Green Investing, Information Asymmetry, and Category Learning

Shasha Li* Biao Yang†

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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 an investor with green taste endogenously allocates limited attention to study market-level or firm-specific fundamental shocks. We find that more green-motivated investors tend to pay more attention to green firm-level information than market-level information. Thus higher green taste leads to less category learning behaviour. It reduces the information asymmetry of green firms, leading to lower leverage and lower cost of equity capital. Moreover, the information asymmetry of brown firms and the market increases with the green taste. Greater green attention is associated with less market efficiency. We provide empirical evidence to support our model predictions by using US 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, Category Learning

JEL classification: D82, G11.

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

†Antai College of Economics and Management, Shanghai Jiao Tong University, biao.yang@sjtu.edu.cn.

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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. 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 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) and Pedersen, Fitzgibbons, and Pomorski (2020).[2] The model is a two-period portfolio

[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.

[2] We consider the 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

choice 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 green taste induces investors to allocate more attention to specific information to the green firm. In other words, the signal on the payoff of the green asset becomes more precise. This is not surprising given that investors now care more about holding the green asset thus, reducing uncertainty related to the green asset becomes more rewarding. 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 lower price comovement between green stock and the market and leads to a reduction of category learning of green firms (Peng and Xiong, 2006). Finally, the model implies a reduction in the cost of equity capital for green firms when climate concern is more significant.

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,

investor, this is equivalent to an increase in the green taste.

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 taste. 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.

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 particular group of firms as a single category and completely ignore information about the firm's fundamentals. Our results indicate that green taste alleviates category learning issues of green firms by affecting attention allocation.

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, 2021). 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. 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 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 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 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:

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

where μ_1, μ_2 and μ_3 are the means of f_1, f_2 and f_3 respectively. $\tilde{m}$ 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 $\tau_{z,1}$, $\tau_{z,2}$ and τ_m are the inverse of variances of the shocks $\tilde{z}_1$, and $\tilde{z}_2$, and $\tilde{m}$ respectively. These parameters denote the precision of investor's prior beliefs to these shocks. We can write the payoff vector in the following matrix form: $f = \mu + \Gamma\tilde{f}$, where $f = [f_1, f_2, f_3]'$, $\mu = [\mu_1, \mu_2, \mu_3]'$, $\tilde{f} = [\tilde{z}_1, \tilde{z}_2, \tilde{m}]'$, 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 stocks.

Let W_0 and W as the initial and final wealth. We use E_0 and V_0 to denote the mean and variance operators conditional on the prior beliefs, and E_1 and V_1 to denote the mean and variance operators conditional on information obtained through attention allocation. Thus, at $t = 1$, the investor chooses the holding of stocks, X, to maximized 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. $X = [x_g \; x_b \; x_m]'$, and x_g, x_b, and x_m are green stock, brown stock and market portfolio holdings respectively. 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". She is happier and obtaining utility simply by holding the stocks of green firms.

At $t = 0$, the investor choose 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 by Bayesian inference. 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 $\varepsilon_{z,1}$ are independent. The noisiness of signals depend on the attention κ_m, $\kappa_{z,1}$, and $\kappa_{z,2}$ that investors 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. Investors update their beliefs about the market by forming a Bayesian posterior with mean and variance expressed below,

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

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 can be similarly expressed. We get $\hat{\mu} \equiv E_1\left(\tilde{f}\right) = [\hat{\mu}_{z,1}, \hat{\mu}_{z,2}, \hat{\mu}_m]'$ and $\hat{\Sigma} \equiv V_1\left(\tilde{f}\right) = diag\left(\left[\hat{\Sigma}_{z,1}, \hat{\Sigma}_{z,2}, \hat{\Sigma}_m\right]\right)$, 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 $V_0\left[\hat{\mu}\right] = \Sigma - \hat{\Sigma}$ according to the law of total variance.

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

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

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.

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).

Without loss of generality, we assume a square root learning function $\rho(x) = \sqrt{x}$ to generate closed-form solutions. The conclusion will hold for any increasing concave role.

3.2. The equilibrium

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

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

The solution is given by

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

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 over the final wealth, 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

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

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*

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

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 marginal 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.

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.*

Corollary 1 is the key prediction of our model. It says that a higher green taste g increases the synthetic excess payoff of the specific factor of the green firm, θ_1. As a result, she allocates more attention to that factor. In sum, a higher green taste leads to more attention to green firms. Thus investors receive a more precise signal about the green firms' fundamentals. This will eventually reduce the information gap between investors and firm managers, which indicates a lower information asymmetry.

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 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 more minor discrepancy between the investor's information and the manager, who presumably knows exactly the total value. Therefore, 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.*

An interesting implication from proposition 2 is, when the green taste g increases, not only do brown firms suffer from higher information asymmetry but also the whole market becomes less transparent and efficient. Thus such a reallocation of attention is actually bad for the aggregate market.

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

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

Substituting the expressions of these variables into the formula, we get the correlation between prices of green stocks 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 equity capital as the unconditional expected value of the payoff minus the price $E_0(f-p)$. Thus

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

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, 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.[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 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 1 plots monthly aggregate Google Trends search frequency for both *Climate Change* and *Global Warming* starting from 2014 January. We

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

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

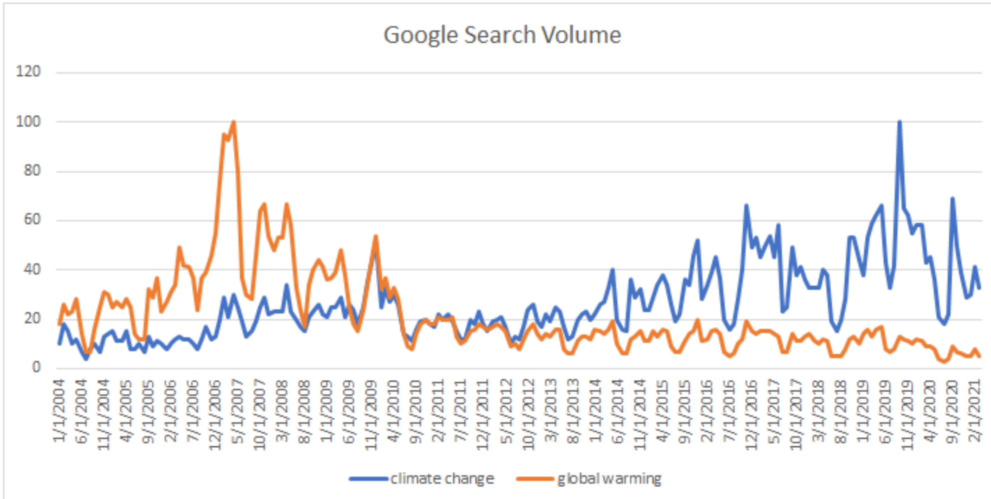

Fig. 1. Google Search Volume

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 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 [4]. 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.

[4] 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 $t = 2004, 2015, ..., 2014$ 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 (4). 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 on Table 3 implies that greater green GSV reduces information asymmetry.

Tables 3 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 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 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.

$$\begin{aligned} Leverage_{it} = \quad & a + \mu_i + b_1 ASY_{it} + b_2 Cat_{it} + b_3 Tangibility_{it} + b_4 Qratio_{it} \\ & + b_5 Firmsize_{it} + b_6 Profitability_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

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 6 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 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 (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 6 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 6, 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 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.

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.

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,

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

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

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

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

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

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

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

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

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

  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 C. 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) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) 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) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) 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) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) 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) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) 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)	(2)	(3)
	booklev	booklev	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 (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.