Green Investing, Information Asymmetry, and Capital Structure

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ABSTRACT

We investigate how optimal 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 investors with heterogeneous green preferences endogenously allocate limited attention to learn market-level or firm-specific fundamental shocks. We find that a higher fraction of green investors in the market leads to higher aggregate attention to green firms. This reduces the information asymmetry of green firms, leading to higher price informativeness and lower leverage. Moreover, the information asymmetry of brown firms and the market increases with the share of green investors. Therefore, greater green attention is associated with less market efficiency. We provide empirical evidence to support our model predictions using U.S. data. Our paper shows how the growing demand for sustainable investing shifts investors' attention and benefits eco-friendly firms.

Keywords: Climate Finance, Information Asymmetry, Rational Inattention, Capital Structure

JEL classification: D82, G11.

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1. Introduction

Recent years have witnessed an increasing appetite for sustainable investments, and investors care more and more about the environmental, social, and government (ESG) impacts of their investments. According to the 2020 Report on U.S. 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 at the beginning of 2018 to $17.1 trillion at the beginning of 2020. See Figure 1 for details. Along with the dramatic rise in green investing over the past decade, the concept of rational inattention has attracted increasing interest from economic researchers, which is first introduced by Sims (2003). The idea is that human attention is a limited cognitive resource, and rational agents have to allocate their attention to various sources of information optimally. Investors' limited attention will then affect the information asymmetry in the financial market. Despite the natural link between investors' rational inattention and the information asymmetry,[1] few studies investigated how the relationship between these two terms interacts with the rising preference for sustainable investing.

This paper tries to fill in the gap and answer how investors' taste for investing in "green" and limited attention affects information asymmetry of firms with different "greenness". Specifically, we investigate the impact of greater investor interest in environmental issues, measured by the Google Search Volume (GSV) on the keyword *Climate Change*, on green firms' information asymmetry. We further explore how investors' green taste affects the information asymmetry of brown firms and the market.

We propose a model based on Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) to guide the empirical analysis and incorporate green preference into the framework. In this economy, a continuum of investors with heterogeneous "green taste" chooses to invest into a group of risky assets. Green investors derives non-pecuniary benefit from holding green assets following Pástor, Stambaugh, and Taylor (2020) and Pedersen, Fitzgibbons, and Pomorski (2020), whereas the traditional investors only cares about the financial payoffs. The model is a two-period portfolio choice

[1] This paper follows Myers and Majluf (1984) to define the information asymmetry of a firm as the difference of information about the firm's fundamentals between firm managers and investors. Firm managers are supposedly more informed about the firm's fundamentals than investors. Information asymmetry is an essential aspect because it affects both a firm's cost of equity capital and financing decisions.

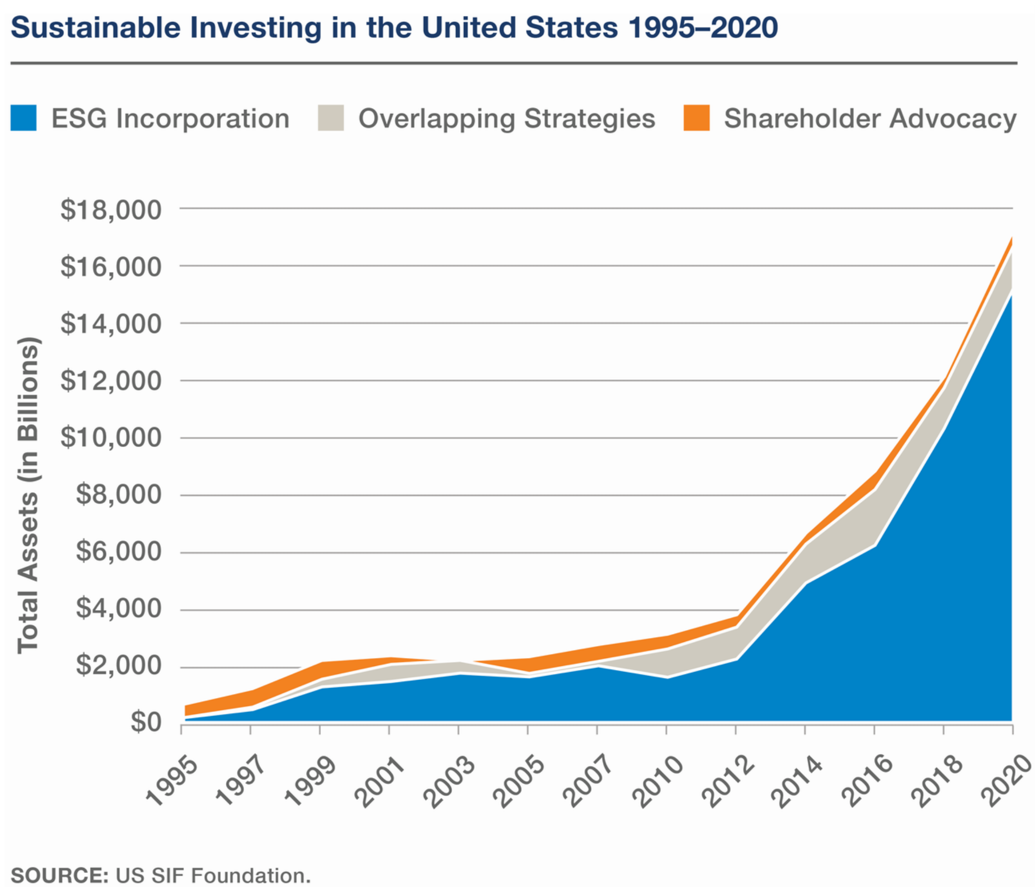

Fig. 1. Green investing in the U.S.

problem. An investor chooses to invest into a set of risky assets whose uncertain payoffs depend on the fundamental shocks to a green firm, a brown firm, and the market. The investor observes signals of the fundamentals, where the precision of a signal depends on the attention that he assigned to that signal. Therefore, the investor solves a two-step optimization. In the first step, he chooses to allocate limited attention to market-level or firm-level information to resolve uncertainty. The second step is a standard portfolio allocation problem conditional on posterior beliefs formed in the first step.

The model predicts that higher fraction of green investors induces an increase of aggregate attention to the specific information of the green firm. In other words, the signal on the payoff of the green asset becomes more precise. As a result, green firms' information asymmetry, measured as the knowledge difference between investors (outsiders) and managers (insiders), decreases. Since the total attention is limited, investors allocate less attention to the brown firms. As a result, brown firms experience a higher information asymmetry. In addition, increased learning on green firms makes the price of the green asset more aligned with the idiosyncratic shock to the green firm, which generates a higher price informativeness of the green stock. Finally, the model implies a reduction in the leverage for green firms when more investors cares about investing.

In addition, our model provides new insight by showing that an increase in green taste decreases the information quality of the *aggregate market*. In other words, investors are learning less about the market as a whole. This is particularly interesting: while higher green taste encourages learning about green firms, it's bad for the aggregate market since it hinders price discovery and market efficiency.

To empirically 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 primary measure on firm-level 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). We further construct a proxy of aggregate efficiency from the measure of price informativeness in Bai, Philippon, and Savov (2016). We focus on Standard & Poor's (S&P) 500 firms and run yearly cross-sectional regressions. For each year, we regress future earnings on current stock market prices and take the predicted variance of future earnings from market prices as the efficiency measure of the year.

To define the greenness of firms, we use 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 proxy to measure firm-level category learning (Huang, Huang, and Lin, 2019). Finally, we retrieve the Google Search Volume (GSV) of keyword *Climate Change* in the U.S. market as the measure of green investing shares. Our sample covers more than 2,500 U.S. firms 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 quarterly 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 high abnormal temperature following Choi, Gao, and Jiang (2020) as the instrumental variable for the growth rate of GSV on the keyword *climate change*. We find that 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. Strikingly, the market price informativeness is low when GSV on *Climate Change* is high. The aggregate market level is negatively correlated with green attention.

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. Therefore, 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. This 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 monthly 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 implies that when the public's green taste is higher (greater GSV on *Climate Change*), greener firms are more likely to choose equity 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. And the last section concludes.

2. Literature Review

First, this paper contributes to the literature on the consequences of investors' ESG preferences on the financial markets (Pedersen et al., 2020; Pástor et al., 2020; Goldstein, Kopytov, Shen, and Xiang, 2022). A growing body of research has discussed the impact of ESG on firms' financial performance. Previous studies show that ESG consideration could either 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 it affects both the investor's preference and firm fundamentals, bridging the gap between the opposite findings. Zhou and Kang (2023) incorporate non-pecuniary ESG motive into information acquisition decisions of investors and discuss how ESG investing affects asset prices. Studies also find climate concerns affect bond pricing (see e.g., Seltzer, Starks, and Zhu, 2022). In our paper, investors also 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 cost of capital.

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).

Finally, this paper adds to the literature on how ESG concerns impact firms' capital structure decisions (see e.g., Ginglinger and Moreau, 2019; Nguyen and Phan, 2020; Chang, Fu, Li, Tam, and Wong, 2021; Shu, Tan, and Wei, 2023). Nguyen and Phan (2020) find that the rise in carbon risk results in greater financial distress risk, and thus motivates companies to reduce their financial leverage. Chang et al. (2021) document that firms with higher environmental liabilities maintain lower debt-to-assets ratios, particularly among larger firms followed by more financial analysts. In this paper, we emphasize the channel related to external investors' limited attention.

3. Model: Green Investing and Attention Allocation

To show how green taste affects attention allocation, learning behavior, and eventually 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 continuum of investors with a measure of one choose to allocate their attention across different assets. There is a fraction λ of green investors, who derives non-pecuniary utility by holding the green stocks. The other fraction of $1-\lambda$ are traditional investors, who only cares about the financial payoffs. There are three risky asset and a riskless asset in the market. The risky assets include a market portfolio, a green stock, and a brown stock. Allocated attention reduces the variance (or, in other words, improves the precision of the signal) 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 an 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 chooses the allocation to different 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, and random payoffs f_i with the following factor structure:

$$\begin{aligned} f_1 &= \mu_1 + b_1\tilde{z}_3 + \tilde{z}_1 \\ f_2 &= \mu_2 + b_2\tilde{z}_3 + \tilde{z}_2 \\ f_3 &= \mu_3 + \tilde{z}_3 \end{aligned}$$

where μ_1, μ_2 and μ_3 are the means of f_1, f_2 and f_3 respectively. $\tilde{z}_3$ is an aggregate shock to all stocks. $\tilde{z}_i$ for $i = 1, 2$ is a 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 Σ. Σ is a diagonal matrix with σ_i in the (i, i) entry.

Following Kacperczyk et al. (2016), we write the payoff vector in the following matrix form: $f = \mu + \Gamma\tilde{f}$, where $f = [f_1, f_2, f_3]'$, $\mu = [\mu_1, \mu_2, \mu_3]'$, $\tilde{f} = [\tilde{z}_1, \tilde{z}_2, \tilde{z}_3]'$, and $\Gamma = \begin{bmatrix} 1 & 0 & b_1 \\ 0 & 1 & b_2 \\ 0 & 0 & 1 \end{bmatrix}$. For the later part, we work on the portfolio optimization and attention allocation on the *factors* instead of the *assets*. This way greatly simplifies the analytical solution because of the independence among factor returns.

We assign *greenness* to each of the factors, these are assumed to be constant and exogenously given, known by all investors. We specify a positive "green score" for the green stock, $s > 0$. We also assume a negative score, $-s$, for the brown stock, and assume that the market is neutral in terms of its environment performance, i.e., a zero score for the market.[2] Thus, the greenness score of the three factors are denoted by $g = [s, -s, 0]'$.

At last, we assume stochastic supply for each factor, denoted by $\bar{x}_i + x_i$ for factor i, where $\bar{x}$ is the fixed supply and $x \sim N(0, \Sigma_x)$ being the noisy supply with a diagonal variance-covariance

[2]Change this assumption does not affect our main result qualitatively as long as the green stock has the highest greenness.

matrix Σ_x.

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 stocks.

Let W_{0j} and W_j as the initial ($t = 0$) and the final ($t = 2$) wealth for investor j, respectively. For any investor j, we use E_{0j} (V_{0j}) to denote the mean and variance operators conditional on the prior beliefs, and E_{1j} (V_{1j}) to denote the mean and variance operators conditional on information obtained through attention allocation at $t = 0$. At $t = 1$, the investor chooses the holding of factors, $\tilde{q}_j$, to maximized the expected utility

$$U_{1j} = E_{1j}\left[W_j\right] - \frac{\gamma}{2}\mathrm{V}_{1j}\left[W_j\right] + d_j \cdot \tilde{q}_j' g \tag{1}$$

subjective to the budget constraint $W_j = W_{0j} + \tilde{q}_j'(\tilde{f} - \tilde{p})$. Here γ is the risk aversion coefficient; $\tilde{q}_j$ is the factor holdings of investor j; $\tilde{p}$ is a vector of factor price, determined in the equilibrium using the market clear condition $\int \tilde{q}_j dj = \overline{x} + x$. d_j is the green preference parameter, which takes a value of $d > 0$ for green investors, and a value of zero for traditional investors. Finally, g is a vector denoting the greenness for each factor.

Learning At$t = 0$, each investor j can attentively learn the financial payoffs $\tilde{z}_i$, to maximize her *unconditional expected utility*, $E_{0j}\left[U_{1j}\right]$. Learning improves the precision of stock payoffs by Bayesian inference, and the total amount of attention is limited (Peng and Xiong, 2006). Specifically, through learning, a investor receives signals of the fundamental shocks through the structure:

$$\eta_j = \tilde{z} + \epsilon_j \tag{2}$$

where ϵ_j is the signal noises which follow the distribution $N(0, \Sigma_{\eta,j})$ where $\Sigma_{\eta,j}$ is a diagonal matrix. In general, the precision of the signal depends on how much attention is allocated to that factor. Specifically, we assume that the (i, i) entry of the matrix $\Sigma_{\eta,j}$ is given by $\frac{1}{K_{ij}}$, where K_{ij} is the amount of attention allocated to shock $\tilde{z}_i$ by investor j. This indicates that the more attention allocated to a shock, the more precise the signal becomes.

In addition to her private signal, each investor also observes the price, $\tilde{p}$, which is a public signal. We will conjecture and prove a linear functional form of the price, so that the price will be a linear unbiased signal on the fundamental shock $\tilde{z}$, i.e., $\eta_p = \tilde{z} + \epsilon_p$. This signal is common to all investors.

Based on the private and the public signals, a investor updates her beliefs about the factors by forming a Bayesian posterior with mean and variance expressed below,

$$\hat{\mu}_z = \hat{\Sigma}_j(\Sigma_{\eta,j}^{-1}\eta_j + \Sigma_p^{-1}\eta_p), \quad \hat{\Sigma}_j^{-1} = \Sigma^{-1} + \Sigma_{\eta,j}^{-1} + \Sigma_p^{-1}$$

where $\hat{\mu}_z \equiv E\left[\tilde{z}|\eta_j,\eta_p\right]$ and $\hat{\Sigma}_j \equiv V\left[\tilde{z}|\eta_j,\eta_p\right]$. From the time-0 perspective, $\hat{\Sigma}_j$ is deterministic, depending on the attention allocation K_j; $\hat{\mu}$ is normally distributed with zero mean and variance-covariance matrix $V_{0j}\left[\hat{\mu}_j\right] = \Sigma - \hat{\Sigma}_j$ according to the law of total variance.

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

$$\sum_{i=1}^{3} K_{i,j} \leq K, \quad K_{i,j} \geq 0 \text{ for } i \in \{1,2,3\} \tag{3}$$

where K is the exogenous limit in attention. 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.

3.2. The equilibrium

We proceed this part with two steps. The first step solves the optimal portfolio allocation at $t = 1$, and solves the price formula using the market clear condition. In the second step, we derive the optimal attention allocation.

Portfolio allocation The optimization problem is given by

$$\begin{aligned} \max_{\tilde{q}_j} \quad & U_{1j} = E_{1j}\left[W_{1j}\right] - \tfrac{\gamma}{2}\,\mathrm{V}_{1j}\left[W_{1j}\right] + d_j \cdot \tilde{q}_j{}'g \\ \text{s.t.} \quad & W_{1j} = W_{0j} + \tilde{q}_j{}'(\tilde{f} - \tilde{p}) \end{aligned}$$

which gives the solution

$$\tilde{q}_j = \frac{1}{\gamma} V_{1j}(\tilde{f})^{-1} \left[E_{1j}(\tilde{f}) - \tilde{p} + d_j \cdot g \right] \tag{4}$$

Then we plugin this demand function to the market clear condition, $\int \tilde{q}_j dj = \overline{x} + x$, and obtains the following Lemma.

Lemma 1. *The equilibrium price of the factors is*

$$\tilde{p} = A + B\tilde{z} + Cx$$

where

$$\begin{aligned} A &= \Gamma^{-1}\boldsymbol{\mu} - \gamma\bar{\Sigma}\overline{\boldsymbol{x}} + \overline{\boldsymbol{d}}\boldsymbol{g} \\ B &= I - \bar{\Sigma}\Sigma^{-1} \\ C &= -\gamma\bar{\Sigma}\left(I + \frac{1}{\gamma^2\sigma_x}\bar{\Sigma}_\eta^{-1'}\right) \end{aligned}$$

and $\bar{d} \equiv \left(\int_j \hat{\Sigma}_j^{-1} dj\right)^{-1} \left(\int_j \hat{\Sigma}_j^{-1} d_j dj\right)$ *is the aggregate green preference in the market.*

Proof. See appendix A. □

Lemma 1 shows that the equilibrium price is a linear function on the fundamental shocks $\tilde{z}$ and the noise in the supply x. Therefore, the price serves as a unbiased linear signal on $\tilde{z}$, where the signal is given by $\eta_p = B^{-1}(\tilde{p} - A) = \tilde{z} + B^{-1}Cx$ and the variance of the noise is $\Sigma_p = B^{-1}C\Sigma_x C' B^{-1'}$.

Lemma 1 also tells us the expected excess returns of each stocks, $r^e = E_0(f - p)$. Specifically, we derive the following corollary.

Corollary 1. *The expected excess return of each stocks are*

$$\begin{aligned} \textit{Green stock: } r_1^e &= b_1 r_3^e + \gamma\bar{\sigma}_1\bar{x}_1 - \bar{d}s \\ \textit{Brown stock: } r_2^e &= b_2 r_3^e + \gamma\bar{\sigma}_2\bar{x}_2 + \bar{d}s \\ \textit{Market stock: } r_3^e &= \gamma\bar{\sigma}_3\bar{x}_3 \end{aligned}$$

Corollary 1 presents the CAPM alpha of green and brown stocks, which depends on the two parts. The first part is due to the posterior variance, which is positive for both stocks. More learning would reduce the posterior variance and decrease the alpha. The second part is due to the green preference, which is negative (positive) for green (brown) stock. This is consistent with models with green preference but no learning (Pástor et al., 2020), except that the way that aggregate green preference is formed in a different way.[3] The first term can also affect the green premium if the induced learning behaviors are different on green and brown stocks, this is in additional to existing models without learning. Overall, the findings are consistent with those derived in Avramov, Cheng, and Tarelli (2022).

Attention allocation At $t = 0$, an investor chooses attention allocation vector K_j to maximize time-0 expected utility $U_{0j} = E_{0j}[U_{1j}^*]$, where U_{1j}^* is the maximized time-1 utility given by the demand function (4), subjective to the attention constraint in equation (3).

Appendix B shows that the time-0 expected utility can be written as a linear function on the attention allocated to the fundamental shocks

$$U_{0j} = \sum_{i=1}^{3} \kappa_{ij} K_{ij} + \text{ constant} \tag{5}$$

where the marginal benefit of attention on shock $\tilde{z}_i$,

$$\kappa_{ij} = \bar{\sigma}_i + \left(\gamma \sigma_{x,i} + \bar{K}_i\right) \bar{\sigma}_i^2 + \left(\gamma \bar{x}_i \bar{\sigma}_i + \left(d_j - \bar{d}_i\right) g_i\right)^2 .$$

Here $\bar{K}_i = \int_j K_{ij} dj$ is the aggregate attention allocated to the shock $\tilde{z}_i$, $\bar{\sigma}_i$ is the aggregate posterior precision on the shock $\tilde{z}_i$. Compared with the solution derived in Kacperczyk et al. (2016), we have an additional term reflected by investor's green preference and the greenness, $\left(d_j - \bar{d}_i\right) g_i$. Thus, a green investor with $d_j = d > \bar{d}_i$ has higher incentive to learn about the green shock, whereas a brown investor with $d_j = 0 < \bar{d}_i$ has a higher incentive to allocate attention to the brown shock. This is interesting in the sense that, even though traditional investors do not care about greenness, they actually have incentives (disincentive) to learn the brown (green) stock, particularly because the brown (green) stock carries a higher (lower) return after adjusting for the market risk, due to the existence of green investors.

[3] In Pástor et al. (2020), green preference is aggregated by wealth, whereas here it is aggregated using posterior precision.

The solution to the maximization of equation (5) is simple: investor j will allocate all her attention capacity K to the shock(s) with the highest κ_{ij}. If there exists multiple risks that has the highest κ_{ij}, the investor is indifferent in learning them. In this paper, we focus on a symmetric equilibrium. That is, we consider the case where investors of the same type (green or traditional) have the same attention allocation decisions. Then we reach the following lemma.

Lemma 2. *When the market supply is sufficiently larger than the stock-specific supply $\bar{x}_3 > \bar{x}_1, \bar{x}_2$, and the attention capacity is small $K < \underline{K}$:*

1. *For green investors, there exists $\lambda_1^G < \lambda_2^G$ such that, when $\lambda < \lambda_1^G$ ($\lambda > \lambda_2^G$), they will allocate full attention to the green factor (market factor)*
2. *For traditional investors, there exists $\lambda_1^N < \lambda_2^N$ such that, when $\lambda > \lambda_2^N$ ($\lambda < \lambda_1^N$), they will allocate full attention to the brown factor (market factor)*

Lemma 2 demonstrates an interesting observation: when the proportion of green investors within the market falls below a specific threshold, the valuation of the green risk factor fails to adequately capture the preferences associated with green investments. This situation results in a substantial premium available for green investors to exploit, as denoted by the expression $(d_j - \bar{d}_i)g_i$. Consequently, the incremental benefit of directing attention towards the green risk factor surpasses that of the broader market and the brown factor. In response, investors allocate their full attention to the green risk factor.

Conversely, when the proportion of green investors is high enough, the price of the green risk factor appreciates, leaving less room for green investors to exploit. In this scenario, green investors reallocate their attention entirely towards the market factor, which now carries a higher marginal benefit. A similar dynamic unfolds for traditional investors but in the opposite direction: as the proportion of green investors increases, the pricing of the brown factor decreases, making it profitable for traditional investors to focus their full attention on the brown factor.

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

Information asymmetry We define the information asymmetry of a firm as the ratio between the aggregate prior precision over the posterior precision, i.e.,

$$IA_i = \frac{V_0(f_i)^{-1}}{\int_j V_{1j}(f_i)^{-1} dj}. \tag{6}$$

This is intuitive: a higher posterior precision relative to the prior precision indicates a narrow knowledge gap between the investors and the firm manager, and thus a lower information asymmetry. This value is bounded between zero and one. A value close to one implies almost identical prior and posterior precision and a high information asymmetry; when the posterior precision approaches infinity, the information asymmetry goes to zero, indicating a convergence between the investors' and managers' perception about the firms fundamental. We can immediately see that higher learning leads to higher posterior precision, and lower information asymmetry.

Given the findings in lemma 2, when the fraction of green investors is below the threshold λ_1^g, An increase in the fraction of green investors λ would leads to more investor learning about the green risk factor. Therefore the aggregate posterior precision of green firm will increase and the information asymmetry of those firms will decrease. At the same time, due to less learning on the market, the aggregate posterior precision on the market and the brown firm drop, leading to a higher information asymmetry. Thus we reach a first testable model prediction as follows.

Prediction 1. *When the fraction of green investors $\lambda < \lambda_1^G$, an increase in the share of green investors decreases the green firm's information asymmetry and increases that of the brown firm and the market.*

Price informativeness Another interesting finding is related to the price informativeness, i.e., the precision of price signal. Appendix B shows that the price signal precision of risk factor i is given by

$$\Sigma_{p,i}^{-1} = \frac{\bar{K}_i}{\gamma \sigma_{x,i}} \tag{7}$$

We can back out the price informativeness for all the stocks. It shows that these are also related to the attention allocation. With the findings in Lemma 2. We also reach the following testable prediction

Prediction 2. *When the fraction of green investors $\lambda < \lambda_1^G$, an increase in the share of green investors decreases the green firm's information asymmetry and increases that of the brown firm and the market.*

Both predictions show an interesting finding: although the increase in green investors are benefit the green firms through decreasing its information asymmetry (price informativeness), it is at the cost of increasing the information friction on the overall market and the brown firms. Whether such a redistribution effect is beneficial to the whole market is an interesting extension to the model in this paper.

Capital structure According to the Pecking-order theory (Myers and Majluf, 1984), how firms get financed is dependent on the information environment. A key prediction is that, when a firms faces high information asymmetry, it tends to use internal cash or issue debt to get financed, before resorting to equity, which is information-sensitive. Thus, our model also implies an important real effect for green firms when facing a higher fraction of green investors and lower information asymmetry: they would use more equity finance, resulting in a lower leverage measured by debt-to-equity ratio.

Prediction 3. *When the fraction of green investors $\lambda < \lambda_1^G$, an increase in the share of green investors decreases the green firm's leverage and increases that of the brown firm.*

The next section presents a comprehensive empirical study to test these model preditions.

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, management, 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.[4] 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 et al., 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 categories that have the greatest significant positive correlation with other environmental issues are*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 2 plots monthly aggregate Google Trends search frequency for both *Climate Change* and *Global Warming* starting from 2014 January. We

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

convert the monthly basis to a quarterly basis by using the last observation.

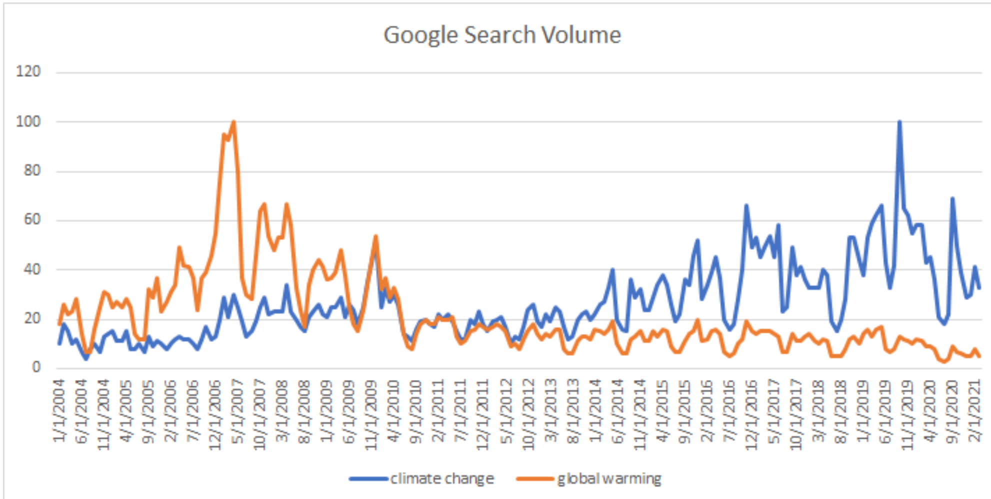

Fig. 2. Google Search Volume

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 how to construct 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 [5]. 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 $TXDITCq$. 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 (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 ($OIBDPq/ATq$).

Summary Statistics We 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.

The average market value of the firms in the sample is around 12,058 million dollars, the medium close price is 28.71. The average firm has an ENSCORE at a value of 0.25 and the medium firm has an ENSCORE 0.15. Given we normalize the ENSCORE into a decimal between 0 (the least green) and 1 (the most green), the average firm is closer to brown.

[5] We also check alternative capital structure measures such as book leverage.

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

5.1.1. Firm-level information asymmetry

To examine the impact of green taste (GSV growth rate) on asymmetric information, we first run the following firm-level regression for the panel data,

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

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 quarterly 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 coefficients of interest are β_0 and β_1. We expect that β_1 is negative and significant, indicating that a higher green taste relatively reduces the information asymmetry of green firms more than that of brown firms. In addition to the OLS setting, we use the global abnormally high 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 and thus the google search volume on climate change. The result of first stage regression is strong. Standard errors are clustered at firm level. And we also have the year fixed effects to avoid the impacts from macroeconomic shocks.

To test the results of category learning, we follow Huang et al. (2019) to construct firm-level category learning proxy 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 also consider 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:

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

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 are β_0 and β_1. If β_1 is negative and significant, a greater climate attention decreases category learning of green firms compared to brown ones. Moreover, the impact of green taste on green firms' category learning is estimated by $(\beta_0 + \beta_1)$, and that on brown firms' category learning is β_0.

5.1.2. Market price informativeness

In this section, we explore the impact of green investing in market efficiency. The market level efficiency is proxied by welfare-based market price informativeness following Bai et al. (2016). First, we run the cross-sectional regressions for each year $t = 2004, 2005, ..., 2014$ and each horizon $h = 1, 2, ..., 5$,

$$\frac{E_{i,t+h}}{A_{i,t}} = a_{t,h} + b_{t,h} + b_{t,h}\log(\frac{M_{i,t}}{A_{i,t}}) + c_{t,h}(\frac{E_{i,t}}{A_{i,t}}) + d^s_{t,h}\mathbf{1}^s_{i,t} + \epsilon_{i,t,h}$$

where $\frac{E_{i,t+h}}{A_{i,t}}$ is firm i's earnings in year $t+h$ over total assets in year t. $\log(\frac{M_{i,t}}{A_{i,t}})$ is the log ratio of market capitalization to total assets in year t. As our CRPS sample ends in 2019, the last year for which we have five-year estimates (h=4) is 2015.

Second, we use the set of coefficients and standard errors of $\log(\frac{M_{i,t}}{A_{i,t}})$ indexed by horizon h and year t from the regressions above to build the price informativeness. We are interested in the measure below,

$$(\sqrt{\nu_{FPE}})_{t,h} = b_{t,h} \times \sigma_t(\log(M/A)).$$

Where $(\sqrt{\nu_{FPE}})_{t,h}$ is the market price informativeness measure at horizon h and in year t. $b_{t,h}$ is the forecasting coefficient of regression (8). We want to see how $(\sqrt{\nu_{FPE}})_{t,h}$ changes with the year t's green attention (GSV).

Table 2 shows the results. Consistent with the model prediction, high green attention (google search volume on Climate Change) is associated with a lower market price informativeness. When investors care about the climate change and allocate their attention in green investing, the current market prices don't contain enough available information. Thus, on aggregate the market is less efficient. However, in short run the correlation is not significant. We cannot see a clear negative relationship between green attention and market efficiency for the one-year horizon. One possible explanation is that market participants reallocate their attention at a relatively lower frequency in real tradings.

Table 2: Correlations of Market Price Informativeness and GSV on Climate Change

Measure	correlations with Price Informativeness, $(\sqrt{\nu_{FPE}})_{t,h}$			
	h=1.	h=2.	h=3.	h=4.
GSV on Climate Change	0.0367	−0.2196	−0.6581**	−0.5263*
growth rate of GSV on Climate Change	−0.2595	0.7543	−0.1647	−0.2249

Notes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .1$

5.2. *Green taste and information asymmetry*

We first test the impact of green taste on green firms' information asymmetry, and the results reported in Table 3 imply that greater green GSV reduces information asymmetry.

Tables 3 reports the results of regressions using *Climate Change* as green keywords when collecting the GSV data to construct green taste measure and using the 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 abnormally high 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 the 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 3: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE × growthcc	-0.174***	-0.164***	-0.677***	-0.697***
	(-6.27)	(-6.03)	(-8.15)	(-8.12)
ENSCORE	-0.467***	0.00355	-0.474***	0.00422
	(-5.39)	(0.04)	(-5.49)	(0.04)
growthcc	0.101***	0.133***	0.180***	0.391***
	(8.48)	(11.14)	(4.61)	(9.64)
logmkv	-1.392***	-1.180***	-1.392***	-1.188***
	(-42.33)	(-32.75)	(-42.32)	(-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 quarterly 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 4 suggests that higher green taste decreases category-learning in green sector,

Table 4: Green Taste and Category Learning

	OLS		IV	
	(1)	(2)	(3)	(4)
	cat_firm	cat_firm_sq	cat_firm	cat_firm_sq
ENSCORE × growthcc	-0.0139***	-0.0223***	-0.0192	-0.0525***
	(-3.22)	(-5.60)	(-1.33)	(-3.78)
ENSCORE	0.0270***	0.0303***	0.0268***	0.0302***
	(2.71)	(3.21)	(2.70)	(3.20)
growthcc	-0.0155***	-0.0176***	-0.0421***	-0.0373***
	(-8.80)	(-12.02)	(-6.76)	(-6.63)
logmkv	0.0276***	0.0275***	0.0288***	0.0286***
	(9.47)	(10.57)	(9.81)	(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.

Furthermore, we test whether the coefficient of green taste, $\beta_0 + \beta_1 \cdot AveENSCORE_{p,q-4}$, is significantly different from zero. The result of F-test rejects the null hypothesis that the coefficient of ΔGSV_q is zero at 5% level, with a F test statistic at the value of 5.55 and p-value 0.0384. It suggests green taste has significant impact on category learning behaviour.

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 5: **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 5 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 delve deeper into the impact of green attention on a firm's capital structure and highlight the significant role of asymmetric information. Additionally, we investigate how the presence of category learning influences capital structure. The Pecking Order Theory posits that the cost of financing and the proportion of debt to equity should increase with asymmetric information (Myers, 1984; Myers and Majluf, 1984). When there's higher green investing, investor learning reduces the information asymmetry of green firms, leading to a reduction in the leverage ratio of these firms. We test the guess by regressions.

To begin with, we follow Bharath et al. (2009) to augment the model of Rajan and Zingales (1995) to show that asymmetric information is indeed important for the corporate capital structure. We run the firm-quarter panel regression,

$$\begin{aligned} Leverage_{it} = \quad & a + \mu_i + b_1 ASY_{it} + b_2 Cat_{it} + b_3 Tangibility_{it} + b_4 Qratio_{it} \\ & + b_5 Firmsize_{it} + b_6 Profitability_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where $Leverage_{it}$ is firm i's market leverage at quarter t, which is total debt divided by the 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 the 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 the 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 6 reports estimates for coefficients from the above equation (8). 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 6: Leverage, Asymmetric Information and Category Learning

	(1)	(2)	(3)
	mktlev	mktlev	mktlev
ASY	0.0194***	-0.00185	0.0198***
	(0.00222)	(0.00266)	(0.00230)
tangibility	0.191**	0.163**	0.189**
	(0.0767)	(0.0764)	(0.0765)
qratio	-0.0168***	-0.0137***	-0.0166***
	(0.00304)	(0.00277)	(0.00304)
firmsize	1.365**	1.720***	1.448**
	(0.551)	(0.596)	(0.560)
profit	-0.364***	-0.364***	-0.377***
	(0.0848)	(0.0907)	(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 (8). 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 6 suggests that investors' category learning behaviour decreases the leverage level of firms. For robustness check, we also test the results of alternative leverage measures. As higher green attention reduces information asymmetry, according to the results of table 6, the leverage will decrease with lower information asymmetry. Table A4 reports the results of book leverage. The main conclusions still hold.

Next, we test the impact of green attention on corporate capital structure. Since decisions regarding capital structure tend to occur infrequently, we narrow our focus to a significant attention-grabbing event: the Paris Agreement in December 2015, coinciding with the peak in Google search volume for "Climate Change." The Paris Agreement was a landmark international treaty on climate change adopted at the COP21 conference in Paris on December 12 2015. The goal is to limit global warming.

The main regression specification we use for this test is as below,

$$\begin{aligned} Leverage_{it} = \quad & a + \mu_i + b_1 XEnscore_{it} \times Post_{it} + b_2 Tangibility_{it} + b_3 Qratio_{it} \\ & + b_4 Firmsize_{it} + b_5 Profitability_{it} + \varepsilon_{it} \end{aligned} \tag{9}$$

Where *Post* equals one if the time is after the 2015 Quarter 4 when Paris Agreement was adopted. $XEnscore$ is the greenness quartile index that represents how environmentally friendly ("Green") the firm is, with index 4 as the greenest. We categorize the firms into four groups and have the quartile index for each group (4 is the greenest).

Table 7 displays the results. The coefficients of the interaction term imply that a significant reduction in the leverage ratio of greener firms occurs when there is a substantial increase in green attention after the Paris Agreement. This is particularly noticeable when comparing the two quartile groups with the highest degree of environmental score to the two quartile groups with the lowest level of environmental score.

Table 7: Leverage and Green Attention

	(1)
	mktlev
4 quantiles of enscore=2	0.0215
	(0.0206)
4 quantiles of enscore=3	0.0526**
	(0.0215)
4 quantiles of enscore=4	0.0698**
	(0.0307)
afterparis=1	0.0461***
	(0.0178)
4 quantiles of enscore=2 × afterparis=1	-0.000615
	(0.0228)
4 quantiles of enscore=3 × afterparis=1	-0.0552**
	(0.0247)
4 quantiles of enscore=4 × afterparis=1	-0.0488*
	(0.0255)
tangibility	0.322***
	(0.122)
qratio	-0.0179***
	(0.00384)
firmsize	0.609
	(0.876)
profitability_q	-0.728***
	(0.143)
Firm FE	Yes
Year FE	Yes
N	7237
R^2	0.853

This table reports estimates for the coefficients from the regression of Equation (9). 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.

We also conducted dynamic regressions, using the adoption quarter of the Paris Agreement as the event time. Figure 3 draws the coefficients of the time-to-treatment variables and the corresponding conference intervals. It's evident that for firms with lower Enscore rankings, the impact of the Paris Agreement on their capital structure is not significant. However, for green firms categorized in groups 3 and 4, the Paris Agreement has a significant effect in reducing their reliance on debt for financing. As green investing increases, these green firms are less inclined to use debt as a financing source. This observation aligns with model predictions that higher attention to environmental factors decreases the information asymmetry associated with green firms. Consequently, following the pecking order theory, when information asymmetry is less pronounced, firms have less reliance on debt financing.

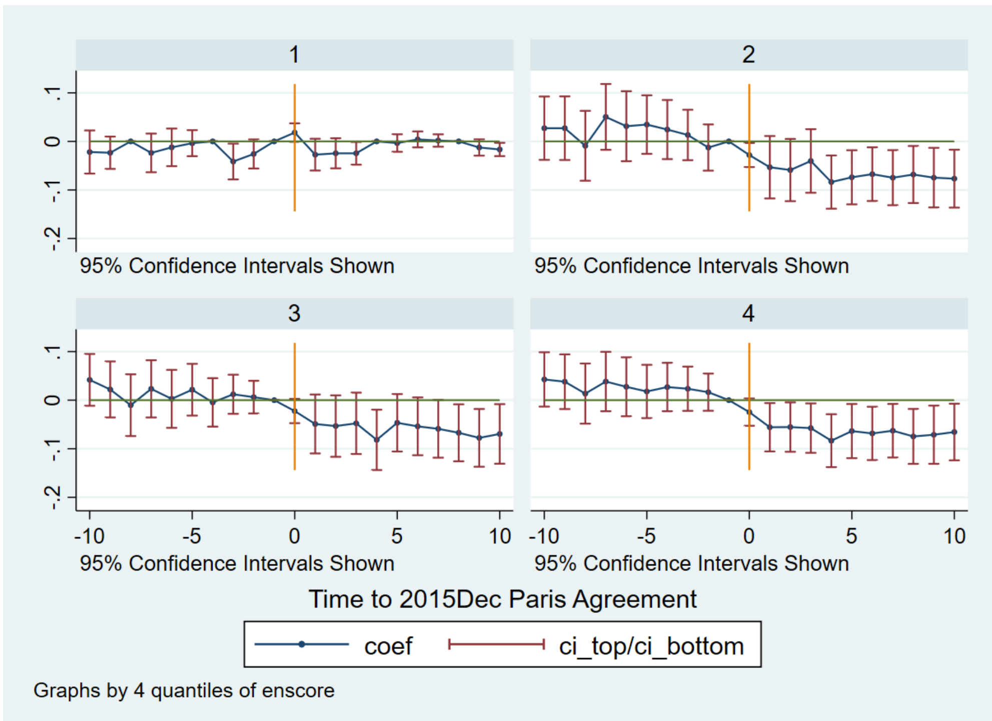

Fig. 3. 2015 December Paris Agreement and Capital Structure

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 interest in environmental issues reduces asymmetric information of the green firms which have high ENSCORE. In addition, higher green taste also leads to less category learning behaviour 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. In contrast, the information asymmetry of brown firms and the aggregate market price informativeness decreases with the green taste. We propose a model with green preference and attention allocation to explain the empirical results. 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.

Avramov, D., Cheng, S., Tarelli, A., 2022. Active fund management when esg matters: An equilibrium perspective. Available at SSRN 4182602 .

Bai, J., Philippon, T., Savov, A., 2016. Have financial markets become more informative? Journal of Financial Economics 122, 625–654.

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.

Chang, X., Fu, K., Li, T., Tam, L., Wong, G., 2021. Corporate environmental liabilities and capital structure. Available at SSRN 3200991 .

Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. The Review of Financial Studies 33, 1112–1145.

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.

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.

Ginglinger, E., Moreau, Q., 2019. Climate risk and capital structure. Université Paris-Dauphine Research Paper .

Goldstein, I., Kopytov, A., Shen, L., Xiang, H., 2022. On esg investing: Heterogeneous preferences, information, and asset prices. Tech. rep., National Bureau of Economic Research.

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.

Nguyen, J. H., Phan, H. V., 2020. Carbon risk and corporate capital structure. Journal of Corporate Finance 64, 101713.

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.

Seltzer, L. H., Starks, L., Zhu, Q., 2022. Climate regulatory risk and corporate bonds. Tech. rep., National Bureau of Economic Research.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance 19, 425–442.

Shu, H., Tan, W., Wei, P., 2023. Carbon policy risk and corporate capital structure decision. International Review of Financial Analysis 86, 102523.

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.

Zhou, X., Kang, J., 2023. Searching for esg information: Heterogeneous preferences and information acquisition. Journal of Economic Dynamics and Control p. 104693.

Appendix A. Derivation of prices

We start from the portfolio demand function of an investor j

$$\tilde{q}_j = \frac{1}{\gamma} V_{1j}(\tilde{f})^{-1} \left[E_{1j}(\tilde{f}) - \tilde{p} + d_j \cdot g \right]$$

Through Baysian updating, we get

$$E_{1j}(\tilde{f}) = \Gamma^{-1}\mu + E(\tilde{z}|\eta_j, \tilde{p}) = \Gamma^{-1}\mu + \hat{\Sigma}_j \left(\Sigma_{\eta,j}^{-1}\eta_j + \Sigma_p^{-1}\eta_p \right)$$

$$V_{1j}(\tilde{f})^{-1} = \hat{\Sigma}_j^{-1} = \Sigma^{-1} + \Sigma_{\eta,j}^{-1} + \Sigma_p^{-1}$$

Then the demand function can be writen as

$$\tilde{q}_j = \frac{1}{\gamma} \left[\hat{\Sigma}_j^{-1}(\Gamma^{-1}\mu - \tilde{p} + d_j \cdot g) + \Sigma_{\eta,j}^{-1}\eta_j + \Sigma_p^{-1}\eta_p \right]$$

Given the symmetric equilibrium, the market clear condition is

$$\lambda \tilde{q}_j^G + (1-\lambda)\tilde{q}_j^N = \bar{x} + x$$

where $\tilde{q}_j^G$ and $\tilde{q}_j^N$ are demand functions for green and traditional investors, respectively. Note that through integration, private signal noises are dispersed. So that

$$\frac{1}{\gamma} \left[\bar{\Sigma}^{-1}(\Gamma^{-1}\mu - \tilde{p} + \bar{d}g) + \bar{\Sigma}_\eta^{-1}\tilde{z} + \Sigma_p^{-1}\tilde{z} \right] = \bar{x} + x \tag{10}$$

where $\bar{\Sigma}^{-1} = \int_j \hat{\Sigma}_j^{-1} dj$ is the aggregate posterior precision, and $\bar{d} = \left(\int_j \hat{\Sigma}_j^{-1} dj \right)^{-1} \left(\int_j \hat{\Sigma}_j^{-1} d_j dj \right)$ is the posterior-precision-weighted average green preference.

Substituting the price formula $\tilde{p} = A + B\tilde{z} + Cx$ into the market clear condition (10), and match the coefficients for the intercept and shocks $\tilde{z}$ and x, we get the following equations:

$$\begin{aligned}
\frac{1}{\gamma}\bar{\Sigma}^{-1}(\Gamma^{-1}\mu - A + \bar{d}g) &= \bar{x} \\
-\bar{\Sigma}^{-1}B + \bar{\Sigma}_{\eta}^{-1} + \Sigma_p^{-1} &= 0 \\
\frac{1}{\gamma}\left(-\bar{\Sigma}^{-1}B + \Sigma_p^{-1}B^{-1}C\right) &= I
\end{aligned}$$

which delivers us the following solutions

$$\begin{aligned}
&A = \Gamma^{-1}\boldsymbol{\mu} - \gamma\bar{\Sigma}\overline{\boldsymbol{x}} + \overline{\boldsymbol{d}}\boldsymbol{g} \\
&B = I - \bar{\Sigma}\Sigma^{-1} \\
&C = -\gamma\bar{\Sigma}\left(I + \frac{1}{\gamma^2\sigma_x}\bar{\Sigma}_{\eta}^{-1\prime}\right)
\end{aligned}$$

where the last equation uses the fact that $\Sigma_p^{-1} \equiv \left(\sigma_x B^{-1}CC'B^{-1\prime}\right)^{-1} = \frac{1}{\rho^2\sigma_x}\bar{\Sigma}_{\eta}^{-1\prime}\bar{\Sigma}_{\eta}^{-1}$. Therefore we get the price formula in the lemma 1.

Appendix B. Derivation of attention allocation

Put the expression of the demand function $\tilde{q}_j$ to U_{0j},

$$\begin{aligned}
U_{0j} &= E_0\Bigg[W_0 + \frac{1}{\gamma}\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right]' V_{1j}(\tilde{f})^{-1}\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right] \\
&\quad -\frac{\gamma}{2}\left[\frac{1}{\gamma^2}\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right]' V_{1j}(\tilde{f})^{-1}V_{1j}(\tilde{f})V_{1j}(\tilde{f})^{-1}\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right]\right]\Bigg] \\
&= W_0 + \frac{1}{2\gamma}E_0\left\{\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right]'\hat{\Sigma}_j^{-1}\left[E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right]\right\}
\end{aligned}$$

Note that $E_{1j}(\tilde{f})$ 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

$$\begin{aligned}
U_{0j} &= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left[\hat{\Sigma}_j^{-1}V_{0j}\left(E_{1j}(\tilde{f}) - \tilde{p} + d_j\cdot g\right)\right] + E_0\left(\tilde{f} - \tilde{p} + d_j\cdot g\right)'\hat{\Sigma}_j^{-1}E_0\left(\tilde{f} - \tilde{p} + d_j\cdot g\right)\right] \\
&= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left[\hat{\Sigma}_j^{-1}V_{0j}\left(\tilde{f} - \tilde{p} + d_j\cdot g\right) - I\right] + \left(\gamma\bar{\Sigma}\bar{x} + (d_j - \bar{d})g\right)'\hat{\Sigma}_j^{-1}\left(\gamma\bar{\Sigma}\bar{x} + (d_j - \bar{d})g\right)\right]
\end{aligned}$$

where Trace$(\cdot)$ is the trace of a matrix. The second equality uses the law of total variance. Note that

$$
\begin{aligned}
V_{0j}\left(\tilde{f}-\tilde{p}+d_j\cdot g\right) &= (I-B)\Sigma(I-B)'+CC'\sigma_x \\
&= \bar{\Sigma}\Sigma^{-1'}\bar{\Sigma}'+\gamma^2\sigma_x\bar{\Sigma}\left(I+\frac{1}{\gamma^2\sigma_x}\bar{\Sigma}_\eta^{-1'}\right)\left(I+\frac{1}{\gamma^2\sigma_x}\bar{\Sigma}_\eta^{-1'}\right)'\bar{\Sigma}' \\
&= \bar{\Sigma}\left[\Sigma^{-1'}+\gamma^2\sigma_x+\bar{\Sigma}_\eta^{-1}+\bar{\Sigma}_\eta^{-1'}+\Sigma_p^{-1}\right]\bar{\Sigma}' \\
&= \bar{\Sigma}\left[\gamma^2\sigma_x+\bar{\Sigma}_\eta^{-1'}\right]\bar{\Sigma}'+\bar{\Sigma}
\end{aligned}
$$

Note that $\hat{\Sigma}_j(i,i)=\Sigma^{-1}(i,i)+K_{ij}+\Sigma_p^{-1}(i,i)$, and every matrices are diagonal here due to the independence structure of risk factors. This greatly simplifies the derivation and allows us to write the time-0 expected utility as a function on the attention allocations.

$$
U_{0j}=\sum_{i=1}^{3}\kappa_{ij}K_{ij}+\text{ constant}
$$

where

$$
\kappa_{ij}=\bar{\sigma}_i+\left(\gamma\sigma_{x,i}+\bar{K}_i\right)\bar{\sigma}_i^2+\left(\gamma\bar{x}_i\bar{\sigma}_i+\left(d_j-\bar{d}_i\right)g_i\right)^2
$$

Appendix C. 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

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

  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 D. Additional Results

Table A1: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE × growthgm	-0.235***	-0.222***	-0.514***	-0.502***
	(-7.18)	(-6.96)	(-8.34)	(-7.86)
ENSCORE	-0.472***	-0.00608	-0.498***	-0.0188
	(-5.45)	(-0.06)	(-5.78)	(-0.20)
growthgm	0.145***	0.191***	0.128***	0.272***
	(10.67)	(14.11)	(4.68)	(9.69)
logmkv	-1.394***	-1.184***	-1.391***	-1.185***
	(-42.33)	(-32.82)	(-42.31)	(-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 quarterly 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 × growthcc	-0.159***	0.0357	0.124***	-0.0927***	-0.119***	0.117***	-0.0741**	-0.164***
	(-4.70)	(1.33)	(3.58)	(-8.16)	(-7.72)	(5.92)	(-2.45)	(-6.03)
ENSCORE	-0.0650*	-0.0167	0.0164	-0.0122	-0.0212	0.0147	-0.0768	0.00355
	(-1.79)	(-0.47)	(0.42)	(-0.22)	(-0.34)	(0.36)	(-1.53)	(0.04)
growthcc	0.0316**	-0.0126	0.0165	0.0121***	0.0828***	0.142***	0.00760	0.133***
	(2.24)	(-1.10)	(1.19)	(2.75)	(11.40)	(18.51)	(0.66)	(11.14)
logmkv	0.111***	0.0311***	-0.0343***	-0.663***	-1.125***	-0.338***	-0.0455***	-1.180***
	(9.40)	(2.98)	(-3.15)	(-26.10)	(-38.74)	(-22.62)	(-2.90)	(-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 × growthcc	-0.230**	0.0327	-0.349***	-0.288***	-0.483***	-0.317***	-0.139	-0.697***
	(-1.96)	(0.37)	(-3.19)	(-8.37)	(-9.69)	(-5.51)	(-1.46)	(-8.12)
growthcc	-0.0245	-0.152***	-0.112**	0.0705***	0.364***	0.107***	0.379***	0.391***
	(-0.43)	(-3.61)	(-2.45)	(4.67)	(15.86)	(4.35)	(9.19)	(9.64)
ENSCORE	-0.0653*	-0.0172	0.0155	-0.0120	-0.0201	0.0145	-0.0756	0.00422
	(-1.80)	(-0.48)	(0.40)	(-0.22)	(-0.32)	(0.35)	(-1.50)	(0.04)
logmkv	0.114***	0.0374***	-0.0257**	-0.664***	-1.134***	-0.334***	-0.0617***	-1.188***
	(9.58)	(3.56)	(-2.36)	(-26.15)	(-38.84)	(-22.43)	(-3.91)	(-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 quarterly 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 × growthgm	-0.196***	0.0236	0.0903**	-0.0872***	-0.125***	0.0699***	0.00635	-0.222***
	(-4.76)	(0.66)	(2.38)	(-6.31)	(-7.39)	(3.44)	(0.19)	(-6.96)
ENSCORE	-0.0742**	-0.0157	0.0201	-0.0156	-0.0261	0.0178	-0.0754	-0.00608
	(-2.05)	(-0.44)	(0.51)	(-0.28)	(-0.42)	(0.43)	(-1.50)	(-0.06)
growthgm	0.0264	-0.0268*	0.0219	0.0303***	0.0899***	0.124***	0.154***	0.191***
	(1.61)	(-1.92)	(1.48)	(5.82)	(12.19)	(15.05)	(11.55)	(14.11)
logmkv	0.112***	0.0320***	-0.0345***	-0.664***	-1.126***	-0.338***	-0.0539***	-1.184***
	(9.46)	(3.07)	(-3.17)	(-26.10)	(-38.73)	(-22.66)	(-3.45)	(-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 × growthgm	-0.186**	0.00603	-0.290***	-0.221***	-0.341***	-0.240***	-0.0571	-0.502***
	(-2.13)	(0.09)	(-3.49)	(-8.52)	(-9.08)	(-5.48)	(-0.80)	(-7.86)
growthgm	-0.0147	-0.104***	-0.0747**	0.0512***	0.256***	0.0766***	0.257***	0.272***
	(-0.37)	(-3.55)	(-2.31)	(4.81)	(15.88)	(4.42)	(9.08)	(9.69)
ENSCORE	-0.0740**	-0.0170	0.00377	-0.0210	-0.0338	0.00479	-0.0775	-0.0188
	(-2.03)	(-0.48)	(0.10)	(-0.38)	(-0.54)	(0.12)	(-1.54)	(-0.20)
logmkv	0.114***	0.0362***	-0.0268**	-0.664***	-1.132***	-0.333***	-0.0588***	-1.185***
	(9.59)	(3.46)	(-2.47)	(-26.14)	(-38.85)	(-22.41)	(-3.75)	(-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 quarterly 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) booklev	(2) booklev	(3) booklev
ASY	0.00490**	-0.00252	0.00528**
	(0.00212)	(0.00279)	(0.00226)
tangibility	0.125	0.121	0.124
	(0.0876)	(0.0882)	(0.0877)
qratio	-0.00148	-0.00103	-0.00137
	(0.00453)	(0.00471)	(0.00454)
firmsize	1.474	1.685*	1.562
	(0.994)	(1.019)	(1.009)
profit	-0.408***	-0.425***	-0.414***
	(0.111)	(0.125)	(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 (8) 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.