How Do Mutual Fund Investors React to Text-Based Uncertainty?*

Shema F. Mitali†

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Abstract

This paper measures the extent of uncertainty in mutual fund communication and its effects on fund flows. I test the hypothesis that mutual funds communicating more about uncertainty might avoid large outflows. Investors appear to react to this form of communication, as the use of uncertain terms has a positive effect on fund flows for poorly performing funds. This finding helps explain the convexity of the flow-performance relationship. A word embedding approach shows that market-related uncertainty discussion matters for fund flows, rather than specific risks. Investors' reaction to uncertainty in mutual fund communication results in capital misallocation across funds.

Keywords: Uncertainty, Information, Mutual Funds, Fund Flows, Textual Analysis, Disclosure

JEL codes: D80, D83, G11, G14, G23

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†EPFL. Email: Shema.Mitali@epfl.ch

1 Introduction

Information provision by firms is important for consumers as it affects their propensity to buy a product. Corporations use different forms of communication, such as advertising or mandated disclosure, notably with the purpose of persuading consumers. Similarly, mutual funds might communicate strategically in order to influence investors' allocation decisions. As mutual funds compete for investors' capital, the literature has focused on studying how mutual funds differentiate themselves through their products (e.g., Wahal and Wang 2011, Khorana and Servaes 2012, Hoberg, Kumar, and Prabhala 2018). Recently, researchers have highlighted the importance of mutual fund prospectuses on fund flows (e.g., Kostovetsky and Warner 2019, Abis, Buffa, Javadekar, and Lines 2021). However, important questions remain on the type of communication between mutual funds and investors in explaining the industry's size and survival of poorly performing funds.[1]

In this paper, I explore how mutual funds' use of terms related to uncertainty in their communication channels can affect their investors' assessment of their products. Mutual funds are required by the Securities and Exchange Commission to describe their investment strategies in prospectuses on a regular basis. There is little guidance about how extensively they can discuss the many aspects related to fund characteristics such as the investment strategy, recent performance or the state of the economy. Thus, even in the presence of disclosure mandates, mutual funds have room for strategic communication by, for instance, providing uninformative details.[2] I hypothesize that the use of terms related to uncertainty might affect investors' investment decisions and that mutual funds in the bottom distribution of performance might engage

[1]As of 2021, the size of the mutual fund industry represented approximately $27 trillion of assets under management according to the Investment Company Institute. Figure 1 shows the evolution of the total assets under management of U.S. active equity mutual funds.

[2]For example, Persson (2018) shows theoretically that even with disclosure mandates, information overload can arise in equilibrium, which obfuscates financially-relevant characteristics.

in strategic communication to mitigate outflow risk.

Using a dictionary-based textual analysis of U.S. mutual funds prospectuses from 2011 to 2020, I count the number of occurrences of words related to uncertainty, following Loughran and McDonald (2011). Conditional on poor performance, mutual funds that discuss uncertainty receive higher fund flows. More precisely, a one standard deviation increase in the proportion of uncertain words leads to a $1.8M average increase in flows in the following month for a poorly performing mutual fund, or a 12% increase relative to the sample average fund flows.

To illustrate the economic magnitude of the effect of text-based uncertainty on fund flows, instead of being punished by a hypothetical $5M of outflows in a given month, as would be predicted by a rational framework (Berk and Green 2004), a poorly performing mutual fund would experience only $3.2M of outflows if its prospectus emphasizes uncertainty. Over an entire year, this amounts to more than $21M, *per fund*, that are misallocated or an aggregate $10B per year, i.e., capital that remained in a poorly performing fund while it could have been reallocated to another mutual fund in the top of the performance distribution.[3]

To understand why uncertain language is related to fund flows, Mullainathan, Schwartzstein, and Shleifer (2008)'s model offers general insights to rationalize this result. They show, in a theoretical framework, how advertisers can take advantage of information receivers' perception of a product's quality through uninformative messages. The authors also document that around market downturns, mutual funds and other financial actors advertise relatively less their own performance. For example, anecdotal evidence shows that Merrill Lynch would emphasize the uncertainty in the world after market downturns. This paper contributes to this theoretical explanation

[3] The economic effect takes into account the average number of funds in the bottom distribution of performance while discussing uncertainty. It also assumes a form of performance persistence, that is mutual funds in the bottom performance distribution would continue to underperform (Carhart 1997). In additional results, I find that investors who remained with poorly performing funds that discussed uncertainty keep underperforming going forward.

by providing new empirical evidence showing that investors are affected by uninformative disclosure when assessing mutual funds' products; especially when these institutions personally experience downturns. The relationship between uncertain language and fund flows has important implications for investors and regulators as mutual funds still have room for strategic communication.[4]

Investors judge mutual fund managers on their past relative performance (Chevalier and Ellison 1997; Berk and Green 2004); i.e., the fund's returns over the benchmark returns (e.g., S&P 500). While a mutual fund can hardly obfuscate the first component of relative performance in its mandatory disclosed documents, it can emphasize on the volatility of the second component, i.e., the benchmark. Thus, a poorly performing fund could benefit from uncertain language when its own performance is poor. I show, using a word embedding model (e.g., Cong, Liang, and Zhang 2019; Hanley and Hoberg 2019; Li, Mai, Shen, and Yan 2021), that the uncertainty-flow relationship appears to be concentrated among funds that associate uncertainty with terms related to the market and the economy, rather than terms related to firm-specific risk.

One concern behind this empirical exercise is the possibility that mutual funds discuss uncertainty as a truthful reflection of their investment approach and risk from their positions, thus making uncertainty in the text possibly correlated with risk from investments. To examine if firm-level risk relates to uncertainty discussion, I use a measure of firm-level risk exposures (Alfaro, Bloom, and Lin 2018), aggregated at the portfolio level, as additional control. Yet, it is also possible that risky positions are absent from reported holdings, making holdings-based risk measures partially reliable.[5] Thus, using both holdings-based measures of risk from investments, and non-holdings

[4] Figure 2 shows that uncertain language from poorly performing mutual funds amplifies during uncertain periods as proxied by the VIX index, consistent with Mullainathan et al. (2008).

[5] Fund managers might window-dress risky positions (Musto 1997, 1999; Agarwal, Gay, and Ling 2014) and thus making investors unaware of the risky stocks that are present in the fund returns but absent of the holdings in the reported period.

based measures (e.g., standard deviation of recent fund returns), as well as a measure of discrepancy between holdings-based return measure and realized returns as proxy for unobserved actions of mutual funds (i.e., *Return Gap* from Kacperczyk, Sialm, and Zheng 2008), I find that the flow-uncertainty discussion relationship cannot be explained by other measures of risk from investments.

An alternative explanation for the influence of language on investors decision is limited attention. It is possible that investors don't read these documents or perhaps face more difficulties processing information in a large document that contains more words related to uncertainty as in limited information processing models (e.g., Sims 2003). Alternatively, sophisticated investors might spend more time examining other information related to mutual funds. To test this possibility, I explore the role of uncertainty language on flows separately for retail funds and institutional funds and find that institutional investors react more, suggesting that retail investors are less likely to read these documents and that more resources are devoted by institutions to extract additional signals from prospectuses.

This paper's contribution is threefold. First, it contributes to the large literature on mutual fund performance and the active fund puzzle. Gruber (1996) argues that the growth of the active fund management industry represents a puzzle given the lack of evidence of performance. Chevalier and Ellison (1997) and Sirri and Tufano (1998) show that flows to funds are strongly related to past performance. Later, Berk and Green (2004) provide a rational model to explain this flow-performance relationship. Jiang, Starks, and Sun (2016) find that this relationship changes in periods of high economic policy uncertainty or in extreme market periods (Franzoni and Schmalz 2017). More recently, Dou, Kogan, and Wu (2021) show how common outflow risk, which is negatively impacted by economic uncertainty, is important for mutual funds and how it can affect portfolio positions. This study shows that *individual* fund flows, as opposed to common, can be positively impacted by uncertainty discussion, in the spirit of Mullainathan et al. (2008). This study also expands this strand of the literature by providing novel evidence that fund-level uncertainty, measured from prospectuses, affects outflows.

Second, this paper contributes to the literature on the application of text analysis in finance. While many researchers have focused on firms reports, fewer have looked at the institutional investors reporting language. Hillert, Niessen-Ruenzi, and Ruenzi (2020) look at sentiment measures in fund communication and find that positive tones positively affect fund flows while Kostovetsky and Warner (2020) show that investors respond strongly to a measure of textual uniqueness of the strategy section of the prospectus. This paper differs from these as it focuses on uncertainty in mutual fund communication rather than positive or negative sentiment measures or uniqueness measures. Prior research has shown the importance of uncertainty, whether political, economic or financial, in a number of contexts such as the relationship between uncertainty and corporate investment (e.g., Gulen and Ion 2016, Kim and Kung 2017), stock returns (e.g., Bali, Brown, and Tang 2017) or attention to firm-level news (Andrei, Friedman, and Ozel 2021). However, uncertainty hasn't been explored yet in the context of mutual funds prospectuses and potential effects for investors' capital allocation decisions and this paper aims to fill this gap. A growing literature takes a closer look at mutual funds from the perspective of the products they offer. More recently, Bonelli, Buyalskaya, and Yao (2021) study choices of product differentiation through textual descriptions of fund prospectuses. Also building on prospectuses, Abis and Lines (2020) build peer groups from prospectuses and show that mutual funds invest according to the descriptions of prospectuses. This paper adds that communication might change conditional on outflow risk and that this affects investors' capital allocation decisions. Abis et al. (2021) show in a related study that more descriptive prospectuses show a greater flow-performance sensitivity while generic descriptions of strategies are more volatile in terms of flows. Finally, another recent study by Sheng, Xu, and Zheng (2022) match risks disclosed in other fund documents to academic risk factors but find little relationship with flows, except for sophisticated investors, and that mutual funds might overdisclose risk when experiencing outflows and underperforming, which is consistent with this paper's results. This paper adds that discussion of uncertainty in prospectuses matters for poorly performing funds' flows, thus providing additional explanations to the the convexity of the flow-performance relationship.

Third, this study contributes to an extensive literature on information economics and communication. Researchers have long studied asymmetric information between economic agents its consequences on strategic communication (e.g., Grossman 1981; Milgrom 1981; and Crawford and Sobel 1982). Thus communication between two parties can be a useful tool for an information receiver (Stigler 1961), but also a strategic one for the sender (Lippmann 1922). For example, Bertrand, Karlan, Mullainathan, Shafir, and Zinman (2010) show that consumers can be persuaded to take up loans in the context of direct-mail solicitations in South Africa. In politics, DellaVigna and Kaplan (2007) show that having access to Fox News made voters more likely to choose the Republican party in 2000. In financial markets, Engelberg and Parsons (2011) show that local trading responds to local coverage of earnings announcements. In Sweden's mutual fund industry, Cronqvist (2006) shows how mutual funds' advertising can be uninformative for investors. This paper shows how investors are influenced by the way mutual fund communicate in prospectuses with important consequences on fund flows and size.

2 Institutional Background

Registered management investment companies have to complete and file prospectuses and semiannual reports with the Securities and Exchange Commission according to the Investment Company Act of 1940. Management investment companies are firms that sell fund shares to the public.

Prospectuses must include a "principal investment strategies" (PIS) section. This section is used by funds to describe in what type of securities fund managers primarly invest and how they choose which securities to purchase in general terms (Abis and Lines 2020). Prospectuses must be updated at least once a year.

"Hard" information related to the performance, risk, and fees are mandatory in the prospectus. However, there are no requirements regarding the length of the discussion, especially in the strategy section. Thus, even in the presence of a disclosure mandate, information overload and additional "soft" information can arise, potentially at the expense of consumers (Persson 2018). Moreover, the narrative used in the PIS sections related to investment strategies are more discretionary (Andrikogiannopoulou, Krueger, Mitali, and Papakonstantinou 2022). The only requirements are that these documents must be written in plain english and simple language.

3 Hypotheses

Recent research shows that description of fund prospectuses, and more specifically the uniqueness of the text, matter for investors (Kostovetsky and Warner 2020). Moreover, strategic communication can arise even in a regulated framework. Given the recent evidence on the importance of uncertainty in text documents (e.g., Baker, Bloom, and Davis 2016), the first tests explore whether mutual funds that discuss uncertainty in their prospectuses experience a change in fund flows, the hypothesis being that investors shouldn't be influenced by "soft" information, such as uncertainty-related terms, over hard information.

- ***Hypothesis 1* (no effect)**: Investors make capital allocation decision purely based on hard information, i.e. performance, risk, fees, and thus do not react to uncertainty in prospectuses.

If mutual funds face significant outflow risk, typically following low relative performance, funds might engage in strategic communication, typically via information overload or by discussing the economy or its uncertain states. Thus, investors might be sensitive to uncertainty in prospectuses, if funds experience poor performance, and the effect might be due to mutual funds being strategic and mentioning uncertainty as the reason for poor performance and/or investors interpreting uncertainty as separate from fund managers' skills. In other words, mutual funds might be reacting to low performance, to address outflow risk, or investors might be reacting to uncertainty in the text, or both.

- ***Hypothesis 2*** **(non-zero effect conditional on low performance)**: Uncertainty discussion in prospectuses affects fund flows, conditional on poor performance, as investors might be paying more attention to other sources of information, such as soft information, when mutual funds perform badly.
- ***Hypothesis 2A*** **(positive effect due to strategic communication)**: The positive effect on fund flows of uncertainty might be resulting from funds strategically blaming uncertainty for poor performance so that investors interpret uncertainty as responsible for poor performance and thus do not punish fund managers with significant outflows. In this way, mutual funds can mitigate outflow risk.

Finally, risk and uncertainty can typically be separated in different categories such as systematic risk or indiosyncratic risk. Fund managers might be very active and be exposed to idiosyncratic risk or be closet indexers and mainly experience market risk. As fund managers might potentially engage in strategic communication, they would likely blame market risk, which is outside of their control as responsible for poor performance or investors might interpret systematic risk as responsible for poor performance. Thus, the final hypothesis is as follows:

- ***Hypothesis 2B* (positive effect conditional on performance and market-related uncertain terms)**: Uncertainty discussion in prospectuses has a positive effect on fund flows, conditional on poor performance and market-related uncertainty discussion.

4 Data and Methodology

In this section I describe the various data sources and variables used in the empirical analysis.

4.1 Mutual Fund Characteristics

I obtain monthly mutual fund characteristics and holdings from the CRSP Survivorship-Bias-Free Mutual Fund Database. Namely, I collect information on fund size (total net assets; TNA), returns, age, turnover ratio, and expense ratio. I focus on U.S. active mutual funds by using the CRSP index fund identifier.[6] I impose funds to have a minimum size of $10 million. I compute monthly flows as the percentage change of fund size on top of fund returns. More specifically, flows is computed as follows:

$$flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{1}$$

where $TNA_{i,t-1}$ and $TNA_{i,t}$ are fund i's total net assets at the end of month $t-1$ and t, respectively, while $R_{i,t}$ is fund i's return over the month t.

To measure fund performance, I follow prior studies (e.g., Kacperczyk, Sialm, and Zheng 2005; Ben-David, Li, Rossi, and Song 2022) and define it as the difference

[6] In further tests, I restrict the sample to active domestic equity funds by requiring the CRSP investment objective code to start with "ED", where the "E" stands for equity and the "D" stands for domestic.

between a fund's realized return and its return predicted by a factor model. I use the Carhart (1997) four-factor model using monthly data. With a rolling window of 60 months as in Ben-David et al. (2022), I estimate factor loadings and use the estimates without the intercept the obtain the predicted return. More specifically, I estimate the following four-factor model for fund i at month t:

$$R_{i,\tau} - Rf_{\tau} = a_{i,t} + \beta_{i,t}(MKT_{\tau} - Rf_{\tau}) + s_{i,\tau}SMB_{\tau} + h_{i,\tau}HML_{\tau} + u_{i,\tau}UMD_{\tau} + \epsilon_{i,\tau}, \quad (2)$$

where $\tau = t-60, ..., t-1$, $R_{i,\tau}$ is the fund i's net return in month τ, Rf is the one month Treasury bill, MKT (market), SMB (size), HML (value), and UMD (momentum) are the four factors as in Carhart (1997). Then, I define fund performance α as follows:

$$\alpha_{i,t} = R_{i,t} - Rf_t - [\hat{\beta}_{i,t}(MKT_t - Rf_t) + \hat{s}_{i,t}SMB_t + \hat{h}_{i,t}HML_t + \hat{u}_{i,t}UMD_t], \quad (3)$$

where the coefficient denote by a hat are estimated from equation (2).

To proxy for a fund's propensity to take systematic risk, such as deviating from a benchmark, I use the factor loading on the market factor from the CAPM (β from equation (2) but based on the CAPM, that is, without the factors SMB, HML, and UMD).

4.2 Mutual Fund Communication

I collect mutual fund prospectuses' PIS descriptions from the SEC Edgar database starting from 2011:Q1. These documents are identified by a fund's series CIK (central index key; which is the identifier for the SEC Edgar database) which is matched to CRSP data using the CRSP-CIK table.

The documents are cleaned following Gentzkow, Kelly, and Taddy (2019). I first remove all elements of the text other than words (e.g., html tags, numbers, punctuations). Then, I remove stop words using Porter (1980).[7] I provide in the Appendix a detailed description of the steps involved in the text analysis from the collection of fund documents to the measurement of uncertainty.

4.3 Text-Based Uncertainty

To measure uncertainty in the mutual fund strategy section of the prospectus, I start by using a dictionary-based method following Loughran and McDonald (2011). The authors measure the frequency of words related to uncertainty in firms' SEC 10K filings. While these terms might be more relevant for firms than mutual funds, it picks up the most important uncertainty terms that appear in prospectuses, such as "risk", "volatility"; and "uncertain" or "unpredictable".[8] Thus, uncertainty is measured as:

$$Uncertainty_{i,t-1} = \frac{c_{i,t-1}}{wc_{i,t-1}}, \tag{4}$$

where $c_{i,t-1}$ is the raw count of words in the uncertainty list of Loughran and McDonald (2011) in PIS of fund i in period $t-1$ and $wc_{i,t-1}$ is the total word count of the strategy section. The Appendix shows an example of content from a principal investment strategies section with highlighted selected relevant words.

As an alternative measure, I use the economic policy uncertainty (EPU) index from Baker et al. (2016). This measure can be relevant as it correlates with stock market volatility and potentially allows funds to emphasize the degree of uncertainty by using more words taken from the list proposed by the authors. As it echoes the words used by journalists in top U.S. newspapers, it amplifies the degree of uncertainty of investors who potentially read both mutual fund prospectuses and U.S. newspapers.

[7] Stopwords include words such as "the", "a", or "and".
[8] The full list is included in the Appendix.

Moreover, measuring market uncertainty is relevant since mutual fund managers measure performance relative to an index which often refers to a market index. Thus, a text measure of economic policy uncertainty could also serve as a proxy of volatility of the second component of fund performance.[9]

These dictionary-based methods might raise concerns, when other more recent unsupervised methods are available. The objective of this study is to examine the role of uncertainty discussion on mutual funds investors allocation decisions. Having such prior about the economic relationship at play makes these approaches appropriate (Gentzkow et al. 2019), while other studies, e.g., Abis et al. (2021), would rely on unsupervising methods to uncover qualitative information from prospectuses. Exisiting text measures of uncertainty have proven useful in capturing other measures of volatility, whether it is uncertainty from Loughran and McDonald (2011) or economic policy uncertainty from Baker et al. (2016). Moreover, these measures are known and have been adopted by other market participants (Baker et al. 2016). Figure 2 shows that the time series of the average of $Uncertainty$ for low performing mutual funds manages to capture most of large variations of the VIX index and amplifies them. Therefore, it is especially useful to use simple existing dictionary-based methods when studying potential strategic behavior from mutual funds in their communication, as recently shown by Cao, Jiang, Yang, and Zhang (2020) in the case of firms. Nonetheless, final sections of this study include word embeddings approach around uncertainty to uncover the types of risk that mutual funds discuss.

Table 1 summarizes the variables used in this study. Thus, the sample period is 2011 to 2020 and contains 1,182,281 fund-month observations. Uncertainty represents on average, as well as median, 2.8% of the strategy section of the prospectus. How-

[9] Jiang et al. (2016) show that economic policy uncertainty is important in the context of mutual funds as investors face more difficulties when evaluating managers skills and thus changing the flow-performance relationship in periods of high uncertainty. At the firm-level, prior research shows that economic policy uncertainty is relevant for mergers and acquisitions, as well as corporate investments (Gulen and Ion 2016; Bonaime, Gulen, and Ion 2018).

ever, it shows substantial variation across funds with a standard deviation of 1.6% with a maximum of 14% of the strategy section discussing uncertainty. Moreover, mutual funds tend to write more positive than negative strategy sections as proxied by Loughran and McDonald (2011) sentiment dictionaries (on average 1% of the PIS is positive words and the average number of negative words is 0.5%). Panel B shows that the average fund has monthly flows of 0.8%, is 13 years old, and has an annual turnover of 82%.

5 Results

In this section I present the results of the various tests performed to explore how uncertainty language might affect investors' behavior.

5.1 Fund Flows and Uncertainty Language

To explore if fund uncertainty discussion has any effect on funds flows, I first estimate the following regression:

$$flows_{i,t} = \beta_0 + \beta_1 Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}, \tag{5}$$

where $Uncertainty_{i,t-1}$ is measured following Loughran and McDonald (2011). The set of controls in $X_{i,t-1}$ includes fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), turnover ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, the squared of fund performance to account for the convexity of the flow-performance relationship (Chevalier and Ellison 1997), and fund systematic risk as measured by the beta coefficient from the CAPM model. I include fund and style $\times$ time (month) fixed effects and double-cluster standard errors by fund and time.

Table 2 column (1) presents the results. $Uncertainty_{i,t-1}$ appears to be insignificant. That is, mutual funds that discuss uncertainty in the strategy section of their prospectuses do not experience higher or lower fund flows. This confirms *Hypothesis 1* which states that investors mostly use hard information, contained in the set of controls, when choosing allocating money to mutual funds.

Then, I investigate if uncertainty discussion might matter for funds flows when these experience outflow risk, the reason being that mutual funds might engage in strategic communication to avoid significant outflows. To test this hypothesis (*Hypothesis 2*) I estimate the following regression:

$$flows_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \quad (6)$$

I define $LowPerf_{i,t-1}$ as an indicator variable that takes the value 1 whenever fund i is in the bottom decile of the performance distribution as of the end of month $t-1$ in each style category (56 CRSP objective investment code).[10] The set of controls contains the same set of fund characteristics as in Equation (5) but also includes the two terms of the interaction separately ($LowPerf_{i,t-1}$ and $Uncertainty_{i,t-1}$). Columns (2)-(5) of Table 2 present the results. The interaction term shows a positive and statistically significant coefficient (0.059; t-stat= 2.41 in column (5)). The effect of uncertainty language has a positive effect on fund flows for funds with low performance. A poorly performing mutual fund that increases the proportion of uncertain words by 1.6 percentage points (one standard deviation) would experience a 9% increase relative to average monthly flows. In economic terms, a fund with low performance relative to its peers will have higher flows (or avoid outflows) by approximately \$1.8M if it increases its uncertainty language by one standard deviation. For example, supposed

[10]In robustness tests, I restrict the sample to active equity domestic funds, using the CRSP objective investment code and find similar results (see Table A1 in the Appendix). I also use different cutoffs when identifying low performing funds and find similar results. Additionally, Table A2 shows similar results when using a continuous measure of performance, rather than a dummy.

that investors should withdraw a hypothetical \$5M of outflows for poor performance in month $t-1$ (and reallocate it to better performing funds; Berk and Green 2004), it will experience only approximately \$3.2M of outflows if the fund discusses uncertainty in its prospectus. Other controls are consistent with prior literature. Fund flows are persistent, that is lagged flows positively predicts future flows. Moreover, investors are highly responsive to performance.[11] They punish poorly performing funds with outflows and reward good performing funds with inflows. Old and large funds receive less flows which is consistent with the decreasing returns to scale explanation (Berk and Green 2004). Overall, this suggests that investors look closer to soft information when observing low performance from their investments, which supports *Hypothesis 2*.

5.1.1 Robustness. Table 3 presents different tests with alternative measures of uncertainty and low performance definition. Removing fund fixed effects decreases the statistical significance of the positive relationship between uncertain language for poorly performing funds and flows (column (1)), suggesting that most effects come through within-fund variation and less on the cross-section.[12] Column (2) of Table 3 shows that the main results are robust to alternative cutoffs for defining mutual funds with low performance (quintile vs decile). Using the economic policy uncertainty (EPU) measure from Baker et al. (2016) also shows that investors positively react to EPU language in prospectuses for poorly performing funds. Moreover, using alternative groups for clustering standard errors provides similar results (see Table

[11]It is also important to note that investors reward poorly performing funds that discuss uncertainty, but they do not rightfully do so, as Table A3 in the Appendix shows that low performing funds that discuss uncertainty keep performing poorly going forward. Moreover, low performing funds that discuss uncertainty spend more on marketing expenses as shows Table A4, highlighting the important role of marketing in reducing investor welfare (Roussanov, Ruan, and Wei 2021). This difference is also illustrated in Table A5 which shows a larger negative effect on net returns of uncertainty discussion from poorly performing funds, compared with gross returns.

[12]Moreover, the effects appear to be short-lived as Table A6 in the Appendix shows that the effects for fund flows at $t+2$ are weaker.

A8 in the Appendix).[13] When building on measuring of skills in the spirit of Berk and Van Binsbergen (2015) which captures the dollar value created by fund managers, rather than abnormal performance, Table A7 shows that results are similar, i.e., fund managers in the bottom of the skill distribution benefit from better fund flows when discussing uncertainty.

In the interest of exploring how uncertainty might interact with other fund characteristics, Table A10 in the Appendix shows results from panel regressions of (6) with additional independent variables that interact each fund control with $Uncertainty_{i,t-1}$. Results show that high uncertainty discussion accompanied with high return, beta, or past fund flows negatively affect subsequent flows, while expenses positively affect fund flows when interacted with uncertainty discussion. It is possible that high past return and fund flows negatively affects fund flows when funds discuss uncertainty if investors see uncertainty as a negative signal going forward, as opposed to uncertainty acting as an exonerating device in the case of low performing funds. If a fund exhibit a high beta while discussing uncertainty experiences lower subsequent fund flows possibly reflects higher risk aversion from investors. Interstingly, uncertainty discussion together with high expense ratio has a positive effect on fund flows. One potential explanation is the obfuscating role of uncertainty discussion, which is consistent with (DeHaan, Song, Xie, and Zhu 2021). More importantly, the interaction term between uncertainty discussion and low performance remains positive and statistically significant in column (2) of Table A10 where fund fixed effects are included.

[13]Table A9 in the Appendix also shows that results are robust when excluding the subsample post-March 2020 (Covid), yet weaker suggesting that uncertainty communication played a large role at the height of the market turmoil caused by the Covid crisis. Nonetheless, when estimating 1000 times the regression described in (6) while dropping each time a random small subsample of the observations (e.g., dropping 5%; Broderick, Giordano, and Meager 2020, Gormley, Kaviani, and Maleki 2021), results appear strongly robust as Figure A3 in the Appendix shows the p-values of the main cofficient ($LowPerf_{i,t-1} \times Uncertainty_{i,t-1}$ with a maximum p-value of 0.088). Figure A4 also shows that the main coefficient on $LowPerf_{i,t-1} \times Uncertainty_{i,t-1}$ remains stable, positive and importantly statistically significant when using various combinations of control variables as shown in the specification curve (Simonsohn, Simmons, and Nelson 2020).

Recent research by Ben-David et al. (2022) shows that investors strongly respond to simple measures such as five-globe Morningstar ratings. Given the increasing importance of Morningstar in the industry, I examine whether the results are robust to the presence of Morningstar ratings as additional control. I find, in Table A11 in the Appendixm that the main results are robust to the inclusion of the Morningstar rating as independent variable. Consistent with Ben-David et al. (2022), Morningstar ratings are strong predictors of fund flows. Similarly, when using Morningstar categories as style classification for the low performance dummy doesn't alter the conclusions (see Table A12 in the Appendix).[14]

5.1.2 Uncertainty Language and Other Textual Sentiment Measures.

Following the result that uncertainty language influences investors' investment decisions, I examine if uncertainty isn't capturing other sentiment measures. Higher uncertainty language could be driven by complex language in the prospectus or negative tone for instance. To distinguish the effect of uncertainty from these alternative explanations, I estimate the regression described in equation (6) and control for additional characteristics related to fund language. To control for the sentiment of the text, I control for positive and negative tone of the principal investment strategy section of the prospectus following Loughran and McDonald (2011).[15] I also control for other measures that could relate to the difficulty of information processing for readers, namely document length in number of words. Loughran and McDonald (2014) show that file size is simple measure of document readability.

Table 4 presents the results. When controlling for all additional text measures,

[14]To merge Morningstar information with the CRSP sample, I follow Pástor, Stambaugh, and Taylor (2015) and use CUSIPs as well as tickers for the merging procedure.

[15]In relation with the positive sentiment, it is also possible that mutual funds address uncertainty in a positive way, such that their strategies consider market uncertainty in a risk management fashion. In Section 5.3.1, I explore the most recurrent terms that mutual funds associate risk and uncertainty but terms such as "management" and other positive risk associations do not co-occur with risk or uncertainty.

namely negative document tone ($Tone^{-}_{i,t-1}$), positive document tone ($Tone^{+}_{i,t-1}$), and document length ($Length_{i,t-1}$), each interacted with $LowPerf_{i,t-1}$, the main independent variable of uncertainty interacted with a low performance dummy remains related to fund flows. The coefficient remains statistically significant with a t-statistic between 2.23 and 2.85. Positive tone doesn't appear to affect fund flows while a negative tone affects negatively fund flows. Finally, document length positively affects fund flows independent of the performance. It is possible that investors reward mutual funds that provide more information. Abis et al. (2021) show that detailed sections are positively linked to the flow-performance sensitivity and it is possible that the level of details is positively correlated with the length of the section. Overall, the results of this section confirm the hypothesis that document uncertainty benefits fund flows for funds with low performance and does not capture other document-related measures.

5.2 The Heterogeneous Effects of Uncertainty

5.2.1 Fund Flows, Expenses, and Uncertainty Language. Barber, Odean, and Zheng (2005) find that front-end loads are more salient for investors when purchasing funds. Thus, investors respond to front-end load funds by allocating less capital to expensive funds. Another recent study advocates for the important role of such fees for mutual funds investors (Roussanov et al. 2021). Given that poorly performing mutual funds benefit from uncertainty language by avoiding significant outflows, it is possible that uncertainty language serves as a tool to obfuscate other relevant, salient information such as fees. Thus, front-end loads could be less salient for mutual funds discussing uncertainty. To test this hypothesis, I investigate how investors respond to expense ratio as well as 12b-1 fees (marketing expenses) for funds with low performance and high uncertainty in the text:

$$flows_{i,t} = \beta_0+\beta_1 expense_i * LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{7}$$

Table 5 shows the results. The triple interaction shows a negative and statistically significant coefficient. However, the interaction between $Uncertainty_{i,t-1}$ and $Expense_{i,t-1}$ appears positive and statistically significant at the 5% level. This suggests that expensive mutual funds could benefit from discussing uncertainty in their prospectus. Therefore, relevant financial information such as expense ratio becomes less salient when investors read about uncertainty in the prospectus. Yet, if an expensive fund performs poorly and discusses uncertainty, it won't benefit from the higher fund flows, i.e. the uncertainty-flow-performance relationship is effective only if accompanied with low fees.

When it comes to marketing expenses, Table A4 shows similar results. First, 12b-1 fees negatively affect fund flows, which is consistent with recent research by Roussanov et al. (2021) which shows that market expenses are important for understanding fund flows, although the coefficients are statistically insignificant. Second, the interaction between $Uncertainty_{i,t-1}$ and $12b-1fees_{i,t-1}$ is positive and statistically significant at the 5% level. Which confirms the obfuscation role of $Uncertainty$ in the PIS section of the prospectus. It helps poorly performing funds avoid significant outflows and it similarly helps expensive funds. Yet, overall Tables 5 and A4 show that $Uncertainty$ is not beneficial for flows for funds that are both poorly performing and expensive.

5.2.2 Fund Flows, Clienteles, and Uncertainty Language. A potential explanation for investors being influenced by the language of shareholders' report is limited attention. Persson (2018) shows that information overload is optimal for a firm subject to disclosure mandates in order to hide financially relevant information.

Motivated by this mechanism, I investigate if the effect of uncertainty in mutual fund communication is stronger for institutional or retail investors.

Odean (1999) shows that retail investors are more subject to behavioral biases and could respond more to cosmetic text-based measures. On the other hand, institutional investors through their sophistication could be searching for more signals to extract information from prospectuses and other sources (e.g., Del Guercio and Tkac 2002; Evans and Fahlenbrach 2012; Andrikogiannopoulou et al. 2022). To investigate which group of investors might be responding more to text-base uncertainty, I identify funds targeted to institutional investors using the CRSP indicator variable.[16] I estimate the effect of $Uncertainty$ conditional on the fund's clientele as in equation (6) with a triple interaction term to condition on funds targeted to retail investors.

$$flows_{i,t} = \beta_0 + \beta_1 Retail_i * LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{8}$$

Table 7 presents the results. The triple interaction appears negative but statistically insignificant. This suggests that the effect of uncertainty language on flows, conditional on low performance, is concentrated among funds targeted to institutional investors. This is consistent with institutional investors devoting more resources to extract signal from alternative sources, such as prospectuses while retail investors might be paying less attention to such documents or not reading at all prospectuses (e.g., Andrikogiannopoulou et al. 2022). The fact that investors respond differently also supports the investor channel (*Hypothesis 1.2*) behind that uncertainty-flow relationship. The next subsection examines the fund channel of *Hypothesis 1.2*, i.e., the possibility of strategic communication when facing outflow risk.

[16] Mutual funds targeted to institutional investors are funds sold to other financial companies. I hypothesize that these investors devote more resources to the fund products they buy and are less inattentive.

5.3 Strategic Communication

5.3.1 Truthfully reporting risk. A key challenge in identifying the effect of uncertainty of fund flows is to disentangle it from other sources of risk. It is possible that mutual funds truthfully report firm-level uncertainty in their documents and thus do not engage in strategic communication. If that were the case, then the flow-uncertainty discussion relationship could be explained by other measures of risk that stem from hard information (e.g., holdings, returns). To test this hypothesis, I use a firm-level uncertainty variables as additional control to examine if it can explain the effect of uncertainty in poorly performing mutual fund communication on fund flows. Following prior literature, I use a firm-level variable that include second moment exposures to economic policy uncertainty (Alfaro et al. 2018). I then aggregate firm-level EPU at the mutual fund portfolio level using mutual fund holdings by taking a value-weighted average.

However, it is also important to consider the possibility that mutual funds might engage in window-dressing, especially for risky firms, thus making investors unaware of the risky stocks of the holdings in the reported period. To consider this possibility, I use returns-based measures of risk from investments (standard deviation of fund returns in the prior 6 and 12 months) as additional control in the baseline test (equation 6). Moreover, I also control for unobserved actions of mutual funds, proxied by *Return Gap* from Kacperczyk et al. (2008).

As in prior tests, now augmented with the additional controls that proxy for risk from investments, I use a panel regression to capture the potential effect of uncertainty discussion fro poorly performing funds ($Uncertainty \times LowPerf$) on fund flows, along with fund controls described in equation (6), fund and style $\times$ time fixed effects as well as standard errors double-clustered by fund and time.

The results are presented in Table 8. The results suggest that the uncertainty discussion-fund flows relationship cannot be explained by risky investments, suggesting strategic communication. That is, if uncertain language truly reflected higher exposure to risk from firms in the portfolio, then investors would react to the measures that capture risk from investments and uncertainty in the prospectus wouldn't carry any weight in the investors' capital allocation decision. Overall, the results suggests that fund managers rely on uncertainty-related words possibly to influence investor behavior through flows.

5.3.2 Uncertainty and fund characteristics.

So far, results show that poorly performing mutual funds that discuss uncertainty benefit from less severe outflows. A natural follow-up question regarding strategic communication would be: is performance an explanatory variable of uncertainty and what fund characteristics correlate with uncertainty discussion? To answer this question, I explore the determinants of mutual funds with high uncertainty language by using the following regression approach:

$$Uncertainty_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{9}$$

$X_{i,t-1}$ is a matrix that contains the following fund characteristics: fund flows, the natural logarithm of fund age, the natural logarithm of fund size (TNA), turnover ratio, expense ratio, fund performance measured with the Carhart (1997) four-factor model, and fund risk as measured by both the beta coefficient from the CAPM model and past fund return volatility (6 months). To account for potential correlation in the residuals at the fund and time level, I include fund and style × time (year-month) fixed effects and double-cluster standard errors by fund and time.

Table 4 shows the results. Young, expensive funds are more likely to discuss uncertainty in prospectuses. Most importantly, mutual funds that perform well (*Four-factor alpha*) are less likely to discuss uncertainty. Finally, funds with low beta funds tend to discuss more uncertainty in prospectuses. This relationship is statistically significant at the 10% significance level when including fund fixed effects. Overall, these results support the idea that the investor channel is also responsible for the uncertainty-flow relationship ((*Hypothesis 1.2*).[17]

One interpretation for this result is that even though some funds take on less risk, they could end up performing poorly, and thus investors interpret broad market risk as responsible for low performance, rather than idiosyncratic risk, when judging funds and making investment decisions.[18] Moreover, fund managers would want to focus the discussion on market forces, that are outside of the manager's control, as possibly related to poor performance, rather than higher specific risks that would have resulted from investment decisions. To verify this hypothesis (*Hypothesis 1.3*), the next test implements a machine learning approach to identify which words mutual funds associate most risk and uncertainty with. Mutual funds associating broad economic terms with risk might represent those benefit most from the fund flow-uncertainty relationship.

5.3.3 Systematic vs. Specific Risks Discussion. In order to identify which type of risk mutual funds discuss, an appropriate measure would identify words that are located close to the term "risk". One model that can serve this purpose is the word embedding approach *word2vec*. It is an increasingly popular technique to identify co-occurences of words in order to determine its semantics. It is useful if one wants to create a dictionary, without manually identifying words associated with a particular theme. It has been recently used to identify corporate culture for instance (Li et al. 2021) or to identify emerging risks (Hanley and Hoberg 2019).

The model starts with a seed word, "risk" in this context. The algorithm identifies

[17] Additional results in Table A13 in this Appendix show that poorly performing mutual funds tend to write longer, less readable strategy sections.

[18] This is also suggested by results from Table 3 which uses *EPU* as an alternative uncertainty measure and builds from broader economic uncertainty.

the seed word in documents and learns its meaning. The meaning of a word is define by a vector that represents co-occuring words, which the algorithm identifies as being associated with. A famous example of word analogies is the meaning of the word "queen" which can be represented as a vector composed of the words "king" and "woman" minus "man".

The word2vec model is a natural language processing algorithm developed by Mikolov, Sutskever, Chen, Corrado, and Dean (2013). For this study, the model will predict words associated with "risk" to identify those that co-occur the most. At first, the word "risk" is represented by random numbers associated with words that appear in the document. The model then learns through all the documents using a neural network. I use the whole time series of prospectuses for each fund to learn which words are associated with "risk", thus the resulting vector of words, which has a fixed length, are on the cross-section. More details on the word2vec model is provided in the Appendix.

After training the model with "risk" as a seed word, I obtain a vector of words that word2vec predicts to be associated and co-occuring with risk. I report the most representative words across all funds in Table 10 with the seed words: risk, economic-economy, uncertainty-uncertain. Interestingly, several words appear related to the risk terms that reflect the results from the determinants of uncertainty (Table 4).

Table 4 identified *beta* as being a variable marginally correlated with uncertainty in fund prospectuses. When going into the documents, I find that words such as: market or index are co-occuring with "risk" (Table 10). This reflects that some funds discuss risk and uncertainty, which affects flows as previously documented, and when discussing such topic, they associate it with broader, systematic risk. Some funds also associate risk and uncertainty with "company", thus illustrating heterogeneity in the types of risks discussed by funds. The key hypothesis is that the positive effect on flows documented in previous sections is concentrated among mutual funds discussing uncertainty and associating it with broad economic terms, i.e. systematic, rather that company or investment-specific (*Hypothesis 1.3*).

To test this hypothesis and based on Table 10, I define a dummy variable that identifies funds that have the "systematic"-risk related words "economy", "economic", "market", "index", "indexing", or "benchmark" in the top 5 (i.e. the most co-occuring words in the vector of word representation associated with "risk" as learned by the word2vec model), in spirit of Baker et al. (2016).

To investigate if mutual funds discussing systematic risk benefit more from the uncertainy-performance relationship, I estimate the effect of uncertainty conditional on *Systematic-Risk in text* for poorly performing funds with a triple interaction term:

$$flows_{i,t} = \beta_0 + \beta_1 \textit{Systematic-Risk in Text}_i * LowPerf_{i,t-1} * EU_{i,t-1} + \beta_2 X_{i,t-1} + S \times T + \epsilon_{i,1}. \tag{10}$$

The set of fund controls include the double interactions between each of the variables *Systematic-Risk in text*, $LowPerf$, and $Uncertainty$ as well as fund characteristics included in prior analysis. Style × year-month fixed effects as well as double-clustered standard errors are included in all models (fund and time).

Table 11 shows the results. The triple interaction between *Systematic-Risk in Text*, $LowPerf$, and $Uncertainty$ shows a positive and statistically significant coefficient, while the double interaction between $LowPerf$ and $Uncertainty$ is now statistically insignificant in most models. This suggests that poorly performing mutual funds discussing uncertainty benefit from less extreme outflows but only if they associate risk with broad economic terms. This is consistent with the idea that mutual fund managers might emphasize uncertain markets if performing poorly (Mullainathan et al. 2008). Since they are evaluated relative to a benchmark, fund investors do not punish them as theory would predict (Berk and Green 2004).

6 Conclusion

In this paper, I study uncertainty in mutual fund communication. Even in the presence of disclosure mandates, information providers have room for strategic communication. This includes an emphasis on uncertainty in mutual fund communication which could make a signal about a fund's products quality less precise.

When measuring uncertainty in mutual fund prospectuses' strategy section, I find that uncertainty helps mutual funds with low performance experience less severe outflows of capital.

This paper highlights a new channel through which mutual fund communication matters for understanding fund flows and investors' behavior. The results have implications for language requirements from the S.E.C. regarding mutual fund investors' documents where a neutral tone and easy-to-read language would be preferrable in the strategy section.

References

Abis, S., A. M. Buffa, A. Javadekar, and A. Lines. 2021. Learning from prospectuses Working paper, Columbia University.

Abis, S., and A. Lines. 2020. Do Mutual Funds Keep Their Promises? Working paper, Columbia University.

Agarwal, V., G. D. Gay, and L. Ling. 2014. Window dressing in mutual funds. *Review of Financial Studies* 27:3133–3170.

Alfaro, I., N. Bloom, and X. Lin. 2018. The finance uncertainty multiplier. Tech. rep., Working paper, Stanford University.

Andrei, D., H. L. Friedman, and N. B. Ozel. 2021. Economic uncertainty and investor attention Working paper, McGill University.

Andrikogiannopoulou, A., P. Krueger, S. F. Mitali, and F. Papakonstantinou. 2022. Discretionary Information in ESG Investing: A Text Analysis of Mutual Fund Prospectuses Working paper, King's College.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131:1593–1636.

Bali, T. G., S. J. Brown, and Y. Tang. 2017. Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics* 126:471–489.

Barber, B. M., T. Odean, and L. Zheng. 2005. Out of sight, out of mind: The effects of expenses on mutual fund flows. *Journal of Business* 78:2095–2120.

Ben-David, I., J. Li, A. Rossi, and Y. Song. 2022. What do mutual fund investors really care about? *Review of Financial Studies* 35:1723–1774.

Berk, J. B., and R. C. Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112:1269–1295.

Berk, J. B., and J. H. Van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118:1–20.

Bertrand, M., D. Karlan, S. Mullainathan, E. Shafir, and J. Zinman. 2010. What's advertising content worth? Evidence from a consumer credit marketing field experiment. *Quarterly Journal of Economics* 125:263–306.

Bonaime, A., H. Gulen, and M. Ion. 2018. Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics* 129:531–558.

Bonelli, M., A. Buyalskaya, and T. Yao. 2021. Quality and Product Differentiation: Theory and Evidence from the Mutual Fund Industry Working paper, HEC Paris.

Broderick, T., R. Giordano, and R. Meager. 2020. An Automatic Finite-Sample Robustness Metric: When Can Dropping a Little Data Make a Big Difference? *arXiv preprint arXiv:2011.14999* .

Cao, S., W. Jiang, B. Yang, and A. L. Zhang. 2020. How to talk when a machine is listening: Corporate disclosure in the age of AI Working paper, University of Maryland.

Carhart, M. M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105:1167–1200.

Cong, L. W., T. Liang, and X. Zhang. 2019. Textual factors: A scalable, interpretable, and data-driven approach to analyzing unstructured information Working paper, Cornell University.

Crawford, V. P., and J. Sobel. 1982. Strategic information transmission. *Econometrica* pp. 1431–1451.

Cronqvist, H. 2006. Advertising and portfolio choice Working paper, Chapman University.

DeHaan, E., Y. Song, C. Xie, and C. Zhu. 2021. Obfuscation in mutual funds. *Journal of Accounting and Economics* 72:101429.

Del Guercio, D., and P. A. Tkac. 2002. The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis* 37:523–557.

DellaVigna, S., and E. Kaplan. 2007. The Fox News effect: Media bias and voting. *Quarterly Journal of Economics* 122:1187–1234.

Dou, W., L. Kogan, and W. Wu. 2021. Common fund flows: Flow hedging and factor pricing Working paper, Wharton School, University of Pennsylvania.

Engelberg, J. E., and C. A. Parsons. 2011. The causal impact of media in financial markets. *Journal of Finance* 66:67–97.

Evans, R. B., and R. Fahlenbrach. 2012. Institutional investors and mutual fund governance: Evidence from retail–institutional fund twins. *Review of Financial Studies* 25:3530–3571.

Franzoni, F., and M. C. Schmalz. 2017. Fund flows and market states. *Review of Financial Studies* 30:2621–2673.

Gentzkow, M., B. Kelly, and M. Taddy. 2019. Text as data. *Journal of Economic Literature* 57:535–74.

Gormley, T. A., M. Kaviani, and H. Maleki. 2021. When do Judges Throw the Book at Companies? The Influence of Partisanship in Corporate Prosecutions Working paper, Washington University in St. Louis.

Grossman, S. J. 1981. The informational role of warranties and private disclosure about product quality. *The Journal of Law and Economics* 24:461–483.

Gruber, M. J. 1996. Another puzzle: The growth in actively managed mutual funds. *Journal of Finance* 51:783–810.

Gulen, H., and M. Ion. 2016. Policy uncertainty and corporate investment. *Review of Financial Studies* 29:523–564.

Hanley, K. W., and G. Hoberg. 2019. Dynamic interpretation of emerging risks in the financial sector. *Review of Financial Studies* 32:4543–4603.

Hillert, A., A. Niessen-Ruenzi, and S. Ruenzi. 2020. Mutual Fund Shareholder Letters: Flows, Performance, and Managerial Behavior Working paper, University of Mannheim.

Hoberg, G., N. Kumar, and N. Prabhala. 2018. Mutual fund competition, managerial skill, and alpha persistence. *Review of Financial Studies* 31:1896–1929.

Jiang, E. X., L. T. Starks, and S. Sun. 2016. Economic policy uncertainty and learning: Theory and evidence on mutual funds Working paper, University of Texas at Austin.

Kacperczyk, M., C. Sialm, and L. Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *Journal of Finance* 60:1983–2011.

Kacperczyk, M., C. Sialm, and L. Zheng. 2008. Unobserved actions of mutual funds. *Review of Financial Studies* 21:2379–2416.

Khorana, A., and H. Servaes. 2012. What drives market share in the mutual fund industry? *Review of Finance* 16:81–113.

Kim, H., and H. Kung. 2017. The asset redeployability channel: How uncertainty affects corporate investment. *Review of Financial Studies* 30:245–280.

Kostovetsky, L., and J. B. Warner. 2019. Measuring innovation and product differentiation: Evidence from mutual funds. *Journal of Finance* .

Kostovetsky, L., and J. B. Warner. 2020. Measuring innovation and product differentiation: Evidence from mutual funds. *Journal of Finance* 75:779–823.

Li, K., F. Mai, R. Shen, and X. Yan. 2021. Measuring corporate culture using machine learning. *Review of Financial Studies* 34:3265–3315.

Lippmann, W. 1922. Public opinion. *New York* .

Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66:35–65.

Loughran, T., and B. McDonald. 2014. Measuring readability in financial disclosures. *Journal of Finance* 69:1643–1671.

Mikolov, T., I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. 2013. Distributed representations of words and phrases and their compositionality. *Advances in neural information processing systems* 26.

Milgrom, P. R. 1981. Good news and bad news: Representation theorems and applications. *Bell Journal of Economics* pp. 380–391.

Mullainathan, S., J. Schwartzstein, and A. Shleifer. 2008. Coarse thinking and persuasion. *Quarterly Journal of Economics* 123:577–619.

Musto, D. K. 1997. Portfolio disclosures and year-end price shifts. *Journal of Finance* 52:1563–1588.

Musto, D. K. 1999. Investment decisions depend on portfolio disclosures. *Journal of Finance* 54:935–952.

Odean, T. 1999. Do investors trade too much? *American Economic Review* 89:1279–1298.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2015. Scale and skill in active management. *Journal of Financial Economics* 116:23–45.

Persson, P. 2018. Attention manipulation and information overload. *Behavioural Public Policy* 2:78–106.

Porter, M. F. 1980. An algorithm for suffix stripping. *Program* 14:130–137.

Roussanov, N., H. Ruan, and Y. Wei. 2021. Marketing mutual funds. *Review of Financial Studies* 34:3045–3094.

Sheng, J., N. Xu, and L. Zheng. 2022. Do mutual funds walk the talk? A textual analysis of risk disclosure by mutual funds Working paper, University of California Irvine.

Simonsohn, U., J. P. Simmons, and L. D. Nelson. 2020. Specification curve analysis. *Nature Human Behaviour* 4:1208–1214.

Sims, C. A. 2003. Implications of rational inattention. *Journal of Monetary Economics* 50:665–690.

Sirri, E. R., and P. Tufano. 1998. Costly search and mutual fund flows. *Journal of Finance* 53:1589–1622.

Stigler, G. J. 1961. The economics of information. *Journal of Political Economy* 69:213–225.

Wahal, S., and A. Y. Wang. 2011. Competition among mutual funds. *Journal of Financial Economics* 99:40–59.

7 Figures and Tables

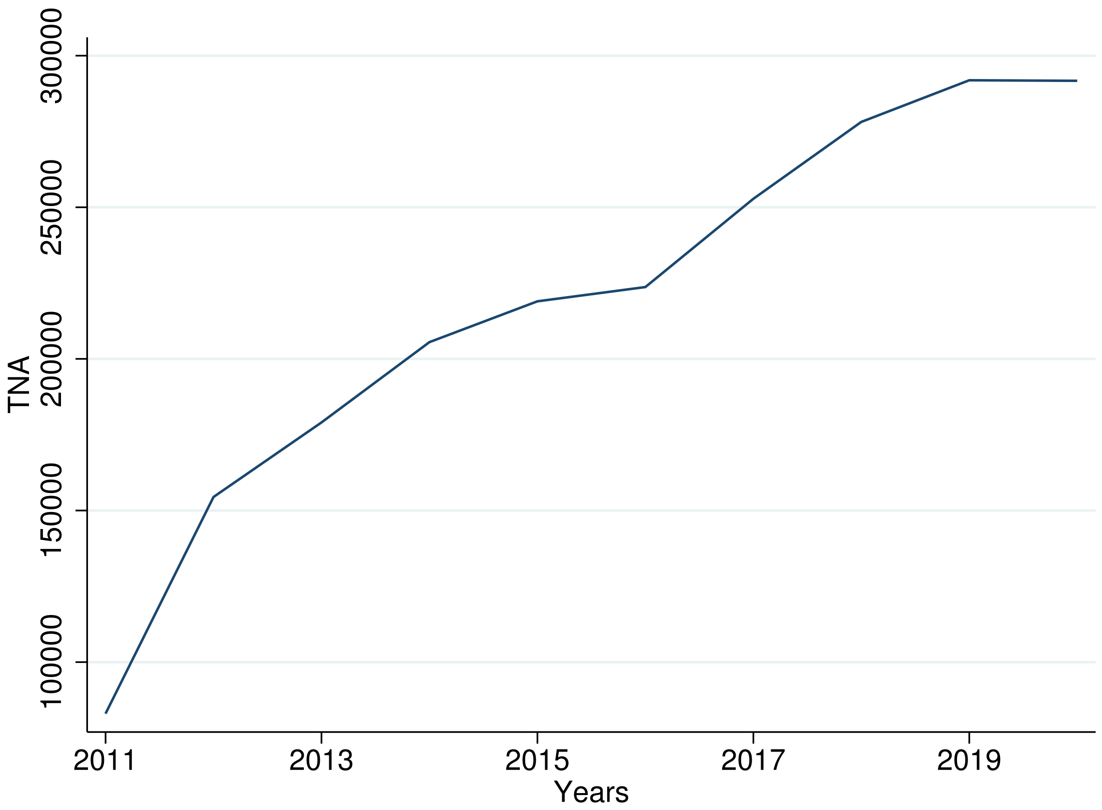

Figure 1. This figure shows the evolution of U.S. active equity mutual funds total assets under management in billions of U.S. dollars.

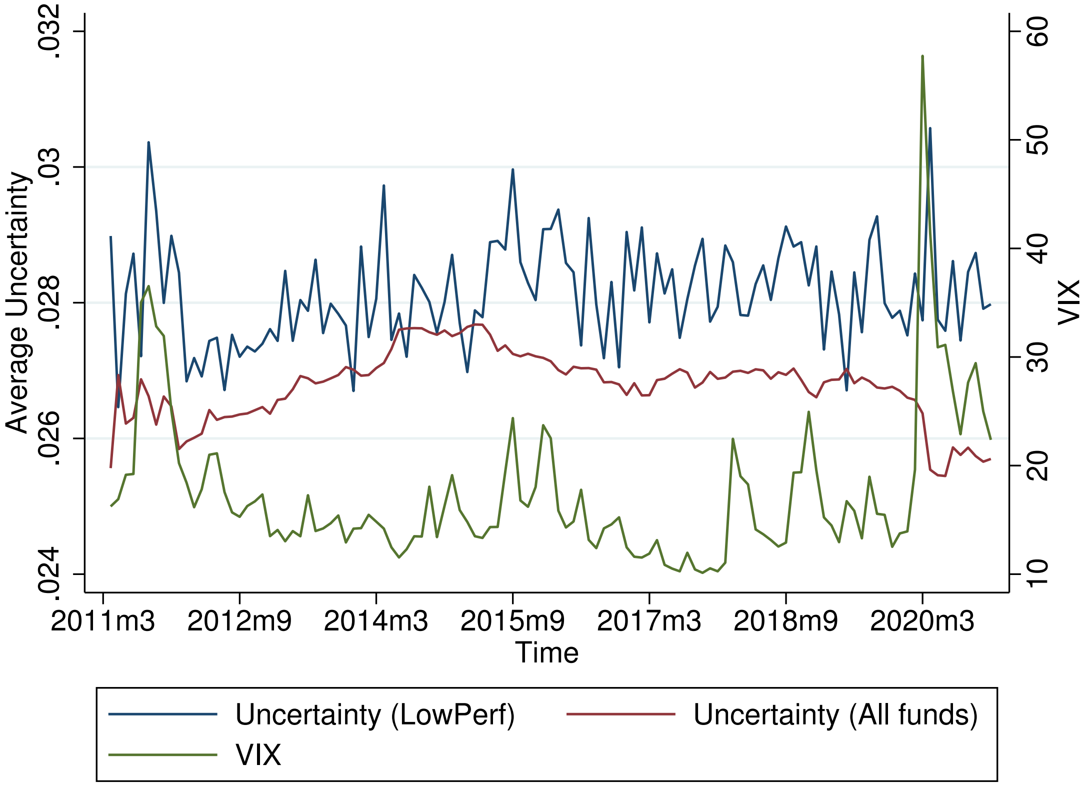

Figure 2. This figure shows the evolution of a average *Uncertainty* in prospectuses over time from poorly performing mutual funds (bottom decile within category-month) on the left y-axis and the *VIX* index on the right y-axis.

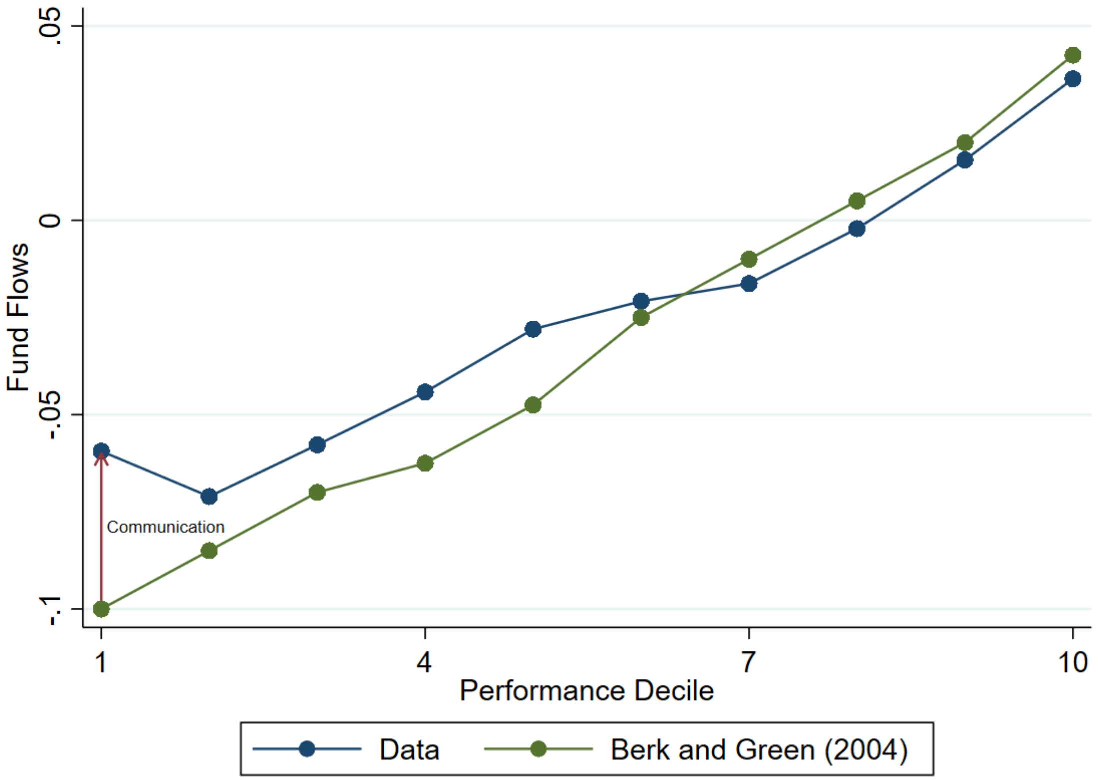

Figure 3. This figure shows the flow-performance relationship where performance is the average alpha over the previous 3 years ranked in deciles and flow is the median of the annual flow ratio in each performance decile for the data, while *Model* shows simulated flow response for hypothetical funds in each performance, following Berk and Green (2004).

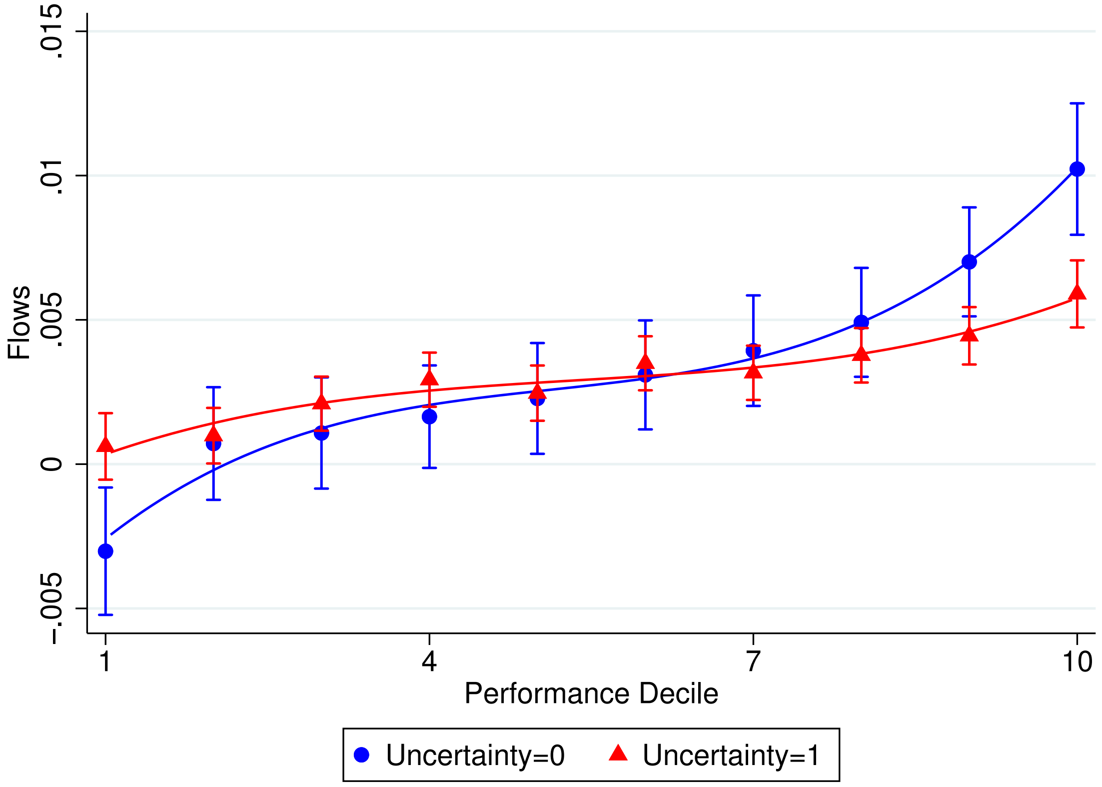

Figure 4. This figure shows the average response of uncertainty on mutual fund flows for each performance decile. $Uncertainty = 1$ is defined as mutual funds located in the top decile of $Uncertainty$ while $Uncertainty = 0$ are mutual funds that are in the bottom decile of the $Uncertainty$ distribution.

Table 1. Summary statistics

This table presents summary statistics of the uncertainty measure (Loughran and McDonald 2011) from mutual fund prospectuses as well as textual characteristics from the strategy section in Panel A. Panel B presents mutual fund characteristics from 2011 to 2020 at the monthly frequency. Fund age is measured in years from the fund's inception. Total net assets (TNA) are measured in millions of U.S. dollars. Beta is measured from the CAPM model.

	mean	sd	p10	p25	p50	p75	p90
Panel A: Text measures							
Uncertainty	0.028	0.014	0.012	0.020	0.028	0.037	0.045
WordCount	464.004	304.667	150	257	401	601	851
$Tone^{+}$	0.009	0.008	0	0.003	0.007	0.012	0.018
$Tone^{-}$	0.005	0.006	0	0	0.004	0.008	0.012
Panel B: Fund characteristics							
Expense ratio	0.008	0.005	0.002	0.005	0.008	0.011	0.015
TNA	1879.071	1.0e+04	12.900	55.900	254.000	998.500	3261.500
Return	0.006	0.043	-0.035	-0.007	0.005	0.023	0.047
Fund age	13.243	10.966	2.000	5.000	11.000	19.000	27.000
Fund flow	0.008	0.082	-0.035	-0.013	-0.002	0.013	0.053
Turnover ratio	0.822	2.051	0.080	0.190	0.420	0.830	1.570
Beta	0.588	0.574	-0.040	0.148	0.696	0.970	1.090
Four-factor alpha	0.000	0.025	-0.019	-0.007	0.001	0.008	0.019

Table 2. Text-Based Uncertainty, Performance, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$		0.051**	0.055**	0.059**	0.059**
		(2.29)	(2.48)	(2.39)	(2.41)
$Uncertainty_{i,t-1}$	-0.027	-0.010	-0.020	-0.033	-0.033
	(-0.83)	(-0.37)	(-0.72)	(-1.00)	(-1.00)
$LowPerf_{i,t-1}$		-0.004***	-0.004***	-0.005***	-0.005***
		(-5.51)	(-5.63)	(-5.83)	(-6.01)
$\log(TNA)_{i,t-1}$	-0.012***	-0.013***	-0.013***	-0.012***	-0.012***
	(-17.76)	(-20.44)	(-19.45)	(-17.73)	(-17.75)
$Return_{i,t-1}$	0.097***	0.086***	0.086***	0.084***	0.085***
	(4.87)	(4.27)	(4.30)	(4.18)	(4.24)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.015***	-0.014***	-0.014***	-0.014***
	(-14.82)	(-16.29)	(-16.49)	(-14.88)	(-14.88)
$Flows_{i,t-1}$	0.052***	0.017**	0.031***	0.052***	0.052***
	(6.29)	(2.26)	(3.87)	(6.31)	(6.26)
$Beta_{i,t-1}$	-0.001		-0.001	-0.001	-0.001
	(-0.86)		(-0.58)	(-0.47)	(-0.53)
$Expense_{i,t-1}$	-0.467***			-0.463***	-0.465***
	(-2.73)			(-2.70)	(-2.72)
$Turnover_{i,t-1}$	0.000*			0.000*	0.000*
	(1.70)			(1.74)	(1.72)
$Four\text{-}factor\ alpha^2_{i,t-1}$	0.163***				0.169***
	(3.09)				(3.26)
Style x Year-Month FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	836037	1080279	1030536	836037	836037
R^2	0.130	0.118	0.124	0.130	0.130

Table 3. Text-Based Economic Uncertainty, Performance, and Fund Flows: Robustness

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *EPU* (Economic Policy Uncertainty) is measured following Baker et al. (2016) and is a dummy for mutual funds mention with a positive count of economic uncertain words . *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. The first column considers funds with low performance as defined by the lowest quintile. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age*, fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	(1)	(2)	(3)
$Uncertainty_{i,t-1}$	-0.034***	-0.035	
	(-2.84)	(-1.06)	
$LowPerf_{i,t-1}$	-0.006***		
	(-6.25)		
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.044		
	(1.56)		
$LowPerf^{quintile}_{i,t-1}$		-0.004***	-0.003***
		(-6.63)	(-7.70)
$Uncertainty_{i,t-1} \times LowPerf^{quintile}_{i,t-1}$		0.039**	
		(2.05)	
$EPU_{i,t-1}$			-0.011
			(-0.50)
$EPU_{i,t-1} \times LowPerf^{quintile}_{i,t-1}$			0.034*
			(1.74)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	No	Yes	Yes
Observations	836046	836037	836037
R^2	0.076	0.131	0.131

Table 4. Uncertainty Language and Other Textual Sentiment Measures
This table presents estimates from panel regressions of mutual funds' flows on documents uncertainty interacted with fund performance controlling for text and fund characteristics. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. I control for lagged monthly fund-level characteristics, namely *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Additionally, controls include the frequency of positive, negative words (Loughran and McDonald 2011) as well as the average sentence length. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	(1)	(2)	(3)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.055**	0.070***	0.058**
	(2.23)	(2.85)	(2.39)
$Uncertainty_{i,t-1}$	-0.036	-0.035	-0.025
	(-1.09)	(-1.06)	(-0.76)
$LowPerf_{i,t-1}$	-0.005***	-0.005***	-0.005***
	(-6.09)	(-5.56)	(-3.22)
$Tone^{+}_{i,t-1}$	0.074		
	(1.19)		
$LowPerf_{i,t-1} \times Tone^{+}_{i,t-1}$	0.051		
	(1.34)		
$Tone^{-}_{i,t-1}$		0.018	
		(0.22)	
$LowPerf_{i,t-1} \times Tone^{-}_{i,t-1}$		-0.116**	
		(-2.04)	
$Length_{i,t-1}$			0.000**
			(2.35)
$LowPerf_{i,t-1} \times Length_{i,t-1}$			0.000
			(0.33)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	836037	836037	836037
R^2	0.130	0.130	0.130

Table 5. Text-Based Uncertainty, Expenses, and Fund Flows
This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy and expense ratio. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1} \times Expense_{i,t-1}$	-16.818***	-17.256***	-18.055***	-18.177***
	(-2.90)	(-3.02)	(-3.12)	(-3.15)
$LowPerf_{i,t-1} \times Expense_{i,t-1}$	0.569***	0.606***	0.622***	0.622***
	(3.51)	(3.85)	(3.93)	(3.93)
$Uncertainty_{i,t-1} \times Expense_{i,t-1}$	11.468**	12.146**	12.200**	12.186**
	(2.30)	(2.36)	(2.37)	(2.37)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.213***	0.220***	0.230***	0.231***
	(3.70)	(3.92)	(4.04)	(4.08)
$Uncertainty_{i,t-1}$	-0.125**	-0.144***	-0.145***	-0.145***
	(-2.58)	(-2.82)	(-2.85)	(-2.85)
$LowPerf_{i,t-1}$	-0.010***	-0.011***	-0.011***	-0.011***
	(-5.57)	(-6.07)	(-6.14)	(-6.22)
$Expense_{i,t-1}$	-0.820***	-0.824***	-0.840***	-0.840***
	(-3.80)	(-3.73)	(-3.78)	(-3.79)
$\log(TNA)_{i,t-1}$	-0.012***	-0.012***	-0.012***	-0.012***
	(-19.02)	(-17.88)	(-17.74)	(-17.75)
$Return_{i,t-1}$	0.084***	0.084***	0.084***	0.085***
	(4.10)	(4.17)	(4.18)	(4.24)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.014***	-0.014***	-0.014***
	(-14.72)	(-14.97)	(-14.88)	(-14.88)
$Flows_{i,t-1}$	0.037***	0.052***	0.052***	0.052***
	(4.61)	(6.27)	(6.30)	(6.25)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.49)	(-0.47)	(-0.53)
$Turnover_{i,t-1}$			0.000*	0.000*
			(1.74)	(1.73)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.169***
				(3.26)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	880643	839011	836037	836037
R^2	0.123	0.131	0.130	0.130

Table 6. Text-Based Uncertainty, Performance, and Fund Flows: Marketing

This table presents estimates from panel regressions of mutual funds' marketing expenses (effective 12b-1 fees) on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$12b\text{-}1_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.058**	0.055**	0.070*	0.070*
	(2.11)	(2.02)	(1.95)	(1.95)
$Uncertainty_{i,t-1}$	-0.060	-0.040	-0.011	-0.012
	(-0.62)	(-0.40)	(-0.08)	(-0.08)
$LowPerf_{i,t-1}$	-0.001	-0.001	-0.001	-0.001
	(-1.03)	(-1.06)	(-1.14)	(-1.14)
$\log(TNA)_{i,t-1}$	0.002**	0.003**	0.005***	0.005***
	(2.07)	(2.01)	(3.09)	(3.09)
$Return_{i,t-1}$	0.003	0.004	0.006	0.006
	(0.67)	(0.86)	(1.08)	(1.06)
$\log(Fund\ age)_{i,t-1}$	0.005**	0.005**	0.004*	0.004*
	(2.54)	(2.44)	(1.74)	(1.74)
$Flows_{i,t-1}$	-0.000	-0.001	-0.001	-0.001
	(-0.17)	(-0.30)	(-0.23)	(-0.22)
$Beta_{i,t-1}$		0.002**	0.002**	0.002**
		(2.42)	(2.40)	(2.44)
$Turnover_{i,t-1}$			0.000	0.000
			(0.64)	(0.64)
$Expense_{i,t-1}$			5.407***	5.408***
			(6.65)	(6.65)
$Four\text{-}factor\ alpha^2_{i,t-1}$				-0.008
				(-1.46)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1083641	1033636	838995	838995
R^2	0.971	0.972	0.967	0.967

Table 7. Text-Based Uncertainty, Clientele, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy and a indicator for funds sold to retail investors. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Retail_i$=1 × $Uncertainty_{i,t-1}$ × $LowPerf_{i,t-1}$	-0.001	-0.014	-0.015	-0.016
	(-0.03)	(-0.36)	(-0.35)	(-0.36)
$Retail_i$=1 × $Uncertainty_{i,t-1}$	0.007	0.033	0.055	0.055
	(0.18)	(0.85)	(1.19)	(1.19)
$Retail_i$=1 × $LowPerf_{i,t-1}$	-0.001	-0.000	0.001	0.001
	(-0.46)	(-0.03)	(0.47)	(0.55)
$Uncertainty_{i,t-1}$ × $LowPerf_{i,t-1}$	0.051*	0.060**	0.065**	0.065**
	(1.85)	(2.19)	(2.01)	(2.03)
$Uncertainty_{i,t-1}$	-0.014	-0.034	-0.063	-0.063
	(-0.44)	(-1.03)	(-1.40)	(-1.40)
$LowPerf_{i,t-1}$	-0.004***	-0.004***	-0.005***	-0.005***
	(-4.01)	(-4.39)	(-4.43)	(-4.62)
$\log(TNA)_{i,t-1}$	-0.013***	-0.013***	-0.012***	-0.012***
	(-20.59)	(-19.61)	(-17.85)	(-17.87)
$Return_{i,t-1}$	0.086***	0.086***	0.084***	0.085***
	(4.27)	(4.30)	(4.16)	(4.23)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.014***	-0.014***	-0.014***
	(-16.17)	(-16.35)	(-14.75)	(-14.75)
$Flows_{i,t-1}$	0.017**	0.030***	0.052***	0.052***
	(2.24)	(3.85)	(6.29)	(6.23)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.59)	(-0.47)	(-0.53)
$Expense_{i,t-1}$			-0.379**	-0.380**
			(-2.29)	(-2.31)
$Turnover_{i,t-1}$			0.000*	0.000*
			(1.72)	(1.70)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.169***
				(3.26)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1080279	1030536	836037	836037
R^2	0.118	0.125	0.130	0.131

Table 8. Text-Based Uncertainty, Performance, and Firm Risk

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a low performance dummy controlling for risk from investments. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. The main independent variables are firm-level uncertainty instrument of firms' exposures to economic policy uncertainty (*Holdings-EPU*; Alfaro et al. 2021), the standard deviation of fund returns in the prior 6 and 12 months, and *Return Gap* is measured following Kacperczyk et al. (2008). *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	(1)	(2)	(3)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.086**	0.087**	0.087**
	(2.35)	(2.38)	(2.39)
$Uncertainty_{i,t-1}$	-0.042	-0.043	-0.044
	(-0.77)	(-0.79)	(-0.82)
$LowPerf_{i,t-1}$	-0.002**	-0.002**	-0.002**
	(-2.02)	(-2.01)	(-2.01)
$Holdings\text{-}EPU_{i,t-1}$	5.767	6.082	6.515
	(0.84)	(0.89)	(0.96)
$Return\ Vol.\ 6\text{-}m_{i,t-1}$		-0.102**	
		(-2.09)	
$Return\ Vol.\ 12\text{-}m_{i,t-1}$			-0.168***
			(-2.96)
$Return\ Gap_{i,t-1}$	-0.021	-0.021	-0.021
	(-0.71)	(-0.71)	(-0.71)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	228576	228576	228576
R^2	0.140	0.140	0.140

Table 9. Text-Based Uncertainty and Fund Characteristics

This table presents estimates from panel regressions of mutual funds' documents uncertainty on fund characteristics. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. I control for lagged monthly fund-level characteristics, namely *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Uncertainty_{i,t}$	
	(1)	(2)
$Expense_{i,t-1}$	21.559***	-8.332***
	(6.71)	(-2.79)
$\log(TNA)_{i,t-1}$	0.023***	-0.003
	(3.24)	(-0.54)
$Return_{i,t-1}$	0.296**	0.050
	(2.29)	(0.98)
$\log(Fund\ age)_{i,t-1}$	-0.016	-0.025**
	(-1.17)	(-2.10)
$Flows_{i,t-1}$	-0.058	-0.001
	(-1.50)	(-0.09)
$Turnover_{i,t-1}$	0.020***	-0.000
	(4.01)	(-0.17)
$Beta_{i,t-1}$	-0.159***	-0.011*
	(-7.34)	(-1.91)
$Four\text{-}factor\ alpha_{i,t-1}$	-0.821***	-0.095**
	(-5.26)	(-2.26)
$Return\ Vol.\ 6\text{-}m_{i,t-1}$	-3.931***	-0.119
	(-10.36)	(-0.82)
Fund FE	No	Yes
Style x Year-Month FE	Yes	Yes
Observations	837204	837194
R^2	0.098	0.904

Table 10. This table shows the 14 words most frequently cooccuring with the word "risk", "economic", "economy" as well as "uncertainty" or "uncertain". The words are obtained using a word embedding or word2vec model trained and estimated throughout the series of prospectuses filed by each fund.

	Risk	**Economic**	**Economy**	**Uncertain(ty)**
1	Fund	Fund	Fund	Advisor
2	Security	Security	Security	Fund
3	Index	Investment	Market	Company
4	Investment	May	May	Security
5	Portfolio	Market	Investment	Rate
6	May	Company	Index	May
7	Company	Portfolio	Portfolio	Issuer
8	Asset	Asset	Country	Investment
9	Market	Index	Asset	Income
10	Underlying	Stock	Stock	Domestic
11	Stock	Invest	Underlying	Fund
12	Adviser	Country	Adviser	Foreign
13	Bond	Adviser	Emerging	Portfolio
14	Invest	Underlying	Segment	Market

Table 11. Text-Based Uncertainty and Associated Terms, Performance, and Fund Flows

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a low performance dummy and a dummy indentifying if funds associate risk with broader, systematic components such as benchmark or the economy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. A word-embedding model is used to identify funds that associate benchmark or index with the word 'risk'. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. The first column considers funds with low performance as defined by the lowest quintile. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$	
	(1)	(2)
$\textit{Systematic-Risk in Text}_i{=}1 \times \textit{Uncertainty}_{i,t-1} \times \textit{LowPerf}_{i,t-1}$	0.064	0.173**
	(0.85)	(2.08)
$\textit{Uncertainty}_{i,t-1}$	-0.055***	-0.026**
	(-3.44)	(-2.08)
$\textit{LowPerf}_{i,t-1}$	-0.005***	-0.005***
	(-5.78)	(-5.34)
$\textit{Uncertainty}_{i,t-1} \times \textit{LowPerf}_{i,t-1}$	-0.002	0.019
	(-0.07)	(0.68)
$\textit{Systematic-Risk in Text}_i{=}1$	0.005***	0.003***
	(3.59)	(3.06)
$\textit{Systematic-Risk in Text}_i{=}1 \times \textit{Uncertainty}_{i,t-1}$	-0.084**	-0.075**
	(-2.25)	(-2.38)
$\textit{Systematic-Risk in Text}_i{=}1 \times \textit{LowPerf}_{i,t-1}$	-0.003	-0.006**
	(-1.29)	(-2.35)
Fund controls	No	Yes
Style x Year-Month FE	Yes	Yes
Fund FE	No	No
Observations	1138158	836046
R^2	0.034	0.076

Appendix

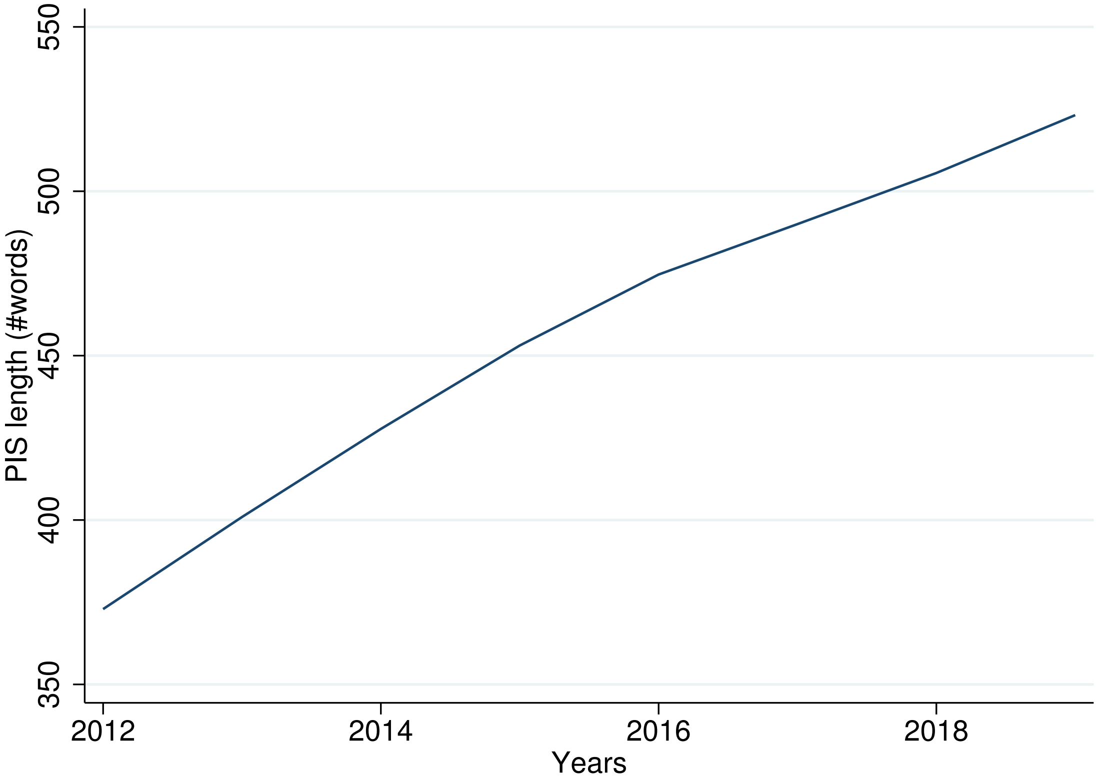

Figure A1. This figure shows the evolution of the average U.S. active equity mutual funds prospectus strategy section length in number of words.

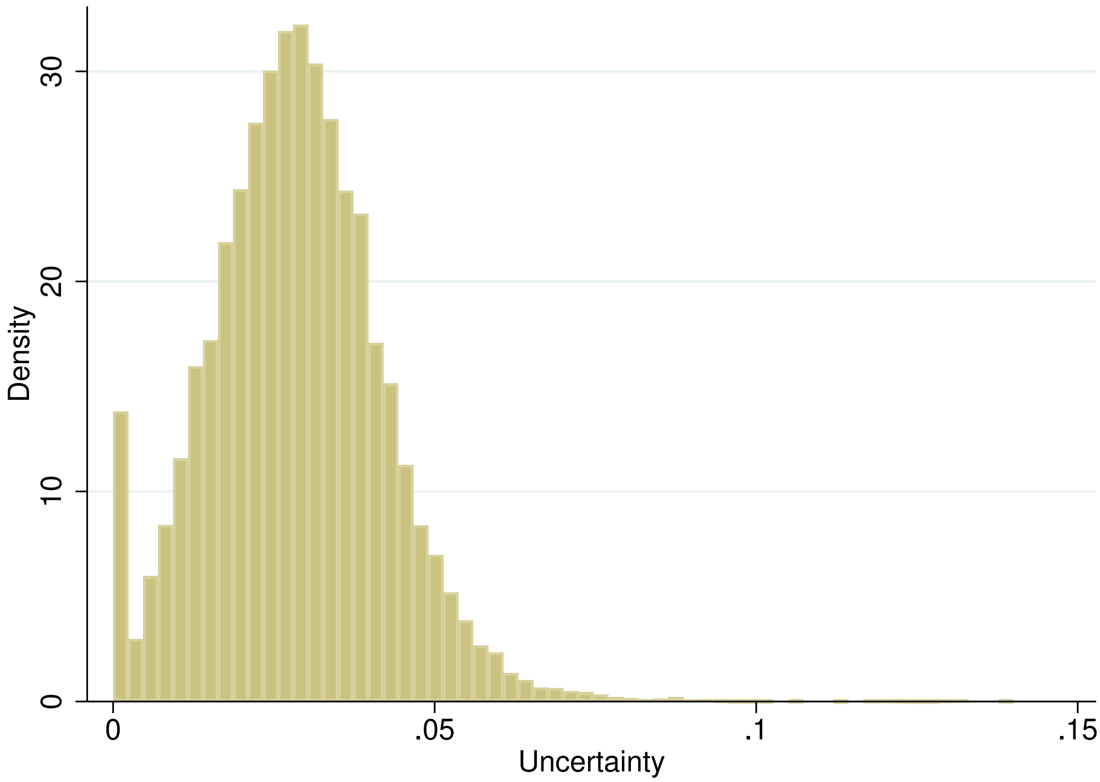

Figure A2. This figure shows the histogram of the *Uncertainty* variable with the proportion of mutual funds on the y-axis for each level of uncertainty discussion in the strategy section of the prospectus.

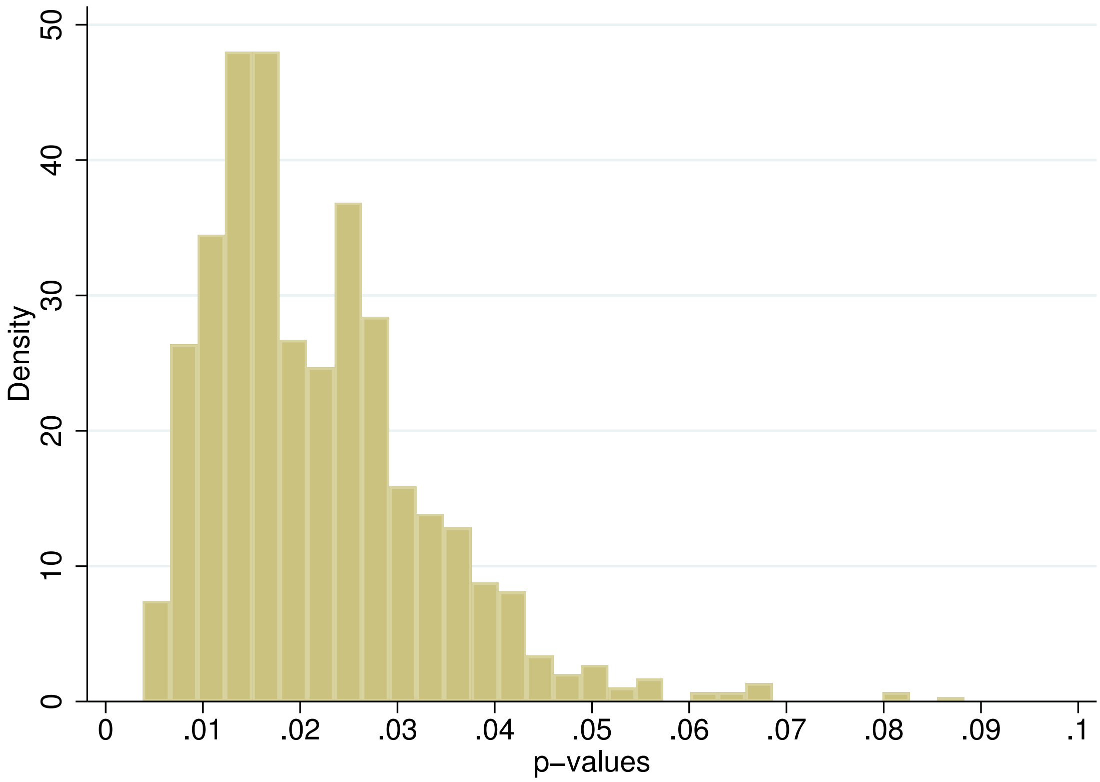

Figure A3. This figure shows the density of p-values of the coefficient on $Uncertainty \times LowPerf$, using the specification of regression (6) estimated 1000 times but excluding each time randomly 5% of the sample.

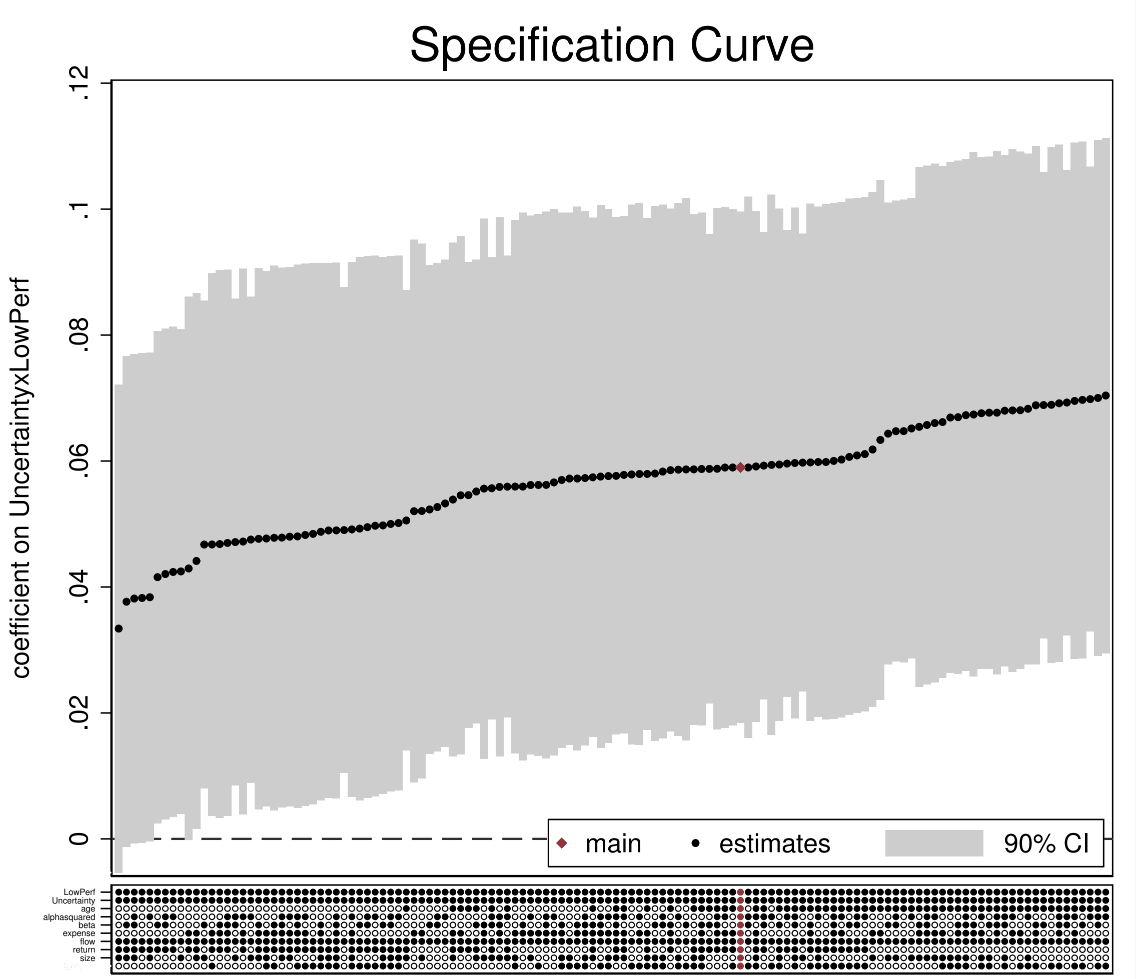

Figure A4. This figure shows the specification curve with the coefficient on $Uncertainty \times LowPerf$ on the y-axis and various regressions specifications on the x-axis with different combinations of control variables (Simonsohn et al. 2020).

Table A1. Text-Based Uncertainty, Performance, and Fund Flows: Equity Domestic Funds

This table presents estimates from panel regressions of equity domestic mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.090***	0.090***	0.108***	0.108***
	(3.00)	(2.99)	(2.98)	(2.98)
$Uncertainty_{i,t-1}$	-0.030	-0.032	-0.073	-0.074
	(-0.77)	(-0.82)	(-1.48)	(-1.48)
$LowPerf_{i,t-1}$	-0.005***	-0.005***	-0.006***	-0.006***
	(-4.46)	(-4.38)	(-4.80)	(-4.92)
$\log(TNA)_{i,t-1}$	-0.014***	-0.014***	-0.014***	-0.014***
	(-17.02)	(-16.97)	(-15.33)	(-15.35)
$Return_{i,t-1}$	0.060**	0.060**	0.057**	0.058**
	(2.43)	(2.42)	(2.30)	(2.34)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.014***	-0.013***	-0.013***
	(-11.51)	(-11.50)	(-10.27)	(-10.29)
$Flows_{i,t-1}$	-0.016	-0.015	0.006	0.005
	(-1.50)	(-1.40)	(0.52)	(0.47)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.34)	(-0.35)	(-0.40)
$Expense_{i,t-1}$			-0.355	-0.356
			(-1.49)	(-1.49)
$Turnover_{i,t-1}$			0.000**	0.000**
			(2.04)	(2.03)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.158***
				(3.03)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	495749	494029	383026	383026
R^2	0.118	0.118	0.121	0.122

Table A2. Text-Based Uncertainty, Continuous Performance, and Fund Flows: Interactions

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with the inverse of performance (Four-factor alpha). *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with (Morningstar) style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1}$ × $1/Four\text{-}factor\ alpha_{i,t-1}$	0.157**	0.157**	0.200*	0.199*
	(2.04)	(2.04)	(1.78)	(1.78)
$Uncertainty_{i,t-1}$	-0.015	-0.015	-0.027	-0.028
	(-0.53)	(-0.54)	(-0.82)	(-0.83)
$1/Four\text{-}factor\ alpha_{i,t-1}$	-0.003**	-0.003**	-0.004*	-0.004*
	(-2.17)	(-2.17)	(-1.88)	(-1.88)
$\log(TNA)_{i,t-1}$	-0.013***	-0.013***	-0.012***	-0.012***
	(-19.46)	(-19.46)	(-17.74)	(-17.76)
$Return_{i,t-1}$	0.097***	0.096***	0.096***	0.097***
	(4.90)	(4.86)	(4.78)	(4.87)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.014***	-0.014***	-0.014***
	(-16.43)	(-16.43)	(-14.82)	(-14.82)
$Flows_{i,t-1}$	0.031***	0.031***	0.053***	0.052***
	(3.90)	(3.89)	(6.34)	(6.29)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.88)	(-0.79)	(-0.86)
$Expense_{i,t-1}$			-0.466***	-0.467***
			(-2.72)	(-2.73)
$Turnover_{i,t-1}$			0.000*	0.000*
			(1.71)	(1.70)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.163***
				(3.09)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1030536	1030536	836037	836037
R^2	0.124	0.124	0.130	0.130

Table A3. Text-Based Uncertainty, Performance, and Fund Flows: Future Performance

This table presents estimates from panel regressions of mutual funds' *% Four-factor alpha* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$\textit{Four-factor alpha}_{i,t}$			
	(1)	(2)	(3)	(4)
$\textit{Uncertainty}_{i,t-1} \times \textit{LowPerf}_{i,t-1}$	-0.021**	-0.022**	-0.024**	-0.024**
	(-2.06)	(-2.17)	(-2.02)	(-2.02)
$\textit{Uncertainty}_{i,t-1}$	-0.004	-0.005	-0.006	-0.006
	(-0.76)	(-0.90)	(-0.85)	(-0.85)
$\textit{LowPerf}_{i,t-1}$	0.001	0.001	0.001	0.001
	(0.97)	(1.43)	(1.39)	(1.37)
$\log(\textit{TNA})_{i,t-1}$	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.47)	(-7.42)	(-7.76)	(-7.75)
$\textit{Return}_{i,t-1}$	-0.013	-0.015	-0.016	-0.016
	(-0.83)	(-0.93)	(-0.98)	(-0.97)
$\log(\textit{Fund age})_{i,t-1}$	0.001***	0.001***	0.001***	0.001***
	(2.87)	(2.95)	(2.73)	(2.73)
$\textit{Flows}_{i,t-1}$	-0.000	-0.000	-0.000	-0.000
	(-0.07)	(-0.13)	(-0.08)	(-0.12)
$\textit{Beta}_{i,t-1}$		-0.004**	-0.003*	-0.003*
		(-2.10)	(-1.96)	(-1.97)
$\textit{Expense}_{i,t-1}$			-0.075***	-0.076***
			(-2.94)	(-2.95)
$\textit{Turnover}_{i,t-1}$			0.000	0.000
			(1.04)	(1.02)
$\textit{Four-factor alpha}^2_{i,t-1}$				0.020***
				(5.02)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1035025	1032559	836478	836478
R^2	0.382	0.383	0.380	0.380

Table A4. Text-Based Uncertainty, Performance, and Fund Flows: Marketing

This table presents estimates from panel regressions of mutual funds' marketing expenses (effective 12b-1 fees) on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$12b\text{-}1_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.058**	0.055**	0.070*	0.070*
	(2.11)	(2.02)	(1.95)	(1.95)
$Uncertainty_{i,t-1}$	-0.060	-0.040	-0.011	-0.012
	(-0.62)	(-0.40)	(-0.08)	(-0.08)
$LowPerf_{i,t-1}$	-0.001	-0.001	-0.001	-0.001
	(-1.03)	(-1.06)	(-1.14)	(-1.14)
$\log(TNA)_{i,t-1}$	0.002**	0.003**	0.005***	0.005***
	(2.07)	(2.01)	(3.09)	(3.09)
$Return_{i,t-1}$	0.003	0.004	0.006	0.006
	(0.67)	(0.86)	(1.08)	(1.06)
$\log(Fund\ age)_{i,t-1}$	0.005**	0.005**	0.004*	0.004*
	(2.54)	(2.44)	(1.74)	(1.74)
$Flows_{i,t-1}$	-0.000	-0.001	-0.001	-0.001
	(-0.17)	(-0.30)	(-0.23)	(-0.22)
$Beta_{i,t-1}$		0.002**	0.002**	0.002**
		(2.42)	(2.40)	(2.44)
$Turnover_{i,t-1}$			0.000	0.000
			(0.64)	(0.64)
$Expense_{i,t-1}$			5.407***	5.408***
			(6.65)	(6.65)
$Four\text{-}factor\ alpha^2_{i,t-1}$				-0.008
				(-1.46)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1083641	1033636	838995	838995
R^2	0.971	0.972	0.967	0.967

Table A5. Text-Based Uncertainty, Performance, and Fund Flows: Net vs. Gross Returns

This table presents estimates from panel regressions of mutual funds' net and gross returns on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Net\ ret._{i,t}$	$Gross\ ret._{i,t}$
	(1)	(2)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	-0.689	-0.670
	(-0.58)	(-0.57)
$Uncertainty_{i,t-1}$	1.119	1.120
	(0.91)	(0.91)
$LowPerf_{i,t-1}$	-0.114	-0.115
	(-0.81)	(-0.82)
$\log(TNA)_{i,t-1}$	-0.125***	-0.126***
	(-6.41)	(-6.43)
$Return_{i,t-1}$	-3.687	-3.688
	(-0.67)	(-0.67)
$\log(Fund\ age)_{i,t-1}$	0.056	0.057
	(1.49)	(1.49)
$Flows_{i,t-1}$	-0.110	-0.114
	(-0.77)	(-0.79)
$Expense_{i,t-1}$	-8.169**	-0.953
	(-2.06)	(-0.24)
$Turnover_{i,t-1}$	0.001	0.001
	(0.22)	(0.22)
$Beta_{i,t-1}$	-0.143	-0.143
	(-0.67)	(-0.66)
$Four\text{-}factor\ alpha^2_{i,t-1}$	0.104	0.102
	(0.06)	(0.06)
Style x Year-Month FE	Yes	Yes
Fund FE	Yes	Yes
Observations	837171	837165
R^2	0.724	0.724

Table A6. Text-Based Uncertainty, Performance, and Fund Flows in Months Ahead

This table presents estimates from panel regressions of mutual funds' *% flows* at t+2 on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t+1}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.040*	0.044*	0.027	0.027
	(1.72)	(1.86)	(1.14)	(1.14)
$Uncertainty_{i,t-1}$	-0.019	-0.024	-0.035	-0.035
	(-0.72)	(-0.88)	(-1.04)	(-1.04)
$LowPerf_{i,t-1}$	-0.003***	-0.003***	-0.003***	-0.003***
	(-4.19)	(-4.35)	(-4.09)	(-4.06)
$\log(TNA)_{i,t-1}$	-0.013***	-0.013***	-0.013***	-0.013***
	(-21.09)	(-20.44)	(-19.27)	(-19.27)
$Return_{i,t-1}$	0.038***	0.038***	0.047***	0.047***
	(2.82)	(2.86)	(3.20)	(3.21)
$\log(Fund\ age)_{i,t-1}$	-0.013***	-0.012***	-0.012***	-0.012***
	(-14.78)	(-14.61)	(-12.57)	(-12.57)
$Flows_{i,t-1}$	0.050***	0.056***	0.065***	0.065***
	(8.90)	(9.70)	(11.93)	(11.94)
$Beta_{i,t-1}$		0.001	0.001	0.001
		(0.52)	(0.61)	(0.62)
$Expense_{i,t-1}$			-0.551***	-0.550***
			(-3.25)	(-3.25)
$Turnover_{i,t-1}$			0.000**	0.000**
			(2.00)	(2.00)
$Four\text{-}factor\ alpha^2_{i,t-1}$				-0.022
				(-0.90)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1064218	1015268	824600	824600

Table A7. Text-Based Uncertainty, Skill, and Fund Flows
This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of a skill measure (Berk and Van Binsbergen 2015) distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowSkill_{i,t-1}$	0.060**	0.064**	0.067***	0.068***
	(2.48)	(2.60)	(2.79)	(2.80)
$Uncertainty_{i,t-1}$	-0.009	-0.019	-0.034	-0.034
	(-0.35)	(-0.69)	(-1.02)	(-1.02)
$LowSkill_{i,t-1}$	-0.005***	-0.005***	-0.005***	-0.005***
	(-6.25)	(-6.40)	(-6.47)	(-6.67)
$\log(TNA)_{i,t-1}$	-0.013***	-0.013***	-0.012***	-0.012***
	(-20.43)	(-19.45)	(-17.73)	(-17.74)
$Return_{i,t-1}$	0.085***	0.085***	0.084***	0.085***
	(4.27)	(4.30)	(4.16)	(4.22)
$\log(Fund\ age)_{i,t-1}$	-0.015***	-0.014***	-0.014***	-0.014***
	(-16.29)	(-16.48)	(-14.88)	(-14.88)
$Flows_{i,t-1}$	0.017**	0.031***	0.052***	0.052***
	(2.26)	(3.87)	(6.31)	(6.26)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.56)	(-0.46)	(-0.52)
$Expense_{i,t-1}$			-0.468***	-0.469***
			(-2.72)	(-2.74)
$Turnover_{i,t-1}$			0.000*	0.000*
			(1.73)	(1.72)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.169***
				(3.27)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1080279	1030536	836037	836037
R^2	0.118	0.125	0.130	0.130

Table A8. Text-Based Uncertainty, Performance, and Fund Flows: Alternative Clusters For Standard Errors

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are clustered by the different groups mentioned in the table. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	(1)	(2)	(3)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.059**	0.059**	0.059**
	(2.58)	(2.52)	(2.56)
$Uncertainty_{i,t-1}$	-0.033*	-0.033	-0.033
	(-1.66)	(-1.02)	(-1.60)
$LowPerf_{i,t-1}$	-0.005***	-0.005***	-0.005***
	(-6.43)	(-6.67)	(-6.30)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Cluster S.E.	Year-Month	Fund	Style x Year-Month
Observations	836037	836037	836037

Table A9. Text-Based Uncertainty, Performance, and Fund Flows: Pre-Covid

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy excluding the Covid period (post March 2020). *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$		
	(1)	(2)	(3)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.040*	0.047*	0.048*
	(1.73)	(1.80)	(1.83)
$Uncertainty_{i,t-1}$	-0.019	-0.035	-0.035
	(-0.65)	(-0.98)	(-0.99)
$LowPerf_{i,t-1}$	-0.004***	-0.004***	-0.004***
	(-4.85)	(-4.85)	(-5.01)
$\log(TNA)_{i,t-1}$	-0.014***	-0.013***	-0.013***
	(-18.49)	(-17.59)	(-17.60)
$Return_{i,t-1}$	0.105***	0.106***	0.107***
	(5.54)	(5.34)	(5.37)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.013***	-0.013***
	(-14.48)	(-13.17)	(-13.16)
$Flows_{i,t-1}$	0.019**	0.040***	0.039***
	(2.40)	(4.86)	(4.81)
$Beta_{i,t-1}$	-0.000	-0.000	-0.000
	(-0.40)	(-0.25)	(-0.31)
$Expense_{i,t-1}$		-0.443**	-0.445**
		(-2.44)	(-2.46)
$Turnover_{i,t-1}$		0.000	0.000
		(0.72)	(0.70)
$Four\text{-}factor\ alpha^2_{i,t-1}$			0.186***
			(3.35)
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	939909	764419	764419
R^2	0.125	0.132	0.132

Table A10. Text-Based Uncertainty, Performance, and Fund Flows: Interactions

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy, as well as each fund characteristic. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with (Morningstar) style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$	
	(1)	(2)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.032	0.051**
	(1.14)	(2.08)
$Uncertainty_{i,t-1}$	-0.071	-0.103
	(-1.19)	(-0.71)
$LowPerf_{i,t-1}$	-0.005***	-0.005***
	(-5.82)	(-5.54)
$Expense_{i,t-1}$	-0.494***	-0.842***
	(-5.09)	(-3.46)
$Uncertainty_{i,t-1} \times Expense_{i,t-1}$	1.151	13.447**
	(0.40)	(2.40)
$\log(TNA)_{i,t-1}$	-0.000**	-0.013***
	(-2.37)	(-15.24)
$Uncertainty_{i,t-1} \times \log(TNA)_{i,t-1}$	-0.006	0.022
	(-0.94)	(1.18)
$Return_{i,t-1}$	0.123***	0.104***
	(5.63)	(4.60)
$Uncertainty_{i,t-1} \times Return_{i,t-1}$	-0.708**	-0.750***
	(-2.57)	(-2.69)
$\log(Fund\ age)_{i,t-1}$	-0.010***	-0.013***
	(-19.27)	(-10.49)
$Uncertainty_{i,t-1} \times \log(Fund\ age)_{i,t-1}$	0.036**	-0.035
	(2.47)	(-1.15)
$Flows_{i,t-1}$	0.136***	0.086***
	(9.44)	(6.01)
$Uncertainty_{i,t-1} \times Flows_{i,t-1}$	-0.757	-1.229**
	(-1.49)	(-2.44)
$Turnover_{i,t-1}$	-0.000	0.000
	(-0.27)	(0.41)
$Uncertainty_{i,t-1} \times Turnover_{i,t-1}$	0.009	0.004
	(0.88)	(0.41)
$Beta_{i,t-1}$	0.001	0.003
	(0.93)	(1.25)
$Uncertainty_{i,t-1} \times Beta_{i,t-1}$	-0.022	-0.129**
	(-0.64)	(-2.22)
$Four\text{-}factor\ alpha^2_{i,t-1}$	0.381***	0.269
	(2.63)	(1.43)
$Uncertainty_{i,t-1} \times Four\text{-}factor\ alpha^2_{i,t-1}$	-4.361	-3.961
	(-0.78)	(-0.59)
Fund controls	Yes	Yes
Style x Year-Month FE	Yes	Yes
Fund FE	No	Yes
Observations	836046	836037
R^2	0.077	0.131

Table A11. Text-Based Uncertainty, Performance, and Fund Flows: Morningstar Ratings

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy, controlling for Morningstar ratings. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, Morningstar rating, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.043**	0.043**	0.044**	0.044**
	(2.12)	(2.10)	(2.15)	(2.15)
$Uncertainty_{i,t-1}$	0.023	0.022	0.020	0.020
	(0.65)	(0.61)	(0.57)	(0.57)
$LowPerf_{i,t-1}$	-0.002***	-0.002**	-0.002**	-0.002**
	(-2.74)	(-2.49)	(-2.59)	(-2.61)
$\log(TNA)_{i,t-1}$	-0.009***	-0.009***	-0.009***	-0.009***
	(-16.30)	(-16.21)	(-16.34)	(-16.35)
$Return_{i,t-1}$	0.105***	0.105***	0.105***	0.105***
	(8.79)	(8.85)	(8.78)	(8.80)
$\log(Fund\ age)_{i,t-1}$	-0.013***	-0.013***	-0.013***	-0.013***
	(-8.51)	(-8.54)	(-8.59)	(-8.59)
$Flows_{i,t-1}$	0.129***	0.128***	0.129***	0.129***
	(12.91)	(12.89)	(12.92)	(12.92)
$Beta_{i,t-1}$		-0.003***	-0.002***	-0.003***
		(-3.05)	(-3.00)	(-3.10)
$Expense_{i,t-1}$			-0.086	-0.087
			(-0.53)	(-0.54)
$Turnover_{i,t-1}$			0.000	0.000
			(1.11)	(1.11)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.065
				(1.53)
$Morningstar_{i,t-1}$	0.010***	0.010***	0.010***	0.010***
	(31.77)	(31.77)	(31.80)	(31.80)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	328165	328136	327772	327772
R^2	0.174	0.174	0.174	0.174

Table A12. Text-Based Uncertainty, Performance, and Fund Flows: Morningstar Categories

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy. *Uncertainty* is measured following Loughran and McDonald (2011) and represents the proportion of uncertainty-related words in the funds' strategy section of the prospectus. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with (Morningstar) style categories ($MorningCat$) and time periods. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Flows_{i,t}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf^{MorningCat}_{i,t-1}$	0.105***	0.107***	0.092***	0.092***
	(4.32)	(4.39)	(3.56)	(3.58)
$Uncertainty_{i,t-1}$	-0.015	-0.025	-0.036	-0.037
	(-0.56)	(-0.91)	(-1.10)	(-1.11)
$LowPerf^{MorningCat}_{i,t-1}$	-0.006***	-0.006***	-0.007***	-0.007***
	(-6.86)	(-6.76)	(-6.65)	(-6.80)
$\log(TNA)_{i,t-1}$	-0.013***	-0.013***	-0.012***	-0.012***
	(-20.45)	(-19.46)	(-17.73)	(-17.75)
$Return_{i,t-1}$	0.085***	0.086***	0.082***	0.083***
	(4.25)	(4.31)	(4.10)	(4.18)
$\log(Fund\ age)_{i,t-1}$	-0.015***	-0.014***	-0.014***	-0.014***
	(-16.28)	(-16.47)	(-14.87)	(-14.87)
$Flows_{i,t-1}$	0.017**	0.031***	0.052***	0.052***
	(2.26)	(3.87)	(6.30)	(6.25)
$Beta_{i,t-1}$		-0.001	-0.001	-0.001
		(-0.59)	(-0.44)	(-0.50)
$Expense_{i,t-1}$			-0.463***	-0.464***
			(-2.70)	(-2.72)
$Turnover_{i,t-1}$			0.000*	0.000*
			(1.76)	(1.75)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.169***
				(3.26)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1080279	1030536	836037	836037
R^2	0.118	0.125	0.130	0.130

Table A13. Language from Poorly Performing Funds

This table presents estimates from panel regressions of text characteristics (readability and text length) on a low performance dummy. Readability is proxied by the Gunning-Fog Index. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. The first column considers funds with low performance as defined by the lowest quintile. I control for lagged monthly fund-level characteristics, namely squared *alpha* based on the Carhart (1997) four-factor model, *beta* based on the CAPM, *turnover*, fund *flow*, the natural logarithm of *fund age* , fund returns, market beta, the natural logarithm of fund size (*TNA*), *expense* ratio, and *turnover* ratio. Standard errors are double-clustered by fund and year-month. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	$Fog_{i,t}$	$SentenceCount_{i,t}$	$WordCount_{i,t}$
	(1)	(2)	(3)
$LowPerf_{i,t-1}$	0.080***	0.557***	13.736***
	(2.69)	(5.51)	(4.50)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	No	No	No
Observations	839031	839031	839031
R^2	0.074	0.240	0.273

Prospectus example

Below is the full principal invesment strategy with selected relevant parts in bold for the fund: Comstock Funds, Inc: Comstock Capital Value Fund; Class A Shares. August 2017

The Fund follows a value oriented strategy and seeks to achieve its investment objective by investing in equity and debt securities, money market instruments, and derivatives. The Fund may invest in, and may shift frequently among, a wide range of asset classes and market sectors. Thus, during the course of a business cycle, for example, the Fund may invest solely in equity securities, debt securities, or money market instruments, or in a combination of these classes of investments. As a result, Gabelli Funds, LLC (the "Adviser") has considerable flexibility in selecting the types of investments and market sectors for investment of the Fund's assets and is not required to maintain any minimum portion of the Fund's assets in any particular asset class. The Fund may use either long or short positions in pursuit of its investment objective. The Fund's investment performance will depend in large part on the asset allocation selected by the portfolio managers. ***For each asset class, the Adviser uses a valuation approach to investing by examining the overall economic picture, the characteristics of individual securities and historical market information and technical analysis to determine securities which it believes are overvalued or undervalued. As of the date of this prospectus, the portfolio managers view the U.S. equity markets as overvalued by most traditional measures and have positioned the Fund to seek profits from a major U.S. equity market decline through a variety of investment practices, including puts and short sales, together with its investments in short-term fixed-income securities. As presently positioned, in the event that U.S. equity markets do not experience a significant decline, the Fund can be expected to underperform other funds that are not similarly positioned for a bear market.*** *The Fund is, however,* *flexibly managed and the Adviser may, consistent with the Fund's investment strategies, without prior notice to shareholders, change the Fund's asset positioning quickly and decisively. The equity securities in which the Fund invests include common and preferred stock (including convertible preferred stock), warrants, and depository receipts. There is no restriction on the market capitalization of the Fund's equity securities. The debt securities in which the Fund may invest include: U.S. corporate debt, U.S. government and agency debt, and foreign sovereign and other debt securities (including debt securities from emerging market issuers). The Fund may invest up to 65% of its assets in equity and debt securities of foreign issuers, including those in emerging markets. The Fund may also invest in debt securities convertible into shares of common stock. The Fund's debt securities may have fixed, floating, or variable rates of interest. The Fund may invest without limit in high yield debt securities (commonly referred to as "junk bonds"), but currently intends to limit such investments to 35% of its assets. High yield debt securities are those rated "Baa" or lower by Moody's Investors Service, Inc. ("Moody's"), or "BBB" or lower by Standard & Poor's Rating Services ("S&P"), a division of McGraw-Hill Companies or, if unrated, judged by the Adviser to be of comparable quality. There is no restriction on the maturity of the Fund's portfolio or on any individual debt security in the Fund's portfolio. The Adviser may adjust the average maturity according to actual or anticipated changes in the market. The Fund may invest in high quality domestic and foreign money market instruments, and may enter into repurchase agreements. In addition, when the Adviser determines that a temporary defensive position is advisable or to meet anticipated redemption requests, the Fund may invest without limit in short term debt obligations, such as commercial paper, bank obligations, and U.S. Treasury bills. The Fund may make short sales, which are transactions in which the Fund sells a security it does not own, with the expectation that the security's value will decline. To complete a short sale, the Fund must borrow the security to make delivery, and then replace the security by purchasing it. The total market value of all of the Fund's short sales may not exceed 50% of the value of the Fund's net assets. In addition,* *the Fund's short sales of the securities of any single issuer listed on a national securities exchange may not exceed 5% of the value of the Fund's net assets, and the Fund may not sell short more than 5% of the outstanding securities of a single class of securities of an issuer. The Fund may enter into short sales of securities the Fund owns, but such sales cannot exceed 15% of the value of the Fund's net assets. The Fund's compliance with these limitations is calculated at the time a transaction is effected. The Fund intends to invest in derivatives, which are financial instruments whose value is based on another security, an index of securities or market changes, or exchange rate movements. The Fund may use derivatives to hedge various market risks. Derivative strategies the Fund may use include writing covered call or put options or purchasing put and call options on securities, foreign currencies, or stock indices. The Fund may also purchase or sell stock index futures contracts or interest rate futures contracts and may enter into interest rate or forward currency transactions. In addition, the Fund may purchase futures and options on futures and may purchase options on securities or securities indices for speculative purposes in order to increase the Fund's income or gain. The Fund may enter into futures contracts and options on futures for speculative purposes if, immediately thereafter, the sum of the amount of its initial margin on futures contracts and premiums on options on futures would not exceed 5% of the liquidation value of the Fund's portfolio, provided that in the case of an option that is in-the-money at the time of purchase, the in-the-money amount may be excluded in calculating this 5% limitation. In addition to the preceding limitation, the value of all uncovered put and call options held by the Fund cannot exceed 10% of the Fund's net assets. The Fund may not write covered call and put option contracts in excess of 20% of its net assets. The Fund's compliance with these limitations is only calculated at the time any new position is added, with the result that the limitations may be exceeded if derivative positions held by the Fund appreciate after the new position is added.*

John Hancock Variable Insurance Trust: Financial Services Trust. April 2012

Under normal market conditions, the fund invests at least 80% of its net assets (plus any borrowings for investment purposes) in companies that, at the time of investment, are principally engaged in financial services, and the fund invests primarily in common stocks of financial services companies. A company is "principally engaged" in financial services if it owns financial services-related assets constituting at least 50% of the value of its total assets, or if at least 50% of its revenues are derived from its provision of financial services. Companies in the financial services industry include commercial banks, industrial banks, savings institutions, finance companies, diversified financial services companies, investment banking firms, securities brokerage houses, investment advisory companies, leasing companies, insurance companies and companies providing similar services. The fund may also invest in other equity securities and in foreign and fixed-income securities. The subadviser uses the Davis Investment Discipline in managing the fund's portfolio. The subadviser conducts extensive research to try to identify companies with durable business models that can be purchased at attractive valuations relative to their intrinsic value. The subadviser emphasizes individual stock selection and believes that the ability to evaluate management is critical. The subadviser routinely visits managers at their places of business in order to gain insight into the relative value of different businesses. Such research, however rigorous, involves predictions and forecasts that are inherently uncertain. The subadviser has developed the following list of characteristics that it believes help companies to create shareholder value over the long term and manage ***risk****. While few companies possess all of these characteristics at any given time, the subadviser seeks to invest in companies that demonstrate a majority, or an appropriate mix of these characteristics, although there is no guarantee that it will be successful in doing so. Proven track record Significant alignment of interest in business Strong balance sheet Low cost structure High returns on capital Non-obsolescent products/services Dominant or growing market share Global presence and brand names Intelligent application of capital The subadviser's goal is to invest in companies for the long* *term. The subadviser considers selling a company if it believes the stock's* ***market*** *price exceeds its estimates of intrinsic value, or if the ratio of the* ***risks*** *and rewards of continuing to own the company is no longer attractive. The fund may engage in active and frequent trading to achieve its principal investment strategies which will increase transaction costs. The fund concentrates (that is, invests at least 25% or more) its investments in securities of companies engaged in the financial services industries, a comparatively narrow segment of the economy, and may therefore experience greater* ***volatility*** *than funds investing in a broader range of industries. Moreover, a fund which concentrates its investments in a particular sector is particularly susceptible to the impact of* ***market****, economic, regulatory and other factors affecting that sector. The fund is non-diversified, which means that it may invest its assets in a smaller number of issuers than a diversified fund.*

AQR Funds: AQR Multi-Strategy Alternative Fund; Class I Shares, May 2016

The Fund pursues its investment objective by aiming to provide exposure to several strategies often referred to as "alternative" or "absolute return" strategies and more traditionally made available through unregistered funds ("hedge funds"). Utilizing a well-diversified portfolio of Instruments (as defined below), the Fund seeks exposure to the following strategies: Convertible Arbitrage, Event Driven (including Merger Arbitrage), Fixed Income Relative Value, Equity Market Neutral, Long/Short Equity, Dedicated Short Bias, Global Macro, Managed Futures and Emerging Markets. Through exposure to these strategies, the Fund attempts to generate positive absolute returns over time. The Fund implements these strategies by investing globally (including in emerging markets) in a broad range of instruments, including, but not limited to, equities (primarily those issued by large- and mid-cap companies), bonds, convertible securities, futures (including commodity futures, index futures, equity futures, bond futures and interest rate futures), currency forwards, options and swaps (including commodity swaps, swaps on commodity futures, equity swaps, swaps on index futures, total return swaps, interest rate swaps, and credit default swaps) (collectively, the "Instruments"), either by investing directly in these instruments or, indirectly, by investing in the Subsidiary (as described below) that invests in these instruments. The securities in which the Fund invests may be restricted and/or Rule 144A securities. The Fund may also invest in exchange-traded funds or exchange-traded notes through which the Fund can participate in the performance of one or more Instruments. The Fund currently intends to achieve its exposure to equities and convertible securities by either holding securities or holding cash and using derivatives, rather than holding those securities directly. The Fund will not invest in hedge funds and is not designed to match the performance of any hedge fund index. However, the Adviser believes that, based on a comprehensive analysis of the key drivers of return from these strategies (which are traditionally made available through hedge funds), it can capture a meaningful portion of the return that these strategies can be expected to provide. The Fund is generally intended to have a low average correlation to the equity, *bond and credit markets. The Fund has no limits with respect to the credit rating, maturity or duration of the debt securities in which it may invest, and may invest in debt securities of any credit rating, maturity or duration, which may include high-yield or "junk" bonds. The Fund will utilize proprietary trading algorithms in order to minimize market impact and reduce trading costs. The Adviser will attempt to mitigate risk through diversification of holdings and through active monitoring of volatility, counterparties and other risk measures. There is no assurance, however, that the Fund will achieve its investment objective. As of the date of this prospectus, the Adviser generally considers large- and mid-cap companies to be those companies with market capitalizations around the range of the MSCI World Index at the time of purchase. The strategies employed by the Fund include: Long/Short Equity, Equity Market Neutral and Dedicated Short Bias: These strategies provide long and short exposure to a diversified portfolio of equities which involves simultaneously investing in equities (i.e., investing long) the Adviser expects to increase in value and immediately selling equities (i.e., short sales or short selling) the Adviser expects to decrease in value. Equity Market Neutral is not expected to have industry overweights and seeks to profit by exploiting pricing inefficiencies between related equity securities and neutralizing exposure to market risk by maintaining long and short positions. Long/Short Equity may maintain overweights of industry exposures and also seeks to exploit pricing inefficiencies between related equity securities. The Dedicated Short Bias strategy seeks to profit by shorting stocks that have negative market sentiment and neutralizing exposure to market risk by maintaining long and short positions. When taking a "short" position, the Fund may sell an instrument that it does not own and would then borrow to meet its settlement obligations. The Fund may also take "short" positions in futures, forwards or swaps. A "short" position will benefit from a decrease in price of the underlying instrument and will lose value if the price of the underlying instrument increases. Long positions will profit if the value of the equity security increases and short positions will profit if the value of the equity security declines and the borrowed shares can be replaced at lower cost. Simultaneously engaging in* *long investing and short selling reduces the net exposure of the overall portfolio to general market movements. Global Macro: Global Macro strategies seek to profit from movement in the prices of securities that are highly sensitive to macroeconomic conditions, across a broad spectrum of assets. This strategy provides long and short exposure to developed country equities, currencies, bonds, interest rates and commodities markets. Emerging Markets: This strategy seeks to profit from investing in equities, fixed income instruments and currencies of issuers in emerging markets. This strategy provides long and short exposure to emerging country equity, fixed income and currency markets, and long and short exposure to a basket of liquid equity securities traded on emerging and developed market exchanges. Convertible Arbitrage: Convertible Arbitrage strategies seek to profit from the complexity of the pricing of convertible bonds (which contain elements of both a fixed income security and an equity option) by structuring trades using multiple securities within the capital structure of a convertible bond issuer. The Fund may purchase the convertible bond of a given issuer and simultaneously sell short the common stock of that same issuer to take advantage of a mispricing of either security. This strategy takes positions in various global convertible debt and preferred securities and an offsetting position in various global equities directly linked to the convertible securities. In implementing this strategy, the Fund may use derivatives to hedge against a decline in interest rates or credit exposure. The Adviser collaborates with the Sub-Adviser for this strategy. Managed Futures: Managed Futures strategies seek to profit from the design and implementation of quantitative selection models to help predict upcoming movements in any combination of fixed income, currency, commodity or equity markets. This strategy provides long and short exposure to commodities; long and short exposure to developed country equities, bonds and currencies markets and long and short exposure to emerging country equity and currency markets. Event Driven: Event Driven strategies seek to profit from investing in the securities of companies based not on a value or growth investment style but rather on the basis that a specific event or catalyst will affect future prices. This strategy attempts to capitalize on price discrepancies and returns gen-*

erated by corporate activity, such as mergers. In merger arbitrage, the Fund will employ a diversified, disciplined strategy to attempt to capture the returns from holding a long/short portfolio of stocks of companies involved in mergers. The Adviser collaborates with the Sub-Adviser for this strategy. Fixed Income Relative Value: Fixed Income Relative Value seeks to profit from exploiting mispricing of various, liquid fixed income or interest rate sensitive securities. This strategy provides long and short exposure to developed country bonds, interest rates and currencies, long and short exposure to investment grade and high-yield credit instruments and long and short exposure to forward mortgage-backed securities trading in the to-be-announced market. ***The Fund provides exposure to several absolute return strategies through one fund offering. The Fund may add additional strategies from time to time. The Fund currently intends to have exposure to each of the strategies, however, it may vary its level of allocation among the strategies depending on market conditions, including reducing the exposure to any strategy to zero. The Fund's returns are expected to be volatile. The Adviser, on average, will target an annualized volatility level for the Fund of 10%, which compares to a historical volatility level of approximately 4% for the Barclays U.S. Aggregate Bond Index and a historical volatility level of approximately 18% for the S&P 500 Index of U.S. large-cap stocks over the past five years. The actual or realized volatility level of the Fund can and will be materially higher or lower than its target volatility depending on market conditions.*** *If derivative instruments and instruments with remaining maturities of one year or less are taken into account, the Fund's strategy will result in frequent portfolio trading and high portfolio turnover (typically greater than 100%). Portfolio Construction The Fund is constructed, at both the strategy level and the portfolio level, to provide returns that are not correlated to the equity, bond and credit markets. The Fund will be managed to be broadly diversified across a range of global markets. In addition, the Fund is monitored to avoid traditional long equity market exposure at the overall portfolio level, while at times allowing modest active long or short* *equity market exposure through tactical decisions. Strategy Level Each of the strategies is constructed using a bottom up systematic process. In addition, two or more strategies may be used in combination to achieve a particular investment exposure or goal. Although the overall Fund is designed to be equity market neutral on average over time, unless the Fund is tactically positioned for a long or short equity market exposure, at the strategy level, the Fund may have equity-based systematic risk. For example, the equity long/short strategy will typically have a slightly net long equity market exposure (depending on the market's recent performance), while the dedicated short bias strategy is expected to have a slightly negative net equity market exposure. The equity market neutral strategy, on the other hand, is intended to be equity market neutral at all times. Although the Fund may simultaneously use one type of exposure in more than one strategy (e.g., use long exposure to developed market equities for the Global Macro and Managed Futures strategies), the exposure will be independently selected to achieve the goal of the particular strategy. Portfolio Level Once each strategy has been individually constructed or groupings of strategies developed, the Adviser combines them into a single portfolio using a long term strategic risk weighting process and a tactical risk allocation. By combining these two methods, the Adviser seeks to implement the overall strategy while opportunistically taking advantage of strategies that are particularly attractive currently. In general, however, the Adviser's portfolio construction process focuses on adding value through diversified risk weighting over the long-term. Sizing Positions The Adviser sets both the long-term strategic risk weights across the individual strategies or grouped strategies, which are expected to vary only slightly over time, as well as short-term tactical weightings which may deviate from the long-term strategic targets due to shorter term market risks or opportunities. Both the long-term strategic risk weights and the shorter term tactical shifts are determined by the Adviser using quantitative inputs and subjective assessment of the current market environment. The short-term tactical underweights or overweights are intended to vary only modestly from the strategic weights. However, there is no limit on the tactical underweights or overweights and the Adviser has the discretion to* *not employ a strategy either temporarily or permanently if the perceived risks of the strategy outweigh the potential benefits. Risk Management The Adviser will use quantitative and qualitative methods to assess the level of risk (i.e., volatility of return) for the Fund. The Adviser expects that the use of systematic risk control generally should lead to a highly diversified portfolio across asset classes, geographies, Instruments and strategies. The Fund intends to make investments through the Subsidiary and may invest up to 25% of its total assets in the Subsidiary. The Subsidiary is a wholly-owned and controlled subsidiary of the Fund, organized under the laws of the Cayman Islands as an exempted company. Generally, the Subsidiary will invest primarily in commodity index swaps and other commodity-linked derivative instruments but it may also invest in financial futures, option and swap contracts, fixed income securities, pooled investment vehicles, including those that are not registered pursuant to the 1940 Act, and other investments intended to serve as margin or collateral for the Subsidiary's derivative positions. The Fund will invest in the Subsidiary in order to gain exposure to the commodities markets within the limitations of the federal tax laws, rules and regulations that apply to registered investment companies. Unlike the Fund, the Subsidiary may invest without limitation in commodity-linked derivative instruments, however, the Subsidiary will comply with the same 1940 Act asset coverage requirements with respect to its investments in commodity-linked derivatives that are applicable to the Fund's transactions in derivatives. In addition, to the extent applicable to the investment activities of the Subsidiary, the Subsidiary will be subject to the same fundamental investment restrictions and will follow the same compliance policies and procedures as the Fund. Unlike the Fund, the Subsidiary will not seek to qualify as a regulated investment company under Subchapter M of the Code. The Fund is the sole shareholder of the Subsidiary and does not expect shares of the Subsidiary to be offered or sold to other investors. A portion of the Fund's assets may be held in cash or cash equivalent investments, including, but not limited to, short-term investment funds and/or U.S. Government securities.*

Textual analysis

Preprocessing and dictionary-based measures

1. All available prospectuses are collected from EDGAR for each mutual fund.
2. The text is stripped of special characters: punctuation, numbers, html tags, URLs.
3. Following Porter (1980), I remove all stopwords and single letter words. This step helps removing common words that would typically have an impact on the word count and document length for example. This step is usually accompanied by a removal of rare words in text analysis, However, since financial vocabulary might contain other uncommon words, I skip this test in order for the documents to include potential uncommon but relevant words from a financial vocabulary.
4. For each principal investment strategy section (PIS), I count the relative number of occurrences of the words that appear in the dictionaries from Loughran and McDonald (2011) in order to measure financial uncertainty, as well as positive and negative tones.

Word2vec

The *Word2vec* model is a word embedding approach that takes into account the meaning of words (Mikolov et al. 2013). It translates a word into a vector of neighboring words which helps understanding its meaning. The vector is composed of other words that are mostly associated with. It uses a neural network that reads through documents in order to identify neighboring words and then learns to predict these. In finance, Li et al. (2021) use this model to identify corporate culture, notably through the cosine similarity of different words in order to see if these are synonyms. In this paper, the goal is simpler. I use word2vec in order to see which words co-occur most with risk and uncertainty and then to see if investors react most to certain types of text-based uncertainty.

Uncertainty word list

"ABEYANCE", "ABEYANCES", "ALMOST", "ALTERATION", "ALTERATIONS", "AMBIGUITIES", "AMBIGUITY", "AMBIGUOUS", "ANOMALIES", "ANOMALOUS", "ANOMALOUSLY", "ANOMALY", "ANTICIPATE", "ANTICIPATED", "ANTICIPATES", "ANTICIPATING", "ANTICIPATION", "ANTICIPATIONS", "APPARENT", "APPARENTLY", "APPEAR", "APPEARED", "APPEARING", "APPEARS", "APPROXIMATE", "APPROXIMATED", "APPROXIMATELY", "APPROXIMATES", "APPROXIMATING", "APPROXIMATION", "APPROXIMATIONS", "ARBITRARILY", "ARBITRARINESS", "ARBITRARY", "ASSUME", "ASSUMED", "ASSUMES", "ASSUMING", "ASSUMPTION", "ASSUMPTIONS", "BELIEVE", "BELIEVED", "BELIEVES", "BELIEVING", "CAUTIOUS", "CAUTIOUSLY", "CAUTIOUSNESS", "CLARIFICATION", "CLARIFICATIONS", "CONCEIVABLE", "CONCEIVABLY", "CONDITIONAL", "CONDITIONALLY", "CONFUSES", "CONFUSING", "CONFUSINGLY", "CONFUSION", "CONTINGENCIES", "CONTINGENCY", "CONTINGENT", "CONTINGENTLY", "CONTINGENTS", "COULD", "CROSSROAD", "CROSSROADS", "DEPEND", "DEPENDED", "DEPENDENCE", "DEPENDENCIES", "DEPENDENCY", "DEPENDENT", "DEPENDING", "DEPENDS", "DESTABILIZING", "DEVIATE", "DEVIATED", "DEVIATES", "DEVIATING", "DEVIATION", "DEVIATIONS", "DIFFER", "DIFFERED", "DIFFERING", "DIFFERS", "DOUBT", "DOUBTED", "DOUBTFUL", "DOUBTS", "EXPOSURE", "EXPOSURES", "FLUCTUATE", "FLUCTUATED", "FLUCTUATES", "FLUCTUATING", "FLUCTUATION", "FLUCTUATIONS", "HIDDEN", "HINGES", "IMPRECISE", "IMPRECISION", "IMPRECISIONS", "IMPROBABILITY", "IMPROBABLE", "INCOMPLETENESS", "INDEFINITE", "INDEFINITELY", "INDEFI-

NITENESS", "INDETERMINABLE", "INDETERMINATE", "INEXACT", "INEXACTNESS", "INSTABILITIES", "INSTABILITY", "INTANGIBLE", "INTANGIBLES", "LIKELIHOOD", "MAY", "MAYBE", "MIGHT", "NEARLY", "NONASSESSABLE", "OCCASIONALLY", "ORDINARILY", "PENDING", "PERHAPS", "POSSIBILITIES", "POSSIBILITY", "POSSIBLE", "POSSIBLY", "PRECAUTION", "PRECAUTIONARY", "PRECAUTIONS", "PREDICT", "PREDICTABILITY", "PREDICTED", "PREDICTING", "PREDICTION", "PREDICTIONS", "PREDICTIVE", "PREDICTOR", "PREDICTORS", "PREDICTS", "PRELIMINARILY", "PRELIMINARY", "PRESUMABLY", "PRESUME", "PRESUMED", "PRESUMES", "PRESUMING", "PRESUMPTION", "PRESUMPTIONS", "PROBABILISTIC", "PROBABILITIES", "PROBABILITY", "PROBABLE", "PROBABLY", "RANDOM", "RANDOMIZE", "RANDOMIZED", "RANDOMIZES", "RANDOMIZING", "RANDOMLY", "RANDOMNESS", "REASSESS", "REASSESSED", "REASSESSES", "REASSESSING", "REASSESSMENT", "REASSESSMENTS", "RECALCULATE", "RECALCULATED", "RECALCULATES", "RECALCULATING", "RECALCULATION", "RECALCULATIONS", "RECONSIDER", "RECONSIDERED", "RECONSIDERING", "RECONSIDERS", "REEXAMINATION", "REEXAMINE", "REEXAMINING", "REINTERPRET", "REINTERPRETATION", "REINTERPRETATIONS", "REINTERPRETED", "REINTERPRETING", "REINTERPRETS", "REVISE", "REVISED", "RISK", "RISKED", "RISKIER", "RISKIEST", "RISKINESS", "RISKING", "RISKS", "RISKY", "ROUGHLY", "RUMORS", "SEEMS", "SELDOM", "SELDOMLY", "SOMETIME", "SOMETIMES", "SOMEWHAT", "SOMEWHERE", "SPECULATE", "SPECULATED", "SPECULATES", "SPECULATING", "SPECULATION", "SPECULATIONS", "SPECULATIVE", "SPECULATIVELY", "SPORADIC", "SPORADICALLY", "SUDDEN", "SUDDENLY", "SUGGEST", "SUGGESTED", "SUGGESTING", "SUGGESTS", "SUSCEPTIBILITY", "TENDING", "TENTATIVE", "TENTATIVELY", "TURBULENCE", "UNCERTAIN", "UNCER-

TAINLY", "UNCERTAINTIES", "UNCERTAINTY", "UNCLEAR", "UNCONFIRMED", "UNDECIDED", "UNDEFINED", "UNDESIGNATED", "UNDETECTABLE", "UNDETERMINABLE", "UNDETERMINED", "UNDOCUMENTED", "UNEXPECTED", "UNEXPECTEDLY", "UNFAMILIAR", "UNFAMILIARITY", "UNGUARANTEED", "UNHEDGED", "UNIDENTIFIABLE", "UNIDENTIFIED", "UNKNOWN", "UNKNOWNS", "UNOBSERVABLE", "UNPLANNED", "UNPREDICTABILITY", "UNPREDICTABLE", "UNPREDICTABLY", "UNPROVED", "UNPROVEN", "UNSEASONABLE", "UNSEASONABLY", "UNSETTLED", "UNSPECIFIC", "UNSPECIFIED", "UNTESTED", "UNUSUAL", "UNUSUALLY", "UNWRITTEN", "UNFORECASTED", "UNFORSEEN", "UNPREDICTED", "UNQUANTIFIABLE", "UNQUANTIFIED", "UNRECONCILED", "VAGARIES", "VAGUE", "VAGUELY", "VAGUENESS", "VAGUENESSES", "VAGUER", "VAGUEST", "VARIABILITY", "VARIABLE", "VARIABLES", "VARIABLY", "VARIANCE", "VARIANCES", "VARIANT", "VARIANTS", "VARIATION", "VARIATIONS", "VARIED", "VARIES", "VARY", "VARYING", "VOLATILITY", "VOLATILE", "VOLATILITIES "