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

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Abstract

This paper studies how underperforming mutual funds' communication in prospectuses relates to investors' capital allocation decisions. Underperforming mutual funds use more uncertain language. Investors appear to react to this form of communication, as underperforming funds experience less negative outflows when their language includes higher uncertainty. Additionally, the use of uncertain language by underperforming funds is negatively associated with future performance. Investors' response to uncertain language in mutual fund communication contributes to a misallocation of capital across funds. Overall, underperforming mutual funds' language in prospectuses helps explain the convexity of the flow-performance relationship and serves as a signal about future performance.

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

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

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1 Introduction

Information provision by firms is important for consumers as it affects their propensity to buy a product. Corporations use various forms of communication, such as advertising or mandated disclosure, notably to persuade 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 how communication differs across mutual funds and how effective it is in influencing investors' propensity to invest in order to explain the industry's size. With the recent decline in assets under management for actively managed funds, it is crucial to understand how mutual funds' incentives interact with outflow risk (Cen, Dou, Kogan, and Wu 2023).[1]

In this paper, I explore how mutual funds communicate in prospectuses depending on performance and how mutual funds' use of terms related to uncertainty can influence investors' assessment of their products. The Securities and Exchange Commission mandates mutual funds to detail their investment strategies in prospectuses. 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 current state of the economy. Thus, even in the presence of disclosure mandates, mutual funds have room for strategic communication by, for instance, providing unin-

[1] As of 2022, the size of the mutual fund industry represented approximately $29 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. Recent numbers from the Investment Company Institute show that actively managed domestic equity mutual funds in the U.S. experienced net outflows of approximately $2.6 trillion over the last 10 years.

formative details.[2] I hypothesize that underperforming funds may use more uncertain language to mitigate outflow risk. By doing so, mutual funds use framing to present information about a fund's characteristics less negatively, potentially influencing investors' capital allocation decisions.

Using U.S. mutual funds prospectuses from 2011 to 2020, I find that underperforming mutual funds use more words related to uncertainty in prospectuses, as revealed by both a dictionary-based approach and embeddings obtained from a transformer model. Conditional on underperformance, mutual funds experience less negative flows when using more uncertainty-related terms, as proxied by Loughran and McDonald (2011). 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 an underperforming mutual fund, or a 12% increase relative to the sample average fund flows.

Dictionary-based methods have shortcomings such as subjectivity in term selection and lack of contextual understanding. To overcome these issues, I use large language models, specifically GPT-4 by OpenAI, to capture uncertain language as an alternative measure. The results confirm that uncertainty extracted using large language models is positively related to fund flows for underperforming funds. Moreover, using transformers and double machine-learning to control the many aspects of the text that could correlated with uncertainty in the text and fund flows (Chernozhukov, Chetverikov, Demirer, Duflo, Hansen, and Newey 2017), I find that the results are robust and uncertainty is positively related to fund flows for underperforming funds.

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

[2]For example, Persson (2018) shows theoretically that even with disclosure mandates, information overload can arise in equilibrium, which obfuscates financially-relevant characteristics. The longest investment strategy sections of fund prospectuses have up to 3700 words, while the average strategy section contains around 440 words.

month an underperforming mutual fund would experience only $3.2M of outflows on average if its prospectus emphasizes uncertainty. Over an entire year, this amounts to more than $21M, *per fund*; or an aggregate $10B per year, that are misallocated as results show that underperforming funds that discuss uncertainty keep underperforming going-forward.[3]

To understand why uncertain language might relate to fund flows, Mullainathan, Schwartzstein, and Shleifer (2008)'s model offers general insights to rationalize this result. They show, in a theoretical framework, how one can take advantage of information receivers' perception of a product's quality through framing. The authors also document that around market downturns, mutual funds and other financial institutions 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 provides new empirical evidence showing that investors are influenced by uninformative wording when assessing mutual funds' products; especially when these institutions experience downturns, consistent with framing and coarse thinking as in Mullainathan et al. (2008). The relationship between uncertain language and fund flows has important implications for both investors and regulators, as mutual funds can communicate strategically in mandated disclosure, at investors' expense.[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 em-

[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).

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

phasize on the volatility of the second component, i.e., the benchmark. Thus, an underperforming fund could benefit from uncertain language to make the signal about its own skills less precise. Indeed, results show that underperforming mutual funds that use uncertain terms keep underperforming going forward, suggesting that they might have an incentive to blur the signal about their own performance.[5]

One concern behind this empirical exercise is the possibility that mutual funds might use uncertain terms to truthfully reflect 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 2024), 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.[6] Thus, using both holdings-based measures of risk, and non-holdings 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.

Investors' positive reaction to uncertain terms in underperforming funds' prospectuses, conditional on other key fund characteristics, suggests a possible bias from investors. The results are consistent with coarse thinking where investors transfer information to an uncertain context, and adjust negative flows more slowly (Roussanov, Ruan, and Wei 2022), while partially neglecting other baseline information. An alternative explanation for the influence of language on investors decision is lim-

[5]This is akin to fund managers choosing benchmarks strategically to influence investors' capital allocation decisions (e.g., Sensoy 2009).

[6]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.

ited attention. It is possible that investors do not 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 (2023) 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 provides new evidence that individual fund flows, as opposed to common, can be positively associated with uncertainty discussion, consistent with investors' biases Mullainathan et al. (2008) and informational frictions (Roussanov et al. 2022), and provides a novel measure that predicts performance.

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 focuses on a distinct communication channel, uncertainty, in mutual fund communication for the left tail of the performance distribution rather than positive, negative or uniqueness measures from an average fund. 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 2023). 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 (2024) build peer groups from prospectuses and show that capital flows to mutual funds that 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. 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. Finally, Gueciouer (2023) shows that fund managers discussion of risk in letters influences fund flows. This paper adds

that discussion of uncertainty in prospectuses matters for underperforming funds' flows, and therefore fund managers compensation (Cen et al. 2023). Overall, the paper provides additional explanations to the convexity of the tail flow-performance relationship.[7]

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.

[7] Cen et al. (2023) also show that assets under management and fund flows are key determinants of fund managers' compensation.

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 2024). 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

3.1 Performance and Communication

Recent research shows that fund prospectuses, and more specifically the principal investment strategy section, matter for investors (Kostovetsky and Warner 2020). Strategic communication can arise even in a regulated framework (Persson 2018). Given the recent evidence on the importance of uncertainty in text documents and the importance of uncertainty from a macroeconomic perspective (e.g., Jurado, Ludvigson, and Ng 2015; Baker, Bloom, and Davis 2016), the first set of tests explore whether underperforming mutual funds communicate frame information differently through prospectuses (Tversky and Kahneman 1981) . More specifically:

- ***Hypothesis 1: Framing*** **(Funds communication differently conditional on performance)**: Underperforming funds write prospectuses differently and

use more uncertain terms to frame background information about the fund (e.g., relative performance) less negatively consistent with Mullainathan et al. (2008).

3.2 Communication and Fund Flows

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 such as performance or fees.

- ***Hypothesis 2: Rational Investors*** **(No effect of text-based uncertainty on fund flows)**: Investors make capital allocation decision purely based on hard information, i.e. performance, risk, fees, and thus do not react to uncertainty in prospectuses.

3.3 Communication and Fund Flows Conditional on Performance

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 underperform, and the effect might be due to mutual funds being strategic and mentioning uncertainty as the reason for underperformance 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 3: Coarse thinking*** **(Positive effect of text-based uncertainty on fund flows conditional on underperformance)**: Uncertainty

discussion in prospectuses can influence fund flows, conditional on underperformance, as investors might be paying more attention to other sources of information, such as soft information, when mutual funds perform badly. The positive effect on fund flows of uncertainty might be resulting from funds strategically emphasizing uncertainty when delivering bad returns so that investors interpret uncertainty as responsible for underperformance and thus do not punish fund managers with significant outflows, partially neglecting baseline hard information about recent performance in a manner consistent with coarse thinking. In this way, investors slowly adjust their withdrawal of funds (Roussanov et al. 2022) and mutual funds can mitigate outflow risk.

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.[8] I require funds to have a minimum size of $10M. I compute monthly flows as the percentage change of fund size on top of fund returns. More specifically, the fund flows ($flows_{i,t}$) are

[8]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.

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 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:

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

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:

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

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).[9] I provide in the Internet 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

4.3.1 Dictionary-based approach. 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". 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 Internet Appendix shows an example of content from a

[9] Stopwords include words such as "the", "a", or "and".

principal investment strategies section with highlighted relevant words.

The dictionary-based methods might raise concerns. 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). Existing 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 existing dictionary-based methods when studying potential strategic behavior from mutual funds in their communication, as recently shown by Cao, Jiang, Yang, and Zhang (2023). Nonetheless, such dictionary-based approaches suffer from the static nature of dictionaries and might not be able to capture negation when discussing uncertainty. Therefore, as an alternative measure I use recent developments in language models to capture uncertain language in prospectuses.

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. However, 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 relate investors' behavior.

5.1 How Do Underperforming Mutual Funds Communicate?

Does performance alter the way mutual funds write their prospectuses? To answer this question, I examine, in the cross-section, the language of underperforming mutual funds. Specifically, I regress different characteristics of prospectuses on fund performance, as well as other fund characteristics.

As dependent variables, I used several text measures, namely Fog Index (Gunning 1952) frequency of positive, negative, and uncertain words.

$$Text_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + S \times T + \epsilon_{i,1}. \tag{5}$$

$X_{i,t-1}$ 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 style $\times$ time (year-month) fixed effects and double-cluster standard errors by fund and time.

Table 2 presents the results. Underperforming mutual funds tend to write less readable strategy sections. This reinforces the idea that mutual funds might be strategically communicating to influence fund flows. Underperforming mutual funds discuss more negatively but with more uncertain words, potentially with effects on

investor behavior that are explored next. However, underperforming mutual funds do not systematically communicate more positively.

5.1.1 Validation. Results show that underperforming funds write less readable; more negatively and with more uncertain terms. However, other features of the text could be related to fund performance but not captured with this approach. Recent advances in textual analysis and machine learning allows for features extraction that can reveal more about how language is associated with performance.[10]

To uncover how language is associated with fund performance, I extract embeddings using BERT (Bidirectional Encoder Representations from Transformers) from prospectus sentences. The contextualized embeddings are then used in a multivariate logistic regression with regularization where, for each sentence qs given by their numerical representations, I predict the performance quintile. More specifically, I estimate the following model:

$$P(Y = k \mid \mathbf{X}) = \frac{e^{\beta_{0k} + \mathbf{X} \cdot \beta_k}}{\sum_{j=1}^{K} e^{\beta_{0j} + \mathbf{X} \cdot \beta_j}}, \tag{6}$$

where X_1, X_2 ,..., X_P are the numerical features or contextualized embeddings obtained from prospectuses using BERT and k is the performance quintile. There are $P = 768$ features extracted from BERT as set by the hidden layers of the model.

Table A1 in the Internet Appendix shows the sentences that are most associated with the underperforming group of funds as defined by funds in the bottom quintile within each time period and style category. While sentences might not reveal apparent information by reading these sentences, they contain features, as extracted from BERT that make these sentences most related with underperforming funds. Moreover, looking at differences with the overperforming group of funds might be

[10]BERT proved useful in numerous recent finance and economics applications (e.g., Jha, Liu, and Manela 2021; Cao et al. 2023; Gorodnichenko, Pham, and Talavera 2023).

informative.

Table 3 shows differences in characteristics of sentences used by underperforming (bottom quintile) and overperforming funds (top quintile). As shown in the supervised approach (Table 2), underperforming funds use significantly more uncertain terms relative to overperforming funds. Therefore, using features extracted from an unsupervised model, results show that sentences associated with underperforming funds tend to contain more uncertain terms which confirms, as in Mullainathan et al. (2008), that in bad times funds might communicate differently to mitigate outflows.

5.2 Fund Flows and Uncertainty Language

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

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

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 4 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 2* 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 3*) I estimate the following regression:

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

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).[11] The set of controls contains the same set of fund characteristics as in Equation (7) but also includes the two terms of the interaction separately ($LowPerf_{i,t-1}$ and $Uncertainty_{i,t-1}$). Columns (2)-(5) of Table 4 present the results. The interaction term shows a positive and statistically significant coefficient (0.140; t-stat= 2.57 in column (5)). The effect of uncertainty language has a positive effect on fund flows for funds with low performance. An underperforming mutual fund that increases the proportion of uncertain words by 1.4 percentage points (one standard deviation) would experience a 7% 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 that investors should withdraw a hypothetical \$5M of outflows for underperformance 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

[11] In robustness tests, I use different cutoffs when identifying low performing funds and find similar results. Additionally, Table A3 shows similar results when using a continuous measure of performance, rather than a dummy.

persistent, that is lagged flows positively predicts future flows. Moreover, investors are highly responsive to performance. They punish underperforming 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 some investors are responding to such communication, when presented this uncertain, underperforming, context, consistent with *Hypothesis 3*. This also suggests that investors look closer to soft information, but only when observing underperformance from their investments, discount hard information, and think coarsely in the uncertain context of the text.

5.2.1 Robustness Checks. In robustness checks, I first 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 (8) 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).[12] 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 5 presents the results. When controlling for all additional text measures, 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 inde-

[12]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.

pendent 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.

Finally, Table 5 also 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 underperforming funds and flows (column (4)), suggesting that most effects come through within-fund variation and less on the cross-section.[13] Column (5) of Table 5 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 underperforming funds. Moreover, using alternative groups for clustering standard errors provides similar results (see Table A8 in the Internet Appendix).[14] When building on measuring of skills in the spirit

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

[14]Table A9 in the Internet 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 (8) 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 A2 in the Internet Appendix shows the p-values of the main cofficient ($LowPerf_{i,t-1} \times Uncertainty_{i,t-1}$ with a maximum p-value of

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 Internet Appendix shows results from panel regressions of (8) 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.

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

0.088). Figure A3 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).

the Internet Appendix 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 Internet Appendix).[15]

5.3 GPT-Uncertainty

Table 4 shows that dictionary-based uncertainty is positively related to fund flows for underperforming funds. While Table 3 validates the use of uncertain language by underperforming funds, using embeddings, dictionary-based methods present different flaws that can make the results less robust. These flaws include the subjectivity in the choice of dictionary terms, the inability to capture contextual nuances, negations, and possibly ignoring the dynamic nature of the language, where new terms and usages emerge over time, especially by firms (Cao et al. 2023). To address these issues, I use state-of-the-art large language models to capture uncertainty in the text and examine how it relates to fund flows for underperforming funds. I use the GPT-4 model developed by OpenAI to capture the level of uncertainty present in prospectuses, using a prompt designed to address the flaws presented by dictionary-based methods. GPT-4 is one of the most advanced large language models, designed to solve complex tasks with a broad general knowledge.[16]

Table 6 presents the results. The results are quantitatively similar to the dictionary-based methods, which shows the robustness of the main results. Column (1) of Table (6) shows that $Uncertainty - GPT$ is unrelated to fund flows, when it is not condi-

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

[16]A growing number of studies use large language models to learn from text data as well as generating beliefs(e.g., Bartik, Gupta, and Milo 2023; Bybee 2023; Fedyk, Kakhbod, Li, and Malmendier 2024; Jha, Qian, Weber, and Yang 2024). Section 7 in the Internet Appendix provides more information about the use of GPT-4 to capture text-based uncertainty.

tional on performance. Conditional on underperformance, columns (2) to (4) confirm that uncertainty, extracted using large language models, is positively related to the fund flows. The relationship is statistically significant at the 5 and 10% significance levels.

5.4 Controlling for confounding aspects of the text

A potential issue behind the results presented in Table 4 is that uncertainty is related both to the underperformance dummy variable as well as the outcome variable, i.e., fund flows. To strengthen the idea that uncertain text leads to less negative fund flows for underperforming funds, it is necessary to control for other aspects of the text that correlated both with uncertain tone and fund flows, e.g. length, complexity or other unobserved characteristics of the text. Recent methods from natural language processing (e.g., Pryzant, Card, Jurafsky, Veitch, and Sridhar 2020; Gui and Veitch 2022; Hochberg, Kakhbod, Li, and Sachdeva 2023) propose the use of transformers in a context of causal inference. The methodology from Gui and Veitch (2022) uses a three-stage approach to estimate how linguistic features (uncertainty in writing) affect outcomes (fund flows). The first stage uses a neural network to estimate conditional outcomes, essentially creating a model that can predict outcomes both with and without the treatment (in this case, different levels of uncertainty in the text).

The second and third stages involve propensity score estimation and final causal effect estimation using double machine learning techniques (Chernozhukov et al. 2017). This approach is particularly relevant here as it helps address potential endogeneity concerns with confounding many aspects of the prospectus (high-dimensional). The methodology provides robust confidence intervals for the estimated effects, as detailed in the textual analysis section of the Internet Appendix.

I use this method in the context of mutual fund prospectuses and the effect of

writing with an uncertain tone on fund flows. Using the same terminology as Gui and Veitch (2022), the 'treatment' A in this case represents linguistic uncertainty in fund prospectuses, where $A = 1$ if uncertainty is above the mean and 0 otherwise. The outcome variable Y represents fund flows in the subsequent period. For the language model, I use the pretrained DistilBert. The model is trained on 80% of the data for underperforming funds and tested on the remaining 20%. The results show that average 'treatment' effect is equal to 0.160817 with a 95% confidence interval of [0.116508, 0.205126] with a standard error of 0.022607. This shows that the results are robust and quantitatively similar when using the double machine learning approach to control for confounding, high-dimensional, features of the text.

5.5 Uncertainty Language and Future Performance

The results indicate that investors do not entirely shift their capital away from underperforming mutual funds that use uncertain terms. An important follow-up question is whether investors make the right capital allocation decision. Indeed, underperforming mutual funds that discuss uncertainty might exhibit superior future performance, potentially rewarding investors who maintain their capital in these funds. To explore this, I analyze how future performance correlates with uncertain terms in prospectuses for underperforming funds. More specifically, I estimate the following regression:

$$Performance_{i,t} = \beta_0 + \beta_1 LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{9}$$

The dependent variable is the performance of fund i in period t as proxied by the Carhart (1997) four-factor model. $Uncertainty_{i,t-1}$ 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, lagged fund performance, 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 × time (month) fixed effects and double-cluster standard errors by fund and time.

Table 7 shows the results. The use of uncertain terms is negatively associated with future performance, measured by the four-factor alpha, particularly in previously underperforming mutual funds. That is, mutual funds that use uncertain terms in their prospectus, while underperforming, perform even worse going forward and thus hurt investors. These results suggest that the writing style of prospectuses can be informative about future performance and a factor that investors should take into account. To understand what potential mechanism might be at play, as discussed further in section 5.8, this suggests that the use of uncertain terms might diminish the precision of performance signals that investors rely on when making capital allocation decisions across funds. Moreover, funds that discuss uncertainty spend more on marketing expenses as shows Table A5, highlighting the important role of marketing in reducing investor welfare (Roussanov, Ruan, and Wei 2021).

5.5.1 Do Investors Learn?. Section 5.5 indicates a correlation between discussions on uncertainty and reduced negative outflows for underperforming mutual funds, which is detrimental to investors' future returns. A related question would be to investigate if investors learn from this by withdrawing more capital from a fund that previously used uncertain terms in its prospectus. An indirect approach to answer this would involve estimating equation (8) while controlling for lagged *Uncertainty* to capture the extent of uncertain terms discussed in earlier prospectuses.

The results in Table A4 indicate that investors do not seem to react to prior discussions of uncertain terms in prospectuses. Lagged *Uncertainty* (one, two, and three years) exhibits no significant relation to fund flows in period t but *Uncertainty*

in period $t-1$ interacted with underperformance remains significant. Therefore, results suggest that investors do not learn from prior prospectuses and especially, the lower performance associated with it.

5.6 The Heterogeneous Effects of Uncertainty

5.6.1 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 underperforming 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, fees could be less salient for mutual funds discussing uncertainty. To test this hypothesis, I investigate how investors respond to expense ratio for funds with low performance and high uncertainty in the text:

$$flows_{i,t} = \beta_0 + \beta_1 expense_i * LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{10}$$

Table 8 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 might benefit from discussing uncertainty in their prospectus. Therefore, relevant financial information such as expense ratio become less salient when investors read uncertain prospectuses. Yet, if an expensive fund underperforms 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.

5.6.2 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.[17] I estimate the effect of $Uncertainty$ conditional on the fund's clientele as in equation (8) with a triple interaction term to condition on funds targeted to retail investors.

$$flows_{i,t} = \beta_0 + \beta_1 Retail_i * LowPerf_{i,t-1} * Uncertainty_{i,t-1} + \beta_2 X_{i,t-1} + F + S \times T + \epsilon_{i,1}. \tag{11}$$

Table 9 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

[17] 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.

(e.g., Andrikogiannopoulou et al. 2022). The fact that investors respond differently also supports the investor bias channel (*Hypothesis 3*) behind that uncertainty-flow relationship, i.e. some investors think coarsely. The next subsection examines in more details the strategic communication channel of *Hypothesis 1*, i.e., the possibility of funds communicating differently when facing outflow risk.

5.7 Strategic Communication

5.7.1 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 underperforming 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. 2024). 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 8). 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 for underperforming funds ($Uncertainty \times LowPerf$) on fund flows, along with fund controls described in equation (8), fund and style $\times$ time fixed effects as well as standard errors double-clustered by fund and time.

The results are presented in Table 10. 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.

5.7.2 Why don't all mutual funds discuss uncertainty?. Given that underperforming funds benefit from using an uncertain tone in their strategy section, a natural question arises: Why don't funds, regardless of performance, consistently use such language? Two potential explanations emerge. First, equilibrium concepts suggest funds weigh the benefits and costs of communication changes. Mutual funds incur regulatory costs when modifying their strategy sections, and these costs might outweigh the potential benefits of reduced negative fund flows. Second, behavioral finance and overconfidence provide an alternative explanation. After periods of bad performance, funds may strongly believe their underperformance stems from temporary bad luck, convincing themselves they will deliver better returns in subsequent periods. Consequently, they see no need to alter their communication strategy at an additional cost, firmly believing in their future good returns.

5.8 Underlying Mechanism

5.8.1 Framing by Mutual Funds. As presented in the framework of Mullainathan et al. (2008), mutual funds, especially underperforming ones, might frame information in a way to mitigate outflows. The authors provide anedoctal evidence in context mutual fund advertising where mutual funds report less their own performance when underperforming but instead would emphasize surrounding uncertainty. In a similar way, the results presented in this paper show that mutual funds might write less clear strategy sections and use more uncertain terms when underperforming. Moreover, this communication appears to be effective as investors shift less capital to better performing funds when reading prospectuses from underperforming funds with an uncertain tone. Which leads to understanding why investors might do so, especially when it hurts their performance.

5.8.2 Investors' biases. The model presented by Mullainathan et al. (2008) applies to individuals that think coarsely and group categories and think the same way in different categories. When presented with more uncertain terms, investors might apply the less precise signal about fund managers' skill and thus shift less capital way from such fund. The way information is presented to investors can influence investors' allocation decisions as they might associate background information contained in hard data such as gross returns to a noisy environment (Kahneman and Tversky 1973; Roussanov et al. 2022). Overall, the results are in line with recent studies that suggest that investors do not use highly sophisticated thinking when making allocation decisions across funds (e.g., Barber, Huang, and Odean 2016; Ben-David et al. 2022).

6 Concluding Remarks

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.

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7 Figures and Tables

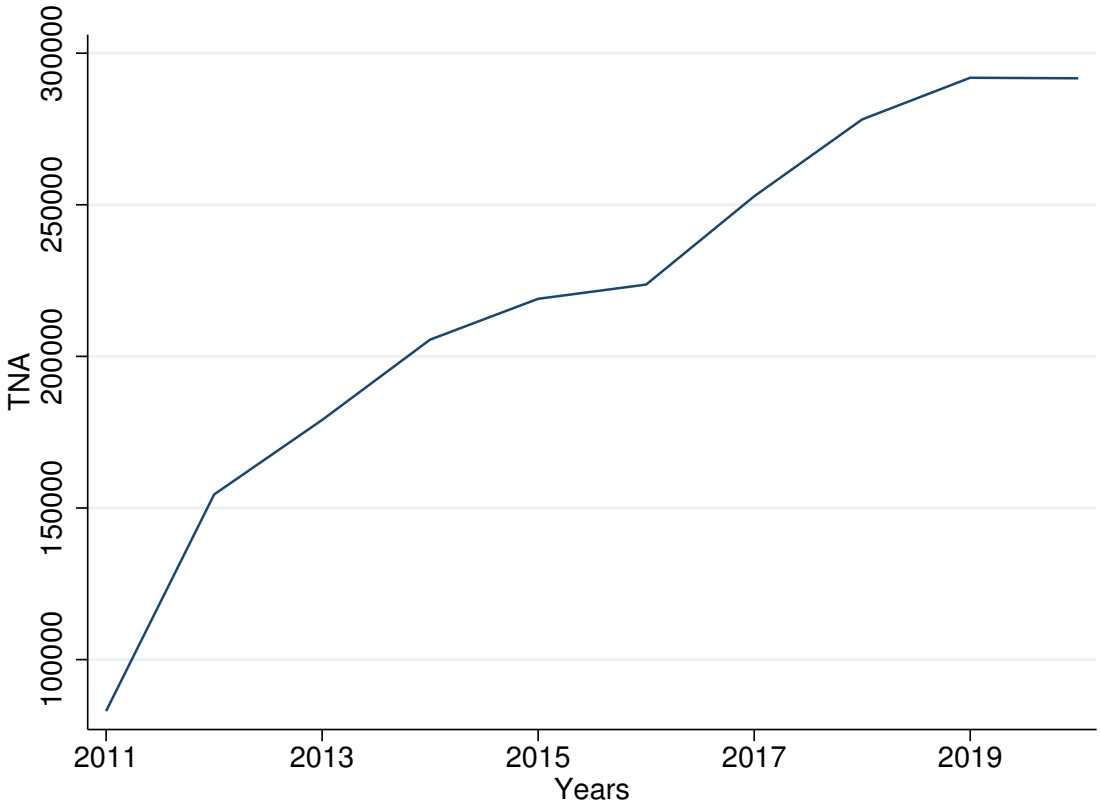


Figure 1. This figure shows the evolution of U.S. active equity mutual funds total assets under management in billions of U.S. dollars.

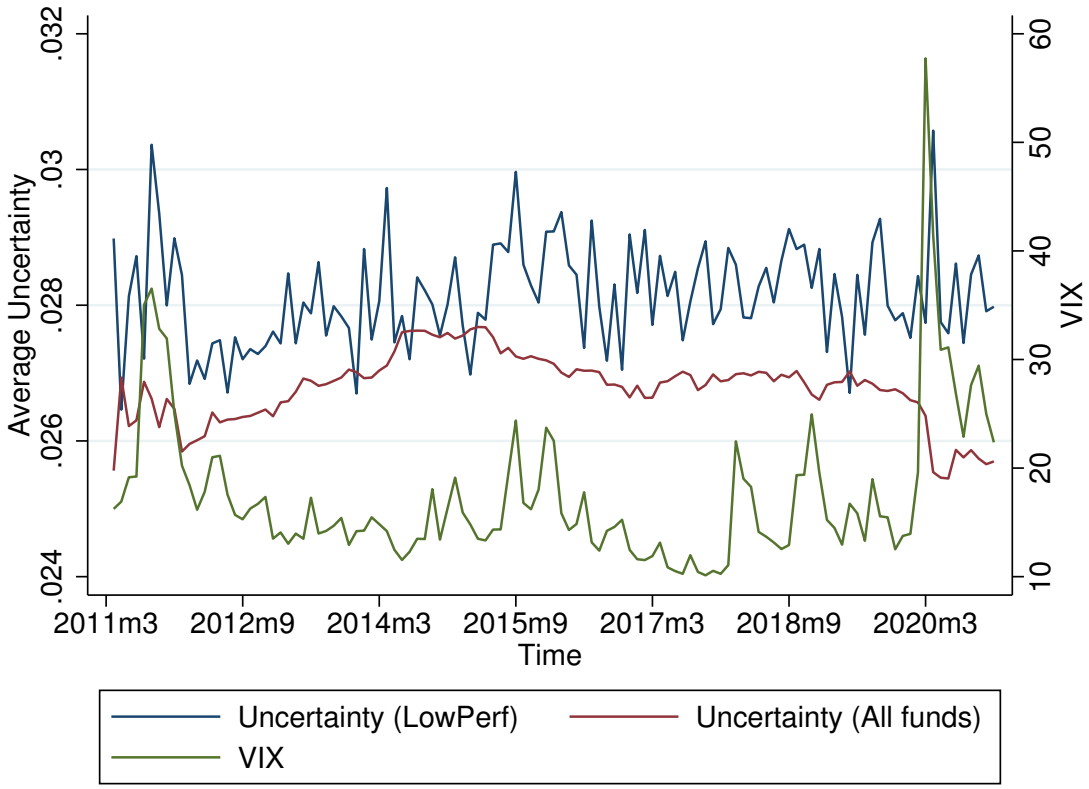


Figure 2. This figure shows the evolution of a average *Uncertainty* in prospectuses over time from poorly performing mutual funds (bottom decile within category-month) on the left y-axis and the VIX index on the right y-axis.

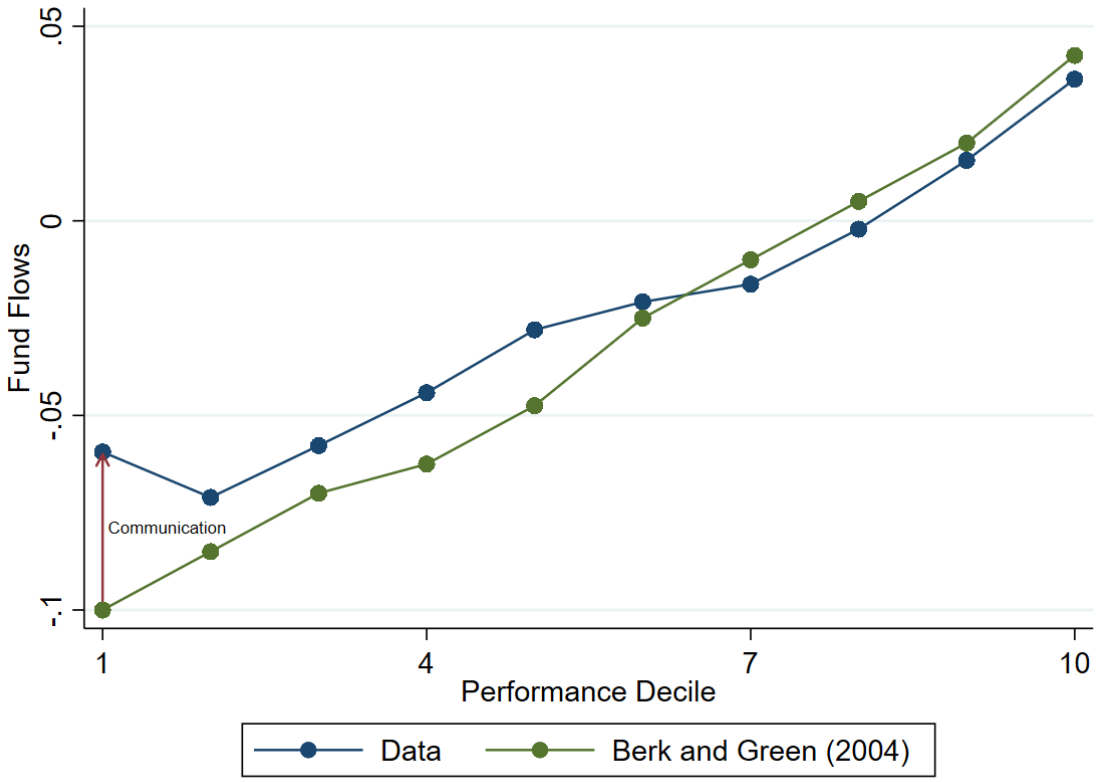


Figure 3. This figure shows the flow-performance relationship where performance is the average alpha over the previous 3 years ranked in deciles and flow is the median of the annual flow ratio in each performance decile for the data, while *Model* shows simulated flow response for hypothetical funds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

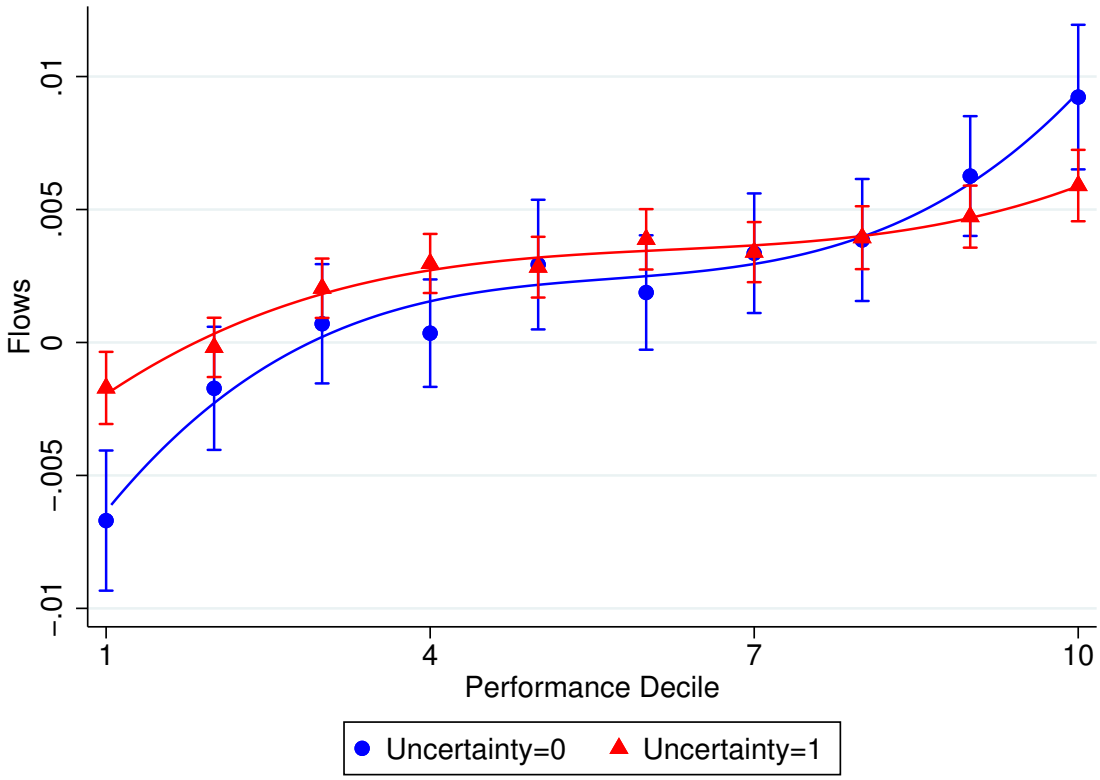


Figure 4. This figure shows the average response of uncertainty on mutual fund flows for each performance decile. $Uncertainty = 1$ is defined as mutual funds located in the top decile of $Uncertainty$ while $Uncertainty = 0$ are mutual funds that are in the bottom decile of the $Uncertainty$ distribution.

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. Language and Performance

This table presents estimates from panel regressions of text characteristics of mutual fund prospectuses on fund characteristics. Readability is proxied by the Gunning-Fog Index (Gunning 1952) and Flesch Reading Index (Flesch 1948). Positive, negative, and uncertainty-related proportion of words are measured using Loughran and McDonald (2011). Lagged monthly fund-level characteristics include *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.

	$Fog_{i,t}$	$Tone^{+}_{i,t}$	$Tone^{-}_{i,t}$	$Uncertainty_{i,t}$
	(1)	(2)	(3)	(4)
Four-factor alpha$_{i,t-1}$	1.435***	-0.002	-0.002***	-0.008***
	(3.59)	(-1.17)	(-2.72)	(-3.73)
$Expense_{i,t-1}$	-2.102	0.252***	0.172***	0.183***
	(-0.20)	(8.32)	(7.69)	(3.88)
$\log(TNA)_{i,t-1}$	0.034	0.000	0.000	-0.000
	(1.43)	(1.36)	(0.86)	(-1.27)
$Return_{i,t-1}$	-0.013	0.004**	-0.001	0.002
	(-0.05)	(2.25)	(-1.12)	(0.89)
$\log(Fund\ age)_{i,t-1}$	0.180***	0.001***	-0.001***	0.000
	(3.57)	(4.09)	(-5.79)	(0.62)
$Flows_{i,t-1}$	0.107	0.000	-0.001**	-0.001
	(0.96)	(0.68)	(-2.41)	(-1.64)
$Turnover_{i,t-1}$	-0.005	-0.000	0.000**	0.000**
	(-0.44)	(-0.62)	(2.61)	(2.02)
$Beta_{i,t-1}$	0.531***	-0.000	-0.001***	-0.003***
	(8.05)	(-1.19)	(-8.97)	(-9.39)
Four-factor alpha$^2_{i,t-1}$	-1.557*	0.004**	0.002	0.003
	(-1.66)	(1.98)	(0.59)	(0.39)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Observations	350399	350399	350399	350399
R^2	0.072	0.104	0.079	0.124

Table 3. Language Features and Performance

This table presents characteristics of prospectuses' sentences that are most associated with performance quintiles (within style and month). Numeric features from sentences are obtained from BERT. The features are used as inputs in a multinomial logistic regression to predict the performance quintile to which the fund (and associated sentences) belongs to. As independent variables in the model, the regression contains fund-level characteristics include *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, *turnover* ratio, and style dummies as well as time dummies. The table shows characteristics of sentences (frequency of $Tone^{+}$, $Tone^{-}$, *Uncertainty*-related words; Loughran and McDonald 2011) only for sentences that are most associated with underperforming funds (bottom quintile), and overperforming funds (top quintile), with probabilites above 51%. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Underperforming		*Overperforming*		*Difference*
	N	Mean	N	Mean	
$Tone^{+}$	485	0.95%	252	1.05%	0.01%
					(0.50)
$Tone^{-}$	485	0.29%	252	0.41%	0.11%
					(0.26)
Uncertainty	485	2.15%	252	1.65%	-0.50%**
					(-2.18)

Table 4. 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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$		0.122***	0.121**	0.140**	0.140**
		(2.64)	(2.61)	(2.58)	(2.57)
$Uncertainty_{i,t-1}$	-0.088	-0.049	-0.053	-0.103	-0.102
	(-1.16)	(-0.83)	(-0.89)	(-1.36)	(-1.36)
$LowPerf_{i,t-1}$		-0.500***	-0.474***	-0.589***	-0.600***
		(-3.81)	(-3.60)	(-4.06)	(-4.14)
$\log(TNA)_{i,t-1}$	-1.480***	-1.545***	-1.551***	-1.476***	-1.478***
	(-15.25)	(-16.95)	(-16.98)	(-15.22)	(-15.24)
$Return_{i,t-1}$	8.018***	7.341**	7.281**	6.927**	7.100**
	(2.85)	(2.60)	(2.58)	(2.39)	(2.46)
$\log(Fund\ age)_{i,t-1}$	-1.324***	-1.400***	-1.392***	-1.329***	-1.330***
	(-9.63)	(-11.15)	(-11.10)	(-9.67)	(-9.69)
$Flows_{i,t-1}$	0.285	-1.684	-1.600	0.301	0.259
	(0.24)	(-1.53)	(-1.45)	(0.25)	(0.22)
$Beta_{i,t-1}$	-0.409**		-0.323*	-0.356*	-0.371**
	(-2.31)		(-1.94)	(-1.98)	(-2.08)
$Expense_{i,t-1}$	-41.459*			-41.207	-41.502*
	(-1.66)			(-1.66)	(-1.67)
$Turnover_{i,t-1}$	0.056**			0.057**	0.056**
	(2.34)			(2.39)	(2.37)
Four-factor alpha$^2_{i,t-1}$	15.392***				15.821***
	(4.48)				(4.59)
Style x Year-Month FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	349172	450081	448595	349172	349172
R^2	0.119	0.115	0.116	0.119	0.119

Table 5. Text-Based Uncertainty, Performance, and Fund Flows

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. *LowPerf* is a dummy that identifies funds in the bottom decile of the four-factor alpha distribution with style categories and time periods. The second column considers funds with low performance as defined by the lowest quintile. 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)	(4)	(5)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.135**	0.151***	0.131**	0.122**	
	(2.48)	(2.68)	(2.40)	(2.05)	
$Uncertainty_{i,t-1} \times LowPerf^{quintile}_{i,t-1}$					0.100**
					(2.36)
$Uncertainty_{i,t-1}$	-0.111	-0.087	-0.086	-0.062**	-0.109
	(-1.48)	(-1.17)	(-1.13)	(-2.24)	(-1.44)
$LowPerf_{i,t-1}$	-0.626***	-0.577***	-1.000***	-0.694***	
	(-3.91)	(-3.97)	(-3.93)	(-4.72)	
$Tone^{+}_{i,t-1}$	11.751				
	(1.35)				
$LowPerf_{i,t-1} \times Tone^{+}_{i,t-1}$	3.190				
	(0.55)				
$Tone^{-}_{i,t-1}$		-11.447			
		(-0.85)			
$LowPerf_{i,t-1} \times Tone^{-}_{i,t-1}$		-8.734			
		(-0.98)			
$Length_{i,t-1}$			0.027**		
			(2.40)		
$LowPerf_{i,t-1} \times Length_{i,t-1}$			0.015*		
			(1.73)		
$LowPerf^{quintile}_{i,t-1}$					-0.546***
					(-5.09)
Fund controls	Yes	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes	Yes
Observations	349172	349172	349172	349174	349172
R^2	0.119	0.119	0.119	0.065	0.119

Table 6. Text-Based Uncertainty from GPT, 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 using generative pre-trained transformers (OpenAI GPT 4). *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)
$Uncertainty\text{-}GPT_{i,t-1} \times LowPerf_{i,t-1}$		0.171*	0.181*	0.218**	0.202*
		(1.75)	(1.87)	(2.00)	(1.88)
$Uncertainty\text{-}GPT_{i,t-1}$	-0.027	-0.006	-0.011	-0.052	-0.050
	(-0.49)	(-0.14)	(-0.24)	(-0.92)	(-0.89)
$LowPerf_{i,t-1}$		-0.803***	-0.810***	-1.012***	-0.974***
		(-2.65)	(-2.67)	(-3.00)	(-2.91)
$\log(TNA)_{i,t-1}$	-1.480***	-1.545***	-1.551***	-1.476***	-1.477***
	(-15.24)	(-16.95)	(-16.98)	(-15.21)	(-15.23)
$Return_{i,t-1}$	8.015***	7.437***	7.380**	7.045**	7.209**
	(2.85)	(2.63)	(2.61)	(2.43)	(2.49)
$\log(Fund\ age)_{i,t-1}$	-1.324***	-1.401***	-1.393***	-1.329***	-1.330***
	(-9.63)	(-11.15)	(-11.10)	(-9.67)	(-9.68)
$Flows_{i,t-1}$	0.286	-1.678	-1.594	0.304	0.262
	(0.24)	(-1.52)	(-1.45)	(0.25)	(0.22)
$Beta_{i,t-1}$	-0.409**		-0.328*	-0.362**	-0.376**
	(-2.31)		(-1.97)	(-2.01)	(-2.12)
$Expense_{i,t-1}$	-40.541			-40.272	-40.561
	(-1.63)			(-1.62)	(-1.63)
$Turnover_{i,t-1}$	0.055**			0.057**	0.056**
	(2.34)			(2.38)	(2.36)
$Four\text{-}factor\ alpha^2_{i,t-1}$	15.393***				15.684***
	(4.48)				(4.59)
Style x Year-Month FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	349172	450070	448584	349172	349172
R^2	0.119	0.115	0.116	0.119	0.119

Table 7. 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.

	Four-factor alpha$_{i,t}$			
	(1)	(2)	(3)	(4)
Uncertainty$_{i,t-1}$ × *LowPerf*$_{i,t-1}$	-0.047**	-0.047**	-0.053**	-0.053**
	(-2.30)	(-2.31)	(-2.08)	(-2.08)
Uncertainty$_{i,t-1}$	-0.000	-0.000	-0.002	-0.002
	(-0.01)	(-0.03)	(-0.12)	(-0.12)
LowPerf$_{i,t-1}$	0.140*	0.149*	0.164*	0.163*
	(1.80)	(1.91)	(1.87)	(1.86)
log(TNA)$_{i,t-1}$	-0.120***	-0.119***	-0.131***	-0.132***
	(-7.49)	(-7.48)	(-7.89)	(-7.90)
Return$_{i,t-1}$	-1.572	-1.600	-2.008	-2.001
	(-1.01)	(-1.03)	(-1.21)	(-1.21)
log(*Fund age*)$_{i,t-1}$	0.111***	0.111***	0.116***	0.116***
	(3.37)	(3.35)	(3.25)	(3.25)
Flows$_{i,t-1}$	-0.053	-0.057	-0.070	-0.071
	(-0.39)	(-0.42)	(-0.45)	(-0.46)
Beta$_{i,t-1}$		-0.118	-0.094	-0.094
		(-0.56)	(-0.42)	(-0.42)
Expense$_{i,t-1}$			-9.966**	-9.978**
			(-2.31)	(-2.30)
Turnover$_{i,t-1}$			0.002	0.002
			(0.27)	(0.26)
Four-factor alpha$^2_{i,t-1}$				0.630
				(0.83)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	450593	450482	350097	350097
R^2	0.289	0.289	0.284	0.284

Table 8. 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)
$Uncertainty_{i,t-1}$	-0.415***	-0.413***	-0.416***	-0.416***
	(-3.40)	(-3.39)	(-3.43)	(-3.43)
$LowPerf_{i,t-1}$	-1.320***	-1.292***	-1.289***	-1.302***
	(-4.98)	(-4.89)	(-4.89)	(-4.94)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.570***	0.568***	0.569***	0.570***
	(4.82)	(4.81)	(4.80)	(4.81)
$Expense_{i,t-1}$	-107.157***	-105.225***	-106.439***	-106.737***
	(-3.11)	(-3.07)	(-3.10)	(-3.10)
$Uncertainty_{i,t-1} \times Expense_{i,t-1}$	31.749***	31.607***	31.546***	31.556***
	(2.92)	(2.92)	(2.92)	(2.92)
$LowPerf_{i,t-1} \times Expense_{i,t-1}$	71.309***	71.236***	70.781***	70.958***
	(3.20)	(3.19)	(3.18)	(3.19)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1} \times Expense_{i,t-1}$	-42.142***	-42.030***	-42.033***	-42.189***
	(-3.82)	(-3.81)	(-3.79)	(-3.81)
$\log(TNA)_{i,t-1}$	-1.486***	-1.484***	-1.480***	-1.482***
	(-15.33)	(-15.26)	(-15.22)	(-15.24)
$Return_{i,t-1}$	6.952**	6.872**	6.873**	7.047**
	(2.40)	(2.38)	(2.37)	(2.44)
$\log(Fund\ age)_{i,t-1}$	-1.330***	-1.331***	-1.325***	-1.326***
	(-9.67)	(-9.69)	(-9.66)	(-9.67)
$Flows_{i,t-1}$	0.324	0.310	0.288	0.245
	(0.27)	(0.26)	(0.24)	(0.21)
$Beta_{i,t-1}$		-0.356*	-0.353*	-0.368**
		(-1.97)	(-1.96)	(-2.07)
$Turnover_{i,t-1}$			0.057**	0.056**
			(2.39)	(2.37)
$Four\text{-}factor\ alpha^2_{i,t-1}$				15.841***
				(4.59)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	350101	350066	349172	349172
R^2	0.120	0.120	0.119	0.119

Table 9. 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 × $Uncertainty_{i,t-1}$ × $LowPerf_{i,t-1}$	-0.052	-0.052	-0.096	-0.096
	(-0.98)	(-0.99)	(-1.46)	(-1.46)
$Retail_i$=1 × $Uncertainty_{i,t-1}$	0.044	0.051	0.088	0.088
	(0.73)	(0.83)	(1.14)	(1.14)
$Retail_i$=1 × $LowPerf_{i,t-1}$	-0.001	-0.001	0.001	0.001
	(-0.66)	(-0.68)	(0.32)	(0.36)
$Uncertainty_{i,t-1}$ × $LowPerf_{i,t-1}$	0.104**	0.103**	0.151**	0.150**
	(2.49)	(2.46)	(2.58)	(2.57)
$Uncertainty_{i,t-1}$	-0.052	-0.057	-0.119	-0.119
	(-1.06)	(-1.14)	(-1.57)	(-1.57)
$LowPerf_{i,t-1}$	-0.004**	-0.004**	-0.006***	-0.007***
	(-2.62)	(-2.46)	(-2.99)	(-3.07)
$\log(TNA)_{i,t-1}$	-0.016***	-0.016***	-0.015***	-0.015***
	(-17.08)	(-17.13)	(-15.33)	(-15.35)
$Return_{i,t-1}$	0.074**	0.073**	0.070**	0.071**
	(2.60)	(2.58)	(2.39)	(2.46)
$\log(Fund\ age)_{i,t-1}$	-0.014***	-0.014***	-0.013***	-0.013***
	(-11.05)	(-10.99)	(-9.55)	(-9.56)
$Flows_{i,t-1}$	-0.017	-0.016	0.003	0.002
	(-1.55)	(-1.47)	(0.23)	(0.20)
$Beta_{i,t-1}$		-0.003*	-0.004**	-0.004**
		(-1.96)	(-2.00)	(-2.10)
$Expense_{i,t-1}$			-0.304	-0.307
			(-1.24)	(-1.25)
$Turnover_{i,t-1}$			0.001**	0.001**
			(2.39)	(2.37)
$Four\text{-}factor\ alpha^2_{i,t-1}$				0.158***
				(4.59)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	450081	448595	349172	349172
R^2	0.116	0.116	0.119	0.120

Table 10. 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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.149**	0.151**	0.151**
	(2.37)	(2.40)	(2.40)
$Holdings\text{-}EPU_{i,t-1}$	757.987	836.808	873.872
	(0.76)	(0.84)	(0.88)
Return Vol. 6-m$_{i,t-1}$		-12.599**	
		(-2.21)	
Return Vol. 12-m$_{i,t-1}$			-17.748**
			(-2.53)
$Return\ Gap_{i,t-1}$	-6.611	-6.465	-6.569
	(-1.27)	(-1.24)	(-1.26)
$Uncertainty_{i,t-1}$	-0.037	-0.038	-0.041
	(-0.38)	(-0.40)	(-0.42)
$LowPerf_{i,t-1}$	-0.264*	-0.260*	-0.260*
	(-1.89)	(-1.87)	(-1.88)
Fund controls	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	166262	166262	166262
R^2	0.128	0.128	0.128

Internet Appendix

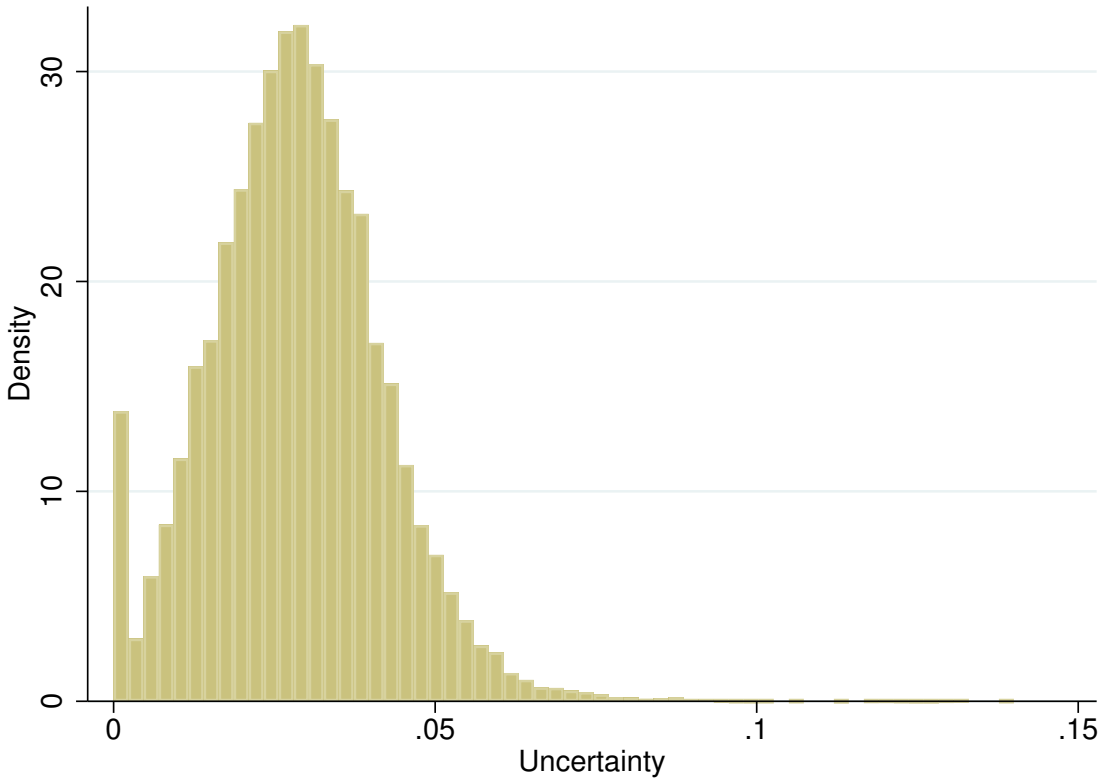


Figure A1. This figure shows the histogram of the *Uncertainty* variable with the proportion of mutual funds on the y-axis for each level of uncertainty discussion in the strategy section of the prospectus.

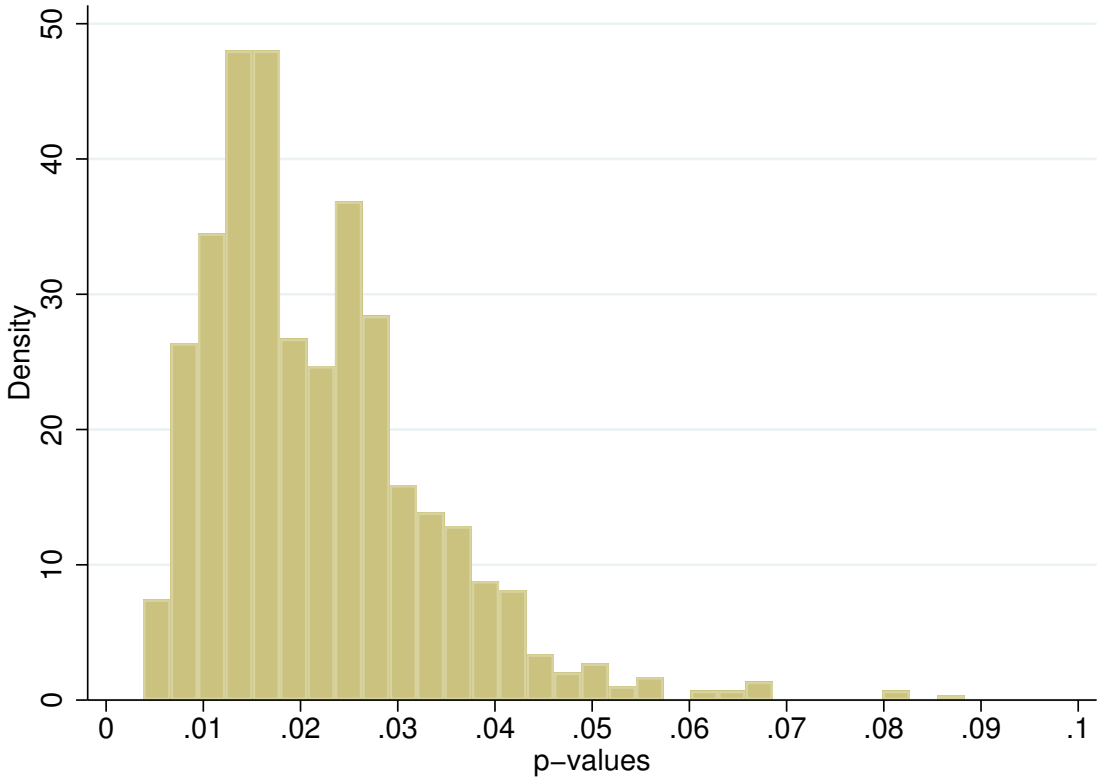


Figure A2. This figure shows the density of p-values of the coefficient on $Uncertainty \times LowPerf$, using the specification of regression (8) estimated 1000 times but excluding each time randomly 5% of the sample.

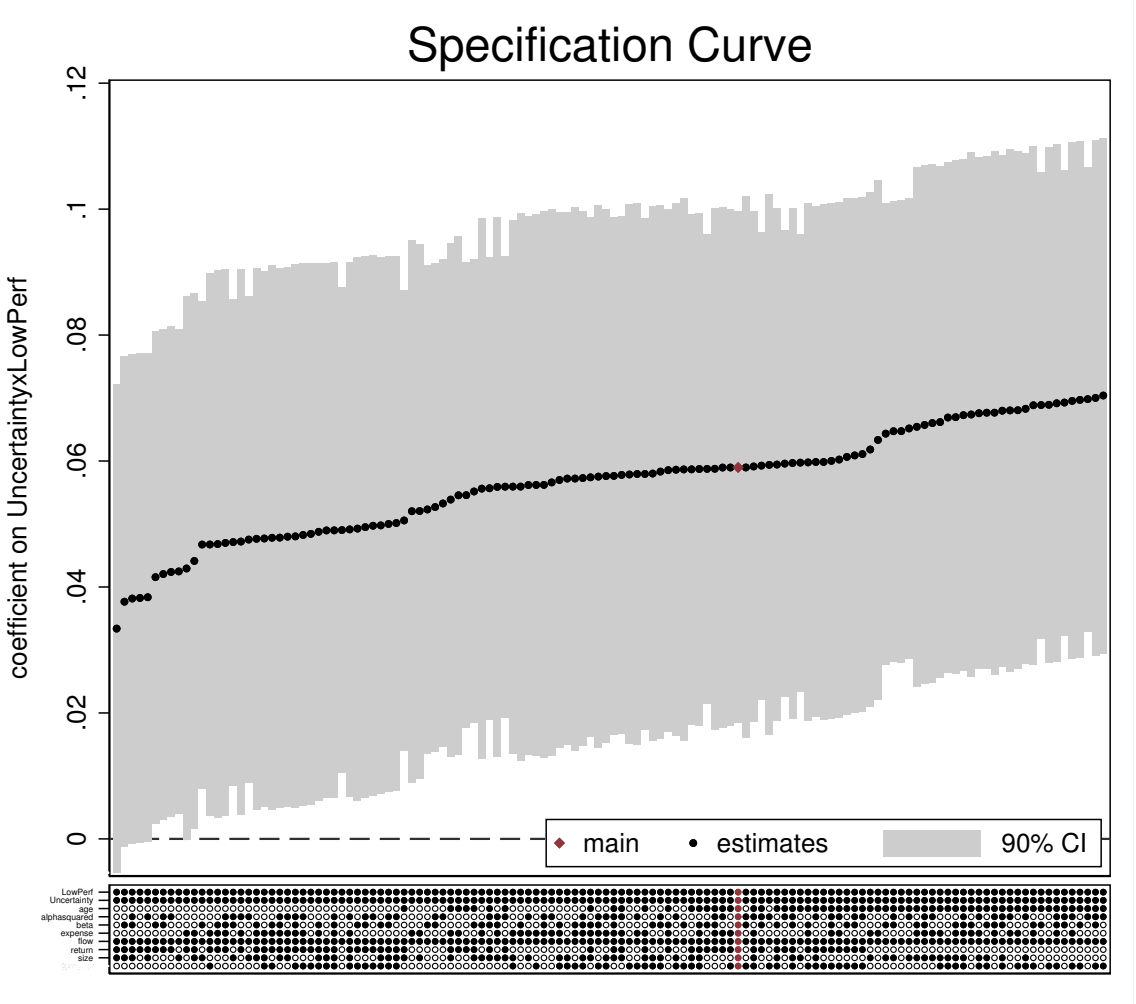


Figure A3. This figure shows the specification curve with the coefficient on $Uncertainty \times LowPerf$ on the y-axis and various regressions specifications on the x-axis with different combinations of control variables (Simonsohn et al. 2020).

Table A1. This table shows the sentences from prospectuses associated with the highest probability of being in the bottom of the abnormal performance distribution (bottom quintile). The probabilities are obtained from a multinomial logistic regression where independent variables include features obtained from BERT as well as fund characteristics and time and style dummies. The table shows only the sentences associated with the highest (top 25 sentences) probabilities of being in the bottom quintile.

Sentences	**Probabilities**
Assets of the Portfolio not invested in the SP 500 Index or Index Derivatives may be invested in short term fixed income obligations including U.S. government obligations, U.S. government agency obligations, corporate debt obligations, bank obligations, commercial paper, repurchase agreements, foreign government and agency obligations, supranational organization obligations, foreign issuer obligations and eurodollar obligations.	0.85146
There is no guarantee that the Fund will achieve its objective.	0.829034
The Fund seeks to invest primarily in common stock but may also invest in preferred stock and convertible securities.	0.829034
In assessing profitability, the Advisor may consider different ratios, such as that of earnings or profits from operations relative to book value or assets.	0.815838
	Continued

Table A1 – continued

Sentences	**Probabilities**
The Fund employs a multi style (growth, value and market oriented) and multi manager approach whereby portions of the Fund are allocated to different money managers who employ distinct investment styles.	0.808391
Please refer to the Investment Objective and Investment Strategies section in the Fund s Prospectus for further information.	0.79932
The Fund may invest a large percentage of its assets in a few sectors, including information technology, industrials, consumer discretionary, health care, energy and financials.	0.782383
In selecting investments for the Equity Income Fund, the Adviser focuses on issuers that have strong free cash flow and pay regular dividends have potential for long term earnings per share growth may be subject to a value catalyst, such as industry developments, regulatory changes, changes in management, sale or spin off of a division, or the development of a profitable new business are well managed will benefit from sustainable long term economic dynamics, such as globalization of an issuers industry or an issuers increased focus on productivity or enhancement of services.	0.773411
	Continued

Table A1 – continued

Sentences	**Probabilities**
For purposes of this Fund, large capitalization companies are defined as companies with a market capitalization found within the Russell 1000 Index (between approximately $306M and $419B as of February 28, 2013) at the time of purchase.	0.763556
The Fund may invest up to 25 of its total assets in the securities of foreign issuers, including issuers located or doing business in emerging markets.	0.751236
In general, the higher the relative market capitalization of the U.S. company, the greater its representation in the Tax Managed Value Series.	0.743048
NWQ typically either eliminates or trims positions when NWQ believes a security no longer meets the three criteria at the core of its investment discipline attractive valuation, favorable risk reward ratio and belief in a catalyst.	0.743048
The fund may invest in derivatives to a limited extent.	0.741396
The Equity Fund may also invest in foreign debt securities.	0.730218
	Continued

Table A1 – continued

Sentences	Probabilities
Under normal circumstances, the Fund invests at least 80 of its net assets in securities of domestic or foreign companies that are involved to a substantial extent in providing products, services or equipment for the generation or distribution of electricity, gas, and water and the provision of infrastructure operations or telecommunications services, such as telephone, telegraph, satellite, cable, microwave, radiotelephone, mobile communication and cellular, paging, electronic mail, videotext, voice communications, data communications, and internet and that derive at least 50 of their revenue or earnings from, or devote at least 50 of their assets to, utilities (each, a Utility Company and collectively, Utility Companies) that the Funds investment adviser, Gabelli Funds, LLC (the Adviser), believes have the potential to provide either capital appreciation or current income.	0.728944
The Fund may invest up to 25 of its total assets in foreign securities.	0.727389
As of December 31, 2018, the capitalization of issuers in the Russell Midcap Index ranged from $386.5M to $67.9B.	0.721556
The analysis of market action includes measurements of price behavior and trading volume.	0.721556
The Fund invests primarily in equity securities, principally common and preferred stocks of large cap companies.	0.718825
	Continued

Table A1 – continued

Sentences	Probabilities
The Adviser selects stocks using a unique, value oriented approach focusing on high quality companies with long term capital appreciation potential that are available at reasonable prices, which combines the use of proprietary analytical tools and the qualitative judgments of the investment team.	0.714185
Dimensional Fund Advisors LP (the Advisor) believes that equity investing should involve a long term view and a systematic focus on sources of expected returns, not on stock picking or market timing.	0.711247
In buying and selling securities for the Fund, PNC Capital Advisors, LLC (the Adviser) uses a value oriented approach.	0.709887
The fund may invest in the stocks of companies of any size, although it focuses on large cap companies.	0.708609
As of May 31, 2019, the market capitalization of the companies in the Russell 2000 Index was between approximately $10.0M and $9.9B.	0.70427
The portfolio managers focus on seeking downside protection.	0.703414

Table A2. Text-Based Uncertainty, Performance, and Fund Flows: Controlling for 12b-1 fees

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy controlling for 12b-1 fees. *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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.126**	0.139**
	(2.12)	(2.56)
$Uncertainty_{i,t-1}$	-0.073***	-0.104
	(-2.68)	(-1.38)
$LowPerf_{i,t-1}$	-0.691***	-0.600***
	(-4.71)	(-4.14)
$12b\text{-}1_{i,t-1}$	26.695***	28.353
	(4.09)	(0.73)
Fund controls	Yes	Yes
Style x Year-Month FE	Yes	Yes
Fund FE	No	Yes
Observations	349174	349172
R^2	0.065	0.119

Table A3. 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-factor alpha*$_{i,t-1}$	0.534*	0.536*	0.623*	0.621*
	(1.71)	(1.72)	(1.84)	(1.83)
$Uncertainty_{i,t-1}$	-0.041	-0.042	-0.088	-0.088
	(-0.68)	(-0.69)	(-1.16)	(-1.16)
1/Four-factor alpha$_{i,t-1}$	-0.754*	-0.757*	-0.870*	-0.868*
	(-1.83)	(-1.84)	(-1.94)	(-1.94)
$\log(TNA)_{i,t-1}$	-1.553***	-1.552***	-1.479***	-1.480***
	(-16.98)	(-16.98)	(-15.22)	(-15.24)
$Return_{i,t-1}$	8.106***	7.955***	7.815***	8.017***
	(2.96)	(2.91)	(2.78)	(2.85)
$\log(Fund\ age)_{i,t-1}$	-1.387***	-1.388***	-1.324***	-1.324***
	(-11.05)	(-11.06)	(-9.62)	(-9.64)
$Flows_{i,t-1}$	-1.572	-1.584	0.326	0.285
	(-1.43)	(-1.44)	(0.27)	(0.24)
$Beta_{i,t-1}$		-0.352**	-0.393**	-0.409**
		(-2.12)	(-2.20)	(-2.31)
$Expense_{i,t-1}$			-41.170	-41.458*
			(-1.65)	(-1.66)
$Turnover_{i,t-1}$			0.056**	0.056**
			(2.36)	(2.34)
Four-factor alpha$^2_{i,t-1}$				15.392***
				(4.48)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	448595	448595	349172	349172
R^2	0.115	0.115	0.119	0.119

Table A4. Text-Based Uncertainty, Performance, and Fund Flows: Controlling for Lagged Uncertainty

This table presents estimates from panel regressions of mutual funds' *% flows* on their document's uncertainty interacted with a performance dummy controlling for uncertainty in the previous one, two, and three years. *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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.149***	0.140**	0.185***
	(2.63)	(2.45)	(2.91)
$Uncertainty_{i,t-1}$	-0.079	-0.056	-0.053
	(-0.90)	(-0.59)	(-0.50)
$LowPerf_{i,t-1}$	-0.678***	-0.624***	-0.700***
	(-4.65)	(-4.23)	(-4.33)
$Uncertainty_{i,t-12}$	0.055	0.152	0.120
	(0.61)	(1.50)	(1.05)
$Uncertainty_{i,t-24}$		-0.136	-0.133
		(-1.42)	(-1.19)
$Uncertainty_{i,t-36}$			0.009
			(0.09)
$Expense_{i,t-1}$	-54.645**	-55.782*	-61.475*
	(-2.00)	(-1.81)	(-1.69)
$\log(TNA)_{i,t-1}$	-1.465***	-1.527***	-1.840***
	(-14.57)	(-12.23)	(-12.31)
$Return_{i,t-1}$	6.223**	4.802	3.594
	(2.05)	(1.54)	(1.13)
$\log(Fund\ age)_{i,t-1}$	-1.254***	-1.126***	-1.067***
	(-7.78)	(-4.75)	(-3.02)
$Flows_{i,t-1}$	-1.062	-2.367*	-3.845**
	(-0.84)	(-1.69)	(-2.43)
$Turnover_{i,t-1}$	0.052**	0.018	0.016
	(2.12)	(0.55)	(0.37)
$Beta_{i,t-1}$	-0.276	-0.247	-0.134
	(-1.42)	(-1.15)	(-0.62)
$Four\text{-}factor\ alpha^2_{i,t-1}$	16.303***	12.304**	7.817
	(3.02)	(2.34)	(1.31)
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	310978	261097	212902
R^2	0.119	0.116	0.121

Table A5. 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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.001	0.001	0.001	0.001
	(1.56)	(1.55)	(1.52)	(1.53)
$Uncertainty_{i,t-1}$	0.003	0.003	0.006*	0.006*
	(1.60)	(1.58)	(1.79)	(1.79)
$LowPerf_{i,t-1}$	-0.001	-0.001	-0.001	-0.001
	(-0.89)	(-0.89)	(-0.98)	(-0.98)
$\log(TNA)_{i,t-1}$	0.002	0.002	0.004**	0.004**
	(1.23)	(1.25)	(2.35)	(2.35)
$Return_{i,t-1}$	0.006	0.006	0.009	0.008
	(1.32)	(1.31)	(1.53)	(1.49)
$\log(Fund\ age)_{i,t-1}$	0.003	0.003	0.002	0.002
	(1.13)	(1.14)	(0.60)	(0.60)
$Flows_{i,t-1}$	-0.003	-0.003	-0.004	-0.004
	(-1.04)	(-1.02)	(-1.09)	(-1.09)
$Beta_{i,t-1}$		0.000	0.001	0.001
		(0.51)	(0.83)	(0.88)
$Expense_{i,t-1}$			7.103***	7.103***
			(7.82)	(7.82)
$Turnover_{i,t-1}$			0.001	0.001
			(1.44)	(1.44)
$Four\text{-}factor\ alpha^2_{i,t-1}$				-0.008*
				(-1.71)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	451591	450022	350389	350389
R^2	0.975	0.975	0.971	0.971

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.

	$Flows_{i,t+2}$			
	(1)	(2)	(3)	(4)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.086*	0.085*	0.059	0.059
	(1.96)	(1.95)	(1.20)	(1.21)
$Uncertainty_{i,t-1}$	-0.062	-0.066	-0.107	-0.107
	(-1.07)	(-1.11)	(-1.44)	(-1.44)
$LowPerf_{i,t-1}$	-0.369***	-0.356***	-0.339***	-0.337***
	(-3.42)	(-3.25)	(-2.78)	(-2.76)
$\log(TNA)_{i,t-1}$	-1.477***	-1.488***	-1.475***	-1.474***
	(-16.94)	(-17.07)	(-15.91)	(-15.91)
$Return_{i,t-1}$	3.438*	3.380*	4.175**	4.142**
	(1.86)	(1.84)	(2.08)	(2.07)
$\log(Fund\ age)_{i,t-1}$	-1.187***	-1.174***	-1.126***	-1.126***
	(-10.05)	(-9.93)	(-8.25)	(-8.25)
$Flows_{i,t-1}$	3.245***	3.266***	3.816***	3.824***
	(4.74)	(4.74)	(5.49)	(5.50)
$Beta_{i,t-1}$		-0.167	-0.132	-0.130
		(-1.12)	(-0.84)	(-0.82)
$Expense_{i,t-1}$			-53.836**	-53.785**
			(-2.25)	(-2.25)
$Turnover_{i,t-1}$			0.053**	0.053**
			(2.38)	(2.38)
$Four\text{-}factor\ alpha^2_{i,t-1}$				-2.864
				(-0.63)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	443206	441773	344284	344284

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)
$Uncertainty_{i,t-1} \times LowSkill_{i,t-1}$	0.149**	0.149**	0.162***	0.161***
	(2.56)	(2.55)	(2.81)	(2.80)
$Uncertainty_{i,t-1}$	-0.048	-0.052	-0.104	-0.104
	(-0.80)	(-0.86)	(-1.38)	(-1.38)
$LowSkill_{i,t-1}$	-0.666***	-0.642***	-0.660***	-0.671***
	(-4.42)	(-4.28)	(-4.46)	(-4.53)
$\log(TNA)_{i,t-1}$	-1.545***	-1.550***	-1.476***	-1.478***
	(-16.95)	(-16.98)	(-15.22)	(-15.24)
$Return_{i,t-1}$	7.171**	7.103**	6.860**	7.034**
	(2.56)	(2.54)	(2.37)	(2.44)
$\log(Fund\ age)_{i,t-1}$	-1.401***	-1.392***	-1.329***	-1.330***
	(-11.15)	(-11.10)	(-9.67)	(-9.69)
$Flows_{i,t-1}$	-1.686	-1.603	0.301	0.258
	(-1.53)	(-1.46)	(0.25)	(0.22)
$Beta_{i,t-1}$		-0.316*	-0.354*	-0.369**
		(-1.89)	(-1.96)	(-2.07)
$Expense_{i,t-1}$			-41.432*	-41.735*
			(-1.67)	(-1.68)
$Turnover_{i,t-1}$			0.057**	0.056**
			(2.39)	(2.37)
$Four\text{-}factor\ alpha^2_{i,t-1}$				15.868***
				(4.60)
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	450081	448595	349172	349172
R^2	0.115	0.116	0.119	0.119

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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.140***	0.140***	0.140***
	(2.68)	(2.77)	(2.67)
$Uncertainty_{i,t-1}$	-0.102**	-0.102	-0.102*
	(-2.10)	(-1.38)	(-1.91)
$LowPerf_{i,t-1}$	-0.600***	-0.600***	-0.600***
	(-4.35)	(-5.12)	(-4.59)
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	349172	349172	349172

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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.105**	0.129**	0.128**
	(2.13)	(2.17)	(2.16)
$Uncertainty_{i,t-1}$	-0.069	-0.123	-0.123
	(-1.04)	(-1.50)	(-1.49)
$LowPerf_{i,t-1}$	-0.394***	-0.501***	-0.509***
	(-3.12)	(-3.36)	(-3.42)
$\log(TNA)_{i,t-1}$	-1.674***	-1.603***	-1.604***
	(-16.25)	(-14.87)	(-14.88)
$Return_{i,t-1}$	10.029***	10.012***	10.241***
	(3.96)	(3.68)	(3.78)
$\log(Fund\ age)_{i,t-1}$	-1.371***	-1.305***	-1.306***
	(-9.94)	(-8.65)	(-8.66)
$Flows_{i,t-1}$	-2.994***	-1.237	-1.275
	(-2.85)	(-1.10)	(-1.13)
$Beta_{i,t-1}$	-0.273	-0.300*	-0.312*
	(-1.65)	(-1.68)	(-1.77)
$Expense_{i,t-1}$		-33.793	-34.041
		(-1.30)	(-1.30)
$Turnover_{i,t-1}$		0.054*	0.053*
		(1.88)	(1.86)
$Four\text{-}factor\ alpha^2_{i,t-1}$			14.384***
			(3.88)
Style x Year-Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	409935	319921	319921
R^2	0.116	0.120	0.120

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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.107*	0.160***
	(1.79)	(2.87)
$Uncertainty_{i,t-1}$	-0.059	-0.440
	(-0.30)	(-1.30)
$LowPerf_{i,t-1}$	-0.667***	-0.638***
	(-4.36)	(-4.22)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Expense_{i,t-1}$	-61.211***	-121.935***
	(-4.32)	(-3.33)
$Uncertainty_{i,t-1} \times Expense_{i,t-1}$	2.933	38.222***
	(0.45)	(3.11)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$\log(TNA)_{i,t-1}$	-0.110***	-1.629***
	(-3.08)	(-12.91)
$Uncertainty_{i,t-1} \times \log(TNA)_{i,t-1}$	-0.023	0.073*
	(-1.30)	(1.76)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Return_{i,t-1}$	9.196***	7.259**
	(2.87)	(2.20)
$Uncertainty_{i,t-1} \times Return_{i,t-1}$	-0.094	-0.107
	(-0.16)	(-0.18)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$\log(Fund\ age)_{i,t-1}$	-0.975***	-1.263***
	(-11.93)	(-6.70)
$Uncertainty_{i,t-1} \times \log(Fund\ age)_{i,t-1}$	0.047	-0.031
	(1.32)	(-0.42)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Flows_{i,t-1}$	10.828***	5.731***
	(5.10)	(2.79)
$Uncertainty_{i,t-1} \times Flows_{i,t-1}$	-2.159**	-2.749***
	(-2.17)	(-2.87)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Turnover_{i,t-1}$	0.018	0.098
	(0.40)	(1.54)
$Uncertainty_{i,t-1} \times Turnover_{i,t-1}$	-0.000	-0.017
	(-0.00)	(-0.78)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Beta_{i,t-1}$	0.006	0.373
	(0.02)	(0.90)
$Uncertainty_{i,t-1} \times Beta_{i,t-1}$	0.003	-0.389**
	(0.02)	(-2.14)
$Uncertainty_{i,t-1}$	0.000	0.000
	(0.00)	(0.00)
$Four\text{-}factor\ alpha^2_{i,t-1}$	51.509*	45.914*
	(1.82)	(1.78)
$Uncertainty_{i,t-1} \times Four\text{-}factor\ alpha^2_{i,t-1}$	-11.736	-15.688
	(-0.82)	(-1.20)
Fund controls	Yes	Yes
Style x Year-Month FE	Yes	Yes
Fund FE	No	Yes
Observations	349174	349172
R^2	0.066	0.120

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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}$	0.085*	0.086*	0.088*	0.088*
	(1.87)	(1.88)	(1.92)	(1.92)
$Uncertainty_{i,t-1}$	0.091	0.089	0.085	0.085
	(1.57)	(1.54)	(1.48)	(1.48)
$LowPerf_{i,t-1}$	-0.195*	-0.176*	-0.183*	-0.184*
	(-1.91)	(-1.73)	(-1.80)	(-1.82)
$\log(TNA)_{i,t-1}$	-0.944***	-0.940***	-0.937***	-0.937***
	(-13.72)	(-13.63)	(-13.78)	(-13.78)
$Return_{i,t-1}$	11.718***	11.825***	11.837***	11.809***
	(8.77)	(8.85)	(8.88)	(8.88)
$\log(Fund\ age)_{i,t-1}$	-1.279***	-1.289***	-1.295***	-1.295***
	(-6.82)	(-6.88)	(-6.92)	(-6.93)
$Flows_{i,t-1}$	11.297***	11.274***	11.369***	11.369***
	(10.13)	(10.11)	(10.19)	(10.19)
$Beta_{i,t-1}$		-0.354***	-0.349***	-0.357***
		(-3.07)	(-3.05)	(-3.08)
$Expense_{i,t-1}$			-17.160	-17.199
			(-0.83)	(-0.83)
$Turnover_{i,t-1}$			0.006	0.006
			(0.29)	(0.29)
$Four\text{-}factor\ alpha^2_{i,t-1}$				3.464
				(1.43)
$Morningstar_{i,t-1}$	0.988***	0.987***	0.984***	0.984***
	(28.20)	(28.19)	(28.22)	(28.23)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	227855	227841	227618	227618
R^2	0.159	0.159	0.159	0.159

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 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)
$Uncertainty_{i,t-1} \times LowPerf_{i,t-1}^{MorningCat}$	0.175***	0.172***	0.163***	0.163***
	(3.26)	(3.21)	(2.80)	(2.80)
$Uncertainty_{i,t-1}$	-0.052	-0.056	-0.104	-0.104
	(-0.88)	(-0.93)	(-1.39)	(-1.39)
$LowPerf_{i,t-1}^{MorningCat}$	-0.746***	-0.714***	-0.771***	-0.780***
	(-5.37)	(-5.15)	(-5.35)	(-5.41)
$\log(TNA)_{i,t-1}$	-1.544***	-1.550***	-1.475***	-1.476***
	(-16.95)	(-16.98)	(-15.21)	(-15.23)
$Return_{i,t-1}$	6.999**	6.945**	6.578**	6.764**
	(2.50)	(2.48)	(2.29)	(2.36)
$\log(Fund\ age)_{i,t-1}$	-1.399***	-1.391***	-1.327***	-1.328***
	(-11.15)	(-11.10)	(-9.66)	(-9.67)
$Flows_{i,t-1}$	-1.698	-1.613	0.286	0.243
	(-1.54)	(-1.47)	(0.24)	(0.20)
$Beta_{i,t-1}$		-0.308*	-0.340*	-0.355**
		(-1.85)	(-1.89)	(-2.00)
$Expense_{i,t-1}$			-40.625	-40.913
			(-1.63)	(-1.64)
$Turnover_{i,t-1}$			0.057**	0.057**
			(2.41)	(2.39)
$Four\text{-}factor\ alpha_{i,t-1}^2$				15.801***
				(4.56)
Fund controls	Yes	Yes	Yes	Yes
Style x Year-Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	450081	448595	349172	349172
R^2	0.115	0.116	0.119	0.120

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 U.S. actively managed equity 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 (see list below), as well as positive and negative tones.

Other textual methods

This section provides additional information about the use of a transformer model to uncover the type of language associated with underperforming funds. I use the Bidirectional Encoder Representations from Transformers (BERT; Devlin, Chang, Lee, and Toutanova 2018) as language model to encode sentences into numerical features. Sentences are encoded into a high dimensional output vector of size 768 which is the standard dimension for BERT. BERT is trained on the corpus of books and Wikipedia. This large language model uses a transformer architecture for its

networks and aims to predict, using SoftMax functions, conditional probabilities for words given in a certain context. The model combines attention and feedforward layers to achieve this prediction task. BERT outputs contextualized embeddings for each sentences. The embeddings are then used in a regression framework to predict the performance group of each fund to which each sentence is associated.
Prompt to capture uncertainty in text from mutual fund prospectuses:

Following Jha et al. (2024) I capture funds' uncertain language from prospectuses using the following prompt to ChatGPT in an API using GPT-4.
The following text is an excerpt from a mutual fund's prospectus (the principal investment strategy). You are a finance expert. Based on this text only, please answer the following question. How much uncertainty is contained in each principal investment strategy? Please provide a score of how uncertainty each excerpt is based on a scale from 1 to 5 and provide a one-sentence explanation of your choice for each question. The format for the answer to each question should be "score - explanation." If no relevant information is provided related to the question, answer "no information is provided."

Double-machine learning to control for high-dimensional features of the text

This method uses Gui and Veitch (2022) to investigate the effect of using an uncertain tone on fund flows, conditional on underperformance. More specifically, since it is unclear which aspects of the text we should control for, the best approach is to use transformers to capture the many features of the text. This method is particulary useful when the 'treatment' is an aspect of the text.

The problem can be stated as: Does writing an uncertain (A) strategy description in the prospectus (X) affect fund flows (Y) for underperforming funds? The main

issue is that writing uncertain text is correlated with other features of the text (Z) that matter for fund flows as well. The controlled direct effect (CDE) can be expressed as:

$$\tau_{\text{CDE}} = \mathbb{E}_{X|A=1}\big[\mathbb{E}(Y \mid A = 1, X) - \mathbb{E}(Y \mid A = 0, X)\big]. \tag{12}$$

Then, Gui and Veitch (2022) define the conditional outcome Q as follows:

$$Q(\tilde{A}, X) := \mathbb{E}(Y \mid \tilde{A}, X), \tag{13}$$

Since $Q(A, X)$ is a function of the entire text data X, which can be estimated as:

$$Q = \arg\min_{\tilde{Q}} \mathbb{E}\big[(Y - \tilde{Q}(A, X))^2\big], \tag{14}$$

and the estimator of the effect would be:

$$\hat{\tau}^Q := \frac{1}{n_1} \sum_{i:A_i=1} \big(\hat{Q}_1(X_i) - \hat{Q}_0(X_i)\big), \tag{15}$$

with variance:

$$\text{var}(\hat{\tau}_Q) := \frac{1}{n} \text{var}\left(\hat{Q}_1(X_i) - \hat{Q}_0(X_i) \mid \hat{Q}\right), \tag{16}$$

In practice, the first step involves the use of a transformer model (DistilBERT; Sanh, Debut, Chaumond, and Wolf 2019) to obtain $\hat{Q}(X)$ both under treatment and non-treatment. Then; in a second step, the methodology estimates the propensity score: $P(A = 1|\hat{Q}_0(X), \hat{Q}_1(X))$, that is the propensity of $A = 1$ conditional on the how the text predicts Y under treatment and non-treatment. Finally, the method ends with the estimation of the controlled direct effect using the double machine

learning estimation (Chernozhukov et al. 2017):

$$\hat{\tau}_{\text{TI}} = \frac{1}{n}\sum_{i=1}^{n}\hat{\phi}_i, \tag{17}$$

with

$$\phi_i = A_i \cdot \frac{Y_i - \hat{Q}_0(X_i)}{\hat{p}} - \frac{\hat{g}_\eta(X_i)}{\hat{p}\cdot(1-\hat{g}_\eta(X_i))}\cdot(1-A_i)\cdot(Y_i - \hat{Q}_0(X_i)), \quad i = 1,\ldots,n, \tag{18}$$

where $\hat{p} = \frac{1}{n}\sum_{i=1}^{n} A_i$ that is, the propensity that $A = 1$ and $\hat{g}$ is the propensity that $A = 1$ conditional on X, the text. The figure below, summarizes the procedure proposed by Gui and Veitch (2022):

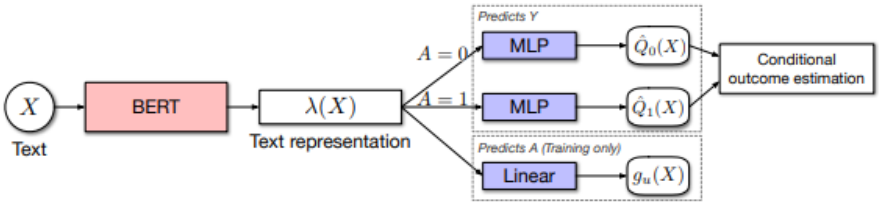


Figure A4. A representation of the estimation procedure from Gui and Veitch (2022).