The Virtue of Transparency: Evidence from Asset Management

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Abstract

Communication can build trust, not just transmit information. I show that asset managers' voluntary transparency about risk fosters trust and encourages investors to bear risk. Among otherwise-identical S&P 500 index mutual funds, investor letters discussing risk in more detail attract higher flows. To strengthen causality, I exploit corner bunching in risk detail using a control function approach. A pre-registered, randomized experiment isolates the mechanism: transparency raises trust in management even as perceived risk rises and expected returns fall, contradicting a standard learning-based explanation. The effect concentrates among inexperienced investors, in high risk-aversion market states, and among anxious readerships.

Keywords: Fund Flows, Trust, Risk Aversion, Randomized Experiment, Text Data
JEL Codes: D14, D83, D91, G11, G20, G41

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1 Introduction

Communication is central to financial markets. Most directly, communication conveys information about an asset: a large literature in economics, finance, and accounting examines firms' choices of what to disclose about themselves, and investors' responses to those disclosures.[1] A second, less well understood, route runs through trust: confidence that a counterparty will deal honestly and fairly where its actions, intentions, or competence cannot be fully observed or contracted upon (Arrow, 1972). Voluntarily providing information may be one way to earn that confidence, and many practitioners regard such transparency as a means of building trust.[2] Yet whether transparency builds trust, and thereby alters economically consequential behavior, is not established (Thakor and Merton, 2023).

I investigate this possibility in the context of the asset management industry, where trust is thought to play a central role: Gennaioli, Shleifer, and Vishny (2015) argue that asset managers provide investors with "peace of mind," giving them the confidence to bear risks they would otherwise avoid. Consistent with the importance of this role, prior work shows that fraud and other trust-breaking events lead investors to withdraw capital and reduce risk-taking (Kostovetsky, 2016; Giannetti and Wang, 2016; Gurun, Stoffman, and Yonker, 2018). Much less is known about how intermediaries can build trust and thereby encourage risk-taking. This question is particularly important because many households remain reluctant to bear risk.[3]

I show that transparent communication by intermediaries fosters trust and thereby encourages risk-taking; in this context, trust-building reduces investors' effective risk aversion. I demonstrate this mechanism by examining letters that are written voluntarily by asset managers to their existing clients – a widespread industry practice (Cassar, Gerakos, Green, Hand, and Neal, 2018; Hillert, Niessen-Ruenzi, and Ruenzi, 2025) – and I focus on S&P 500 index mutual funds, which deliver the same exposure to market risk. In this setting, whatever investors *could* learn about portfolio risk is common across funds at a point in time, yet the letters themselves vary widely in how they discuss this common risk exposure.[4]

[1] See, for example, Grossman (1981) and Milgrom (1981). Healy and Palepu (2001) and Verrecchia (2001) review the empirical and theoretical corporate disclosure literature, respectively.

[2] Laying out his management principles, former General Electric CEO Jack Welch wrote, "Trust happens when leaders are transparent" (Welch and Welch, 2005, Chapter 5). In a PricewaterhouseCoopers survey, 70% of firm directors agreed that "enhancing shareholder communications (e.g., disclosures or reporting) can have a positive impact on stakeholder trust." Source: `https://corpgov.law.harvard.edu/2023/04/11/using-transparency-to-build-trust-a-corporate-directors-guide/`

[3] Even stock market participants display a low intensive margin of risk-taking: 40% of such households hold less than 20% of their financial wealth in stocks (Calvet, Célérier, Sodini, and Vallée, 2023), a much lower share than that prescribed by realistic lifecycle models (e.g., Cocco, Gomes, and Maenhout, 2005).

[4] The letters I examine are voluntary, free-form communication, distinct from the mandatory risk disclosures

The key hypothesis is that voluntary transparency builds trust with investors; in this setting, the prediction is that letters with more detailed risk discussion should attract larger inflows, holding the common objective risk exposure fixed. This sign test distinguishes trust from learning about payoffs: if letters convey information about risk exposures then more detailed discussion should *reduce* flows, as investors perceive or notice higher risk; but if transparency builds trust, then more detail should *increase* flows.

I show that letters with a more detailed voluntary discussion of risks do indeed encourage higher fund flows, consistent with a trust-building role for communication. Letters containing more detailed forward-looking information about risks – in the sense of dedicating a larger proportion of the letter to discussing this topic – are followed by a higher fund flow immediately after they are disseminated to investors, even though the actual risk exposure of the underlying portfolio is the same.[5] Furthermore, the reaction of investors is not explained by whether the letter conveys a high or low level of risk. The direction of the effect is fully consistent with a trust-building mechanism: higher trust levels are known to translate into a greater willingness to hold a risky asset (Guiso, Sapienza, and Zingales, 2008; Bottazzi, Da Rin, and Hellmann, 2016; Giannetti and Wang, 2016; Merkoulova and Veld, 2022; Germann, Mertes, Weber, and Loos, 2025). Investors are rewarded for their trust, earning a positive Sharpe ratio, net of fees, for holding periods longer than one month.

Pinning down the effect of communication using observational data is challenging, but my focus on quasi-identical S&P 500 index funds addresses many potential concerns. The passive and standardized nature of these index funds rules out the possibility that investors react to communication because they are learning about private information, such as funds' investment strategies or their managers' skill. Furthermore, any differences in the funds' portfolios, risk and returns are minimal, implicitly controlling for these potential drivers of flows. I also explicitly control for observable drivers of fund flows highlighted by prior research, most notably past performance, fees and other fund and family characteristics. Importantly, I incorporate time effects, which control for investors' prior beliefs about risk and return, the growth in passive investing, and any news about or shocks to the common portfolio that might simultaneously (and independently) drive both flows and communication. I also include fund fixed effects to

contained in prospectuses and other filings. Providing information about future *performance* is discouraged under regulations relating to the Investment Company Act (Rule 34b-1, 17 C.F.R. § 270.34b-1) and the Securities Act (Rule 156, 17 C.F.R. § 230.156). Discussion of *risk*, by contrast, is neither discouraged nor mandated in these letters, and accordingly varies in the cross-section of letters despite the common risk exposure.

[5] By linking *changes* in risk-taking (i.e., flows) to changes in trust, I follow a common approach in the literature (Kostovetsky, 2016; Giannetti and Wang, 2016; Gurun, Stoffman, and Yonker, 2018) that sidesteps the difficult empirical problem of measuring *levels* of trust and risk-taking for specific investor–asset manager pairs. I later directly measure perceived trust in a controlled experimental setting to confirm the mechanism.

control for unobservable persistent differences between funds, the families they belong to, and their investor bases.

The effect of voluntary transparency on flows is economically significant: a one standard deviation (SD) growth in the amount of detail voluntarily communicated about risk predicts a 0.09–0.17 SD growth in assets under management during the subsequent month. This is equivalent to an additional 0.28–0.50 percentage points of assets, on average, and up to one-third of the magnitude of the well-known association between fees and flows.

To further mitigate concerns that other variables might be driving flows – such as unobservable marketing activities or other content within the fund letters – I employ an additional identification strategy that exploits a natural feature of my treatment variable: the distribution of the fraction of a letter discussing risk exhibits corner bunching at the lower end of the support. This pattern enables me to adjust for selection bias using a control function methodology developed by Caetano, Caetano, and Nielsen (2024) specifically for settings with corner bunching. When correcting for potential endogeneity, the relationship between risk detail and flows remains significant and becomes larger in magnitude; estimated coefficients on the correction term are also consistent with a negative selection bias in the baseline estimate. This analysis further strengthens the causal interpretation that voluntary transparency increases fund flows.

Having established that transparency about risk raises risk-taking in the field, I examine the mechanism more closely by conducting a pre-registered, randomized experiment that tests the trust-building channel directly. The design mirrors the field setting. Each subject takes the role of an investor in a generic S&P 500 index fund, and reads a single randomly assigned letter: either a constructed Transparent letter that openly discusses the fund's forward-looking risks, or a Baseline outlook letter that does not.[6] Subjects rate Transparent letters as having more focus on risk and a less positive focus than Baseline letters do, confirming the manipulation. This randomized experiment shows that transparency about risk causally builds trust: reading a Transparent letter raises subjects' reported trust in the fund's manager. Transparency also raises trust in the information contained in the letter, consistent with the perceived credibility of the letter mediating trust in a fund's management.

Furthermore, the experiment rules out subjects learning about the return distribution as an explanation for my main results. Transparent letters are perceived as implying lower returns on average, besides their increased focus on risk. Both perceived moments have the same impli-

[6]Altogether, six constructed letter stimuli are randomly assigned to 400 subjects. The Transparent stimuli are constructed based on actual forward-looking risk-related statements that my textual analysis methodology extracts from the fund letter corpus, followed by manual edits to remove fund and event-specific references.

cation for investor demand: lower expected returns and higher perceived risk each predict less risk-taking, which is the opposite of the increased inflows observed in the field. An additional experimental task presents subjects with two side-by-side letters to evaluate, drawn from each condition (Transparent vs. Baseline), and a similar pattern emerges: a majority of investors prefer the Transparent letter, even while subjects overwhelmingly judge it the riskier one that simultaneously implies worse returns. The randomized experiment thus isolates a causal effect of transparency on trust, and rejects the alternative explanation that subjects expect higher returns based on a more detailed discussion of risk. Coupled with existing evidence that trust raises investors' willingness to take financial risk (e.g., Merkoulova and Veld, 2022; Germann, Mertes, Weber, and Loos, 2025), these experimental findings explain the increased risk-taking observed among mutual fund investors in the field.

If transparency builds trust and trust alleviates investors' reluctance to bear risk, then the effect should be strongest where this reluctance binds most tightly. I find this prediction borne out in three distinct settings. At the individual level, the experimental trust effect concentrates among inexperienced, pessimistic investors with little existing allocation to equities. In the timeseries, I interact the transparency–flow relationship with Bekaert, Engstrom, and Xu's (2022) measure of aggregate risk aversion: flows are lower when aggregate risk aversion is high, but transparency's effect is significantly stronger in precisely those states, the sign predicted if trust-building communication reduces investors' effective risk aversion. In the cross-section, combining local Google search intensity for anxiety-related terms with the geolocations of fund letter readerships, I find the effect concentrated among funds whose readership exhibits high baseline anxiety (which is an important component of risk aversion (Guiso, Sapienza, and Zingales, 2018)). Across all three settings, trust-building transparency has its strongest effect where inexperience, risk aversion, or anxiety are most important.

A final set of tests systematically evaluates and rejects a dozen potential explanations for the main transparency–risk taking effect that I uncover. Most notably, various learning channels, including learning about risk, the return distribution, or tracking error, find no support in the data. My tests also reject other channels, including shrouding risks through complexity, and marketing to attract new investors. This battery of tests strengthens confidence that the observed effect of communication by funds to their investors operates through trust-building, rather than alternative mechanisms.

Economists have long sought to understand the origins of trust attitudes (e.g., Fisman and Khanna, 1999; Alesina and La Ferrara, 2002; Algan and Cahuc, 2010). I contribute by showing that transparency in communication fosters trust and influences financial decision-making in

an important economic setting. My paper also sheds light on the role of communication in economic interactions. Persuasive communication is a widespread phenomenon (McCloskey and Klamer, 1995), and I show it can act to build trust.

The accounting literature studies how privately informed managers make disclosures credible as signals about payoffs (Skinner, 1994; Hutton, Miller, and Skinner, 2003; Rogers and Stocken, 2005). Credibility in this literature matters because it governs how investors' beliefs about payoffs update, and the manager's problem is to be believed. By contrast, in my setting transparent letters are read as implying higher risk and lower returns; investors' increased willingness to take risk thus stems from trust in the manager rather than from beliefs about returns. Some prior work examines the effect of trust on disclosure and price responses: in high-trust countries, Pevzner, Xie, and Xin (2015) find earnings announcements move prices more and Guan, Lobo, Tsang, and Xin (2020) document that firms issue earnings forecasts more often. My paper shows how disclosure and information provision can foster trust.

This paper shows that trust-building actions, in the form of voluntary transparency, are a determinant of investor flows into mutual funds. These actions are thus part of the value added by asset managers (Berk and Van Binsbergen, 2015), who behave as "money doctors" (Gennaioli, Shleifer, and Vishny, 2015). Understanding the drivers of investor flows to mutual funds has long been an important research question (e.g., Sirri and Tufano, 1998; Chevalier and Ellison, 1999), and my results provide further evidence on the behavioral drivers of fund flows (e.g., Cooper, Gulen, and Rau, 2005; Bailey, Kumar, and Ng, 2011; Ben-David, Li, Rossi, and Song, 2022). My main empirical design also builds on studies by Elton, Gruber, and Busse (2004), Hortaçsu and Syverson (2004), and deHaan, Song, Xie, and Zhu (2021) that use homogeneous S&P 500 index funds as a useful laboratory for identification.

Finally, this paper advances the literature on information transmission in the mutual fund industry, which has so far focused on understanding what disclosures reveal about the strategies or skills of active managers. Sheng, Xu, and Zheng (2026) and Abis, Buffa, Javadekar, and Lines (2022) examine the accuracy of mandatory disclosures in prospectuses. Hillert, Niessen-Ruenzi, and Ruenzi (2025) and Cao, Yang, and Zhang (2025) study whether shareholder letters are informative about manager skill or future performance, and what investors could thus potentially learn from this communication. My paper focuses on letters addressed to investors in homogeneous, passive S&P 500 index mutual funds where learning about strategy and skill is absent by construction; this identifies a novel effect in which transparency fosters trust.

I describe the institutional setting further in Section 2. Section 3 identifies the effect of transparency on investors' risk-taking. Section 4 provides complementary experimental evidence

that transparency increases investor trust. Section 5 analyzes timeseries and cross-sectional variation in the strength of the effect. Section 6 evaluates and rules out a number of potential alternative explanations, including various learning mechanisms. Section 7 concludes. The Appendix contains tables and figures. An Internet Appendix contains additional analyses and data checks.

2 Institutional Setting and Data

2.1 Fund Letters

The SEC requires funds to disseminate annual reports and semi-annual reports to their investor clients, and these must also be filed within 10 days on the SEC's EDGAR system as Form N-CSR and N-CSRS, respectively. These reports contain mandatory information about historical performance, fees and holdings. They may also contain free-form text communications to shareholders. Such communications do not follow a standardized format, are completely optional, and may contain unaudited statements. I label these discussions "fund letters."[7,8]

Fund letters are often formatted as just that, beginning with phrases such as "Dear investors" and ending with a signoff; refer to Internet Appendix B for an example. However, such free-form voluntary text may also appear in other guises; for example, under a section titled "Management discussion and analysis" or "Interview with portfolio manager." Extracting them requires casting a net wide enough to cover the many forms that these letters can take.

I define a customized set of patterns that identify the start and end locations of letters based on common phrases and section headings. To do this, I manually sample from N-CSR and N-CSRS filings and read through them to identify fund letters, then I define patterns that match the start and end of detected letters. I also sample among extracted letters and cross-check them against the reports from which they were extracted to verify the accuracy of the results. This procedure yields a set of letter-detecting patterns that is simple yet effective, consistently identifying letters in over nine out of ten annual reports and eight out of ten semi-annual reports every year throughout my sample. This high rate of detection indicates that discretionary letters are a very common form of communication by funds and their managers.

[7] According to an Investment Company Institute (2018) survey, 81% of mutual fund investors recall receiving shareholder reports; of those investors, 37% read at least some portion of it. Note that fund letters appear near the beginning of shareholder reports, and are thus likely to be read.

[8] The literature also uses the more general phrase "shareholder letter" (Hillert, Niessen-Ruenzi, and Ruenzi, 2025) when letter contents are not matched to individual funds. I use "fund letter" to emphasize that the letters I extract are targeted at the investors in an individual fund.

As part of regular and high-profile shareholder reports, the letters I examine provide a vehicle for funds to broadcast messages to their investor bases. Because fund letters are entirely voluntary and can take flexible formats, they represent discretionary communication by fund managers, making them an ideal setting to test for a trust-building mechanism in communication. Furthermore, by focusing on next-month flow responses immediately following letter dissemination, I can cleanly measure investors' reactions to this voluntary communication while avoiding the challenge of identifying longer-lasting trust effects that would be confounded over long horizons.

Extracting Individual Fund Letters From Reports. Annual and semi-annual reports are published at the level of a legal entity, as identified by a Central Index Key (CIK), and this is not necessarily at the level of an individual fund.[9] To deal with cases where one CIK nests several funds, I match letters in the report to individual funds by detecting fund names or fund tickers in the contents of each letter. Letters that do not contain a fund name or ticker are matched to every fund associated with that report (which may just be a single fund).

My sample begins in 2006, which is the first year individual fund letters can be identified; prior to that, the SEC EDGAR database did not record the mappings from funds to CIKs that are needed for my matching procedure. The sample ends in August 2021.[10]

2.2 Extracting and Quantifying Risk Discussions in Fund Letters

I contribute a reproducible and interpretable methodology to measure the contents of fund letters that discuss risk. I find that discussions about risk are prevalent in fund letters: 8.47% of sentences in the entire corpus are about this topic.

2.2.1 Extracting Sentences That Discuss Risk

Extracting Valid Non-Boilerplate Sentences. To prepare the text corpus, I first extract grammatically valid sentences from fund letters using Stanford CoreNLP tools (Manning et al., 2014); this is the only step of my procedure that relies upon machine learning tools. I next define a set of patterns that match to non-informative boilerplate text. I construct this set of patterns by randomly sampling from valid sentences and defining patterns that match sentences that are legal disclaimers, then remove these boilerplate sentences from the database.

[9] For example, "Schwab Equity Index Funds" rather than "Schwab S&P 500 Index Fund."

[10] The SEC announced reforms to the format of N-CSR and N-CSRS filings in 2022. My sample period running from 2006–2021 benefits from a consistent regulatory regime, while also capturing major financial and economic shocks (the global financial crisis and the Covid shock).

The remaining steps in my text extraction methodology likewise screen sentences using patterns of words or phrases that are manually defined by sampling and reading through the database of fund letters. The key advantage of such a bag-of-words approach is ensuring the textual analysis procedure is adapted to the corpus of fund letters, rather than a different setting where phrases can have entirely different meanings: Loughran and McDonald (2011) argue persuasively that adapting textual analysis procedures to a financial context is crucial.

Screening for Sentences that Discuss Risk. I use two sets of word and phrase patterns to screen for sentences that discuss the topic of risk. An important challenge in isolating information provision about risks is excluding discussions that simply recap past events: fund letters frequently discuss past portfolio holdings, returns, and economic and world events from recent months. However, investors' portfolio choices are forward-looking, and this paper focuses on communication about the unknown, yet-to-be-realized risks that investors dislike. I therefore screen separately for sentences that contain risk-related words and phrases, as well as forward-looking words and phrases, and extract sentences that jointly meet both criteria. Figure 1 graphically illustrates this conjunction.

[Insert Figure 1 here]

Sentence-level matching is preferable to counting forward-looking and risk-related words separately across the letter: such an approach would struggle to capture whether these concepts appear together, since individual words rarely convey both meanings. Sentences provide the natural unit for identifying where forward-looking and risk-related content intersect.

Validating the Matching Patterns. In Internet Appendix D, I compare my customized set of words and phrases to those taken from other contexts, or that are encoded in off-the-shelf software. I find that my customized approach detects a comprehensive set of forward-looking and risk-related statements, while also being transparent and adapted to the context of fund letters. Quantitatively, this methodology meets or exceeds the fraction of forward-looking or risk-related statements detected by state-of-the-art software used in the psychology literature.

2.2.2 Quantifying the Amount of Risk Detail Present in a Letter's Text

The key measure used in this paper is the fraction of a fund letter devoted to discussing risk:

$$\text{Risk Detail Fraction}_{i,t} = \frac{\text{Number of words about risk}_{i,t}}{\text{Total number of words in letter}_{i,t}}. \tag{1}$$

Similar share-based measures are typically used to measure objective risk exposures; for example, Hassan, Hollander, van Lent, and Tahoun (2019) measure firms' exposure to political

risk by the share of their earnings calls that discuss that topic. By contrast, the current paper focuses on homogeneous S&P 500 tracker funds that have near-identical risk exposures by construction. This allows me to interpret Eqn. (1) as variation in how funds subjectively and voluntarily discuss the *same* risk exposure when communicating with their investor clients.

2.2.3 Quantifying the Level of Risk Conveyed by Text

As well as my main measure of transparency, it is also important to quantify the level of risk: i.e., whether the letter implies risk is high or low. This signal is potentially independent of the amount of detail provided. I measure the level of risk conveyed by a fund letter using two approaches. Since each approach is a reasonable *ex ante* measure, I remain agnostic about which to prefer and so employ both in my subsequent analyses.

Sentiment-Based Approach. My first approach measures the level of the risk conveyed using the net sentiment of the text that discusses risk. Individual words are classified as having positive or negative (or neutral) sentiment using Loughran and McDonald's (2011) financial sentiment dictionary, with an adjustment to correct for negations in the 3 words preceding positive terms. The net sentiment is then calculated as the difference of positive-sentiment and negative-sentiment word counts, normalized by the total word count of the discussion about risk:

$$\text{Net sentiment of risk text} = \frac{\text{Positive word count} - \text{Negative word count}}{\text{Total word count}} \tag{2}$$

Finally, the level of risk implied by the sentiment of this text is simply the negative of the net sentiment, standardized within each fund to account for any fund-specific mean sentiment due to writing styles. My empirical results are not dependent on this standardization:

$$\text{Risk Level} = -z(\text{Net sentiment of risk text}). \tag{3}$$

Contextual Approach. My second approach focuses on words in the neighborhood of each occurrence of the word "risk" (or its synonyms such as "volatility" or "uncertainty") and counts the number of words denoting a high level of risk (such as "high," "increased," "elevated," "severe," and so on) and the number of words denoting a low level of risk (such as "low," "decreased," "reduced," "moderate," and so on). The window around "risk" or its synonym consists of the 3 words before and the 3 words after. (The results are not affected by widening the window to 5 words.) The contextual measure of the level of risk conveyed is simply the difference of the high-risk and low-risk descriptor word counts in the fund letter:

$$\text{Risk Level} = \text{High risk word count} - \text{Low risk word count} \tag{4}$$

2.2.4 Variation in Communication About Risk

Cross-Sectional Dispersion. Figure 2 summarizes the cross-sectional dispersion in the amount of detail communicated about risk (by the fraction of the letter) and the net sentiment of the same risk-related text. Cross-sectional variation in both variables is considerable, even though S&P 500 funds by construction deliver a common risk exposure to their investor clients. As one might expect from discussions of risk, the tone is on average net-negative, but both positive-sentiment and negative-sentiment letters coexist.

[Insert Figure 2 here]

Timeseries Variation & Determinants. There is also considerable timeseries variation. Even within a fund, there is considerable variation in both the amount of communication about risk, as well as the level of the risk conveyed by the textual discussion. The mean (median) within-fund autocorrelation of the fraction of the letter about risk is only 0.12 (0.09). The mean (median) within-fund autocorrelation of the number of words devoted to risk is similar, at 0.13 (0.18). The mean (median) within-fund autocorrelation of the level of risk conveyed by the sentiment is only 0.02 (0.08). The mean (median) within-fund autocorrelation of the level of risk conveyed by contextual words is also low, at -0.05 (-0.05). As I show next, market conditions are an important determinant of this timeseries variation.

[Insert Table 1 here]

Table 1 analyzes timeseries indices of two risk detail measures and two risk level measures. Each measure shown in the table is an equally weighted cross-sectional year-month t mean of the within-fund-standardized (i.e. z-scores) equivalents; every measure is thus a simple time-varying index. The primary driver of all four timeseries is the contemporaneous level of the VIX. Within-fund variation in their communication to investors about risk is thus informative, in the sense that fund letters provide more detail about risk at precisely the moments when the VIX is higher. The communication is also informative about the level of risk: managers write more pessimistically about risk when the VIX is high, as one might expect if the VIX proxies for investors' perceived risk,[11] or for investors' demand for information about the fund's risk exposure.

[11]Note that the VIX embeds both expected volatility and a risk premium. Therefore, when controlling for perceived risk in subsequent analyses, I avoid relying upon the VIX.

2.3 Mutual Fund Classifications and Characteristics

My source of mutual fund and fund family characteristics is the CRSP US Survivor-Bias-Free Mutual Fund Database (MFDB).

I clean fee data and calculate total fund fees by closely following the procedure of Roussanov, Ruan, and Wei (2021, Internet Appendix). Total fees are therefore defined as the sum of expense ratios (which include management fees, and other expenses) and front loads (annualized by dividing by 7).

Funds are defined based on EDGAR identifiers; namely, CIKs and Series IDs. CRSP fund characteristics are matched to SEC identifiers using the "CRSP_cik_map" table from CRSP MFDB. Share class-level characteristics are aggregated to the fund level by total net assets (TNA).

I obtain fund-level monthly net returns from the CRSP MFDB using a similar procedure. These are then winsorized at the 5% and 95% levels over the entire sample (i.e., before screening for index funds) to avoid the undue influence of outliers.

My main results focus on communication by S&P 500 index mutual funds. A supplementary result relies on measuring communication by active funds; to identify these, I first classify index funds (in general) based on their names, following the list of keywords proposed by Ben-David, Li, Rossi, and Song (2022). Active funds are then defined as non-index funds.

Fund Flows. Following the extant literature, mutual funds' monthly net flows (from the end of month t to the end of month $t+1$) are calculated based on the fund returns and Total Net Assets (TNA) recorded in the CRSP US Survivor-Bias-Free Mutual Fund Database:

$$\text{Net Flow}_{i,t\to t+1}(\$) \;=\; \text{TNA}_{i,t+1} \;-\; (1+R_{i,t\to t+1}) \times \text{TNA}_{i,t}. \tag{5}$$

In addition to the above measure of net flows, I also make use of data on gross monthly inflows and outflows reported to the SEC at a fund level. These gross dollar flows are extracted from mandatory SEC filing documents (N-SAR, N-PORT, and any amendments), with the latest available observation retained per month.

All dollar flows are normalized to a percentage of lagged assets. A similar normalization to the net flow (below) is applied to gross inflows and gross outflows:

$$\text{Net Flow}_{i,t\to t+1}(\%) \;=\; \frac{\text{Net Flow}_{i,t\to t+1}(\$)}{\text{TNA}_{i,t}} \times 100\%. \tag{6}$$

To avoid the undue influence of outliers, including those due to corporate actions, the net flow percentage variable is winsorized at the 5% and 95% levels over the full sample. Similarly,

each gross flow percentage variable is winsorized at the 95% level. These steps occur before screening for S&P 500 index funds.

S&P 500 Index Funds. To select S&P 500 index mutual funds for my main sample, I compare fund-level returns to the returns on the S&P 500 index and discard funds with a correlation of less than 98%. I then filter out funds whose names indicate they are not following a pure passive indexing strategy (such as quant funds, funds tilted to a particular sector, or funds that track a different index). This procedure selects a total of 197 S&P 500 index mutual funds (over the entire sample) for which SEC EDGAR identifiers are also available. In my main tests, I focus on fund-months where a fund letter was disseminated to investors; summary statistics for my main sample are shown in Internet Appendix A.

3 Transparent Communication and Investor Risk-Taking

This section shows that more detailed voluntary communication about risks encourages investor risk-taking. Section 3.1 quantifies the relationship between risk transparency and S&P 500 index fund flows. I show that the detail provided about risk plays a distinct role, beyond the level of risk that letters might convey. Section 3.2 strengthens causality by exploiting corner bunching in the treatment variable. Section 3.3 and Section 3.4 interpret the effect and present evidence consistent with a trust-driven willingness to bear risk by investors.

3.1 Relationship Between Transparency and Fund Flows

I begin by analyzing the relationship between net flows into S&P 500 index mutual funds and the amount of information about risk that funds voluntarily transmit to their existing investors. The panel that I analyze consists of fund i and year-month t pairs for each disseminated fund letter. Letters are published at a semi-annual frequency (approximately) and I focus on months t during which a letter was disseminated. The baseline panel regression is the following:

$$\text{Net Flow}_{i,t\to t+1}(\%) = \beta \times \text{Risk Detail}_{i,t} + \Gamma \times \text{Fund Controls}_{i,t} + \pi_i + \phi_t + \epsilon_{i,t}. \tag{7}$$

That is, I measure the strength of the relationship β between the degree of voluntary transparency about risks during a month t and the normalized percentage flow into the fund from the end of month t to the end of month $t+1$; due to the monthly frequency of the flows dataset, this is the most immediate period following the dissemination of a fund letter. The baseline specification (Eqn. (7)) includes fund fixed effects π_i to capture any time-invariant unobservable fund-, family- and investor base-specific characteristics that might drive flows, as well as year-month time effects ϕ_t that capture any time-varying characteristics of the common port-

folio, such as its actual risk exposure, and any common shocks that might drive flows. I also include controls for time-varying fund-level characteristics that have been previously found to drive fund flows (Sirri and Tufano, 1998; Chevalier and Ellison, 1999) including the fund's past returns (and its square, to allow for a nonlinear relationship), fees and size, and the fund family's age and size. Γ is a vector of coefficients on the set of controls.

[Insert Table 2 here]

Baseline Relationship. Table 2 column 1 shows the result of estimating the panel regression (Eqn. (7)). The estimated coefficient value $\widehat{\beta} \approx 0.02$ is positive and significant at the 5% level, with double-clustered standard errors. This estimate establishes a key result: when a larger share of a fund's letter is devoted to discussing risk, net flows into the fund are higher in the month immediately following the dissemination of this letter. Since the choice of text content examined in this paper is voluntary, this result shows that voluntary transparency about risks by a fund is positively related to investors' willingness to bear risk in that fund.

Including the Level of Risk Conveyed by Fund Letters. The baseline result above is that more transparent and informative discussion of risk predicts higher subsequent flows. However, investors might also be reacting to whether the letter characterizes risk as being high or low going forward. This could be conveyed through the tone with which a letter discusses risk, or even by explicit descriptions like risk being "high" or "low." Indeed, both features of the text are correlated with market conditions (see Table 1). I test for this possibility by augmenting the baseline specification with a control for the level of risk conveyed (wherever letters discuss risk at all):

$$\begin{aligned}\text{Net Flow}_{i,t\to t+1}(\%) = \beta_1 \times \text{Risk Detail}_{i,t} + \beta_2 \times \text{Risk Level}_{i,t} \\ + \Gamma \times \text{Fund Controls}_{i,t} + \pi_i + \phi_t + \epsilon_{i,t}.\end{aligned} \tag{8}$$

Table 2 columns 2, 4 and 5 show estimates of Eqn. (8), using three different measures of the risk level conveyed by fund letters. These measures are defined based on either the Loughran and McDonald (2011) sentiment of the text discussing risk, or the presence of descriptive words, and are described further in Section 2.2.3. The results are similar irrespective of the measure used: the baseline coefficient estimate $\widehat{\beta}_1 \approx 0.03$ remains positive, significant, and has increased in magnitude with the inclusion of the risk level control. As for the coefficient estimated on the control itself, $\widehat{\beta}_2$, it is not significantly different from zero. These results suggest that investors respond to the amount of detail provided about risk (i.e., the transparency of the fund letters) rather than any signals transmitted about the actual level of risk.

I next test whether the level of risk matters by attenuating the importance of transparency,

rather than entering as a direct control. To do so, I augment the panel specification with interaction effects between the risk detail and an indicator for conveying a high risk level (once again, through the sentiment of the text, or via the presence of certain descriptors):

$$\begin{aligned}\text{Net Flow}_{i,t\to t+1}(\%) = {} & \beta_1 \times \text{Risk Detail}_{i,t} + \beta_2 \times \mathbb{1}\{\text{High Risk Level}\}_{i,t} \\ & + \beta_3 \times \mathbb{1}\{\text{High Risk Level}\}_{i,t} \times \text{Risk Detail}_{i,t} \\ & + \Gamma \times \text{Controls}_{i,t} + \pi_i + \phi_t + \epsilon_{i,t}. \end{aligned} \tag{9}$$

Table 2 columns 3 and 6 show estimates of Eqn. (9). Neither the interaction $\widehat{\beta}_3$ nor the high-risk indicator alone $\widehat{\beta}_2$ is statistically significant, and the interaction effects are in any case small. This indicates that the positive impact of risk detail on flows does not differ systematically depending on whether the risk discussion conveys a relatively high or low level of risk.

Overall, Table 2 shows that flows into S&P 500 index mutual funds are consistently higher when funds communicate more detail about risk in their voluntary letters. This effect is robust to controlling for various textual measures of the risk level conveyed in the same fund letters, and is not moderated by whether the discussion frames risk as especially high.

[Insert Figure 3 here]

Figure 3 visualizes the relationship between risk detail and fund flows in a binscatter plot. The displayed net flow is residualized against the level of risk (defined using sentiment) and the fund controls and fixed effects employed in prior specifications, in order to include them as controls in the binscatter. Net flows are monotonically increasing in risk detail quintiles.

Economic Significance. The relationship between flows and transparency about risks is an economically meaningful one. This is most clear when regressing standardized net flows against the standardized risk detail, the results of which are displayed in Table 3. The estimates show that a one standard deviation (SD) increase in the detail provided about risk predicts a next-month increase in the fund's assets in the range of 0.09–0.17 SDs in magnitude; i.e., 0.28–0.50 percentage points of assets (on average), depending on the controls employed. By way of comparison, the well-known, strong and negative association between flows and total fees has a magnitude in the range of 0.44–0.52 SDs. The magnitude of the flow-detail relationship is thus approximately one-sixth to one-third of the magnitude of the association between quantities and prices, demonstrating the economic importance of trust-building communication.

[Insert Table 3 here]

Robustness of the Transparency–Risk Taking Relationship. I conduct a battery of robustness tests in Internet Appendix G, and find no change to the direction of the association between risk detail and fund flows. Encouragingly, the magnitude mostly remains similar, and sometimes increases. The robustness tests are as follows. I explicitly *(i)* control for (the near-identical) fund risk exposures, *(ii)* control for different trailing past return windows, *(iii)* control for past fund flows, and *(iv)* control for Morningstar ratings (Ben-David, Li, Rossi, and Song, 2022). I next *(v)* employ a different measure of risk detail: the Shannon's entropy of the distributions of words employed in each risk discussion. I also *(vi)* repeat the analysis when focusing on the sub-sample of letters that explicitly communicate a high level of risk. I next *(vii)* verify the presence of a pure within-fund effect, consistent with an ongoing relationship between a fund and its investor base over time. I finally *(viii)* confirm the relationship between fund flows and the features of communication about risk is similar when flows are measured using gross inflows instead of net flows.

3.2 Identification Based On Corner Bunching

To strengthen causality, I analyze the flow–risk detail relationship using an econometric technique that exploits the presence of corner bunching.

The central pillar of this paper's identification strategy is its focus on quasi-identical S&P 500 index funds. Because these funds passively replicate the same benchmark, important confounding channels – such as signaling managers' stock-picking abilities – are absent by construction. Furthermore, the empirical design controls for a variety of fund-level and time-varying confounders, both observed and unobserved, through the inclusion of fixed effects.

That said, the possibility of unobserved shocks that vary at the fund–month level remains a potential concern. For instance, contemporaneous changes in distribution networks, marketing intensity, or idiosyncratic letter content could affect both transparency and flows. To address these residual unobservables, I exploit an empirical feature of the treatment variable's distribution.

[Insert Figure 4 here]

Figure 4 visualizes the distribution of my key treatment variable, defined in Eqn. (1) as the fraction of each detected fund letter devoted to discussing risk. A striking feature of this empirical distribution is the mass of observations bunched at the corner value of 0% (highlighted by the red bar in the histogram). This bunching at the lower support produces a discontinuity

in the empirical cumulative distribution function that can be exploited for identification.[12]

Recent methodological contributions by Caetano, Caetano, and Nielsen (2024) have been developed to exploit precisely this pattern of corner bunching in order to identify the treatment effect. Their key insight is that, while the observed treatment intensity is censored at the corner, the unobservables that threaten identification are not. By modeling the shape of the treatment distribution around the corner, one can construct a control function to capture the latent selection component. Intuitively, the excess mass at the corner value of 0% reveals the types of funds and months in which the latent propensity to be transparent is low, and therefore allows the econometrician to control for this selection directly. Further details of the econometric methodology are described in Internet Appendix E.

[Insert Table 4 here]

I augment this paper's baseline regression (7), which relates the risk detail provided in a fund letter to subsequent fund flows. The main coefficient of interest is β, and I once more include the usual fund controls and additive year-month & fund fixed effects. The modified specification includes a control function $\lambda(\cdot)$ that corrects for potential endogeneity, and is specified using Caetano, Caetano, and Nielsen's (2024) methodology. This control function exploits the presence of corner bunching in the treatment variable $\text{Risk Detail}_{i,t}$:

$$\begin{aligned}\text{Flow}_{i,t\to t+1}(\%) = \beta \times \text{Risk Detail}_{i,t} + \delta \times \overbrace{\lambda\big(\text{Risk Detail}_{i,t};\, \text{Fund Controls}_{i,t},\, \pi_i,\, \phi_t\big)}^{\text{control function}} \\ + \Gamma \times \text{Fund Controls}_{i,t} + \pi_i + \phi_t + \epsilon_{i,t}. \end{aligned} \tag{10}$$

Table 4 reports the results. Column (1) estimates Eqn. (10) without the control function. The resulting estimate, $\widehat{\beta} = 0.014$, is similar in magnitude to my baseline panel regressions: positive, statistically significant, but still potentially biased by unobserved fund–month shocks.

The specifications reported in columns 2–4 incorporate the control function $\lambda(\cdot)$ constructed according to Caetano, Caetano, and Nielsen's (2024) methodology. This control function exploits the presence of corner bunching in the treatment variable, $\text{Risk Detail}_{i,t}$, to correct for potential endogeneity in β. Specification 2 constructs $\lambda(\cdot)$ under a Tobit shape restriction; specification 3 relaxes this to a semiparametric Tobit; and specification 4 exploits a still weaker, nonparametric restriction that the distribution's tails are symmetric. Each column also reports estimates of δ, the coefficient on the correction term, which provides a direct measure of the

[12] My setting has parallels to a fuzzy regression discontinuity design: in the standard case, treatment propensity jumps at an interior cutoff of a separate running variable. By contrast, the discontinuity here is at the corner of the support, and the treatment itself doubles as the running variable.

bias arising from selection on unobservables.

The estimates $\widehat{\delta}$ are consistently negative (and statistically significant at the 10% level). This pattern indicates that the baseline specification is subject to a downward bias due to selection on unobservables. Once the bias is corrected, the causal treatment effect estimates $\widehat{\beta}$ in columns 2–4 are substantially larger than the baseline association in column 1, ranging from 0.035 to 0.050. The implied causal effect is thus between 2.5–3.5 times the magnitude of the uncorrected estimate, depending on the shape restriction used to implement the control function.

3.3 Trust-Building Transparency, or Learning From Information?

Having shown that transparency about risks drives fund flows, I now explain how this evidence aligns with a trust-building channel.

My focus on voluntary transparency about risks provides a sharp comparative test between a trust-building channel and a learning channel. Since risk is inherently undesirable, investors who perceive or notice a higher level of risk should be *less* willing to bear that risk. Thus, if investors use these letters to learn about risks, one would expect that providing more detail about risks should decrease fund flows. Empirically, however, the effect takes the opposite direction: flows are *increasing* in the letters' risk detail.

While this result may appear puzzling from a learning perspective, it aligns naturally with a trust-building channel. The very undesirability of risk makes voluntary disclosure about this attribute a credible signal that can build investor trust. A higher level of trust then translates into a higher willingness to bear risk, as shown by Guiso, Sapienza, and Zingales (2008), Giannetti and Wang (2016), Gurun, Stoffman, and Yonker (2018), and Germann, Mertes, Weber, and Loos (2025).

Section 4 elaborates this mechanism in greater detail with additional empirical evidence from a controlled, randomized experiment. Section 6.1 systematically rules out various learning-based channels.

3.4 Further Understanding Investor Risk-Taking

Testing for a Flight to Safety. Greater voluntary transparency about risks in fund letters disseminated by S&P 500 index funds causes higher flows into these funds. I now assess whether this fact could (paradoxically) reveal that investors are actually taking *less* risk: this

could occur if investors perceive higher risk levels from the disclosures, or if detailed risk information otherwise reduces their willingness to bear risk. I find this is not the case.

An ideal test would exploit individual investor-level data rather than aggregate fund-level flows, but this limitation is mitigated by the structure of investors' switching costs: mutual fund investors face high switching costs across fund families but lower costs for within-family switches (Massa, 2003). Therefore, testing whether intra-family flows into index funds are rebalanced from riskier funds within the same family captures the most frictionless setting, where such risk-reducing behavior would most likely be apparent if it exists.

[Insert Table 5 here]

My test is to measure the predictive association between the risk detail in S&P 500 index funds' letters disseminated during a month t and the gross outflows from riskier funds within the same family during the subsequent month $t+1$. I thus test whether outflows from riskier funds are occurring simultaneously with flows into the less-risky S&P 500 index funds that comprise my main sample. If communication-driven flows into S&P 500 funds are due to outflows from riskier funds, then a higher amount of risk detail should predict higher outflows from the riskier funds, just as it is known to predict higher flows into the less-risky S&P 500 index funds.

The negative and significant coefficients in columns 1–2 of Table 5 show that this is not the case. In fact, the direction is the opposite to what one might expect under the rebalancing hypothesis: a higher risk detail in S&P 500 fund letters predicts *lower* outflows from riskier sibling funds. A similar result obtains when using the risk detail contained in the sibling funds' letters to predict the sibling funds' outflows, in columns 3–4.

Based on this test, I interpret higher transparency-flows into S&P 500 index funds as evidence of greater-risk taking by their existing investors, to whom fund letters are disseminated.

Investors Benefit By Bearing More Risk. Having established that investor flows are indeed consistent with higher risk-taking, I now quantify the gains that accrue to investors. At first blush, one might think it obvious that it should benefit investors to place their savings in a broadly-diversified market portfolio, particularly since their outside option appears to be holding cash or another less-risky alternative. However, this may not be the case if the timing of fund letters (and variation in how they discuss risk) leads investors to mis-time the stock market cycle. Furthermore, the mutual funds in my sample levy fees on investors' holdings, which must be taken into account.

[Insert Figure 5 here]

I aggregate up all flows in my sample of S&P 500 index funds that are attributable to fund letters' transparency about risk in the prior month, and then quantify the Sharpe ratio of holding these flows in the stock market over a variety of horizons, accounting for fund fees. Figure 5 presents the resulting annualized Sharpe ratios. The Sharpe ratio is always positive and significant except in the case of a short-term holding period of only 1 month, in which case it remains positive but statistically indistinguishable from zero. Given that mutual fund holdings tend to be held over multiple years (Sirri and Tufano, 1998), I conclude that investors do indeed benefit from responding to trust-building transparency in fund letters.

Having established the role of transparency in building trust, I conduct further tests of the economic mechanism in Section 4 and Section 6.

4 Inspecting the Mechanism: A Randomized Experiment

Having identified a positive effect of transparency on risk-taking, I now turn to the mechanism and test whether a trust-building channel can account for it. I design and administer a pre-registered, randomized experiment with investors to causally identify the effect of transparency on trust. Coupled with existing evidence that trust raises investors' willingness to take financial risk (Guiso, Sapienza, and Zingales, 2008; Giannetti and Wang, 2016; Gurun, Stoffman, and Yonker, 2018; Germann, Mertes, Weber, and Loos, 2025), this mechanism can explain my main results.

The experimental results confirm that transparency about risks causally builds trust. Moreover, beliefs move in the wrong direction to provide an alternative explanation: transparency lowers subjects' expected returns and raises the fund's perceived risk, so a beliefs channel would predict *less* risk-taking, not the increase I observe in the field. The belief responses are thus inconsistent with a beliefs channel, and leave trust as the operative channel.

4.1 Experimental Design

My experimental design mirrors the field setting studied in the rest of the paper. Subjects take the role of individual investors in an index fund, and consider periodic letters sent by the fund's management to its investors. More specifically, each participant is placed in the role of an investor in a fictional, low-cost index fund, the "Acme U.S. Stock Index Fund," which tracks the S&P 500. They are told they already hold savings in the fund, are weighing whether to add to those savings (versus a savings account), and are about to read the manager's twice-

yearly letter to investors. The fund and its manager are deliberately generic: no information is provided about the manager's identity so that any difference in investor response is attributable to the effect of communication, rather than any manager-specific characteristics.

The experimental design, exclusion criteria, main analyses and predicted effects were pre-registered before launch.[13] Participants were recruited on Prolific and the study was fielded in June 2026. Subjects received fixed compensation of $4.50 each, which amounted to an average rate of $24.07/hr. To be eligible, subjects had to be US residents who had indicated to Prolific that they had invested in funds prior to the study. I collected 400 complete responses. Following the pre-registered exclusion rule, I drop any participant who failed either of two checks (an instructed-response attention check, or a comprehension check confirming they understood that the fund's value can rise or fall) leaving a final sample of $N = 368$ (comprising 189 in the Transparent condition, 179 in the Baseline condition, to be described shortly). Subjects' main demographic characteristics are displayed in Internet Appendix F, which also confirms subjects are balanced across arms by the randomization.

Blocks, Conditions (Transparent vs. Baseline), and Randomization. The design has three main blocks. The first elicits a set of investor characteristics used to describe the sample, including a range of dispositional and attitudinal traits; basic demographics are also collected at the very end of the experiment. In the second block, each investor is randomly assigned, with balanced allocation across investors, to read a *single* letter from one of two conditions: a Transparent letter that openly discusses the fund's forward-looking risks, or a Baseline letter that does not. Investors then report their reactions: trust in the manager and in the information, perceptions of the letter, and beliefs about the fund's prospects. In the third block, a within-subjects *joint evaluation*, the investor sees a pair of letters side-by-side: the one they just read, together with a randomly-chosen letter from the opposite condition. The subject then makes a series of relative comparisons between each of them, choosing one of { Transparent, Baseline, Same } for each question; the joint-evaluation questions ask the subject to compare the pair of letters on a range of criteria.

The two evaluation blocks are designed to measure different aspects of investors' response to transparency. The between-subjects block mirrors the field: an investor reads a single letter in isolation, with no counterfactual letter to difference against, so it identifies the effect of transparent communication on trust as it would operate in practice. The joint-evaluation block then asks whether investors can perceive and articulate the difference once the comparison is placed in front of them, thus revealing what investors understand the two communication

[13] Link to pre-registration: `https://aspredicted.org/2kp3jk.pdf`

styles to mean. The two blocks are therefore complementary: one measures the magnitude of the effect under field-like conditions, the other its perceptibility under direct comparison. Results are consistent across both modes; I focus my reporting on the single-letter evaluation block, which comprises the majority of my pre-registered tests.

Pre-Registered Tests. In the single-letter evaluation, the primary outcome is trust in the fund's manager, with trust in the information contained in the letter as the hypothesized proximate channel; both are measured with multi-item seven-point scales. Secondary outcomes cover perceptions of the letter (how much it discusses risks, how exclusively it focuses on positives) and beliefs about the fund's return. These five directional predictions for the single-letter block were pre-registered: transparency raises trust in the manager and in the information, raises the perception that the letter discusses risks, lowers the perception that it focuses only on positives, and does not raise expected returns. In addition, one prediction from the joint-evaluation block was pre-registered: that fewer than one-third of investors read the transparent letter as the one promising the higher return. The last two predictions address the alternative explanation that more detailed discussion about risks might instead be read as a positive signal about returns. All other analyses are exploratory.

Constructed Letters. The letters themselves are constructed to isolate transparency about risk. Both conditions are built from real forward-looking sentences drawn from S&P 500 fund shareholder communications: the Transparent letters from sentences identified by this paper's screening methodology as forward-looking and risk-related, and the Baseline letters from non-risk outlook sentences of the same kind. The sentences were lightly edited for flow and assembled into short letters of similar length that share a common opening. Each condition comprises 3 variants, for a total of 6 letters, so that results are not driven by idiosyncratic content from any one letter. The two conditions thus differ in whether the letter openly names the fund's forward-looking risks. How participants perceived the letters' risk content and tone is measured within the experiment itself and reported below as the manipulation checks. The full texts of the constructed letters are shown in Internet Appendix F.

Measuring Trust in the Manager and Trust in the Letter. After subjects read a single letter, their trust in the fund's management and their trust in the letter they have just read are measured separately. To reduce noise and sharpen measurement, both of these two key trust outcomes are measured as four-item scales, each item a seven-point agreement rating, scored as the unweighted mean of its items so that item-specific measurement error averages out. The items are chosen to span the facets of trust relevant to an investor entrusting money to a manager. For trust in the manager, the primary outcome, participants rate their agreement

that the fund's management "was honest and straightforward with me," "is acting in my best interest," "can be counted on to act fairly toward investors," and, most directly, "I trust the [fund]'s management with my money." For trust in the information, participants rate the letter they just read: it "was open and transparent about the fund's risks," "gave me the full picture, without leaving out important things," "seemed credible," and "I could rely on the information in this letter." Item order within each scale is randomized per participant. The items cohere strongly: Cronbach's α is 0.91 for the manager-trust scale and 0.86 for the information-trust scale, so each scale behaves as a single reliable construct rather than a bundle of unrelated judgments.

4.2 Evaluating a Single Letter: Pre-Registered Tests

Table 6 reports the pre-registered regressions of the five primary outcomes on an indicator for whether each subject was presented with a Transparent letter in the single-letter evaluation block (vs. a Baseline letter). As well as showing the coefficient estimates of the pre-registered regression tests, the table also shows predicted signs for each coefficient (which were also recorded in the pre-registration document). All five coefficient estimates are statistically significant and match the predicted signs.

[Insert Table 6 here]

Table 6 column (1) shows the primary result: transparency about risk raises trust in the fund's manager, by 0.30 points on the 1–7 scale. Because participants are randomly assigned and the fund and its manager are identical across conditions, the two arms share the same expected pre-letter trust, so this coefficient is the average treatment effect of the communication itself: trust created by displaying a single letter, rather than by manager characteristics (which are deliberately omitted in this generic setting). This positive treatment effect confirms that transparency about risk causally builds trust in the manager.

Column (2) shows a related, secondary result: transparency about risk raises trust in the letter itself, by 0.49 points on the 1–7 scale. This larger effect is consistent with information trust acting as the proximate channel: transparency first makes the communication itself appear credible and complete, and this credibility extends to the manager behind it.

Column (3) shows that transparency about risk lowers the return expected by the letter reader. This rules out an alternative story in which a higher perceived risk (or greater risk salience) is associated with a higher expected return in the minds of the subjects. Rather, the

opposite direction holds.[14]

Table 6 columns 4–5 confirm that the constructed letters are read as intended: the experimental subjects perceive that Transparent letters discuss risk more and have a less positive focus than Baseline letters do. Therefore, the effects in the first three columns of the table cannot be explained by a lack of understanding of the message about risk conveyed by the Transparent letters, or by a perception that these read as more upbeat. For the same reason, the response pattern is inconsistent with an undifferentiated halo: participants do not simply rate the Transparent letter more favorably on every dimension, but grow more pessimistic about risk and returns even as their trust in the manager rises.

A trust-building mechanism predicts that trust rises despite the unfavorability of the news conveyed, precisely what the causal effects in Table 6 show. The positive effect of transparency on trust is the counterpart of the earlier field-based result that flows rise despite letters conveying risk.

4.3 Joint Evaluation of a Pair of Letters

The closing block places the two letter types side by side and elicits relative comparisons, in which subjects pick Transparent, Baseline, or "about the same" for each criterion. Table 7 reports the choice shares.

[Insert Table 7 here]

One comparison in the joint evaluation task was pre-registered: whether participants read the Transparent letter as the one promising the higher return. The prediction was that fewer than one-third of all participants would do so, against the benchmark of three equally likely options. In fact only 11.4% did (42 of 368; one-sided exact binomial, $p < .001$). Even under direct comparison, where the difference between the letters is maximally evaluable, transparency about risk is not read as a signal of higher returns; rather, the Transparent letter is overwhelmingly read as implying the lower return.

The remaining (non-preregistered) comparisons complete the picture coherently. Participants recognize what the Transparent letter is: among those expressing an opinion, 84.8% judge it the riskier letter and 88.6% the one that discusses downsides more. Yet on every trust-relevant dimension it is rated higher: 77.2% judge it more credible and transparent, 62.6%

[14] One possible driver of this association, as in Giglio, Maggiori, Stroebel, and Utkus (2021, Table 10), is that investors consider disaster risk, or the probability of a loss (Holzmeister et al., 2020). Another possibility is systematic misperception of the risk–return relationship, as in Finucane, Alhakami, Slovic, and Johnson (2000), Shefrin (2001), and Jo, Lin, and You (2022).

rate its manager more trustworthy, and when asked directly which letter they prefer 64.1% choose the Transparent one. A majority of investors thus prefer the very letter they themselves read as riskier and as promising worse returns. Acknowledging risk does not cost the manager trust under direct comparison, and instead earns it.

Side-by-side presentation makes differences between constructed letters highly evaluable, whereas the single-letter estimates (in which one letter is judged in isolation, as in the field) provide the more conservative tests, and are thus reported as my main results. The two evaluation modes are complementary measures of the same underlying effect and provide a consistent account of subjects' evaluations of the randomly-presented letter stimuli.

Based on the results of my randomized, pre-registered experiment, I conclude that transparency about risks causally increases trust in a fund's management, despite the letter conveying unwelcome information about the fund's risk and return.

5 When Does Trust-Building Have the Strongest Effect?

This section investigates cross-sectional and timeseries heterogeneity in the trust-building effect of transparency.

5.1 Among Inexperienced and Pessimistic Investors

My experimental setting offers an individual-level look at where the trust-building effect is strongest. Table 8 presents the main transparency–trust effect in column (1), and the remaining three columns add interactions with certain key participant attributes.

[Insert Table 8 here]

The effect of transparency is attenuated for more experienced investors (column 2), those with a more generally optimistic outlook (column 3), and those who typically hold a greater fraction of their financial assets in stocks or stock funds (column 4).

Reversing the interpretation, the effect of transparency on trust is strongest precisely among those investors most in need of reassurance: those who are inexperienced (column 2), more generally pessimistic (column 3) and with a lower baseline intensive margin of equity risk-taking (column 4).

These findings are consistent with the argument that asset managers have scope to encourage risk-bearing among reluctant investors by fostering trust, and that transparency about risks

can serve this purpose.

5.2 When Risk Appetite Is Low

I next return to the field setting and examine heterogeneity in market states. Classic asset-pricing models (e.g., Campbell and Cochrane, 1999) link cyclicality in risk premia (and thus market states) to time-varying risk aversion γ_t. I test whether the trust-building effect varies with the timeseries of aggregate risk appetite. If trust-building communication acts through a risk aversion-based mechanism, then basic portfolio choice intuition would predict a stronger (more positive) effect on flows when γ_t is higher, holding beliefs fixed.[15] Thus, testing the sign of the interaction also tests whether trust operates by reducing effective risk aversion.

Empirically, I capture the aggregate risk aversion γ_t with a monthly timeseries of the relative risk aversion of a representative investor constructed by Bekaert, Engstrom, and Xu (2022). I then augment the baseline panel regression with an interaction with $\mathbb{1}\{\text{High Risk Aversion}\}_t$, an indicator that takes the value 1 when the Bekaert, Engstrom, and Xu (2022) measure of relative risk aversion is above its long-run median:

$$\begin{aligned}\text{Net Flow}_{i,t\to t+1}(\%) = {} & \beta_1 \times \text{Risk Detail}_{i,t} + \beta_2 \times \mathbb{1}\{\text{High Risk Aversion}\}_t \\ & + \beta_3 \times \mathbb{1}\{\text{High Risk Aversion}\}_t \times \text{Risk Detail}_{i,t} \\ & + \Gamma \times \text{Controls}_{i,t} + \pi_i + \epsilon_{i,t}. \end{aligned} \tag{11}$$

If trust-building communication reduces investors' effective risk aversion, portfolio choice intuition predicts a positive coefficient β_3 on the interaction term.

[Insert Table 9 here]

Table 9 reports estimates of Eqn. (11) in columns 2–3, and the baseline non-augmented panel regression in column 1 for comparison. The estimate $\widehat{\beta}_2 < 0$ reveals that a high level of risk aversion coincides with lower fund flows: investors are less willing to take risk when they are more risk averse, in accordance with basic economic intuition.

Columns 2–3 of Table 9 show that $\widehat{\beta}_3 > 0$, which is precisely the sign predicted by a risk

[15] To see this, consider an investor who accesses a riskless asset that returns R^f_{t+1} and a risky asset with excess return R^e_{t+1} above the riskless rate (e.g., an S&P 500 index fund), to which she allocates fraction x_t of her portfolio. Standard portfolio choice setups (e.g., mean variance) predict $x_t = \frac{\mathbb{E}_t[R^e_{t+1}]}{\gamma_t \mathbb{V}\text{ar}_t(R^e_{t+1})}$. Holding beliefs fixed, and allowing risk aversion γ_{t+1} to be a function of prior risk aversion γ_t and the amount of transparency τ provided about risk, we have: $\text{Flow}_{t\to t+1} \triangleq \frac{x_{t+1}-x_t}{x_t} = \frac{\gamma_t}{\gamma_{t+1}(\tau,\gamma_t)} - 1$. Taking the partial derivative, $\frac{\partial \text{Flow}_{t\to t+1}}{\partial \tau} = \frac{-1}{\gamma_{t+1}(\tau,\gamma_t)^2} \frac{\partial \gamma_{t+1}(\tau,\gamma_t)}{\partial \tau} \gamma_t$. The first term is negative. If risk aversion is decreasing in transparency, then the second term should also be negative, and thus the interaction should be positive.

aversion channel. While investors are initially less willing to take risk during periods of high risk aversion, trust-building communication has a stronger effect at precisely these moments.

The loss of significance on $\widehat{\beta}_1$ (which nevertheless remains positive in sign) suggests that the soothing effect of communication is concentrated during these times when investors are more risk averse. Trust-building communication therefore acts as a stabilizing force that counteracts the effects of time-varying risk aversion. The results of this mechanism test are robust to the inclusion of additional controls (in column 3) for month-to-month changes in expected returns and the VIX.

5.3 Among Anxious Investors

I present complementary, cross-sectional evidence that suggests a role for the anxiety component of investors' risk aversion. An anxiety-based mechanism would align with both Gennaioli, Shleifer, and Vishny (2015)'s money doctors theory, which explicitly models investor anxiety in the context of trusted money managers, and Guiso, Sapienza, and Zingales (2008)'s laboratory evidence showing that anxiety constitutes an important component of risk aversion in financial decision-making more generally. I provide evidence that the effect of risk transparency on risk-taking is concentrated among funds whose investors have a high baseline level of anxiety.

This analysis relies on a fund-level measure of investors' baseline anxiety attitudes. I begin by constructing a measure based on local search activity on Google for anxiety-related terms, and combine this geographic index with the geolocations of fund letter readers in order to arrive at a fund letter readership measure of anxiety attitudes. My main assumption is that overall anxiety attitudes spill over into investors' anxiety about bearing risk; this is supported both by experimental evidence (e.g., Kuhnen and Knutson, 2011; Giorgetta et al., 2012; Guiso, Sapienza, and Zingales, 2018) and by empirical analysis of mutual fund flows (Wang and Young, 2020).

[Insert Table 10 here]

SEC EDGAR Data on Letter Readership Locations. The SEC makes mutual funds' filings available for download from its EDGAR website, which is the only comprehensive and free source of such documents. These filings include the N-CSR and N-CSRS reports containing the fund letters that this paper focuses on. The SEC makes usage logs for EDGAR filing downloads available to researchers, and I use this dataset to geolocate where the readers of fund letters contained in this filings were located at the time of each download.

Merging with the SEC EDGAR usage logs dataset shortens my sample – which now ends in June 2017 – but the sample still includes the global financial crisis. I follow Lee, Ma, and Wang (2015) in identifying and removing robots from the usage logs, and de-anonymize IP addresses using the lookup table provided by Chen, Cohen, Gurun, Lou, and Malloy (2020). Similarly to Grice and Gueciouer (2023), I then geolocate IP addresses using historical mapping tables provided by the MaxMind geolocation service. I recalculate the geographic distribution of a fund's investor base (as measured through their readership of fund letters) at an annual frequency.

In using EDGAR data, I assume that the geographic distributions of filing downloads from EDGAR are a reasonable proxy for the geographic distributions of the readers of fund letters. EDGAR links to filings often appear in search engine results, and may be linked to directly from funds' websites, making it a natural source of filing downloads to utilize for this purpose. Importantly, I do *not* assume that all fund letter readers must be using EDGAR. One might be concerned that readership locations inferred from this dataset are somehow unrepresentative of investors who might read fund letters through other means, so I describe my dataset of readership geolocations in Internet Appendix I. Reassuringly, the fund letter reader locations inferred from EDGAR downloads are geographically distributed very similarly to the overall population of the United States, and are not concentrated in regions where we would expect financial professionals to cluster (i.e., New York and Massachusetts).

Google Trends Data on Anxiety Attitudes. I measure geographic variation in anxiety attitudes using revealed search activity on Google. Google's Trends engine compiles Search Volume Indexes (SVIs) for umbrella "topics," which group together related search terms, and defines the following two anxiety-related topics:

1. "Psychological Stress" (labelled by Google), which includes search terms such as "stressed", "what is stress", "anxiety" & "relieve stress."

2. "Worry" (labelled by Google), which includes search terms such as "worry about", "anxiety", "stop worrying" & "bible worry."

The example search terms above reveal that the indices capture broad anxiety attitudes and a demand for reassurance. I employ panels of these SVI measures (varying at a geographic and monthly level) as measures of the aggregate anxiety levels of the population in each US state. Specifically, I take the sum of both anxiety indices.[16] Then, for this geographic state s-month t anxiety measure, I aggregate across fund letter readers j to construct a panel of the prior

[16]Internet Appendix J charts geographic variation in the SVIs of the above anxiety topics, which highlights broad similarity in the patterns revealed by each topic separately.

anxiety attitudes of the readers of the letter issued by fund i at month t:

$$\text{Readership Anxiety}_{i,t} = \frac{\sum_j \text{Investor Assets}_{j,t} \times \text{Geographic Anxiety}_{j,t}}{\sum_j \text{Investor Assets}_{j,t}}. \tag{12}$$

In constructing the weighted average (12), I proxy for the aggregate financial assets held by investors in a geographic region by the mean dollar investment in a mutual fund, according to the Census Bureau's latest Surveys of Income and Program Participation (SIPP); these vary at an annual frequency. Figure 6 illustrates my aggregation procedure.

[Insert Figure 6 here]

Split-Sample Analysis. My cross-sectional analysis continues its focus on the sample of S&P 500 index mutual funds i that disseminate a letter during year-month t. Each cross-section t is split at the cross-sectional median: fund letters whose readership has an above-median level of anxiety, and fund letters whose readership has a below-median level of anxiety, according to Eqn. (12). I report regression results separately for each sub-sample. Specifically, I estimate the baseline panel regression (7) with an augmented set of controls for each fund letter readership's (mean asset-weighted) sociodemographic attributes – based upon Census Bureau geographic surveys – as well as each readership's exposure to local economic growth and to inflation, as measured by the state-level Philadelphia Fed Coincident Index and by Hazell, Herreno, Nakamura, and Steinsson's (2022) state-level inflation rates, respectively. This rich set of controls limits the statistical power of my analysis, but the direction of any heterogeneity can be informative.

[Insert Table 10 here]

Table 10 shows the results of my cross-sectional test. Fund letters that are read by low-anxiety investors have only a weak impact on flows (columns 1–2). Instead, the risk transparency–fund flow relationship is concentrated among high-anxiety investors, in columns 3–4. These directional results point to the anxiety component of investors' risk aversion being soothed by trust-building communication.

6 Evaluating Potential Alternative Mechanisms in the Field

This section further reinforces a trust-building interpretation for my empirical evidence by laying out a range of alternative potential explanations, and describing empirical strategies to test whether each alternative explanation holds up. The tests evaluate fund flows in my primary, field-based setting, and comparise a dozen panel regressions that are presented sep-

arately in Internet Appendix H. I conclude that the evidence is not consistent with any of the alternative explanations considered, which include multiple learning-based explanations.

6.1 Learning

Learning about the fund's portfolio or its manager's skill is perhaps the most obvious explanation for how information could affect investor decisions. I begin by systematically testing a variety of learning-related mechanisms.

6.1.1 Bayesian Updating About Risk: Receiving a Directional Signal

To fix ideas, consider a Bayesian investor who learns about the variance parameter σ^2 of the return distribution, or indeed some other distributional parameter that captures the notion of risk. The Bayesian investor starts with a Gaussian prior on this parameter, $\sigma_p^2 \sim \mathcal{N}(m_p, {}^1/_{\rho_p})$, in which ρ_p denotes the prior precision.[17]

The investor receives a signal $s = m_s + \varepsilon$ about the variance, with $\varepsilon \sim \mathcal{N}(0, {}^1/_{\rho_s})$. Upon receipt of the signal, the investor updates her beliefs and so now perceives the posterior distribution of the variance to be the following:

$$\sigma^2 | s \sim \mathcal{N}\left(\alpha s + (1-\alpha) m_p \ , \ \frac{1}{\rho_s + \rho_p}\right), \tag{13}$$

where $\alpha = \frac{\rho_s}{\rho_s + \rho_p}$. Upon receipt of the signal, therefore, the shift in the investor's expected variance from her prior mean m_p to the posterior is:

$$\Delta(\sigma^2) \ = \ [\alpha s + (1-\alpha) m_p] - m_p \ = \ (s - m_p) \frac{\rho_s}{\rho_s + \rho_p}. \tag{14}$$

As Equation (14) makes clear, the difference between the signal value and the investor's prior, $(s - m_p)$ is a first-order determinant of the change in her perceived risk. If the investor chooses her portfolio as in Section 4, the difference $(s - m_p)$ should be proportional to her *reduction* of her allocation to the risky asset. Changes in risk perceptions can thus drive fund flows.

Given the above, perhaps greater transparency about risk attracts inflows because it conveys a lower level of risk σ^2 going forward? In fact, the evidence runs counter to this possibility. Table 1 indicates that risk detail is positively related to the VIX, which is an objective measure of the S&P 500's implied volatility. It is therefore possible to draw inferences about the level of risk – a greater degree of risk transparency correlates with higher implied volatility – but

[17] The conclusions from this example apply more generally. In fact, the current argument using Normal-Normal updating carries through exactly if the *log* of the variance is assumed to be Normally distributed, which is a standard assumption for guaranteeing a positive variance. I present the Normal-Normal case for ease of exposition.

this effect would reverse the flow-risk detail relationship described in Table 2. Because a high risk detail indicates objective risk is higher, it should predict a *decrease* in fund flows, yet the effect is precisely the opposite. It is therefore implausible that investors' flows are due to them learning about risk from the degree of transparency about risk in fund letters.

Another feature of how fund letters discuss risk is their sentiment or tone, or explicit descriptors of whether risk is high or low. Once again, these features of the text convey information about the objective level of risk (see Table 1). In this case, however, investors appear to ignore this signal, as the coefficients on risk level in Table 2 are all insignificant.

In sum, investors are provided with the opportunity to learn about risks from the information conveyed in fund letters, and yet they either act counter to this information (in the case of risk detail conveyed) or ignore it (in the case of risk level conveyed). Investors do not act upon this information in a manner consistent with learning about risk from fund letters.

In the above discussion, I assumed that fund investors' priors (m_p) are adequately controlled for by an additive combination of fund fixed effects and time effects. This allows priors to vary across funds and time heterogeneously. To allay any concerns that even this flexible specification is too restrictive, I introduce a measure of prior risk perceptions that can vary within funds over time as well as across funds. My conclusions are robust to this richer specification. The details of this analysis are in Internet Appendix H.1.

6.1.2 Bayesian-Like Updating About Risk: Gaining Precision

I next devise an additional, complementary test for whether investors might be learning about the risk of the fund. The intuition behind this new test (which I derive below) is that if investors are updating their beliefs upon receipt of a signal, then investors should update more strongly whenever their prior precision is weaker. A key advantage of this test is that it also applies to belief-based models in which agents deviate from rational Bayesian updating, as long as their behavior varies less as they are *ex ante* more certain about the state of the world before receiving the communication.

Consider once more the Bayesian investor who learns about the variance parameter σ^2 of the return distribution, as described in Section 6.1.1. Define the strength of her update from the prior mean m_p to the posterior as the magnitude of the signed update (Eqn. 14):

$$\left|\Delta(\sigma^2)\right| \;=\; \left|s - m_p\right| \frac{\rho_s}{\rho_s + \rho_p}. \tag{15}$$

It follows immediately that the strength of the update is decreasing in the strength of the prior:

$$\frac{\partial}{\partial \rho_p}\left|\Delta(\sigma^2)\right| \;=\; -\left|s-m_p\right|\frac{\rho_s}{(\rho_s+\rho_p)^2} \;<\; 0. \tag{16}$$

I introduce a measure of investors' prior precision ρ_p, and test for a negative interaction between the strength of the update $|\Delta(\sigma^2)|$, captured by the magnitude of the inflow, and the prior precision of investors' risk perception ρ_p. I find this interaction is not significantly different from zero, and therefore it is unlikely investors are updating their beliefs about perceived risk. Details of this test are presented in Internet Appendix H.2.

DellaVigna and Gentzkow (2010, pp. 654) argue this test applies to the entire class of belief-based persuasion models: "persuasion will tend to be more effective when receivers are less certain about the truth. In Bayesian models, the weaker receivers' priors are, the more their beliefs are affected by a given piece of new information (holding everything else constant)." Based on their argument, it is unlikely that any form of belief-based persuasion is taking place as regards fund letters' transparency about risk.

6.1.3 Learning About the Return: Gaining Precision as a Bayesian

Instead of updating their beliefs about risk directly, could the results be explained by investors learning about general properties of the return distribution? After all, discussing risk also provides a more precise signal about the overall return.

Specifically, consider an investor who learns about the return r (or payoff, or fundamental value) of an asset in general – instead of learning solely about the variance or some risk-related parameter. The investor starts with a Gaussian prior on the return, $r_p \sim \mathcal{N}(m_p, {}^1\!/_{\rho_p})$, in which ρ_p denotes the prior precision. The investor receives a signal $s = m_s + \varepsilon$ about the overall return, with $\varepsilon \sim \mathcal{N}(0, {}^1\!/_{\rho_s})$. Upon receipt of the signal, the investor updates her beliefs and so now perceives the posterior distribution of the return to be the following:

$$r|s \;\sim\; \mathcal{N}\left(\alpha s + (1-\alpha)m_p \;,\; \frac{1}{\rho_s+\rho_p}\right), \tag{17}$$

where $\alpha = \frac{\rho_s}{\rho_s+\rho_p}$. Importantly, the precision has increased from ρ_p to $(\rho_s+\rho_p)$; equivalently the posterior variance $\mathbb{V}\mathrm{ar}[r|s] = {}^1\!/_{(\rho_s+\rho_p)}$ has decreased in comparison to the prior variance ${}^1\!/_{\rho_p}$. Uncertainty is thus always reduced, irrespective of the actual value (realization) of the signal s that the investor receives. As usual, we assume the investor chooses between the riskless asset and this risky asset with subjectively perceived moments $\mathbb{E}[r|s]$ and $\mathbb{V}\mathrm{ar}[r|s]$.

In this scenario, the receipt of *any* signal about the return will mechanically reduce the investor's perceived uncertainty $\mathbb{V}\text{ar}[r|s]$ and hence potentially lead her to increase her allocation to the risky asset. Could this mechanism explain my results?

I test for this possibility by repeating my entire text extraction procedure to measure the amount of forward-looking detail that fund letters provide about returns and performance (rather than risk), and then assessing whether a higher amount of detail about returns predicts higher inflows. The logic behind this test is simple: if investors are learning about returns from *risk* discussions, then they should be learning about returns from *return* discussions also. One might even expect the effect to be more pronounced in this scenario. However, I do not find any evidence that flows respond to the amount of detail provided about returns and performance. This placebo test therefore conflicts with the possibility that investors are learning about returns through more detailed discussion of the risk feature of the return distribution. Details of this test are presented in Internet Appendix H.3.

6.1.4 Learning About the Return: Predicting the Return

One might argue that investors may be using the amount of risk detail in fund letters to infer whether expected returns are high (or low). Furthermore, such a learning channel might not necessarily involve Bayesian-like updating. To test for this possibility, I first aggregate letters' risk detail similarly to the indexes constructed for Table 1. I then assess whether this index of communicated risk detail predicts future realized returns of the underlying S&P 500 index over 1-month, 3-month and 5-month horizons (i.e., until the arrival of the next fund letter). I do not detect any significance. Furthermore, an index of the level of risk conveyed by the text (another feature that investors might use as a predictor) is also insignificant, with an opposing sign to risk detail. These results suggest there is nothing to learn about returns from the risk-related information conveyed by fund letters. The test results are presented in Internet Appendix H.4.

6.1.5 Other Forms of Learning

Learning About Manager Skill. An important advantage of focusing on S&P 500 index funds is the absence of active management: since funds passively track a common index, there is no role for stock-picking skill or for managers to hold private information, and thus a limited role for communication to act as a signal of skill or ability. One might argue that minimizing a passive fund's tracking error is a form of manager skill, however, and thus letters might be signalling this ability. I therefore check whether transparency about risk might attract flows because it signals a low tracking error in the future. I test for this by using my measure of risk detail as a predictor for the fund's tracking error over a variety of horizons, and find it to be

a poor predictor: the direction of the relationship is inconsistent, typically in contradiction to what we might expect under this hypothesis, and never significant at the 5% level. The test results are presented in Internet Appendix H.5.

Being Educated By Information Provision. Information provision might educate investors to make better financial decisions. For instance, low-financial literacy investors could be educated on the desirability of bearing diversified market risk. Could transparency about risks be educational? Risk discussions in fund letters typically have a negative tone, and this is hard to square with the possibility that the text is extolling the benefits of risk-taking. In addition, I develop an explicit empirical test for an educational effect: under this mechanism, the effect should be stronger among investors with a lower baseline level of financial literacy. However, I do not find any significant heterogeneity on inflows. Details of this test are presented in Internet Appendix H.6.

Learning About Opportunities. Might fund letters contain more information about risk because they are describing buying opportunities to investors? This alternative explanation would rationalize the arrival of fund flows following risk discussions, if those risk discussions talk about risk as an opportunity. To assess this possibility, I re-estimate the baseline flow-risk detail relationship on a sample of fund letters that completely omit any discussion of opportunities (to be conservative). I implement this test by discarding every fund letter that contains the characters "opportun" (as in the words opportune and opportunity) or the phrase "chance to" from the sample, and re-estimating variants of Eqn. (8). The results remain qualitatively and quantitatively similar, indicating this channel is not responsible for the main effect. The test results are presented in Internet Appendix H.7.

Ambiguity Alleviation. Perhaps communication acts to decrease investors' perceived ambiguity about the distribution of future returns? Receiving a signal about risk might increase the perceived level of risk, which is one form of uncertainty, but it could also decrease the amount of Knightian uncertainty perceived by investors.[18] If investors are averse to such ambiguity, a decrease in perceived ambiguity could plausibly make investors more willing to hold the asset, driving inflows. Testing this alternative explanation requires a measure of perceived ambiguity of the S&P 500 index return, which Brenner and Izhakian (2018) compute. Using their measure, I find the effect of providing more information about risk does not significantly interact with the prior level of perceived ambiguity, as one would expect for an ambiguity-alleviating channel. Details of this test are presented in Internet Appendix H.8.

[18]This channel is related to the gain in precision a Bayesian experiences upon receipt of a signal (see Section 6.1.3) but is potentially more general.

6.2 Shrouding

Risk is typically considered an undesirable attribute from investors' perspective. For instance, portfolio choice decisions typically model risk-averse investors, leading to a negative relationship between perceived risk and the optimal level of risk-taking. It is for this reason that transparency about risk can usefully distinguish between a trust-building channel and learning channels, since a higher level of perceived risk produces opposite predictions to a higher level of trust.

The salience, or visibility, of a fund's risk exposure may also be an important channel, and in this paper's setting it acts in a similar direction to a learning channel: since risk is a negative attribute, more detailed risk discussions that make this attribute more salient or noticeable should reduce investors' willingness to invest in the fund that makes risk a more visible attribute to the consumer. One might therefore argue a salience-based mechanism could explain my results through the shrouding or obfuscation of this undesirable attribute (Gabaix and Laibson, 2006; Bordalo, Gennaioli, and Shleifer, 2013). The argument is that talking more about risk could make it harder for the investor to discern the level of risk, and thereby increases her willingess to bear this risk.

However, there are two reasons shrouding cannot explain my results. *First*, the interaction between risk detail and the level of risk conveyed in the text is insignificant in Table 2 columns 3 and 6. Talking more about risk neither eases nor impedes investors' ability to extract the signal about risk (conveyed by the sentiment of the discussion or by explicit descriptors). Moreover, the coefficient on the risk level variable remains consistently insignificant, and has the wrong sign for an investor who dislikes risk.

Second, I follow the literature on shrouding (e.g., Célérier and Vallée, 2017; deHaan, Song, Xie, and Zhu, 2021) and explicitly measure the complexity of the text discussing risk in fund letters. This allows for the possibility that letters obfuscate risk by employing complex language that obscures the information content of their risk discussions. Controlling for complexity in the flow-risk detail predictive regression thus allows me to disentangle the role of transparency from that of obfuscation. I find that my baseline results survive when I control for four standard measures of textual complexity employed in the accounting literature. The very feature of the text that should shroud risks (its complexity) is therefore not responsible for my main effect. The test results are presented in Internet Appendix H.9.

6.3 Marketing

This paper shows that more transparent voluntary discussions about risk (targeted at existing investors) encourage greater risk-taking, which manifests as inflows immediately following the dissemination of these fund letters. One might think that attracting flows from investors using communication is a form of marketing to new investors, akin to advertising; however, I now show that the evidence does not line up with such an explanation.

Attracting New Investors with Transparency. The marketing-based alternative hypothesis is that transparency about risks attracts new investors, rather than encouraging existing investors to bear more risk. This could be the case if potential new investors read the fund letters targeted at existing investors. While this result would not necessarily conflict with a trust-based interpretation, it could throw doubt on the interpretation of greater risk-taking by *existing* investors. I therefore test explicitly for the presence of this effect by measuring the rate of arrival of new investors into funds via prospectus readership. I find no significant relationship between this measure and the detail funds provide about risk in their letters addressed to their existing investors. Details of this test are presented in Internet Appendix H.10.

Correlation with Overall Marketing Intensity. Another potential objection is that transparency about risks in fund letters might merely covary with marketing intensity, and so the inflows that I document are due to the fund's general marketing activities, which may be unobserved. However, there are four reasons that this possibility is unlikely. *First*, if marketing activities are time-invariant or slow-moving, the fund fixed effects I use in my baseline panel regressions should absorb this effect. *Second*, if unobserved marketing activities vary at the fund-month-level, then the corner bunching-based identification strategy I presented in Section 3.2 likewise corrects for potential endogeneity that is due to this omitted variable. *Third*, my baseline results are robust to controlling for funds' 12b-1 fees as proxies for marketing intensity (see Roussanov, Ruan, and Wei (2021)). *Fourth*, I conduct an additional robustness test using another, independent measure of time-varying marketing intensity: the share of labor employed in marketing functions (see Chen, Jiang, and Xiaolan (2022)). Including this as an explicit control does not affect my main results, suggesting once again that marketing activities are a separate channel. Both robustness tests are presented in Internet Appendix H.11.

6.4 Pandering

A self-interested sender seeking to persuade a receiver may do so by tailoring their message to fit the receiver's prior beliefs (Mullainathan and Shleifer, 2005). Under such a pandering mechanism, funds might persuade investors to take more risk by framing risk communications

to align with investors' pre-existing risk perceptions. To concretely test whether communication about risk panders to investors' priors, I introduce a measure of the distance of the message from the receiver's priors. Under a pandering-based explanation, one would expect messages that align most closely with investors' priors to generate the strongest responses. However, I do not find any significant heterogeneity; moreover, the interaction takes the opposite sign. Details of this test are presented in Internet Appendix H.12.

7 Conclusion and Discussion

In this paper, I show that asset managers who provide more transparency about risk encourage inflows from investors, as this voluntary transparency fosters trust. This effect supports the view that asset managers act as "money doctors" (Gennaioli, Shleifer, and Vishny, 2015) to investors by actively taking steps to reduce their effective risk aversion (in this case, through trust-building communication). Investors benefit from exposure to the broadly-diversified S&P 500-indexed equity portfolio managed by the funds in my sample.

More broadly, my findings shed new light on the role of transparency in information provision. Beyond transmitting information and mitigating information asymmetries, communication can foster trust – and in doing so, alter economically consequential behavior.

Recent evidence by Merkoulova and Veld (2022) indicates that many investors do not form return expectations at all. The channel identified in my paper shows how information can still matter for such investors: through trust rather than through beliefs about an asset's return.

I examine a straightforward aspect of communication: its transparency about a negative attribute that the recipients dislike (i.e., risk exposure). In other settings such as interactive communications, building trust might be also be achievable through nonverbal cues (e.g., Gorodnichenko, Pham, and Talavera, 2023). Likewise, investigating whether non-human communication can build trust remains an open question (see Laudenbach and Siegel, 2025).

Beyond the asset management setting, policymakers have recently moved to scale back disclosure by public companies and communication by central banks (Securities and Exchange Commission, 2026; Warsh, 2026). The trust-building role of transparency identified in this paper is one consideration that should inform such policy debates.

Finally, my findings suggest that the asset managers who provide information and the investors who consume it are engaged in a mutually beneficial ongoing interaction, beyond the initial investment delegation decision. Understanding how economic relationships are actively

sustained over an extended period is an interesting and wide-ranging question.

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Appendix

Tables

Table 1: Timeseries Variation in Fund Letters' Risk Details and Risk Levels

This table reports timeseries regressions relating cross-fund indices of fund letters' risk descriptions to market-wide conditions. The dependent variables are equally-weighted indices of the amount of detail in fund letters devoted to risk using the number of words (column 1) or fraction of the total number of words (column 2), and of the level of the risk conveyed using the negative of the Loughran and McDonald (2011) net sentiment of the risk discussion (column 3) or the net score of contextual risk words defined by Equation (4) (column 4). Each dependent variable y_t is calculated as the cross-sectional mean over individual fund i variables, $y_t = \frac{1}{N_t}\sum_i z_{i,t}$. These individual fund variables $z_{i,t}$ are pre-standardized to focus purely on within-fund variation, $z_{i,t} = (x_{i,t} - \overline{x_i})/\sigma(x_i)$. As well as the (log) VIX and prior month's return of the S&P 500 portfolio, the independent variables measure aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)), and the perceived ambiguity of the S&P 500 portfolio (measured by Brenner and Izhakian (2018)). The sample of letters used to construct the dependent variables are letters written by S&P 500 index funds only.

Dependent Variables:	Risk Detail Index$_t$		Risk Level Index$_t$	
Measure:	Number of Words	Fraction of Letter	Using Sentiment	Using Context
	(1)	(2)	(3)	(4)
Log VIX$_t$	0.2719**	0.2332**	0.3205***	0.2459**
	(0.1191)	(0.1151)	(0.1205)	(0.1174)
AAII Expected Return$_t$ (%)	-0.0002	0.0003	0.0060	-0.0072**
	(0.0022)	(0.0024)	(0.0040)	(0.0033)
Log Ambiguity$_t$	0.0387	0.0115	-0.1327**	0.1500**
	(0.0556)	(0.0596)	(0.0603)	(0.0626)
S&P 500 Return$_{t-1}$ (%)	0.0087	0.0040	0.0029	0.0128*
	(0.0060)	(0.0063)	(0.0079)	(0.0072)
Intercept	✓	✓	✓	✓
N	183	183	183	183
R^2	0.05	0.04	0.14	0.05

Newey-West standard errors (in parentheses) use automatically selected lags.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Relationship Between Letters' Risk Details, Risk Levels, and the Subsequent-Month S&P 500 Index Fund Flows

The panel regressions in this table describe the relationship between how risk is discussed in the voluntary letter disseminated by a fund i during year-month t and the subsequent flow into the fund, and show that flows are higher when communication about risk is more transparent. The two (potentially independent) textual features of the risk discussions used as independent variables are the amount of detail provided about risk, and the level of risk conveyed by each discussion. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter written by fund i at time t discussing risk; see Eqn. (1). Column (1) shows the key relationship between Risk Detail$_{i,t}$ and the subsequent Net Flow$_{i,t\to t+1}$. Columns (2), (4) and (5) augment this regression with the secondary covariate Risk Level$_{i,t}$, measured in one of three ways: as the negative of the within-fund-standardized net sentiment of the text that discusses risk, using the Loughran and McDonald (2011) sentiment dictionary (column 2), or the net score of contextual risk words defined by Equation (4) (column 4), or a modified score that counts only high-risk words (column 5). Columns (3) and (6) include an interaction between the Risk Detail$_{i,t}$ and an indicator $\mathbb{1}\{\text{High Risk Level}\}_{i,t}$ for whether the letter conveys a high level of risk, defined as a below-median sentiment (column 3), or the presence of one or more high-risk words (column 6). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Detail$_{i,t}$	0.0156**	0.0279***	0.0262***	0.0293***	0.0290***	0.0303**
	(0.0068)	(0.0102)	(0.0095)	(0.0106)	(0.0106)	(0.0118)
Risk Level$_{i,t}$		0.0173		0.0077	0.0162	
		(0.0185)		(0.0153)	(0.0172)	
$\mathbb{1}\{\text{High Risk Level}\}_{i,t}$			0.0144			0.5685
			(0.2141)			(0.4029)
Risk Detail$_{i,t}$			0.0040			-0.0186
$\times\ \mathbb{1}\{\text{High Risk Level}\}_{i,t}$			(0.0082)			(0.0167)
Risk Level measure		Sentiment	Sentiment	High-Low Words	High Words	High Words
$\mathbb{1}\{\text{High Risk Level}\}$ threshold			Median			0
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓	✓
N	2,238	1,588	1,569	1,579	1,579	1,579
R^2	0.37	0.41	0.40	0.41	0.41	0.41

*Clustered (Fund & Year-month) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Assessing the Economic Significance of the Flow–Risk Detail Relationship

The first covariate is the total annual fee charged by the fund i at time t. The second covariate Risk Detail$_{i,t}$ measures the fraction of the letter written by fund i at time t discussing risk. The third covariate is the negative of the net sentiment of this risk discussion, calculated by Eqn. (2). All independent variables are in units of standard deviation after having been transformed by z-scoring over the entire sample (hence the $\sigma(\cdot)$ labels). In columns 4–6, the dependent variable is also standardized. *Fund controls* (not shown) are for the fund's prior month return, square of this return & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variables:	Net Flow$_{i,t\to t+1}$ (%)			σ(Net Flow$_{i,t\to t+1}$)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
σ(Total Fee$_{i,t}$)	-1.582**	-1.588**	-1.327**	-0.5201**	-0.5218**	-0.4360**
	(0.6472)	(0.6361)	(0.6126)	(0.2127)	(0.2091)	(0.2014)
σ(Risk Detail$_{i,t}$)		0.2829**	0.5073***		0.0930**	0.1667***
		(0.1238)	(0.1856)		(0.0407)	(0.0610)
σ(-Risk Net Sentiment$_{i,t}$)			0.0647			0.0213
			(0.0693)			(0.0228)
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓	✓
N	2,238	2,238	1,588	2,238	2,238	1,588
R^2	0.37	0.37	0.41	0.37	0.37	0.41

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Corner Bunching Control Function Estimates of the Effect of Risk Detail on Fund Flows

This table reports estimates of Eqn. (10), which augments the baseline flow–risk detail regression with a control function $\lambda(\cdot)$ constructed from corner bunching in the treatment variable in order to correct for endogeneity. Columns 2–4 report results from various specifications of the control function, following Caetano, Caetano, and Nielsen (2024): a Tobit restriction, a semiparametric Tobit, and a nonparametric symmetry restriction. The coefficient β captures the effect of Risk Detail$_{i,t}$ (the fraction of the letter (%) written by fund i at time t discussing risk) on subsequent fund flows. The coefficient δ is on the correction term $\lambda(\cdot)$; it absorbs the component of variation in risk detail that is correlated with unobservables and therefore provides a direct estimate of the bias in the uncorrected regression. The procedures for estimating the endogeneity correction terms used in columns 2–4 are described in Internet Appendix E. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. Standard errors are based on 10,000 bootstrap replicates. The sample consists of S&P 500 index funds only, and slightly exceeds that of OLS tables because fund controls enter as cluster indicators in this econometric procedure; these clusters remain defined for observations with missing control values.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)			
Correction:	Uncorrected	Tobit	Semiparam. Tobit	Symmetric
	(1)	(2)	(3)	(4)
β	0.014***	0.049***	0.050***	0.035***
	(0.005)	(0.017)	(0.014)	(0.013)
δ		-0.027*	-0.029***	-0.017*
		(0.014)	(0.01)	(0.01)
Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	2,353	2,353	2,353	2,353

*Bootstrapped standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Testing for Any Communication-Driven Rebalancing Flows Out of Sibling Active Funds

Columns (1) and (2) show the relationship between outflows from active domestic equity funds and the amount of detail about risk contained in the letters of their sibling S&P 500 index tracker funds. As a robustness check, the analysis is repeated for the active funds' letters' own risk detail measure in columns (3) and (4). Sibling active funds are defined as non-index domestic equity funds within the same family as the S&P 500 index funds that this study focuses on; columns (2) and (4) impose a further filter by requiring these active funds to also have a high market beta. The amount of risk detail is consistently measured as the letter fraction (%) discussing risk. *Fund controls* (not shown) are for the active fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of active domestic equity funds that belong to fund families that also contain an S&P 500 index fund.

Dependent Variable:	Sibling Outflow$_{i,t\to t+1}$ (%)			
	(1)	(2)	(3)	(4)
S&P 500 Index Fund Risk Detail$_{i,t}$	-0.0086**	-0.0120***		
	(0.0040)	(0.0046)		
Sibling Active Fund Risk Detail$_{i,t}$			-0.0080**	-0.0135***
			(0.0039)	(0.0048)
Sibling Active Funds	All	$\beta^{MKT} > 1$	All	$\beta^{MKT} > 1$
Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	14,788	7,662	14,788	7,662
R^2	0.77	0.78	0.77	0.78

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Experimental Results: Effect of Transparency on Reported Trust and Other Outcomes

This table reports the pre-registered analyses of the single-letter evaluation block of the randomized experiment. In this block, each participant read one randomly assigned constructed letter and then reported their reactions (final $N = 368$; 189 Transparent, 179 Baseline). Each column shows estimates from an OLS regression of the outcome on an indicator for the Transparent condition. Trust in the manager, the primary outcome, and trust in the information are four-item scales (1–7); perceived risk focus and perceived positive focus are single 1–7 items; perceived implied return is a single 1–5 item. Every analysis in this table was pre-registered, including the directional prediction for each coefficient, which is displayed immediately above the corresponding estimate ($-$ or 0 denotes the prediction of at most no increase).

Dependent Vars.:	Trust in Manager	Trust in Information	Perceived Implied Return	Perceived Risk Focus	Perceived Positive Focus
	(1)	(2)	(3)	(4)	(5)
Pre-registered coefficient predictions	+	+	− or 0	+	−
$\mathbb{1}${Transparent}	0.2951***	0.4921***	-0.3612***	2.128***	-1.781***
	(0.1103)	(0.1122)	(0.0829)	(0.1276)	(0.1351)
Intercept	4.623***	4.475***	2.726***	3.380***	4.860***
	(0.0852)	(0.0829)	(0.0542)	(0.1033)	(0.0950)
N	368	368	368	368	368
R^2	0.02	0.05	0.05	0.44	0.32

*Heteroskedasticity-robust standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Experimental Results: Joint Evaluation of a Transparent Letter vs. a Baseline Letter

This table reports experimental results from the joint-evaluation block ($N = 368$), in which each participant viewed their own letter and a randomly chosen opposite-condition letter side-by-side and made multiple relative comparisons, selecting the Transparent vs. Baseline vs. "about the same" option for each (display side randomized). For each criterion, the table reports the three-way counts, the share choosing the Transparent letter among all responses (tested against the 1/3 equal-choice benchmark), and the share among Transparent vs. Baseline only (tested against 1/2), using exact binomial tests.

	Selected Letter Counts			Among All Responses		Excluding "Same" Responses	
Criterion: which letter is...	Transparent	Baseline	Same	Transparent %	p (vs. 1/3)	Transparent %	p (vs. 1/2)
Riskier	**278**	50	40	75.5%	< 0.001	84.8%	< 0.001
Higher return	42	**223**	103	11.4%	< 0.001	15.8%	< 0.001
More trustworthy	**189**	113	66	51.4%	< 0.001	62.6%	< 0.001
More credible / transparent	**230**	68	70	62.5%	< 0.001	77.2%	< 0.001
Discusses downsides more	**296**	38	34	80.4%	< 0.001	88.6%	< 0.001
Preferred	**214**	120	34	58.2%	< 0.001	64.1%	< 0.001

Table 8: Experimental Results: Participant Attributes and the Effect of Transparency on Trust

This table reports heterogeneity in the experimental trust effect. Column 1 repeats the pre-registered primary regression of trust in the manager (4-item scale, 1–7) on the Transparent indicator. Columns 2–4 each add one pre-treatment participant attribute and its interaction with the Transparent indicator. Investing experience is elicited as a free numeric response to "About how many years have you been investing in or trading financial assets such as stocks, funds, or bonds?" (entered in years; 0 if none). Dispositional optimism is a seven-point agreement rating of the statement "Overall, I expect more good things to happen to me than bad." Equity propensity is a free numeric response to "When you put money into savings or investments, about what percentage do you typically put into stocks or stock funds, versus other financial assets such as cash, savings accounts, bonds, or bond funds?" (entered as a percentage from 0 to 100). All three attributes are measured before the letter is shown.

Dependent Variable:	Trust in Manager			
	(1)	(2)	(3)	(4)
$\mathbb{1}${Transparent}	0.2951***	0.5757***	1.058***	0.5051***
	(0.1103)	(0.1638)	(0.3968)	(0.1712)
Investing experience (years)		0.0149**		
		(0.0072)		
$\mathbb{1}${Transparent} × Investing experience (years)		-0.0255***		
		(0.0097)		
Dispositional optimism			0.2454***	
			(0.0600)	
$\mathbb{1}${Transparent} × Dispositional optimism			-0.1569**	
			(0.0778)	
Equity propensity (%)				0.0085***
				(0.0028)
$\mathbb{1}${Transparent} × Equity propensity (%)				-0.0069**
				(0.0035)
Intercept	✓	✓	✓	✓
N	368	368	368	368
R^2	0.02	0.03	0.09	0.05

*Heteroskedasticity-robust standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Interaction of Communicated Risk Detail With the Aggregate Market Risk Aversion

This table shows that the positive effect of providing more transparency about risks on flows is higher during times when investors' prior risk aversion levels are on average higher. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. Risk aversion is measured by Bekaert, Engstrom, and Xu (2022) as a monthly, market-wide estimate of the coefficient of relative risk aversion of the representative investor; the indicator $\mathbb{1}\{\text{High Risk Aversion}\}_t$ takes the value 1 when their risk aversion measure is currently above its median. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. *Market controls* (not shown) are for the changes in the VIX and in the subjective aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)) from t to $t+1$.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0135**	0.0045	0.0044
	(0.0065)	(0.0058)	(0.0058)
$\mathbb{1}\{\text{High Risk Aversion}\}_t$		-0.3344**	-0.3222**
		(0.1457)	(0.1472)
Risk Detail$_{i,t}$		0.0146**	0.0147**
$\times\ \mathbb{1}\{\text{High Risk Aversion}\}_t$		(0.0060)	(0.0060)
Fund Controls$_{i,t}$	✓	✓	✓
Market Controls$_t$			✓
Fund FEs	✓	✓	✓
N	2,238	2,238	2,238
R^2	0.31	0.31	0.31

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Variation in the Effect of Communicated Risk Detail Across Letter Readerships' Anxiety Attitudes

This table shows that the effect of providing more transparency about risks on flows is concentrated among more anxious readers, as revealed by local Google search activity. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The level of risk conveyed is calculated according to Eqn. (3). The sample consists of fund letters disseminated during each year-month t, and is further split into fund letter readerships with below-median anxiety levels (columns 1–2), and those with anxiety levels at the median or greater (columns 3–4) within each cross-section t. In measuring readership anxiety levels, the sum of Search Volume Indices for the Google Trends topics of "Psychological Stress" and "Worry" is used. *Local economy controls* (not shown) are for each fund letter readership's contemporaneous asset-weighted exposure to local economic activity & employment (measured by the Philadelphia Fed's State Coincident Index) and to local inflation rates (measured at a state level by Hazell, Herreno, Nakamura, and Steinsson (2022)). *Demographic controls* (not shown) are for the (log) geographic distance to the headquarters of the fund company, (log) regional median age of the population, regional fraction of the population with a Bachelor's degree, (log) regional mean household income, regional fraction of the voting population that voted for a Democrat president, regional fraction of the population living in an urban area; each fund-level demographic control is the asset-weighted average, across the letter's readership, of the corresponding state-level variable. *Fund controls* (not shown) are for the prior month return, square of this return, fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)			
Sub-sample:	Low Anxiety		High Anxiety	
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0093	0.0142	0.0199**	0.0374**
	(0.0111)	(0.0119)	(0.0097)	(0.0172)
Risk Level$_{i,t}$		0.0563		0.2332*
		(0.1035)		(0.1221)
Local Economy Controls$_{i,t}$	✓	✓	✓	✓
Demographic Controls$_{i,t}$	✓	✓	✓	✓
Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	809	563	923	671
R^2	0.53	0.62	0.50	0.52

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figures

Figure 1: Screening for Sentences that Discuss Risk

Statements about risk are defined as valid English sentences that are matched by both forward-looking and risk-related patterns. The percentage figures denote the fraction of all sentences in the overall fund letter corpus that are matched by each type of pattern.

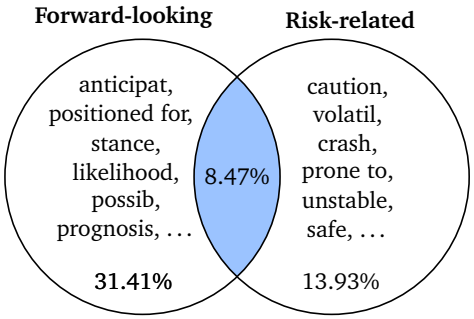


Figure 2: Cross-Sectional Dispersion in How Fund Letters Discuss Risk

These charts summarize dispersion in the fraction of a fund letter that discusses risk (left-hand side) and the net sentiment of the words in that discussion (right-hand side). The net sentiment is computed using the Loughran and McDonald (2011) dictionary, according to Eqn. (2).

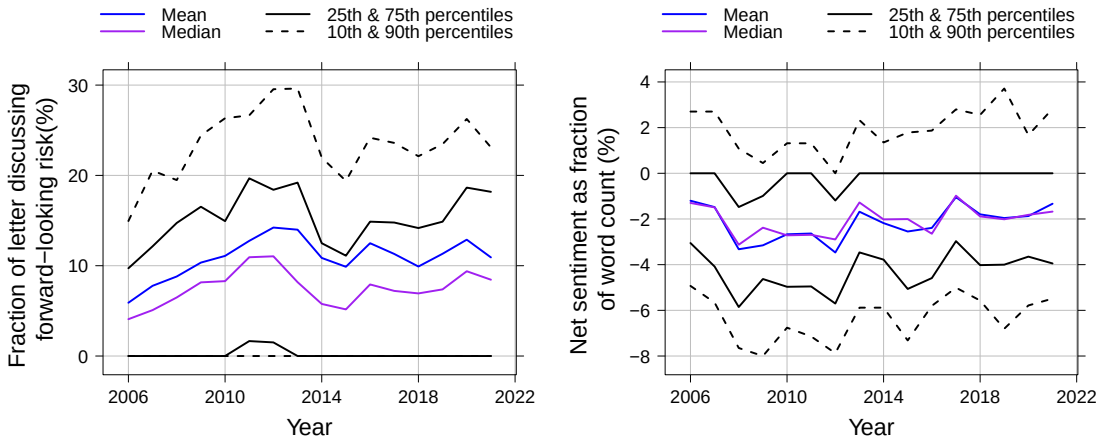


Figure 3: Binned Scatterplot of Risk Detail vs Residualized Net Flow

The x-axis shows Risk Detail$_{i,t}$, which measures the fraction of the letter (%) written by fund i at time t discussing risk. The y-axis shows the corresponding Net Flow$_{i,t\to t+1}$ (%) after it has been residualized against controls. The set of controls comprises fund fixed effects, year-month fixed effects, the Risk Level$_{i,t}$ conveyed by the letter (computed using net sentiment scores), and other fund controls: the prior month return, square of this return, fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

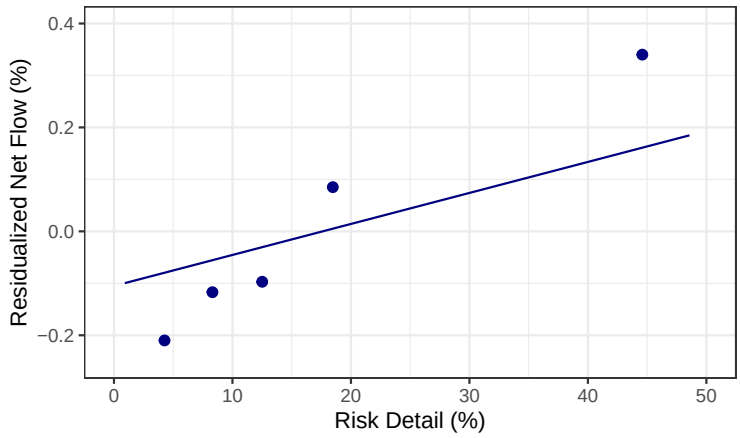


Figure 4: Corner Bunching in the Treatment Variable Used for Identification

These charts visualize the distribution of Risk Detail$_{i,t}$, which measures the fraction of the letter (%) written by fund i at time t discussing risk. The left chart shows the empirical CDF of this variable, and the right chart shows its histogram. The histogram highlights corner bunching at the value 0%: this is shown by the single bar colored red, while all other bars are colored blue. A corresponding sharp discontinuity is also visible in the empirical CDF at the 0% value. The presence of this feature of the empirical distribution is used in the corner bunching identification strategy described in Section 3.2.

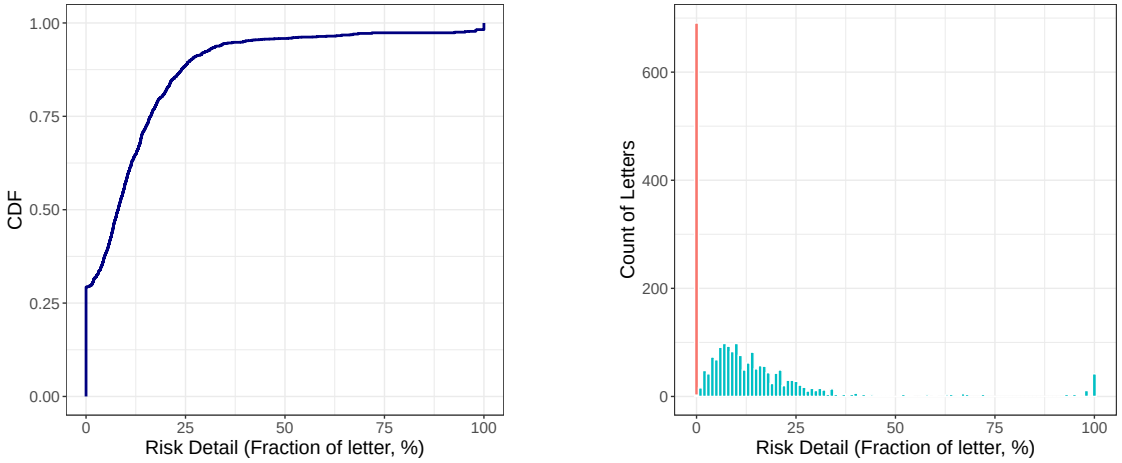


Figure 5: Performance of Aggregate Communication-Driven Incremental Excess Returns

Sharpe ratio of the total additional holdings of S&P 500 index mutual funds that have been induced by risk transparency in fund letters (y-axis), assuming a variety of holding periods before those initial flows are withdrawn (x-axis). The excess returns used in the Sharpe ratio calculations are net of the fees levied by the S&P 500 index mutual funds that are disseminating each fund letter. The risk-free rate is computed using T-bills. Sharpe ratios are annualized. The shaded area represents the 95% confidence interval for each Sharpe ratio, calculated using quantile bootstraps with 1,000 replicates each.

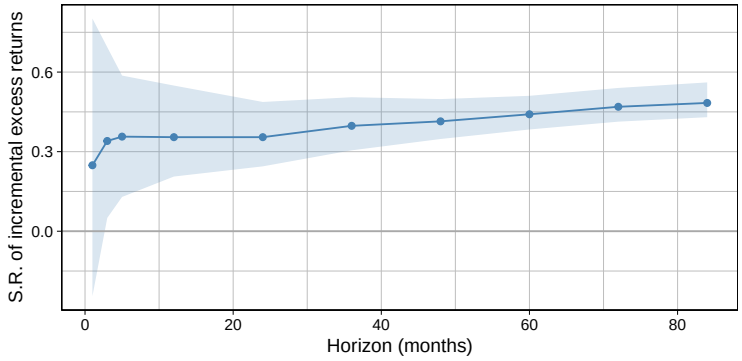
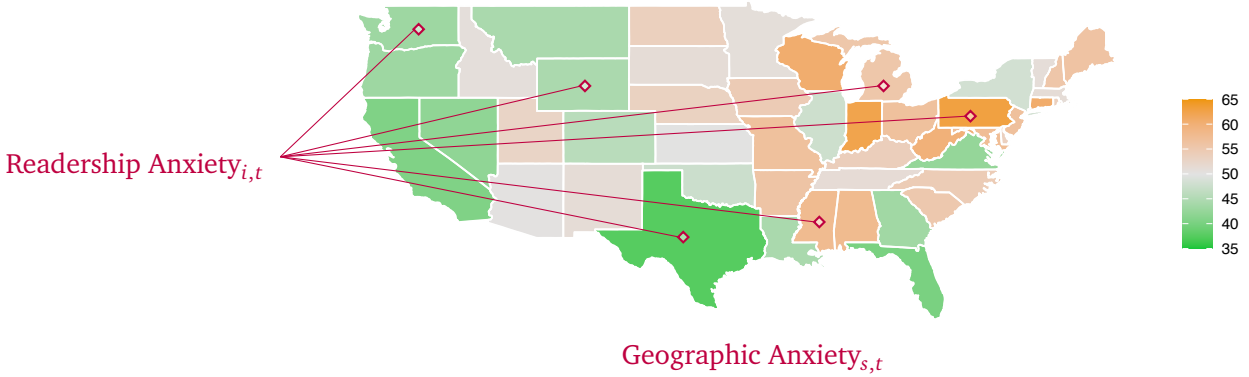


Figure 6: Illustration of Geographic Anxiety and its Aggregation to Readership Anxiety

This chart summarizes geographic variation in local anxiety attitudes revealed through Google search activity. Specifically, it displays means of cross-sectional rank percentiles for the combination of two Google Search Volume Indices for the topics of "psychological stress" and "worry", which Google themselves have defined. This index of anxiety attitudes, Geographic Anxiety$_{s,t}$, varies over time as well as geographically. By construction, the chart colors display persistent geographic variation: orange states denote a cross-sectionally higher level of anxiety; green states denote a lower level of anxiety; the legend is for mean cross-sectional rank-percentiles. The figure also illustrates the procedure of aggregating from Geographic Anxiety$_{s,t}$ to a fund-level measure of Readership Anxiety$_{i,t}$ using Eqn. (12).



Internet Appendix for "The Virtue of Transparency: Evidence from Asset Management"

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A Summary Statistics: Mutual Fund Letters & Market Conditions

Table IA.1 summarizes monthly S&P 500 market-level variables over my study's sample period of 2006-2021.

My main sample is a panel of fund letters disseminated by S&P 500 index mutual funds i during year-months t, merged with characteristics of the funds disseminating these letters and of the families to which the funds belong. Table IA.2 summarizes this panel.

Figure IA.1 summarizes the fraction of N-CSR and N-CSRS filings that contain a fund letter.

Table IA.1: Summary of S&P 500 Characteristics

This table summarizes market timeseries during the period 2006-2021, all at a monthly frequency.

Market Variable	N	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
AAII Survey Expected Return (%) (Greenwood and Shleifer, 2014)	192	3.277	12.145	−5.569	3.991	11.536
VIX	192	19.727	8.713	13.742	17.070	23.425
VVIX	190	91.375	15.983	81.460	89.920	100.542
Ambiguity (Brenner and Izhakian, 2018)	184	0.068	0.051	0.031	0.057	0.088
Risk Aversion (Bekaert, Engstrom, and Xu, 2022)	192	3.098	0.868	2.657	2.828	3.180

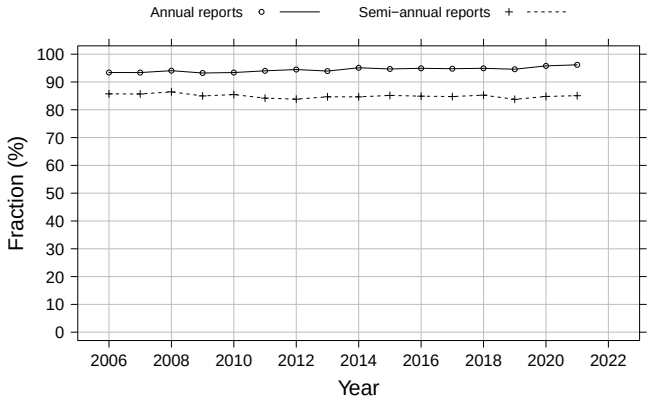
Table IA.2: Summary of Fund Letter Characteristics

This table shows summary statistics for the main sample used in the paper, which consists of letters disseminated by S&P 500 index mutual funds i during year-months t.

Fund Variable	N	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Net Flow during month $t+1$ (%)	2,353	−0.104	3.042	−1.101	−0.454	0.358
Fraction of Letter about Risk (%)	2,353	12.535	18.170	0.000	8.040	16.231
Loughran and McDonald (2011) Net Sentiment (%) of Letter Portion about Risk	1,664	−2.135	3.739	−4.387	−2.083	0.000
Return during month $t-1$ (%)	2,353	1.049	3.556	−1.449	1.641	3.676
Total Fee (%)	2,239	0.428	0.505	0.000	0.200	0.840
Log of Fund Size	2,351	20.286	2.017	18.961	20.435	21.629
Log of Family Age (in months)	2,310	5.213	0.361	4.990	5.275	5.454
Log of Family Size	2,310	11.035	2.047	9.985	11.321	12.305

Figure IA.1: Fraction of Filed Reports Containing Fund Letters

The vast majority of annual (N-CSR) and semi-annual (N-CSRS) reports published by fund families since 2006 contain at least one letter intended for investor clients. Fund letters within reports were detected using my text extraction methodology. A consistently high and stable fraction of filings were detected to have at least one fund letter.



B Example of a Fund Letter

Figure IA.2 shows an example fund letter addressed to the investors in one S&P 500 index fund.

Figure IA.2: Example Fund Letter

This letter opens the section on the Schwab S&P 500 Index Fund, within the Schwab Equity Index Funds 2020 semi-annual report (filed with the SEC on 2nd July 2020).

From the President



Jonathan de St. Paer
President of Charles Schwab Investment Management, Inc. and the funds covered in this report.

Dear Shareholder,

The six-month reporting period ended April 30, 2020 represented one of the most volatile investing environments on record, as the COVID-19 pandemic continued to impact nearly every aspect of daily life. Up until the last week of February 2020, U.S. stock market performance was strong, with the longest bull market cycle in history continuing and major equity indices hitting new highs. But the rapid spread of COVID-19 around the world in late February and throughout March prompted increasingly strict government social distancing policies and travel restrictions that brought many economies to an abrupt halt and sent stock markets reeling. Against this unprecedented backdrop, a new record was set for the fastest U.S. market decline, with the S&P 500® Index, a bellwether for the overall U.S. stock market, dropping 30% in just 22 trading days. Global markets saw similar sell-offs. Stocks in the U.S. and abroad regained some lost ground in April, but investors continued to grapple with historic market volatility. For the six-month reporting period ended April 30, 2020, the S&P 500® Index returned -3.2%, while the Russell 2000® Index, a measure of U.S. small-cap stocks, returned -15.5% and the MSCI EAFE® Index (Net)*, a broad measure of developed international equity performance, returned -14.2%.

We don't know yet what the full impact of the COVID-19 pandemic will be or how long it will last. The sudden health crisis, sharp increase in unemployment, and market declines have understandably rattled investors, leading many to seek the perceived safety of asset classes such as cash. Market volatility and declines can be difficult to withstand, and can engender strong emotional reactions, such as selling out of fear or staying on the sidelines. In the longer-term, this can often make investing outcomes worse, as investors who missed out on the market's rebound in April may now realize. At times like these it's important to remember that all market cycles, no matter how long, ultimately come to an end.

At Charles Schwab Investment Management, we believe that maintaining a long-term investing plan and a portfolio with exposure to a mix of asset classes that perform differently over time is one way to weather the ups and downs that come with investing. We designed the Schwab Equity Index Funds with this long-term perspective in mind. The funds provide access to broad segments of the equities markets with different risk and return profiles, including small-cap, mid-cap, and large-cap stocks, those oriented toward value or growth, and equities from both U.S. and international markets. In addition, the Schwab Equity Index Funds can help investors achieve their

C Examples of Sentences Discussing Risk in Fund Letters

This appendix shows example statements about risk extracted from a wide sample of fund letters using this paper's methodology – first from the sample of S&P 500 index fund letters that this paper focuses on, and also from the wider overall corpus of fund letters.

Example Sentences About Risk From S&P 500 Index Fund Letters.

- *"As such, we continue to expect to see higher interest rates and increased equity market volatility."*
- *"Periods of investment uncertainty can present challenges, but experience has taught us that maintaining long-term investment goals can be an effective way to plan for the future."*
- *"While equity market volatility and political uncertainties are likely to remain with us for the rest of 2018, we remain fairly constructive on equities and credit markets, but are carefully monitoring economic and political developments."*
- *"Risks in the new year include the possible end of the boom in the housing market, where we believe prices are more likely to stall than plunge."*
- *"Looking ahead, we expect to see positive returns from equity markets, though the potential for a market correction remains high."*

Example Sentences About Risk From Overall Fund Letter Corpus.

- *"Market volatility readings have been remarkably low of late, but conditions can change quickly."*
- *"While we optimistically await to see what next year will bring, we note that many of the major cap-weighted and equal-weighted indices still carry significant and diversifiable related business risk."*
- *"For that reason, the portfolio manager remains vigilant, and stands ready to move the portfolio back into a "Risk Off" position should his quantitative model dictate such a move."*
- *"However, we do recognize that tighter U.S. labor markets and continued very easy monetary policy could give rise to an inflation scare later in 2016, with a temporary sell-off in risky assets and a more sustained sell-off in government bonds due to market concerns about the Fed being behind the curve a possibility."*

D Validation of Textual Measures

This appendix validates my study's methodology for detecting sentence types in the fund letter corpus. To do this, I compare my methodology – which has been manually adapted to the fund letter setting – with methodologies from other studies that are not intentionally adapted to my study's context. This includes a widely-used psychometrics software package that additionally suffers from a lack of transparency.

I compare and contrast the power of each of these methodologies to detect forward-looking and risk-related statements in the context of fund letters. I find that the present paper's methodology is either comparable to, or exceeds, the ability of other methodologies employed in other parts of the accounting and psychology literatures to detect such statements. This paper's methodology thus succeeds in its goal, while also having the advantages of being (i) transparent, and (ii) intentionally designed for the fund letter corpus studied in this paper.

The first two alternative methodologies that I examine in this section (Li, 2010; Hassan, Hollander, van Lent, and Tahoun, 2019) were designed for detecting either forward-looking (only) or risk-related (only) statements in listed companies' communications.

A statement is classified as forward-looking if it contains at least one forward-looking word, as defined by Li (2010). Note that this dictionary was also employed by Hillert, Niessen-Ruenzi, and Ruenzi (2025).

Similarly, using the methodology of Hassan, Hollander, van Lent, and Tahoun (2019), a statement is classified as risk-related if it contains at least one risk-related word, as defined by Hassan, Hollander, van Lent, and Tahoun (2019) & the Oxford English Dictionary.

The next alternative methodology I consider is the Linguistic Inquiry and Word Count (LIWC) software, of which I use the latest version, LIWC-22 (Boyd, Ashokkumar, Seraj, and Pennebaker, 2022). This software contains a number of proprietary dictionaries that are kept confidential by its vendor; it is likely these dictionaries comprise both individual word stems and regular expressions. It is operated by inputting a block of text, and returns the number of words in the input text that match a given dictionary. While the software is well accepted in the field of psychology, its lack of transparency is a barrier to adopting this software for analyzing fund letters. I run the software to count the number of words matching two dictionaries – future focus in time orientation, and risk motives – in order to detect forward-looking and risk-related statements (respectively) in my fund letter corpus. To be precise, a statement is defined as being forward-looking if it contains at least one forward-looking word, as determined by the LIWC software; similarly, a statement is defined as being risk-related if the LIWC software detects

the presence of a risk-related word.

Table IA.3 compares the results of this paper's baseline methodology for detecting forward-looking sentences to the two alternative measures. The baseline methodology detects the highest fraction of forward-looking sentences, and its classifications are positively correlated with both alternative methodologies'.

Table IA.4 compares the results of this paper's baseline methodology for detecting risk-related sentences to the two alternative measures. The baseline methodology detects a higher fraction of risk-related statements than that of Hassan, Hollander, van Lent, and Tahoun (2019), and a comparable rate to the LIWC-22 software. The baseline method's classifications are positively correlated with both alternative methodologies'.

Table IA.3: Forward-Looking Sentence Detection

Number & fraction of forward-looking sentences detected in my fund letter corpus using three different methodologies, and (in the final column) the correlations of statement classifications of the two alternative methodologies with my own.

Methodology	Description	Sentences detected	Fraction of corpus	Correlation to baseline
This paper	Set of patterns customized for the fund letter corpus	1,529,823	31.41%	—
Li (2010, Appendix B)	17 words used by Li (2010) to detect forward-looking statements in listed company 10-K & 10-Q filings	877,338	18.01%	0.3103
LIWC-22 (Boyd, Ashokkumar, Seraj, and Pennebaker, 2022)	Proprietary set of 138 words & word stems related to future focus in time orientation, designed for general-purpose psychology research	854,105	17.53%	0.4023

Table IA.4: Risk-Related Sentence Detection

Number & fraction of risk-related sentences detected in my fund letter corpus using three different methodologies, and (in the final column) the correlations of statement classifications of the two alternative methodologies with my own.

Methodology	Description	Sentences detected	Fraction of corpus	Correlation to baseline
This paper	Set of patterns customized for the fund letter corpus	678,338	13.93%	—
Hassan, Hollander, van Lent, and Tahoun (2019, Internet Appendix Table 3)	111 synonyms for the word "risk" according to the Oxford Dictionary, used to analyze listed companies' communications by Hassan, Hollander, van Lent, and Tahoun (2019)	380,268	7.81%	0.6341
LIWC-22 (Boyd, Ashokkumar, Seraj, and Pennebaker, 2022)	Proprietary set of 128 words & word stems related to risk motives, designed for general-purpose psychology research	689,979	14.17%	0.4684

E Corner Bunching Identification Methodology

I implement an identification strategy based on the methodology of Caetano, Caetano, and Nielsen (2024, henceforth **CCN**). This section is an informal exposition of CCN's methodology for identifying treatment effects by exploiting corner bunching, and uses similar notation to theirs. Refer to their paper for a more formal exposition, as well as a companion paper (Caetano, Caetano, Nielsen, and Sanfelice, forthcoming).

The goal is to estimate the causal effect β of a treatment variable X on an outcome Y, in settings where the treatment variable is constrained to be non-negative, $X \geq 0$.

Assumption 1 (Linearity). The treatment and outcome are related by a linear model:

$$Y \;=\; \beta X \;+\; Z'\gamma \;+\; \underbrace{\delta\eta + \varepsilon}_{\text{Unobservable}}\,, \qquad \mathbb{E}[\varepsilon | X, Z, \eta] = 0, \tag{18}$$

where Z is a vector of observable controls, and η is an unobservable confounder. Note, therefore, that X is exogenous when $\delta = 0$ but endogenous otherwise.

Assumption 2 (Corner bunching). The (unobserved) unconstrained choice of X^* is related to the (observed) constrained treatment variable X by the controls Z and confounder η:

$$X = \max\{0, X^*\} = \max\{0,\, Z'\pi + \eta\}. \tag{19}$$

Also, the non-negativity constraint is binding for part of the population:

$$0 < \mathbb{P}(X^* < 0) < 1; \tag{20}$$

i.e. part of the population exhibits no variation in X at the corner value $X = 0$, but *does* have variation in the unobserved confounder η that drives the endogeneity.

From these first two assumptions, it follows that:

$$\begin{aligned} \mathbb{E}[Y|X,Z] \;&=\; (\beta+\delta)X + Z'(\gamma - \pi\delta) + \delta\mathbb{E}[X^*|X^* \leq 0,\, Z]\,\mathbb{1}\{X=0\} && (21)\\ &=\; \beta X + Z'(\gamma - \pi\delta) + \delta\Big(\underbrace{X + \mathbb{E}[X^*|X^* \leq 0,\, Z]\,\mathbb{1}\{X=0\}}_{\text{Correction term}}\Big). && (22) \end{aligned}$$

That is, the causal effect β may be estimated if a correction term is also estimated and included in a regression. The coefficient on this correction term is δ. The sign and significance of δ are informative about the presence and direction of endogeneity.

In order to generate the correction term, note that since X and $\mathbb{1}\{X = 0\}$ are observed, only $\mathbb{E}[X^*|X^* \leq 0, Z]$ must be identified. For this purpose, a shape restriction is required. I now review a classic parametric shape restriction, a semiparametric version of it, and a weaker nonparametric shape restriction.

Assumption 3a (Tobit shape restriction). If we assume $\eta|Z \sim \mathcal{N}(Z'\mu, \sigma^2)$, then

$$\mathbb{E}[X^*|X^* \leq 0, Z] = \mathbb{E}[Z'\pi + \eta|X^* \leq 0, Z] \tag{23}$$

$$= Z'(\pi+\mu) - \sigma\lambda\left(\frac{-Z'(\pi+\mu)}{\sigma}\right), \tag{24}$$

where $\lambda(x) = \frac{\text{Gaussian PDF } \phi(x)}{\text{Gaussian CDF } \Phi(x)}$; i.e. the function $\lambda(\cdot)$ is the Inverse Mills Ratio. Therefore, the parameters μ, σ^2 can be estimated by a Tobit regression of the treatment X onto the controls Z with censoring below 0.

Assumption 3b (Semiparametric Tobit shape restriction). If we assume $\eta|Z \sim \mathcal{N}\big(\mu(Z), \sigma^2(Z)\big)$; i.e. allowing μ, σ to be functions of Z, then

$$\mathbb{E}[X^*|X^* \leq 0, Z] \;=\; \alpha(Z) - \sigma(Z)\,\lambda\left(\frac{-\alpha(Z)}{\sigma(Z)}\right), \tag{25}$$

$$\text{where } \alpha(Z) \;=\; Z'\pi + \mu(Z). \tag{26}$$

The parameters may be estimated by a Tobit regression of X onto a constant with censoring below 0, for the subset of observations where $Z = z$.

Assumption 3c (Nonparametric Symmetric Tails shape restriction). We can make the nonparametric assumption that the distribution $\eta|Z$ has symmetric tails. Many distributions satisfy this assumption (including the Gaussian, Student's t and Uniform distributions). Since this assumption does *not* assume the entire distribution is symmetric, it is quite general in scope. Following from this (weak) assumption,

$$\begin{aligned}\mathbb{E}[X^*|X^* \leq 0, Z = z] \;=\;& F^{-1}_{X|Z=z}\big(1 - F_{X|Z=z}(0)\big) \\ & - \mathbb{E}\Big[X\Big|X \geq F^{-1}_{X|Z=z}\big(1 - F_{X|Z=z}(0)\big), Z = z\Big].\end{aligned} \tag{27}$$

Therefore, the empirical CDF can be used to identify the correction term, assuming that $\mathbb{P}(X = 0|Z = z) \leq 0.5$. The bunching probability $F_{X|Z=z}(0)$ is estimated using sample frequencies. The quantile $F^{-1}_{X|Z=z}\big(1 - F_{X|Z=z}(0)\big)$ is estimated using the empirical quantile of X among the observations with $Z = z$. And finally, the conditional trimmed mean $\mathbb{E}\Big[X\Big|X \geq F^{-1}_{X|Z=z}\big(1 -$

$F_{X|Z=z}(0)\big)$, $Z = z\big]$ is estimated using a sample analog.

Assumptions 3a, 3b & 3c above offer alternative distributional assumptions for identifying the endogeneity correction term that is required by Equation (22), for the ultimate purpose of identifying the treatment effect β. All three shape restrictions are used in the empirical analysis of Section 3.2 in the main paper.

Given Assumptions 1, 2 and 3 (a, b, or c), CCN show that the terms β, $(\gamma - \pi\delta)$ and δ in Equation (22) are identified, and furthermore that standard errors are consistently estimated by the bootstrap.

CCN also discuss the nuances of estimation when the vector of controls Z is high-dimensional. I closely follow their suggested approach of discretizing Z into clusters. Since my set of controls includes a variety of fixed effects, I use a large $K = 50$ clusters; this is identical to the cluster size used in the companion paper by Caetano, Caetano, Nielsen, and Sanfelice (forthcoming).

F Randomized Experiment: Further Details

Table IA.5: Attributes of Experimental Subjects

This table shows the characteristics of the experimental subjects, together with the randomization balance. In addition to summary statistics in the overall analysis sample ($N = 368$; 189 Transparent, 179 Baseline), separate means are reported for the Transparent arm and the Baseline arm, together with the standardized between-arm difference in means (i.e., Transparent minus Baseline, expressed in SD units for comparability), as well as the p-value from a two-sample t-test of that difference. Attributes are reported on their native scales (binary traits as proportions, ordinal traits as category indices). None of these attributes differ significantly across arms, confirming that randomization balanced subjects' characteristics; the treatment-effect estimates therefore require no covariate adjustment.

	Overall					Comparing Means Across Arms			
Subject Attribute	*N*	Mean	SD	Min	Max	Transparent	Baseline	Std. diff.	*p*
Age (years)	368	41.55	12.62	20.00	79.00	41.59	41.50	+0.007	0.95
Female (0/1)	368	0.37	0.48	0.00	1.00	0.37	0.37	-0.019	0.86
Education (1–4)	367	2.80	0.91	1.00	4.00	2.84	2.77	+0.077	0.46
Income (1–5)	362	3.12	1.23	1.00	5.00	3.17	3.07	+0.084	0.42
Financial literacy (0–4)	368	3.78	0.53	0.00	4.00	3.76	3.80	-0.070	0.50
Investing experience (years)	368	10.90	9.72	0.00	50.00	10.29	11.54	-0.129	0.22
Risk tolerance: financial (0–10)	368	5.56	2.38	0.00	10.00	5.60	5.52	+0.033	0.75
Risk tolerance: general (0–10)	368	5.56	2.13	1.00	10.00	5.48	5.65	-0.083	0.42
Equity propensity (%)	368	33.91	30.96	0.00	100.00	36.28	31.40	+0.158	0.13
Dispositional optimism (1–7)	368	4.89	1.47	1.00	7.00	4.90	4.88	+0.019	0.86

Table IA.6: Constructed Letter Stimuli Used in Experiment

This table displays the six constructed letters used as experimental stimuli, shown in full. Each participant first reads a single, randomly assigned letter, and then another letter from the opposite condition in a joint evaluation block. Both conditions are assembled from real forward-looking sentences drawn from S&P 500 fund shareholder communications and share a common opening line; the three Transparent variants openly discuss the fund's forward-looking risks, while the three Baseline variants provide a market outlook of the same kind that does not. Letters were displayed to participants under a header identifying them as hypothetical and illustrative.

Stimulus	Full Text of Constructed Letters Used in Experiment
Transparent variant 1	*Dear Investor, here is our perspective on market conditions. We remain in a dynamic, uncertain macroeconomic landscape, and this year's political environment certainly isn't reassuring nervous investors. Large-cap stocks are well positioned to weather an uncertain economic climate. We caution against complacency and believe investors should continue to expect some market volatility. We believe U.S. stocks can move higher, but we caution against extrapolating recent strong returns into the future. The global growth outlook has become more uncertain, and we are mindful of the risks ahead. We remain focused on the long term; in today's uncertain political environment, the underlying economic reality is generally positive.*
Transparent variant 2	*Dear Investor, here is our perspective on market conditions. We are paying close attention to stretched valuations and to parts of the market that look especially risky. That makes the market more vulnerable to a sharp pullback than it was a year ago. We believe the risk of increased volatility remains elevated from here. We caution against complacency: investors are being compensated less for the risk they bear. We believe there are more risks in the market now than there were earlier in the year. We remain focused on the long term; while the backdrop is more demanding, the underlying economy is still expanding.*
Transparent variant 3	*Dear Investor, here is our perspective on market conditions. We remain in an environment where political and policy uncertainty, both at home and abroad, is likely to rise. We expect this uncertainty to produce periodic volatility across equity markets in the months ahead. We are also mindful that the risk of renewed inflation pressure has been building. Macroeconomic uncertainty remains at the forefront, and the range of potential outcomes is unusually wide. We would caution investors against extrapolating the calm of recent months into the future. We remain focused on the long term; despite these uncertainties, the underlying economic picture remains broadly constructive.*
Baseline variant 1	*Dear Investor, here is our perspective on market conditions. We anticipate that U.S. economic growth will continue at a moderate pace, much as it has in recent years. Inflation is likely to remain contained, and we expect interest rates to stay range-bound. Corporate earnings have been broadly in line with expectations. Conditions across the developed world remain mixed, with some regions firmer than others. For equities, it seems rational to expect more modest returns than in the past couple of years. Overall, market conditions have been relatively stable over the period. We look forward to helping you meet your investment goals in the years ahead.*
Baseline variant 2	*Dear Investor, here is our perspective on market conditions. We expect consumer spending to hold up, though its pace has moderated in areas such as housing and home improvement. The U.S. is likely to continue growing at a moderate pace, even as other countries struggle with sluggish growth. We expect the global low-rate environment to continue. Employment trends have been steady, while wage growth has remained subdued. Economists' forecasts are mixed, and broad stock indices have largely moved sideways. We continue to seek to invest for the long term with our time-tested approach. We strongly believe that this focus will reward our shareholders over time.*
Baseline variant 3	*Dear Investor, here is our perspective on market conditions. We believe the U.S. economy remains on a path of moderate, if slower, growth. Global growth could pick up modestly over time, though unevenly across regions. Central banks are expected to keep policy steady for now. Markets anticipate additional rate cuts in the coming quarters. We also expect inflation to stay contained over the coming year, keeping price pressures subdued. Equity valuations are roughly in line with their longer-term history. A long-term perspective can help investors navigate a slower-growth environment. We look forward to helping you meet your investment goals in the years ahead.*

G Field Setting: Robustness Checks

G.1 Including Additional Fund-Level Controls

Table IA.7: Controlling for Fund Risk Exposure

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. Net flows are calculated using the CRSP Mutual Fund Database, as in Eqn. (6). *Common fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. In addition, specifications 2-4 include each fund's CAPM β^{MKT} as an explicit control for its risk exposure, estimated from monthly fund returns over a rolling window (10, 5, and 2 years, respectively). The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)			
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0156**	0.0168**	0.0167**	0.0170**
	(0.0068)	(0.0072)	(0.0073)	(0.0073)
Estimation window for $\beta_{i,t}^{MKT}$ control	No control	10 years	5 years	2 years
Common Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	2,238	2,023	2,023	2,014
R^2	0.37	0.34	0.34	0.34

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA.8: Controlling for Different Horizons of Past Fund Return

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. Net flows are calculated using the CRSP Mutual Fund Database, as in Eqn. (6). *Common fund controls* (not shown) are for the fund's fees & (log) size, and for the overall fund family's (log) age and (log) size. In addition, each specification includes its own set of *past return controls*, consisting of the fund's return over the prior k months and the square of this term. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)			
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0156**	0.0158**	0.0156**	0.0157**
	(0.0068)	(0.0068)	(0.0068)	(0.0068)
Horizon k for past return controls	1 month	3 months	6 months	12 months
Common Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	2,238	2,238	2,238	2,238
R^2	0.37	0.37	0.37	0.37

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA.9: Controlling for Past Fund Flows

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. In addition, specifications 2-4 include past fund flows as additional control variables; for the past month, past quarter, and past 6-month flows, respectively. Net flows are calculated using the CRSP Mutual Fund Database, as in Eqn. (6). *Fund controls* (not shown) are for the fund's prior month t return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only. Each flow variable is measured in percentage points of TNA.

Dependent Variable:	Net Flow$_{i,t\to t+1}$			
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$ (%)	0.0156**	0.0147**	0.0125**	0.0139**
	(0.0068)	(0.0068)	(0.0062)	(0.0065)
Net Flow$_{i,t-1\to t}$		0.1692**		
		(0.0665)		
Net Flow$_{i,t-3\to t}$			0.1286***	
			(0.0233)	
Net Flow$_{i,t-6\to t}$				0.0473***
				(0.0112)
Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	2,238	2,205	2,215	2,216
R^2	0.37	0.38	0.42	0.39

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA.10: Controlling for Morningstar Ratings

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. In addition, I include controls for each fund's Morningstar rating (also known as the Star Rating) where available, using a similar dataset of ratings to that of Ben-David, Li, Rossi, and Song (2022). The Star Rating control is implemented as a covariate in column (2), and as a set of fixed effects in column (3). *Fund controls* (not shown) are for the fund's prior month returns, fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0156**	0.0224**	0.0221**
	(0.0068)	(0.0100)	(0.0110)
Morningstar controls:			
Star Rating$_{i,t}$		0.5104**	
		(0.2199)	
Star Rating FEs			✓
Other controls:			
Fund Controls$_{i,t}$	✓	✓	✓
Year-month FEs	✓	✓	✓
Fund FEs	✓	✓	✓
N	2,238	1,220	1,220
R^2	0.37	0.41	0.44

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.2 Shannon's Entropy as an Alternative Measure of Risk Detail

Table IA.11: Using Shannon's Entropy to Measure Risk Detail

The analysis in this table confirms that the informational content of risk descriptions drives fund flows. Both main covariates measure the amount of detail contained in the letter written by fund i at time t about risk, either using the fraction of the letter (column 1) or the Shannon's entropy of the distribution of word frequencies discussing risk (column 2), as follows:

$$H_{i,t} = -\sum_{k} \mathbb{P}(\text{word}_k) \log_2 \mathbb{P}(\text{word}_k). \tag{28}$$

This alternative measure of the risk detail is the Shannon's entropy of the discrete empirical distribution of the frequency of all k words that discuss risk, computed for each letter disseminated by fund i during month t. Net flows are calculated using the CRSP Mutual Fund Database, as in Eqn. (6). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)	
	(1)	(2)
Letter Fraction$_{i,t}$ (%)	0.0156**	
	(0.0068)	
Shannon's Entropy $H_{i,t}$		0.3181***
		(0.1102)
Fund Controls$_{i,t}$	✓	✓
Year-month FEs	✓	✓
Fund FEs	✓	✓
N	2,238	1,579
R^2	0.37	0.41

Clustered (Fund & Year-month) std. errs.

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.3 Focusing on Within-Fund Variation

Table IA.12: Within-Fund Flow–Risk Detail Relationship

This table repeats the baseline flow-risk detail panel regression with time effects removed, in order to confirm the main effect exists within-fund, i.e., for the important case of an ongoing relationship maintained over time between a fund and its investor base. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. Variables labeled $\sigma(\cdot)$ have been standardized to be interpretable as z-scores. *Fund controls* (not shown) are for each fund letter's total (log) word count, for the fund's prior month returns, fees & (log) size, and for the overall fund family's (log) age and (log) size. *Market controls* (not shown) are for the changes in the VIX and in the subjective aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)) from t to $t+1$. The sample consists of S&P 500 index funds only.

Dependent Variables:	Net Flow$_{i,t\to t+1}$ (%)		σ(Net Flow$_{i,t\to t+1}$)	
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0135**	0.0135**		
	(0.0065)	(0.0065)		
σ(Risk Detail$_{i,t}$)			0.0806**	0.0805**
			(0.0389)	(0.0390)
Fund Controls$_{i,t}$	✓	✓	✓	✓
Market Controls$_t$		✓		✓
Fund FEs	✓	✓	✓	✓
N	2,238	2,238	2,238	2,238
R^2	0.31	0.31	0.31	0.31

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.4 Gross Inflow vs. Risk Detail and Risk Level

Table IA.13: Relationship Between Letters' Risk Details, Risk Levels, and the Subsequent-Month S&P 500 Index Fund Gross Inflows

This table shows the relationship between how risk is discussed in the voluntary letter disseminated by a fund i during year-month t and the subsequent gross inflow into the fund, confirming the baseline results that use net flows. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter written by fund i at time t discussing risk; see Eqn. (1). Column (1) shows the key relationship between Risk Detail$_{i,t}$ and the subsequent Gross Inflow$_{i,t\to t+1}$. Columns (2), (4) and (5) augment this regression with the secondary covariate Risk Level$_{i,t}$, measured in one of three ways: as the negative of the within-fund-standardized net sentiment of the text that discusses risk, using the Loughran and McDonald (2011) sentiment dictionary (column 2), or the net score of contextual risk words defined by Equation (4) (column 4), or a modified score that counts only high-risk words (column 5). Columns (3) and (6) include an interaction between the Risk Detail$_{i,t}$ and an indicator $\mathbb{1}\{\text{High Risk Level}\}_{i,t}$ for whether the letter conveys a high level of risk, defined as a below-median sentiment (column 3), or the presence of one or more high-risk words in (column 6). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Gross Inflow$_{i,t\to t+1}$ (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Detail$_{i,t}$	0.0184*	0.0344**	0.0302**	0.0356**	0.0355**	0.0369**
	(0.0100)	(0.0138)	(0.0128)	(0.0149)	(0.0149)	(0.0163)
Risk Level$_{i,t}$		0.0110		0.0082	0.0106	
		(0.1448)		(0.0192)	(0.0225)	
$\mathbb{1}\{\text{High Risk Level}\}_{i,t}$			0.1046			0.5471
			(0.2711)			(0.5129)
Risk Detail$_{i,t}$			0.0079			-0.0194
$\times\ \mathbb{1}\{\text{High Risk Level}\}_{i,t}$			(0.0078)			(0.0186)
Risk Level measure		Sentiment	Sentiment	High-Low Words	High Words	High Words
$\mathbb{1}\{\text{High Risk Level}\}$ threshold			Median			0
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓	✓
N	2,238	1,569	1,569	1,579	1,579	1,579
R^2	0.74	0.77	0.77	0.77	0.77	0.77

*Clustered (Fund & Year-month) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H Field Setting: Ruling Out Further Alternative Explanations

H.1 Bayesian Updating About Risk: Interactive Prior Risk Perceptions

This appendix presents details of the analysis described in Section 6.1.1, for the case of investor prior risk perceptions that are allowed to vary at the interacted fund i × year-month t level.

The measure of investors' prior perceived risk that I use is a fund i- and year-month t-varying asset-weighted average of local Google search activity. Previous work by Da, Engelberg, and Gao (2015) uses Google search activity to measure aggregate sentiment; I show how to measure the prior risk perceptions of mutual fund investors.

SEC EDGAR-Based Letter Readership Measure. I begin by creating a measure of who reads each letter. To meet this challenge, I focus on the readers of fund letters who download them in the form of shareholder reports from the SEC's EDGAR website. The SEC makes EDGAR website usage data up to June 2017 public (Lee, Ma, and Wang, 2015), and a number of studies have used these logs to measure information consumption. Further details on the SEC EDGAR usage logs are provided in Section 5.3 and Internet Appendix I.

I measure which states the readers of fund shareholder reports are located in; these fund shareholder reports contain the fund letters that the present paper focuses on. I then use the geo-locations of these readers j to construct an aggregate index for the prior held about risk by the readership of each fund i at each year-month t:

$$\text{Readership Prior}_{i,t} = z\left(\frac{1}{\sum_j \text{Investor Assets}_{j,t}} \sum_j \text{Investor Assets}_{j,t} \times \text{Geographic Prior}_{j,t}\right). \quad (29)$$

The above index is standardized within-fund to ensure comparability. Asset weights are proxied using SIPP survey values. A Geographic Prior index, which varies at a state-month level, is used to compute the aggregate Readership Prior. The state-to-fund mappings for each fund's investor base are re-computed annually.

Google SVI-Based Risk Perception Measure. To define the Geographic Prior index, I obtain state s- and year-month t-varying Search Volume Indices (SVI) from the Google Trends API, for search terms relating to the general topic of stock market crashes. This topic is defined by Google's search engine itself, and nests individual searches for "stock market crash" and related terms such as "market crash" and "stock crash." I obtain a monthly timeseries of the aggregated SVI across the entire United States, as well as within-month SVIs across the cross-section of states. For each term, I separately merge and rescale individual SVIs to produce a term-specific month-state panel $\text{SVI}_{s,t}$ of comparable values. The Geographic Prior is defined

simply as the local Google search volume for the stock market crash topic:

$$\text{Geographic Prior}_{s,t} = \text{SVI}_{s,t}^{\text{stock market crash topic}} \tag{30}$$

Validation of the Google SVI-Based Measure. The United States-wide aggregate version of the index $\text{SVI}_t^{\text{stock market crash topic}}$ covaries strongly with the VIX. Table IA.14 compares the aggregate United States-wide version of the index, SVI_t, to the VIX index of aggregate implied stock market volatility. Columns 1-3 compare levels and include controls for a time t trend and quadratic t^2 trend: the SVI_t and VIX are positively and significantly associated in each. Columns 4-5 of the same table regress the log of the SVI_t against the log of the VIX. Interpreting the log-log coefficient in column (4), a 10% increase in the level of the VIX is associated with an approximately 3% increase in Google search volume about the topic of stock market crashes. The positive association between the growths of the two variables thus parallels the positive association between their levels. I conclude from these validation checks that Google search interest in the topic of a stock market crash is a valid measure of perceived stock market risk at an aggregate, country-wide level. Therefore geographic variation in Google search interest should also be a valid measure of *local* perceptions about stock market risk.

Defining the Cross-Section of Geographic Priors. Having confirmed that the Google SVI measure captures investor perceptions about stock market risk, I now make use of state s-month t cross-sectional variation in this index. Figure IA.3 charts geographic dispersion in the population's stock market risk perceptions (but does not show variation over time). Note that this measure has little overlap with the geographic anxiety attitudes shown in Internet Appendix J – the lack of overlap with anxiety attitudes (which influence risk aversion) confirms that this measure (which captures the perceived level of risk) is distinct.

Defining the Cross-Section of Belief Updates. I measure the strength of belief updating about investors' perceived level of risk that is induced by the receipt of a fund letter as follows. In close analogy to the term $s-m_p$ in Eqn. (14), the update is defined as the difference between the letter's signal about risk and investors' priors,

$$\text{Risk Level Update}_{i,t} = \text{Letter Signal}_{i,t} - \text{Readership Prior}_{i,t}, \tag{31}$$

with the first term defined by either Eqn. (3) or (4) (depending on the measure employed), and the second term is defined by Eqn. (29).

Results. Table IA.15 shows a set of panel regression estimates that build upon the previous regressions of Table 2, with a further modification: as well as including the level of the risk conveyed by the communication, the specifications also incorporate fund i-year-month-t-varying

priors about risk held by the letter's readership. This prior is incorporated implicitly into the Risk Update$_{i,t}$ term in columns 2-3, or explicitly as a standalone covariate in the bottom row of columns 4-5.

The coefficients on Risk Level Update$_{i,t}$ in columns 2-3 of Table IA.15 are positive in sign. If fund letter readers update their prior about risk using the signal conveyed in the letter, one would expect *negative* and significant estimates for these coefficients — that is, a revision upwards in the level of perceived risk should predict a smaller net flow. In columns 4-5, the Risk Update$_{i,t}$ term is split apart into its constituent signal and prior terms; the estimated coefficients on both are not significant. By contrast, the main coefficient on the amount of detail in the first row always remains positive and significant.

Once again, these results are not consistent with a classic belief-updating mechanism in which the investor is a Bayesian who learns from the content of the fund letter about some risk parameter (such as the variance parameter of a conditional distribution of market returns).

Figure IA.3: Geography of Stock Market Risk Perceptions Revealed Through Search Interest

Means of cross-sectional rank-percentiles of state-level Google Search Volume indices, over the period 2006 to 2017, for the "stock market crash" topic. Purple states denote a cross-sectionally higher level of perceived stock market risk; teal states denote a lower level of perceived risk. The legend is for mean cross-sectional rank-percentiles.

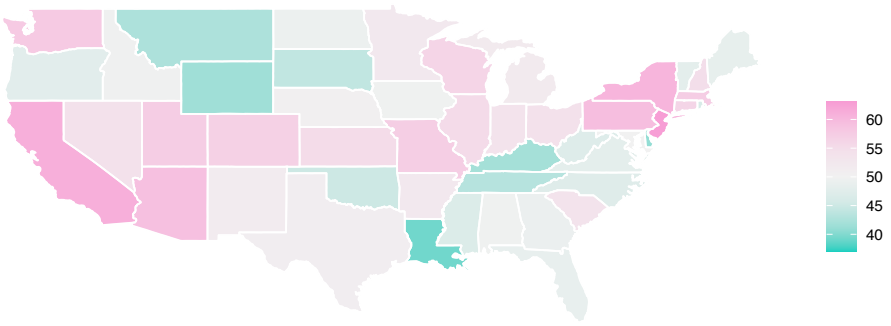


Table IA.14: Comparing Aggregate Google Search Interest to the VIX

SVI_t is the monthly Google Search Volume Index across the United States about the topic of a stock market crash, as defined by Google themselves. The controls t and t^2 denote the presence of time trends and a quadratic growth term, respectively. The sample period of this analysis runs from 2004-2022.

Dependent Variables:		SVI_t		Log SVI_t	
	(1)	(2)	(3)	(4)	(5)
VIX_t	0.5228***	0.4938***	0.4896***		
	(0.1723)	(0.1669)	(0.1643)		
Log VIX_t				0.3076**	0.2638**
				(0.1291)	(0.1180)
Constant	10.25***	5.148	11.65***	2.020***	1.884***
	(3.022)	(3.265)	(3.165)	(0.3597)	(0.3464)
t		0.0501***	-0.1197***		0.0023***
		(0.0109)	(0.0342)		(0.0007)
t^2			0.0008***		
			(0.0002)		
N	225	225	225	225	225
R^2	0.15	0.23	0.29	0.07	0.19

Newey-West standard errors (in parentheses) use automatically selected lags.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA.15: Controlling for Updates in Perceived Risk Levels With Fund × Time-Varying Priors

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The letter's signal about risk is measured in columns (2) and (4) based on the net sentiment of the text discussing risk, as defined by Eqn. (3); in columns (3) and (5) it is measured as the net score of contextual risk words, as defined by Eqn. (4). The prior perceived level of risk varies at the interacted fund × year-month level and is measured based on local Google searches, as defined by Eqn. (29). The update term is the difference between the two, as defined by Eqn. (31). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)				
	(1)	(2)	(3)	(4)	(5)
Risk Detail$_{i,t}$	0.0179**	0.0281**	0.0167**	0.0283**	0.0169**
	(0.0081)	(0.0110)	(0.0082)	(0.0111)	(0.0083)
Risk Level Update$_{i,t}$		0.1394	0.1602*		
		(0.1000)	(0.0889)		
Letter Signal$_{i,t}$				0.1294	0.1374
				(0.1009)	(0.0953)
Readership Prior$_{i,t}$				-0.3424	-0.3606
				(0.3167)	(0.3474)
Risk Level measure		Sentiment	High-Low Words	Sentiment	High-Low Words
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓
N	1,755	1,219	1,745	1,219	1,745
R^2	0.34	0.37	0.34	0.37	0.34

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.2 Bayesian-Like Updating About Risk: Gaining Precision

Based on the alternative hypothesis laid out in Section 6.1.2, this appendix tests whether more detailed communication about risk interacts with the strength of investors' priors about the level of risk.

I measure the prior precision of the representative investor by the VVIX, the so-called "VIX of the VIX." This publicly-available index measures the expected volatility of the 30-day forward price of the VIX. The VVIX is therefore informative of "the degree of confidence the market has in its forecast of future values of the VIX," according to its publisher, the CBOE.[19]

I interpret a higher level of the VVIX as corresponding to a weaker, more diffuse prior about the level of risk held by an investor before receiving communication via a fund letter. A high value of the VVIX thus indicates the investor is less confident about her assessment of risk. Under a belief-based persuasion model, two identical signals (with the same level of precision) should invoke different responses according to whether the investor has strong priors or weak priors: if she holds a strong prior, the investor should respond only weakly and take little action; if her prior is weak, the investor should update her beliefs more strongly, thus manifesting as higher inflows.

Table IA.16 presents the results of just such an analysis. To be precise, I repeat this paper's main flow–risk detail panel regressions, and also include an interaction term for low prior strength/precision in the level of risk. This corresponds to market states with above-median levels of the VVIX. The coefficient on this interaction between having low prior strength about risk and the amount of detail about risk conveyed in fund letters is insignificant. These results suggest the underlying persuasive mechanism is unlikely to be belief-based.

[19] Source: "How can an investor use the VVIX?", `https://www.cboe.com/us/indices/dashboard/vvix/`.

Table IA.16: Flow–Risk Detail Relationship Interacted With the *Ex Ante* Strength of the Prior About Risk

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The indicator variable $\mathbb{1}\{\text{Low Prior Strength}\}_t$ is 1 when the $\underline{V}$VIX is above the median, and 0 otherwise; a baseline effect is estimated in addition to the interaction shown in the table. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variables:	Net Flow$_{i,t\to t+1}$ (%)		Inflow$_{i,t\to t+1}$ (%)	
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0156**	0.0129*	0.0184*	0.0146*
	(0.0068)	(0.0074)	(0.0100)	(0.0087)
Risk Detail$_{i,t}$		0.0056		0.0080
$\times\ \mathbb{1}\{\text{Low Prior Strength}\}_t$		(0.0063)		(0.0076)
Fund Controls$_{i,t}$	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
N	2,238	2,238	2,238	2,238
R^2	0.37	0.37	0.74	0.74

Clustered (Fund & Year-month) std.errs. in parentheses:
****: 0.01, **: 0.05, *: 0.1*

H.3 Learning About the Return: Gaining Precision as a Bayesian

Based on the alternative hypothesis laid out in Section 6.1.3, this appendix tests whether information provision about risk leads to a higher posterior precision of the return. I test for such an uncertainty-reduction channel precisely where it is most likely to be apparent: I focus on statements in fund letters that are forward-looking and devoted to performance or returns specifically (rather than risk).

I extract such sentences by modifying the set of patterns used in the main text. The new set of screens is illustrated by Figure IA.4. While statements devoted to performance and returns occur frequently in the fund letter corpus, only 23% of these are also forward-looking (compared to 61% of risk-related statements).

I next examine how fund flows respond to the amount of detail in fund letters concerning future performance or returns, explicitly. The logic behind this test is the following: if investors are learning about the return from statements about risk, they should do the same from statements that are explicitly about the return itself — if anything, the effect should be even stronger when using this measure. Conversely, if a different channel specifically related to risk-related information is at play, the analysis will be a placebo with no effect detected.

Table IA.17 presents the results of repeating the paper's main flow-detail regressions, but where the amount of detail in fund letters is measured from forward-looking performance- and return-related statements. The estimated coefficients in Table IA.17 exhibit no significant relation between the amount of detail conveyed and fund flows. The absence of such an effect suggests that detailed textual communication about performance or returns (explicitly) does not act to reduce investors' perceived risks via a mechanical reduction in perceived uncertainty. It is thus even less likely that communication specifically about risk will have such an effect.

Figure IA.4: Screening for Sentences that Discuss Performance or Returns

Statements about performance or returns are defined as valid English sentences that are matched by both forward-looking and performance or return-related patterns. The percentage figures denote the fraction of all sentences in the fund letter corpus that are matched by each type.

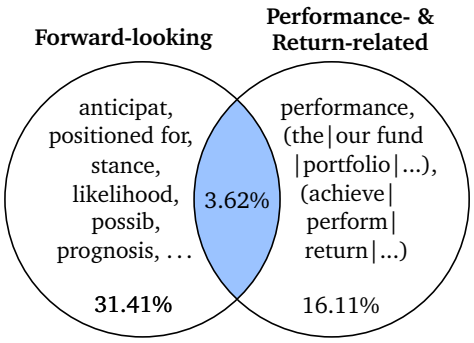


Table IA.17: Placebo Test for the Amount of Detail Communicated about Future Performance and Returns on S&P 500 Index Fund Flows

The main covariate measures the fraction of the letter written by fund i at time t about performance & returns in a forward-looking manner. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only. Each flow variable is the next month's flow, in percentage points of TNA.

Dependent Variables:	Net Flow	Inflow	Outflow
	(1)	(2)	(3)
Detail about Performance & Returns$_{i,t}$	0.0003	0.0079	0.0020
	(0.0080)	(0.0164)	(0.0037)
Fund Controls$_{i,t}$	✓	✓	✓
Year-month FEs	✓	✓	✓
Fund FEs	✓	✓	✓
N	2,238	2,238	2,238
R^2	0.37	0.74	0.83

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.4 Learning About the Return: Predicting the Return

Table IA.18: Placebo Test for Predicting the S&P 500 Return Using Timeseries Indices of Risk Detail and Risk Level

The dependent variables (in percentage points) are the return of the S&P 500 index from the end of month t to the end of month $t+h$, for various horizons of h. The independent variables are the equally-weighted across funds and standardized within fund number of words devoted to discussing risk, and our standard measure of the level of risk implied by the sentiment of that communication. Each independent variable is calculated as the cross-sectional mean over individual fund i variables, $\frac{1}{N_t}\sum_i z_{i,t}$, and these individual fund variables $z_{i,t}$ are pre-standardized to focus purely on within-fund variation, $z_{i,t} = (x_{i,t} - \overline{x_i})/\sigma(x_i)$. The sample of funds used to construct the independent variables consists of S&P 500 index funds only.

Dependent Variables:	S&P 500 Return$_{t\to t+1}$		S&P 500 Return$_{t\to t+3}$		S&P 500 Return$_{t\to t+5}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Detail$_t$	0.3937		1.105		1.166	
	(0.6247)		(1.416)		(1.878)	
Risk Level$_t$		-0.4570		-0.1984		-1.335
		(0.7359)		(1.269)		(2.638)
N	187	187	187	187	187	187
R^2	0.001	0.003	0.003	0.0001	0.002	0.004

Newey-West standard errors (in parentheses) use automatically selected lags.

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.5 Learning About Manager Skill

Table IA.19: Placebo Test for Predicting the Tracking Error

Consistent with Chevalier and Ellison, 1997; Grinold and Kahn, 1999; Cremers and Petajisto, 2009, the tracking error is defined as the standard deviation of the difference between monthly fund returns and the S&P 500 index returns, from the end of the current month t over some future horizon of h months:

$$\text{Tracking Error}_{i,t\to t+h} = \text{StdDev}\Big\{r^{Fund}_{i,t+k} - r^{S\&P\,500}_{t+k} \;\Big|\; 1 \le k \le h\Big\}. \tag{32}$$

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variables:	Tracking Error$_{i,t\to t+h}$			
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.00003	-0.00007*	0.00005	0.0001
	(0.00003)	(0.00004)	(0.00006)	(0.00006)
Horizon h (months)	6	12	24	36
Fund Controls$_{i,t}$	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓
N	1,153	1,147	959	895
R^2	0.83	0.75	0.60	0.60

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.6 Being Educated by Information Provision

I now assess whether the communication related to risk actually educates investors rather than simply reassuring them. While both channels involve information provision, they have distinct implications.

First, I note it is likely that investors in S&P 500 index funds already possess a relatively high level of financial literacy. Bailey, Kumar, and Ng (2011) find that unsophisticated investors exhibiting "strong behavioral biases [...] tend to avoid" index mutual funds altogether. Nonetheless, I directly consider this potential explanation.

To conduct this test, I employ state-level financial literacy scores that have been computed by Lusardi, Bumcrot, and Lin (2013) using geographically-targeted surveys. By matching fund letter readers' locations to geographic states, I am able to aggregate these state-level scores to fund letter readership measures. Next I assess how the strength of the main flow-detail regressions varies with the financial literacy of fund letter readers. Panel regression results are displayed in Table IA.20; these incorporate an interaction term for below-median levels of financial literacy among fund letter readerships.

If an educational mechanism is at play, the coefficients on the interaction term in columns (1) and (2) should be positive and significantly different from zero; however, they are not significant. These results do not support an educational channel.

Table IA.20: Flow–Risk Detail Relationship Interacted With Letter Readers' Financial Literacy

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The indicator captures a fund letter readership with a below-median level of financial literacy; a baseline effect is estimated in addition to the interaction shown in the table. Financial literacy is measured at a state level by Lusardi, Bumcrot, and Lin (2013), and then aggregated to a fund letter readership level. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fees & (log) size, and for the overall fund family's (log) age and (log) size. *Market controls* (not shown) are for the changes in the VIX and in the subjective aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)) from t to $t+1$. The sample consists of S&P 500 index funds only.

Dependent Variables:	Net Flow	Inflow	Outflow
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0126*	0.0133	-0.0067*
	(0.0075)	(0.0116)	(0.0039)
Risk Detail$_{i,t}$	0.0062	0.0104	0.0054
$\times$ $\mathbb{1}\{\text{Low Financial Literacy}\}_{i,t}$	(0.0060)	(0.0080)	(0.0036)
Fund Controls$_{i,t}$	✓	✓	✓
Market Controls$_t$	✓	✓	✓
Fund FEs	✓	✓	✓
N	1,755	1,755	1,755
R^2	0.27	0.64	0.78

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.7 Are Letters Conveying Opportunities to Time the Market?

Table IA.21: Robustness to Excluding Any Discussion of Opportunities

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The level of risk conveyed, Risk Level$_{i,t}$, is measured based on the net sentiment of the text discussing risk, and is defined by Eqn. (3). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. *Market controls* (not shown) are for the changes in the VIX and in the subjective aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)) from t to $t+1$. The sample consists of S&P 500 index funds only, and only those letters that do not discuss an opportunity.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)			
	(1)	(2)	(3)	(4)
Risk Detail$_{i,t}$	0.0106**	0.0242**	0.0245**	0.0333**
	(0.0052)	(0.0106)	(0.0105)	(0.0130)
Risk Level$_{i,t}$	0.0153	0.0095	0.0104	-0.0019
	(0.0848)	(0.0689)	(0.0690)	(0.0772)
Fund Controls$_{i,t}$	✓	✓	✓	✓
Market Controls$_t$			✓	
Year-month FEs	✓			✓
Fund FEs		✓	✓	✓
N	1,408	1,408	1,408	1,408
R^2	0.17	0.32	0.32	0.42

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.8 Does More Communication Reduce Perceived Ambiguity?

Measuring investors' perceived ambiguity about the payoff of the S&P 500 market portfolio is not a simple task, as it requires a measure that is independent of perceived risk and ambiguity aversion (i.e., the strength of any potential preference against ambiguity). Brenner and Izhakian (2018) propose one such measure of the perceived level of ambiguity, which they base on the expected volatility of probabilities across the relevant outcomes:

$$\mho^2 = \int \mathbb{E}[\varphi(r)]\,\mathbb{V}\text{ar}[\varphi(r)]\,dr, \tag{33}$$

where $\varphi(\cdot)$ is a probability density function and r is a rate of return. As Brenner and Izhakian (2018, pp. 504) explain, "the intuition of $\mho^2$ is that, as the degree of risk can be measured by the volatility of returns, so too can the degree of ambiguity be measured by the volatility of the probabilities of returns."[20]

Brenner and Izhakian (2018, pp. 510-512) show how to estimate a monthly timeseries of the perceived ambiguity of the S&P 500 portfolio using high-frequency realized returns. In this appendix, I employ their measure to test the role played by ambiguity perceptions in investors' response to communication by fund managers.

Table IA.22 repeats the paper's baseline flow-versus-risk detail panel regressions, now including interactions with the level of perceived ambiguity, in aggregate. The effect of increased communication about risk on flows remains positive and significant, and is now somewhat attenuated by an increase in the level of perceived ambiguity: when ambiguity is perceived to be higher in the month prior to the arrival of the flow, the magnitude of the inflow is reduced. The coefficient on this interaction is not significant.

This result is not consistent with increased communication acting to reduce the perceived level of ambiguity. If that were the case, one would expect communication to have a greater effect when investors need it the most – when ambiguity is the highest (i.e., a positive and significant interaction).

[20] As a theoretical foundation, Brenner and Izhakian (2018) show that $\mho^2$ enters into the uncertainty premium of the risky asset if the investor makes her decisions under Expected Utility with Uncertain Probabilities.

Table IA.22: Flow–Risk Detail Relationship Interacted With the Perceived Ambiguity of the S&P 500 Return

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The indicator variable $\mathbb{1}\{\text{High Ambiguity}\}_t$ is 1 when the aggregate ambiguity perception of the market is above the median, and zero otherwise; a baseline effect is estimated in addition to the interaction shown in the table. The variable Ambiguity$_t$ is rank-standardized, and thus runs from 0 to 1; a baseline effect is estimated in addition to the interaction shown in the table. The level of perceived ambiguity is Brenner and Izhakian's (2018) $\mho^2$ measure, as defined in Eqn. (33). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. *Market controls* (not shown) are for the changes in the VIX and in the subjective aggregate expected returns (proxied by the AAII survey employed by Greenwood and Shleifer (2014)) from t to $t+1$. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0134**	0.0214**	0.0171**
	(0.0065)	(0.0104)	(0.0084)
Risk Detail$_{i,t}$ × Ambiguity$_t$		-0.0160	
		(0.0107)	
Risk Detail$_{i,t}$ × $\mathbb{1}\{\text{High Ambiguity}\}_t$			-0.0070
			(0.0059)
Fund Controls$_{i,t}$	✓	✓	✓
Market Controls$_t$	✓	✓	✓
Fund FEs	✓	✓	✓
N	2,238	2,238	2,238
R^2	0.31	0.31	0.31

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.9 Shrouding: Textual Complexity

Table IA.23: Controlling for the Textual Complexity of Risk Discussions

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. In addition, I control first separately and then jointly for four alternative measures of textual complexity, which are computed on the risk-related portions of the letters: the Flesch Reading Ease (Flesch, 1948), the Flesch-Kincaid Grade Level (Kincaid, Fishburne Jr, Rogers, and Chissom, 1975), the FOG Index (Gunning, 1952), and the SMOG Index (McLaughlin, 1969). *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Detail$_{i,t}$	0.0299***	0.0298***	0.0282***	0.0280***	0.0281***	0.0258***
	(0.0104)	(0.0105)	(0.0101)	(0.0105)	(0.0105)	(0.0099)
Flesch Reading Ease$_{i,t}$		-0.0031				0.0234*
		(0.0062)				(0.0141)
Flesch-Kincaid Grade Level$_{i,t}$			0.0500*			0.1036
			(0.0260)			(0.0797)
FOG Index$_{i,t}$				0.0413*		0.0035
				(0.0236)		(0.0958)
SMOG Index$_{i,t}$					0.0539	0.0457
					(0.0349)	(0.1370)
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓	✓
N	1,579	1,579	1,579	1,579	1,579	1,579
R^2	0.41	0.41	0.41	0.41	0.41	0.41

Clustered (Fund & Year-month) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.10 Marketing: Attracting New Investors

This appendix tests whether new investors are attracted by voluntary transparency about risk addressed to existing investors (in fund letters).

I introduce a novel measure of the number of new investors in a fund during the month t in which a fund letter is filed, and during the subsequent month $t+1$ (which is the same period over which I compute fund flows in this paper's main analyses). A new investor is defined as an investor who has acquired a prospectus for the fund during this period, and has also *not* acquired a prospectus for the same fund during some past period beginning in month $t-k$ and ending in month $t-1$; i.e. over a k month lookback window. Similarly to Grice and Gueciouer (2023), a prospectus acquisition is defined as a download from the SEC's EDGAR website, and an investor is identified by her IP address. Grice and Gueciouer (2023) discuss that EDGAR is a widely-used source of prospectus information for investors (and is also indexed by search engines) and that this sample of investors are representative of the broader US population.

The test is to compare whether more communication about risks attracts any new investors above a baseline average. I implement this test by predicting the number of new investors using Poisson regressions with fixed effects (Cohn, Liu, and Wardlaw, 2022). Fund and year-month fixed effects control for fund-level and time-specific averages, and I additionally measure the mean monthly new investor count over the lookback window and include this variable as an explicit control. The specifications are completed with fund-level controls that are identical to those in the main paper's baseline (OLS) panel regressions.

Table IA.24 presents the results of such Poisson panel regressions, varying the lookback window k across specifications. As might be expected, the historical rate of arrival of new investors is a positive and (mostly) significant predictor of the number of new investors concurrent with the dissemination of a fund letter. However, the amount of detail communicated about risk is not: coefficients in the first row are not significantly different from zero. Moreover, the negative sign is the opposite to that which we would expect, if more communication about risk attracts additional investors to the fund.

These results strongly suggest that the effect of risk detail communicated acts on the existing base of investor clients, rather than attracting new ones.

Table IA.24: Risk Detail Does Not Predict New Investor Counts

This table shows the estimates of Poisson panel regressions. The number of new investors in fund i over months t and $t+1$, measured using prospectus acquisition decisions on the SEC EDGAR website, is the common dependent variable of interest. The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. In addition, the historical monthly mean number of new investors is included as a control. Existing and new investors are determined based on prospectus acquisition decisions made over the trailing k month window prior to the filing of each fund letter at time t. *Fund controls* (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	New Investors in Fund i During $\{t, t+1\}$				
	(1)	(2)	(3)	(4)	(5)
Risk Detail$_{i,t}$	-0.0032	-0.0031	-0.0036	-0.0049	-0.0053
	(0.0029)	(0.0034)	(0.0035)	(0.0036)	(0.0035)
Historical Mean of New Investors$_{i,t}$	0.0161***	0.0112***	0.0115***	0.0053	0.0049
	(0.0032)	(0.0031)	(0.0039)	(0.0039)	(0.0037)
Lookback k (months)	12	24	36	48	60
Fund Controls$_{i,t}$	✓	✓	✓	✓	✓
Year-month FEs	✓	✓	✓	✓	✓
Fund FEs	✓	✓	✓	✓	✓
N	1,632	1,550	1,477	1,326	1,164

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.11 Marketing: Potential Omitted Variable

Table IA.25: Controlling for Marketing Intensity Using a Fee-Based Measure

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. Actual 12b-1 Fee$_{i,t}$ is the fee recorded in the CRSP Mutual Fund Database. Effective 12b-1 Fee$_{i,t}$ is an alternative measure: the sum of the actual 12b-1 fee and the annualized front load, following Roussanov, Ruan, and Wei (2021). *Fund controls* (not shown) are for the fund's prior month returns (and square), fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0156**	0.0159**	0.0157**
	(0.0068)	(0.0069)	(0.0068)
Actual 12b-1 Fee$_{i,t}$ (bps)		0.0307	
		(0.0198)	
Effective 12b-1 Fee$_{i,t}$ (bps)			-0.0123
			(0.0275)
Fund Controls$_{i,t}$	✓	✓	✓
Fund FEs	✓	✓	✓
Year-month FEs	✓	✓	✓
N	2,238	2,238	2,238
R^2	0.37	0.37	0.37

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA.26: Controlling for Marketing Intensity Using a Labor-Based Measure

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The regressions in columns (2) and (3) include additional control variables that are constructed by closely following Chen, Jiang, and Xiaolan (2022) and similarly using Form ADV filings: MKT is the share of the fund company's employees engaged in marketing- and sales-related functions, and EMP is the total number employees disclosed on Form ADV. *Fund controls* (not shown) are for the fund's prior month returns (and square), fees & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0156**	0.0150**	0.0150**
	(0.0068)	(0.0068)	(0.0068)
MKT$_{i,t}$		0.9924**	1.027*
		(0.4548)	(0.5848)
log(1+EMP$_{i,t}$)			-0.0071
			(0.0569)
Fund Controls$_{i,t}$	✓	✓	✓
Year-month FEs	✓	✓	✓
Fund FEs	✓	✓	✓
N	2,238	2,238	2,238
R^2	0.37	0.37	0.37

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H.12 Pandering

Table IA.27: Flow–Risk Detail Relationship Interacted With the Distance of the Signal from Investors' Priors

The main covariate Risk Detail$_{i,t}$ measures the fraction of the letter (%) written by fund i at time t discussing risk. The specifications in columns 2–3 furthermore incorporate the distance between investors' prior perceived risk and the signal conveyed by the fund letter:

$$\text{Distance from Prior}_{i,t} = |\text{Letter Signal}_{i,t} - \text{Readership Prior}_{i,t}|, \tag{34}$$

where the letter's signal about risk is measured based on the net sentiment of the text discussing risk (Eqn. (3)), and the prior perceived level of risk is measured based on local Google searches (Eqn. (29)). Controls (not shown) are for the fund's prior month return, square of this return, total fee & (log) size, and for the overall fund family's (log) age and (log) size. The sample consists of S&P 500 index funds only.

Dependent Variable:	Net Flow$_{i,t\to t+1}$ (%)		
	(1)	(2)	(3)
Risk Detail$_{i,t}$	0.0179**	0.0311***	0.0248**
	(0.0081)	(0.0118)	(0.0115)
Distance from Prior$_{i,t}$		0.1510	0.0498
		(0.0934)	(0.1267)
Risk Detail$_{i,t}$ × Distance from Prior$_{i,t}$			0.0062
			(0.0045)
Fund Controls$_{i,t}$	✓	✓	✓
Year-month FEs	✓	✓	✓
Fund FEs	✓	✓	✓
N	1,755	1,219	1,219
R^2	0.34	0.37	0.37

Clustered (Fund & Year-month) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

I Validation of EDGAR-Based Fund Letter Readership Measure

This section presents evidence that the individuals who downloaded annual & semi-annual reports from the SEC EDGAR system are broadly representative of the overall US population, based on their observable geographic dispersion. The locations of these readers are used to measure their characteristics, such as their anxiety attitudes, by matching fund reader locations with geographic local anxiety attitudes data.

Figure IA.5(a) charts the state-level counts of annual and semi-annual report downloads from the SEC EDGAR system. Readers of funds' annual & semi-annual reports – which contain the fund letters used in this study – are located throughout the United States, rather than being concentrated in states that are home to financial institutions and professional investors, such as New York and Massachusetts (Kim, Wang, and Wang, 2022).

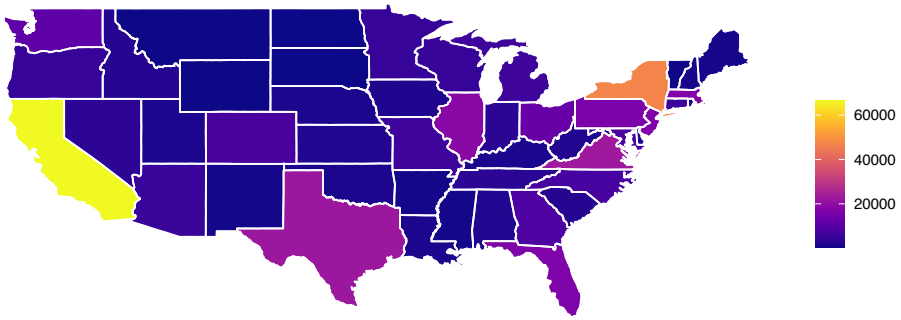
In fact, the correlation between state-level reader counts and the total state populations is 0.90 over the full sample used in this study, which runs from 2006 to the end of the SEC EDGAR log files in June 2017. At a more fine-grained unit of analysis, the correlation between county-level reader counts and the total county populations is also high, at 0.72. Figure IA.5(b) visualizes how county-level correlations between unique readers and the total population vary from state to state. All such correlations are positive, and for the most part uniformly high.

It is worth highlighting that similarly high downloader-to-population correlations were found by Grice and Gueciouer (2023), who used a related (but separate) sample of fund *prospectus* readerships from SEC EDGAR, and found that model-derived competition measures based on this prospectus readership dataset are predictive of mutual fund fee dispersion. Their study's findings validate SEC EDGAR as a source of information on investor behavior.

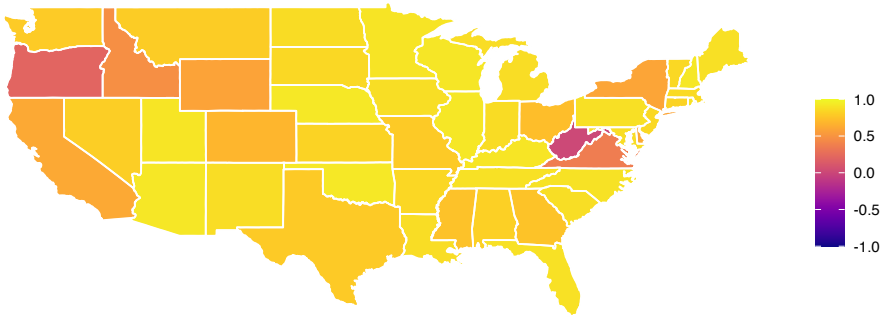
Figure IA.5: Representativeness of Readership Geographic Distributions

Both charts visualize statistics derived from unique EDGAR user counts over the sample period 2006-2017. Users are geolocated based on their IP addresses. Sub-figure (a) displays the number of unique EDGAR annual & semi-annual report downloaders per state; lighter states have more unique readers, colored according to the legend. These reader counts are highly correlated with total population counts. Sub-figure (b) displays the correlations of unique reader counts with county population counts, for each state; lighter states exhibit higher correlations, colored according to the legend.

(a) State-level unique reader counts.



(b) Within-state reader-to-population correlations.



J The Geography of Anxiety

This appendix charts the geographic variation in Google search-based measures of anxiety (Figure IA.6). These geographic measures are used in the main paper to construct fund letter readership-level measures of anxiety, which is an important component of risk aversion.

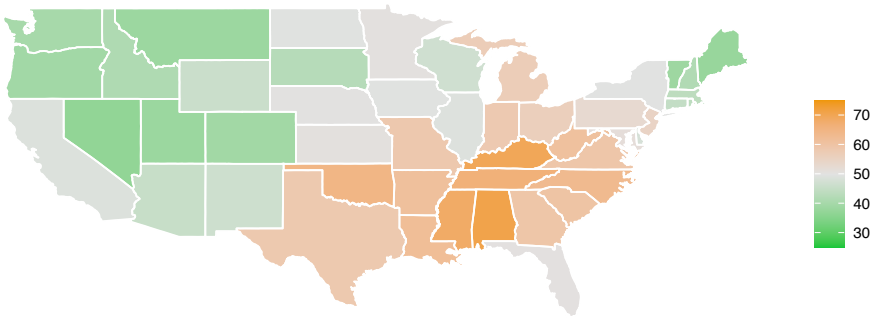
Recall that the Google search volume index (SVI) panel consists of state s and year-month t search volume indices for a particular topic k: $\text{SVI}_{s,t}^{k}$. To produce visualizations of search activity for a particular topic k, I first compute the rank-percentiles for each state s within a given month t, and then take the mean of these rank-percentiles over the sample period. These mean rank-percentiles are then displayed on a map of the continental United States, in order to visualize time-invariant geographic dispersion in Google-search based measures of anxiety and stock market risk perceptions (with the topic k defined accordingly).

Figure IA.6 charts geographic dispersion in the population's anxiety attitudes. Panel (a) measures anxiety attitudes by the SVI for Google's "Psychological Stress" topic. Panel (b) measures anxiety attitudes by the SVI for Google's "Worry" topic. Finally, panel (c) shows the average of both topic SVIs. Figure IA.6 reveals that anxiety is not persistently high in any one geographic region: the East Coast, the South and the Midwest all contain a mixture of high-anxiety and low-anxiety investors. This suggests that anxiety attitudes are not driven by persistent demographic attributes, such as the level of urbanization or cultural values.

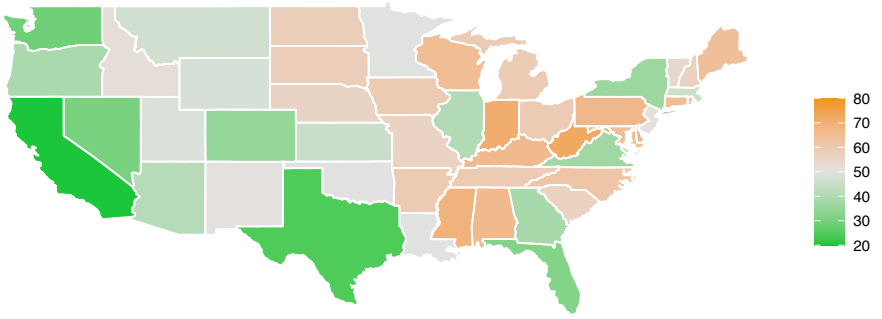
Figure IA.6: Geography of Anxiety Attitudes Revealed Through Search Interest

Means of cross-sectional rank-percentiles of state-level Google Search Volume Indices, over the period 2006 to 2017, for various search topics. Sub-figure (a) shows the distribution of the "Psychological Stress" topic. Sub-figure (b) shows the distribution of the "Worry" topic. Sub-figure (c) shows the distribution of the mean of both topics. Orange states denote a cross-sectionally higher level of anxiety; green states denote a lower level of anxiety. The legends are for mean cross-sectional rank-percentiles.

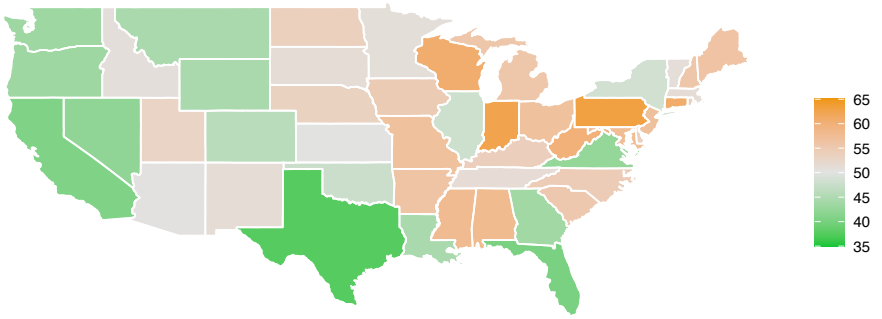
(a) "Psychological Stress" topic.



(b) "Worry" topic.



(c) Mean of both topics.



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