Manager Uncertainty and Cross-Sectional Stock Returns*

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Abstract

This paper evidences the explanatory power of managers' uncertainty for cross-sectional stock returns. I introduce a novel measure of the degree of managers' uncertain beliefs about future states: manager uncertainty (MU), defined as the count of the word "uncertainty" over the sum of the count of the word "uncertainty" and the count of the word "risk" in filings and conference calls. I find that manager's level of uncertainty reveals valuation information about real options and thereby has significantly negative explanatory power for cross-sectional stock returns. Beyond existing market-based uncertainty measures, the manager uncertainty measure has incremental pricing power by capturing information frictions between managers' reported uncertainty and investors' perception of uncertainty. Moreover, a short-long portfolio sorted by manager uncertainty has a significantly positive premium and cannot be spanned by existing factor models. An application on COVID-19 uncertainty shows consistent results.

Keywords: Uncertainty, Manager, Heterogeneous Beliefs, Real Options, Cross-Sectional Stock Returns, Premium, Asset Pricing, Textual Analysis, COVID-19

JEL Classification: G11, G12, G41, D81, E44

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Abstract

This paper evidences the explanatory power of managers' uncertainty for cross-sectional stock returns. I introduce a novel measure of the degree of managers' uncertain beliefs about future states: manager uncertainty (MU), defined as the count of the word "uncertainty" over the sum of the count of the word "uncertainty" and the count of the word "risk" in filings and conference calls. I find that manager's level of uncertainty reveals valuation information about real options and thereby has significantly negative explanatory power for cross-sectional stock returns. Beyond existing market-based uncertainty measures, the manager uncertainty measure has incremental pricing power by capturing information frictions between managers' reported uncertainty and investors' perception of uncertainty. Moreover, a short-long portfolio sorted by manager uncertainty has a significantly positive premium and cannot be spanned by existing factor models. An application on COVID-19 uncertainty shows consistent results.

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1. Introduction

Along with documenting hundreds of risk factors in the finance literature, researchers have proposed an increasing number of uncertainty measures (e.g., Jurado, Ludvigson, and Ng, 2015; Baker, Bloom, and Davis, 2016; Bali and Zhou, 2016; Brenner and Izhakian, 2018). However, most existing uncertainty measures are market based and reflect investors' perception of uncertainty. Few papers measure managers' uncertainty at the firm level.[1] Mele and Sangiorgi (2015, p. 1533) show that investors' costly information acquisition in the asset market not only "reduces the expected variability of the fundamentals for a given distribution (i.e., risk). It also mitigates the uncertainty about the true distribution of the fundamentals." However, a large body of literature acknowledges the limitations, such as readability and investors' inattention, keeping investors from fully incorporating firms' exposure information into asset prices (Loughran and McDonald, 2014; Andrei, Friedman, and Ozel, 2019; Cohen, Malloy, and Nguyen, 2020). Therefore, managers' disclosed exposure information might reveal additional information about firms' uncertainty exposure.

This paper provides a novel measure of managers' uncertainty at the firm level and finds it has incremental asset pricing performance beyond existing market-based uncertainty measures. Manager uncertainty (MU) is defined as the count of the word "uncertainty" divided by the sum of the count of the word "uncertainty" and the count of the word "risk" in filings and conference calls. MU reflects the degree of managers' uncertain beliefs about future states. In other words,

[1] In this paper, I use (Knightian) uncertainty and ambiguity interchangeably. In his classical work, Knight (1921) suggests that uncertainty describes situations in which agents do not know the probability distribution of future outcomes, whereas risk refers to situations in which agents know the probability distribution (such as the mean and variance) of future outcomes. The COVID-19 (coronavirus) pandemic exemplifies the concept of uncertainty. A *Wall Street Journal* paper, titled "Risk, Uncertainty, and Coronavirus", discusses why coronavirus is an uncertain event rather than a risk event (Schrager, 2020).

MU measures the percentage of cases that managers think future outcomes are unpredictable or the percentage of cases that managers think the impact of exposure is unmeasurable.

The measure is motivated by the phenomenon whereby firms use the words "risk" and "uncertainty" differently (see Figures 1 to 3). When firms use the word "risk," they are more likely to be describing firm-specific risk, such as derivative hedging risk, consumer-related services risk, and collateral risk. However, they are more likely to use the word "uncertainty" to describe macroeconomic-related or rare events, such as policy changes, terrorism, and disasters.

Risky events generally have known probability distributions, and managers can adopt strategies to manage it. In contrast, managers usually have no prior knowledge of uncertain events, such as rare disasters, thereby unable to generate distributions of these events. This is consistent with the distinct definition between risk and uncertainty proposed by Knight (1921), in which uncertainty describes a situation with unknown probability distributions and unknown outcomes, and risk describes a situation with known probability distributions and unknown outcomes. [2] Therefore, the wording choice used by managers reveals their heterogenous beliefs about whether they can form probability distributions of future states.

The MU measure has strong negative explanatory power for cross-sectional stock returns, even after controlling for existing firm-level uncertainty measures, textual-based sentiments, and

[2] Knight (1921, chapter VIII, p. 233) states that "the practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either through calculation a priori or from statistics of past experience), while in the case of uncertainty this is not true, the reason being in general that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique. The best example of uncertainty is in connection with the exercise of judgment or the formation of those opinions as to the future course of events, which opinions (and not scientific knowledge) actually guide most of our conduct." One classical example that illustrates this difference is that people prefer taking bets with known odds rather than unknown odds (Ellsberg, 1961).

other firm characteristics.[3] A one-standard-deviation increase in a firm's MU (0.192) is associated with 0.1-percentage-point (pp) monthly drop in its return, or a 1.5-pp annual drop. A firm without managers' uncertainty (MU = 0) has 8.0-pp higher return than a firm with managers' full uncertainty (MU = 1). This result is consistent with existing literature that has uncovered a negative relation between uncertainty and stock returns (e.g., Jiang, Lee, and Zhang, 2005; Ozoguz, 2009; Bali, Brown, and Tang, 2017).

The real options theory supports the negative explanatory power of MU for stock returns (Brennan and Schwartz, 1985; McDonald and Siegel, 1986; Dixit and Pindyck, 1994; Bloom, Bond, and van Reenen, 2007). Firms with high MU are more exposed to uncertainty shocks; thus, they have high real option values and would like to wait-and-see. Therefore, uncertainty-averse managers will invest with precaution and conservativism, and devise contingency plans, which increase their flexibility and lower their adjustment costs in bad times.

Investors favor high uncertainty firms and are willing to receive a low premium to hold these assets. In contrast, firms with low MU have low real options values and thereby induce managers to be aggressive on investments, a scenario that leads to low flexibility and high adjustment costs in bad times. Investors require higher compensation to hold these assets, and

[3] There are dozens of firm-level uncertainty measures in the literature. Dew-Becker, Giglio, and Kelly (2019) find that option-implied volatility is over 90 percent correlated with their regression-based forecasts of future volatilities. They claim that "Option-implied volatility is a good, if not a perfect, proxy for true (physical) uncertainty." The correlation between the manager uncertainty measure and option-implied volatility is 0.17. Diether, Malloy, and Scherbina (2002) interpret dispersions of analysts' earnings forecasts as uncertainty about firm fundamentals. Jiang, Lee, and Zhang (2005) use firm age, stock volatility, trading volume, and implied equity duration to measure investors' information uncertainty. In addition, Zhang (2006) uses firm size, analyst coverage, and cash flow volatility to measure information uncertainty. Panousi and Papanikolaou (2012) use idiosyncratic volatility of equity returns as the measure of firm-specific uncertainty. Bali and Zhou (2016) claim that the variance risk premium (VRP) can be taken as economic uncertainty and they use the beta loadings of VRP as firm-level uncertainty. Baltussen et al. (2018) use the volatility of expected option-implied volatility as uncertainty about volatility.

thereby expected returns are higher for firms with low MU. Consistent with the real options explanation, I find that MU has significantly negative impacts on firms' future investment and hiring and positive effects on firms' working capital and cash holdings.

The negative effect of managers' uncertainty on stock returns is more pronounced for stocks without stock options. Besides, the negative explanatory power of MU for cross-sectional stock returns became stronger after December 2005, when the U.S. Securities and Exchange Commission (SEC) began requiring firms to mandatorily disclose their exposure information. This change in mandatory regulation allows investors to more accurately identify firms' risk and uncertainty exposure.[4] Moreover, the predictive relationship between MU and future cross-sectional stock returns lasts over a longer horizon, from one to nine months. These results testify about MU's incremental explanatory power for cross-sectional stock returns by capturing the information gap between managers' actual level of uncertainty and investors' uncertainty.

Moreover, I construct the managers' uncertainty factor (MUF) as an equal-weighted portfolio that longs low-MU (first quintile) stocks and shorts high-MU (fifth quintile) stocks. Since the low-MU stocks have higher expected returns than high-MU stocks, MUF has a significant premium of 0.48% per month. MUF is marginally related to existing aggregate uncertainty measures, and five aggregate uncertainty variables explain only 10% of the variation in MUF,

[4] Since December 1, 2005, firms have been required to report their exposure information through the Item 1A "Risk Factors" section in Form 10-K/10-Q filings. The document on this regulation change is available at https://www.sec.gov/rules/final/33-8591.pdf. Although the section is named "Risk Factors," firms usually discuss both risk and uncertainty in Item 1A.

indicating that MU mainly captures the premium from managers' heterogeneous uncertainty rather than fundamental uncertainty of the economy.[5]

MUF is strongly related to existing risk factor models in the asset pricing literature. However, the spanning tests that regress MUF on the eight existing factor models show that none of the existing factor models can fully span the premium for MUF. Among them, Fama and French (2018) six-factor model has the strongest explanatory power for MUF, and Stambaugh and Yuan (2017) four-factor model has the smallest alpha. Overall, these results illustrate that MUF contains exposure beyond existing risk factors though these factors strongly correlate with MUF; thus, MUF is a mispricing factor.

Furthermore, I run a horse race between beta loadings of aggregate uncertainty measures and firm-level uncertainty measures to ascertain their asset pricing performance. Instead of beta loading of MUF, MU measure survives in a horse race test between the 12 beta loadings and 15 characteristics, indicating that the measure captures mispricing information. Finally, the methodology in this paper can be applied to measure specific uncertainties. I provide a discussion on COVID-19 uncertainty and find firms with mangers' high COVID-19 uncertainty have lower return during the pandemic.

This paper makes several contributions to the literature. First, whereas most existing measures of uncertainty in the literature are investor or market based, I introduce a novel measure of firm-level uncertainty based on managers' perspective. This measure has additional explanatory power for cross-sectional stock returns beyond existing firm-level uncertainty measures. MU

[5] Aggregate uncertainty proxies include, but are not limited to, the volatility index (VIX) (Bloom, 2009), the macroeconomic uncertainty index (Jurado, Ludvigson, and Ng, 2015), the economic policy uncertainty index (Baker, Bloom, and Davis, 2016), the equity market volatility index (Baker et al., 2019), and the variance risk premium (Bollerslev, Tauchen, and Zhou, 2009; Bali and Zhou, 2016).

conveys valuation information through the real options channel and reflects the mispricing of the information frictions between firms' reported exposure and investors' uncertainty. Recent literature shows that some aggregate uncertainty measures have significant explanatory power for cross-sectional returns (Bali, Brown, and Tang, 2017; Brogaard and Detzel, 2015; Bali, Subrahmanyam, and Wen, 2020), but a systematic comparison of a large category of uncertainty measures to determine their asset pricing performance has not been performed. This paper helps to fill this gap.

Second, this paper is related to a vein of the finance literature that applies textual-based analysis to measure uncertainty and sentiments. Most of this literature uses risk and uncertainty interchangeably and aggregates them together to construct uncertainty measures (see, e.g., Loughran and McDonald, 2011; Baker et al., 2019; Hassan et al., 2019). Some recent papers count the word "uncertainty" over the length of document to construct firm-level uncertainties (Handley and Li, 2018; Caldara et al., 2020). Different from these papers, this paper utilizes the relative numbers of the words "uncertainty" and "risk." Doing so allows the MU measure to be more cross-sectionally comparable. Jiang et al. (2019) propose a management sentiment measure (subtracting the number of negative words from the number of positive words) by utilizing 10-K/10-Q filings and earnings conference calls. Their management sentiment measure captures managers' optimistic beliefs, in which they implicitly assume managers know the distribution of future states so that managers can estimate expected values as sentiments. For comparison, my MU measure captures managers' uncertain beliefs about the degree of managers' uncertainty about probability distribution of future states.

The remainder of this paper is organized as follows. Section 2 introduces the MU measure, hypothesis development, and provides summary statistics for the variables. Section 3 examines

MU and stock returns. Section 4 examines MUF and stock returns. Section 5 provides several discussions, applications on COVID-19 uncertainty, and robustness tests. Section 6 concludes.

2. Measurement, Hypothesis, and Sample

2.1 Construction of manager uncertainty

Existing literature shows that firms' financial disclosures provide critical information to investors.[6] For example, firms report their exposures to investors in their filings, such as the Item 1A "Risk Factors" and Item 7 "Management's Discussion and Analysis" (MD&A) in Form 10-K filings. These disclosures provide investors a critical channel to assess firms' exposure and thus make optimal portfolio allocations.

Analogous to the differentiation between risk and uncertainty in the theoretical literature, managers distinguish between risk and uncertainty in their filings. By performing sentence analysis on Form 10-K filings, I find that firms describe different types of exposure using the word "uncertainty" compared with the word "risk." Specifically, I extract sentences from Form 10-K filings that contain the word "uncertainty," but not have the word "risk." I refer to them as "uncertainty" sentences. Then I count words with which "uncertainty" sentences are used and extract the most frequent words. Similarly, I compute the most frequent words in "risk" sentences.

Figures 1 to 3 show the results, which show that when firms use the word "risk," they are more likely to be describing firm-specific issues, such as hedging risk, concentration risk, services risk, and collateral risk. However, they are more likely to use the word "uncertainty" to refer to

[6] For example, recent research documents that textual-based risk factors extracted from filings have explanatory power for stock returns (Campbell et al., 2014; Hope, Hu, and Lu, 2016; Hu, Johnson, and Liu, 2018; Lopez-Lira, 2019; Muslu et al., 2015; Nordlund, 2019).

macroeconomic-related exposure, such as political events, policy regulatory changes, terrorism, and environmental disasters.

[Figure 1 to Figure 3]

Motivated by this distinction, I conjecture that the choice of phrasing reflects managers' knowledge of uncertain events and implicitly conveys managers' uncertain beliefs about future business conditions.

The decision-making process comprises two stages (Brenner and Izhakian, 2018; Izhakian, 2020). The first is a beliefs formation stage, in which agents generate their beliefs about future states in the form of a probability (distribution). Agents' information, knowledge, and experience inform their beliefs. If agents believe (or are confident that) they have the knowledge of future states, they can estimate a probability distribution of future states. Otherwise, if no probability distribution is generated or managers think a future state is unpredictable, managers will form uncertain beliefs.[7] Besides, the measure of degree of uncertain beliefs should be independent of agents' attitudes (tastes or preferences) about uncertainty, such as uncertainty aversion or uncertainty loving (Izhaian, 2020).

The second is the valuation stage, in which agents face unknown outcomes. Risk plays a crucial role in this stage. For example, managers can compute the expected cash flow, compute the variance of an investment, and make decisions according to the net present value (NPV). The degree or magnitude of risk in the second stage relates to the magnitude of expected values; thus, risk is outcome dependent. The degree or magnitude of uncertainty in the first stage only relates to the probabilities of future states; thus, uncertainty is outcome independent.

[7] It is often referred to as model uncertainty in the theoretical literature (see, e.g., Hansen and Sargent, 2001).

Wording usage between uncertainty and risk in filings captures the likelihood that managers do not know the probability distribution of future states in the beliefs formation stage; thus, this information could be desirable to measure managers' uncertain beliefs. Accordingly, I propose a novel measure of managers' uncertainty in their beliefs formation stage, manager uncertainty (MU), defined as the word count of "uncertainty" divided by the sum of the word count of "uncertainty" and the word count of "risk" in Form 10-K/10-Q filings:

$$MU = \frac{N_{uncertain}}{N_{uncertain} + N_{risk}} = \frac{N^{*}_{uncertain} - N_{risk\_uncertainty} - N_{uncertain\_tax}}{N^{*}_{uncertain} - 2 \times N_{risk\_uncertainty} - N_{uncertain\_tax} + N^{*}_{risk} - N_{risk\_factor}} \quad (1)$$

where MU refers to manager uncertainty, $N_{uncertain}$ refers to the word "uncertainty," and N_{risk} refers to the word "risk." $N_{uncertain}^{*}$ refers to the total number of times the word "uncertainty" ("uncertainty," "uncertainties," "uncertain," "ambiguity," "ambiguities," and "ambiguous") appears. N_{risk}^{*} is the total number of times the word "risk" (includes "risk," "risks," "risked," "riskier," "riskiest," "risking," and "risky") appears. In some cases, firms use two words together, for example, "risk and uncertainty" (includes "risk and uncertainty," "risk and uncertainties," "risks and uncertainty," and "risks and uncertainties"), in general discussions, and I exclude these counts to reduce noise. Firms must disclose their risk factors in Item 1A of Form 10-K filings, so the term has no economic meaning and mostly is used as subtitles, I exclude this term as well (includes "risk factors"). The term "uncertain tax" is mostly used along with financial statements to interpret uncertain tax provisions, I exclude this term ("uncertain tax") as well.

I search the count of words and phrases by using DirectEdgar and sum up these words in each calendar year. I just keep the initial filings if any revision due to some revisions are lagged for a long time. Thus, a typical firm has four filings each year, including one Form 10-K and three 10-Q filings. I sum up the filings by the calendar year to in line with stock returns in main sections. In section 5.1, I sum up MU by each firm's fiscal year to analyze the firm's behavior. The final

MU measure is firm-year-level data with a range from zero to one. Zero MU means the firm never uses "uncertainty" in the calendar year. If the firm only uses "uncertainty" and not "risk," its MU equals one. The sample period ranges from 1993 to 2018. The MU data cover 9,840 firms on average each year.

As an alternative measure, I also construct the MU measure by utilizing both 10-K/10-Q filings and earnings conference call transcripts. I obtain earning conference call transcripts from S&P Capital IQ. The sample period ranges from 2007 to 2017. On average, there are 1,863 firms each year. I exclude texts by analysts. Following formula (1), I construct the MU measure in earnings calls as MU^{cc}. The alternative measure MU_A is computed as the average of MU in filings and MU^{cc}:

$$\text{MU\_A} = \frac{1}{2}\text{MU} + \frac{1}{2}\text{MU}^{\text{cc}} \tag{2}$$

Because of the relatively short sample of MU_A, I will use it for the robust tests and apply MU to the main analysis.

Compared with MU, $N_{uncertainty}$ alone is not a desirable measure of firm-level uncertainty, because it is not comparable across firms considering that firms adopt different writing styles. Loughran and McDonald (2016) suggest that $\frac{N_{uncertain}}{N_{doc}}$ is a better measure of firm-level uncertainty magnitude, where N_{doc} is the total number of words in a filing (excluding meaningless words such as prepositions). Loughran and McDonald (2016) also compute $N_{uncertain}$ as a sum of the words "uncertainty", "risk", and other related words Figures 1 to 3 show that the two terms mostly reflect managers' differing beliefs or are used with different frequencies if referring to the same type of exposure. Aggregating the two terms would add noise to the uncertainty measure. Handley and Li (2018) sum the total count word of "uncertainty" over the total number of words in filings as a measure of uncertainty. However, N_{doc} may not be a perfect denominator, because it does not only reflect firms' exposure. In contrast, MU more precisely measures firm-level uncertainty. "$N_{uncertian}+N_{risk}$" reflects managers' overall beliefs about firms' exposure, and the ratio ($\frac{N_{uncertain}}{N_{uncertain}+N_{risk}}$) measures managers' uncertain beliefs over their overall beliefs. Overall, the MU measure is more comparable across firms.[8]

2.2 Hypothesis development

High MU refers to managers with high uncertainty beliefs. Managers' beliefs and expectations affect firms' decision-makings, such as about investment and hiring. The neoclassical investment model, such as the NPV theorem, does not consider uncertainty. Instead, the real options theory accommodates firms' investment dynamics under uncertainty (Brennan and Schwartz, 1985; McDonald and Siegel, 1986; Dixit and Pindyck, 1994). With the irreversibility of investments and the uncertainty of future outcomes, firms' investment decisions are analogous to financial call options.

High uncertainty increases real option values and makes firms more cautious about their investment decisions (Bloom, Bond, and van Reenen, 2007). In this circumstance, firms adopt a wait-and-see strategy, and firms with high uncertainty are more precautious and are likely to delay their investment or invest conservatively.[9]

[8] MU assumes that managers' vocabulary choice between "risk" and "uncertainty" are evolving in opposite ways. Managers' word choice depends on their ability to estimate the probability distribution of a future state when forming a belief. At the macro level, Doan, Douglas, and Yang (2019) uncover high uncertainty (proxied for by the volatility of probabilities of market returns by Brenner and Izhakian (2018)) and low risk (proxied for by realized variance of market returns) before Federal Open Market Committee (FOMC) announcements and low uncertainty and high risk after FOMC announcements. Hu et al. (2019) shows that heightened uncertainty (proxied for by the VIX) leads to positive pre-FOMC-announcement drift in market returns. However, relative to other firms in the cross section, a firm can simultaneously have high uncertainty and high risk.

[9] A large number of empirical studies document the effect of uncertainty on investments and production. For example, Bachmann, Elstner, and Sims (2013) show that firms' uncertainty leads to persistent reductions in production. In section 5.1, I will show that high MU leads to fewer investments, less hiring, and more working capital and cash holdings.

Managers with high uncertain beliefs (high-MU firms) would make more contingency plans. Therefore, high-MU firms have high flexibility and lower adjustment cost and are more resilient to shocks. In contrast, firms with low uncertainty (low-MU firms) are less cautious and overinvest in good times, making them more vulnerable in bad times because of the inflexibility and high adjustment costs incurred from irreversible investments. Investors favor firms with high uncertainty and are willing to pay higher prices to hold these stocks; thus, they accept lower returns for high-MU firms.

In contrast, investors dislike firms with low uncertainty and require high compensation to hold these stocks; thus, a higher expected return for low-MU firms is required. In a frictionless economy, investors identify managers' heterogeneous uncertain beliefs and their consequent real options values and make their portfolio allocation decisions accordingly. Therefore, I hypothesize a negative relation between MU and cross-sectional stock returns.[10] The first hypothesis (H1) is described below.

H1: Firms that frequently use the word "uncertainty" (high-MU firms) have lower expected returns than firms that less frequently use the word "uncertainty" (low-MU firms).

Hypothesis 1 (H1) assumes investors have full knowledge of firms' uncertainty exposure through the information and linguistic usage found in firms' mandatory disclosures. Ideally, a firm's reported uncertainty should match the market-based uncertainty measures of this firm. Market-based uncertainty measures include implied volatility, realized volatility, analysts'

[10] The negative premium of investors' uncertainty is well documented in the literature. Related theoretical explanations include ambiguity (uncertainty) aversion, the intemporal asset pricing model (ICAPM), limited participation, and the long-run risk model (e.g., Ai and Kiku, 2017; Ang et al., 2006; Bali, Brown, and Tang, 2017; Bali, Subrahmanyam, and Wen, 2020; Baltussen, van Bekkum, and van der Grient, 2018; Brogaard and Detzel, 2015; Cao Wang, and Zhang, 2005; Jiang, Lee, and Zhang, 2005; Ozoguz, 2009).

dispersion of forecast, etc. However, investors are limited in being able to fully perceive managers' uncertainty. First, the complexities of the disclosures hinder investors' identification of firms' uncertainty exposure. Complexities are due to disclosure qualities, such as readability (Loughran and McDonald, 2014; Bushee, Gow, and Taylor, 2018). Second, investors are inattentive (rationally or irrationally) to disclosures (Andrei, Friedman, and Ozel, 2019; Cohen, Malloy, and Nguyen, 2020). These frictions create an information gap between firms' reported exposure and investors' perceived exposure that impedes investors' ability to optimally allocate assets and leads to mispriced asset returns. Therefore, MU has additional pricing power for cross-sectional stock returns beyond existing firm-level uncertainty measures. Based on this conjecture, the second hypothesis (H2) posits that the information gap captured by MU has incremental asset pricing implications relative to existing uncertainty measures.

H2: MU still has significantly negative explanatory power for cross-sectional stock returns after controlling for market-based uncertainty measures.

The SEC regulation change in December 2005 required public firms to publicly disclose their risk and uncertainty exposure in detail in forward-looking statements, the aim of which is to increase information transparency. Following the regulatory change, investors have relied more on firms' disclosures when making asset allocations as it is easier for them to acquire uncertainty information through filings/calls. Therefore, I conjecture that MU begins to have more explanatory power for cross-sectional stock returns after the SEC disclosure policy change in 2005.

The options market provides investors a window into firms' exposure information. Investors encounter difficulties in obtaining firms' uncertainty exposure information from stocks without stock options; thus, investors have more attention to mandatory disclosures. Therefore, I conjecture that MU has more explanatory power for cross-sectional stock returns of stocks without stock options, compared with stocks with stock options.

2.3 Summary statistics

Table 1 presents the summary statistics of the variables used in this paper. Panel A lists the results of variables at the firm-year level. The mean value for MU is 0.166 with a standard deviation of 0.152. $N_{uncertain}$ has a mean of 15.162 and N_{risk} has a mean of 88.78, indicating firms' use the word much more frequently than using the word "uncertainty". Figure 4 shows the yearly median value of MU. It shows there is an increasing trend of MU with a spike after 2005. The peak of managers' uncertainty is in 2007 when the financial crisis started. Figure 5 presents the average MU by Fama and French 12 industries. On average, firms in healthcare and telecommunication industries have higher MU, whereas firms in financial and utilities industries have lower MU.

[Figure 4 and Figure 5]

Panel B of Table 1 lists the results for variables at the stock-month level. The excess return is winsorized at 0.5% and 99.5% thresholds to exclude extreme values of returns and/or potentially recording errors. For the panel dataset, the Pearson correlation between MU and excess stock return is -0.016 (T-statistic=-10.09). The time-series average of cross-sectional correlations is -0.041 (T-statistic=-10.05) and the cross-sectional average of time-series correlations is -0.067 (T-statistic=-16.32). Therefore, both the time-series correlations and cross-sectional correlations indicate a negative relation between MU and excess stock returns.

[Table 1]

3. Manager Uncertainty (MU) and Cross-Sectional Stock Returns

In this section, I examine the properties of the manager uncertainty measure (MU). First, I assess the relations between MU and firm characteristics, especially existing firm-level uncertainty measures. Second, I evaluate the explanatory power of MU for the cross-sectional stock returns. Third, I evaluate the effect of the pricing performance of an alternative measure MU. Lastly, I examine the predictive power of MU over longer-horizons.

3.1 Relations with firm-specific characteristics

In this part, I test the relations between MU and firm characteristics based on the Fama-MacBeth (1973) cross-sectional regressions. Specifically, I regress MU on firm characteristics each month and then compute the time-series average of the estimated coefficients from the regression each month.

$$MU_{it} = \alpha_t + \beta_t C_{it} + \epsilon_{it} \tag{3}$$

Where MU_{it} is manager uncertainty of firm i in month t and C_{it} is a collection of firm-specific characteristics. The cross-sectional regressions are implemented at a monthly frequency within the period from January 1993 to December 2018. Then, I compute the average of time-series of these estimates as the average effect.

$$\bar{\beta} = \frac{\sum_{t=1}^{T} \beta_t}{T} \tag{4}$$

Where $\bar{\beta}$ is the average effects and T is the total number of months. The corresponding T-statistics that are adjusted by Newey-West standard errors are reported in parentheses.

[Table 2]

Panel A of Table 2 shows the results of regressing MU on firm characteristics. Firms' market betas have a significantly positive relation with MU, indicating managers in firms with high market betas usually have high uncertain beliefs. Firm size has a negative relation with MU, indicating small firms have high-MU. The firm profitability has a strong negative relation with

MU but the relation between MU and asset growth is minimal. Furthermore, firms that have strong momentum and reversal effects are more likely to have less uncertainty exposure. The Amihud (2002) illiquidity measure has a negative relation with MU. Finally, MU has negative relations with skewness and kurtosis, but both lose significance in the multivariate regression (Column 11 of Panel B).

The relations between MU with existing firm-level uncertainty proxies validate MU as a new proxy for firm-level uncertainty. Panel B of Table 2 reports the results of regressing MU on these existing firm-level uncertainty and textual related characteristics. Existing literature manifests that option-implied volatility (VOLI) is a good proxy for uncertainty (e.g., Dew-Becker, Giglio, and Kelly, 2019). The Pearson correlation between UM and VOLI is 0.14 over the whole sample period. The cross-sectional correlation has an upward trend, increasing from 0.04 in 1996 to 0.32 in 2017. Column 1 shows that the VOLI is significantly related to MU. One unit increase of VOLI will is associated with 9.7 percent increase of MU. Besides, there are significant relations between MU and other uncertainty proxies, including realized volatility (VOLR), volatility of volatility (VOV), idiosyncratic volatility (IDVOL), and dispersion of analysts' earnings forecast (DISP).

Moreover, MU has strong positive relations with the positive sentiment ($LM_{positive}$) and the negative sentiment ($LM_{negative}$) but has a negative relation with management tone (Tone), indicating manager uncertainty are high if managers have more pessimistic beliefs. MU also has strong positive relations with two readability measures, the Fog index and the Smog index. The last column shows only VOLI, IDVOL, $LM_{ucertain}$, Tone, and Smog remain significant in multivariate regression.

In summary, High-MU firms usually have high implied volatility, high idiosyncratic volatility, high uncertain sentiment, low management tone, low readability, high market beta, small size, low book-to-market, low investment, low profitability, high momentum, low short-term reversal, and high liquidity. However, the strong significance of constant terms and low R^2 indicate much cross-sectional variation of MU is unexplained.

3.3 Relation with cross-sectional stock returns

In this part, I examine whether MU is priced on cross-sectional stock returns by using Fama-MacBeth (1973) regressions.

$$R_{it} = \alpha_t + \beta_t MU_{it} + \gamma_t Control_{it} + \epsilon_{it} \quad (5)$$

Where R_{it} is the return of stock i at month t, MU_{it} is MU for firm i at time t, and $Control_{it}$ is a broad category of control variables. β_t is the marginal effect of MU on cross-sectional stock returns at month t. The reported coefficients in Table 3 are time-series average of estimated coefficients in the model (5) and the values in parentheses are T-statistics adjusted by Newey-West standard errors. The cross-sectional regressions are run at a monthly frequency from January 1993 to December 2018.

[Table 3]

Panel A of Table 3 reports the regression results when controlling for related textual-based variables. Column 1 controls the number of the word “uncertainty” ($N_{uncertain}$) and the number of the word “risk” (N_{risk}) in Form 10-K/10-Q filings. In column 2, similar results are found when using the ratios of the word “uncertainty” and the word “risk” over the total number of words in filings. In contrast, manager uncertainty (MU) is significantly associated with cross-sectional stock returns. These results illustrate that it is the relative frequency of the word “uncertainty” and the word “risk” rather frequencies of these two words matters to cross-sectional stock returns.

Columns 3 of Panel A of Table 4 shows the results of adding three sentiment variables as controls and the result shows that MU keeps significant in this specification. Both negative and positive sentiments have significant explanatory power for stock returns, but the uncertain sentiment is insignificant. Uncertainty has a negative premium according to the investors' hedging demand to uncertainty in the intemporal capital asset pricing model (ICAPM) or real options value of manager uncertainty. Risks usually have a positive premium according to the CAPM. Therefore, aggregating risk words and uncertainty words would mitigate the effects of each of the two. Moreover, a regression that includes all these textual-based variables in column 4 shows similar results. In column 5, I replace negative sentiment and positive sentiment by management tone and find that MU remains significantly negative. The positive relation between management tone and return is also documented by Loughran and MacDonald (2011). In short, these results show that MU is significantly priced.

The SEC requires public firms to mandatorily disclosure their exposure information through Item 1A in 10-K/10-Q filings since December 1st, 2005. This regulation change allows investors to identify their investment risk through firms' exposures information. After the regulation change, it is easier for investors to perceive firms' exposures information accurately thereby the effect of MU on stock returns should be stronger after this policy change. To proxy this regulation change, I create a dummy variable, D_year, which equals to one if after 2005 (since 2006) and to be zero if before 2006. Then, I add an interaction term between MU and the dummy variable into the regression. The result is shown in column 6 of Panel A of Table 3, in which the regression is implemented by panel regression with firm-level fixed effect rather than Fama-MacBeth (1973) regression. Consistent with the conjecture, the negative pricing power of MU to stock return is stronger after the regulation change as the coefficient of the interaction term is significantly negative.

Panel B of Table 3 reports the results that control several firm-level uncertainty measures and firm characteristics. Column 1 controls for several uncertainty measures and the result show that most of these measures are priced except realized volatility (VOLR).[11] The implied volatility (VOLI) has a strong negative relationship with returns, which is consistent to existing well-documented literature (Dennis, Mayhew, and Stivers, 2006; Bali and Hovakimian, 2009; Yan, 2011). In column (2), I control firm characteristics including firm size, the book to market, asset growth, profitability, momentum, reversal, illiquidity, skewness, and kurtosis. Despite controlling for more variables, the significance and the magnitude of the effect of MU on asset returns increase. Column 3 reports the results that control all these firm-level characteristics and uncertainty measures. The coefficient of MU reduces to -0.646 (T- statistic=-2.35), while the VOLI has a strong statistical significance (T-statistic=-8.21).

This result not only shows that MU can be an alternative proxy for firm-level uncertainty but also shows that MU has additional explanatory power beyond existing firm-level uncertainty measures for cross-sectional stock returns. The additional explanatory power is due to MU captures managers' uncertainty whereas the other measures may mostly capture financial market-

[11] All of these variables are negatively priced in bivariate regressions that include MU and one of the other variables (VOLI, VOLR, VOV, IDVOL, and DISP). Taking idiosyncratic volatility (IDVOL) as an example, Ang et al. (2006) find similar results that the high IDVOL stocks have lower returns. and they explain it by using the ICAMP framework. Specifically, investors do not favor volatility because it represents a deterioration in investment opportunities, thus risk-averse investors will prefer stocks that have high sensitivities to aggregate volatility, which also have larger idiosyncratic volatility because both of them show up in the residuals of the Fama-French model (p.261). Therefore, stocks with higher idiosyncratic volatility will be more attractive and investors push up their current price thus they have lower expected returns.

related uncertainties. The information diffusion loss from firms' reporting and investor perception may be due to physical limitations such as filing readability and investors' subjective inattention.

I conjecture that the explanatory power of MU for returns should be stronger to stocks that do not have stock options than that to stocks with stock options. For stocks with stock options, investors have an additional channel to perceive firms' uncertainty exposures through their options market. In contrast, investors have fewer channels to perceive firms' uncertainty exposures if stocks do not have options, thus investors will rely more on managers' reported uncertainty. Column 4 in panel B of Table 3 shows the result of adding an option dummy variable and its interaction term with MU. The dummy variable, D_option, is equal to one if a stock has at least one near-the-money stock option and equals zero if the stock has no stock options. Consistent with this conjecture, the interaction term between D_option and MU is significantly positive, indicating the explanatory power of MU to returns is stronger for stocks without stock options. Column 5 shows that the result still holds when controlling firm characteristics.

In summary, these results evidence that MU provides additional uncertainty information from managers and thus has incremental explanatory power for cross-sectional stock returns beyond existing market-based uncertainty measures.

3.3 Relation with cross-sectional stock returns by using an alternative measure

In this subsection, I examine the pricing power of an alternative measure of manager uncertain beliefs, MU_A, which utilizing textual information from both 10-Q/10-K filings and earnings conference calls. MU_A has much less coverage as many firms do not have earnings calls and some earnings calls are too short to mention both risk and uncertainty. On average, there are 1,328 firms each year with MU_A available. The mean value of MU_A is 0.25, which is slightly bigger than the mean of MU (0.17), indicating managers mention uncertainty more frequently in earnings calls. The correlation between MU and MU_A is 0.38.

Column (1) of Table 4 shows the univariate regression result. Without controlling for other variables, MU_A has a significantly negative effect on cross-sectional stock returns. One-standard-deviation increase of MU_A (0.184) is associated with a 0.12-pp in excess returns on a monthly basis. Columns (2) to (6) shows the results that control firm-characteristics, textual-based characteristics, and several existing firm-level uncertainty measures. The significant pricing power of MU_A is robust in these specifications. Therefore, using this alternative measure provides robust evidence that manager uncertainty is negatively priced.

3.4 Predictive power over longer horizons

In this subsection, I examine the predictive power of manager uncertainty on cross-sectional stock returns over longer horizons. Specifically, I run future cross-sectional stock returns on MU. Instead of using yearly MU, I compute MU at month t, MU_M, as the number of the word "uncertainty" over the sum of the number of the word "uncertainty" and the word "risk" in the period from month t-11 to the current month t. MU_M is slow-moving since it is analogous to moving-average over 12 months.

Table 5 presents the results by regressing n-month-ahead cross-sectional stock returns on MU_M and control variables by using the multivariate Fama-MacBeth regression. Consistent with using yearly MU, MU_M has significant pricing power to contemporary stock returns. More importantly, the results show that the predictive power of MU_M decreases over longer horizons. The significance decreases to 10% significance level when predicting 10-month-ahead returns and the significance disappears when predicting 18-month-ahead returns.[12] The long-horizon predictive power of MU suggests that manager uncertainty captures fundamental information about underlying firms.

4. Manager Uncertainty Factor (MUF)

In this section, I create a manager uncertainty factor (MUF) from portfolio analysis first. Then I evaluate the relation between MUF and existing aggregate uncertainty measures. After then, I examine whether MUF can be explained by existing factor models in asset pricing. Finally, I run a horse-race asset pricing test between beta loadings of aggregate uncertainty measures and firm-level uncertainty measures.

3.1 Portfolio analysis: MUF construction

One way to examine whether MU is a desirable proxy for firm-level uncertainty is to test whether average returns are different in different groups sorted by MU levels. I sort the stocks into quintile portfolios based on firms' MU. Specifically, I separate stocks into five groups by their magnitudes of MU each calendar year, the first group (1st quintile) is 20% firms that have the smallest MU, and the fifth group (quintile) is 20% firms that have the largest MU. Then, I compute the simple average returns of each group in each month (I do not use firm size weighting or value weighting to avoid blurring the effect of size effect). These portfolios are rebalanced annually based on firms' MU in each calendar year from 1993 to 2018.

[Table 6]

Panel A of Table 6 shows the average returns of each portfolio across 312 months. In the table, the second column reports the average MU in each group, the third and the fourth column

[12] Similarly, Bali, Brown, and Tang (2017) find that beta loadings of the economic uncertainty index, developed by Jurado, Ludvigson, and Ng (2015), predicts future returns up to 11 months.

reports the average of raw returns and the average of excess returns, respectively. The first quintile portfolio's average MU is 0.023, in which most firms have zero MU, meaning these firms do not use the word "uncertainty" at all. The average return is 1.1% per month and the average return in excess risk-free rate is 0.96% per month, and both are statistically significant at 1% significance level. The second portfolio has an average MU to be 0.083. Its average returns are similar to the 1 first portfolio but have smaller T-statistics. The third and the fourth portfolios have further smaller average returns monotonously. The fifth portfolio has the highest average MU (0.379) but has the smallest average returns as well. Its average raw return is 0.61% and the average excess return is 0.78% per month. Its T-statistics are the smallest among the five groups.

Furthermore, I form a portfolio that long the first group stocks (with low-MU) and short stocks in the fifth group (high-MU portfolio). The long-short portfolio has a highly significant premium. The monthly raw return for the long-short portfolio is 0.48% (T-statistics=2.74) and its corresponding average excess return is 0.43% per month (T-statistics =2.44). The monotonous decrease of T-statistics by groups indicates the significance of the short-long portfolios is more likely to be driven by the high returns of firms that have low uncertainty exposures. The large difference between the average raw return and average excess return of the long-short portfolio indicates MU captures firms' interest rate exposure and thus is more likely to be discount rate effect rather than the cash flow effect on asset valuation.

Following the portfolio analysis, I propose a manager uncertainty factor (MUF), which is constructed by the equal-weighting portfolio that longs the stocks in the first quintile (low-MU firms) and shorts the stocks in the fifth quintile (high-MU firms). This portfolio takes additional exposure to uncertainty, thus requires extra compensation to hold.[13] MUF also reflects the magnitude of aggregate uncertainty in time-series. MUF is a portfolio that earns a positive return on average thus it contains a positive premium.

Panel B of Table 6 shows the 25 portfolio returns sorted by MU and firm size. Most portfolio returns have significant premiums, in which the firms in the smallest MU group as well as the smallest firm group have the highest expected return 1.09% per month. Consistent with the negative uncertainty premium, portfolio returns are higher for firms that have smaller MU. Consistent with the univariate sorting, the significant returns are mainly in portfolios with small and middle MU and some portfolio returns in the 4th and 5th MU quintiles are not significant. Besides, portfolio returns are higher for smaller small firms, except for the fifth quintile by MU, which is consistent with negative size premium by Fama and French (1993, 2015, and 2018). More importantly, the last row shows that the long-short portfolios that long the low-MU stocks (1st MU quintile) and short the high-MU stocks (5th MU quintile) are only significant in the 1st to 3rd size quintiles, indicating the uncertainty premium is mainly concentrated in small-size and middle-size firms. The last column shows that there are no significant return differences between portfolios in different size quintiles in each MU quintile, illustrating that MU premium is not driven by firm size effect.

4.1 Relations with existing aggregate uncertainty measures

The textual-based MU is shown to have strong relations with existing firm-level uncertainty measures in section 3, but whether the manager uncertainty measure captures aggregate uncertainty in time-series is still not studied. MUF reflects the time-series variation of

[13] It is similar to construct the SMB (small-minus-big) factor. Small firms usually have higher returns than large firms, thus a portfolio than longs small-size firms and shorts large-size firms takes additional exposure on size, thereby the SMB factor has a positive premium.

manager uncertainty premium. In this part, I examine the effectiveness of MUF in terms of its relations with existing aggregate uncertainty measures. Specifically, I regress MUF on existing aggregate uncertainty measures and check whether there are significantly positive relations.

$$MUF_t = \alpha_0 + bU_t + \epsilon_t \tag{6}$$

Where MUF_t is the return of MUF portfolio at month t, U_t is a category of existing aggregate uncertainty measures, such as the macroeconomic uncertainty index by Jurado, Ludvigson, and Ng (2015), the economic uncertainty index by Baker, Bloom, and Davis (2016), the equity market volatility index by Baker et al. (2019), the CBOE volatility index (VIX), and the variance risk premium from Zhou (2018).

[Table 7]

Table 7 reports the results of the slope coefficients from regressing MUF on these existing aggregate uncertainty measures. Jurado, Ludvigson, and Ng (2015) develop the macroeconomic uncertainty indices that are estimated by aggregating conditional volatility of a broad category of macroeconomic factors. Specifically, they provide three forward-looking indices, one-month ahead economic uncertainty (UNC1), three-month ahead economic uncertainty (UNC2), and twelve-month ahead economic uncertainty (UNC12). The column 1-3 of Panel 5 shows that all of the three have insignificant relation with MU in univariate regressions, indicating managers' heterogeneous uncertainty is not strongly related to macroeconomic uncertainty.

Baker, Bloom, and Davis (2016) propose the economic policy uncertainty index (EPU) by searching policy-related uncertainty terms from newspapers. Column 4 of Table 7 shows that the EPU has a slightly positive relation with MUF. Baker et al. (2019) suggest the equity market volatility index (EMV) by using similar methods from newspapers but focusing on the asset market-related volatility. Column 5 of Table 7 manifests that MUF is strongly associated with the

EMV. Column 6 of Table 7 shows that MUF is positively linked with the CBOE volatility index (VIX). Both EMV and VIX result shows manager uncertainty is associated with market volatility. Zhou (2018) claims that it is the difference between implied volatility and realized volatility that captures the variation of uncertainty and the difference is described as the variance risk premium (VRP). Panel 7 of Table 5 shows that there is a very weak link between MUF and the VRP.

Panel 9 of Table 7 shows the result of the multivariate regression. After including all aggregate uncertainty measures above, EMV and VRP remain significant while UNC1 becomes significant, which may be due to correlations among explanatory variables. However, the low R^2 indicates that the uncertainty premium from managers' uncertainty uncertain beliefs contains mainly firm-specific uncertainties rather than the trend of aggregate uncertainty.

4.2 Relations with existing factor models in asset pricing

The second way to validate MUF is to examine the relations between MUF and risk factors from existing asset pricing models. MUF is expected to have correlations with risk factors but would not be fully spanned by risk factors because MUF captures managers' uncertainty that is beyond risk exposures. To explore this, I regress MUF on several existing factor models in asset pricing.

$$MUF_t = \alpha_0 + bF_t + \epsilon_t \tag{7}$$

Where MUF_t is the portfolio return of MUF at month t and F_t is a set of risk factors.

[Table 8]

Column 1 of Table 8 shows that the excess market return factor (MKT_RF) has a significantly negative impact on MUF, which is consistent with the negative premium of uncertainty and positive premium for the market return. Column 2 of Table 8 regresses MUF on Fama and French (1993) three-factor model (FF3), including the MKT_RF, the small-minus-big size factor (SMB), and the high-minus-low value factor (HML). The SMB factor has a negative coefficient possibly because MUF is constructed by equally weighting. Panel 3 of Table 8 regresses MUF on Fama and French (2015) five-factor model (FF5), augmenting the robust-minus-weak operating profitability factor (RMW) and the conservative-minus-aggressive investment factor (CMA). The RMW is positively related to MUF, indicating the uncertainty premium is high during the high profitability premium period. The CMA has a negative relation with MUF, indicating the uncertainty premium is lower in the high investment premium period. Column 4 of Table 8 shows the results with Fama and French (2018) six-factor model, adding the up-minus-down momentum factor (UMD). All the six factors are significant and the UMD factor has a positive relation with MUF, indicating MUF premium is high during the high momentum period.

Column 5 of Table 8 shows the results with Hou, Xue, and Zhang (2015) four-factor model (HXZ4), including the MKT_RF, SMB, and two redefined profitability and investment factors (R_I/A and R_ROE). This model reduces the constant term to 0.272 but the R^2 is lower than the FF6. Column 6 of Table 8 shows the results with Daniel et al. (2020)'s adjusted five-factor model, in which they adjust FF5 factors by excluding their corresponding hedged portfolios. This model has weak explanatory power for MUF as its R^2 is 0.174.

Column 7 of Table 8 shows the results with Stambaugh and Yuan (2017) four-factor model (SY4), including MKT_RF, SMB, and two mispricing factors, specifically, the management quality factor (MGMT) and the performance factor (PERF). The SY4 has a strong explanatory power in terms of reducing the intercept term to 0.275. The MGMT factor has a strong association with MUF as a one percent increase of management premium will lead to the uncertainty premium increases by 0.512 percent (T-statistic=8.86). Column 8 of Table 8 shows the results with Daniel, Hirshleifer, and Sun (2020)'s three-factor model (DHS3) that includes the MKT_RF, the financing factor (FIN) as long-horizon mispricing and the post-earning-announcement-drift factor (PEAD) as short-run mispricing. The financing factor has a significantly positive relation with MUF, illustrating the uncertainty premium is associated with long-horizon mispricing.

Furthermore, I evaluate whether MUF premium still holds after controlling all risk factors discussed above. Due to strong correlations among risk factors, adding them together in one model will lead to multicollinearity issue. To resolve this issue, I apply the adaptive LASSO method to select the most important predictors. Column 9 of Table 8 shows that the FF6 factors plus the MGMT factor are selected, and all of them have significant explanatory power for MUF. The R^2 increases to 0.666, which is the highest among all the ten models. However, the intercept term remains significant, indicating managers' uncertainty premium cannot be fully spanned by this factor model.

The spanning tests in Table 8 have two implications. First, the uncertainty factor has strong correlations with existing risk factors, indicating there is strong co-movement between risk series and uncertainty series. Second, the existing factor models cannot fully span the uncertainty factor, testifying the uncertainty premium has components that are independent to risk factors and uncertainty has incremental pricing effect.

4.3 Horse race of uncertainty measures: covariance versus characteristics

There is a long literature in asset pricing on the dispute of "covariance versus characteristics" (e.g., Kelly, Pruitt, and Su, 2019; Kozak, Nagel, and Santosh, 2019). There are two ways to reflect uncertainty exposure. One is to use firm-level exposures, such as the VOLI and MU. The other is to use the covariance, beta loadings of aggregate uncertainty measures, such as the beta loading of MUF. In this part, I explore the relations among uncertainty measures from the two categories and then comparing their pricing performance in cross-sectional asset pricing tests.

I estimate beta loadings of aggregate uncertainty measures from monthly rolling regressions that regressing individual firms' excess returns on aggregate uncertainty measures and control variables. The rolling regressions are over a 60-month rolling window and require at least 24 non-missing return observations in the window. Following Bali, Brown, and Tang (2017), control variables are risk factors that include MKT_RF, SMB, HML, UMD, liquidity (LIQ), investment (CMA), and profitability (RMW).

$$R_{it} = \alpha_t + \beta_{it} U_t + \gamma_{it} Control_{it} + \epsilon_{it} \tag{8}$$

Where R_{it} is the excess return of stock i at month t, U_t is the aggregate uncertainty measure at month t. For beta loading at t, I use t-60 to t-1 as its rolling window. I estimate the beta loadings for each aggregate uncertainty measures separately to avoid multicollinearity problems. The aggregate uncertainty measures include MUF, UNC1, UNC3, UNC12, EPU, EMV, and VIX.

To examine whether the beta loadings of MUF (β^{MUF}) can be an effective proxy for firm-level uncertainty exposures, I run Fama-MacBeth regression of β^{MUF} on beta loadings of existing aggregate uncertainty measures and existing firm-level uncertainty measures (MU, VOLI, and VOLR).

$$\beta_{it}^{MUF} = \alpha_t + \gamma_t \beta_{it} + \theta_t Cha_{it} + \mu_t Control1_{it} + \rho_t Control2_{it} + \epsilon_{it} \tag{9}$$

Where β_{it} is a category of beta loadings of existing aggregate uncertainty measures, including β^{UNC1}, β^{EPU}, β^{EMV}, β^{VIX}, and β^{VRP}. Cha_{it} is a series of firm-level uncertainty measures, including MU, VOLI, VOLR, IDVOL, VOV, and DISP. Control set 1 is a set of firm characteristics, including SIZE, BM, I/A, ROE, MOM, REV, LIQ, SKEW, and KURT. Control set 2 is a set of beta loadings of risk factors, including β^{MKT}, β^{SMB}, β^{HML}, β^{CMA}, β^{RMW}, β^{LIQ}, and β^{UMD}.

[Table 9]

Panel A of Table 9 reports the results. Columns 1, 2, and 3 show that the β^{MUF} is strongly associated with MU. It is as expected because MUF is constructed by longing low-MU stocks and shorting high-MU stocks. Columns 4 and 5 show that the β^{MUF} is strongly related to beta loadings of EMV but not with beta loadings with other three aggregate uncertainty measures. Column 6 shows that the VOLI has a strong negative relation with the β^{MUF}. Column 7 shows the results that include all beta loadings, firm-level uncertainties, and two control sets. The results are consistent with columns 1-6 and this specification has an R^2 about 0.34, illustrating the β^{MUF} captures a portion of similar uncertainty exposures as other uncertainty exposure measures.

More importantly, it is critical to examine which uncertainty exposure measures, covariance or characteristics, have better explanatory power for cross-sectional stock returns. Specifically, I run Fama-MacBeth (1973) regressions that regressing cross-sectional stock returns on these uncertainty exposures.

$$R_{it} = \alpha_t + \gamma_t \beta_{it} + \theta_t Cha_{it} + \mu_t Control1_{it} + \rho_t Control2_{it} + \epsilon_{it} \tag{10}$$

Where R_{it} is the excess return of stock i at month t, β_{it} is beta loadings of aggregate uncertainty measures of firm i at month t, and Cha_{it} is firm-level uncertainty measures of firm i at month t. Control sets are the same as formula (8). After running cross-sectional regressions in each month, I compute the time-series average of estimated coefficients as the average effects.

Table B of Table 9 reports these results with different specifications. Column 1 shows that the β^{MUF} has a significantly positive coefficient on stock returns, which is consistent with existing findings on "negative uncertainty premium", because MUF is an against uncertainty factor that longs low stocks with low uncertainty exposures and shorts stocks with high uncertainty exposures. Columns 2 and 3 show that the coefficient for the β^{MUF} is still significant after controlling for MU, firm characteristics, and beta loadings of risk factors, which means both the uncertainty covariance (β^{MUF}) and uncertainty characteristics (MU) have significant explanatory power for stock returns.

Columns 4 and 5 of Table 9 shows the comparison among beta loadings of aggregate uncertainty measures. The β^{MUF} loses its significance in this battle whereas β^{EPU} and β^{EMV} are significant. Similarly, in column 6 of Table 9, the β^{MUF} loses its significance after adding firm-level uncertainties into the regression. The VOLI has very strong explanatory power for returns as its T-statistics are larger than 7, and its negative coefficient also testifies the negative uncertainty premium.

Column 7 of Table 9 shows the final horse race by including all uncertainty exposure measures and controls. The VOLI remains the most significant predictor. MU remains significant while its corresponding covariance, β^{MUF}, loses significance.

To sum up, the β^{MUF} can be an effective proxy for firm-level uncertainty exposures, but it has weaker explanatory power for stock returns than other uncertainty exposure measures. MU survives in all specifications, indicating its effectiveness in terms of pricing and it provides additional information to existing uncertainty exposure measures. Overall, the uncertainty characteristics (MU) have better pricing performance than uncertainty covariance (beta loadings of aggregate uncertainty measures) after controlling for beta loadings of risk factors and firm characteristics, evidencing the manager uncertainty capture mispricing in the long-run, thus manager uncertainty is an anomaly that beyond existing risk-based explanations.

5. Discussions and Robustness Tests

5.1 Manager uncertainty and firms' real activities

Existing literature shows that uncertainty has detrimental effects on economic activities (Bloom et al., 2018; Handley and Li, 2018; Hassan et al., 2019). In this part, I examine whether firms' behavior changes conditional on manager uncertainty. Following real options theory, firms with high uncertainty will wait-and-see and are precautionary. Therefore, managers with high uncertain beliefs are more likely to invest and hire less, and to hold more cash and working capitals. To testify this conjecture, I run panel regressions of one-year-ahead firm's behavior variables on MU. Different from computing MU by calendar years in sections 3 and 4, I compute firms' behavior variables and MU by firm's fiscal years.

$$Y_{i(t+1)} = \alpha + \varphi MU_{it} + \emptyset TA_{it} + Firm\ FE + Year\ FE + \epsilon_{it} \tag{11}$$

Where $Y_{i(t+1)}$ is reaction variables of firm i in fiscal year t+1, including the growth rate of investment in physical assets (INV), the growth rate of employees (EMP), the growth rate of the share of working capitals in total assets (WC), and the growth rate of cash and short-term investments (CASH). In this specification, I control the logarithm of total assets (TA), firm fixed effects, and year fixed effects.

[Table 10]

Results in Table 10 support the argument that managers with higher uncertainty beliefs are more precautionary and resilient. Columns 1 and 2 show that both firms' investment growth of physical capital and growth rate of the number of employees are significantly lower if managers have higher uncertainty beliefs. One-standard-deviation increase of MU (0.163) is associated with 1.2% decrease in physical investment and 0.5% drop in hiring. Columns 3 and 4 show that the significant negative effects of MU on working capitals and cash holdings. One-standard-deviation increase of MU is associated with 2.0% increase in working capitals over total assets and 4.9% increase in cash holdings.

5.2 Does manager uncertainty proxy firms' strategic reporting

One assumption of the MU measure is that firms should objectively report their risk and uncertainty exposures. Some firms with bad management may choose to use the word "uncertainty" more frequently than using the word "risk" to attribute their management failures to the macroeconomic environment and uncertain economy-wide events that are out of firms' control. If it is this case, MU captures mainly firms' behavior anomalies (such as bad management) but not true uncertainty exposures. I do find that MUF has a very strong positive correlation with the management quality factor (MGMT) from Stambaugh and Yuan (2017). Since MUF is an against-uncertainty factor, this negative relationship suggests that the low manager uncertainty is corresponding to high management quality (less mispriced portfolios due to management quality). However, as shown in column 10 of Table 6, the MGMT factor has a much less significant relation with MUF after controlling for FF6 factors and the intercept term remains significant, indicating there is still a large portion of uncertainty premium (67% by intercept term (0.324/0.482) and 33% by R^2) cannot be explained by those factors. More importantly, as shown in Table 6, the premium for MU is mainly driven by the high returns for firms with small MU. In contrast, high-MU firms have large return cross-sectional variation and its corresponding portfolio return is not significant. If the high-MU is due to bad management, the portfolio return for the high-MU group should be negative.

In the online appendix, I control the beta loadings of the MGMT factor in tests of the Panel B of Table 7 and find that all the results still hold, indicating the management quality, report quality, or reporting ambiguity concerns are not the main driver of manager uncertainty measure. The other way to resolve this concern is to regress the VOLI on MU and use the estimated coefficient to extrapolate the implied volatility for firms that do not have stock options. Then I use

MU-predicted values as pseudo-option-implied volatility and this pseudo volatility has significantly negative explanatory power on stock returns. Since the pseudo volatility excludes components of MU that are uncorrelated with the VOLI, including potentially management quality components that have no direct link to the VOLI, the robust results further confirm that MU mainly contains uncertainty exposures rather than other risk exposures.

Another supporting evidence is that MU has an autocorrelation around 0.85, which means MU varies not much year-by-year. The stickiness of MU indicates firms do not change their risk and uncertainty exposure disclosures much, which mitigates the concern that managers strategically choose the words “risk” and “uncertainty”.

5.3 A case study: Managers’ uncertainty about COVID-19

This method proposed in this paper can be applied to construct specific uncertainties. In this subsection, I construct a measure of managers’ uncertainty on COVID-19 by using conference calls. Specifically, I compute manager uncertainty in COVID-19-related paragraphs in conference calls. COVID-19-related paragraphs is paragraphs within conference calls in the first quarter of 2020 that include COVID-19 and its synonyms at least once. Following Li et al. (2020), I obtain synonyms of COVID-19 by using word embedding. There are 1,980 U.S. public firms mentioned uncertainty or risk at least once in their conference calls in the first quarter of 2020.

Then, I run cross-sectional regression of stock returns in the first quarter of 2020 on the managers’ uncertainty on COVID-19 and beta loadings of Fama and French (2018)’s six factors. Consistent with main results of this paper, firms with high COVID-19 uncertainty is associated with lower stock returns. Since the COVID-19 is an unprecedented event and beyond managers’ expectations, the stock market reaction to managers’ uncertainty on COVID-19 is mainly through discount rate channel rather than firm fundamentals. Investors does not favor managers with uncertain beliefs and have higher uncertainty aversion during this period, thus sell these assets more, leading to the negative relation between COVID-19 uncertainty and stock returns.

5.4 Robustness tests

The main results in section 3 and section 4 pass several robust tests. First, the results are robust to alternative manager uncertainty measures. In section 2.1, I construct manager uncertainty (MU) by using clean numbers of the word “uncertainty” and the word “risk”, such as excluding the word “risk and uncertainty”. I construct a noisy manager uncertainty measure that includes the word “risk and uncertainty” since firms may use the term to discuss future states that are related to both uncertainty and risk and/or firms may the term to discuss their general exposures. The noisy measures have a strong correlation with the clean MU and the main results are robust to using the noisy measures though less significance in some cases. Besides, the empirical results still hold in the case of dropping extreme values (0 and 1). Besides, all results still hold when limiting the word count in Item 1A and Item 7 in 10-K/10-Q filings. Moreover, all results still hold by using the data after the regulation change in 2005.

Second, the results are robust to return adjustments and firm sample choices. In this paper, I winsorize stock returns at 0.5% and 99.5% level, which means 1% extreme returns are winsorized. This is critical to construct MUF since I use equally weighting so that one extreme return will largely change the portfolio returns. Truncating these extreme returns yields similar results. For cross-sectional asset pricing tests, winsorizing return or not has less effect on the results. The test assets in this paper are individual stock returns. I find that MU is priced on portfolios as well. I use two different sets of portfolios as test assets. The first is Fama and French 25 portfolios sorted by size and book to market. The other is 25 portfolios sorted by size and MU. I find that MU has significantly negative effects on returns of these two sets of test assets.

Third, the results are robust to alternative methodology choice that resolves omitted variables concerns. Despite controlling for a set of firm characteristics and/or beta loadings of risk factors (the total number of independent variables are 35), these specifications may still omit some important variables in the Fama-MacBeth (1973) regressions. Also, all empirical results still hold by adding Fama and French 12 industry fixed effects. As an alternative methodology, I apply panel regression with fixed effects and find similar results. To resolve the omitted variable problem, Giglio and Xiu (2018) provides a three-step framework. First, they extract the principal components from the covariance matrix of stock returns. Second, they regress cross-sectional stock returns on these principle components to estimate their premium x. Third, they regress a target factor on these principle components to get estimated coefficients, y, and then the risk premium is computed as the sum of multiplying x and y. I apply their methodology to the manager uncertainty factor. The result shows that the monthly premium of manger uncertainty factor is 0.2 percentage point and highly significant (the joint significance by F-statistics is 72.25, P-value is 0.00), indicating the omitted variable problems are not severe in my specifications.

6. Conclusion

Following the observation that firms distinguish the vocabulary choice between the word “uncertainty” and the word “risk” in filings, I develop a novel firm-level uncertainty measure, manager uncertainty (MU), which captures managers’ uncertain beliefs to future states. MU is constructed by the count of the word “uncertainty” over the sum of the count of the word “uncertainty” and the count of the word “risk” in firms’ Form 10-K/10-Q filings. An alternative measure of MU encompasses filings as well as earnings call transcripts.

MU has significantly negative explanatory power for cross-sectional stock returns even after controlling for a set of firm characteristics. Real options theory helps explain this anomaly.

Managers’ high uncertain beliefs increases real options value of investment, leading to managers to be precautionary in investment and hiring and to be more resilient. Investors favor high-MU firms thus require a lower premium. An equally weighted portfolio that longs low-MU stocks and shorts high-MU stocks, named manager uncertainty factor (MUF), has a significant positive premium. Existing factor models in asset pricing literature cannot fully span MUF. Instead of beta loading of MUF, MU survives in a horse race test between the 12 beta loadings and 15 characteristics, indicating manager uncertainty captures incremental mispricing information.

The final takeaway is that this paper raises the question of how uncertainty is identified. Specifically, how investors perceive firms’ uncertainty exposures and how managers inform their uncertainty to investors? This paper implies that managers’ reported uncertainty in disclosures can be one of the channels. A detailed analysis to answer these questions with other channels shall be explored in the future.

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Appendix

Variable Definition

Variables	Definition
Firm-Year Level	
MU	Manager uncertainty, which equals the count of the word "uncertainty" over the sum of the count of the word "uncertainty" and the count of the word "risk" in a firm' 10-K/10-Q filings each calendar year. Source: DirectEdgar.
MU_A	Alternative measure of manager uncertainty, which equals the average of MU in 10-K/10-Q filings and MU in earnings call transcripts each calendar year. Source: DirectEdgar and S&P Capital IQ.
$N_{uncertain}$	The number of the word "uncertainty" in a firm' 10-K/10-Q filings each calendar year. Source: DirectEdgar.
N_{risk}	The number of the word "risk" in a firm' 10-K/10-Q filings each calendar year. Source: DirectEdgar.
$NR_{uncertain}$	The percentage (%) of the number of the word "uncertainty" over the total number of words in a firm' 10-K/10-Q filings each calendar year. Source: DirectEdgar and Loughran and McDonald (2011).
NR_{risk}	The percentage (%) of the number of the word "risk" over the total number of words in a firm' 10-K/10-Q filings each calendar year. Source: DirectEdgar and Loughran and McDonald (2011).
$LM_{postive}$	The positive sentiment, which is the ratio of the number of positive words over the total number of words in a firm' 10-K/10-Q filings each calendar year. Source: Loughran and McDonald (2011).
$LM_{negative}$	The negative sentiment, which is the ratio of the frequency of negative words over the total number of words in a firm' 10-K/10-Q filings each calendar year. Source: Loughran and McDonald (2011).
$LM_{uncertain}$	The uncertain sentiment, which is the ratio of the frequency of the uncertain words over the total number of words in a firm' 10-K/10-Q filings each calendar year. Source: Loughran and McDonald (2011).
Tone	The positive sentiment ($LM_{postive}$) subtracts the negative sentiment ($LM_{negative}$). Source: Loughran and McDonald (2011).
Fog	Gunning Fog readability index in a firm's 10-K/10-Q filings. The index is computed by 0.4 (($\#\ words/\#\ sentences$) +100($\#\ complex\ words/\#\ words$)). # indicates count. Source: SEC Analytic Suite
Smog	Smog readability index in a firm's 10-K/10-Q filings. The index is computed by 4.71($\#\ characters/\#\ words$) + 0.5($\#\ words/\#\ sentences$) $-$ 21.43. Source: SEC Analytic Suite.
VOLI	Option-implied volatility. The annual data is computed as the average of daily implied-volatility of near-of-money call options within each year. If a firm has multiple call options, the simple averaged is used. The moneyness is required between 0.9 and 1.1. Source: WRDS Option Suite.
VOLR	Realized volatility of stock returns, which is the annual standard deviation of daily stock returns. Source: CRSP.
VOV	Volatility of volatility (vol-of-vol), which is the annual standard deviation of daily option-implied volatility. Source: OptionMetric.
INV	Annual growth rate of physical assets (gross property, plant, and equipment) in fiscal year t. The variable is winsorized at 1% and 99% level. Source: Compustat.
EMP	Annual employment growth rate in fiscal year t. The variable is winsorized at 1% and 99% level. Source: Compustat.
WC	Annual growth rate of the share of working capital over total assets in fiscal year t. The variable is winsorized at 1% and 99% level. Source: Compustat.
CASH	Annual growth rate of cash and short-term investments and in fiscal year t. The variable is winsorized at 1% and 99% level. Source: Compustat.
TA	The logarithm of total assets in fiscal year t-1. The variable is winsorized at 1% and 99% level. Source: Compustat.

Firm-month level

R_{raw}	Individual stock return. The data is winsorized at 0.5% and 99.5% level. Source: CRSP
R	Individual stock return in excess of the risk-free rate. The data is winsorized at 0.5% and 99.5% level. Source: CCM.
IDVOL	Idiosyncratic volatility of stock returns. Following Ang et al. (2006), the monthly idiosyncratic volatility is computed as the standard deviation of the residuals from daily regressions each month. The regression is regressing excess individual stock returns onto Fama and French (1993) three-factors. Source: CRSP.
SKEW	Skewness. The estimated coefficient of the squared term of excess market return (MKT_RF) in the daily regression of regressing excess individual stock return onto MKT_RF, the squared term of MKT_RF, and the cubed term of MKT_RF within each month. The reported coefficient in table 1 is the estimated coefficient divided by 100. Source: CRSP.
KURT	Kurtosis. The estimated coefficient of the cubed term of excess market return (MKT_RF) in the daily regression of regressing excess individual stock return onto MKT_RF, the squared term of MKT_RF, and the cubed term of MKT_RF within each month. The reported coefficient in table 1 is the estimated coefficient divided by 1000. Source: CRSP.
DISP	Analysts' forecast dispersion. Following Garfinkel (2009), the analysts' forecast dispersion is computed as standard deviations of analysts' earnings forecast in each month, and it is scaled by the absolute value of the mean analysts' forecast. Source: I/B/E/S.
SIZE	The logarithm of firm size (market capitalization) at year T-1 following Fama and French (1993)'s definition. Source: Compustat and CRSP.
BM	Book-to-market. The ratio of a firm's book value at year T-1 over its market value at year t-1 following Fama and French (1993)'s definition. Source: Compustat and CRSP.
I/A	Growth rate of total assets for year t is computed by a firm's change of total asset from year T-2 to year T-1 divided by its total asset in year T-2. This follows Fama and French (2015)'s definition. Source: Compustat.
ROE	Operating profitability at year T-1, which is computed by revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, and then divided by book equity. This follows Fama and French (2015)'s definition. Source: Compustat.
MOM	Momentum. The cumulative return of a stock return from month t-12 to t-2 following Jegadeesh and Titman (1993). Source: CRSP.
REV	Short-term reversal. The return at month t-1. Source: CRSP.
LIQ	Illiquidity. Following Amihud (2002), the illiquidity is computed as the monthly average of the ratios of a stock's daily absolute stock return over its daily dollar trading volume in each trading day within each month. The data is winsorized at 0.5% and 99.5% level. The number is multiplied by 10^6. Source: CRSP.
D_O	A dummy variable that is one if a stock has stock option-implied volatility and otherwise is zero.
D_Y	A dummy variable that is to is one if the month is after December 2005 and otherwise is zero.

Time-Series

MUF	MUF is the manager uncertainty factor that longs stocks in the 1st MU quintile (low-MU) and shorts stocks in the 5th MU quintile.
UNC1	One-month-ahead economic uncertainty indices from Jurado, Ludvigson, and Ng (2015), which is computed as the aggregate conditional volatility from a category of macroeconomic variables.
UNC3	Three-month-ahead economic uncertainty indices from Jurado, Ludvigson, and Ng (2015).
UNC12	12-month-ahead economic uncertainty indices from Jurado, Ludvigson, and Ng (2015).
EPU	EPU is the economic policy uncertainty index from Baker, Bloom, and Davis (2016).
EMV	EMV is the equity market volatility index from Baker et al. (2019).
VRP	VRP is the variance risk premium from Zhou (2018).
VIX	VIX is the volatility index from the Chicago Board Options Exchange (CBOE).
MKT_RF	Excess market return from Kenneth R. French's data library.
SMB	The small-minus-big size factor (SMB) from Kenneth R. French's data library.
HML	The high-minus-low book-to-market factor (HML) from Kenneth R. French's data library.

RMW	The robust-minus-weak operating profitability factor (RMW) from Kenneth R. French's data library.
CMA	The conservative-minus-aggressive investment factor (CMA) from Kenneth R. French's data library.
RF	The risk-free rate, proxied by the 3-month treasury bill rate is from Kenneth R. French's data library.
UMD	The up-minus-down momentum factor (UMD) from Kenneth R. French's data library.
ST_REV	The short-term reversal factor (ST_REV) from Kenneth R. French's data library.
LT_REV	The long-term reversal factor (LT_REV) from Kenneth R. French's data library.
LIQ	The liquidity factor (LIQ) from Pastor and Stambaugh (2003).
R_IA	The investment-to-assets (R_I/A) factor from Hou, Xue, and Zhang (2015)'s q-factor model.
R_ROE	The profitability factor (R_ROE) factor from Hou, Xue, and Zhang (2015)'s q-factor model.
MGMT	MGMT is the management factor from Stambaugh and Yuan (2017).
PERF	PERF is the performance factor (PERF) from Stambaugh and Yuan (2017).
MKTRF_STAR	MKTRF_STAR is Daniel et al. (2020)'s adjusted MKT_RF factor, which is a combination of the MKT_RF factor from the Fama and French (2015)'s five-factor model with a corresponding hedge-portfolios.
SMB_STAR	SMB_STAR is Daniel et al. (2020)'s adjusted SMB factor, which is a combination of the SMB factor from the Fama and French (2015)'s five-factor model with a corresponding hedge-portfolio.
HML_STAR	HML_STAR is Daniel et al. (2020)'s adjusted HML factor, which is a combination of the HML factor from the Fama and French (2015)'s five-factor model with a corresponding hedge-portfolio.
RMW_STAR	RMW_STAR is Daniel et al. (2020)'s adjusted RMW factor, which is a combination of the RMW factor from Fama and French (2015)'s five-factor model with a corresponding hedge-portfolio.
CMA_STAR	CMA_STAR is Daniel et al. (2020)'s adjusted CMA factor, which is a combination of the CMA factor from Fama and French (2015)'s five-factor model with a hedge-corresponding portfolio.
PEAD	PEAD is the post-earning-announcement-drift factor from Daniel, Hirshleifer, and Sun (2020). This factor captures short-horizon mispricing.
FIN	FIN is the financing factor from Daniel, Hirshleifer, and Sun (2020). This factor captures long-horizon/persistent mispricing.

Figure 1. The word cloud for sentences that have the word "uncertainty"

Note: This figure shows that the most frequent words in sentences that have the word "uncertainty" but not have the word "risk". Specifically, I extract all sentences are from Form 10-K filings in DirectEdgar that have the word "uncertainty" (include "uncertainty", or "uncertainties", or "uncertain", or "uncertainly") but not have the word "risk" (include "risk", or "risks", or "risky", or "risked", or "riskier", or "riskiest", or "risking", or "riskness"), I call these sentence as "uncertainty" sentences.Then, I count the frequencies of words in these sentences. To be included, these words have to occur at least once in 100 "uncertainty" sentences ($N1_{word}/N_{uncertianty}$>1%). Useless words, such as prepositions and verbs, are excluded.

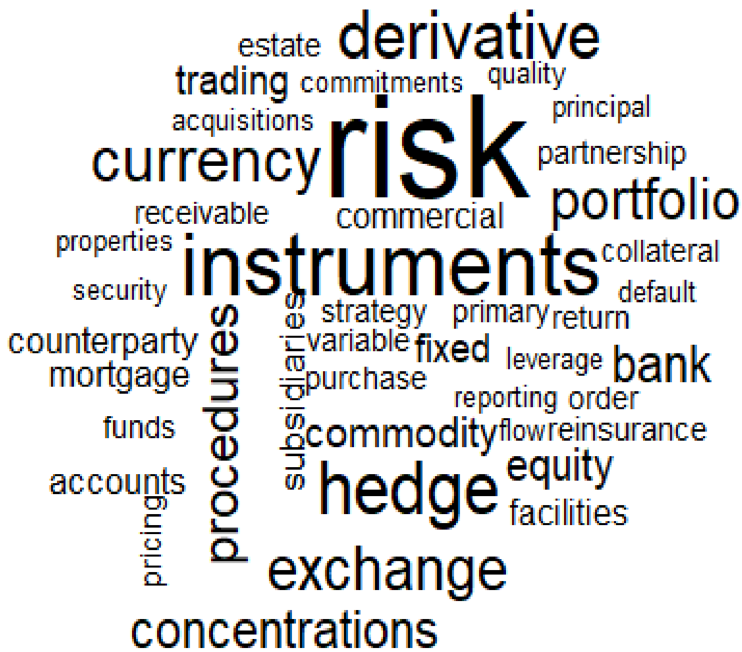

Figure 2. The word cloud for sentences that have the word "risk"

Note: This figure shows that the most frequent words in sentences that have the word "risk" but not have the word "uncertainty". Specifically, I extract all sentences are from Form 10-K filings in DirectEdgar that have the word "risk" (include "risk", or "risks", or "risky", or "risked", or "riskier", or "riskiest", or "risking", or "riskness") but not have the word "uncertainty" (include "uncertainty", or "uncertainties", or "uncertain", or "uncertainly"), I call these sentence as "risk" sentences.Then I count the frequencies of words in these "risk" sentences. To be included, these words have to occur at least once in 100 "risk" sentences ($N2_{word}/N_{risk}$>1%). Useless words, such as prepositions and verbs, are excluded.

Figure 3. The word cloud for words that occur in both "uncertianty" sentences and "risk" sentences

Note: This figure shows that the most frequent words that occur in both "uncertainty" sentences as well as "risk" sentences. The definitions for "uncertainty" sentences and "risk" sentences are the same as that in Figure 1 and Figure 2, respectively. To be included, these words have to occur at least once in 100 "uncertainty" sentences ($N1_{word}/N_{uncertainty}>1\%$) as well as have to occur at least once in 100 "risk" sentences ($N2_{word}/N_{risk}>1\%$). Useless words, such as, prepositions and verbs are excluded. The words in blue color are common words that occurs more frequently in "uncertainty" sentences ($N1_{word}/N_{uncertainty} > N2_{word}/N_{risk}$). The words in black color are common words that occurs more frequently in "risk" sentences ($N1_{word}/N_{uncertainty} <= N2_{word}/N_{risk}$).

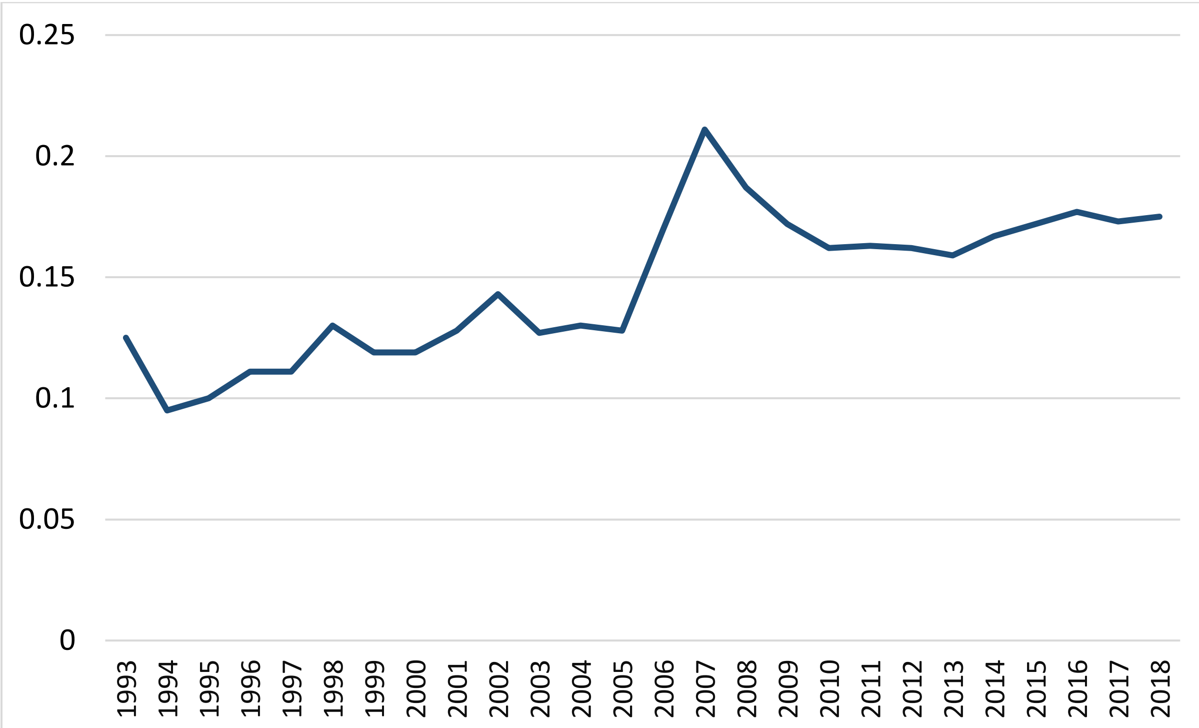

Figure 4 The median of manager uncertainty (MU) by year

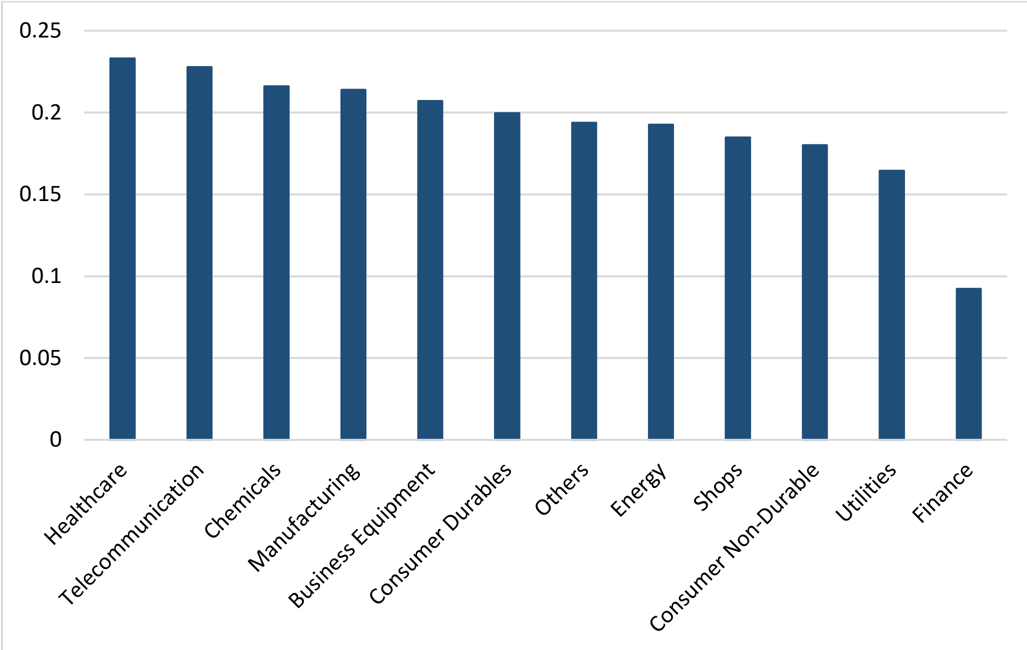

Figure 5 Manager uncertainty (MU) by Fama and French 12 industries

Table 1

Summary statistics

This table presents the summary statistics of variables. The statistics include the number of observations (N), mean, standard deviation (S.D.), minimum (min), 25% percentile, median, 75% percentile, and maximum (max). Panel A shows firm-year level variables. Panel B reports firm-month level variables. In the last columns of panel A and panel B, the correlations with manager uncertainty (MU) are reported. Panel C lists time-series variables. In the last column of panel C, correlations with the manager uncertainty factor (MUF) are reported. Definitions are in the Appendix. The sample period is January 1993 to December 2018.

Panel A: Firm-year level variables

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max	Corr(MU,X)
MU	125,379	0.166	0.152	0	0.06	0.14	0.232	1	1
$N_{uncertain}$	125,420	15.162	17.22	0	3	10	22	406	0.289
N_{risk}	125,420	88.785	122.925	0	21	57	111	3,089	-0.194
$NR_{uncertain}$	123,040	0.018	0.024	0	0.005	0.013	0.025	2.452	0.370
NR_{risk}	123,040	0.103	0.137	0	0.037	0.075	0.125	10.595	-0.219
$LM_{negative}$	123,040	1.487	0.518	0	1.135	1.425	1.787	10.555	0.083
$LM_{postive}$	123,040	0.588	0.184	0	0.468	0.566	0.682	2.451	0.081
$LM_{uncertain}$	123,040	1.133	0.37	0	0.888	1.099	1.331	16.33	0.006
Tone	123,040	-0.9	0.491	-9.95	-1.184	-0.858	-0.574	1.516	-0.058
Fog	115,052	19.627	1.586	12.195	18.787	19.605	20.414	99.558	0.050
Smog	115,052	17.091	0.984	10.956	16.514	17.102	17.673	37.766	0.058
VOLI	68,743	0.644	0.378	0.147	0.373	0.543	0.807	2.738	0.137
VOLR	53,952	0.478	0.241	0.016	0.301	0.42	0.598	1.977	0.102
VOV	53,798	0.087	0.069	0	0.042	0.067	0.11	1.383	0.078
INV	108,767	0.177	0.581	-0.926	0.005	0.065	0.184	4.073	-0.007
EMP	111,282	-0.913	0.428	-1.8	-1.058	-0.985	-0.869	1.75	-0.015
WC	107,407	0.126	1.652	-0.98	-0.092	0	0.084	47.922	0.054
CASH	118,515	1.134	5.082	-0.999	-0.347	0.017	0.558	40.489	0.036

Panel B: Firm-month level variables

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max	Corr(MU,X)
R_{raw}	1,210,889	0.947	16.223	-50.057	-6.707	0.161	7.227	83.333	-0.015
R	1,210,889	0.712	16.101	-48.956	-6.903	0	6.996	80.27	-0.016
IDVOL	1,206,676	0.028	0.028	0	0.012	0.02	0.034	3.137	0.126
SKEW	1,206,752	-0.057	3.186	-341.644	-0.504	-0.022	0.414	555.371	-0.004
KURT	1,206,752	-0.398	48.614	-7,269.30	-3.86	-0.049	3.569	4,704.520	-0.002
DISP	617,034	0.199	0.682	0	0.017	0.041	0.118	7.288	0.041
β^{MKT}	914,922	1.078	0.803	-8.152	0.532	0.966	1.483	10.349	0.101
SIZE	1,200,463	5.662	2.153	-2.852	4.084	5.556	7.119	13.91	-0.074
BM	1,157,236	-0.679	1.072	-10.003	-1.258	-0.623	-0.063	6.357	-0.038
I/A	1,074,123	0.179	1.195	-1	-0.025	0.062	0.191	233.36	-0.004
ROE	1,074,123	-0.025	8.5	-100	-0.008	0.02	0.04	1,221.508	-0.002
MOM	1,200,085	13.669	57.802	-420.763	-13.22	11.699	36.467	2,070.002	-0.027

(continue)

REV	1,200,347	1.161	18.397	-99.36	-6.667	0.189	7.225	1,349.505	-0.010
LIQ	1,210,581	10.877	49.869	0.000	0.046	0.281	2.634	663.579	-0.021
D_option	1,210,889	0.447	0.497	0	0	0	1	1	-0.009
D_year	1,210,889	0.450	0.497	0	0	0	1	1	0.042

Panel C: Time-series variables

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max	Corr(MUF,X)
MUF	312	0.482	3.037	-12.683	-1.171	0.39	2.006	9.916	1.000
UNC1	312	0.646	0.09	0.549	0.586	0.624	0.675	1.079	-0.059
UNC3	312	0.779	0.09	0.679	0.714	0.759	0.809	1.214	-0.057
UNC12	312	0.906	0.052	0.846	0.871	0.9	0.921	1.147	-0.061
EPU	312	113.123	43.547	44.783	82.013	102.932	136.117	283.666	0.108
EMV	312	20.498	7.886	9.57	15.298	18.168	23.253	69.835	0.244
VRP	312	15.05	20.753	-218.564	7.023	11.589	22.049	115.853	-0.104
VIX	312	19.402	7.686	9.51	13.46	17.53	23.585	59.89	0.123
MKT_RF	312	0.627	4.228	-17.23	-1.915	1.175	3.34	11.35	-0.485
SMB	312	0.15	3.071	-14.91	-1.865	0.055	2.105	18.32	-0.445
HML	312	0.197	3.03	-11.18	-1.415	-0.05	1.705	12.87	0.496
RMW	312	0.307	2.709	-18.33	-0.955	0.38	1.3	13.33	0.686
CMA	312	0.25	2.08	-6.86	-1.04	0.045	1.325	9.56	0.356
RF	312	0.198	0.177	0	0.01	0.15	0.39	0.56	0.078
UMD	312	0.483	4.868	-34.39	-1.29	0.545	2.94	18.36	0.183
ST_REV	312	0.275	3.547	-14.6	-1.115	0.145	1.64	16.21	-0.161
LT_REV	312	0.166	2.456	-7.04	-1.53	0.175	1.63	11	-0.039
LIQ	312	0.004	0.06	-0.257	-0.023	0.006	0.036	0.279	-0.123
R_IA	312	0.244	2.021	-7.153	-0.975	0.202	1.32	9.248	0.415
R_ROE	312	0.4	2.761	-13.846	-0.775	0.538	1.745	10.378	0.674
MGMT	288	0.006	0.03	-0.089	-0.011	0.004	0.019	0.146	0.633
PERF	288	0.007	0.046	-0.215	-0.017	0.004	0.029	0.185	0.292
MKTRF_STAR	312	0.004	0.031	-0.205	-0.011	0.008	0.024	0.116	0.194
SMB_STAR	312	0.001	0.021	-0.089	-0.012	0	0.012	0.102	-0.131
HML_STAR	312	0.001	0.016	-0.055	-0.009	0	0.01	0.064	0.142
RMW_STAR	312	0.003	0.015	-0.097	-0.005	0.003	0.011	0.086	0.274
CMA_STAR	312	0.002	0.011	-0.025	-0.005	0.001	0.009	0.056	-0.126
PEAD	312	0.461	2.071	-9.03	-0.63	0.545	1.535	11.98	0.018
FIN	312	0.537	4.386	-24.56	-1.515	0.275	2.435	20.42	0.724

Table 2

Manager uncertainty (MU) and firm-specific characteristics

This table shows results from Fama-MacBeth regressions of MU on firm-level characteristics. Panel A shows the results of regressing MU on firms' characteristics, including the beta loading of excess market return (β^{MKT}), the logarithm of market capitalization (SIZE), the logarithm of book to market ratio (BE), book asset growth (I/A), operating profitability (ROE), momentum (MOM), short-term reversal (REV), Amihud illiquidity (LIQ), Skewness (SKEW), and Kurtosis (KURT). Panel B shows the results of regressing MU on firms' uncertainty-related and textual- related characteristics, including option-implied volatility (VOLI), realized volatility (VOLR), volatility of volatility (VOV), idiosyncratic volatility (IDVOL), analysts' forecast dispersion (DISP), the ratio of positive words ($LM_{positive}$), the ratio of negative words ($LM_{negative}$), the ratio of uncertainty words ($LM_{uncertain}$), management tone (Tone), fog readability index (Fog), and smog readability index (Smog). The t-statistics are in parentheses, which are adjusted by Newey-West standard errors. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. "Obs." is the average number of observations (stocks) from each cross-sectional regression. "Adj. R2" is the average of adjusted R squares. The sample period is January 1993 to December 2018.

Panel A: Regressing manager uncertainty on firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
β^{MKT}	1.711***										1.525***
	(11.52)										(8.09)
SIZE		-0.691***									-0.754***
		(-7.76)									(-8.82)
BM			-0.452***								-1.241***
			(-2.63)								(-8.01)
I/A				-0.637*							-0.322*
				(-1.70)							(-1.94)
ROE					-0.632***						-1.492***
					(-3.58)						(-3.27)
MOM						-0.011***					-0.014***
						(-2.95)					(-4.58)
REV							-0.018***				-0.013**
							(-3.49)				(-2.57)
LIQ								-0.010***			-0.015***
								(-3.41)			(-2.71)
SKEW									-0.096**		-0.090
									(-2.35)		(-1.57)
KURT										-0.041*	-0.024
										(-1.76)	(-1.03)
Constant	15.288***	21.287***	16.779***	17.312***	17.268***	17.367***	17.242***	17.302***	14.477***	14.199***	19.077***
	(17.47)	(18.55)	(22.63)	(21.95)	(22.37)	(22.36)	(23.13)	(23.61)	(19.03)	(18.74)	(14.65)
Obs.	4604	3846	3442	3442	3442	3845	3846	4604	4604	4604	2734
Adj. R^2	0.019	0.011	0.007	0.001	0.001	0.007	0.004	0.003	0.001	0.001	0.049

Panel B: Regressing manager uncertainty on existing firm-level uncertainty measures and textual related characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VOLI	9.679***											2.544***
	(15.88)											(2.88)
VOLR		5.844***										0.244
		(13.60)										(0.32)
VOV			18.576***									2.044
			(6.86)									(0.72)
IDVOL				98.924***								3.742**
				(13.86)								(1.99)
DISP					0.383**							0.020
					(2.46)							(1.58)
$LM_{negative}$						3.354***						
						(5.08)						
$LM_{postive}$							9.157***					
							(5.93)					
$LM_{uncertain}$								0.276				0.993***
								(0.20)				(3.59)
Tone									-1.947***			-1.633***
									(-4.64)			(-13.97)
Fog										1.098***		-1.013
										(4.57)		(-1.23)
Smog											1.581***	2.737**
											(5.62)	(2.27)
Constant	11.597***	14.510***	14.745***	14.524***	16.479***	12.127***	11.417***	16.169***	15.390***	-4.904	-10.393**	-14.202***
	(17.95)	(19.03)	(24.67)	(22.81)	(25.33)	(11.59)	(21.09)	(10.60)	(10.60)	(-1.02)	(-2.11)	(-2.70)
Obs.	2371	3228	2366	4604	2271	4520	4520	4520	4520	4103	4103	1436
Adj. R^2	0.047	0.029	0.015	0.032	0.001	0.020	0.030	0.027	0.009	0.048	0.049	0.065

Table 3

Cross-sectional asset pricing tests for manager uncertainty

This table reports results of the Fama-Macbeth regressions of regressing individual excess stock returns on the firm-specific variables. The core explanatory variable is the firm-level MU. In Panel A, the control variables include the number of the word "uncertainty" ($N_{uncertain}$), the number of the word "risk" (N_{risk}), the ratio of positive words ($LM_{positive}$), the ratio of negative words ($LM_{negative}$), the ratio of uncertainty words ($LM_{uncertain}$), Management tone (Tone), and Smog readability (Smog). In Panel B, the control variables includes the implied volatility (VOLI), realized volatility (VOLR), volatility of volatility (VOV), idiosyncratic volatility (IDVOL), dispersion of analysts' earnings forecast (DISP), beta loadings of excess market return (β^{MKT}), the logarithm of market capitalization (SIZE), the logarithm of book to market ratio (BE), book asset growth (I/A), operating profitability (ROE), momentum (MOM), short-term reversal (REV), Amihud illiquidity (LIQ), Skewness (SKEW), and Kurtosis (KURT). The t-statistics are in parentheses, which are adjusted by Newey-West standard errors. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. "Obs." is the average number of observations from each cross-sectional regression. "Adj. R^2" is the average of adjusted R squares from each cross-sectional regression. The sample period is January 1993 to December 2018.

Panel A: Controlling for textual-based factors from Form 10-K/10-Q filings

	(1)	(2)	(3)	(4)	(5)	(6)
MU	-1.274***	-1.663***	-1.421**	-1.155***	-1.107***	-0.782***
	(-3.47)	(-3.56)	(-2.23)	(-3.42)	(-3.03)	(-5.35)
$N_{uncertain}$	-0.010					
	(-1.39)					
N_{risk}	0.000					
	(0.06)					
$NR_{uncertain}$		1.815		-0.548	-0.390	
		(0.42)		(-0.20)	(-0.14)	
NR_{risk}		-0.476		-0.324	-0.404	
		(-0.57)		(-0.38)	(-0.45)	
$LM_{negative}$			-0.295**	-0.325*		
			(-2.48)	(-1.86)		
$LM_{postive}$			1.063***	1.020***		
			(3.25)	(4.76)		
$LM_{uncertain}$			0.064	0.143	0.265	
			(0.35)	(0.84)	(1.26)	
Tone					0.382***	
					(3.49)	
Smog				-0.064*	-0.046	
				(-1.67)	(-1.29)	
MU#D_year						-0.026***
						(-8.86)
D_year						-0.313***
						(-5.61)
Constant	1.042***	1.034***	0.669	1.897***	1.890***	1.176***
	(3.46)	(2.85)	(1.43)	(2.75)	(2.92)	(44.83)
Obs.	3801	3801	3752	3599	3599	3801
Adj. R^2	0.009	0.039	0.0509	0.0569	0.053	0.005

Panel B: Controlling for firm characteristics

	(1)	(2)	(3)	(4)	(5)
MU	-0.931***	-1.472***	-0.646**	-1.931***	-1.971***
	(-3.08)	(-4.54)	(-2.35)	(-2.85)	(-4.54)
VOLI	-2.814***		-6.572***		
	(-3.36)		(-8.21)		
VOLR	-0.202		-0.225		
	(-0.27)		(-0.35)		
VOV	71.551***		62.189***		
	(5.07)		(4.01)		
IDVOL	-6.536***		-2.322		
	(-3.32)		(-1.32)		
DISP	-0.055*		-0.084**		
	(-1.87)		(-2.00)		
β^{MKT}		-0.077	0.279**		-0.169
		(-0.55)	(2.15)		(-1.28)
SIZE		-0.247***	-0.631***		-0.353***
		(-5.22)	(-10.21)		(-6.18)
BM		-1.018***	-1.056***		-1.011***
		(-7.35)	(-6.55)		(-7.26)
I/A		-0.361***	-0.343***		-0.366***
		(-6.52)	(-4.05)		(-6.64)
ROE		0.128	-0.939***		0.133
		(1.45)	(-3.88)		(1.50)
MOM		-0.005***	-0.006***		-0.004***
		(-3.09)	(-2.67)		(-2.87)
REV		-0.008**	-0.017***		-0.008**
		(-2.48)	(-3.25)		(-2.43)
LIQ		-0.009***	-1.482***		-0.009***
		(-6.17)	(-5.08)		(-6.17)
SKEW		-0.051	0.045		-0.042
		(-0.30)	(0.13)		(-0.24)
KURT		-0.140	-0.116		-0.144
		(-1.28)	(-0.84)		(-1.29)
MU#D_option				1.012**	0.636*
				(2.38)	(1.82)
D_option				0.129	0.593***
				(0.97)	(4.31)
Constant	1.819***	1.991***	6.768***	0.879***	2.422***
	(4.29)	(5.56)	(8.89)	(3.11)	(6.08)
Obs.	1385	2734	1084	3801	2734
Adj. R^2	0.085	0.070	0.158	0.009	0.073

Table 4

Cross-sectional asset pricing tests for an alternative manager uncertainty measure

This table reports the results of the Fama-Macbeth regressions of regressing individual excess stock returns on the firm-specific variables. The alternative manager uncertainty (MU_A) is average between MU in 10-K/10-Q filings and MU in earnings call transcripts. Tabulated control variables include the ratio of positive words ($LM_{positive}$), the ratio of negative words ($LM_{negative}$), and the ratio of uncertainty words ($LM_{uncertain}$), the implied volatility (VOLI), realized volatility (VOLR), volatility of volatility (VOV), idiosyncratic volatility (IDVOL), dispersion of analysts' earnings forecast (DISP). Untabulated control variables include beta loadings of excess market return (β^{MKT}), the logarithm of market capitalization (SIZE), the logarithm of book to market ratio (BE), book asset growth (I/A), operating profitability (ROE), momentum (MOM), short-term reversal (REV), Amihud illiquidity (LIQ), Skewness (SKEW), and Kurtosis (KURT). The t-statistics are in parentheses, which are adjusted by Newey-West standard errors. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. "Obs." is the average number of observations from each cross-sectional regression. "Adj. R2" is the average of adjusted R squares from each cross-sectional regression. The sample period is January 2007 to December 2017.

	(1)	(2)	(3)	(4)	(5)	(6)
MU_A	-0.651**	-0.627***	-0.673***	-0.696***	-0.600**	-0.608**
	(-2.26)	(-2.67)	(-2.84)	(-2.90)	(-2.10)	(-2.15)
$LM_{negative}$			-0.193			
			(-0.92)			
$LM_{positive}$			0.595			
			(0.93)			
$LM_{uncertain}$			-0.529*	-0.419		-0.530
			(-1.88)	(-1.37)		(-1.53)
Tone				0.176		0.024
				(0.87)		(0.11)
Smog				-0.083		-0.081
				(-1.35)		(-1.29)
VOLI					-7.253***	-7.063***
					(-5.03)	(-5.07)
VOLR					0.297	0.376
					(0.20)	(0.25)
VOV					100.754***	101.397***
					(4.06)	(4.10)
IDVOL					1.465	0.622
					(0.61)	(0.26)
DISP					-0.071	-0.061
					(-1.45)	(-1.23)
Constant	1.078**	0.911*	1.209**	2.646**	3.988***	5.624***
	(2.30)	(1.94)	(2.59)	(2.44)	(5.71)	(4.13)
Control	No	Yes	Yes	Yes	Yes	Yes
Obs.	1328	1200	1100	1099	679	679
Adj. R^2	0.003	0.085	0.090	0.087	0.158	0.160

Table 5

Predictive power of manager uncertainty over long horizons

This table presents the predictive power of manager uncertainty (MU) to cross-sectional stock returns. Specifically, I run Fama-Macbeth regressions of future stock returns on the monthly MU (MU_M) and firm characteristics (beta, SIZE, BM, I/A, ROE, MOM, and REV). Column (1) shows the n-month-ahead future return, e.g., "T+2" indicates using MU to predict 2-month-ahead stock returns. Column (2) shows the estimated coefficients of MU_M. Column (3) shows T-statistics of the coefficients, adjusted by the Newey-West standard errors. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. Column (4) shows the average number of stocks in cross-sectional regressions. Column (5) shows the average adjusted R squares. The sample period is from January 1994 to December 2018.

(1)	(2) Coef	(3) T-statistics	(4) Obs.	(5) Adj. R^2
T	-0.711**	(-2.22)	2,687	0.058
T+1	-0.673**	(-2.08)	2,682	0.057
T+2	-0.680**	(-2.12)	2,679	0.059
T+3	-0.643**	(-2.01)	2,676	0.058
T+4	-0.634**	(-1.98)	2,673	0.059
T+5	-0.663**	(-2.11)	2,670	0.059
T+6	-0.640**	(-2.03)	2,667	0.059
T+7	-0.611**	(-1.96)	2,662	0.060
T+8	-0.625**	(-2.02)	2,660	0.059
T+9	-0.653**	(-2.09)	2,658	0.059
T+10	-0.578*	(-1.86)	2,655	0.059
T+11	-0.569*	(-1.82)	2,652	0.059
T+12	-0.587*	(-1.88)	2,649	0.059
T+13	-0.570*	(-1.82)	2,648	0.059
T+14	-0.638**	(-2.03)	2,646	0.060
T+15	-0.609*	(-1.94)	2,642	0.059
T+16	-0.553*	(-1.73)	2,641	0.060
T+17	-0.534*	(-1.66)	2,636	0.060
T+18	-0.523	(-1.62)	2,635	0.060

Table 6

Portfolio analysis by sorting manager uncertainty

This table shows the average monthly portfolio returns sorted by manager uncertainty (MU). Panel A lists the result for univariate sorting by MU. For each year, quintile portfolios are formed by sorting individual stocks based on managers' uncertainty. The second column reports the average uncertainty ratio in each quintile. The third column is the average return in each quintile. The fourth column reports the average excess return for each quintile, which is the raw stock return minus the risk-free rate. Panel B reports the average excess return for portfolios that are sorted by MU and firm size. The last column and last row are portfolios that long the 1st quintile and short the 5th quintile. The t-statistics are in the parentheses. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. The sample period is January 1993 to December 2018.

Panel A: Univariate sorting by manager uncertainty

Quintiles	MU	R_{raw}	R
1 (low)	0.023	1.100***	0.879***
		(4.52)	(3.56)
2	0.083	1.090***	0.951***
		(3.47)	(3.12)
3	0.134	0.953***	0.784***
		(3.00)	(2.44)
4	0.218	0.813***	0.636*
		(2.36)	(1.85)
5 (high)	0.379	0.617*	0.451
		(1.76)	(1.28)
low (1)-high(5)		0.482***	0.427***
		(2.74)	(2.44)

Panel B: Bivariate sorting by manager uncertainty and firm size

		Firm Size					
	Quintile	1	2	3	4	5	1-5
MU	1	1.088***	0.882***	0.969***	0.769***	0.734***	0.354
		(3.93)	(3.51)	(3.23)	(2.70)	(2.97)	(1.48)
	2	1.108***	0.959***	1.049***	0.994***	0.744***	0.365
		(3.16)	(2.94)	(3.01)	(2.90)	(2.61)	(1.33)
	3	0.852**	0.808**	0.797**	0.787**	0.708***	0.144
		(2.14)	(2.25)	(2.28)	(2.30)	(2.56)	(0.49)
	4	0.739*	0.604	0.658*	0.638*	0.558*	0.180
		(1.80)	(1.51)	(1.69)	(1.79)	(1.95)	(0.59)
	5	0.454	0.249	0.442	0.559	0.660***	-0.206
		(1.27)	(0.63)	(1.08)	(1.54)	(2.47)	(-0.64)
	1-5	0.635***	0.632***	0.527***	0.211	0.075	
		(2.90)	(2.82)	(2.46)	(1.17)	(0.66)	

Table 7

Manager uncertainty factor and aggregate uncertainty measures

This table reports the slope coefficients from regressing the manager uncertainty factor (MUF) on existing uncertainty factors. UNC1, UNC3, and UNC12 are the one-month, three-month, and 12-month-ahead economic uncertainty indices from Jurado, Ludvigson, and Ng (2015). EPU is the economic policy uncertainty index from Baker, Bloom, and Davis (2016). EMV is the equity market volatility index from Baker et al. (2019). VIX is the CBOE volatility index. VRP is the variance risk premium from Zhou (2018). The t-statistics reported in the parentheses are adjusted for heteroscedasticity and autocorrelations. "Adj. R^2" is the adjusted R squares from each regression. "Obs." is the number of observations. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. The sample period is January 1993 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
UNC1	-2.003							-7.606***
	(-0.92)							(-3.43)
UNC3		-1.928						
		(-0.89)						
UNC12			-3.575					
			(-0.94)					
EPU				0.008*				0.000
				(1.85)				(0.09)
EMV					0.094***			0.102**
					(4.55)			(2.34)
VIX						0.049**		0.031
						(2.06)		(0.70)
VRP							-0.015*	-0.017**
							(-1.75)	(-2.30)
Constant	1.776	1.984	3.722	-0.371	-1.444***	-0.461	0.712***	2.914**
	(1.30)	(1.22)	(1.10)	(-0.80)	(-3.60)	(-1.12)	(3.62)	(2.17)
Obs.	312	312	312	312	312	312	312	312
Adj. R^2	0.004	0.003	0.004	0.012	0.060	0.015	0.011	0.100

Table 8

Spanning manager uncertainty factor by using existing factor models

This table reports the slope coefficients obtained by regressing manager uncertainty factor (MUF) on factors from existing factor models. The column (1) includes the excess market return (MKT_RF) as the CAPM model. Column (2) is Fama and French (1993) three-factor model, which includes MKT_RF, the small-minus-big size factor (SMB), and the high-minus-low book-to-market factor (HML). Column (3 is Fama and French (2015) five-factor model that adds with the robust-minus-weak operating profitability factor (RMW) and the conservative-minus-aggressive investment factor (CMA). Column (4) is Fama and French (2018) six-factor model with adding the up-minus-down momentum factor (UMD). Column (5) is Hou, Xue, and Zhang (2015)'s 4-factor model, which includes MKT_RF, SMB, the investment-to-assets (R_I/A, in line with CMA) and the profitability factor (R_Roe, in line with RMW). Column (6) is Daniel et al. (2020)'s adjusted five-factor model, which is a combination of each of the Fama and French (2015) five factors with five hedge-portfolios. Column (7) is Stambaugh and Yuan (2017)'s four-factor model that includes MKT_RF, SMB, and two mispricing factors, specifically, management factor (MGMT) and performance factor (PERF). Column (8) is Daniel, Hirshleifer, and Sun (2020)'s three-factor model that includes the MKT_RF, the financing factor (FIN), and the post-earning-announcement-drift factor (PEAD). Column (9) is the factor model that is selected by the adaptive LASSO method from all the factors mentioned above and augmented factors, such as the liquidity factor (LIQ), the short-term reversal factor (ST_REV) and the long-term reversal factor (LT_REV). The t-statistics are reported in the parentheses are adjusted for heteroscedasticity and autocorrelations. "Adj. R^2" is the adjusted R squares from each regression. "Obs." is the number of observations. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. The sample period is January 1993 to December 2018.

	(1) CAPM	(2) FF3	(3) FF5	(4) FF6	(5) HXZ4	(6) DMRS5	(7) SY4	(8) DHS3	(9) LASSO
MKT_RF	-0.348***	-0.256***	-0.193***	-0.155***	-0.099***	0.105	-0.114**	-0.093**	-0.106***
	(-8.36)	(-7.87)	(-5.61)	(-4.90)	(-2.63)	(1.15)	(-2.48)	(-2.42)	(-3.35)
SMB		-0.321***	-0.177***	-0.198***	-0.167***	-0.031	-0.218***		-0.159***
		(-7.02)	(-3.54)	(-4.39)	(-4.20)	(-0.30)	(-3.88)		(-3.45)
HML		0.406***	0.336***	0.379***		0.655***			0.266***
		(8.88)	(6.65)	(7.83)		(3.77)			(4.76)
RMW			0.352***	0.338***	0.543***	0.566***			0.332***
			(4.64)	(4.84)	(8.15)	(3.11)			(4.72)
CMA			-0.341**	-0.310**	0.377***	-0.512***			-0.417***
			(-2.29)	(-2.33)	(5.84)	(-2.88)			(-3.10)
UMD				0.112***					0.102***
				(3.77)					(3.57)
MGMT							0.512***		0.198***
							(8.86)		(2.82)
PERF							0.085**		
							(2.03)		
PEAD								0.101	
								(1.52)	
FIN								0.459***	
								(12.88)	
Constant	0.701***	0.611***	0.523***	0.438***	0.272**	0.313*	0.275*	0.247*	0.324***
	(4.47)	(4.97)	(4.55)	(3.90)	(2.10)	(1.96)	(1.74)	(1.71)	(2.73)
Obs.	312	312	312	312	312	312	288	312	288
Adj. R^2	0.235	0.518	0.608	0.635	0.576	0.174	0.496	0.544	0.666

Table 9

Horse race: beta loadings of aggregate uncertainty versus firm-level uncertainty

This table shows the comparison of beta loadings of manager uncertainty factor (β^{MUF}) and manager uncertainty (MU). Panel A shows the spanning test of regressing β^{MUF} on firm-level uncertainty measures and beta loadings of aggregate uncertainty factors. Panel B shows the asset pricing tests by regressing cross-sectional stock returns on these beta loadings of uncertainty factors and firm-level uncertainty measures. β^{UNC1} is beta loadings of the 1-month-ahead economic uncertainty index. β^{EPU} is beta loadings of the economic policy uncertainty index. β^{EMV} is beta loadings of the equity market volatility index. β^{VIX} is beta loadings of the VIX. Beta loadings for each factor above are obtained by regressing individual stock returns on the target factor and other control factors (MKT_RF, SMB, HML, CMA, RMW, LIQ, and UMD). The regression is implemented by a 60-month rolling window and requires at least 24 non-missing observations. Firm-level uncertainty measures include option-implied volatility (VOLI), realized volatility (VOLR), idiosyncratic volatility (IDVOL), volatility of volatility (VOV), analysts' earnings forecast dispersion (DISP). "Control 1" is a set of firm-level characteristics, including SIZE, BM, I/A, ROE, MOM, and REV. "Control 2" is a set of beta loadings for risk factors, including β^{MKT}, β^{SMB}, β^{HML}, β^{CMA}, β^{RMW}, β^{LIQ}, and β^{UMD}. T-statistics in parentheses are adjusted by Newey-West standard errors. "Obs." is the average number of observations from each cross-sectional regression. "Adj. R^2" is the average of adjusted R squares from each cross-sectional regression. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. The sample period is January 1993 to December 2018.

Panel A: Regressing beta loadings of manager uncertainty factor (β^{MUF}) on other uncertainty measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MU	-1.941***	-1.621***	-1.042***	-1.727***	-0.856***	-0.111***	-0.177***
	(-5.37)	(-18.56)	(-16.13)	(-10.69)	(-16.72)	(-3.06)	(-6.44)
β^{UNC1}				-0.001	0.001		0.002*
				(-0.85)	(0.87)		(1.76)
β^{EPU}				0.458	-0.453		-0.470
				(0.66)	(-0.75)		(-0.57)
β^{EMV}				0.555**	0.564***		0.541***
				(2.56)	(3.23)		(2.70)
β^{VIX}				0.056	0.030		0.039
				(0.25)	(0.16)		(0.18)
VOLI						-1.656***	-1.560***
						(-12.50)	(-13.91)
VOLR						0.070	0.098
						(0.96)	(1.31)
IDVOL						-0.484	-0.902**
						(-1.27)	(-2.36)
VOV						0.568***	0.536***
						(2.64)	(2.75)
DISP						0.004	0.004
						(1.10)	(1.00)
Constant	0.085***	-0.889***	-0.460***	0.069***	-0.386***	1.130***	0.960***
	(2.96)	(-7.69)	(-8.43)	(3.10)	(-7.34)	(15.04)	(15.47)
Control 1	No	Yes	Yes	No	Yes	Yes	Yes
Control 2	No	No	Yes	No	Yes	Yes	Yes
Obs.	2,993	2,789	2,788	2,992	2,788	1,085	1,085
Adj. R2	0.032	0.156	0.262	0.188	0.367	0.225	0.344

Panel B: Asset pricing tests: covariance versus characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β^{MUF}	0.106**	0.086**	0.086**	0.081	0.090*	0.004	-0.022
	(2.51)	(2.16)	(2.39)	(1.50)	(1.95)	(0.12)	(-0.43)
MU		-1.403***	-1.373***	-1.391***	-1.519***	-0.627***	-0.556***
		(-4.04)	(-5.81)	(-4.29)	(-6.93)	(-2.73)	(-2.72)
β^{UNC1}				-0.000	-0.001		0.002
				(-0.04)	(-0.13)		(0.17)
β^{EPU}				9.228**	11.822**		11.943**
				(2.19)	(2.59)		(2.37)
β^{EMV}				-1.370*	-1.607**		-1.885**
				(-1.87)	(-2.23)		(-2.21)
β^{VIX}				1.133	1.418		1.852*
				(1.18)	(1.48)		(1.69)
VOLI						-5.585***	-5.341***
						(-7.44)	(-8.36)
VOLR						-0.613	-0.270
						(-1.19)	(-0.55)
IDVOL						51.017***	50.524***
						(3.60)	(4.00)
VOV						-2.095	-0.847
						(-1.41)	(-0.64)
DISP						-0.080**	-0.066***
						(-2.50)	(-2.66)
Constant	1.837***	2.072***	1.731***	1.934***	1.488***	5.824***	5.110***
	(4.18)	(4.99)	(6.60)	(4.96)	(7.01)	(12.47)	(12.52)
Control 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control 2	No	No	Yes	No	Yes	Yes	Yes
Obs.	2,839	2,789	2,788	2,788	2,788	1,085	1,085
Adj. R^2	0.063	0.066	0.196	0.155	0.285	0.259	0.345

Table 10

Manager uncertainty and firm behaviors

This table shows the regressions of variables of firm behaviors on manager uncertainty (MU). INV is a firm's annual growth rate of physical assets in fiscal year t+1. EMP is a firm's annual employment growth rate in fiscal year t+1. WC is a firm's annual growth rate of the share of working capital over total assets in fiscal year t+1. CASH is a firm's annual growth rate of cash and short-term investments and in fiscal year t+1. MU_F is a firm's manager uncertainty in fiscal year t. TA is a firm's logarithm of total assets in fiscal year t. T-statistics in parentheses are adjusted by clustered standard errors. "Obs." is the number of observations. "Adj. R^2" is the overall R squares. I control firm-fixed and year-fixed effects. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively. The sample period is 1993 to 2018.

	(1) INV	(2) EMP	(3) WC	(4) CASH
MU_F	-0.075***	-0.032**	0.122**	0.299*
	(-4.25)	(-2.32)	(2.19)	(1.79)
TA	-0.092***	-0.094***	-0.051**	-1.174***
	(-16.56)	(-24.46)	(-2.51)	(-25.16)
Constant	0.706***	-0.419***	0.297***	6.432***
	(24.18)	(-18.90)	(3.25)	(22.17)
Firm-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
Obs.	108,767	111,282	107,407	118,515
Adj. R^2	0.192	0.136	0.101	0.076

Table 11

Managers' Uncertainty about COVID-19 and Cross-Sectional Returns in 2020Q1

This table presents the results of regressing excess stock returns in the first quarter of 2020 on managers' uncertainty about COVID-19 and control variables. The managers' uncertainty on COVID-19, COVID_MU, is computed as the number of the word "uncertainty" divided by the sum of the number of the word "uncertainty" and the number of the word "risk" within COVID-19-related paragraphs in the first quarter of 2020. The data of COVID-19-related paragraphs in conference calls is from Li et al. (2020). Stock return data is from CRSP. Controls variables include beta loadings of Fama and French (2018)'s six factors, estimated from regressing stock returns on these six factors in previous 60 months (January 2015 to December 2019). T-statistics in parentheses are adjusted by robust standard errors. "Obs." is the number of observations. "Adj. R^2" is the adjusted R squares. *, **, and *** indicate the significance level at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Covid_MU	-4.928***	-4.921***	-4.610***	-3.772***	-4.198***	-2.908**
	(-3.57)	(-3.56)	(-3.34)	(-2.76)	(-3.07)	(-2.16)
β^{MKT}		0.035	0.070	-0.355	0.424	-0.025
		(0.12)	(0.19)	(-0.77)	(1.22)	(-0.06)
β^{SMB}			-0.006	-0.284	-0.019	-0.423
			(-0.02)	(-1.09)	(-0.08)	(-1.57)
β^{HML}			-1.245***	-3.264***	-2.899***	-6.759***
			(-3.88)	(-7.52)	(-6.26)	(-11.17)
β^{UMD}				5.133***		7.207***
				(7.16)		(9.04)
β^{RMW}					-0.627***	-0.686***
					(-2.78)	(-3.23)
β^{CMA}					-1.725***	-2.876***
					(-5.41)	(-7.83)
Constant	-33.976***	-34.017***	-34.250***	-33.526***	-34.902***	-34.107***
	(-34.05)	(-33.23)	(-31.90)	(-30.74)	(-32.95)	(-32.40)
Obs.	1,980	1,980	1,980	1,980	1,980	1,980
R^2	0.007	0.007	0.017	0.055	0.038	0.105