capture the variation of interest. Table 4 reports the results of this analysis using annual Fama-MacBeth regressions.

In column (1), we regress *VU* on our first proxy, firm size, measured by the natural logarithm of market value of equity (*log(ME)*). The coefficient on *log(ME)* is negative, consistent with the common wisdom that smaller firms are subject to greater valuation uncertainty. This association is not surprising, given that book value of equity – another measure of size – is part of our valuation model and has a negative *IQR* coefficient in most industries. The R^2 of this regression is 28.4%,

[11] See, e.g., Zhang (2006) and Kumar (2009) for asset pricing contexts; Ritter (1984), Loughran and Ritter (2004) and Lee and Masulis (2009) for corporate finance examples.

suggesting that size explains about 28% of the cross-sectional variation in valuation uncertainty. Given that this is a univariate regression, swapping the left-hand side and right hand-side variables would result in the same R^2. Thus, taking our measure as a benchmark, as much as 100% – 28.4% = 72.6% of the variation in size is *un*related to valuation uncertainty.

In column (2), we use firm age, measured by the (log) number of years since the first record in CRSP, as our second proxy. We find a negative coefficient on *log(Age)*, consistent with the intuition that younger firms are subject to greater valuation uncertainty. The R^2 of this regression is 12%, suggesting that firm age explains only 12% of the variation in valuation uncertainty. Similarly, taking our measure as a benchmark, as much as 88% of the variation in firm age is orthogonal to valuation uncertainty.

Column (3) reports the same analysis using stock return volatility (*σ(returns)*) as a proxy. The coefficient on *σ(returns)* is positive, implying that more volatile stocks exhibit higher levels of valuation uncertainty. The R^2 of this univariate regression suggests that stock return volatility explains 24.5% of the variation in our new measure. Once again, taking our proxy as the benchmark, 75.5% of the variation in stock return volatility is unrelated to valuation uncertainty.

In column (4) we use the ratio of intangible assets to total assets (*Intan/Assets*) as our next proxy. The coefficient on *Intan/Assets* is positive, consistent with the intuition that the value of intangible assets is more uncertain. However, the R^2 of this regression is low, equal to 0.4%, suggesting that asset intangibility explains only 0.4% of the variation in valuation uncertainty. Similarly, 99.6% of the variation in asset intangibility is unrelated to valuation uncertainty if one accepts our measure as the benchmark.

In columns (5) and (6), we use as proxies two indicator variables for firms reporting negative earnings ($I_{EARN<0}$) and for dividend-payers ($I_{DIV>0}$), respectively.[12] The common wisdom is that loss-making firms are more difficult to value because of uncertainty regarding their steady-state earnings, whereas the payment of dividends is viewed as an indication of more certain (stable) future cash flows. Consistent with these ideas, the coefficient on $I_{EARN<0}$ is positive while the coefficient on $I_{DIV>0}$ is negative. The R^2s from the regressions suggest that both the sign of earnings and the payment (or not) of dividends explain about 19% of the variation in valuation uncertainty.

[12] We use our adjusted earnings figure in defining loss-making firms. Dividend-payers are defined based on the Compustat item *dvc*.

In columns (7) and (8) we use affiliation with two specific industries, namely high-tech industries and utilities, as proxies for valuation uncertainty. The definition of high-tech industries follows Loughran and Ritter (2004), who use this proxy to analyze time-series variation in IPO underpricing. The intuition is that high-tech firms tend to be young, have little-to-no earnings (or even revenues), and derive most of their value from growth options rather than assets-in-place. By contrast, utilities firms are characterized by relatively stable and predictable cash flows (e.g., they tend to have long-term contracts, operate subject to price regulations, etc.), have mostly tangible assets, and often pay dividends. We therefore expect utilities firms to have lower valuation uncertainty. Utilities are defined the same way as in our industry-level estimation of the valuation model (Fama-French 12 industries classification). Regressing *VU* on the high-tech industry dummy, we find that high-tech firms are indeed associated with higher levels of valuation uncertainty according to our measure. The explanatory power of the high-tech dummy for our new measure is low, with an R^2 of only 5.6%. The coefficient on the utilities dummy is negative, consistent with our expectation that utilities firms' values are less uncertain. The R^2 of this regression indicates that the utility industry affiliation explains about 23% of the variation in valuation uncertainty.

In columns (9) and (10) we use our last two proxies of valuation uncertainty, namely, the dispersion in analysts' earnings forecasts (*σ(E[EPS]))* from I/B/E/S and option-implied volatility (*σ(implied)*) from OptionMetrics. Although these proxies track the notion of valuation uncertainty more closely, they are only available for firms that are covered by analysts or have options that are traded on them.[13] The coefficient on *σ(E[EPS])* is positive, consistent with the intuition that disagreement among analysts is indicative of valuation uncertainty. The explanatory power of this proxy is modest with an R^2 of about 4.4%. Option-implied volatility also obtains a positive coefficient, and its association with our new measure is stronger than that of analysts' forecast dispersion: it explains 26.1% of the variation in *VU*.

Our final step in these validation tests is to combine all proxies in a single regression. This allows us to see i) whether any of the existing proxies are redundant after controlling for others, and ii) whether our new measure is just a linear combination of existing proxies. To avoid loss of observations, we first run a multivariate regression with all proxies except for dispersion in analysts' earnings forecasts and option-implied volatility, reported in column (11). We then

[13] The loss of observations for option-implied volatility is more severe because OptionMetrics coverage starts in 1996.

progressively add *σ(E[EPS])* and *σ(implied)* in columns (12) and (13), respectively. Our insights remain the same regardless of whether analysts' forecast dispersion and option-implied volatility are included in the regression. First, all variables are significant in the joint regressions. In other words, none of the existing proxies is redundant; each one of them captures some unique aspect of valuation uncertainty. We view this as an indication that our new measure is comprehensive in capturing these various aspects. Second, and perhaps most importantly, ten existing proxies *combined* explain about 60% of the variation in our new measure. In other words, our measure is not just a linear combination of existing proxies – it offers substantial incremental variation.

Lastly, we consider one potential source of noise in our measure. Recall that part of the variation in *VU* comes from the variation in IQR coefficients across industries: greater dispersion in valuation multiples within industry-years translates into higher values of *VU*. If the quality of peers is not the same across our industry groupings (e.g., "utilities" vs. "business equipment"), then the less homogenous industry groups may exhibit greater dispersion in valuation multiples, raising the values of *VU* for the associated firms. To examine the impact of any such noise, we re-estimate our valuation model and our *VU* measure using finer industry groupings, namely, Fama-French 17, 30, and 38 industry classifications. We also experiment with *firm-specific* peer sets, according to the product similarity scores of Hoberg and Phillips (2010, 2016), which allow us to fix the minimum similarity threshold for every sample firm. The cost of these alternatives, however, is that the cross-section of our sample shrinks considerably due to the insufficient number of peers within industries (we require a minimum of 30 to estimate the valuation model).[14] We find a high degree of correlation between the alternative *VU* measures and our baseline measure obtained from Fama-French 12 industries. These correlations range from 0.83 for Fama-French 30 industries to 0.74 for product market peer sets. Moreover, when we repeat the validation tests discussed above, we find that the univariate and multivariate regression coefficients, as well as model R^2s, are highly similar to those reported in Table 4. Thus, it appears that uneven quality of industry peers does not impart significant amounts of noise.

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[14] In the case of product market peers, the time-series also shrinks, because the Hoberg and Phillips (2010, 2016) similarity scores are not available prior to 1989. We use their full TNIC file and set the minimum similarity threshold at 0.03. We thank Gerrard Hoberg and Gordon Phillips for making their data available on their website: https://hobergphillips.tuck.dartmouth.edu.

4. Application: Valuation uncertainty and valuation mistakes

While there are many possible uses of our new measure of valuation uncertainty in finance research (we briefly discuss some of them in the conclusion section), we demonstrate its power through one particular application to cross-sectional asset pricing. In particular, we test the hypothesis that valuation uncertainty is conducive to valuation mistakes. We develop this hypothesis below leading to five specific empirical predictions.

4.1. Hypothesis development and empirical predictions

We identify three theoretical settings in which greater valuation uncertainty is associated with greater deviations of prices from fundamental value. While these theories share a common prediction regarding the effect of valuation uncertainty on potential valuation mistakes, the underlying economic mechanisms are quite different. We now briefly discuss the three settings and the logic behind the prediction.

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: p. 1151). Therefore, in the presence of uncertainty, 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 of investors holding specific beliefs is prevented from impounding their forecasts into prices due to trading frictions (e.g., short-sale constraints for pessimists, leverage constraints for optimists). In this framework, greater valuation uncertainty should be associated with a higher likelihood of mispricing, because truncating the left or right tail of a more dispersed distribution shifts the mean of represented opinions to a greater extent. See Figure 3 for a graphical illustration.

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.[15] In this setup, pricing mistakes arise despite investors being rational: they attempt to resolve their uncertainty by updating their beliefs 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 expectations) and limits to arbitrage, as in Daniel, Hirshleifer, and Subrahmanyam (1998). First, stocks with more uncertain valuations are more prone to speculation. For instance, Baker and Wurgler (2006: p. 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, are wary of temporary further price dislocations and limit their trading. 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 positive and negative. Hence, we do not expect valuation uncertainty to be associated with valuation mistakes of a particular sign, only with a higher propensity for absolute mistakes. Instead of assuming that one type of trading friction dominates on average (e.g., assuming that short-sale constraints are more binding than constraints on bullish positions, 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 eq. (3) 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. Price-to-value is analogous to the priced component of

[15] In the case where prior belief is away from the true value but the signal moves investors' perceptions towards it, pricing mistakes moderate – and more so when uncertainty is high.

market-to-book ("firm-specific error") in Golubov and Konstantinidi (2019), except for the valuation model refinements discussed above.

If valuation uncertainty is conducive to valuation mistakes, then we expect to see a number of effects. In particular, we develop five specific predictions.

H1: Stocks in the extreme portfolios of price-to-value ("value" and "growth") are characterized by greater levels of valuation uncertainty than moderately priced stocks.

In other words, if deviations of prices from fundamental values are due to valuation mistakes, then we expect greater levels of valuation uncertainty among stocks for which greater mistakes have occurred. Thus, hypothesis *H1* predicts a U-shaped relationship between price-to-value and valuation uncertainty.[16]

H2: 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 *H2*.

H3: 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 the pricing of high valuation uncertainty stocks (Baker and Wurgler (2006)), then the ability of sentiment to time the returns of these stocks should increase with valuation uncertainty.[17]

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[16] One may have expected "growth" stocks to exhibit greater levels of valuation uncertainty than "value" stocks, since greater uncertainty raises growth-option value reflected in equity prices. However, our definition of "value" and "growth" differs from the conventional one – it is based on price-to-value rather than price-to-book. Golubov and Konstantinidi (2019) show that any variation in growth-option intensity proxies that exists along price-to-book is passed on to the value-to-book component, with no remaining differences across price-to-value.

[17] Unlike our other hypotheses, prediction H3 is uniquely associated with models of sentiment traders (i.e. biased investor beliefs).

H4: "Value" ("growth") stocks are associated with positive (negative) surprises about future fundamentals, and this association intensifies with valuation uncertainty.

To the extent that valuation mistakes are brought to the fore by subsequent earnings announcements, we expect market participants to be positively (negatively) surprised by future realizations of fundamentals of "value" ("growth") stocks. In addition, if valuation mistakes are more likely when valuation uncertainty is high, then the magnitude of subsequent surprises should increase with valuation uncertainty.

H5: Insiders of "value" ("growth") firms are more likely to buy (sell) shares in their firms, and this trading is amplified by valuation uncertainty.

Hypothesis *H5* builds on the idea that insiders, who tend to be better informed about their firms' prospects than outside investors, can capitalize on valuation mistakes by taking advantage of favorable prices (see, e.g., Piotroski and Roulstone (2005) and Rozeff and Zaman (1998)).

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 i) valuation mistakes are more likely when valuation uncertainty is high, and ii) our sorting variable, price-to-value, identifies valuation mistakes at least to some extent. While we cannot fully overcome this joint-hypothesis problem, in our discussion of the results that follow we appeal to economic theory as a means of limiting the validity of alternative interpretations. For instance, theory constrains the signs and/or magnitudes of certain parameters of interest, such as risk premia.

4.2. Analysis sample

We implement our tests of the above predictions using our main universe of 112,048 firm-year observations over the period 1974–2018, but after excluding megacaps. Megacaps are defined as firms whose market capitalizations as of June 30 are above the top quartile (75^{th} percentile) of market capitalization of NYSE-listed firms. This requirement is not onerous on the data: it eliminates 10.5% of firm-year observations (11,741) and only 2.3% (298) of unique firms. 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 (e.g., Israel and Moskowitz (2013)). 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 et al. (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 et al. (2020)) poses a measurement challenge for asset pricing tests. While economists have focused on the implications of the rise of superstar firms for industry concentration and market power, the emergence of firms with market capitalizations in the hundreds of billions of dollars generates excessive concentration in value-weighted portfolios commonly used in asset pricing. For instance, when computing value-weighted returns for our double-sorted portfolios with megacaps included, the largest stock in a portfolio has an *average* weight of 17%, and can be as high as 68%. This is despite there being over 150 stocks per portfolio, on average. Such concentration results in inferences that are driven by a small number of megacaps, which may not represent large sample evidence. By eliminating megacaps, we reduce the weight of the largest stock per portfolio to 6% on average, and it never exceeds 26%. An alternative approach is to exclude the top largest stocks from each portfolio (e.g., top 10-15), or to focus on portfolio weighting schemes that do not prioritize large caps. Our conclusions are robust to these alternatives.

4.3. Deviations from fundamental value and valuation uncertainty

We first examine the relationship between price-to-value and valuation uncertainty, as predicted by *H1*. Table 5 presents the associated results. In Panel A, we sort stocks into equal-sized deciles according to price-to-value and compute the average valuation uncertainty of stocks in each decile. Column (1) reports the resulting decile means of *VU*. The corresponding *p*-values in column (2) indicate whether these means are significantly different from the average valuation uncertainty of moderately priced stocks, namely those in deciles 5 and 6.

The results reported in Panel A reveal a U-shaped pattern of valuation uncertainty along price-to-value. In particular, “value” stocks and “growth” stocks have higher valuation uncertainty than stocks in the intermediate portfolios. The economic magnitude of the differences is large: the valuation uncertainty of stocks in the extreme “value” and “growth” deciles exceeds that of the moderately priced stocks (deciles 5–6) by about 0.65 standard deviations.[18] Given the strong correlation between valuation uncertainty and size, and the fact that value stocks tend to be small, in Column (3) and (4) we repeat the test using a measure of valuation uncertainty that is orthogonalized to size. To avoid look-ahead bias in subsequent tests, this orthogonalization is performed by year, whereby we run annual cross-sectional regressions of *VU* on *log(ME)* and take the residuals. This regression corresponds to the one reported in column (1) of Table 4, and the resulting measure is denoted by $VU^{\perp}$. After orthogonalization, we still find that stocks in the intermediate portfolios of price-to-value have lower levels of orthogonalized valuation uncertainty than stocks in the extreme portfolios of price-to-value. The relationship turns from being U-shaped to being J-shaped, whereby "growth" stocks have particularly high levels of valuation uncertainty when using the orthogonalized measure.

We also perform a stock-level counterpart to this test, whereby we impose a quadratic relationship between valuation uncertainty and price-to-value. Specifically, in regressions reported in Panel B, we regress *VU* and $VU^{\perp}$ on price-to-value and price-to-value squared. The quadratic term obtains a positive and highly statistically significant coefficient in both regressions, confirming a U-shaped association between valuation uncertainty and price-to-value.

To ensure that our subsequent tests do not pick up the well-known fact that value-like strategies are stronger among small stocks, we use the orthogonalized valuation uncertainty measure $VU^{\perp}$ in the remainder of our analysis. To the extent that size indeed contributes to valuation uncertainty, our use of the orthogonalized measure represents over-controlling. We proceed with the orthogonalized measure to remain conservative; we obtain stronger results when using the raw measure.

4.4. Double-sorting on valuation uncertainty and deviations of stock prices from predicted value

We now turn to testing *H2*, 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 x 4 portfolios sorted on valuation uncertainty and price-to-value. We use conditional sorts, whereby we first sort stocks into four quartiles based on valuation uncertainty and then further sort on price-to-value within each valuation uncertainty

[18] The average VU of stocks in the extreme "value" ("growth") decile is 0.863 (0.879), while the average VU of deciles 5–6 is 0.716. The standard deviation of VU is 0.2355.

quartile. Given our earlier finding that "value" and "growth" stocks are characterized by high average valuation uncertainty, conditional sorts ensure that our 4 x 4 portfolios are well-populated.[19] 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 that pertains to the average firm and not to the average dollar invested. This implies that the equal-weighted portfolio return is a more appropriate way to test our hypothesis regarding the occurrence of valuation mistakes. However, equal-weighted portfolio returns are known to 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, Bessembinder, and Kalcheva (2013) recommend using weighting schemes that induce a negative covariance between return measurement bias and portfolio weight, namely, 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 portfolio returns given the arguments above.[20]

Panel A reports the RW returns of double-sorted portfolios. Focusing on low valuation uncertainty stocks in the left-most column, we find that "value" stocks earn an average return of 1.27% per month, while "growth" stocks earn an average return of 0.94%. The difference between the two is 0.33% per month, significant at the 1% level. Moving across the columns to the right, we find that the returns of "value" stocks increase, from 1.28% to 1.64% per month, as valuation uncertainty goes up. At the same time, the returns of "growth" stocks decline with valuation uncertainty, from 0.94% to as low as 0.44%. As a result, the long-short return is monotonically

[19] Towards 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. We note that our results and inferences are not sensitive to this choice.

[20] 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 eq. (3) places equal weight on each stock-level observation within an industry-year.

increasing with valuation uncertainty, from 0.33% per month to 1.20% per month. The difference in long-short returns between high and low valuation uncertainty stocks is 0.87%, significant at the 1% level. The volatility of long-short returns also increases with valuation uncertainty, but this increase is modest, resulting in a substantially higher Sharpe ratio of the long-short strategy among high valuation uncertainty stocks as compared to the same strategy among low valuation uncertainty stocks (1.08 vs. 0.43, respectively).

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 valuation uncertainty stocks is 0.26% per month, growing monotonically as valuation uncertainty increases, reaching 0.74% for high valuation uncertainty stocks. The difference in hedge returns between extreme quartiles of valuation uncertainty is 0.48% per month, with a *p*-value of 0.011. 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 4 reports the cumulative performance of our long-short strategies over the sample period. Panel A depicts the performance of the RW strategies, and Panel B reports the returns earned by the VW strategies. Focusing first on the RW strategies, this time-series presentation shows that an investor in the long-short strategy among high valuation uncertainty stocks would have earned a cumulative return of 627% over the 44-year sample period, as compared to only 176% for the same strategy among low valuation uncertainty stocks. Turning to the VW strategies, we find that an investor trading on price-to-value among high valuation uncertainty stocks would have earned a cumulative return of 385%, whereas this return would be only 139% if the strategy was implemented among low valuation uncertainty stocks. Both RW and VW graphs suggest that the well-known deterioration of the value strategy's performance over the recent decade is partly due to low valuation uncertainty stocks; the long-short strategy among stocks with the highest level of valuation uncertainty continues to be profitable up until the very last few months of our sample that ends in June 2019.[21]

Overall, the results reported in this section provide strong support for prediction *H2*: the long-short strategy that exploits deviations of stock prices from fundamental value is significantly

[21] Another reason for the relatively robust recent performance of our value strategy is that we use price-to-value as opposed to the conventional price-to-book. The price-to-value strategy is largely immune to the recent outperformance of conventionally defined growth over value.

more profitable among high valuation uncertainty stocks. This finding is consistent with our overarching hypothesis, namely, that valuation uncertainty promotes valuation mistakes. Nevertheless, it is important to note that this result is also consistent with a risk premium interpretation. Indeed, there is a substantial debate in the literature on the economic origins of the value premium and premia associated with related strategies (see, e.g. Golubov and Konstantinidi (2019)). 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. Under this alternative/complementary interpretation, conditioning on high valuation uncertainty 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 valuation uncertainty 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 that this may be the case. The first one pertains to the magnitude of the return on high valuation uncertainty "growth" stocks. On average, "growth" stocks characterized by high valuation uncertainty earn a monthly return of 0.44% (Panel A of Table 6). For comparison, the return on the one-month T-bill over our sample period is 0.37%.[22] In other words, high valuation uncertainty "growth" stocks have delivered average returns that are statistically indistinguishable from those on the risk-free asset (using the most conservative definition of the risk-free rate). Put differently, if the returns we document are determined purely by risk premia, then our portfolio of high valuation uncertainty "growth" stocks must be risk-free. We view this as unlikely. A more plausible interpretation is that the average returns on these stocks are low because they contain corrections of overvaluation. In the next section, we further show that the returns on these stocks are, on average, *negative* in one third of our sample period and, specifically, following periods of high investor sentiment.

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 valuation uncertainty stocks the Sharpe ratio is as high as 1.08. For comparison, the market risk premium (excess market return) over our sample period is 0.64% per month, with a Sharpe ratio of 0.50. In other words, the compensation demanded by investors for bearing the risk embedded in our value-like strategy is twice as high as that for bearing overall market risk. Once again, while this is not

[22] Data from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

entirely impossible, a more realistic explanation is that the return premium among high valuation uncertainty stocks is *at least partially* due to resolution of mispricing. Our tests of predictions *H3-H5* below provide further support for this interpretation.

4.5. Timing long and short returns with investor sentiment

Our next test builds on the work of Stambaugh, Yu, and Yuan (2012), who examine the relationship between investor sentiment and the returns of cross-sectional anomalies. Specifically, they show that the returns of stocks in the short leg of 11 prominent anomaly strategies are significantly lower following periods of high investor sentiment, making those short positions more profitable. They 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 basis of 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. This is our prediction *H3* 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 from Baker and Wurgler (2006, 2007).[23] 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, i.e. the long and the short legs of the value strategy across all levels of valuation uncertainty.

We find that that the returns of stocks in the short leg ("growth" stocks) are consistently lower following periods of high investor sentiment, and this difference increases monotonically with valuation uncertainty. For instance, using RW portfolios, the difference in the returns of low valuation uncertainty "growth" stocks between low and high sentiment periods is 1.23% per month and increases to 3.21% per month for high valuation uncertainty "growth" stocks. For VW portfolios, the difference across periods for low valuation uncertainty "growth" stocks is 0.76% (with a *p*-value of 0.132) and reaches a highly significant difference of 2.55% per month for the

[23] We thank Jeffrey Wurgler for making these data available on his website: http://people.stern.nyu.edu/jwurgler/.

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 valuation uncertainty stocks.

Perhaps the most interesting result from this analysis is the magnitude of the returns on high valuation uncertainty "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 –1.32%, which is significantly different from zero at the 5% level. When portfolios are value-weighted, the average return is –0.63%, although not significantly different from zero with a *p*-value of 0.296. Recall from our earlier findings that these same stocks exhibit an average return over the sample period that is indistinguishable from the risk-free rate. If these stocks were indeed a surrogate for the risk-free asset, then an investor in such riskless security would have lost money during at least a third of our sample period. While this combination of results is not entirely inconceivable in a risk-return framework, the fact that the period of negative returns coincides with periods following high investor sentiment is suggestive of temporary valuation mistakes and subsequent corrections.

4.6. Investor surprises on information days

Valuation mistakes are likely to be highlighted and corrected when firms report their subsequent fundamentals, which is the premise of our prediction *H4*. For instance, Engelberg, McLean, and Pontiff (2018) show that the returns on a wide range of cross-sectional anomaly strategies are six times higher on earnings announcement days than on other days.

We examine earnings announcement returns of stocks in our double-sorted portfolios following portfolio formation. Specifically, for each stock in our portfolios, we measure abnormal returns around four quarterly earnings announcements subsequent to portfolio formation. Abnormal returns are measured over an event window of [–5, +5] trading days around the earnings announcement, and they are aggregated across the four quarters. The benchmark return is calculated based on the market model, estimated over a 200 trading day period ending 35 days prior to the announcement.

Table 8 reports the results of this analysis. We find that low price-to-value stocks exhibit significantly positive abnormal returns around subsequent earnings announcements, on the order of 2.5%. The earnings announcement returns on high price-to-value stocks, on the other hand are reliably negative, with magnitudes ranging from –1.9% to –6.3%. Differences between "value" and "growth" are all economically large and statistically significant. Consistent with all of our results above, we find that the differential between value and growth is amplified by valuation uncertainty. This amplification is driven by "growth" stocks – those that are in the short leg of our strategy. The value loss around earnings announcements for high valuation uncertainty "growth" stocks is as large as 6.3%.

The latter result is consistent with our hypothesis regarding valuation uncertainty amplifying potential valuation mistakes. A loss of 6.3% in equity value on earnings announcement days is hard to rationalize in a risk premium framework. As noted above, if earnings announcement returns represent risk premia earned on information-rich days, then we would expect to find lower yet still *positive* announcement returns for supposedly less risky "growth" stocks subject to high valuation uncertainty. A more palatable explanation is that the negative returns at least partially reflect unraveling of overly optimistic expectations about certain firms.

4.7. Trading by corporate insiders

Our final test builds on the works of Rozeff and Zaman (1998) and Jenter (2005), who show that corporate insiders behave as if they have contrarian views on their firms' valuations. In particular, executives of value firms are more likely to be buying their firms' shares, while executives of growth firms are more likely to be selling theirs. Both studies interpret this finding as consistent with insiders taking advantage of temporary mispricing, i.e. valuation mistakes. We therefore expect that the same result should hold for our sorting variable – price-to-value – a component of market-to-book that we classify as presumed valuation error. Moreover, if insider buying and selling activity is motivated by insiders' contrarian views on valuation, we expect such trading to intensify with valuation uncertainty. This is our prediction *H5* above.

We gather data on insider trading from Thomson Reuters, which collects its data from mandatory filings made with the Securities and Exchange Commission. From the raw dataset, we keep securities with non-missing identifiers (8 digit CUSIPs) that are classified as common or ordinary stock, or where security type is missing. Since the Thomson Reuters dataset is a filing-level dataset, absence of purchase/sale entries for a security over a given period can reflect either no trading by insiders, or simply lack of coverage by Thomson Reuters. To distinguish between these two possibilities, we search for *any* filing (including statements of holdings) associated with the firm in the one year before and one year after portfolio formation date. If a given CUSIP from our firm-year panel is not associated with any filing in the Thomson Reuters dataset over that period, we consider the stock as being not covered and exclude it from the analysis.[24] Further below we discuss our treatment of cases when the stock is covered (some filings are found) but is not associated with any purchase or sale transaction.

Following the literature, in measuring insider trading we focus on transactions classified as "P" (open market or private purchase) and "S" (open market or private sale) made on Form 4 or where form code is missing. We focus on trading by directors, executives, and senior officers, excluding the so-called "Level 4" relationships. Level 4 connections are considered the least related of all insiders and include former executives, custodians and trustees, and shareholders/beneficial owners/founders who are *not* executives or directors. Trading by these groups is more likely to be motivated by control and liquidity considerations rather than their views on valuation.[25]

We measure insider trading over one calendar year following portfolio formation, which corresponds to the horizon over which our portfolio returns are computed. We count all purchases and all sales by all relevant insiders, with and without regard for the number of shares traded. Our first measure is the ratio of purchase transactions to all trades. For example, when a firm is associated with an equal number of purchases and sales by insiders over a given period, the measure takes the value of 0.50. Values above 0.50 indicate prevalence of purchases, and values below 0.50 indicate that sale trades dominate. For firms identified as covered but not associated with any trades, we impute a value of 0.50 (our results are robust to excluding such cases). Our second measure is net buying as a fraction of shares outstanding, defined as the number of shares purchased minus the number of shares sold, divided by shares outstanding at the beginning of the period. Positive values of this measure indicate net buying by insiders, whereas negative values indicate net selling. For firms identified as covered but not associated with any purchases or sales over the period of interest, we impute net buying of 0% (once again, our results are robust to excluding these cases). We drop values above 100% and below –100% to avoid likely data errors.

[24] While Thomson Reuters data go back to 1980, coverage in the early 1980s is very sparse. For this reason, our sample period in the tests that follow starts in 1986, when coverage reaches around 85% of our universe of stocks.
[25] Our inferences are unchanged if we include trading by this group of insiders.

Table 9 documents average insider trading in firms of our double sorted portfolios. In Panel A we use our first measure, the ratio of purchases to all trades. We find that "value" stocks have significantly higher incidence of insider purchases than "growth" stocks. The average ratio is between 0.48 and 0.50 for value stocks, and between 0.26 and 0.36 for "growth" stocks. To put these numbers into perspective, the sample-wide average ratio of purchases to all trades is 0.378.[26] Therefore, "value" stocks are associated with significantly greater insider buying than the average stock, while "growth" stocks are associated with significantly greater insider selling. The difference between "value" and "growth" is both economically large and statistically significant. Perhaps most importantly from the point of view of our hypothesis, we find that the wedge in insider trading between "value" and "growth" is monotonically increasing with valuation uncertainty, from 0.142 among low valuation uncertainty stocks to 0.217 among high valuation uncertainty firms. The difference represents a 50% relative increase and is statistically significant at the 1% level. This difference is driven entirely by "growth" stocks: insider selling at high valuation uncertainty "growth" stocks is particularly high, whereby as many as three out of four insider trades are sale transactions.

We repeat this test using our second measure of insider trading, net buying as a percentage of shares outstanding, and report the results in Panel B. Our findings here are in line with those above. Net buying across all portfolios is negative, consistent with insiders being net sellers of their firms' shares (sample-wide average of –0.51%). However, there are significant differences between "value" and "growth" stocks. Insiders of "value" firms sell significantly less, almost reaching parity between buying and selling. At the same time, insiders of "growth" firms are selling large amounts of their shares. Differences between "value" and "growth" are, once again, economically large and statistically significant. Moreover, the spread in insider selling between "value" and "growth" increases with valuation uncertainty, from 0.39% for low valuation uncertainty stocks to 1.02% for high valuation uncertainty stocks. As with our first measure, the difference is driven by "growth" stocks, where net selling by insiders grows from 0.55% to 1.17% of outstanding shares. Overall, our evidence here is consistent with insiders trading against presumed valuation mistakes.

[26] The prevalence of sales over purchases on average is consistent with the literature on insider trading, see, e.g., Lakonishok and Lee (2001).

5. Conclusion

Valuation uncertainty is one of the fundamental concepts in finance, featuring prominently in many theoretical finance models. Yet, existing empirical proxies for valuation uncertainty are indirect and ad-hoc. We develop a novel measure of valuation uncertainty that closely tracks the associated theoretical notion, namely, the dispersion of possible valuation outcomes. To calculate this measure, we obtain a distribution of predicted fundamental values by estimating an empirical multiples-based valuation model using quantile regressions. We use the spread of the resulting distribution as a measure of valuation uncertainty. This measure performs remarkably well in validation tests using a number of existing proxies. Moreover, it offers substantial incremental variation beyond the information contained in all existing proxies combined.

We demonstrate the power of our new measure through an application to cross-sectional asset pricing. Specifically, we test the hypothesis that valuation uncertainty is conducive to valuation mistakes. We show that low price-to-value stocks (a variant of value stocks) and high price-to-value stocks (a variant of growth stocks) have significantly higher valuation uncertainty as compared to moderately priced stocks. Moreover, the profitability of a long-short price-to-value strategy is increasing with valuation uncertainty. The returns of high valuation uncertainty "growth" and "value" stocks are predictable by investor sentiment. Investor reactions to subsequent earnings announcements for "value" and "growth" stocks are amplified by valuation uncertainty, with reliably negative returns for the most uncertain "growth" stocks. We also show that corporate insiders trade against the presumed valuation mistakes.

We argue that our results are most consistent with valuation mistakes because the average returns earned by the highest valuation uncertainty "growth" stocks are as low as the risk-free rate. At the same time, these returns are on average negative following periods of high sentiment. Average realized returns equal to the risk-free rate and significant negative returns following periods of high sentiment are hard to reconcile with a framework whereby these stocks earn low returns due to their lower risk. Large negative returns around subsequent earnings announcements for this same set of stocks is also consistent with ex-post resolution of mispricing rather than lower risk premia that accrue on information-rich days.

Finally, as our sorting variable in these tests is part of the market-to-book ratio – and the only part that is associated with a return premium – our findings shed new light on the origins of the value premium. While not entirely inconceivable in a risk premium framework, our evidence is most easily interpreted through a framework whereby valuation uncertainty promotes valuation mistakes and subsequent resolution of such mispricing.

Future research could utilize our measure of valuation uncertainty for a variety of applications. While we have focused on an asset pricing context, we envision our measure to be useful in a number of corporate finance settings. For instance, various asymmetric information theories predict that valuation uncertainty should be the primary driver of IPO underpricing. If those theories are correct, we should expect our measure to predict first-day IPO returns with a positive sign and to explain a significant fraction of the variation in those returns. It would also be interesting to see whether our measure drives out the effect of other predictors of IPO returns that have been linked to alternative mechanisms. Similarly, models of adverse selection in equity issuance predict that valuation uncertainty is a driver of (negative) announcement returns to seasoned equity offerings and stock-financed mergers. Our measure could be used for testing those predictions, as well as for distinguishing adverse selection theories from competing explanations, such as event arbitrage-related price pressure effects.

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Figure 1
Valuation uncertainty as the spread of the distribution of possible values

This figure depicts valuation uncertainty as the spread of the distribution of possible valuation outcomes. The density functions of two normal distributions are plotted. The blue line corresponds to the density function of a normal distribution with a mean of 0 and a standard deviation of 1 (low valuation uncertainty). The red line corresponds to the density function of a normal distribution with a mean of 0 and a standard deviation of 2 (high valuation uncertainty). The dashed lines indicate the respective interquartile ranges.

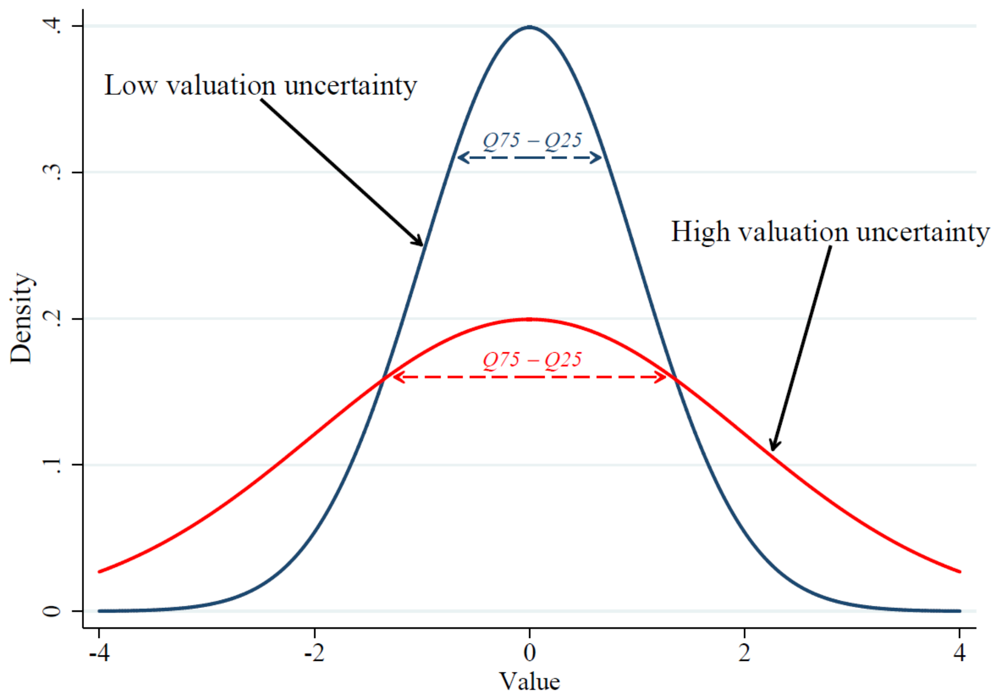


Figure 2
Illustrative example of valuation uncertainty estimation for three sample firms

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, 2018). 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 Connecticut Water Services Incorporated (FF12 industry - utilities). The blue line depicts the estimates for Polaris Incorporated (FF12 industry – manufacturing). The green line depicts the estimates for NVidia Corporation (FF12 industry – business equipment).

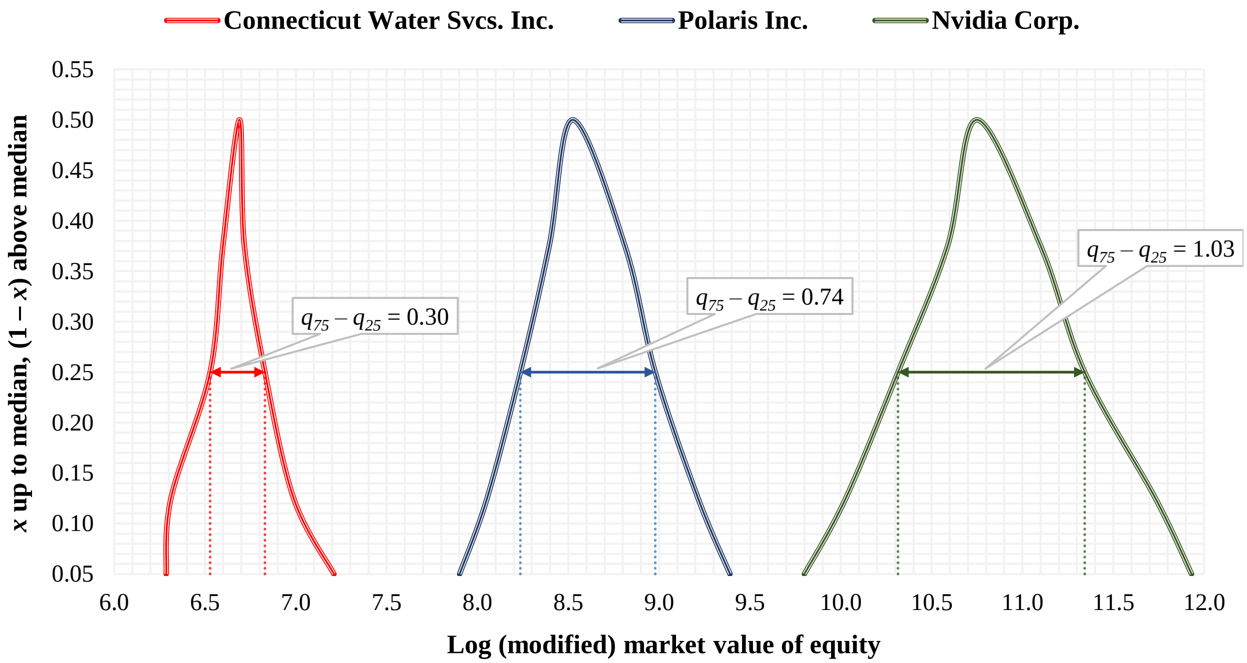
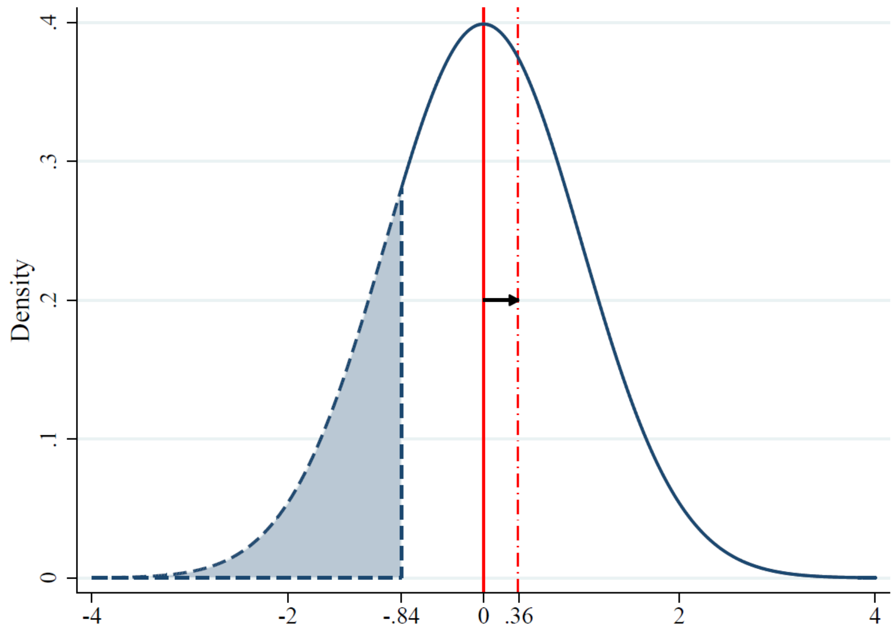


Figure 3
Truncation effect from trading frictions for low and high valuation uncertainty stocks

This figure depicts the effect of truncating the left 20% tail of the distribution on its mean. In Panel A, values are drawn from a normal distribution with a mean of 0 and a standard deviation of 1 (low valuation uncertainty). In Panel B, values are drawn from a normal distribution with a mean of 0 and a standard deviation of 2 (high valuation uncertainty). The dashed-and-dotted red line indicates the mean after truncation.

Panel A: Low valuation uncertainty



Panel B: High valuation uncertainty

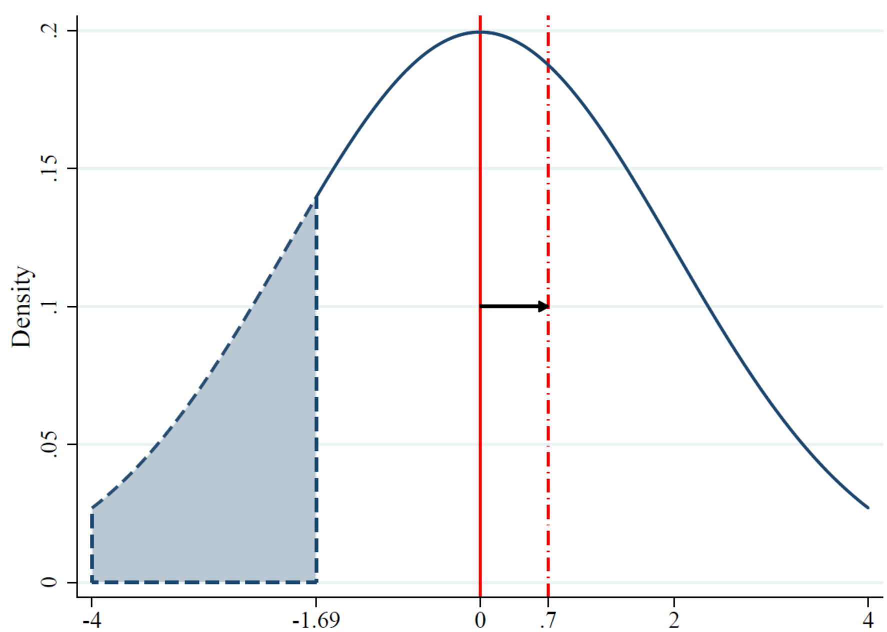


Figure 4
Cumulative performance of price-to-value strategies conditional on valuation uncertainty

This figure depicts the cumulative return of long-short trading strategies formed on the basis of price-to-value, conditional on valuation uncertainty. One unit on the y-scale corresponds to one hundred percent. Valuation uncertainty is orthogonalized with respect to log market value of equity ($VU^{\perp}$). 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, sorted separately within each valuation uncertainty quartile. The sorts are performed annually and portfolios are formed 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 2019. Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B.

Panel A: RW portfolios

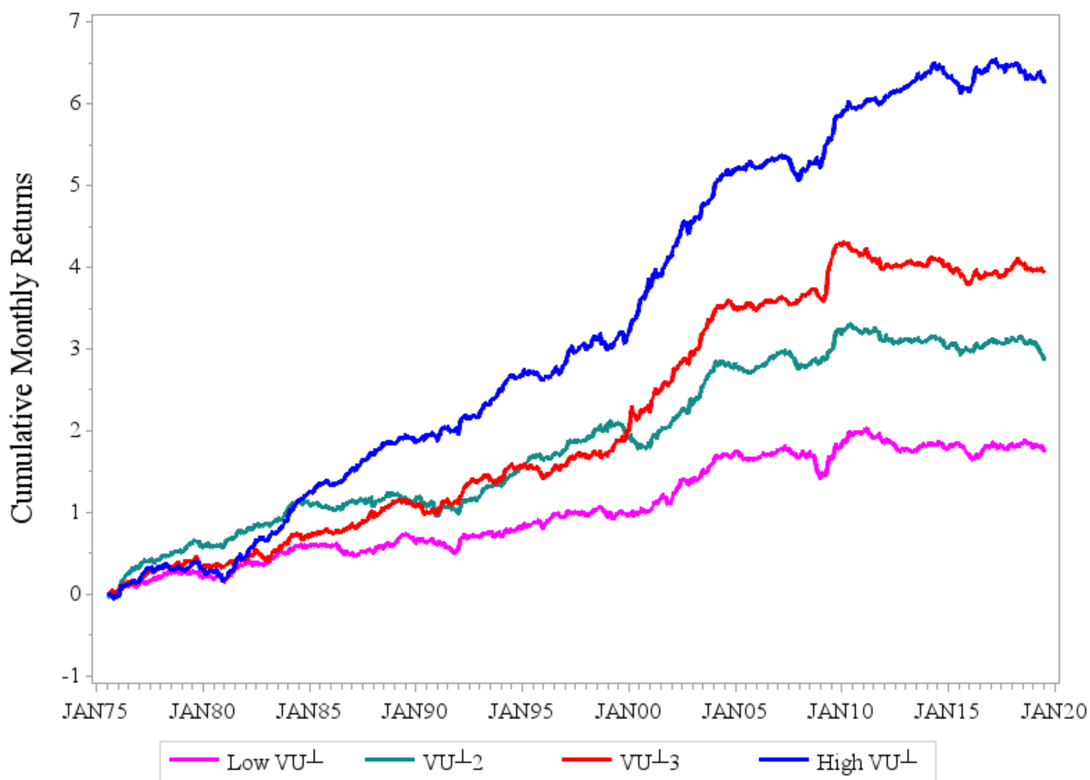


Figure 4 – continued

Panel B: VW portfolios

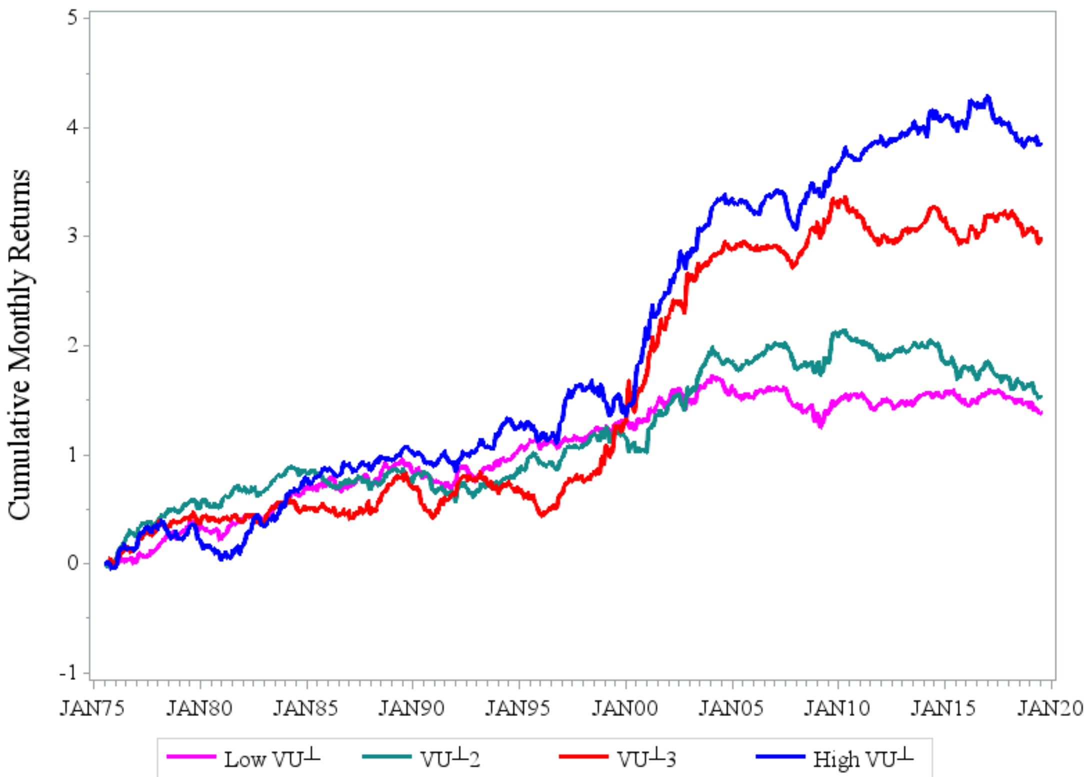


Table 1
Estimation sample description

This table reports descriptive statistics for the valuation model estimation sample. Variables whose names are in upper case letters are raw variables, whereas variables whose names are in lower case are in logs. ME is market value of equity as of June 30. BE is book value of common equity plus balance sheet deferred taxes as of the last reported fiscal year-end. EARN are adjusted earnings as of the last reported fiscal year-end, equal to income before extraordinary items attributable to common stockholders minus special items plus R&D expense minus R&D amortization. RD is capitalized R&D as of the last reported fiscal year-end, computed under the assumptions of useful life of five years and a straight-line amortization of 20%. ROE is return on equity computed as adjusted earnings (EARN) divided by book value of common equity (BE). LEV is book leverage computed as short-term debt plus long-term debt, divided by total assets. I_{EARN}<0 is an indicator variable for firms with negative adjusted earnings. *m* is log market value of equity as of June 30. *b* is log book value of equity as of the last reported fiscal year-end. |*earn*| is log of absolute adjusted earnings as of the last reported fiscal year-end. *rd* is log of capitalized R&D as of the last reported fiscal year-end (zero for firms with no capitalized R&D). The sample includes 120,405 firm-year observations. The sample period runs from 1975 to 2018 (44 years). Detailed variables definitions are provided in the Appendix.

	N	Mean	SD	Min	1%	5%	25%	Median	75%	95%	99%	Max
Raw values												
ME	120,405	2,329.99	14,714.31	10.00	10.85	14.28	43.86	166.11	797.32	7,568.99	38,120.82	912,411.17
BE	120,405	873.49	4,797.72	0.19	2.33	6.40	27.05	87.56	364.95	3,096.00	14,113.50	214,581.00
EARN	120,405	122.67	894.61	-9,918.00	-97.80	-18.42	0.75	6.52	38.61	424.40	2,090.00	57,839.40
RD	120,405	106.74	919.08	0.00	0.00	0.00	0.00	0.00	15.85	249.78	1,873.60	48,035.00
ROE	120,405	0.07	0.21	-1.00	-0.75	-0.36	0.03	0.10	0.17	0.31	0.52	1.00
LEV	120,405	0.21	0.18	0.00	0.00	0.00	0.04	0.20	0.34	0.54	0.68	0.95
$I_{EARN<0}$	120,405	0.21	0.40	0	0	0	0	0	0	1	1	1
Log values												
m	120,405	5.36	1.96	2.30	2.38	2.66	3.78	5.11	6.68	8.93	10.55	13.72
b	120,405	4.67	1.90	-1.68	0.85	1.86	3.30	4.47	5.90	8.04	9.55	12.28
|*earn*|	120,405	2.49	2.08	-7.82	-2.29	-0.67	1.07	2.36	3.83	6.09	7.67	10.97
rd	120,405	1.38	2.11	-8.52	-2.06	0.00	0.00	0.00	2.76	5.52	7.54	10.78

Table 2
Valuation model estimation

This table reports the results of estimating the valuation model in eq. (3) using annual cross-sectional regressions (Fama-MacBeth style) for three representative industries from the Fama-French 12-industry 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 capitalized R&D (taking the value of zero for firms with no R&D capital), and ε_{it} is an error term. The estimation sample includes 120,405 firm-year observations. The sample period runs from 1975 to 2018 (44 years). Detailed variables definitions are provided in the Appendix.

	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	1.580	1.093	2.061	0.968	1.914	1.338	2.470	1.131	1.406	1.451	1.588	0.137
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.085)
b	0.561	0.567	0.518	-0.048	0.533	0.550	0.493	-0.057	0.578	0.481	0.561	0.080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
$\|earn\|$	0.349	0.412	0.374	-0.038	0.339	0.381	0.364	-0.017	0.364	0.478	0.380	-0.097
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.157)	(0.000)	(0.000)	(0.000)	(0.001)
$\|earn\|\times I_{EARN<0}$	-0.222	-0.286	-0.161	0.125	-0.282	-0.335	-0.259	0.076	-0.164	-0.176	-0.116	0.060
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.148)	(0.205)	(0.200)	(0.268)
LEV	0.032	-0.041	0.013	0.054	-0.056	-0.076	-0.082	-0.006	0.180	0.131	0.237	0.105
	(0.590)	(0.459)	(0.843)	(0.229)	(0.360)	(0.128)	(0.270)	(0.917)	(0.120)	(0.130)	(0.048)	(0.307)
rd	0.079	0.055	0.075	0.019	0.081	0.059	0.081	0.022	0.003	-0.057	-0.070	-0.013
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.978)	(0.684)	(0.487)	(0.776)
R^2	0.892	0.687	0.695		0.830	0.572	0.606		0.959	0.844	0.808	

Table 3
Representative examples using firms from the most recent sample year

This table reports the valuation uncertainty measure VU for three representative firms from each of the Fama-French 12 industries (except financials), as of the most recent sample year (June 30, 2018). Firms are sorted in descending order according to VU. Detailed variables definitions are provided in the Appendix.

Company name	VU	Fama-French 12 industry
eBay Inc.	1.0971	Business equipment
NCR Corp.	1.0782	Business equipment
NVidia Corp.	0.9460	Business equipment
Cable One Inc.	0.8993	Telecommunications
FibroGen Inc.	0.8847	Health
Wendy's Co.	0.8740	Retail and Some Services
Williams-Sonoma Inc.	0.8668	Retail and Some Services
Sprint Corp.	0.8566	Telecommunications
Nordstrom Inc.	0.8476	Retail and Some Services
Boston Scientific Corp.	0.8403	Health
Campbell Soup Co.	0.8324	Consumer non-durables
Alaska Air Group Inc.	0.7865	Other
Marriott International Inc.	0.7831	Other
Frontier Communications Corp.	0.7458	Telecommunications
Bristol-Myers Squibb Co.	0.7436	Health
Polaris Inc.	0.7102	Manufacturing
AECOM	0.7089	Other
General Mills Inc.	0.7040	Consumer non-durables
Leggett & Platt Inc.	0.6688	Consumer durables
Columbia Sportswear Co.	0.6223	Consumer non-durables
Dana Inc.	0.6090	Consumer durables
Donaldson Co Inc.	0.6047	Consumer durables
Peabody Energy Corp	0.5874	Energy
Eastman Chemical Co.	0.5598	Chemicals
Hexcel Corp.	0.5411	Chemicals
Ingersoll Rand Inc.	0.5281	Manufacturing
WD-40 Co.	0.5051	Chemicals
Goodyear Tire & Rubber Co.	0.4972	Manufacturing
ConocoPhillips	0.4352	Energy
Apache Corp.	0.3863	Energy
CenterPoint Energy Inc.	0.3720	Utilities
Connecticut Water Services Inc.	0.2995	Utilities
Xcel Energy Inc.	0.2627	Utilities

Table 4

Validation of the valuation uncertainty measure

This table reports estimation results from annual Fama-MacBeth regressions of the valuation uncertainty measure (VU) on existing proxies for valuation uncertainty. The proxy in column (1) is firm size, measured by the (log) market value of equity on June 30. The proxy in column (2) is firm age, measured as the (log) number of years the stock is covered in CRSP. The proxy in column (3) is realized past stock return volatility, measured using daily returns over prior one year. The proxy in column (4) is the ratio of intangible assets to total assets. The proxy in column (5) is an indicator for firms with negative (adjusted) earnings. The proxy in column (6) is an indicator for dividend-paying firms. The proxy in column (7) is an indicator for high-tech firms, with high-tech firms defined following Loughran and Ritter (2004). The proxy in column (8) is an indicator for utilities firms, with utilities defined as firms with SIC codes 4900-4949. The proxy in column (9) is the standard deviation of one-year ahead analysts' earnings forecasts from I/B/E/S scaled by the absolute value of mean consensus forecast. The proxy in column (10) is option-implied volatility, computed as the average implied volatility of the 30-day at-the-money-forward put and call options from the OptionMetrics standardized options file. Columns (11), (12) and (13) report multivariate regressions with the same proxies. The sample period runs from 1975 to 2018 (44 years), except for columns (10) and (13) where option implied volatility is not available prior to 1996. *p*-values in parentheses correspond to Newey-West standard errors with 3 lags. Continuous variables (except for logs) are winsorized at the 1st and 99th percentiles. Detailed variables definitions are provided in the Appendix.

Table 4 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Intercept	1.088	0.912	0.532	0.757	0.711	0.838	0.734	0.780	0.689	0.513	0.933	0.905	0.929
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	-0.063										-0.035	-0.035	-0.029
	(0.000)										(0.000)	(0.000)	(0.000)
log(Age)		-0.067									-0.011	-0.012	-0.014
		(0.000)									(0.000)	(0.000)	(0.000)
σ(Returns)			7.264								0.932	1.407	1.047
			(0.000)								(0.000)	(0.000)	(0.000)
Intan/Assets				0.087							0.028	0.036	0.026
				(0.060)							(0.040)	(0.006)	(0.003)
$I_{EARN<0}$					0.225						0.119	0.148	0.200
					(0.000)						(0.000)	(0.000)	(0.000)
$I_{DIV>0}$						-0.196					-0.042	-0.038	-0.033
						(0.000)					(0.000)	(0.000)	(0.000)
$I_{HIGH-TECH}$							0.118				0.060	0.067	0.070
							(0.000)				(0.000)	(0.000)	(0.005)
$I_{UTILITY}$								-0.463			-0.321	-0.294	-0.269
								(0.000)			(0.000)	(0.000)	(0.000)
σ(E[EPS])									0.118			0.012	0.008
									(0.000)			(0.008)	(0.086)
σ(implied)										0.550			0.030
										(0.000)			(0.039)
R^2	0.284	0.120	0.245	0.004	0.192	0.190	0.056	0.233	0.044	0.261	0.573	0.611	0.572
N	112,048	112,048	112,013	112,047	112,048	112,048	112,048	112,048	64,190	26,462	112,012	64,184	23,715

Table 5
The relationship between price-to-value and valuation uncertainty

This table reports tests of the relationship between price-to-value and valuation uncertainty. Panel A presents average valuation uncertainty of stocks in decile portfolios sorted on the basis of price-to-value. The sorts are performed annually. The valuation uncertainty measure in column (1) is the raw measure (VU), whereas the valuation uncertainty measure in column (3) is orthogonalized with respect to log market value of equity ($VU^{\perp}$). Columns (2) and (4) report *p*-values for the test of differences between average valuation uncertainty for that decile and the average valuation uncertainty for deciles 5 and 6. Panel B presents results from regressing VU in column (1) and $VU^{\perp}$ in column 2 on price-to-value and price-to-value squared. *p*-values correspond to Newey-West standard errors with 3 lags. 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 1975 to 2018 (44 years). Detailed variables definitions are provided in the Appendix.

Panel A: Decile sorts

	VU	*p*-value (diff. from deciles 5-6)	$VU^{\perp}$	*p*-value (diff. from deciles 5-6)
	(1)	(2)	(3)	(4)
Price-to-value				
Low	0.863	(0.000)	0.006	(0.000)
2	0.818	(0.000)	-0.005	(0.000)
3	0.781	(0.000)	-0.021	(0.000)
4	0.751	(0.000)	-0.034	(0.000)
5	0.720		-0.052	
6	0.712		-0.051	
7	0.723	(0.169)	-0.033	(0.000)
8	0.758	(0.000)	0.004	(0.000)
9	0.809	(0.000)	0.060	(0.000)
High	0.879	(0.000)	0.133	(0.000)

Panel B: Stock-level regressions

	VU	$VU^{\perp}$
	(1)	(2)
Intercept	0.753	-0.017
	(0.000)	(0.000)
Price-to-value	-0.003	0.050
	(0.330)	(0.000)
$(\text{Price-to-value})^2$	0.073	0.051
	(0.000)	(0.000)
Adj. R^2	0.060	0.089
N	100,306	100,306

Table 6
Price-to-value sorts conditional on valuation uncertainty

This table reports average monthly returns of portfolios formed on the basis of price-to-value, conditional on valuation uncertainty. Valuation uncertainty is orthogonalized with respect to log market value of equity ($VU^{\perp}$). Stocks are sorted on price-to-value within each valuation uncertainty quartile separately. The sorts are performed annually and portfolios are formed 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 2019 (528 months). Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B. Detailed variables definitions are provided in the Appendix.

Panel A: RW portfolios

			$VU^{\perp}$			
	Low	2	3	High	High – Low	*p*-value
Price-to-value						
Low	1.276	1.373	1.496	1.637	0.361	(0.075)
2	1.333	1.172	1.181	1.095	-0.238	(0.236)
3	1.214	1.069	0.992	0.902	-0.311	(0.142)
High	0.944	0.826	0.737	0.439	-0.505	(0.014)
Low – High	0.331	0.547	0.759	1.197	0.866	(0.000)
p-value	(0.005)	(0.000)	(0.000)	(0.000)		
Volatility (st.dev.)	2.691	2.997	3.411	3.846		
Annualized Sharpe ratio	0.427	0.632	0.770	1.078		

Panel B: VW portfolios

			$VU^{\perp}$			
	Low	2	3	High	High – Low	*p*-value
Price-to-value						
Low	1.286	1.384	1.536	1.655	0.370	(0.080)
2	1.283	1.278	1.316	1.214	-0.069	(0.745)
3	1.186	1.206	1.125	1.029	-0.157	(0.463)
High	1.027	1.089	0.964	0.919	-0.108	(0.657)
Low – High	0.258	0.296	0.572	0.736	0.478	(0.011)
p-value	(0.027)	(0.044)	(0.002)	(0.000)		
Volatility (st.dev.)	2.683	3.365	4.156	4.295		
Annualized Sharpe ratio	0.333	0.305	0.477	0.594		

Table 7
Timing returns with investor sentiment

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 (long leg) and top quartile (short leg) of price-to-value, as well as the long-short (hedge) portfolios are reported. Valuation uncertainty is orthogonalized with respect to log market value of equity ($VU^{\perp}$). Investor sentiment is the orthogonalized sentiment index from Baker and Wurgler (2006). Stocks are sorted on price-to-value within each valuation uncertainty quartile separately. The sorts are performed annually and portfolios are formed 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 2019 (528 months). Portfolio returns are prior month gross return weighted (RW) in Panel A and value weighted (VW) in Panel B. Detailed variables definitions are provided in the Appendix.

Panel A: RW portfolios

$VU^{\perp}$		Low SENT	Medium SENT	High SENT	High – Low	*t*-stat	*p*-value
	Long leg	2.243	0.519	1.033	-1.21	-2.00	(0.046)
		(0.000)	(0.230)	(0.016)			
Low	Short leg	1.724	0.561	0.494	-1.23	-2.29	(0.023)
		(0.000)	(0.146)	(0.195)			
	Hedge	0.518	-0.042	0.539	0.02	0.07	(0.942)
		(0.011)	(0.839)	(0.008)			
	Long leg	2.562	0.733	0.829	-1.73	-2.69	(0.007)
		(0.000)	(0.113)	(0.070)			
2	Short leg	1.672	0.737	-0.037	-1.71	-2.79	(0.005)
		(0.000)	(0.094)	(0.931)			
	Hedge	0.890	-0.003	0.866	-0.02	-0.08	(0.939)
		(0.000)	(0.988)	(0.000)			
	Long leg	2.882	0.905	0.603	-2.28	-3.10	(0.002)
		(0.000)	(0.087)	(0.248)			
3	Short leg	1.734	0.738	-0.375	-2.11	-3.06	(0.002)
		(0.000)	(0.135)	(0.443)			
	Hedge	1.148	0.167	0.977	-0.17	-0.47	(0.640)
		(0.000)	(0.522)	(0.000)			
	Long leg	3.091	1.090	0.669	-2.42	-2.87	(0.004)
		(0.000)	(0.073)	(0.264)			
High	Short leg	1.888	0.648	-1.323	-3.21	-3.81	(0.000)
		(0.002)	(0.283)	(0.027)			
	Hedge	1.203	0.441	1.992	0.79	1.95	(0.052)
		(0.000)	(0.129)	(0.000)			

Table 7 - continued

Panel B: VW portfolios

$VU^{\perp}$		Low SENT	Medium SENT	High SENT	High – Low	*t*-stat	*p*-value
	Long leg	1.862	0.637	1.300	-0.56	-0.95	(0.342)
		(0.000)	(0.133)	(0.002)			
Low	Short leg	1.568	0.620	0.808	-0.76	-1.51	(0.132)
		(0.000)	(0.086)	(0.024)			
	Hedge	0.294	0.016	0.492	0.20	0.69	(0.488)
		(0.146)	(0.937)	(0.015)			
	Long leg	2.205	0.901	1.026	-1.18	-1.77	(0.077)
		(0.000)	(0.059)	(0.030)			
2	Short leg	1.595	0.938	0.651	-0.94	-1.64	(0.102)
		(0.000)	(0.024)	(0.112)			
	Hedge	0.611	-0.037	0.375	-0.24	-0.66	(0.512)
		(0.016)	(0.885)	(0.140)			
	Long leg	2.654	1.062	0.835	-1.82	-2.55	(0.011)
		(0.000)	(0.038)	(0.099)			
3	Short leg	1.572	0.917	0.288	-1.28	-1.98	(0.048)
		(0.001)	(0.049)	(0.532)			
	Hedge	1.081	0.145	0.547	-0.53	-1.21	(0.226)
		(0.001)	(0.646)	(0.081)			
	Long leg	2.472	1.462	0.965	-1.51	-1.93	(0.054)
		(0.000)	(0.009)	(0.081)			
High	Short leg	1.923	1.357	-0.626	-2.55	-3.01	(0.003)
		(0.001)	(0.026)	(0.296)			
	Hedge	0.549	0.105	1.591	1.04	2.29	(0.023)
		(0.088)	(0.747)	(0.000)			

Table 8

Surprises around earnings announcements along price-to-value conditional on valuation uncertainty

This table reports average excess returns of stocks in portfolios formed on the basis of price-to-value, conditional on valuation uncertainty, aggregated across four quarterly earnings announcements following portfolio formation. Cumulative excess returns are computed over the event widow [-5, +5] trading days around each of the four subsequent quarterly earnings announcements and then aggregated across the four events. The benchmark return is that predicted by a market model estimated over a period of 200 trading days ending 35 days prior to the announcement. Valuation uncertainty is orthogonalized with respect to log market value of equity ($VU^{\perp}$). Stocks are sorted on price-to-value within each valuation uncertainty quartile separately. The sorts are performed annually and portfolios are formed 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 2019 (44 years). Detailed variables definitions are provided in the Appendix.

	$VU^{\perp}$					
	Low	2	3	High	High – Low	*p*-value
Price-to-value						
Low	0.027	0.027	0.020	0.024	-0.003	(0.683)
	(0.001)	(0.001)	(0.051)	(0.008)		
2	0.008	0.005	-0.001	-0.013	-0.021	(0.009)
	(0.062)	(0.415)	(0.854)	(0.107)		
3	-0.002	-0.011	-0.018	-0.026	-0.024	(0.003)
	(0.624)	(0.078)	(0.009)	(0.001)		
High	-0.019	-0.030	-0.047	-0.063	-0.044	(0.000)
	(0.000)	(0.000)	(0.000)	(0.000)		
Low – High	0.045	0.057	0.067	0.086	0.041	(0.000)
p-value	(0.000)	(0.000)	(0.000)	(0.000)		

Table 9
Insider trading along price-to-value conditional on valuation uncertainty

This table reports average insider trading activity for stocks in portfolios formed on the basis of price-to-value, conditional on valuation uncertainty. Insider trading activity refers to open market and private sales and purchases of the stock by directors, officers, and senior executives over the 12 months following portfolio formation. Only stocks covered in the Thomson Reuters insider trading dataset are included in the sample. The measure of insider trading activity in Panel A is the ratio of purchases to all trades (regardless of the number of shares traded). A value of 0.5 is imputed for stocks that are covered by the database but no trading activity is reported. The measure of insider trading activity in Panel B is net buying (number of shares bought minus shares sold), scaled by the number of shares outstanding at portfolio formation. A value of 0% is imputed for stocks that are covered by the databse but no trading is reported. Valuation uncertainty is orthogonalized with respect to log market value of equity ($VU^{\perp}$). Stocks are sorted on price-to-value within each valuation uncertainty quartile separately. The sorts are performed annually and portfolios are formed 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 1986 to June 2019 (33 years). Detailed variables definitions are provided in the Appendix.

Panel A: Ratio of purchases to all trades

	$VU^{\perp}$					
	Low	2	3	High	High – Low	*p*-value
Price-to-value						
Low	0.502	0.476	0.481	0.476	-0.026	(0.075)
2	0.422	0.391	0.383	0.379	-0.043	(0.020)
3	0.374	0.337	0.335	0.311	-0.064	(0.003)
High	0.357	0.295	0.277	0.259	-0.098	(0.000)
Low – High	0.145	0.181	0.204	0.217	0.072	(0.000)
p-value	(0.000)	(0.000)	(0.000)	(0.000)		

Panel B: Net buying, % of shares outstanding

	$VU^{\perp}$					
	Low	2	3	High	High – Low	*p*-value
Price-to-value						
Low	-0.162	-0.186	-0.213	-0.146	0.015	(0.701)
2	-0.309	-0.369	-0.417	-0.472	-0.163	(0.002)
3	-0.373	-0.539	-0.653	-0.774	-0.401	(0.000)
High	-0.551	-0.870	-0.979	-1.168	-0.618	(0.000)
Low – High	0.389	0.684	0.766	1.022	0.633	(0.000)
p-value	(0.000)	(0.000)	(0.000)	(0.000)		

Appendix. Definitions of variables

Valuation uncertainty measures	
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.
$VU^{\perp}$	Valuation uncertainty orthogonalized with respect to size, defined as the residual from annual cross-sectional regressions of VU on the natural logarithm of ME.
Variables pertaining to the estimation of fundamental value	
Price-to-value	Deviation of market value from expected fundamental value (presumed valuation mistakes). Defined as the residual from estimating the valuation model in eq. (3) using OLS regressions by industry-year.
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*). Note: When estimating the valuation model in eq. (3), we modify the above definition in two ways: (i) 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 the fiscal-year end from Compustat. The ratio is capped at 0.5 from below and at 1.0 from above. (ii) 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 r*etx*).
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 5-year useful life and straight-line amortization of 20% (Chan, Lakonishok, and Sougiannis (2001)). Specifically, RD = $xrd_t + 0.8\times xrd_{t-1} + 0.6\times xrd_{t-2} + 0.4\times xrd_{t-3} + 0.2\times xrd_{t-4}$. Note: Missing values of *xrd* are set to zero. For newly listed firms without sufficient reporting history, RD is imputed as a multiple of current *xrd*, where the multiple is the average ratio of RD to current *xrd* of all firms 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 is equal to $0.2\times(xrd_{t-1} + xrd_{t-2} + xrd_{t-3} + xrd_{t-4} + xrd_{t-5})$.

	Note: Missing values of *xrd* are set to zero. For newly listed firms without sufficient reporting history, R&D amortization is imputed as a fraction of capitalized R&D, where the fraction is the average ratio of RD to current R&D amortization of all firms in the same industry-year.
$I_{EARN<0}$	An indicator variable taking the value of one for firm-years with negative EARN as defined above, and zero otherwise.
LEV	Book leverage, defined as long-term debt (Copmustat item *dltt*) plus debt in short-term liabilities (Compustat item *dlc*) divided by total assets (Copmustat 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 RD as defined above when RD is positive, and zero otherwise.
Existing valuation uncertainty proxies	
Log(ME)	Natural logarithm of ME as defined above.
Log(Age)	Natural logarithm of firm age, defined as the number of years since the first observation in CRSP.
σ(Returns)	Stock return volatility, calculated as the standard deviation of daily stock returns over a one-year period prior to June 30, requiring a minimum of 60 daily return observations.
Intan/Assets	Ratio of intangible assets (Compustat item *intan*) to total assets (Compustat item *at*) as of the fiscal-year end.
$I_{DIV>0}$	Indicator variable taking the value of one for firm-years with positive dividends on common stock (Compustat item *dvc*) and zero otherwise.
$I_{EARN<0}$	Indicator variable taking the value of one for firm-years with negative EARN, and zero otherwise.
$I_{HIGH-TECH}$	Indicator variable taking the value of one for high-tech firms, and zero otherwise. High-tech firms are defined following Loughran and Ritter (2004).
$I_{UTILITY}$	Indicator variable taking the value of one for utilities firms, and zero otherwise. Utilities firms defined as firms with SIC codes 4900–4949.
σ(E[EPS])	Dispersion of analysts' earnings forecasts, defined as the standard deviation of one-year ahead analysts' earnings forecasts from I/B/E/S scaled by the absolute value of mean consensus EPS forecast.
σ(implied)	Option-implied volatility on the last trading day of June, defined as the average implied volatility of the 30-day at-the-money-forward put and call options from the OptionMetrics standardized options file.

Time-series variables	
SENT	Sentiment index of Baker and Wurgler (2006). We use the version of the index that is orthogonalized with respect to macroeconomic fundamentals.
Insider trading measures	
Ratio of purchases to all trades	Ratio of purchases (transaction types "P") to all trades (transaction types "P" and "S") by the firm's insiders over a one-year period following June 30, as reported on Form 4 (or missing form type) in Thomson Reuters. Transactions by Level-4 insiders are excluded. When a firm is covered in Thomson Reuters but no relevant transactions are found, a value of 0.5 is imputed.
Net buying	Difference between all shares purchased (in transaction types "P") and all shares sold (in transaction types "S") by the firm's insiders over a one-year period following June 30, scaled by the number of shares outstanding. Transactions by Level-4 insiders are excluded. When a firm is covered in Thomson Reuters but no relevant transactions are found, a value of 0% is imputed.