Uncertainty, Momentum, and Profitability

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Abstract

In this article, the authors argue that momentum and profitability factors share a common source in uncertainty. Specifically, the authors find that uncertainty subsumes price momentum and operating profitability; it also accounts for the majority of the profits associated with earnings momentum and return on equity, especially in large firms. Further, the profits of these four aforementioned momentum/profitability strategies concentrate in periods of negative market returns, consistent with high uncertainty stocks' greater vulnerability to bad market states documented in recent literature. The market-state dependence of momentum/profitability strategies has significant implications to portfolio managers who attempt to profit from these strategies. Understanding the sources of the profits also helps portfolio managers better employ these factors in constructing investment portfolios.

Investors dislike both uncertainty and risk. Although both lead to uncertain outcomes, risk and uncertainty are different in nature. Risk is the “known unknown” or “measurable uncertainty” where investors know the probability distribution of potential outcomes in advance, such as rolling a dice. Uncertainty is the “unknown unknown” or “unmeasurable uncertainty” where investors do not know for sure the probability distribution (Knight (1921)). While investors are risk averse, they appear to avoid uncertainty even more (uncertainty or ambiguity aversion), as illustrated by the Ellsberg paradox (Ellsberg (1961)): Investors seem to prefer gambles with known probabilities of payoffs, even with low odds of winning, to gambles with unknown probabilities. The inherent distinction between risk and uncertainty aversion suggests that uncertainty may have unique asset pricing implications.

Many business activities are highly uncertain, such as developing a new technology for an unproven product market or a new drug for cancer treatment. In such ventures, investors do not possess precise knowledge of potential outcomes or the probability distribution in advance. However, uncertainty has been studied to a lesser extent compared to risk in the finance literature. Meanwhile, studies show that risk alone cannot fully describe asset pricing patterns and many anomalies have been documented. For example, the CAPM beta, a conventional measure for systematic risk, has been found to have low explanatory power of returns (Fama and French (1992)). Instead, many firm characteristics or factors, such as size and value, show strong return predictive power.

An increasing number of studies incorporate uncertainty into risk-based models to explain market-level anomalies, such as high equity risk premium and high equity return volatility (Leippold et al. (2008), Ju and Miao (2012), Johannes et al. (2016)). Studies that apply uncertainty to cross-sectional return anomalies are still scarce, but two recent studies made such an attempt.

First, Barron et al. (2009) decompose analyst forecast dispersion into uncertainty and information asymmetry, and find that only the uncertainty component predicts negative future returns. Subsequently, Liang and Tang (2018) attribute the negative relation between idiosyncratic stock return volatility and future returns to uncertainty after decomposing idiosyncratic volatility into uncertainty and residual volatility. These results indicate that uncertainty has significant return predictive power in the cross-section.

Could uncertainty help explain some other return anomalies in addition to forecast dispersion and idiosyncratic volatility? Our article investigates this question. We first examine price and earnings momentum. Both are prominent anomalies. Prior empirical studies show that they are closely related to each other and both are stronger in firms with high uncertainty (Jiang et al. (2005), Zhang (2006), Chordia and Shivakumar (2006)). Behavioral explanations also use uncertainty to motivate their models. Daniel et al. (1998) model momentum as a result of self-attribution bias and posit that investors are more susceptible to this bias when uncertainty is high. Barberis et al. (1998) consider the failures of individual judgment under uncertainty documented in the psychology literature and posit that investors may chase past returns or update their models too slowly in the face of new evidence when uncertainty is high. Brav and Heaton (2002) further illustrate that when rational investors are uncertain about the pricing parameters, they may appear to overreact to past returns in the process of learning about the unknown pricing parameters; however, when there is a sudden shift in the parameters, such as an earnings surprise, they may appear to underreact to the news. These models suggest that high uncertainty may induce investors to show behavioral patterns that are consistent with under-/over-reaction that leads to momentum.

We next consider profitability. Recent studies suggest that profitability is closely related to momentum. We examine two profitability measures that are included in the latest multi-factor pricing models: operating profitability in the Fama-French five-factor model (FF-5f; Fama and French (2015)) and return on equity in the investment-based four-factor model (Inv-4f; Hou et al. (2015)). Hou et al. (2015) show that the profitability factor has a high correlation with the price momentum factor. Novy-Marx (2015) further documents that the profitability factor in the Inv-4f model explains price momentum but it is subsumed by earnings momentum. He posits that profitability's explanatory power of price momentum comes from the latest earnings news embedded in the profitability measure (high surprise firms tend to have high profitability). Both the FF-5f and Inv-4f models have shown improved return predictive power than the conventional Fama-French three-factor (Fama and French (1993)) or Carhart four-factor (Carhart (1997)) model. Understanding the connection between uncertainty and profitability can help us better understand the source of the improved pricing power of these two multi-factor models. If uncertainty induces momentum, it may also help explain the profitability anomaly.

We construct the uncertainty measure, UNC, using analyst earnings forecasts following Barron et al. (2009) and Liang and Tang (2018). Every month t we sort firms into quintiles by uncertainty (UNC), price momentum (MOM), earnings momentum (SUE), operating profitability (OP) in the FF-5f model, and return on equity (ROE) in the Inv-4f model. The return spreads of the long-short strategies (Q5: the quintile with highest values of sorting variable – Q1: the quintile with lowest values of sorting variable) based on these five firm characteristics are then measured in the following month t+1. To test UNC's explanatory power on the four aforementioned momentum/profitability factors, we regress the return spreads of MOM/SUE/OP/ROE against those of UNC. If UNC has significant explanatory power on these factors, the intercepts of the regressions should be small in magnitude or become statistically insignificant.

Our results indicate that uncertainty has significant explanatory power on momentum and profitability. Specifically, uncertainty subsumes price momentum and operating profitability. The positive return spreads of MOM and OP shrink in magnitude and become statistically insignificant when UNC is controlled for. As to earnings momentum and return on equity, the positive spreads also weaken to insignificance in value-weighted portfolios. Although significant spreads remain in equal-weighted portfolios, UNC explains nearly half (45%) of the SUE profits, and the majority (61%) of the ROE spreads. We also conduct robustness checks with Fama-MacBeth regressions (Fama and MacBeth (1973)) and obtain similar results.

The different explanatory power of uncertainty on OP versus ROE may seem puzzling because both measure profitability. A closer examination reveals that OP and ROE are sourced from different periods: OP in the FF-5f model uses earnings from the last fiscal year while ROE in the Inv-4f model employs earnings from the latest quarter. Further analysis suggests that the residual returns of ROE not entirely explained by UNC in equal-weighted portfolios come from the earnings news embedded in the latest quarterly earnings, consistent with Novy-Marx (2015).

Overall, these results indicate that uncertainty is an important source of the profits of momentum/profitability-based trading strategies, especially in large firms that dominate value-weighted portfolios. What uncertainty does not explain well is the price drift following earnings surprises in equal-weighted portfolios, likely driven by small firms due to market frictions. Prior research finds that small stocks have low liquidity and high trading costs, which makes it harder for prices to incorporate earnings news in a timely manner (Ng et al. (2008), Chordia et al. (2009)). We also investigate whether uncertainty explains other non-market factors in the FF-5f and Inv-4f models, including size, value, and investment. However, we do not find uncertainty to exhibit significant explanatory power of these factors.

If momentum and profitability profits stem from uncertainty, they may vary across good and bad market states according to Liang and Tang (2018). Liang and Tang show that high uncertainty stocks underreact to good market news and overreact to bad market news, consistent with investor ambiguity aversion modeled by Epstein and Schneider (2008).[1] Hence, the negative uncertainty-return relation concentrates in periods of negative market returns. Similarly, we find that the positive returns associated with these four momentum/profitability factors primarily come from periods of negative market returns, and largely disappear or even reverse in positive return periods. The asymmetric patterns lends further support to our conjecture that these anomalies stem from uncertainty.[2]

The results discussed thus far suggest that uncertainty has significant explanatory power of momentum and profitability. Replacing momentum and profitability in portfolio managers' screening or factor-investing models with uncertainty could potentially simplify the screening process or improve portfolio performance. However, the uncertainty measure, UNC, can only be constructed if a firm is covered by research analysts. We explore whether idiosyncratic return volatility (IVOL), which can be constructed for any stock with trading data, is an effective substitute for UNC. Our results show that IVOL performs similarly well with profitability but worse with momentum compared to UNC. These results indicate that although IVOL is not on par with UNC, it may serve as a potential substitute for UNC in replacing profitability.

One of the reasons why uncertainty has not had much success in explaining return anomalies may be due to the noisy proxies used in prior studies. In addition to IVOL, analyst forecast dispersion (DISP) is another widely used proxy for firm information uncertainty (Zhang (2006), Hou and Loh (2016)). However, Barron et al. (2009) show that DISP consists of two

[1] Epstein and Schneider (2008) posit that investors assume the worst-case scenario when facing uncertainty, so they tend to underreact to good news and overreact to bad news when trading high uncertainty stocks.
[2] However, the fact that momentum/profitability factors pay well in bad market states (i.e. having negative betas) but yield positive returns may seem puzzling. We provide a detailed discussion regarding this issue in pp.14-15.

components: uncertainty and information asymmetry. Although the former predicts negative returns, the latter does the opposite. This may limit DISP's return explanatory power. Consistent with Barron et al. (2009), we find that DISP performs worse than both UNC and IVOL in explaining momentum/profitability, suggesting that UNC is a superior measure of uncertainty compared to the widely used DISP.

Overall, our study finds that the uncertainty measure UNC in Barron et al. (2009) explains all or substantial portions of the profits associated with four momentum/profitability factors, including price momentum, earnings momentum, operating profitability, and return on equity. Since Fama and French published their seminal research on the three-factor model (Fama and French (1993)), researchers have documented hundreds of pricing factors that cannot be accounted for by existing theories (Harvey et al. (2016)). The challenge going forward is to summarize existing anomalies and understand their sources in the hope that a unifying framework may emerge over time. Our findings, combined with prior research, suggest that uncertainty is a common thread underlying the return anomalies related to profitability, momentum, forecast dispersion, and idiosyncratic volatility. Uncertainty helps summarize a subgroup of return anomalies.

Our findings also suggest that part of the improved performance of the FF-5f and Inv-4f models likely come from the uncertainty content embedded in the profitability factor. In practice, our finding that these four momentum/profitability factors share a common source can help portfolio managers optimize the designs of screening process as well as trading strategy. For example, screening by both momentum and profitability would likely yield little improvement compared to screening by momentum or profitability alone given the similarity. A trading strategy based on momentum and profitability may achieve less diversification benefits compared to another strategy based on two unrelated factors, such as momentum and value advocated by Asness et al. (2014).

Price momentum is one of the most prominent pricing factors, but it has not seen wide adoption in the investment community due to concerns about its periodic "crashes" (Asness et al. (2014)). Some investors may feel relatively more at ease with profitability-based trading strategies. However, our results indicate that these two factors share the same source. In fact, profitability strategies are more susceptible to market states relative to momentum and may incur significant losses in up markets. This has important implications to portfolio managers who employ a momentum- or profitability-based trading strategy.

Further, our uncertainty-based explanation of price momentum may help understand why momentum crashes concentrate in periods of sharp market rebounds on the heels of a high-uncertainty bear market documented by Daniel and Moskowitz (2016). Liang and Tang (2018) show that high uncertainty stocks suffer greater negative return shocks during bad market states, such as periods of negative market returns or increased market volatility due to investor aversion to ambiguity (Epstein and Schneider (2008)). Therefore, investors avoid high uncertainty stocks during "panic states" characterized by an extended period of negative market returns and high volatility, resulting in depressed valuations for these stocks. As panic eases, volatility falls, the market rebounds, and investors buy back high uncertainty stocks that were previously dumped during the panic states. Consequently, the values of high uncertainty stocks rise sharply. Because the uncertainty factor negatively correlates with the momentum factor, the returns of high uncertainty stocks behave similarly to the returns of losers in the momentum strategy. This helps explain the large gains of loser stocks and associated momentum crashes during periods of sharp market rebounds following a high-uncertainty bear market, such as the three-month period from March to May 2009 in the latest financial crisis. Daniel and Moskowitz (2016) attempt to explain the sharp rises of loser stocks during a momentum crash with the option model proposed by Merton (1974), but they concede that the option story cannot explain momentum crashes in non-equity markets, such as futures, currencies, and commodities. In contrast, the uncertainty-based explanation does not require the existence of debt and can be extended to momentum crashes in non-equity markets.

Practitioners often say "investors hate uncertainty". However, only in recent years have we seen increasing studies about uncertainty's implications on asset pricing. Our study adds to this growing literature. We hope our findings may inspire further research in this area.

Uncertainty explains momentum and profitability

Uncertainty measure (UNC)

We first calculate the uncertainty measure UNC derived from analyst earnings forecasts following Barron et al. (2009), and Liang and Tang (2018). Uncertainty (V) in eq. (1) is the mean of the squared differences between individual analysts' forecasts (FC_i) and reported earnings per share (EPS). It can be expressed as the sum of $\left(1-\frac{1}{n}\right)D$ and SE, where D is analyst forecast dispersion (eq. (2a)) and SE is the squared error in the mean forecast (eq. (2b)). These two terms depict analysts' uncertainty about the data structure of potential outcomes: the 2nd term (SE) relates to uncertainty about the mean, and the 1st term (D) relates to uncertainty about the dispersion around the mean (i.e. the standard deviation).

$$Uncertainty = V = \frac{\sum_{i=1}^{n}(FC_i - EPS)^2}{n} = \left(1-\frac{1}{n}\right)D + SE \qquad (1)$$

$$Dispersion = D = \frac{\sum_{i=1}^{n}(FC_i-\overline{FC})^2}{n-1} \qquad (2a); \qquad SE = (EPS - \overline{FC})^2 \qquad (2b)$$

We estimate V monthly, using analyst forecasts about the current fiscal year's earnings (FY1 EPS) from I/B/E/S. We then take the squared root of V and scale it by stock price (P) to obtain our uncertainty measure, UNC. Our analysis starts in 1983, when the I/B/E/S coverage of FY1 EPS forecasts becomes more complete, and ends in 2013. Exhibit 1 summarizes the descriptive statistics of firm-level variables used in the study.

Uncertainty and momentum

After we obtain the uncertainty measure UNC, we first examine its effects on momentum profits. In every month t, we sort firms into quintiles by UNC and price/earnings momentum. Price momentum (MOM) is the returns from the prior 12 months with the most recent month skipped (t-2 to t-12; Fama and French (2016)). The earnings surprise measure (SUE) is seasonally differenced earnings (most recently announced quarterly earnings subtract earnings from the same quarter a year ago) scaled by the standard deviation of the seasonally differenced earnings from the previous eight quarters (Chordia and Shivakumar (2006)). Then the returns of the long-short strategy (Q5: high UNC/MOM/SUE – Q1: low UNC/MOM/SUE) in the subsequent month t+1 are measured. Exhibit 2 Panel A reports the return spreads of the long-short portfolios formed by sorting firms on MOM and SUE.

For MOM, the equal-weighted (ew) and value-weighted (vw) portfolios yield average returns of 1.337% and 0.949% respectively (columns 1 and 3). When the return is regressed on that of the UNC long-short portfolio, the residual returns (the intercepts) shrink to 0.304% and 0.389% (columns 2 and 4), representing 77% and 59% reduction in magnitude, and become statistically insignificant. These results indicate that the price momentum profits primarily come from uncertainty. Chordia and Shivakumar (2006) show that price and earnings momentum are closely related but the latter subsumes the former. Therefore, we expect uncertainty to explain perhaps a lesser portion of earnings momentum profits.

The SUE long-short portfolio yields an average return of 0.956% / 0.260% under the ew/vw scheme, consistent with the findings in the prior literature that the profits associated with earnings momentum concentrate in small firms (Chordia et al. (2009)). When we control for UNC, the ew portfolio return shrinks nearly by half (0.523%; 45% reduction), but remains statistically significant; the vw portfolio return weakens by roughly two-thirds (0.074%; 72% reduction) and becomes insignificant. The results indicate that uncertainty explains significant portions of earnings momentum profits, especially in large firms that dominate value-weighted portfolios.

Overall, the results in Exhibit 2 Panel A suggest that nearly all of the profits associated with price momentum can be attributed to uncertainty. Uncertainty also explains the majority of the profits associated with earnings momentum, especially for large firms.

Uncertainty and profitability

We next examine uncertainty's effects on operating profitability (OP) in the FF-5f model and return on equity (ROE) in the Inv-4f model. OP is annual revenues minus costs of goods sold, interest expenses, and selling, general, and administrative expenses, divided by book equity from the last fiscal year (Fama and French (2015)). The OP long-short strategy yields an average return of 0.882% / 0.771% for the ew/vw portfolio (Exhibit 2 Panel B). However, when UNC is included as a control, the returns greatly shrink (0.279%/0.324%; 68%/58% reduction) and become insignificant. The results indicate that uncertainty is responsible for OP profits.

ROE is earnings before extraordinary items from the most recent quarter divided by 1-quarter-lagged book equity (Hou et al. (2015). The ew/vw portfolio yields an average return of 1.417%/0.635%, but the return shrinks to 0.559%/0.217% (61%/66% reduction), with only the latter being statistically insignificant, when we control for UNC. These results suggest that uncertainty explains the majority of the ROE profits. The effect is most prominent in large firms that dominate in value-weighted portfolios.

Hou et al. (2015) posit that their profitability factor based on quarterly ROE is better than its counterpart, annual OP, in the FF-5f model, thanks to quarterly data's timeliness. However, Novy-Marx (2015) attributes quarterly ROE's superior return predictive power to the earnings surprise embedded in recently announced quarterly earnings. Indeed, we find that when ROE is calculated with earnings from last fiscal year, it is subsumed by UNC, similar to OP. Further, no significant returns remain in the ROE long-short ew portfolio when the SUE spread is included as an additional control alongside the UNC spread. However, the reverse is not true, i.e. ROE does not explain away the residual returns associated with SUE (Appendix A).

The results thus far suggest that uncertainty has significant explanatory power on the profits associated momentum and profitability. The effects are most pronounced with price momentum and operating profitability. What uncertainty does not explain well are the profits associated with earnings momentum in small firms, which tend to have less efficient prices due to poor liquidity and high trading costs (Ng et al. (2008), Chordia et al. (2009)).

Robustness checks

We conduct robustness checks with Fama-MacBeth regressions (Fama and MacBeth (1973)) by regressing returns on uncertainty and each of the four momentum/profitability variables. The CAPM beta and some firm characteristics found to predict returns, such as size, book-to-market, investment, and liquidity, are included as controls. As shown in Exhibit 3, the factor loadings on the anomaly variables are all significantly positive in the absence of uncertainty. When uncertainty is included, the loadings become insignificant or negative except for SUE, but the coefficient of SUE shrinks a significant portion in size (0.109 to 0.066; 40% reduction). The results are consistent with those of portfolio-level tests discussed previously.

Uncertainty and other anomalies

Given the results discussed in the previous sections, it is natural to wonder whether uncertainty explains other anomalies. Although a detailed study is beyond the scope of this article, we briefly discuss uncertainty's relations with the other three non-market factors in the FF-5f / Inv-4f model: size, value, and investment.[3] We find that uncertainty has little explanatory power of the value or investment factor (Exhibit 4). As to size, the presence of uncertainty actually makes the profits associated with size more prominent. Liang and Tang (2018) document a similar finding.

The results in Exhibit 4 are consistent with the findings by Fama and French (2015) and Hou et al. (2015). Fama and French (2015) find that the value factor (HML) becomes redundant in the presence of profitability and investment factors. Hou et al. (2015) further show that HML has a high correlation with the investment factor and can be explained by the Inv-4f model. Hence, the independent factors in these two multi-factor models are market, size, investment, and profitability. Uncertainty spans the dimension of profitability.

Our results in Exhibit 4 that uncertainty does not explain HML but makes the profit associated with HML more prominent in value-weighted portfolios is also consistent with Asness et al. (2014) who view value and momentum as complements and best used in combination.

Market state dependence

Liang and Tang (2018) posit that high uncertainty stocks have more asymmetric price responses to good and bad market states (underreact to good and overreact to bad) due to investor aversion to ambiguity suggested by Epstein and Schneider (2008). Hence, the UNC factor (high-low UNC) yields small gains in good states that are overpowered by large losses in bad states,

[3] The FF-5f model includes market, size, value, investment, and profitability factors; the Inv-4f model leaves out value and includes only market, size, investment, and profitability factors.

leading to an average negative return and most of the negative returns concentrating in bad market states. If uncertainty explains substantial portions of the profits associated with momentum and profitability, we should expect to see similar asymmetry and market state dependence with these anomalies.

We next measure the returns of the momentum/profitability portfolios conditioning on the stock market return of month t+1. As shown in Exhibit 5, the profits concentrate in periods of negative market returns (column 2), similar to uncertainty. For price momentum (MOM), the long-short strategy yields small and statistically insignificant returns in periods of positive market returns (0.521% (ew) / 0.096% (vw)); but in periods of negative market returns, the profits are much greater (2.684% (ew) / 2.356% (vw)) and significant at the 1% level. For earnings momentum (SUE), the results of the vw portfolio are similar to those of price momentum. The contrast is less sharp with the ew portfolio: the spreads are 0.602% and 1.540% in up and down market respectively, but the difference is statistically significant at the 1% level.

Out of the four anomalies, operating profitability (OP) displays the sharpest contrast. The long-short strategy generates significantly negative (positive) returns in periods of positive (negative) market returns with both ew and vw portfolios. Return on equity (ROE) has a similar negative/positive divide but with a slightly weaker contrast.

Overall, the results in Exhibit 5 show that the positive returns associated with momentum and profitability concentrate in periods of negative market returns, similar to uncertainty. These results are consistent with our earlier finding that uncertainty is responsible for most of the profits associated with momentum and profitability. Further, the concentration of profits in down markets indicates that betting on momentum or profitability is equivalent to betting that the market would fall. What is even more concerning is that a profitability-based strategy carries significant downside risk (significant losses in good market states), a finding not discussed in prior literature.

The negative correlations between momentum/profitability profits and the market may appear puzzling, especially under the classical CAPM framework (Sharpe (1964); Lintner (1965)), because securities with greater returns in negative market states act as market insurance and should command negative risk premiums. For this reason, Barroso and Santa-Clara (2015) also consider momentum profits particularly puzzling because of their negative correlation with the market. However, the CAPM has quite restrictive assumptions that are subject to theoretical criticism.[4] Subsequent models, such as ICAPM (Merton (1973)) and APT (Ross (1976)), relax some restrictive assumptions in the CAPM and expand the single-factor CAPM into multi-factor models. Under the multi-factor frameworks, market is no longer the only risk factor, and market risk is not the only source of risk that is priced. Empirical evidence is also more consistent with multi-factor models than with the single-factor CAPM. For example, Fama and French (1992) find that the CAPM beta has no significant pricing power of cross-sectional stock returns, either on its own or in the presence of size and value. Fama and French (1993, 1996) summarize this finding into the Fama-French three-factor (FF-3f) model. Since then, researchers have documented hundreds of firm characteristics or factors unrelated to market risk that predict stock returns (Harvey et al. (2016)), and the FF-3f model has been further expanded to the FF-5f and Inv-4f models in recent years (Fama and French (2015); Hou et al. (2015)). If market risk is not the only source affecting returns, then it is possible to observe positive risk premiums associated with pricing factors that have no correlation or even a negative correlation with the market, such as momentum and profitability examined in this study.

Hence, under the multi-factor frameworks, such as the ICAPM or APT, expected returns

[4] For example, see Merton (1973) for a detailed discussion.

may arise from non-market risk factors. As Fama and French (1996) point out, the essence for multi-factor pricing is multiple common sources of variation in returns, such as those demonstrated by the FF-3f / FF-5f / Inv-4f models or the connections between uncertainty and momentum/ profitability shown in this study. In this sense, our uncertainty-based interpretation of momentum/profitability anomalies can be understood as cross-sectional return covariation arising from investor aversion of uncertainty. This uncertainty aversion causes high uncertainty (low momentum/profitability) stocks to show more asymmetric price responses to good versus bad market states. Such asymmetry leads to no profits or small negative profits for the momentum/ profitability factors in good states and large positive profits in bad states, distinct from the usual symmetric price responses to good/bad states under the CAPM. [5]

IVOL/DISP explains momentum and profitability

Idiosyncratic stock return volatility (IVOL)

In the previous section, we show that the uncertainty measure in Barron et al. (2009), UNC, explains most of the positive returns associated with momentum and profitability. However, UNC may not be available for firms not covered by research analysts. In this subsection, we explore whether idiosyncratic stock return volatility (IVOL), which can be constructed for every firm with stock trading data, could serve as a substitute.

We regress the long-short return spread of MOM, SUE, OP, or ROE on that of IVOL. IVOL is obtained by regressing daily returns from CRSP against the Fama-French three factors

[5] Alternatively, behavioral or market friction explanations suggest that high uncertainty stocks tend to be overvalued because they are easier to buy and harder to short sell and their prices reflect the opinions of most optimistic investors (Miller (1977), Stambaugh et al. (2015)). This leads to lower future returns for high uncertainty stocks and the negative (positive) profits of uncertainty (momentum/profitability) factors. In addition, the profits may concentrate in bad market states because bad market states tend to follow high sentiment periods during which overpricing is more severe (Stambaugh et al. (2015)). In untabulated tests, we do find that the market return is negatively correlated ($\rho = -0.12$; p-value < 0.01) with the one-month lagged market sentiment (from Jeffrey Wurgler's website; see Baker and Wurgler (2006)).

(Fama and French (1993)) and then taking the square root of the variance of the residuals, following Ang et al. (2006). In Exhibit 6 Panel A, the residual returns of MOM remain sizable and statistical significant. Compared to UNC in Exhibit 2, IVOL's effect on MOM is much weaker. For SUE, the residual returns are also larger than those of UNC. IVOL performs better with profitability. For OP, the residual returns are smaller than those of UNC. For ROE, IVOL does slightly worse (better) than UNC in the ew (vw) portfolio.

Overall, these results indicate that IVOL performs similarly well compared to UNC in explaining the returns associated with profitability but worse with momentum. IVOL could potentially serve as a substitute for UNC, especially in profitability-based strategies.

Analyst forecast dispersion (DISP)

Analyst forecast dispersion is widely used as a proxy for information uncertainty in the finance and accounting literature. However, as illustrated by Barron et al. (2009), DISP consists of two components (uncertainty and information asymmetry) that have opposing effects on future returns. Hence, we expect DISP to show weaker explanatory power on momentum and profitability factors relative to UNC and IVOL.

We repeat the tests in the previous subsection, but replace IVOL with DISP. DISP is the standard deviation of analyst forecasts of FY1 EPS from I/B/E/S, scaled by the absolute value of the mean earnings forecast, following Diether et al. (2002). As shown in Exhibit 6 Panel B, out of the eight residual returns, only one is statistically insignificant compared to four for IVOL and six for UNC. The results are consistent with our conjecture that the information asymmetry component in DISP weakens its explanatory power on momentum and profitability.

DISP's lackluster pricing power on these four anomalies may help explain why uncertainty has not achieved much success in explaining cross-sectional return anomalies in the literature where DISP often serves as the proxy for uncertainty.

Conclusion

We investigate uncertainty's explanatory power on four return anomalies that prior literature has shown to be related to uncertainty. The results are encouraging: Uncertainty subsumes price momentum and operating profitability; it also explains a significant portion of the profits associated with earnings momentum and return on equity.

Further analysis indicates that the profits of these four momentum and profitability factors concentrate in periods of negative market returns, consistent with high uncertainty stocks' greater vulnerability to bad market states due to investor ambiguity aversion. In addition to providing further evidence on the connections between uncertainty, momentum, and profitability, this finding also suggests that a momentum- or profitability-based trading strategy is an implicit bet against the market. It has significant implications for portfolio managers who employ these factors in constructing their investment portfolios.

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Exhibit 1: Summary Statistics

UNC (the uncertainty measure) is the squared root of [the mean of the squared differences between individual analysts' forecasts of FY1 EPS from I/B/E/S and reported EPS] scaled by price per share (the bracket [] equals V in eq. (1)), following Barron et al. (2009) and Liang and Tang (2018).

MOM (price momentum) is the returns from the prior 12 months with the most recent month skipped (t-2 to t-12), following Fama and French (2016).

SUE (earnings surprise) is calculated as seasonally differenced earnings (most recently announced quarterly earnings subtract earnings from the same quarter a year ago) scaled by the standard deviation of the seasonally differenced earnings from the previous eight quarters, following Chordia and Shivakumar (2006).

OP (operating profit) is annual revenues minus cost of goods sold, interest expense, selling, general, and administrative expenses, scaled by book equity from the last fiscal year, following Fama and French (2015). Financial firms are excluded.

ROE (return on equity) is income before extraordinary items from the most recent quarter divided by one-quarter-lagged book equity, following Hou et al. (2015). Financial firms are excluded.

IVOL (idiosyncratic return volatility) is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals, following Ang et al. (2006).

DISP (analyst forecast dispersion) is the standard deviation of analyst forecasts of FY1 EPS from I/B/E/S, scaled by the absolute value of the mean earnings forecast, following Diether et al. (2002).

RET (return) is the monthly stock return from CRSP.

Analysis period: January 1983 – December 2013. We include all stocks listed on the NYSE, Amex, and Nasdaq during the period in the analysis, except for penny stocks (price per share < $1).

	UNC	MOM	SUE	OP	ROE	IVOL	DISP	RET
N	967,850	1,772,725	1,217,151	1,220,574	1,392,552	1,916,706	967,850	1,917,154
Mean	0.031	0.154	0.201	0.131	-0.033	0.031	0.168	0.013
Standard deviation	0.066	0.576	1.850	0.505	0.266	0.023	0.412	0.148
25th Percentile	0.004	-0.191	-0.445	0.053	-0.012	0.015	0.021	-0.063
50th Percentile	0.010	0.067	0.150	0.202	0.020	0.025	0.048	0.000
75th Percentile	0.028	0.358	0.939	0.330	0.044	0.040	0.125	0.075

Exhibit 2: Uncertainty (UNC) Explains Momentum and Profitability

This exhibit examines whether uncertainty (UNC) explains significant portions of the positive returns associated with momentum (Panel A) and profitability (Panel B).

In every month t, firms are sorted into quintiles by UNC and one of the momentum/profitability variables, and then the returns of the long-short portfolio (Q5: high – Q1: low) in the following month t+1 are measured. UNC-ew/-vw denotes the return of the long-short portfolio formed by sorting firms on UNC with an equal-weighting (ew)/value-weighting (vw) scheme. The same notation applies to momentum/profitability factors.

Odd columns report the average returns of the long-short momentum/profitability portfolios. Even columns report the residual returns (i.e. the intercepts) of regressing the return of the long-short momentum/profitability portfolio on that of the long-short UNC portfolio. For example, in Panel A column 2, the regression model estimated is MOM-ew = b*UNC-ew + residual return. Return reduction = 1- (residual return/return).

Analysis period: January 1983 – December 2013. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Momentum (MOM and SUE)

	Price Momentum (MOM)				*Earnings Momentum (SUE)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MOM-ew	MOM-ew	MOM-vw	MOM-vw	SUE-ew	SUE-ew	SUE-vw	SUE-vw
UNC-ew		-0.864***				-0.362***		
		(10.79)				(14.10)		
UNC-vw				-0.750***				-0.248***
				(6.53)				(6.97)
Return/Residual	1.337***	0.304	0.949***	0.389	0.956***	0.523***	0.260*	0.074
Return	(4.60)	(1.32)	(2.73)	(1.21)	(7.50)	(5.39)	(1.93)	(0.60)
Observations	371	371	371	371	371	371	371	371
R-squared	--	0.57	--	0.29	--	0.52	--	0.21
Return reduction	--	77%	--	59%	--	45%	--	72%

Panel B: Profitability (OP and ROE)

	Operating Profitability (OP)				*Return on Equity (ROE)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OP-ew	OP-ew	OP-vw	OP-vw	ROE-ew	ROE-ew	ROE-vw	ROE-vw
UNC-ew		-0.504***				-0.718***		
		(5.58)				(15.60)		
UNC-vw				-0.599***				-0.559***
				(8.03)				(7.86)
Return/	0.882***	0.279	0.771**	0.324	1.417***	0.559***	0.635**	0.217
Residual return	(3.42)	(1.06)	(2.53)	(1.21)	(5.44)	(2.97)	(2.33)	(0.94)
Observations	371	371	371	371	371	371	371	371
R-squared	0.00	0.25	0.00	0.24	0.00	0.49	0.00	0.26
Return reduction	--	68%	--	58%	--	61%	--	66%

Exhibit 3: Fama-MacBeth Regressions

This exhibit reports the estimates of Fama-MacBeth (1973) regressions. The results are similar to those obtained in portfolio-level tests shown in Exhibit 2.

The dependent variable is stock return in month t+1. All control variables are measured in month t. The left (right) panel does not (does) include uncertainty (UNC) in the regressions. All variables are winsorized at the 1% level to limit the influence of outliers.

Beta is the CAPM beta estimated with returns from the previous 52 weeks. ME is equity market value. BM is equity book value divided by equity market value. INV is (assets this year – assets last year)/assets last year. Illiquidity is the average of the Amihud monthly illiquidity measures (Amihud (2002)), defined as the average ratio of the daily absolute return to the dollar trading volume, from the last 12 months.

Analysis period: January 1983 – December 2013. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	without UNC control				*with UNC control*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anomaly =	MOM	SUE	OP	ROE	MOM	SUE	OP	ROE
Anomaly	0.341**	0.109***	0.281**	0.459**	0.023	0.066***	0.009	-0.589***
	(2.07)	(6.11)	(2.54)	(2.23)	(0.15)	(4.08)	(0.08)	(-3.32)
UNC					-8.845***	-8.590***	-9.250***	-9.764***
					(-11.41)	(-9.96)	(-10.68)	(-11.54)
Beta	0.060	0.171	0.186	0.163	0.136	0.223	0.224	0.214
	(0.41)	(1.05)	(1.17)	(1.01)	(0.94)	(1.40)	(1.44)	(1.36)
Log(ME)	-0.070	-0.070	-0.067	-0.059	-0.142***	-0.133***	-0.133***	-0.129***
	(-1.55)	(-1.52)	(-1.55)	(-1.31)	(-3.27)	(-3.00)	(-3.17)	(-2.93)
Log(BM)	0.057	0.079	0.063	0.061	0.151**	0.155**	0.157**	0.173***
	(0.93)	(1.24)	(1.02)	(0.98)	(2.42)	(2.43)	(2.53)	(2.79)
INV	-0.688***	-0.603***	-0.718***	-0.703***	-0.671***	-0.599***	-0.671***	-0.655***
	(-9.14)	(-7.51)	(-9.28)	(-9.02)	(-9.11)	(-7.66)	(-9.04)	(-8.65)
Illiquidity	0.059	0.080	0.068	0.059	0.091*	0.113*	0.098*	0.094*
	(1.15)	(1.34)	(1.32)	(1.16)	(1.78)	(1.93)	(1.93)	(1.83)
Constant	1.588***	1.593***	1.536***	1.571***	2.314***	2.236***	2.293***	2.311***
	(4.16)	(4.19)	(4.02)	(4.11)	(6.35)	(6.09)	(6.22)	(6.25)
Observations	686,634	619,903	686,216	686,111	686,634	619,903	686,216	686,111
R-squared	0.057	0.052	0.051	0.050	0.063	0.059	0.058	0.057
Periods	371	371	371	371	371	371	371	371

Exhibit 4: Size, Value, and Investment

This exhibit investigates whether uncertainty explains the three non-market, non-profitability factors in the FF-5f and Inv-4f models: size (SMB), value (HML), and investment (INV) in FF-5f; SMB and INV in Inv-4f. The results indicate that UNC does not have significant explanatory power of these three factors.

SMB/HML/INV-ew/vw are the long-short portfolios with an equal-/value-weighting scheme based on univariate quintile sorts from Ken French data library (size, value, and investment variables are calculated in a similar fashion in both models). Odd columns report the average returns of the long-short SMB/HML/INV portfolios. Even columns report the residual returns (i.e. the intercepts) of regressing the return of the long-short SMB/HML/INV portfolio on that of the long-short UNC portfolio. Return reduction = 1- (residual return/return). Analysis period: January 1983 – December 2013.

Panel A: Size

	(1) SMB-ew	(2) SMB-ew	(3) SMB-vw	(4) SMB-vw
UNC-ew		0.489***		
		(7.47)		
UNC-vw				0.320***
				(5.83)
Return/	0.084	0.668***	0.038	0.277
Residual return	(0.38)	(3.09)	(0.17)	(1.32)
Observations	371	371	371	371
R-squared	0.00	0.31	0.00	0.13

Panel B: Value

	(1) HML-ew	(2) HML-ew	(3) HML-vw	(4) HML-vw
UNC-ew		-0.081		
		(1.15)		
UNC-vw				0.239***
				(5.09)
Return/	1.002***	0.906***	0.267	0.445***
Residual return	(5.51)	(4.33)	(1.52)	(2.64)
Observations	371	371	371	371
R-squared	0.00	0.01	0.00	0.12

Panel C: Investment

	(1) INV-ew	(2) INV-ew	(3) INV-vw	(4) INV-vw
UNC-ew		-0.121***		
		(2.71)		
UNC-vw				-0.012
				(0.27)
Return/	-1.004***	-1.148***	-0.372**	-0.381**
Residual return	(7.65)	(7.54)	(2.43)	(2.44)
Observations	371	371	371	371
R-squared	0.00	0.05	0.00	0.00

Exhibit 5: Momentum and Profitability Strategies: Partitioned by Market Returns

This exhibit tests whether the profits associated with momentum and profitability concentrate in periods of negative market returns. We use the return of the CRSP equal-weighted index as our proxy for the stock market return following Liang and Tang (2018).

In every month t, firms are sorted into quintiles by MOM, SUE, OP, and ROE, and then the returns of the long-short portfolios (Q5: high MOM/SUE/OP/ROE – Q1: low MOM/SUE/OP/ROE) in the following month t+1 are measured. MOM-ew/-vw denotes the return of the long-short portfolio formed by sorting firms on MOM with an equal-weighting (ew)/value-weighting (vw) scheme. The same notation applies to SUE, OP, and ROE. The cells report the returns of the long-short portfolios.

The return measurement periods are divided into two sub groups: periods of positive (column 1) or negative (column 2) market returns (MktRet) based on the return of the CRSP-equal weighted index in the return measurement or portfolio holding month t+1.

Analysis period: January 1983 – December 2013. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Equal-Weighted Portfolios

	(1)	(2)	(3)
Return (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
MOM-ew	0.521	2.684***	2.163***
	(1.33)	(6.83)	(3.89)
SUE-ew	0.602***	1.540***	0.938***
	(3.61)	(8.25)	(3.75)
OP-ew	-0.666**	3.435***	4.101***
	(2.10)	(9.93)	(8.75)
ROE-ew	-0.078	3.885***	3.963***
	(0.24)	(10.95)	(8.27)
Periods	231	140	--

Panel B: Value-Weighted Portfolios

	(1)	(2)	(3)
Return (in %)	Positive MktRet Q5-Q1 (a)	Negative MktRet Q5-Q1 (b)	Neg. - Pos. (b) - (a)
MOM-vw	0.096	2.356***	2.260***
	(0.22)	(4.40)	(3.25)
SUE-vw	0.067	0.577**	0.510*
	(0.43)	(2.34)	(1.75)
OP-vw	-1.731***	4.899***	6.629***
	(5.63)	(10.91)	(12.19)
ROE-vw	-1.214***	3.684***	4.898***
	(4.24)	(8.36)	(9.33)
Periods	231	140	--

Exhibit 6: Idiosyncratic Volatility (IVOL) or Forecast Dispersion (DISP) Explains Momentum and Profitability

This exhibit tests whether IVOL or DISP explains significant portions of the positive returns associated with momentum and profitability. These tests repeat those of even columns in Exhibit 2, but replace UNC with IVOL (Panel A) or DISP (Panel B).

IVOL (idiosyncratic return volatility) is calculated monthly by regressing daily returns from CRSP against the Fama-French (1993) three factors and then taking the square root of the variance of the residuals following Ang et al. (2006).

DISP (analyst forecast dispersion) is the standard deviation of analyst forecasts of FY1 EPS from I/B/E/S, scaled by the absolute value of the mean earnings forecast, following Diether et al. (2002).

Analysis period: January 1983 – December 2013. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IVOL Explains Momentum and Profitability

	(1) MOM-ew	(2) MOM-vw	(3) SUE-ew	(4) SUE-vw	(5) OP-ew	(6) OP-vw	(7) ROE-ew	(8) ROE-vw
IVOL-ew	-0.351**		-0.245***		-0.699***		-0.717***	
	(2.46)		(8.98)		(15.70)		(30.08)	
IVOL-vw		-0.228**		-0.095***		-0.667***		-0.578***
		(1.97)		(3.63)		(19.91)		(20.35)
Residual	0.998***	0.699*	0.719***	0.156	0.206	0.039	0.724***	0.000
return	(2.82)	(1.80)	(6.69)	(1.12)	(1.39)	(0.23)	(5.83)	(0.00)
Observations	371	371	371	371	371	371	371	371
R-squared	0.15	0.06	0.39	0.07	0.77	0.72	0.80	0.67
Return reduction	25%	26%	25%	40%	77%	95%	49%	100%

Panel B: DISP Explains Momentum and Profitability

	(1) MOM-ew	(2) MOM-vw	(3) SUE-ew	(4) SUE-vw	(5) OP-ew	(6) OP-vw	(7) ROE-ew	(8) ROE-vw
DISP-ew	-0.638***		-0.405***		-0.844***		-0.995***	
	(3.71)		(11.92)		(7.79)		(18.28)	
DISP-vw		-0.501***		-0.251***		-0.916***		-0.868***
		(3.34)		(6.39)		(16.01)		(17.93)
Residual	0.956***	0.770**	0.714***	0.170	0.378*	0.443**	0.823***	0.324**
return	(3.05)	(2.24)	(7.57)	(1.40)	(1.81)	(2.26)	(5.88)	(2.07)
Observations	371	371	371	371	371	371	371	371
R-squared	0.25	0.14	0.52	0.23	0.55	0.59	0.75	0.66
Return reduction	28%	19%	25%	35%	57%	43%	42%	49%

Appendix A: Return on Equity: Further Analysis

Panel A1: Return on Equity: Using Annual Earnings (ROE(ann.))

This panel repeats the tests in Exhibit 2 Panel B columns 5-8, but uses ROE measured with annual earnings. The results indicate that when ROE is calculated with annual earnings (instead of quarterly), there are no significant positive returns remaining when uncertainty is controlled for. ROE(ann.) = annual income before extraordinary items / book equity from the last fiscal year). Return reduction = 1- (residual return/return).

	(1)	(2)	(3)	(4)
	ROE(ann.)-ew	ROE(ann.)-ew	ROE(ann.)-vw	ROE(ann.)-vw
UNC-ew		-0.592***		
		(7.76)		
UNC-vw				-0.521***
				(6.68)
Return/	0.627**	-0.081	0.293	-0.096
Residual return	(2.41)	(0.34)	(1.10)	(0.40)
Observations	371	371	371	371
R-squared	0.00	0.34	0.00	0.24
Return reduction	--	113%	--	133%

Panel A2: Return on Equity (ROE) vs. Earnings Surprise (SUE)

Columns 1 and 2 test whether uncertainty (UNC) combined with earnings surprise (SUE) can explain away the positive returns associated with quarterly ROE in equal-weighted portfolios. Columns 3 and 4 examine whether UNC combined with quarterly ROE can explain away the profits of SUE-ew portfolios. Return reduction = 1- (residual return/return). ROE in this panel is measured with earnings from the latest quarter (same as the ROE in Exhibit 2).

	(1)	(2)	(3)	(4)
	ROE-ew	ROE-ew	SUE-ew	SUE-ew
UNC-ew		-0.361***		-0.204***
		(3.54)		(5.39)
SUE-ew		0.986***		
		(4.08)		
ROE-ew				0.221***
				(6.96)
Return/	1.417***	0.044	0.956***	0.399***
Residual return	(5.44)	(0.18)	(7.50)	(4.56)
Observations	371	371	371	371
R-squared	0.00	0.60	0.00	0.63
Return reduction	--	97%	--	58%