Essays in Empirical Asset Pricing

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DOCTORAL THESIS

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Dedication

"To my parents, for the values and knowledge implanted in me to be up to this life and beyond."

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Chapter 1

Introduction

1.1 Thesis Objective

This dissertation aims at empirically uncovering new aspects of the cross-section of equity returns and providing theoretical-backed and empirical explanations of the main findings. Earlier versions of asset pricing models and empirical work have paid great attention to the mean and volatility of returns. They have also focused on risk factors as pricing determinants of the cross-section of returns. However, these risk factors can be uncertain, imprecise, or volatile themselves. When investors initiate investing strategies based on a risk factor, they tend to focus on the level of this risk factor and put less emphasis on other dimensions. While the mean risk factor level provides some information regarding expected returns, its volatility, for instance, can be a proxy of the uncertainty of this information. The dissertation hence documents novel pricing predictors and factors related to the uncertainty and imprecision levels of the information content embedded in different risk measures. The main findings are empirical contributions that are insightful to the behavior of equity returns.

1.2 Overarching Framework

Identifying pricing and risk factors has gained great attention in the asset pricing literature to the extent that factors are referred to as the factor zoo (Cochrane (2011)). Researchers have identified more than 450 pricing anomalies (Hou et al. (2018)). Some pricing factors are related to fundamental firm characteristics. Three main factors have been widely accepted in the literature as important pricing factors which include: i) book-to-market (BM), ii) profitability, and iii) asset growth (see e.g., Fama and French (1993, 2006b, 2008a, 2015), Zhang (2005), Novy-Marx (2013), Hou et al. (2015), Cohen et al. (2003), and Hou et al. (2020)).

Book-to-market is the ratio of book value of equity to market value of equity, known as a common proxy for value investing. For decades, financial economists sought to understand what this "value" ratio captures. Fama and French (1992) attribute the higher average returns of high-BM firms to fundamental (distress) risk. Firms with high book-to-market ratio are presumably more exposed to a systematic risk factor and thus require higher expected returns. Production-based asset pricing models (e.g., Zhang (2005), Petkova and Zhang (2005), Cooper (2006), Liu et al. (2009) and Lin and Zhang (2013)) relate higher values of BM ratio to higher exposure to systematic risk factors. Based on the investment CAPM doctrine, high values of BM are due either to lower firm productivity or a positive correlation between firm productivity and consumption growth, which depress market values. Behavioral proponents, such as De Bondt and Thaler (1985, 1987) and Lakonishok et al. (1994), instead argue that higher returns of value stocks with higher BM represent mispricing. Despite the difference among scholars in explaining the true risk associated with value investing, they agree that "value" stocks with higher BM generate higher average returns than growth stocks with lower BM.

If negative news regarding a firm's ongoing investment activities conveyed information regarding lower future earnings or lower firm productivity, then the current market value would decline and the book-to-market ratio would increase. Positive news, by contrast, would lead to the opposite effect. This interpretation, nonetheless, discards the possibility that market value may change for reasons unrelated to future earnings and firm productivity. As Daniel and Titman (2006) point out, the presence of future growth options might also affect market value (and hence BM) while leaving untouched the book value of equity. Daniel and Titman (2006) state (p. 1607): “Consider, for example, a firm that receives good news about future growth options; this information will not affect its book value, but its market value will increase in response to the good news, thereby decreasing the firm’s BM”. On the other hand, news regarding ongoing or future firm profitability and growth options, while leaving untouched current book value of equity, will have an impact on investor expectations about the future book value of equity. Thus, the expected book-to-market ratio might differ from the current book-to-market ratio. Other related studies, such as Zhang (2006) and Jiang et al. (2005), provide further evidence that information uncertainty may have a significant impact on equity returns. If the BM ratio reflects information regarding future productivity and growth prospects and, moreover, adjusts imperfectly to the flow of such information, then high information uncertainty or ambiguity may also affect the intrinsic value and information content of the BM ratio. Since higher uncertainty surrounding future productivity and growth forecasts also increases the current value of future growth options, this in turn will affect the BM ratio and firms’ exposure to systematic risk factors (see, e.g., Cooper (2006) and Lin and Zhang (2013)).

Motivated by this intuition, Chapter 2 of the dissertation investigates whether the time-series volatility of book-to-market estimates, or value uncertainty (UNC), is associated with future growth information and has a predictive relation with the cross-section of future equity returns. If BM is a proxy for fundamental risk, high volatility of BM associated with the flow of new information regarding future earnings prospects or firm productivity can be viewed as uncertainty concerning such fundamental risk. Chapter 2 shows in the neoclassical setting of Cooper (2006) that the beta (loading) of a firm’s returns on a generic risk-factor is a function of book-to-market volatility. Guided by this theoretical prediction, Chapter 2 tests whether stocks that exhibit high standard deviation of their estimated end-of-year book value scaled by the market value of equity earn a premium beyond standard cross-sectional predictors, including price and earnings momentum, investment, profitability, and the book-to-market ratio itself.

The relation between book-to-market and uncertainty about a firm’s profitability has been 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 its current profitability gets lower and market-to-book decreases. Uncertainty about future profitability, however, tends to raise the firm's market value as it increases the expected future growth option payoff (due to the convex relation between growth and terminal value) without affecting discount rates. Separately, theoretical models of production-based asset pricing (e.g., Cooper (2006); Lin and Zhang (2013); Liu et al. (2009); Zhang (2005)) 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. Inspired by the models of Pástor and Veronesi (2003) and Cooper (2006), Chapter 2 relates the uncertainty in book-to-market estimates to key variables like expected growth and volatility of profitability, the quality of information about the true value of accounting variables such as the book value of productive assets, and required return. The work of Cooper (2006) and Liu et al. (2009) is extended to show that the volatility of the book-to-market ratio is positively associated with future returns.

Similarly, profitability as a pricing factor has been documented in the literature. Fama and French (2008a) find that more profitable firms are associated with abnormally high returns, but provide little evidence that unprofitable firms earn unusually low returns. The profitability anomaly was also identified by Novy-Marx (2013) who documents that more profitable firms generate significantly higher returns than less profitable firms. He finds that profitability strategy is a growth strategy and hence identifies it as a good hedge for value investing. Cohen et al. (2003) empirically find that 75-80% of the unconditional cross-sectional variance of book-to-market is explained by expected future 15-year profitability and persistence of book-to-market 15 years into the future.

Scholars generally agree that more profitable firms tend to deliver higher equity returns on average (see e.g., Novy-Marx (2013), Fama and French (2015), and Hou et al. (2015)). However, they have different approaches in explaining this pricing anomaly. For instance, Fama and French (2015) use the dividend discount model in conjunction with clean surplus accounting to explain the relationship between profitability and average returns. From a rational pricing view, higher profitability indicates higher required rates, hence higher profitability firms would generate higher average returns. From an investment-based asset pricing approach, Hou et al. (2015) state that high expected profitability relative to low investment implies high discount rates, which are necessary to offset the high expected profitability to induce low net present values of new capital and new investment. Otherwise, firms would witness high net present values of new capital and keep on investing. On the other hand, low expected profitability relative to high investment implies low discount rates to counteract the low expected profitability or otherwise firms would observe the low net present values of new injected capital and hence decrease their investments. Therefore, a dividend discount model and capital budgeting perspective agree on the positive direction of expected returns for profitable firms.

Despite the substantial profitability-related studies in the accounting and asset pricing literature, less attention has been drawn to the uncertainty surrounding profitability in empirical research. In common asset pricing models, a prevalent assumption is that all investors have the same estimates of expected returns and probability distribution of returns for all securities. This assumption is not necessarily valid, as pointed out by Knight (1921). Pástor and Veronesi (2003) argue that uncertainty about profitability raises the firm's valuation and show that idiosyncratic volatility of equity return increases with this uncertainty. However, they did not document an effect of this uncertainty on expected stock returns.

Motivated by the above research on profitability and findings of Chapter 2, Chapter 3 investigates whether persistent profitability makes a difference in the realm of cross-sectional equity returns. In other words, if profitability is a pricing factor, would uncertainty surrounding profitability have a predictive power in the cross-section of returns? Chapter 3 is hence motivated by the idea that the level of risk faced by investors in making decisions can itself be uncertain. One way to capture this uncertainty is by assessing the volatility of risk proxies such as the uncertainty surrounding profitability. Considering the case of two firms with the same expected profitability but one's profitability is more certain than the other, ceteris paribus. Would they have the same expected returns? For example, two firms in the oil and gas industry with similar profitability expectations but one's geographical location makes it more vulnerable to some uncertain weather conditions. Can both firms have similar expected returns? More specifically, Chapter 3 investigates whether the time-series volatility of expected profitability would have an impact on the cross-section of future equity returns, ceteris paribus.

Fama and French (2015) have also introduced investment (or asset growth) as pricing factor in their five-factor model. They argue that the five-factor model performs better than the three-factor model of Fama and French (1993). Complementing the investment and profitability studies, Hou et al. (2020) study the impact of expected investment growth on equity returns. They build a factor based on the the expected investment growth and complement the $q-$factor model of Hou et al. (2015) with this new factor to explain a wide range of pricing anomalies including profitability and investment. Based on these findings and following the same intuition of investigating the volatility of profitability, Chapter 3 also investigates the time-series volatility of asset growth.

Other factors that were documented to have an impact on equity returns are management earnings forecasts. Management earnings guidance has been widely investigated particularly in the disclosure literature. Chen et al. (2011) find that firms that stop providing guidance experience an increase in analyst dispersion, a decrease in forecast accuracy, and a decline in returns around the time of announcing the guidance halt. On the aggregate level, there is no clear evidence of the relation between guidance measure and market returns (see e.g., Anilowski et al. (2007) and Shivakumar (2007)). Other studies have looked into the impact of management disclosure and stocks' returns volatility. Billings et al. (2015) argue that managers mitigate share price volatility with guidance since investors' uncertainty is positively correlated with future stock volatility and as disclosures lower volatility, it also reduces subsequent volatility.

Past research investigated the pricing consequences of imprecise management forecasts (e.g., Baginski et al. (1993); Pownall et al. (1993); Cheng et al. (2013)). That research, however, is limited to the pricing consequences of the level of guidance precision at the date of the forecast announcement and thus does not paint a complete picture of pricing impact. The study conducted in Chapter 4 aims to complete the picture by documenting the future-period pricing effects of imprecise management earnings forecasts and providing explanation to this effect.

The focus of past research on event date pricing is based on the theory that low precision forecasts will attenuate the price response to the unexpected earnings conveyed by a disclosure (Kim and Verrecchia (1991)). That is, in a regression of unexpected returns on unexpected earnings conveyed by a management forecast, the coefficient on the unexpected earnings will be smaller when the management forecast is less precise. Results in Baginski et al. (1993) and Cheng et al. (2013) are consistent with the attenuation effect.

Different from event studies, Chapter 4 focuses on the effect of forecast imprecision on the cross-section of equity returns on average. Prior studies do not hypothesize a mean effect of imprecision on returns because it is not clear what that effect would be. While Miller's (1977) conjecture suggests that optimistic investors would drive price upward when forecasts are imprecise, a countervailing effect is also in play. Management forecast imprecision is evidence of the type of uncertainty about the future earnings fundamental that can lead to increases in cost of equity capital (Barry and Brown (1985), Coles et al. (1995), Lambert et al. (2007)), which would decrease the mean price reaction to a forecast, regardless of its content (i.e., good or bad news). Chapter 4 tests whether Miller's (1977) prediction about the association of imprecision and future returns will manifest in a negative relation between management forecast precision and future returns after controlling for other well-known measures of uncertainty and predictors of future returns.

Management forecasts are disclosures that can affect belief consensus. Holthausen and Verrecchia (1990) analytically demonstrate that disagreement over a given signal's implications reduces consensus. Baginski et al. (1993) present evidence that the width of a management forecast range (relative to the width of the distribution of analyst forecasts) is associated with a decrease in analyst consensus pursuant to the management forecast disclosure. Therefore, the uncertainty about future earnings conveyed in a management forecast can be different from the uncertainty reflected in analysts' forecasts. As reported in Baginski et al. (1993), not all management forecasts decrease uncertainty. In fact, Cotter et al. (2006) find that management guidance is more likely to be disclosed when analysts' initial forecast dispersion is low, suggesting the possibility that, in some cases, forecast dispersion subsequently increases. This suggests that earnings' uncertainty coming from the imprecision of management guidance is distinct from the uncertainty reflected in analysts' forecasts.

1.3 Main Contribution

Contributing to the asset pricing literature by studying the uncertainty surrounding the identified above three pricing factors, Chapters 2 and 3 of this dissertation discuss the volatility of i) book-to-market, ii) profitability, and iii) asset growth. More specifically, Chapter 2 investigates whether the time-series volatility of book-to-market, called value uncertainty, is priced in the cross-section of equity returns. As discussed above, this is motivated by the intuition that the BM ratio reflects information regarding future productivity and growth prospects and adjusts imperfectly to the flow of such information as proposed by Zhang (2005), Petkova and Zhang (2005), Cooper (2006), Liu et al. (2009) and Lin and Zhang (2013). Hence, high information uncertainty may also affect the intrinsic value and information content of the BM ratio. Since higher uncertainty surrounding future productivity and growth forecasts also increases the current value of future growth options, this in turn will affect the BM ratio and firms' exposure to systematic risk factors. In other words, if BM is a proxy for fundamental risk, high volatility of BM associated with the flow of new information regarding future earnings prospects or firm productivity can be viewed as uncertainty concerning such fundamental risk.

The main findings of Chapter 2 confirm that investors require a positive premium for holding stocks with high uncertainty surrounding their BM ratio. An investment strategy that takes a long position in stocks with high-UNC and a short position in stocks with low-UNC generates a risk-adjusted return of about 13% per annum. Importantly, this value uncertainty premium is not explained by established risk-factors or firm characteristics. A rational asset pricing explanation of the value premium is provided. Other finding implications include that the UNC premium is related to fundamental uncertainty measures in the economy and the stock market and that UNC satisfies the restrictions of Merton's (1973) intertemporal capital asset pricing model (ICAPM).

In line with the value premium uncovered in Chapter 2, findings of Chapter 3 suggest that investors require a premium for holding stocks with high volatility surrounding expected profitability. An investment strategy that takes a long position in stocks with high uncertainty of profitability (UP) and a short position in stocks with low UP generates an annual excess (risk-adjusted) return of 8% (10%). This premium can not be explained by traditional risk-factors or firm characteristics in both portfolio and stock-level analyses. Analogously, a portfolio that takes a long position in stocks with high uncertainty of asset growth (UAG) and a short position in stocks with low UAG generates an annual excess (risk-adjusted) return of 7% (12%).

Documenting both the volatility of profitability and asset growth has several implications. First, high idiosyncratic volatility is found to be partially caused by high volatility of profitability and high volatility of asset growth. In a feedback relation between returns' idiosyncratic volatility and UP (UAG), UP (UAG) tends to better explain volatility (rather than the other way around). Second, both the UP (UAG) premia is conditional on the level of profitability (asset growth). That is, the UP premium is higher for high profitable firms in an implication that investors are more averse to the volatility of profitability for firms with favorable returns (high profitability). Similarly, the UAG premium is higher for firms with low investment growth, implying that investors are more averse to the volatility of asset growth for firms with favorable returns (low asset growth). Finally, the UP strategy can largely improve the profitability strategy by forming a portfolio that is high on both profitability and UP generating a monthly risk-adjusted return of 1.04% compared to of the profitability strategy alpha of 0.38%. Overall, Chapter 2 and 3 highlight the significance of the volatility of common risk factors as potential fundamental uncertainty proxies.

Chapter 4 deviates from the volatility theme of common risk factors and look into another aspect that can also impact the cross-section of equity returns. Specifically, it examines the impact that imprecision (IMP) in management earnings guidance has on equity returns. It documents an inverse relationship between management forecast imprecision and future returns. Empirical analysis shows that firms with high IMP deliver on average 8% lower risk-adjusted return per annum compared to those with high precision. The low returns associated with guidance imprecision are robust after controlling for a wide battery of documented equity return predictors. The negative impact on returns is mainly due to the underperformance of high-IMP stocks rather than the outperformance of low-IMP stocks.

Two complementary and non-mutually exclusive explanations are provided to justify the low returns. First, management forecasts is considered as a disclosure that can affect consensus beliefs and high imprecision in these forecasts can lead to higher dispersion of opinion among investors. Hence, the low returns associated with high-IMP firms is consistent with Miller's (1977) conjecture suggesting that in a market that exhibits diversion of opinion regarding earnings estimates and short-selling constraints, high IMP discourages pessimistic investors while optimists believe in the high bound of the range and take long positions based on these beliefs, leading to stocks' overpricing and hence to lower subsequent returns. In line with this conjecture, high-IMP stocks are more likely to be overpriced and susceptible to short-sale constraints.

Second, high IMP may reflect genuine uncertainty regarding future earnings appealing to growth and lottery investors. That is, managers provide earnings forecasts either in terms of a range or simply as point estimates depending on the best knowledge they have. For firms that are still in a growing phase, managers may genuinely be more uncertain of their future earnings prospects and hence tend to provide wider ranges of performance indicators to avoid being liable in case of not meeting the pre-announced estimates. Firms with such uncertain growth profiles can induce investors to have lottery-like positions in them. In other words, investors would like to hold stocks with high uncertainty regarding their future earnings which can offer lottery-like payoffs. Empirical evidence reveal a strong association between guidance imprecision on the one hand and potential growth (but not realized $ex-post$ growth) and lottery characteristics on the other. Moreover, IMP's impact on returns is found to be more evident for those firms with lottery characteristics, providing empirical evidence for the lottery hypothesis.

High-IMP firms tend to be prone to default risk. This provides additional insights regarding the puzzling low returns associated with firms with high default probability documented in the literature (see e.g., Campbell et al. (2008) and Conrad et al. (2014)). Chapter 4 goes beyond testing Miller's (1977) conjecture and provides a complete picture of the low returns associated with highly imprecise forecasts by linking potential and realized growth, lottery features and arbitrage asymmetry to guidance imprecision.

Overall, the three chapters comprising this dissertation provide novel insights in empirical asset pricing research. They introduce new and easy to estimate uncertainty proxies and pave the path to exploring the impact of other volatility, uncertainty, and imprecision measures as focus of future research.

1.4 Structure of the Thesis

This PhD dissertation is a compendium of three studies presented in chapters (2, 3 , and 4). At the end of each chapter, the corresponding tables and figures are presented. Chapter 5 provides general discussion. Finally, a comprehensive list of references is provided in the bibliography at the end of the dissertation.

The thesis is structured as follows:

- Chapter 2 empirically investigates whether the time-series volatility of book-to-market, called value uncertainty, is priced in the cross-section of equity returns. It shows in the neoclassical setting of Cooper (2006) that the beta (loading) of a firm's returns on a generic risk-factor is a function of book-to-market volatility. Guided by this theoretical prediction, it tests whether stocks that exhibit high standard deviation of their estimated end-of-year book value scaled by the BM earn a premium beyond standard cross-sectional predictors, including price and earnings momentum, investment, profitability, and the book-to-market ratio itself. Finally, the chapter provides a rational asset-pricing explanation of the uncovered uncertainty premium.

- Chapter 3 extends Chapter 2 and empirically examines the predictive power of the uncertainty of profitability and the uncertainty surrounding asset growth on the cross-section of equity returns. Moreover, it extends Hou et al.'s (2020) model and shows that the standard deviations of both expected profitability and expected asset growth have an impact equity returns.

- Chapter 4 empirically examines the impact that imprecision in management earnings guidance has on equity returns and provides explanations to justify this impact. Findings are in accordance with previous theoretical contributions such as Miller's (1977) conjecture regarding diversion of opinion.

- Chapter 5 provides a synthesized discussion and conclusion of the three main chapters. It further discusses limitations and proposes avenues for future research.

Chapter 2

The Value Uncertainty Premium

Abstract

This chapter investigates whether the time-series volatility of book-to-market (BM), called value uncertainty (UNC), is priced in the cross-section of equity returns. A size-adjusted value-weighted factor with a long (short) position in high-UNC (low-UNC) stocks generates an annualized alpha of 6-8%. This value uncertainty premium is driven by outperformance of high-UNC firms and is not explained by established risk factors or firm characteristics, such as price and earnings momentum, investment, profitability, or BM itself. At the aggregate level, UNC is correlated with macroeconomic fundamentals and predicts future market returns and market volatility. The study provides a rational asset-pricing explanation of the uncovered UNC premium.

2.1 Introduction

One of the most studied factors in asset pricing is the ratio of book value of equity to market value of equity, known as 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 average returns of high-BM firms to fundamental (distress) risk. Firms with high book-to-market ratio are presumably more exposed to a systematic risk factor and thus require higher expected returns. Behavioral proponents, such as De Bondt and Thaler (1985, 1987) and Lakonishok et al. (1994), instead argue that higher returns of value stocks with higher BM represent mispricing. Daniel and Titman (2006) suggest that higher returns on value stocks might be attributable to "intangible" information. When investors expect lower future earnings (not reflected in current book value), market values react negatively to these expectations leading to a higher book-to-market ratio. They argue that investors overreact to such intangible information and this makes high-BM firms generate higher returns on average. Production-based asset pricing models (e.g., Zhang (2005), Petkova and Zhang (2005), Cooper (2006), Liu et al. (2009) and Lin and Zhang (2013)) relate higher values of BM ratio to higher exposure to systematic risk factors. Based on the investment CAPM doctrine, high values of BM are due either to lower firm productivity or a positive correlation between firm productivity and consumption growth, which depress market values. Despite their differences, the behavioral and production-based approaches all agree that "value" stocks with higher BM generate higher average returns than growth stocks with lower BM.

If negative news regarding a firm's ongoing investment activities conveyed information regarding lower future earnings or lower firm productivity, then the current market value would decline and the book-to-market ratio would increase. Positive news, by contrast, would lead to the opposite effect. This interpretation, nonetheless, discards the possibility that market value may change for reasons unrelated to future earnings and firm productivity. As Daniel and Titman (2006) point out, the presence of future growth options might also affect market value (and hence BM) while leaving untouched the book value of equity.[1] On the other hand, news regarding ongoing or future firm profitability and growth options, while leaving untouched current book value of equity, will have an impact on investor expectations about the future book value of equity. Thus, the expected book-to-market ratio might differ from the current book-to-market ratio. Other related studies, such as Zhang (2006) and Jiang et al. (2005), provide further evidence that information uncertainty may have a significant impact on equity returns. If the BM ratio reflects information regarding future productivity and growth prospects and,

[1] Daniel and Titman (2006) state (p. 1607): "Consider, for example, a firm that receives good news about future growth options; this information will not affect its book value, but its market value will increase in response to the good news, thereby decreasing the firm's BM."

moreover, adjusts imperfectly to the flow of such information, then high information uncertainty or ambiguity may also affect the intrinsic value and information content of the BM ratio. Since higher uncertainty surrounding future productivity and growth forecasts also increases the current value of future growth options, this in turn will affect the BM ratio and firms' exposure to systematic risk factors (see, e.g., Cooper (2006) and Lin and Zhang (2013)).

Motivated by this intuition, this chapter investigates whether the time-series volatility of book-to-market estimates, or value uncertainty (UNC), is associated with future growth information and has a positive predictive relation with the cross-section of future equity returns. If BM is a proxy for fundamental risk, high volatility of BM associated with the flow of new information regarding future earnings prospects or firm productivity can be viewed as uncertainty concerning such fundamental risk. This study shows in the neoclassical setting of Cooper (2006) that the beta (loading) of a firm's returns on a generic risk-factor is a function of book-to-market volatility. Guided by this theoretical prediction, this study tests whether stocks that exhibit high standard deviation of their estimated end-of-year book value scaled by the market value of equity (BM) earn a premium beyond standard cross-sectional predictors, including price and earnings momentum, investment, profitability, and the book-to-market ratio itself. The forecasts by professional analysts of one-period-ahead book values are considered given past available information. This allows to test if the uncertainty about BM estimates is an ex-ante priced factor.

Findings confirm that investors require a positive premium for holding stocks with high uncertainty surrounding their book-to-market ratio. An investment strategy that takes a long position in stocks with high-UNC and a short position in stocks with low-UNC generates a risk-adjusted return of about 13% per annum. Importantly, this value uncertainty premium is not explained by established risk-factors or firm characteristics. A new "uncertainty" factor, HML_{UNC}, constructed analogously to the book-to-market factor (HML) of Fama and French (1993), is not explained by the size (SMB), book-to-market (HML), investment (CMA), or profitability (RMW) factors of Fama and French (2015). In cross-sectional stock level analysis, UNC remains significant in the presence of size, investment, profitability, idiosyncratic volatility, and the value (BM) premium itself. The UNC premium is also robust to controls for the variance risk premium (VRP), price momentum (MOM), post-earnings announcement drift (PEAD), and after excluding microcap and illiquid stocks (Hou et al. (2018)). Besides the theoretical foundation of value uncertainty, the t-statistics of the alpha spreads on the value-weighted HML_{UNC} factor are above 3 so that the new value uncertainty factor passes more demanding significance thresholds arising from correlated multiple testing, data mining and publication bias concerns highlighted by Harvey et al. (2016).

This chapter further examines how the UNC premium is related to fundamental uncertainty in the economy or the stock market. If book-to-market is a fundamental risk proxy that has predictive power for future returns, its volatility may represent a priced risk factor. An uncertainty index based on a cross-sectional average of book-to-market volatilities (UNC^{avg}) is correlated with well-known economic uncertainty indices, such as the Chicago Fed National Activity Index (CFNAI), Jurado et al.'s (2015) macro uncertainty index, and Robert Shiller's crash confidence index. However, unlike these forward-looking economic uncertainty indicators that are positively associated with future growth options and negatively associated with investment and future stock returns, UNC represents analyst or investor uncertainty about the true current market value of shareholders' investment in productive assets. UNC is also a significant predictor of future market return and future market volatility and satisfies the restrictions of Merton's (1973) intertemporal capital asset pricing model (ICAPM) with an implied relative risk aversion of 1.43 (see, e.g., Maio and Santa-Clara (2012)). The study further documents that the BM uncertainty factor (HML_{UNC}) is high when productivity and consumption growth are both high, and that high-UNC stocks are negatively associated with changes in market volatility.

The novel UNC measure may serve as a different proxy for contemporaneous economic uncertainty reflecting ambiguity about the true current value of the underlying investment in operating productive assets.[2] There is no consensus in the literature regarding economic uncertainty measures. Some firm-specific uncertainty measures, such as firm size or stock

[2] As will be discussed later, stock exposure to macroeconomic and policy uncertainty indices is controlled for (e.g., Jurado et al. (2015), Baker et al. (2016), and Bali et al. (2017a)) and neither economic uncertainty nor policy uncertainty does explain the positive premium associated with the value uncertainty premium, confirming that UNC captures something different from the standard uncertainty indices in the cross-sectional pricing of individual stocks.

volatility, are not clean proxies for uncertainty (Zhang, 2006). Moreover, various uncertainty measures yield contradicting or insignificant forward return premia. For instance, divergence of opinion among financial analysts yields contradictory cross-sectional associations with future stock returns in different studies (e.g., Anderson et al. (2009); Diether et al. (2002); Park (2005)). This mixed evidence casts doubt on prevailing economic uncertainty indicators and makes it difficult to conclude whether different types of uncertainty require a premium and whether the premium should be positive or negative. Relying on financial analyst data, this study focuses on contemporaneous uncertainty about the true current value of investment in productive assets and provides a novel yet simple economic uncertainty measure. More broadly, results highlight the significance of the volatility of common risk factors as potential fundamental uncertainty proxies. This is the first study investigating the contemporaneous uncertainty surrounding book-to-market and helps provide a rational explanation for the uncovered value uncertainty premium.

The remainder of the chapter is organized as follows. Section 2.2 provides a brief literature review. Section 2.3 offers a theoretical perspective on the volatility of book-to-market. Section 2.4 describes the data and variables. Section 2.5 discusses empirical findings. Section 2.6 examines the characteristics of high-UNC firms and discusses potential explanations for the uncertainty premium. Section 2.7 offers robustness checks and Section 2.8 concludes.

2.2 Literature Review

Investigating the variability in price-scaled variables is not new. Fama and French (1995) suggest that high-BM ratios signal poor profitability. Value firms are more likely to be distressed so investors require higher return to hold these stocks. Cohen et al. (2003) decompose the cross-sectional variance of book-to-market and suggest that the biggest part of this variation is attributed to cross-sectional variation in expected long-term profitability.[3] They show that the expected return on a value-minus-growth portfolio strategy is high when the cross-sectional

[3]Different from Cohen et al. (2003), who decompose the cross-sectional variance of book-to-market, this study focuses on the time-series variance of firms' book-to-market ratios. The proposed measure is more directly related to the quality of forward-looking information content of the BM ratio.

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. They also find that the time to capture the value premium is when the value spread is large and the earnings growth spread is small. 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 future 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 Loughran (1997) and Kothari et al. (1995). Fama and French (2006b) also confirm earlier studies that the CAPM does not explain the value premium. Further linking book-to-market, profitability and investment, Fama and French (2006a) provide evidence that value stocks have higher expected return when profitability (measured by ROE) and investment (measured by asset growth) are controlled for.[4] When controlling for book-to-market and expected profitability, lower expected returns imply higher rates of investment. In a related study, Novy-Marx (2013) shows that the value strategy can be significantly improved once profitability is controlled for. He documents a significant negative correlation between gross profits-to-assets (a profitability proxy) 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 and can potentially improve a value investor's investment opportunity set.

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 its current profitability gets lower and

[4]More recently, Fama and French (2015) and Hou et al. (2015) indicate that the value premium is not significant after controlling for the investment and profitability factors.

market-to-book decreases. Uncertainty about future profitability, however, tends to raise the firm's market value as it increases the expected future growth option payoff (due to the convex relation between growth and terminal value) without affecting discount rates.

The literature further distinguishes between risk and uncertainty, where investors are not only concerned about the risk associated with an asset's mean and variance but also the uncertainty of the future return distribution (e.g., Izhakian and Benninga (2011), Izhakian (2017), Epstein and Schneider (2008)).[5] The level of risk faced by investors can itself also be uncertain or ambiguous. One way to capture this uncertainty is by assessing the volatility of risk proxies.

Theoretical models of production-based asset pricing (e.g., Cooper (2006); Lin and Zhang (2013); Liu et al. (2009); Zhang (2005)) 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. The work of Cooper (2006) and Liu et al. (2009) is extended to show that the volatility of the book-to-market ratio is positively associated with future returns.

2.3 BM Uncertainty with Noisy Information

This section relates the uncertainty (UNC) in current book-to-market (BM) estimates to key variables like expected growth and volatility of profitability, the quality of information about the true value of accounting variables such as the book value of productive assets, and required return. If the book value of equity (BE) is observable only at infrequent discrete times, such as t and T, when the firm discloses its accounting information, there will be interim contemporaneous uncertainty about the true current book value of productive assets. Suppose now BE evolves according to the clean surplus relation so that book value of equity at time T is $\mathrm{BE}_T = \mathrm{BE}_t + \mathrm{E}_{T-t} - \mathrm{D}_{T-t}$, where E_{T-t} is current earnings and D_{T-t} is dividends paid over the

[5]Risk refers to unknown future returns under given probabilities, while uncertainty refers to conditions where future returns are unknown and the associated probabilities are not known (Miller, 1977). In common asset pricing models, a prevalent assumption is that all investors have the same estimates of expected returns and probability distribution of returns for all securities. This assumption is not necessarily valid, as pointed out by Knight (1921).

period $[t, T]$. For simplicity, consider a growth firm that does not pay dividends for some time ($\mathrm{D}_{T-t} = 0$) such that book value of equity grows at a constant rate g, i.e., $\mathrm{BE}_T = \mathrm{BE}_t e^{g(T-t)}$. In-between the two disclosure event dates t and T, investors are uncertain about the true book value as they only have access to a noisy signal $s = g + \epsilon$, where g is the (unobservable) growth in future earnings and ϵ is the noise surrounding current accounting earnings figures. Assuming that the growth in future earnings g and the noise of the signal ϵ follow two independent normal distributions with parameters $g \sim N(\bar{g}, \sigma_g^2)$ and $\epsilon \sim N(0, \sigma_\epsilon^2)$,[6] the book-to-market ratio at any time τ between the two disclosure events (t and T) is given by:

$$\mathrm{BM}_\tau = \frac{\mathrm{BE}_t e^{g\tau}}{\mathrm{BE}_t e^{(g-r)T}} = e^{-(g-r)(T-\tau)} e^{r\tau}. \tag{2.1}$$

Assuming log-normal distribution, the expected value and standard deviation of BM_τ are:

$$\begin{aligned} \mathrm{E}_\tau[\mathrm{BM}] &= e^{-(\mu-r)(T-\tau)+\frac{1}{2}\sigma_\mu^2(T-\tau)^2} e^{r\tau}, && (2.2) \\ \mathrm{Std}_\tau[\mathrm{BM}] &= \mathrm{M}_\tau \mathrm{E}_\tau[\mathrm{BM}]. && (2.3) \end{aligned}$$

where $\mathrm{M}_\tau \equiv \sqrt{\left(e^{\sigma_\mu^2(T-\tau)^2} - 1\right)}$. As shown in Equations (2.2) and (2.3), the standard deviation of the BM ratio ($\mathrm{Std}_\tau[\mathrm{BM}]$) contains similar information extractable from the expectation of BM in Equation (2.2), multiplied by an extra term M_τ that is increasing in the volatility of the associated underlying variables. From Equation (2.2) average book-to-market is affected both by the expected future profitability μ and the volatility of profitability σ_μ making it difficult to disentangle the two. Dividing Equation (2.2) by Equation (2.3) allows to isolate the multiplier M_τ which is more informative than the average BM ratio alone about changes in the riskiness of future profitability, σ_g, and the quality of current accounting information, σ_ϵ. M_τ depends

[6] Investors at time t observe signal s and make an estimation of future earnings growth g. From Bayes' theorem, the posterior distribution of earnings growth, g, conditional on the observed signal, s, is normally distributed with parameters $g|s \sim N(\mu, \sigma_\mu^2)$ where:

$$\begin{cases} \mu &= a\bar{g} + (1-a)s \\ \sigma_\mu^2 &= \frac{\sigma_g^2 \sigma_\epsilon^2}{\sigma_g^2 + \sigma_\epsilon^2} \\ a &= \frac{\sigma_\epsilon^2}{\sigma_g^2 + \sigma_\epsilon^2} \end{cases}$$

As in Pástor and Veronesi (2003), competition eliminates expected abnormal earnings at time T so that firm value at time t is the present value of the expected book value of equity at time T discounted at a (known) rate of return r.

monotonically only on the uncertainty of current profitability σ_μ.

The uncertainty in current BM estimates is thus more informative than the expected value of the BM ratio concerning the risk associated with profitability and the quality of available accounting information. Section A2.1 in the Appendix shows that the elasticity of the standard deviation of book-to-market estimates with respect to the uncertainty of future profitability is higher than the elasticity of the expected value of book-to-market with respect to the uncertainty of future profitability. Bivariate portfolio analysis and firm-level cross-sectional regressions, discussed in Section 2.5, show that stocks with high uncertainty of BM estimates (UNC) generate a higher risk-adjusted return compared to stocks with low BM uncertainty even after controlling for the value (BM) effect. Section 2.6.1 directly relates the uncertainty in book-to-market estimates to the firm's risk exposure and expected return, enhancing the theoretical rationale for the impact of the volatility of book-to-market on equity returns.

2.4 Data and Variables

The sample consists of all NYSE/AMEX/NASDAQ ordinary common equity shares (with share code 10 and 11). Regulated and financial services firms (one-digit SIC codes 4 and 6) are excluded. Each stock has to have a non-missing book value of common equity in COMPUSTAT and to be covered by the Institutional Brokers' Estimate System (IBES) database due to the use of analyst forecasts in the estimation of UNC. If analysts' forecasts are missing for a given month, the previous month forecast in the same fiscal year is used. At least three months of analyst forecasts in a year is required for UNC computation. Stocks with negative book value are excluded. Each stock is also required to have at least 36 months of CRSP and COMPUSTAT data. The sample extends from January 1985 to December 2016.[7] Given that UNC is computed over the previous 12 months, cross-sectional return predictability is reported from January 1986 to December 2016. To reduce liquidity concerns, stocks with price per share less than \$5 are excluded (see Jegadeesh and Titman (2001), Zhang (2006), Diether et al. (2002)).[8] Monthly

[7] The selection of the sample period is dictated by the low coverage of IBES before 1985.

[8] As will be discussed later, the analysis is repeated by removing stocks with share per price less than \$1 and the main results remained qualitatively similar.

and daily returns as well as trading data are obtained from CRSP. Accounting data are obtained from COMPUSTAT and earnings estimates from IBES.[9]

2.4.1 Uncertainty of Book-to-Market

Uncertainty of 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 over the previous 12 months. For firm i on day d in year y, the expected book-to-market ratio is calculated as:

$$\mathrm{BM}_{i,d} = \frac{\mathrm{E}_d[\mathrm{BE}_{i,y}]}{\mathrm{ME}_{i,d}}, \tag{2.4}$$

where $\mathrm{ME}_{i,d}$ is market value of equity for firm i on day d, computed as total shares outstanding times stock price on day d; $\mathrm{E}_d[\mathrm{BE}_{i,y}]$ is expected book value of equity at the end of year y, estimated based on the last available book value of equity of firm i in quarter q of year y, plus net income estimated by analysts on day d ($\mathrm{NI}_{i,y}$) minus expected dividends ($\mathrm{D}_{i,d}$):[10]

$$\mathrm{E}_d[\mathrm{BE}_{i,y}] = \mathrm{BE}_{i,q} + \mathrm{E}_d[\mathrm{NI}_{i,y} - \mathrm{D}_{i,y}]. \tag{2.5}$$

Book value of equity ($\mathrm{BE}_{i,q}$) in Equation (2.5) is updated quarterly and is computed as the book value of shareholders' equity (COMPUSTAT item seqq), plus deferred taxes and investment tax credit (txditcq) minus book value of preferred stock (pstkq). Accounting data used in Equations (2.4) and (2.5) are lagged three months and analysts' forecasts are lagged one month compared to market data to avoid look-ahead bias. For the first three months of the fiscal year in the UNC estimation, $\mathrm{BE}_{i,y-1}$ of the previous fiscal year may not yet be known; $\mathrm{BE}_{i,y-1}$ is thus estimated by using the previous year analyst forecasts of earnings per share (EPS):

$$\mathrm{BE}_{i,y-1} = \mathrm{BE}_{i,y-2} + \mathrm{E}[\mathrm{NI}_{i,y-1}]. \tag{2.6}$$

[9]Fama and French (1993, 2015) factors are obtained from the online data 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/`.

[10]Estimated net income by analysts are adjusted to reflect only the earnings forecast of the remaining months of the year when the 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 $\mathrm{BE}_{i,y-1} + \mathrm{E}_d[\mathrm{NI}_{i,y}]$. Expected net income for the end of the 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 IBES) and the total number of shares outstanding:[11]

$$\mathrm{E}_d[\mathrm{NI}_{i,y}] = \mathrm{E}_d[\mathrm{EPS}_{i,y}] \times \text{Shares Outstanding}. \tag{2.7}$$

The uncertainty (UNC) of estimated book-to-market in month t for firm i is then computed as the standard deviation of the daily estimated book-to-market ratios as per Equation (2.4) scaled by their mean over the previous 12 months:

$$\mathrm{UNC}_{i,t} = \frac{\mathrm{Std}_t[\mathrm{BM}_i]}{\overline{\mathrm{BM}}_i}, \tag{2.8}$$

where

$$\mathrm{Std}_t[\mathrm{BM}_i] = \sqrt{\frac{\sum_{d=1}^{N} \left(\mathrm{BM}_{i,d} - \mathrm{E}_t[\mathrm{BM}_i]\right)^2}{N}}, \tag{2.9}$$

$$\overline{\mathrm{BM}}_i = \frac{\sum_{d=1}^{N} \mathrm{BM}_{i,d}}{N}. \tag{2.10}$$

In Equations (2.8)-(2.10), $\mathrm{Std}_t[\mathrm{BM}_i]$ is the standard deviation of the estimated book-to-market ratio of stock i in month t, $\mathrm{BM}_{i,d}$ is the book-to-market ratio estimated as per Equation (2.4) on day d, $\overline{\mathrm{BM}}_i$ is the average of $\mathrm{BM}_{i,d}$, with N the total number of trading days over the previous 12 months. Equation (2.3) above is useful in understanding whether the BM premium is arising from information regarding future growth in earnings $\bar{g}$ or the uncertainty related to earnings σ_g and σ_ϵ. Scaling Equation (2.3) with the expected BM ratio helps isolate the impact the

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

first term alone $\left(\mathrm{M}_\tau = \sqrt{\left(e^{\sigma_\mu^2 (T-\tau)^2} - 1\right)}\right)$ plays. For this reason, the UNC indicator as per Equation (2.8) is the scaled standard deviation of the book-to-market ratio.

2.4.2 Control Variables

To ensure that the uncertainty related to the measurement of book-to-market ratio is not a proxy for well-known risk factors, a battery of control variables as standard in the literature is used, described below.

- Market beta (β^{MKT}), estimated following Dimson (1979):

$$R_{i,d} = \alpha_i + \sum_{k=-n}^{n} \beta_{k,i} R_{m,d+k} + \epsilon_{i,d}, \tag{2.11}$$

  where $R_{i,d}$ and $R_{m,d}$ are the excess return of stock i and 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.

- SIZE, the natural logarithm of market capitalization (MCAP) calculated as the product of price per share and common shares outstanding (Fama and French (1992)).

- 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 data. To be consistent in the estimation of standard deviation of book-to-market and monthly rebalancing as per Equations (2.4) and (2.8), BM is updated each month. For robustness, a BM variant is constructed as in Fama and French (1992, 1993), where BMFF is BM at the end of June of year y computed as book value of shareholders' equity plus deferred taxes minus redemptions, liquidation or par value of preferred stock (depending on availability at the end of the latest fiscal year ending in calendar year $y-1$) scaled by the market value of equity at the end of December of year $y-1$.[12]

- 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).

- Stock momentum (MOM), the cumulative return over the previous 11 months excluding the most recent month prior to the portfolio formation as in Jegadeesh and Titman (1993).

- Illiquidity (ILLIQ), measured following Amihud (2002) as

$$\text{ILLIQ}_{i,t} = Average\left[\frac{|R_{i,d}|}{\text{VOLD}_{i,d}}\right] \tag{2.12}$$

  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.

- Short-term reversal (STR), measured as the last month return (the return of the portfolio formation month) as in Jegadeesh (1990).

- 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):[13]

$$R_{i,d} = \alpha_{i,d} + \beta_{i,d}^{\text{MKT}} R_{m,d} + \beta_{i,d}^{\text{SMB}} \text{SMB}_d + \beta_{i,d}^{\text{HML}} \text{HML}_d + \epsilon_{i,d}. \tag{2.13}$$

- Dispersion in analyst forecasts (DISP), the standard deviation of annual earnings per share forecasts scaled by absolute mean earnings forecast (see Diether et al. (2002)).

[12] The natural logarithm of BM and BMFF is used as controls across all analysis, except in Table 2.3 presenting firm characteristics.

[13] Following Ang et al. (2006), idiosyncratic volatility (IVOL) and market beta (BETA) are estimated based on daily data in a month. Estimating IVOL and BETA using daily data over a year does not materially change the results. Using total volatility as an additional control (alternative to IVOL) generates similar results (untabulated).

- Idiosyncratic Skewness (ISKEW), measured as the skewness of the stock's daily residuals over the past month and co-skewness (COSK) being the loading q on the square of daily excess market returns over the past month based on the following regression, in line with Harvey and Siddique (2000):

$$R_{i,d} = a_i + b_i R_{m,d} + q_i R_{m,d}^2 + \epsilon_{i,d}. \tag{2.14}$$

- Stock i's exposure to market volatility (β^{VXO}) is calculated from a bivariate time-series regression of the stock excess returns on the market excess return and changes in implied volatility using daily data in a month following Ang et al. (2006):

$$R_{i,d} = \alpha_i + \beta_i^{\text{MKT}} R_{m,d} + \beta_i^{\text{VXO}} \Delta\text{VXO}_d + \epsilon_{i,d}, \tag{2.15}$$

  where ΔVXO is the innovation in the S&P100 implied volatility index (VXO); β_i^{MKT} and β_i^{VXO} are the loadings of stock i in month t on the aggregate market and aggregate market volatility, respectively.[14]

- Maximum return (MAX), the average of the five highest daily returns of a stock in the previous month, controling for lottery-like features as in Bali et al. (2011).

- The standard deviation of estimated net income as in Section 2.4.1 and the inverse of SIZE are used as additional controls.

2.5 Empirical Results

2.5.1 Univariate Portfolio Analysis

Each month from January 1986 to December 2016, 10 value-weighted and equal-weighted decile portfolios are formed by sorting individual stocks on the basis of their estimated book-

[14] For robustness, change in the S&P500 implied volatility index (VIX) is used and the main findings are similar. Reported results are for VXO due to its data availability that fully covers the sample period.

to-market volatility (UNC), where decile 1 (decile 10) contains stocks with the lowest (highest) UNC. Each month contains, on average, 851 stocks over the sample period, with a monthly minimum and maximum of 642 and 1,061 stocks, respectively. Table 2.1 reports the average monthly excess (raw) and risk-adjusted returns in percentage for value-weighted portfolios. Risk-adjusted returns are estimated using five different factor models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM alpha); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ (QF alpha); and (v) the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (7F alpha). The second set of models in Table 2.1 considers the 3F, 5F, and QF models augmented by Carhart's (1997) momentum factor (MOM), while the last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the 3F and QF models.

Table 2.1 shows that the risk-adjusted returns increase almost monotonically in moving from the first (low) to the last (high) UNC decile across different asset pricing models. The main set of models, the CAPM, 3F, 5F, QF and 7F, fails to explain the UNC premium as seen in the last row reporting 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. Specifically, the monthly alpha generated by the 7F model for the high-UNC decile is 1.04% greater than the low-UNC decile, with a t-statistic of 4.25. This indicates an annualized 12.5% higher return for the high-UNC decile. The risk-adjusted returns for the 5F and QF models are similar. They are also very similar in the extended models of Table 2.1 (with MOM or MOM+LIQ added). In terms of average raw returns, the high-UNC decile delivers an economically and statistically significant 0.95% (t-statistic of 3.17) higher return per month compared to the low-UNC decile.

Next, the source of the risk-adjusted return differences between the low- and high-UNC portfolios is investigated, specifically whether they are due to outperformance by high-UNC stocks, underperformance by low-UNC stocks, or both? For this, the focus is on the economic and statistical significance of the risk-adjusted returns (alphas) of decile 1 versus decile 10 in the value-weighted portfolios. As seen in the last row of Table 2.1, the CAPM, 3F, 5F, QF, and 7F alphas of stocks in decile 10 (high-UNC) are all positive as well as economically and statistically significant (without exception), whereas the corresponding 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. For the remainder of this chapter, the 7F model is used as the base model since it is the most comprehensive and includes the investment, profitability, and value factors relevant to UNC.

Table A2.1 of the Appendix replicates Table 2.1 for the equal-weighted portfolios of stocks sorted by UNC. As expected, the corresponding return and alpha spreads between high- and low-UNC deciles are analogous though somewhat more pronounced due to the greater influence of smaller and higher UNC stocks in equal-weighted portfolios. The significant and positive value uncertainty premium is again robust to alternative asset pricing models. Analogous robust results are obtained when portfolios are built using the NYSE breakpoints (see Table A2.2 of the Appendix).

2.5.2 Alternative Samples, Portfolio Breakpoints and Weighting

Hou et al. (2018) investigate 452 equity market anomalies and find that most of them are not significant if microcap stocks with market capitalization smaller than the 20th NYSE size percentile are excluded. When removing microcap stocks and using value-weighted portfolios with NYSE breakpoints, they find that 65% of the anomalies cannot pass the standard hurdle with absolute t-value of 1.96. When imposing the higher multiple-test hurdle of 2.78 at 5% significance, the failure rate rises to 82%. To address the concern raised by Hou et al. (2018), we replicate the value-weighted portfolio analysis with NYSE breakpoints using alternative stock samples that exclude small, illiquid, low-priced, and microcap stocks.

First,Table 2.1 is reproduced using NYSE stocks only, thus leaving out relatively small and illiquid stocks trading on AMEX and NASDAQ. Second, an additional size screen is implemented by removing the smaller NYSE stocks with market capitalization in the smallest NYSE size decile. Third, a liquidity screen is implemented based on the illiquidity measure of Amihud (2002) by excluding NYSE stocks in the lowest NYSE liquidity decile. Fourth, as in Fama and French (2008b) and Hou et al. (2018), microcaps are removed from the NYSE/AMEX/NASDAQ stock universe (with market capitalization less than the 20th NYSE size percentile) and form value-weighted portfolios with the NYSE breakpoints.

Panel A of Table 2.2 presents in the first column the 7-factor (7F) alphas on value-weighted decile portfolios of stocks trading on the NYSE only. Similar to the earlier findings, the 10-1 alpha spread for a hedge portfolio long in the highest UNC stocks and short in the lowest UNC decile is positive and highly significant, generating 0.71% per month with a t-statistic of 2.69. Similarly, for the individual size and liquidity screened samples of NYSE stocks, shown in columns (2)-(3) of Panel A of Table 2.2, the alpha spreads between high-UNC and low-UNC deciles remain economically significant, in the range of 0.83% and 1.08% per month, with t-statistics from 3.89 to 4.16. The last column in Panel A of Table 2.2 confirms that the alpha spread is highly significant, both economically and statistically, for the stock sample that excludes microcaps, offering 0.81% per month with a t-statistic of 3.76.

For further robustness, the analysis using alternative stock samples is repeated: (i) excluding stocks trading below \$1 per share, (ii) including only large stocks with market cap greater than the median NYSE size breakpoint, (iii) including only the largest 500 stocks based on market capitalization, (iv) including only the most liquid 500 stocks based on the Amihud (2002) illiquidity measure, and (v) including only the 500 stocks with the lowest idiosyncratic volatility (IVOL). Panel B of Table 2.2 reports the 7F model alphas for value-weighted portfolios involving stocks sorted by UNC. The last row reports the $10-1$ differences in alphas between high- and low-UNC deciles with Newey-West t-statistics. These findings confirm that the positive value uncertainty premium is not driven by small, illiquid or volatile stocks.

To further test whether the positive UNC premium reported in Table 2.1 might be partly explained by market volatility, additional analysis includes the variance risk premium (VRP) as in Bollerslev et al. (2009). Specifically, the change in VRP is added as an additional explanatory variable to the previous risk factors in the various model specifications of Table 2.1. Results, shown in Table A2.3 of the Appendix, reaffirm the positive and significant premium associated with high-UNC firms, even after controlling for changes in VRP.[15]

For further robustness, Table A2.4 of the Appendix additionally includes betting against beta (BAB) of Frazzini and Pedersen (2014), quality minus junk (QMJ) of Asness et al. (2019), lottery demand (FMAX) of Bali et al. (2017b), the post-earnings announcement drift (PEAD) and modified financing (FIN) factors of Daniel et al. (2019) beyond the 7F model. Results confirm that the significant UNC premium is unaffected. Overall, the main analysis indicates that the volatility of estimated book-to-market ratios can not be explained by established risk factors.

2.5.3 Analysis of Portfolio Characteristics

This section examines how average portfolio characteristics vary for different levels of UNC. Table 2.3 reports the average firm characteristics in the sample for each UNC decile. These characteristics include market beta (β^{MKT}), market capitalization (MCAP) in million US dollars, book-to-market (BM, BMFF), investment (INV), operating profitability (OP), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility exposure (β^{VXO}), and lottery-demand (MAX). Characteristics are reported for the month of portfolio formation.

As shown in Table 2.3, several interesting patterns are observable when moving from low-UNC (decile 1) to high-UNC (decile 10). First, β^{MKT} tends to increase monotonically with UNC. High-UNC stocks tend to be smaller (lower market capitalization), though there is no clear monotonic pattern in MCAP in moving from decile 1 to 10. Second, high-UNC stocks tend to be growth stocks with higher investment as inferred from a monotonic decline in BM and an increase in INV in moving from low- to high-UNC deciles. Regarding past returns,

[15] The sample period for this analysis spans January 1990 to December 2016 due to VRP data availability.

high-UNC stocks appear to be past short-term and medium-term winners as manifested by the increasing pattern of MOM and STR. High-UNC stocks are also more negatively co-skewed and have relatively higher turnover. Table 2.3 also shows a monotonically increasing pattern in IVOL and MAX as UNC increases, implying lottery features may also be associated with high-UNC stocks.

The above characteristics in Table 2.3 help draw preliminary inferences regarding potential stock return predictors that may contribute to the explanation of the UNC premium. These include higher market beta, smaller size, higher momentum and more negative co-skewness, as stocks with these characteristics tend to generate higher future returns (Fama and French (1993); Harvey and Siddique (2000); Jegadeesh and Titman (1993); Sharpe (1964)).

Table A2.5 in the Appendix reports the monthly time-series averages of the cross-sectional correlations among various key variables. The average cross-sectional correlation between UNC and BM is -0.17, suggesting that growth stocks are more prone to exhibit higher uncertainty in the measurement of BM ratios. UNC is positively correlated with β^{MKT}, IVOL and MAX. It is not surprising that IVOL and MAX are positively correlated with UNC as volatility and lottery-demand are highly correlated. It is also more likely that volatile stocks exhibit high uncertainty of BM. A stock in a risky industry, for instance, is more likely to exhibit high volatility on arrival of new information regarding book value estimates compared to a stock in a stable sector. The positive correlation between UNC and TURN may be attributed to the latter capturing some uncertainty and divergence of opinion (Hong and Stein (2007)). We also find a positive relation between UNC and INV, suggesting that high-UNC stocks are more likely to be growth firms and invest more.

2.5.4 Bivariate Portfolio Analysis

To address a further concern that the standard deviation of BM might be a proxy for another common risk factor or firm characteristic, bivariate portfolio analysis is conducted using a wide range of control variables. Portfolios are first sorted into deciles using one of the following characteristics (controls): market beta (β^{MKT}), market capitalization (SIZE), book-to-market (BM, BMFF), investment (INV), operating profitability (OP), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of estimated net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)). Then, stocks within each control decile are further sorted into deciles based on UNC, with decile 1 (10) containing stocks with the lowest (highest) UNC. For example, stocks are first sorted according to their SIZE forming ten portfolios. Then, within each SIZE decile, stocks are further sorted into decile portfolios according to their UNC. A simple average of value-weighted monthly returns for each UNC decile is then computed across all SIZE deciles. In this way, each UNC decile contains stocks of roughly equivalent size. Table 2.4 reports the risk-adjusted returns based on the 7F model using value-weighted returns for each UNC decile, averaged across each of the characteristics (controls), with their corresponding Newey-West t-statistic shown in parenthesis. The last row in Table 2.4 reports differences in alphas between UNC deciles 10 and 1 and their t-statistics.

Table 2.4 shows that after controlling for the above established cross-sectional predictors, including BM and IVOL, the difference in alphas between UNC deciles 10 and 1 remains positive and significant. For instance, controlling for value (BM), the portfolio with highest UNC generates an economically and statistically significant 1.04% higher monthly risk-adjusted return (with a t-statistic of 5.39), compared to the lowest UNC decile portfolio. Hence, BM (analogously, the other aforementioned control variables) cannot explain the high abnormal returns associated with high book-to-market uncertainty (UNC). To specifically rule out the possibility that UNC may proxy for the volatility of estimated net income (NI) or the volatility of the inverse of SIZE, these two controls are specifically examined in the bivariate portfolio analysis in the last two columns in Table 2.4, confirming that the value uncertainty premium remains highly significant. To further rule out that UNC may proxy for profitability (OP) or investment (INV), a conditional double sorting on these variables is conducted, confirming that the UNC premium remains statistically and economically significant.[16]

Finally, a trivariate portfolio sorting on UNC is performed controlling for both book-to-market ratio (BM) and the standard deviation of expected profitability (Std. (ROE)), where ROE is expected net income as per Equation (2.7) scaled by the most recent book value of equity. This test helps isolate the impact of the quality of information (σ_ϵ in Equation (2.3)). The results, shown in Table A2.7 of the Appendix, indicate that the significantly positive value uncertainty premium remains significant even after controlling for both BM and the standard deviation of expected profitability (Std. (ROE) or σ_g).

2.5.5 Stock Level Cross-Sectional Regressions

This section examines the cross-sectional relation between book-to-market volatility (UNC) and expected returns at the individual stock-level using the Fama and MacBeth (1973) regression procedure. This methodology helps control for several risk factors and firm characteristics concurrently to ensure that UNC is distinct from common cross-sectional return predictors. Table 2.5 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 battery of controls, based on the following specification:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}\mathrm{UNC}_{i,t} + \gamma_{2,t}X_{i,t} + \epsilon_{i,t+1}, \tag{2.16}$$

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 Equation (2.8), and $X_{i,t}$ is a set of lagged firm-specific control variables. These include market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), and illiquidity (ILLIQ). Additional control variables are added one at a time: short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic

[16] The value-weighted bivariate portfolio results reported in Table 2.4 are robust to using the NYSE breakpoints. Table A2.6 of the Appendix confirms that the UNC premium remains significant and positive after accounting for these control variables in bivariate portfolios sorted based on the NYSE breakpoints.

skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)).[17] The t-statistics are corrected for autocorrelation and heteroscedasticity using Newey-West estimator with six lags.

As shown in Table 2.5, both in the univariate (column(1)) and multivariate regressions with various sets of control variables (columns (2-17)), the uncertainty of the book-to-market ratio (UNC) predicts higher future returns. Furthermore, this positive UNC premium is both economically and statistically significant. The average slope coefficient of UNC in the univariate regression is 2.96 and ranges between 2.46 and 3.47 in the multivariate regressions. Considering the lower (upper) bound of 2.42 (3.47), moving from decile 1 to decile 10 would see a stock's UNC measure increase from 0.06 to 0.38 (as shown in the first column of Table 2.3). This implies a monthly increase of 0.8% (1.1%) in the typical stock's expected return in moving from decile 1 to decile 10. Thus, the economic significance of the UNC premium in stock-level Fama-MacBeth regressions is consistent with the value uncertainty premium obtained from the portfolio-level analysis reported in Tables 2.1 and 2.4.

Besides UNC, columns (2-3) of Table 2.5 include standard risk factors, SIZE and BM, one at a time. Columns (4-5) report the coefficient of a cross-sectional specification corresponding to the Fama and French (1993) 3-factor and the Fama and French (2015) 5-factor models, respectively. Columns (6-7) add momentum (MOM) and illiquidity (ILLIQ) factors. Columns (8-17) add STR, TURN, DISP, IVOL, ISKEW, COSK, β^{VXO}, MAX, Std(NI), and Std(1/SIZE) one at a time to the baseline specification of column (7). Concerning the other coefficients in the baseline regression model of column (7), β^{MKT} is positive but insignificant, in line with earlier studies. Consistent with prior findings, the coefficient of SIZE is negative, while BM is positively related to future returns (Fama and French (1992, 1993)). INV is negative but insignificant. The positive and significant OP coefficient is in line with the profitability premium (Fama and French (1995); Novy-Marx (2013)). Momentum and illiquidity premia are generally positive but insignificant.

[17] Replacing BM with BMFF generates analogous results.

Regarding the extended models (8-17), the negative and significant coefficients of STR and MAX in columns (8) and (15) are in line with previous empirical studies (Bali et al. (2011); Jegadeesh (1990)). The significantly negative coefficient of market volatility beta (β^{VXO}) in column (14) is in line with Ang et al. (2006). The turnover (TURN) coefficient in column (9) is insignificant. The positive but insignificant DISP coefficient in column (10) is different from the negative and significant DISP premium documented by Diether et al. (2002). Idiosyncratic volatility in column (11) is positive albeit insignificant, which does not support the idiosyncratic volatility puzzle (Ang et al. (2006)) but is in accordance with other empirical findings (e.g., Bali and Cakici (2008)). ISKEW and COSK coefficients in columns (12) and (13) are insignificant. Coefficients of Std(NI) and Std(1/SIZE) in columns (16) and (17) are positive and significant.[18]

2.5.6 Do Existing Factor Models Explain the UNC Factor?

The correlation matrix in Table A2.5 of the Appendix reveals a positive correlation of UNC with INV and a negative one with BM. To examine if UNC is explained by these factors, we generate a new factor, $\mathrm{HML_{UNC}}$, constructed in a similar way as the HML factor of Fama and French (1993) but based on the volatility of BM rather than BM itself. Specifically, the $\mathrm{HML_{UNC}}$ factor is built based on independently sorted 2×3 value-weighted portfolios of SIZE and UNC using the median NYSE breakpoints for SIZE and 30%, 40%, 30% NYSE breakpoints for UNC. The factor is formed as the difference between the average top 30% (high UNC) minus the bottom 30% (low UNC), with portfolio components rebalanced monthly.

Table 2.6 reports the time-series regression of the $\mathrm{HML_{UNC}}$ factor on the three factors of Fama and French (1993) with the excess market return (MKT), size (SMB) and value (HML), augmented by the momentum factor (MOM) of Carhart (1997) and the liquidity factor (LIQ) of Pástor and Stambaugh (2003) in Specification (1). Specification (2) is a regression of the $\mathrm{HML_{UNC}}$ factor on the five factors of Fama and French (2015) (5F): MKT, SMB, HML, investment (CMA), and profitability (RMW). Specification (3) adds MOM and LIQ factors to the latter specification (7F). Specification (4) is based on the four Q-factors (QF) of Hou et al.

[18]Stock-level cross-sectional analysis controlling for industry effects confirms the robustness of the UNC premium. The corresponding results are presented in Table A2.8 of the Appendix.

(2015), namely MKT, size (SMB_Q), investment ($\mathrm{R}_{I/A}$), and profitability (R_{ROE}). Specification (5) adds MOM and LIQ factors to Specification (4). In all these specifications, the intercept (alpha) remains positive and highly significant, implying that none of these established factors is able to explain UNC. The alpha on the $\mathrm{HML_{UNC}}$ factor is in the range of 0.52% to 0.70% per month (an annualized alpha of 6.3% to 8.4%) with t-statistics ranging from 4.10 to 5.02.[19]

Harvey et al. (2016) indicate that due to data mining and the large amount of research examining the cross-section of expected returns, a five percent level of significance is too low a threshold and suggest using much more stringent requirements for accepting new anomalous empirical results as evidence of true economic phenomena.[20] They emphasize that a new factor needs to clear a much higher hurdle with a t-statistic greater than 3. As shown in Table 2.6, the $\mathrm{HML_{UNC}}$ factor passes the higher bar set by Harvey et al. (2016). In addition to the theoretical foundation of value uncertainty, even after multiple testing correlation, the t-statistics of average raw and risk-adjusted return spreads are above 3 in value-weighted portfolios. Similarly, the alphas on the value uncertainty factor ($\mathrm{HML_{UNC}}$) have t-statistics greater than 3 using alternative factor models.

2.6 A Rational Asset Pricing Explanation of UNC

So far, it was shown that UNC requires a premium in the cross-section of stock returns and that it is not explained by known cross-sectional predictors or risk factors. Next, complementary economic rationale for the value uncertainty premium is provided in line with a production-based asset pricing model. Subsequent analysis shows the consistency of UNC premium with the intertemporal capital asset pricing model (ICAPM) of Merton (1973).

[19] The positive loadings on the MKT and SMB factors and the negative loadings on the HML factor in Table 2.6 are in line with earlier findings that firms with higher uncertainty in their BM estimation are likely smaller, growth firms with higher market risk. The negative loadings on the MOM, $\mathrm{R}_{I/A}$ and R_{ROE} factors indicate that firms with higher BM volatility are likely momentum losers with lower asset growth and lower profitability.

[20] The study in this chapter adds to the recent literature on the multidimensionality of the cross-section of expected stock returns. Hou et al. (2018) study a large collection of anomalies and illustrate the p-hacking concern through anomaly replication and argue, following Harvey (2017), that many of the anomalies have been p-hacked. McLean and Pontiff (2016) use an out-of-sample approach to study the post-publication bias of discovered anomalies. Harvey and Liu (2018) indicate that many discovered factors are likely false and they provide a new testing framework that simultaneously addresses multiple testing, variable selection, and test dependence in the context of regression models.

2.6.1 Value Uncertainty in Production-based Asset Pricing

This section provides a complementary economic rationale for the pricing of UNC in the cross-section of equity returns. The intuition in the context of production-based asset pricing comes from an extension of the theoretical model of Cooper (2006). A presentation of his main results is given in the Appendix. Considering $Z = K/\theta$ as the ratio between the stock of capital K and the firm's productivity θ, the book-to-market ratio, BM, can be written as $Z/V = K/(\theta V) = K/J$, where $J \equiv \theta V$ is the market value of the firm. Firm productivity is given by the product of aggregate productivity level (θ_A) and idiosyncratic productivity (θ_i), i.e., $\theta = \theta_A \theta_i$. Applying Itô's Lemma to the log of book-to-market, $\ln(\text{BM}) = \ln(K) - \ln(\theta) - \ln(V)$, changes in ln(BM) follow:

$$d\ln(\text{BM}) = \Gamma\, dt - \sigma_{\ln(\text{BM})} dw, \tag{2.17}$$

where

$$\Gamma = -\delta - \mu_A - \frac{V_Z Z}{V}(\sigma^2 - \mu - \delta) + \frac{1}{2}\sigma^2 \left(1 + \left(\frac{V_Z Z}{V}\right)^2 - \frac{V_{ZZ} Z^2}{V}\right), \tag{2.18}$$

$$\sigma_{\ln(\text{BM})} = \sigma \left(1 - \frac{V_Z Z}{V}\right). \tag{2.19}$$

In Equations (2.18) and (2.19), δ is the capital depreciation rate, μ_A is the drift rate of aggregate productivity shocks (θ_A), and σ is volatility of the firm's productivity (θ). That is, ln(BM) follows a diffusion process with drift rate Γ and volatility $\sigma_{\ln(\text{BM})}$. Equation (20) in Cooper (2006) shows that the beta (loading) of the firm's return with respect to the systematic risk factor return R_s, denoted with β_s, is given by:

$$\beta_s = \frac{V}{(V - \pi)} \sigma \left(1 - \frac{V_Z Z}{V}\right) Cov(dw, R_s) \times \frac{1}{Var(R_s)}. \tag{2.20}$$

Using the expression of Equation (2.17), β_s can thus be rewritten as a function of the covariance between changes in book-to-market (BM) and the systematic risk factor R_s:

$$\beta_s = -\frac{V}{(V - \pi)} \frac{Cov(d\ln(\text{BM}), R_s)}{Var(R_s)}, \tag{2.21}$$

where

$$Cov(d\ln(\mathrm{BM}), R_s) = -\sigma_{\ln(\mathrm{BM})} Cov(dw, R_s). \tag{2.22}$$

Denoting the risk-free rate with r_f and assuming that β_s is the only pricing factor with market price of risk γ, the expected return of the firm can be written as:

$$E[r] \quad = \quad r_f + \beta_s \gamma. \tag{2.23}$$

That is, a stock whose BM ratio covaries positively (negatively) with the systematic risk factor R_s should have a lower (higher) β_s and, from Equation (2.23), a lower (higher) expected return.[21] The economic intuition for this prediction is that higher values of BM are associated with lower firm productivity or are due to productivity covarying positively with consumption growth, features disliked by investors. Consequently, a firm with changes in BM covarying positively with systematic risk factor R_s provides a hedge against bad states of the economy, while a firm with changes in BM covarying negatively with R_s would increase risk.[22] Thus, the theoretical model of Cooper (2006) provides a risk-based rationale for why stocks with more (less) volatile book-to-market ratios are expected to generate high (low) returns.

2.6.2 Explanation of UNC in Production-based Asset Pricing

As shown in Equations (2.21) and (2.22), high variance of book-to-market (UNC) leads to high exposure of a firm's equity returns to the systematic risk-factor (β_s). Whether high-UNC leads to higher or lower β_s ultimately depends on the sign of the covariance of the firm's productivity with consumption growth. If the firm's productivity covaries positively with consumption growth, high-UNC will lead to high exposure to the systematic risk factor and consequently high expected return. Next, it is investigated whether high-UNC and the

[21] See also Equation (A2.31) in the Appendix.

[22] An alternative expression for Equation (2.21) is:

$$\beta_s = \sigma_{\ln(\mathrm{BM})} \frac{V}{(V-\pi)} \frac{Cov(dw, R_s)}{Var(R_s)},$$

When $Cov(dw, R_s) > 0$, higher values of $\sigma_{\ln(\mathrm{BM})}$ will increase β_s and thus the expected return of a stock.

premium associated with HML_{UNC} are high when productivity and consumption growth covary positively.

First, this conjecture is tested at the aggregate level. Specifically, a time-series regression is conducted of the HML_{UNC} factor (constructed as in Section 2.5.6) on one-year-lagged growth in private consumption (ΔC), one-year-lagged growth in productivity (ΔP) and their interaction $(\Delta C \times \Delta P)\mathbb{1}_{\{\Delta C \times \Delta P\}>0}$ as follows:[23]

$$\text{HML}_{\text{UNC}} = \beta_0 + \beta_1 \Delta\text{C} + \beta_2 \Delta\text{P} + \beta_3 (\Delta C \times \Delta P)\mathbb{1}_{\{\Delta C \times \Delta P\}>0} + \epsilon, \tag{2.24}$$

where $\mathbb{1}_{\{\Delta C \times \Delta P\}>0}$ is a binary dummy variable taking value one if the product between productivity and consumption growth is positive and zero otherwise, thereby capturing positive co-movements between productivity and consumption growth. Panel A of Table 2.7 reports the estimated coefficients with Newey and West corrected t-statistics in parentheses. In particular, β_1, β_2, and β_3 are -4.56 (t-stat.=-3.50), -6.91 (t-stat.=-3.59), and 2.31 (t-stat.=3.20), respectively, with an R^2 of 36.5% as reported in Specification (1) of Table 2.7, Panel A. These findings suggest that the HML_{UNC} factor covaries negatively with changes in consumption and productivity, indicating that HML_{UNC} provides higher return during bad states of the economy (with low consumption or low productivity). At the same time, it covaries positively with joint changes in productivity and consumption as suggested by the significant positive coefficient β_3, providing a risk-based justification for the significant positive premium of high-UNC firms. Specification (2) in Panel A of Table 2.7 reports the estimated coefficients from regressing an uncertainty index, built as the cross-sectional average of individual firms' UNC (UNC^{avg}), against consumption and productivity growth as per Equation (2.24). Results show that UNC is negatively related to consumption and productivity growth separately, but is positively related to their interaction in line with a risk-based explanation for the positive premium of high-UNC firms.

Next, it is tested whether the above results are robust when productivity is measured at

[23] Growth in annual consumption (DPCERO1Q156NBEA) and productivity (PRS85006161) indices are obtained from the Federal Reserve Bank of Saint Louis over the period 1986-2016.

the industry level. First, the covariance between annual growth in total factor productivity of industry i in year y ($\Delta\mathrm{TFP}_{i,y}$) and annual growth in aggregate consumption ($\Delta\mathrm{C}_y$) is estimated by running a rolling time-series regression over a 10-year window as follows:[24]

$$\Delta\mathrm{TFP}_{i,y} = \alpha_{i,y} + \beta_{i,y}\Delta C_y + \epsilon_{i,y}, \tag{2.25}$$

where $\beta_{i,y}$ captures the covariance between changes in productivity of industry i and consumption growth. Then, industry i's annual return, $R_{i,y}$, is regressed against $\hat{\beta}_{i,y}$ as follows:

$$R_{i,y} = \gamma_{0,y} + \gamma_{1,y}\hat{\beta}_{i,y} + \gamma_{2,y}\Delta\mathrm{TFP}_{i,y} + e_{i,y}. \tag{2.26}$$

Equation (2.26) is estimated as a series of cross-sectional regressions as per Fama and MacBeth (1973) and as a pooled panel regression. Panel B of Table 2.7 reports the time-series average slope coefficients from Fama-MacBeth regressions and the pooled panel regression coefficients obtained from the estimation of Equation (2.26) for low-UNC (bottom 25%) and high-UNC (top 25%) industries. Results reported in Panel B of Table 2.7 indicate that the price of risk associated with $\hat{\beta}_{i,y}$ is higher for the high-UNC (top 25%) group, confirming that high-UNC is associated with high stock return and high price of risk when the covariance between changes in productivity and consumption growth is high.

Results based on Equation (2.24) shown in Table 2.7 confirm that the aggregate measure of UNC is positively associated with the interaction between ΔC and ΔP (or ΔTFP), implying higher productivity and consumption risk for stocks with high-UNC. Thus, risk-averse investors demand extra compensation in the form of higher expected return when holding high-UNC stocks. As investors' risk aversion is generally higher during economic downturns, it is expected that the value uncertainty premium will be higher during bad economic states. To test this conjecture, the alphas on the $\mathrm{HML}_{\mathrm{UNC}}$ factor is estimated over good and bad states of the economy separately. Economic states are determined based on positive (good states) and negative (bad states) values of the Chicago Fed National Activity Index (CFNAI). Results

[24]Industry total factor productivity data are collected from the National Bureau of Economic Research Manufacturing Industry Database: `http://www.nber.org/nberces/nberces5811/`. Data are up to 2011.

reported in Table 2.8 show economically and statistically stronger risk-adjusted return (alpha) on HML_{UNC} in bad states of the economy, confirming a higher premium associated with high-UNC stocks in bad economic states. The magnitude of the UNC premium is then measured over different states (cycles) of the economy. In particular, the univariate sorting portfolio analysis of Table 2.1 is repeated over different states of the economy. Table 2.9 reports the risk-adjusted return (alphas) over good vs. bad economic states (calculated using positive and negative values of the CFNAI) and low vs. high volatility periods (using the median value of the VXO index). The reported alphas are based on the 7F model for value-weighted portfolios formed as in Table 2.1. Results in Panels A and B of Table 2.9 show that the UNC premium is generally higher and statistically more significant in bad states of the economy (CFNAI<0) and in high volatility periods (VXO>Median), thus providing a risk-based justification for the significant positive UNC premium as investors require higher future returns to hold these stocks during bad or high volatility states of the economy.

2.6.3 Further Analysis in an ICAPM Framework

Assuming that the book-to-market ratio captures some form of fundamental risk (Cooper (2006); Fama and French (1993); Lin and Zhang (2013); Liu et al. (2009); Petkova and Zhang (2005); Zhang (2005)), it can be conjectured that the standard deviation of book-to-market (UNC) might be partly driven by difficulties in generating clear expectations about the source of fundamental risk. Thus, the relation between UNC and common uncertainty indices capturing sources of fundamental risk in the economy is examined. In particular, the correlation is estimated between the aggregate measure of UNC (UNC^{avg}) and the first difference of UNC^{avg} (ΔUNC^{avg}) with CFNAI, future market return, and the first difference in the following economic and financial indicators: i) Shiller's Crash Confidence Index (ΔCrash Index);[25] ii) Jurado et al.'s (2015) macro uncertainty index (ΔJLN);[26] iii) Baker et al.'s (2016) economic policy uncertainty

[25]Shiller's crash confidence index is from the online database of the International Center for Finance: `https://som.yale.edu/faculty-research/our-centers/international-center-finance/data`.

[26]JLN index is from the online data library of Sydney Ludvigson: `https://www.sydneyludvigson.com/data-and-appendixes/`.

index (ΔPUI);[27] iv) CBOE's VXO volatility index (ΔVXO); and v) the aggregate default risk factor capturing the spread between BAA- and AAA-rated corporate bonds (ΔDEF).

Table 2.10 shows that ΔUNC^{avg} has a high positive correlation with ΔJLN macro uncertainty index, ΔVXO and the ΔDEF factor, with correlations from 0.69 to 0.71. The change in UNC^{avg} has a strong negative correlation with CFNAI and the change in Shiller's Crash Confidence Index, suggesting that value uncertainty is associated with low economic activity and low investor confidence (that there will be no stock market crash in the subsequent six months). The last row of Table 2.10 indicates a significantly positive relation with one-year-ahead market return. The correlations in Table 2.10 collectively suggest that UNC^{avg} is associated with standard measures of economic and financial uncertainty. In order to gain further insight on the joint dynamics of UNC^{avg} with these uncertainty measures, Figure 2.1 plots the three-month moving average of UNC^{avg} and those of CFNAI, JLN, VXO and DEF indices. The figure shows that UNC^{avg} shares common shocks with these economic uncertainty indices but exhibits more smooth and persistent dynamics. Motivated by this, an additional test is conducted to investigate whether the UNC^{avg} index predicts future market return. Panel A of Table 2.11 shows the slope coefficients from regressing one-year-ahead market return on changes in UNC^{avg} and other common measures of economic uncertainty. Models (1-3) in Panel A show that ΔUNC^{avg}, CFNAI, and ΔCrash Index are the three main uncertainty predictors with significant ability to forecast one-year-ahead market return.

Panel B of Table 2.11 examines the predictive power of ΔUNC^{avg} in forecasting future changes in market volatility. Panel B shows the slope coefficients from regressing one-year-ahead changes in VXO against changes in UNC^{avg} and other economic uncertainty measures. The results indicate that ΔUNC^{avg} is a significant predictor of VXO changes (ΔVXO). Results of both Panels A and B in Table 2.11, along with the positive premium associated with high-UNC firms discussed earlier, suggest that UNC^{avg} is a plausible state variable affecting investors' consumption and investment decisions in an ICAPM framework. Given that high-UNC firms earn on average higher equity returns in the cross-section and aggregate UNC^{avg} significantly forecasts high market return and low market volatility, it is tested whether UNC^{avg} satisfies

[27] Economic policy uncertainty data are collected from `http://www.policyuncertainty.com/`.

the ICAPM restrictions examined by Maio and Santa-Clara (2012).[28] Panels A and B of Table 2.11 confirm that UNC^{avg} forecasts the first and second moments of aggregate market return. The positive sign of the UNC^{avg} coefficient shown in Panel A of Table 2.11 requires a positive price of risk associated with innovations in UNC^{avg} in cross-sectional tests. The price of risk associated with innovations in UNC^{avg} is estimated following Maio and Santa-Clara (2012) using 25 portfolios sorted on size and book-to-market (SBM25) and 25 portfolios sorted on size and momentum (SM25). Both sets of portfolios are augmented with the market return. The price of risk is estimated using the generalized method of moments (GMM) procedure (Hansen (1982)). The GMM system consists of $N + K$ moment conditions, where N is the number of test portfolios and K the number of factors:

$$g_T(\mathbf{b}) \equiv \frac{1}{T}\sum_{t=1}^{T} \left\{ \begin{array}{rcl} (R_{i,t} - R_{f,t}) - \sum_{j=1}^{K} \gamma_j (R_{i,t} - R_{f,t})(f_{j,t} - \mu_j) & = & 0 \\ (f_{j,t} - \mu_j) & = & 0 \end{array} \right. \tag{2.27}$$

In the above, $(R_{i,t} - R_{f,t})$ is asset i excess return, $f_{j,t}$ are the factors, and μ_j are the respective factor means. For example, for the Fama and French (1993) 3-factor model $K = 3$ with $f_{1,t} \equiv$ MKT, $f_{2,t} \equiv$ SMB and $f_{3,t} \equiv$ HML. The system allows to simultaneously estimate the covariance risk prices associated with the hedging factors (γ_j) and the factor means (μ_j). Panels A and B of Table 2.12 report the estimated prices of risk, along with robust GMM standard errors and the mean absolute pricing errors. As shown, changes in UNC^{avg} are associated with positive prices of risk (γ_{unc}). For robustness, two-stage Fama and MacBeth (1973) cross-sectional regressions are also conducted at the individual stock-level to estimate the price of risk associated with the HML$_{\text{UNC}}$ factor. The factor loadings (the MKT, SMB, HML, RMW, CMA, and HML$_{\text{UNC}}$ betas) are estimated at the first-stage using 12-month time-series rolling window regressions. The results from the second stage cross-sectional regressions are shown in Panel C of Table 2.12, confirming the positive price of risk associated with HML$_{\text{UNC}}$.

Finally, it is tested whether the price of systematic risk estimated from the cross-sectional regressions generates an economically sensible estimate of the coefficient of relative risk aversion

[28]These restrictions include: i) the ICAPM candidate should forecast the first or second moment of the aggregate stock return; and ii) if the candidate forecasts positive (negative) aggregate returns, its innovation should earn a positive (negative) risk price in the cross-sectional tests.

of the representative investor. The implied relative risk aversion estimated at the individual stock level obtained from Panel C of Table 2.12 is 1.43 (a magnitude consistent with Bali (2008), Bali and Engle (2010)). Using the first row in Panel C of Table 2.12, the expected excess return of the market is estimated as:

$$\mathrm{E[MKT]} = \gamma_{\mathrm{MKT}} + \frac{\gamma_{\mathrm{HML_{UNC}}}}{\sigma(\mathrm{HML_{UNC}})^2} \times \mathrm{COV}(\mathrm{MKT}, \mathrm{HML_{UNC}}), \tag{2.28}$$

obtaining an estimate of 0.39% monthly expected return, close to the actual mean excess market return of 0.65% per month. In Equation (2.28), MKT is the market excess return while $\gamma_{\mathrm{MKT}} = 0.283$ and $\gamma_{\mathrm{HML_{UNC}}} = 0.148$ are the beta prices of risk of the market and $\mathrm{HML_{UNC}}$ factors in the first row of Panel C of Table 2.12, respectively; and $\sigma(\mathrm{HML_{UNC}}) = 3.32\%$ and $\mathrm{COV}(\mathrm{MKT}, \mathrm{HML_{UNC}}) = 0.000814$ are the standard deviation of the $\mathrm{HML_{UNC}}$ factor and its covariance with the market, respectively. Overall, the results in Table 2.12 confirm that UNC^{avg} can be viewed as a state variable affecting investors' consumption and investment decisions in line with the ICAPM.

2.6.4 UNC and Standard Uncertainty Indices

The earlier section provides evidence that UNC is positively correlated with standard uncertainty indices, such as Jurado et al.'s (2015) macro uncertainty index (ΔJLN) and Baker et al.'s (2016) economic policy uncertainty index (ΔPUI). A natural question that might arise is whether UNC is just a proxy for standard economic uncertainty or policy uncertainty factors. The next test is whether the return premium associated with the UNC factor ($\mathrm{HML_{UNC}}$) can be explained by the return premium of factors built from stock exposures to changes in the Jurado et al. (2015) or Baker et al. (2016) uncertainty indices. Following Bali et al. (2017a), an uncertainty beta factor (JLN^{β}) is formed on changes in Jurado et al.'s (2015) economic uncertainty index using standard 2×3 portfolio formation based on two SIZE portfolios using the NYSE median market capitalization and independently sorting three (30th and 70th percentile) portfolios based on their pre-formation exposure (beta) to changes in Jurado et al.'s (2015) uncertainty index using 60 monthly observations. The uncertainty beta factor return

(JLN^{β}) is the average return of the two value-weighted high-exposure portfolios minus those of the low-exposure portfolios. Similarly, a policy uncertainty risk factor (PUI^{β}) is estimated using stock exposures to changes in Baker et al.'s (2016) policy uncertainty index. HML_{UNC} is then regressed against the Fama and French (2015) 5-factor model augmented by MOM and LIQ (7F), plus the two factors constructed based on stock exposures to macroeconomic and policy uncertainty indices (JLN^{β} and PUI^{β}). As shown in Table 2.13, inclusion of the two uncertainty factors does not explain the positive premium associated with HML_{UNC}, confirming that UNC captures something different from the standard uncertainty indices in the cross-sectional pricing of individual stocks.

2.7 Further Robustness Checks

2.7.1 Longer-term Predictive Power of UNC

Earlier analysis in this chapter examined the one-month-ahead predictive power of UNC, that is, the investment strategy used to generate portfolio returns was 12/0/1. Specifically, UNC is computed with daily data over the last 12 months and held the arbitrage portfolio for one month. To address potential market micro-structure concerns or potential correlation of UNC with some of the control variables that have significant next-month return predictability, the trading strategy is alternated to 12/1/1. That is, one month is skipped between the portfolio formation month and holding period and then returns are examined at t+2 for UNC observed in month t. Table A2.9 of the Appendix (second column) confirms that UNC predicts cross-sectional differences in two-month-ahead returns (month t+2). Finally, the longer-term return predictability of UNC is examined. Specifically, risk-adjusted returns of value-weighted portfolios are calculated using (t+3), (t+6), and (t+12)-month-ahead returns for portfolios formed based on UNC observed in month t. The last row in Table A2.9 shows economically and statistically significant (10−1) alpha differences for 3-, 6-, and 12-month-ahead returns, indicating that the value uncertainty premium is not just a one-month affair. UNC predicts cross-sectional variation in stock returns 12 months into the future.

2.7.2 Subsample Analysis

In further subsample robustness, the sample is divided into two sub-periods: January 1986 to December 2000, and January 2001 to December 2016. Table A2.10 of the Appendix reports the risk-adjusted returns based on the 7F model for value- and equal-weighted portfolios of stocks sorted by UNC. In both sub-periods, the premium associated with the volatility of estimated book-to-market ratio (UNC) remains positive and significant.

2.7.3 Alternative Measurement of UNC

In Equation (2.3) the volatility of estimated BM ratio captures information regarding changes in the risk of future growth (σ_g) and the quality of information (σ_ϵ). That is, the volatility of BM contains information regarding the volatility of earnings growth (σ_μ) as discussed in Section 2.3. σ_μ is estimated as the value that minimizes the difference between the theoretical BM volatility ($\mathrm{Std}_t[\mathrm{BM}_i]$) of Equation (2.3) and its empirical estimation as per Equation (2.9). 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. Stocks are then sorted into 10 decile portfolios (as described in Table 2.1) but now based on estimated σ_μ rather than UNC as measured previously based on Equation (2.8). Results, shown in Table A2.11 of the Appendix, are in line with previous findings in Table 2.1. 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 the value uncertainty premium.

2.8 Conclusion

This study has uncovered a new "value uncertainty" anomaly related to uncertainty about the true current value of the book-to-market ratio and investigated the predictive power of the volatility of book-to-market on the cross-sectional variation in future equity returns. The value uncertainty (UNC) equity premium is not explained by common risk factors or 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 13% per annum. This significant positive premium is confirmed in bivariate 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, short-term reversal, liquidity, turnover, idiosyncratic volatility, skewness, co-skewness, market volatility beta, dispersion in analysts' earnings estimates, demand for lottery-like stocks, and variance risk-premium.

A novel factor (HML_{UNC}) constructed using the value uncertainty measure and size generates an annualized alpha of 6% to 8% and is not explained by the market, size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and liquidity (LIQ) factors of Fama and French (1993, 2015), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015). A UNC index based on the cross-sectional average of firms' BM volatility (UNC^{avg}) is correlated with standard economic uncertainty indicators. However, UNC is distinct as it reflects contemporaneous uncertainty about the true current value of shareholders' investment in productive assets rather than prospective or forward-looking economic uncertainty that is associated with growth options and depresses investment. This chapter documents that the value uncertainty factor (HML_{UNC}) covaries with productivity and consumption growth co-movements, justifying the positive premium.

It can be conjectured that the high-UNC premium is partly driven by lower information quality about the current true value of productive assets and by uncertainty regarding future profitability, likely inducing feedback effects on BM. High-UNC may also increase a firm's return exposure to broad systematic risk factors. Value uncertainty is correlated with macroeconomic fundamentals and is a significant predictor of aggregate market return and market volatility. Overall, results support a rational asset pricing explanation of the value uncertainty premium consistent with the ICAPM and production-based asset pricing frameworks. This chapter's findings highlight the significance of the volatility of book-to-market as a fundamental uncertainty variable and pave the way to exploring the impact of the volatility of other common risk factors as a focus of future research.

2.9 Tables and Figures

Table 2.1

Value-Weighted Univariate Portfolio Analysis

Each month value-weighted decile portfolios are sorted according to the standard deviation of estimated book-to-market ratio scaled by its mean (UNC) over the past twelve months with decile 1 (10) containing stocks with the lowest (highest) decile. The table reports raw excess (second column) and risk-adjusted returns (alphas) generated based on different sets of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM alpha); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF alpha); and (v) the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (7F alpha). The second set of models considers the 3F, 5F, and QF factor models augmented by Carhart's (1997) momentum factor (MOM), while the last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the previous 3F and QF models. The last two rows report the difference High−Low (10−1) excess returns and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2016.

		Risk-Adjusted Return					+ MOM			+ MOM + LIQ	
UNC Decile	Excess (Raw) Return	CAPM	3F	5F	QF	7F	3F	5F	QF	3F	QF
1 (Low)	0.516	-0.032	-0.001	0.003	0.019	-0.043	-0.080	-0.052	0.005	-0.073	0.029
	(2.07)	(-0.19)	(-0.01)	(0.02)	(0.12)	(-0.29)	(-0.52)	(-0.36)	(0.04)	(-0.47)	(0.20)
2	0.774	0.221	0.195	-0.025	-0.026	-0.084	0.100	-0.073	-0.028	0.093	-0.038
	(3.83)	(1.63)	(1.59)	(-0.25)	(-0.23)	(-0.84)	(0.81)	(-0.73)	(-0.26)	(0.76)	(-0.34)
3	0.726	0.158	0.158	0.069	0.053	0.029	0.087	0.026	0.049	0.090	0.058
	(2.94)	(1.50)	(1.54)	(0.65)	(0.46)	(0.26)	(0.78)	(0.24)	(0.43)	(0.82)	(0.51)
4	0.707	0.135	0.138	-0.036	-0.036	-0.046	0.122	-0.033	-0.032	0.113	-0.046
	(3.15)	(1.15)	(1.22)	(-0.34)	(-0.32)	(-0.43)	(1.03)	(-0.30)	(-0.29)	(0.94)	(-0.42)
5	0.913	0.322	0.322	0.133	0.210	0.157	0.330	0.155	0.215	0.334	0.222
	(3.71)	(2.26)	(2.34)	(0.96)	(1.41)	(1.18)	(2.41)	(1.16)	(1.44)	(2.45)	(1.48)
6	0.850	0.161	0.207	0.039	0.076	0.043	0.214	0.059	0.080	0.202	0.065
	(3.10)	(1.40)	(1.88)	(0.34)	(0.60)	(0.33)	(1.80)	(0.46)	(0.60)	(1.66)	(0.48)
7	1.035	0.334	0.331	0.170	0.188	0.214	0.343	0.191	0.197	0.366	0.225
	(3.51)	(2.17)	(2.18)	(1.12)	(1.22)	(1.43)	(2.38)	(1.26)	(1.30)	(2.56)	(1.51)
8	1.016	0.309	0.386	0.400	0.483	0.478	0.474	0.460	0.489	0.489	0.517
	(3.75)	(1.84)	(2.36)	(2.48)	(2.71)	(2.89)	(2.88)	(2.82)	(2.68)	(2.97)	(2.81)
9	0.929	0.127	0.238	0.233	0.416	0.346	0.430	0.367	0.433	0.412	0.414
	(3.06)	(0.75)	(1.72)	(1.63)	(2.39)	(2.29)	(2.91)	(2.45)	(2.53)	(2.76)	(2.40)
10 (High)	1.464	0.576	0.722	0.856	1.078	1.002	0.910	0.976	1.086	0.932	1.132
	(4.10)	(2.77)	(4.21)	(4.57)	(5.19)	(5.76)	(5.96)	(5.56)	(5.12)	(6.03)	(5.48)
High−Low (10−1)	0.949	0.608	0.722	0.853	1.059	1.044	0.990	1.028	1.081	1.005	1.103
t-stat	(3.17)	(2.14)	(2.91)	(3.48)	(4.15)	(4.25)	(4.18)	(4.25)	(4.13)	(4.12)	(4.19)

Table 2.2

Robustness to Alternative Stock Samples: NYSE, Large, Liquid or Low IVOL

The table presents robustness results to alternative subsamples. UNC-based univariate portfolio sorting is conducted in the same way as described in Table 2.1 for alternative subsamples. Panel A contains results obtained by using NYSE stocks only, excluding the bottom 10th size decile using NYSE breakpoints, excluding illiquid stocks (bottom 10th liquidity decile) and exclduing microcaps stocks (bottom 20th size decile using NYSE breakpoints). Panel B contains results obtained excluding stocks with price below 1 US dollars (Exc. 1$), considering only largest stocks based on the 50th NYSE size percentile, considering only the largest 500 stocks, considering only the most liquid 500 stocks in the sample, and considering the 500 stocks with the lowest IVOL. The table reports the 7F model alphas of deciles 1 through 10 of value-weighted portfolios. The last two rows report the difference of alphas between the high and low portfolio deciles, with the Newey-West t-statistics in parentheses. The sample period is from January 1986 to December 2016.

Panel A.

UNC Decile	NYSE Only	Excl. 10th Small	Excl. Illiquid	Excl. Microcaps
1 (Low)	-0.05	-0.02	-0.04	-0.03
	(-0.30)	(-0.13)	(-0.30)	(-0.27)
2	0.18	-0.11	-0.11	-0.06
	(1.38)	(-1.21)	(-0.97)	(-0.65)
3	0.11	-0.21	0.12	-0.21
	(0.87)	(-2.16)	(1.25)	(-2.21)
4	0.13	0.11	-0.10	0.11
	(1.10)	(1.41)	(-0.86)	(1.25)
5	0.11	0.01	0.15	0.04
	(0.81)	(0.07)	(1.20)	(0.31)
6	0.12	0.07	0.01	-0.01
	(0.91)	(0.65)	(0.06)	(-0.10)
7	0.26	0.08	0.29	0.05
	(1.88)	(0.59)	(2.01)	(0.41)
8	0.34	0.32	0.41	0.37
	(2.03)	(2.13)	(2.94)	(2.50)
9	0.36	0.33	0.37	0.32
	(2.09)	(2.73)	(2.33)	(2.81)
10 (High)	0.66	0.82	1.04	0.78
	(3.85)	(5.32)	(4.86)	(5.01)
High−Low (10−1)	0.71	0.83	1.08	0.81
t-stat	(2.69)	(3.89)	(4.16)	(3.76)

Panel B.

UNC Decile	Exc. USD1	Large	Largest 500	Most Liquid 500	Lowest IVOL 500
1 (Low)	0.016	-0.09	-0.04	0.00	-0.18
	(0.13)	(-0.78)	(-0.31)	(-0.03)	(-1.17)
2	-0.136	-0.12	-0.10	-0.16	0.10
	(-1.24)	(-1.05)	(-0.87)	(-1.30)	(0.79)
3	-0.100	-0.11	0.08	0.19	-0.05
	(-1.03)	(-1.24)	(0.78)	(2.04)	(-0.35)
4	0.107	0.06	-0.14	-0.24	-0.10
	(0.87)	(0.55)	(-1.21)	(-2.50)	(-0.80)
5	0.088	0.07	0.10	0.21	-0.13
	(0.70)	(0.69)	(0.78)	(1.55)	(-1.02)
6	0.124	0.00	0.00	0.05	0.05
	(0.84)	(-0.03)	(0.03)	(0.38)	(0.38)
7	0.438	0.02	0.28	0.30	-0.07
	(2.68)	(0.13)	(1.85)	(2.00)	(-0.49)
8	0.310	0.35	0.49	0.35	0.22
	(2.17)	(2.31)	(2.72)	(2.56)	(1.41)
9	0.514	0.25	0.34	0.29	0.47
	(3.16)	(2.16)	(2.34)	(1.95)	(2.68)
10 (High)	0.909	0.68	0.90	1.03	0.47
	(4.31)	(4.51)	(5.43)	(4.51)	(2.75)
High−Low (10−1)	0.893	0.77	0.95	1.04	0.65
t-stat	(3.37)	(3.62)	(4.27)	(3.83)	(2.98)

Table 2.3

Average Stock Characteristics for Book-to-Market Uncertainty (UNC) Sorted Decile Portfolios

This table reports the average portfolio characteristics for each decile sorted on book-to-market uncertainty (UNC). Each month stocks are divided in 10 deciles based on UNC and the average firm characteristic is calculated in each decile. The characteristics are: UNC is BM uncertainty as per Equation (2.8), β^{MKT} is market beta, SIZE is market capitalization (in million US dollars), BM is book-to-market ratio, BMFF is book-to-market computed as per Fama and French (1993), 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, STR is short-term reversal calculated as previous month return, TURN is the ratio of trading volume in a month to shares outstanding, DISP is analysts' forecast dispersion, IVOL is idiosyncratic volatility (in %), ISKEW is idiosyncratic skewness of the stock's daily excess return over the past month, COSK is co-skewness of past 12-month returns, β^{VXO} is the market volatility (VXO) exposure (in %), and MAX is the average of the highest five daily returns over the month, proxing for lottery demand as in Bali et al. (2011). The last two rows report the difference High−Low (10−1) of the average firm characteristics, with corresponding Newey-West adjusted t-statistics given in parentheses. The sample period covers January 1986 to December 2016.

UNC Decile	UNC	β^{MKT}	SIZE	BM	BMFF	INV	OP	MOM	ILLIQ	STR	TURN	DISP	IVOL	ISKEW	COSK	β^{VXO}	MAX
1 (Low)	0.064	0.697	6,182	0.656	0.682	0.105	0.096	11.923	0.306	1.193	0.093	0.096	1.465	14.490	-1.742	0.030	2.337
2	0.087	0.789	7,448	0.565	0.586	0.114	0.100	12.163	0.191	1.307	0.103	0.081	1.517	14.745	-1.904	0.035	2.453
3	0.101	0.851	8,087	0.540	0.558	0.123	0.103	12.794	0.188	1.304	0.112	0.091	1.599	14.320	-1.543	0.038	2.582
4	0.115	0.894	7,283	0.529	0.545	0.137	0.105	13.281	0.187	1.376	0.122	0.099	1.674	15.559	-1.805	0.045	2.700
5	0.130	0.937	6,996	0.517	0.534	0.149	0.108	13.967	0.189	1.425	0.133	0.107	1.766	14.965	-1.652	0.052	2.835
6	0.147	1.006	6,402	0.508	0.523	0.160	0.110	15.146	0.192	1.456	0.144	0.117	1.869	15.798	-3.361	0.045	2.995
7	0.167	1.049	5,844	0.496	0.509	0.180	0.113	16.872	0.185	1.584	0.161	0.122	1.987	16.942	-3.342	0.056	3.183
8	0.196	1.150	4,873	0.493	0.500	0.208	0.113	19.379	0.222	1.656	0.182	0.154	2.129	16.950	-4.066	0.062	3.401
9	0.240	1.267	4,149	0.481	0.485	0.241	0.113	22.827	0.184	1.738	0.215	0.179	2.345	17.832	-5.919	0.061	3.726
10 (High)	0.378	1.356	3,387	0.457	0.423	0.346	0.106	28.023	0.128	1.919	0.269	0.231	2.653	18.751	-7.179	0.086	4.174
High−Low (10−1)	0.315	0.660	-2,795	-0.199	-0.258	0.241	0.010	16.100	-0.178	0.726	0.177	0.135	1.189	4.261	-5.437	0.056	1.838
t-stat	(37.43)	(16.69)	(-8.53)	(-8.68)	(-13.99)	(13.57)	(4.93)	3.5177	(-5.00)	(2.54)	(22.22)	(6.53)	(20.34)	(5.10)	(-3.31)	(3.68)	(17.71)

Table 2.4

Value-Weighted Bivariate Portfolio Analysis

In this table, stocks are sorted into decile portfolios based on one of the following control variables: market beta (β^{MKT}), market capitalization (SIZE), book-to-market (BM), book-to-market (BMFF) following Fama and French (1993), investment (INV), operating profitability (OP), momentum (MOM), illiquidity (ILLIQ), short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of estimated net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)). Stocks within each control variable decile are further sorted into deciles based on the volatility of estimated book-to-market (UNC). The table reports risk-adjusted returns (based on the 7F model) of value-weighted monthly returns for each UNC decile averaged across each of the controls with the corresponding t-statistics in parentheses. Values are in percentage. The last two rows report the difference between decile 10 and 1 alphas and the Newey-West adjusted t-statistics in parentheses. The sample period is from January 1986 to December 2016.

UNC Decile	β^{MKT}	SIZE	BM	BMFF	INV	OP	MOM	ILLIQ	STR	TURN	DISP	IVOL	ISKEW	COSK	β^{VXO}	MAX	Std (NI)	Std (1/SIZE)
1 (Low)	-0.047	0.120	-0.051	-0.032	0.049	0.072	0.052	0.028	-0.076	0.029	-0.058	-0.045	-0.011	-0.044	-0.050	-0.103	0.085	0.259
	(-0.46)	(1.35)	(-0.55)	(-0.30)	(0.57)	(0.76)	(0.60)	(0.33)	(-0.70)	(0.33)	(-0.63)	(-0.45)	(-0.10)	(-0.41)	(-0.52)	(-0.99)	(1.02)	(3.00)
2	-0.008	-0.012	0.087	-0.035	-0.093	-0.163	0.125	-0.089	-0.071	-0.019	0.048	0.014	-0.038	-0.073	-0.081	-0.056	-0.043	0.034
	(-0.10)	(-0.14)	(1.07)	(-0.40)	(-0.95)	(-2.12)	(1.47)	(-1.06)	(-0.75)	(-0.22)	(0.52)	(0.12)	(-0.44)	(-0.76)	(-0.86)	(-0.63)	(-0.58)	(0.41)
3	-0.022	0.104	-0.046	0.004	0.000	-0.047	0.050	-0.047	0.037	0.004	-0.059	0.064	0.009	-0.018	-0.051	0.071	-0.004	0.094
	(-0.23)	(1.34)	(-0.43)	(0.05)	(-0.00)	(-0.49)	0.533	(-0.58)	(0.44)	(0.05)	(-0.62)	(0.68)	(0.09)	(-0.18)	(-0.52)	(0.70)	(-0.06)	(1.17)
4	0.003	0.095	0.038	-0.146	0.018	-0.040	-0.030	-0.014	0.116	0.237	-0.023	0.111	-0.036	-0.079	0.062	0.082	0.012	0.192
	(0.04)	(1.33)	(0.45)	(-1.51)	(0.22)	(-0.46)	(-0.32)	(-0.19)	(1.22)	(2.94)	(-0.22)	(1.24)	(-0.38)	(-0.95)	(0.72)	(0.86)	(0.17)	(2.28)
5	0.053	0.194	0.124	0.011	-0.018	-0.014	-0.035	0.061	0.037	0.032	-0.040	0.136	0.008	0.038	-0.016	0.036	0.018	0.217
	(0.55)	(2.21)	(1.18)	(0.11)	(-0.17)	(-0.13)	(-0.37)	(0.67)	(0.41)	(0.32)	(-0.42)	(1.27)	(0.09)	(0.36)	(-0.19)	(0.32)	(0.22)	(2.46)
6	0.054	0.264	0.093	0.058	0.029	0.084	0.118	0.161	-0.050	-0.019	0.216	0.052	0.046	0.070	0.109	0.083	0.068	0.252
	(0.62)	(2.98)	(0.96)	(0.54)	(0.26)	(0.74)	(1.32)	(1.97)	(-0.53)	(-0.19)	(1.85)	(0.42)	(0.42)	(0.73)	(0.92)	(0.79)	(0.67)	(2.72)
7	0.186	0.440	0.143	0.126	0.082	0.039	0.197	0.287	0.167	0.282	0.160	0.214	0.248	0.107	0.122	0.187	0.339	0.393
	(1.67)	(5.57)	(1.41)	(1.21)	(0.79)	(0.37)	(1.91)	(3.24)	(1.34)	(2.76)	(1.33)	(1.66)	(2.18)	(0.94)	(1.07)	(1.71)	(3.79)	(3.76)
8	0.274	0.614	0.284	0.284	0.232	0.374	0.326	0.531	0.379	0.287	0.512	0.081	0.404	0.364	0.325	0.232	0.382	0.501
	(2.53)	(6.83)	(2.42)	(2.62)	(1.69)	(2.95)	(3.72)	(6.06)	(3.01)	(2.30)	(3.73)	(0.60)	(3.46)	(2.98)	(2.53)	(1.97)	(3.33)	(3.85)
9	0.562	0.856	0.480	0.277	0.341	0.477	0.530	0.644	0.505	0.370	0.571	0.723	0.352	0.468	0.479	0.572	0.690	0.723
	(4.16)	(6.55)	(3.57)	(1.82)	(2.45)	(3.12)	(3.95)	(6.15)	(3.68)	(2.95)	(4.06)	(5.30)	(2.29)	(3.46)	(3.50)	(4.26)	(4.82)	(5.08)
10 (High)	0.870	1.326	0.989	0.829	0.954	0.954	0.674	1.165	0.780	0.630	1.031	0.832	1.201	1.122	1.013	0.815	1.217	1.129
	(6.75)	(9.07)	(6.39)	(5.14)	(6.63)	(6.71)	(5.38)	(7.84)	(5.11)	(5.00)	(6.22)	(5.46)	(7.24)	(6.90)	(7.02)	(5.34)	(7.26)	(6.99)
High−Low (10−1)	0.917	1.207	1.039	0.861	0.905	0.882	0.623	1.137	0.856	0.602	1.089	0.878	1.212	1.166	1.063	0.918	1.131	0.871
t-stat	(5.35)	(6.44)	(5.39)	(4.07)	(4.78)	(4.84)	(4.04)	(6.28)	(3.83)	(3.64)	(5.38)	(4.77)	(5.44)	(5.31)	(5.52)	(4.58)	(5.59)	(4.60)

Table 2.5

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 the Fama and MacBeth (1973) approach. The controls include: market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), momentum (MOM), and illiquidity (ILLIQ). Additional control variables are added one at a time: short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)). t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample is from January 1986 to December 2016.

Dependent variable: one-month ahead return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Constant	0.621	3.263	0.866	2.861	2.192	3.015	2.353	2.529	2.350	2.185	2.169	2.385	2.404	2.425	2.916	2.676	1.505
	(2.81)	(5.53)	(3.50)	(5.52)	(4.07)	(5.49)	(4.21)	(4.34)	(4.22)	(3.68)	(3.91)	(4.25)	(4.36)	(4.31)	(5.08)	(4.70)	(2.54)
UNC	3.165	2.936	3.466	3.135	3.138	2.885	2.891	2.727	2.926	2.926	2.737	2.891	2.878	2.927	3.341	2.815	2.46
	(4.51)	(4.21)	(5.18)	(5.23)	(5.26)	(4.98)	(5.01)	(4.61)	(6.06)	(5.10)	(5.33)	(5.00)	(4.98)	(5.15)	(6.09)	(4.84)	(4.14)
β^{MKT}				0.022	0.018	0.011	0.007	0.008	0.012	-0.006	-0.012	0.008	0.013	0.012	0.055	0.007	0.009
				(0.44)	(0.36)	(0.23)	(0.14)	(0.16)	(0.27)	(-0.13)	(-0.26)	(0.18)	(0.28)	(0.26)	(1.30)	(0.16)	(0.19)
SIZE		-0.185		-0.149	-0.115	-0.159	-0.125	-0.138	-0.124	-0.115	-0.117	-0.127	-0.129	-0.13	-0.151	-0.15	-0.066
		(-5.05)		(-4.34)	(-3.31)	(-4.47)	(-3.52)	(-3.72)	(-3.52)	(-3.10)	(-3.37)	(-3.57)	(-3.67)	(-3.60)	(-4.23)	(-4.01)	(-1.83)
BM			0.324	0.174	0.232	0.223	0.287	0.177	0.290	0.298	0.285	0.286	0.283	0.285	0.260	0.274	0.280
			(3.17)	(1.71)	(2.13)	(2.41)	(2.92)	(1.83)	(3.08)	(2.97)	(2.98)	(2.92)	(2.89)	(2.91)	(2.79)	(2.77)	(2.86)
INV					-0.044		-0.034	-0.050	-0.052	-0.049	-0.044	-0.034	-0.029	-0.032	-0.033	-0.033	-0.041
					(-0.62)		(-0.49)	(-0.69)	(-0.77)	(-0.70)	(-0.65)	(-0.50)	(-0.43)	(-0.45)	(-0.49)	(-0.48)	(-0.60)
OP					1.571		1.467	1.172	1.437	1.621	1.422	1.455	1.439	1.446	1.336	1.446	1.391
					(2.39)		(2.28)	(1.81)	(2.23)	(2.45)	(2.23)	(2.27)	(2.25)	(2.23)	(2.10)	(2.25)	(2.16)
MOM						0.002	0.003	0.002	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.002
						(1.28)	(1.79)	(1.31)	(1.78)	(2.13)	(1.84)	(1.77)	(1.76)	(1.74)	(1.86)	(1.79)	(1.36)
ILLIQ						0.055	0.189	0.220	0.058	3.125	0.200	0.184	0.178	0.207	0.237	0.154	-0.124
						(0.23)	(0.67)	(0.75)	(0.28)	(2.26)	(0.70)	(0.66)	(0.63)	(0.71)	(0.80)	(0.56)	(-0.67)
STR								-0.046									
								(-9.33)									
TURN									0.299								
									(0.65)								
DISP										0.14							
										(1.33)							
IVOL											0.038						
											(0.87)						
ISKEW												-0.043					
												(-1.47)					
COSK													0.005				
													(0.78)				
β^{VXO}														-13.780			
														(-3.05)			
MAX															-0.111		
															(-3.59)		
Std (NI)																0.001	
																(3.36)	
Std (1/SIZE)																	0.357
																	(3.83)
R^2	0.015	0.025	0.027	0.045	0.056	0.056	0.067	0.075	0.076	0.072	0.072	0.068	0.071	0.070	0.073	0.068	0.070

Table 2.6

HML_{UNC} Factor vs. Standard Equity Market Factors

This table presents regressions of the HML_{UNC} factor to test if it is explained by other standard pricing factors: i) the Fama and French (1993) excess market return (MKT), size (SMB), value (HML) 3-factor model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (3F+MOM+LIQ); ii) the Fama and French (2015) 5-factor model (5F); iii) the Fama and French (2015) 5-factor model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (7F); iv) Hou et al.'s (2015) Q-model: size (SMB_Q), investment ($R_{I/A}$), and profitability (R_{ROE}) (QF); v) Hou et al.'s (2015) Q-model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (QF+MOM+LIQ). HML_{UNC} is formed based on monthly stocks' UNC and size, with portfolios rebalanced monthly. All regressions in this table are over the period January 1986 to December 2016. Newey-West adjusted t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
HML_{UNC}	3F+MOM+LIQ	5F	7F	QF	QF+MOM+LIQ
Constant	0.600	0.524	0.667	0.672	0.702
	(4.10)	(4.28)	(5.02)	(4.31)	(4.29)
MKT	0.268	0.281	0.244	0.250	0.239
	(8.77)	(5.79)	(7.83)	(7.23)	(7.25)
SMB	0.291	0.219	0.247		
	(4.99)	(2.94)	(3.99)		
HML	-0.412	-0.186	-0.355		
	(-6.38)	(-1.85)	(-5.58)		
MOM	-0.259		-0.248		-0.161
	(-4.18)		(-3.98)		(-2.61)
LIQ	-0.027		-0.031		-0.037
	(-0.83)		(-0.98)		(-0.97)
RMW		-0.216	-0.144		
		(-1.87)	(-1.40)		
CMA		-0.178	-0.052		
		(-1.01)	(-0.36)		
SMB_Q				0.183	0.239
				(3.17)	(3.57)
$R_{I/A}$				-0.421	-0.450
				(-3.50)	(-4.22)
R_{ROE}				-0.349	-0.199
				(-2.82)	(-2.06)
R^2	0.569	0.471	0.577	0.488	0.526

Table 2.7

$\mathbf{HML_{UNC}}$, $\mathbf{UNC^{avg}}$, Consumption and Productivity

Panel A reports the regression coefficients obtained from regressing the annual return of the HML_{UNC} factor and the annual UNC^{avg} index against several factors: ΔC is consumption growth; ΔP is growth in productivity; and $(\Delta C \times \Delta P)\mathbb{1}_{\{\Delta C \times \Delta P\}>0}$ is the interaction between growth in consumption and growth in productivity when positive. T is the number of years in each regression. Panel B reports the Fama and MacBeth (1973) time-series average coefficients and the pooled regression coefficients obtained from estimation of Equation (2.26) for low (bottom 25%) and high (top 25%) UNC industries. The sample period for Panel A is from 1986 to 2016 and for Panel B is from 1986 to 2011 due to availability of industry productivity data. Newey and West (1987) adjusted t-statistics are shown in parentheses.

Panel A. Aggregate Productivity

	(1) HML_{UNC}	(2) UNC^{avg}
Constant	18.410	4.280
	(5.58)	(6.92)
ΔC	-4.560	-0.372
	(-3.50)	(-2.00)
ΔP	-6.910	-0.425
	(-3.59)	(-5.48)
$(\Delta C \times \Delta P)\mathbb{1}_{\{\Delta C \times \Delta P\}>0}$	2.311	0.156
	(3.20)	(4.13)
T	30	30
R^2	0.365	0.143

Panel B. Industry Productivity

Cross-Sectional Regression			Pooled Regression		
	(1) Low UNC	(2) High UNC		(1) Low UNC	(2) High UNC
Constant	0.120	0.137	Constant	0.130	0.142
	(11.02)	(5.02)		(15.50)	(7.13)
$\hat{\beta}$	1.050	1.681	$\hat{\beta}$	0.382	1.670
	(1.96)	(2.98)		(2.35)	(2.49)
ΔTFP	-0.063	0.071	ΔTFP	0.180	0.218
	(-0.87)	(0.77)		(1.56)	(0.72)
No. Obs	574	581	No. Obs	574	581
R^2	0.062	0.057	R^2	0.008	0.008

Table 2.8

HML_{UNC} Factor vs. Standard Factors over Different States of the Economy

This table presents regressions of the HML_{UNC} factor to test if it is explained by other standard factors over good and bad economic states. Good and bad economic states are represented by positive and negative values of CFNAI over the period January 1986 to December 2016, respectively. The HML_{UNC} factor is regressed against: i) the Fama and French (1993) excess market return (MKT), size (SMB), value (HML) 3-factor model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (3F+MOM+LIQ); ii) the Fama and French (2015) 5-factor model (5F); iii) the Fama and French (2015) 5-factor model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (7F); iv) Hou et al.'s (2015) Q-model: size (SMB_Q), investment ($R_{I/A}$), and profitability (R_{ROE}) (QF); v) Hou et al.'s (2015) Q-model augmented by momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (QF+MOM+LIQ). HML_{UNC} is formed based on monthly stocks' UNC and size, with portfolios rebalanced monthly. All regressions in this table are over the period January 1986 to December 2016. Newey-West adjusted t-statistics are reported in parentheses.

Bad States (CFNAI<0)

HML_{UNC}	3F+LIQ+MOM	5F	7F	QF	QF+LIQ+MOM
Constant	0.600	0.586	0.697	0.752	0.702
	(3.64)	(3.36)	(4.40)	(4.02)	(4.54)
MKT	0.262	0.319	0.232	0.256	0.228
	(6.95)	(4.80)	(5.14)	(5.46)	(5.24)
SMB	0.294	0.211	0.244		
	(2.27)	(2.03)	(2.45)		
HML	-0.397	-0.103	-0.322	-0.209	-0.366
	(-4.30)	(-0.74)	(-3.50)	(-1.86)	(-3.98)
MOM	-0.319		-0.304		-0.272
	(-4.56)		(-4.00)		(-3.20)
LIQ	0.003		0.004		-0.008
	(0.07)		(0.09)		(-0.18)
RMW		-0.281	-0.149		
		(-1.78)	(-1.01)		
CMA		-0.261	-0.056		
		(-1.00)	(-0.31)		
SMBQ				0.113	0.245
				(1.58)	(2.24)
$R_{I/A}$				-0.180	-0.061
				(-0.96)	(-0.37)
R_{ROE}				-0.514	-0.174
				(-3.24)	(-1.11)
R^2	0.648	0.498	0.656	0.590	0.663

Good States (CFNAI>0)

HML_{UNC}	3F+LIQ+MOM	5F	7F	QF	QF+LIQ+MOM
Constant	0.543	0.511	0.566	0.480	0.523
	(2.81)	(3.20)	(3.09)	(2.65)	(2.57)
MKT	0.221	0.21	0.214	0.199	0.207
	(4.93)	(4.53)	(4.81)	(4.75)	(4.95)
SMB	0.233	0.223	0.216		
	(3.89)	(3.30)	(3.16)		
HML	-0.413	-0.375	-0.396	-0.362	-0.393
	(-4.26)	(-4.94)	(-5.07)	(-4.42)	(-4.68)
MOM	-0.068		-0.072		-0.075
	(-0.94)		(-0.98)		(-1.17)
LIQ	-0.056		-0.061		-0.055
	(-1.03)		(-1.31)		(-1.10)
RMW		-0.025	-0.059		
		(-0.19)	(-0.45)		
CMA		-0.018	-0.031		
		(-0.11)	(-0.20)		
SMBQ				0.271	0.276
				(4.01)	(4.26)
$R_{I/A}$				-0.054	-0.051
				(-0.40)	(-0.42)
R_{ROE}				0.029	0.032
				(0.25)	(0.32)
R^2	0.483	0.474	0.485	0.494	0.504

Table 2.9

Value-Weighted Univariate Portfolio Analysis over Different States of the Economy

The table reports the excess (raw) and risk-adjusted returns of value-weighted portfolios over good vs. bad economic states (Panel A) and low vs. high volatility times (Panel B) over the period January 1986 to December 2016. In Panel A good and bad economic states are represented by positive and negative values of CFNAI, respectively. In Panel B low and high volatility states are defined with the VXO being below or above its median value, respectively. Each month decile portfolios are formed according to UNC as discussed in Table 2.1. The reported alphas are obtained using the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (Alpha 7F). The last two rows report the difference in alphas between decile 10 and 1, with the corresponding Newey-West adjusted t-statistics given in parentheses.

Panel A. Chicago Fed National Activity Index (CFNAI)

	Bad States (CFNAI<0)			Good States (CFNAI>0)		
UNC Decile	UNC	Excess Return	Alpha 7F	UNC	Excess Return	Alpha 7F
1 (Low)	0.03	0.33	-0.10	0.03	0.72	0.04
		(1.13)	(-0.53)		(4.16)	(0.16)
2	0.05	0.78	0.00	0.04	0.78	-0.13
		(3.15)	(-0.01)		(4.86)	(-0.83)
3	0.05	0.77	0.12	0.05	0.68	-0.04
		(2.58)	(0.74)		(3.58)	(-0.27)
4	0.06	0.98	0.25	0.05	0.44	-0.29
		(3.55)	(1.50)		(2.42)	(-2.07)
5	0.07	0.76	-0.02	0.06	1.09	0.38
		(2.69)	(-0.13)		(4.99)	(1.72)
6	0.08	0.90	0.06	0.07	0.80	0.11
		(2.60)	(0.32)		(3.72)	(0.70)
7	0.09	0.99	0.27	0.08	1.08	0.11
		(2.74)	(1.28)		(4.15)	(0.52)
8	0.10	0.92	0.31	0.09	1.10	0.57
		(3.14)	(1.95)		(4.66)	(2.24)
9	0.13	1.14	0.61	0.11	0.71	0.01
		(2.94)	(2.57)		(3.49)	(0.07)
10 (High)	0.20	1.53	1.18	0.18	1.43	0.82
		(3.77)	(6.01)		(5.13)	(2.93)
High−Low (10−1)		1.20	1.29		0.71	0.78
t-stat		(3.91)	(4.42)		(2.55)	(1.99)

Panel B. CBOE S&P 100 Volatility Index (VXO)

	Low Volatility (VXO<Median)			High Volatility (VXO>Median)		
UNC Decile	UNC	Excess Return	Alpha 7F	UNC	Excess Return	Alpha 7F
1 (Low)	0.03	1.38	-0.06	0.04	-0.34	-0.15
		(11.06)	(-0.31)		(-1.06)	(-0.67)
2	0.04	1.33	0.00	0.05	0.23	0.01
		(11.11)	(-0.00)		(0.86)	(0.06)
3	0.05	1.52	0.22	0.06	-0.07	-0.05
		(11.30)	(1.51)		(-0.22)	(-0.27)
4	0.05	1.23	-0.30	0.07	0.20	0.12
		(8.25)	(-2.04)		(0.67)	(0.72)
5	0.06	1.60	0.08	0.07	0.24	0.14
		(10.71)	(0.62)		(0.70)	(0.52)
6	0.07	1.62	0.22	0.08	0.08	-0.03
		(9.38)	(1.35)		(0.22)	(-0.15)
7	0.07	1.87	0.31	0.10	0.19	0.24
		(10.16)	(1.51)		(0.51)	(1.01)
8	0.09	1.53	0.09	0.11	0.49	0.76
		(10.89)	(0.44)		(1.30)	(2.58)
9	0.11	1.50	-0.02	0.14	0.35	0.60
		(8.85)	(-0.08)		(0.86)	(2.73)
10 (High)	0.18	1.95	0.35	0.21	1.01	1.61
		(10.45)	(1.76)		(2.05)	(4.85)
High-Low (10-1)		0.58	0.41		1.35	1.77
t-stat		(3.59)	(1.43)		(3.48)	(3.90)

Table 2.10

UNC^{avg} Correlation with Key Economic and Uncertainty Indices

This table reports the annual correlation coefficients among key uncertainty and economic indices. ΔUNC^{avg} is first difference of the cross-sectional average of the variance of book-to-market calculated as per Equation (2.8); CFNAI is the Chicago Fed National Activity Index; Δ Crash Index is the first difference of Robert Shiller's one-year crash index; ΔJLN is the first difference of Jurado, Ludvigson, and Ng's (2015) macro uncertainty index; ΔPUI is the first difference of Baker et al.'s (2016) economic policy uncertainty index; ΔVXO is the annual difference of the CBOE S&P 100 volatility index; ΔDEF is the annual change of the spread between BAA- and AAA-rated corporate bonds; Future MKT is one-year-ahead market excess returns.

	ΔUNC^{avg}	CFNAI	ΔCrash Index	ΔJLN	ΔPUI	ΔVXO	ΔDEF	Future MKT
ΔUNC^{avg}	1							
CFNAI	-0.707	1						
ΔCrash Index	-0.288	0.598	1					
ΔJLN	0.711	-0.509	-0.172	1				
ΔPUI	0.161	-0.309	-0.337	0.365	1			
ΔVXO	0.693	-0.466	-0.371	0.690	0.578	1		
ΔDEF	0.707	-0.543	-0.259	0.903	0.451	0.769	1	
Future MKT	0.269	-0.225	-0.186	-0.056	-0.169	-0.014	-0.034	1

Table 2.11

UNC^{avg}, Other Uncertainty Indices and One-year-ahead Market Return and Volatility

In this table, Panel A reports the regression coefficients from regressing future yearly market return against several factors: ΔUNC^{avg}, the first difference of the cross-sectional average of the variance of book-to-market calculated as per Equation (2.8); CFNAI, the Chicago Fed National Activity Index; Δ Crash Index, the first difference of Robert Shiller's one-year crash index; ΔJLN, the first difference of the Jurado, Ludvigson, and Ng's (2015) macro uncertainty index; Δ PUI, the first difference of Baker et al.'s (2016) economic policy uncertainty index; ΔVXO, the annual difference of the CBOE S&P 100 volatility index; ΔDEF, the annual change of the spread between BAA- and AAA-rated corporate bonds. The dependent variable is the one year-ahead market return (in percentage). Panel B contains similar analysis as in Panel A, but with the dependent variable being the one year-ahead change in the CBOE volatility index (ΔVXO). T is the number of periods in each regression. Newey and West (1987) adjusted t-statistics are shown in parentheses.

Panel A. Forecasting One-year Ahead Market Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	8.497	8.040	9.417	8.550	8.565	8.586	8.585
	(3.50)	(3.29)	(3.09)	(3.59)	(3.62)	(3.54)	(3.52)
ΔUNC^{avg}	2.175						
	(2.51)						
CFNAI		-2.945					
		(-3.09)					
ΔCrash Index			0.542				
			(2.25)				
ΔJLN				-18.150			
				(-0.59)			
ΔPUI					-0.061		
					(-0.78)		
ΔVXO						0.032	
						(0.13)	
ΔDEF							0.789
							(0.38)
T	29	30	14	29	29	29	29
R^2	0.056	0.032	0.102	0.009	0.010	0.000	0.001

Panel B. Forecasting Future Changes in CBOE Volatility Index (ΔVXO)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.811	0.001	-1.261	-0.921	-0.916	-0.903	-0.896
	(-0.72)	(0.00)	(-0.91)	(-0.84)	(-0.82)	(-0.79)	(-0.81)
ΔUNC^{avg}	-2.126						
	(-6.20)						
CFNAI		3.881					
		(6.57)					
ΔCrash Index			-0.063				
			(-0.48)				
ΔJLN				-11.750			
				(-0.65)			
ΔPUI					-0.057		
					(-1.66)		
ΔVXO						-0.288	
						(-2.40)	
ΔDEF							-2.162
							(-1.27)
T	29	30	14	29	29	29	29
R^2	0.223	0.194	0.005	0.015	0.037	0.101	0.028

Table 2.12

HML_{UNC} Factor Risk Premium

This table reports the factor risk-premium estimated on the 25 size/book-to-market (Panel A) and 25 size/momentum (Panel B) portfolios. γ_{MKT} is the risk-premium associated with the market. γ_{SMB}, γ_{HML}, γ_{RMW}, γ_{CMA}, are the risk-premia associated with the Fama and French (2015) size, book-to-market, profitability, and investment factors, respectively. γ_{UNC} is the risk-premium associated with changes in the UNC^{avg} index. GMM robust t-statistics are in parentheses. MAE (%) is the mean absolute pricing error (in percentage). Panel C reports the price of market risk and the HML_{UNC} factor from the second stage of Fama and MacBeth's (1973) cross-sectional regressions at the stock-level where the first stage beta is estimated using a 12-month rolling time-series regression. The average market monthly excess return and volatility are 0.651% and 4.44%, respectively. The average HML_{UNC} monthly return and volatility are 0.554% and 3.32%, respectively. The covariance between monthly excess market return and the monthly HML_{UNC} factor is 0.000814.

Panel A. Size/Book-to-Market 25 Portfolios (SBM25)

	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{RMW}	γ_{CMA}	γ_{UNC}	MAE %
CAPM	0.050						0.275
	(3.48)						
CAPM+UNC	0.061					0.085	0.208
	(4.33)					(2.70)	
3F	0.056	-0.005	0.038				0.304
	(3.76)	(-0.25)	(1.89)				
3F+UNC	0.073	0.072	0.085			0.210	0.144
	(4.59)	(3.40)	(3.50)			(4.10)	
5F	0.097	-0.042	-0.184	-0.149	0.574		0.552
	(4.35)	(-1.52)	(-3.73)	(-3.20)	(5.67)		
5F+UNC	0.090	0.064	-0.068	0.094	0.257	0.079	0.135
	(4.44)	(2.39)	(-1.54)	(2.25)	(2.84)	(2.68)	

Panel B. Size/Momentum 25 Portfolios (SM25)

	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{RMW}	γ_{CMA}	γ_{UNC}	MAE (%)
CAPM	0.037						0.265
	(2.78)						
CAPM+UNC	0.055					0.060	0.266
	(4.04)					(2.05)	
3F	0.049	-0.065	0.157				0.561
	(3.13)	(-2.80)	(4.01)				
3F+UNC	0.083	0.076	0.099			0.254	0.263
	(4.66)	(3.00)	(2.77)			(4.16)	
5F	0.100	0.005	-0.225	0.063	0.450		0.134
	(4.19)	(0.18)	(-3.55)	(0.93)	(4.21)		
5F+UNC	0.117	0.096	-0.106	0.113	0.375	0.153	0.104
	(4.72)	(2.51)	(-1.34)	(1.47)	(3.26)	(2.88)	

Panel C. Fama-MacBeth Second Stage

	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{RMW}	γ_{CMA}	$\gamma_{HML_{UNC}}$
CAPM + HML_{UNC}	0.283					0.148
	(2.84)					(2.15)
3F + HML_{UNC}	0.294	0.106	0.034			0.165
	(3.01)	(1.99)	(0.54)			(2.43)
5F + HML_{UNC}	0.291	0.106	0.106	-0.018	-0.044	0.160
	(3.01)	(2.01)	(0.65)	(-0.24)	(-1.04)	(2.37)

Table 2.13

HML_{UNC} Factor vs. Standard Uncertainty Factors

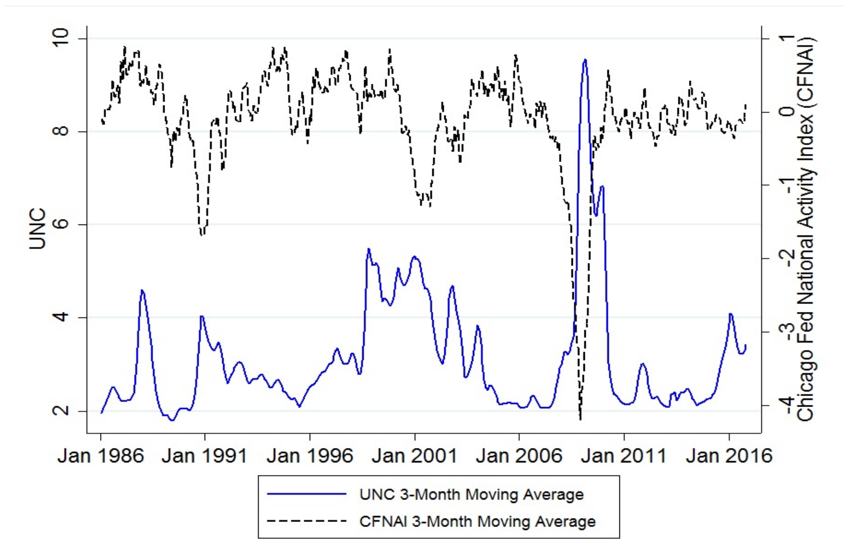
This table presents regressions of the HML_{UNC} factor to test if it is explained by other standard uncertainty pricing factors. Model (1) contains results obtained by regressing the HML_{UNC} factor against the Fama and French (2015) 5-factor model augmented by the momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (7F). Models (2)-(4) contain results obtained by augmenting model (1) with two factors: JLN^{β} built on the exposure to the Jurado et al. (2015) uncertainty index estimated as in Bali et al. (2017a); PUI^{β} built on the exposure to the Baker et al. (2016) news-based political uncertainty index. HML_{UNC} is formed based on monthly stocks' UNC and size, with portfolios rebalanced monthly. All regressions in this table are over the period January 1986 to December 2016. Newey-West adjusted t-statistics are reported in parentheses.

HML_{UNC}	(1) 7F	(2) 7F+JLN^{β}	(3) 7F+PUI^{β}	(4) 7F+JLN^{β}+PUI^{β}
Constant	0.667	0.584	0.649	0.580
	(5.02)	(4.67)	(4.76)	(4.74)
MKT	0.244	0.264	0.279	0.271
	(7.83)	(7.34)	(7.90)	(7.30)
SMB	0.247	0.240	0.256	0.245
	(3.99)	(4.11)	(4.07)	(4.31)
HML	-0.355	-0.408	-0.375	-0.405
	(-5.58)	(-6.37)	(-5.85)	(-6.51)
MOM	-0.248	-0.209	-0.258	-0.214
	(-3.98)	(-3.94)	(-4.16)	(-4.06)
LIQ	-0.031	-0.072	-0.036	-0.065
	(-0.98)	(-2.25)	(-1.11)	(-2.03)
RMW	-0.144	-0.155	-0.128	-0.154
	(-1.40)	(-1.53)	(-1.26)	(-1.61)
CMA	-0.052	-0.051	-0.029	-0.066
	(-0.36)	(-0.32)	(-0.20)	(-0.43)
JLN^{β}		-0.264		-0.265
		(-3.12)		(-3.17)
PUI^{β}			0.069	0.070
			(0.92)	(0.99)
R^2	0.577	0.603	0.588	0.604

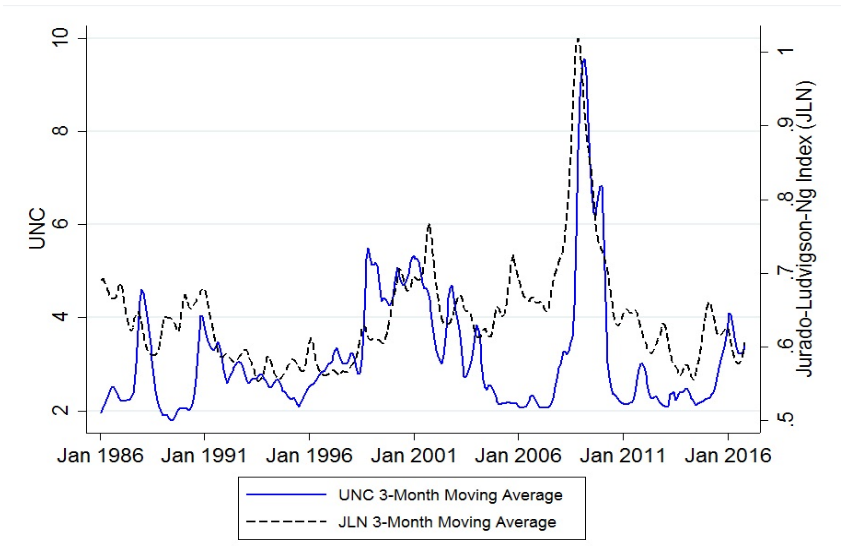
Figure 2.1

This figure contains plots of the 3-month moving average of the UNC index vs. the 3-month moving average of alternative uncertainty indices. UNC is the cross-sectional average of the variance of book-to-market ratios calculated as per Equation (2.8); CFNAI is the Chicago Fed National Activity Index; JLN is Jurado, Ludvigson, and Ng's (2015) uncertainty index; VXO is the monthly CBOE S&P 100 volatility index; DEF is the monthly default spread between BAA- and AAA-rated corporate bonds.

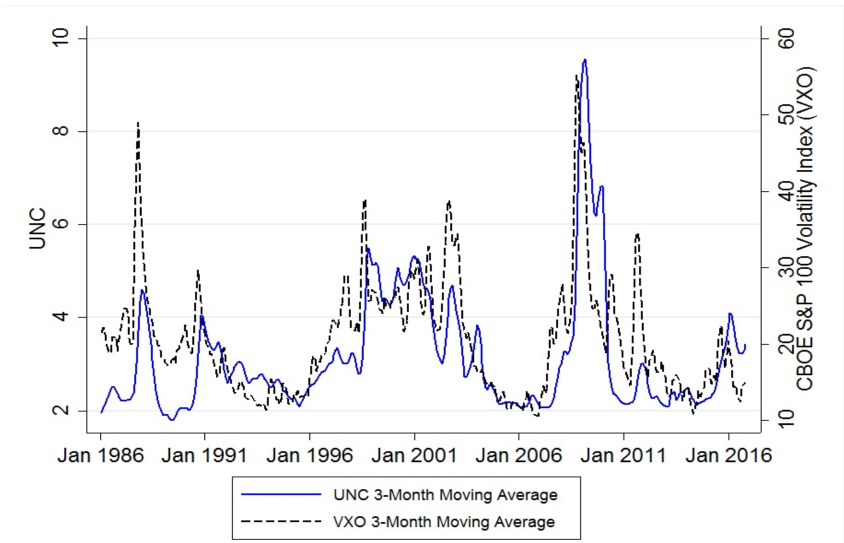
(a) UNC vs. Chicago Fed National Activity Index (CFNAI)



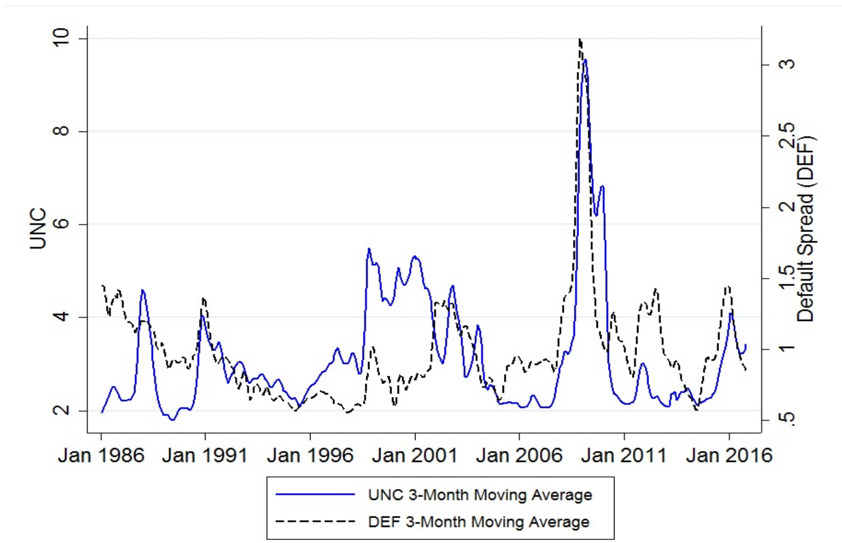
(b) UNC vs. Jurado, Ludvigson, and Ng's Macro Uncertainty Index (JLN)



(c) UNC vs. CBOE S&P 100 Volatility Index (VXO)



(d) UNC vs. Corporate Default Spread Index (DEF)



A2 Appendix - Chapter 2

A2.1 Information Uncertainty and BM Ratio

This section provides some proofs that the standard deviation of BM estimates is more informative than the expected value of the BM ratio concerning the risk associated with profitability and the quality of available accounting information.

When investors can observe the true growth in earnings g, obtained by replacing $\mu = \bar{g}$ and $\sigma_\mu = \sigma_g$ in Equations (2.2) and (2.3), the expected BM ratio in Equation (2.2) is a decreasing function of the expected growth in earnings, $\bar{g}$, and an increasing function of its volatility σ_g. Similar results hold for the standard deviation of the BM ratio in Equation (2.3) as $\text{Std}_\tau[\text{BM}]$ is decreasing in $\mu = \bar{g}$ and increasing in $\sigma_\mu = \sigma_g$. This is consistent with previous work.

If investors have access only to noisy information s, however, then the impact of an increase in $\bar{g}$, σ_g and σ_ϵ in Equations (2.2) and (2.3) is unclear (or mixed). Increases in expected growth in earnings $\bar{g}$ or in the observed signal s have a direct positive impact on the posterior expected growth μ, leaving σ_μ untouched. An increase in μ thus produces a decrease in both the expected value and the standard deviation of the book-to-market ratio.

The impact of an increase in σ_g and σ_ϵ is more involved. First, the impact that an increase in σ_g and σ_ϵ has on the expected BM ratio as per Equation (2.2) is analyzed. As the noise of the signal is σ_ϵ, the precision of the signal is denoted by $1/\sigma_\epsilon^2$. Equation (6) shows that an increase in σ_ϵ has a direct positive impact on σ_μ, producing in turn an increase in both the expected value and the standard deviation of the BM ratio as per Equations (2.2) and (2.3). At the same time, an increase in the noise of the signal will reduce its precision, rendering signal s less informative. A lower precision of the signal has an indirect impact on the posterior expected growth in earnings μ. In particular, higher values of σ_ϵ will increase a in Equation (6) and consequently investors will form their expectations giving more weight to the average growth in earnings, $\bar{g}$, rather than the observed signal, s, itself. Thus, the net impact of an increase in noise σ_ϵ on the expected BM ratio depends on the sign and magnitude of $\bar{g}$. If $\bar{g} < g^*$, where

$g^* \equiv s + \frac{1}{2}\sigma_g^2(T-\tau)$, then an increase in σ_ϵ leads to an increase in the expected BM ratio in Equation (2.2), whereas if $\bar{g} > g^*$ the opposite occurs. In other words, if the signal s is of poor quality (low precision), a further deterioration in its precision increases the expected BM ratio only if the expected growth rate from the prior belief $\bar{g}$ is sufficiently low. On the other hand, an increase in the volatility of the earnings growth σ_g leads investors to rely more on the observed signal s. Therefore, an increase in σ_g has a direct positive impact on σ_μ and an indirect impact on μ through a reduction of weight a. Under this circumstance, the expected BM ratio increases as long as $\bar{g} > s - \frac{1}{2}\sigma_\epsilon^2(T-\tau)$.[29]

Regarding the standard deviation of BM in Equation (2.3), an increase in both the expected growth in earnings, $\bar{g}$, and the observed signal, s, increasing the posterior expected growth in earnings, μ, reduces the standard deviation of the book-to-market ratio. On the other hand, an increase in σ_ϵ or σ_g produces mixed effects on the standard deviation of BM, depending on the sign and magnitude of $\bar{g}$.

Interestingly, the standard deviation of BM is more sensitive to the risk associated with changes in the expected growth in earnings and the quality of accounting information. While changes in $\bar{g}$, s and r produce a similar impact on the expected value and standard deviation of BM since Equations (2.2) and (2.3) involve the same elasticity with respect to changes in $\bar{g}$, s and r, the standard deviation of BM has a higher sensitivity to changes in the news regarding the volatility of the earnings process, σ_ϵ and σ_g. To see this, consider the elasticities of Equations (2.2) and (2.3) with respect to σ_ϵ:

$$\frac{\partial \mathrm{E}_\tau[\mathrm{BM}]}{\partial \sigma_\epsilon}\frac{\sigma_\epsilon}{\mathrm{E}_\tau[\mathrm{BM}]} = \frac{\partial F}{\partial \sigma_\epsilon}\sigma_\epsilon \, , \tag{A2.1}$$

$$\frac{\partial \mathrm{Std}_\tau[\mathrm{BM}]}{\partial \sigma_\epsilon}\frac{\sigma_\epsilon}{\mathrm{Std}_\tau[\mathrm{BM}]} = \tag{A2.2}$$

$$\frac{1}{2}\frac{\left(\frac{\partial \sigma_\mu^2 (T-\tau)^2}{\partial \sigma_\epsilon} e^{\sigma_\mu^2 (T-\tau)^2} + 2\frac{\partial F}{\sigma_\epsilon}\left(e^{\sigma_\mu^2(T-\tau)^2} - 1\right)\right)}{e^{\sigma_\mu^2(T-\tau)^2} - 1}\sigma_\epsilon \, , \tag{A2.3}$$

where $F = -(\mu - r)(T-\tau) + \frac{1}{2}\sigma_\mu^2(T-\tau)^2 + r\tau$. The difference between the elasticity of

[29] This is valid only if $2\sigma_\epsilon^2\sigma_g(T-\tau)/((\sigma_\epsilon^2+\sigma_g^2)^2) > 0$, which is always verified as long as $\sigma_\epsilon, \sigma_g > 0$.

the standard deviation of BM and the elasticity of the expected value of BM is:

$$\Delta = \frac{1}{2}\sigma_\epsilon \frac{\frac{\partial \sigma_\mu^2 (T-\tau)^2}{\partial \sigma_\epsilon} e^{\sigma_\mu^2 (T-\tau)^2}}{e^{\sigma_\mu^2 (T-\tau)^2} - 1}, \tag{A2.4}$$

where $\Delta > 0$. The difference in the elasticity with respect to σ_g is obtained by replacing σ_ϵ with σ_g in Equation (A2.4).

A2.2 Production-Based Model

In this appendix, an additional economic rationale for UNC is provided. The intuition comes from a rearrangement and extension of the theoretical model of Cooper (2006). To ease and simplify the analysis, the basic results contained in Cooper (2006) is reviewed first. The firm's profit per unit of time is given by the following expression:

$$\Pi(\theta,\, K) = \theta^{1-\gamma} K^{\gamma} - mK, \tag{A2.5}$$

where K is the stock of capital, θ is productivity, $0 < \gamma < 1$, and m is the production cost per unit of capital. Capital evolves following:

$$dK = -\delta K\, dt + I, \tag{A2.6}$$

where δ is capital depreciation rate and I is investment. It is assumed that when a firm invests, the adjustment costs $C(\theta,\, K)$ are a fraction of the profits:

$$C(\theta,\, K) = F\theta^{1-\gamma} K^{\gamma}, \tag{A2.7}$$

with $0 < F < 1$. This assumptions guarantees that adjustment costs do not become negligible as the firm's size increase. The produced goods can be used for either consumption or investment. Firm's productivity is given by the product of aggregate productivity shocks and an idiosyncratic productivity factor:

$$\theta = \theta_A \theta_i, \tag{A2.8}$$

where θ_A is the aggregate productivity and θ_i is the idiosyncratic productivity. θ_A and θ_i follow two independent Brownian motions:

$$\frac{d\theta_A}{\theta_A} = \mu_A dt + \sigma_A dw_A, \tag{A2.9}$$
$$\frac{d\theta_i}{\theta_i} = \sigma_i dw_i, \tag{A2.10}$$

where μ_A is the drift of the aggregate productivity shock; σ_A and σ_i are the volatilities of the aggregate and idiosyncratic productivity levels; and dw_A and dw_i are two independent Wiener processes. Following Itô's Lemma, the total productivity follows a Brownian motion:

$$\frac{d\theta}{\theta} = \mu_A dt + \sigma dw, \tag{A2.11}$$

where $\sigma = \sqrt{\sigma_A^2 + \sigma_i^2}$ and $d_w = \frac{\sigma_A dw_A + \sigma_i dw_i}{\sqrt{\sigma_A^2 + \sigma_i^2}}$.
Both the profit function and the adjustment costs are homogeneous of degree 1 with respect to K and θ. This leads that the value of the firm $J(\theta, K)$ is also homogeneous of degree 1 in K and θ. Let $Z = \frac{K}{\theta}$ then profits, adjustment costs and the value of the firm can be written as:

$$\Pi(\theta, K) = \theta Z^\gamma - m\theta Z = \theta\pi(Z), \tag{A2.12}$$
$$C(\theta, K) = F\theta Z^\gamma = \theta c(Z), \tag{A2.13}$$
$$J(\theta, K) = \theta V(Z), \tag{A2.14}$$

where $\pi(Z) = Z^\gamma - mZ$ and $c(Z) = FZ^\gamma$. Under these assumptions the Bellman's equation for the firm's problem in the region in which operates is:

$$V^0(Z) = \max_{I \geq 0} \left\{ \pi(Z) - \overline{I} - c(Z)\mathbf{1}_{I>0} + e^{-r\,dt} \int_0^\infty V(Z')\phi(\theta'/\theta)d\theta' \right\}, \tag{A2.15}$$

where $\overline{I} = I/\theta$, r is the risk-free rate, θ' and Z' are the future values of θ and Z, and $\phi(\theta'/\theta)$ is the conditional density of future value of θ' conditional on today's θ. Following Itô's Lemma the variable Z evolves as:

$$\frac{dZ}{Z} = (\sigma^2 - \mu - \delta)dt - \sigma\, dw. \tag{A2.16}$$

$Z = K/\theta$ is positively related to the book-to-market and the excess capacity. Low Z implies that the capital is low compared to the productivity and a firm has an incentive to invest. High Z indicates that the firms has excess capital compared to the productivity and it might shut down the activity. The solution for the firm's value $J(\theta,\, K)$ is:

$$J(\theta,\, K) = \theta V(Z) = \theta \left[AZ^{\gamma} - SZ + D_N Z^{\lambda_N} + D_P Z^{\lambda_P} \right], \tag{A2.17}$$

where:

$$S = \frac{m}{r - \sigma^2 + \mu + \delta}, \tag{A2.18}$$

$$A = \frac{1}{r + \gamma\mu + \gamma\delta - \gamma\sigma^2 - \frac{1}{2}\sigma^2\gamma(\gamma - 1)}, \tag{A2.19}$$

$$D_N = \frac{\left(\left(\text{-}A\text{-}F\right) L^{\gamma} + AG^{\gamma}\text{-} \left(S+1\right) \left(G\text{-}L\right)\right) U^{\lambda_P}\text{-} \left(\text{-}L^{\lambda_P} + G^{\lambda_P}\right) \left(AU^{\gamma}\text{-}SU\right)}{\left(L^{\lambda_N}\text{-}G^{\lambda_N}\right) U^{\lambda_P} + \left(\text{-}L^{\lambda_P} + G^{\lambda_P}\right) U^{\lambda_N}}, \tag{A2.20}$$

$$D_P = \frac{\left(\left(A+F\right) L^{\gamma}\text{-}AG^{\gamma} + \left(S+1\right) \left(G\text{-}L\right)\right) U^{\lambda_N} + \left(G^{\lambda_N}\text{-}L^{\lambda_N}\right) \left(AU^{\gamma}\text{-}SU\right)}{\left(\text{-}L^{\lambda_P} + G^{\lambda_P}\right) U^{\lambda_N}\text{-}U^{\lambda_P} \left(G^{\lambda_N}\text{-}L^{\lambda_N}\right)}, \tag{A2.21}$$

where L, G and U are the investment, target and shut down boundaries. As in Cooper (2006) they can be calculated by smooth pasting conditions. The thresholds L, G and U are written in terms of $Z = K/\theta$, Z is the ratio between the current stock of capital K and firm's productivity θ. Low Z indicates that the stock of capital is low compared to the productivity of the firm. For sufficiently low $Z = L$ the firm will have the incentive to invest because the benefits to adjust capital are higher than the marginal costs. The firm invests an amount I such that the ratio between new capital and productivity is at a target level $Z = G$. When productivity is low compared to the stock of capital (high Z) the firm does not have the incentive to invest, for sufficiently low productivity level it is assumed that the firm will shut down activities $Z = U$. λ_P and λ_N are the positive and negative roots of the following quadratic equation, respectively:

$$\frac{1}{2}\sigma^2\lambda + \left(\mu_Z - \frac{1}{2}\sigma^2\right)\lambda - r = 0. \tag{A2.22}$$

Given the definition of $Z = K/\theta$, the book-to-market ratio BM is equal to $Z/V = K/(\theta V) = K/J$. Applying Itô's Lemma to the log of $\ln(\text{BM}) = \ln(K) - \ln(\theta) - \ln(V)$, changes in log book-to-market $d\ \ln(\mathrm{BM})$ follow:

$$d\ln(\mathrm{BM}) = \Gamma\, dt - \sigma_{\ln(\mathrm{BM})} dw, \tag{A2.23}$$

where

$$\Gamma = -\delta - \mu_A - \frac{V_Z Z}{V}(\sigma^2 - \mu - \delta) + \frac{1}{2}\sigma^2 \left(1 + \left(\frac{V_Z Z}{V}\right)^2 - \frac{V_{ZZ} Z^2}{V}\right), \tag{A2.24}$$

$$\sigma_{\ln(\mathrm{BM})} = \sigma \left(1 - \frac{V_Z Z}{V}\right). \tag{A2.25}$$

In Equations (A2.24) and (A2.25), δ is the capital depreciation rate, μ_A is the drift rate of the aggregate productivity shocks (θ_A), and σ is the volatility of the firm's productivity (θ). That is, ln(BM) follows a diffusion process with drift rate Γ and volatility $\sigma_{\ln(\mathrm{BM})}$. Equation (20) in Cooper (2006) indicates that the beta (loading) of the firm's returns with respect to the systematic risk factor return R_s, denoted with β_s, is given by:

$$\beta_s = \frac{V}{(V-\pi)}\sigma \left(1 - \frac{V_Z Z}{V}\right) Cov(dw, R_s) \times \frac{1}{Var(R_s)}. \tag{A2.26}$$

Using the expression in Equation (A2.23), β_s can be rewritten as a function of the covariance between changes in book-to-market (BM) and the systematic risk factor R_s:

$$\beta_s = -\frac{V}{(V-\pi)} \frac{Cov(d\ln(\mathrm{BM}), R_s)}{Var(R_s)}, \tag{A2.27}$$

where

$$Cov(d\ln(\mathrm{BM}), R_s) = -\sigma_{\ln(\mathrm{BM})} Cov(dw, R_s). \tag{A2.28}$$

Further indicating with r_f the risk-free rate and assuming that β_s is the only pricing factor with market price of risk γ, the expected return of a firm can be rewritten as:

$$E[r] \;=\; r_f + \beta_s \gamma. \tag{A2.29}$$

Substituting Equations (A2.27) and (A2.28), Equation (A2.29) can be written as:

$$E[r] = r_f - \left(\frac{V}{(V-\pi)} \frac{Cov(d\ln(\text{BM}), R_s)}{Var(R_s)} \right) \gamma \tag{A2.30}$$

$$= r_f + \sigma_{\ln(\text{BM})} \left(\frac{V}{(V-\pi)} \frac{Cov(dw, R_s)}{Var(R_s)} \right) \gamma. \tag{A2.31}$$

Therefore, a firm whose BM ratio covaries positively (negatively) with the systematic risk factor R_s should have a lower (higher) β_s and a lower (higher) expected return. The economic intuition for this prediction is that higher values of BM are associated with lower firm productivity or are due to productivity covarying positively with consumption growth, both features disliked by investors. Consequently, a firm with changes in BM covarying positively with the systematic risk factor R_s provides a hedge against bad states of the economy while a firm with changes in BM covarying negatively with R_s would increase risk. This can be readily observed by examining Equation (4) in Lin and Zhang (2013). The first-order condition gives:

$$1 + a\frac{I_{i0}}{K_{i0}} = E_0[M_1 \Pi_{i1}], \tag{A2.32}$$

where 1 is the marginal cost of capital (unity), $a\frac{I_{i0}}{K_{i0}}$ is the marginal adjustment cost with $a > 0$, with I_{i0} and K_{i0} indicating the investment for date 0 and the initial (date-0) capital, respectively. $M_1 \equiv \rho U'(C_1)/U'(C_0)$ is the stochastic discount factor and Π_{i1} is the firm's productivity at date 1. Intuitively, this equation equates the marginal cost of 1 unit of capital (left hand-side) to the marginal Tobin's q (right hand-side). Market-to-book or marginal q can be rewritten as:

$$E_0[M_1 \Pi_{i1}] = E_0[\Pi_{i1}]E_0[M_1] + Cov(\Pi_{i1}, M_1) \tag{A2.33}$$

$$= \frac{E_0[\Pi_{i1}]}{1+r} + Cov\left(\Pi_{i1}, \rho\frac{U'(C_1)}{U'(C_0)} \right). \tag{A2.34}$$

Given the concavity of the utility function U, higher values of book-to-market (the reciprocal of Equation (A2.34)) are associated with lower firm productivity or are due to the firm's productivity covarying positively with consumption growth. If macroeconomic states are captured by the return on the factor R_s, then a firm with BM covarying positively with R_s will have high productivity and/or low covariance between productivity and consumption in bad states of the economy, thus providing a hedge against bad macroeconomic states. As noted from Equation (A2.28), the covariance between changes in book-to-market and the risk factor R_s will depend on the sign of $Cov(dw, R_s)$ and is amplified by multiplicative factor $\sigma_{\ln(\mathrm{BM})}$, representing the diffusion part of the dynamics of $d\ln(\mathrm{BM})$. Thus, for the same level of covariance between dw and R_s, a more volatile book-to-market with higher $\left(\sigma_{\ln(\mathrm{BM})}\right)$ will have a stronger effect on systematic risk β_s. Whenever $Cov(dw, R_s) > 0$ ($Cov(dw, R_s) < 0$) higher $\sigma_{\ln(\mathrm{BM})}$ would lead to higher (lower) expected return. This helps provide an alternative risk-based theoretical rationale for examining the impact that a more volatile book-to-market ratio has on equity returns.

Another interesting relation that can be observed from Equation (A2.28) is that $Cov(d\ln(\mathrm{BM}), R_s)$ is positive (negative) whenever $Cov(dw, R_s)$ is negative (positive). As book-to-market increases if $Cov(dw, R_s) > 0$, it would be expected that $Cov(d\ln(\mathrm{BM}), R_s) > 0$ instead of $Cov(d\ln(\mathrm{BM}), R_s) < 0$ as per Equation (A2.28). $Cov(dw, R_s) > 0$ means that productivity increases ($dw(+)$) when the risk-factor return increases ($R_s(+)$) and vice-versa (i.e., $dw(-)$ when $R_s(-)$). As BM is negatively related to dw but positively related with $Cov(dw, R_s)$, i.e. BM$= f(-dw, Cov(dw, R_s))$, when productivity decreases ($dw(-)$) (and this is on average associated with negative factor returns $R_s(-)$ for the positive covariance $Cov(dw, R_s) > 0$), both effects will add up and book-to-market will increase (BM(+)) due to both the lower productivity and the positive covariance BM(+) $= f(+, +)$. On the other hand, when productivity increases (and as consequence $R_s(+)$) then book-to-market would increase due to the effect of the positive covariance but the higher productivity would act in the opposite direction thus reducing the net effect BM($-$/+) $= f(-, +)$. As a consequence book-to-market increases more proportionally (BM(+)) when $R_s(-)$ leading to a negative covariance between BM and R_s, i.e., $Cov(d\ln(\mathrm{BM}), R_s) < 0$. A similar logic applies when $Cov(dw, R_s) > 0$ leading to $Cov(d\ln(\mathrm{BM}), R_s) < 0$.

A2.3 Main Drivers of the Value Uncertainty Premium

It is further examined whether UNC^{avg} and the UNC premium is subsumed by traditional systematic risk factors. Following Cooper and Priestley (2011), this section tests if a set of risk factors might account for the positive UNC spread using standard factor mimicking portfolios (see, e.g., Ang et al. (2006), Vassalou (2003), Ferson and Harvey (1991), Chan et al. (1998), Breeden et al. (1989), Cooper and Priestley (2011)). Chen et al.'s (1986) factors and changes in CBOE's VXO index (ΔVXO) are used as common risk-factors and mimicking portfolios are constructed following Lehmann and Modest (1988). Six-factor mimicking portfolios are built as in Cooper and Priestley (2011) using the Fama and French (1997) 49-industry portfolios. Each portfolio i's excess returns in month t, $r_{i,t}$, are then regressed against six factors: growth in industrial production (PROD), unexpected inflation (UINF), changes in expected inflation (ΔEINF), term premium (TERM), default premium (DEF), and ΔVXO. These 49 time-series regressions produce a (6×49) matrix of estimated slope coefficients $\mathbf{B}$ according to:

$$r_{i,t} = \alpha + b_1\,\mathrm{PROD}_t + b_2\,\mathrm{UINF}_t + b_3\,\Delta\mathrm{EINF}_t + b_4\,\mathrm{TERM}_t + b_5\,\mathrm{DEF}_t + b_6\,\Delta\mathrm{VXO}_t + \epsilon_{i,t}. \quad (\mathrm{A2.35})$$

In Equation (A2.35),, the growth rate of industrial production (PROD) is given by $\mathrm{PROD}_t = \ln(\mathrm{IP}_t) - \ln(\mathrm{IP}_{t-1})$, where IP_t is the index of industrial production in month t from the Federal Reserve Bank of St. Louis; unexpected inflation (UINF) and changes in expected inflation (ΔEINF) are measured as in Chen et al. (1986), where inflation is calculated as log differences of the CPI index and expected inflation is from consumer surveys of the University of Michigan; term (TERM) and default (DEF) premia are, respectively, the spread between the 10-year Treasury rate and the 3-month T-bill, and the spread between BAA- and AAA-rated corporate bonds. The five series above are obtained from the Federal Reserve Bank of St. Louis. Changes in VXO (ΔVXO) are the first differences of CBOE's S&P100 index option implied volatility.

From Equation (A2.35), $\mathbf{\Omega} = \epsilon^{'}\epsilon/(T-K-1)$ is a (49×49) covariance matrix obtained from the residuals of regressing Equation (A2.35) for each of the 49 portfolios. The weights on the factor-mimicking portfolios are calculated as $\mathbf{w} = (\mathbf{B\Omega^{-1}B^{'}})^{-\mathbf{1}}\mathbf{B\Omega^{-1}}$. Matrix $\mathbf{F}$ containing the above six risk-factor mimicking portfolios is calculated as $\mathbf{F} = \mathbf{w}\mathbf{R}'$, where $\mathbf{R}$ is the (T×49) matrix of the 49 portfolio returns. Each row of $\mathbf{F}$ contains the time series of each risk-factor mimicking portfolio. This procedure produces a mimicking portfolio for a specific factor that has a beta of one with respect to that factor and zero with respect to all other factors. The excess returns of portfolios built by sorting firms in 10 deciles based on UNC are then regressed against the matrix $\mathbf{F}$ of risk-factor mimicking portfolios.[30]

Table A2.12 reports the risk-adjusted returns and loadings obtained from regressing 10 univariate value-weighted portfolios of UNC against two sets of factors: (i) seven traditional factors (7F), namely, MKT, SMB, HML, CMA, RMW, MOM, and LIQ, and (ii) six risk-factor mimicking portfolios, based on PROD, UINF, ΔEINF, TERM, DEF and ΔVXO. Panel A shows results from regressing each UNC portfolio against the 7 factors (7F) over a 30-year period, from July 1986 to December 2016. The monthly risk-adjusted return of the high (decile 10) minus low (decile 1) hedge portfolio is both economically and statistically significant (1.10%, t-stat. = 4.18). Panel B reports results from regressing the 10 UNC portfolios on the six risk-factor mimicking portfolios. While the risk-adjusted return spread remains significant (t-stat. = 2.06), its size is reduced (0.63% per month). A significant negative exposure of high-UNC firms to changes in VXO is observed. High-UNC firms provide lower returns when market volatility increases. This provides supporting evidence for the positive premium associated with high-UNC firms in line with Merton's (1973) ICAPM.

To help determine the main contributors to the UNC spread, the portion of the difference between high- and low-UNC portfolios accounted for by the risk-factor mimicking portfolios is estimated as in Cooper and Priestley (2011). Specifically, the fraction of the average return spread accounted for by the spread in expected returns implied by the six factors is calculated. R-HEDGE$_t$=$(r_{H,t} - r_{L,t})$ denotes the real spread between the High (top 10^{th}) and Low (bottom

[30] Cooper and Priestley (2011) estimate Equation (A2.35) using 40 test portfolios gathered from 10 equal-weighted book-to-market portfolios, 10 equal-weighted size portfolios, 10 value-weighted momentum portfolios, and 10 equal-weighted asset growth portfolios. The Fama and French (1997) 49-industry portfolios are used for two main reasons: i) to reduce the impact that firm characteristics have on equity returns; ii) to avoid the same stock to be considered multiple times (compared to Cooper and Priestley (2011)).

1^{st}) UNC deciles. The following specification is estimated:

$$\text{R-HEDGE}_t = \alpha + \beta_1 \, f_{\text{PROD},t} + \beta_2 \, f_{\text{UINF},t} + \beta_3 \, f_{\Delta\text{EINF},t} + \beta_4 \, f_{\text{TERM},t} + \beta_5 \, f_{\text{DEF},t} + \beta_6 \, f_{\Delta\text{VXO},t} + \epsilon_{i,t}, \tag{A2.36}$$

where $f_{j,t}$ is the return of risk-factor mimicking portfolio j at time t. The High minus Low expected return implied by the six factors is computed as:

$$\text{E-HEDGE} = \alpha + \hat{\beta}_1 \, \hat{\gamma}_{\text{PROD}} + \hat{\beta}_2 \, \hat{\gamma}_{\text{UINF}} + \hat{\beta}_3 \, \hat{\gamma}_{\Delta\text{EINF}} + \hat{\beta}_4 \, \hat{\gamma}_{\text{TERM}} + \hat{\beta}_5 \, \hat{\gamma}_{\text{DEF}} + \hat{\beta}_6 \, \hat{\gamma}_{\Delta\text{VXO}} + u_i, \tag{A2.37}$$

where β_s are the estimated factor loadings and γ_s are the estimated risk-factor premia. The average ratio of E-HEDGE/R-HEDGE is then calculated and the null hypothesis that ABS(E-HEDGE/R-HEDGE$-1) \approx 0$ is tested. Results are reported in Panel C of Table A2.12. Using the full specification of Equation (A2.37) (with loadings $\hat{\beta}$ and risk premia $\hat{\gamma}$ on all factors), Panel C reports that the expected hedge premium accounts for 36.8% (t-stat.=5.63) of the actual spread between high- and low-UNC portfolios. The marginal role of each risk-factor in accounting for R-HEDGE is also tested. Results in Panel C of Table A2.12 indicate that ΔVXO alone accounts for 29.6% of R-HEDGE, confirming that exposure to changes in market volatility is the most relevant factor associated with the UNC spread. Panel B of Table 2.9 shows that the positive return premium associated with high-UNC firms is higher and statistically more significant during periods of high market volatility, suggesting that high-UNC firms are good hedges to guard against significant losses in times of high market volatility.

A2.4 Tables (Appendix)

Table A2.1

Univariate Portfolio Analysis (Equal-Weighted)

Each month equal-weighted decile portfolios are sorted according to the standard deviation of estimated book-to-market ratio scaled by its mean (UNC) over the past twelve months with decile 1 (10) containing stocks with the lowest (highest) UNC. This table reports raw excess (second column) and risk-adjusted returns (alphas) generated based on different sets of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM alpha); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF alpha); and (v) the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (7F alpha). The second set of models in Table 2.1 considers the 3F, 5F, and QF factor models augmented by Carhart's (1997) momentum factor, while the last set adds the liquidity factor of Pástor and Stambaugh (2003) to the previous 3F and QF models. The last two rows report the difference High−Low (10−1) excess returns and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2016.

		Risk-Adjusted Returns					+ MOM			+ MOM + LIQ	
UNC Decile	Excess (Raw) Returns	CAPM	3F	5F	QF	7F	3F	5F	QF	3F	QF
1 (Low)	0.906	0.417	0.328	0.162	0.179	0.128	0.290	0.148	0.183	0.274	0.161
	(4.38)	(3.31)	(3.50)	(1.93)	(1.50)	(1.50)	(2.98)	(1.70)	(1.60)	(2.89)	(1.44)
2	0.951	0.402	0.283	0.049	0.060	0.035	0.257	0.050	0.070	0.248	0.052
	(4.12)	(2.59)	(2.83)	(0.62)	(0.53)	(0.46)	(2.53)	(0.63)	(0.70)	(2.51)	(0.55)
3	0.995	0.400	0.290	0.079	0.125	0.085	0.292	0.097	0.136	0.284	0.123
	(4.20)	(2.77)	(3.04)	(1.01)	(1.17)	(1.11)	(3.05)	(1.25)	(1.44)	(3.03)	(1.33)
4	1.003	0.398	0.298	0.087	0.120	0.102	0.318	0.118	0.134	0.307	0.114
	(4.15)	(2.58)	(2.88)	(1.17)	(1.11)	(1.53)	(3.24)	(1.70)	(1.62)	(3.23)	(1.45)
5	1.090	0.437	0.334	0.170	0.229	0.208	0.381	0.216	0.244	0.377	0.236
	(4.27)	(3.01)	(3.32)	(2.09)	(2.05)	(2.68)	(3.95)	(2.75)	(2.68)	(3.98)	(2.65)
6	1.107	0.417	0.345	0.172	0.242	0.211	0.393	0.220	0.255	0.388	0.247
	(4.19)	(2.85)	(3.44)	(2.31)	(2.48)	(2.57)	(3.90)	(2.71)	(2.86)	(3.84)	(2.74)
7	1.350	0.625	0.553	0.400	0.448	0.440	0.622	0.460	0.464	0.606	0.441
	(4.69)	(3.86)	(5.20)	(4.43)	(4.71)	(4.69)	(5.59)	(4.86)	(5.24)	(5.47)	(4.95)
8	1.388	0.625	0.593	0.536	0.629	0.613	0.707	0.620	0.645	0.703	0.640
	(4.87)	(3.91)	(5.25)	(5.48)	(5.99)	(5.96)	(6.33)	(6.14)	(6.40)	(6.21)	(6.32)
9	1.521	0.685	0.685	0.699	0.873	0.823	0.890	0.840	0.894	0.876	0.881
	(4.72)	(3.52)	(5.11)	(5.51)	(5.91)	(6.95)	(6.73)	(7.22)	(6.60)	(6.51)	(6.41)
10 (High)	2.027	1.083	1.144	1.281	1.508	1.469	1.428	1.467	1.531	1.429	1.544
	(5.62)	(4.70)	(7.13)	(7.84)	(8.29)	(9.73)	(8.79)	(9.79)	(9.00)	(8.73)	(9.13)
High−Low (10−1)	1.120	0.665	0.817	1.119	1.329	1.341	1.138	1.319	1.348	1.155	1.383
t-stat	(4.25)	(2.84)	(4.31)	(5.66)	(5.94)	(6.87)	(5.76)	(6.78)	(5.93)	(5.83)	(6.13)

Table A2.2

Robustness on Univariate Portfolio Analysis with NYSE Breakpoints

This table tests the robustness of the UNC premium to alternative portfolio breakpoints and asset pricing models. Over the period January 1986-December 2016, each month decile portfolio are formed according to UNC over the past twelve months. Decile 1 (10) contains stocks with the lowest (highest) decile of the previous month. Portfolios are formed using NYSE breakpoints. Panel A and Panel B report both raw excess (second column) and risk-adjusted returns of value- and equal-weighted portfolios for the month following portfolio formation, respectively. The alphas reported are generated based on different sets of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM alpha); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF alpha); and (v) the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (7F alpha). The second set of models in Table 2.1 considers the 3F, 5F, and Q factor models augmented by Carhart's (1997) momentum factor, while the last set adds the liquidity factor of Pástor and Stambaugh (2003) to the previous 3F and QF models.The last two rows report the difference High−Low (10-1) excess returns and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2016.

Panel A. Value-Weighted Portfolios

		Risk-Adjusted Returns					+ MOM			+ MOM + LIQ	
UNC Decile	Excess (Raw) Returns	CAPM	3F	5F	QF	7F	3F	5F	QF	3F	QF
1 (Low)	0.462	-0.088	-0.063	-0.065	-0.040	-0.121	-0.146	-0.122	-0.055	-0.147	-0.047
	(1.85)	(-0.53)	(-0.43)	(-0.46)	(-0.27)	(-0.82)	(-0.96)	(-0.83)	(-0.39)	(-0.95)	(-0.33)
2	0.780	0.233	0.215	0.013	0.040	-0.021	0.141	-0.022	0.037	0.144	0.035
	(4.00)	(1.83)	(1.82)	(0.13)	(0.36)	(-0.21)	(1.17)	(-0.22)	(0.34)	(1.18)	(0.32)
3	0.743	0.187	0.182	0.075	0.035	0.014	0.087	0.017	0.030	0.086	0.023
	(3.10)	(1.32)	(1.36)	(0.60)	(0.28)	(0.11)	(0.65)	(0.14)	(0.24)	(0.63)	(0.18)
4	0.742	0.179	0.178	0.016	0.035	0.002	0.164	0.019	0.040	0.151	0.013
	(3.10)	(1.68)	(1.66)	(0.16)	(0.29)	(0.02)	(1.41)	(0.18)	(0.34)	(1.31)	(0.12)
5	0.783	0.205	0.195	0.021	0.070	0.024	0.184	0.028	0.073	0.183	0.064
	(3.62)	(1.64)	(1.65)	(0.18)	(0.58)	(0.21)	(1.52)	(0.25)	(0.62)	(1.49)	(0.54)
6	0.843	0.196	0.189	-0.027	0.032	0.005	0.208	0.006	0.039	0.210	0.032
	(3.18)	(1.49)	(1.50)	(-0.22)	(0.25)	(0.04)	(1.68)	(0.05)	(0.30)	(1.64)	(0.24)
7	0.939	0.229	0.255	0.132	0.122	0.149	0.265	0.150	0.126	0.266	0.119
	(3.22)	(1.95)	(2.20)	(1.02)	(0.80)	(1.01)	(2.00)	(1.01)	(0.81)	(2.02)	(0.76)
8	1.130	0.412	0.446	0.334	0.433	0.375	0.476	0.363	0.439	0.488	0.451
	(3.95)	(2.48)	(2.81)	(2.07)	(2.71)	(2.21)	(2.90)	(2.19)	(2.66)	(2.93)	(2.67)
9	1.010	0.239	0.295	0.272	0.419	0.389	0.463	0.391	0.435	0.462	0.430
	(3.49)	(1.60)	(2.14)	(1.93)	(2.52)	(2.77)	(3.42)	(2.84)	(2.79)	(3.37)	(2.73)
10 (High)	1.345	0.510	0.634	0.675	0.879	0.820	0.826	0.806	0.892	0.839	0.911
	(4.13)	(2.77)	(4.24)	(4.56)	(5.06)	(5.67)	(5.72)	(5.61)	(5.02)	(5.71)	(5.16)
High−Low (10−1)	0.884	0.598	0.698	0.739	0.920	0.941	0.972	0.927	0.946	0.986	0.958
t-stat	(3.16)	(2.22)	(2.95)	(3.35)	(3.70)	(4.08)	(4.05)	(4.11)	(3.85)	(3.99)	(3.83)

Table A2.2 (continued)

Panel B. Equal-Weighted Portfolios

		Risk-Adjusted Returns					+ MOM			+ MOM + LIQ	
UNC Decile	Excess (Raw) Returns	CAPM	3F	5F	QF	7F	3F	5F	QF	3F	QF
1 (Low)	0.922	0.436	0.344	0.173	0.193	0.135	0.302	0.157	0.196	0.284	0.164
	(4.40)	(3.38)	(3.63)	(2.05)	(1.62)	(1.55)	(3.04)	(1.78)	(1.72)	(2.94)	(1.48)
2	0.945	0.402	0.285	0.056	0.078	0.048	0.266	0.061	0.088	0.257	0.064
	(4.19)	(2.70)	(2.91)	(0.72)	(0.70)	(0.61)	(2.65)	(0.76)	(0.88)	(2.66)	(0.68)
3	0.972	0.390	0.270	0.036	0.077	0.040	0.265	0.051	0.087	0.258	0.066
	(4.09)	(2.55)	(2.56)	(0.41)	(0.64)	(0.48)	(2.58)	(0.61)	(0.85)	(2.56)	(0.66)
4	1.022	0.428	0.323	0.124	0.152	0.132	0.332	0.146	0.164	0.324	0.140
	(4.28)	(2.77)	(3.28)	(1.65)	(1.43)	(1.87)	(3.48)	(2.02)	(1.95)	(3.52)	(1.74)
5	1.044	0.399	0.284	0.078	0.153	0.112	0.333	0.128	0.169	0.322	0.142
	(4.05)	(2.48)	(2.40)	(0.89)	(1.21)	(1.38)	(2.84)	(1.54)	(1.69)	(2.78)	(1.46)
6	1.058	0.391	0.296	0.129	0.202	0.178	0.352	0.181	0.217	0.352	0.207
	(4.16)	(2.78)	(3.10)	(1.75)	(1.98)	(2.43)	(3.82)	(2.48)	(2.74)	(3.89)	(2.68)
7	1.257	0.539	0.461	0.286	0.344	0.329	0.521	0.342	0.358	0.512	0.335
	(4.42)	(3.61)	(4.21)	(2.90)	(3.06)	(2.96)	(4.26)	(3.07)	(3.29)	(4.16)	(3.02)
8	1.398	0.669	0.599	0.474	0.555	0.535	0.685	0.544	0.572	0.680	0.555
	(4.86)	(3.94)	(5.13)	(4.91)	(5.06)	(5.26)	(5.80)	(5.44)	(5.76)	(5.71)	(5.45)
9	1.487	0.683	0.643	0.588	0.728	0.703	0.820	0.716	0.751	0.811	0.731
	(4.79)	(3.80)	(5.16)	(5.31)	(5.68)	(5.94)	(6.50)	(6.22)	(6.30)	(6.26)	(5.93)
10 (High)	1.919	1.000	1.042	1.146	1.380	1.313	1.304	1.320	1.401	1.298	1.396
	(5.42)	(4.48)	(6.89)	(7.65)	(7.91)	(9.18)	(8.31)	(9.26)	(8.60)	(8.25)	(8.69)
High−Low (10−1)	0.997	0.564	0.699	0.973	1.188	1.179	1.002	1.162	1.205	1.014	1.232
t-stat	(3.87)	(2.47)	(3.83)	(5.22)	(5.39)	(6.15)	(5.13)	(6.08)	(5.37)	(5.18)	(5.54)

Table A2.3

Adding Change in Value Risk Premia (ΔVRP) in Univariate Portfolio Analysis (Value-Weighted)

Each month value-weighted decile portfolios are sorted according to the BM uncertainty (UNC) with decile 1 (10) containing stocks with the lowest (highest) UNC. The table reports risk-adjusted returns (alphas) after including the net change in the value risk premia (ΔVRP) of Bollerslev et al. (2009) to the following sets of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM alpha); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF alpha); and (v) the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (7F alpha). The second set of models in Table 2.1 considers the 3F, 5F, and QF factor models augmented by Carhart's (1997) momentum factor, while the last set adds the liquidity factor of Pástor and Stambaugh (2003) to the previous 3F and QF models. The last two rows report the difference High−Low (10−1) excess returns and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1990 to December 2016 given the availability of the VRP data.

	+ ΔVRP					+ ΔVRP + MOM			+ ΔVRP + MOM + LIQ	
UNC Decile	CAPM	3F	5F	QF	7F	3F	5F	QF	3F	QF
1 (Low)	-0.068	-0.028	0.055	0.029	-0.004	-0.110	-0.009	0.010	-0.104	0.032
	(-0.37)	(-0.18)	(0.41)	(0.19)	(-0.03)	(-0.72)	(-0.07)	(0.07)	(-0.68)	(0.22)
2	0.271	0.254	0.030	0.020	-0.045	0.165	-0.028	0.018	0.149	-0.001
	(1.89)	(2.00)	(0.31)	(0.17)	(-0.42)	(1.26)	(-0.26)	(0.15)	(1.15)	(-0.01)
3	0.123	0.127	0.055	0.021	-0.004	0.059	0.003	0.017	0.052	0.014
	(1.08)	(1.14)	(0.47)	(0.17)	(-0.03)	(0.49)	(0.02)	(0.13)	(0.43)	(0.11)
4	0.135	0.131	-0.051	-0.037	-0.078	0.115	-0.053	-0.033	0.091	-0.061
	(1.08)	(1.09)	(-0.44)	(-0.30)	(-0.67)	(0.89)	(-0.45)	(-0.27)	(0.72)	(-0.51)
5	0.435	0.438	0.229	0.332	0.251	0.448	0.248	0.338	0.451	0.345
	(2.84)	(2.95)	(1.53)	(2.06)	(1.74)	(2.97)	(1.72)	(2.12)	(3.01)	(2.16)
6	0.148	0.196	0.018	0.063	0.016	0.204	0.037	0.068	0.184	0.045
	(1.21)	(1.66)	(0.14)	(0.47)	(0.11)	(1.62)	(0.26)	(0.49)	(1.41)	(0.32)
7	0.345	0.345	0.155	0.218	0.205	0.372	0.182	0.231	0.395	0.262
	(2.00)	(2.06)	(0.92)	(1.30)	(1.24)	(2.31)	(1.08)	(1.39)	(2.47)	(1.59)
8	0.303	0.356	0.373	0.478	0.465	0.454	0.447	0.487	0.472	0.517
	(1.60)	(1.94)	(2.01)	(2.47)	(2.45)	(2.48)	(2.39)	(2.46)	(2.56)	(2.58)
9	0.115	0.206	0.187	0.391	0.318	0.410	0.343	0.414	0.384	0.387
	(0.63)	(1.39)	(1.24)	(2.12)	(1.93)	(2.63)	(2.10)	(2.29)	(2.44)	(2.13)
10 (High)	0.576	0.683	0.841	1.044	1.003	0.874	0.978	1.056	0.898	1.100
	(2.56)	(3.75)	(4.25)	(4.75)	(5.47)	(5.36)	(5.30)	(4.75)	(5.38)	(5.08)
High−Low (10−1)	0.644	0.711	0.786	1.015	1.007	0.984	0.987	1.046	1.002	1.069
t-stat	(2.12)	(2.71)	(3.19)	(3.90)	(4.11)	(3.98)	(4.12)	(4.01)	(3.93)	(4.06)

Table A2.4

Robustness with Additional Factors in Univariate Portfolio Analysis

Each month value- and equal-weighted decile portfolios are sorted according to the book-to-market uncertainty (UNC) with decile 1 (10) containing stocks with the lowest (highest) UNC. The table reports the risk-adjusted returns (alphas) of the 7F model after adding, one at a time, other factors: betting against beta factor (BAB) of Frazzini and Pedersen (2014), the quality minus junk factor (QMJ) of Asness et al. (2019), the lottery demand factor (FMAX) of Bali et al. (2017b), the post-earnings announcement drift factor (PEAD) and modified financing factor (FIN) of Daniel et al. (2019). The last two rows report the difference High−Low (10−1) excess returns and alphas. Newey-West adjusted *t*-statistics are given in parentheses. The sample period is from January 1986 to December 2016 with the exception of PEAD and FIN where the sample period is from January 1986 to December 2014 given data availability.

	Value-Weighted 7F					Equal-Weighted 7F				
UNC Decile	+BAB	+FMAX	+QMJ	+PEAD	+FIN	+BAB	+FMAX	+QMJ	+PEAD	+FIN
1 (Low)	-0.048	-0.049	0.018	-0.017	-0.074	0.099	0.085	0.074	0.140	0.088
	(-0.31)	(-0.33)	(0.12)	(-0.10)	(-0.45)	(1.17)	(1.04)	(0.82)	(1.59)	(0.98)
2	-0.083	-0.115	-0.136	-0.135	-0.095	0.010	-0.013	-0.058	0.046	0.010
	(-0.81)	(-1.17)	(-1.27)	(-1.29)	(-0.90)	(0.14)	(-0.19)	(-0.72)	(0.57)	(0.12)
3	0.019	0.004	-0.001	0.053	0.016	0.068	0.050	0.031	0.109	0.061
	(0.17)	(0.03)	(-0.01)	(0.51)	(0.14)	(0.89)	(0.69)	(0.40)	(1.37)	(0.73)
4	-0.036	-0.056	-0.063	-0.002	-0.038	0.092	0.066	0.050	0.119	0.084
	(-0.33)	(-0.52)	(-0.57)	(-0.01)	(-0.34)	(1.32)	(1.03)	(0.74)	(1.63)	(1.14)
5	0.157	0.147	0.096	0.112	0.125	0.201	0.190	0.130	0.203	0.196
	(1.17)	(1.08)	(0.68)	(0.83)	(0.91)	(2.60)	(2.48)	(1.62)	(2.46)	(2.36)
6	0.060	0.054	-0.047	-0.044	0.027	0.204	0.196	0.145	0.212	0.187
	(0.45)	(0.41)	(-0.35)	(-0.31)	(0.20)	(2.48)	(2.43)	(1.79)	(2.45)	(2.12)
7	0.230	0.234	0.094	0.210	0.226	0.447	0.440	0.390	0.479	0.443
	(1.50)	(1.54)	(0.58)	(1.19)	(1.45)	(4.67)	(4.80)	(4.18)	(4.41)	(4.40)
8	0.533	0.515	0.399	0.549	0.564	0.642	0.616	0.575	0.659	0.680
	(3.23)	(3.21)	(2.70)	(3.10)	(3.26)	(6.54)	(6.12)	(5.79)	(6.23)	(6.19)
9	0.365	0.413	0.281	0.205	0.397	0.868	0.852	0.821	0.846	0.889
	(2.36)	(2.76)	(1.66)	(1.06)	(2.52)	(7.82)	(7.49)	(7.02)	(6.81)	(6.97)
10 (High)	1.054	1.070	0.952	0.992	1.068	1.508	1.506	1.454	1.492	1.570
	(6.03)	(6.12)	(5.87)	(5.76)	(5.91)	(10.85)	(10.28)	(10.65)	(9.61)	(9.53)
High−Low (10−1)	1.102	1.120	0.934	1.009	1.141	1.409	1.421	1.381	1.353	1.483
t-stat	(4.25)	(4.48)	(3.90)	(4.09)	(4.32)	(8.03)	(7.58)	(7.31)	(6.82)	(7.23)

Table A2.5

Cross-Sectional Correlations Among Key Variables

This table reports the time-series monthly average of the cross-sectional correlation between different factors: standard deviation of estimated book-to-market (UNC), market beta (β^{MKT}), market capitalization (SIZE), book-to-market (BM), book-to-market (BMFF) as in Fama and French (1993), investment (INV), operational profitability (OP), momentum (MOM), illiquidity (ILLIQ), short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), and standard deviation of the inverse of SIZE (Std (1/SIZE)). The sample horizon is January 1986-December 2016.

	UNC	β^{MKT}	SIZE	BM	BMFF	INV	OP	MOM	ILLIQ	STR	TURN	DISP	IVOL	ISKEW	COSK	β^{VXO}	MAX	Std (1/SIZE)
UNC	1																	
β^{MKT}	0.15	1																
SIZE	-0.07	-0.02	1															
BM	-0.17	-0.06	-0.16	1														
BMFF	-0.23	-0.05	-0.15	0.87	1													
INV	0.22	0.08	-0.03	-0.15	-0.20	1												
OP	0.02	-0.01	0.00	-0.39	-0.37	0.00	1											
MOM	0.07	0.08	0.02	-0.33	-0.05	0.04	0.10	1										
ILLIQ	-0.01	-0.06	-0.07	0.13	0.11	-0.01	0.01	-0.07	1									
STR	0.01	0.01	0.01	-0.12	0.01	0.00	0.01	0.00	-0.01	1								
TURN	0.34	0.19	-0.07	-0.14	-0.14	0.21	0.07	0.15	-0.13	0.01	1							
DISP	0.08	0.02	-0.04	0.09	0.08	0.00	-0.09	-0.07	0.04	0.00	0.04	1						
IVOL	0.35	0.14	-0.18	0.00	-0.03	0.19	0.03	0.02	0.19	0.05	0.45	0.09	1					
ISKEW	0.02	0.02	-0.01	-0.03	0.01	0.00	-0.02	-0.03	0.00	0.39	-0.02	0.01	0.05	1				
COSK	-0.01	0.02	0.01	-0.01	-0.01	-0.01	0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.03	-0.12	1			
β^{VXO}	0.02	0.11	-0.03	0.01	0.01	0.01	-0.01	-0.01	0.00	0.01	0.02	0.01	0.03	-0.01	0.17	1		
MAX	0.35	0.28	-0.14	-0.05	-0.03	0.18	0.01	0.04	0.16	0.44	0.41	0.09	0.81	0.30	0.01	0.05	1	
Std (1/SIZE)	0.30	0.00	-0.16	0.15	0.16	0.07	0.04	0.07	0.41	0.03	0.04	0.09	0.36	0.02	-0.02	0.01	0.33	1

Table A2.6

Bivariate Portfolio Analysis with NYSE Breakpoints

In this table, stocks are sorted into decile portfolios, using NYSE breakpoints, based on one of the following control variables: market beta (β^{MKT}), market capitalization (SIZE), book-to-market (BM), book-to-market (BMFF) following Fama and French (1993), investment (INV), operating profitability (OP), stock momentum (MOM), illiquidity (ILLIQ), short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of estimated net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)). Stocks within each control variable decile are further sorted into deciles based on the volatility of estimated book-to-market (UNC). The table reports risk-adjusted returns (based on the 7F model) of value-weighted monthly returns for each UNC decile averaged across each of the controls with the corresponding t-statistics in parentheses. Values are in percentage. The last two rows report the difference between decile 10 and 1 alphas and the Newey-West adjusted t-statistics in parentheses. The sample period is from January 1986 to December 2016.

	β^{MKT}	SIZE	BM	BMFF	INV	OP	MOM	ILLIQ	STR	TURN	DISP	IVOL	ISKEW	COSK	β^{BVXO}	MAX	Std (NI)	Std (1/SIZE)
1 (Low)	-0.054	0.001	0.000	-0.031	0.000	0.022	0.020	-0.022	-0.138	-0.056	-0.118	-0.045	-0.023	-0.108	-0.105	-0.278	0.049	0.108
	(-0.56)	(0.01)	(-0.00)	(-0.30)	(0.00)	(0.22)	(0.21)	(-0.25)	(-1.29)	(-0.57)	(-1.24)	(-0.45)	(-0.19)	(-0.97)	(-1.12)	(-2.59)	(0.58)	(1.23)
2	-0.081	-0.034	0.070	-0.101	-0.028	-0.064	0.093	-0.068	-0.040	-0.078	0.059	-0.054	-0.019	-0.136	-0.081	-0.078	-0.053	-0.044
	(-0.94)	(-0.40)	(0.87)	(-1.06)	(-0.31)	(-0.80)	(1.21)	(-0.80)	(-0.44)	(-0.85)	(0.62)	(-0.56)	(-0.23)	(-1.43)	(-0.82)	(-0.87)	(-0.72)	(-0.56)
3	0.014	0.014	0.019	-0.019	0.013	-0.212	0.014	-0.116	-0.085	0.063	-0.038	-0.077	-0.050	-0.038	-0.064	-0.049	-0.097	0.064
	(0.15)	(0.19)	(0.18)	(-0.18)	(0.13)	(-2.18)	(0.13)	(-1.38)	(-0.85)	(0.69)	(-0.41)	(-0.80)	(-0.53)	(-0.44)	(-0.63)	(-0.53)	(-1.30)	(0.80)
4	0.063	0.057	0.072	-0.138	-0.029	-0.012	-0.076	-0.015	0.064	0.052	-0.083	-0.006	-0.090	-0.014	0.022	-0.062	0.015	0.114
	(0.77)	(0.76)	(0.91)	(-1.60)	(-0.31)	-(0.14)	(-0.79)	(-0.21)	(0.66)	(0.59)	(-0.97)	(-0.07)	(-1.01)	(-0.15)	(0.26)	(-0.64)	(0.20)	(1.42)
5	0.024	0.084	-0.009	-0.092	-0.034	-0.003	-0.121	0.078	0.008	-0.115	-0.017	-0.004	0.003	0.021	-0.035	-0.073	0.029	0.021
	(0.26)	(1.05)	(-0.10)	(-0.89)	(-0.35)	(-0.04)	(-1.25)	(0.88)	(0.09)	(-1.28)	(-0.16)	(-0.04)	(0.03)	(0.19)	(-0.35)	(-0.77)	(0.34)	(0.24)
6	0.037	0.147	0.132	0.122	0.155	0.078	0.050	0.080	-0.163	-0.041	0.251	0.023	0.097	0.085	0.021	-0.064	0.030	0.177
	(0.39)	(1.79)	(1.37)	(1.13)	(1.34)	(0.65)	(0.54)	(0.94)	(-1.56)	(-0.45)	(2.01)	(0.21)	(0.83)	(0.89)	(0.19)	(-0.66)	(0.28)	(2.04)
7	0.048	0.370	0.120	0.039	0.088	0.106	0.138	0.199	0.124	0.036	0.131	-0.062	0.208	0.111	0.185	0.074	0.216	0.182
	(0.38)	(3.65)	(1.12)	(0.35)	(0.86)	(0.93)	(1.25)	(1.85)	(1.13)	(0.36)	(1.18)	(-0.51)	(1.95)	(0.95)	(1.49)	(0.59)	(2.41)	(1.70)
8	0.344	0.432	0.273	0.054	0.184	0.328	0.247	0.401	0.289	0.261	0.467	0.138	0.316	0.273	0.216	0.166	0.538	0.318
	(2.86)	(4.52)	(2.19)	(0.48)	(1.38)	(2.44)	(2.51)	(4.59)	(2.06)	(2.04)	(3.53)	(1.22)	(2.63)	(2.13)	(1.64)	(1.34)	(4.53)	(2.58)
9	0.429	0.623	0.520	0.452	0.247	0.530	0.514	0.585	0.573	0.213	0.586	0.507	0.520	0.456	0.400	0.458	0.442	0.557
	(3.39)	(5.29)	(3.60)	(2.79)	(1.96)	(3.64)	(4.58)	(5.52)	(4.26)	(1.53)	(4.51)	(4.02)	(3.52)	(3.27)	(2.95)	(3.75)	(3.02)	(4.88)
10 (High)	0.878	1.150	1.002	0.808	1.007	0.831	0.554	1.098	0.843	0.485	1.040	0.662	1.180	0.986	1.059	0.690	1.189	0.922
	(6.89)	(7.52)	(6.44)	(4.35)	(6.18)	(5.81)	(4.64)	(7.28)	(5.08)	(3.72)	(6.80)	(5.37)	(7.20)	(6.50)	(6.98)	(4.66)	(6.61)	(6.54)
High−Low (10−1)	0.932	1.150	1.002	0.839	1.007	0.809	0.534	1.119	0.981	0.541	1.159	0.707	1.203	1.094	1.163	0.967	1.139	0.814
t-stat	(5.72)	(6.04)	(5.19)	(3.69)	(4.74)	(4.31)	(3.47)	(6.07)	(4.27)	(3.10)	(5.96)	(4.15)	(5.32)	(4.99)	(5.79)	(5.25)	(5.41)	(4.43)

Table A2.7

Three-Way Dependent Portfolio Sorting

In this table, stocks are sorted into tercile portfolios, based on book-to-market (BM). Stocks within each BM tercile are sorted into terciles based on the volatility of expected profitability (Std. (ROE)) and then within each Std. (ROE) terciles stocks are further sorted into UNC terciles. The table reports excess returns and risk-adjusted returns (based on the 7F model) of value-weighted monthly returns for each UNC tercile for the three BM groups (High, Medium, Low). The last column within each BM group reports returns averaged across the Std. (ROE) terciles. Values are in percentage. The last two rows report the difference between terciles 3 (high-UNC) and 1 (low-UNC) excess returns and alphas and the Newey-West adjusted t-statistics in parentheses. The sample period is from January 1986 to December 2016.

Low BM

	Excess (Raw) Return				Risk-Adjusted Return			
Std. (ROE)→	Low	Med.	High	Average	Low	Med.	High	Average
Low UNC	0.759	0.655	0.949	0.787	-0.011	-0.102	0.177	0.021
Med. UNC	1.012	0.732	0.946	0.897	0.285	0.029	0.176	0.163
High UNC	1.294	1.078	1.517	1.296	0.770	0.543	0.811	0.708
High−Low	0.535	0.423	0.568	0.509	0.781	0.645	0.634	0.687
t-stat	(1.90)	(1.65)	(2.70)	(2.41)	(3.76)	(3.21)	(3.46)	(4.48)

Medium BM

	Excess (Raw) Return				Risk-Adjusted Return			
Std. (ROE)→	Low	Med.	High	Average	Low	Med.	High	Average
Low UNC	0.764	0.874	0.919	0.852	-0.098	-0.035	0.012	-0.040
Med. UNC	0.874	0.793	1.192	0.953	-0.071	-0.158	0.273	0.015
High UNC	1.121	1.417	1.715	1.418	0.318	0.571	0.994	0.628
High−Low	0.357	0.543	0.796	0.565	0.416	0.606	0.982	0.668
t-stat	(1.81)	(2.95)	(3.39)	(3.41)	(2.50)	(3.39)	(4.34)	(4.98)

High BM

	Excess (Raw) Return				Risk-Adjusted Return			
Std. (ROE)→	Low	Med.	High	Average	Low	Med.	High	Average
Low UNC	1.256	1.060	1.245	1.187	0.381	0.151	0.285	0.272
Med. UNC	1.398	1.370	1.475	1.414	0.468	0.399	0.484	0.450
High UNC	1.761	2.164	2.300	2.075	0.952	1.193	1.490	1.212
High−Low	0.505	1.104	1.055	0.888	0.571	1.042	1.205	0.939
t-stat	(2.77)	(5.79)	(4.76)	(5.69)	(2.94)	(5.53)	(5.44)	(6.23)

Table A2.8

Stock Level Cross-Sectional Analysis with Industry Controls

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 and controlling for industries following the Fama and MacBeth (1973) approach. The main controls set include: market beta (β^{MKT}), market cap (SIZE), book-to-market (BM), investment (INV), operating profitability (OP), stock momentum (MOM), illiquidity (ILLIQ). Additional control variables are added one at a time: short-term reversal (STR), turnover (TURN), analysts' forecast dispersion (DISP), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), market volatility beta (β^{VXO}), lottery-stock demand (MAX), standard deviation of net income (Std (NI)), and standard deviation of the inverse of SIZE (Std (1/SIZE)). t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. The sample is from January 1986 to December 2016.

Dependent variable: one-month ahead return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Constant	-0.279	3.777	0.861	3.932	2.481	2.585	2.73	3.163	2.368	2.401	2.629	2.55	2.675	2.734	3.512	2.982	2.507
	(-0.40)	(4.81)	(1.24)	(5.05)	(3.27)	(3.64)	(3.59)	(4.09)	(3.20)	(2.98)	(3.21)	(3.29)	(3.50)	(3.61)	(4.68)	(3.89)	(2.85)
UNC	2.911	2.679	3.256	2.912	2.995	2.689	2.756	2.588	2.811	2.786	2.632	2.756	2.753	2.766	3.244	2.693	2.358
	(4.66)	(4.34)	(5.39)	(5.30)	(5.43)	(5.14)	(5.25)	(4.78)	(6.08)	(5.36)	(5.52)	(5.26)	(5.22)	(5.36)	(6.36)	(5.09)	(4.32)
β^{MKT}				0.037	0.035	0.028	0.025	0.030	0.030	0.007	0.009	0.026	0.030	0.027	0.071	0.028	0.026
				(0.81)	(0.79)	(0.63)	(0.59)	(0.65)	(0.72)	(0.17)	(0.20)	(0.61)	(0.70)	(0.63)	(1.77)	(0.65)	(0.62)
SIZE		-0.191		-0.146	-0.113	-0.157	-0.124	-0.140	-0.124	-0.116	-0.118	-0.126	-0.126	-0.127	-0.157	-0.146	-0.069
		(-5.34)		(-4.42)	(-3.39)	(-4.57)	(-3.61)	(-3.86)	(-3.60)	(-3.23)	(-3.50)	(-3.64)	(-3.71)	(-3.64)	(-4.49)	(-4.08)	(-1.93)
BM			0.373	0.223	0.276	0.269	0.329	0.202	0.329	0.345	0.325	0.328	0.328	0.327	0.291	0.317	0.322
			(4.10)	(2.53)	(2.91)	(3.42)	(3.95)	(2.46)	(4.05)	(4.09)	(3.98)	(3.96)	(3.95)	(3.93)	(3.64)	(3.77)	(3.87)
INV					-0.055		-0.047	-0.062	-0.053	-0.054	-0.052	-0.048	-0.043	-0.043	-0.038	-0.046	-0.054
					(-0.84)		(-0.73)	(-0.92)	(-0.84)	(-0.84)	(-0.82)	(-0.76)	(-0.68)	(-0.67)	(-0.61)	(-0.73)	(-0.85)
OP					1.876		1.785	1.492	1.781	1.873	1.786	1.776	1.783	1.775	1.656	1.751	1.73
					(3.38)		(3.23)	(2.64)	(3.20)	(3.32)	(3.28)	(3.21)	(3.23)	(3.19)	(2.99)	(3.19)	(3.13)
MOM						0.002	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002
						(1.13)	(1.61)	(1.05)	(1.63)	(2.05)	(1.61)	(1.60)	(1.58)	(1.55)	(1.61)	(1.62)	(1.16)
ILLIQ						0.047	0.209	0.232	0.119	2.135	0.220	0.205	0.213	0.223	0.261	0.197	-0.051
						(0.24)	(0.80)	(0.86)	(0.53)	(2.01)	(0.82)	(0.79)	(0.80)	(0.83)	(0.94)	(0.75)	(-0.27)
STR								-0.052									
								(-10.05)									
TURN									0.203								
									(0.49)								
DISP										0.110							
										(1.15)							
IVOL											0.0343						
											(0.86)						
ISKEW												-0.043					
												(-1.46)					
COSK													0.005				
													(0.80)				
β^{VXO}														-8.773			
														(-2.31)			
MAX															-0.127		
															(-4.46)		
Std (NI)																0.001	
																(2.94)	
Std (1/SIZE)																	0.324
																	(3.89)
R^2	0.125	0.134	0.133	0.147	0.158	0.155	0.167	0.174	0.174	0.179	0.171	0.168	0.170	0.169	0.171	0.168	0.170

Table A2.9

UNC Predictability n Months Ahead

This table reports risk-adjusted returns of value-weighted portfolios using t+2, t+3, t+6, and t+12 risk-adjusted returns for portfolios formed based on UNC computed in month t. Decile 1 (10) contains stocks with the lowest (highest) UNC. The reported alphas are obtained using the five-factor model of Fama and French (2015), augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003) (Alpha 7F). The last two rows show the difference in alphas of deciles 10 and 1. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2016.

	Alpha 7F			
UNC Decile	$t+2$	$t+3$	$t+6$	$t+12$
1 (Low)	0.001	-0.039	-0.165	0.105
	(0.01)	(-0.25)	(-1.11)	(0.75)
2	-0.148	-0.223	-0.196	-0.009
	(-1.27)	(-1.93)	(-1.73)	(-0.08)
3	0.135	0.139	0.172	-0.230
	(1.20)	(1.24)	(1.14)	(-1.84)
4	0.141	-0.028	-0.021	0.041
	(1.18)	(-0.25)	(-0.18)	(0.38)
5	-0.026	0.240	0.022	0.275
	(-0.21)	(1.94)	(0.17)	(2.47)
6	0.117	0.052	-0.003	0.464
	(0.84)	(0.41)	(-0.03)	(2.54)
7	0.216	0.221	0.388	0.194
	(1.71)	(1.40)	(2.41)	(1.39)
8	0.439	0.389	0.244	0.276
	(2.67)	(2.14)	(1.56)	(2.00)
9	0.468	0.499	0.786	0.364
	(3.02)	(3.12)	(4.13)	(2.00)
10 (High)	0.859	0.818	0.582	0.432
	(5.40)	(4.26)	(2.69)	(2.87)
High−Low (10−1)	0.86	0.86	0.75	0.33
t-stat	(3.62)	(3.01)	(2.60)	(1.71)

Table A2.10

Robustness of Univariate Portfolio Analysis over Different Sub-Samples

This table reports risk-adjusted returns of value- and equal-weighted portfolios over two different sub-samples: Jan 1986 - Dec 2000 and Jan 2001 - Dec 2016. Each month decile portfolio are formed according to UNC over the past twelve months. Decile 1 (10) contains stocks with the lowest (highest) decile. The reported alphas are obtained using the Fama and French (2015) 5-factor model augmented by Carhart's (1997) momentum and Pástor and Stambaugh's (2003) liquidity factors (7F). The last two rows show the difference in alphas between deciles 10 and 1, with the corresponding Newey-West adjusted t-statistics given in parentheses.

	1986-2000		2001-2016	
UNC Decile	VW	EW	VW	EW
1 (Low)	-0.16	-0.03	0.10	0.35
	(-0.63)	(-0.27)	(0.59)	(3.85)
2	-0.29	-0.04	0.18	0.19
	(-2.02)	(-0.32)	(1.67)	(2.47)
3	0.05	0.04	0.07	0.21
	(0.35)	(0.38)	(0.53)	(2.46)
4	-0.06	0.05	-0.05	0.24
	(-0.30)	(0.38)	(-0.41)	(3.08)
5	0.25	0.16	0.12	0.32
	(0.93)	(1.16)	(0.90)	(3.37)
6	0.39	0.34	-0.10	0.23
	(2.47)	(2.42)	(-0.62)	(2.62)
7	0.45	0.63	0.15	0.37
	(2.06)	(3.68)	(0.92)	(3.50)
8	0.63	0.89	0.12	0.40
	(2.28)	(5.38)	(0.85)	(3.27)
9	0.48	0.93	0.25	0.73
	(2.26)	(4.84)	(1.20)	(5.25)
10 (High)	1.04	1.58	0.79	1.30
	(3.79)	(7.12)	(4.22)	(6.42)
High−Low (10−1)	1.20	1.61	0.69	0.95
t-stat	(2.71)	(5.86)	(3.01)	(3.89)

Table A2.11

Univariate Portfolio Analysis with Alternative UNC Measure

Each month decile portfolios are sorted according to earnings growth (σ_μ) over the past twelve months with decile 1 (10) containing stocks with the lowest (highest) decile. The table reports both raw excess and risk-adjusted returns of value- and equal-weighted portfolios for the month following portfolio formation. The alphas reported are based on the Fama and French (2015) factors (MARKET, SIZE, BM, RMW, CMA), augmented by Carhart's (1997) momentum and Pástor and Stambaugh's (2003) liquidity factors (7F model). The second column reports the average σ_μ across each decile. The last two rows report the difference High−Low (10-1) excess returns and alphas. Newey-West adjusted t-statistics are given in parentheses. The sample period is from January 1986 to December 2016.

		Value-Weighted (VW) Portfolios		Equal-Weighted (EW) Portfolios	
UNC Decile	σ_μ	Excess Return	Alpha 7F	Excess Return	Alpha 7F
1 (Low)	0.06	0.50	-0.04	0.96	0.20
		(2.01)	(-0.28)	(4.66)	(2.42)
2	0.09	0.80	-0.06	0.92	0.01
		(4.04)	(-0.57)	(4.05)	(0.12)
3	0.10	0.74	0.05	0.99	0.08
		(3.04)	(0.46)	(4.20)	(1.01)
4	0.11	0.65	-0.10	1.01	0.11
		(2.91)	(-0.92)	(4.17)	(1.66)
5	0.13	0.89	0.13	1.08	0.20
		(3.56)	(0.96)	(4.21)	(2.44)
6	0.14	0.87	0.07	1.11	0.21
		(3.12)	(0.51)	(4.27)	(2.58)
7	0.17	1.03	0.19	1.36	0.44
		(3.58)	(1.32)	(4.71)	(4.69)
8	0.19	1.04	0.48	1.38	0.60
		(3.75)	(2.90)	(4.81)	(6.04)
9	0.24	0.92	0.34	1.52	0.82
		(3.00)	(2.21)	(4.68)	(6.84)
10 (High)	0.36	1.48	1.02	2.03	1.47
		(4.16)	(5.86)	(5.65)	(9.93)
High−Low (10−1)		0.98	1.06	1.06	1.27
t-stat		(3.30)	(4.36)	(4.16)	(6.83)

Table A2.12

UNC Portfolios and Risk Dynamics

The table reports excess (raw) and risk-adjusted returns of value-weighted portfolios for the month following portfolio formation. Each month decile portfolios are sorted according to the standard deviation of estimated book-to-market ratio scaled by its mean over the past twelve months (UNC), with decile 1 (10) containing stocks with the lowest (highest) decile. In Panel A, the reported alphas are based on the MKT, SIZE, BM, RMW, CMA factors, augmented by momentum and liquidity factors (the 7F model). In Panel B, reported alphas are based on risk-factor mimicking portfolios based on production growth (PROD), unexpected inflation (UINF), changes in expected inflation (ΔEINF), the yield spread between long and short-term treasury bonds (TRES), the spread between BAA- and AAA-rated corporate bonds, and changes in CBOE's volatility index (ΔVXO). Panel C contains the ratio between the expected (E-HEDGE) and the realized (R-HEDGE) hedge return premium of High vs. Low UNC portfolios. Newey-West adjusted *t*-statistics are given in parentheses. t-stats in Panel C test the null hypothesis that ABS(E-HEDGE/R-HEDGE−1) ≈ 0. The sample period is from July 1986 to December 2016 (T=366 months).

Panel A. UNC Portfolios against Seven Risk Factors (7F)

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High−Low (10−1)
Constant	-0.034	-0.054	0.017	-0.036	0.166	0.054	0.213	0.465	0.338	1.068	1.102
	(-0.23)	(-0.55)	(0.16)	-(0.33)	(1.27)	(0.41)	(1.43)	(2.73)	(2.37)	(5.52)	(4.18)
MKT	0.863	0.977	0.937	0.949	0.987	1.110	1.149	1.007	1.127	1.165	0.302
	(18.67)	(24.20)	(30.18)	(32.94)	(39.63)	(33.48)	(30.00)	(30.28)	(25.02)	(29.06)	(5.05)
SMB	-0.164	-0.049	-0.052	0.032	0.011	-0.030	-0.006	0.172	0.192	0.402	0.566
	(-2.12)	(-0.86)	(-1.22)	(0.75)	(0.18)	(-0.72)	(-0.09)	(2.30)	(2.63)	(5.98)	(4.80)
HML	-0.053	0.000	0.021	-0.126	-0.166	-0.278	-0.080	-0.298	-0.483	-0.509	-0.456
	(-0.63)	(0.01)	(0.34)	(-1.98)	(-2.02)	(-4.40)	(-0.93)	(-3.99)	(-6.41)	(-7.11)	(-4.54)
RMW	-0.159	0.389	0.200	0.330	0.356	0.283	0.410	0.005	0.152	-0.188	-0.029
	(-1.36)	(5.11)	(3.49)	(3.90)	(3.52)	(4.07)	(3.62)	(0.05)	(1.86)	(-1.32)	(-0.12)
CMA	0.100	0.117	-0.035	0.135	0.191	0.209	-0.014	0.018	0.057	-0.050	-0.150
	(0.68)	(0.87)	(-0.29)	(1.38)	(1.23)	(1.81)	(-0.10)	(0.14)	(0.42)	(-0.26)	(-0.55)
MOM	0.108	0.093	0.088	-0.007	-0.041	-0.041	-0.037	-0.109	-0.259	-0.210	-0.318
	(2.15)	(2.53)	(2.71)	(-0.20)	(-1.36)	(-0.81)	(-0.82)	(-2.24)	(-4.82)	(-2.58)	(-2.77)
LIQ	-0.027	0.040	-0.001	0.038	-0.007	0.047	-0.064	-0.047	0.061	-0.075	-0.048
	(-0.62)	(1.27)	(-0.03)	(1.24)	(-0.25)	(1.37)	(-1.16)	(-1.06)	(1.48)	(-1.84)	(-0.90)
R^2	0.735	0.796	0.822	0.801	0.782	0.840	0.791	0.783	0.796	0.809	0.396
T	366	366	366	366	366	366	366	366	366	366	366

Panel B. UNC Portfolios against Six Risk Factor Mimicking Portfolios

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High−Low (10−1)
Constant	-0.010	0.199	0.113	0.143	0.274	0.190	0.317	0.283	0.195	0.621	0.631
	(-0.05)	(1.56)	(0.82)	(1.00)	(1.81)	(1.18)	(1.70)	(1.41)	(1.01)	(2.17)	(2.06)
PROD	-0.072	-0.247	-0.370	-0.081	-0.387	-0.049	-0.354	-0.263	-0.071	-0.520	-0.449
	(-0.42)	(-1.93)	(-3.24)	(-0.60)	(-3.15)	(-0.28)	(-2.42)	(-1.88)	(-0.27)	(-2.35)	(-1.82)
UNIF	0.615	0.484	0.488	1.093	0.253	0.653	-0.047	1.601	1.147	1.849	1.234
	(1.63)	(1.42)	(1.43)	(2.82)	(0.68)	(1.99)	-(0.09)	(3.36)	(2.80)	(3.43)	(2.20)
ΔEINF	0.010	-0.007	0.007	-0.053	0.009	-0.015	-0.016	-0.091	-0.033	-0.071	-0.081
	(0.38)	(-0.32)	(0.33)	(-2.10)	(0.26)	(-0.39)	(-0.36)	(-2.08)	(-0.64)	(-0.99)	(-1.02)
TRES	-0.018	-0.143	-0.065	-0.092	-0.136	-0.066	-0.106	-0.116	0.082	-0.067	-0.049
	(-0.25)	(-2.73)	(-1.32)	(-1.78)	(-2.15)	(-0.99)	(-1.37)	(-1.55)	(0.85)	(-0.61)	(-0.37)
DEF	-1.369	-1.287	-1.376	-0.855	-1.336	-1.426	-1.597	-1.195	-1.381	-1.828	-0.459
	(-5.72)	(-6.36)	(-7.35)	(-3.44)	(-6.20)	(-5.39)	(-5.38)	(-5.28)	(-3.80)	(-4.66)	(-1.16)
ΔVXO	-0.527	-0.542	-0.556	-0.547	-0.568	-0.662	-0.674	-0.674	-0.770	-0.846	-0.319
	(-10.74)	(-16.05)	(-20.89)	(-20.63)	(-17.79)	(-24.05)	(-16.62)	(-18.05)	(-17.68)	(-15.26)	(-6.04)
R^2	0.579	0.620	0.681	0.629	0.614	0.658	0.616	0.617	0.607	0.573	0.168
T	366	366	366	366	366	366	366	366	366	366	366

Panel C. Risk Factor Premia of Mimicking Portfolios of Panel B

	Total	PROD	UINF	EINF	TRES	DEF	ΔVXO
E-HEDGE/R-HEDGE	0.368	0.069	0.026	-0.030	0.014	-0.008	0.296
t-stat	(5.63)	(9.77)	(5.69)	(8.75)	(7.31)	(5.55)	(7.18)

Chapter 3

The Uncertainty of Profitability and Asset Growth

Abstract

This chapter examines the predictive power of the uncertainty of profitability (UP) on cross-sectional equity returns. A portfolio strategy that goes long in the high-UP decile portfolio and short in the low-UP decile portfolio generates an annual excess raw (risk-adjusted) return of 8% (10%). The main portion of this premium comes from the over-performance of firms with more uncertainty surrounding their future profitability rather than the underperformance of firms with low UP. High-UP stocks would have higher returns during times of higher market-wide profitability, lower market volatility, and higher expected inflation justifying the documented premium. Firms with high uncertainty surrounding their asset growth (UAG) would outperform those with low asset growth uncertainty by 7% (12%) in terms of excess raw (risk-adjusted) return. Results shed light on the importance of the volatility of risk factors in investment decisions.

3.1 Introduction

The profitability anomaly has been extensively documented in the literature. Novy-Marx (2013), Fama and French (2015), and Hou et al. (2015) among others show that more profitable firms tend to deliver on average higher equity returns. Scholars have different approaches in explaining this pricing anomaly. For instance, Fama and French (2015) use the dividend discount model in conjunction with clean surplus accounting to explain the relationship between profitability and average returns. From a rational pricing view, higher profitability indicates higher required rates, hence higher profitability firms would generate higher average returns. From an investment-based asset pricing approach, Hou et al. (2015) state that high expected profitability relative to low investment implies high discount rates, which are necessary to offset the high expected profitability to induce low net present values of new capital and new investment. Otherwise, firms would witness high net present values of new capital and keep on investing. On the other hand, low expected profitability relative to high investment implies low discount rates to counteract the low expected profitability or otherwise firms would observe the low net present values of new injected capital and hence decrease their investments. Therefore, a dividend discount model and capital budgeting perspective agree on the positive direction of expected returns for profitable firms.

A research question that evolves from the profitability anomaly is whether persistent profitability makes a difference in the realm of equity returns. In other words, if profitability is a pricing factor, would uncertainty surrounding profitability be priced in the cross-section of returns? Considering the case of two firms with the same expected profitability but one's profitability is more certain than the other, ceteris paribus. Would they have the same expected returns? For example, two firms in the oil and gas industry with similar profitability expectations but one's geographical location makes it more vulnerable to some uncertain weather conditions. Can both firms have similar expected returns? Motivated by this intuition, this chapter investigates whether the time-series volatility of expected profitability would have an impact on the cross-section of future equity returns, ceteris paribus.

This study shows that in the theoretical setting of Hou et al. (2015), expected stock return is an increasing function of both expected profitability growth and its volatility. Moreover, motivated by a model provided by Hou et al. (2020), this chapter shows that the standard deviation of both expected profitability and expected asset growth have an impact equity returns. While the profitability-returns relationship has been extensively studied, the volatility of profitability has received less focus in the literature. This study aims to fill this gap. Specifically, the impact of the volatility of expected profitability on the cross-section of stock returns is examined.

A new proxy of the uncertainty surrounding firms expected profitability is introduced. More specifically, the standard deviation of expected changes in profitability for the coming 5-years is estimated where change of profitability are computed as the changes of net income provided by equity analysts scaled by the most recent book-value of assets. For robustness, alternative measure of expected profitability is used to alleviate sample selection bias and overcome the limitation of using only stocks covered by analysts. Finally, the impact of the volatility of historical asset growth on the cross-section of stock returns is examined.

Findings suggest that investors require a significant positive premium for holding stocks with high volatility surrounding expected profitability. An investment strategy that takes a long position in stocks with high uncertainty of profitability (UP) and a short position in stocks with low UP generates an annual excess (risk-adjusted) return of 8% (10%). This premium can not be explained by traditional risk-factors or firm characteristics in both portfolio and stock-level analyses. Analogously, a portfolio that take a long position in stocks with high uncertainty of asset growth (UAG) and take a short position in stocks with low UAG generates an annual excess (risk-adjusted) return of 7% (12%).

An uncertainty of profitability factor (UPF) of high minus low volatile profitability firms and an uncertainty of asset growth factor (UAGF), cannot be explained by the size (SMB), book-to-market (HML), investment (CMA), and profitability (RMW) factors of Fama and French (2015), or the profitability (R_{ROE}) and investment ($R_{I/A}$), factors of Hou et al. (2015). UPF generates higher returns in economic states when: i) the market-wide profitability is high, ii) the market volatility is low, iii) the default spread is low, and/or iv) the expected inflation increases, justifying the premium earned by the high-UP firms.

This chapter documents that the predictive power of UP and UAG is robust even after accounting for the profitability and investment premium. The premium associated with UP and UAG remain significant in the presence of a wide control battery including size, investment, profitability, and idiosyncratic volatility and is robust to different asset pricing models. Results highlight the significance of the volatility of common risk factors as potential fundamental uncertainty proxies.

This chapter findings have several implications. First, high idiosyncratic volatility might be partially caused by high volatility of profitability and/or high volatility of asset growth. In a feedback relation between returns' idiosyncratic volatility and UP (UAG), UP (UAG) tends to better explain volatility (rather than the other way around). Second, the chapter documents that the UP (UAG) premia is conditional on the level of profitability (asset growth). That is, the UP premium is higher for high profitable firms in an implication that investors are more averse to the volatility of profitability for more profitable firms (i.e. firms with higher returns). Similarly, the UAG premium is higher for firms with low investment growth, implying that investors are more averse to the volatility of asset growth for firms with low asset growth (i.e. firms with higher returns). Finally, the chapter documents that the UP strategy can largely improve the profitability strategy by forming a portfolio that is high on both profitability and UP generating a monthly risk-adjusted return of 1.04% compared to of the profitability strategy alpha of 0.38%.

The remainder of the chapter is organized as follows. Section 3.2 provides a brief literature review. Section 3.3 presents a theoretical motivation to investigate the volatility of profitability and asset growth. Section 3.4 provides details of variables estimation including the uncertainty of profitability and asset growth and describes sample. Section 3.5 presents empirical findings. Section 3.6 discusses some implications of the UP and UAG premium earned. Section 3.7 provides some robustness tests. Section 3.8 concludes.

3.2 Literature Review

Profitability, cash-based earnings, accruals, and asset growth were previously identified as pricing anomalies and were substantially studied in the literature (e.g., Haugen and Baker (1996), Cohen et al. (2002), Fama and French (2006a, 2008a, 2015), Novy-Marx (2013), and Hou et al. (2015)). Fama and French (2008a) find that more profitable firms (where profitability is measured as equity income scaled by book value of equity) are associated with abnormally high returns, but provide little evidence that unprofitable firms earn unusually low returns. The profitability anomaly was also identified by Novy-Marx (2013) who documents that profitable firms (where profitability is measured as high gross profit to assets) generate significantly higher returns than unprofitable firms. He finds that profitability strategy is a growth strategy and hence identifies it as a good hedge for value investing. Cohen et al. (2003) empirically find that 75-80% of the unconditional cross-sectional variance of book-to-market is explained by expected future 15-year profitability and persistence of book-to-market 15 years into the future. Complementing the investment and profitability studies, Hou et al. (2020) study the impact of expected investment growth on equity returns. They build a factor based on the the expected investment growth and complement the $q-$factor model of Hou et al. (2015) with this new factor to explain a wide range of pricing anomalies including profitability and investment.[1]

A literature initiated by Sloan (1996) shows that high accruals are associated with lower stock returns. He posits that earnings performance attributed to the accrual component exhibits lower persistence than earnings performance attributed to the cash flow component. He concludes that the accrual anomaly arises because investors believe that accruals are as persistent as cash flows, which leads to mispricing. Thus, firms with relatively high (low) accruals would generate negative (positive) future returns. In contrast, Ball et al. (2016) explain the accrual anomaly differently: firms with high accruals earn lower future returns because they are less profitable on a cash basis. They showed that cash-based operating profitability better explains the cross-section of expected returns than gross or operating profitability and net income and it subsumes the accruals anomaly.

Despite the substantial profitability-related studies in the accounting and asset pricing literature, less attention has been drawn to the uncertainty surrounding the pricing factors (such as profitability and asset growth) in empirical research. In common asset pricing models, a prevalent assumption is that all investors have the same estimates of expected returns and probability distribution of returns for all securities. This assumption is not necessarily valid, as pointed out by Knight (1921). Pástor and Veronesi (2003) argue that uncertainty about profitability raises the firm's valuation because it increases expected future payoffs without

[1]With the exception of Hou et al.'s (2020) work, many of the profitability studies would use past performance as a proxy for future profitability without accounting for potential risk that can be associated with the expected profitability.

impacting the discount rate thanks to the convex relation between growth rate and terminal value. They show that idiosyncratic volatility of equity return increases with this uncertainty. However, they did not document an effect of this uncertainty on expected stock returns.

This study is motivated by the idea that the level of risk faced by investors in making decisions can itself be uncertain. One way to capture this uncertainty is by assessing the volatility of risk proxies such as the uncertainty surrounding profitability, which is the focus of this study. Hence, this study does not focus on profitability per se but on how the volatility of expected profitability as perceived by consensus (captured by the mean analysts forecasts) would impact future equity returns.[2] This chapter extends the classical profitability pricing anomaly and shows that the volatility of profitability is also associated with future returns. Analogously, the uncertainty of asset growth is also investigated.

3.3 Theoretical Motivation

The theoretical motivation to study the volatility of profitability is based on an economic model presented by Hou et al. (2020). This section briefly discusses the model and its implication. Consider a stochastic general equilibrium model with infinite periods $s \in \{0, \infty\}$ and and N heterogeneous firms indexed with $i \in \{1, N\}$. Each period, firms have to decide the optimal inputs to maximize the operating profits. Firm i at time t owns productive assets $\mathrm{A}_{i,t}$ and return on assets (profitability) of $\Pi_{i,t}$. The following period profitability, $\Pi_{i,t+1}$, is stochastic and is subject to a vector of aggregate shocks and a vector of firm-specific shocks that impact only firm i. At time t, firm's i investments is $\mathrm{I}_{i,t}$ and productive assets depreciate at a rate δ, i.e., $\mathrm{A}_{i,t+1} = \mathrm{I}_{i,t} + (1-\delta)\mathrm{A}_{i,t}$. To install new capital firms are subject to quadratic adjustment costs, $(\mathrm{a}/2)(\mathrm{I}_{i,t}/\mathrm{A}_{i,t})^2\mathrm{A}_{i,t}$ where a>0 is a constant parameter.

[2] Incorporating analysts' forecasts of earnings to estimate expected stock returns is not novel to the literature. Abarbanell and Bushee (1998) provide evidence that firms' fundamental signals provide information about future returns that is associated with future earnings news. Frankel and Lee (1998) find that errors in consensus analyst earnings forecasts are predictable and document that the ratio of a firm's fundamental values to its market price is a good predictor of long-term cross-sectional returns. Diether et al. (2002) document that firms that are prone to more dispersion of opinions among analysts regarding end-of-year earnings forecasts, exhibit lower future stock returns.

Operating cash flow of firm i at t are $\Pi_{i,t}\mathrm{A}_{i,t}$, that is used to finance investment and adjustment costs. If the free cash flow is positive, it is distributed to the household in terms of dividends, $\mathrm{D}_{i,t} = \Pi_{i,t}\mathrm{A}_{i,t} - \mathrm{I}_{i,t} - (\mathrm{a}/2)(\mathrm{I}_{i,t}/\mathrm{A}_{i,t})^2\mathrm{A}_{i,t}$. Otherwise, a negative $\mathrm{D}_{i,t}$ implies equity issuance. Firms are only equity financed. Let M_{t+1} be the stochastic discount factor, firm i chooses the optimal stream of investment $\{\mathrm{I}_{i,t+s}\}_{s=0}^{\infty}$ to maximize cumulative dividends, $\mathrm{V}_{i,t} \equiv \max_{\{I_{t+s},\, A_{t+s+1}\}} E_t[\sum_{s=0}^{\infty} M_{t+s}D_{i,t+s}]$. Let $q_{i,t}$ be the Lagrangian multiplier associated with the capital accumulation equation $\mathrm{A}_{i,t+1} = \mathrm{I}_{i,t} + (1-\delta)\mathrm{A}_{i,t}$. The investor maximization problem of firm i becomes:

$$
\begin{aligned}
\mathcal{L} &= E_t\left[\sum_{s=0}^{\infty} M_{t+s}D_{i,t+s} - q_{i,t+s}\left(\mathrm{A}_{i,t+1+s} - \mathrm{I}_{i,t+s} - (1-\delta)\mathrm{A}_{i,t+s}\right)\right] \\
&= \Pi_{i,t}\mathrm{A}_{i,t} - \mathrm{I}_{i,t} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t}}{\mathrm{A}_{i,t}}\right)^2 \mathrm{A}_{i,t} - q_{i,t}\left(\mathrm{A}_{i,t+1} - \mathrm{I}_{i,t} - (1-\delta)\mathrm{A}_{i,t}\right) + \\
&\quad + E_t\Big[M_{t+1}\Big(\Pi_{i,t+1}\mathrm{A}_{i,t+1} - \mathrm{I}_{i,t+1} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 \mathrm{A}_{i,t+1} \\
&\quad - q_{i,t+1}\left(\mathrm{A}_{i,t+2} - \mathrm{I}_{i,t+1} - (1-\delta)\mathrm{A}_{i,t+1}\right)\Big) + \ldots\Big].
\end{aligned}
\tag{3.1}
$$

The first order conditions with respect to $\mathrm{I}_{i,t}$ and $\mathrm{A}_{i,t+1}$ are:

$$
q_{i,t} = 1 + a\frac{\mathrm{I}_{i,t}}{\mathrm{A}_{i,t}}, \tag{3.2}
$$

$$
q_{i,t} = E_t\left[M_{t+1}\left(\Pi_{i,t+1} + \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 + q_{i,t+1}(1-\delta)\right)\right]. \tag{3.3}
$$

Substituting Equations (3.2) and (3.3) into Equation (3.1) and using the linear homogeneity of the adjustment costs ($\Phi = a/2(I/A)^2A = I\partial\Phi/\partial I + A\partial\Phi/\partial A$), $V_{i,t}$ can be written as:

$$
\begin{aligned}
V_{i,t} =& \Pi_{i,t}\mathrm{A}_{i,t} - \mathrm{I}_{i,t} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t}}{\mathrm{A}_{i,t}}\right)^2 \mathrm{A}_{i,t} - q_{i,t}\left(\mathrm{A}_{i,t+1} - \mathrm{I}_{i,t} - (1-\delta)\mathrm{A}_{i,t}\right) + \\
& + E_t\Big[M_{t+1}\Big(\Pi_{i,t+1}\mathrm{A}_{i,t+1} - \mathrm{I}_{i,t+1} - a\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)\mathrm{I}_{i,t+1} + \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 \mathrm{A}_{i,t+1} \\
& - q_{i,t+1}\left(\mathrm{A}_{i,t+2} - \mathrm{I}_{i,t+1} - (1-\delta)\mathrm{A}_{i,t+1}\right)\Big) + \dots\Big] \\
=& \Pi_{i,t}\mathrm{A}_{i,t} - \mathrm{I}_{i,t} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t}}{\mathrm{A}_{i,t}}\right)^2 \mathrm{A}_{i,t} + q_{i,t}(\mathrm{I}_{i,t} + (1-\delta)\mathrm{A}_{i,t}) \\
=& \underbrace{\Pi_{i,t}\mathrm{A}_{i,t} - \mathrm{I}_{i,t} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t}}{\mathrm{A}_{i,t}}\right)^2 \mathrm{A}_{i,t}}_{\mathrm{D}_{i,t}} + \underbrace{q_{i,t}\mathrm{A}_{i,t+1}}_{\mathrm{P}_{i,t}},
\end{aligned}
\tag{3.4}
$$

where $\mathrm{D}_{i,t}$ is dividend and $\mathrm{P}_{i,t}$ is the ex-dividend stock price. Equity returns at time $t+1$ ($r^S_{i,t+1}$) is equal to investment return ($r^I_{i,t+1}$) and can be written as:

$$
\begin{aligned}
r^S_{i,t+1} &= \frac{\mathrm{P}_{i,t+1} + \Pi_{i,t+1}\mathrm{A}_{i,t+1} - \mathrm{I}_{i,t+1} - \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 \mathrm{A}_{i,t+1}}{\mathrm{P}_{i,t}} \\
&= \frac{\Pi_{i,t+1} + \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 + q_{i,t+1}(1-\delta)}{q_{i,t}} = r^I_{i,t+1}.
\end{aligned}
\tag{3.5}
$$

Substituting Equations (3.2) and (3.3), the following formula for equity return is obtained:

$$
r^S_{i,t+1} = \frac{\Pi_{i,t+1} + \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 + \left(1 + a\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)(1-\delta)}{E_t\left[M_{t+1}\left(\Pi_{i,t+1} + \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 + \left(1 + a\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)(1-\delta)\right)\right]}.
\tag{3.6}
$$

Equation (3.6) can be decomposed into a part related to expected profitability $\mathrm{OP}_{i,t+1} = \Pi_{i,t+1}$ and a part related to expected asset growth $\mathrm{AG}_{i,t+1} = \frac{a}{2}\left(\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)^2 + \left(1 + a\frac{\mathrm{I}_{i,t+1}}{\mathrm{A}_{i,t+1}}\right)(1-\delta)$:

$$
\begin{aligned}
r^S_{i,t+1} &= \frac{\mathrm{OP}_{i,t+1} + \mathrm{AG}_{i,t+1}}{E_t\left[M_{t+1}\left(\mathrm{OP}_{i,t+1} + \mathrm{AG}_{i,t+1}\right)\right]} \\
&= \frac{\mathrm{OP}_{i,t+1} + \mathrm{AG}_{i,t+1}}{cov(M_{t+1}, \mathrm{OP}_{i,t+1}) + cov(M_{t+1}, \mathrm{AG}_{i,t+1}) + \left(E[\mathrm{OP}_{i,t+1}] + E[\mathrm{AG}_{i,t+1}]\right)E[M_{t+1}]} \\
&= \frac{\mathrm{OP}_{i,t+1} + \mathrm{AG}_{i,t+1}}{(\rho_{OP,M}\sigma_{OP} + \rho_{AG,M}\sigma_{AG})\sigma_M + \left(E[\mathrm{OP}_{i,t+1}] + E[\mathrm{AG}_{i,t+1}]\right)E[M_{t+1}]}.
\end{aligned}
\tag{3.7}
$$

From Equation (3.7), the standard deviation of both expected profitability and expected asset growth impact equity returns. If expected profitability and asset growth covary negatively with the stochastic discount factor (they are high when consumption growth is high) then *ceteris paribus* higher volatility of profitability and volatility of asset growth would lead to higher equity return. Considering a constant $q_{i,t}$ at the denominator Hou et al. (2020) use Equation (3.5) to justify the positive premium associated with expected asset growth. Different from Hou et al. (2020) in Equation (3.7), this section considers the case when $q_{i,t}$ is optimally determined. From Equation (3.7), if a firm's profitability and asset growth do not covary with the stochastic discount factor, then the expected stock return will be exactly the risk-free rate while a positive (negative) covariance between profitability and asset growth with the stochastic discount factor would lead to a negative (positive) excess return. In this last case the standard deviations of profitability and asset growth (σ_{OP} and σ_{AG}) would amplify the required premium.

3.4 Data and Variables

The sample consists of all NYSE/AMEX/NASDAQ ordinary common equity shares (with share code 10 and 11). Each stock has to be covered by the Institutional Brokers' Estimate System (IBES) database due to the use of analyst forecasts in the estimation of the profitability growth and its volatility. Regulated and financial services firms (one-digit SIC codes 4 and 6) are excluded from the sample. The sample extends from January 1984 to December 2016. The starting date of the sample is restricted to the implementation of more sophisticated electronic system by the New York Stock Exchange in addition to the availability of rich data by IBES. As will be illustrated below, the uncertainty of profitability (UP) is computed as the standard deviation of expected profitability growth over the previous 60 months. Hence, cross-sectional return predictability is reported from January 1989 to December 2016. Stocks with price per share less than $1 are excluded to reduce liquidity concerns. Each month contains, on average, 1,824 stocks over the sample horizon, with a monthly minimum and maximum of 1,279 and 2,282 stocks, respectively. Accounting data are 3-months lagged and accounting ratios are winsorized at the 1%-99% level. Monthly and daily returns are from CRSP and accounting data are from COMPUSTAT.[3]

3.4.1 The Uncertainty of Profitability

The IBES database provides analysts' annual earnings per share forecasts up to 5 years ahead. At the end of each month, the expected net income, ($\mathrm{E}_t[\mathrm{NI}_{i,y}]$), is computed for each of the following 5 years as the product of the mean analysts' earnings per share forecast ($\mathrm{E}_t[\mathrm{EPS}_{i,y}]$) for firm i for year y and the number of shares outstanding:

$$\mathrm{E}_t[\mathrm{NI}_{i,y}] = \mathrm{E}_t[\mathrm{EPS}_{i,y}] \times \text{Shares Outstanding}. \tag{3.8}$$

The expected profitability at each year, $\mathrm{E}_t[\Pi_{i,y}]$, for firm i is then computed as:

$$\mathrm{E}_t[\Pi_{i,y]} = \frac{\mathrm{E}_t[\mathrm{NI}_{i,y}]}{TA_{i,t}}, \tag{3.9}$$

where $\mathrm{TA}_{i,t}$ is the most recent annual book value of assets observed at month t and y=1,..,5. Estimated net income is deflated by assets, rather than book value of equity, in order to avoid a weak-defined profitability measure in case of negative book value of equity.[4] It is opted not to scale net income by market capitalization to avoid conflating the profitability with the book-to-market estimation. Each firm will have a maximum of 5-years of profitability forecasts and a minimum of 1 year forecast for the following 5 years depending on data availability. At each month, the changes for each of the 5-years ahead expected profitability ($\Delta\Pi_{i,y=1,..,5}$) are estimated. Then, the uncertainty of expected profitability change, $\mathrm{UP}_{i,t}$, is computed at each month as the standard deviation of the total annual changes of the 5 years-ahead expected profitability over the previous 60 months as follows:

$$\mathrm{UP}_{i,t} = \sqrt{\frac{\sum_{n=1}^{N}(\pi_n - \mathrm{E}_t[\pi])^2}{N}} \tag{3.10}$$

[3]Fama and French (1993, 2015) factors are obtained from the online data 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/`.

[4]For robustness, net income is also scaled by the book value of equity and the values for firms with negative book value of equity are replaced with missing values (see Section 3.7).

where $\pi_n = \sum_{y=1}^{5} \Delta\Pi_{i,y}$ is the total annual changes of the 5 years-ahead expected profitability and N is the total number of months over which the standard deviation is computed and is equal to 60 months.[5]

Changes in profitability scaled by assets are used instead of profitability growth as proposed in Section 3.3 as changes in profitability allow to account for observations where net income is estimated to be null or turns to positive earnings from a previous year's losses. Moreover, it is opted to account for the total changes in profitability, instead of a one-year ahead total changes for several reasons. First, the one-year ahead forecast may not be an adequate investing horizon particularly for long-term equity investors who would consider profitability for longer horizons in their investment decisions. Second, taking the total changes mitigates the effect that earnings might be delayed due to slower investment's implementation. For instance, assuming a firm that is undergoing some investments that would generate expected cash flows over the following year. Any delay in the investment implementation would urge analysts to defer the expected rise in earnings forecasts for at least one extra year. By accounting for up to 5-years ahead in forecasts help in accounting for such delays.

3.4.2 The Asset Growth Uncertainty

The uncertainty of asset growth (UAG) is estimated as the standard deviation over the previous 5 years of a firm's tangible asset growth where tangible asset growth (AG) is measured as the sum of the change of gross property plant and equipment (GPPE) and the change of working capital (WC) scaled by the sum of lagged GPPE and WC as follows:[6]

$$\mathrm{AG}_{i,t} = \frac{\Delta\mathrm{GPPE}_{i,t} + \Delta\mathrm{WC}_{i,t}}{\mathrm{GPPE}_{i,t-1} + \mathrm{WC}_{i,t-1}}, \tag{3.11}$$

and

$$\mathrm{UAG}_{i,t} = \sqrt{\frac{\sum_{n=1}^{5}(\mathrm{AG}_n - \mathrm{E}_t[\mathrm{AG}])^2}{5}}. \tag{3.12}$$

[5]Section 3.7 provides several robustness tests to different time horizons of the estimated UP.

[6]As the IBES database does not provide analysts' forecast regarding asset growth, the volatility of past asset growth is used.

It is opted to use asset growth as the tangible asset growth rather than the total growth in assets as common in the literature in order to account more strictly to the portion of assets that impact operations (i.e., to exclude goodwill and other non-operations-related assets).

3.4.3 Control Variables

To ensure that the uncertainty surrounding profitability is not a proxy for common risk factors, a battery of control variables is used:

(A) Standard-Risk Controls:

- Market beta (β^{MKT}) is estimated with the Capital Asset Pricing Model with daily returns over a month.
- SIZE is computed as the natural logarithm of market capitalization (MCAP) calculated as the product of price per share and common shares outstanding (Fama and French (1992)).
- Book-to-market (BM) is computed as the book value of shareholders' (Compustat annual item seq) equity plus deferred taxes and investment tax credit (txditc) minus redemption (pstkrv), liquidation (pstkl) or par value (pstkl) of preferred stock (depending on availability) all scaled by current equity market value. Following Davis et al. (2000), if the book value of shareholders' is not available, shareholders' equity is the common equity (ceq) plus the par value preferred stock, or otherwise the book value of assets (at) minus total liabilities (lt). Accounting data are updated annually and are lagged three months compared to market data.

(B) Profitability and Investment-Related Controls:

- Operating profitability (OP) is measured as revenues (revt) minus cost of goods sold (cogs), minus selling, general, and administrative expenses (xsga), minus interest expense (xint) all divided by book equity for the previous fiscal year ending Fama and French (2015). For this measure, OP for firms with negative book value of equity is replace with missing values.

- Gross profit to assets (GPA) is computed as revenues minus cost of goods sold scaled by total assets (at) as in Novy-Marx (2013).
- Return on Assets (ROA) is estimated as the firm's most recent net income (ni) scaled by the previous fiscal year's book value of total assets (at).
- Since the main measure is the standard deviation of the expected profitability changes over the following 5 years, a relevant control which the total return on assets for the following 5 years (TROA5) is included. TROA5 is estimated as the sum of annual changes of the 5 years-ahead expected profitability.
- Investment (INV) is defined as the change of total assets (at) from the fiscal year ending y-2 to the fiscal year ending y-1, divided by t-2 total assets, as in Fama and French (2015).

(C) Uncertainty-Related Controls:

- Uncertainty of book-to-market (UNC) is estimated by the standard deviation of the time-series of daily expected book-to-market ratios scaled by their mean over the previous 12 months as explained in Chapter 2 .
- Turnover (TURN) of each stock is computed as the ratio of trading volume to shares outstanding in a month.
- Dispersion in analyst forecasts (DISP) is the standard deviation of annual earnings per share forecasts, scaled by the absolute value of the mean earnings forecast (see Diether et al. (2002)).
- Exposure to market volatility (β^{VXO}) is estimated from a bivariate time series regression of the stock excess returns against the market excess return and the changes in implied volatility using daily data in a month following Ang et al. (2006).

(D) Trading- and Distribution-Related Controls:

- Momentum (MOM) is the cumulative return of a stock over the previous 11 months, excluding the most recent (portfolio formation) month (Jegadeesh and Titman, 1993).
- Illiquidity (ILLIQ) is measured following Amihud (2002) as

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

  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.
- Short-term reversal (STR) is the stock's last month return (the return of the portfolio formation month) as in Jegadeesh (1990).
- Maximum return (MAX) is the highest daily return of a stock in the previous month, used to control for lottery-like features as in Bali et al. (2011).
- Idiosyncratic volatility (IVOL) is measured as the standard deviation of daily excess residuals based on the Fama and French (1992) SMB and HML factors over the previous month as in Ang et al. (2006).
- Total volatility (TVOL) is computed as the standard deviation of daily returns over the previous month.
- Idiosyncratic Skewness (ISKEW) is computed as the skewness of the stock's daily residuals over the past month based on the following regression (Harvey and Siddique, 2000):

$$R_{i,d} = a_i + b_i R_{m,d} + c_i R_{m,d}^2 + \epsilon_{i,d}. \tag{3.13}$$

- Coskewness (COSK) is estimated as the loading c on the square of daily excess market returns over the past month based on Equation 3.13.

3.5 Empirical Results

3.5.1 Analysis of UP Portfolio Characteristics

This section examines how the time-series average portfolio characteristics vary for different levels of the uncertainty of profitability (UP). Specifically, each month stocks are divided in 10 decile portfolios based on UP and the time-series average of the cross-sectional mean firm characteristics is computed in each decile. Results are reported in Table 3.1. These characteristics include the market beta (β^{MKT}), market capitalization in million US dollars (MCAP), book-to-market ratio (BM), operational profitability (OP) as per Fama and French (2015), gross profit to assets (GPA) as per Novy-Marx (2013), return on assets (ROA), the total expected return on assets for the following 5 years (TROA5), investment (INV) following Fama and French (2015), the uncertainty surrounding book-to-market (UNC) estimated in Chapter 2, the uncertainty surrounding asset growth (UAG) as per Equation 3.12, turnover (TURN), dispersion in analysts' forecast (DISP) as per Diether et al. (2002), exposure to market volatility (β^{VXO}), momentum (MOM), the Amihud (2002) illiquidity indicator (ILLIQ), short-term reversal (STR), proxy for lottery-like stocks (MAX) as in Bali et al. (2011), idiosyncratic volatility (IVOL), total volatility (TVOL), idiosyncratic skewness (ISKEW), co-skewness (COSK), and age is the firm's number of years since it first appeared on CRSP. Price per share (Pr./Shr.) is the average price per share per portfolio decile in US dollars. Market share (Mkt. shr.) is the market capitalization of each decile to the total sample market capitalization. Number of stocks is the average number of firms in each decile. Characteristics are reported for the month of portfolio formation.

There are several characteristics patterns when moving from low-UP (decile 1) to high-UP decile (decile 10), as shown in Table 3.1. First, there is a clear monotonic increase in β^{MKT} with UP increasing while there is no pattern in MCAP when moving from decile 1 to 10. High-UP stocks are more likely to be growth stocks with higher investment as inferred from a monotonic decline in BM and an increase in INV when moving from low to high-UP deciles. Profitability (estimated using different proxies- OP, GPA, and ROA) is declining with UP increasing. That is, high-UP stocks tend to be low on profitability, indicating that firms with lower realized profitability are more prone to exhibit higher uncertainty in the expected profitability. However, the outlook for high UP-firms future profitability is positive as these firms have higher expected profitability on average for the following five years as indicating by the increasing pattern of TROA5. Firms with high uncertainty regarding their expected profitability are also exhibiting higher uncertainty of book-to-market and asset growth as indicated by the almost monotonic increase of UNC and UAG, respectively. Additionally, high-UP firms have higher turnover and dispersion in analysts' forecasts given that these two measure are established in the literature as proxies for uncertainty and divergence of opinions (see e.g., Hong and Stein (2007) and Diether et al. (2002)). There is an increasing pattern in IVOL and MAX as UP increases, implying lottery characteristics may also be associated with high-UP stocks. High-UP stocks are also more negatively co-skewed and are relatively younger firms.

In line with Pástor and Stambaugh (2003), Table 3.1 documents that high uncertainty surrounding profitability decreases with BM and increases with idiosyncratic volatility and firm's age. This helps draw preliminary inferences regarding these firms for which expected profitability is more volatile given that they are new to investors and may have some uncertain growth potential. Results in Table 3.1 may also provide some inference regarding potential stock return predictors that contribute in explaining the UP premium. These include higher market beta, higher UNC, more negative co-skewness as stocks with these characteristics tend to generate higher future returns (Sharpe (1964), Harvey and Siddique (2000)).

Table 3.2 reports the monthly time-series averages of the cross-sectional correlations among various key variables. The negative UP-BM and positive UP-INV correlations confirm that high-UP stocks are more likely to be growth firms and invest more on average. UP is positively correlated with IVOL, TVOL, and MAX. This suggest that it is more likely that firms with more volatile profitability are more prone to returns volatility. Yet, it can also imply that volatile stocks are likely to exhibit high uncertainty surrounding profitability. For this, the relationship between IVOL on one hand and UP and UAG on the other hand, will be examined thoroughly in Section 3.6.

3.5.2 Univariate Portfolio Analysis

UP - Univariate Portfolio Analysis

To test the impact of the uncertainty surrounding profitability (UP) on equity returns, UP is analyzed on the portfolio level. Ten value-weighted and equal-weighted decile portfolios are formed by sorting individual stocks on the basis of UP, where decile 1 (decile 10) contains stocks with the lowest (highest) UP. Table 3.3 reports the average excess and risk-adjusted returns for value-weighted portfolios (Panel A) and equal-weighted portfolios (Panel B) for the month subsequent to portfolios formation. Risk-adjusted returns are estimated using different factor models: (i) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F alpha); (ii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); and (iii) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $\text{R}_{I/A}$ (QF alpha). The second set of models in Table 3.3 considers the 3F, 5F, and QF factor models augmented by Carhart's (1997) momentum factor (MOM), while the last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the second set.

Table 3.3 shows that risk-adjusted returns increase when moving from the first (low) to the last (high) UP decile across the different asset pricing models. All models cannot explain the UP premium as observed in the last row reporting the difference in alphas between the high- and low-UP decile ($10-1$) hedge portfolios, with the corresponding Newey and West (1987) t-statistic (adjusted for six lags) shown in parentheses. For instance, the alpha spread between high and low UP portfolios generated by the different models ranges from 0.66% (t-stat. 2.47) for the 3F model augmented by momentum to 0.95 (t-stat 2.36) for case of the QF model. This implies an annualized 7.9-11.4% higher return for the high UP decile. In terms of average raw returns, the high-UP decile delivers an economically and statistically significant 0.70% (t-stat of 2.15) higher return per month compared to the low-UP decile.

Next, it is examined whether the risk-adjusted return differences between the low- and high-UP portfolios are due to outperformance of high-UP stocks or underperformance of low-

UP stocks by focusing on the economic and statistical significance of the risk-adjusted returns (alphas) of decile 1 versus decile 10 in the value-weighted portfolios presented in Panel (A). As seen in the last row of Table 3.3, alphas of stocks in decile 10 (high-UP) are all positive as well as economically and statistically significant for all models, whereas the corresponding alphas of stocks in decile 1 (low-UP stocks) are negative and/or statistically insignificant. For example, in the 7F model (5F + MOM + LIQ), the outperformance of the high decile alpha contributes approximately 80% to the overall alpha spread while the performance of the first decile contributes is statistically insignificant. It can hence be concluded that the significantly positive alpha spread between the low- and high-UP stocks is mainly due to outperformance by high-UP stocks.

Panel B Table 3.3 reports excess and risk-adjusted returns for the equal-weighted portfolios of stocks sorted by UP. The differential return spread between high- and low-UP deciles prevails and is somewhat more pronounced due to the greater influence of smaller and higher UP stocks in equal-weighted portfolios. Overall, this set of findings indicate that the volatility of estimated profitability cannot be explained by long-established key risk factors including the market, size, value, investment, profitability, momentum and liquidity factors of Fama and French (1993, 2015), Carhart (1997), and Pástor and Stambaugh (2003).

UAG - Univariate Portfolio Analysis

Motivated by the theoretical intuition of Section 3.5.4 and the premium associated with firms exhibiting volatility surrounding their expected profitability, the volatility of asset growth is investigated. More specifically, each month stocks are sorted into 10 decile portfolios based on the uncertainty of their asset growth (UAG) estimated as per equation 3.12 and then examine the subsequent month excess and risk-adjusted returns of these 10 portfolios and a hedging portfolio that goes long in the high UAG decile and short in the low UAG decile.

Table 3.4 reports the average excess (raw) and risk-adjusted returns for value-weighted portfolios (Panel A) and equal-weighted portfolios (Panel B). Risk-adjusted returns are estimated using different factor models: (i) the three-factor model of Fama and French (1993) with

MKT, SMB, and HML factors (3F alpha); (ii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F alpha); and (iii) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $\text{R}_{I/A}$ (QF alpha). The second set of models in Table 3.4 considers the 3F, 5F, and QF factor models augmented by Carhart's (1997) momentum factor (MOM), and the last set adds the liquidity factor (LIQ) of Pástor and Stambaugh (2003) to the second set. Table 3.4 shows that risk-adjusted returns increase when moving from the first (low) to the last (high) UAG decile across the different asset pricing models. The alpha spread between high and low UAG portfolios generated by the different models ranges from 0.37% (t-stat. 1.73) for the 3F model to 1.04 (t-stat. 5.07) for the QF model augmented by the momentum and liquidity factors. Overall, results in Table 3.4 confirm a premium associated with high-UAG firms.

3.5.3 Stock Level Cross-Sectional Regressions

To test the UP premium on the stock-level, this section examines the cross-sectional relation between the volatility of estimated profitability and expected returns at the individual stock-level using the Fama and MacBeth (1973) rolling regression approach. This methodology helps control for several risk factors and firm characteristics simultaneously to ensure that UP is distinct from common cross-sectional return predictors. Table 3.5 shows the time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month-ahead excess stock returns on UP and a battery of controls based on the following specification:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}\text{UP}_{i,t} + \gamma_{2,t}X_{i,t} + \epsilon_{i,t+1}, \tag{3.14}$$

where $R_{i,t+1}$ is the excess return on stock i in month t+1, $\text{UP}_{i,t}$ is uncertainty of profitability estimated as per Equation (3.10), and $X_{i,t}$ is a set of lagged firm-specific control variables. These include the market beta (β^{MKT}), market capitalization (SIZE), book-to-market (BM), operating profitability (OP), investment (INV), gross profit to assets (GPA), return on asset (ROA), the total estimated returns on assets for the following 5 years (TROA5), momentum (MOM), illiquidity (ILLIQ), uncertainty of book-to-market (UNC), uncertainty of asset growth

(UAG), turnover (TURN), dispersion in analysts forecasts (DISP), aggregate volatility exposure (β^{VXO}), short-term reversal (STR), lottery-stock demand (MAX), idiosyncratic volatility (IVOL), and idiosyncratic skewness (ISKEW). The t-statistics shown in parentheses in Table 3.5 are corrected for autocorrelation and heteroscedasticity using Newey-West estimator with six lags.

As shown in Table 3.5, both in the univariate (column(1)) and all the multivariate regressions with different sets of control variables (columns (2-18)), the uncertainty of profitability predicts higher future returns. Furthermore, the UP premium is both economically and statistically significant. The average slope coefficient of UP in the univariate and multivariate regressions is around 2.04. Hence, moving from decile 1 to decile 10, a stock's UP measure increase from 0.003 to 0.524 (as shown in the first row of Table 3.1). This implies a monthly increase of 1.06% in the typical stock's expected return when it moves from decile 1 to decile 10.

Columns (2-3) of Table 3.5 report the coefficient of a cross-sectional specification corresponding to the Fama and French (1993) 3-factor and Fama and French (2015) 5-factor models, respectively. Columns (4-5) add the momentum (MOM) and liquidity (ILLIQ) factors to the specification in columns (2-3). Columns (6-8) substitute the operating profitability of with alternative profitability measure GPA, ROA, TROA5 one at a time of Fama and French (2015) 5-factor corresponding to the specification of column (5). Columns (9-13) add uncertainty-related characteristics: UNC, UAG, TURN, DISP, and β^{VXO} one at a time to the baseline specification of column (5). Similarly, columns (13-18) add trading and distribution-related characteristics STR, MAX, IVOL, ISKEW, and COSK one at a time.

Concerning the other coefficients in the baseline regression model of column (5), β^{MKT} is statistically insignificant, in line with earlier studies. Consistent with prior findings, the coefficients of SIZE and INV are significantly negative, and a significant positive value (BM) effect is present (e.g., Fama and French (1992, 1993, 2015)). OP coefficient is positive but insignificant different from Fama and French's (2015) findings. Momentum is positive but insignificant in contrast to previous findings (e.g., Carhart (1997), Jegadeesh and Titman (1993)). Illiquidity coefficient is positive albeit insignificant, different from earlier empirical findings. Concerning the profitability alternative measure in column (6), the coefficient of GPA is positive and significant in line with Novy-Marx's (2013) findings.

Regarding the extended specifications (9-18), the positive and significant UNC is inline with the value uncertainty premium documented in Chapter 2. The positive coefficient of UAG is in line with the theoretical prediction in Section 3.5.4. The positive and slightly significant coefficients of TURN can be justified if turnover is considered as a proxy for uncertainty (Hong and Stein (2007)). DISP is negative but insignificant in contrast with the negative significant premium identified by Diether et al. (2002). The negative significant coefficient of β^{VXO} is consistent with prior studies (Ang et al. (2006)). STR negative significant coefficient is also in line with previous empirical results (Bali et al. (2011); Jegadeesh (1990)). Idiosyncratic volatility in column (16) is positive albeit insignificant is in contrast to the idiosyncratic volatility puzzle (Ang et al. (2006)). MAX, ISKEW, and COSK are all insignificant in contrast to prior findings (Bali et al. (2011), Harvey and Siddique (2000)). Stock-level analysis with controlling for the industry effect also confirms a robust UP premium. The corresponding results are presented in Panel B of Table 3.5. Overall, stock level cross-sectional analysis confirms the premium associated with volatility of profitability, and volatility of asset growth albeit the latter is not robust once UNC is controlled for. This cast some doubt on the correlation between the three volatility-related characteristics which is explored further in Section 3.5.4.

3.5.4 UP and UAG Factors Explained vs. Common Pricing Factors

This section tests if a risk-factor, that reflects the uncertainty of the profitability, is explained by other common risk factors. A new factor, UPF (uncertainty of profitability factor) is constructed from a triple ($3 \times 3 \times 3$) portfolios on size, operational profitability and uncertainty of profitability. Specifically, at the end of each month, the sample is divided into 3 groups based on market capitalization using the NYSE breakpoints for big (high 30%), medium-sized (middle 40%) and small stocks (low 30%). Independently, the sample is divided into 3 groups based on operational profitability using the NYSE breakpoints for the low, middle and high of the ranked values of gross profit to assets. Independently, the sample is divided into 3 groups (high 30%, middle 40%, and low 30%) based on the uncertainty of profitability using the NYSE breakpoints. Finally, 27 portfolios are formed by taking the intersection of the 3 size, 3 operational profitability, 3 uncertainty of profitability. Monthly value-weighted portfolios returns are computed for the following month, and the portfolios are rebalanced monthly. The profitability uncertainty factor (UPF) is the difference between high and low uncertainty of profitability (i.e. the difference between the simple average of the returns on the 9 high-UP portfolios and the simple average of the returns of the 9 low-UP portfolios after controlling for size and profitability).

Analogously, a factor based on the uncertainty of asset growth is constructed. At the end of each month, he sample is divided into 3 groups based on size using the NYSE breakpoints for big (high 30%), medium-sized (middle 40%) and small stocks (low 30%). Independently, the sample is divided into 3 groups based on the NYSE breakpoints for the low, middle and high of the ranked values of asset growth. Independently, the sample is divided into 3 groups (high 30%, middle 40%, and low 30%) based on the uncertainty of asset growth using the NYSE breakpoints. Finally, 27 portfolios are formed by taking the intersection of the 3 size, 3 asset growth, 3 uncertainty of asset growth. Monthly value-weighted portfolios returns are computed for the following month, and the portfolios are rebalanced monthly. The asset growth uncertainty factor (UAGF) is the difference between high and low asset growth uncertainty portfolios (i.e. the difference between the simple average of the returns on the 9 high-UAG portfolios and the simple average of the returns of the 9 low-UAG portfolios after controlling for size and asset growth).

First, it is examined whether the profitability uncertainty factor can be explained by documented pricing factors in the literature. Particularly, time-series regressions are conducted of the UPF against: i) the size (SMB), value (HML), profitability (RMW), and investment (CMA) factors of the Fama and French (2015) 5-factor model (5F) in Specification (1) in Panel A of Table 3.6 and its extension that is augmented by momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (7F) in Specification (2); ii) Hou et al.'s (2015) Q-model: size (SMB_Q), investment ($\text{R}_{I/A}$), and profitability (R_{ROE}) (QF) in

Specification (3) and its extension that is augmented by MOM and LIQ (6QF) in Specification (4). In all these specifications, the intercept (alpha) remains significant, implying that none of the above factors is able to fully explain the UPF returns. The alpha on the UPF is on average 0.4% per month (or annualized alpha of 4.4%).

Results in Panel A of Table 3.6 also confirm earlier inference (see Table 3.1 and 3.2) that firms with high UP are likely growth firms with lower profitability and higher investments given the corresponding negative significant loadings on HML in specifications and RMW and R_{ROE} in specifications (1-2), and $R_{I/A}$ in specifications (3-4).[7]

Similarly, Panel B of Table 3.6 report results of the time-series regressions of the UAGF on the same set of specifications of Panel A. Results of Panel B suggest that firms with high volatility concerning their asset growth are also likely to be growth, low profitability firms with high asset growth. Most importantly, results indicate that the uncertainty of asset growth can be a risk factor that can not be explained by common risk factors including asset growth itself as indicated by the economically and statically significant constant.

3.6 Discussion

This section further explores the characteristics of firms with high uncertainty of profitability in order to uncover some of the main factors generating the above documented premium.

3.6.1 Conditioning on Co-movement with Consumption Growth

Section 3.3 shows that if expected profitability and asset growth covary negatively with the stochastic discount factor (they covary positively consumption growth) then *ceteris paribus* higher volatility of profitability and volatility of asset growth would lead to higher equity return. This section tests this conjecture. Specifically, the UP and UAG premium are examined during

[7] $R_{I/A}$ reflects the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks.

periods when i) the expected one-year change in profitability and asset growth co-move with consumption growth (i.e., $\Delta C_y \times \Delta\Pi_{i,y} > 0$ and $\Delta C_y \times \text{AG}_{i,y} > 0$) and ii) the expected one-year change in profitability and asset growth do not co-move with consumption growth (i.e., $\Delta C_y \times \Delta\Pi_{i,y} < 0$ and $\Delta C_y \times \text{AG}_{i,y} < 0$).[8] Table 3.7 shows the results of the time series averages of the cross-sectional slope coefficients obtained by regressing monthly excess returns (in percentage) on lagged uncertainty of profitability (UP), and uncertainty of asset growth (UAG). Specification (1) shows results for the overall sample. Specification (2) shows results for the subsample where the expected change in profitability and asset growth co-move with consumption growth. Specification (3) shows results for the subsample where the expected change in profitability and asset growth do not co-move with consumption growth. The UP and UAG premium are positive and significant for the overall sample (specification (1)) and when the expected change in profitability and asset growth co-move with consumption growth (specification (2)), in line with the conjecture presented in Section 3.3.

3.6.2 UP and UAG vs. Market-wide and Macroeconomic Indicators

To better understand the behavior of the uncertainty in profitability in an economic and market context, periods when the UP spread is high are examined. The term UP spread is inspired by the HML value spread variable of Cohen et al. (2003). They refer to HML value spread as the difference between the log book-to-market of the high-value and the low-value portfolios. Similarly, the variable UP_{spread} is constructed as the difference between the average uncertainty of profitability of the high-UP decile portfolio and that of the low-UP decile where portfolios are sorted based on UP. Then, the time-series regressions are conducted of UP_{spread} against: i) the market profitability defined as the median GPA of firms in the sample, ii) the default spread (DEFS) defined as the spread between BAA- and AAA-rated corporate bonds, iii) expected inflation (EINF), iv) the change in the S&P100 volatility index (ΔVXO), and v) change in the Chicago Federal National Activity Index (ΔCFNAI), respectively. Results

[8] Consumption growth is obtained from the Federal Reserve Bank of Saint Louis. $\Delta\Pi_{i,y}$ is the expected one-year change in profitability ($\text{E}_t[\Pi_{i,y}]$) estimated as per Equation 3.9 and asset growth ($\text{AG}_{i,y}$) is estimated as per Equation 3.11.

in specification (1) of Panel A of Table 3.8 indicate that the UP_{spread} is lower when the overall market profitability is increasing as indicated by the negative significant coefficient of the market median GPA. In specification (2), there is no significant relationship between DEFS and UP_{spread}. Results in specification (3) indicate that the UP_{spread} is lower when expected inflation rises. Overall, the above results suggest that the UP_{spread} is likely to increase in states of economic conditions of low profitability, and lower expected inflation. In other words, the outlook of future earnings becomes uncertain during times of low profitability on the aggregate level.

Next, periods with relatively higher factor (UPF) returns are examined. Time-series regression is conducted of the UPF, constructed as explained in Section 3.5.4, as the dependent variables against the same regressors (GPA (market), DEF, EINF, ΔVXO, and ΔCFNAI) to test how high-UP stock returns would co-move with these variables. Results, shown in Panel B of Table 3.8, indicate that the UPF is likely to deliver higher returns during times of i) higher market-wide profitability (specification (1)), ii) lower default spread (specification (2)), iii) higher expected inflation (specification (3)), iv) lower changes in implied volatility (specification (4)), and v) higher changes of economic activity (specification (5)). Results in Panel B suggest that the returns of portfolio that is long on high-UP stocks and short in low UP-stocks co-move with good economic and low aggregate risk indicators, providing justification for the positive premium associated with high-UP stocks.

Analogously, Table 3.9 repeats the same analysis of Table 3.8 but for the UAG_{spread} and UAGF in Panels A and B, respectively. Specifically, the variable UAG_{spread} is constructed as the difference between the average uncertainty of asset growth of the high-UAG decile portfolio and that of the low-UAG decile where portfolios are sorted based on UAG. Then, the time-series regressions are conducted of the UAG_{spread} against: i) the market profitability defined as the median GPA of firms in the sample, ii) the default spread (DEFS) defined as the spread between BAA- and AAA-rated corporate bonds, iii) expected inflation (EINF), iv) the change in the S&P100 volatility index (ΔVXO), and v) change in the Chicago Federal National Activity Index (ΔCFNAI), respectively. Results in Panel A of Table 3.9 reveal a positive significant DEFS coefficient in specification (2). Results in specification (3) suggest that the UAG_{spread}

is lower when expected inflation rises. Overall, results in Panel A suggest that the UAG_{spread} is likely to increase in states of economic conditions of high default spread and lower expected inflation. In other words, the outlook of earnings growth is more uncertain during less favorable economic periods.

In Panel B of Table 3.9, a regression is conducted of the UAGF, constructed as explained in Section 3.5.4, as the dependent variables against the same regressors of Panel A to test how high-UAG stock returns would co-move with these variables. Results, shown in Panel B of Table 3.9, suggest that the UAGF is likely to deliver higher returns during times of i) higher market-wide profitability (specification (1)), ii) lower default spread (specification (2)), iii) lower changes in implied volatility (specification (4)), and iv) higher changes of economic activity (specification (5)). Results in Panel B suggest that UAGF co-move with favorable economic indicators, providing a justification for the positive premium associated with high-UAG stocks.

3.6.3 UP versus IVOL

Results in Tables (3.1) and (3.2) indicate that high-UP firms tend also to exhibit high idiosyncratic volatility. There is possibility of a feedback relation between UP and IVOL. For instance, it can be the case that firms' idiosyncratic volatility can be a pricing reflection of the uncertainty surrounding their profitability. Alternatively, high-UP stocks can be prone to high idiosyncratic returns volatility, which induce analysts (or consensus) to alter their estimates more often as a response to this idiosyncratic volatility. To analyze UP-IVOL relationship, we run the following system of panel regressions:

$$\text{IVOL}_{t+1} = \alpha_t + \beta_{\text{UP},t}\text{UP}_t + \gamma_t\text{X}_t \tag{3.15}$$

$$\text{UP}_t = \alpha_{t-60} + \beta_{\text{IVOL},t}\text{IVOL}_{t-60} + \delta_t\text{X}_{t-60}, \tag{3.16}$$

where X_t is a set of variables including standard controls (β^{MKT}, SIZE, BM, OP, INV, MOM, ILLIQ, and β^{VXO}). For better comparison among all coefficients, variables in this analysis are cross-sectionally standardized. Note the 1 and 60 months lags in equations 3.15 and 3.16, respectively given that IVOL is estimated over the previous month while volatility of profitability is estimated over the previous 60 months.

Results of the above system of regression equations are presented in Table 3.10 with and without firm fixed effect in models (1) and (2), respectively. The coefficient UP_t is 0.048 (t-stat of 8.86) in model (1) of Panel A, higher than the coefficient IVOL_{t-60} of 0.029 (t-stat of 6.68) in model (3) of Panel B. Results are similar when firm fixed effect are accounted for in specifications (2) and (4) of both Panels A and B, respectively. Moreover, R^2 Panel A are higher than the R^2 in Panel B, implying that UP is more likely to do a better job in explaining future IVOL than the other way around. While UP and IVOL are highly correlated, the impact of UP on future IVOL is higher than the impact of IVOL on future UP. In other words, in a feedback relation between UP and IVOL the impact that high UP has on IVOL is much higher than the impact that IVOL has on subsequent volatility of profitability. It can hence be concludes that high returns idiosyncratic volatility can be partially caused by high uncertainty of profitability.

Similar results would also hold for the volatility of asset growth. UP is replaced in equations 3.15 and 3.16 by UAG. It is then tested whether the relationship between UAG and IVOL would follow a similar feedback relation. Results in Panels A and B of Table 3.11 show that the volatility of asset growth has a stronger impact on idiosyncratic volatility as given by the higher UAG coefficients in Panel A compared to the IVOL coefficients in Panel B.

3.6.4 Asymmetrical UP-UAG Premium

Previous findings in behavioral and pricing literature have suggested agents' asymmetric behavior towards ambiguity depending on the probabilities of favorable (or unfavorable) outcomes where ambiguity refers to situations where the probabilities associated with equity realizations are not known or not uniquely assigned (Abdellaoui et al. (2005), Abdellaoui et al. (2011), Du and Budescu (2005)). Investors can be ambiguity-averse if returns are expected to be favorable (Viscusi and Chesson (1999), Brenner and Izhakian (2018)). This conjecture is tested by looking at the premium associated with the uncertainty of profitability for high versus low profitability firms. The measure of volatility of profitability is not intending to estimate ambiguity per se but the uncertainty surrounding profitability. If profitability is considered as a predictor of positive returns (favorable outcome) as previously documented in the literature (see e.g., Novy-Marx (2013) Fama and French (2015), and Hou et al. (2015)), hence, it is expected that investors would require a higher UP premium for more profitable firms. In contrast, this premium is expected to decrease or fade away in case of low profitable firms which on average would deliver lower returns (unfavorable outcome). Panel A of Table 3.12 tests this conjecture and reports the time-series coefficients of the cross-sectional individual stock-level regressions of the one month-ahead excess returns on UP, the univariate regression in specifications (1-2), and a set of controls in specifications (3-8) for the high (top 25%) and low (bottom 25%) profitability firms. In specification (1) for firms with low profitability, the UP coefficient is statistically insignificant while it more than doubles in specification (2) to 2.47 and become highly significant (t-stat of 3.36). Similarly in the multivariate regressions of specifications (3-8), the UP coefficients is statically and economically stronger for firms with high expected profitability. This suggests that investors are likely to be more averse to the profitability uncertainty when profitability is high and require higher premium while this premium becomes weaker when profitability is low.

Similarly, the premium associated with high UAG is examined for firms that have high investments or asset growth as they are more likely to deliver low returns (unfavorable outcome) as previously indicated in the literature (see e.g., Fama and French (2015), and Hou et al. (2015)). Panel B of Table 3.12 reports the time-series coefficients of the cross-sectional individual stock-level regressions of the one month-ahead excess returns on UAG (specification (1-2)), and a set of controls in specifications (3-8) for the high (top 25%) and low (bottom 25%) asset growth firms. The premium associated with volatility of asset growth is not significant for high asset growth firms (which are mostly associated with lower subsequent returns). However, this premium is economically and statistically significant for low asset growth firms. For instance, in specification (1) the UAG coefficient is 0.50 (t-stat of 2.20) for the low asset growth firms, almost triple that of the high asset growth firms of 0.18 (t-stat of 1.09). Results of Panels A and B suggest that investors would behave asymmetrically to the volatility of risk factors pending on returns' expectations where they would require an extra premium when they expect positive returns.

3.6.5 Can UP Improve the Profitability Premium?

As stated in Section 3.2, the profitability anomaly has been well-documented in the literature where more profitable firms would deliver on average higher returns. Previous sections have shown that when there is some uncertainty regarding future profitability, investors would require a return premium. Additionally, results of Table 3.6 show a significant negative coefficient on both profitability factors (RMW and R_{ROE}). All the above motivate to test whether a trading strategy based on UP and profitability would improve the profitability strategy. Stocks are first sorted based on their profitability measured as gross profit to asset (GPA) following Novy-Marx (2013) to estimate the magnitude of the profitability premium. In Panel A of Table 3.13, the largest 1,000 firms by market capitalization in the sample are sorted into 10 decile portfolios based on their GPA. The risk-adjusted returns of the 10 portfolios are generated based on: i) the 5F and QF models excluding the profitability factors RMW and R_{ROE}, respectively; ii) the above models augmented by MOM and LIQ factors. Results in Panel A confirm that the firms with in the highest GPA decile would on average have higher returns in line with the profitability anomaly documented by Novy-Marx (2013) and Fama and French (2015). In Panel B, the largest 1,000 firms are independently sorted on the gross profit to assets and the volatility of expected profitability in a way that decile 1 (10) would have firms with the lowest (highest) GPA and UP in the sample. Panel B reports the risk-adjusted returns of the same set of models of Panel A. Results in Panel B show that the profitability premium more than doubles across all models once the profitability sorting is also accounting for UP. For example, the profitability strategy of taking a long position in those stocks with high profitability and a short position in those stocks with the lowest profitability delivers on average a 0.43 (tstat. of 2.26) risk-adjusted returns for the 5F model (excluding RMW) of of Panel A. The equivalent risk-adjusted returns for the portfolio that takes a long position in those stocks with high profitability and high volatility of profitability and a short position with those stocks with low profitability and low volatility of profitability is 1.03 (tstat. of 2.43) as shown in Panel B. Overall, results of Table 3.13 indicate that the UP investing can improve the alpha generated by the profitability strategy.

3.7 Robustness Tests

3.7.1 Extended Sample and Alternative Volatility Measure

Matched Sample

One limitation of the sample used in the above analysis is that it is restricted to only firms that are covered by the IBES database for analysts' coverage. This can raise some doubt of sample selection bias given that analysts may be inclined to cover large firms. To alleviate this concern, the sample is extended to include other CRSP stocks that are not covered by analysts. More specifically, a propensity score is estimated for each firm using a probit regression based on size and operating profitability. Then, firms of the CRSP universe, which are not covered by IBES, are matched to the nearest neighbor firm (i.e. with the closest propensity score) in the original sample. Propensity score matching is conducted on a monthly basis without replacement (i.e. each stock of the remainder CRSP stocks can be matched with only one stock of of the original merged CRSP-IBES sample). The average number of firms in the new extended sample is 2,132 stocks over the sample horizon, with a monthly minimum and maximum of 1,717 and 2,849 stocks, respectively.

For the extended sample, a similar univariate portfolio analysis is performed as of Tables 3.3 and 3.4. Results are shown in Table 3.14 where stocks are sorted into decile portfolios according to their UP in Panel A and UAG in Panel B. In Panel A, the excess and risk-adjusted returns associated with high-UP firms remain significant across different pricing models, alleviating sample bias selection concerns.[9] Panel B, analogously report the the excess (raw) and

[9] Untabulated results confirm the premium associated with both high-UP and high-UAG firms for the stock level cross-sectional analysis.

risk-adjusted returns of UAG decile portfolios. Results in Panel B confirm the the premium associated with high-UAG stocks. Results are economically and statistically significant for the risk-adjusted returns yet statistically less significant for the raw returns of the hedging portfolio that takes a long position in high-UAG stocks and a short position in low-UAG stocks.

Historical Volatility of Profitability

It can be argued that analysts forecasts may not be a fair proxy for what the average investor believes due to analysts' herding behavior or other forecasts bias such as the ones documented by Trueman (1994) and Welch (2000). Moreover, including stocks that are covered by analysts may raise some concerns regarding sample selection bias. For this, alternative measures for expected profitability are used to extend the sample beyond those firms covered by analysts. These measures are some proxies for past operating performance computed following Ball et al. (2016):

i) Operating profitability (OPB) = Revenue (REVT) − cost of goods sold (COGS) − sales general and administrative expenses (XSGA-XRD) where expenditure on research and development (XRD) is subtracted to undo the adjustment that Standard & Poor's makes to accounting statements.[10]

ii) Cash-based Operating Profitability (CBOP) = OPB + Decrease in accounts receivables (RECCH) + Decrease in inventory (INVCH) + Increase in accounts payable and accrued liabilities (APALCH).

iii) Accrulas:[11]

   (a) Accruals based on balance sheet and income statement items = Δ Current assets (ACT) − Δ Cash (CH) − [Δ Current liabilities (LCT) − Δ Debt in current liabilities (DLC) − Δ Income taxes payable (TXP)] - Depreciation (DP)

[10] The main difference between operating profitability (OP) computed earlier in this chapter following Fama and French (2015) and the operating profitability following Ball et al. (2016) (OPB) is the research and development adjustment

[11] Accruals are the non-cash component of earnings and can hence can be used as a proxy for the expected cash receipts of goods and/or services delivered but not earned in cash during the fiscal period.

(b) Accruals based on cash flow statement items = − Decrease in accounts receivables (RECCH) − Decrease in Inventory (INVCH) − Increase in accounts payable and accrued liabilities (APALCH) − Net change in other liabilities (AOLOCH) − Increase in accrued income taxes (TXACH).

For each of the above operating performance, the annual change is computed. Then, the standard deviation of the change in each operating performance measure deflated by the previous year's book value of total assets is estimated over the previous 5 years. Additionally, the 5-year volatility of the change in gross profit (GP) is used where GP is computed as the revenue (REVT) minus cost of goods sold (COGS) scaled by the previous year's book value of assets. Finally, the 5-year volatility of change in return on assets (ROA) is estimated where change in ROA is computed as the fiscal year's change in net income scaled by the book value of assets of the previous year.[12]

Next, 10 decile portfolios are formed based on the computed standard deviation of each measure, one at a time. Table 3.15 report the risk-adjusted returns of value and equal-weighted portfolios generated using the 7F model. For the volatility of each of the 5 different measures, firms in the high volatility of profitability decile always outperform those in the low decile, confirming results in Section 3.5. These alternative measures ensure that the primary results are not driven by bias in analysts forecasts or by restricting the sample to the IBES database.[13] Overall, results show that the premium associated with the volatility of profitability remains positive and significant for different proxies of uncertainty of profitability.

3.7.2 Excluding Stocks with Null UP

For a firm to have a null UP, there are two possibilities: either this firm has less volatile earnings estimate (i.e., more certain earnings forecasts) or analysts do not update their estimate frequently (i.e. the firm is not well-covered). To rule out the latter possibility, the univariate

[12] Untabulated results are similar for the standard deviation of each operating performance measure over the previous 5 years (rather than change).

[13] Similar results are obtained if the sample is restricted to the IBES database.

portfolio analysis of Table 3.3 and the stock level cross-sectional analysis of Table 3.5 are repeated after excluding stocks with null UP. Results are shown in Panel A and B of Table 3.16, respectively. The persistent positive UP premium alleviate potential concerns regarding the frequency of updating earnings by analysts.

3.7.3 Robustness to Number of Analysts

The above analysis accounted for the mean earnings forecasts provided by analysts regardless of how many analysts are contributing to the forecast. Hence, a robustness test to the number of analysts providing earnings forecasts is conducted. The univariate portfolio analysis is repeated after accounting for the mean forecasts if the number of analysts is at least three, five, or ten analysts. In Table 3.17, value- and equal-weighted decile portfolios are formed each month based on UP where portfolio 1 (10) contains stocks with the lowest (highest) UP measure. The table reports risk-adjusted returns of the 5-factor of Fama and French (2015) augmented by the momentum (MOM) factor of Carhart (1997) and the liquidity (LIQ) factor of Pástor and Stambaugh (2003). Results, shown in Table 3.17, indicate that UP premium remains both statistically and economically significant at different thresholds of the number of estimations.

3.7.4 Sensitivity to Different Forecast Horizon and UP Measures

In Section 3.4, UP is defined as the standard deviation of the total annual changes of the 5 years-ahead expected profitability over the previous 60 months. In order to rule out possible data mining concerns, similar univariate portfolio analyses to that in Section 3.5 are repeated but for different forecasting horizon. In other words, UP is computed as the volatility of total annual changes of the 1, 2, 3, 4, or 5 years-ahead expected profitability over the previous 60 months. Then, value-weighted decile portfolios are sorted according to UP. Results are shown in Panel A of Table 3.18 where risk -adjusted returns are generated using the 7F model. The prevailing positive premium associated with high-UP stocks indicate that findings are not specific to the time-horizon selection of 5 years of forecasts.

For further robustness, the univariate portfolio analysis is performed but with the standard deviation rolling over different windows. That is, UP is computed as the volatility of total annual changes of the 5 years-ahead expected profitability over the previous 18, 24, 36, 48, or 60 months and then value-weighted decile portfolios are formed based on UP accordingly. Results shown in Panel B of Table 3.18 also confirm that the UP premium is not specific to the estimation window of the volatility of profitability.

3.7.5 Screening out Small, Illiquid , and Volatile Stocks

To further ensure that the results are not driven by small, illiquid or simply highly volatile stocks, univariate portfolio analysis is conducted using alternative stock samples: (i) excluding stocks with price per share below \$5; (ii) large stocks with market capitalization greater than the median size breakpoint in each month; (iii) excluding stocks with the highest 30% illiquidity, and (iv) excluding stocks with the highest 30% idiosyncratic volatility. Table 3.19 reports the 7F alphas of the 10 value-weighted portfolios of stocks sorted by UP for each of the above subsamples. The last row presents the 10−1 differences in alphas between the high- and low-UP deciles (with Newey-West t-statistics). The results show that the significantly positive UP premium is mainly not driven by small, illiquid or high idiosyncratic volatility stocks.

3.7.6 Alternative Scaling for Profitability

In Equation 3.9, expected net income is scaled by book value of assets. For further robustness, net income is scaled by the book value of equity and the values for firms with negative book value of equity are replaced with missing values. Then, UP is estimated as the standard deviation of profitability as in Equation 3.10. The univariate portfolio analysis (similar to that of Table 3.3) is conducted based on this alternative UP measure. Results, shows in Table 3.20, confirm the premium associated with firms with high UP versus those with low UP as indicated by the positive and significant alphas differences between the high- and low-UP deciles in both value-weighted (Panel A) and equal-weighted portfolios (Panel B).

3.8 Conclusion

This chapter investigates the predictive power of the time-series volatility of expected profitability (UP) on cross-sectional returns. The proposed UP measure captures an equity premium that is not explained by common risk factors previously considered in the literature. The reported UP premium is significant both statistically and economically, and is robust to a large scrutiny levels and robustness checks. This significant positive premium is confirmed in univariate portfolio-level analyses and stock-level cross-sectional regressions that control for a wide battery of well-known pricing effects. A portfolio that goes long in high-UP firms and short in low-UP firms would generate an annual excess (risk-adjusted) returns of 8% (10%). Analogously, this chapter investigates the uncertainty of asset growth (UAG) and find that high-UAG firms and short in low-UAG firms would generate an annual excess (risk-adjusted) returns of 7% (12%).

Two novel factors, UPF and UAGF, are constructed for the uncertainty of profitability and asset growth, respectively. These factors cannot be explained by the market, size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and liquidity (LIQ) factors of Fama and French (1993, 2015), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015). Each of UPF and UAG factors generates an annual return of 4%.

The UPF generates higher returns in good economic states when: i) the market-wide profitability is high, ii) the aggregate default risk is low, iii) the expected inflation increases, iv) the market volatility is low, and when v) the economic activity index is improving, partially justifying the premium earned by high-UP firms. High-UP would increase firms' idiosyncratic volatility fo equity returns. Moreover, UP investing can improve the profitability strategy given the negative relation between profitability and its volatility.

A main contribution of this chapter is to shed light on the importance of the volatility of common risk factors. While profitability and asset growth are empirically well-documented as pricing anomalies, their corresponding volatility also matters in the cross-section of equity returns and should be accounted for in investment decisions.

3.9 Tables

Table 3.1

Summary Statistics for Decile Portfolio of Stocks Sorted by UP

This table reports for each UP decile portfolio the average across the months in the sample of the mean values within each month of various stocks characteristics. The characteristics are: β^{MKT} is the market beta, MCAP is market capitalization (in million US dollars), BM is book-to-market ratio, operational profitability as per Fama and French (2015), GP is another profitability measure as per Novy-Marx (2013), ROA is return on assets, TROA5 is the total expected return on assets over the coming 5 years, INV is investment following Fama and French (2015), UNC is the volatility of book-to-market estimated in Chapter 2, UAG is the volatility of asset growth, TURN is the ratio of trading volume in a month to shares outstanding, DISP is analysts' forecast dispersion, β^{VXO} is the market volatility VXO exposure (in %), MOM is momentum, ILLIQ is the Amihud (2002) illiquidity indicator scaled by 10^6, STR is short-term reversal, MAX is a proxy for lottery demand as in Bali et al. (2011), IVOL is idiosyncratic volatility (in %), TVOL is total volatility, ISKEW is idiosyncratic skewness, TSKEW is total stocks' returns skewness, COSK is the co-skewness of past month daily returns, age is the firm's number of years since it first appeared on CRSP. Pr./Shr. is the average price per share per decile in USD. Mkt. shr. (in %) is the market capitalization of each decile to the total sample market capitalization. No. of stocks is the average number of stocks in each decile. The last two columns report the difference High−Low (10-1) of average firm characteristics with corresponding Newey-West adjusted t-statistics given in parentheses.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High−Low	t-stat
UP	0.003	0.012	0.018	0.025	0.033	0.043	0.058	0.083	0.135	0.524	0.521	(24.26)
β^{MKT}	0.666	0.819	0.863	0.892	0.958	1.019	1.066	1.134	1.243	1.347	0.681	(15.96)
MCAP	2,205	4,368	3,801	3,661	5,058	4,977	3,494	3,854	3,791	2,229	24	(0.08)
BM	0.895	0.728	0.676	0.637	0.593	0.574	0.564	0.539	0.467	0.352	-0.543	(-20.21)
OP	0.234	0.276	0.277	0.282	0.275	0.261	0.249	0.220	0.182	-0.050	-0.284	(-12.08)
GPA	0.386	0.390	0.394	0.404	0.420	0.418	0.428	0.430	0.420	0.324	-0.062	(-6.99)
ROA	0.040	0.052	0.054	0.057	0.060	0.060	0.055	0.045	0.019	-0.123	-0.163	(-10.91)
TROA5	0.197	0.292	0.343	0.381	0.440	0.487	0.518	0.581	0.615	0.648	0.450	(19.19)
INV	0.194	0.176	0.159	0.167	0.176	0.186	0.197	0.210	0.252	0.404	0.210	(8.97)
UNC	0.147	0.146	0.151	0.161	0.167	0.174	0.184	0.201	0.231	0.282	0.134	(21.51)
UAG	0.175	0.188	0.190	0.207	0.217	0.237	0.291	0.341	0.445	0.720	0.545	(26.74)
TURN	0.857	1.155	1.236	1.325	1.453	1.543	1.663	1.845	2.146	2.399	1.542	(24.69)
DISP	0.099	0.106	0.111	0.136	0.143	0.164	0.203	0.241	0.287	0.358	0.259	(14.64)
β^{VXO}	0.048	0.051	0.049	0.049	0.056	0.072	0.065	0.073	0.082	0.089	0.041	(2.22)
MOM	17.414	12.280	10.526	11.450	11.746	10.665	11.069	12.705	16.948	27.756	10.341	(2.41)
ILLIQ	4.164	0.967	0.850	0.949	0.874	1.121	0.829	1.043	0.899	0.586	-3.579	(-7.09)
STR	1.463	1.407	1.379	1.507	1.518	1.561	1.566	1.640	1.820	2.224	0.761	(2.36)
MAX	6.381	5.550	5.588	5.864	6.026	6.219	6.576	7.033	7.714	8.696	2.316	(11.82)
IVOL	0.024	0.021	0.021	0.022	0.022	0.023	0.024	0.026	0.028	0.031	0.007	(10.84)
TVOL	0.028	0.025	0.025	0.026	0.027	0.028	0.029	0.031	0.034	0.038	0.010	(11.40)
ISKEW	0.187	0.166	0.166	0.171	0.170	0.170	0.187	0.194	0.210	0.241	0.054	(6.65)
COSK	-4.554	-4.557	-2.975	-3.714	-5.490	-5.451	-4.975	-4.854	-7.265	-9.261	-4.707	(-2.37)
Age	18.71	20.18	21.18	20.75	19.98	19.44	18.19	16.76	14.10	10.28	-8.426	(-17.44)
Pr./Shr.	29.07	42.95	36.55	37.81	40.47	40.57	38.19	39.43	37.48	26.58		
No. of Stocks	173	173	173	173	173	173	173	173	173	173		

Table 3.2

Stocks Cross-Sectional Correlation

This table reports the time series monthly average of the cross-sectional correlation between different pricing factors: uncertainty of profitability (UP), market beta (β^{MKT}), market capitalization (MCAP), book-to-market (BM), operational profitability (OP) and gross profit to assets (GPA), return on assets (ROA), total expected return on assets over the coming 5 years (TROA5), investment (INV), uncertainty of book-to-market (UNC), uncertainty of asset growth (UAG), turnover (TURN), analysts' forecast dispersion (DISP), market volatility beta (β^{VXO}), stock momentum (MOM), illiquidity (ILLIQ), short-term reversal (STR), lottery-stocks demand (MAX), idiosyncratic volatility (IVOL), total volatility (TVOL), idiosyncratic skewness (ISKEW), and co-skewness (COSK).

	UP	β^{MKT}	SIZE	BM	OP	GPA	ROA	TROA5	INV	UNC	UAG	TURN	DISP	β^{VXO}	MOM	ILLIQ	STR	MAX	IVOL	TVOL	ISKEW	COSK
UP	1																					
β^{MKT}	0.064	1																				
SIZE	-0.060	-0.005	1																			
BM	-0.258	-0.034	-0.266	1																		
OP	-0.056	-0.038	0.405	-0.336	1																	
GPA	0.057	-0.040	-0.035	-0.122	0.113	1																
ROA	-0.069	-0.015	0.217	-0.291	0.592	0.050	1															
TROA5	0.194	0.015	0.401	-0.463	0.415	0.032	0.471	1														
INV	0.127	0.061	0.023	-0.169	0.045	-0.120	0.421	0.208	1													
UNC	0.255	0.091	-0.074	-0.064	0.126	0.058	-0.087	-0.005	-0.009	1												
UAG	0.299	0.057	-0.155	-0.105	-0.141	0.029	-0.057	-0.039	0.205	0.227	1											
TURN	0.145	0.160	0.015	-0.125	0.077	-0.064	0.127	0.142	0.242	0.216	0.121	1										
DISP	0.194	0.031	-0.157	0.196	-0.243	0.035	-0.337	-0.185	-0.094	0.201	0.156	-0.039	1									
β^{VXO}	0.003	0.085	-0.024	0.013	0.020	-0.019	0.011	-0.007	0.009	0.020	0.000	0.014	0.009	1								
MOM	0.035	-0.110	-0.190	0.235	-0.199	0.040	-0.260	-0.258	-0.129	0.050	0.120	-0.263	0.198	-0.018	1							
ILLIQ	0.051	0.071	-0.015	-0.224	-0.055	-0.029	-0.029	0.044	0.042	-0.010	0.022	0.149	-0.110	-0.011	-0.124	1						
STR	0.001	0.029	0.022	-0.107	-0.006	0.005	-0.009	-0.002	-0.018	-0.015	-0.005	0.032	-0.008	0.005	-0.041	-0.001	1					
MAX	0.182	0.152	-0.212	0.091	-0.193	-0.005	-0.217	-0.156	0.011	0.257	0.194	0.257	0.215	0.040	0.238	-0.014	0.358	1				
IVOL	0.218	0.088	-0.289	0.154	-0.232	0.009	-0.256	-0.196	0.012	0.326	0.243	0.313	0.274	0.032	0.342	-0.021	0.042	0.798	1			
TVOL	0.222	0.177	-0.275	0.149	-0.228	-0.002	-0.247	-0.184	0.021	0.331	0.236	0.341	0.266	0.033	0.304	-0.004	0.040	0.819	0.966	1		
ISKEW	0.034	0.045	-0.020	-0.007	-0.055	0.003	-0.073	-0.052	-0.023	0.024	0.028	-0.005	0.044	0.003	0.023	-0.016	0.424	0.468	0.083	0.080	1	
COSK	-0.019	-0.003	0.029	-0.019	0.013	-0.009	0.029	0.031	0.005	-0.049	-0.028	-0.035	-0.017	0.147	-0.023	-0.009	-0.030	-0.033	-0.061	-0.056	-0.131	1

Table 3.3

UP Univariate Portfolio Analysis

This table tests the robustness of the uncertainty of profitability (UP) premium to alternative asset pricing models. Value- and equal-weighted decile portfolios are formed each month based on UP in Panels A and B, respectively. Portfolio 1 (10) contains stocks with the lowest (highest) UP measure. Panel A (B) reports excess and risk-adjusted returns of value-weighted (equal-weighted) portfolios for the month subsequent to the portfolios formation month using different sets of asset pricing models: i) 3-factor of Fama and French (1993), 5-factor of Fama and French (2015), and Q-factor models of Hou et al. (2015) , ii) the above models augmented by the momentum (MOM) factor of Carhart (1997); and iii) the above augmented by the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The last two rows show the difference in returns between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

Panel A. Value-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UP Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	0.514	-0.234	-0.266	-0.250	-0.137	-0.191	-0.225	-0.117	-0.171	-0.194
	(1.68)	(-1.54)	(-1.66)	(-1.30)	(-0.87)	(-1.20)	(-1.25)	(-0.74)	(-1.06)	(-1.09)
2	0.984	0.436	0.310	0.301	0.414	0.304	0.305	0.409	0.298	0.302
	(4.92)	(3.74)	(2.67)	(2.51)	(3.45)	(2.62)	(2.53)	(3.52)	(2.62)	(2.58)
3	0.649	0.046	-0.085	-0.061	0.103	-0.032	-0.043	0.105	-0.031	-0.039
	(2.64)	(0.41)	(-0.73)	(-0.48)	(0.99)	(-0.29)	(-0.39)	(0.99)	(-0.28)	(-0.36)
4	0.860	0.235	-0.003	0.049	0.246	0.026	0.065	0.245	0.023	0.063
	(3.78)	(1.89)	-(0.03)	(0.40)	(2.01)	(0.23)	(0.54)	(2.00)	(0.20)	(0.52)
5	0.797	0.193	0.086	0.124	0.226	0.116	0.140	0.222	0.111	0.137
	(3.82)	(1.77)	(0.82)	(1.00)	(2.01)	(1.10)	(1.23)	(1.98)	(1.06)	(1.21)
6	0.760	0.167	-0.055	-0.003	0.156	-0.046	0.008	0.118	-0.087	-0.041
	(3.31)	(1.30)	(-0.46)	(-0.03)	(1.23)	(-0.38)	(0.06)	(0.93)	(-0.74)	(-0.32)
7	0.839	0.195	0.046	0.102	0.118	0.001	0.091	0.085	-0.034	0.058
	(3.22)	(1.77)	(0.36)	(0.76)	(1.10)	(0.01)	(0.73)	(0.80)	(-0.29)	(0.45)
8	0.908	0.238	0.158	0.223	0.336	0.240	0.236	0.333	0.236	0.238
	(3.02)	(1.80)	(1.15)	(1.37)	(2.39)	(1.68)	(1.46)	(2.42)	(1.67)	(1.54)
9	0.747	0.082	0.206	0.325	0.149	0.243	0.317	0.134	0.228	0.311
	(2.12)	(0.54)	(1.24)	(1.57)	(0.93)	(1.43)	(1.55)	(0.83)	(1.33)	(1.52)
10 (High)	1.213	0.544	0.676	0.699	0.520	0.650	0.674	0.558	0.691	0.735
	(3.14)	(3.17)	(3.73)	(2.67)	(2.76)	(3.43)	(2.84)	(2.99)	(3.71)	(3.23)
High−Low (10−1)	0.699	0.777	0.942	0.949	0.657	0.841	0.899	0.676	0.862	0.929
t-stat	(2.15)	(3.03)	(3.33)	(2.36)	(2.47)	(2.97)	(2.52)	(2.57)	(3.09)	(2.71)

Table 3.3 (continued)

Panel B. Equal-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UP Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	1.172	0.484	0.403	0.492	0.597	0.489	0.520	0.586	0.478	0.510
	(4.07)	(4.38)	(3.56)	(3.12)	(5.33)	(4.62)	(4.47)	(5.31)	(4.50)	(4.44)
2	1.128	0.386	0.249	0.366	0.513	0.349	0.399	0.495	0.330	0.379
	(3.99)	(3.52)	(2.37)	(2.19)	(4.88)	(4.01)	(3.53)	(5.03)	(3.99)	(3.60)
3	1.132	0.357	0.228	0.357	0.495	0.335	0.392	0.470	0.310	0.364
	(3.98)	(2.99)	(2.06)	(2.12)	(4.49)	(3.74)	(3.58)	(4.53)	(3.72)	(3.61)
4	1.251	0.437	0.285	0.410	0.584	0.402	0.448	0.569	0.386	0.432
	(4.24)	(3.96)	(2.94)	(2.83)	(5.42)	(4.76)	(5.30)	(5.40)	(4.64)	(5.14)
5	1.256	0.439	0.342	0.425	0.548	0.426	0.454	0.527	0.405	0.431
	(4.17)	(4.49)	(3.87)	(3.83)	(5.37)	(4.95)	(5.88)	(5.39)	(4.84)	(5.82)
6	1.255	0.417	0.328	0.431	0.546	0.427	0.461	0.519	0.399	0.431
	(4.02)	(4.03)	(3.47)	(3.55)	(5.56)	(5.13)	(5.29)	(5.54)	(5.03)	(5.19)
7	1.280	0.403	0.389	0.538	0.562	0.504	0.565	0.547	0.490	0.556
	(3.82)	(3.50)	(3.54)	(4.38)	(4.99)	(4.96)	(5.39)	(4.91)	(4.85)	(5.34)
8	1.395	0.517	0.557	0.778	0.745	0.720	0.807	0.719	0.693	0.786
	(3.92)	(3.91)	(4.07)	(4.93)	(5.94)	(6.41)	(6.38)	(5.95)	(6.39)	(6.49)
9	1.497	0.608	0.801	1.027	0.824	0.944	1.040	0.805	0.926	1.034
	(3.77)	(3.92)	(5.41)	(6.10)	(5.12)	(6.56)	(6.04)	(5.11)	(6.55)	(6.13)
10 (High)	1.906	1.073	1.367	1.618	1.236	1.464	1.607	1.256	1.488	1.656
	(4.32)	(5.58)	(7.90)	(6.98)	(6.29)	(8.42)	(7.03)	(6.43)	(8.61)	(7.43)
High−Low (10−1)	0.735	0.589	0.964	1.126	0.639	0.975	1.087	0.670	1.010	1.146
t-stat	(2.32)	(2.48)	(4.54)	(3.49)	(2.67)	(4.55)	(3.84)	(2.84)	(4.72)	(4.16)

Table 3.4

UAG Univariate Portfolio Analysis

Value- and equal-weighted decile portfolios are formed each month based on UAG in Panels A and B, respectively. Portfolio 1 (10) contains stocks with the lowest (highest) UAG measure. The table reports excess and risk-adjusted returns of value-weighted (equal-weighted) portfolios in Panel A (B) using different set of asset pricing models: i) 3-factor of Fama and French (1993), 5-factor of Fama and French (2015), and Q-factor models of Hou et al. (2015), ii) the above models augmented by the momentum (MOM) factor of Carhart (1997); and iii) the above augmented by the liquidity (LIQ) factor of Pástor and Stambaugh (2003). Returns are for the month following the portfolio formation month. The last two rows show the difference in returns between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

Panel A. Value-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UAG Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	0.704	0.129	-0.054	-0.085	0.077	-0.076	-0.081	0.089	-0.065	-0.065
	(3.30)	(1.53)	(-0.63)	(-0.93)	(0.93)	(-0.93)	(-0.90)	(1.07)	(-0.83)	(-0.73)
2	0.840	0.251	0.053	0.130	0.260	0.078	0.135	0.242	0.058	0.117
	(3.75)	(2.00)	(0.46)	(1.00)	(2.07)	(0.70)	(1.06)	(1.94)	(0.52)	(0.91)
3	0.920	0.321	0.293	0.332	0.298	0.277	0.326	0.284	0.263	0.317
	(3.80)	(3.17)	(2.83)	(2.79)	(2.89)	(2.55)	(2.81)	(2.79)	(2.45)	(2.73)
4	0.682	0.057	-0.012	0.034	0.146	0.057	0.056	0.119	0.028	0.024
	(2.53)	(0.42)	-(0.08)	(0.22)	(1.16)	(0.42)	(0.38)	(0.95)	(0.21)	(0.16)
5	0.813	0.235	0.185	0.231	0.244	0.196	0.231	0.242	0.194	0.234
	(2.73)	(1.36)	(0.97)	(1.22)	(1.46)	(1.04)	(1.24)	(1.41)	(1.01)	(1.23)
6	0.865	0.253	0.121	0.233	0.321	0.179	0.248	0.317	0.174	0.244
	(3.30)	(1.93)	(0.91)	(1.47)	(2.32)	(1.35)	(1.72)	(2.39)	(1.36)	(1.79)
7	0.890	0.277	0.225	0.296	0.300	0.246	0.300	0.285	0.229	0.285
	(3.25)	(2.22)	(1.79)	(2.32)	(2.33)	(1.96)	(2.32)	(2.22)	(1.83)	(2.18)
8	0.740	0.118	0.143	0.155	0.091	0.118	0.146	0.104	0.133	0.171
	(2.54)	(0.83)	(0.99)	(1.00)	(0.65)	(0.83)	(0.94)	(0.74)	(0.91)	(1.07)
9	1.063	0.366	0.539	0.601	0.399	0.549	0.586	0.419	0.571	0.627
	(2.77)	(2.22)	(2.96)	(2.51)	(2.39)	(2.97)	(2.63)	(2.59)	(3.22)	(2.95)
10 (High)	1.250	0.494	0.854	0.922	0.570	0.882	0.902	0.610	0.926	0.975
	(2.98)	(2.61)	(5.25)	(4.10)	(3.00)	(5.05)	(4.42)	(3.20)	(5.42)	(4.99)
High−Low (10−1)	0.545	0.365	0.907	1.006	0.493	0.958	0.983	0.522	0.992	1.040
t-stat	(1.81)	(1.73)	(5.27)	(4.32)	(2.38)	(5.33)	(4.67)	(2.48)	(5.59)	(5.07)

Table 3.4 (continued)

Panel B. Equal-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UAG Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	1.091	0.365	0.177	0.251	0.448	0.250	0.282	0.422	0.221	0.251
	(4.29)	(4.30)	(2.29)	(2.06)	(5.51)	(3.50)	(3.52)	(5.34)	(3.22)	(3.28)
2	1.220	0.442	0.272	0.351	0.542	0.356	0.384	0.517	0.329	0.355
	(4.39)	(4.28)	(2.94)	(2.59)	(5.23)	(4.31)	(4.28)	(5.14)	(4.09)	(4.16)
3	1.254	0.461	0.303	0.386	0.561	0.385	0.417	0.528	0.350	0.378
	(4.23)	(3.97)	(2.91)	(2.81)	(4.64)	(3.77)	(4.31)	(4.64)	(3.60)	(4.16)
4	1.181	0.356	0.257	0.342	0.487	0.356	0.376	0.456	0.325	0.342
	(3.88)	(3.46)	(2.64)	(2.63)	(5.08)	(4.23)	(4.77)	(5.06)	(4.07)	(4.53)
5	1.264	0.477	0.412	0.531	0.625	0.522	0.564	0.593	0.489	0.529
	(4.16)	(4.29)	(3.52)	(3.41)	(6.26)	(5.60)	(5.67)	(6.59)	(5.77)	(6.01)
6	1.256	0.439	0.366	0.485	0.607	0.490	0.523	0.584	0.467	0.498
	(4.00)	(3.84)	(3.26)	(3.16)	(5.97)	(5.65)	(5.36)	(6.14)	(5.77)	(5.54)
7	1.525	0.712	0.642	0.818	0.871	0.763	0.845	0.842	0.733	0.817
	(4.74)	(5.66)	(5.42)	(5.64)	(6.93)	(7.10)	(6.99)	(7.14)	(7.30)	(7.21)
8	1.361	0.496	0.509	0.690	0.691	0.648	0.722	0.683	0.641	0.722
	(3.86)	(3.67)	(3.70)	(4.56)	(5.20)	(5.36)	(5.91)	(5.20)	(5.34)	(6.01)
9	1.472	0.648	0.678	0.833	0.785	0.775	0.848	0.784	0.775	0.858
	(4.24)	(5.01)	(6.16)	(6.32)	(6.00)	(6.92)	(6.30)	(6.00)	(6.93)	(6.53)
10 (High)	1.709	0.901	1.099	1.356	1.102	1.229	1.364	1.128	1.259	1.416
	(4.36)	(6.66)	(7.88)	(8.40)	(7.71)	(9.44)	(8.35)	(7.79)	(9.62)	(8.67)
High−Low (10−1)	0.618	0.535	0.922	1.105	0.654	0.980	1.082	0.706	1.037	1.165
t-stat	(2.38)	(3.34)	(5.74)	(5.20)	(3.90)	(6.14)	(5.41)	(4.20)	(6.61)	(5.93)

Table 3.5

Stock Level Fama-MacBeth Cross-Sectional Regressions

Panel A reports the time series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on the uncertainty of profitability (UP) and a set of lagged controls following the Fama and MacBeth (1973) approach. The controls include: market beta (β^{MKT}), log of market capitalization (SIZE), book-to-market (BM), operational profitability (OP), investment (INV), stock momentum (MOM), illiquidity (ILLIQ), gross profit to assets (GPA), return on assets (ROA), total expected return on assets over the following 5 years (TROA5), uncertainty of book-to-market (UNC), uncertainty of asset growth (UAG), turnover (TURN), analysts' forecast dispersion (DISP), market volatility beta (β^{VXO}), short-term reversal (STR), lottery-stocks demand (MAX), idiosyncratic volatility (IVOL), total volatility (TVOL), idiosyncratic skewness (ISKEW), and co-skewness (COSK). t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. Panel B repeats the same analysis but controlling for industry. The sample is from January 1984 to December 2016.

Panel A. Cross-Sectional Analysis

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Constant	1.206	2.955	2.800	2.862	2.602	2.446	2.776	2.901	2.604	2.660	2.636	1.652	1.997	2.765	2.616	2.260	2.628	2.640
	(4.14)	(4.56)	(4.65)	(4.51)	(4.27)	(3.74)	(4.51)	(4.67)	(4.32)	(3.78)	(4.30)	(2.84)	(3.61)	(4.46)	(4.65)	(4.27)	(4.32)	(4.32)
UP	1.608	2.037	2.239	1.928	2.234	2.006	1.818	2.008	2.022	1.921	2.250	1.440	2.192	2.135	2.240	2.095	2.229	2.255
	(2.57)	(3.84)	(5.07)	(3.65)	(4.76)	(3.92)	(4.00)	(3.85)	(4.87)	(4.44)	(4.82)	(3.55)	(4.92)	(4.53)	(4.89)	(4.81)	(4.75)	(4.82)
β^{MKT}		0.043	0.041	0.026	0.021	0.014	0.012	0.021	0.012	0.000	0.019	-0.031	0.031	0.012	0.017	0.002	0.021	0.024
		(0.76)	(0.75)	(0.48)	(0.41)	(0.27)	(0.23)	(0.40)	(0.26)	(-0.01)	(0.35)	(-0.67)	(0.63)	(0.23)	(0.35)	(0.05)	(0.41)	(0.44)
SIZE		-0.164	-0.151	-0.158	-0.142	-0.134	-0.134	-0.156	-0.148	-0.145	-0.143	-0.1	-0.115	-0.144	-0.142	-0.125	-0.144	-0.145
		(-4.46)	(-4.76)	(-4.33)	(-4.36)	(-3.83)	(-4.00)	(-4.41)	(-4.37)	(-3.70)	(-4.37)	(-3.00)	(-3.76)	(-4.33)	(-4.60)	(-4.31)	(-4.41)	(-4.41)
BM		0.435	0.415	0.457	0.489	0.449	0.345	0.415	0.503	0.574	0.477	0.551	0.599	0.365	0.485	0.482	0.486	0.477
		(2.45)	(2.15)	(2.85)	(2.74)	(2.66)	(2.17)	(2.60)	(2.96)	(2.63)	(2.68)	(2.87)	(3.56)	(2.13)	(2.80)	(2.78)	(2.74)	(2.68)
OP			0.002		0.003				0.003	0.003	0.003	0.003	0.006	0.002	0.003	0.003	0.003	0.003
			(0.77)		(1.21)				(1.39)	(1.14)	(1.16)	(1.05)	(2.37)	(0.86)	(1.29)	(1.41)	(1.19)	(1.18)
INV			-0.005		-0.006	-0.006	-0.006	-0.006	-0.007	-0.005	-0.006	-0.007	-0.006	-0.007	-0.006	-0.006	-0.006	-0.006
			(-5.48)		(-6.26)	(-6.14)	(-6.17)	(-5.93)	(-6.61)	(-5.88)	(-6.18)	(-7.20)	(-5.41)	(-6.65)	(-6.26)	(-6.31)	(-6.31)	(-6.20)
MOM				0.001	0.001	0.001	0.000	0.002	0.001	0.001	0.001	0.003	0.002	0.001	0.001	0.002	0.001	0.001
				(1.19)	(1.21)	(0.56)	(0.29)	(1.46)	(1.09)	(0.64)	(1.17)	(1.80)	(1.05)	(1.04)	(1.23)	(1.43)	(1.17)	(1.18)
ILLIQ				0.010	0.003	0.003	0.003	-0.003	0.003	-0.089	0.003	-0.034	0.004	0.003	0.004	0.002	0.003	0.003
				(0.94)	(0.28)	(0.25)	(0.31)	(-0.37)	(0.28)	(-0.83)	(0.31)	(-0.78)	(0.33)	(0.25)	(0.41)	(0.21)	(0.26)	(0.27)
GPA						0.004												
						(2.25)												
ROA							-0.012											
							(-2.94)											
TROA5								0.001										
								(1.63)										
UNC									2.217									
									(3.60)									
UAG										0.268								
										(2.42)								
TURN											0.092							
											(1.96)							
DISP												-0.027						
												(-0.68)						
β^{VXO}													-10.920					
													(-2.75)					
STR														-0.028				
														(-7.38)				
MAX															-0.003			
															(-0.41)			
IVOL																0.040		
																(1.16)		
ISKEW																	-0.0002	
																	(-0.80)	
COSK																		-0.00001
																		(-0.96)
No. of Obs.	575,318	564,008	523,312	533,356	500,016	519,587	524,574	518,577	500,016	404,243	500,016	420,570	431,986	500,015	500,016	500,016	500,004	500,016
R^2	0.008	0.030	0.036	0.037	0.042	0.043	0.043	0.040	0.049	0.052	0.044	0.054	0.046	0.047	0.044	0.046	0.043	0.044

Table 3.5 (continued)

Panel B. Cross-Sectional Analysis with Industry Controls

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Constant	0.223	2.821	1.553	2.421	0.789	2.680	1.226	2.263	0.581	0.356	1.522	0.423	0.718	1.166	1.439	0.928	0.827	1.110
	(0.34)	(3.27)	(1.75)	(2.59)	(0.89)	(2.56)	(1.28)	(2.67)	(0.74)	(0.49)	(1.84)	(0.51)	(0.81)	(1.49)	(1.73)	(1.13)	(0.96)	(1.44)
UP	1.32	1.712	1.989	1.597	1.988	1.726	1.565	1.754	1.277	1.97	1.845	1.737	1.992	1.885	2.018	1.896	1.984	1.998
	(2.45)	(3.50)	(4.64)	(3.27)	(4.43)	(3.66)	(3.80)	(3.54)	(3.24)	(4.54)	(4.57)	(4.24)	(4.47)	(4.17)	(4.57)	(4.48)	(4.43)	(4.47)
β^{MKT}		0.045	0.043	0.029	0.024	0.019	0.017	0.025	-0.021	0.034	0.019	-0.002	0.018	0.017	0.023	0.011	0.024	0.026
		(0.86)	(0.85)	(0.59)	(0.52)	(0.40)	(0.37)	(0.51)	(-0.52)	(0.75)	(0.43)	(-0.03)	(0.37)	(0.36)	(0.51)	(0.24)	(0.51)	(0.52)
SIZE		-0.148	-0.131	-0.143	-0.125	-0.115	-0.12	-0.137	-0.0878	-0.104	-0.133	-0.124	-0.125	-0.127	-0.131	-0.116	-0.126	-0.127
		(-4.32)	(-4.21)	(-4.15)	(-3.89)	(-3.46)	(-3.75)	(-4.29)	(-2.59)	(-3.41)	(-4.07)	(-3.27)	(-3.89)	(-3.83)	(-4.21)	(-3.89)	(-3.93)	(-3.97)
BM		0.542	0.564	0.552	0.618	0.570	0.452	0.516	0.663	0.705	0.616	0.735	0.608	0.460	0.606	0.601	0.616	0.607
		(3.68)	(3.41)	(4.12)	(4.03)	(3.94)	(3.40)	(3.80)	(4.04)	(4.82)	(4.12)	(3.95)	(3.97)	(3.08)	(3.99)	(3.97)	(4.03)	(3.95)
OP			0.003		0.004				0.004	0.007	0.004	0.004	0.004	0.003	0.004	0.004	0.004	0.004
			(1.29)		(1.84)				(1.56)	(3.09)	(1.96)	(1.64)	(1.80)	(1.33)	(1.86)	(1.97)	(1.82)	(1.79)
INV			-0.004		-0.006	-0.006	-0.006	-0.006	-0.007	-0.006	-0.006	-0.005	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
			(-5.88)		(-6.54)	(-6.47)	(-6.51)	(-6.16)	(-7.31)	(-5.51)	(-6.75)	(-6.14)	(-6.46)	(-7.00)	(-6.52)	(-6.55)	(-6.60)	(-6.52)
MOM				0.001	0.001	0.000	0.000	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
				(0.80)	(0.94)	(0.20)	(-0.07)	(1.08)	(1.51)	(0.59)	(0.83)	(0.51)	(0.88)	(0.69)	(0.94)	(1.14)	(0.90)	(0.92)
ILLIQ				0.012	0.004	0.005	0.005	-0.001	-0.036	0.006	0.004	-0.041	0.005	0.004	0.007	0.005	0.004	0.004
				(1.06)	(0.43)	(0.41)	(0.43)	(-0.09)	(-0.90)	(0.51)	(0.39)	(-0.37)	(0.46)	(0.38)	(0.63)	(0.47)	(0.42)	(0.44)
GPA						0.005												
						(3.24)												
ROA							-0.011											
							(-2.46)											
TROA5								0.001										
								(1.45)										
UNC									2.009									
									(3.47)									
UAG										0.215								
										(2.14)								
TURN											0.071							
											(1.74)							
DISP												-0.021						
												(-0.61)						
β^{VXO}													-8.727					
													(-2.44)					
STR														-0.034				
														(-9.19)				
MAX															-0.009			
															(-1.39)			
IVOL																0.021		
																(0.70)		
ISKEW																	0.000	
																	(-1.03)	
COSK																		0.000
																		(-0.12)
No. of Obs.	575,246	563,936	523,253	533,304	499,975	519,535	524,522	518,525	420,537	431,981	499,975	404,238	499,975	499,974	499,975	499,975	499,963	499,975
R^2	0.074	0.091	0.100	0.100	0.107	0.105	0.105	0.104	0.129	0.115	0.112	0.131	0.108	0.111	0.109	0.110	0.108	0.108

Table 3.6

UPF and UAGF Factor vs. Standard Pricing Factors

Panel A shows results of regressing UPF on i) the size (SMB), value (HML), profitability (RMW), and investment (CMA) factors of the Fama and French (2015) 5-factor model (5F) in Specification (1) and its extension that is augmented by momentum factor (MOM) of Carhart (1997) and liquidity factor (LIQ) of Pástor and Stambaugh (2003) (7F) in Specification (2); ii) Hou et al.'s (2015) Q-factor model: size (SMB_Q), investment ($R_{I/A}$), and profitability (R_{ROE}) (QF) in Specification (3) and its extension that is augmented by MOM and LIQ (6QF) in Specification (4). Panel B shows results of regressing the UAGF on the same set of risk factors. Newey-West adjusted *t*-statistics are reported in parentheses.

Panel A. Uncertainty of Profitability Factor (UPF)

UPF	(1) 5F	(2) 7F	(3) QF	(4) 6QF
Constant	0.369	0.364	0.433	0.422
	(3.18)	(3.18)	(2.26)	(2.73)
MKTRF	0.176	0.179	0.164	0.186
	(5.58)	(5.62)	(2.95)	(4.09)
SMB	0.135	0.134		
	(2.99)	(3.03)		
HML	-0.396	-0.387		
	(-8.61)	(-8.19)		
RMW	-0.494	-0.497		
	(-6.19)	(-6.35)		
CMA	-0.049	-0.056		
	(-0.46)	(-0.55)		
MOM		0.014		0.184
		(0.54)		(4.72)
LIQ		-0.009		-0.029
		(-0.36)		(-0.81)
SMBQ			0.215	0.143
			(2.04)	(2.07)
R_{ROE}			-0.327	-0.509
			(-3.32)	(-5.24)
$R_{I/A}$			-0.639	-0.605
			(-5.73)	(-6.70)
No. of Obs.	336	336	336	336
R^2	0.735	0.736	0.571	0.625

Panel B. Uncertainty of Asset Growth Factor (UAGF)

UAG	(1) 5F	(2) 7F	(3) QF	(4) 6QF
Constant	0.359	0.374	0.402	0.423
	(3.65)	(4.20)	(2.59)	(3.53)
MKTRF	0.073	0.083	0.064	0.085
	(2.22)	(2.64)	(1.40)	(2.25)
SMB	0.117	0.115		
	(3.34)	(3.48)		
HML	-0.357	-0.349		
	(-8.98)	(-9.14)		
RMW	-0.376	-0.383		
	(-4.55)	(-4.59)		
CMA	-0.040	-0.052		
	(-0.39)	(-0.53)		
MOM		0.022		0.157
		(0.95)		(4.08)
LIQ		-0.076		-0.090
		(-2.92)		(-3.34)
SMBQ			0.186	0.123
			(2.14)	(2.24)
R_{ROE}			-0.227	-0.389
			(-2.61)	(-4.32)
$R_{I/A}$			-0.563	-0.540
			(-5.81)	(-6.76)
No. of Obs.	336	336	336	336
R^2	0.649	0.662	0.472	0.540

Table 3.7

UP and UAG Premium Conditional on Co-movement with Consumption Growth

This table reports the time series averages of the cross-sectional slope coefficients obtained by regressing monthly excess returns (in percentage) on lagged uncertainty of profitability (UP), lagged uncertainty of asset growth (UAG) and a set of lagged controls following the Fama and MacBeth (1973) approach. The controls include: market beta (β^{MKT}), log of market capitalization (SIZE), book-to-market (BM), operational profitability (OP), and investment (INV). Specification (1) shows results of the overall sample. Specification (2) shows results for the subsample where the expected one-year change in profitability and asset growth co-move with consumption growth (i.e., $\Delta C_y \times \Delta\Pi_{i,y} > 0$ and $\Delta C_y \times \text{AG}_{i,y} > 0$). Specification (3) shows results for the subsample where the expected one-year change in profitability and asset growth do not co-move with consumption growth (i.e., $\Delta C_y \times \Delta\Pi_{i,y} < 0$ and $\Delta C_y \times \text{AG}_{i,y} < 0$). $\Delta\Pi_{i,y}$ is the expected one-year change in profitability ($\text{E}_t[\Pi_{i,y}]$) estimated as per Equation 3.9 and asset growth ($\text{AG}_{i,y}$) is estimated as per Equation 3.11. t-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses.

R_{t+1}	(1) All Firms	(2) Positive	(3) Negative
Constant	2.055	2.663	1.813
	(3.74)	(4.84)	(1.73)
UP	1.971	2.115	1.577
	(4.57)	(3.42)	(1.23)
UAG	0.311	0.202	0.480
	(2.95)	(1.84)	(1.47)
β^{MKT}	0.043	0.083	-0.107
	(0.80)	(1.15)	(-0.94)
SIZE	-0.115	-0.150	-0.114
	(-3.84)	(-4.82)	(-1.73)
BM	0.547	0.376	0.680
	(2.91)	(1.85)	(2.01)
OP	0.006	0.005	0.008
	(2.32)	(2.04)	(1.45)
INV	-0.007	-0.006	-0.001
	(-5.69)	(-3.59)	(-0.28)
No. of Obs.	434,009	220,501	33,588
R^2	0.039	0.05	0.173

Table 3.8

Market-wide Indicators versus UPF

Panel A shows results of the yearly time-series regressions of UP spread defined as the difference between the volatility of expected profitability of the high-UP and low-UP portfolios (UP_{spread}) on i) the median market profitability (GPA (market)), ii) the default spread (DEFS) defined as the spread between BAA- and AAA-rated corporate bonds, iii) expected inflation (EINF), change in the VXO (ΔVXO), or iv) change in the CFNAI (ΔCFNAI). In Panel B, a regression of the UPF as the dependent variables is conducted against the same regressors. *t*-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. T is the number of years.

Panel A. UP_{spread} vs. Marketwide Indicators

UP_{spread}	(1)	(2)	(3)	(4)	(5)
Constant	1.067	0.381	0.621	0.388	0.388
	(6.85)	(8.24)	(8.23)	(11.51)	(11.44)
GPA (market)	-1.847				
	(-4.31)				
DEFS		0.002			
		(0.13)			
EINF			-0.082		
			(-3.04)		
ΔVXO				-0.001	
				(-0.87)	
ΔCFNAI					0.005
					(0.53)
T	29	29	29	28	28
R^2	0.649	0.000	0.276	0.005	0.004

Panel B. UPF vs. Marketwide Indicators

UPF	(1)	(2)	(3)	(4)	(5)
Constant	-24.380	8.859	-10.290	2.891	3.007
	(-2.54)	(2.15)	(-1.58)	(1.46)	(1.58)
GPA (market)	73.650				
	(2.75)				
DEFS		-5.737			
		(-1.93)			
EINF			4.571		
			(2.03)		
ΔVXO				-0.336	
				(-3.07)	
ΔCFNAI					2.767
					(2.26)
T	29	29	29	28	28
R^2	0.050	0.053	0.041	0.038	0.046

Table 3.9

Market-wide Indicators versus UAGF

Panel A shows results of the yearly time-series regressions of UAG spread defined as the difference between the volatility of expected profitability of the high-UAG and low-UAG portfolios (UAG_{spread}) on i) the median market profitability (GPA (market)), ii) the default spread (DEFS) defined as the spread between BAA- and AAA-rated corporate bonds, iii) expected inflation (EINF), change in the VXO (ΔVXO), or iv) change in the CFNAI (ΔCFNAI). In Panel B, a regression of the UAGF as the dependent variables is conducted against the same regressors. *t*-statistics corrected for autocorrelation and heteroscedasticity with 6 lags are given in parentheses. T is the number of years.

Panel A: UAG_{spread} vs. Marketwide Indicators

UP_{spread}	(1)	(2)	(3)	(4)	(5)
Constant	2.003	1.432	1.809	1.492	1.492
	(4.73)	(20.28)	(19.80)	(28.58)	(28.43)
GPA (market)	-1.396				
	(-1.32)				
DEFS		0.051			
		(1.91)			
EINF			-0.112		
			(-4.70)		
ΔVXO				-0.002	
				(-0.91)	
ΔCFNAI					0.001
					(0.04)
T	29	29	29	28	28
R^2	0.152	0.035	0.208	0.017	0.000

Panel B: UAGF vs. Marketwide Indicators

UAGF	(1)	(2)	(3)	(4)	(5)
Constant	-12.840	7.617	0.738	2.515	2.617
	(-1.47)	(2.70)	(0.09)	(1.66)	(1.77)
GPA (market)	41.420				
	(1.77)				
DEFS		-4.934			
		(-2.58)			
EINF			0.613		
			(0.24)		
ΔVXO				-0.310	
				(-2.87)	
ΔCFNAI					2.354
					(2.66)
T	29	29	29	28	28
R^2	0.025	0.061	0.001	0.05	0.052

Table 3.10

UP versus IVOL

Panel A reports the slope coefficients obtained of the panel regression of the one-month ahead IVOL on UP and other controls as per Equation 3.15. These controls include: β^{MKT}, SIZE, BM, OP, INV, DISP, and β^{VXO}. Panel B reports the slope coefficients the panel regression of UP on 60-months lagged IVOL along with the same controls as per Equation 3.16. All variables in this analysis are cross-sectionally standardized. t-statistics reported in parentheses.

Panel A. Regressing IVOL_{t+1} on UP_t as per Eq. 3.15

	(1) IVOL_{t+1}	(2) IVOL_{t+1}
Constant	0.063	-0.037
	(9.68)	(-11.31)
UP_t	0.048	0.037
	(8.86)	(6.45)
β_t^{MKT}	0.054	0.053
	(27.49)	(26.13)
SIZE_t	-0.348	-0.325
	(-33.90)	(-25.85)
BM_t	0.038	0.046
	(7.49)	(8.57)
GPA_t	0.004	0.006
	(0.69)	(0.86)
INV_t	0.045	0.041
	(16.67)	(14.71)
DISP_t	0.009	0.008
	(4.49)	(3.81)
β_t^{VXO}	0.002	0.002
	(1.04)	(1.10)
No. of Obs.	442,808	442,808
R^2	0.187	0.183
Fixed Effects	No	Yes

Panel B. Regressing UP_t on IVOL_{t-60} as per Eq. 3.16

	(1) UP_t	(2) UP_t
Constant	0.046	-0.035
	(2.62)	(-2.86)
IVOL_{t-60}	0.029	0.028
	(6.68)	(6.43)
$\beta_{t-60}^{\text{MKT}}$	0.012	0.012
	(4.84)	(4.79)
SIZE_{t-60}	-0.123	-0.122
	(-3.67)	(-3.55)
BM_{t-60}	-0.047	-0.046
	(-3.60)	(-3.41)
GPA_{t-60}	-0.039	-0.036
	(-1.87)	(-1.71)
INV_{t-60}	0.028	0.028
	(2.98)	(2.93)
DISP_{t-60}	-0.001	-0.002
	(-0.47)	(-0.55)
$\beta_{t-60}^{\text{VXO}}$	0.000	0.000
	(-0.09)	(-0.11)
No. of Obs.	256,273	256,273
R^2	0.058	0.056
Fixed Effects	No	Yes

Table 3.11

UAG versus IVOL

Panel A reports the slope coefficients obtained of the panel regression of the one-month ahead IVOL on UAG and other controls. These controls include: β^{MKT}, SIZE, BM, OP, INV, DISP, and β^{VXO}. Panel B reports the slope coefficients the panel regression of UAG on 60-months lagged IVOL along with the same controls. All variables in this analysis are cross-sectionally standardized. t-statistics reported in parentheses.

Panel A. Regressing IVOL_{t+1} on UAG_t

	(1) IVOL_{t+1}	(2) IVOL_{t+1}
Constant	-0.017	-0.084
	(-2.45)	(-17.58)
UAG_t	0.045	0.040
	(10.18)	(8.55)
β_t^{MKT}	0.058	0.056
	(27.28)	(26.33)
SIZE_t	-0.324	-0.309
	(-27.99)	(-22.11)
BM_t	0.038	0.0431
	(6.93)	(7.42)
GPA_t	0.017	0.020
	(2.66)	(2.71)
INV_t	0.030	0.028
	(9.06)	(8.44)
DISP_t	0.011	0.010
	(4.68)	(4.24)
β_t^{VXO}	0.003	0.003
	(1.41)	(1.48)
No. of Obs.	361,416	361,416
R^2	0.176	0.175
Fixed Effects	No	Yes

Panel B. Regressing UAG_t on IVOL_{t-60}

	(1) UAG_t	(2) UAG_t
Constant	-0.095	-0.156
	(-7.30)	(-16.04)
IVOL_{t-60}	0.019	0.018
	(4.41)	(4.18)
$\beta_{t-60}^{\text{MKT}}$	0.005	0.005
	(2.25)	(2.22)
SIZE_{t-60}	-0.200	-0.203
	(-7.64)	(-7.42)
BM_{t-60}	-0.145	-0.144
	(-11.52)	(-11.21)
GPA_{t-60}	0.046	0.051
	(2.47)	(2.68)
INV_{t-60}	0.017	0.016
	(2.72)	(2.57)
DISP_{t-60}	0.004	0.004
	(1.59)	(1.53)
$\beta_{t-60}^{\text{VXO}}$	0.001	0.002
	(1.15)	(1.16)
No. of Obs.	248,450	248,450
R^2	0.055	0.052
Fixed Effects	No	Yes

Table 3.12

Asymmetrical UP and UAG Premium

This table reports the time-series coefficients of the cross-sectional individual stock-level regressions of the one month-ahead excess returns on UP and a set of controls for the high (top 25%) and low (bottom 25%) profitable firms in Panel A where profitability is estimated by the gross profit to assets (GPA). Panel B reports the time-series coefficients of the cross-sectional individual stock-level regressions of the one month-ahead excess returns on UAG and a set of controls for the high (top 25%) and low (bottom 25%) asset growth (AG) firms.

Panel A. UP Premium for Low vs. High Profitability Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_{t+1}	Low GPA	High GPA	Low GPA	High GPA	Low GPA	High GPA	Low GPA	High GPA
Constant	1.162	1.302	2.613	3.61	2.8	3.787	2.643	3.184
	(3.57)	(4.61)	(3.70)	(4.38)	(3.92)	(4.77)	(3.61)	(4.05)
UP	0.932	2.474	1.191	2.919	1.245	2.857	1.153	3.101
	(1.37)	(3.36)	(2.09)	(4.55)	(2.28)	(4.29)	(2.03)	(4.72)
β^{MKT}			0.135	0.052	0.132	0.054	0.090	0.029
			(1.99)	(0.80)	(1.94)	(0.86)	(1.40)	(0.48)
SIZE			-0.163	-0.202	-0.159	-0.204	-0.149	-0.162
			(-3.75)	(-4.06)	(-3.70)	(-4.23)	(-3.35)	(-3.38)
BM			0.527	0.441	0.396	0.292	0.374	0.384
			(2.73)	(1.84)	(2.12)	(1.26)	(2.14)	(1.71)
INV					-0.004	-0.007	-0.005	-0.010
					(-4.05)	(-3.79)	(-4.49)	(-4.40)
MOM							0.000	0.003
							(-0.23)	(2.28)
ILLIQ							-0.031	0.048
							(-1.29)	(2.21)
No. of Obs.	138,127	152,250	134,345	149,283	129,711	147,314	122,355	140,038
R^2	0.015	0.012	0.045	0.04	0.052	0.047	0.068	0.061

Table 3.12 (continued)

Panel B. UAG Premium for Low vs. High Asset Growth Firms

R_{t+1}	(1) Low AG	(2) High AG	(3) Low AG	(4) High AG	(5) Low AG	(6) High AG	(7) Low AG	(8) High AG
Constant	1.607	1.007	3.883	1.762	3.411	0.692	3.003	0.854
	(4.86)	(3.32)	(5.71)	(2.43)	(4.67)	(0.97)	(3.85)	(1.16)
UAG	0.499	0.184	0.531	0.189	0.436	0.257	0.449	0.236
	(2.20)	(1.09)	(2.80)	(1.25)	(2.54)	(1.71)	(2.58)	(1.65)
β^{MKT}			0.067	0.027	0.066	0.009	0.041	-0.010
			(0.91)	(0.42)	(0.87)	(0.15)	(0.59)	(-0.17)
SIZE			-0.216	-0.076	-0.198	-0.040	-0.182	-0.057
			(-5.51)	(-1.71)	(-5.04)	(-0.95)	(-4.17)	(-1.33)
BM			0.347	0.557	0.429	0.792	0.489	0.929
			(2.09)	(1.94)	(2.44)	(2.71)	(3.04)	(3.31)
GPA					0.004	0.011	0.004	0.011
					(1.69)	(4.06)	(1.54)	(3.94)
MOM							0.000	0.002
							(0.19)	(1.01)
ILLIQ							0.061	-0.094
							(1.53)	(-1.28)
No. of Obs.	123,513	98,172	119,104	97,032	115,946	95,102	115,683	94,796
R^2	0.009	0.009	0.039	0.044	0.045	0.052	0.060	0.068

Table 3.13

UP and the Profitability Premium

This table reports the risk-adjusted returns of decile portfolios for the largest 1000 firms in the sample based on stocks' gross profit to assets (GPA) in Panel A and sorted on both GPA and the volatility of profitability (UP) in Panel B. The reported alphas are generated based on: i) the 5F, and QF models, ii) the same set of models augmented by MOM and LIQ factors with the 5F and QF models excluding in both sets the profitability factors RMW and R_{ROE}), respectively. The last two rows show the difference in alphas between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

Panel A. Portfolio Sorting on GPA

			+MOM+LIQ	
GPA Decile	5F	QF	5F	QF
1 (Low)	-0.083	-0.086	-0.046	-0.040
	(-0.66)	(-0.65)	(-0.35)	(-0.31)
2	-0.079	-0.088	-0.096	-0.088
	(-0.57)	(-0.67)	(-0.69)	(-0.67)
3	-0.141	-0.141	-0.150	-0.130
	(-1.06)	(-1.16)	(-1.18)	(-1.07)
4	0.113	0.131	0.136	0.163
	(0.91)	(1.10)	(1.25)	(1.53)
5	0.038	0.120	-0.002	0.063
	(0.29)	(0.95)	-(0.02)	(0.51)
6	0.211	0.324	0.339	0.412
	(1.33)	(1.89)	(2.03)	(2.33)
7	0.391	0.443	0.427	0.456
	(2.65)	(2.80)	(2.72)	(2.66)
8	0.320	0.390	0.329	0.365
	(2.57)	(2.67)	(2.65)	(2.61)
9	0.541	0.551	0.494	0.488
	(4.25)	(3.99)	(3.91)	(3.64)
10 (High)	0.348	0.376	0.338	0.345
	(2.58)	(2.61)	(2.38)	(2.36)
High−Low (10−1)	0.431	0.462	0.384	0.385
t-stat	(2.26)	(2.36)	(1.92)	(1.89)

Panel B. Portfolio Sorting on GPA and UP Independently

			+MOM+LIQ	
GPA and UP Decile	5F	QF	5F	QF
1 (Low)	-0.285	-0.315	-0.140	-0.124
	(-1.43)	(-1.39)	(-0.72)	(-0.57)
2	0.145	0.071	0.165	0.141
	(0.77)	(0.37)	(0.88)	(0.80)
3	0.022	-0.022	0.050	0.059
	(0.10)	-(0.10)	(0.23)	(0.27)
4	0.117	0.102	0.143	0.172
	(0.64)	(0.54)	(0.72)	(0.82)
5	0.150	0.229	0.264	0.329
	(0.58)	(0.88)	(1.05)	(1.28)
6	0.036	0.088	0.080	0.146
	(0.13)	(0.31)	(0.28)	(0.52)
7	0.368	0.430	0.173	0.257
	(1.05)	(1.17)	(0.52)	(0.77)
8	0.023	0.120	0.049	0.102
	(0.09)	(0.46)	(0.18)	(0.36)
9	0.576	0.641	0.500	0.549
	(1.94)	(2.11)	(1.57)	(1.77)
10 (High)	0.745	0.899	0.871	0.916
	(2.08)	(2.28)	(2.18)	(2.14)
High−Low (10−1)	1.030	1.214	1.011	1.040
t-stat	(2.43)	(2.46)	(2.27)	(2.04)

Table 3.14

Extended Sample Analysis

In Panel A, value-weighted decile portfolios are formed each month based on UP for the extended sample. Portfolio 1 (10) contains stocks with the lowest (highest) UP measure. Analogously, in Panel B value-weighted decile portfolios are formed each month based on UAG for the extended sample. Both Panels report excess returns and risk-adjusted returns of portfolios using different sets of asset pricing models: i) 5-factor of Fama and French (2015), and Q-factor models of Hou et al. (2015) , ii) the above models augmented by the momentum (MOM) factor of Carhart (1997) and the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The last two rows show the difference in returns between deciles 10 and 1. *t*-statistics (in parentheses) are corrected for autocorrelation and heteroscedasticity.

Panel A. Value-Weighted Portfolios for the Extended Sample (UP Decile)

				+ MOM + LIQ	
UP Decile	Exc. Ret.	5F	QF	5F	QF
1 (Low UP)	0.561	-0.131	-0.082	-0.068	-0.057
	(1.83)	(-0.82)	(-0.46)	(-0.40)	(-0.31)
2	0.892	0.271	0.244	0.285	0.266
	(3.99)	(2.69)	(2.49)	(2.79)	(2.68)
3	0.722	0.058	0.178	0.137	0.186
	(3.16)	(0.48)	(1.24)	(1.30)	(1.61)
4	0.800	0.050	0.069	0.079	0.099
	(3.54)	(0.47)	(0.64)	(0.78)	(0.96)
5	0.781	0.095	0.103	0.081	0.111
	(3.47)	(0.86)	(0.98)	(0.78)	(1.06)
6	0.689	-0.102	-0.043	-0.117	-0.065
	(3.20)	(-0.94)	(-0.36)	(-1.12)	(-0.56)
7	0.777	0.022	0.038	-0.047	-0.004
	(3.14)	(0.22)	(0.38)	(-0.47)	-(0.04)
8	0.849	0.054	0.137	0.097	0.136
	(2.83)	(0.40)	(0.85)	(0.63)	(0.84)
9	0.787	0.236	0.344	0.253	0.324
	(2.38)	(1.45)	(1.73)	(1.52)	(1.63)
10 (High UP)	1.130	0.592	0.622	0.619	0.658
	(3.14)	(3.42)	(2.57)	(3.48)	(3.09)
High−Low (10−1)	0.568	0.723	0.704	0.687	0.714
t-stat	(2.00)	(2.74)	(2.11)	(2.56)	(2.33)

Panel B. Value-Weighted Portfolios for the Extended Sample (UAG Decile)

				+ MOM + LIQ	
UAG Decile	Exc. Ret.	5F	QF	5F	QF
1 (Low UAG)	0.627	-0.100	-0.113	-0.114	-0.096
	(2.92)	(-1.30)	(-1.35)	(-1.56)	(-1.18)
2	0.776	0.001	0.060	0.002	0.047
	(3.49)	(0.01)	(0.51)	(0.02)	(0.40)
3	0.817	0.236	0.281	0.210	0.269
	(3.24)	(2.35)	(2.54)	(2.07)	(2.54)
4	0.708	0.000	0.054	0.071	0.058
	(2.75)	(0.00)	(0.37)	(0.64)	(0.45)
5	0.851	0.223	0.260	0.216	0.262
	(3.05)	(1.35)	(1.61)	(1.33)	(1.66)
6	0.835	0.154	0.245	0.176	0.232
	(3.31)	(1.10)	(1.42)	(1.24)	(1.47)
7	0.794	0.175	0.233	0.181	0.231
	(2.95)	(1.46)	(2.02)	(1.53)	(1.97)
8	0.686	-0.025	-0.012	-0.008	0.015
	(2.36)	(-0.18)	(-0.07)	(-0.05)	(0.09)
9	1.004	0.479	0.511	0.512	0.555
	(2.91)	(3.25)	(2.74)	(3.80)	(3.53)
10 (High UAG)	0.988	0.488	0.581	0.547	0.609
	(2.83)	(3.03)	(3.17)	(3.43)	(3.35)
High−Low (10−1)	0.361	0.588	0.694	0.661	0.705
t-stat	(1.71)	(3.20)	(3.50)	(3.81)	(3.56)

Table 3.15

Robustness to Alternative Profitability Measures

This table tests the robustness of profitability volatility premium to alternative profitability measures. Value- and equal-weighted decile portfolios are formed each month based on the volatility of change in realized profitability over the previous 5 years for each of the following profitability estimate: i) operating profitability computed following Ball et al. (2016) (OPB), ii) cash-based operating profitability (CBOP), iii) accruals based on balance sheet and income statement items, iv) accruals based on cash flow statement items, v) gross profit to assets (GP), and vi) return on assets (ROA). Changes of all the above profitability measures are then deflated by the previous year's total assets. Portfolio 1 (10) contains stocks with the lowest (highest) volatility of change in profitability. The table reports risk-adjusted returns of the 5-factor of Fama and French (2015) augmented by the momentum (MOM) factor of Carhart (1997) and the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The last two rows show the difference in alphas between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

Panel A. Risk-Adjusted Returns of Value-Weighted Portfolios

Decile	OPB	CBOP	Acc (BS)	Acc (CF)	GPA	ROA
1 (Low)	0.023	-0.159	-0.028	-0.024	0.012	0.040
	(0.28)	(-1.24)	(-0.40)	(-0.19)	(0.15)	(0.53)
2	-0.031	0.006	-0.009	0.220	-0.003	0.051
	(-0.36)	(0.04)	(-0.09)	(0.74)	(-0.03)	(0.54)
3	0.097	0.244	0.059	0.002	0.153	-0.131
	(0.92)	(1.71)	(0.61)	(0.01)	(1.64)	(-1.24)
4	0.106	0.171	0.178	0.329	0.035	0.057
	(1.00)	(1.10)	(1.66)	(1.66)	(0.33)	(0.42)
5	-0.072	0.363	0.101	0.199	0.134	0.229
	(-0.58)	(1.76)	(0.83)	(0.96)	(1.07)	(1.90)
6	0.167	-0.204	0.248	0.474	0.253	0.235
	(1.08)	(-0.91)	(1.78)	(1.93)	(1.74)	(1.54)
7	0.602	0.552	0.304	0.132	0.338	0.063
	(3.40)	(2.66)	(2.20)	(0.49)	(2.27)	(0.48)
8	-0.048	0.654	0.291	0.407	0.254	0.301
	(-0.25)	(1.45)	(1.62)	(1.52)	(1.33)	(1.78)
9	0.382	0.278	0.281	0.310	0.173	0.403
	(1.90)	(1.28)	(1.62)	(1.38)	(0.90)	(2.38)
10 (High)	0.729	0.615	0.842	0.689	0.540	0.727
	(3.23)	(1.84)	(3.66)	(2.19)	(2.95)	(3.49)
High−Low (10−1)	0.707	0.774	0.871	0.713	0.528	0.687
t-stat	(2.75)	(2.13)	(3.62)	(2.07)	(2.67)	(3.04)

Panel B. Risk-Adjusted Returns of Equal-Weighted Portfolios

Decile	OPB	CBOP (CF)	Acc (BS)	Acc (CF)	GPA	ROA
1 (Low)	0.140	0.031	0.145	0.287	0.238	0.149
	(1.88)	(0.23)	(1.81)	(3.11)	(2.91)	(2.22)
2	0.177	0.129	0.215	0.482	0.183	0.167
	(2.29)	(1.06)	(2.21)	(1.80)	(2.89)	(2.49)
3	0.278	0.344	0.361	0.370	0.255	0.172
	(3.31)	(3.46)	(4.12)	(2.95)	(3.77)	(2.26)
4	0.398	0.500	0.311	0.551	0.453	0.297
	(5.62)	(5.54)	(3.75)	(4.78)	(4.67)	(3.24)
5	0.323	0.383	0.419	0.509	0.431	0.346
	(3.33)	(3.62)	(4.71)	(4.58)	(5.26)	(4.55)
6	0.421	0.411	0.445	0.611	0.404	0.502
	(5.13)	(4.23)	(5.23)	(6.62)	(5.13)	(5.28)
7	0.582	0.536	0.623	0.725	0.646	0.654
	(6.36)	(5.24)	(8.27)	(4.55)	(7.03)	(6.55)
8	0.691	1.126	0.584	0.755	0.763	0.787
	(6.69)	(2.61)	(6.09)	(6.48)	(6.70)	(8.08)
9	0.788	0.729	0.757	0.741	0.830	1.039
	(7.09)	(5.94)	(6.20)	(4.59)	(7.19)	(8.67)
10 (High)	1.244	0.903	1.126	0.875	1.223	1.313
	(7.07)	(3.51)	(7.65)	(5.62)	(7.60)	(9.43)
High−Low (10−1)	1.104	1.079	0.980	0.599	0.986	1.164
t-stat	(5.38)	(3.89)	(5.35)	(2.86)	(4.93)	(7.38)

Table 3.16

Excluding Stocks with Null UP

In Panel A, value-weighted decile portfolios are formed each month based UP after excluding stocks with null UP. Portfolio 1 (10) contains stocks with the lowest (highest) UP measure. Panel A reports risk-adjusted returns of value-weighted portfolios using different sets of asset pricing models: i) 3-factor of Fama and French (1993), 5-factor of Fama and French (2015), and Q-factor models of Hou et al. (2015) , ii) the above models augmented by the momentum (MOM) factor of Carhart (1997); and iii) the above augmented by the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The last two rows show the difference in alphas between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses. Panel B reports the time-series averages of the slope coefficients obtained by regressing monthly excess returns (in percentage) on UP and a set of lagged controls following the Fama and MacBeth (1973) approach after excluding stock with null UP. The control variables are the same of Table 3.5.

Panel A. Univariate Portfolio Analysis Excluding Stocks with Null UP

					+ MOM			+ MOM + LIQ		
UP Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	0.630	-0.074	-0.162	-0.135	0.002	-0.098	-0.112	0.018	-0.082	-0.087
	(2.28)	(-0.53)	(-1.05)	(-0.75)	(0.02)	(-0.65)	(-0.67)	(0.12)	(-0.53)	(-0.53)
2	0.951	0.411	0.284	0.287	0.375	0.268	0.287	0.367	0.259	0.281
	(4.77)	(3.62)	(2.56)	(2.49)	(3.24)	(2.42)	(2.48)	(3.30)	(2.39)	(2.51)
3	0.680	0.066	-0.049	-0.024	0.146	0.020	-0.002	0.154	0.027	0.009
	(2.80)	(0.63)	(-0.47)	(-0.20)	(1.46)	(0.19)	-(0.02)	(1.55)	(0.26)	(0.08)
4	0.851	0.250	0.055	0.110	0.248	0.070	0.119	0.259	0.080	0.136
	(3.88)	(2.32)	(0.52)	(1.00)	(2.25)	(0.63)	(1.07)	(2.35)	(0.73)	(1.22)
5	0.791	0.192	0.050	0.071	0.191	0.057	0.083	0.177	0.041	0.065
	(3.84)	(1.64)	(0.48)	(0.54)	(1.53)	(0.52)	(0.67)	(1.45)	(0.38)	(0.54)
6	0.715	0.100	-0.124	-0.055	0.101	-0.106	-0.041	0.055	-0.156	-0.100
	(3.06)	(0.77)	(-1.00)	(-0.40)	(0.81)	(-0.87)	(-0.33)	(0.44)	(-1.30)	(-0.77)
7	0.853	0.228	0.102	0.158	0.171	0.070	0.147	0.151	0.049	0.131
	(3.26)	(2.29)	(0.89)	(1.26)	(1.65)	(0.63)	(1.24)	(1.47)	(0.45)	(1.08)
8	0.875	0.215	0.138	0.199	0.296	0.208	0.209	0.294	0.205	0.212
	(2.92)	(1.59)	(1.01)	(1.19)	(2.01)	(1.39)	(1.23)	(2.05)	(1.40)	(1.30)
9	0.790	0.114	0.244	0.361	0.185	0.285	0.352	0.165	0.264	0.340
	(2.15)	(0.70)	(1.38)	(1.64)	(1.08)	(1.57)	(1.62)	(0.97)	(1.46)	(1.58)
10 (High)	1.233	0.559	0.675	0.697	0.535	0.649	0.673	0.578	0.695	0.740
	(3.28)	(3.31)	(3.70)	(2.72)	(2.86)	(3.41)	(2.86)	(3.13)	(3.74)	(3.29)
High−Low (10−1)	0.602	0.634	0.836	0.832	0.532	0.747	0.785	0.560	0.777	0.827
t-stat	(1.85)	(2.46)	(2.93)	(2.11)	(1.97)	(2.61)	(2.23)	(2.09)	(2.75)	(2.44)

Table 3.16 (continued)

Panel B. Stock level Cross-Sectional Analysis Excluding Stocks with Null UP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Constant	1.202	3.072	2.907	2.990	2.713	2.567	2.900	3.036	1.654	2.091	2.711	2.657	2.743	2.870	2.726	2.390	2.727	2.752
	(4.11)	(4.56)	(4.66)	(4.54)	(4.34)	(3.84)	(4.58)	(4.73)	(2.84)	(3.69)	(4.39)	(3.77)	(4.36)	(4.51)	(4.70)	(4.38)	(4.37)	(4.38)
UP	1.619	1.991	2.184	1.87	2.175	1.951	1.775	1.937	1.439	2.133	1.961	1.923	2.188	2.085	2.186	2.054	2.172	2.198
	(2.63)	(3.83)	(5.11)	(3.61)	(4.75)	(3.89)	(3.98)	(3.78)	(3.54)	(4.88)	(4.83)	(4.45)	(4.80)	(4.55)	(4.89)	(4.82)	(4.74)	(4.82)
β^{MKT}		0.035	0.031	0.017	0.011	0.005	0.002	0.014	-0.031	0.021	0.002	0.000	0.008	0.002	0.005	-0.008	0.011	0.014
		(0.62)	(0.58)	(0.31)	(0.21)	(0.09)	(0.03)	(0.25)	(-0.68)	(0.42)	(0.04)	(-0.01)	(0.15)	(0.04)	(0.11)	(-0.17)	(0.20)	(0.25)
SIZE		-0.172	-0.158	-0.166	-0.149	-0.142	-0.143	-0.166	-0.1	-0.12	-0.155	-0.145	-0.15	-0.15	-0.15	-0.134	-0.15	-0.152
		(-4.45)	(-4.78)	(-4.34)	(-4.42)	(-3.90)	(-4.08)	(-4.48)	(-3.00)	(-3.80)	(-4.43)	(-3.69)	(-4.42)	(-4.36)	(-4.67)	(-4.44)	(-4.46)	(-4.46)
BM		0.463	0.445	0.474	0.514	0.471	0.364	0.439	0.551	0.618	0.530	0.575	0.500	0.389	0.509	0.504	0.513	0.503
		(2.50)	(2.21)	(2.83)	(2.73)	(2.67)	(2.18)	(2.62)	(2.87)	(3.50)	(2.96)	(2.63)	(2.67)	(2.16)	(2.78)	(2.76)	(2.75)	(2.68)
OP			0.002		0.003				0.003	0.006	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.003
			(0.73)		(1.16)				(1.05)	(2.23)	(1.33)	(1.15)	(1.11)	(0.82)	(1.24)	(1.34)	(1.14)	(1.12)
INV			-0.005		-0.006	-0.006	-0.006	-0.006	-0.007	-0.006	-0.007	-0.005	-0.006	-0.007	-0.006	-0.006	-0.006	-0.006
			(-5.48)		(-6.28)	(-6.18)	(-6.30)	(-5.97)	(-7.20)	(-5.43)	(-6.62)	(-5.88)	(-6.21)	(-6.65)	(-6.28)	(-6.32)	(-6.32)	(-6.22)
MOM				0.001	0.001	0.001	0.000	0.002	0.003	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001
				(1.11)	(1.14)	(0.50)	(0.22)	(1.42)	(1.80)	(0.99)	(1.02)	(0.65)	(1.10)	(0.97)	(1.18)	(1.37)	(1.12)	(1.12)
ILLIQ				0.015	0.000	0.001	0.003	0.002	-0.034	0.004	-0.001	-0.089	0.001	0.001	0.002	-0.001	0.000	0.000
				(0.95)	(0.02)	(0.10)	(0.22)	(0.16)	(-0.78)	(0.26)	(-0.06)	(-0.83)	(0.09)	(0.08)	(0.14)	(-0.04)	(0.03)	(-0.02)
GPA						0.004												
						(2.21)												
ROA							-0.012											
							(-2.87)											
TROA5								0.001										
								(1.84)										
UNC									2.216									
									(3.60)									
UAG										0.252								
										(2.31)								
TURN											0.093							
											(2.02)							
DISP												-0.026						
												(-0.67)						
β^{VXO}													-10.6					
													(-2.65)					
STR														-0.027				
														(-7.09)				
MAX															-0.003			
															(-0.38)			
IVOL																0.036		
																(1.01)		
ISKEW																	0.0000	
																	(-0.13)	
COSK																		-0.000007
																		(-0.76)
No. of Obs.	558,430	547,952	508,029	517,561	484,950	504,398	509,031	503,106	420,558	418,082	484,950	404,229	484,950	484,949	484,950	484,950	484,943	484,950
R^2	0.008	0.030	0.037	0.038	0.043	0.044	0.044	0.041	0.054	0.047	0.050	0.052	0.045	0.048	0.046	0.047	0.044	0.045

Table 3.17

UP Robustness to the Number of Analysts

This table tests the robustness of the uncertainty of profitability (UP) premium to the number of analysts providing earnings forecast. Value- and equal-weighted decile portfolios are formed each month based on UP where portfolio 1 (10) contains stocks with the lowest (highest) UP measure. The table reports risk-adjusted returns of the 5-factor of Fama and French (2015) augmented by the momentum (MOM) factor of Carhart (1997) and the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The different sets include forecasts that are provided by at least three, five, or ten analysts, respectively. The last two rows show the difference in alphas between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

	3 Analysts		5 Analysts		10 Analysts	
UP Decile	VW	EW	VW	EW	VW	EW
1 (Low)	-0.008	0.540	0.015	0.600	-0.181	0.291
	(-0.04)	(5.11)	(0.12)	(5.96)	(-1.49)	(2.90)
2	0.137	0.363	0.057	0.286	0.078	0.258
	(1.27)	(4.33)	(0.46)	(3.57)	(0.52)	(2.73)
3	0.132	0.271	0.191	0.370	0.096	0.296
	(1.05)	(3.15)	(1.53)	(4.21)	(0.78)	(2.94)
4	0.030	0.286	0.028	0.110	0.116	0.177
	(0.31)	(3.40)	(0.24)	(1.43)	(1.00)	(1.77)
5	-0.106	0.267	0.003	0.362	0.057	0.138
	(-1.23)	(3.29)	(0.03)	(3.44)	(0.49)	(1.58)
6	0.079	0.330	0.071	0.323	0.134	0.261
	(0.83)	(3.77)	(0.73)	(3.13)	(1.51)	(2.47)
7	-0.036	0.499	-0.070	0.312	-0.039	0.207
	(-0.33)	(4.94)	-(0.65)	(2.92)	(-0.38)	(1.84)
8	0.160	0.566	0.130	0.409	-0.029	0.291
	(1.49)	(4.85)	(0.97)	(3.82)	(-0.21)	(2.02)
9	0.227	0.830	0.165	0.796	0.175	0.660
	(1.44)	(6.11)	(1.14)	(5.64)	(1.22)	(4.11)
10 (High)	0.701	1.405	0.693	1.261	0.652	1.109
	(3.72)	(7.86)	(3.91)	(6.74)	(3.55)	(5.84)
High−Low (10−1)	0.709	0.865	0.679	0.660	0.833	0.818
t-stat	(2.27)	(3.79)	(2.83)	(3.12)	(3.66)	(3.82)

Table 3.18

UP Robustness to Alternative Time-Horizon

In this table, value-weighted decile portfolios are formed each month based on the standard deviation of the estimated profitability. Portfolio 1 (10) contains stocks with the lowest (highest) UP measure. Panel A reports the risk-adjusted returns based on the 7F model where UP is computed as the volatility of the total annual changes of the expected profitability based on analysts forecasts over the coming 1, 2, 3, 4, or 5 years. In Panel B, the volatility of expected profitability is computed over the previous 18, 24, 36, 48, or 60 months. The last two rows report the difference of alphas between the high and low portfolio deciles, with the Newey-West t-statistics in parentheses.

Panel A. Robustness to Analyst Forecast Horizon

UP Decile	1	2	3	4	5
1 (Low)	-0.091	-0.072	-0.048	-0.048	-0.171
	(-0.65)	(-0.46)	(-0.33)	(-0.29)	(-1.06)
2	0.283	0.250	0.239	0.257	0.298
	(2.70)	(2.37)	(2.19)	(2.33)	(2.62)
3	-0.003	-0.050	-0.075	-0.012	-0.031
	-(0.02)	(-0.42)	(-0.67)	(-0.11)	(-0.28)
4	0.081	0.076	0.097	-0.073	0.023
	(0.79)	(0.94)	(0.91)	(-0.64)	(0.20)
5	0.058	0.077	0.070	0.056	0.111
	(0.60)	(0.76)	(0.65)	(0.49)	(1.06)
6	-0.067	-0.024	-0.022	-0.051	-0.087
	(-0.63)	(-0.24)	(-0.25)	(-0.53)	(-0.74)
7	-0.093	-0.172	-0.074	-0.016	-0.034
	(-0.85)	(-1.34)	(-0.55)	(-0.16)	(-0.29)
8	0.122	0.125	0.134	0.227	0.236
	(0.84)	(0.82)	(0.89)	(1.64)	(1.67)
9	0.398	0.406	0.466	0.221	0.228
	(2.56)	(2.38)	(2.56)	(1.14)	(1.33)
10 (High)	0.673	0.907	0.782	0.773	0.691
	(3.93)	(4.58)	(3.69)	(3.83)	(3.71)
High−Low (10−1)	0.764	0.980	0.830	0.821	0.862
t-stat	(3.29)	(3.51)	(2.89)	(2.78)	(3.09)

Panel B. Robustness to UP Estimation Horizon

UP Decile	18	24	36	48	60
1 (Low)	-0.017	-0.063	-0.114	-0.043	-0.171
	(-0.12)	(-0.42)	(-0.56)	(-0.28)	(-1.06)
2	0.049	0.066	0.127	0.229	0.298
	(0.42)	(0.65)	(1.18)	(2.04)	(2.62)
3	-0.073	0.079	0.099	0.051	-0.031
	(-0.77)	(0.82)	(0.98)	(0.44)	(-0.28)
4	0.135	0.056	0.069	0.109	0.023
	(1.19)	(0.55)	(0.63)	(0.97)	(0.20)
5	0.055	-0.073	0.109	0.122	0.111
	(0.51)	(-0.63)	(0.89)	(1.08)	(1.06)
6	-0.184	0.111	0.021	-0.073	-0.087
	(-1.72)	(1.06)	(0.18)	(-0.59)	(-0.74)
7	0.033	-0.047	-0.061	0.064	-0.034
	(0.27)	(-0.40)	(-0.63)	(0.52)	(-0.29)
8	0.253	0.132	0.014	-0.007	0.236
	(2.31)	(1.19)	(0.10)	(-0.04)	(1.67)
9	0.375	0.378	0.523	0.383	0.228
	(2.21)	(2.39)	(3.17)	(2.23)	(1.33)
10 (High)	0.645	0.608	0.555	0.608	0.691
	(3.17)	(2.86)	(2.68)	(2.99)	(3.71)
High−Low (10−1)	0.66	0.67	0.67	0.65	0.862
t-stat	(2.37)	(2.29)	(2.10)	(2.26)	(3.09)

Table 3.19

UP Robustness to Alternative Subsamples

The table presents robustness results of the univariate portfolio sorting based on UP to different subsamples: (i) excluding stocks with price per share below \$5 (\$5), (ii) large stocks with market capitalization greater than the sample monthly median size breakpoint (Large 50^{th}), (iii) excluding stocks with the highest 30% illiquidity (30% ILLIQ), and (iv) excluding stocks with the highest 30% idiosyncratic volatility (30% IVOL). The table reports the 7F model alphas of deciles 1 through 10 of value-weighted portfolios sorted based on UP. The last two rows report the difference of alphas between the high and low portfolio deciles, with the Newey-West t-statistics in parentheses.

UP Decile	Exc. \$5	Large 50^{th}	30% ILLIQ	30% IVOL
1 (Low)	-0.101	-0.03	0.00	-0.17
	(-0.64)	(-0.20)	(-0.03)	(-0.94)
2	0.358	0.24	0.24	0.29
	(2.91)	(2.02)	(1.88)	(2.30)
3	0.122	-0.08	-0.02	0.13
	(0.91)	(-0.69)	(-0.20)	(1.07)
4	0.103	0.26	0.23	-0.02
	(0.87)	(2.53)	(2.32)	(-0.20)
5	0.167	-0.08	-0.06	0.10
	(1.62)	(-0.76)	(-0.61)	(0.94)
6	-0.063	-0.19	-0.14	-0.10
	(-0.50)	(-1.59)	(-1.31)	(-0.84)
7	-0.072	0.13	0.09	-0.07
	(-0.63)	(1.11)	(0.84)	(-0.74)
8	0.066	0.11	0.10	0.03
	(0.59)	(0.86)	(0.75)	(0.21)
9	0.228	0.41	0.43	0.25
	(1.88)	(2.44)	(2.18)	(1.81)
10 (High)	0.603	0.55	0.59	0.49
	(3.04)	(2.81)	(3.02)	(2.31)
High−Low (10−1)	0.704	0.57	0.59	0.66
t-stat	(2.56)	(2.15)	(2.26)	(2.12)

Table 3.20

UP Robustness to Alternative Scaling

Value- and equal-weighted decile portfolios are formed each month based on UP in Panels A and B, respectively where the expected profitability is expected net income scaled by the book value of equity. Portfolio 1 (10) contains stocks with the lowest (highest) UP measure. The table reports risk-adjusted returns of value-weighted portfolios for the month following the portfolio formation month using different sets of asset pricing models: i) 3-factor of Fama and French (1993), 5-factor of Fama and French (2015), and Q-factor models of Hou et al. (2015) , ii) the above models augmented by the momentum (MOM) factor of Carhart (1997); and iii) the above augmented by the liquidity (LIQ) factor of Pástor and Stambaugh (2003). The last two rows show the difference in returns between deciles 10 and 1 and the corresponding Newey-West adjusted t-statistics in parentheses.

Panel A. Value-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UP Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	0.514	-0.120	-0.195	-0.188	-0.074	-0.157	-0.171	-0.037	-0.119	-0.122
	(1.79)	(-0.80)	(-1.32)	(-1.13)	(-0.53)	(-1.16)	(-1.17)	(-0.27)	(-0.88)	(-0.84)
2	0.774	0.151	0.028	0.057	0.186	0.065	0.073	0.179	0.056	0.067
	(3.43)	(1.28)	(0.23)	(0.40)	(1.43)	(0.50)	(0.51)	(1.39)	(0.44)	(0.49)
3	0.746	0.153	0.016	0.048	0.222	0.076	0.073	0.219	0.072	0.069
	(3.58)	(1.25)	(0.13)	(0.35)	(1.94)	(0.67)	(0.61)	(1.94)	(0.65)	(0.59)
4	0.622	0.006	-0.193	-0.121	0.005	-0.177	-0.111	-0.010	-0.194	-0.128
	(2.82)	(0.04)	(-1.66)	(-1.00)	(0.04)	(-1.54)	(-0.93)	-(0.08)	-(1.67)	-(1.04)
5	0.901	0.305	0.204	0.239	0.315	0.217	0.248	0.285	0.186	0.213
	(4.09)	(2.67)	(1.97)	(1.93)	(2.62)	(2.02)	(2.05)	(2.39)	(1.73)	(1.74)
6	0.811	0.220	0.075	0.082	0.160	0.041	0.081	0.143	0.022	0.062
	(3.65)	(2.43)	(0.80)	(0.90)	(1.80)	(0.47)	(0.90)	(1.63)	(0.26)	(0.69)
7	0.758	0.106	0.045	0.145	0.178	0.102	0.156	0.159	0.081	0.137
	(3.04)	(1.00)	(0.41)	(1.20)	(1.68)	(0.99)	(1.35)	(1.50)	(0.78)	(1.17)
8	0.843	0.184	0.212	0.270	0.247	0.254	0.273	0.236	0.243	0.268
	(2.79)	(1.43)	(1.55)	(1.62)	(1.74)	(1.77)	(1.63)	(1.65)	(1.65)	(1.59)
9	0.933	0.256	0.153	0.253	0.265	0.169	0.249	0.253	0.157	0.243
	(2.75)	(1.82)	(0.98)	(1.51)	(1.72)	(1.03)	(1.50)	(1.63)	(0.94)	(1.47)
10 (High)	1.105	0.475	0.585	0.594	0.446	0.556	0.573	0.501	0.614	0.653
	(3.34)	(3.61)	(4.08)	(2.82)	(3.18)	(3.70)	(3.03)	(3.63)	(4.29)	(3.76)
High−Low (10−1)	0.591	0.596	0.780	0.782	0.520	0.713	0.744	0.538	0.733	0.776
t-stat	(2.33)	(2.69)	(3.32)	(2.42)	(2.49)	(3.19)	(2.73)	(2.59)	(3.30)	(2.92)

Table 3.20 (continued)

Panel B. Equal-Weighted Portfolios

					+ MOM			+ MOM + LIQ		
UP Decile	Exc. Ret.	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	1.147	0.494	0.437	0.542	0.607	0.521	0.567	0.591	0.505	0.551
	(4.17)	(4.96)	(4.09)	(3.60)	(6.01)	(5.17)	(4.88)	(6.00)	(5.06)	(4.84)
2	1.095	0.361	0.259	0.345	0.460	0.335	0.373	0.446	0.322	0.358
	(4.01)	(3.64)	(2.90)	(2.43)	(4.61)	(4.22)	(3.66)	(4.64)	(4.17)	(3.72)
3	1.146	0.386	0.270	0.384	0.520	0.374	0.417	0.504	0.358	0.400
	(4.15)	(3.41)	(2.60)	(2.37)	(4.77)	(4.37)	(3.91)	(4.82)	(4.39)	(4.02)
4	1.203	0.419	0.317	0.434	0.536	0.408	0.462	0.516	0.387	0.441
	(4.10)	(4.27)	(3.44)	(3.43)	(5.94)	(5.27)	(5.11)	(5.96)	(5.12)	(5.05)
5	1.267	0.438	0.308	0.424	0.573	0.414	0.457	0.553	0.394	0.436
	(4.12)	(3.80)	(3.09)	(3.44)	(5.05)	(4.51)	(5.58)	(5.03)	(4.38)	(5.46)
6	1.228	0.387	0.302	0.445	0.524	0.407	0.471	0.500	0.382	0.447
	(3.85)	(3.73)	(3.12)	(3.86)	(5.24)	(4.76)	(5.65)	(5.12)	(4.57)	(5.51)
7	1.292	0.422	0.482	0.670	0.645	0.639	0.701	0.620	0.614	0.681
	(3.89)	(3.89)	(4.19)	(5.42)	(6.24)	(6.66)	(7.03)	(6.29)	(6.68)	(7.06)
8	1.379	0.490	0.562	0.758	0.711	0.716	0.787	0.688	0.693	0.770
	(3.76)	(4.02)	(4.41)	(5.19)	(5.92)	(6.57)	(6.52)	(6.02)	(6.65)	(6.71)
9	1.664	0.732	0.855	1.053	0.916	0.979	1.069	0.896	0.961	1.061
	(4.21)	(5.18)	(6.35)	(7.55)	(6.34)	(7.52)	(7.68)	(6.25)	(7.37)	(7.68)
10 (High)	1.836	0.980	1.158	1.379	1.144	1.265	1.381	1.162	1.286	1.423
	(4.65)	(5.99)	(7.84)	(7.89)	(6.74)	(8.53)	(7.77)	(6.86)	(8.73)	(8.17)
High−Low (10−1)	0.690	0.486	0.721	0.837	0.538	0.744	0.814	0.572	0.781	0.872
t-stat	(2.83)	(2.47)	(4.05)	(3.43)	(2.70)	(4.08)	(3.64)	(2.88)	(4.30)	(3.98)

Chapter 4

Optimism or Uncertainty Preference: Why Investors Prefer Stocks with Guidance Imprecision?

Abstract

This chapter examines the impact that imprecision in management earnings guidance (IMP) has on equity returns. Empirical evidence reveals that high IMP (wider interval in the forecasted earnings) is associated with lower subsequent stock returns. Two complementary explanations are provided to justify the low returns. First, in a market that exhibits short-selling constraints and diversion of opinion regarding earnings estimates, high IMP discourages pessimistic investors while optimists believe in the high bound of the range and take long positions based on these beliefs, leading to stocks' overpricing and hence to lower subsequent returns. Second, high IMP may reflect genuine uncertainty regarding future earnings appealing to growth and lottery investors. Findings are robust at the portfolio and stock level of analysis, to the measurement of imprecision, and to different asset pricing models.

4.1 Introduction

A substantial amount of research examines the properties of management earnings forecasts. One of the most intriguing forecast properties is forecast form. Management earnings forecasts or guidance are voluntary acts and forecast form is unregulated. Therefore, managers may choose to issue point forecast, range forecasts, or point forecasts with conditioning phrases such as less than and greater than. Past research has considered why managers issue imprecise forecasts, with explanations including credible conveyance of management uncertainty (e.g., Baginski and Hassell (1997)), protection from legal liability or loss of reputation while inducing a heuristic bias toward the midpoint to meet or beat street expectations (Ciconte et al. (2014)), and manipulation of beliefs to maximize insider trading profits (e.g. Cheng et al. (2013)). King et al. (1990) argue that managers will convey the precision of forecasts in order to maintain a reputation of high quality disclosure. Also, past research has investigated the pricing consequences of imprecise forecasts (e.g., Baginski et al. (1993); Pownall et al. (1993); Cheng et al. (2013)). That research, however, is limited to the pricing consequences of precision at the date of the forecast announcement and thus does not paint a complete picture of pricing consequences. This study aims to complete the picture by documenting the future-period pricing effects of imprecise management earnings forecasts and providing explanation to this effect.

The focus of past research on event date pricing is based on the theory that low precision forecasts will attenuate the price response to the unexpected earnings conveyed by a disclosure (Kim and Verrecchia (1991)). That is, in a regression of unexpected returns on unexpected earnings conveyed by a management forecast, the coefficient (impact) on the unexpected earnings will be smaller when the management forecast is less precise. Results in Baginski et al. (1993) and Cheng et al. (2013) are consistent with the attenuation effect.

Different from event studies, this study focuses on the effect of forecast imprecision. It documents an inverse relationship between management forecast imprecision and future returns. Management forecasts is considered as a disclosure that can affect belief consensus. Holthausen and Verrecchia (1990) analytically demonstrate that disagreement over a given signal's implications reduces consensus. Baginski et al. (1993) present evidence that the width of a management forecast range (relative to the width of the distribution of analyst forecasts) is associated with a decrease in analyst consensus pursuant to the management forecast disclosure. Miller (1977) argues that when investors disagree and pessimists face short sale constraints, optimists may set the price of the firm's stock, leading to higher current prices and lower future returns. Miller's (1977) prediction has been formalized, tested and verified in previous research (e.g., Chen et al. (2002); Diether et al. (2002); Giannini et al. (2019)). Therefore, it is expected that management forecast imprecision is associated with overpricing and hence lower future returns. This study goes beyond testing Miller's (1977) conjecture to examine the full set of reasons for the low returns associated with imprecise forecasts, including the link between potential and realized earnings growth, lottery-like preferences and arbitrage asymmetry.

Using a sample of management earnings forecasts of annual earnings from 1995-2018, this study documents a negative relation between management forecast imprecision (IMP) and subsequent-month stock returns at the portfolio and stock-levels of analysis. More specifically, empirical analysis shows that firms with high IMP deliver on average 8% lower risk-adjusted return per annum compared to those with high precision. The low returns associated with guidance imprecision are robust after controlling for a wide battery of equity return predictors. The negative impact on returns is mainly due to the underperformance of high-IMP stocks rather than the outperformance of low-IMP stocks.

Guidance imprecision is found to be negatively related to returns around earnings announcements when the announced earnings are poor (bad news). This relation is not observed when earnings involve good news. This result is consistent with Miller's (1977) conjecture. That is, optimist investors acquire the stock based on the upper bound of the range provided by the firm's management and then are disappointed when realized earnings are below the higher bound of the guidance range, justifying the low subsequent returns. In line with this conjecture, overstated guidance is also found to be more imprecise. Moreover, high-IMP stocks are more likely to be overpriced and susceptible to short-sale constraints.

Another potential explanation of the documented IMP impact on future equity returns is that managers provide earnings forecasts either in terms of a range or simply as point estimates depending on the best knowledge they have. For firms that are still in a growing phase, managers may genuinely be more uncertain of the firms' future earnings prospects and hence tend to provide wider ranges of performance indicators to avoid being liable in case of not meeting the pre-announced estimates.[1] Firms with uncertain growth profiles may also attract

[1]This idea contrasts with the notion that managers may strategically choose the precision of given forecasts, such as to influence the price prior to insider sales or purchases (see Cheng et al. (2013); Jensen and Plumlee (2019)).

investors with lottery-like preferences. In other words, investors would like to hold stocks with high uncertainty regarding their future earnings which can offer lottery-like payoffs. Empirical evidence reveal a strong association between guidance imprecision on the one hand and potential growth (but not realized expost growth) and lottery characteristics on the other. Moreover, IMP's impact on returns is found to be more evident for those firms with lottery characteristics, providing empirical evidence for the lottery hypothesis.

A potential concern is that bad news (low earnings expectations) are associated with range forecast as documented by Baginski et al. (2011). This implies that the negative premium associated with IMP can be due to the type of news embedded in the forecast rather than the form of the forecast itself. Although this concern cannot be completely ruled out, I show that the low returns associated with guidance imprecision are related to the level of uncertainty in the forecast and are incremental to the type of news embedded in the guidance. More specifically, the estimated residuals of the cross-sectional regression of IMP on earnings growth are found to be negatively associated with future excess returns. In a separate test, the firm's estimated IMP based on the industry average (excluding that firm's IMP level) is also significantly associated with lower subsequent equity returns. Using the IMP-industry level helps isolate the true visibility regarding earnings prospects from managers' different intentions in issuing imprecise forecast. In other words, estimating the firm's IMP based on its industry level is more likely to reflect the overall industry uncertainty rather than firms' internal factors that would induce managers to disclose imprecise forecasts.

This chapter's findings have several implications. While some managers would choose to announce a wider range of managerial guidance to minimize their forecast errors and be "on the safe side" in delivering their estimates, they may inadvertently create more investor uncertainty and a resulting IMP negative return premium. Moreover, high-IMP firms tend to be more prone to default risk. This provides additional insight regarding the puzzling low returns associated with firms with high default probability documented in the literature (see e.g., Campbell et al. (2008) and Conrad et al. (2014)).

The remainder of the chapter is organized as follows: Section 4.2 provides a review of related literature, Section 4.3 describes the data and variables, Section 4.4 discusses empirical results, and Section 4.5 discusses potential explanations for the negative IMP premium. Robustness tests are presented in Section 4.6. Section 4.7 concludes.

4.2 Literature Review

Miller (1977) argues that the price of a security will be high when there is high divergence of investors' opinion regarding returns on the security. Miller's rationale is that in security markets, investment decisions are made based on an individual investor's specific opinions rather than the average of all investors. When investors have different opinions regarding expected returns from holding a security, the entire supply of the security can be purchased by a small portion of investors, specifically those investors who have an optimistic view regarding its expected return. Restrictions on short sales will further drive pessimists out of securities that are subject to higher dispersion of opinion, although they would like to take a short position in stocks on which they hold a negative view, driving the market price to rise above the mean assessment of the average investor. Future realizations, on average, mirror the mean assessment of the average investor, resulting in lower subsequent returns. Chen et al. (2002) develop a model showing that when short-sales constraints are binding, prices are high relative to fundamentals leading to lower future returns. Miller's (1977) prediction has been tested in previous research (e.g., Diether et al. (2002); Giannini et al. (2019)).

Assuming that Miller's rationale holds, a wider range in the forecasted earnings will deter pessimists (who subscribe more to the worst-case scenario) from investing in the specific stock. On the other hand, optimists (who believe more in the best-case scenario) will actively purchase the stock, leading to overvaluation of those stocks that are more prone to higher uncertainty and hence lead to lower subsequent returns. This hypothesis can be tested by considering the degree of imprecision of management guidance and its impact on subsequent stock returns.

The dispersion of opinion among investors has been widely studied using alternative proxies for dispersion. Using dispersion of analysts' forecasts, Diether et al. (2002) document that stocks subject to high dispersion of analysts' earnings forecasts on average generate lower returns. Ackert and Athanassakos (1997) find a positive relation between optimism in analyst forecasts and uncertainty (as proxied by the standard deviation of earnings forecasts). They document that higher prior uncertainty increases analysts' optimism and causes market overvaluation leading to lower returns for those stocks characterized by high uncertainty. In contrast to these findings, Anderson et al. (2009) find evidence for an uncertainty-return trade-off when uncertainty is measured by the degree of disagreement among professional forecasters, with different weights assigned to each forecaster.

Management earnings guidance has also been widely investigated particularly in the disclosure literature. Chen et al. (2011) find that firms that stop providing guidance experience an increase in analyst dispersion, a decrease in forecast accuracy, and a decline in returns around the time of announcing the guidance halt. On the aggregate level, there is no clear evidence on the relation between management guidance and market returns (see e.g., Anilowski et al. (2007) and Shivakumar (2007)). Additionally, several studies have examined the impact of management disclosure on the stocks' volatility. Billings et al. (2015) argue that managers mitigate share price volatility with guidance since investors' uncertainty is positively correlated with future stock volatility and as disclosures lower volatility, it also reduces subsequent volatility.

A substantial number of studies document that management forecasts are useful to investors (e.g. Waymire (1984)), even if issued in imprecise form (e.g., Baginski et al. (1993), Pownall et al. (1993)). Theory suggests that low precision forecasts will attenuate the price response to the unexpected earnings conveyed by a disclosure (Kim and Verrecchia (1991)). Consistent with theory, Baginski et al. (1993) and Cheng et al. (2013) find that, in a regression of unexpected returns on unexpected earnings conveyed by a management forecast, the coefficient on the unexpected earnings is smaller when the management forecast is less precise. Prior studies do not hypothesize a mean effect of imprecision on announcement day returns because it is not clear what that effect would be. While Miller's (1977) conjecture suggests that optimistic investors would drive price upward when forecasts are imprecise, a countervailing effect is also in play. Management forecast imprecision is evidence of the type of uncertainty about future earnings fundamental that can lead to increases in cost of equity capital (Barry and Brown (1985), Coles et al. (1995), Lambert et al. (2007)), which would decrease the mean price reaction to a forecast, regardless of its content (i.e., good or bad news).

Instead of the current announcement-day price reaction, this study focuses on future returns associated with forecast imprecision. Management forecasts are a disclosure that can affect belief consensus. Holthausen and Verrecchia (1990) analytically demonstrate that disagreement over a given signal's implications reduces consensus. Baginski et al. (1993) present evidence that the width of a management forecast range (relative to the width of the distribution of analyst forecasts) is associated with a decrease in analyst consensus pursuant to the management forecast disclosure. Therefore, the uncertainty about future earnings conveyed in a management forecast can be distinct from the uncertainty reflected in analysts' forecasts. As reported in Baginski et al. (1993), not all management forecasts decrease uncertainty. In fact, Cotter et al. (2006) find that management guidance is more likely to be disclosed when analysts' initial forecast dispersion is low, suggesting the possibility that, in some cases, forecast dispersion subsequently increases.

For these reasons, it is expected that Miller's (1977) prediction about the association of imprecision and future returns will manifest in a negative relation between management forecast precision and future returns after controlling for other well-known measures of uncertainty and predictors of future returns. This study's empirical evidence goes beyond testing this prediction and provides additional explanation of the low returns of high-IMP stocks. It also presents a complete picture of the low returns associated with high-IMP stocks by linking potential and realized growth, lottery features and arbitrage asymmetry to guidance imprecision. Finally, it provides further insights regarding the distress risk anomaly.

4.3 Data and Variables

The sample consists of all NYSE/AMEX/NASDAQ ordinary common equity shares (with share code 10 and 11), excluding regulated and financial service firms (one-digit SIC codes of 4 and 6). Each stock is required to be covered by the Institutional Brokers' Estimate System

(IBES) database for management guidance estimates from which the main variable regarding the precision of guidance is derived. The sample period is from July 1995 to December 2018. Although guidance data are available from February 1993, the sample period starts in 1995 to guarantee at least 40 firm observations in a given month. Management guidance involving earnings of fiscal years extending more than 3 months in the past are excluded. The rationale is that for those cases where the fiscal year ended 3 months earlier, the actual earnings would more likely have been disclosed. Guidance cases for more than 12 months ahead are excluded to roughly unify the guidance horizon of the sample. In a given month, if guidance is provided for more than one fiscal year, the nearest fiscal year end is used. If a firm's guidance is missing for a given month, the previous month's guidance in the same fiscal year is used. Monthly and daily returns and trading data are obtained from CRSP. Accounting data are from Compustat and are lagged three months to market data. Fama and French (1993) and Fama and French (2015) factors are obtained from the online data library of Kenneth French.[2] The liquidity factor is obtained from Lubos Pastor's online data library.[3] Management stock and options ownership data are obtained from Executive Compustat Annual Compensation database. The average number of firms in a given month is 453, with a maximum of 646 firms and a minimum of 44 firms. On average, 81% of firms provide closed intervals.[4]

4.3.1 Imprecision of Management Guidance

The IBES guidance database provides management expectations on several key performance indicators (KPIs) including earnings per share (EPS). An annual earnings guidance may be given as an expected "crisp" value (point estimate), in terms of a range (closed interval), or in terms of an open interval. An imprecision management performance (IMP) measure is developed to capture the degree to which managers are uncertain regarding their firms' annual earnings prospects. Each firm's IMP is computed as the difference between the upper and lower

[2] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.`

[3] `http://faculty.chicagobooth.edu/lubos.pastor/research/.`

[4] Open intervals guidance, which constitutes less than 6% of the earnings guidance database, is excluded from the sample.

bound of management's guidance on EPS scaled by the firm's lagged total assets per share.[5] If managers disclose a point estimate, imprecision (IMP) is set to zero (i.e. the guidance is set to be very precise). Imprecision for firm i in month t is computed as follows:

$$\mathrm{IMP}_{i,t} = \frac{\mathrm{H}_{i,t} - \mathrm{L}_{i,t}}{\text{Total Assets}}, \tag{4.1}$$

where $\mathrm{H}_{i,t}$ and $\mathrm{L}_{i,t}$ are the highest and lowest bound of the estimated EPS in month t for the nearest fiscal year end.

4.3.2 Control Variables

To ensure that management's guidance imprecision is not captured by other common risk factors, a battery of control variables is employed. These relate to standard risk variables, profitability and growth variables, dispersion of opinion and volatility variables, and various trading and distribution-related variables

Standard Risk Variables

- Market beta (β^{MKT}) is estimated using the market model using daily excess returns over the previous 12 months (Sharpe (1964), Lintner (1965), and Mossin (1966)).
- SIZE is measured as the natural logarithm of market capitalization (MCAP) calculated as the product of price per share and common shares outstanding (Fama and French (1992)).
- Book-to-market (BM) is computed following Fama and French (1992, 1993) as the log of book value of shareholders' equity plus deferred taxes minus redemption, liquidation or par value of preferred stock (depending on availability) scaled by the market value of equity as of the most recent June.

[5]Section 4.6 provides robustness to the main results with alternative scaling of imprecision.

Profitability and Growth Variables

- Operating profitability (OP) is computed as revenues (revt) minus cost of goods sold (cogs) minus selling, general and administrative expense (xsga) minus interest expense (xint) scaled by book value of equity as in Fama and French (2015).
- Return on assets (ROA) is estimated as net income scaled by the previous fiscal year book value of equity.
- Investment (INV) is measured as the change of total book 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).

Dispersion of Opinion and Volatility Variables

- Divergence of opinion is proxied by the dispersion in analysts' forecasts (DISP). This is computed following Diether et al. (2002) as the standard deviation of annual earnings per share forecast scaled by the absolute value of the median earnings forecast.
- Imprecision in analysts' forecast (AF^{IMP}) is computed analogous to IMP as the difference between the highest and lowest analyst's EPS forecast scaled by the firm's total assets per share.
- Turnover (TURN) is the ratio of trading volume in a month to shares outstanding.
- Idiosyncratic volatility (IVOL) is measured as the standard deviation of the daily residuals based on Fama and French (1992) SMB and HML factors over the last month (Ang et al. (2006)).
- The stock's exposure to market volatility (β^{VXO}) is calculated following Ang et al. (2006) from a bivariate time-series regression of the stock's excess returns on the market excess return and changes in implied volatility using daily data in a month:

$$R_{i,d} = \alpha_{i,d} + \beta_{i,d}^{mkt} R_{m,d} + \beta_{i,d}^{\mathrm{VXO}} \Delta\mathrm{VXO}_d + \epsilon_{i,d},$$

where ΔVXO is the shock in the S&P 100 implied volatility index , $\beta_{i,d}^{\mathrm{VXO}}$, $\beta_{i,d}^{mkt}$ are the loadings on aggregate volatility and market risk of stock i in month t, respectively.

Trading and Distribution-Related Variables

- Momentum (MOM) measured as the cumulative return of a stock over the previous 11 months, excluding the most recent month (portfolio formation month) following Jegadeesh and Titman (1993).

- Short-term reversal (STR) measured as the stock's last month return (the return of the portfolio's formation month) as in Jegadeesh (1990).

- Illiquidity (ILLIQ) measured following Amihud (2002) as

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

  where $|R_{i,d}|$ is the absolute daily return, and $\mathrm{VOLD}_{i,d}$ is the dollar trading volume for stock i on day d. ILLIQ is scaled by 10^6.

- Idiosyncratic skewness (ISKEW) computed as the skewness of daily residuals over a month from a regression of the stock's daily excess return on the daily excess market return and the square of daily excess market return (Harvey and Siddique (2000)).

- Coskewness (COSK) estimated as the loading on the square of daily excess market return in a month from a regression of the stock's daily excess return on the daily excess market return and the square of daily excess market return (Harvey and Siddique (2000)).

- Total skewness (TSKEW) is the total skewness of returns over the previous month.

- Maximum return (MAX) measured as the highest daily return of a stock in the previous month, used to control for lottery-like features as in Bali et al. (2011).

4.4 Empirical Results

4.4.1 Sample Characteristics

This section examines how average firm characteristics vary for different levels of IMP. Table 4.1 reports the averages of the cross-sectional median firm characteristics of stocks in the sample for each IMP quintile. These characteristics include: market beta (β^{MKT}), market capitalization in million US dollars (MCAP), book-to-market (BM), operating profitability (OP), return on assets (ROA), investment (INV), analysts' forecast dispersion (DISP), analysts' forecasts imprecision (AF^{IMP}), turnover (TURN), idiosyncratic volatility (IVOL), market volatility exposure (β^{VXO}), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskewness (COSK), total skewness (TSKEW), and lottery-demand (MAX). These characteristics are reported for the month of portfolio formation (not for the subsequent month when returns are generated).

Table 4.1 reveals some interesting patterns moving from the low to the high quintiles of IMP. For several characteristics, there is almost a monotonic pattern moving from low to high IMP quintiles. For instance, moving from quintile 1 to 5, there is a decline of MCAP, with managers of smaller firms being less precise about their firms' expected performance. Observing the characteristics of high IMP stocks, they tend to have higher market exposure (higher β^{MKT}) and lower profitability as shown by the declining OP and ROA in quintile 5. High-IMP firms are also those with high dispersion and imprecision in analysts' forecasts, in line with earlier findings that analysts' forecasts may reflect management guidance particularity in short-term horizons (Baginski et al., 2011; Feng and McVay, 2010; Tang and Zhang, 2018). They are also characterized by high IVOL, low MOM, and STR. Finally, they tend to be more illiquid stocks with lottery-demand characteristics (MAX).

The above pattern concerning declining profitability and MOM but increasing DISP, IVOL, MAX in the high-IMP quintile may help provide partial explanation for the negative return premium associated with high-IMP stocks. Stocks with these characteristics were generally found to deliver a negative premium in previous studies (e.g., Fama and French (2015), Diether et al. (2002), Ang et al. (2006), Jegadeesh and Titman (1993), and Bali et al. (2011)). Managers may be more likely to provide imprecise guidance when faced with high idiosyncratic risk, which may also justify lower market momentum on the stock. The economic differences for other firm characteristics (such as BM, INV, and β^{VXO}, and TSKEW) are not significant across IMP quintiles. Surprisingly, there is no clear pattern in turnover (TURN) that has been commonly used as an uncertainty proxy.

There is an unavoidable issue of data selection when using the IBES database since not all CRSP firms provide voluntary earnings forecasts. Moreover, many firms listed on CRSP may be not covered by the IBES management guidance database. Table 4.2 compares the sample of stocks at the intersection of CRSP, COMPUSTAT, and IBES to the overall CRSP universe excluding regulated and financial service firms. Panel A reports cross-section mean and median market cap (in millions) for all CRSP stocks at December of each year, while Panel B limits the sample to only eligible stocks for which management earnings forecasts are provided in the IBES database. On average over the sample period, the number of firms in the sample are about 13% of the overall CRPS universe (see last column labelled % of CRSP). However, the most salient observation from Table 4.2 is that the sample is heavily tilted toward big stocks, as indicated by the higher market cap of stocks in Panel B compared to those in Panel A. For this, data selection concerns are addressed and discussed in Section 4.6.

4.4.2 Univariate Portfolio Analysis

This section provides the first test of imprecision's impact on subsequent returns. Univariate portfolio analysis is conducted by sorting stocks into five quintile portfolios based on the level of guidance imprecision (IMP). When managers provide only a point estimate of earnings, IMP is zero (i.e., guidance is considered very precise). Otherwise, IMP is computed as in equation 4.1. Thus, quintile 1 (5) contains stocks where IMP is low (high) and managers are more (un)certain regarding their forecasts.

Table 4.3 reports raw excess and risk-adjusted returns for both value-weighted (VW) and equally-weighted (EW) portfolios. Risk-adjusted returns are estimated using the Fama and French (2015) five-factor model (5F model henceforth). Moving from IMP quintile 1 (low) to 5 (high), a decline in returns is observed. The alpha (excess return) differential between quintiles 5 and 1 in the value-weighted portfolios is -0.64% (-0.58%), with a Newey and West (1987) t-statistics adjusted for six lags of -2.23 (-2.07). This translates into a -7.6% (-7.0%) lower return per annum for the high IMP quintile compared to the low quintile. The return spread between high and low quintiles is also significant in EW portfolios. Results indicate that high imprecision in managerial guidance (IMP) cannot be explained by the standard market, size, BM, profitability, and investment factors comprising the Fama and French (2015) 5F model. Table 4.3 also shows that the low returns of the hedging portfolio are due to the underperformance of the highest IMP portfolio rather than the outperformance of the low IMP quintile portfolio in VW portfolios. Overall, the Fama and French (2015) 5F model looks to be a good candidate model in explaining VW portfolio returns across quintile portfolios, with the exception of high-IMP quintile (5). That is, in the value-weighted portfolios, the 5F model does not explain the underperformance of the high-IMP quintile (5) while it satisfactorily explains the risk-adjusted returns across the remaining quintiles. Section 4.6 shows that these findings are robust using alternative univariate portfolio sorting based on different pricing factors and models.

4.4.3 Bivariate Portfolio Analysis

Some of the firm characteristics identified above, such as IMP's association with low profitability, high analysts' forecast dispersion or low momentum might help explain the lower returns observed for high IMP stocks. To ensure that the low return associated with high IMP is not only a proxy for these characteristics, bivariate portfolio-level analysis is conducted. This analysis helps control for certain common stock return predictors one at a time. Stocks are first sorted into quintile portfolios using one of the following controls: beta of the market (β^{MKT}), the log of market capitalization (SIZE), book-to-market (BM), operating profitability (OP), return on assets (ROA), investment (INV), analysts' forecast dispersion (DISP), analyst forecast imprecision (AF^{IMP}), turnover (TURN), idiosyncratic volatility (IVOL), market volatility beta (β^{VXO}), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskweness (COSK), total skewness (TSKEW), and lottery-stock demand (MAX). Then stocks within each control quintile are further sorted into 5 quintiles based on IMP such that quintile 1 (5) contains stocks with low (high) imprecision of management guidance. A simple average of value-weighted monthly returns for each IMP quintile is computed across each control quintile. In this way, each IMP quintile contains stocks that are relatively equivalent in terms of each one of these controls. Table 4.4 reports the risk-adjusted returns of value-weighted portfolios (based on the 5F model) using this conditional sorting. The last two rows in Table 4.4 report the difference in alphas between quintiles 5 and 1, with corresponding Newey-west t-statistics adjusted for six lags.

Table 4.4 shows that after controlling for common cross-sectional predictors, the alpha difference between quintiles 5 and 1 remains negative and significant for all control variables. For instance, controlling for SIZE, the underperformance of high-IMP stocks remains economically and statistically significant, with the high-IMP quintile generating 0.52% lower risk-adjusted return than the low IMP quintile (with a t-statistics of -3.07). Turnover and volatility of analysts' forecasts have been previously identified as proxies for dispersion of opinion of investors (Diether et al., 2002; Hong and Stein, 2007). The significant negative risk-adjusted return differences (high−low IMP) based on conditional sorting shown in Table 4.4 suggests the imprecision of management guidance (IMP) captures some incremental degree of uncertainty about future earnings forecasts that is not captured by these factors.

4.4.4 Stock-Level Analysis

Next, stock-level cross-sectional regression analysis following Fama and MacBeth (1973) is conducted to account for a wide battery of controls at the same time. The stock-level regression analysis also allows to preserve the full amount of individual stock-level information that is otherwise disregarded in the portfolio-level analysis due to aggregation. Table 4.5 shows the time-series averages of the slope coefficients from the cross-sectional regression of one-month ahead stock excess returns on IMP and a set of controls. More specifically, monthly cross-sectional regressions are run as follows:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}\text{IMP}_{i,t} + \gamma_{2,t}X_{i,t} + \epsilon_{i,t+1}, \tag{4.2}$$

where $R_{i,t+1}$ is the excess return realized in month t+1 for stock i, $\text{IMP}_{i,t}$ is the imprecision of managerial annual earnings guidance estimated as per Equation (4.1). $X_{i,t}$ is a set of lagged firm-specific control variables. These include beta of the market (β^{MKT}), the log of market capitalization (SIZE), book-to-market (BM), operating profitability (OP), investment (INV), return on assets (ROA), analysts' forecast dispersion (DISP), analyst forecast imprecision (AF^{IMP}), turnover (TURN), idiosyncratic volatility (IVOL), market volatility beta (β^{VXO}), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskweness (COSK), total skewness (TSKEW), and lottery-stock demand (MAX). All independent variables are standardized at the industry level to better capture the imprecision level compared to firms in the same industry as the uncertainty of management forecasts can be industry-specific.

As shown in Table 4.5, in all multivariate regressions with different sets of controls, the IMP coefficient is negative and is statistically and economically significant. The average slope coefficient for IMP is -0.25 and ranges between -0.29 and -0.23 in Table 4.5. Considering the high (low) bound of -0.23 (-0.29), moving from quintile 1 to 5 would see a stock's IMP increase from 0.01 to 1.05 (see also Table 4.1) implying a monthly decrease of 0.24% (0.30%) in the average stock's expected return.

Columns (1) and (2) of Table 2.5 report the IMP coefficients in cross-sectional specifications corresponding to the 3-factor model of Fama and French (1993) (specification 1) and the 5-factor model of Fama and French (2015) that includes OP and INV (specification 2). Column (3) uses ROA as proxy for profitability instead of OP. Columns (4) through (15) add each of the above cross-sectional predictors, one at a time, to the baseline specification of column (3).

Concerning the other variable coefficients in the baseline regression of column (2) representing model (5F), β^{MKT} is positive and marginally significant, in line with the CAPM prediction (Sharpe (1964)). The coefficients of SIZE and INV are negative and significant, in line with previous findings (Fama and French (2015), Hou et al. (2015)). BM and OP are insignificant in contrast these variables predicting power documented in the literature (see e.g., Fama and French (2015) and Novy-Marx (2013)). Concerning the additional controls, DISP is insignificant in column (4) in contrast with the negative premium documented by Diether et al. (2002). Different from the negative coefficient of IMP, AF^{IMP} in column (5) is not associated with future excess return. These latter results indicate that the negative return associated with high IMP is not dependent on DISP or AF^{IMP}. MOM is positive and significant (column 9) in line with the momentum effect of Jegadeesh and Titman (1993). Consistent with previous findings, IVOL, STR and MAX coefficients in columns (7, 10 and 15), respectively have a negative and significant coefficient (Ang et al. (2006), Jegadeesh (1990), and Bali et al. (2011)). Overall, the results of Table 4.5 confirm that lower returns are associated with firms whose managers disclose more imprecise earnings guidance even after controlling for common risk factors. The low returns associated with high IMP are also confirmed when the cross-sectional analysis is conducted with industry controls as shown in Panel B of Table 4.5.

Previous literature showed that guidance imprecision is associated with lower earnings expectations (see e.g., Baginski et al. (2011). It might thus be argued that the negative premium associated with IMP may be due to poor earnings mainly rather than the uncertainty of forecasts embedded in IMP. To address this potential concern, the following control variables are added to baseline 5F regression analysis:[6]

- Estimated earnings growth (EEG), measured as the difference between the mid-point estimate of the management guidance range (or crisp value) and the previous fiscal year EPS scaled by the previous fiscal year EPS.
- Realized earnings growth (REG), estimated as the one-year expost EPS growth (or net income if EPS is not available) for the fiscal year for which the managerial guidance is

[6]This concern is more rigorously investigated in Section 4.5.3.

provided.[7]

- Realized revenue growth (RRG), estimated as the one-year expost revenue growth for the fiscal year for which the managerial guidance is provided.

- Realized asset growth (RAG), estimated as the one-year expost asset growth for the fiscal year for which the managerial guidance is provided.

The rationale in this analysis is to account for the expected and realized earnings, revenue or asset growth that might alternatively be the main drivers of the low returns. Panel C of Table 2.5 shows the results of stock-level cross-sectional analysis after including the above four growth control variables (one at a time) to the baseline 5F regression. In all specifications (1)-(4), the low returns associated with high IMP remain significant after controlling for these expected or realized growth variables, suggesting that this negative IMP premium is most likely associated with the form of guidance rather than the expected or realized growth itself. While expected earnings growth (EEG) does not appear significant in explaining future returns as seen in column (1), realized earnings, revenue or asset growth measures are significantly associated with future returns (columns (2-4)). This is in line with previous findings that earnings forecasts (expectations) are less informative than realized earnings (Pownall et al. (1993)).

4.5 Discussion

The portfolio and stock-level analyses reveal a negative relation between management earnings guidance imprecision and subsequent-month stock returns. One possible explanation is that when there is high uncertainty regarding future earnings prospects resulting in a wider range of managerial estimates, optimists who believe in the high bound of the range take long positions based on these beliefs and drive up stock prices. In accordance with Miller's (1977) conjecture, in a market that exhibits short-selling constraints, pessimists will choose not to participate in such stocks, leading to their overpricing and hence to lower subsequent returns.

[7]If previous year EPS is negative, values are replaced with missing observations for EEG and REG estimations.

Another potential explanation for the negative abnormal IMP returns is that managers provide earnings forecasts either in terms of a range or simply as point estimates depending on the best knowledge and confidence they have in the firm's prospects. For firms that are still in a growing phase, managers may genuinely be more uncertain of their future earnings prospects and hence may tend to provide wider ranges of performance indicators to avoid being liable in case of not meeting the pre-announced estimates. Moreover, firms with such uncertain growth profiles may attract investors with lottery-like preferences. In other words, investors would like to hold stocks with high uncertainty regarding their future earnings as they offer lottery-like payoffs.

A potential confounding effect is that less precise guidance is associated with bad news (i.e. low earnings expectations) as documented by Baginski et al. (2011). This implies that the negative premium associated with IMP is more associated to the news embedded in the forecast rather than the form of the forecast itself. This section discusses each of the above potential explanations in turn.

4.5.1 Investors' Optimism and Arbitrage Asymmetry

A. Investors' Optimism

First, the relation between the degree of guidance imprecision and abnormal returns around earnings announcement dates is studied. One way to test if Miller's optimistic-based prediction is a plausible explanation for the negative returns associated with high-IMP stocks is to examine how IMP is priced in bad and good earnings times. If Miller's argument is valid and high-IMP stocks are mainly held by optimists, it is not expected to observe low subsequent returns associated with guidance imprecision in times of good realized earnings. Conversely, negative subsequent returns associated with imprecise forecasts should be more pronounced in bad earnings times when mispricing begins to be resolved.

This conjecture is tested by checking whether IMP has a differential impact on abnormal returns depending on whether the earnings announcement is considered to be good or bad news. Abnormal returns are estimated based on the residuals of the CAPM with coefficients estimated using daily returns over a 12-month period that ends 3 months prior to the earnings announcement month.[8] Good or bad earnings times are identified based on whether the expost quarterly EPS change is positive or negative, respectively.

For stocks with a fiscal-year end in December, only first-quarter earnings are known at the end of June. When managers disclose (or maintain) imprecise (wide range) fiscal-year end guidance in June, this uncertainty would be resolved when the second, third, and fourth quarter earnings are released. The IMP impact on returns around earnings announcement days is examined in the second, third, and fourth quarter as per the following cross-sectional regression:

$$AR^{Q}_{i,t} = \beta_0 + \beta_1 \mathrm{IMPD}_{i,t} + \beta_2 \mathrm{X}_{i,t} + \beta_3 \mathrm{EPS}^{qc}_{i,t}, \tag{4.3}$$

where $AR^{Q}_{i,t}$ ($R^{Q}_{i,t}$) is the abnormal (simple) returns around the quarterly earnings announcement period. For each quarter, the earnings announcement period is 3 days starting 1 day prior to actual earnings disclosure and ending 1 day post disclosure. $\mathrm{IMPD}_{i,t}$ is a dummy variable on earnings guidance imprecision for stock i as of June of year t that equals 0 if the stock's IMP is below the cross-sectional median IMP of stocks as of June and equals 1 otherwise. $\mathrm{X}_{i,t}$ is the set of controls (β^{MKT}, SIZE, BM, OP, INV) as of June of year t. $\mathrm{EPS}^{qc}_{i,t}$ is the quarterly change of earnings per share (compared to the same quarter of the previous year) scaled by the previous quarter's closing price.

Results are reported in Table 4.6. The first (left) panel, examining all firms with fiscal year ending in December, reveals a negative coefficient found for IMP (IMPD<0) suggesting that high-IMP stocks provide lower returns around earnings announcement while controlling for earnings growth. Interestingly, returns are inversely associated with imprecision in low earnings periods, as shown via the lower IMPD coefficient in the second (middle) panel of Table 4.6. In times of good earnings announcements (the last panel of regressions in Table 4.6), imprecision has an insignificant impact on returns around earnings days. The above results imply that the

[8]For robustness, the same analysis is conducted computing abnormal returns based on the residuals of the 3-factor pricing model of Fama and French (1993). Untabulated results are qualitatively similar to those reported in Table 4.6.

form of earnings guidance matters. Investors react to imprecise guidance mainly in low earnings times, providing some supportive evidence that the underperformance of high-IMP stocks is partly due to optimist investors adjusting their previous positions with as uncertainty around earnings gets resolved.

To test whether imprecise managerial guidance is associated with earnings overestimation, the following cross-sectional regression is conducted along the lines of Diether et al. (2002):

$$\mathrm{FE}_{i,t} = \beta_0 + \beta_1 \mathrm{IMP}_{i,t} + \beta_2 \mathrm{X}_{i,t} + \epsilon_{i,t}, \tag{4.4}$$

where $\mathrm{FE}_{i,t}$ is the expost forecast error for firm i in month t for the yearly earnings per share estimated as the difference between the point estimate and the realized earnings (expost) for firms with IMP equal to zero. $\mathrm{FE}_{i,t}$ is estimated as the difference between the upper bound (or the mid point) of management guidance and the realized earnings for firms with range forecasts, all scaled by the absolute value of realized earnings as in Ackert and Athanassakos (1997); $\mathrm{IMP}_{i,t}$ is the imprecision guidance as per Equation 4.1 and $X_{i,t}$ includes the baseline controls β^{MKT}, SIZE, BM, OP, and INV.

Table 4.7 reports the average time-series slope coefficients of the above cross-sectional regression in Equation 4.4. Models (1) and (2) report forecast errors estimated using the upper bound (FE^U) and the mid-point (FE^M) in the case of firms with strictly positive IMP, respectively. Higher values of $\mathrm{FE}_{i,t}$ imply optimistic expected earnings compared to the realized earnings expost. The IMP coefficients are 0.923 (t-stat of 3.68) and 0.813 (t-stat of 3.42) in models (1) and (2), respectively. The significant positive coefficients on IMP indicate a positive relationship between the optimism level embedded in the earnings guidance and the level of guidance imprecision. In other words, overestimated earnings guidance is more likely to also be imprecise.

Guidance imprecision can also reflect managers overconfidence and optimism. Hribar and Yang (2016) provide evidence that overconfidence increases the upward bias in management's forecasts. Moreover, overconfident executives are more likely to exhibit an optimistic bias and overestimate the return of their investment projects (see e.g., Schrand and Zechman (2012) and Malmendier and Tate (2005)). It is hence expected to observe the IMP negative impact on returns for firms whose managers are overconfident regarding their firms' future earnings. Following Malmendier and Tate (2005), Holder 67 is used as management overconfidence proxy whereby CEOs are considered overconfident if they hold stock options that are more than 67% in-the-money. The selection of 67% comes from calibrating Hall and Murphy's (2002) model using a detailed dataset on executive stock option holdings and exercises. Holder 67 equals to 1 if a CEO's unexercised but exercisable options are more than 67% in-the-money for at least two times during his/her tenure. The first instance at which the CEO did not exercise the option is identified as the starting point where he or she is considered as overconfident. Otherwise, Holder 67 equals zero.

Table 4.8 shows results of the time-series averages of the slope coefficients of cross-sectional regressions of one month-ahead excess returns on IMP (along with controls) for firms with low (Holder 67=0) and high (Holder 67=1) overconfident managers. The impact of guidance imprecision on future returns is evident only for the subsample of firms whose managers are found to be overconfident as seen by the significant IMP coefficient of -0.184 (t-stat of -2.02) in the last column of Table 4.8. If overconfidence is associated with upward biased forecasts, hence the negative IMP coefficient is likely due to earnings overestimation.

Additional corroborative evidence supports the optimism bias in imprecise guidance. For example, Table 4.1 shows that high IMP stocks are more likely to be past losers (exhibiting negative momentum) and untabulated results also indicate a significant cross-sectional negative correlation between IMP and MOM. Previous research pointed out that a possible behavioral explanation of price momentum is a gradual diffusion of firm-specific information across the investing public (Hong et al., 2000; Hong and Stein, 1999). That is, negative momentum is more in line with bad news diffusing into prices as investors gradually adjust their positions to the bad news. High imprecision of managerial guidance does not necessarily imply bad news across the overall investing public, yet it might imply that there is a proportion of this public (i.e., those investors with more optimists views associated with the upper guidance bound) that may get disappointed, justifying the declining momentum across the IMP quintiles of Table 4.1

and the negative returns in Table 4.3.

B. Arbitrage Asymmetry

Stambaugh et al. (2015) has shown that the negative impact of idiosyncratic volatility on returns is more evident for stocks with high arbitrage risk and arbitrage asymmetry. Arbitrage risk is the risk that deters arbitrage while arbitrage asymmetry is the higher ability to take long positions versus short positions when mispricing is identified. Stocks with greater IVOL and hence arbitrage risk are more prone to mispricing that is not eliminated by arbitrageurs. Stocks with high guidance imprecision are characterized by high idiosyncratic volatility (see Table 4.3).[9] This implies that high-IMP firms are susceptible to arbitrage risk and hence mispricing. IMP is also positively associated with optimism (see Table 4.7), and hence overpricing rather than underpricing. With arbitrage asymmetry, the IMP impact on returns is therefore expected to be more evident for overpriced stocks.

To test the above conjecture, a mispricing proxy is developed following the notion of Stambaugh et al. (2015) based on several anomalies well-documented in the literature:

1. Ohlson's (1980) measure of bankruptcy risk defined as:

$$OH_t = -4.07ln(AT_t) + 6.03LT_t/AT_t - 1.43(CA_t - CL_t)/AT_t + 0.0757CL_t/CA_t$$
$$-2.37NI_t/AT_t + 0.285Loss_t - 1.72NegBook_t - 0.521\Delta NI_t - 1.83FO_t/LT_t,$$

   where AT_t is total assets, LT_t is total liabilities, CA_t is total current assets, CL_t is total current liabilities, Loss_t is a dummy variable which equals 1 when net income is negative and 0 otherwise, $\mathrm{NegBook}_t$ is 1 when liabilities are greater than assets and 0 otherwise, ΔNI_t is the change in net income from t-1 to t divided by the sum of the absolute values of net income in t-1 and t, $(\mathrm{NI}_t - \mathrm{NI}_{t-1}) / (|\mathrm{NI}_t| + |\mathrm{NI}_{t-1}|)$, FO_t are funds from operations defined as earnings before extraordinary items (Compustat item, ib) plus income-statement deferred taxes (txdi) plus equity's share of depreciation expense

[9] The relation between IMP and IVOL is discussed in Section 4.5.2.

defined as MCAP/(AT − BV + MCAP) times total depreciation expense (dp), where MCAP is market value of equity computed as the product of common shares outstanding and the closing price. Higher OH values imply high risk of bankruptcy.

2. Net stock issue computed following Fama and French (2008a) as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year end in $t-1$ divided by the split-adjusted shares outstanding at fiscal year end in $t-2$. The split-adjusted shares outstanding is the product of Compustat shares outstanding (csho) and the adjustment factor (ajex).

3. Total accruals to total assets where accruals are estimated following Sloan (1996):

$$Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep, \tag{4.5}$$

where ΔCA = change in current assets, $\Delta Cash$ = change in cash and cash equivalents, ΔCL = change in current liabilities, ΔSTD = change in short-term debt, ΔTP = change in income tax payable, and Dep = depreciation and amortization expenses.

4. Investment (or asset growth) estimated following Fama and French (2015) as in Section 4.3.

Stocks are then sorted independently on each anomaly variable whereby the highest rank is assigned to the value of the anomaly associated with the lowest average abnormal return as documented in the literature. For example, high asset growth stocks are reported to generate lower subsequent returns than low asset growth firms (Fama and French (2015)). Each month, stocks are sorted into quintile sorts according to asset growth and those with the highest asset growth receive the highest rank (1) and those with the lowest asset growth receive the lowest rank (5). Stocks with the highest rank are deemed those with the highest level of overpricing. A stock's composite rank is formed as the arithmetic average of its ranking for each of the above anomalies.

The impact of IMP on subsequent returns is tested for stocks of high rank (below than or equal 3) and low rank (above 3) for the cross-sectional regressions as in Equation 4.2. Results, presented in Table 4.9, show that the IMP impact on returns is only significant for stocks that are overpriced (high rank). In column (2) of Table 4.9, the IMP coefficient is -0.267 (t-stat of -4.10) for firms with rank up to 3 on the overpricing proxy (i.e. overpriced firms), while the IMP coefficient is insignificant for firms that are not overpriced (low rank). This implies that arbitrage asymmetry plays a role in the way guidance imprecision impacts returns. This finding is inline with the Miller's (1977) conjecture that dispersion of opinion is likely associated with high prices and lower expected returns due to short-sale constraints or arbitrage asymmetry.

Additional corroborative evidence is supportive of the above explanation. From Table 4.1, stocks in the high IMP quintile have low market capitalization and high illiquidity. Small and illiquid firms are likely to be the hardest to short-sell and least likely to have traded derivatives. Moreover, a rolling cross-sectional regression is conducted for two subsamples containing those firms with institutional ownership below and above the cross-sectional sample monthly median. The rationale is that institutional investors are more likely to invest in stocks where short-sale is allowed. Results, presented in Table 4.10, suggest that the impact of IMP on subsequent returns is evident only in the low institutional ownership subsample where stocks are more likely to be prone to higher short-sale costs. Additionally, there is an asymmetry in the return differential between quintiles 5 and 1 whereby the risk-adjusted return spread of value-weighted portfolios mainly comes from underperformance of quintile 5 (high IMP) stocks where arbitrage is more difficult, rather than outperformance of quintile 1 (low IMP) stocks.

4.5.2 The Case of Firms with Growth and Lottery Potential and Distressed Firms

Another possible explanation for the negative returns associated with stocks with high imprecise management guidance is that the vagueness embedded in managers' imprecise guidance is a reflection of management's genuine uncertainty regarding future earnings, rather than a strategic management choice. Baginski and Hassell (1997) reported that imprecise management forecasts may convey management's true uncertainty regarding future earnings. This may well be the case for many growth stocks where future growth is vague and less visible for many managers.

To test this hypothesis, potential growth proxies are cross-sectionally regressed on IMP. These potential growth proxies are: i) IVOL, given that firms with real growth options likely involve higher idiosyncratic volatility (e.g., see Cao et al. (2008), Galai and Masulis (1976)), ii) firms' present value of growth opportunities (GO) estimated by subtracting from the firm's current market value the perpetual free cash flow discounted at the weighted average cost of capital (WACC) under a no-growth assumption (following Cao et al. (2008), Del Viva et al. (2017), Lambertides and Trigeorgis (2014)) where market value of the firm is estimated as market capitalization (as of the latest June) plus the book value of total debt, iii) capital expenditure growth (CAPFIXG) computed as the net growth in capital expenditure (capx), and iv) Research and Development intensity (RD) used as a common real option measure, computed as R&D expenses (xrd) scaled by assets (at).[10] Other standard controls include β^{MKT}, SIZE, BM, OP, INV.

Results are summarized in Panel A of Table 4.11. In all 4 specifications, IMP is strongly associated with potential growth proxies as observed in the significant positive coefficient of IMP. A positive relation between IMP and IVOL has also been identified in earlier studies (Baginski and Hassell, 1997). Overall, Panel A findings suggest that more imprecise forecasts are more likely issued by managers of growing firms for which it is difficult to estimate future earnings.

Panel B of Table 4.11 investigates further the relationship between IMP and expost realized growth estimated using annual growth in total assets over the following 3 or 5 years (AG_{t+3}, AG_{t+5}). In column 1 and 2, the reported time-series average of the cross-sectional coefficients of AG_{t+3} (-1.239) and AG_{t+5} (-3.663) are negative insignificant and significant, respectively. Robustness on the realized growth proxies or the time horizon does not reveal any positive association between IMP and realized growth. Comparing these results with those of Panel A, firms that have higher imprecision of management earnings guidance tend to have higher growth potential compared to others with lower imprecision. However, there is a negative (or unclear)

[10]Missing R&D (xrd) values are replaced with zeros; relaxing this assumption does not qualitatively change results.

relation between IMP and realized growth. This finding is also in line with the conjecture on investors' optimism discussed in section 4.5.1. That is, investors purchasing stocks characterized by high IMP may be optimistic regarding the potential growth they expect to be realized by these firms and get disappointed when such growth does not get realized in the future, resulting in negative returns as found in Section 4.4.

This suggests that firms with high imprecision may be lottery-like investments as investors like them for the growth potential. Moreover, Table 4.3 reveals that firms with high imprecision do also have some lottery characteristics as manifested by the increasing MAX along the IMP quintile. To test further the relationship between guidance imprecision, asset growth and lottery characteristics, the second and third set of Panel B show results of the cross-section regression of realized asset growth AG_{t+3} and AG_{t+5} on IMP conditional on lottery characteristics for the high and low MAX subsamples. The negative relationship between IMP and realized asset growth is negative and significant only for the subsample with high lottery characteristics (i.e. the subsample where MAX is above the monthly cross-section median). However, this relationship is positive (IMP coefficient of 2.24) or insignificant (IMP coefficient of -0.94) for the subsample with low lottery features (i.e. MAX is below the monthly cross-section median), confirming the conjecture that firms with high imprecision can be lottery-like investments.

The relationship between IMP and lottery features is further tested on the stock-level and for different lottery levels. Panel A of Table 4.12 reports the time-series averages of the cross-sectional slope coefficients obtained by regressing IMP on MAX and standard controls that include: β^{MKT}, SIZE, BM, OP, INV for all firms, and separately for firm with high lottery characteristics versus firms with low lottery features. Results reveal that IMP is associated with lottery characteristics only for the high MAX group of firms (MAX coefficient of 0.029 (t-stat of 3.29)) while there is no significant relation between MAX and IMP for the low MAX group.

Next, the impact of imprecision on returns is examined in the case of lottery demand stocks. Panel B of Table 4.12 reports the time-series averages of the cross-sectional slope coefficients obtained by regressing stocks' excess returns on lagged IMP and the above-mentioned lagged controls. Results show that the impact of IMP on returns is more pronounced in the case of lottery demand stocks. For example, the coefficient of IMP becomes insignificant for low MAX firms compared to -0.323 (t-stat of -3.45) for high MAX firms. Results hence imply that firms with high guidance imprecision would earn lower returns on average but particularly when those firms are lottery-like investments. In case of stocks with low lottery features, the uncertainty regarding management guidance is not associated with any negative premium. In other words, investors' preference of high IMP decays with lower lottery features.

Results of Table 4.11 reveal that firms with high guidance imprecision don't deliver high realization expost growth, despite having growth potential. These firms are also small firms with poor profitability (see Table 4.3), which imply they can be prone to distress risk. Given the lower returns associated with distress risk (see e.g,. Campbell et al. (2008) and Conrad et al. (2014)), firms with high IMP can also be distressed firms. This conjecture is tested using the negative of Merton's (1974) distance-to-default (DD) and OH (defined above) as distress proxies, where higher values of OH and DD imply higher distress risk. DD is computed following Bharath and Shumway (2008) as:

$$DD = -\frac{\left(log\left(\frac{V}{F}\right)\right) + \left(r_{i,y-1} - \sigma_V^2/2\right)T}{\sigma_V\sqrt{T}}, \tag{4.6}$$

where

$$\sigma_V = \left(\frac{E}{V}\right)\sigma_E + \left(\frac{F}{V}\right)\left(0.05 + 0.25\sigma_E\right),$$

where V is firm's i total value, F is the face value of its debt, E is the market value of equity, σ_E is the stock return volatility estimated over the previous year, $r_{i,y-1}$ is the stock return over the previous year, and T is the number of years set to one.

Panel A of Table 4.13 reports the coefficients of panel regression of annual DD or OH proxies on lagged IMP along with the 5F controls. Annual IMP is measured as the average IMP during the year. The positive and significant coefficients of IMP_t shown in Table 4.13 indicate that firms with high guidance imprecision are also more likely to be under distress risk. This finding corroborates and sheds further light on the distress risk anomaly reported by Campbell et al.

(2008) and attributed to lottery features by Conrad et al. (2014).

To explore further the negative IMP premium conditional on distress risk, the cross-sectional regression of monthly excess returns on IMP and a set of lagged is conducted controls following the Fama and MacBeth (1973) approach for the subsamples with high distance-to-default, DD, (Ohlson's (1980) bankruptcy risk, OH) or low DD (OH) as shown in the second (third) set in Panel B of Table 4.13. Results indicate that the low returns associated with IMP are evident only for firms that are under distress risk as seen by the significant IMP coefficients of -0.272 (*t*-stat of -4.17) and -0.199 (-2.88) for the high DD and OH subsamples, respectively. This result implies that the low returns associated with IMP may be due to an increase in the option value of equity for firms with high uncertainty regarding their future earnings growth and hence expected cash flows. When earnings growth is unobservable, imprecision in management earnings forecasts (reflecting uncertainty for this growth) can be considered as idiosyncratic asset risk. For levered firms under distress risk, expected equity returns will generally decline with idiosyncratic risk due to convexity (which increases the option value of equity). This result is in line with Johnson's (2004) finding that the negative impact of dispersion of analysts' earnings forecasts on stock returns is conditional on the firm's leverage level.

4.5.3 The Case of Firms with Low Earnings

Previous literature suggested that range forecasts are associated with bad news Baginski et al. (2011). In other words, managers tend to provide imprecise forecast when the earnings expectations are low and hence IMP is associated with lower subsequent returns. This might cast doubt on the negative premium associated with IMP reported in Tables 4.3, 4.4 and 4.5. To address this concern, the relationship between guidance imprecision and earnings expectations is tested. Panel A of Table 4.14 shows the cross-sectional average coefficient of IMP on REG expost for i) the overall sample, ii) firms with low EEG (below cross-sectional median), and iii) firms with high EEG (above the median). Specification (1) of Panel A shows a negative significant relationship between REG and IMP. This finding is in accordance with results of Table 4.11 where IMP is reported to be negatively related to future growth albeit not significant in some cases. More importantly, the negative association is significant for both groups of firms with low earnings expectations (specification (2)) and high earnings expectations (specification (3) of Panel A). This implies that guidance imprecision is not particularly associated with expost earnings growth when earnings expectations are low.

The IMP impact on future returns is tested for the same groups of Panel A, after isolating the potential relation between IMP and realized earnings. More specifically, each month the residuals of the following cross-sectional regression are estimated:

$$\mathrm{IMP}_{i,t} = \alpha_{0,t} + \alpha_{1,t}\mathrm{REG}_{i,t} + \alpha_{2,t}X_{i,t} + e_{i,t}, \tag{4.7}$$

where X includes β^{MKT} SIZE, BM, OP, INV as controls and $e_{i,t}$ are the residuals. Then, monthly cross-sectional regressions are estimated as follows:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}e_{i,t} + \gamma_{2,t}X_{i,t} + \gamma_{3,t}\mathrm{REG}_{i,t} + \epsilon_{i,t}, \tag{4.8}$$

Panel B reports the coefficients of Equation 4.8 for the overall sample and for the subsamples of firms with low and high earnings expectations, respectively. Results indicate that high-IMP stocks would deliver lower returns for both groups of low earnings expectations (specification 2) and high earnings expectations (specification 3). Isolating the expost earnings growth (REG) from IMP in Equation 4.7 and controlling for it in Equation 4.8 helps alleviate potential concerns that the low returns of high-IMP firms are merely due to the association between IMP and low earnings results.

To further alleviate this concern, the average imprecision at the industry level (2-digit SIC) is used as an instrumental variable (IV) for the firm's imprecision level. More specifically, for each firm, its IMP industry average (IMP^{IA}) is computed excluding that firm's IMP. IMP^{IA} is then used as an IV for the firm's IMP. The rationale is that while some managers may choose to disclose imprecise forecasts for firm-specific reasons such as in case of low expected earnings, others would do so for other external factors such as unclear earnings visibility at the overall industry or economy level. Using the IMP-industry level (excluding that of the firm itself) helps isolate the true visibility regarding earnings prospects from managers' different intentions in issuing imprecise forecast. In other words, estimating the firm's IMP based on the industry level is more likely to reflect the overall industry uncertainty rather than internal firms' factors that would induce managers to disclose imprecise forecasts. Table 4.15 shows the results of first and second stages of the 2SLS regression in columns (1) and (2), respectively. Results imply that the firm's IMP is highly associated with industry IMP as shown by the significant IMP^{IA} coefficient of 0.179 ($t-$stat of 11.18) in column (1). More importantly, the firm's IMP estimated based on the industry average is significantly associated with lower subsequent equity returns as shown by the IMP coefficient of -0.703 ($t-$stat of -2.64), in line with the above main set of findings.

4.6 Robustness Tests

4.6.1 Different Scaling of IMP

In Equation (4.1) IMP was measured as the difference between the upper and lower bound in the earnings forecast provided by managers scaled by the book value of assets as of June of the previous calendar year. IMP was set to zero in case point estimates were given. For robustness in the scaling, IMP is alternatively computed as the difference between the upper and lower bound of earnings guidance range: i) scaled by market value of equity as of the latest June, or ii) scaled by the mid point of estimates. Table 4.16 reports the risk-adjusted returns for value (VW) and equally weighted (EW) quintile portfolios sorted according to IMP for each of the above sets. The reported alphas are based on the 5F model. The last two rows report the difference in alphas between quintiles 5 and 1, confirming that IMP's impact on future returns is robust to different scaling alternatives.

4.6.2 Excluding Stocks with Point Estimates

In Section 4.4.2, univariate portfolio analysis shows that the imprecision in management guidance has a pricing impact. For robustness, the analysis is repeated after excluding those firms with point estimates (i.e., having IMP=0). Raw excess and risk-adjusted returns for both value-weighted and equally-weighted portfolios are reported in Table 4.17, with stocks sorted into quintiles as in Table 4.3. Results again indicate that a hedging portfolio that goes long in stocks with high IMP and short in stocks with low IMP (where IMP>0) will on average deliver negative returns, implying that the degree of guidance imprecision also matters regardless of the form (point estimates versus closed interval).

4.6.3 Different Economic Cycles and Institutional Pessimism

The negative IMP premium is next examined over different market sub-periods depending on investors' overall optimism or pessimism level. Optimistic and pessimistic periods are proxied by the level of Shiller's One-Year Confidence Index for Institutions (SCII) being above or below the overall sample median over the period July 1995 to December 2018. The SCII index reports the percentage of survey respondents expecting an increase in the Dow Jones in the coming year. With portfolios formed as in Table 4.3, Table 4.18 shows the raw excess returns and the risk-adjusted returns for value-weighted portfolios over different sub-periods when institutional investors are considered optimistic or pessimistic. The reported alphas are based on the 5F model. Results in Table 4.18 confirm a significant negative IMP premium for the high − low portfolio in periods when investors are pessimistic regarding the future market outlook. This negative premium is not evident when investors are optimistic. Results of Table 4.18 imply that investors preference concerning guidance imprecision depends on their level of optimism or pessimism. Investors are more tolerant to uncertainty accepting guidance imprecision when overall market sentiment is down; such uncertainty may increase the appeal of growth options and lottery-like stocks.

4.6.4 Alternative Pricing Factors

To ensure that the documented negative returns associated with high-IMP stocks are not specific to the use of the 5F model (the base model used in the univariate and bivariate portfolio analysis), robustness tests are performed using alternative asset pricing models and factors. Table 4.19 implements the univariate sorting described in Table 4.3 where stocks are allocated into quintile portfolios based on their IMP. The table reports risk-adjusted returns of value-weighted portfolios using alternative asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF). The second set includes the latter three models augmented by the momentum factor of Carhart (1997). The last set adds both momentum factor and the liquidity factor of Pástor and Stambaugh (2003). The last two rows report the differences in alphas between the high and low quintile portfolios (all significant at 5% using Newey-West adjusted t-statistics in parentheses). Results in Table 4.19 confirm the significant underperformance of high-IMP firms when using different asset pricing models.

4.6.5 Extending the Sample

A limitation of the sample used in the above analysis is that it is restricted to only firms that are covered by the IBES database for management guidance. This can raise some doubt regarding sample selection bias in favor of large firms that are covered in the IBES database. To address this concern, the sample is extended to include other stocks covered in CRSP that are not in the initial IBES-based sample. Specifically, a propensity score is estimated for each firm in CRSP using a probit regression based on the firm's size and log of book-to-market. Then firms of the CRSP universe, which are not covered by IBES, are matched to the nearest neighbor firm (with the closest propensity score) from the original sample. Propensity score matching is conducted on a monthly basis without replacement (i.e., each stock from the remaining CRSP stocks can be matched with only one stock from the original IBES sample). The average number of firms in the new extended sample is 3,373 over the same sample horizon, with a monthly minimum and maximum of 2,481 and 4,613 stocks, respectively.

For the extended sample, univariate portfolio analysis similar to that of Tables 4.19 is conducted. Results are shown in Panel A of Table 4.20 where stocks are sorted into 5 quintile portfolios according to their IMP level. In Panel A, raw and risk-adjusted returns of the hedging portfolio that takes a long position in high-IMP stocks and a short position in low-IMP stocks are negative and significant, showing robustness to different asset pricing models. Panel B shows results based on stock level cross-sectional analysis analogous to Table 4.5 but for the extended sample. Results again confirm that IMP is associated with low subsequent returns in the extended sample. Overall, the robustness of results in Panels A and B should alleviate sample bias selection concerns.

4.7 Conclusion

This chapter documents that imprecision surrounding management guidance is associated with low subsequent excess and risk-adjusted equity returns. Results show that firms in the high-IMP quintile portfolio of management guidance imprecision deliver on average 8% lower risk-adjusted returns per annum compared to those in the low-IMP quintile. Empirical evidence suggests that the low return associated with high-IMP firms may be due to two sources: i) the presence of more optimist investors in play for high-IMP stocks, causing mispricing particularity when short sale constraints and arbitrage asymmetries keep out pessimists, and ii) genuine uncertainty of future earnings particularly evident in growth stocks. Firms with high guidance imprecision are more likely to be lottery-like or growing firms and under distress risk. In this regard, the low-return of high-IMP stocks may provide additional insight regarding the distress risk anomaly that involves both growth and lottery-like and distress stocks (Campbell et al. (2008), Conrad et al. (2014)). The negative IMP return premium is related to mispricing as it is more evident in stocks likely to be overpriced. Moreover, as confident managers tend to overestimate expected earnings growth leading to overvaluation, the impact of IMP is more pronounced for firms with overconfident managers.

Overall, imprecision in management guidance captures uncertainty in earnings prospects not captured by other uncertainty factors, including idiosyncratic volatility, turnover and dispersion in analysts' forecasts that are widely used as proxies for divergence of opinion. Results hold in both portfolio and stock level analyses and are robust to different measurement, samples and alternative pricing factors.

4.8 Tables

Table 4.1

Average Firm Characteristics per IMP Quintile

This table reports the average firm characteristics for each quintile portfolio sorted on management guidance imprecision. Each month stocks are divided into 5 portfolios based on IMP and the time-series average of the cross-sectional median firm characteristics is computed in each quintile. The characteristics are: IMP is the guidance imprecision indicator as per Equation (4.1) in percentage, β^{MKT} is the market beta, MCAP is the market capitalization in millions US dollars, BM is the book-to-market ratio, OP is operating profitability computed following Novy-Marx (2013), ROA is return in assets, INV is investment following Fama and French (2015), DISP is the analysts' forecast dispersion, AF^{IMP} is the imprecision in analysts forecasts, TURN is the ratio of volume traded in a month to shares outstanding, IVOL is idiosyncratic volatility (in %), β^{VXO} is the market volatility VXO exposure (in %), MOM is stock momentum, STR is short-term reversal, ILLIQ is the Amihud (2002) illiquidity indicator scaled by 10^6, ISKEW is idiosyncratic skewness, COSK is coskewness, TSKEW is total skewness. The last two columns report the difference High−Low (5-1) of average firm characteristics with corresponding Newey-West adjusted t-statistics given in parentheses.

	1 (Low)	2	3	4	5 (High)	High−Low	t-stat
IMP	0.013	0.163	0.257	0.421	1.036	1.024	(21.16)
β^{MKT}	0.949	0.937	0.939	0.973	1.025	0.076	(3.11)
SIZE	2,667	2,982	1,758	1,575	638	-2,029	(-6.33)
BM	0.348	0.401	0.410	0.382	0.346	-0.002	(-0.18)
OP	0.269	0.275	0.278	0.272	0.210	-0.060	(-7.64)
ROA	0.069	0.062	0.066	0.071	0.060	-0.008	(-2.34)
INV	0.104	0.067	0.077	0.084	0.108	0.005	(0.63)
DISP	0.016	0.013	0.017	0.021	0.036	0.020	(15.49)
AF^{IMP}	0.004	0.003	0.004	0.006	0.010	0.006	(18.40)
TURN	1.494	1.487	1.394	1.369	1.439	-0.055	(-1.66)
IVOL	1.663	1.309	1.500	1.702	2.224	0.562	(9.69)
β^{VXO}	0.030	0.028	0.054	0.046	0.052	0.022	(1.62)
MOM	12.630	13.292	11.570	7.099	1.534	-11.096	(-5.72)
STR	1.039	1.109	0.772	0.778	0.060	-0.979	(-5.14)
ILLIQ	0.002	0.001	0.003	0.004	0.010	0.008	(5.13)
ISKEW	0.249	0.206	0.181	0.176	0.236	-0.012	(-0.35)
COSK	-0.874	-0.138	-0.323	-0.345	-1.620	-0.747	(-1.53)
TSKEW	0.164	0.110	0.139	0.128	0.181	0.018	(0.59)
MAX	4.454	3.648	4.083	4.551	5.623	1.169	(7.68)

Table 4.2

Sample versus All CRSP Stocks

This table reports cross-section mean and median market cap (in millions US dollars) for all CRSP stocks at December of each year in Panel A, while Panel B limits the sample to only eligible stocks for which management earnings forecasts are provided in the IBES database. N firms is the number of firms and % of CRSP is the proportion of firms eligible in the sample to the overall CRSP firms. In both Panels, regulated and financial services firms are excluded.

Panel A: All CRSP Stocks

Year	Mean Size	Med Size	N firms
1995	842	85	5,175
1996	981	94	5,563
1997	1,217	104	5,631
1998	1,637	96	5,293
1999	2,352	144	5,054
2000	2,120	105	4,888
2001	2,095	147	4,324
2002	1,738	121	3,983
2003	2,478	274	3,688
2004	2,784	333	3,632
2005	2,951	343	3,536
2006	3,252	399	3,480
2007	3,543	365	3,376
2008	2,345	198	3,175
2009	3,170	337	3,016
2010	3,743	449	2,933
2011	3,811	417	2,824
2012	4,328	489	2,761
2013	5,609	707	2,770
2014	5,761	629	2,890
2015	5,581	543	2,880
2016	6,010	626	2,798
2017	7,150	693	2,808
2018	7,152	641	2,863

Panel B: Sample Stocks

Year	Mean Size	Med Size	N firms	% of CRSP
1995	4,377	638	89	2%
1996	4,538	734	114	2%
1997	6,414	1,032	113	2%
1998	9,812	660	189	4%
1999	14,052	880	266	5%
2000	11,959	985	285	6%
2001	7,417	603	554	13%
2002	5,817	521	621	16%
2003	6,216	821	640	17%
2004	7,079	955	628	17%
2005	7,621	1,051	646	18%
2006	7,968	1,141	609	18%
2007	8,776	1,158	596	18%
2008	6,104	751	559	18%
2009	7,132	1,220	508	17%
2010	8,240	1,556	431	15%
2011	7,819	1,484	445	16%
2012	8,678	1,815	441	16%
2013	11,506	2,455	430	16%
2014	13,437	2,468	429	15%
2015	14,416	2,436	426	15%
2016	15,036	2,623	392	14%
2017	17,394	3,331	397	14%
2018	18,102	3,434	391	14%

Table 4.3

Univariate Portfolio Sorting on IMP

Each month quintile portfolios are sorted according to the imprecision of management earnings guidance (IMP). This table reports excess raw and risk-adjusted returns of value-weighted (VW) and equally-weighted (EW) portfolios. The alphas reported are generated using the Fama and French (2015) five-factor regression model (5F). The last two rows report the difference of alphas between quintiles 5 and 1 and the corresponding Newey-West adjusted t-statistics for 6 lags in parentheses.

	Value-Weighted Portfolios		Equally-Weighted Portfolios	
IMP Quintile	Excess Ret.	Alpha 5F	Excess Ret.	Alpha 5F
1 (Low)	0.654	0.004	1.088	0.266
	(2.47)	(0.03)	(3.29)	(2.14)
2	0.508	0.091	1.121	0.406
	(2.36)	(0.64)	(3.82)	(4.35)
3	1.047	0.337	1.329	0.404
	(3.16)	(1.28)	(3.57)	(1.90)
4	0.647	-0.040	0.851	-0.058
	(2.17)	(-0.25)	(2.55)	(-0.33)
5 (High)	0.074	-0.631	0.660	-0.106
	(0.19)	(-2.75)	(1.56)	(-0.48)
High-Low	-0.580	-0.635	-0.427	-0.372
t-stat	(-2.07)	(-2.23)	(-2.38)	(-1.98)

Table 4.4

Bivariate Dependent Portfolio-Level Analysis

Stocks are sorted into quintile portfolios based on one of these control variables: beta of the market (β^{MKT}), the log of market capitalization (SIZE), book-to-market (BM), operating profitability (OP), return on assets (ROA), investment (INV), analysts' forecast dispersion (DISP), analyst forecast imprecision (AF^{IMP}), turnover (TURN), idiosyncratic volatility (IVOL), market volatility beta (β^{VXO}), momentum (MOM), short-term reversal (STR), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), coskweness (COSK), total skewness (TSKEW), and lottery-stocks demand (MAX). Stocks within each control variable quintile are further sorted into quintile portfolios based on IMP. The table reports risk-adjusted returns (based on 5F model) of value-weighted portfolios. Values are in percentage. The last two rows report the difference between quintiles 5 and 1 alphas and the Newey-West adjusted t-statistics in parentheses.

IMP	β^{MKT}	SIZE	BM	OP	ROA	INV	DISP	AF^{IMP}	TURN	IVOL	β^{VXO}	MOM	STR	ILLIQ	ISKEW	COSK	TSKEW	MAX
1 (Low)	-0.104	0.282	0.095	0.099	0.113	0.063	-0.038	0.111	0.160	-0.083	-0.009	-0.064	0.127	0.168	0.042	0.072	0.131	-0.038
2	0.431	0.460	0.254	0.406	0.385	0.197	0.465	0.016	0.302	0.250	0.412	0.639	0.580	0.217	0.335	0.529	0.547	0.274
3	-0.148	0.068	0.155	-0.137	-0.077	-0.082	0.000	0.094	-0.177	0.268	0.195	-0.092	0.137	-0.160	0.104	0.064	0.024	-0.233
4	-0.268	0.023	0.086	-0.284	-0.116	-0.071	-0.171	-0.107	-0.043	-0.211	-0.111	-0.299	-0.234	-0.039	-0.201	-0.182	-0.235	-0.111
5 (High)	-0.540	-0.239	-0.575	-0.507	-0.648	-0.555	-0.462	-0.418	-0.422	-0.552	-0.568	-0.455	-0.499	-0.273	-0.446	-0.456	-0.375	-0.563
High-Low	-0.435	-0.521	-0.670	-0.606	-0.762	-0.618	-0.424	-0.529	-0.582	-0.469	-0.559	-0.391	-0.625	-0.442	-0.488	-0.528	-0.507	-0.525
t-stat	(-2.41)	(-3.07)	(-2.46)	(-2.78)	(-3.73)	(-3.12)	(-1.98)	(-2.44)	(-2.81)	(-2.39)	(-3.13)	(-2.20)	(-3.07)	(-3.27)	(-2.49)	(-2.59)	(-2.42)	(-2.83)

Table 4.5

Stock Level Fama-MacBeth Cross-Sectional Regressions

This table reports the time series averages of the slope coefficients obtained by cross-sectionally regressing monthly excess returns (in percentage) on IMP and a set of lagged controls following the Fama and MacBeth (1973) approach. Panel A uses common risk factors as controls defined in Section 4.3.2. Panel B repeats Panel A regressions with industry controls. Panel C uses potential and realized growth as control variables. t-statistics in parentheses are corrected for autocorrelation and heteroscedasticity.

Panel A. Analysis with Common Risk Factor Controls

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Constant	0.832	0.868	0.901	0.912	0.875	0.857	0.866	0.876	0.807	0.887	0.902	0.873	0.875	0.874	0.911
	(2.69)	(2.87)	(2.98)	(3.14)	(3.03)	(2.81)	(2.84)	(2.89)	(2.67)	(2.90)	(2.98)	(2.89)	(2.90)	(2.90)	(3.03)
IMP	-0.261	-0.251	-0.235	-0.263	-0.293	-0.245	-0.253	-0.245	-0.230	-0.255	-0.256	-0.235	-0.248	-0.239	-0.237
	(-4.61)	(-4.57)	(-4.11)	(-4.39)	(-4.76)	(-4.33)	(-4.57)	(-4.62)	(-4.13)	(-4.55)	(-4.75)	(-4.21)	(-4.43)	(-4.23)	(-4.20)
β^{MKT}	0.110	0.191	0.164	0.201	0.185	0.212	0.206	0.192	0.172	0.182	0.183	0.185	0.197	0.187	0.227
	(1.12)	(1.96)	(1.74)	(2.04)	(1.97)	(2.19)	(2.14)	(2.00)	(1.92)	(1.80)	(1.91)	(1.91)	(2.02)	(1.92)	(2.27)
SIZE	-0.504	-0.527	-0.505	-0.496	-0.468	-0.411	-0.573	-0.526	-0.539	-0.488	-0.516	-0.531	-0.521	-0.529	-0.580
	(-4.91)	(-4.99)	(-4.86)	(-4.46)	(-4.20)	(-3.10)	(-5.58)	(-5.04)	(-5.23)	(-4.73)	(-4.51)	(-5.07)	(-4.99)	(-5.05)	(-5.35)
BM	0.156	0.114	0.130	0.059	0.118	0.124	0.094	0.118	0.174	0.140	0.124	0.129	0.103	0.130	0.114
	(1.83)	(1.00)	(1.42)	(0.50)	(0.90)	(1.09)	(0.82)	(1.05)	(1.53)	(1.19)	(1.09)	(1.10)	(0.90)	(1.12)	(0.99)
OP		0.026		-0.062	-0.017	0.023	0.011	0.027	0.049	0.033	0.032	0.036	0.015	0.032	0.008
		(0.30)		(-0.61)	(-0.15)	(0.27)	(0.13)	(0.32)	(0.57)	(0.39)	(0.38)	(0.43)	(0.18)	(0.39)	(0.09)
INV		-0.192	-0.177	-0.177	-0.17	-0.185	-0.175	-0.184	-0.175	-0.19	-0.192	-0.184	-0.194	-0.186	-0.177
		(-4.11)	(-3.88)	(-3.06)	(-3.32)	(-3.94)	(-3.79)	(-3.90)	(-3.99)	(-4.08)	(-4.03)	(-3.91)	(-4.01)	(-3.91)	(-3.92)
ROA			-0.031												
			(-0.46)												
DISP				0.053											
				(0.70)											
AF^{IMP}					-0.034										
					(-0.48)										
TURN						-0.172									
						(-1.48)									
IVOL							-0.142								
							(-1.98)								
β^{VXO}								0.007							
								(0.09)							
MOM									0.193						
									(2.09)						
STR										-0.387					
										(-4.84)					
ILLIQ											0.128				
											(1.09)				
ISKEW												-0.014			
												(-0.19)			
COSK													-0.164		
													(-1.84)		
TSKEW														-0.048	
														(-0.71)	
MAX															-0.24
															(-3.42)
No. of Obs.	105,094	102,158	103,299	73,566	71,891	102,158	102,158	102,158	101,998	102,158	102,158	102,158	102,158	102,158	102,158
R^2	0.045	0.06	0.058	0.082	0.082	0.067	0.066	0.067	0.072	0.07	0.068	0.066	0.066	0.066	0.066

Table 4.5 (continued)

Panel B. Cross-Sectional Analysis with Industry Controls

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Constant	1.394	2.735	2.139	2.869	3.109	2.701	3.13	2.788	2.485	3.232	2.973	3.033	2.894	2.691	3.385
	(1.31)	(2.14)	(1.59)	(2.58)	(2.86)	(1.92)	(2.77)	(2.19)	(1.81)	(2.52)	(2.39)	(2.37)	(2.16)	(2.16)	(2.87)
IMP	-0.233	-0.241	-0.228	-0.727	-0.754	-0.244	-0.228	-0.226	-0.216	-0.221	-0.243	-0.254	-0.244	-0.249	-0.196
	(-2.51)	(-2.49)	(-2.45)	(-2.25)	(-2.48)	(-2.52)	(-2.49)	(-2.35)	(-2.29)	(-2.23)	(-2.51)	(-2.69)	(-2.57)	(-2.64)	(-2.08)
β^{MKT}	0.112	0.167	0.169	0.225	0.192	0.161	0.174	0.174	0.0526	0.227	0.17	0.146	0.174	0.148	0.255
	(0.44)	(0.63)	(0.67)	(0.78)	(0.61)	(0.61)	(0.67)	(0.67)	(0.22)	(0.83)	(0.64)	(0.55)	(0.65)	(0.56)	(0.95)
SIZE	-0.111	-0.126	-0.113	-0.151	-0.129	-0.126	-0.147	-0.129	-0.122	-0.114	-0.141	-0.131	-0.12	-0.13	-0.159
	(-1.68)	(-1.95)	(-1.73)	(-2.56)	(-1.90)	(-1.64)	(-2.39)	(-1.99)	(-1.93)	(-1.79)	(-2.30)	(-2.04)	(-1.94)	(-2.03)	(-2.58)
BM	-0.0571	-0.149	-0.111	-0.211	-0.107	-0.149	-0.202	-0.141	-0.0807	-0.122	-0.125	-0.14	-0.16	-0.143	-0.148
	(-0.47)	(-0.80)	(-0.75)	(-1.13)	(-0.53)	(-0.80)	(-1.13)	(-0.78)	(-0.44)	(-0.63)	(-0.67)	(-0.74)	(-0.86)	(-0.75)	(-0.79)
OP		0.005		0.273	0.528	-0.014	-0.140	0.072	0.007	0.127	0.091	0.008	0.001	-0.005	0.006
		(0.01)		(0.51)	(0.89)	(-0.03)	(-0.28)	(0.14)	(0.01)	(0.23)	(0.16)	(0.02)	(0.00)	(-0.01)	(0.01)
INV		-0.278	-0.307	-0.384	-0.535	-0.272	-0.212	-0.273	-0.313	-0.289	-0.268	-0.277	-0.304	-0.276	-0.223
		(-1.84)	(-2.07)	(-1.55)	(-2.12)	(-1.76)	(-1.33)	(-1.81)	(-2.01)	(-1.87)	(-1.79)	(-1.83)	(-1.94)	(-1.83)	(-1.47)
ROA			-0.451												
			(-0.61)												
DISP				1.823											
				(0.85)											
AF^{IMP}					5.499										
					(0.39)										
TURN						0.004									
						(0.95)									
IVOL							-4.897								
							(-0.74)								
β^{VXO}								8.635							
								(1.07)							
MOM									0.329						
									(1.35)						
STR										-3.195					
										(-5.22)					
ILLIQ											-0.165				
											(-0.64)				
ISKEW												-0.0523			
												(-1.05)			
COSK													-0.018		
													(-2.36)		
TSKEW														-0.060	
														(-1.09)	
MAX															-3.739
															(-2.22)
No. of Obs.	105,631	102,709	103,850	73,794	72,119	102,709	102,709	102,709	102,546	102,709	102,709	102,709	102,709	102,709	102,709
R^2	0.161	0.179	0.180	0.233	0.236	0.182	0.187	0.186	0.192	0.188	0.189	0.185	0.186	0.185	0.186
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.5 (continued)

Panel C. Cross-Sectional Analysis with Growth Controls

R_{t+1}	(1)	(2)	(3)	(4)
Constant	0.881	0.921	0.859	0.887
	(3.17)	(3.20)	(2.80)	(2.93)
IMP	-0.243	-0.216	-0.169	-0.203
	(-3.38)	(-3.68)	(-2.45)	(-2.94)
β^{MKT}	0.182	0.181	0.13	0.136
	(1.93)	(1.70)	(1.36)	(1.43)
SIZE	-0.450	-0.500	-0.507	-0.499
	(-5.01)	(-4.58)	(-4.22)	(-3.90)
BM	0.123	0.18	0.184	0.155
	(1.08)	(1.53)	(1.59)	(1.35)
OP	0.068	0.078	0.066	-0.020
	(0.77)	(0.81)	(0.84)	(-0.26)
INV	-0.161	-0.173	-0.319	-0.214
	(-2.55)	(-2.94)	(-6.03)	(-3.68)
EEG	0.058			
	(0.86)			
REG		0.422		
		(6.85)		
RRG			0.462	
			(6.13)	
RAG				0.284
				(3.58)
No. of Obs.	86,983	77,836	88,562	88,594
R^2	0.067	0.084	0.083	0.083

Table 4.6

IMP and Returns around Earnings Announcement Days

This table reports the cross-sectional slope coefficients obtained by regressing abnormal returns ($AR^{Q}_{i,t}$) or simple returns ($R^{Q}_{i,t}$) in percentage over the 3 days around earnings announcement of 2Q, 3Q, and 4Q on a set of independent variables: IMPD is a dummy variable of guidance imprecision for stock i as of June of year t that equals 0 if the stock's IMP is below the cross-sectional IMP median as of June and equals 1 otherwise, β^{MKT}, SIZE, BM, OP, INV, and EPS^{qc}. Earnings announcement is considered as bad when change in realized quarterly earnings is below zero and good otherwise. Results are reported only for firms with fiscal year ending in December. t-statistics are provided in parentheses.

	All Firms		EPS^{qc}<0		EPS^{qc}≥0	
	$AR^{Q}_{i,t}$	$R^{Q}_{i,t}$	$AR^{Q}_{i,t}$	$R^{Q}_{i,t}$	$AR^{Q}_{i,t}$	$R^{Q}_{i,t}$
Constant	-1.582	-1.081	-5.314	-5.436	1.094	2.048
	(-2.59)	(-1.71)	(-4.90)	(-4.92)	(1.43)	(2.65)
IMPD	-0.343	-0.422	-0.561	-0.594	-0.0694	-0.169
	(-2.35)	(-2.81)	(-2.16)	(-2.23)	(-0.38)	(-0.89)
β^{MKT}	0.025	0.150	0.032	0.143	0.034	0.169
	(0.14)	(0.80)	(0.11)	(0.44)	(0.15)	(0.72)
SIZE	0.102	0.076	0.309	0.321	-0.058	-0.110
	(2.51)	(1.82)	(4.31)	(4.36)	(-1.17)	(-2.16)
BM	0.107	0.095	0.293	0.258	0.044	0.057
	(0.85)	(0.74)	(1.34)	(1.15)	(0.28)	(0.35)
OP	0.405	0.228	0.476	0.276	0.536	0.397
	(1.06)	(0.58)	(0.78)	(0.44)	(1.13)	(0.82)
INV	-0.923	-1.007	-0.756	-0.761	-0.938	-1.082
	(-2.90)	(-3.02)	(-1.29)	(-1.24)	(-2.31)	(-2.64)
EPS^{qc}	10.060	12.690	2.231	4.259	6.885	8.867
	(4.47)	(5.62)	(0.65)	(1.24)	(2.11)	(2.87)
No. of Obs.	16,562	16,562	6,591	6,591	9,971	9,971
R^2	0.005	0.007	0.006	0.006	0.002	0.004

Table 4.7

IMP and Forecast Errors

This table reports the average time-series slope coefficients of the cross-sectional regression of the forecast error of earnings on IMP, β^{MKT}, SIZE, BM, OP, and INV. Forecast error is estimated as the difference between the point estimate and the realized earnings (expost) for firms with null IMP and as the difference between the upper bound (or the mid point) of management guidance and the realized earnings for firms with range forecasts, all scaled by the absolute value of realized earnings. Models (1) and (2) report forecast errors estimated using the upper bound (FE^U) and the mid forecast point (FE^M), respectively. *t*-statistics are provided in parentheses.

	(1) FE^U	(2) FE^M
Constant	1.833	1.820
	(3.09)	(3.19)
IMP	0.923	0.813
	(3.68)	(3.42)
β^{MKT}	0.349	0.327
	(2.68)	(2.55)
SIZE	-0.047	-0.049
	(-1.31)	(-1.40)
BM	0.621	0.563
	(5.74)	(5.45)
OP	-0.048	-0.118
	(-0.16)	(-0.41)
INV	0.449	0.439
	(2.55)	(2.59)
No. of Obs.	98,067	98,067
R^2	0.056	0.055

Table 4.8

IMP and Managerial Overconfidence

This table shows the time-series averages of the slope coefficients of the cross-sectional regression of the one month-ahead excess return on IMP (along with controls) for the low (Holder 67=0) and high (Holder 67=1) managerial overconfidence subsamples. t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity.

	R_{t+1}	
	Low Conf.	High Conf.
Constant	1.011	1.202
	(1.92)	(2.60)
IMP	-0.281	-0.184
	(-0.93)	(-2.02)
β^{MKT}	-0.248	0.205
	(-1.03)	(1.14)
SIZE	-0.168	-0.520
	(-0.62)	(-3.35)
BM	0.110	0.021
	(0.41)	(0.15)
OP	-0.057	-0.019
	(-0.26)	(-0.18)
INV	0.198	0.102
	(0.82)	(0.99)
No. of Obs.	5,790	19,714
R^2	0.225	0.081

Table 4.9

Arbitrage Asymmetry

This table reports the average time-series slope coefficients of the cross-sectional regression of stocks' excess returns on lagged IMP, SIZE, β^{MKT}, BM, OP, and INV for all firms (specification 1), overpriced firms with rank up to 3 (specification 2), and underpriced firms with rank above 3 (specification 3). t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity.

R_{t+1}	(1) All Firms	(2) High Rank	(3) Low Rank
Constant	0.868	0.794	1.293
	(2.87)	(2.49)	(3.36)
IMP	-0.251	-0.267	0.210
	(-4.57)	(-4.10)	(0.99)
β^{MKT}	0.191	0.144	0.281
	(1.96)	(1.39)	(0.92)
SIZE	-0.527	-0.515	-0.883
	(-4.99)	(-4.84)	(-2.33)
BM	0.114	0.092	-0.263
	(1.00)	(0.75)	(-1.07)
OP	0.026	0.001	-0.091
	(0.30)	(0.01)	(-0.60)
INV	-0.192	-0.189	0.191
	(-4.11)	(-3.52)	(0.55)
No. of Obs.	102,158	70,791	31,367
R^2	0.060	0.065	0.207

Table 4.10

IMP and Institutional Ownership

This table reports the average time-series slope coefficients of the cross-sectional regression of stocks' excess returns on lagged IMP, SIZE, β^{MKT}, BM, OP, and INV for firms with low and high institutional ownership (INST) in specifications (1) and (2), respectively. Stocks are considered to have low (high) institutional ownership if institutions ownership is below (above) the cross-section median. t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity.

R_{t+1}	(1) Low INST	(2) High INST
Constant	1.663	1.179
	(1.35)	(1.09)
IMP	-0.474	-0.130
	(-2.40)	(-0.43)
β^{MKT}	0.394	0.212
	(1.24)	(0.66)
SIZE	-0.077	-0.032
	(-0.92)	(-0.44)
BM	-0.137	0.022
	(-0.68)	(0.10)
OP	-0.031	0.062
	(-0.05)	(0.09)
INV	-0.494	-0.218
	(-1.69)	(-0.78)
No. of Obs.	43,149	44,091
R^2	0.128	0.125

Table 4.11

IMP and Growth

This table reports the time-series averages of the cross-sectional slope coefficients obtained by regressing on stocks' IMP potential growth proxies (Panel A) or realized growth (Panel B). The set of controls includes β^{MKT}, SIZE, BM, OP, INV. Potential growth proxies in Panel A include: idiosyncratic volatility (IVOL), growth option (GO) intensity, capital expenditures growth (CAPFIXG), and Research and Development expenses scaled by total assets (RD). Realized future growth proxies in Panel B include: average asset growth over the following 3 or 5 years (AG_{t+3}, AG_{t+5}). The second and third set of Panel B show results for the subsample with high lottery characteristics (MAX above the monthly cross-section median) and subsample with low lottery characteristics (MAX below the median). t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity with 6 lags.

Panel A: Potential Growth Proxies versus IMP

	(1)	(2)	(3)	(4)
	IVOL	GO	CAPFIXG	RD
Constant	0.017	0.053	0.032	0.020
	(0.29)	(1.40)	(1.35)	(1.15)
IMP	4.342	4.117	3.962	4.145
	(6.35)	(3.93)	(3.24)	(2.61)
β^{MKT}	0.120	0.063	0.026	0.068
	(14.81)	(5.42)	(2.24)	(4.89)
SIZE	-0.356	-0.136	-0.071	-0.043
	(-31.54)	(-11.52)	(-8.51)	(-2.75)
BM	-0.068	-0.189	-0.047	-0.237
	(-5.82)	(-12.84)	(-3.74)	(-13.10)
OP	-0.052	-0.285	0.017	-0.136
	(-7.02)	(-25.77)	(1.83)	(-8.32)
INV	0.057	0.097	0.280	-0.072
	(7.29)	(8.11)	(17.83)	(-4.90)
No. of Obs.	106,398	102,891	106,130	82,405
R^2	0.213	0.140	0.124	0.103

Panel B: Realized Growth versus IMP Conditional on Lottery Characteristics

	All		High MAX		Low MAX	
	AG_{t+3}	AG_{t+5}	AG_{t+3}	AG_{t+5}	AG_{t+3}	AG_{t+5}
Constant	0.049	0.051	0.099	0.114	0.031	0.034
	(1.57)	(1.55)	(3.01)	(2.92)	(0.97)	(0.97)
IMP	-1.239	-3.663	-3.683	-4.232	2.235	-0.940
	(-0.76)	(-2.14)	(-2.05)	(-2.12)	(1.71)	(-0.55)
β^{MKT}	0.029	0.016	0.029	0.022	0.028	0.014
	(1.66)	(1.01)	(1.48)	(0.99)	(1.74)	(0.87)
SIZE	-0.051	-0.099	-0.004	-0.054	-0.097	-0.138
	(-2.86)	(-4.53)	(-0.21)	(-2.70)	(-5.20)	(-5.36)
BM	-0.249	-0.230	-0.259	-0.217	-0.250	-0.253
	(-12.69)	(-11.22)	(-12.15)	(-8.35)	(-10.26)	(-10.23)
OP	-0.049	-0.042	-0.053	-0.042	-0.060	-0.055
	(-4.27)	(-3.07)	(-3.23)	(-2.36)	(-3.80)	(-3.38)
INV	0.123	0.120	0.147	0.146	0.108	0.111
	(4.69)	(5.29)	(5.23)	(5.99)	(4.14)	(4.62)
No. of Obs.	102,016	98,627	49,818	47,543	52,198	51,084
R^2	0.128	0.115	0.173	0.148	0.144	0.139

Table 4.12

IMP vs. Lottery Characteristics

Panel A reports the time series averages of the cross-sectional slope coefficients obtained by regressing stocks' IMP on MAX and other controls that include: β^{MKT}, SIZE, BM, OP, and INV, for all stocks, and for stocks with high and low lottery characteristics. Panel B reports the time series averages of the cross-sectional slope coefficients obtained by regressing stocks' excess returns on lagged IMP and lagged controls. Stocks are considered to have high (low) lottery characteristics if their MAX is above (below) the sample monthly cross-sectional MAX median. t-statistics reported in parentheses are corrected for autocorrelation and heteroscedasticity with 6 lags.

Panel A: IMP vs. MAX

IMP	All Stocks	High MAX	Low MAX
Constant	-0.051	-0.040	-0.113
	(-1.26)	(-0.94)	(-2.49)
MAX	0.041	0.029	-0.015
	(5.47)	(3.35)	(-0.48)
β^{MKT}	0.054	0.045	0.063
	(5.45)	(3.30)	(5.84)
SIZE	-0.214	-0.245	-0.164
	(-17.04)	(-17.71)	(-12.22)
BM	-0.173	-0.196	-0.123
	(-9.07)	(-9.31)	(-5.84)
OP	-0.090	-0.111	-0.047
	(-5.56)	(-5.94)	(-2.71)
INV	-0.012	-0.022	0.000
	(-1.80)	(-2.53)	(-0.00)
No. of Obs.	102,202	50,328	51,874
R^2	0.097	0.137	0.108

Panel B: IMP's Impact on Returns for Lottery Stocks

R_{t+1}	All Stocks	High MAX	Low MAX
Constant	0.868	0.797	1.073
	(2.87)	(2.17)	(4.03)
IMP_t	-0.251	-0.323	-0.091
	(-4.57)	(-3.45)	(-1.43)
β_t^{MKT}	0.191	0.214	0.239
	(1.96)	(1.64)	(2.54)
SIZE_t	-0.527	-0.608	-0.493
	(-4.99)	(-4.53)	(-5.37)
BM_t	0.114	0.184	-0.002
	(1.00)	(1.19)	(-0.02)
OP_t	0.026	0.038	-0.034
	(0.30)	(0.33)	(-0.34)
INV_t	-0.192	-0.203	-0.127
	(-4.11)	(-2.82)	(-2.31)
No. of Obs.	102,158	50,314	51,844
R^2	0.060	0.087	0.082

Table 4.13

IMP and Distress Risk

Panel A reports the coefficients of the panel annual regression of distress risk proxied by distance-to-default (DD) or Ohlson's (1980) bankruptcy risk (OH) on lagged IMP and a set of lagged controls that include β^{MKT}, SIZE, BM, OP, and INV. Annual IMP is estimated as the average IMP in a year. Panel B reports the time series averages of the slope coefficients obtained by cross-sectionally regressing monthly excess returns (in percentage) on a set of lagged controls following the Fama and MacBeth (1973) approach. The second (third) set of Panel B shows results for the subsample with high DD (OH) for values above the monthly cross-section DD (OH) median and the subsample with low DD (OH) for values above the monthly cross-section DD (OH) median. t-statistics are reported in parentheses.

Panel A: IMP vs. Distress Risk

	DD_{y+1}	OH_{y+1}
Constant	0.055	-4.270
	(0.58)	(-6.43)
IMP_y	0.248	6.974
	(2.50)	(3.18)
β_y^{MKT}	0.010	0.015
	(2.01)	(0.85)
SIZE_y	-0.114	-2.921
	(-10.33)	(-37.18)
BM_y	0.042	-0.883
	(2.27)	(-4.83)
OP_y	0.000	0.000
	(1.89)	(0.42)
INV_y	0.017	0.417
	(2.19)	(1.85)
No. of Obs.	7,770	8,738
R^2	0.183	0.426

Panel B: IMP Premium Conditional on Distress and Leverage Levels

R_{t+1}	All Firms	High DD	Low DD	High OH	Low OH
Constant	0.868	0.799	1.374	0.746	0.796
	(2.87)	(2.52)	(3.73)	(2.31)	(2.17)
IMP_t	-0.251	-0.272	0.279	-0.199	-0.216
	(-4.57)	(-4.17)	(0.81)	(-2.88)	(-0.81)
β_t^{MKT}	0.191	0.213	-0.093	0.205	0.103
	(1.96)	(2.09)	(-0.44)	(1.90)	(0.84)
SIZE_t	-0.527	-0.551	-0.689	-0.602	-0.657
	(-4.99)	(-4.82)	(-1.84)	(-4.53)	(-4.20)
BM_t	0.114	0.100	-0.097	0.108	-0.326
	(1.00)	(0.80)	(-0.26)	(0.89)	(-1.41)
OP_t	0.026	-0.016	-0.017	0.016	0.062
	(0.30)	(-0.16)	(-0.07)	(0.16)	(0.38)
INV_t	-0.192	-0.176	-0.504	-0.230	-0.058
	(-4.11)	(-3.36)	(-1.77)	(-3.69)	(-0.28)
No. of Obs.	102,158	65,401	36,757	62,750	39,408
R^2	0.060	0.066	0.155	0.066	0.152

Table 4.14

IMP and Low Earnings Expectations

Panel A reports the times-series average slope coefficients of the cross-sectional regression of IMP on REG and a set of controls following Fama and MacBeth (1973) for i) all firms, ii) low EEG firms (below cross-sectional median), and iii) high EEG firms (above cross-sectional median). Panel B also reports the average coefficients of cross-sectionally regressing monthly excess returns on lagged residuals (e) (estimated as per Equation 4.7) and REG along with a set of controls for the same sample groups as in Panel A. t-statistics are reported in parentheses.

Panel A. IMP vs. REG for EEG groups

	(1)	(2)	(3)
IMP	All Firms	Low EEG	High EEG
Constant	-0.095	-0.478	0.234
	(-2.31)	(-11.50)	(8.34)
β^{MKT}	0.065	0.049	0.054
	(6.46)	(5.11)	(2.81)
SIZE	-0.174	0.002	-0.166
	(-11.44)	(0.19)	(-8.60)
BM	-0.115	-0.023	-0.218
	(-5.24)	(-1.99)	(-5.78)
OP	-0.003	0.057	0.006
	(-0.15)	(5.52)	(0.18)
INV	0.008	0.005	0.025
	(0.88)	(0.53)	(1.65)
REG	-0.047	-0.034	-0.069
	(-3.94)	(-2.05)	(-3.58)
No. of Obs.	77,847	39,006	36,715
R^2	0.093	0.118	0.156

Panel B. Returns for EEG groups

	(1)	(2)	(3)
R_{t+1}	All Firms	Low EEG	High EEG
Constant	0.919	0.843	0.897
	(3.18)	(2.57)	(2.93)
e	-0.216	-0.402	-0.324
	(-3.68)	(-3.46)	(-3.02)
β^{MKT}	0.163	-0.001	0.302
	(1.53)	(-0.01)	(2.18)
SIZE	-0.465	-0.380	-0.552
	(-4.32)	(-3.67)	(-3.55)
BM	0.215	0.249	0.113
	(1.85)	(2.27)	(0.89)
OP	0.088	0.065	0.111
	(0.91)	(0.70)	(1.06)
INV	-0.172	-0.115	-0.035
	(-2.91)	(-1.46)	(-0.37)
REG	0.418	0.527	0.619
	(7.15)	(4.43)	(5.67)
No. of Obs.	77,836	36,560	36,710
R^2	0.084	0.101	0.142

Table 4.15

Two-Stage Regressions using Industry IMP as IV

This table reports the results of first and second stages of the two-SLS regression in columns (1) and (2), respectively. The industry-average IMP (IMP^{IA}) is used as an instrument for the firm's IMP level. In the first stage, the firm's IMP is regressed on its industry-average IMP (excluding the firm's IMP) along with controls. In the second stage, excess returns are regressed on the estimated firm's lagged IMP along with lagged controls. t-statistics are shown in parentheses.

	(1) IMP	(2) R_{t+1}
Constant	3.015	5.321
	(25.66)	(5.78)
IMP		-0.703
		(-2.64)
IMP^{IA}	0.179	
	(11.18)	
β^{MKT}	0.460	0.420
	(14.92)	(2.62)
SIZE	-0.208	-0.290
	(-24.43)	(-4.64)
BM	-0.380	-0.023
	(-17.70)	(-0.19)
OP	-1.309	-0.573
	(-22.37)	(-1.42)
INV	-0.023	-0.621
	(-0.56)	(-5.02)
No. of Obs.	100,955	100,955

Table 4.16

Univariate Sorting on IMP with Alternative Scaling

Each month quintile portfolios are sorted according to the imprecision of management forecasts (IMP) where the difference between the higher and lower bound of management earnings guidance is scaled by market cap (MCAP) as of the most recent December, or by the midpoint between higher and lower bound estimate. The table reports risk-adjusted returns of value-weighted (VW) and equally-weighted (EW) portfolios. The alpha reported are generated using the 5F model. The last two rows report the difference of alphas between quintiles 5 and 1 and the corresponding Newey-West adjusted t-statistics for 6 lags in parentheses.

	IMP Scaled by MCAP		IMP Scaled by Midpoint	
	VW	EW	VW	EW
1 (Low)	0.107	0.316	0.077	0.269
	(0.78)	(2.47)	(0.54)	(1.83)
2	-0.070	0.433	-0.032	0.225
	-(0.63)	(4.28)	-(0.27)	(2.41)
3	0.414	0.427	0.026	0.143
	(1.70)	(2.22)	(0.15)	(1.08)
4	-0.293	0.012	-0.255	0.086
	(-1.72)	(0.09)	-(1.58)	(0.53)
5 (High)	-0.401	-0.272	-0.484	-0.109
	(-1.86)	(-1.11)	(-2.22)	(-0.56)
High-Low	-0.508	-0.588	-0.561	-0.378
t-stat	(-1.80)	(-2.97)	(-2.16)	(-2.62)

Table 4.17

Robustness to Different IMP Levels

This table replicates the quintile portfolio sorting of Table 4.3 based on IMP but after removing firms with point estimates (null IMP) of management's earnings guidance. It reports excess and risk-adjusted returns of value-weighted and equally-weighted portfolios.The risk-adjusted returns reported are generated using the 5F model. The second column reports the time-series average of the cross-sectional median IMP in each quintile portfolio. The last two rows report the difference of alphas between high and low IMP quantiles and the corresponding Newey-West adjusted *t*-statistics in parentheses.

		Value-Weighted Portfolios		Equally-Weighted Portfolios	
Quintile	IMP	Excess Ret.	Aplha 5F	Excess Ret.	Aplha 5F
1 (Low)	0.101	1.044	0.344	1.421	0.475
		(3.78)	(1.77)	(4.60)	(2.87)
2	0.205	0.780	0.194	0.822	-0.093
		(3.21)	(1.23)	(2.70)	(-0.58)
3	0.344	0.576	-0.164	0.843	-0.082
		(1.92)	-(0.91)	(2.44)	(-0.42)
4	0.563	0.271	-0.428	0.704	-0.038
		(0.83)	(-1.72)	(2.17)	(-0.22)
5 (High)	1.342	-0.070	-0.626	0.610	-0.130
		(-0.16)	(-2.03)	(1.36)	(-0.57)
High-Low	1.241	-1.114	-0.970	-0.811	-0.605
t-stat	(21.63)	(-2.59)	(-2.58)	(-2.35)	(-2.74)

Table 4.18

Univariate Sorting across Different States of the Economy and Institutional Pessimism

This table reports excess raw returns and risk-adjusted returns of value-weighted portfolios over different sub-periods when investors are optimistic or pessimistic. Optimistic and pessimistic periods are defined based on whether the level of the Shiller One-Year Confidence Index for Institutions (SCII) is above or below the overall sample median from July 1995 to December 2018. Each month quintile portfolios are formed based on IMP as discussed in Table 4.3. The reported alphas are obtained based on the 5F model. The last two rows report the difference in alphas between quintiles 5 and 1, with the corresponding Newey-West adjusted t-statistics given in parentheses.

	Optimism (SCII>Med.)		Pessimism (SCII<Med.)	
	Excess Ret.	Aplha 5F	Excess Ret.	Aplha 5F
1 (Low)	0.340	0.130	0.947	-0.051
	(1.09)	(0.68)	(4.95)	(-0.27)
2	0.173	0.073	0.894	0.284
	(0.65)	(0.41)	(5.58)	(1.27)
3	0.447	0.152	1.045	0.292
	(1.58)	(1.00)	(4.64)	(0.79)
4	0.048	-0.168	1.019	0.002
	(0.16)	(-0.91)	(3.96)	(0.01)
5 (High)	0.058	0.013	0.136	-1.011
	(0.14)	(0.04)	(0.36)	(-3.75)
High-Low	-0.283	-0.117	-0.811	-0.959
t-stat	(-0.98)	(-0.27)	(-3.20)	(-2.91)

Table 4.19

Robustness to Different Asset Pricing Models

Quintile portfolios are formed every month based on management guidance imprecision. Portfolio 1 (5) contains stocks with the lowest (highest) IMP measure. This table reports risk adjusted returns of value-weighted portfolios using a base set of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF). The second set includes the latter three models augmented by the momentum factor of Carhart (1997). The last set adds both momentum factor and the liquidity factor of Pástor and Stambaugh (2003). The last two rows show the difference of alphas between quintiles 5 and 1 with the corresponding Newey-West adjusted t-statistics in parentheses.

					+ MOM			+ MOM + LIQ		
IMP Quintile	CAPM	3F	5F	3Q	3F	5F	3Q	3F	5F	3Q
1 (Low)	0.138	0.142	0.004	0.003	0.126	0.000	0.006	0.158	0.032	0.048
	(1.18)	(1.26)	(0.03)	(0.02)	(1.11)	(0.00)	(0.05)	(1.41)	(0.23)	(0.35)
2	0.198	0.168	0.091	0.126	0.200	0.119	0.131	0.226	0.142	0.161
	(1.23)	(1.11)	(0.64)	(0.76)	(1.29)	(0.80)	(0.79)	(1.42)	(0.94)	(0.94)
3	0.623	0.571	0.337	0.473	0.665	0.419	0.489	0.683	0.435	0.508
	(2.20)	(2.18)	(1.28)	(1.61)	(2.43)	(1.53)	(1.65)	(2.52)	(1.60)	(1.74)
4	0.089	0.112	-0.040	-0.103	0.064	-0.065	-0.105	0.102	-0.029	-0.057
	(0.54)	(0.69)	(-0.25)	(-0.58)	(0.41)	(-0.41)	(-0.60)	(0.66)	(-0.19)	(-0.33)
5 (High)	-0.567	-0.582	-0.631	-0.661	-0.474	-0.550	-0.647	-0.447	-0.526	-0.616
	(-2.55)	(-2.61)	(-2.75)	(-2.73)	(-2.32)	(-2.62)	(-2.80)	(-2.24)	(-2.52)	(-2.69)
High-Low	-0.706	-0.724	-0.635	-0.664	-0.599	-0.550	-0.654	-0.605	-0.558	-0.664
t-stat	(-2.66)	(-2.75)	(-2.23)	(-2.30)	(-2.51)	(-2.19)	(-2.38)	(-2.53)	(-2.18)	(-2.38)

Table 4.20

Robustness to an Extended Sample

In Panel A, quintile portfolios are formed every month based on management guidance imprecision for the extended sample. Portfolio 1 (5) contains stocks with the lowest (highest) IMP measure for the extended sample that is matched to the original sample based on size and log of book-to-market. Panel A reports risk adjusted returns of value-weighted portfolios using a base set of asset pricing models: (i) the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) with MKT factor (CAPM); (ii) the three-factor model of Fama and French (1993) with MKT, SMB, and HML factors (3F); (iii) the five-factor model of Fama and French (2015) with MKT, SMB, HML, RMW, and CMA factors (5F); (iv) the Q-factor model of Hou et al. (2015) with MKT, SMB_Q, R_{ROE}, and $R_{I/A}$ factors (QF). The second set includes the latter three models augmented by the momentum factor of Carhart (1997). The last set adds both momentum factor and the liquidity factor of Pástor and Stambaugh (2003). The last two rows show the difference of alphas between quintiles 5 and 1 with the corresponding Newey-West adjusted t-statistics in parentheses. Panel B reports the time series averages of the slope coefficients obtained by cross-sectionally regressing monthly excess returns (in percentage) on IMP and a set of lagged controls following the Fama and MacBeth (1973) approach for the extended sample.

Panel A. Univariate Quintile Portfolio Sorting on IMP for the Extended Sample

						+ MOM			+ MOM + LIQ		
IMP Quintile	Exc. Ret.	CAPM	3F	5F	QF	3F	5F	QF	3F	5F	QF
1 (Low)	0.774	0.123	0.156	0.070	0.155	0.139	0.062	0.154	0.139	0.064	0.153
	(2.83)	(1.75)	(2.40)	(1.09)	(1.94)	(2.01)	(0.96)	(1.91)	(2.02)	(0.99)	(1.92)
2	0.574	0.158	0.121	0.043	0.114	0.168	0.081	0.118	0.157	0.069	0.093
	(2.39)	(1.00)	(0.86)	(0.31)	(0.80)	(1.26)	(0.61)	(0.85)	(1.17)	(0.52)	(0.67)
3	0.709	0.098	0.107	0.042	0.108	0.117	0.052	0.104	0.129	0.062	0.121
	(2.57)	(0.76)	(0.78)	(0.27)	(0.65)	(0.84)	(0.32)	(0.61)	(0.91)	(0.38)	(0.69)
4	0.636	-0.058	-0.036	-0.040	0.010	-0.033	-0.037	0.009	-0.019	-0.026	0.029
	(1.98)	(-0.48)	(-0.34)	(-0.39)	(0.08)	(-0.31)	-(0.37)	(0.07)	(-0.19)	(-0.26)	(0.26)
5 (High)	0.383	-0.389	-0.381	-0.278	-0.280	-0.301	-0.226	-0.274	-0.342	-0.264	-0.330
	(0.99)	(-2.45)	(-2.58)	(-1.90)	(-1.75)	(-2.09)	(-1.59)	(-1.75)	(-2.35)	(-1.86)	(-2.12)
High-Low	-0.391	-0.511	-0.537	-0.348	-0.436	-0.440	-0.288	-0.427	-0.481	-0.329	-0.483
t-stat	(-2.12)	(-2.97)	(-3.22)	(-2.14)	(-2.29)	(-2.59)	(-1.84)	(-2.28)	(-2.77)	(-2.07)	(-2.55)

Table 4.20 (continued)

Panel B. Stock Level Cross-Sectional Regressions for the Extended Sample

R_{t+1}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Constant	0.837	0.844	0.841	1.019	0.847	0.848	0.791	0.855	0.781	0.799	0.858	0.84	0.851	0.839	0.854
	(2.04)	(2.12)	(2.09)	(2.68)	(2.51)	(2.12)	(2.01)	(2.15)	(2.00)	(1.95)	(2.16)	(2.11)	(2.13)	(2.11)	(2.17)
IMP	-0.114	-0.096	-0.102	-0.105	-0.450	-0.096	-0.093	-0.093	-0.092	-0.096	-0.086	-0.095	-0.097	-0.095	-0.093
	(-3.60)	(-3.08)	(-3.28)	(-2.35)	(-3.55)	(-3.11)	(-3.03)	(-2.98)	(-2.95)	(-3.03)	(-2.78)	(-3.02)	(-3.14)	(-3.00)	(-3.04)
β^{MKT}	-0.018	0.060	0.033	0.137	0.188	0.051	0.087	0.069	0.020	0.037	0.062	0.062	0.060	0.061	0.109
	(-0.13)	(0.47)	(0.25)	(0.96)	(1.41)	(0.40)	(0.70)	(0.54)	(0.16)	(0.28)	(0.48)	(0.49)	(0.47)	(0.48)	(0.86)
SIZE	-0.205	-0.312	-0.239	-0.326	-0.301	-0.238	-0.415	-0.314	-0.335	-0.267	-0.295	-0.318	-0.305	-0.321	-0.383
	(-1.45)	(-2.66)	(-1.90)	(-3.04)	(-2.46)	(-1.64)	(-3.80)	(-2.68)	(-2.90)	(-2.30)	(-2.45)	(-2.71)	(-2.64)	(-2.73)	(-3.25)
BM	0.242	0.241	0.212	0.141	0.0619	0.234	0.224	0.242	0.284	0.255	0.234	0.245	0.237	0.245	0.237
	(3.15)	(2.72)	(2.76)	(1.31)	(0.51)	(2.66)	(2.59)	(2.73)	(3.50)	(2.76)	(2.66)	(2.75)	(2.71)	(2.75)	(2.69)
OP		0.342		0.192	0.0937	0.337	0.312	0.338	0.342	0.351	0.338	0.339	0.341	0.337	0.318
		(3.73)		(2.21)	(0.67)	(3.70)	(3.55)	(3.68)	(3.91)	(3.80)	(3.70)	(3.77)	(3.78)	(3.74)	(3.62)
INV		-0.287	-0.319	-0.258	-0.186	-0.286	-0.278	-0.288	-0.286	-0.295	-0.284	-0.291	-0.285	-0.292	-0.285
		(-5.84)	(-6.51)	(-5.07)	(-2.68)	(-5.81)	(-5.58)	(-5.87)	(-5.84)	(-6.02)	(-5.80)	(-5.90)	(-5.78)	(-5.90)	(-5.80)
ROA			0.304												
			(3.81)												
DISP				-0.051											
				(-1.22)											
AF^{IMP}					0.038										
					(0.59)										
TURN						-0.050									
						(-0.74)									
IVOL							-0.328								
							(-3.74)								
β^{VXO}								-0.076							
								(-1.00)							
MOM									0.254						
									(2.41)						
STR										-0.348					
										(-3.36)					
ILLIQ											0.216				
											(1.42)				
ISKEW												-0.061			
												(-1.39)			
COSK													-0.091		
													(-0.98)		
TSKEW														-0.077	
														(-1.81)	
MAX															-0.283
															(-3.42)
No. of Obs.	626,907	598,469	611,044	297,979	73,294	598,469	598,469	598,469	596,826	598,469	598,465	598,469	598,469	598,469	598,469
R^2	0.027	0.033	0.03	0.05	0.082	0.035	0.036	0.035	0.038	0.039	0.036	0.034	0.035	0.034	0.036

Chapter 5

General Discussion

5.1 General Conclusion

This dissertation consists of three essays that provide novel insights in empirical asset pricing research. Chapters 2 and 3 discuss the impact of the volatility of some common risk factors on the cross-section of equity returns and provide explanation of this pricing impact. Chapter 4 documents the pricing impact of the imprecision in management earnings forecasts along with empirical justification of this impact. This section provides a synthesized discussion and conclusion of the three chapters and their contributions to the literature.

Chapter 2 uncovers a new “value uncertainty” anomaly related to uncertainty about the true current value of the book-to-market ratio (UNC) and investigates the predictive power of this uncertainty on the cross-sectional variation in future equity returns. The value uncertainty equity premium is not explained by common risk factors or 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 13% per annum.

A novel factor (HML_{UNC}) constructed using the value uncertainty measure and size generates an annualized alpha of 6% to 8% and is not explained by the market, size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and liquidity (LIQ) factors of Fama and French (1993, 2015), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015). A UNC index based on the cross-sectional average of firms' BM volatility (UNC^{avg}) is correlated with standard economic uncertainty indicators. However, UNC is distinct as it reflects contemporaneous uncertainty about the true current value of shareholders' investment in productive assets rather than prospective or forward-looking economic uncertainty that is associated with growth options and depresses investment. Chapter 2 documents that the value uncertainty factor, HML_{UNC}, covaries with productivity and consumption growth co-movements, justifying the positive premium.

The high-UNC premium is partly driven by lower information quality about the current true value of productive assets. High-UNC may also increase a firm's return exposure to broad systematic risk factors. Value uncertainty is correlated with macroeconomic fundamentals and is a significant predictor of aggregate market return and market volatility. Finally, Chapter 2 provides a rational asset pricing explanation of the value uncertainty premium consistent with the ICAPM and production-based asset pricing frameworks.

Chapter 3 is a natural extension of Chapter 2 as it investigates the predictive power of the time-series volatility of expected profitability (UP) on cross-sectional returns. It documents a UP-equity premium that is not explained by common risk factors previously considered in the literature. The reported UP premium is significant both statistically and economically, and is robust to a large scrutiny levels and robustness checks. It is confirmed in portfolio-level analyses and stock-level cross-sectional regressions that control for a wide battery of well-known pricing effects. A portfolio that goes long in high-UP firms and short in low-UP firms would generate an annual excess (risk-adjusted) returns of 8% (10%). Analogously, Chapter 3 also investigates the uncertainty of asset growth (UAG) and finds that high-UAG firms and short in low-UAG firms would generate an annual excess (risk-adjusted) returns of 7% (12%).

Two novel factors, UPF and UAGF, are constructed for the uncertainty of profitability and asset growth, respectively. These factors cannot be explained by the market, size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and liquidity (LIQ) factors of Fama and French (1993, 2015), Carhart (1997), Pástor and Stambaugh (2003), and Hou et al. (2015). Each of the uncertainty of profitability and asset growth factors generates an annual return of 4%.

The UPF generates higher returns in good economic states when: i) the market-wide profitability is high, ii) the aggregate default risk is low, iii) the expected inflation increases, iv) the market volatility is low, and v) the economic activity index is improving, partially justifying the premium earned by high-UP firms.

Finally, Chapter 4 documents a novel firm characteristic that would have an impact on equity returns. More specifically, it documents that imprecision surrounding management earnings guidance is associated with low excess and risk-adjusted equity returns. Firms in the high quintile portfolio of management guidance imprecision would deliver on average 8% lower risk-adjusted returns per annum compared to those in the low quintile.

Results can be counter-intuitive if imprecision is considered as a source of risk yet empirical evidence suggests that the low return associated with high-IMP firms can be due to two reasons: i) the presence of more optimists in play, causing mispricing particularity when short sale constraints and arbitrage asymmetry exist, and ii) managers' genuine uncertainty of future earnings particularly evident in growth firms.

5.2 Limitations and Future Research

The studies conducted in this dissertation have some limitations that will be discussed in this section. First, as in other asset pricing research, realized future returns is used as a proxy of expected returns when assessing the impact of the uncovered pricing factors on the cross-section of returns. It will hence be informative to explore how these pricing factors impact expected equity returns (rather than realized future returns), which can be the focus of future research.

Second, using realized uncertainty as a proxy for future uncertainty can be a considered as another limitation. Particularly, in Chapter 3, the realized volatility of asset growth is used as a proxy for future asset growth volatility. With firms eventually growing and investors learning more about firms' operation, this assumption that past growth uncertainty is a good proxy for future uncertainty is not necessarily true.

Moreover, analysts forecasts are the main input in the estimation of expected book-to-market and profitability in Chapters 2 and 3, respectively. These forecasts can be a noisy proxy of earnings expectations and may not be a true reflection of investors' estimations particularly with the analysts' herding behavior and other forecast biases identified in the disclosure literature (see e.g., Trueman (1994) and Welch (2000)). Moreover, restricting the sample to only firms that are covered by the IBES database of analysts' coverage or management earnings guidance casts some doubt on sample selection bias in the studies in hand. This concern can be partially alleviated by matching the sample with the overall CRSP universe as demonstrated in Chapters 3 and 4. Future work can hence provide robust models to estimate future asset growth, book-to-market, and profitability for which the volatility can be estimated.

A third limitation is the lack of a complete explanation of the uncovered pricing factors. For instance, Chapter 2 uncovers the uncertainty premium and provides a theoretical and empirical explanation of the premium earned within a framework of a production-based asset pricing model. Other possible explanations can still be investigated to better understand this uncertainty premium. Potential explanation, for instance, can be related to the quality of information embedded in the book-to-market ratio or the uncertainty of firms exercising real options. The rationale is that the BM ratio is related to the existence of valuable real options (Pástor and Veronesi (2003)). If the BM ratio reflects the level of moneyness of a firm's real options, then changes in BM driven by the flow of new information (e.g., regarding future productivity, growth prospects, or the cost of exercising such options), may partly reflect changes in the moneyness of the firm's real options and the likelihood of their exercise and conversion into asset-in-place. Hence, the volatility of BM may partly reflect the uncertainty surrounding the exercise of the firm's real options and can have a significant impact on the firm's investment plans and equity returns. This can be the focus for future research to provide in-depth understanding of the value uncertainty premium. Analogously, extended research is required to investigate further the premium associated with the volatility of profitability and asset growth beyond the current findings documented in Chapter 3.

Findings of Chapters 2 and 3 highlight the significance of the volatility of book-to-market, profitability and asset growth as fundamental uncertainty variables and pave the way to explore the impact of the volatility of other common risk factors as focus of future research. Potential expansion of this research line is to investigate the impact of the volatility of other common risk factors on the cross-section of returns. The initial intuition is to combine factors with correlated volatility and build a z-score, principal component, or index accordingly in a way that would allow to consider the overall volatility of related risk factors as one pricing factor when pricing assets. It will be important to explore the relationship between this overall volatility index on the one hand and the well-documented pricing anomalies in the literature on the other hand and investigate how this overall volatility index can be distinct from common volatility and uncertainty indices. Moreover, future research work can further investigate the value, profitability, and asset growth uncertainty in other equity markets outside the US.

Chapter 4 documents that firms with high guidance imprecision are more likely to be under distress risk. This preliminary finding can provide further insights regarding the distress risk anomaly reported by Campbell et al. (2008) and attributed to lottery features by Conrad et al. (2014) and hence require further investigation. Moreover, a rational equilibrium framework can still be provided for more in-depth understanding of the IMP negative premium as findings provided in Chapter 4 never ruled out a risk explanation of this negative premium. Another future research avenue regarding management guidance forecasts is to study the impact of the Regulation Fair Disclosure (RFD) on the level of imprecision of management earnings forecasts and on returns. RFD was implemented in 2000 to prevent firms from selectively disclosing important information. Firms were required to update analysts simultaneously and to make information available to the general public at the same time. The intention of this regulation was to limit unfair disclosure practices. Despite this regulation, preliminary analysis shows that the average level of guidance imprecision has more than doubled post the RFD implementation. This finding is puzzling and may cast doubt on the effectiveness of the regulation and opens the door for an empirical investigation to better understand the implications of the RFD.

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