Value Uncertainty

Turan G. Bali[*], Luca Del Viva[†], Menatalla El Hefnawy[‡], Lenos Trigeorgis[§]

Abstract

We examine how time-series volatility of book-to-market (UNC) is priced in equity returns and the relative contributions of its book volatility (variations in earnings and book value) and market volatility components (shocks in required return). UNC captures valuation risk, so stocks with high valuation risk earn higher return. An investment strategy long in high-UNC and short in low-UNC firms generates 8.5% annual risk-adjusted return. UNC valuation risk premium is driven by outperformance of high-UNC firms facing higher information risk and is not explained by established risk factors and firm characteristics.

JEL: G11, G12.

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[*]Robert S. Parker Chair Professor of Business Administration, McDonough School of Business, Georgetown University, Washington, D.C. 20057, Phone: (202) 687-5388, E-mail: Turan.Bali@georgetown.edu.

[†]ESADE Business School (Ramon Llull University), Avinguda de la Torre Blanca, 59, 08172 Sant Cugat del Vallès, Barcelona, Spain. E-mail: luca.delviva@esade.edu.

[‡]CUNEF Universidad, Calle de los Pirineos, 55, 28040 Madrid, Spain. E-mail: menna.eh@cunef.edu.

[§]Professor of Strategy and Finance, Durham University Business School, Millhill Ln, Durham DH1 3LB, United Kingdom, and Emeritus Professor, University of Cyprus. E-mail: lenos.trigeorgis@durham.ac.uk.

1 Introduction

One of the most investigated factors in asset pricing is the book-to-market ratio (BM). For decades, financial economists sought to understand what this "value" ratio captures. Fama and French (1992) attribute the higher returns of high-BM firms to fundamental risk: firms with high BM are more exposed to systematic risk and thus require higher expected return. Behavioral proponents, such as De Bondt and Thaler (1985, 1987) and Lakonishok et al. (1994), argue instead that the higher return of "value" stocks represents mispricing. Daniel and Titman (2006) suggest that these excess returns might be attributable to "intangible" information. When investors expect low future earnings, market values react negatively leading to higher BM. They argue that investors overreact to intangible information leading high-BM firms to generate high returns.

In this paper we investigate whether the time-series volatility of book-to-market derived from analyst forecasts, which we refer to as value uncertainty (UNC), has a priced impact on the cross-section of equity returns. In particular, we propose a novel measure of firm-specific uncertainty and test whether it contains significant, incremental information beyond existing measures such as dispersion of analysts' forecasts and predicts future stock returns after controlling for a wide variety of firm characteristics and risk measures. Our novel UNC measure partially reflects time-series variations of expected book values derived from analyst earnings forecasts. Our measure is constructed as the standard deviation of daily expected book-to-market (BM) ratios, where expected BM on a given day is defined as the expected book value (derived from expected analyst forecasts for the current year earnings) scaled by the market value on that day. An alternative proxy based on the range (maximum over minimum) of BM ratios over the previous year gives similar results. To make them comparable over different sets of firms with different means of book to market ratios, both measures are scaled by the average book-to-market calculated over the same period.

Our time-series UNC measure is different from established measures of investor disagreement, proxied by dispersion of analysts' opinions (DISP). UNC refers to time-series uncertainty in the BM ratio partly reflecting adjustments (shocks) over time in both the book value of future earnings and cash flows ("book volatility" in the numerator) as well as adjustments in the required return or discount rate ("market volatility" in the denominator). UNC thus reflects partly the variability of analysts adjusting their forecasts over time with the arrival of new firm-specific and market-wide information rather than merely reflecting the level of disagreement among analysts at a point in time, as is the case with analyst dispersion. That is, there are two sources of uncertainty driving UNC: one coming from the volatility of expected book values (or expected net income and cash flows) and another being driven by the volatility of market prices (required returns or discount rates). The two components of book and market volatility are analogous to Vuolteenaho's (2002) breakdown of the main drivers of returns arising from cash flows versus discount rates, though applied to BM uncertainty rather than returns. According to clean-surplus identity and Vuolteenaho (2002), BM changes summarize cash flow and discount rate news, so UNC can be viewed as information uncertainty or valuation risk associated with both types of news.

Part of the uncertainty arises due to infrequent (quarterly) and imperfect analyst estimates regarding the future book value of productive assets and information risk related to managerial policies and information quality. Consistent with this, we find that UNC is positively associated with various measures of information risk (IR), such as dispersion in analyst forecasts (DISP) and idiosyncratic volatility (IVOL). Given this higher embedded information risk, we test whether stocks that exhibit high UNC, measured as the standard deviation of estimated end-of-year book value scaled by the market value of equity (BM), earn a positive risk premium beyond standard predictors such as dispersion in analyst earnings estimates, idiosyncratic volatility, and the BM ratio itself. We use analyst forecasts of one-period-ahead earnings to update estimated book value of equity and test if the time-series information uncertainty about BM estimates constitutes an ex-ante priced risk measure.

Our empirical findings confirm a positive return premium for holding stocks of firms having high information risk surrounding their book-to-market ratio. An investment strategy taking a long position in high-UNC stocks and a short position in low-UNC stocks generates a risk-adjusted return premium of about 8.5% per annum in value-weighted portfolios. This value uncertainty premium is not explained by established risk factors and firm characteristics. Unlike the dispersion effect in Diether et al. (2002, pp. 2137-2138) which is more pronounced for small and growth stocks, our UNC effect is more pronounced for firms that have less leverage and growth options. Notably, the asymmetry in the return differential is different for UNC (than for dispersion) as the alphas are strongly positive for the high-UNC deciles. That is, the positive UNC premium is driven by outperformance of high-UNC firms facing higher information risk.

We also examine whether the UNC effect varies with leverage due to the option-like nature of levered equity. Based on rational pricing predictions, firms with low leverage facing more uncertainty or information risk about future cash flows or growth rates should realize higher returns but those firms with greater optionality such as high leverage firms might be exposed to less asset risk (Johnson (2004), Lyle (2019), Bali et al. (2020)) and exhibit a lower UNC effect. Johnson (2004) highlights that when the firm's equity is levered (option-like), the risk premium of the firm assets is amplified by an elasticity multiplier which is decreasing in firm-specific volatility. Thus, a higher firm-specific uncertainty or idiosyncratic information risk about the underlying asset value of a levered firm leads to a lower expected return for the levered equity than for the assets of an equivalent unlevered firm. Idiosyncratic asset risk raises the option value of the levered equity which has less exposure to priced asset risk.

We find that the UNC valuation risk effect is more pronounced for low-leverage firms and it is lower and less significant for high-leverage option-like firms, in line with the rational theory predictions of Johnson (2004). Importantly, the UNC effect remains positive and significant in Fama-MacBeth cross-sectional regressions after controlling for analyst dispersion and its interaction with leverage, which remains negative and significant in line with the empirical findings of Johnson (2004). Further, to show that the UNC measure is novel and not spanned by existing variables, we orthogonalize UNC with respect to BM, momentum, investment and profitability. The orthogonalized UNC remains statistically significant after controlling for dispersion, leverage, their interaction, and other key variables. This confirms that our UNC measure is not spanned by established firm characteristics.

We further examine the relative roles and contribution of the book volatility and market volatility UNC components to the overall UNC effect. We estimate the book volatility component of UNC by setting market value of equity (ME) in the denominator at the beginning of the calendar year and do analogously for the market volatility component (setting the numerator at book value of equity (BE) at the beginning of the year). Our findings confirm that both components contribute significantly to UNC's return predictability. Results are robust to alternative specifications for measuring the UNC components. Although a larger fraction (70%) of UNC's return predictability is driven by market return volatility, book equity volatility accounts for a sizable part (30%) of UNC's return predictability. That is, 30% of the annual UNC premium of 8.5% is still an economically significant number.

Our overall findings indicate that our newly proposed measure of value uncertainty can be viewed as a proxy for *valuation risk* or information uncertainty for which investors rationally require higher compensation – in contrast to prevailing measures of investor disagreement intended to capture mispricing or overvaluation driven by the views of behaviorally biased (mainly optimistic) investors. In line with this, we find that high-UNC firms are riskier along several dimensions: compared to low-UNC firms, high-UNC firms have higher levels of market risk, total risk and downside (left-tail) risk for which investors rationally require compensation in the form of higher expected return.

Our UNC measure may serve as a different proxy for valuation risk. Based on financial analyst forecast data about one-period-ahead book values, UNC relates to information uncertainty. More broadly, our results highlight the significance of information uncertainty concerning common risk factors as potential fundamental uncertainty proxies. This is the first empirical study investigating the time-series uncertainty surrounding book-to-market ratios and providing a risk-based explanation for the value uncertainty premium.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes our data and variables. Section 4 discusses our empirical findings. Section 5 offers robustness checks, and Section 6 concludes.

2 Literature Review

Investigating the variability in price-scaled variables is not new. Fama and French (1995) suggest that high BM ratios signal poor profitability. Cohen et al. (2003) decompose the variance of book-to-market and suggest the biggest part is attributed to cross-sectional variation in expected long-term profitability.[1] They show that the expected return on a value-

[1]Different from Cohen et al. (2003), who decompose the cross-sectional variance of book-to-market, we focus on the time-series variance of firms' book-to-market estimates.

minus-growth portfolio strategy is high when the cross-sectional value spread is large (i.e., value stocks are abnormally cheap compared to growth stocks) and the market is down. Along similar lines, Asness et al. (2000) find that differences in projected earnings growth and cross-sectional value spreads largely predict the time-series of monthly returns of value versus growth strategies. Other studies investigate the time-series variation of price-scaled ratios with expected returns and cash flows. Campbell and Shiller (1988) show that the price-dividend ratio (PD) co-moves with expected growth in dividends. Cochrane (1992) finds that the time-series variance of PD is accounted for by forecasts of dividend growth and returns rather than discount rates.

Fama and French (2006b) study the relation between the value premium and size. They document a large value premium for small US stocks during 1963-2004, as found previously by Kothari et al. (1995) and Loughran (1997). Further linking book-to-market, profitability and investment, Fama and French (2006a) provide evidence that value stocks have higher expected return when profitability and investment are controlled for. When controlling for book-to-market and expected profitability, lower expected returns lead to higher rates of investment. In a related study, Novy-Marx (2013) shows that the value strategy can be improved once profitability is controlled for. He documents a significant negative correlation between gross profits-to-assets and book-to-market, suggesting that strategies based on profitability are (inversely) analogous to growth strategies. Accordingly, a profitability strategy can be viewed as a good hedge for a value strategy.

The relation between book-to-market and uncertainty about a firm's profitability is investigated by Pástor and Veronesi (2003). They document that the more uncertain a firm's current profitability (e.g., for young and newly listed firms), the higher the market-to-book ratio. As the firm's age increases, uncertainty regarding the firm's current profitability gets lower and market-to-book decreases. Uncertainty about future profitability, however, raises the firm's market value as it increases the growth option value without affecting discount rates. The level of risk faced by investors can itself also be uncertain. One way to capture this uncertainty is by assessing the volatility of risk proxies.[2]

[2]Theoretical models of production-based asset pricing (e.g., Zhang (2005), Cooper (2006)) indicate that high book-to-market ratios, often associated with high return and high risk-factor exposure, are the result of low productivity or a positive covariance between the firm's productivity and consumption growth.

Our work has some relation to Grullon et al. (2012) but also contains important differences. Grullon et al. (2012) study the contemporaneous return-volatility relation and relate the identified positive association to the existence of real options and higher value convexity. The positive UNC risk premium we uncover reflects higher information uncertainty and is supported by the higher risk associated with high-UNC firms. Our analysis is complementary to Grullon et al. (2012) and provides a more comprehensive measure of uncertainty. Our results are also in line with Piotroski and So (2012) in that information risk makes it harder for investors to appraise the firm, rendering the BM ratio more uncertain. We find that the UNC premium is higher for higher levels of standard risk measures.

Our work is also closely related to the vast literature on the impact of investors' disagreement and analysts' dispersion of opinion (DISP) on stock prices and their return dynamics. This literature has provided mixed empirical evidence on the relation between dispersion and stock returns.[3] Although also derived from analysts' forecasts, our UNC measure is different from the standard measures of analysts' divergence of opinions. As noted, UNC refers to time-series uncertainty in the BM ratio partly reflecting adjustments (shocks) over time in both the book value of future earnings and cash flows ("book volatility" in the numerator) as well as adjustments in required returns and discount rates ("market volatility" in the denominator). It thus partly reflects the variability of analysts adjusting their forecasts over time with the arrival of new firm-specific and market-wide information, rather than merely reflecting the level of disagreement among analysts.

By contrast, DISP captures cross-sectional differences of opinion among analysts or investors at a point in time. Diether et al. (2002) find a negative dispersion effect whereby high-DISP predicts low future returns. This negative effect is primarily based on the conjecture of Miller (1977) that investors have divergence of opinion and face binding short-sale constraints. Thus, whenever stock valuations differ, stock prices are determined by optimistic investors (and hence reflect a more optimistic valuation) because pessimistic investors

[3]A number of studies find a negative cross-sectional relation between investor disagreement and average stock returns, e.g., Diether et al. (2002), Chen et al. (2002), Goetzmann and Massa (2005), Park (2005), Berkman et al. (2009), Yu (2011). Others provide evidence that the negative relation holds only for a sample of stocks with certain characteristics, e.g., small, illiquid, low credit quality, or short sale constrained. In fact, Cragg and Malkiel (1982), Qu et al. (2003), Doukas et al. (2006), Avramov et al. (2009), and Carlin et al. (2014) find either a positive or no significant relation between disagreement and future stock returns. Atmaz and Basak (2018) provide a theoretical framework for these mixed empirical results.

are forced to hold zero shares (although they would want to hold negative quantity) and are kept out of the market due to high short-sale costs or binding short-sales constraints. This leads to overvaluation of stocks and future underperformance (low alpha), explaining the apparent negative cross-sectional relation between DISP and future stock returns. The bigger the disagreement of opinion about a stock's value, the higher the upwardly-biased market price of the stock relative to its true value, and hence the lower the future returns. Besides divergence of opinions, Miller's model assumes investors are overconfident about their valuations and face short-sale constraints. By contrast, our UNC effect does not require short-sale constraints and it is based on rational behavior of investors and analysts — in fact we explicitly rule out a behavioral/mispricing explanation in Section 5.4.

Johnson (2004) has subsequently shown that the negative DISP effect is mainly due to the interaction of DISP with leverage (LEV), specifically that the interaction is significantly negative and, after controlling for the interaction term, the direct DISP effect is insignificant and sometimes it is positive (see Tables I and II in Johnson (2004)).[4] We confirm the results in Johnson (2004) showing that there is no contradiction between our UNC results and dispersion as these are somewhat distinct measures of uncertainty and the direct dispersion effect is insignificant (especially so in the more recent period).[5]

Johnson (2004) further highlights that when the firm's equity is levered (option-like), the risk premium of the firm assets is amplified by an elasticity multiplier which is decreasing in firm-specific volatility. Thus, a higher firm-specific uncertainty or idiosyncratic information

[4] Since the dispersion measure of Diether et al. (2002) scales the standard deviation of analysts' earnings forecasts by the mean earnings forecast, it assigns unusually high DISP values and inflates observations when the mean forecast is close to zero, sacrificing some valid data. To remedy this, Johnson (2004) normalizes by the book value of assets. Further, he transforms both dispersion measures into percentile ranks to increase the power to detect interaction effects. For these reasons, and to be able to confirm the negative interaction effect among dispersion and leverage, we estimate dispersion (DISP) following Johnson (2004).

[5] As acknowledged in Diether et al. (2002) (p. 2137) based on the subperiod analysis in Table VIII, the DISP effect "has declined in the latter part of their sample period, becoming insignificant for all but the smallest size quintile." In the latter part of our extended sample period, the DISP effect is also confirmed to be insignificant. The authors attribute this to short-sale costs having come down over time (we may also add the presence of put options facilitating this by creating an alternative possibility to short selling), resulting in less binding short-sale constraints and to firm-related information processing and availability having improved over time, leading to lower levels of disagreement in more recent periods. Their DISP effect is more pronounced for small and growth stocks since "future returns on growth stocks are more sensitive to differences of opinion about the firm's expected earnings... uncertainty about current earnings projected forward gives a further magnified uncertainty about the value of the growth stock" (pp. 2137-2138). By contrast, our UNC effect does not require short-sale constraints and it is based on rational behavior of investors and analysts.

risk about the underlying asset value of a levered firm leads to a lower expected return for the levered equity than for the assets of an equivalent unlevered firm. Idiosyncratic asset risk raises the option value of the levered equity which has lower exposure to priced asset risk. This implies that the UNC effect for more levered (option-like) equity firms should be lower than for no or low leverage firms. In Section 4.5 we provide empirical evidence that the UNC effect for option-like firms with high leverage is lower compared to low-leverage firms in line with Johnson's (2004) rational theory prediction.

3 Data and Variables

Our sample consists of all NYSE/AMEX/NASDAQ common equity shares (with share code 10 and 11). We exclude regulated and financial services firms (one-digit SIC codes 4 and 6). Stocks with a negative book value are also excluded. We require each stock to have non-missing book values of equity in COMPUSTAT and to be covered by the Institutional Brokers' Estimate System (I/B/E/S) database due to our use of analyst earnings forecasts to update expected book values in-between quarterly reports. If analysts' forecasts are missing for a given month, we use the previous month forecast in the same fiscal year. We require at least three months of analyst forecasts in a year for UNC computation. We also require that each stock has at least 36 months of CRSP and COMPUSTAT data. Our sample extends from January 1986 to December 2020.[6] In line with extant literature, to reduce liquidity concerns we exclude penny stocks with price per share less than \$5.[7] Monthly and daily returns as well as trading data are obtained from CRSP. Accounting data are from COMPUSTAT and earnings estimates from I/B/E/S.[8]

3.1 Uncertainty of Book-to-Market (UNC)

The uncertainty of estimated book-to-market (UNC) is computed as the standard deviation of the time-series of daily expected book-to-market (BM) ratios scaled by their mean

[6]The selection of the sample period is dictated by the low coverage of IBES before 1986.

[7]In robustness, we repeat the main empirical analysis without removing penny stocks with price per share less than \$5 and the main results are similar.

[8]Fama and French (1993, 2015, 2018) factors are obtained from the online library of Kenneth French: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. The liquidity factor is obtained from Lubos Pastor's online data library: `http://faculty.chicagobooth.edu/lubos.pastor/research/`.

over the previous 12 months:[9]

$$\text{UNC}_{i,t} = \frac{\text{Std}_t[\text{BM}_i]}{\overline{\text{BM}}_i}, \tag{1}$$

where

$$\text{Std}_t[\text{BM}_i] = \sqrt{\frac{\sum_{d=1}^{D}\left(\text{BM}_{i,d} - \overline{\text{BM}}_i\right)^2}{D}}, \tag{2}$$

$$\text{BM}_{i,d} = \frac{\text{E}_d[\text{BE}_{i,y}]/((1+\text{Ke}_i)^{h_{i,d}})}{\text{ME}_{i,d}}, \tag{3}$$

$$\overline{\text{BM}}_i = \frac{\sum_{d=1}^{D}\text{BM}_{i,d}}{D}. \tag{4}$$

$\text{ME}_{i,d}$ is the market value of equity for firm i on day d, computed as shares outstanding times stock price on day d; Ke_i is the cost of equity calculated using the CAPM with market beta estimated over the previous 12 months, with negative values of Ke_i being replaced by the risk-free rate; $h_{i,d}$ is the time horizon defined as the difference between the end of the firm's fiscal year and the month at which the book value of equity is estimated (all scaled by 12); D is the number of trading days over the previous 12 months. $\text{E}_d[\text{BE}_{i,y}]$ is expected book equity (as of day d) for firm i at the end of year y. This is estimated based on the latest available quarterly book equity data for firm i in quarter q of year y, plus the forecasted net income on day d ($\text{NI}_{i,y}$) minus expected dividends ($\text{Div}_{i,d}$):[10]

$$\text{E}_d[\text{BE}_{i,y}] = \text{BE}_{i,q-2} + \text{E}_d[\text{NI}_{i,y} - \text{Div}_{i,y}]. \tag{5}$$

The book value of equity ($\text{BE}_{i,q-2}$) in Eq. (5), lagged two quarters from the current quarter and updated quarterly, is computed as the book value of shareholders' equity (COMPUSTAT item seqq) plus deferred taxes and investment tax credit (txditcq) minus book value of

[9]Eqs. (A.1) and (A.2) in the Section A of the Online Appendix are useful in understanding whether the BM premium is arising from information regarding future growth in earnings $\bar{g}$ or the uncertainty related to earnings growth σ_g and information uncertainty σ_ϵ. Scaling $\text{Std}_t[\text{BM}_i]$ in Eq. (1) with the expected BM ratio helps isolate the impact played by the first term alone $\left(\text{M}_\tau = \sqrt{\left(e^{\sigma_\mu^2(T-\tau)^2} - 1\right)}\right)$ from Eq. (A.2) of the Online Appendix. For this reason, UNC as per Eq. (1) is the scaled (by the mean) standard deviation of the book-to-market ratio.

[10]Estimated net income by analysts is adjusted to reflect only the earnings forecast of the remaining months of the year when book value is updated quarterly to avoid double counting of earnings. Assuming no dividend distribution or further equity issuance, the clean-surplus relation between income statement and balance sheet dynamics dictate that BE in year y is $\text{BE}_{i,y-1} + \text{E}_d[\text{NI}_{i,y}]$.

preferred stock (pstkq).[11] Accounting data used in Eqs. (4) and (5) are lagged three months and analysts' income forecasts are lagged one month to avoid look-ahead bias.

Expected net income for the end of fiscal year y, given the information available up to day d, is estimated as the product of expected earnings per share given by the mean of analysts' forecasts up to day d from I/B/E/S and the total number of shares outstanding:[12]

$$\mathrm{E}_d[\mathrm{NI}_{i,y}] = \mathrm{E}_d[\mathrm{EPS}_{i,y}] \times \text{Shares Outstanding}. \tag{6}$$

3.2 Control Variables

To ensure that the uncertainty of book-to-market (UNC) is not a proxy for known stock return predictors or firm characteristics, we use a set of control variables, described below.

- SIZE, the natural logarithm of market value of equity calculated as the product of price per share and common shares outstanding (Fama and French (1992)).
- Market beta (β^{MKT}), estimated following Dimson (1979):

$$R_{i,d} = \alpha_i + \sum_{k=-n}^{n} \beta_{k,i} R_{m,d+k} + \epsilon_{i,d}, \tag{7}$$

  where $R_{i,d}$ and $R_{m,d}$ are the excess return of stock i and of the market portfolio m on day d, respectively. Market beta is estimated using daily returns within a month and is defined as $\beta^{\mathrm{MKT}} = \sum_{k=-n}^{n} \beta_{k,i}$ where n=1, i.e., it is the summation of the betas of a security's returns against one-day lagged, one-day lead and same-day market returns.[13]
- Book-to-market (BM) measured as book value of shareholders' equity plus deferred taxes minus par value of preferred stock scaled by current equity market value. Accounting data are updated quarterly and are lagged three months compared to market

[11] "q" refers to the most recent quarterly update which is 2 quarters earlier or the third quarter of the previous year when we are in the first three months of a fiscal year. For instance, in January 2019 (Q1), we cannot use book value of equity as of December 2018 (Q4) as it would not be observed in January 2019 yet. Thus, we use the book value of equity of September 2018 (Q3), (i.e., 2 quarters before to the prevailing quarter).

[12] The mean of analysts' forecasts used in this paper is from the unadjusted summary statistics database following Diether et al. (2002); this is to avoid forecasts that contain ex-post information due to rounding in I/B/E/S mean computation post stock splits. We also conduct the same analysis by computing the mean of individual analyst forecasts obtained from the Detail History file. Results do not change materially. We report the values based on I/B/E/S computed mean. The monthly mean value of earnings forecasts is used to update our book value estimation each month with a one month lag. That is, when new mean income forecasts $\mathrm{E}_d[\mathrm{NI}_{i,y}]$ become available from analysts in a given month, we use this forecast starting the following month to avoid any forward-looking bias in our analysis.

[13] Our main finding, available upon request, is similar when we use Scholes and Williams (1977) beta.

data. To be consistent in the estimation of standard deviation of book-to-market and monthly rebalancing, we update BM each month.[14]

- Investment (INV), the change in total assets from the fiscal year ending $y-2$ to the fiscal year ending $y-1$, divided by $y-2$ total assets, as in Fama and French (2015).
- Operating profitability (OP), updated quarterly, computed as revenues (REVT) minus cost of goods sold (COGS) scaled by total assets (AT) as in Novy-Marx (2013).
- Momentum (MOM), the cumulative return over the previous 12 months excluding the most recent month prior to the portfolio formation (Jegadeesh and Titman (1993)).
- Illiquidity (ILLIQ), measured following Amihud (2002) as

$$\text{ILLIQ}_{i,t} = Average\left[\frac{|R_{i,d}|}{\text{VOLD}_{i,d}}\right] \tag{8}$$

  where $|R_{i,d}|$ is the absolute daily return and $\text{VOLD}_{i,d}$ is the dollar trading volume for stock i on day d. ILLIQ is scaled by 10^6.
- Turnover (TURN), the ratio of trading volume to shares outstanding in a month.
- Idiosyncratic volatility (IVOL), the standard deviation of daily residuals based on the Fama and French (1993) SMB and HML factors following Ang et al. (2006):[15]

$$R_{i,d} = \alpha_{i,d} + \beta_{i,d}^{\text{MKT}} R_{m,d} + \beta_{i,d}^{\text{SMB}} \text{SMB}_d + \beta_{i,d}^{\text{HML}} \text{HML}_d + \epsilon_{i,d}. \tag{9}$$

- Leverage (LEV), the ratio of book value of debt to book value of debt plus market value of equity.
- Dispersion in analysts' earnings forecasts (DISP), the standard deviation of annual earnings per share forecasts scaled by book value of assets as per Johnson (2004).
- The UNC components driven by changes in expected book value of equity (BVOL) and changes in the market value of equity (MVOL). BVOL is measured as the UNC effect after setting the denominator to ME observed at the beginning of the calendar year, and MVOL after analogously setting the numerator to BE observed at the beginning

[14]We use the natural logarithm of BM as controls across all our analysis, except in Table 1 presenting firm characteristics.

[15]Following Ang et al. (2006), idiosyncratic volatility (IVOL) is estimated based on daily data in a month. Estimating IVOL using daily data over a year does not materially change the results. We also used total volatility as an additional control (alternative to IVOL) generating similar results, which are available upon request.

of the calendar year.

4 Empirical Results

4.1 Descriptive Statistics

Table 1 reports summary statistics and correlation coefficients among the main variables. As expected, UNC is highly correlated with its two components, BVOL and MVOL. The average cross-sectional correlation between UNC and BM is close to zero. We find a positive relation between UNC and INV. UNC is also positively correlated with β^{MKT} and IVOL. A stock in a risky industry is more likely to exhibit high volatility on arrival of new information regarding book value estimates compared to a stock in a stable sector. Turnover (TURN) and dispersion in analyst forecasts (DISP) are also positively correlated with UNC. The positive correlation between UNC and TURN may be attributed to the latter capturing some uncertainty and divergence of opinion (Hong and Stein (2007)).

4.2 Value Uncertainty and Information Risk

Table 2 confirms that value uncertainty is associated with the quality of available information or information risk. If UNC captures more information uncertainty about the book value of the firm's productive assets, higher levels of UNC should be associated with higher levels of information risk. Table 2 shows the relation between UNC and various measures of information risk (IR): a) dispersion in analyst forecasts (DISP) as per Johnson (2004); b) idiosycnratic volatility (IVOL) as per Ang et al. (2006); c) accruals volatility (AVJ) based on the modified Jones (1991) model; and d) Bid-ask spread (BAS) as in Corwin and Schultz (2012). We regress the above measures of information risk on UNC and a series of standard controls. Table 2 reports the estimated coefficients and confirms that a higher level of value uncertainty (UNC) is positively associated with these measures of information risk.

4.3 Univariate Portfolio Analysis

To examine the size of risk-adjusted returns on UNC-sorted long-short portfolios, each month we form 10 value-weighted decile portfolios by sorting stocks on the basis of their estimated book-to-market volatility (UNC), where decile 1 (decile 10) contains stocks with the lowest (highest) UNC. Each month contains, on average, 849 stocks over the sample period, with a monthly minimum and maximum of 678 and 1,141 stocks, respectively. Panel A of Table 3 reports the average monthly excess (raw) and risk-adjusted returns for value-weighted portfolios over the sample period. Risk-adjusted returns are estimated using three different factor models: (i) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW and CMA factors (5F alpha) and the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE} and $R_{I/A}$ (QF alpha); (ii) the 5F and QF models augmented by the momentum factor of Carhart (1997); and (iii) the 5F and QF models augmented by the momentum factor of Carhart (1997) and the liquidity (LIQ) factor of Pástor and Stambaugh (2003).

Panel A shows that the risk-adjusted returns increase when moving from the first (low) to the tenth (high) UNC decile across different asset pricing models. The main set of models, 5F and QF, fail to explain the UNC premium as seen in the last row that reports the difference in alphas between the high- and low-UNC decile (10-1) portfolios. Corresponding Newey and West (1987) t-statistics (estimated with six lags) are shown in parentheses. The risk-adjusted returns for the 5F and QF models are similar. They are also quite similar in the extended models (with MOM or MOM+LIQ added). For example, the monthly alpha generated by the 5F+MOM+LIQ model for the high-UNC decile is 0.84% greater than the low-UNC decile, with a t-statistic of 3.18. This indicates an annualized 10% higher return for the high-UNC decile. In terms of average raw returns, the high-UNC decile delivers an economically and statistically significant 0.88% (t-statistic of 2.59) higher raw return per month compared to the low-UNC decile.

We next investigate the source of the risk-adjusted return differences between the low- and high-UNC portfolios, specifically whether they are due to outperformance by high-UNC stocks, underperformance by low-UNC stocks, or both. For this, we focus on the economic and statistical significance of the risk-adjusted returns (alphas) of decile 1 versus decile 10 in the value-weighted portfolios. As observed in the last row of Table 3 Panel A across the alternative model specifications, the alphas of stocks in decile 10 (high-UNC) are all positive as well as economically and statistically significant, whereas the alphas of stocks in decile 1 (low-UNC stocks) are economically and statistically insignificant. Thus, the significantly positive alpha spread between the low- and high-UNC stocks is due to outperformance by high-UNC stocks, not to underperformance by low-UNC stocks. Panel B of Table 3 provides robustness replicating the results of Panel A using quintiles rather than deciles. The corresponding return and alpha spreads from these alternative portfolio breakpoints are similar to those reported in Table 3 Panel A. Section 5.2 contains further robustness on the portfolio analysis.

4.4 Stock Level Cross-Sectional Regressions and Dispersion

We next examine the cross-sectional relation between book-to-market volatility (UNC) and expected returns at the individual stock-level using the Fama and MacBeth (1973) rolling regression procedure relating UNC with analyst dispersion and leverage as in Johnson (2004). Individual firm cross-sectional regressions also help to control for several risk factors and firm characteristics concurrently to ensure that UNC is distinct from common cross-sectional return predictors. Table 4 shows the time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month-ahead excess stock returns on UNC and a set of controls based on the following specification:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}\mathrm{UNC}_{i,t} + \gamma_{2,t}X_{i,t} + \epsilon_{i,t+1}, \tag{10}$$

where $R_{i,t+1}$ is excess return on stock i in month $t+1$, $\mathrm{UNC}_{i,t}$ is the uncertainty of the book-to-market ratio estimated as per Eq. (1), and $X_{i,t}$ is a set of lagged firm-specific control variables. The controls include: analysts' forecast dispersion ranked into percentiles (DISP_R) as per Johnson (2004), leverage (LEV), their interaction, market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), illiquidity (ILLIQ), turnover (TURN) and idiosyncratic volatility (IVOL).

Specifications (1) to (3) in Table 4 confirm the empirical results in Johnson (2004) indicating that in the presence of the interaction term among dispersion in analysts' forecasts and leverage, there is no significant dispersion effect. Only the interaction coefficient itself is negative and significant. Specifications (4) to (8') show that the uncertainty of the book-to-market ratio (UNC) predicts higher future returns, even after controlling for DISP_R, LEV and their interaction and various standard controls. Furthermore, this positive UNC premium is both economically and statistically significant. The average slope coefficient of UNC in the univariate regression is 1.717 and ranges between 1.305 and 1.734 in the multivariate regressions. This implies a monthly increase ranging from 1.2% to 1.5% in future return in moving from UNC decile 1 to decile 10. Model (6') contains the same variables as in the original specification in Johnson (2004). Model (8') shows the comprehensive results of model (8) including controls for industry fixed effects. Overall, the economic significance of the UNC premium in stock-level Fama-MacBeth regressions is consistent with the value uncertainty premium obtained from portfolio-level analysis reported in Table 3.[16]

Further, to show that the UNC measure is novel and not spanned by existing variables, we orthogonalize UNC with respect to book-to-market (BM), investment (INV), operating profitability (OP) and momentum (MOM), obtaining UNC^{Res} (in the spirit of Johnson (2004), Fama and French (2015) and Hou et al. (2015)). Panel A of Table A.3 of the Online Appendix shows that UNC^{Res} (not ranked) remains statistically significant after controlling for DISP, LEV, their interaction, and other key variables. This confirms that UNC is not spanned by other common firm characteristics. Results are robust if UNC residuals are ranked into percentiles (Panel B of Table A.3).[17]

4.5 Leverage Effects

In this section we test Johnson's (2004) rational prediction that when the firm's equity is levered (option-like), the risk premium of the firm assets is amplified by an elasticity multiplier which is decreasing in firm-specific volatility. Based on this, a higher firm-specific uncertainty or idiosyncratic information risk about the underlying asset value of a levered firm should lead to a lower expected return for the levered equity –than for the assets of an equivalent unlevered firm. Idiosyncratic asset risk raises the option value of the levered equity which has lower exposure to priced asset risk. Thus, the UNC effect for more levered (option-like) equity firms should be *lower* than for no or low leverage firms.

Table 5 provides evidence in line with Johnson's (2004) rational theoretical prediction

[16]Stock-level cross-sectional regression analyses with additional controls confirm the robustness of the UNC premium. The corresponding results are presented in Table A.1 of the Online Appendix. Table A.2 of the Online Appendix replicates results in Johnson (2004) using his sample period from January 1983 to December 2001.

[17]Johnson (2004) orthogonalized his disagreement proxy with respect to size, BM, and MOM. We exclude size since "size" proxied by market cap (ME) is a part of UNC (being in the denominator of our UNC measure) and orthogonalizing w.r.t. size is like removing the market volatility component of UNC (which we find explains 70% of the UNC effect) with the book volatility part (which we find explains 30%) being less significant.

based on the option-like nature of levered equity (convexity). The table reports the time-series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on the same set of lagged variables following Fama and MacBeth (1973) cross-sectional regressions. Low LEV is a dummy variable equal to 1 when the firm's leverage is in the bottom 30% and zero otherwise. High LEV is a dummy variable equal to 1 when the firm's leverage is in the top 30% and zero otherwise. As noted from Table 5, the interaction between UNC and Low LEV is positive and significant whereas the interaction of UNC and High LEV is lower and statistically insignificant as predicted by Johnson (2004), indicating that the positive UNC return premium is only observable for the sample of firms with low leverage. The above is in line with our interpretation that UNC captures information uncertainty about the book value of the firm's productive assets. Table A.4 in the Online Appendix contains similar results obtained with portfolio analysis for low and high leverage subsamples.

4.6 Relative Roles and Contribution of Book and Market Volatilities

Our main uncertainty measure in Eq. (1) reflects the uncertainty coming from both the volatility of book value of equity (BE) and the volatility from market value of equity (ME). To examine the different roles and the differential impact of the two volatility components of UNC on future stock returns, we differentiate between the UNC volatility component driven by changes in the expected book value of equity (BVOL) and the UNC component driven by changes in the market value of equity (MVOL).

The UNC premium is thus due to the combined effect of the volatility of expected book value of equity (or expected net income) and the volatility of market value of equity (discount rates or required returns). In order to see which components are driving the UNC premium, in Table 6 we present Fama and MacBeth (1973) cross-sectional regressions of UNC, BVOL and MVOL on one-month-ahead returns, controlling for market beta (β^{MKT}), SIZE and BM. Results are similar when controlling for more variables. We further investigate how BVOL and MVOL contribute to the overall (positive) UNC premium. In Panel A of Table 6, BVOL (book volatility) is measured as the UNC effect after setting the denominator to ME estimated at the beginning of the calendar year. MVOL (market volatility) is estimated analogously by setting the numerator to BE at the beginning of the calendar year.

In Panel B we use a different approach decomposing the original UNC measure based on an orthogonalization of the measures. Specifically, for each firm i at time t we estimate the following model using a 36-month rolling time-series regression:

$$UNC_{i,t} = \beta_1 \Delta \ln(BV_{i,t}) + \beta_2 \Delta \ln(MV_{i,t}) + \epsilon_{i,t} \tag{11}$$

where $\Delta \ln(BV_{i,t})$ is the monthly change in the log of estimated book value of equity and $\Delta \ln(MV_{i,t})$ is the monthly change in the log of market value of equity. BVOL and MVOL are then estimated as the fitted values using the last available monthly observations over the 36 month window, i.e., $BVOL_{i,t} = \hat{\beta}_1 \Delta \ln(BV_{i,t})$ and $MVOL_{i,t} = \hat{\beta}_2 \Delta \ln(MV_{i,t})$.

In Panel A and Panel B of Table 6, BVOL and MVOL are both significantly related to future returns using stock-level cross-sectional regressions, except in specification (5) of Panel A. The significant premium of BVOL and MVOL disappears once UNC is included in the regression due to the high correlation between the variables (as seen previously in Table 1). Results contained in Table 6 Panel B indicate that both BVOL and MVOL are significantly and consistently associated with higher future return. These results hold also when BVOL and MVOL are included in the same regression. Further, when also including UNC in the same specification all three measures (UNC and its two components) are positive and significant, indicating that UNC contains additional information not spanned by the separate changes in BVOL and MVOL. Table A.5 in the Online Appendix shows the raw and risk-adjusted returns of BVOL- and MVOL-sorted portfolios with analogous results showing that both BVOL and MVOL contribute significantly to the UNC effect.

To further complement the analysis on the relative roles of the two UNC components, we next examine how much of the total volatility of book-to-market (UNC) is generated by the volatility of the expected book value of equity (BV) and the volatility of the market value of equity (ME). In particular, we run a dominance analysis test (Luchman (2021)) to estimate the incremental predictive power of each independent variable in the following pooled regression:

$$BM_i = \beta_0 + \beta_1 \, BV_i + \beta_2 \, ME_i + \epsilon_i. \tag{12}$$

The main idea here is to decompose the overall fit statistic associated with the above regression into the contributions associated with each individual regressor. Standardized dominance statistics from estimating Eq. (12) indicate that 70% of the volatility of the book-to-market ratio can be attributed to ME and about 30% to BV.

Further, to account for the correlation between the book value and market value of equity, we augment the model of Eq. (12) with an interaction variable as follows:

$$BM_i = \beta_0 + \beta_1\, BV_i + \beta_2\, ME_i + \beta_3\, BV_i \times ME_i + \epsilon_i. \tag{13}$$

Standardized dominance statistics indicate that 70% of the book-to-market volatility is attributed to ME, 18% to BV directly and 12% to their interaction (correlation). The above confirms that the variations in BM come from both the market and book value of equity with different contributions.

4.7 UNC and Risk Measures

Results in the previous sections show that UNC is positively associated with information risk and commands a positive return premium. These results indicate that UNC can be viewed as a proxy for valuation risk or information uncertainty for which investors rationally require compensation in the form of higher expected return. Untabulated results confirm that higher levels of UNC are associated with higher levels of risk based on various risk measures. High-UNC firms have economically and statistically higher market beta, higher idiosyncratic and total volatility, higher downside market beta (i.e., market beta conditioned on market downturns), higher semi-variance (volatility estimated with negative stock returns) and higher downside (or left-tail) risk proxied by the 95% and 99% value-at-risk (VaR) measures.

4.8 UNC and Dispersion

As noted, UNC is a different measure of uncertainty than divergence of opinion deriving from analyst forecasts (DISP). The empirically documented positive uncertainty premium pertains to UNC but not to dispersion-based measures. To see this, we compare our UNC measure based on the time series of expected book values derived from analyst forecasts to an alternative cross-sectional UNC measure coming from the variance of the book values derived from various analyst forecasts on a given day (averaged over a year). One might expect that higher dispersion of earnings forecasts might indicate a higher degree of disagreement (or uncertainty) about future book values and hence book-to-market ratios. Potentially, our results might be driven by disagreement among analysts about future earnings or net income that gets reflected in future book values rather than information risk reflected in changes from the time series of book-to-market ratios. Section B in the Online Appendix contains a description of this alternative DISP-like UNC measure, UNC^{DISP}. Table A.6 of the Online Appendix reports the raw and risk-adjusted returns obtained using the cross-sectional UNC^{DISP} measure rather than our time-series UNC measure. UNC^{DISP} is not significant, confirming that our time-series UNC measure is a different measure of uncertainty than divergence of investor opinion. UNC refers to time-series uncertainty in the BM ratio partly reflecting adjustments (shocks) over time in both the book value of future earnings and cash flows ("book volatility" in the numerator) as well as adjustments in required returns or discount rates ("market volatility" in the denominator). UNC thus reflects the variability of analysts adjusting their forecasts over time with the arrival of new firm-specific and market-wide information rather than merely reflecting the level of disagreement among analysts.

By contrast, DISP captures cross-sectional differences of opinion among analysts or investors at a point in time. The negative dispersion effect of Diether et al. (2002) is primarily based on the conjecture of Miller (1977) that investors have divergence of opinion and face binding short-sale constraints. Thus, whenever stock valuations differ, stock prices are determined by optimistic investors, which leads to overvaluation of stocks and future underperformance. Contrary to Miller's model which assumes investors are both overconfident about their valuations and face short-sale constraints, our UNC effect does not require short-sale constraints and it is based on rational behavior of investors and analysts (we explicitly rule out a behavioral/mispricing explanation in Section 5.4). Further, the UNC effect is more pronounced for firms that have less leverage and growth options (the opposite to dispersion) in line with a rational pricing of stocks based on Johnson's (2004) prediction viewing levered equity as option-like.

5 Robustness Checks

5.1 Alternative Measurement of UNC

For robustness, we consider two alternative measures of UNC. First, we consider the range of BM ratios over a year. Specifically, UNC is estimated as the absolute value of the difference between the maximum and minimum BM ratios over the previous 12 months scaled by the average BM over the same period. Results shown in Table 7 for the portfolio analysis and Table A.7 in the Online Appendix for the stock-level analysis are similar to those in Tables 3 and 4.

The second alternative measurement approach is based on Eq. (A.2) of the Online Appendix where the volatility of estimated BM ratio captures information regarding changes in the risk of future growth (σ_g) and the quality of information or information risk (σ_ϵ). That is, the volatility of BM contains information regarding the volatility of earnings growth (σ_μ) as discussed in Section A of the Online Appendix. We consequently estimate σ_μ as the value that minimizes the difference between the theoretical BM volatility ($\text{Std}_t[\text{BM}_i]$) of Eq. (A.2) and its empirical estimation as per Eq. (1). This estimation of σ_μ provides an alternative measure of UNC and is a direct representation of what the market views as uncertainty in a firm's fundamentals. We again sort stocks into 10 decile portfolios (as described in Table 3) but now UNC is based on estimated σ_μ rather than as measured previously based on Eq. (1). Results, shown in Tables A.8 and A.9 of the Online Appendix, are again in line with previous findings in Tables 3 and 4. The positive premium for high-σ_μ minus low-σ_μ deciles remains significant in both value- and equal-weighted portfolios, confirming the robustness of our measure.

5.2 Sample Selection and Univariate Portfolios

In further robustness, we test whether our key findings are robust when portfolios are built with equal-weighted returns and when stocks are divided in deciles using NYSE breakpoints. Table A.10 and Table A.11 in the Online Appendix show that the UNC premium is robust to these different classification procedures. Additionally, we perform robustness tests associated with the exclusion of penny stocks and the univariate portfolio sorting. In particular, we repeat the main analysis of Table 3 without excluding penny stocks (with a price per share below \$5). As seen from Table A.12 of the Online Appendix, the UNC premium is robust to the inclusion of penny stocks.

5.3 Subsample and Long-horizon Analyses

Fama and French (2008) show that microcaps have the highest cross-sectional standard deviations of returns and they can inflate the magnitude of many anomalies. To address these concerns, we replicate our value-weighted portfolio analysis using alternative stock samples. Table A.13 in the Online Appendix contains robustness tests using alternative stock samples that exclude small, illiquid, and high volatility stocks. Results in Table A.13 in the Online Appendix confirm that the UNC premium remains significantly positive and is not explained by liquidity or size. We also consider alternative investment horizons to see how fast the UNC performance decays. We find that the UNC premium decays in about three months.

5.4 Testing Behavioral/Mispricing Explanations of UNC

The results in Table 3 indicate that the positive UNC premium is mainly driven by outperformance of stocks in the high-UNC decile. Similarly to what has been argued for high book-to-market ratio (De Bondt and Thaler (1985, 1987), Lakonishok et al. (1994)), such a premium might be attributed to mispricing or behavioral biases as stocks in the high-UNC portfolio could be undervalued or somehow penalized by investors for behavioral reasons. Similarly, the argument in Diether et al. (2002) for explaining dispersion is based on behavioral assumptions that optimistic investors drive market prices. To test these alternative behavioral hypotheses, we consider the management (MGMT) and performance (PERF) related mispricing factors of Stambaugh and Yuan (2017), as well as the short-term horizon post-earnings-announcement drift factor (PEAD) and the long-term horizon financing factor (FIN) of Daniel et al. (2020). We regress the 10 value- and equal-weighted UNC portfolios against two alternative factor models: (i) Stambaugh and Yuan's (2017) model (SY (2017)) that includes market (MKTRF), size (SMB), management (MGMT) and performance (PERF) mispricing factors; and (ii) Daniel et al. (2020) model (DHS (2020)) that includes market (MKTRF), financing (FIN), and post-earnings-announcement drift (PEAD) factors. Table A.14 in the Online Appendix contains the risk-adjusted return (alpha) in each of the 10 UNC portfolios. The UNC premium remains significant after controlling for these factors, indicating that behavioral and mispricing explanations are not the driving force of the UNC premium.

6 Conclusion

We investigate the cross-sectional relation between the time-series volatility of book-to-market ratios (UNC) and future equity returns suggesting that UNC is related to valuation risk or information uncertainty. The uncovered value uncertainty (UNC) premium is driven by outperformance of high-UNC stocks facing higher information risk and is not explained by common risk factors and firm characteristics previously considered in the literature. The reported value uncertainty premium is significant both statistically and economically, and is robust to various scrutiny levels and robustness checks. Univariate portfolio-level analysis indicates that decile portfolios that are long in high book-to-market volatility stocks and short in the less volatile ones yield risk-adjusted returns of about 8.5% per annum. This significant positive premium is confirmed in both portfolio-level analyses and stock-level cross-sectional regressions that control for various well-known pricing effects. These include market beta, size, value (book-to-market), investment, profitability, momentum, leverage, liquidity, turnover, idiosyncratic volatility, and dispersion in analysts' earnings estimates.

Although value uncertainty is positively associated with measures of information risk such as analysts' dispersion and idiosyncratic volatility, UNC is distinct from standard measures of uncertainty and investor disagreement. We document a positive association between value uncertainty and measures of information risk and rule out a behavioral or mispricing explanation. We also show that the UNC premium is due to the combined effect of the volatility of expected book value of equity (or expected net income) and the volatility of market value of equity (discount rates or required returns). Thus, our results indicate that the UNC premium and return predictability is partly driven by valuation risk and information uncertainty concerning the expected book value of productive assets.

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Table 1

Descriptive Statistics

This table reports the basic descriptive statistics and correlation among the variables used in the main analysis. The characteristics are: UNC is BM uncertainty as per Eq. (1), β^{MKT} is market beta, SIZE is market capitalization (in million US dollars), BM is book-to-market ratio, INV is investment following Fama and French (2015), OP is operating profitability as in Novy-Marx (2013), MOM is stock momentum calculated as cumulative return over the previous 11 months ending one month prior to the portfolio formation month, ILLIQ is the Amihud (2002) illiquidity indicator scaled by 10^6, TURN is the ratio of trading volume in a month to shares outstanding, IVOL is idiosyncratic volatility (in %), LEV is the leverage ratio, DISP is analysts' forecast dispersion calculated following Johnson (2004), and BVOL and MVOL are volatility components of the book-to-market ratio attributed to the expected book value of equity and market equity, respectively. The sample period covers January 1986 to December 2020.

Variable	Mean	Sd	UNC	β^{MKT}	SIZE	BM	INV	OP	MOM	ILLIQ	TURN	IVOL	LEV	DISP	BVOL	MVOL
UNC	0.16	0.11	1													
β^{MKT}	1.03	1.54	0.167	1												
MCAP	7,853,486	34,826,155	-0.213	0.004	1											
BM	-0.93	0.75	0.001	-0.035	-0.397	1										
INV	0.25	4.35	0.181	0.074	-0.040	-0.128	1									
OP	0.10	0.06	-0.077	-0.020	0.019	-0.385	-0.015	1								
MOM	16.09	52.31	-0.005	0.059	0.155	-0.359	0.032	0.116	1							
ILLIQ	0.14	1.17	0.015	-0.046	-0.335	0.158	-0.018	0.000	-0.095	1						
TURN	1.71	1.93	0.332	0.176	-0.023	-0.090	0.195	0.059	0.116	-0.133	1					
IVOL	1.95	1.30	0.386	0.141	-0.381	0.076	0.171	-0.001	-0.035	0.199	0.461	1				
LEV	0.17	0.17	0.020	-0.021	-0.101	0.479	-0.077	-0.357	-0.170	0.042	-0.060	-0.029	1			
DISP	0.01	0.01	0.274	0.055	-0.117	-0.096	0.091	-0.104	0.002	0.040	0.168	0.243	-0.160	1		
BVOL	0.14	0.11	0.548	0.112	-0.085	-0.147	0.181	0.001	0.106	0.003	0.226	0.237	-0.037	0.210	1	
MVOL	0.17	0.11	0.785	0.142	-0.208	0.031	0.205	-0.059	-0.018	0.022	0.299	0.352	0.048	0.200	0.431	1

Table 2

Cross-Sectional Regressions of UNC on Information Risk Measures

The table reports the time-series averages of the slope coefficients obtained by regressing monthly measures of information risk (IR) on UNC and a set of controls following the Fama and MacBeth (1973) rolling regression approach. Measures of IR include: (1) Accruals volatility (AVJ) based on the modified Jones (1991) model; (2) Dispersion in analyst forecasts (DISP) as per Johnson (2004); (3) idiosyncratic volatility (IVOL) as per Ang et al. (2006); and (4) Bid-ask spread (BAS) as in Corwin and Schultz (2012). The controls include: market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), illiquidity (ILLIQ), leverage (LEV) and industry fixed effects. *t*-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample period is from January 1986 to December 2020 and N is the total number of firm/month observations.

	(1) DISP	(2) IVOL	(3) AVJ	(4) BAS
Constant	0.013	0.039	0.199	0.025
	(14.83)	(35.99)	(23.30)	(16.54)
UNC	0.022	0.029	0.125	0.010
	(15.73)	(33.02)	(17.52)	(24.33)
β^{MKT}	0.000	0.001	0.002	0.000
	(3.49)	(7.77)	(7.48)	(-0.06)
SIZE	-0.001	-0.002	-0.011	-0.001
	(-14.27)	(-30.02)	(-18.40)	(-11.86)
BM	-0.002	-0.001	-0.019	0.000
	(-17.47)	(-4.64)	(-17.34)	(-3.68)
INV	0.000	0.001	0.023	0.001
	(0.57)	(10.62)	(10.17)	(6.79)
OP	-0.023	0.000	-0.118	-0.001
	(-8.32)	(0.51)	(-8.77)	(-1.91)
MOM	-0.001	0.000	-0.006	-0.001
	(-4.63)	(-0.47)	(-3.66)	(-4.29)
ILLIQ	0.012	0.012	0.046	0.008
	(3.71)	(4.56)	(1.75)	(4.87)
LEV	-0.009	-0.002	-0.063	-0.003
	(-14.70)	(-5.20)	(-21.72)	(-12.36)
Industry FE	Yes	Yes	Yes	Yes
No. of Obs.	254,293	297,185	239,322	285,127
R^2	0.209	0.344	0.291	0.456
No. of Months	408	408	408	384

Table 3

Value-Weighted Univariate Portfolio Analysis

Each month value-weighted decile (Panel A) and quintile (Panel B) portfolios are sorted according to the standard deviation of estimated book-to-market ratio scaled by its mean (UNC) over the past twelve months. Decile 1 (10) contains stocks with the lowest (highest) decile. The table reports raw excess return (second column) and risk-adjusted returns (alphas) based on different asset pricing models: (i) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (ii) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE} and $R_{I/A}$ factors (QF alpha). The second set of models considers the 5F and QF factor models augmented by Carhart's (1997) momentum factor (MOM). The last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the previous 5F and QF models (with MOM). The last two rows report the difference High−Low (10−1) UNC excess return and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2020.

Panel A. Decile portfolios

		Risk-Adjusted Return		+ MOM		+ MOM + LIQ	
UNC Decile	Raw Return	5F	QF	5F	QF	5F	QF
1 (Low)	0.473	-0.111	-0.105	-0.135	-0.116	-0.128	-0.106
	(2.16)	(-0.90)	(-0.82)	(-1.10)	(-0.91)	(-1.05)	(-0.84)
2	0.771	0.043	0.054	-0.005	0.041	-0.009	0.031
	(3.59)	(0.40)	(0.49)	(-0.05)	(0.39)	-(0.09)	(0.30)
3	0.865	0.068	0.131	0.064	0.131	0.060	0.121
	(4.35)	(0.74)	(1.29)	(0.70)	(1.31)	(0.65)	(1.19)
4	0.842	0.021	0.017	0.013	0.024	0.007	0.006
	(4.00)	(0.18)	(0.13)	(0.11)	(0.19)	(0.06)	(0.05)
5	0.827	0.017	0.052	0.025	0.060	0.016	0.042
	(3.74)	(0.14)	(0.43)	(0.21)	(0.49)	(0.13)	(0.33)
6	0.955	0.152	0.174	0.174	0.188	0.164	0.169
	(3.35)	(1.12)	(1.26)	(1.27)	(1.32)	(1.18)	(1.16)
7	1.046	0.210	0.226	0.229	0.238	0.211	0.210
	(3.80)	(1.55)	(1.74)	(1.72)	(1.85)	(1.59)	(1.63)
8	1.127	0.343	0.495	0.422	0.508	0.409	0.499
	(3.95)	(2.14)	(2.61)	(2.50)	(2.65)	(2.41)	(2.59)
9	1.043	0.347	0.473	0.418	0.481	0.405	0.475
	(3.21)	(2.19)	(2.74)	(2.69)	(2.78)	(2.56)	(2.68)
10 (High)	1.357	0.598	0.855	0.717	0.868	0.713	0.883
	(3.42)	(2.76)	(3.71)	(3.56)	(3.87)	(3.55)	(3.89)
High−Low (10−1)	0.884	0.709	0.959	0.852	0.984	0.842	0.989
t-stat	(2.59)	(2.56)	(3.20)	(3.19)	(3.32)	(3.18)	(3.31)

Panel B. Quintile portfolios

		Risk-Adjusted Return		+ MOM		+ MOM + LIQ	
UNC Quintiles	Raw Return	5F	QF	5F	QF	5F	QF
1 (Low)	0.617	-0.019	-0.011	-0.064	-0.028	-0.064	-0.029
	(3.02)	(-0.23)	(-0.11)	(-0.76)	-(0.30)	(-0.76)	(-0.31)
2	0.863	0.051	0.086	0.045	0.090	0.041	0.077
	(4.45)	(0.61)	(0.91)	(0.53)	(0.94)	(0.48)	(0.81)
3	0.931	0.124	0.157	0.137	0.167	0.126	0.147
	(3.95)	(1.34)	(1.67)	(1.46)	(1.73)	(1.32)	(1.45)
4	1.036	0.228	0.328	0.287	0.343	0.273	0.327
	(3.86)	(1.89)	(2.48)	(2.30)	(2.59)	(2.19)	(2.48)
5 (High)	1.167	0.437	0.620	0.521	0.626	0.513	0.632
	(3.45)	(2.98)	(3.84)	(3.74)	(3.93)	(3.63)	(3.90)
High−Low (5−1)	0.550	0.456	0.630	0.585	0.653	0.577	0.660
t-stat	(2.23)	(2.49)	(3.15)	(3.22)	(3.25)	(3.15)	(3.21)

Table 4

Stock Level Fama-MacBeth Cross-Sectional Regressions

The table reports the time-series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on a set of lagged controls following Fama and MacBeth (1973). The controls include: analysts' forecast dispersion (DISP_R) calculated and ranked into percentiles as in Johnson (2004), leverage calculated as debt divided by debt plus equity (LEV), market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), illiquidity (ILLIQ), turnover (TURN) and idiosyncratic volatility (IVOL). t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample period is from January 1986 to December 2020 and N is the total number of firm/month observations.

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(6')	(7)	(8)	(8')
Constant	0.802	0.823	0.697	0.619	0.483	0.431	1.350	0.778	0.936	0.937
	(3.62)	(4.62)	(3.99)	(2.95)	(2.63)	(0.72)	(2.27)	(1.26)	(1.53)	(1.45)
UNC				1.717	1.734	1.638	1.305	1.429	1.477	1.589
				(2.40)	(2.86)	(2.96)	(2.21)	(2.64)	(3.19)	(3.53)
DISP_R	0.003	0.003	0.005		0.002	0.002	0.002	0.003	0.003	0.002
	(1.26)	(1.17)	(1.78)		(1.07)	(0.98)	(1.18)	(1.34)	(1.47)	(1.24)
LEV		-0.049	0.632		0.378	0.223	0.119	0.166	0.234	0.315
		(-0.10)	(1.52)		(0.91)	(0.61)	(0.32)	(0.45)	(0.62)	(0.87)
$\text{DISP}_R \times \text{LEV}$			-0.015		-0.013	-0.012	-0.011	-0.011	-0.012	-0.011
			(-2.18)		(-2.04)	(-1.92)	(-1.80)	(-1.89)	(-2.11)	(-2.09)
β^{MKT}						-0.018		-0.041	-0.038	-0.044
						(-0.35)		(-0.84)	(-0.79)	(-0.97)
SIZE						-0.006	-0.056	-0.027	-0.036	-0.033
						(-0.16)	(-1.52)	(-0.69)	(-0.96)	(-0.91)
BM						0.105	0.096	0.197	0.180	0.241
						(0.92)	(0.96)	(1.80)	(1.71)	(2.52)
INV						-0.080		-0.062	-0.078	-0.101
						(-0.91)		(-0.72)	(-0.90)	(-1.21)
OP						2.012		2.042	1.923	2.346
						(2.28)		(2.38)	(2.22)	(2.87)
MOM							0.003	0.003	0.003	0.003
							(2.01)	(1.91)	(1.85)	(1.96)
ILLIQ								-4.699	-3.421	-3.892
								(-1.29)	(-1.17)	(-1.39)
TURN									0.034	0.024
									(0.86)	(0.66)
IVOL									-0.047	-0.059
									(-1.19)	(-1.55)
Industry FE	No	No	No	No	No	No	No	No	No	Yes
R^2	0.010	0.024	0.028	0.015	0.039	0.080	0.066	0.092	0.104	0.139
N	286,871	279,560	279,560	337,846	279,560	254,088	274,229	254,039	254,039	254,039

Table 5

Cross-sectional Regressions for Low vs. High Leverage Subsamples

The table reports the time-series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on a set of lagged variables following Fama and MacBeth (1973) rolling cross-sectional regressions. The variables include: UNC, market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), illiquidity (ILLIQ), turnover (TURN), and idiosyncratic volatility (IVOL). Low Lev is a dummy variable equal to 1 when the firm's leverage is in the bottom 30% and equal to zero otherwise. High Lev is a dummy variable equal to 1 when the firm's leverage is in the top 30% and equal to zero otherwise. t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample period is from January 1986 to December 2020 and N is the total number of firm/month observations.

R_{t+1}	(1)	(2)	(3)	(4)
Constant	0.750	0.440	0.784	0.917
	(3.65)	(0.76)	(1.36)	(1.62)
UNC	0.325	0.596	0.303	0.400
	(0.40)	(0.80)	(0.41)	(0.59)
Low LEV	-0.125	-0.116	-0.103	-0.111
	(-0.83)	(-0.94)	(-0.83)	(-0.92)
High LEV	-0.115	-0.155	-0.187	-0.165
	(-0.85)	(-1.45)	(-1.74)	(-1.52)
UNC × Low LEV	1.895	1.564	1.618	1.589
	(2.99)	(2.53)	(2.61)	(2.56)
UNC × High LEV	0.768	0.887	1.104	1.008
	(1.05)	(1.21)	(1.50)	(1.38)
β^{MKT}		-0.015	-0.030	-0.026
		(-0.30)	(-0.62)	(-0.55)
SIZE		0.001	-0.020	-0.030
		(0.04)	(-0.57)	(-0.85)
BM		0.087	0.168	0.152
		(0.81)	(1.58)	(1.49)
INV		-0.076	-0.059	-0.069
		(-0.97)	(-0.76)	(-0.93)
OP		2.599	2.729	2.639
		(3.02)	(3.24)	(3.13)
MOM			0.002	0.002
			(1.55)	(1.47)
ILLIQ			-2.206	-1.348
			(-1.10)	(-1.04)
TURN				0.030
				(0.76)
IVOL				-0.035
				(-0.89)
R^2	0.034	0.072	0.083	0.095
N	327,888	297,003	296,938	296,938

Table 6

Cross-sectional Analysis for BVOL and MVOL

The table reports the time-series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on a set of lagged variables following Fama and MacBeth (1973) rolling regressions. The variables include: UNC, volatility of book value (BVOL), volatility of market value (MVOL), market beta (β^{MKT}), market cap (SIZE) and book-to-market (BM). In Panel A BVOL is measured as the UNC effect after setting the denominator to ME estimated at the beginning of the calendar year MVOL (market volatility) is estimated analogously by setting the numerator to BE at the beginning of the calendar year. In Panel B, we use $BVOL_{i,t} = \hat{\beta}_1 \Delta \ln(BV_{i,t})$ and $MVOL_{i,t} = \hat{\beta}_1 \Delta \ln(MV_{i,t})$ with the slope coefficients estimated with 36 monthly observations. t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample period is from January 1986 to December 2020 and N is the total number of firm/month observations.

Panel A.

R_{t+1}	(1)	(2)	(3)	(4)	(5)
Constant	1.664	2.07	1.777	1.693	1.565
	(2.88)	(3.23)	(3.01)	(2.87)	(2.68)
UNC	1.617				1.588
	(2.65)				(2.13)
BVOL		1.082		0.752	0.216
		(2.48)		(1.88)	(0.51)
MVOL			1.000	0.630	-0.366
			(1.91)	(1.30)	(-0.76)
β^{MKT}	-0.002	0.032	0.015	0.009	-0.002
	(-0.04)	(0.56)	(0.28)	(0.18)	(-0.04)
SIZE	-0.078	-0.094	-0.080	-0.076	-0.069
	(-2.08)	(-2.31)	(-2.08)	(-1.99)	(-1.84)
BM	-0.079	-0.050	-0.084	-0.065	-0.068
	(-0.66)	(-0.41)	(-0.70)	(-0.55)	(-0.57)
R^2	0.047	0.042	0.046	0.049	0.053
N	330,673	330,673	325,293	325,293	325,293

Panel B.

R_{t+1}	(1)	(2)	(3)	(4)	(5)
Constant	1.664	2.04	2.068	1.999	1.449
	(2.88)	(3.05)	(3.10)	(3.01)	(2.54)
UNC	1.617				1.365
	(2.65)				(2.13)
BVOL		1.770		1.869	1.516
		(2.32)		(2.43)	(1.99)
MVOL			2.313	2.368	1.946
			(2.72)	(2.72)	(2.34)
β^{MKT}	-0.002	0.042	0.035	0.033	-0.017
	(-0.04)	(0.66)	(0.56)	(0.52)	(-0.32)
SIZE	-0.078	-0.085	-0.087	-0.083	-0.063
	(-2.08)	(-2.08)	(-2.14)	(-2.05)	(-1.73)
BM	-0.079	-0.040	-0.050	-0.038	-0.053
	(-0.66)	(-0.32)	(-0.41)	(-0.31)	(-0.46)
R^2	0.047	0.040	0.041	0.044	0.054
N	330,673	310,732	311,680	310,728	310,728

Table 7

Univariate Portfolio Analysis with Alternative UNC Measure: Range of BM over a Year

Each month decile portfolios are sorted according to UNC estimated as the absolute value of the difference between the maximum and minimum BM ratios over the previous 12 months scaled by the average BM over the same period. Decile 1 (10) contains stocks with the lowest (highest) decile. The table reports raw excess return (second column) and risk-adjusted returns (alphas) based on different asset pricing models: (i) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (ii) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE} and $R_{I/A}$ factors (QF alpha). The second set of models considers the 5F and QF factor models augmented by Carhart's (1997) momentum factor (MOM). The last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the previous 5F and QF models (with MOM). The last two rows report the difference High−Low (10−1) UNC excess return and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2020.

		Risk-Adjusted Return		+ MOM		+ MOM + LIQ	
UNC Decile	Raw Return	5F	QF	5F	QF	5F	QF
1 (Low)	0.588	0.006	-0.012	-0.060	-0.040	-0.054	-0.030
	(2.89)	(0.05)	(-0.10)	(-0.56)	(-0.36)	(-0.50)	(-0.26)
2	0.786	0.032	0.076	-0.009	0.065	-0.003	0.066
	(4.20)	(0.39)	(0.84)	(-0.10)	(0.71)	(-0.04)	(0.72)
3	0.816	0.011	0.023	0.005	0.032	0.002	0.018
	(3.92)	(0.09)	(0.19)	(0.04)	(0.26)	(0.02)	(0.15)
4	0.824	-0.017	0.030	-0.014	0.042	-0.019	0.025
	(3.89)	(-0.15)	(0.25)	(-0.12)	(0.34)	(-0.16)	(0.21)
5	0.876	0.087	0.108	0.084	0.115	0.074	0.096
	(3.78)	(0.73)	(0.89)	(0.69)	(0.94)	(0.60)	(0.76)
6	1.056	0.216	0.273	0.256	0.291	0.236	0.261
	(3.94)	(1.70)	(2.11)	(1.97)	(2.18)	(1.79)	(1.93)
7	1.096	0.222	0.311	0.269	0.322	0.243	0.289
	(3.98)	(1.64)	(2.01)	(1.84)	(2.04)	(1.68)	(1.81)
8	0.828	0.052	0.136	0.111	0.150	0.109	0.152
	(2.49)	(0.34)	(0.90)	(0.76)	(1.01)	(0.73)	(1.00)
9	1.041	0.296	0.450	0.395	0.469	0.367	0.442
	(3.32)	(1.62)	(2.25)	(2.19)	(2.39)	(2.01)	(2.21)
10 (High)	1.358	0.594	0.802	0.710	0.812	0.712	0.837
	(3.23)	(2.62)	(3.28)	(3.30)	(3.39)	(3.32)	(3.49)
High−Low (10−1)	0.770	0.588	0.814	0.770	0.852	0.766	0.866
t-stat	(2.25)	(2.31)	(2.90)	(3.03)	(3.01)	(3.01)	(3.02)