

Green Investing, Information Asymmetry, and Category Learning

Shasha Li* Biao Yang†

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ABSTRACT

We investigate how the attention allocation of green-motivated investors changes information asymmetry in financial markets and thus affects firms' financing costs. To guide our empirical analysis, we propose a model where an investor with green taste endogenously allocates attention to market or firm-specific shocks. We find that more green-motivated investors tend to give more attention to green firm-level information instead of market-level information. Thus higher green taste leads to less category learning behavior and reduces the information asymmetry. Furthermore, it suggests that higher green taste results in lower leverage and lower cost of capital of green firms.

Keywords: Climate Finance, Information Asymmetry, Category Learning

JEL classification: D82, G11.

*Halle Institute for Economic Research (IWH) and University of Magdeburg, shasha.li@iwh-halle.de.

†Bocconi University, biao.yang@phd.unibocconi.it.

1. Introduction

Information processing is costly, and human attention is a limited cognitive resource. As such, rational investor needs to optimally allocate limited attention to various sources of information to resolve uncertainty optimally. The attention allocation will then affect the information asymmetry in the financial market. In addition, in recent years sustainable investments using environmental, social, and government (ESG) investing strategies, especially green investments, has been growing dynamically¹. Despite the natural link between investors’ attention and a firm’s information asymmetry, few studies investigated how the relationship between these two terms interacts with the rising green preference.

In this paper, we aim to answer how investors’ taste for green investing and limited attention affects information asymmetry of firms with different “greenness”. Specifically, we investigate the impact of greater public attention on environmental issues, measured by the Google Search Volume (GSV) on the keyword “Climate Change”, on green firms’ information asymmetry.

To guide the empirical analysis, we propose a model based on Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) and incorporate green preference into the framework. A representative investor chooses to invest into a group of risky assets where she derives non-pecuniary benefit from holding green assets, i.e., a “green taste” following Pástor, Stambaugh, and Taylor (2020); Pedersen, Fitzgibbons, and Pomorski (2020).² Investors have to make two kinds of decisions, asset allocation, and attention allocation. Because the investor faces attention constraints, she has to allocate attention to firm-level or market-level information optimally.

The model predicts that higher green taste induces investors to learn more about the green firm. Specifically, the investor puts more attention on learning the shock that is specific to the green asset. This is not surprising given that investors now care more about holding green, and reducing the uncertainty related to the green asset is more rewarding. As a result, the information asymmetry of green firms decreases. Given that the total amount of attention is limited, less

¹According to the 2020 Report on US Sustainable and Impact Investing Trends released by the US SIF foundation, there’s a rising popularity of sustainable investments among institutional and private investors and the total US-domiciled assets under management using ESG investing criteria grew from \$12.0 trillion in the beginning of 2018 to \$17.1 trillion in the beginning of 2020.

²We consider green taste of a representative investor as an analog of GSV in the data. The rationale is, a higher GSV indicates more investors become green-motivated (Pedersen et al., 2020). In a model with a representative investor, this is equivalent to an increase in the green taste.

attention is allocated to the brown firms, leading to a higher information asymmetry of brown firms. In addition, increased learning on green firms leads to a lower price co-movement between green stock and the market, which explains the reduction of category learning (Peng and Xiong, 2006). Finally, the model also implies a reduction in the cost of equity capital for green firms when climate attention is greater.

To test the predictions from the model, we follow Bharath, Pasquariello, and Wu (2009) to extract the first principal component of seven information asymmetry measures to get our major measure on information asymmetry. These seven measures are based on component of bid-ask spread due to adverse selection (Roll, 1984; George, Kaul, and Nimalendran, 1991); return momentum/reversal Llorente, Michaely, Saar, and Wang (2002); Pástor and Stambaugh (2003); illiquidity Amihud, Mendelson, and Lauterbach (1997); Amihud (2002); and probability of informed trading (Easley, Kiefer, O'hara, and Paperman, 1996). To define the greenness of firms, we apply the environmental pillar score (ENSCORE) from the Refinitive Asset4 ESG database. We calculate the correlation between individual stock return and the market return as a measure of firm-level category learning (Huang, Huang, and Lin, 2019). Finally, we retrieve the Google Search Volume (GSV) of keyword *Climate Change* as the measure of green taste. Our sample covers more than 2,500 U.S. firms that span from 2004 (when GSV is first available) to 2020 on a quarterly frequency.

Consistent with the model predictions, our main empirical results show that an increase in the growth rate of GSV on climate change decreases green firms' information asymmetry relative to the brown ones. To better estimate the causal effects, we use temperature as the instrumental variable for growth rate of GSV on the keyword *climate change*. We find a one-standard-deviation increase in the GSV growth rate decrease 27.8% of information asymmetry for green firms compared to brown ones. In addition, we find that the same increase in GSV decreases category learning of green firms by 5.6% compared to brown firms.

As documented in the previous literature, lower category learning benefits both the stock market and the real economy. For example, Durnev, Morck, Yeung, and Zarowin (2003) shows that stock prices are less informative in industries with more synchronous returns (i.e., higher category learning). Wurgler (2000) shows that capital allocation is less efficient in countries with higher stock return comovement. An example that a high degree of category learning can hurt effective information spread is the Internet Bubble during the early 2000. Firms earned significant positive

returns just by changing their name to dot.com (Cooper, Dimitrov, and Rau, 2001). In other words, investors treat a special group of firms as a single category and completely ignore information about the firm’s fundamentals. Our results indicate that green taste affects attention allocation and thus affects information asymmetry.

Why does information asymmetry matter? A lower information asymmetry means less uncertainty about the firm’s fundamental and more transparent future cash flow from the investor’s perspective. Less uncertainty benefits investors, given that they are usually risk-averse. From the standpoint of firm managers, a lower information asymmetry means a lower cost of equity since the market penalizes stocks with less transparent fundamentals, i.e., equity is information-sensitive. Thus information asymmetry will affect firms’ capital structure decisions, an idea first illustrated by the pecking order theory (Myers, 1984). Consistent with Easley and O’hara (2004), we find that information asymmetry significantly affects the cost of equity capital. A high-minus-low portfolio based on firms sorted by our information asymmetry measure delivers a positive abnormal return of 1.06% after controlling for CAPM. In addition, we test the pecking order theory by regressing firms’ leverage on information asymmetry and find significant positive effects. The fact that our result replicates that from previous literature (Bharath et al., 2009) validates our measure of information asymmetry. The informational channel of pecking order theory also implies that when the public’s green taste is higher (greater GSV on ”climate change”), firms with high ENSCORE is less likely to choose debt as a financing source due to lower information asymmetry.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents our model. Sections 4 and 5 are data construction and empirical analysis. The last section concludes.

2. Literature Review

First, this paper contributes to the literature on the consequences of investors’ ESG preferences in financial markets (Pedersen et al., 2020; Pástor et al., 2020; Goldstein, Kopytov, Shen, and Xiang, 2021). A growing body of research has discussed the impact of ESG on firms’ financial performance. Previous studies show that ESG could raise (Hong and Kacperczyk, 2009; Baker, Bergstresser, Serafeim, and Wurgler, 2018) or lower the implied return (Edmans, 2011). Pedersen et al. (2020)

model ESG in a way that ESG affects both the investor’s preference and firm fundamentals, bridging the gap between the opposite findings. In this paper, investors gain non-pecuniary utility from holding green assets but face endogenous information acquisition with attention constraint. This interaction between taste and attention allocation sheds light on how public attention on climate change affects firms’ information asymmetry and category learning.

Second, our paper is related to the literature on endogenous information acquisition and investor’s limited attention. The rational inattention model by Sims (2003) introduced information processing capacity into standard control problems in the field of macroeconomics. Van Nieuwerburgh and Veldkamp (2010) build a framework to solve jointly for investment and information choices. They find that allowing endogenous information acquisition leads an investor to hold concentrated portfolios. Kacperczyk et al. (2016) investigate how mutual fund managers change attention allocation with respect to the business cycle, which predicts patterns of portfolio investments and returns. Other papers in this field include Peng (2005), Peng and Xiong (2006), and Peress (2010). Our model differs from previous studies in two aspects. First, we introduce a taste parameter in the investor’s portfolio choice problem and examine how information acquisition changes with the taste. Second, we innovate by introducing a convex cost of information processing, such that the more attention allocated, the more difficult it is to reduce noise further. This approach is not only more intuitive but also generates interior optimal attention allocation. Peng and Xiong (2006) find that investors exhibit category learning behavior with limited attention. Our result shows that this phenomenon is lessened with a higher taste.

Third, this paper contributes to the relationship between asymmetric information and capital structure by emphasizing the attention allocation channel. There are several approaches to estimate the information disparity between outside investors and firm manager (or insider traders), including the bid-ask spread component due to adverse selection (George et al., 1991), return reversal or momentum (Llorente et al., 2002; Pástor and Stambaugh, 2003), illiquidity (Amihud et al., 1997; Amihud, 2002), and probability of informed trading (Easley et al., 1996; Easley and O’hara, 2004). Bharath et al. (2009) take the first principal component of all these measures and find information asymmetry indeed plays a significant role in determining the capital structure as implied by pecking order theory. We contribute to the literature by providing a rigorous examination of the relationship between investor attention and information asymmetry with empirical and theoretical evidence. To

our knowledge, this issue remains largely unexplored (Gao, Wang, Wang, and Liu, 2018; Ding and Hou, 2015; Sankaraguruswamy, Shen, and Yamada, 2013).

3. Model: Green Investing and Attention Allocation

To show how green taste affects attention allocation and information asymmetry, we present a theoretical framework based on Kacperczyk et al. (2016) and Van Nieuwerburgh and Veldkamp (2010). The model has three periods $t = 0, 1, 2$. At $t = 0$, a representative investor chooses to allocate her attention across different assets. Allocated attention reduces the variance (or, in other words, improves the precision) of the asset fundamentals. At $t = 1$, the investor chooses the portfolio of risky and riskless assets. At $t = 2$, asset payoffs are realized. The decision problem of the investor is a two-step optimization. In the first step (at $t = 1$), she chooses the portfolio to maximize expected utility conditional on her information set. In the second step (at $t = 0$), she optimally allocates attention across assets to maximize the unconditional expected utility.

3.1. Setup

Assets There are one riskless and three risky assets. The riskless asset (bond) is normalized to have unit return and infinity supply. Risky assets (stocks) have net positive supplies, which are normalized to one. Stock $i \in 1, 2, 3$ has a random payoff f_i with the following factor structure:

$$f_1 = \mu_1 + \tilde{m} + \tilde{z}_1$$

$$f_2 = \mu_2 + \tilde{m} + \tilde{z}_2$$

$$f_3 = \mu_3 + \tilde{m}$$

where \tilde{m} is an aggregate shock to all stocks. \tilde{z}_i is firm-specific shock to stock i . We interpret asset 3 as a composite asset (the market) and asset 1 (2) as the green (brown) stock. These shocks are independent of each other and follow normal distributions with zero means and variance-covariance

matrix

$$\Sigma = \begin{bmatrix} \frac{1}{\tau_{z,1}} & 0 & 0 \\ 0 & \frac{1}{\tau_{z,2}} & 0 \\ 0 & 0 & \frac{1}{\tau_m} \end{bmatrix},$$

where τ_m , $\tau_{z,1}$, and $\tau_{z,2}$ are the inverse of variances of the shocks \tilde{m} , \tilde{z}_1 , and \tilde{z}_2 , respectively. These parameters denote the precision of investor's prior to these shocks. We can write the payoff vector in the following matrix form: $f = \mu + \Gamma \tilde{f}$, where $f = [f_1, f_2, f_3]'$, $\mu = [\mu_1, \mu_2, \mu_3]'$, $\tilde{f} = [\tilde{z}_1, \tilde{z}_2, \tilde{m}]'$,

$$\text{and } \Gamma = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}.$$

Preference Following Kacperczyk et al. (2016) we assume the investor has a mean-variance utility over the final wealth at $t = 2$. In addition, following the literature on green finance (Pástor et al., 2020; Pedersen et al., 2020) we assume investors derive non-pecuniary utility from holding green stock.

Let W_0 and W as the initial and final wealth. We use E_0 and V_0 to denote the mean and variance conditional on the prior beliefs, and E_1 and V_1 to denote the mean and variance conditional on information obtained through attention allocation. Thus, at $t = 1$, the investor chooses the holding of stocks, X , to maximize the expected utility

$$U_1 = E_1[W] - \frac{\gamma}{2} V_1[W] + X'b$$

where γ is the risk aversion coefficient. The budget constraint is $W = W_0 + X'(f - p)$, where X and p are the 3×1 vector of stock holdings and prices. b is the 3×1 vector of non-pecuniary benefit from the stock holdings. For simplicity, we assume b has a positive number g at the first element and zeros otherwise. This number g measures the representative investor's "green taste".

At $t = 0$, the investor chooses attention allocations, κ , across stocks to maximize her unconditional expected utility, $E_0[U_1]$. The following part describes how learning affects the precision of fundamental shocks.

Learning The investor can attentively learn each stock, but the total amount of attention is limited (Peng and Xiong, 2006). Learning improves the precision of stock payoffs through a Bayesian way. Specifically, the investor receives signals of the fundamental shocks from learning,

$$\begin{aligned} s_m &= \tilde{m} + \varepsilon_m, \quad \varepsilon_m \sim N\left(0, \frac{1}{\rho(\kappa_m)}\right) \\ s_{z,1} &= \tilde{z}_1 + \varepsilon_{z,1}, \quad \varepsilon_{z,1} \sim N\left(0, \frac{1}{\rho(\kappa_{z,1})}\right) \\ s_{z,2} &= \tilde{z}_2 + \varepsilon_{z,2}, \quad \varepsilon_{z,2} \sim N\left(0, \frac{1}{\rho(\kappa_{z,2})}\right), \end{aligned}$$

where the signal noises ε_m , $\varepsilon_{z,1}$, and $\varepsilon_{z,2}$ are independent. The noisiness of signals depend on the attention κ_m , $\kappa_{z,1}$, and $\kappa_{z,2}$ that investor allocated to each shock. $\rho(\cdot)$ is the learning function, which determines how much precision improvement can be obtained for a given amount of attention. In general, $\rho(\cdot)$ is an increasing function, indicating that the more attention allocated to a shock, the more precise the signal becomes. Given the signal structure, the posterior mean and variance of the market shock will be

$$\hat{\mu}_m \equiv E[\tilde{m}|s_m] = \frac{\rho(\kappa_m) \cdot s_m}{\tau_m + \rho(\kappa_m)}, \quad \hat{\Sigma}_m \equiv \frac{1}{\tau_m + \rho(\kappa_m)}$$

The posterior means ($\hat{\mu}_{z,1}$ and $\hat{\mu}_{z,2}$) and variances ($\hat{\Sigma}_{z,1}$ and $\hat{\Sigma}_{z,2}$) of the two firm-specific shocks are similarly defined. We get $\hat{\mu} \equiv E_1(\tilde{f}) = [\hat{\mu}_{z,1}, \hat{\mu}_{z,2}, \hat{\mu}_m]'$ and $\hat{\Sigma} \equiv V_1(\tilde{f}) = \text{diag}\left([\hat{\Sigma}_{z,1}, \hat{\Sigma}_{z,2}, \hat{\Sigma}_m]\right)$, where diag is the function that converts a vector to a diagonal matrix. From the time-0 perspective, $\hat{\Sigma}$ is deterministic depending on the attention allocation; $\hat{\mu}$ is normally distributed with zero mean and variance-covariance matrix $V_0[\hat{\mu}] = \Sigma - \hat{\Sigma}$ according to the law of total variance.

The investor's learning capacity is subject to the attention constraint as follows

$$\kappa_m + \kappa_{z,1} + \kappa_{z,2} \leq K, \quad \kappa_m, \kappa_{z,1}, \kappa_{z,2} \geq 0 \quad (1)$$

where K is the exogenous total attention span of the investor. The non-negativity constraint ensures that the investor cannot reduce the prior precision of the shocks, i.e., she cannot “unlearn” what she already knows.

Clearly, the optimal allocation of attention depends on the functional form of $\rho(\cdot)$. Previous

studies usually assume either a linear learning strategy, where ρ is a linear function, or an entropy-based learning strategy, where ρ is an exponential function. In this paper, we assume that the learning function is concave. This approach is intuitive in the sense that the marginal return of learning should be decreasing. That is, more attention is needed to gain one additional unit of precision when the signal is already very precise. This setting is equivalent to introducing a convex learning cost, as in Peress (2010) and Goldstein and Yang (2015). Moreover, decreasing return is necessary to generate an interior solution where the investor allocates nonzero attention to each shock, which is more likely for real investors. Under linear or entropy-based learning function, increasing return induces the investor to allocate attention to only one shocks (Van Nieuwerburgh and Veldkamp, 2010).

To generate closed-form solutions, we assume a square root learning function $\rho(x) = \sqrt{x}$. The conclusion will hold for any increasing concave function.

3.2. *The equilibrium*

First we solve for the optimal portfolio allocation at $t = 1$ as follows:

$$\begin{aligned} \max_X \quad & E_1[W] - \frac{\gamma}{2} V_1[W] + X'b \\ \text{s.t.} \quad & W = W_0 + X'(f - p) \end{aligned}$$

The solution is given by

$$X = \frac{1}{\gamma} V_1(f)^{-1} (E_1(f) - p + b)$$

which is the standard solution in a Grossman-Stiglitz economy (Grossman and Stiglitz, 1980) taking into account the taste. In equilibrium, the market-clearing condition is $X = I$, where I is a 3×1 vector of ones. Thus the price is given by

$$p = E_1(f) + b - \gamma V_1(f) \cdot I \tag{2}$$

At $t = 0$, the investor chooses attention vector κ to maximize time-0 expected utility, taking price and green taste as endogenously given. Appendix A shows that the time-0 expected utility

can be written as a linear function on the posterior precision on the three factors

$$U_0 = W_0 + \frac{1}{2\gamma} \left[\sum_{i=1}^3 \hat{\Sigma}_{ii}^{-1} (\Sigma_{ii} + \theta_i^2) - 3 \right] \quad (3)$$

where $\theta = \begin{bmatrix} \mu_1 - p_1 + g - \mu_3 + p_3 \\ \mu_2 - p_2 - \mu + p_3 \\ \mu_3 - p_3 \end{bmatrix}$, which is the synthetic expected excess payoffs for the three

factors. The optimization problem is to maximize Equation (3) subject to the constraint in Equation (1). Given that the objective function is increasing and concave and the budget constraint is linear, the solution will equalize the marginal benefit of $\kappa_m, \kappa_{z,1}, \kappa_{z,2}$ while making the constraint binding.

Proposition 1. *There is one unique interior solution to the investor's attention allocation problem, where attention to the factor i ($i = 1$: market factor, $i = 2, 3$: firm-specific factor) equals*

$$\kappa_i = \frac{(\Sigma_{ii} + \theta_i^2)^2}{\sum_{j=1}^3 (\Sigma_{jj} + \theta_j^2)^2} K$$

From proposition 1, we find that the investor will allocate attention to the factors that she knows less (with higher prior variance). This is because learning has a decreasing return, so it is optimal to devote more attention with less prior knowledge. In addition, the investor will allocate more attention to factors with higher expected excess payoffs, which is intuitive since increasing the precision of highly profitable stock is more rewarding. At last, we find that when the investor has a higher green taste g , this increases the synthetic excess payoff of the specific factor of the green firm, which is θ_1 . As a result, she allocates more attention to that factor.

Corollary 1. *An increase in the green taste increases an investor's attention to the specific shock of the green firm, and decreases attention to the market shock and firm-specific shock of the brown firm.*

3.3. Information asymmetry, price co-movement, and cost of equity capital

Information asymmetry We measure the information asymmetry of a firm as the fraction of the investor's posterior variance divided by the prior variance on the firm's fundamentals $IA_i = \frac{V_1(f_i)}{V_0(f_i)}$

for $i = 1, 2, 3$. This value is bounded between zero and one. If it is close to one, it implies almost a zero learning about the firm and a high information asymmetry; if the fraction is close to zero, it means investor know the fundamental with very high precision, thus inducing a smaller discrepancy between the investor's information and the manager, who presumably knows exactly the fundamental value. Thus, if an investor process more information of a firm, her posterior about the fundamental will become more precise, and the firm experience less information asymmetry. In sum,

$$IA = \left[\frac{\frac{1}{\tau_m + \sqrt{\kappa_m}} + \frac{1}{\tau_{z,1} + \sqrt{\kappa_{z,1}}}}{\frac{1}{\tau_m} + \frac{1}{\tau_{z,1}}}, \frac{\frac{1}{\tau_m + \sqrt{\kappa_m}} + \frac{1}{\tau_{z,2} + \sqrt{\kappa_{z,2}}}}{\frac{1}{\tau_m} + \frac{1}{\tau_{z,2}}}, \frac{\tau_m}{\tau_m + \sqrt{\kappa_m}} \right]'$$

When there is an increase in the green taste, g , $\kappa_{z,1}$ increases, and κ_m and $\kappa_{z,2}$ decrease. This leads to a decrease in the information asymmetry of green firms.

Proposition 2. *An increase in the green taste decreases the green firm's information asymmetry and increases that of the brown firm and the market.*

Price co-movement According to the Equation (2), we can calculate the variance-covariance matrix of the price vector as

$$V_0(p) = V_0(E_1(f)) = \Gamma V_0(\hat{\mu}) \Gamma' = \Gamma (\Sigma - \hat{\Sigma}) \Gamma'$$

Substituting the expressions of these variables into the expression, we get the correlation between prices of green stock and the market

$$Corr(p_1, p_3) = \sqrt{\frac{\Sigma_{33} - \hat{\Sigma}_{33}}{\Sigma_{11} - \hat{\Sigma}_{11} + \Sigma_{33} - \hat{\Sigma}_{33}}} = \sqrt{\frac{\frac{1}{\tau_m} - \frac{1}{\tau_m + \sqrt{\kappa_m}}}{\frac{1}{\tau_m} - \frac{1}{\tau_m + \sqrt{\kappa_m}} + \frac{1}{\tau_{z,1}} - \frac{1}{\tau_{z,1} + \sqrt{\kappa_{z,1}}}}}$$

According to proposition 2. An increase in the green taste increases the denominator inside the square root, i.e., the green firm gains greater reduction in the variance, and decrease the numerator inside the square root, i.e., market gain less variance reduction. Thus an increase in green taste will reduce the price correlation between the green firm and the market. On the contrary, the correlation between the brown firm and the market increases. Intuitively, this is because investors learn more about the firm-specific shock of the green firm, so that its price reflects more information of that shock, and co-moves less with the market.

Cost of equity capital We define the cost of capital as the unconditional expected value of the payoff minus the price $E_0(f - p)$. Thus

$$CoC = E_0[f - E_1(f) - b + \gamma V_1(f) \cdot I] = -b + \gamma \Gamma \hat{\Sigma} \Gamma' \cdot I$$

The cost of capital of the green firm is given by

$$CoC_1 = -g + \gamma \left(\frac{3}{\tau_m + \sqrt{\kappa_m}} + \frac{1}{\tau_{z,1} + \sqrt{\kappa_{z,1}}} \right)$$

An increase in the green taste affects the cost of equity capital of green firm through two channels: a price channel and a variance channel. In the price channel, increased taste leads to higher demand for the stock, which increases price in equilibrium. Thus this channel serves to decrease the cost of capital. In terms of the variance channel, higher green taste shifts attention towards the green firm, making its fundamental less noisy. As a result, this increases the demand and reduces equilibrium price. In sum, the two channels both work to decrease the cost of capital of the green firm when green taste increases, consistent with the empirical result.

4. Data and empirical methods

Our main sample of empirical analysis consists of LA4CTYUS firms, U.S. firms included in Refinitiv Asset4 database, for which we could get ESG scores between 2004 to 2020. We exclude financial firms (SIC codes 6000-6999). We also remove the firms with the underlying stock price lower than 5 dollars to avoid the impact of penny stocks. The final sample consists of 2844 U.S. firms. We obtain the data of firm financials from COMPUSTAT North America Fundamentals Quarterly database.

4.1. Data Construction

Firm-level greenness indicator We use the environmental pillar score (Datastream code: ENSCORE) from the Refinitiv (formerly known as Thomson Reuters) Asset4 ESG universe. This database covers around 70% of the world cap with over 450 ESG metrics, of which 186 most comparable measures are summarized into ten category scores (e.g., emission, human rights, man-

agement, etc.) and three pillar scores (environmental, social, and governance). The information is mainly collected by Refinitiv from public information, i.e., firms’ annual reports, corporate social report (CRS), company websites, etc.³ The ENSCORE covers three major categories in terms of firms’ environmental responsibility: emission, innovation, and resource use. The score ranges from 0 to 100 and is updated annually. Firms with higher scores are more environmental-friendly. We collect all information of ENSCORE from Refinitiv Eikon, focusing on the U.S. universe from 2004 to 2020. Examples of green firms with high ENSCORE include Tesla and Amazon.

Green taste We collect the Google Search Volume (GSV) on the keyword *Climate Change* as a measure of the investor’s green preference. GSV measure is based on real-time search activities for the keywords on the Google search engine. It is scaled from 0 to 100. The key advantage of GSV is its flexibility in terms of both frequencies (from 8 minutes to one month) and granularity (from city-to country-level). It’s thus becoming a popular measure of investors’ attention in the literature (Da, Engelberg, and Gao, 2011; Ding and Hou, 2015; Bank, Larch, and Peter, 2011; Aouadi, Arouri, and Teulon, 2013; Choi, Gao, and Jiang, 2020). In our context, differently we interpret the GSV index as the measure of investors’ green preference. We use the GSV in the United States as we focus on American firms. Furthermore, we take *Climate Change* as the green keyword according to Djerf-Pierre (2012) and construct the green taste measure with the GSV on this keyword. Djerf-Pierre (2012) found that the environmental issue category that has the greatest significant positive correlation with other environmental issues is *Climate Change* and *Global Warming*. Thus we also use *Global Warming* for the robustness test. In precise, we use the quarterly growth rate of GSV on *Climate Change* as the measure of green taste. Figure 1 plots monthly aggregate Google Trends search frequency for both “climate change” and “global warming” starting from 2014 January.

³See https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/esg-scores-methodology.pdf for more details.

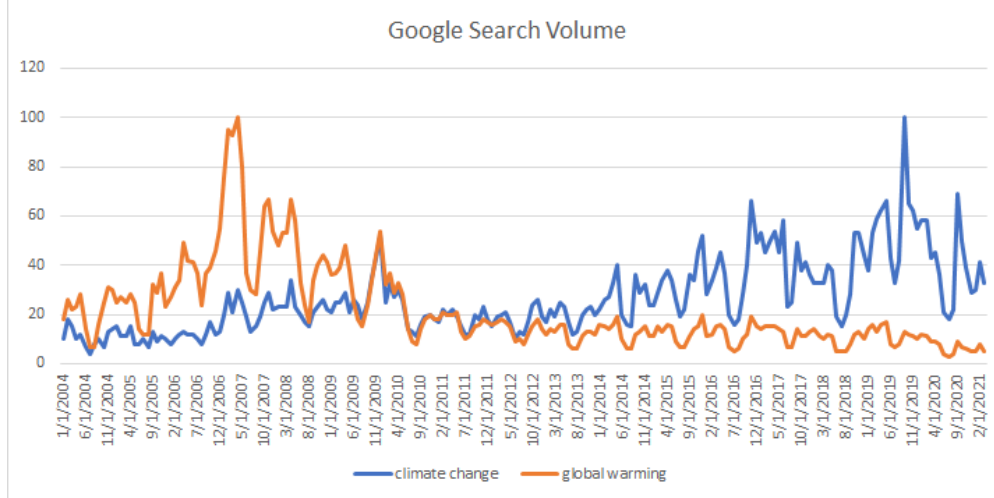


Fig. 1. Google Search Volume

Asymmetric Information In this paper, we follow Bharath et al. (2009) to construct the measures of asymmetric information. We take the first component of seven measures of information asymmetry and liquidity from the most well-known studies in the field of market microstructure, corporate finance, and asset pricing as the main measure of asymmetric information. These measures are based on (1) the adverse selection component of the quoted and effective bid-ask spread, AD and RAD (George et al., 1991; Roll, 1984); (2) stock's volume return dynamics, $C2$ (Llorente et al., 2002); (3) probability of informed trading, PIN (Easley et al., 1996); (4) price impact, ILL and LR (Amihud, 2002; Amihud et al., 1997); and (5) interaction between stock return and order flow, GAM (Pástor and Stambaugh, 2003). Appendix B shows the detailed construction of these measures and explains how these measures capture the information asymmetry. We take the first principal component of these measures as our main measure of information asymmetry, denoted as ASY . An increase in our measure ASY represents an increase in information asymmetry.

Firm Financials Following Ferris, Hanousek, Shamshur, and Tresl (2018) we construct the measures of quarterly firm financials using the data from COMPUSTAT Fundamentals Quarterly database. We are interested in the capital structure of the firms and its determinants. For the capital structure, we use market leverage, which is calculated as total debt divided by market value of total assets ⁴. Total debt is the sum of short-term debt $DLCq$ and the long-term debt $DLTTq$,

⁴We also check alternative capital structure measures such as book leverage.

and the market value of total assets is total debt plus market value of equity ($PRCC_q \times CSHPR_q$) plus preferred stock $PSTK_q$ (or $PSTKR_q$ if missing) minus deferred taxes and investment tax credit $TXDITC_q$. Quarterly sales ($sales_q$) is scaled in million dollars and represents the gross sales reduced by cash or trade discounts, returned sales and allowances to customers. Tangibility is quarterly Property Plant and Equipment Net (PPENT_q) divided by the book value of total assets (AT_q). And Profitability is calculated by operating income before depreciation divided by the book value of total assets ($OIBDP_q/AT_q$).

Summary Statistics We also obtain the closing price and markets value of firms at the beginning of each quarter from Refinitiv Datastream. Table 1 reports the summary statistics of the firm characteristics and the information asymmetric variables constructed over the sample period from 2004Q1 to 2020Q4.

Table 1: Summary Statistics

Panel A. Firm Characteristics

	count	Mean	p50	SD
market value (million dollars)	17522	12057.87	1557.997	58232.3
closing price	17754	185.0698	28.705	4464.139
ENSCORE	9684	.2577533	.1488	.2808584
mktlev	15194	.2270489	.162395	.2316988
qratio	15194	2.162429	1.419565	3.532211
tangibility	18950	.2612459	.1697085	.2517568
sales_q (million dollars)	19819	1553.13	289.418	5108.115
profitability_q	18623	-.0473825	.026711	3.855605

Panel B. Information Asymmetry Variables

	count	Mean	p50	SD
AD	16037	-.2208391	-.0070152	1.321496
RAD	16034	4.11561	2.554354	4.105668
C2	17510	-.0559223	-.0229584	1.01088
PIN	17656	1.078089	.6959364	1.142027
ILL	17652	-1.620119	-1.389836	1.231184
LR	17760	.7363737	.3583898	.9760499
GAM	15590	2.888314	2.773041	1.244558
ASY	14707	-.1702508	-.2279681	1.482204

This table reports summary statistics of the firm characteristics and the information asymmetry variables over the sample period 2004Q1-2020Q4.

5. Empirical Analysis

5.1. Empirical strategy

To examine the impact of green taste (GSV growth rate) on asymmetric information, we run the following regression

$$InfoAsy_{i,q} = \alpha_i + (\beta_0 + \beta_1 \cdot ENSCORE_{i,q-4}) \Delta GSV_{i,q} + \gamma X_{i,q} + \epsilon_{i,q} \quad (1)$$

where $InfoAsy_{i,q}$ is our measure information asymmetry of firm i at quarter q , which is the first principal component of the seven measures. $ENSCORE_{i,q-4}$ is the ENSCORE of firm i in the previous year, $\Delta GSV_{i,q}$ is the growth rate of GSV of keyword *Climate Change* in U.S. $X_{i,q}$ is the control variables, which include market value, stock return volatility, analyst coverage, etc. The coefficient of interest is β_1 . We expect that β_1 is negative and significant, indicating that a higher climate attention reduces green firm's information. In addition to this OLS setting, we use the global temperature as an instrument variable for $\Delta GSV_{i,q}$ to identify the casual relation. Choi et al. (2020) shows that higher temperature increases climate change concern. Standard errors are clustered at firm level. And we also have the year fixed effects to avoids the impacts from macroeconomic shocks.

To test the results of category learning, we follow Huang et al. (2019) to construct firm-level category learning using the daily correlation between the firm's stock return and the market return. We do this for every firm in each quarter. In addition, we consider also the R^2 of univariate regression of the firm's stock return on the market return as an alternative measure of category learning. The latter is simply the square of the former. Then, we run the following regression to test the category learning results:

$$Cat_{i,q} = \alpha_i + (\beta_0 + \beta_1 \cdot ENSCORE_{i,q-4}) \Delta GSV_q + \gamma X_{i,q} + \epsilon_{i,q} \quad (3)$$

where $Cat_{i,q}$ is the category learning measure of firm i on quarter q . $ENSCORE_{i,q-4}$ is the ENSCORE of firm i at the previous year. Again, standard errors are clustered at firm level and we have also year fixed effects.

The parameter of interest is β_1 . If β_1 is negative and significant, it means that a higher climate attention decreases category learning of green firms compared to brown ones.

5.2. *Green taste and information asymmetry*

We first test the impact of green taste on green firms' information asymmetry, and the results reported on Table 2 implies that greater green GSV reduces information asymmetry.

Tables 2 reports the results of regressions using *Climate Change* as green keywords when collect the GSV data to construct green taste measure and using principal component of seven information asymmetry variables following Bharath et al. (2009) as the main information asymmetry measure. Columns (1) and (2) are OLS regression estimates, while columns (3) and (4) are the estimates with the temperature as instrumental variable for green taste. This table shows that greater green taste from investors reduces green firms' information asymmetry. According to the result of column (4), when there's one standard deviation increase of green GSV growth rate, there's 27.8% reduction in information asymmetry of green firms.

We also test the results with alternative green keywords to capture green taste. Table A1 shows the results of regressions using growth rate of GSV on *Global Warming* as green taste measure. The positive and significant effects of green taste remain.

Table 2: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE \times growthcc	-0.174*** (-6.27)	-0.164*** (-6.03)	-0.677*** (-8.15)	-0.697*** (-8.12)
ENSCORE	-0.467*** (-5.39)	0.00355 (0.04)	-0.474*** (-5.49)	0.00422 (0.04)
growthcc	0.101*** (8.48)	0.133*** (11.14)	0.180*** (4.61)	0.391*** (9.64)
logmkv	-1.392*** (-42.33)	-1.180*** (-32.75)	-1.392*** (-42.32)	-1.188*** (-32.92)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adjusted R^2	0.321	0.408	0.231	0.149
Observations	48478	48478	48478	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthcc* is measured by the growth rate of Google Search Volume (GSV) of keywords *Climate Change*. We do not report the coefficient for the intercept. t statistics are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

5.3. Green Taste and category learning

However, Table 3 suggests that higher green taste decreases category-learning in green sector,

Table 3: Green Taste and Category Learning

	OLS		IV	
	(1)	(2)	(3)	(4)
	cat_firm	cat_firm_sq	cat_firm	cat_firm_sq
ENSCORE \times growthcc	-0.0139*** (-3.22)	-0.0223*** (-5.60)	-0.0192 (-1.33)	-0.0525*** (-3.78)
ENSCORE	0.0270*** (2.71)	0.0303*** (3.21)	0.0268*** (2.70)	0.0302*** (3.20)
growthcc	-0.0155*** (-8.80)	-0.0176*** (-12.02)	-0.0421*** (-6.76)	-0.0373*** (-6.63)
logmkv	0.0276*** (9.47)	0.0275*** (10.57)	0.0288*** (9.81)	0.0286*** (10.93)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.395	0.396	0.002	0.003
Observations	52829	52829	52829	52829

This table reports estimates for the coefficients from the regression of Equation (3). The regressions use *Climate Change* as keywords when collect GSV data. We do not report the coefficient for the intercept. t statistics are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.

Further more, we test whether the coefficient of green taste, $\beta_0 + \beta_1 \cdot AveENSCORE_{p,q-4}$, is significantly different from than zero. The result of F-test rejects the null hypothesis that the coefficient of ΔGSV_q is zero, which implies green taste has significant impact on category learning behaviour.

Test $c.aveENSCORE\#c.growthcc + growthcc = 0$

$$F(1, 9) = 5.88$$

$$Prob > F = 0.0384$$

5.4. Asset pricing implications

In this section, we examine the asset pricing implication of information asymmetry. This investigation sheds light on how information asymmetry affect the cost of capital. Specifically, in each quarter, we construct five portfolios based on each firm’s information asymmetry in the last quarter. We then obtain the monthly value-weighted return for each portfolio. We run time-series regression of all the portfolio returns on common asset pricing factors,

$$r_{p,m} = \alpha_p + \beta_p Factor_m + \epsilon_{p,m}$$

where $r_{p,m}$ is the return of portfolio p at month m , $Factor_m$ includes the CAPM (Sharpe, 1964), Fama-french three and five factors (Fama and French, 1993, 2015).

Table 4: **Asset pricing implication**

	L	2	3	4	H	H-L
$E(r_{i,t})$	0.50	0.86	1.09	1.29	1.59	1.09
s.e.	(0.42)	(0.39)	(0.37)	(0.37)	(0.38)	(0.28)
CAPM						
α	-0.39	0.02	0.19	0.44	0.66	1.06
s.e.	(0.13)	(0.14)	(0.11)	(0.16)	(0.22)	(0.30)
FF3						
α	-0.51	0.02	0.28	0.53	0.83	1.34
s.e.	(0.14)	(0.13)	(0.08)	(0.13)	(0.22)	(0.31)
FF5						
α	-0.47	0.01	0.27	0.50	0.85	1.32
s.e.	(0.13)	(0.12)	(0.09)	(0.12)	(0.23)	(0.31)
No. of firms	443	445	444	444	443	

Table 4 shows the abnormal returns α for all the five portfolios and a portfolio that long the top one and shorts the bottom one (a high-minus-low portfolio). First, we find an increasing raw return from low information asymmetry portfolio to high ones. The portfolio with the highest

information asymmetry carries a significant 1.09% (s.e.=0.28%) higher monthly return than that with lowest information asymmetry. This difference remains significant and even becomes larger after controlling for common asset pricing factor (1.06%, 1.34%, and 1.32% for CAPM, Fame-French three and five factors). This result is consistent with Easley and O'hara (2004) that investors demand compensation for holding stocks that are less transparent and more uncertain. Thus lower information asymmetry benefit firms by lowering its cost of equity capital.

5.5. Capital Structure

In this section, we further justify the importance of asymmetric information in firms' capital structure and explore how does the existence of category learning affect the capital structure. Pecking order theory (Myers, 1984; Myers and Majluf, 1984) suggests that the cost of financing and the ratio of debt to equity should increase with the asymmetric information.

Following Bharath et al. (2009), we augment the model of Rajan and Zingales (1995) to include the asymmetric information measures and run firm-quarter panel regression.

$$\begin{aligned} Leverage_{it} = & a + \mu_i + b_1ASY_{it} + b_2Cat_{it} + b_3Tangibility_{it} + b_4Qratio_{it} \\ & + b_5FirmSize_{it} + b_6Profitability_{it} + \varepsilon_{it} \end{aligned} \quad (4)$$

where $Leverage_{it}$ is firm i 's market leverage at quarter t , which is total debt divided by market value of total assets, as in Ferris et al. (2018). Total debt is the sum of short-term debt $DLCq$ and the long-term debt $DLTTq$, and the market value of total assets is total debt plus market value of equity ($PRCCq \times CSHPRq$) plus preferred stock $PSTKq$ (or $PSTKRq$ if missing) minus deferred taxes and investment tax credit $TXDITCq$. Firm size is log of sales scaled by the quarterly GDP deflator with baseline year 2012 ($\log(Sale)/GDPDeflator$). Tangibility is quarterly Property Plant and Equipment Net (PPENTq) divided by the book value of total assets (ATq). And Profitability is calculated by operating income before depreciation divided by the book value of total assets ($OIBDPq/ATq$).

Table 5 reports estimates for coefficients from the above equation (4). It shows that when there's higher asymmetric information, there's higher leverage of firms, which is in line with the

findings of Bharath et al. (2009).

Table 5: Leverage, Asymmetric Information and Category Learning

	(1)	(2)	(3)
	mktlev	mktlev	mktlev
ASY	0.0194*** (0.00222)	-0.00185 (0.00266)	0.0198*** (0.00230)
tangibility	0.191** (0.0767)	0.163** (0.0764)	0.189** (0.0765)
qratio	-0.0168*** (0.00304)	-0.0137*** (0.00277)	-0.0166*** (0.00304)
firmsize	1.365** (0.551)	1.720*** (0.596)	1.448** (0.560)
profit	-0.364*** (0.0848)	-0.364*** (0.0907)	-0.377*** (0.0906)
AD		-0.00194* (0.00111)	
RAD		0.0000849 (0.000793)	
C2		0.000654 (0.000960)	
PIN		0.0217*** (0.00376)	
ILL		0.0237*** (0.00327)	
LR		0.00331* (0.00185)	
GAM		0.00363** (0.00143)	
cat_firm			-0.0202* (0.0105)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	11525	11274	11503
R ²	0.821	0.826	0.819

This table reports estimates for the coefficients from the regression of Equation (4). We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.

Besides, column (3) of the table 5 suggests that investors' category learning behaviour decreases the leverage level of firms.

As higher green attention reduces information asymmetry, according to the results of table 5, the leverage will decrease with lower information asymmetry.

For robustness check, we also test the results of alternative leverage measures. Table A4 reports the results of book leverage. The main conclusions still hold.

6. Conclusion

In this paper, we investigate the impact of green taste on asymmetric information and category learning. Using the GSV on *Climate Change* and asymmetric information measure developed by Bharath et al. (2009), we empirically find that greater public attention on environmental issues reduces asymmetric information, especially for the green firms which have high ENSCORE. In addition, higher green taste also leads to less category learning behavior for green firms (Peng and Xiong, 2006). This is because more attention is allocated to the specific information of green firms, making their price reflect more firm-specific information. We document that such a decrease in information asymmetry and category learning lowers the cost of equity capital and decreases leverage for green firms. We propose a model with green preference and attention allocation to explain the empirical result. The model sheds new light on how the interaction between green taste and attention allocation affects the cross-section of the stock market.

References

- Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets* 5, 31–56.
- Amihud, Y., Mendelson, H., Lauterbach, B., 1997. Market microstructure and securities values: Evidence from the tel aviv stock exchange. *Journal of financial Economics* 45, 365–390.
- Aouadi, A., Arouri, M., Teulon, F., 2013. Investor attention and stock market activity: Evidence from france. *Economic Modelling* 35, 674–681.
- Baker, M., Bergstresser, D., Serafeim, G., Wurgler, J., 2018. Financing the response to climate change: The pricing and ownership of us green bonds. Tech. rep., National Bureau of Economic Research.

- Bank, M., Larch, M., Peter, G., 2011. Google search volume and its influence on liquidity and returns of german stocks. *Financial markets and portfolio management* 25, 239.
- Bharath, S. T., Pasquariello, P., Wu, G., 2009. Does asymmetric information drive capital structure decisions? *The review of financial studies* 22, 3211–3243.
- Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. *The Review of Financial Studies* 33, 1112–1145.
- Cooper, M. J., Dimitrov, O., Rau, P. R., 2001. A rose. com by any other name. *The journal of Finance* 56, 2371–2388.
- Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *The Journal of Finance* 66, 1461–1499.
- Ding, R., Hou, W., 2015. Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money* 37, 12–26.
- Djerf-Pierre, M., 2012. When attention drives attention: Issue dynamics in environmental news reporting over five decades. *European Journal of Communication* 27, 291–304.
- Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research* 41, 797–836.
- Easley, D., Kiefer, N. M., O’hara, M., Paperman, J. B., 1996. Liquidity, information, and infrequently traded stocks. *The Journal of Finance* 51, 1405–1436.
- Easley, D., O’hara, M., 2004. Information and the cost of capital. *The journal of finance* 59, 1553–1583.
- Edmans, A., 2011. Does the stock market fully value intangibles? employee satisfaction and equity prices. *Journal of Financial economics* 101, 621–640.
- Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.
- Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116, 1–22.

- Ferris, S. P., Hanousek, J., Shamshur, A., Tresl, J., 2018. Asymmetries in the firm’s use of debt to changing market values. *Journal of Corporate Finance* 48, 542–555.
- Gao, Y., Wang, Y., Wang, C., Liu, C., 2018. Internet attention and information asymmetry: Evidence from qihoo 360 search data on the chinese stock market. *Physica A: Statistical Mechanics and its Applications* 510, 802–811.
- George, T. J., Kaul, G., Nimalendran, M., 1991. Estimation of the bid–ask spread and its components: A new approach. *The Review of Financial Studies* 4, 623–656.
- Goldstein, I., Kopytov, A., Shen, L., Xiang, H., 2021. On esg investing: Heterogeneous preferences, information, and asset prices. *Information, and Asset Prices* (April 9, 2021) .
- Goldstein, I., Yang, L., 2015. Information diversity and complementarities in trading and information acquisition. *The Journal of Finance* 70, 1723–1765.
- Grossman, S. J., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. *The American economic review* 70, 393–408.
- Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. *Journal of financial economics* 93, 15–36.
- Huang, S., Huang, Y., Lin, T.-C., 2019. Attention allocation and return co-movement: Evidence from repeated natural experiments. *Journal of Financial Economics* 132, 369–383.
- Kacperczyk, M., Van Nieuwerburgh, S., Veldkamp, L., 2016. A rational theory of mutual funds’ attention allocation. *Econometrica* 84, 571–626.
- Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. *The Review of financial studies* 15, 1005–1047.
- Myers, S. C., 1984. The capital structure puzzle. *The Journal of Finance* 39, 574–592.
- Myers, S. C., Majluf, N. S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics* 13, 187–221.
- Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. *Journal of Political economy* 111, 642–685.

- Pástor, L., Stambaugh, R. F., Taylor, L. A., 2020. Sustainable investing in equilibrium. *Journal of Financial Economics* .
- Pedersen, L. H., Fitzgibbons, S., Pomorski, L., 2020. Responsible investing: The esg-efficient frontier. *Journal of Financial Economics* .
- Peng, L., 2005. Learning with information capacity constraints. *Journal of Financial and Quantitative Analysis* 40, 307–329.
- Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80, 563–602.
- Peress, J., 2010. The tradeoff between risk sharing and information production in financial markets. *Journal of Economic Theory* 145, 124–155.
- Rajan, R. G., Zingales, L., 1995. What do we know about capital structure? some evidence from international data. *The journal of Finance* 50, 1421–1460.
- Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance* 39, 1127–1139.
- Sankaraguruswamy, S., Shen, J., Yamada, T., 2013. The relationship between the frequency of news release and the information asymmetry: The role of uninformed trading. *Journal of Banking & Finance* 37, 4134–4143.
- Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19, 425–442.
- Sims, C. A., 2003. Implications of rational inattention. *Journal of monetary Economics* 50, 665–690.
- Van Nieuwerburgh, S., Veldkamp, L., 2010. Information acquisition and under-diversification. *The Review of Economic Studies* 77, 779–805.
- Wurgler, J., 2000. Financial markets and the allocation of capital. *Journal of financial economics* 58, 187–214.

Appendix A. Derivation of time-0 utility

Put the expression of portfolio allocation X to U_0 ,

$$\begin{aligned} U_0 &= E_0 \left[W_0 + \frac{1}{\gamma} (E_1(f) - p + b)' V_1(f)^{-1} (E_1(f) - p + b) \right. \\ &\quad \left. - \frac{\gamma}{2} \left[\frac{1}{\gamma^2} (E_1(f) - p + b)' V_1(f)^{-1} V_1(f) V_1(f)^{-1} (E_1(f) - p + b) \right] \right] \\ &= W_0 + \frac{1}{2\gamma} E_0 [(E_1(f) - p + b)' V_1(f)^{-1} (E_1(f) - p + b)] \end{aligned}$$

Note that $E_1(f) = E_1(\mu + \Gamma \tilde{f}) = \mu + \Gamma \hat{\mu}$, $E_1(f)$ is normally distributed. Thus U_0 is an expectation of a non-central χ^2 -distributed random variable. According to Van Nieuwerburgh and Veldkamp (2010), this equals

$$\begin{aligned} U_0 &= W_0 + \frac{1}{2\gamma} [\text{Trace}(V_1(f)^{-1} V_0(E_1(f))) + E_0(E_1(f) - p + b)' V_1(f)^{-1} E_0(E_1(f) - p + b)] \\ &= W_0 + \frac{1}{2\gamma} \left[\text{Trace} \left(\left(\Gamma \hat{\Sigma} \Gamma' \right)^{-1} \Gamma (\Sigma - \hat{\Sigma}) \Gamma' \right) + (\mu - p + b)' \left(\Gamma \hat{\Sigma} \Gamma' \right)^{-1} (\mu - p + b) \right] \\ &= W_0 + \frac{1}{2\gamma} \left[\text{Trace} \left((\Gamma')^{-1} (\hat{\Sigma}^{-1} \Sigma - I) \Gamma' \right) + (\Gamma^{-1} (\mu - p + b))' \hat{\Sigma}^{-1} (\Gamma^{-1} (\mu - p + b)) \right] \\ &= W_0 + \frac{1}{2\gamma} \left[\text{Trace} \left((\Gamma')^{-1} \hat{\Sigma}^{-1} \Sigma \Gamma' \right) - 3 + (\Gamma^{-1} (\mu - p + b))' \hat{\Sigma}^{-1} (\Gamma^{-1} (\mu - p + b)) \right] \end{aligned}$$

where $\text{Trace}(\cdot)$ is the trace of a matrix. Given the relation that $\text{Trace}(AB) = \text{Trace}(BA)$, $\text{Trace} \left((\Gamma')^{-1} \hat{\Sigma}^{-1} \Sigma \Gamma' \right) = \text{Trace} \left(\Gamma' (\Gamma')^{-1} \hat{\Sigma}^{-1} \Sigma \right) = \text{Trace} \left(\hat{\Sigma}^{-1} \Sigma \right)$. Note that both $\hat{\Sigma}$ and Σ are

diagonal matrix, and considering that $\Gamma^{-1} = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix}$, we can rewrite the objective function as

$$U_0 = W_0 + \frac{1}{2\gamma} \left[\sum_{i=1}^3 \hat{\Sigma}_{ii}^{-1} (\Sigma_{ii} + \theta_i^2) - 3 \right]$$

where the 3×1 vector θ is given by

$$\theta = \Gamma^{-1}(\mu - p + b) = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \mu_1 - p_1 + g \\ \mu_2 - p_2 \\ \mu_3 - p_3 \end{bmatrix} = \begin{bmatrix} \mu_1 - p_1 + g - \mu_3 + p_3 \\ \mu_2 - p_2 - \mu + p_3 \\ \mu_3 - p_3 \end{bmatrix}$$

which is the synthetic expected excess payoffs for three factors, taking into account the green taste. Essentially, the objective function is a linear function on the posterior precision on the three factors, with the weights depending on the prior variances and excess payoffs.

If we assume the learning function to be a square root function, the optimization problem is

$$\begin{aligned} \max_{\kappa_m, \kappa_{z,1}, \kappa_{z,2}} \quad & (\Sigma_{11} + \theta_1^2) \sqrt{\kappa_{z,1}} + (\Sigma_{22} + \theta_2^2) \sqrt{\kappa_{z,2}} + (\Sigma_{33} + \theta_3^2) \sqrt{\kappa_m} \\ \text{s.t.} \quad & \kappa_m + \kappa_{z,1} + \kappa_{z,2} \leq K \end{aligned}$$

Appendix B. Information asymmetry measures

This appendix explains how we construct the measures of information asymmetry.

- George et al. (1991); Roll (1984):

Using a simple price dynamics model, George et al. (1991) find that the proportion of quoted spread due to adverse selection, π_i , can be estimated with the following regression for an individual stock i :

$$\hat{s}_{it} = \alpha_i + \beta_i s_{it} + \epsilon_{it}$$

where s_{it} is the relative quoted bid-ask spread of stock i at time t . \hat{s}_{it} is Roll (1984)'s effective bid-ask spread measure calculated using the squared root of negative autocovariance between consecutive returns,

$$\hat{s}_{it} = \begin{cases} 2\sqrt{-Cov(r_{i,t}, r_{i,t-1})} & \text{if } Cov(r_{i,t}, r_{i,t-1}) < 0 \\ -2\sqrt{Cov(r_{i,t}, r_{i,t-1})} & \text{if } Cov(r_{i,t}, r_{i,t-1}) \geq 0 \end{cases}$$

where the autocovariance is estimated using 60-day rolling windows. According to George et al. (1991), $r_{i,t}$ could be: (i) the abnormal returns (i.e. the residuals of a regression of raw

returns on expected returns), and (ii) the raw returns net of the bid returns. The unbiased estimation of π_i will be $1 - \hat{\beta}_i^2$ for the first case and $1 - \hat{\beta}_i$ for the second. In the following parts, we refer to these two measures as AD and RAD

- Llorente et al. (2002):

Llorente et al. (2002) estimates the relative intensity of speculative vs. hedging trades, based on the idea that speculative (hedging) trades generate momentum (reversal) of stock return when the volume is high. Then the intensity of speculative trading serves as a proxy for information asymmetry. Specifically, they ran the following regression,

$$R_{i,t+1} = C0_i + C1_i R_{i,t} + C2_i V_{i,t} R_{i,t} + \epsilon_{i,t}$$

where $R_{i,t}$ is the raw stock return. $V_{i,t}$ is the logarithm of turnover ratio, detrended by subtracting a 200-day moving average. A high and positive estimated coefficient $C2_i$ indicates a high degree of information asymmetry. We refer to this measure as C2.

- Easley et al. (1996):

Perhaps the most popular measure of information asymmetry is the probability of informed trading (PIN) proposed by Easley et al. (1996). They use the information in the trade data to estimated the probability of informed vs. uninformed trading when new information occurs. Specifically, they use the buy/sell trade quotes to estimate the model parameters and elicit the PIN using maximum likelihood method. We refer to this measure as PIN

- Amihud et al. (1997); Amihud (2002):

These two measures are quite straightforward, both measures the extend to which price responses to the order flow. The sensitivity of price to volume is known to capture the liquidity which is strongly related to adverse selection. Specifically, Amihud (2002) propose the following illiquidity measure

$$ILL_{i\tau} = 1/D_{i\tau} \sum_{t=1}^{D_{i\tau}} \frac{|R_{it}|}{V_{it}}$$

where R_{it} and V_{it} are return and dollar volume of stock i at day t within a time interval τ (quarterly or yearly). $D_{i\tau}$ is the total number of days with available R_{it} and V_{it} .

Alternatively, the Amivest liquidity ratio (Amihud et al., 1997) captures similar notion,

$$LR_{i\tau} = -\frac{\sum_{t=1}^{D_{i\tau}} V_{it}}{\sum_{t=1}^{D_{i\tau}} |R_{it}|}$$

Thus, higher *ILL* and *LR* indicate lower liquidity and a higher degree of information asymmetry. We label them as ILL and LR, respectively.

- Pástor and Stambaugh (2003):

Our last measure of liquidity/information asymmetry is from Pástor and Stambaugh (2003). They measure relies on the idea that order flows induce greater return reversal when liquidity is lower. Thus they propose the following regression

$$r_{i,t+1}^e = \alpha_i + \beta_i r_{i,t} + \gamma_i \text{sign}(r_{i,t}^e) V_{i,t} + \epsilon_{i,t}$$

where r^e is the stock return in excess to the market return. $V_{i,t}$ is the dollar trading volume. When the estimated coefficient γ_i is negative and high in magnitude, the reversal effect is strong and liquidity is low. Thus the negative of γ_i measures the liquidity and information asymmetry. We refer to this measure as GAM.

- Finally, we construct the first principal component of all these measures of information asymmetry. We do this by first normalize each measure for each firm over the whole sample period. Then we take the first principal component of the seven measures for each firm.

Appendix C. Additional Results

Table A1: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE \times growthgm	-0.235*** (-7.18)	-0.222*** (-6.96)	-0.514*** (-8.34)	-0.502*** (-7.86)
ENSCORE	-0.472*** (-5.45)	-0.00608 (-0.06)	-0.498*** (-5.78)	-0.0188 (-0.20)
growthgm	0.145*** (10.67)	0.191*** (14.11)	0.128*** (4.68)	0.272*** (9.69)
logmkv	-1.394*** (-42.33)	-1.184*** (-32.82)	-1.391*** (-42.31)	-1.185*** (-32.89)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adjusted R^2	0.322	0.409	0.233	0.155
Observations	48478	48478	48478	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthgm* is measured by the growth rate of Google Search Volume (GSV) of keywords *Global Warming*. We do not report the coefficient for the intercept. t statistics are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A2: Green Taste and Information Asymmetry

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE \times growthcc	-0.159*** (-4.70)	0.0357 (1.33)	0.124*** (3.58)	-0.0927*** (-8.16)	-0.119*** (-7.72)	0.117*** (5.92)	-0.0741** (-2.45)	-0.164*** (-6.03)
ENSCORE	-0.0650* (-1.79)	-0.0167 (-0.47)	0.0164 (0.42)	-0.0122 (-0.22)	-0.0212 (-0.34)	0.0147 (0.36)	-0.0768 (-1.53)	0.00355 (0.04)
growthcc	0.0316** (2.24)	-0.0126 (-1.10)	0.0165 (1.19)	0.0121*** (2.75)	0.0828*** (11.40)	0.142*** (18.51)	0.00760 (0.66)	0.133*** (11.14)
logmkv	0.111*** (9.40)	0.0311*** (2.98)	-0.0343*** (-3.15)	-0.663*** (-26.10)	-1.125*** (-38.74)	-0.338*** (-22.62)	-0.0455*** (-2.90)	-1.180*** (-32.75)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.212	0.917	0.030	0.715	0.654	0.246	0.332	0.408
Observations	50438	50438	52593	52691	52688	52718	48634	48478

Panel B. IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE \times growthcc	-0.230** (-1.96)	0.0327 (0.37)	-0.349*** (-3.19)	-0.288*** (-8.37)	-0.483*** (-9.69)	-0.317*** (-5.51)	-0.139 (-1.46)	-0.697*** (-8.12)
growthcc	-0.0245 (-0.43)	-0.152*** (-3.61)	-0.112** (-2.45)	0.0705*** (4.67)	0.364*** (15.86)	0.107*** (4.35)	0.379*** (9.19)	0.391*** (9.64)
ENSCORE	-0.0653* (-1.80)	-0.0172 (-0.48)	0.0155 (0.40)	-0.0120 (-0.22)	-0.0201 (-0.32)	0.0145 (0.35)	-0.0756 (-1.50)	0.00422 (0.04)
logmkv	0.114*** (9.58)	0.0374*** (3.56)	-0.0257** (-2.36)	-0.664*** (-26.15)	-1.134*** (-38.84)	-0.334*** (-22.43)	-0.0617*** (-3.91)	-1.188*** (-32.92)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.001	-0.004	-0.015	0.181	0.299	0.027	-0.030	0.149
Observations	50438	50438	52593	52691	52688	52718	48634	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthcc* is measured by the growth rate of Google Search Volume (GSV) of keywords *Climate Change*. We do not report the coefficient for the intercept. *t* statistics are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A3: Green Taste and Information Asymmetry

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE \times growthgm	-0.196*** (-4.76)	0.0236 (0.66)	0.0903** (2.38)	-0.0872*** (-6.31)	-0.125*** (-7.39)	0.0699*** (3.44)	0.00635 (0.19)	-0.222*** (-6.96)
ENSCORE	-0.0742** (-2.05)	-0.0157 (-0.44)	0.0201 (0.51)	-0.0156 (-0.28)	-0.0261 (-0.42)	0.0178 (0.43)	-0.0754 (-1.50)	-0.00608 (-0.06)
growthgm	0.0264 (1.61)	-0.0268* (-1.92)	0.0219 (1.48)	0.0303*** (5.82)	0.0899*** (12.19)	0.124*** (15.05)	0.154*** (11.55)	0.191*** (14.11)
logmkv	0.112*** (9.46)	0.0320*** (3.07)	-0.0345*** (-3.17)	-0.664*** (-26.10)	-1.126*** (-38.73)	-0.338*** (-22.66)	-0.0539*** (-3.45)	-1.184*** (-32.82)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.212	0.917	0.030	0.715	0.654	0.243	0.335	0.409
Observations	50438	50438	52593	52691	52688	52718	48634	48478

Panel B. IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE \times growthgm	-0.186** (-2.13)	0.00603 (0.09)	-0.290*** (-3.49)	-0.221*** (-8.52)	-0.341*** (-9.08)	-0.240*** (-5.48)	-0.0571 (-0.80)	-0.502*** (-7.86)
growthgm	-0.0147 (-0.37)	-0.104*** (-3.55)	-0.0747** (-2.31)	0.0512*** (4.81)	0.256*** (15.88)	0.0766*** (4.42)	0.257*** (9.08)	0.272*** (9.69)
ENSCORE	-0.0740** (-2.03)	-0.0170 (-0.48)	0.00377 (0.10)	-0.0210 (-0.38)	-0.0338 (-0.54)	0.00479 (0.12)	-0.0775 (-1.54)	-0.0188 (-0.20)
logmkv	0.114*** (9.59)	0.0362*** (3.46)	-0.0268** (-2.47)	-0.664*** (-26.14)	-1.132*** (-38.85)	-0.333*** (-22.41)	-0.0588*** (-3.75)	-1.185*** (-32.89)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.002	-0.001	-0.008	0.181	0.309	0.028	0.003	0.155
Observations	50438	50438	52593	52691	52688	52718	48634	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthgm* is measured by the growth rate of Google Search Volume (GSV) of keywords *Global Warming*. We do not report the coefficient for the intercept. *t* statistics are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A4: Book Leverage, Asymmetric Information and Category Learning

	(1)	(2)	(3)
	booklev	booklev	booklev
ASY	0.00490** (0.00212)	-0.00252 (0.00279)	0.00528** (0.00226)
tangibility	0.125 (0.0876)	0.121 (0.0882)	0.124 (0.0877)
qratio	-0.00148 (0.00453)	-0.00103 (0.00471)	-0.00137 (0.00454)
firmsize	1.474 (0.994)	1.685* (1.019)	1.562 (1.009)
profit	-0.408*** (0.111)	-0.425*** (0.125)	-0.414*** (0.117)
AD		0.000537 (0.000998)	
RAD		0.000396 (0.000973)	
C2		0.000710 (0.00118)	
PIN		0.00878* (0.00497)	
ILL		0.00665* (0.00398)	
LR		-0.00109 (0.00183)	
GAM		0.00563*** (0.00186)	
cat_firm			-0.0210 (0.0135)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	11525	11274	11503
R ²	0.780	0.779	0.779

This table reports estimates for the coefficients from the regression of Equation (4) with the book leverage as the capital structure measure. We do not report the coefficient for the intercept. *t* statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.