

May 24, 2025

The Capital Market Implications of Climate Risk Disclosure

Jiang Luo^{*}

Konstantinos Stathopoulos[†]

Avanidhar Subrahmanyam[‡]

Xiaoxia Ye[§]

Ran Zhao[¶]

^{*}Associate Professor of Finance, Nanyang Technological University.

[†]Professor of Accounting and Finance, University of Manchester.

[‡]Professor of Finance, University of California at Los Angeles.

[§]Professor of Finance, University of Nottingham.

[¶]Assistant Professor of Finance, San Diego State University.

We thank Marie Dutordoir and Alex Kostakis for their suggestions on early versions of this paper, and Shumi Akhtar, Joshua Cave, Jie Chen, Kevin Keasey, Gregory Koutmos, Steve Satchel, Bin Xu, Rui Zhong, You Zhou, and participants at the Leeds University Business School seminar, the 2024 Sydney Banking and Finance Conference, the 2024 Massey Sustainable Finance Conference, the 2025 Southwestern Finance Association Meeting, and the Suzhou Workshop of Economics with Heterogeneous Interacting Agents, for their helpful comments. Address correspondence to Avanidhar Subrahmanyam (asubrahm@anderson.ucla.edu).

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Abstract

The implications of firms' climate risk (CR) disclosures remain active topics of policy debates. We propose theoretically that increased CR disclosure enhances ownership breadth via firms' appeal to a larger set of investors. This relaxes shorting constraints, thus improving liquidity and price efficiency. Empirically, firms that increase CR disclosures around the [SEC \(2010\)](#) guidance experience increased market quality thereafter. We show using an IV approach and supplementary tests that reverse causality and joint determination are not likely drivers of our results. Belief heterogeneity and socially responsible funds play key roles in our novel channel from CR disclosures to market quality.

Recent years have witnessed heightened awareness of the effect of climate risk on corporations. Regulators have responded to this increased interest in climate risk (CR) by introducing policies intended to enhance the quality of CR-related corporate information.¹ These initiatives, in turn, have led to debates on costs of compliance (Tett (2024)), as well as on the effect of CR disclosure on firm values (Flammer, Toffel, and Viswanathan (2021)). However, little is known about the capital market implications of CR disclosure. Our study fills this gap. Specifically, we build a model which considers the effect of CR-type disclosures on breadth of ownership, market liquidity, and price efficiency, and test implications arising from our setting.²

Edmans (2023) proposes that firms can enhance their appeal to institutional investors by increasing the quality of CR disclosures. This is because such disclosures enable investors to better assess the resilience of a firm’s business model to climate change, and thus make investing in the firm more attractive. Indeed, Ilhan et al. (2023) find that institutional investors prefer to hold stocks of firms with more informative CR disclosures. Further, Kim, Wang, and Wu (2023) indicate that greater CR disclosure motivates the firm to pursue more environment-friendly policies. As we discuss in detail below, our contributions to this literature are twofold: First, we focus on the relation between CR disclosures and ownership *breadth* (over and beyond the level of institutional holdings). Second, we examine implications of the CR disclosure-ownership relation for financial market quality.

Several lines of thought suggest CR disclosure can increase breadth of ownership. For example, Kim, Li, and Liu (2019) show that firms providing more informative disclosures experience an increase in the total number of shareholders. Further, better CR disclosures are associated with higher sustainability ratings (Lopez-de Silanes, McCahery, and Pudschedl (2020)), which could enhance flows from sustainable funds. Indeed, Pástor, Stambaugh, and Taylor (2022) document a significant increase in socially responsible investment (SRI) during recent times, to the point where it now represents one-third of

¹To be specific, “climate risk” (CR) encompasses the physical and regulatory effects of climate change on corporations, and CR disclosure refers to a company’s efforts to report these risks (see SEC (2024) for details). Recent efforts to promote CR disclosure include global sustainability standards issued by the International Sustainability Standards Board (ISSB) in 2023, the EU’s Corporate Sustainability Reporting Directive of 2023, California’s SB253 and SB261, and the SEC’s new climate disclosure rules SEC (2024).

²As per Kim, Wang, and Wu (2023), we identify CR disclosures from companies’ 10-K statements using text analysis. The full list of words used for CR identification appears in Table B1 of Appendix B. The implementation of this list is discussed in Section 2.2.

the \$51 trillion assets under management in the U.S. ([US-SIF \(2020\)](#)). These pieces of evidence all suggest a positive effect of CR disclosures on breadth of ownership. This increased breadth should lead to less-binding short-selling constraints, which, in turn, should improve market liquidity and quality ([Diamond and Verrecchia \(1987\)](#), [Chen, Hong, and Stein \(2002\)](#), [Grullon, Kanatas, and Weston \(2004\)](#), [Huang, Qin, and Wang \(2024\)](#)).

Our model formalizes the above arguments. In our setting, some investors are short-sale-constrained and have heterogeneous beliefs about a component of cash flow that represents climate risk. Increased CR disclosure allows extreme optimists to correct their beliefs, which, in turn, allows the price to offer a premium to induce additional investors to buy the asset. This enhances ownership breadth and increases the availability of lendable shares for investors who are able to short-sell. In turn, all investors' trades are absorbed more efficiently, which improves liquidity and decreases noisiness in the price. Overall, via our mechanism, CR disclosures increase breadth of ownership, facilitate short-selling, and enhance market quality in equilibrium.

The forces we model are not the only possible ones, however. For example, as an alternative, CR disclosures could lead to enhanced *block* ownership, i.e., an increase in ownership driven by a few market-leading asset managers. This is a realistic possibility since the sustainable investment trend mentioned above has strengthened the dominant position of the largest asset managers, such as BlackRock. These managers have posted significant net Environmental, Social, and Governance (ESG) inflows in recent years ([Schwartzkopff \(2024\)](#)). In addition, [Christensen, Serafeim, and Sikochi \(2022\)](#) show that more CR disclosures lead to ESG rating disagreement/uncertainty, and [Avramov et al. \(2022\)](#) show that such uncertainty acts as a barrier to sustainable investing for some investors. Therefore, CR-disclosure-induced institutional ownership could be driven by a few large investors increasing their block ownership by channeling ESG inflows into existing portfolios. Such increased ownership concentration could imply worse stock market liquidity and price efficiency via an adverse effect of block ownership on market quality ([Brockman, Chung, and Yan \(2009\)](#)). Thus, there are tussling hypotheses on the relation between CR disclosures and firm ownership structure, which need empirical resolution.

In order to test our hypotheses, we use the SEC's publication of the [2010 Commission](#)

[Guidance Regarding Disclosure Related to Climate Change](#), which advised public companies on how to disclose climate risk (see [Kim, Wang, and Wu \(2023\)](#)).³ This is the earliest regulatory intervention on CR disclosures we could find in the U.S., and it allows for sufficiently long pre- and post-event periods for empirical analyses. Also, as [Kim, Wang, and Wu \(2023\)](#) document, the guidance was accompanied by a significant increase in the number of firms enhancing CR disclosures, which facilitates testing of our idea that such disclosures increase breadth of ownership and market quality. An increasing number of other papers also examine the effects of [SEC \(2010\)](#), but from other perspectives.⁴ In our study, we first identify a group of firms that substantially enhanced their CR disclosures around the guidance. We then examine how the ownership dispersion and market quality of these firms changes subsequent to the guidance, relative to other firms.

Consistent with our theory, our analysis confirms that firms which increase CR disclosure (CRD) around the guidance date experience increased ownership breadth relative to other firms post-guidance. Specifically, the CRD-increasing firms experience an increase in the number of institutions as well as a lowered value of the Herfindahl–Hirschman concentration index (HHI). We also show that Socially Responsible Investment (SRI) funds drive the increase in institutional ownership and the reduction in ownership concentration. It is noteworthy that mutual funds exhibit the most robust response to CRD increases. This highlights their pivotal contribution to the increase in ownership dispersion. To our knowledge, we are the first to report evidence on the conjecture that CRD increases promote breadth of ownership in financial markets.

The theoretical framework also suggests that greater ownership breadth from increased CR disclosure leads to an enhanced supply of lendable equity, and to improved stock liquidity and pricing efficiency. We next turn to testing these implications. We indeed find that firms with CRD increases have higher stock lendable supplies and lower borrowing costs. Further, such firms have higher liquidity (lower bid-ask spreads) and improved pricing.

³Although the guidance was formally implemented in 2010, we show later that there was ample anticipation in 2009. Hence, we use 2009 as the event year.

⁴[Berkman, Jona, and Soderstrom \(2024\)](#) study the association between market valuations and their 10-K-based climate risk measures in the post-[SEC \(2010\)](#) period. [Li et al. \(2024\)](#) investigate climate risk pricing before and after [SEC \(2010\)](#). Informed by [SEC \(2010\)](#), [Matsumura, Prakash, and Vera-Muñoz \(2024\)](#) show that firms that disclose CR experience greater reduction in capital costs within industries where CR is more material.

ing efficiency as proxied by variance ratios and the delay measure of [Hou and Moskowitz \(2005\)](#). These findings highlight the role of ownership breadth in channeling CR disclosures' positive effects on liquidity and pricing efficiency. We also demonstrate theoretical and empirical support for the notion that greater belief heterogeneity enhances the positive association between CRD and market quality.

The empirical results are robust to various regression specifications, alternative CR disclosure measures, and commonly used controls. We also provide additional evidence in support for our pathway from CRD to ownership dispersion to market quality. Specifically, we show that within the group of CRD-increasing firms, those that experience the greatest HHI decreases have the highest increases in market liquidity and efficiency metrics. We address joint determination by using a smaller control sample matched on several firm characteristics via propensity scores, and show that our results are qualitatively unchanged. To address possible reverse causality flowing from market quality to CR disclosure, we first note that our market quality measures are established after the identification of CRD-increasing firms, lessening the likelihood of market quality influencing CR disclosure. To address this issue further, we demonstrate the robustness of our results to propensity-score-matching, and also show that CRD-increasing firms do not have significantly higher market quality prior to their increase in disclosure. We use GHG emissions as an instrumental variable for CR disclosure to show that our conclusions survive. Thus, overall, our findings highlight a new aspect of CR disclosure, namely, its association with financial market quality, which adds perspective to the evolving debate on global sustainability reporting standards and regulations ([Ilhan et al. \(2023\)](#), [Cohen, Kadach, and Ormazabal \(2023\)](#)).

Our work adds to the fast-growing body of work on climate finance. The evidence that CRD increases are associated with increased ownership breadth accords with the idea that increasing CR transparency enhances the appeal of the firm to socially conscious investors ([Berk and Van Binsbergen \(2025\)](#)). In a comprehensive review, [Christensen, Hail, and Leuz \(2021\)](#) summarize the proposed economic effects of CR disclosures. Several of the reviewed studies (e.g., [Barth et al. \(2017\)](#), [Grewal, Hauptmann, and Serafeim \(2021\)](#), and [Cho, Lee, and Pfeiffer Jr. \(2013\)](#)) provide important correlational evidence on the relevant mechanisms. [Ramadorai and Zeni \(2024\)](#) argue that firms' current responses to carbon emission regulatory events have economic implications for future corporate decisions and

outcomes. Our study finds evidence that CR disclosures have favorable outcomes for financial market quality via their effect on ownership breadth. We thus shed new light on how environmental disclosures affect financial markets.

We also contribute to the literature on liquidity. Our work builds on many other papers. For example, [Brockman, Chung, and Yan \(2009\)](#) show that block ownership negatively affects a firm's trading activity and secondary market liquidity. [Ng et al. \(2016\)](#) find that foreign direct ownership negatively affects liquidity (the information channel), whereas foreign ownership via indexes has a positive association (the trading activity channel). [Karolyi, Lee, and Van Dijk \(2012\)](#) find evidence that commonality in liquidity is greater during times of large market declines. They argue that it is the trading behavior of institutional investors rather than the funding liquidity of financial intermediaries that explains liquidity commonality. [Lang, Lins, and Maffett \(2012\)](#) show enhanced liquidity for firms with greater transparency in their disclosures.

It may be argued that the insights we consider potentially apply to many forms of disclosure, not just those about climate risk. Our mechanism, that disclosure helps investors with heterogeneous views converge to the true effect of a driving force, applies uniquely to climate risk, however. This is because literature indicates extreme polarization about beliefs related to the effect of climate change (see, for example [Dunlap, McCright, and Yarosh \(2016\)](#), [Chinn, Hart, and Soroka \(2020\)](#), and [Cakanlar \(2024\)](#)). Indeed, it is explicitly conjectured in [Bolsen and Shapiro \(2018\)](#) that credibly disclosing information about climate risk can reduce polarization, which is the mechanism by which climate disclosure enhances financial market quality in our setting. A caveat is that we assume that firms disclose climate risk exposure truthfully; the official SEC guidance may be viewed as a tacit mechanism that signals regulatory enforcement of such veracity. Regardless, however, our mechanism only requires that such disclosures are positively correlated with the true exposure of firms to climate change.

In work directly related to sustainability issues and financial markets, [Wang et al. \(2023\)](#) show that ESG performance is positively associated with firms' stock liquidity in China.⁵ [Krueger et al. \(2024\)](#) provide correlational evidence showing a positive relation

⁵[Meng-tao et al. \(2023\)](#) and [He, Feng, and Hao \(2023\)](#) investigate the relationship between ESG ratings and stock liquidity in China. [Roy, Rao, and Zhu \(2022\)](#) demonstrate that Indian firms adhering to a mandated corporate social responsibility regulation experience significantly increased stock liquidity.

between ESG disclosure mandates and stock liquidity across countries, supporting a link between disclosure regulation and the quality of the information environment. [SEC \(2024\)](#) emphasizes that one aim of CR disclosure rules is to narrow the informational gap between informed and uninformed traders, which can improve stock liquidity. [Christensen, Hail, and Leuz \(2021\)](#), point out, however, that there is only limited large-sample evidence on the liquidity consequences of CSR reporting. We address this issue by providing evidence on the positive association between CR disclosures and dispersion of ownership, and in turn, stock liquidity.

On the price efficiency side, studies have mainly focused on short-selling constraints, limits to arbitrage, and institutional ownership. For example, using return predictability from order flows as an inverse measure of efficiency, [Chordia, Roll, and Subrahmanyam \(2008\)](#) find that liquidity improves efficiency. [Saffi and Sigurdsson \(2011\)](#) use measures similar to ours to show that stocks with higher short-sale constraints, measured as low lending supply, have lower price efficiency. [Asquith, Pathak, and Ritter \(2005\)](#) show that short-sale-constrained stocks, defined by high short interest and low institutional ownership, have significantly lower abnormal stock returns than unconstrained stocks. [Boehmer and Wu \(2013\)](#) and [Chen, Da, and Huang \(2022\)](#) find that price efficiency improves with shorting flows. [Cao et al. \(2023\)](#) find that the presence of SRI is associated with low price efficiency; they attribute this to SRI's ESG preferences and limited attention. We add to this literature by demonstrating a hitherto undocumented theoretical pathway from CRD to ownership dispersion, and, in turn, to lower short-selling constraints and greater pricing efficiency. We also provide empirical evidence on the relevant associations. To our knowledge, we are the first to consider this pathway.

This paper is organized as follows. Section 1 presents a theoretical basis for the link between CR disclosure and market quality, and derives empirical implications. Section 2 describes our various data sources, and defines our variables. Section 3 describes our estimation method and presents summary statistics. Section 4 presents our central empirical results. Section 5 describes some robustness tests, including our analyses ruling out endogeneity issues. Section 6 concludes. All proofs appear in Appendix A, whereas the details of the text analysis used to measure CR disclosures are in Appendix B.

1 A Conceptual Framework

In this section, we present a model that motivates our empirical tests. The setting examines the effect of disclosing information about a specific source of uncertainty, that we term climate risk, on ownership dispersion and market quality.

1.1 The economic setting

We use a setting with two dates, denoted as 1 and 2. Investors trade at Date 1, and consume at Date 2.

1.1.1 Assets

There is a risky stock. We assume that at Date 2, the stock pays a liquidating cash flow comprised of two components: $V = \theta - c$. The first, θ , is drawn from a normal distribution with a mean $\bar{\theta} > 0$ and variance v_θ . We interpret the second, c , as the component of cash flows that is exposed to climate change (or simply, the CR cost). We assume that the mean cost is positive; and specifically, that $c \sim \mathcal{N}(\bar{c}, v_c)$, with $\bar{c} > 0$. We describe the interpretation of c further in Section 1.1.2 below. The supply of the stock is fixed at $Q > 0$. There is also a risk-free asset whose price and gross return are each set to unity.

1.1.2 Investors

There are three types of investor. First, as in the seminal paper on ownership breadth, [Chen, Hong, and Stein \(2002\)](#), we assume that there is a mass M of *active buyers* who can only take long positions. These buyers can be interpreted as institutions such as mutual funds who are precluded from going short by charter. An active buyer, indexed by m , derives utility from final wealth W_{m2} and seeks to maximize the expectation of a standard exponential utility function: $U(W_{m2}) = -\exp(-\gamma W_{m2})$, where γ is a positive constant representing the absolute risk aversion coefficient.

Active buyers hold unbiased beliefs about the distribution of the non-CR cash flow θ . Given the literature which says that beliefs on climate change are heterogeneous and often ideologically-motivated (e.g., [Ortega-Egea, García-de Frutos, and Antolín-López \(2014\)](#)), we assume that beliefs about c vary across buyers. Specifically, buyer m believes that the CR cost c is drawn from a normal distribution with mean $c_m \equiv \bar{c} + \frac{\lambda_m}{\eta}$ and variance v_c , where $\lambda_m \sim \mathcal{N}(0, v_\lambda)$. In this specification, if $\lambda_m < 0$ (> 0), then the buyer is optimistic (pessimistic)

about the CR cost. The parameter v_λ represents the extent of the heterogeneity in beliefs. The scale parameter η , which influences how close the subjective assessment c_m is to the true $\bar{c}$, is influenced by the firm's disclosure policy, which is described in Section 1.1.3 below.⁶ The fraction of active buyers that have non-zero demands is endogenous, as we will see.

Next, there is a mass N of *arbitrageurs* who can take long or short positions costlessly and without the need to borrow shares for their short positions. They can be viewed as large institutions trading on their own account or as hedge funds. These investors hold unbiased beliefs about the distributions of the random variables associated with CR and non-CR cash flows, i.e., θ and c . Each arbitrageur, indexed by n , seeks to maximize the expectation of $U(W_{n2}) = -\exp(-\gamma W_{n2})$, given final wealth W_{n2} .

Third, there is a group of *noise traders*, separated into noise buyers and noise sellers. At Date 1, noise buyers have a positive demand $\ell > 0$, where ℓ is drawn from a distribution with the cumulative density function $G(\ell)$ on the support $(0, \ell_H]$; with $\ell_H > 0$. We let $\ell_H < Q$. If it were otherwise, liquidity buyers' demands could exceed supply, implying that other agents' unconstrained demands might be to short, which would create a disincentive for all potential buyers to submit nonzero demands. Such a scenario is unrealistic. Our assumption is equivalent to postulating that retail investors' long holdings represent a modest portion of the total supply.

Noise sellers have a negative demand $s < 0$. We assume that s is endogenously determined, and is proportional to the mass of active buyers who go long. That is, $s = -\rho MB$, where ρ is a positive constant, B represents the fraction of active buyers with a strictly positive demand, and MB represents the mass of such active buyers. This mechanism is consistent with the notion that at least some of the noise sellers are shorts that need to borrow shares, which emanates from active buyers who participate.⁷ For ease of interpretation, we assume below that the demand of noise shorts is directly proportional to the

⁶In Section IA.1 within the Internet Appendix, we consider a variant of the model where the CR disclosure is via a public informational signal with standard Bayesian updating, and the results are similar.

⁷We consider the noise sellers who wish to short as hedgers or uninformed speculators (Black (1986)). In our model, for tractability, we assume that while the arbitrageurs can short freely, the noise short sellers' demands are restricted by the number of active buyers. This is consistent with the view that arbitrageurs are large investment houses who have free access to shares for shorting, whereas the noise shorts are smaller institutions or individuals that face share borrowing constraints. We conjecture that our results would remain unaltered if some arbitrageurs also faced shorting constraints.

demand of noise sellers.

1.1.3 Information and disclosure

At Date 1, a public signal is available about θ , $\phi = \theta + \zeta$, where $\zeta \sim \mathcal{N}(0, v_\zeta)$. There is also a public disclosure of the firm's climate exposure via the variable η , which influences each active investor's subjective mean $\bar{c} + \frac{\lambda_m}{\eta}$. Specifically, if the firm does not disclose CR, then $\eta = 1$; if the firm discloses, then $\eta > 1$; as the firm discloses more CR, η increases further. Thus, as η increases, the CR disclosure moves active buyers' assessment of the mean of c more towards its actual value $\bar{c}$. So the firm's CR disclosure effectively mitigates the scale of the active buyers' optimism or pessimism about CR costs, and draws buyers closer to a Bayesian. In our paper, we assume the firm's CR disclosure arises from external regulatory pressure. Thus, η is an exogenous parameter in our setting, and represents the quality of the firm's CR disclosure. Let the upper bound of η be $\eta^{\sup}$, which is a positive constant.

1.2 The equilibrium

An equilibrium consists of two elements: (i) Active buyers and arbitrageurs choose their optimal demands given their beliefs and (ii) the market clears. Note that the solution to the equilibrium presents a fixed point problem: The fraction of active buyers with non-zero demands (B) depends on the price, the price depends on the amount of noise selling s , and s depends on B via the lendable supply channel. Nonetheless, we are able to solve this problem and obtain a unique equilibrium in analytic form. It turns out that because of the bounded nature of active buyers' demands, conditions are needed to ensure the existence of such an equilibrium. To describe the conditions, denote

$$v_\phi \equiv v_\theta + v_\zeta, \quad \tau \equiv \frac{v_\theta}{v_\phi}, \quad \text{and} \quad \Gamma \equiv \frac{\gamma[v_\theta(1-\tau) + v_c]}{\sqrt{v_\lambda}}.$$

The following condition then suffices for uniqueness:

$$\rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma \eta^{\sup}}. \tag{1}$$

This assumption holds if the short demand from noise sellers (i.e., $s = -\rho MB$) is not too large. If the noise demands mainly emanate from retail investors, the condition is consistent with the notion that retail investors' short holdings represent a modest portion

of the total.⁸

1.2.1 The equilibrium stock price

To describe the price in equilibrium, it is convenient to define a function of noise buying ℓ , $\kappa(\ell)$, according to the following specification:

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma\eta[Q - \ell + \rho MF(\kappa)] = 0, \quad (2)$$

where $F(\cdot)$ ($f(\cdot)$) represents the cumulative (probability) density function of the standard normal distribution. The following results obtain:⁹

Theorem 1 *The equilibrium stock price is given as follows:*

$$P(\phi, \ell) = \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \frac{\kappa(\ell)}{\eta} \sqrt{v_\lambda},$$

where $\kappa(\ell)$ is specified in Equation (2). Further, $\frac{dP(\phi, \ell)}{d\eta} < 0$.

The component $\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c}$ of the price represents the expectation of the final payoff $V = \theta - c$ conditional on the public signal ϕ . The second component, $-\frac{\kappa(\ell)}{\eta} \sqrt{v_\lambda}$, captures the effect of CR disclosure (i.e., η) on the price.

We now discuss the result in Theorem 1 that $\frac{dP(\phi, \ell)}{d\eta} < 0$. We show in the proof of the theorem (see Appendix A) that the m 'th active buyer's demand can be expressed as

$$x_m = \frac{\max(0, \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \lambda_m/\eta - P)}{\gamma[v_\theta(1 - \tau) + v_c]}. \quad (3)$$

Ceteris paribus, as η increases, there are two direct effects on P . First, optimistic active buyers with long positions (i.e., $\lambda_m < 0$ and $x_m > 0$) underestimate the CR cost to a lesser extent. They buy the stock less aggressively (i.e., x_m is lower); this effect exerts a downward pressure on price. Second, pessimistic active buyers overestimate the CR cost to a lesser

⁸Intuitively, in a unique equilibrium, the total demand, comprising those from active buyers, arbitrageurs, noise buyers (ℓ), and noise sellers ($s = -\rho MB$), should decrease in the stock price. In our model, it can be shown that *ceteris paribus*, as the price increases, combined demand from active buyers and arbitrageurs decreases (a detailed derivation is in the proof of Theorem 1 in Appendix A). But at the same time, as fewer buyers go long (i.e., smaller MB), noise sellers have a smaller short demand (i.e., a less negative $s = -\rho MB$), which counteracts the decrease. A low ρ ensures that the total demand indeed decreases in price.

⁹All proofs appear in Appendix A.

extent; this puts an upward pressure on the price. Since in equilibrium more optimistic buyers take long positions than pessimistic ones (note that the latter do not short-sell), the first effect dominates. There is also an indirect effect. Specifically, as we discuss in detail later, the above price pressure induces more active buyers to go long, and these investors facilitate short-selling by providing additional supply of lendable shares for noise sellers, who also impose price pressure in the same direction.

1.2.2 The implications of CR disclosure

We define ownership breadth as the fraction B of active buyers who go long in equilibrium. Equation (3) implies that the m 'th active buyer goes long (i.e., $x_m > 0$) only if the investor is not too pessimistic, that is,

$$\lambda_m < \eta [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - P(\phi, \ell)] = \kappa(\ell) \sqrt{v_\lambda}.$$

We can compute ownership breadth given ℓ as:

$$B(\ell) = \int_{-\infty}^{\kappa(\ell) \sqrt{v_\lambda}} 1 dF \left(\frac{\lambda_m}{\sqrt{v_\lambda}} \right) = F(\kappa(\ell)). \quad (4)$$

We obtain the following result:

Proposition 1 *Expected ownership breadth, $E[B(\ell)]$, increases in the level of CR disclosure, η .*

As previously shown (see Theorem 1), when CR disclosure (η) increases, the price offers a bigger premium to buyers because it accommodates more sidelined pessimists and noise sellers. The consequence of this is that more active buyers find it attractive to participate; this increases ownership breadth.

Figure 1 illustrates how η affects expected ownership breadth, $E[B(\ell)]$.¹⁰ It can be seen that as η rises, $E[B(\ell)]$ increases; this result is consistent with Proposition 1. We also observe that if belief heterogeneity about the CR cost increases (i.e., v_λ rises), $E[B(\ell)]$ is lower. The intuition for this is that in this case, pessimistic buyers overestimate the CR cost to a greater extent and are less likely to participate via long positions.

¹⁰We assume that ℓ is drawn from a uniform distribution. We use the parameter values $Q = 2$, $\bar{\theta} = 5$, $v_\theta = 1$, $v_\zeta = 0.25$, $\bar{c} = 1$, $v_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$. We have verified that our results are robust to a range of parameter choices.

Note that by assumption noise sellers' demand s is proportional to the mass of utility-maximizing buyers who go long. Thus, given a realization of noise buying ℓ , this demand is given by:

$$s(\ell) = -\rho MB(\ell). \quad (5)$$

We obtain the following result:

Proposition 2 *The expected short interest, $E[|s(\ell)|]$, increases in the level of CR disclosure (η).*

As CR disclosure (η) increases, more active buyers go long (i.e., a higher $E[B(\ell)]$). These investors facilitate more short-selling by providing an additional supply of lendable shares for noise sellers.

Figure 2 illustrates how η affects expected short interest, $E[|s(\ell)|]$. It can be seen that as η rises, $E[|s(\ell)|]$ increases; this result is consistent with Proposition 2. We also observe that if belief heterogeneity about the CR cost increases (i.e., v_λ rises), $E[|s(\ell)|]$ is lower. The reason for this is that in this case, pessimistic buyers overestimate the CR cost to a greater extent and are less likely to participate by taking long positions (i.e., $E[B(\ell)]$ is lower, as shown in Figure 1); this leads to less supply of lendable shares.

We next turn to illiquidity in this market. Let the total noise demand be given by $z(\ell) \equiv \ell + s(\ell)$. Denote

$$\alpha(\phi, \ell) \equiv \frac{dP(\phi, \ell)}{dz(\ell)}.$$

We measure expected illiquidity by $E[\alpha(\phi, \ell)]$, and obtain the following result:

Proposition 3 *The expected illiquidity measure, $E[\alpha(\phi, \ell)]$ (where $\alpha(\phi, \ell) > 0$), decreases when there is an increase in CR disclosure (i.e., a rise in η).*

The increase in active buyers in response to a rise in CR disclosure (Proposition 1) has two effects on liquidity provision. First, there is a direct effect: Additional active buyers provide more liquidity for noise traders. Second, there is an indirect effect: More active buyers facilitate short-selling by providing additional supply of lendable shares for noise sellers; see Proposition 2. These sellers increase liquidity provision for noise buyers. Both of these effects contribute to the positive effect of CR disclosure on liquidity.

Figure 3 depicts how η affects illiquidity, $E[\alpha(\phi, \ell)]$. We can see that as η increases, $E[\alpha(\phi, \ell)]$ decreases; this result is consistent with Proposition 3. It can also be seen that if belief heterogeneity about the CR cost increases (i.e., v_λ rises), then $E[\alpha(\phi, \ell)]$ increases. The reason for this is that in this case, pessimistic buyers overestimate the CR cost to a greater extent and are less likely to take long positions (i.e., $E[B(\ell)]$ is lower as shown in Figure 1); this leads to less liquidity provision for noise traders.

We measure the informational efficiency of the stock price using the inverse of the variance ratio

$$VR \equiv \frac{\text{Var}(V - P) + \text{Var}(P)}{\text{Var}(V)}.$$

Note that when price equals the fundamental (i.e., when P is noiseless), the variance ratio is at its benchmark of unity. The degree to which the ratio exceeds unity is then a metric for how much the price is affected by noise.¹¹ We obtain the following result:

Proposition 4 *Suppose that $Q > \ell_H + \max\left(\frac{M}{\Gamma\sqrt{2\pi}}, \rho N\right)$. Then, the variance ratio, VR , decreases (prices become more efficient) when there is an increase in CR disclosure (i.e., a rise in η).*

As CR disclosure increases (i.e., as η rises), more active buyers go long, leading to additional liquidity provision for noise traders. This mitigates price movements due to the liquidity shock; consequently, the price becomes more aligned with the fundamental. However, there are conditions under which this effect dominates. First, if the supply Q is high relative to ℓ_H , then a rise in η stimulates more pessimistic buyers to enter the market and absorb the excess supply. This tends to reduce the noisiness of the price. A large Q relative to M and ρ implies that the supply is large relative to shorting demand. This ensures that the increase in shorting resulting from the η increase (viz. Proposition 2) does not have too much of an adverse effect on price efficiency.¹² The conditions in Proposition 4 are reasonable, in that intuitively, we would not expect short bets or liquidity buying to be large relative to the total supply of the firm's shares.

¹¹The second term in the numerator of VR can be viewed as variance of the short-term price change from a prior Date 0 to Date 1, where the Date 0 price is non-stochastic because it is established before any signals or noise trades have been realized. Hence the full numerator is a cumulation of short-term variances, and the denominator is the variance of the change in the long-term fundamental (spanning Dates 0 to 2).

¹²Note that the condition for Proposition 4 is stronger than the assumption $Q > \ell_H$ in Section 1.1.2.

Figure 4 depicts how η affects the variance ratio, VR . It can be seen that as η increases, VR decreases; this result is consistent with Proposition 4. We also observe that if belief heterogeneity about the CR cost increases (i.e., v_λ rises), then VR increases (i.e., the stock price becomes less informationally efficient). The reason for this is that in this case, pessimistic buyers overestimate the CR cost to a greater extent; they are less likely to take long positions (i.e., $E[B(\ell)]$ is lower as shown in Figure 1) and provide liquidity. As market liquidity decreases (i.e., $E[\alpha(\phi, \ell)]$ is higher as shown in Figure 3), the noisiness in the price is corrected to a smaller extent.

1.2.3 Belief heterogeneity and CR disclosure

In this section, we analyze how belief heterogeneity about CR (the parameter v_λ) affects the influence of CR disclosure on financial markets. We use our results to develop additional testable implications. We are able to prove the following result:

Proposition 5 *For a sufficiently high stock supply, Q , the marginal effects of CR disclosure η on expected ownership breadth, short interest, and illiquidity are greater when belief heterogeneity about climate costs (measured by v_λ) is higher.*

As previously shown (see Theorem 1 and the ensuing discussion), when η increases, it shifts active buyers' beliefs about the CR cost. Particularly, optimistic active buyers with long positions underestimate CR costs to a lesser extent; consequently, they buy the stock less aggressively, which exerts a downward pressure on price (i.e., $\frac{dP(\phi, \ell)}{d\eta} < 0$). If belief heterogeneity among active buyers about the CR cost is higher (i.e., a higher v_λ), then a given marginal increase in η moves active buyers' beliefs to a greater extent; this eventually leads to a stronger downward pressure on price. Consistent with this intuition, we show in the proof of Proposition 5 that for higher v_λ , the absolute magnitude of $\frac{dP(\phi, \ell)}{d\eta}$ is greater.

As the price offers a higher premium to active buyers for higher v_λ , an increase in v_λ implies a greater per share return to absorbing excess supply. This implies a greater marginal effect of η on active buyers, which results in a larger increase in expected ownership breadth ($E[B(\ell)]$). In turn this implies enhanced supply of lendable shares for noise sellers. Figures 5 and 6 confirm that as belief heterogeneity increases, $\frac{dE[B(\ell)]}{d\eta}$ and $\frac{dE[|s(\ell)|]}{d\eta}$ do so as well. The increased effect of η on active buying also carries over to

liquidity. Specifically, increased active buying provides more liquidity for noise traders, both directly and by facilitating more short-selling. Figure 7 confirms that as v_λ rises, the magnitude of $\frac{dE[\alpha(\phi, \ell)]}{d\eta}$ increases.¹³

Finally, from an intuitive standpoint, because an increase in η increases liquidity to a greater extent when v_λ is high, the informational efficiency of stock price should increase to a greater extent as well. However, we are not able to show this analytically; so we use numerical analysis. Figure 8 shows that consistent with Proposition 4 and Figure 4, the variance ratio VR decreases in η (i.e., $\frac{dVR}{d\eta} < 0$). Also, consistent with intuition, when v_λ rises, $\frac{dVR}{d\eta}$ becomes more negative.

1.3 The model's implications

Based on our theoretical analyses, we formulate four main empirical implications. We provide these below, along with references to the propositions that support them. These implications all refer to the consequences of CR disclosure via the parameter η . Our specific implications are the following:

1. (Proposition 1 and Figure 1) Increased CR disclosure implies reduced ownership concentration (increased ownership breadth).
2. (Proposition 2 and Figure 2) CR disclosure stimulates supply of lendable shares.
3. (Proposition 3 and Figure 3) Greater CR disclosure reduces the price impact of trades (increases stock market liquidity).

Although the conditions underlying Proposition 4 are reasonable, the proposition implies an ambiguous effect of enhanced CR disclosure on price efficiency, and so we let the data guide us on the direction of the effect. We finally present the following implication:

4. (Proposition 5 and Figures 5-8) CR disclosure has stronger effects on financial markets when beliefs are more heterogeneous.

We perform our empirical tests in Section 3, after describing our data in Section 2.

¹³The reasoning for the conditional nature of Proposition 5 (i.e., Q sufficiently high) is the same as that given following the discussion of Proposition 4.

2 Data and Variable Construction

In this section, we describe the sources from which we obtain our data, define our sample, and provide details on the measurement of the variables we use in our empirical analysis. We also present some descriptive statistics.

2.1 Data sources

We select U.S. public firms in Compustat with fiscal years from 2005 to 2014, and explore an alternative, extended sample period in Section 5. We match the Compustat sample with the Center for Research in Security Prices (CRSP), the Trades and Quotes (TAQ) database, and Markit Securities Finance Analytics. Finally, we retain those observations that match with EDGAR SEC 10-K filings.

2.2 Climate risk disclosure in 10-K statements

We extract CR keywords from the firms' 10-K reports. These keywords follow Kim, Wang, and Wu (2023), and are listed in Table B1 within Appendix B. We consider a firm to have CR disclosure when at least one of the keywords in Table B1 is presented in its 10-K report of the fiscal year. The *10-K-Based CR Disclosure* is the number of climate-change-risk related words, scaled by the total number of words in the 10-K reports. Our construction of the CR disclosure is analogous to Sautner et al. (2023)'s CR Exposure quantified from earnings call transcripts. We use their measure in a robustness test within Section 5.¹⁴

In our analysis, we control for the logarithm of the number of words in the 10-K report. This quantity proxies for the report's readability. We approximate the disclosure specificity using the number of unique words divided by the total number of words in the financial statement. We also use the vocabulary lists in Loughran and McDonald (2011) and Bodnaruk, Loughran, and McDonald (2015) to categorize words into positive or negative sentiment groups. We calculate an additional control, net sentiment, as the difference between the number of positive and negative words divided by the total number of words.

¹⁴The measure, termed *Earnings-Call-Based CR Disclosure* is defined as the frequency of climate change-related keywords in the earnings call transcripts. The data are publicly available at: <https://osf.io/fd6jq/>.

2.3 Breadth of ownership measures

The institutional ownership data is obtained from the Thomson Institutional (13F) Holdings database. We compute three measures from the ownership data, including (1) the fraction of ownership by institutional investors, (2) the logarithm of the number of institutional investors, and (3) the institutional ownership concentration measured by the Herfindahl-Hirschman Index (HHI). The frequency of institutional ownership data is quarterly. We take the annual average of the available values. Furthermore, we break down institutional ownership by investor type. We group institutional investors based on their adherence to socially responsible goals, identified by their signatory status to the United Nation’s Principles of Responsible Investment ([Gibson Brandon et al. \(2022\)](#)). We thus classify institutional ownership into Socially Responsible Investment (SRI) and non-SRI. We also partition institutional ownership by fund type; into banks and insurance companies (Banks), mutual funds (Mutual), pension funds (Pension), and others (Other).

2.4 Lendable supply, liquidity, and price efficiency

We use data from the Markit Securities Finance Analytics database to calculate lendable supply value and the borrowing cost score. We follow [Brockman, Chung, and Yan \(2009\)](#) and use the bid-ask spread from the TAQ database as our liquidity measure. This measure can be interpreted as the price impact of small trades by noise traders, as per Proposition 3 (see [Glosten \(1989\)](#)). We omit the [Amihud \(2002\)](#) measure because it exhibits a strong (negative) correlation with the control variable $\log(\text{Market Value})$; see [Goyal, Subrahmanyam, and Swaminathan \(2023\)](#) for a detailed discussion. The lendable supply and liquidity data are at a daily frequency.

We select and construct two stock price efficiency measures. The first is the firm-level Variance Ratio, which is the ratio of the variance of five-week returns to five times the variance of one-week returns for each stock, minus one ([Mech \(1993\)](#), [Griffin, Kelly, and Nardari \(2010\)](#)). This measure is suggested by the discussion following Proposition 4. The second measure is the Delay metric estimated by regressing individual stock returns on current and lagged four weeks’ market portfolio returns ([Hou and Moskowitz \(2005\)](#), [Saffi and Sigurdsson \(2011\)](#)), and comparing R^2 ’s when the lags are included to when they are excluded. Although the Delay measure is not directly suggested by our model, we

include it for completeness. Both measures are inversely related to price efficiency. In other words, the lower the Variance Ratio or Delay, the better the price efficiency. Each of these measures is estimated at an annual level for each stock. We provide detailed definitions of the variables in Table 1.

3 Description of Method and Summary Statistics

Since our goal is to test for the effect of CR disclosure on various firm outcomes such as ownership dispersion, and the quality and efficiency of markets, we seek an event which simultaneously induces a large number of firms to change such disclosures. The SEC (2010) guidance is the earliest such event we could identify. Specifically, the SEC published this guidance in February 2010, which reinforced the standards for public companies' CR disclosures.¹⁵ The guidance encompassed standards for disclosing key climate change matters, including regulatory, physical, and other related business risks. Although the standards mainly apply to 10-K filings, the document also mentions their relevance and implications for voluntary disclosures (for example, earnings calls).¹⁶ Kim, Wang, and Wu (2023) find that the percentage of CR-reporting firms increases by 8% in the first 10-K filing after the publication of the guidance. Therefore, the guidance is a policy shock to both mandatory disclosures (such as 10-K reports) as well as voluntary ones (such as earnings call transcripts). Our implicit assumption is that SEC (2010) guidance tacitly induces some firms to significantly enhance their CR disclosure activity. Our initial aim is to identify such firms, and analyze how their ownership breadth and market quality change post-guidance relative to other firms. Subsequently, we discuss robustness and address alternative interpretations of our results.

3.1 Event year and definition of CR disclosure-increasing firms

We propose a rank-based, data-driven approach for the definition of the firm group that substantially increased its CR disclosure (CRD) post-guidance. In this definition, given

¹⁵The SEC adopted [The Enhancement and Standardization of Climate-Related Disclosures for Investors SEC \(2024\)](https://www.sec.gov/news/press-release/2024-31) on March 6, 2024 (<https://www.sec.gov/news/press-release/2024-31>). These new rules are a substantially enhanced and legally binding version of SEC (2010). In defending these new rules, the then-SEC chair Gary Gensler makes references to the SEC (2010) guidance and mentions requirements for disclosing material climate risks.

¹⁶The details can be found in Section B.3 on pages 8 to 9 of SEC (2010).

an event year, to be classified in the CRD-increasing group, we require that a firm satisfy all three of the following conditions: (1) When the firm is excluded from the sample, the [Wilcoxon Rank Sum Test \(Mann-Whitney U-test\)](#)¹⁷ comparing the 10-K-based CR disclosure measures in the year before the event year relative to those in the year after is less significant; i.e., the p-value of the test statistic is larger when this firm is excluded. This condition is inspired by Jackknife resampling ([Efron \(1982\)](#)) in statistics. (2) The cross-sectional rank of the firm's CR disclosure in the year after the event year is higher than that in the year before. (3) The value of the firm's 10-K-Based CR Disclosure in the year after the event year is higher than that in the year before. Conditions (1) and (2) ensure a significant cross-sectional change in the CR disclosure behavior of the identified firms before and after the given event year. Additionally, Condition (3) ensures that the identified firms enhance the quality of their CR disclosure after the event year. The higher the percentage of firms satisfying the three conditions, the more positive the changes in the overall CR disclosure behavior during the given event year.

In terms of defining the event year, there is good reason to believe that the [SEC \(2010\)](#) CR disclosure guidance was anticipated in the months prior to its announcement. Thus, SEC Commissioner Kathleen Casey delivered a speech on 11/17/2009 at the Executives' Financial Reporting Issues Conference in New York titled "Lessons from the Financial Crisis for Financial Reporting, Standard Setting and Rule Making."¹⁸ The speech included pointers that the introduction of [SEC \(2010\)](#) was imminent. To check the possible pre-announcement effect of the SEC guidance, we annually apply our definition of CRD-increasing firms period 2005-2014 and plot the percentage of identified firms in Figure 9. We find that this percentage peaks in 2009 at 15% (nearly 9% more than that in 2005 and 7% more than that in 2014), signifying that firms' CR disclosure behavior undergoes the most positive change in that year during this period. This observation suggests that a pre-announcement effect of the [SEC \(2010\)](#) guidance does indeed prevail in 2009. We therefore define the CRD-increasing group to be the firms meeting our three criteria for

¹⁷The Wilcoxon rank sum test is equivalent to the Mann-Whitney U-test ([Mann and Whitney \(1947\)](#)). The Mann-Whitney U-test is a nonparametric test for equality of population medians of two samples.

¹⁸The transcript can be accessed online at <https://www.sec.gov/news/speech/2009/spch111709klc.htm>. In lesson 3 of the speech, Casey states: 'For example, there has recently been some discussion of the Commission's disclosure requirements relating to "climate change," including the possibility that the Commission will issue interpretive guidance in this area.'

CRD increases in the year 2009.

In the rest of the sample, there are firms that significantly and negatively change CR disclosure, which in terms of logical operators is Condition (1) & $\overline{\text{Condition (2) \& Condition (3)}}$. These firms are very few and account only for 0.01% of the sample. Technically, however, they do change their CR disclosure behavior significantly and negatively; so we exclude them. All other non-CRD-increasing firms either do not meet Condition (1) or do not meet Conditions (2) and (3) simultaneously. In other words, they do not change their CR disclosure behavior significantly by our criteria.¹⁹

3.2 Discussion of Estimation Method

We aim to establish evidence on CR disclosure using a regression analysis. We expect [SEC \(2010\)](#) to influence firms' climate risk disclosures but not to directly affect variables such as breadth of ownership, lendable equity, market liquidity, or price efficiency. Therefore, if we observe changes in the CRD-increasing firms' financial market environment that differ from those of other firms pre- versus post-[SEC \(2010\)](#), then with high likelihood, we can attribute these changes to CR disclosures. We thus specify our regression as follows:

$$Y_{i,t} = a_0 + a_1 \text{CRDInc}_i \times \text{Post} + a_2 \text{CRDInc}_i + \text{Controls}_{i,t} + \text{Industry and Year Fixed Effects} + \varepsilon_{i,t}, \quad (6)$$

where CRDInc_i is an indicator variable denoting the CRD-increasing firm group (as defined in Section 3.1), Post is a time indicator variable which equals one for 2009-2014, and zero otherwise,²⁰ $\text{CRDInc}_i \times \text{Post}$ is our interaction term of interest, and the Industry Fixed Effects are based on firms' 3-digit SIC codes. The left-hand variable Y represents ownership dispersion, or, in turn, one of our metrics representing liquidity and market efficiency.

Since it is possible that some aspects of the firm may drive both CR disclosures and subsequent market quality, we use a set of Controls to lessen the likelihood of joint determination in tests of our theory. These controls largely follow [Grullon, Kanatas, and](#)

¹⁹In unreported tests, we follow [Kim, Wang, and Wu \(2023\)](#) and define an alternative non-CRD-increasing group as those firms that never disclose CR information. The results remain qualitatively similar.

²⁰In keeping with our definition of the event year, we use 2009-2014 as the Post period, but the results are unaffected if we use 2010-2014 instead.

Weston (2004) and Lang and Stice-Lawrence (2015). Specifically, we use firm age, past stock returns, ROA, market capitalization, nominal share price, return volatility, and controls for general informativeness of financial disclosure (i.e., number of words, count of unique words, and net sentiment). Another possibility is that the firm increases CR disclosures because it anticipates increases in market quality. This phenomenon accords with our pathway, however, because our channel, that CR disclosures increase clientele breadth and thus liquidity, holds whether the firm is able to predict this increase. Based on this observation, and because our controls are comprehensive, we use Equation (6) to present our main results in Section 4 to follow. We further discuss joint determination and reverse causality in Section 5.

3.3 Summary statistics

Panel A of Table 2 summarizes the basic statistics for the breadth of ownership, lendable supply, stock liquidity, price efficiency, and control variables.²¹ The average firm has 51.7% of shares owned by institutions, 41 institutional investors, and an HHI index of 7.6%. The annual mean values of the Lendable Supply and Lendable Demand are 0.191 and 0.040, respectively. The average BA Spread is about 4.6 basis points. The average value of the Variance Ratio measure (i.e., 3.67) is well above its efficient market benchmark of unity. The Delay measure ranges from zero to one theoretically, and the sample mean of this measure is around 0.33. The average firm in our sample exists for 16.2 years in Compustat, has an annual Stock Return of 15.2%, and has a -0.3% ROA.

We also present skewness in Panel A of Table 2. The skewness of nine of the 20 variables is within the conventional range of [-1,1] for insubstantial skewness (Hair et al. (2009)). These nine variables are InstOwn%, InstOwn log#, Lendable Supply, Delay, log(Firm Age), log(Market Value), log(# Words), % Unique Words, and % Net Sentiment. The vast majority of the remaining 11 variables have positive skewness, i.e., are right-skewed, with the only exception being ROA, which has negative skewness (left-skewed). Note that right-skewed sample distributions are not surprising, given that nine out of the ten right-skewed variables (InstOwn HHI, Lendable Demand, Borrow Cost Score, BA Spread, Variance Ratio, Earnings-Call-Based CR Disclosure, 10-K-Based CR disclosure, and 1/(Share Price))

²¹Variables available at frequencies higher than a year are annually averaged. Further, we winsorize all variables at the 1% and 99% levels using their year-by-year distributions.

are positive. Among the three disclosure variables, Earnings-Call-Based CR Disclosure has the largest skewness of 4.66. Stock Return is mildly right-skewed. This is consistent with [Albuquerque \(2012\)](#).

In the institutional ownership analysis by category, we exclude a firm-year observation if we fail to identify the type of institutional investors that own the firm's stock. Consequently, the institutional ownership sample split by category is smaller than the baseline sample. We present summary statistics for institutional ownership by category in Panel B of Table 2. We observe an average of 8.0% SRI and 56.8% non-SRI in the sample. The majority of the institutional ownership is by mutual funds (46.3%), followed by banks and insurance companies (10.9%), others (5.0%), and pension funds (1.8%).

We report correlation coefficients between key variables in Panel A of Table 3. In Panel B, we replace the last nine rows (comprised of controls) of Panel A with 10 rows related to institutional ownership by category. The CR disclosure variables positively correlate with InstOwn% and InstOwn log#. They negatively correlate with institutional ownership concentration (InstOwn HHI) and BA Spread. Notably, Delay is negatively related to Lendable Supply. We also see that Mutual InstOwn% is negatively related to BA Spread and positively related to Lendable Supply; SRI InstOwn% is positively related to CR disclosure measures while Non SRI InstOwn% does not show significant correlations with CR disclosure measures.

4 Main Results

In this section, we first present our principal regression results. We then consider conditional tests based on belief heterogeneity. Following this, we provide additional results to verify our model's mechanism, and also consider the role of socially responsible funds in mediating the effect of CR disclosure on dispersion of ownership.

4.1 Basic regressions

We present the estimates of Regression (6) in Table 4, separately for each of breadth of ownership, lendable equity, liquidity, and price efficiency as our left-hand variables. The

regression is estimated at the firm-year level.²² Panel A shows results with the control variables, and Panel B considers results without controls. Since Panel B confirms all key messages from Panel A, we focus our discussions on Panel A. Also, to save space, we only show the results with the control variables in the subsequent tables.

The interaction coefficients in the first three columns of Table 4 Panel A show that breadth of ownership is significantly related to firms' CR disclosure policy: both InstOwn% and InstOwn log# increase while InstOwn HHI decreases. Specifically, the interaction coefficients of InstOwn% and InstOwn log# are 0.03 (t -statistic = 3.25) and 0.17 (t -statistic = 3.03), respectively, and are significant at the 1% level. The interaction coefficient of InstOwn HHI is -0.01 with a t -statistic of -3.12 and is significant at the 1% level. In economic terms, after 2009, the CRD-increasing group's InstOwn% (InstOwn log#) is, on average, 0.03 (0.17) higher, which is 8% (8%) of InstOwn%'s (InstOwn log#'s) sample standard deviation of 0.36 (2.10) as in Table 2, than that of other firms. For InstOwn HHI, the CRD-increasing group is on average 0.01 lower than other firms, which is 8% of InstOwn HHI's sample standard deviation of 0.10 as in Table 2. The positive interaction coefficients of InstOwn% and InstOwn log# accord with the notion that institutional investors prefer holding stocks of firms with more informative CR disclosure (Ilhan et al. (2023)). The negative coefficient of InstOwn HHI is our novel result that enhanced CR disclosures increase ownership breadth, and this finding supports Implication 1 in Section 1.3.

Using lendable equity data, we next test the effect of CR disclosure on equity lending (our Implication 2). Given the positive association between CR disclosure and ownership breadth, we expect that CRD-increasing firms will have a higher supply of lendable equity and lower borrowing cost, consistent with Chen, Hong, and Stein (2002), D'Avolio (2002), and Porras Prado, Saffi, and Sturgess (2016). Indeed, the positive interaction coefficient for Lendable Supply (0.01, t -statistic = 3.13) and the negative one for Borrow Cost Score (-0.08, t -statistic = -2.68) confirm this expectation. In economic terms, after 2009, the CRD-increasing group's Lendable Supply (Borrow Cost Score) is, on average, 0.01 higher (0.08 lower) than that of other firms. These magnitudes are respectively 8% and 21% of the standard deviations for the two variables (Table 2).

²²The ownership variables lie between zero and 100%, so we perform a robustness check that uses a logit transformation of these variables. The results (not tabulated for brevity) are qualitatively unaltered.

The demand for lendable equity can be associated with overpricing, as it represents increased impetus to short-sell. If CR disclosure is considered an adverse signal, e.g., greenwashing, then firms with more CR disclosure could have a higher demand for lendable equity. However, in untabulated results, the interaction coefficient for Lendable Demand is insignificant, indicating that investors generally do not consider CR disclosure to be an adverse signal. As Lendable Demand does not exhibit significance in the regression, we do not consider it further.

We now use data on the bid-ask spread to examine the effect of CR disclosure on stock liquidity. Specifically, our Implication 3 proposes that CR disclosure can improve liquidity due to increased ownership breadth (see also [Dixon, Fox, and Kelley \(2021\)](#) and [Dixon \(2021\)](#)). The negative interaction coefficients for BA Spread in Table 4 Panel A confirm that higher CR disclosure indeed implies greater liquidity. Specifically, the interaction coefficient of the BA Spread is -0.01 (t -statistic = -4.28) and is significant at the 1% level. In economic terms, after 2009, the CRD-increasing group's BA Spread is, on average, 0.01 lower than other firms', which is 14% of the spread's 0.06 standard deviation as in Table 2.

Market liquidity and easier short-selling have both been linked to enhanced price efficiency in previous studies (e.g., [Diamond and Verrecchia \(1987\)](#), [Hou and Moskowitz \(2005\)](#), [Chordia, Roll, and Subrahmanyam \(2008\)](#), [Saffi and Sigurdsson \(2011\)](#), and [Dixon \(2021\)](#)). This literature indicates that CR disclosure should have a positive effect on price efficiency (as suggested by our theoretical analysis). Using the variance ratio and delay data, we next test this notion. We find significantly negative interaction coefficients for Variance Ratio and Delay in the last two columns in Panel A of Table 4. More concretely, the interaction coefficients are -0.23 (t -statistic = -2.86) and -0.02 (t -statistic = -2.33), respectively. These magnitudes are respectively 10% and 7% of the standard deviations of 2.15 and 0.28 for Variance Ratio and Delay in Table 2, and suggest that market efficiency increases in the CRD-increasing group post-2009 relative to other firms. The results offer evidence that firms with more CR disclosure tend to have better stock price efficiency (inversely) measured by Variance Ratio and Delay.²³

In Panel B of Table 4, we conduct the regressions without the control variables. Not surprisingly, we find greater significance. For instance, the t -statistic of the interaction

²³We provide a parallel trends analysis for key variables in Section [IA.2](#) within the Internet Appendix.

coefficient for InstOwn HHI is -4.31, which is 1.4 times larger in magnitude compared to that in Panel A. Similarly, Lendable Supply's interaction coefficient exhibits a significant increase in t -statistic from 3.13 in Panel A to 4.66 in Panel B. The magnitude of its estimate also increases from 0.010 to 0.017. This implies that, in comparison to other firms, the CRD-increasing group's Lendable Supply is, on average, 14% Lendable Supply's sample standard deviation higher in Panel B as opposed to 8% in Panel A. Overall, the consistency between Panels A and B underscores the robustness of our regression findings.²⁴

4.2 Belief heterogeneity

We next employ data on analyst coverage and forecast dispersion to test the conditional effect of belief heterogeneity, as described in Proposition 5 and the last implication in Section 1.3. We measure investors' belief heterogeneity at the firm level as a combination of analysts' forecast dispersion²⁵ and analyst following. The latter notion arises from the findings of [Easley, O'Hara, and Paperman \(1998\)](#) that analysts produce material public information,²⁶ so that a reliable public signal is missing or very noisy when few or no analysts follow a firm. This dearth of public information can cause a lack of consensus and, in turn, large disagreement among investors if the firm's analyst coverage is sparse. Therefore we define a firm as having high belief heterogeneity either when disagreement among analysts is high or when analyst following is low.

Specifically, we follow [Diether, Malloy, and Scherbina \(2002\)](#) and compute analyst forecast dispersion as the standard deviation of the most recent EPS estimates made within 90 calendar days of the earnings announcement. The data for the EPS estimates are from the Institutional Brokers' Estimate System (I/B/E/S) database. We then split the sample into two groups: Low Belief Heterogeneity and High Belief Heterogeneity. The former group consists of firms with lower than median analysts' forecast dispersion each year, while the latter comprises firms with higher than median forecast dispersion and those

²⁴All regression results are robust to replacing the year-fixed effect with the Post indicator. The results without a year-fixed effect are available upon request.

²⁵Here, the implicit assumption is that greater belief heterogeneity at the analyst level is positively related to belief heterogeneity about CR. Ideally, we would use an analyst dispersion measure focused solely on CR costs to align perfectly with our model. Although this is not feasible empirically, analyst forecasts pertain to the firm's overall earnings, which incorporate CR costs. Therefore, while not a direct measure, analyst dispersion should still capture belief heterogeneity regarding CR costs to some extent.

²⁶See also [Hong and Stein \(1999\)](#) and [Verardo \(2009\)](#).

with fewer than two following analysts each year.

We repeat the regression in Equation (6) for these two groups and report the results in Table 5. The findings indicate that the interaction coefficient is more significant and has a greater magnitude in the High Belief Heterogeneity group compared to the Low Belief Heterogeneity group. This pattern holds not only for the dependent variables in the breadth of ownership category (Panel A) but also across the other three categories (Panels B and C), with the sole exception of Variance Ratio. These results support Proposition 5.

4.3 Breadth of ownership mediating the CRD-market quality relation

Our model proposes a specific two-stage mechanism. First, there is a positive influence of CR disclosure on ownership breadth which stems from institutional investors' preferences (Ilhan et al. (2023)). Next, this increase in ownership breadth facilitates the supply of lendable equity (Chen, Hong, and Stein (2002), D'Avolio (2002), and Porras Prado, Saffi, and Sturgess (2016)), and improves stock liquidity and price efficiency. We now briefly mention evidence which considers the above pathway.

Specifically, within the subgroup of CRD-increasing firms, we check if the firms that experience the greatest decrease in ownership concentration also tend to be the ones that undergo the greatest increase in market quality. We proceed as follows. First, we compute the difference between the average value after and before the event year for InstOwn HHI, Borrow Cost Score, BA Spread, Variance Ratio, and Delay, and the negative of this difference for Lendable Supply. Then, we calculate Pearson's correlations between the change in InstOwn HHI and the changes in the other variables.

We find that the InstOwn HHI change is significantly and positively correlated with the (negative of the) change in Lendable Supply (0.17***). It is also positively correlated with changes in Borrow Cost Score (0.20***), BA Spreads (0.18***), and Delay (0.23***). The only insignificant correlation is for the change in Variance Ratio (-0.02). These correlations are consistent with the main thrust of our argument. In particular, firms that experience the greatest increase in ownership breadth post-CR tend to be the ones that also experience the greatest increase in lendable supply, and in liquidity and efficiency metrics.

4.4 The role of socially responsible investing and mutual funds

In this section, we take a closer look at the effect of CR disclosure on ownership dispersion. Specifically, we consider the extent to which the result arises from specific kinds of assets under management or institutions.

4.4.1 Socially responsible investing

Flammer, Toffel, and Viswanathan (2021) find that investors value transparency about firms' exposure to climate change risks. This is in line with survey evidence by Krueger, Sautner, and Starks (2020), which indicates that large institutional investors consider climate risks financially material for the not-too-distant future. The survey further finds that long-term, larger, and ESG-oriented institutional investors consider climate risk management a better approach than divestment. Hence, we would expect such institutions to value greater climate risk disclosure. This also accords with evidence that socially conscious institutional investors tend to engage more with their investee firms over ESG concerns (Dimson, Karakas, and Li (2015)).

The preceding discussion leads us to expect socially responsible investment (SRI) to be one of the drivers of the increased ownership dispersion we observe for CRD-increasing firms. SRI assets have grown to \$17 trillion at the end of 2020, representing one-in-three dollars of the \$51 trillion U.S. assets under professional management (US-SIF (2020)). We expect such interest in SRI to significantly affect ownership structures as well as financial market outcomes. Our data and framework allow us to explore this issue formally.

We distinguish between SRI and Non-SRI InstOwn% and SRI and Non-SRI InstOwn log#. Specifically, we rerun the regression in Equation (6) with the left-hand variables SRI and Non-SRI InstOwn%, or SRI and Non-SRI InstOwn log#. The results are presented in Panel A of Table 6. If SRI is the driving factor behind the results of InstOwn# and InstOwn log# in Table 4, we would expect more pronounced effects for SRI in comparison to Non-SRI. This expectation is indeed confirmed in Panel A. The interaction coefficient of SRI InstOwn% is 0.02 and highly significant at the 1% level (t -statistic = 6.52), which is about 20% of SRI InstOwn%'s sample standard deviation (0.1 as in Table 2), while the coefficient of Non-SRI InstOwn% is -0.004 and insignificant. Although the interaction coefficients of both SRI and Non-SRI InstOwn log# are significant, SRI InstOwn log#'s coefficient is much

larger (1.5 times) and more significant (1% vs 5%) than Non-SRI InstOwn log#'s. Therefore, the evidence indicates that SRI institutional ownership is a key force driving the results of InstOwn# and InstOwn log# that we observe in Table 4.

Panel A of Table 6 establishes an SRI channel via which the quality of CR disclosure affects InstOwn% and InstOwn log#. Given these results, we explore whether SRI InstOwn% mediates CR disclosure's effect on the overall InstOwn HHI. To this end, we rerun the regression in Equation (6) with InstOwn HHI as the dependent variable on two subsamples: those with nonzero SRI InstOwn% and those with no SRI InstOwn%. The results are presented in Panel B of Table 6. We find that the interaction coefficient in the Nonzero SRI subsample is -0.011 and significant at the 1% level (t -statistic = -5.49). In contrast, the interaction coefficient in the Zero SRI subsample is 0.01 and insignificant. Importantly, the interaction coefficient in the Nonzero SRI subsample is larger and more significant than those for InstOwn HHI in Table 4. Thus, the effect of CR disclosure on ownership breadth largely emanates from SRI in firms that substantially increase their CR disclosure, confirming our prior findings. All in all, the results in Table 6 indicate that institutional SRI plays a significant role in shaping the effect of CR disclosure on the financial markets.

4.4.2 *Mutual funds*

Mutual funds are the institutional investor type with the largest ownership stakes in firms within our data. Indeed, average mutual fund ownership stands at 46.3% (see Table 2). One would therefore expect mutual funds to play a large role in driving our findings. However, there is ambiguity over the role of mutual funds in SRI, which creates uncertainty over mutual funds' reaction to CR disclosure. For example, Bolton et al. (2020) find that the largest mutual funds are "money-conscious," that is, they tend to oppose social- and environment-friendly proposals that could financially cost shareholders. However, Nofsinger and Varma (2014) report that in recent years, total net assets in SRI mutual funds have grown five times as much as those in non-SRI ones.

Given the mixed findings on the relation between SRI and mutual funds, it is worth investigating the role of mutual fund ownership in the results reported in Table 4. To this end, we rerun the regression in Equation (6) with the left-hand variable, in turn, being

Banks, Mutual, Pension, and Other InstOwn% or the respective InstOwn log#. We present the results in Panel A of Table 7. If mutual fund ownership drives the results for InstOwn# and InstOwn log# in Table 4, we expect the most significant results for Mutual compared to other categories. This expectation is indeed confirmed in Panel A. The interaction coefficient of Mutual InstOwn% is 0.02 and significant at the 1% level (t -statistic = 2.83), which is about 10% of Mutual InstOwn%'s sample standard deviation (0.2 as in Table 2). In contrast, the interaction coefficients of the other three categories (Banks, Pension, and Other) are insignificant. Only the interaction coefficients of Mutual and Banks InstOwn log# are significant at the 5% level (the former's magnitude and value of the t -statistic are higher than the latter's). Therefore, the evidence in Panel A confirms mutual funds' ownership as the primary force driving the results for InstOwn# and InstOwn log# in Table 4.

To further explore whether Mutual InstOwn% mediates CR disclosure's effect on the overall InstOwn HHI, we rerun the regression in Equation (6) with InstOwn HHI as the left-hand variable on two subsamples, High and Low, for each type of institutional ownership. The High (Low) subsample includes firms with InstOwn% for each type of institutional ownership higher (lower) than its median InstOwn% in each year. If an ownership type influences CRD's effect on the overall InstOwn HHI, we should expect to find a significant interaction coefficient in the High subsample for that type, and vice versa.

The results are presented in Panel B of Table 7. We find that mutual fund ownership does influence the negative effect of CRD on InstOwn HHI observed in Table 4. Specifically, the interaction coefficient in the High Mutual subsample is -0.01 and significant at the 1% level (t -statistic = -3.65) while the interaction coefficient in the Low Mutual subsample is -0.007 and insignificant. The interaction coefficient in the High Mutual subsample is also the most significant and of the largest magnitude among the High subsamples of the four types of institutional ownership. More importantly, Mutual is the only type of institutional ownership where the interaction coefficient is more significant in the High than in the Low subsample. These results underscore the key role played by mutual funds in the increased ownership breadth arising from enhanced CR disclosure.

5 Robustness Checks

This section presents a set of robustness checks. Specifically, we examine an alternative CR disclosure measure as well as an extended sample period, and address explanations for the results other than our proposed mechanism. We also consider an instrumental variable approach.

5.1 An alternative CR disclosure measure

The SEC (2010) guidance explicitly provides direction on firms' *voluntary* disclosures over and above required statements such as 10-K. It is of interest to incorporate the former type of disclosures into our analysis. Accordingly, we introduce a voluntary disclosure measure based on earnings calls (Sautner et al. (2023)). Specifically, we broaden the definition of the CRD-increasing group to include firms that substantially changed their earnings-call-based CR disclosure behavior in 2009. Thus, we include firms that meet the three conditions in Section 3.1 for earnings-call-based CR disclosure measures (in addition to those based on 10-K measures). Further, our revised non-CRD-increasing group excludes firms that change CR disclosure significantly and negatively around the SEC (2010) guidance (as measured by earnings-call-based CR disclosure); these firms comprise around 2.6% of the sample.

Using these new definitions of the samples, we rerun the regression in Equation (6) and present the results in Table 8. Relative to Panel A of Table 4, the interaction coefficients consistently increase for five of the eight dependent variables. Specifically, for Breadth of Ownership (columns 1 to 3) and Lendable Equity (columns 4 to 5), the coefficients uniformly show a rise in magnitude and statistical significance. Although the interaction coefficient for BA Spread is slightly smaller in magnitude (-0.008 here vs -0.009 in Table 4 Panel A), it is more significant (t -statistic = -4.73 vs. -4.28). Also, while lower in magnitude and significance, the interaction coefficients for Variance Ratio and Delay continue to be statistically significant. Thus, the key messages from Table 4 remain largely unchanged using the enhanced definition of the CRD-increasing group.

5.2 Extended sample period

Next, we check the robustness of our main results by exploring an alternative and extended sample period. Specifically, we extend the timeframe of our data to span 2003 to 2016, which incorporates a seven-year window before and after the event year 2009. The results estimating Equation (6) over this longer timeframe are presented in Table 9. There are no major differences between Table 9 and Table 4, which confirms the robustness of our main results for this longer timeframe.

5.3 Other explanations

While our primary analysis indicates a strong and positive effect of CR disclosure on market quality, alternative explanations could also contribute to the observed effects. In this section, we address three key concerns: joint determination, reverse causality, and the role of volatility. We also present the results of an instrumental variable analysis.

5.3.1 Joint determination

One potential concern is that an unknown factor may jointly determine both CR disclosure and market quality, leading to a spurious relationship. For instance, firms with better governance structures or stronger financial positions might have higher financial market quality and also increase CR disclosure voluntarily. It is of interest to employ methods that mitigate this possibility.

We address the above issue by employing propensity score matching (PSM) to construct a smaller group of non-CRD-increasing firms that are comparable in key characteristics but differ in their CR disclosure practices. Specifically, we first estimate the probability of being a CRD-increasing firm, employing a logit model with the control variables used in Equation (6). Except for log (Firm Age), we replace all control variables' post-2008 values with their 2008 values to avoid any potential influence of SEC (2010) on these variables. We then match each CRD-increasing firm with up to three benchmark control firms without replacement, using the nearest neighbor matching technique within a 3% caliper (see Dehejia and Wahba (2002)). Our results are robust to using various numbers of matching control firms and calipers in the vicinity of our chosen values.

We find that significant sample loss of about 40% occurs due to the matching process.²⁷

²⁷This PSM-induced sample loss is our rationale for using the main sample for the bulk of the paper.

However, Table 10 shows that the main findings remain. Thus, CRD-increasing firms experience higher dispersion of ownership and in general, enhanced market quality measures relative to the PSM-matched sample. The coefficient magnitudes are generally quite close relative to those in Table 4. The single exception is Variance Ratio, which has an insignificant coefficient for $CRDInc_i \times Post$. Note that the PSM-matched sample controls for potential confounders such as firm size, profitability, stock market performance, and general disclosure characteristics, beyond the linear versions of these controls already used in the regressions. Thus, overall, we obtain support for the argument that the CRD-market quality relationship is not driven by joint determination.

5.3.2 Reverse causality

Another alternative explanation is that market quality may drive CRD rather than the other way around. Firms with higher market quality could be more incentivized or better positioned to enhance their CRD, rather than CRD being the driver of improved market quality. It is desirable to rule out this interpretation of our results. We first note that we compute the post-period market quality over several years *after* the measurement of CRD (viz. Section 3.2). It is unlikely the later-established market quality drives the previously-established CR disclosure. Nonetheless, if such quality is persistent, there may still be an interpretational issue surrounding our results.

In order to address the above issue, we analyze market quality *prior to* 2009 for the firms that *later* increased their CR disclosures (the CRD-increasing firms), while comparing them to other firms. Specifically, we run the following panel regression for each dependent variable using the sample from 2005 to 2008:

$$\begin{aligned} \text{Dependent}_{i,t} = & b_0 + b_1 CRDInc_i + \text{Controls}_{i,t} \\ & + \text{Industry and Year Fixed Effects} + \varepsilon_{i,t}. \end{aligned} \tag{7}$$

If market quality were driving subsequent CR disclosure, we would expect CRD-increasing firms to exhibit higher market quality even before their disclosure enhancements. This would mean a significant b_1 in the above panel regression (7).

Table 11 presents the results of the panel regression (7) for this pre-2009 analysis. The

insignificant coefficient estimates of CRDInc in Table 11 indicate that before the event year, the CRD-increasing firms did not have significantly better market quality relative to other firms. This suggests that the observed post-event relationship is unlikely to be a result of reverse causality. Coupled with the significant results in Table 4, our results indeed support the mechanism flowing from increased CR disclosures to breadth of ownership, and, in turn, to market quality.

5.3.3 *The role of volatility*

A third concern is that the observed market quality improvements may be mediated by stock return volatility rather than dispersed ownership. Recall our arguments which propose that CR disclosures alter long-term uncertainty about climate exposure that, in turn, attracts a more dispersed set of institutions which facilitate increased market quality. But, for example, if CR disclosures mitigate short-term volatility, this altered volatility may affect market quality metrics independently of the ownership pathway.

To examine this, we analyze the relationship between CR disclosure and annual stock return volatility. We run the same panel regression as Equation (6) with the dependent variable changed, in turn, to measures of idiosyncratic and total volatility, with the latter excluded from the list of control variables. We follow Ang et al. (2006) and define $\log(\text{Idiosyncratic Volatility})$ as the logarithm of volatility estimated from the Fama-French three-factor model using one year of daily returns, i.e., the annualized standard deviation of residual returns of the three-factor model. $\log(\text{Stock Volatility})$ is explained in Table 1.

Table 12 presents the results, and shows insignificant coefficient estimates of $\text{CRDInc}_i \times \text{Post}$ for both $\log(\text{Idiosyncratic Volatility})$ and $\log(\text{Stock Volatility})$. These results indicate that changes in volatility of CRD-increasing firms and control firms are not significantly different pre- and post-publication of SEC (2010). The findings, together with those documented in Section 4.3, confirm that our results are not merely an artifact of increased volatility but reflect a genuine effect of CR disclosure on market quality via the ownership pathway.

5.3.4 *Instrumental variable regression*

We finally explore an instrumental variable regression to further address any remaining endogeneity issues. Specifically, we construct our variable as the scope 1 (direct) plus

scope 2 (indirect) greenhouse gas (GHG) emission intensity. The data source for the carbon emission levels is Trucost.²⁸ The instrumental variable quantifies a firm's direct and indirect emissions per unit of output (gross sales) and comprehensively represents sources of emissions for companies. It also is a metric that points to opportunities to influence GHG reductions and thereby achieve GHG-related business objectives.²⁹

The scope 1 + 2 GHG emission intensity, as defined above, is a plausible instrument for climate risk disclosure for two reasons. First, it is strongly correlated with the need for, and complexity of, CR disclosures. Firms with higher direct plus indirect carbon emission intensity are more likely to face scrutiny from stakeholders, and therefore would tend to provide more detailed and informative climate disclosures. Second, conditional on CRD and other controls, the emission intensity is unlikely to directly affect market efficiency outcomes. Therefore, the instrument should affect the outcome variables only through its impact on how informative the firm's climate risk disclosures are, and not through any direct channel or reverse causality.

We conduct a two-stage IV estimation. In the first stage, CRD is regressed on the emission intensity and a constant term, using all of our data during the entire sample period. We find that in the first stage regression, the coefficient on the intensity is positively and statistically significant, satisfying the relevance condition for a strong instrument. Based on the fitted values from this regression, we construct a binary instrumented variable, $CRDInc_i-IV$, by following the selection criteria for the CRD increasing group stated in Section 3.1. The $CRDInc_i-IV$ variable indicates the CRD increasing group with an event year of 2009 using the fitted value from the scope 1 + 2 GHG emission intensity.

In the second stage, the outcome variables are regressed on $CRDInc_i-IV \times Post$ and $CRDInc_i-IV$, both with and without the inclusion of baseline control variables. The results appear in Table 13, with Panels A and B respectively representing the versions with included and excluded controls. Our findings confirm that the estimated effects

²⁸Trucost provides carbon emission levels from firms' voluntary disclosures (e.g., in financial statements or reports to the Carbon Disclosure Project) or as estimations by Trucost's proprietary approach. We include both the reported carbon emissions and Trucost estimations to ensure that our estimation sample remains as comprehensive as possible.

²⁹See the Greenhouse Gas Protocol (<https://ghgprotocol.org/sites/default/files/2022-12/FAQ.pdf>) for more details. Missing values for the intensity are replaced with the averages for the corresponding two-digit SIC code. Further, we winsorize the intensity variable at the 1% and 99% levels using its year-by-year distributions.

of $CRDInc_i - IV \times Post$ on key outcome variables are robust to the IV specification (with the exception of Variance Ratio). Further, the proposed effects remain significant in the regression without the baseline control variables. Finally, the IV coefficients in Table 13 are of similar orders of magnitudes as those in our baseline Table 4. This lends comfort to the notion that our results indeed capture a pathway flowing from CRD to ownership breadth to market liquidity/efficiency. Overall, all of the above checks mitigate concerns about alternative explanations, and reinforce the validity of our main conclusions.

6 Conclusions

Media coverage and public awareness of climate-related issues have surged in the past several years. Consequently, market participants and regulators have demanded more and better corporate disclosures on climate risk. We explore the relation between climate risk (CR) disclosures, dispersion in stock ownership, and market quality. We build a model which shows that improved CR disclosures allow investors to better assess the relation between cash flows and climate change (Edmans (2023)), which, in turn, results in enhanced ownership breadth. Our theoretical analysis further demonstrates that this increased ownership dispersion leads to enhanced market liquidity and, under reasonable conditions, increased market efficiency.

We test our model's implications by using a regression analysis around the issuance of the SEC (2010) guiding document on CR disclosures. This event caused a material increase in the number of firms increasing such disclosures, allowing for effective testing of our model. We find that firms whose CR disclosures increase in line with the guidance experience an increase in breadth of ownership and lendable equity supply, relative to other firms. In addition, the CRD-increasing firms exhibit enhanced market liquidity and price efficiency. Our results are robust to alternative methods for constructing CR disclosure measures and control firms, and to additional tests, including an IV approach, that we use to address reverse causality and joint determination. We also find support for the model's implication that greater belief heterogeneity enhances the association between CR disclosure and market quality. Finally, we underscore the crucial role played by SRI mutual funds in the positive effects of CR disclosures on financial market quality.

To our knowledge, we are the first to theoretically and empirically link climate risk

disclosures and financial market quality. There is room for more research, however, on the connections between media-driven CR awareness and firms' reporting policies as well as equilibrium outcomes. Thus, for example, CR disclosures could feed back to real investment via their association with pricing efficiency ([Bond, Edmans, and Goldstein \(2012\)](#)). They could also affect risk perceptions and have a direct association with costs of capital. A related issue worth considering is whether the pathway from a firm's CR disclosure to ownership breadth to market quality is an externality, or internalized by financial markets via a lower cost of capital. Further, we have assumed that CR disclosures are substantively valid, but in some cases they may represent "greenwashing" ([Duchin, Gao, and Xu \(2025\)](#)). Even in these cases, climate risk disclosures in firms' 10-Ks might make holding these firms politically more justifiable to institutions' clients. This might also culminate in enhanced ownership breadth and increased market quality. Analyzing and disentangling these issues is left for the future.

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Figure 1. Ownership breadth

This graph plots the expected ownership breadth, $E[B(\ell)]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

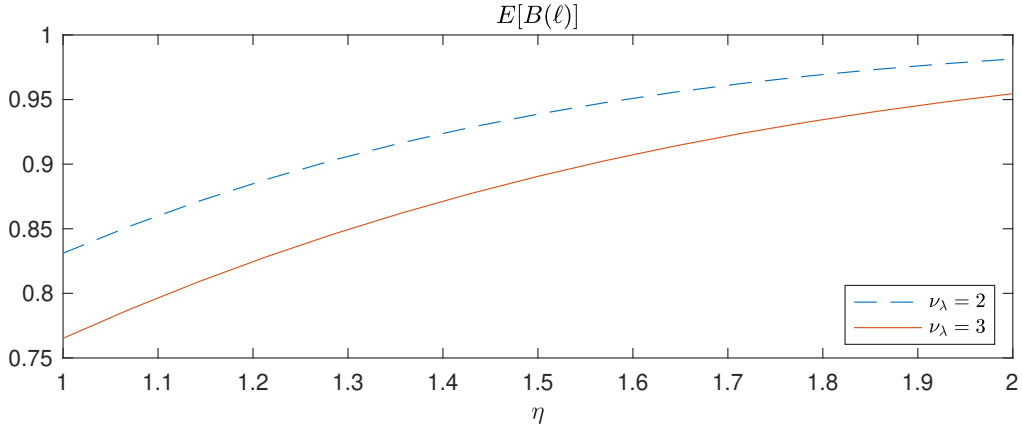


Figure 2. Short interest

This graph plots the expected short interest (in absolute scale), $E[|s(\ell)|]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

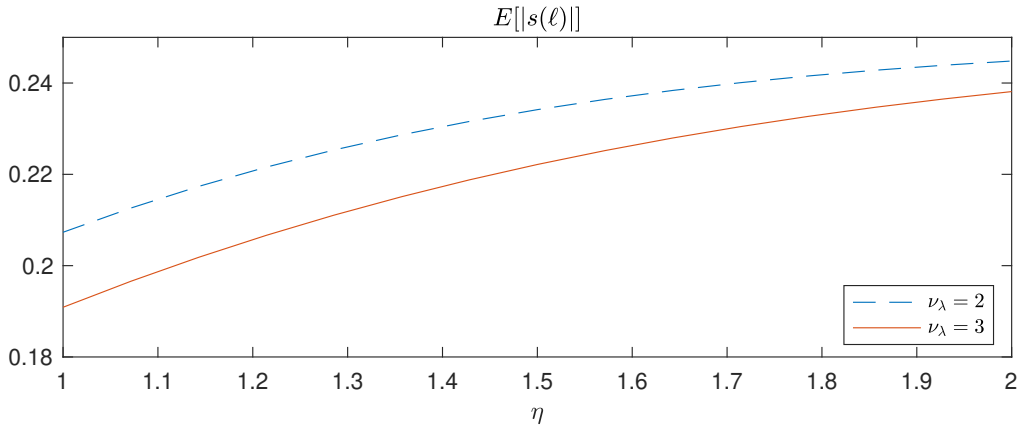


Figure 3. Liquidity

This graph plots the expected illiquidity measure, $E[\alpha(\phi, \ell)]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

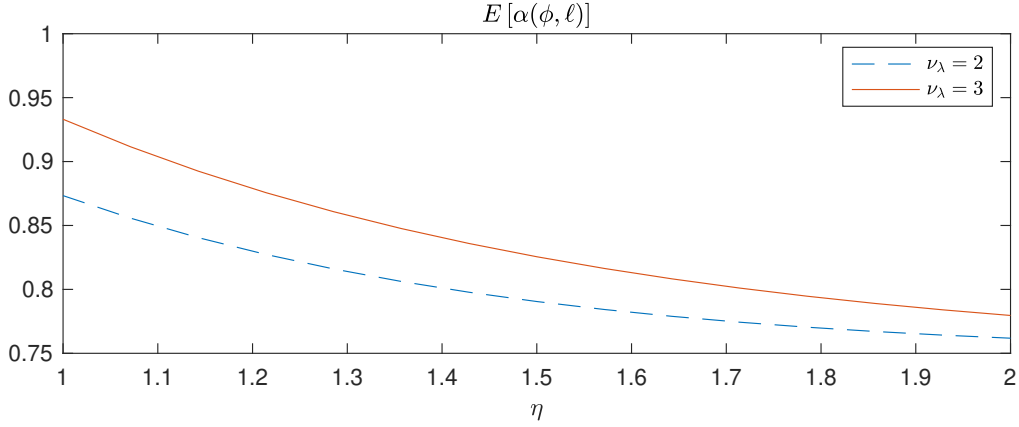


Figure 4. Price efficiency

This graph plots the variance ratio, VR , as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

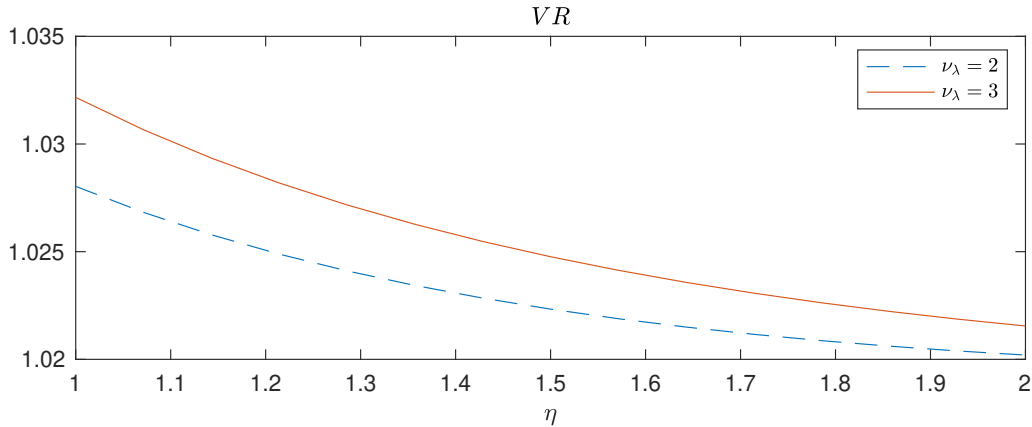


Figure 5. Ownership breadth, CR disclosure, and belief heterogeneity

This graph plots the derivative of the expected ownership breadth, $E[B(\ell)]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

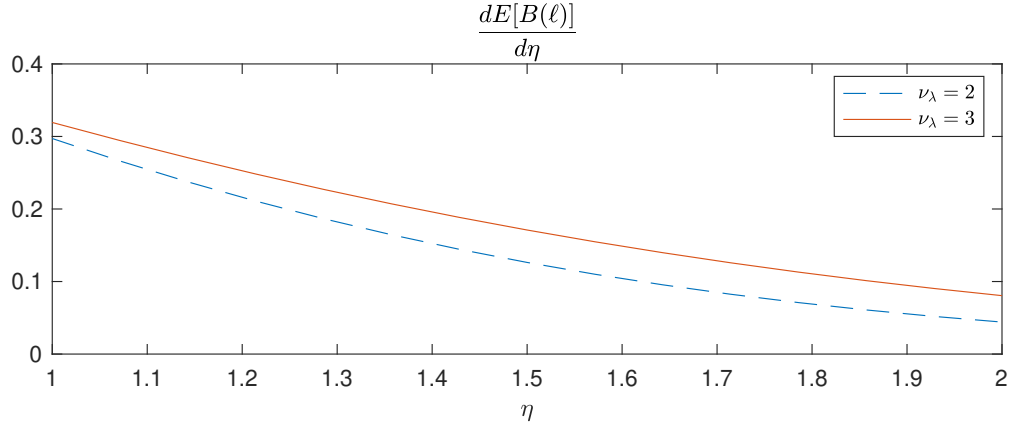


Figure 6. Short interest and belief heterogeneity

This graph plots the derivative of the expected short interest (in absolute scale), $E[|s(\ell)|]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

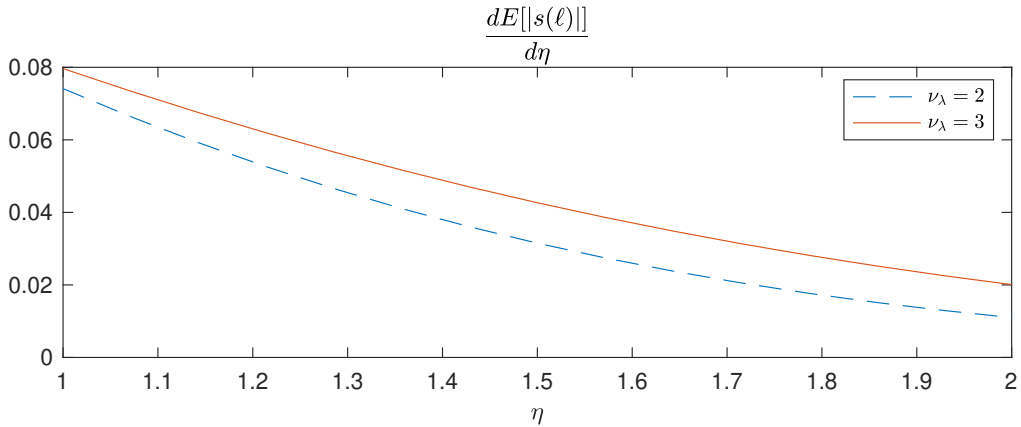


Figure 7. Market quality and belief heterogeneity – liquidity

This graph plots the derivative of the expected illiquidity measure, $E[\alpha(\phi, \ell)]$, as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

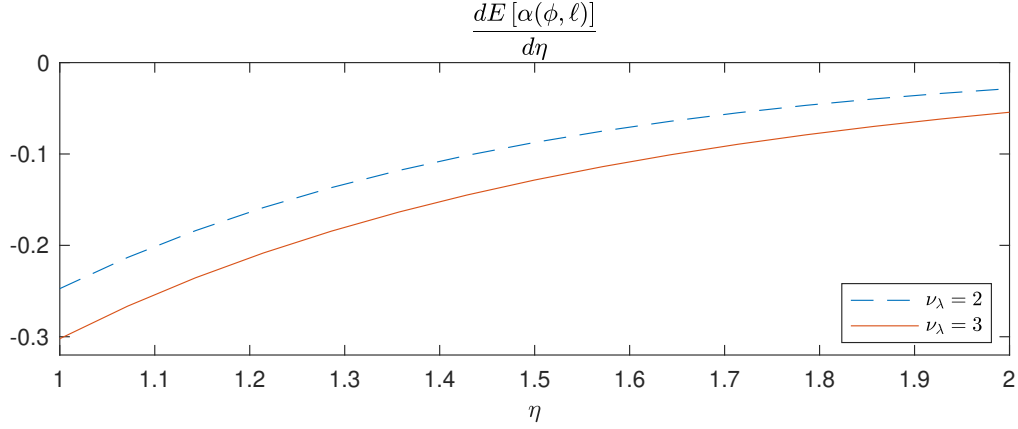


Figure 8. Market quality and belief heterogeneity – price efficiency

This graph plots the derivative of the variance ratio, VR , as a function of the parameter indicating the level of CR disclosure, η , for different values of the parameter representing belief heterogeneity, ν_λ (we let $\nu_\lambda = 2$ or 3). We assume that ℓ is drawn from a uniform distribution with support $(0, \ell_H]$. The parameter values are $Q = 2$, $\bar{\theta} = 5$, $\nu_\theta = 1$, $\nu_\zeta = 0.25$, $\bar{c} = 1$, $\nu_c = 0.25$, $M = 1$, $N = 0.2$, $\gamma = 2$, $\ell_H = 0.5$, and $\rho = 0.25$.

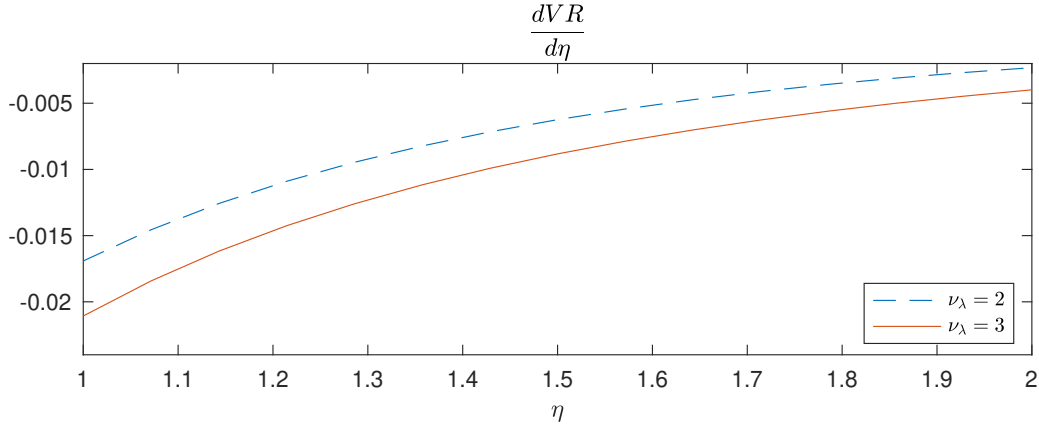


Figure 9. Percentage of firms with significant improvement in CR disclosure over the years

This figure plots the percentage of firms in each year that meet all of the following three conditions: (1) when the firm is excluded from the sample, the [Wilcoxon Rank Sum Test \(Mann-Whitney U-test\)](#) comparing the 10-K-Based CR Disclosure measures in the previous year with those in the next year becomes less significant, i.e., the p -value of the test statistics is larger when this firm is excluded; (2) the rank of the firm's 10-K-Based CR Disclosure in the next year is higher than that in the previous year; and (3) the value of the firm's 10-K-Based CR Disclosure in a particular year is higher than that in the previous year. The time series peaks in 2009 and the peak is highlighted in gray.



Table 1. Variable definitions

Panel A lists the definitions of InstOwn%, InstOwn log#, InstOwn HHI, Lendable Supply, Lendable Demand, Borrow Cost Score, BA Spread, Variance Ratio, Delay, the Earnings-Call-Based CR Disclosure, the 10-K-Based CR Disclosure, and the control variables. Panel B lists the definitions of InstOwn%, InstOwn log#, InstOwn HHI for different institutional ownership categories. These include Socially Responsible Investing (SRI), Non-SRI, banks and insurance companies (Bank), mutual funds (Mutual), pension funds (Pension), and other types (Other). All ownership measures except SRI are calculated from the Thomson Reuters 13F database. The SRI measures are based on [Gibson Brandon et al. \(2022\)](#). Quarterly values of all ownership variables are aggregated up to an annual basis. All logarithms are in natural terms.

Panel A: Main dependent and independent variables

Variable	Definition
InstOwn%	The fraction of common shares owned by institutional investors.
InstOwn log#	Logarithm of the number of institutional investors owning common shares of the underlying firm plus one.
InstOwn HHI	The Herfindahl-Hirschman Index of institutional ownership in a stock.
Lendable Supply	The average relative value of stock inventory available to lend ('LendableValue' in the Markit data scaled by market capitalization) over the year.
Lendable Demand	The average relative value of stock on loan from lenders ('ValueOnLoan' in the Markit data scaled by market capitalization) over the year.
Borrow Cost Score	Logarithm of the number from 1 to 10 indicating the cost of borrowing the underlying security ('DCBS' in the Markit data), where one is the cheapest, and ten is the most expensive. This measure is aggregated to an annual basis.
BA Spread	Difference between the bid and ask quotes for the stock scaled by their midpoint, in percentage terms. This daily measure is aggregated to an annual basis.
Variance Ratio	The absolute value of (VR - 1) where VR is computed as the ratio of the variance of five-week returns to five times the variance of one-week returns for each stock, estimated on an annual basis.
Delay	The regression used for this measure is $r_{i,t} = a_i + b_i r_{m,t} + \sum_{n=1}^4 \delta_i^{(-n)} r_{m,t-n} + \varepsilon_{i,t}$, where $r_{i,t}$ is the return on stock i and $r_{m,t}$ is the return on market index in week t . Delay is calculated as $1 - R^2_{\delta_i^{(-n)}=0, \forall n \in [1,4]} / R^2$, where $R^2_{\delta_i^{(-n)}=0, \forall n \in [1,4]}$ is the R^2 from the above regression when the coefficients on the lags are restricted to zero, and the denominator is the R^2 from the above equation with no restrictions. The measure is estimated on an annual basis.
Earnings-Call-Based CR Disclosure	This firm-level climate risk disclosure proxy reflects the frequency of climate change-related keywords in the firm's transcripts of earnings calls.
10-K-Based CR Disclosure	The frequency of climate change-related keywords scaled by the total number of words in the 10-K reports.
Average CR Disclosure	The average frequency of climate change-related keywords over the total number of words in the transcripts of earnings calls and 10-K reports.
Stock Return	A stock's monthly return from CRSP, grossed up to an annualized return.
ROA	Income before extraordinary items scaled by total assets at the fiscal year-end.
log(Market Value)	Logarithm of the average daily market capitalization over the year.
1/(Share Price)	The reciprocal of the average daily share price over the year.
log(Stock Volatility)	Logarithm of volatility based on daily stock returns over the year.
log(# Words)	Logarithm of the total number of words in the Form 10-K report.
% Unique Words	The fraction of the total number of unique words over the total number of words in the Form 10-K report.
% Net Sentiment	The number of positive minus the number of negative sentiment words, divided by the total number of words in the Form 10-K report.
Scope 1+2 GHG Emission Intensity	The sum of scope 1 carbon emissions and scope 2 carbon emissions (from Trucost), scaled by the total sales of the firm over the year.

Table 1. Variable definitions (contd.)**Panel B:** Institutional ownership by category

Variable	Definition
SRI InstOwn%	The fraction of common shares owned by SRI over the total number of common shares outstanding. An SRI is identified by whether the institution is a signatory to the United Nation's Principles for Responsible Investment, following Gibson Brandon et al. (2022) .
Non SRI InstOwn%	The fraction of common shares owned by non-SRI over the total number of common shares outstanding.
Bank InstOwn%	The fraction of common shares owned by banks and insurance companies over the total number of common shares outstanding.
Mutual InstOwn%	The fraction of common shares owned by mutual funds over the total number of common shares outstanding.
Pension InstOwn%	The fraction of common shares owned by pension funds over the total number of common shares outstanding.
Other InstOwn%	The fraction of common shares owned by institutional investors of a type that does not include banks, insurance companies, mutual funds, and pension funds, divided by the total number of shares outstanding.
SRI InstOwn log#	Logarithm of the number of SRI owning the common shares of the underlying firm plus one. An SRI is identified by whether it is a signatory to the United Nation's Principles for Responsible Investment, following Gibson Brandon et al. (2022) .
Non SRI InstOwn log#	Logarithm of the number of non-SRI owning common shares of the underlying firm plus one.
Bank InstOwn log#	Logarithm of the number of banks and insurance companies owning common shares of the underlying firm plus one.
Mutual InstOwn log#	Logarithm of the number of mutual funds owning common shares of the underlying firm plus one.
Pension InstOwn log#	Logarithm of the number of pension funds owning common shares of the underlying firm plus one.
Other InstOwn log#	Logarithm of the number of institutional investors of a type other than banks, insurance companies, mutual funds, and pension funds, that own common shares of the underlying firm plus one.

Table 2. Summary statistics

Panel A presents the summary statistics for InstOwn%, InstOwn log#, InstOwn HHI, Lendable Supply, Lendable Demand, Borrow Cost Score, BA Spread (in percentage), Variance Ratio, Delay, Earnings-Call-Based CR Disclosure, 10-K-Based CR Disclosure, and the control variables. Panel B presents selected summary statistics for different institutional ownership categories. These categories include Socially Responsible Investing (SRI), Non-SRI, banks and insurance companies (Bank), mutual funds (Mutual), pension funds (Pension), and other types (Other). The summary includes sample size (N), sample mean (Mean), sample standard deviation (S.D.), and sample percentiles at 5% (p5), 25% (p25), 50% (p50), 75% (p75), and 95% (p95). The sample consists of annual data for U.S. public firms from 2005 to 2014. All variables are winsorized at the 1% and 99% levels based on their distributions each year.

Panel A: Main dependent and independent variables

	N	Mean	S.D.	p5	p25	p50	p75	p95	Skewness
InstOwn%	32,150	0.517	0.356	0.000	0.153	0.595	0.838	1.000	-0.279
InstOwn log#	32,154	3.743	2.100	0.000	2.876	4.491	5.175	6.195	-0.849
InstOwn HHI	32,154	0.076	0.102	0.000	0.028	0.047	0.083	0.280	3.132
Lendable Supply	26,277	0.191	0.115	0.013	0.091	0.197	0.281	0.376	0.102
Lendable Demand	26,306	0.040	0.050	0.001	0.008	0.022	0.054	0.146	2.450
Borrow Cost Score	26,306	0.154	0.382	0.000	0.000	0.000	0.020	1.143	2.810
BA Spread	32,119	0.046	0.064	0.010	0.015	0.026	0.049	0.152	4.414
Variance Ratio	28,759	3.666	2.148	1.017	2.154	3.230	4.688	7.897	1.258
Delay	32,101	0.327	0.282	0.028	0.101	0.231	0.490	0.938	0.956
Earnings-Call-Based CR Disclosure	33,690	0.003	0.006	0.000	0.000	0.001	0.002	0.012	4.662
10K-Based CR Disclosure	29,326	0.006	0.017	0.000	0.000	0.000	0.004	0.038	3.967
log(Firm Age)	31,063	2.786	0.768	1.386	2.303	2.773	3.332	4.043	-0.177
Stock Return	33,690	0.152	0.537	-0.585	-0.158	0.090	0.356	1.102	1.594
ROA	32,152	-0.003	0.174	-0.346	-0.004	0.030	0.071	0.161	-3.029
log(Market Value)	31,093	6.717	1.868	3.645	5.430	6.677	7.954	9.977	0.122
1/(Share Price)	32,114	0.109	0.150	0.014	0.028	0.052	0.117	0.429	2.931
log(Stock Volatility)	32,100	0.403	0.246	0.139	0.233	0.345	0.504	0.870	2.008
log(# Words)	29,326	10.871	0.466	10.161	10.556	10.833	11.144	11.724	0.474
% Unique Words	29,326	0.062	0.017	0.034	0.050	0.061	0.073	0.092	0.176
% Net Sentiment	29,326	-0.012	0.004	-0.018	-0.014	-0.012	-0.009	-0.006	-0.335

Table 2. Summary statistics (contd.)**Panel B:** Categorical institutional ownership variables

	<i>N</i>	Mean	S.D.	p5	p25	p50	p75	p95	Skewness
SRI InstOwn%	25,459	0.080	0.098	0.000	0.005	0.035	0.132	0.289	1.313
Non SRI InstOwn%	25,459	0.568	0.246	0.121	0.393	0.598	0.758	0.937	-0.342
Bank InstOwn%	25,922	0.109	0.078	0.002	0.043	0.102	0.162	0.243	0.647
Mutual InstOwn%	25,922	0.463	0.210	0.078	0.310	0.492	0.629	0.762	-0.363
Pension InstOwn%	25,922	0.018	0.016	0.000	0.006	0.015	0.028	0.044	1.950
Other InstOwn%	25,922	0.050	0.058	0.001	0.012	0.031	0.065	0.175	2.328
SRI InstOwn log#	25,381	1.810	1.548	0.000	0.241	1.605	3.053	4.515	0.455
Non SRI InstOwn log#	25,381	4.599	1.016	2.725	4.070	4.664	5.230	6.171	-0.418
Bank InstOwn log#	25,926	0.798	0.549	0.034	0.374	0.737	1.129	1.808	0.808
Mutual InstOwn log#	25,926	3.333	0.815	1.804	2.974	3.472	3.867	4.376	-1.294
Pension InstOwn log#	25,926	0.135	0.114	0.002	0.050	0.110	0.195	0.336	1.586
Other InstOwn log#	25,926	0.366	0.387	0.012	0.105	0.239	0.482	1.211	1.975

Table 3. Correlation coefficients

Panel A presents correlation coefficients for InstOwn%, InstOwn log#, InstOwn HHI, Lendable Supply, Lendable Demand, Borrow Cost Score, BA Spread, Variance Ratio, Delay, Earnings-Call-Based CR Disclosure, 10-K-Based CR Disclosure, and the control variables. In Panel B, we replace the last nine rows (comprised of controls) of Panel A with ten rows related to institutional ownership by category. These categories are Socially Responsible Investing (SRI), Non-SRI, banks and insurance companies (Bank), mutual funds (Mutual), pension funds (Pension), and other types (Other). The sample is from 2005 to 2014.

Panel A: Main dependent and independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) InstOwn%	1.00																			
(2) InstOwn log#	0.86	1.00																		
(3) InstOwn HHI	-0.08	0.04	1.00																	
(4) Lendable Supply	0.69	0.45	-0.49	1.00																
(5) Lendable Demand	0.34	0.13	-0.22	0.43	1.00															
(6) Borrow Cost Score	-0.38	-0.31	0.37	-0.39	0.12	1.00														
(7) BA Spread	-0.18	-0.14	0.29	-0.30	-0.15	0.13	1.00													
(8) Variance Ratio	0.01	-0.03	-0.06	0.03	0.07	-0.04	-0.05	1.00												
(9) Delay	-0.27	-0.25	0.28	-0.40	-0.15	0.26	0.21	-0.09	1.00											
(10) Earnings-Call-Based CR Disclosure	0.06	0.08	-0.07	0.09	0.02	-0.04	-0.07	0.03	-0.11	1.00										
(11) 10K-Based CR Disclosure	0.01	0.07	-0.03	-0.01	-0.07	0.00	-0.03	-0.01	-0.10	0.30	1.00									
(12) log(Firm Age)	0.18	0.23	-0.13	0.28	-0.02	-0.24	-0.04	-0.05	-0.22	0.18	0.08	1.00								
(13) Stock Return	0.02	0.04	0.03	-0.04	-0.10	-0.04	-0.01	-0.01	0.04	-0.01	0.03	0.03	1.00							
(14) ROA	0.22	0.24	-0.06	0.16	-0.03	-0.26	0.03	-0.04	-0.21	0.02	0.07	0.18	0.15	1.00						
(15) log(Market Value)	0.36	0.44	-0.35	0.33	0.05	-0.30	-0.23	-0.09	-0.40	0.10	0.17	0.29	0.15	0.36	1.00					
(16) 1/(Share Price)	-0.40	-0.38	0.21	-0.35	-0.15	0.33	-0.06	-0.08	0.32	-0.05	-0.10	-0.13	-0.05	-0.43	-0.60	1.00				
(17) log(Stock Volatility)	-0.19	-0.22	0.12	-0.11	0.13	0.25	-0.01	0.10	0.18	-0.05	-0.08	-0.19	0.11	-0.35	-0.41	0.44	1.00			
(18) log(N Words)	0.07	0.11	-0.16	0.10	0.03	-0.05	-0.18	0.01	-0.16	0.11	0.12	-0.03	-0.01	-0.04	0.37	-0.14	-0.04	1.00		
(19) % Unique Words	-0.09	-0.12	0.19	-0.12	-0.03	0.08	0.18	-0.03	0.20	-0.10	-0.11	0.01	0.01	0.01	-0.38	0.17	0.07	-0.95	1.00	
(20) % Net Sentiment	-0.03	0.00	0.02	-0.07	0.00	0.03	0.08	0.00	0.02	0.05	0.03	0.02	0.01	0.08	0.02	-0.07	-0.11	-0.29	0.28	1.00

Table 3. Correlation coefficients (contd.)

Panel B: Institutional ownership variables by category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1) InstOwn%	1.00																						
(2) InstOwn log#	0.86	1.00																					
(3) InstOwn HHI	-0.08	0.04	1.00																				
(4) Lendable Supply	0.69	0.45	-0.49	1.00																			
(5) Lendable Demand	0.34	0.13	-0.22	0.43	1.00																		
(6) Borrow Cost Score	-0.38	-0.31	0.37	-0.39	0.12	1.00																	
(7) BA Spread	-0.18	-0.14	0.29	-0.30	-0.15	0.13	1.00																
(8) Variance Ratio	0.01	-0.03	-0.06	0.03	0.07	-0.04	-0.05	1.00															
(9) Delay	-0.27	-0.25	0.28	-0.40	-0.15	0.26	0.21	-0.09	1.00														
(10) Earnings-Call-Based CR Disclosure	0.06	0.08	-0.07	0.09	0.02	-0.04	-0.07	0.03	-0.11	1.00													
(11) 10K-Based CR Disclosure	0.01	0.07	-0.03	-0.01	-0.07	0.00	-0.03	-0.01	-0.10	0.30	1.00												
(12) SRI InstOwn%	0.04	0.09	-0.07	0.07	-0.02	-0.03	-0.07	0.01	-0.13	0.88	0.71	1.00											
(13) Non SRI InstOwn%	0.92	0.56	-0.49	0.66	0.42	-0.37	-0.24	0.05	-0.34	0.03	-0.06	-0.01	1.00										
(14) Bank InstOwn%	0.62	0.59	-0.45	0.56	0.28	-0.34	-0.19	0.06	-0.36	0.07	-0.04	0.03	0.67	1.00									
(15) Mutual InstOwn%	0.94	0.56	-0.47	0.67	0.36	-0.35	-0.27	0.01	-0.29	0.03	-0.01	0.02	0.86	0.41	1.00								
(16) Pension InstOwn%	0.53	0.52	-0.36	0.46	0.18	-0.27	-0.19	-0.01	-0.26	0.05	-0.01	0.03	0.51	0.52	0.38	1.00							
(17) Other InstOwn%	0.40	0.33	-0.19	0.24	0.06	-0.11	-0.18	-0.03	-0.08	0.02	0.05	0.03	0.22	-0.01	0.24	0.14	1.00						
(18) SRI InstOwn log#	0.51	0.67	-0.42	0.55	0.04	-0.26	-0.31	-0.15	-0.31	0.09	0.18	0.16	0.22	0.18	0.45	0.27	0.48	1.00					
(19) Non SRI InstOwn log#	0.64	0.99	-0.71	0.52	0.17	-0.37	-0.38	-0.05	-0.46	0.12	0.13	0.15	0.57	0.62	0.50	0.53	0.28	0.60	1.00				
(20) Bank InstOwn log#	0.29	0.59	-0.39	0.30	0.11	-0.26	-0.14	0.04	-0.33	0.09	0.01	0.07	0.33	0.85	0.07	0.40	-0.11	0.13	0.62	1.00			
(21) Mutual InstOwn log#	0.65	0.79	-0.52	0.45	0.16	-0.29	-0.30	-0.07	-0.32	0.08	0.12	0.12	0.51	0.25	0.73	0.29	0.09	0.59	0.73	0.13	1.00		
(22) Pension InstOwn log#	0.27	0.51	-0.32	0.26	0.04	-0.21	-0.16	-0.04	-0.23	0.08	0.02	0.07	0.25	0.41	0.11	0.89	0.05	0.23	0.53	0.48	0.21	1.00	
(23) Other InstOwn log#	0.18	0.31	-0.14	0.09	-0.03	-0.02	-0.16	-0.05	-0.04	0.03	0.08	0.06	0.00	-0.10	0.02	0.06	0.91	0.44	0.27	-0.10	0.02	0.06	1.00

Table 4. Primary regression results

This table presents the primary regression results for the effect of CR disclosure (CRD) on left-hand variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency. The variables include three measures under Breadth of Ownership (InstOwn %, InstOwn log#, and InstOwn HHI), two measures under Lendable Equity (Lendable Supply and Borrow Cost Score), one measure under Liquidity (BA Spread), and two measures under Price Efficiency (Variance Ratio and Delay). The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), 1/(Share Price), log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Panel A reports the results of the regression with the control variables and Panel B reports the results of the regression without the control variables. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the SEC (2010) guidance, and $Post$ denotes the post-publicization period dummy. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: Results with control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.031*** (3.25)	0.165*** (3.03)	-0.008*** (-3.12)	0.010*** (3.13)	-0.079*** (-2.68)	-0.009*** (-4.28)	-0.225*** (-2.86)	-0.016** (-2.33)
$CRDInc_i$	-0.009 (-0.68)	-0.064 (-0.69)	-0.000 (-0.07)	0.000 (0.05)	-0.005 (-0.21)	0.005* (1.94)	0.189** (2.27)	0.004 (0.62)
Obs.	27,726	27,729	27,729	23,457	23,481	27,729	26,340	27,725
Adj. R ²	0.31	0.33	0.19	0.45	0.19	0.25	0.12	0.33
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Results without control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.040*** (3.96)	0.229*** (3.85)	-0.009*** (-4.31)	0.017*** (4.66)	-0.100*** (-3.17)	-0.008*** (-3.72)	-0.307*** (-3.97)	-0.020** (-2.57)
$CRDInc_i$	0.057*** (3.37)	0.370*** (3.05)	-0.012*** (-3.29)	0.019*** (4.74)	-0.095*** (-3.36)	-0.000 (-0.09)	0.223** (2.46)	-0.034*** (-3.71)
Obs.	32,147	32,151	32,151	26,273	26,302	32,116	28,754	32,098
Adj. R ²	0.12	0.11	0.04	0.26	0.07	0.11	0.08	0.16
Controls	No	No	No	No	No	No	No	No

Table 5. Belief heterogeneity results

This table presents the effect of CR disclosure (CRD) on left-hand variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, conditional on high and low belief heterogeneity groups. The variables for Breadth of Ownership in Panel A are InstOwn %, InstOwn log#, and InstOwn HHI. Those for Lendable Equity in Panel B are Lendable Supply and Borrow Cost Score. Finally, those for Liquidity and Price Efficiency in Panel C are BA Spread, Variance Ratio, and Delay. The High Belief Heterogeneity group is firms with higher than median analyst forecast dispersion and fewer than two following analysts each year. The Low Belief Heterogeneity group is firms with lower than median analyst forecast dispersion each year. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the [SEC \(2010\)](#) guidance, and $Post$ denotes the post-publicization period dummy. The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), $1/(Share\ Price)$, log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: Breadth of ownership

	High Belief Heterogeneity			Low Belief Heterogeneity		
	InstOwn%	InstOwn log#	InstOwn HHI	InstOwn%	InstOwn log#	InstOwn HHI
$CRDInc_i \times Post$	0.054*** (4.11)	0.265*** (3.31)	-0.010** (-2.55)	-0.005 (-0.56)	0.003 (0.21)	-0.005* (-1.79)
$CRDInc_i$	-0.028 (-1.50)	-0.136 (-1.12)	-0.001 (-0.12)	0.019 (1.36)	0.018 (1.02)	-0.001 (-0.41)
Obs.	17,966	17,969	17,969	9,747	9,747	9,747
Adj. R ²	0.24	0.20	0.20	0.29	0.82	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Lendable equity

	High Belief Heterogeneity		Low Belief Heterogeneity	
	Lendable Supply	Borrow Cost Score	Lendable Supply	Borrow Cost Score
$CRDInc_i \times Post$	0.016*** (3.63)	-0.095** (-2.21)	0.002 (0.41)	-0.042 (-1.55)
$CRDInc_i$	-0.004 (-0.76)	-0.005 (-0.12)	0.009 (1.42)	-0.011 (-0.44)
Obs.	13,747	13,770	9,694	9,695
Adj. R ²	0.48	0.20	0.42	0.12
Controls	Yes	Yes	Yes	Yes

Panel C: Liquidity and pricing efficiency

	High Belief Heterogeneity			Low Belief Heterogeneity		
	BA Spread	Variance Ratio	Delay	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	-0.010*** (-3.58)	-0.202* (-1.79)	-0.019* (-1.86)	-0.006** (-2.53)	-0.226** (-2.09)	-0.009 (-0.91)
$CRDInc_i$	0.008** (2.19)	0.178 (1.53)	0.003 (0.35)	0.000 (0.07)	0.203** (2.07)	0.001 (0.11)
Obs.	17,969	16,883	17,965	9,747	9,444	9,747
Adj. R ²	0.28	0.10	0.34	0.24	0.21	0.25
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Regression results for socially responsible investors

This table presents the effect of CR disclosure (CRD) on Breadth of Ownership for SRI and Non-SRI separately. The left-hand variables in Panel A are InstOwn % and InstOwn log#, calculated for SRI and Non-SRI. The left-hand variable in Panel B is InstOwn HHI, and the regressions are conducted on two subsamples: Nonzero SRI and Zero SRI, where the former (latter) are firms with positive (zero) SRI InstOwn% in each year. The SRI group is defined as having ownership by the United Nations Principle of Responsible Investment signatories. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the SEC (2010) guidance, and $Post$ denotes the post-publicization period dummy. The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), $1/(Share\ Price)$, log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: InstOwn% and InstOwn log#

	SRI IO		Non-SRI IO	
	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#
$CRDInc_i \times Post$	0.020*** (6.52)	0.092*** (6.00)	-0.004 (-0.62)	0.060** (3.23)
$CRDInc_i$	-0.007*** (-3.39)	-0.030* (-2.05)	0.001 (0.09)	-0.020 (-0.95)
Obs.	22,807	23,150	22,807	23,150
Adj. R ²	0.70	0.87	0.42	0.78
Controls	Yes	Yes	Yes	Yes

Panel B: InstOwn HHI

	Nonzero SRI	Zero SRI
	InstOwn HHI	InstOwn HHI
$CRDInc_i \times Post$	-0.011*** (-5.49)	0.010 (0.17)
$CRDInc_i$	0.002 (0.59)	0.010 (1.33)
Obs.	20,235	2,532
Adj. R ²	0.33	0.53
Controls	Yes	Yes

Table 7. Results on institutional ownership type

This table presents the effect of CR disclosure (CRD) on the Breadth of Ownership for banks, mutual funds, pension funds, and other types, separately. The left-hand variables in Panel A are InstOwn % and InstOwn log#, calculated separately by type of institutional ownership. The left-hand variable in Panel B is InstOwn HHI. The regressions are conducted on two subsamples: High and Low, for each type of institutional ownership. The High (Low) subsample includes firms with InstOwn % for each type of institutional ownership higher (lower) than the median within each year. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the SEC (2010) guidance, and $Post$ denotes the post-publicization period dummy. The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), $1/(Share\ Price)$, log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: InstOwn% and InstOwn log#

	Banks		Mutual		Pension		Others	
	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#
$CRDInc_i \times Post$	-0.003 (-1.04)	0.036** (2.19)	0.018*** (2.83)	0.047** (2.45)	0.001 (1.07)	0.007 (0.38)	0.003 (1.43)	-0.031 (-1.49)
$CRDInc_i$	0.005 (1.31)	-0.003 (-0.15)	-0.011 (-1.36)	-0.015 (-0.75)	0.001 (1.08)	0.027 (1.31)	0.000 (0.08)	0.037* (1.68)
Obs.	23,147	23,150	23,147	23,150	23,147	23,150	23,147	23,150
Adj. R^2	0.50	0.78	0.31	0.79	0.30	0.79	0.40	0.81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: InstOwn HHI

	Banks		Mutual		Pension		Others	
	High	Low	High	Low	High	Low	High	Low
$CRDInc_i \times Post$	-0.002 (-1.12)	-0.014*** (-2.73)	-0.010*** (-3.65)	-0.007 (-1.48)	-0.002* (-1.93)	-0.016*** (-3.05)	-0.005** (-2.02)	-0.013*** (-2.71)
$CRDInc_i$	0.002 (0.64)	-0.000 (-0.00)	0.004 (1.36)	-0.004 (-0.53)	-0.002 (-0.77)	0.010 (1.18)	0.002 (0.72)	0.003 (0.55)
Obs.	11,942	11,194	12,105	11,033	11,906	11,228	11,709	11,424
Adj. R^2	0.19	0.25	0.23	0.35	0.23	0.27	0.29	0.30
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Robustness of results: CR disclosures using both 10-K and earnings calls

This table presents results for the effect of CR disclosure (CRD) on left-hand variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, based on the CRD-increasing group defined using both 10-K and earnings-call-based CR disclosure measures. The variables include three measures under Breadth of Ownership (InstOwn %, InstOwn log#, and InstOwn HHI), two measures under Lendable Equity (Lendable Supply and Borrow Cost Score), one measure under Liquidity (BA Spread), and two measures under Price Efficiency (Variance Ratio and Delay). The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), 1/(Share Price), log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Panel A reports the results of the regression with the control variables and Panel B reports the results of the regression without the control variables. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the SEC (2010) guidance, and $Post$ denotes the post-publicization period dummy. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: Results with control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.040*** (4.51)	0.191*** (4.45)	-0.010*** (-3.34)	0.017*** (5.85)	-0.142*** (-4.89)	-0.008*** (-4.73)	-0.161*** (-2.62)	-0.012** (-1.99)
$CRDInc_i$	-0.011 (-1.05)	-0.139** (-2.31)	-0.001 (-0.26)	0.004 (1.17)	0.013 (0.52)	0.001 (0.40)	0.209*** (3.18)	-0.013** (-2.37)
Obs.	26,885	26,888	26,888	22,731	22,753	26,888	25,525	26,884
Adj. R ²	0.30	0.33	0.19	0.46	0.19	0.25	0.12	0.33
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Results without control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.051*** (5.73)	0.292*** (6.14)	-0.011*** (-4.16)	0.022*** (6.09)	-0.184*** (-5.70)	-0.007*** (-3.48)	-0.281*** (-4.33)	-0.023*** (-3.77)
$CRDInc_i$	0.036*** (2.85)	0.191** (2.37)	-0.009** (-2.52)	0.016*** (4.41)	-0.048* (-1.94)	-0.003 (-1.09)	0.282*** (3.69)	-0.040*** (-5.54)
Obs.	31,227	31,231	31,231	25,490	25,517	31,196	27,910	31,178
Adj. R ²	0.12	0.11	0.05	0.27	0.07	0.11	0.08	0.17
Controls	No	No	No	No	No	No	No	No

Table 9. Robustness of results: Extended data timeframe

This table presents results for the effect of CR disclosure (CRD) on left-hand variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, based on an alternative, extended timeframe from 2003 to 2016. The variables include three measures under Breadth of Ownership (InstOwn %, InstOwn log#, and InstOwn HHI), two measures under Lendable Equity (Lendable Supply and Borrow Cost Score), one measure under Liquidity (BA Spread), and two measures under Price Efficiency (Variance Ratio and Delay). The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), 1/(Share Price), log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Panel A reports the results of the regression with the control variables and Panel B reports the results of the regression without the control variables. The key explanatory variable is the interaction term $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following the publicization of the SEC (2010) guidance, and $Post$ denotes the post-publicization period dummy. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: Results with control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.037*** (3.64)	0.205*** (3.43)	-0.007** (-2.44)	0.017*** (5.44)	-0.139*** (-5.13)	-0.009*** (-3.62)	-0.414*** (-4.26)	-0.016** (-2.38)
$CRDInc_i$	-0.014 (-1.09)	-0.108 (-1.15)	-0.001 (-0.23)	-0.003 (-0.84)	0.025 (1.05)	0.006** (2.35)	0.323*** (3.55)	0.003 (0.37)
Obs.	38,809	38,813	38,813	32,896	33,017	38,809	36,761	38,807
Adj. R ²	0.32	0.35	0.19	0.56	0.21	0.26	0.12	0.30
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Results without control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i \times Post$	0.053*** (4.99)	0.315*** (4.90)	-0.008*** (-3.46)	0.026*** (7.30)	-0.180*** (-5.84)	-0.009*** (-3.29)	-0.475*** (-4.92)	-0.022*** (-2.85)
$CRDInc_i$	0.051*** (3.26)	0.327*** (2.80)	-0.014*** (-3.78)	0.014*** (4.61)	-0.081*** (-3.45)	0.001 (0.21)	0.326*** (3.60)	-0.038*** (-4.25)
Obs.	45,087	45,092	45,092	37,011	37,147	45,011	40,112	44,986
Adj. R ²	0.12	0.12	0.04	0.41	0.08	0.12	0.09	0.14
Controls	No	No	No	No	No	No	No	No

Table 10. PSM results

This table presents results that use a propensity-score-matched control sample for the effect of CR disclosure (CRD) on left-hand variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency. The key explanatory variable is the interaction term $\text{CRDInc}_i \times \text{Post}$, where CRDInc_i denotes an indicator for CRD-increasing firms following the publicization of the [SEC \(2010\)](#) guidance, and Post denotes the post-publicization period dummy. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$\text{CRDInc}_i \times \text{Post}$	0.029*** (2.95)	0.145** (2.47)	-0.006** (-2.42)	0.008** (2.54)	-0.056* (-1.84)	-0.005** (-2.59)	-0.104 (-1.15)	-0.016** (-2.15)
CRDInc_i	-0.017 (-1.05)	-0.082 (-0.79)	-0.001 (-0.17)	-0.001 (-0.32)	-0.002 (-0.08)	0.003 (1.20)	0.085 (0.89)	0.008 (1.09)
Obs.	15,672	15,675	15,675	13,715	13,715	15,675	15,199	15,675
Adj. R ²	0.28	0.32	0.22	0.45	0.14	0.27	0.17	0.30
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11. Pre-event dependent variables' level comparison

This table presents the results of regressing values of left-hand variables prior to the publicization of the [SEC \(2010\)](#) guidance. The variables fall in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency on the indicator for CRD-increasing firms and controls. The key explanatory variable is $CRDInc_i$, which denotes an indicator for CRD-increasing firms following the publicization of the [SEC \(2010\)](#) guidance, and Post denotes the post-publicization period. The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), $1/(\text{Share Price})$, log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i$	-0.020 (-1.39)	-0.098 (-1.02)	-0.001 (-0.22)	0.001 (0.16)	0.018 (0.67)	0.003 (1.04)	0.097 (1.17)	0.003 (0.49)
Obs.	10,980	10,980	10,980	9,321	9,342	10,980	10,332	10,980
Adj. R^2	0.28	0.30	0.19	0.52	0.23	0.25	0.11	0.30
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12. Results on volatility

This table presents the results for the effect of CR disclosure (CRD) on two volatility variables: $\log(\text{Idiosyncratic Volatility})$ and $\log(\text{Stock Volatility})$. The control variables include: $\log(\text{Firm Age})$, Stock Return , ROA , $\log(\text{Market Value})$, $1/(\text{Share Price})$, $\log(\# \text{ Words})$, $\% \text{ Unique Words}$, and $\% \text{ Net Sentiment}$. The key explanatory variable is the interaction term $\text{CRDInc}_i \times \text{Post}$, where CRDInc_i denotes an indicator for CRD-increasing firms following the publicization of the [SEC \(2010\)](#) guidance, and Post denotes the post-publicization period dummy. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

	$\log(\text{Idio. Volatility})$	$\log(\text{Stock Volatility})$
$\text{CRInc}_i \times \text{Post}$	0.002 (0.84)	0.005 (0.72)
CRInc_i	0.000 (0.01)	0.005 (1.05)
Obs.	22,090	27,729
Adj. R^2	0.69	0.48
Controls	Yes	Yes

Table 13. Results of instrumental variable regressions

This table presents the results of the instrumental variable regressions on outcome variables in four categories: Breadth of Ownership (InstOwn%, InstOwn log# and InstOwn HHI), Lendable Equity (Lendable Supply and Borrow Cost Score), Liquidity (BA Spread), and Price Efficiency (Variance Ratio and Delay). In the first stage, CRD_i is regressed on the instrumental variable, scope 1 plus scope 2 GHG emission levels scaled by the gross sales of the firm, and constant, using a linear panel regression specification. CRD_i denotes the 10-K based climate risk disclosure. The fitted CRD is used to determine the CRD increasing group, following the procedure stated in Section 3.1. Then we compute the indicator of the CRD increasing group firms, $CRDInc_i-IV$, during the event year of 2009. In the second stage, the dependent variables are regressed on $CRDInc_i-IV \times Post$ and $CRDInc_i-IV$ with control variables, where $Post$ denotes the post-publicization period dummy. The control variables include: log (Firm Age), Stock Return, ROA, log (Market Value), $1/(Share\ Price)$, log (Stock Volatility), log (# Words), % Unique Words, and % Net Sentiment. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We include industry- and year-fixed effects, with the industry-fixed effect being based on the 3-digit SIC code.

Panel A: Results with control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
$CRDInc_i-IV \times Post$	0.042*** (3.18)	0.173*** (3.38)	-0.010*** (-2.82)	0.016*** (3.22)	-0.141*** (-4.96)	-0.010* (-1.67)	0.120 (1.29)	-0.029*** (-2.70)
$CRDInc_i-IV$	-0.02 (-1.03)	-0.317*** (-3.08)	-0.018*** (-2.78)	0.020** (2.24)	-0.047 (-0.90)	-0.017*** (-3.03)	0.135 (0.71)	-0.030** (-2.01)
Obs.	27,728	27,731	27,731	23,459	23,483	27,731	26,342	27,727
Adj. R^2	0.31	0.33	0.19	0.45	0.19	0.26	0.12	0.33
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13. Results of instrumental variable regressions (contd.)**Panel B:** Results without control variables

	Breadth of Ownership			Lendable Equity		Liquidity	Pricing Efficiency	
	InstOwn%	InstOwn log#	InstOwn HHI	Lendable Supply	Borrow Cost Score	BA Spread	Variance Ratio	Delay
CRDInc _{<i>i</i>} -IV × Post	0.040*** (3.11)	0.221*** (3.94)	-0.010*** (-3.61)	0.018*** (3.37)	-0.182*** (-6.34)	-0.005 (-0.80)	-0.044 (-0.44)	-0.036*** (-3.61)
CRDInc _{<i>i</i>} -IV	-0.109*** (-5.37)	-0.962*** (-8.07)	0.020*** (4.42)	-0.012* (-1.66)	0.121** (2.27)	-0.001 (-0.18)	0.426*** (2.86)	0.063*** (5.94)
Obs.	32,149	32,153	32,153	26,275	26,304	32,118	28,757	32,100
Adj. R ²	0.11	0.11	0.04	0.25	0.06	0.11	0.08	0.16
Controls	No	No	No	No	No	No	No	No

Appendix A: Proofs

Proof of Theorem 1: (a) Denote $\tau = \frac{v_\theta}{v_\phi}$ where $v_\phi = v_\theta + v_\zeta$. The m 'th buyer believes that $\theta|\phi \sim N(\bar{\theta} + \tau(\phi - \bar{\theta}), v_\theta(1 - \tau))$ and $c \sim N\left(\bar{c} + \frac{\lambda_m}{\eta}, v_c\right)$. Denote the stock price as P , and write the active buyer's Date 2 wealth as $W_{m2} = W_{m1} + x_m(V - P) = W_{m1} + x_m(\theta - c - P)$, where W_{m1} is the wealth at Date 1. The buyer chooses the demand x_m to maximize

$$\begin{aligned} & \hat{E}_m[U(W_{m2})|\phi] \\ &= \hat{E}_m[-\exp[-\gamma W_{m1} - \gamma x_m(\theta - c - P)]|\phi] \\ &= -\exp\left[-\gamma W_{m1} - \gamma x_m\left[\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \frac{\lambda_m}{\eta} - P\right] + 0.5\gamma^2 x_m^2[v_\theta(1 - \tau) + v_c]\right], \end{aligned}$$

where $\hat{E}_m(\cdot)$ indicates taking expectations based on the buyer's belief, and the second equality is based on the normality assumption. The first-order condition with respect to x_m and the short-selling constraint (i.e., the requirement $x_m \geq 0$) imply that the optimal demand is

$$x_m = \frac{\max(0, \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \lambda_m/\eta - P)}{\gamma[v_\theta(1 - \tau) + v_c]} = \frac{\max(0, -\lambda_m/\eta - p)}{\gamma[v_\theta(1 - \tau) + v_c]}, \quad (\text{A.1})$$

where $p = P - [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c}]$.

(b) The mass N of arbitrageurs believe that $\theta|\phi \sim N(\bar{\theta} + \tau(\phi - \bar{\theta}), v_\theta(1 - \tau))$ and $c \sim N(\bar{c}, v_c)$. We can use a similar derivation as that in Part (a) to show that the n 'th such arbitrageur's optimal demand is

$$y = \frac{\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - P}{\gamma[v_\theta(1 - \tau) + v_c]} = \frac{-p}{\gamma[v_\theta(1 - \tau) + v_c]}. \quad (\text{A.2})$$

(c) Let $F(\cdot)$ ($f(\cdot)$) represent the cumulative (probability) density function of the standard

normal distribution.³⁰ The market-clearing condition requires

$$M \int_{-\infty}^{\infty} x_m dF \left(\frac{\lambda_m}{\sqrt{v_\lambda}} \right) + Ny + \ell + s = Q, \quad (\text{A.3})$$

where x_m and y are given in Equations (A.1) and (A.2), respectively.

Equation (A.1) implies that $x_m > 0$ only if $\lambda_m < -\eta p$. Thus, from Equation (A.3),

$$\begin{aligned} M \int_{-\infty}^{-\eta p} \frac{-\lambda_m/\eta - p}{\gamma[v_\theta(1-\tau) + v_c]} dF \left(\frac{\lambda_m}{\sqrt{v_\lambda}} \right) + N \frac{-p}{\gamma[v_\theta(1-\tau) + v_c]} - (Q - \ell - s) &= 0, \\ M \left[\frac{\sqrt{v_\lambda}}{\eta} f \left(-\frac{\eta p}{\sqrt{v_\lambda}} \right) - p F \left(-\frac{\eta p}{\sqrt{v_\lambda}} \right) \right] - Np - \gamma[v_\theta(1-\tau) + v_c] (Q - \ell - s) &= 0. \end{aligned}$$

Denote $\kappa = -\frac{\eta p}{\sqrt{v_\lambda}}$ and $\Gamma = \frac{\gamma[v_\theta(1-\tau) + v_c]}{\sqrt{v_\lambda}}$. It follows that

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma\eta(Q - \ell - s) = 0. \quad (\text{A.4})$$

Because $x_m > 0$ only if $\lambda_m < -\eta p$, the fraction of active buyers who go long is computed as

$$B = \int_{-\infty}^{-\eta p} 1 dF \left(\frac{\lambda_m}{\sqrt{v_\lambda}} \right) = \int_{-\infty}^{\kappa\sqrt{v_\lambda}} 1 dF \left(\frac{\lambda_m}{\sqrt{v_\lambda}} \right) = F(\kappa),$$

where the second equality obtains from $\kappa = -\frac{\eta p}{\sqrt{v_\lambda}}$. It follows from the assumption $s = -\rho MB$ that $s = -\rho MF(\kappa)$; thus, Equation (A.4) becomes

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma\eta[Q - \ell + \rho MF(\kappa)] = 0, \quad (\text{A.5})$$

which is Equation (2).

We need to show that given ℓ , Equation (A.5) specifies a unique κ . Define a function of κ :

$$H(\kappa) \equiv M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma\eta[Q - \ell + \rho MF(\kappa)]. \quad (\text{A.6})$$

³⁰In the ensuing derivations, we use the following facts: $dF(\chi)/d\chi = f(\chi)$ and $df(\chi)/d\chi = -\chi f(\chi)$; $\int dF(\chi) = F(\chi)$ and $\int \chi dF(\chi) = -f(\chi)$; and $f(\chi) \leq f(0) \forall \chi$.

It is straightforward to show that $H(-\infty) < 0$, $H(\infty) > 0$, and

$$\frac{dH(\kappa)}{d\kappa} = MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > N - \Gamma\eta\rho Mf(0) \propto \frac{N}{M} - \frac{\Gamma\eta}{\sqrt{2\pi}}\rho > 0 \quad (\text{A.7})$$

where the last inequality obtains because $\eta \leq \eta^{\sup}$ and $\rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma\eta^{\sup}}$ from Assumption (1).

Therefore, Equation (A.5) specifies a unique κ .

Note that $p = P - [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c}]$ and $\kappa = -\frac{\eta p}{\sqrt{v_\lambda}}$. Further, κ is a function of ℓ ; we henceforth denote this function $\kappa(\ell)$. The price takes the form

$$P(\phi, \ell) = \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \frac{\kappa(\ell)}{\eta} \sqrt{v_\lambda}. \quad (\text{A.8})$$

(d) Now we show that $\frac{dP(\phi, \ell)}{d\eta} < 0$. From Equation (A.5), the implicit derivative

$$\frac{d\kappa}{d\eta} = \frac{\Gamma[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} \propto Q - \ell + \rho MF(\kappa) > Q - \ell \geq Q - \ell_H > 0, \quad (\text{A.9})$$

where the $\propto$ obtains because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7), and the second and third inequalities obtain because $\ell \leq \ell_H < Q$ by assumption.

It then follows from Equation (A.8) that

$$\frac{dP(\phi, \ell)}{d\eta} \propto -\frac{d}{d\eta} \left(\frac{\kappa}{\eta} \right) \propto -\frac{d\kappa}{d\eta} \eta + \kappa = -\frac{\Gamma\eta[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} + \kappa.$$

If $\kappa \leq 0$, then $\frac{dP(\phi, \ell)}{d\eta} < 0$ because $\ell \leq \ell_H < Q$ by assumption and $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7). If $\kappa > 0$, it follows that

$$\begin{aligned} \frac{dP(\phi, \ell)}{d\eta} &\propto -\frac{\Gamma\eta[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} + \kappa \\ &\propto -\Gamma\eta[Q - \ell + \rho MF(\kappa)] + \kappa[MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] \\ &= -M[f(\kappa) + \kappa F(\kappa)] - N\kappa + \kappa[MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] \\ &= -Mf(\kappa) - \kappa\Gamma\eta\rho Mf(\kappa) < 0, \end{aligned}$$

where the second $\propto$ obtains because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7), and the first equality follows from Equation (A.5). This completes the proof. $\square$

Proof of Proposition 1: From the expression of $B(\ell)$ in Equation (4),

$$\frac{dB(\ell)}{d\eta} \propto \frac{d\kappa}{d\eta} > 0, \quad (\text{A.10})$$

where the inequality follows from Equation (A.9). Therefore, $E[B(\ell)]$ increases in η . This completes the proof. $\square$

Proof of Proposition 2: Note that $s(\ell) = -\rho MB(\ell)$ from Equation (5); it follows that $E[s(\ell)]$ has the same monotonic property in η as that of $E[B(\ell)]$ (as given in Proposition 1). This completes the proof. $\square$

Proof of Proposition 3: From Equation (A.5), the implicit derivative

$$\frac{d\kappa}{d\ell} = -\frac{\Gamma\eta}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} < 0 \quad (\text{A.11})$$

because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7). It follows that

$$\frac{dP(\phi, \ell)}{d\ell} = -\frac{d\kappa}{d\ell} \frac{\sqrt{v_\lambda}}{\eta} = \frac{\Gamma\sqrt{v_\lambda}}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} = \frac{\gamma[v_\theta(1-\tau) + v_c]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)}$$

because $\Gamma = \frac{\gamma[v_\theta(1-\tau) + v_c]}{\sqrt{v_\lambda}}$.

From Equations (4) and (5), $s(\ell) = -\rho MB(\ell) = -\rho MF(\kappa(\ell))$; thus,

$$z(\ell) = \ell + s(\ell) = \ell - \rho MF(\kappa(\ell)).$$

It follows that

$$\begin{aligned} \frac{dz(\ell)}{d\ell} &= 1 - \rho Mf(\kappa) \frac{d\kappa}{d\ell} = 1 + \rho Mf(\kappa) \frac{\Gamma\eta}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} \\ &= \frac{M(\kappa) + N}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)}, \end{aligned}$$

where the second equality follows from Equation (A.11).

It follows that

$$\alpha(\phi, \ell) \equiv \frac{dP(\phi, \ell)}{dz(\ell)} = \frac{dP(\phi, \ell)/d\ell}{dz(\ell)/d\ell} = \frac{\gamma[v_\theta(1-\tau) + v_c]}{MF(\kappa) + N} > 0.$$

Then,

$$\frac{d\alpha(\phi, \ell)}{d\eta} = -\frac{\gamma[v_\theta(1-\tau) + v_c]}{M} \frac{f(\kappa)}{[F(\kappa) + N/M]^2} \frac{d\kappa}{d\eta} < 0, \quad (\text{A.12})$$

where the inequality obtains because $\frac{d\kappa}{d\eta} > 0$ from Equation (A.9). It follows that $\frac{dE[\alpha(\phi, \ell)]}{d\eta} < 0$. This completes the proof. $\square$

Proof of Proposition 4: (a) Suppose $Q > \ell_H + \frac{M}{\Gamma\sqrt{2\pi}}$; here we show that given ℓ , Equation (A.5) (or equivalently, Equation (2)) specifies a unique $\kappa > 0$.

Since the function $H(\kappa)$ in Equation (A.6) is specified according to Equation (A.5), it suffices to show that $H(\kappa) = 0$ specifies a unique $\kappa > 0$. Since $H(\infty) > 0$ and $\frac{dH(\kappa)}{d\kappa} > 0$ (from the proof of Theorem 1), it suffices to show that

$$\begin{aligned} H(0) &= Mf(0) - \Gamma\eta[Q - \ell + \rho MF(0)] \\ &< Mf(0) - \Gamma\eta(Q - \ell) \leq Mf(0) - \Gamma\eta(Q - \ell_H) = \frac{M}{\sqrt{2\pi}} - \Gamma\eta(Q - \ell_H) < 0, \end{aligned}$$

where the second inequality follows from $\ell \leq \ell_H$, and the last inequality follows from $\eta \geq 1$ and $Q > \ell_H + \frac{M}{\Gamma\sqrt{2\pi}}$.

(b) Next, also suppose that $Q > \ell_H + \rho N$. Let $K \equiv \frac{\kappa(\ell)}{\eta}$. We show that $\frac{dK}{d\ell} < 0$ and $\frac{d}{d\ell} \left(\frac{dK}{d\eta} \right) > 0$.

It follows from Equation (A.11) that

$$\frac{dK}{d\ell} = \frac{d\kappa}{d\ell} \frac{1}{\eta} = -\frac{\Gamma}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} < 0.$$

Note that

$$\begin{aligned}
\frac{d[MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)]}{d\eta} &= Mf(\kappa)(1 + \Gamma\eta\rho\kappa)\frac{d\kappa}{d\eta} - \Gamma\rho Mf(\kappa) \\
&\propto (1 + \Gamma\eta\rho\kappa)\frac{Q - \ell + \rho MF(\kappa)}{MF(\kappa) + N - \eta\rho Mf(\kappa)} - \rho \\
&> (1 + \Gamma\eta\rho\kappa)\frac{Q - \ell_H + \rho MF(\kappa)}{MF(\kappa) + N} - \rho, \\
&> (1 + \Gamma\eta\rho\kappa)\frac{\rho MF(\kappa) + \rho N}{MF(\kappa) + N} - \rho \\
&= (1 + \Gamma\eta\rho\kappa)\rho - \rho \\
&> 0,
\end{aligned}$$

where the $\propto$ follows from Equation (A.9), the first inequality obtains because $\kappa > 0$ (from the derivation in Part (a)), $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7), and $\ell \leq \ell_H < Q$ by assumption, and the second inequality follows from $Q > \ell_H + \rho N$. It follows that

$$\frac{d}{d\ell} \left(\frac{dK}{d\eta} \right) = \frac{d}{d\eta} \left(\frac{dK}{d\ell} \right) > 0.$$

(c) Now we prove Proposition 4. From Theorem 1 and $K \equiv \frac{\kappa(\ell)}{\eta}$,

$$V - P(\phi, \ell) = \theta - c - [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - K\sqrt{v_\lambda}];$$

and the variance ratio

$$VR \equiv \frac{\text{Var}(V - P) + \text{Var}(P)}{\text{Var}(V)} = 1 + \frac{2v_\lambda \text{Var}(K)}{v_\theta + v_c}.$$

We just need to show that $\text{Var}(K)$ decreases in η .

Since $\text{Var}(K) = E(K^2) - E(K)^2$, it follows that

$$\frac{d\text{Var}(K)}{d\eta} = E\left(2K\frac{dK}{d\eta}\right) - 2E(K)E\left(\frac{dK}{d\eta}\right) \propto \text{Cov}\left(K, \frac{dK}{d\eta}\right).$$

For $\text{Var}(K)$ to decrease in η , it suffices to show that $\text{Cov}\left(K, \frac{dK}{d\eta}\right) < 0$.

Note that both $K = \frac{\kappa(\ell)}{\eta}$ and $\frac{dK}{d\eta}$ depend on the random variable ℓ , and from the derivation in Part (b), $\frac{dK}{d\ell} < 0$ and $\frac{d}{d\ell}\left(\frac{dK}{d\eta}\right) > 0$. From the [Harris \(1960\)](#) inequality, we then obtain that $\text{Cov}\left(K, \frac{dK}{d\eta}\right) < 0$. This completes the proof. $\square$

Proof of Proposition 5: Before we proceed to prove this proposition, we need two preparatory items.

First, suppose that $Q - \ell_H$ is sufficiently high. We can use the same derivation as in Part (a) of the proof of Proposition 4 to show that given ℓ , Equation (A.5) (or equivalently, Equation (2)) specifies a unique $\kappa > 0$. In what follows, we show that $\eta\kappa\frac{d\kappa}{d\eta} > 1$ and $\frac{d}{d\eta}\left(\frac{d\kappa}{d\eta}\right) < 0$.

From Equation (A.5),

$$\begin{aligned} M[f(\kappa) + \kappa F(\kappa)] + N\kappa &= \Gamma\eta[Q - \ell + \rho MF(\kappa)] \\ M[f(0) + \kappa] + N\kappa &> \Gamma\eta(Q - \ell_H), \end{aligned}$$

where the inequality obtains because $f(\kappa) \leq f(0)$, $F(\kappa) \leq 1$, and $\kappa > 0$. This implies that for a sufficiently high $Q - \ell_H$, κ is sufficiently high; i.e., $\kappa > \bar{\kappa}$ where $\bar{\kappa}$ is a positive constant. From Equation (A.9),

$$\begin{aligned} \eta\kappa\frac{d\kappa}{d\eta} &= \eta\kappa\frac{\Gamma[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} \\ &> \eta\bar{\kappa}\frac{\Gamma(Q - \ell_H)}{M + N} \\ &> 1, \end{aligned} \tag{A.13}$$

where the first inequality obtains because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.7), $\ell \leq \ell_H < Q$ by assumption, $\kappa > \bar{\kappa}$, and $F(\kappa) \leq 1$, and where the last inequality again obtains

for sufficiently high $Q - \ell_H$. Also from Equation (A.9),

$$\begin{aligned}
\frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) &\propto \rho [MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] Mf(\kappa) \frac{d\kappa}{d\eta} \\
&\quad - [Q - \ell + \rho MF(\kappa)] \left[Mf(\kappa) \frac{d\kappa}{d\eta} + \Gamma\rho Mf(\kappa) \left(\eta\kappa \frac{d\kappa}{d\eta} - 1 \right) \right] \\
&< \rho [MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] Mf(\kappa) \frac{d\kappa}{d\eta} - [Q - \ell + \rho MF(\kappa)] Mf(\kappa) \frac{d\kappa}{d\eta} \\
&\propto \rho [MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] - [Q - \ell + \rho MF(\kappa)] \\
&< \rho [MF(\kappa) + N] - (Q - \ell_H) < 0
\end{aligned} \tag{A.14}$$

where the first inequality obtains because $\ell \leq \ell_H < Q$ by assumption and $\eta\kappa \frac{d\kappa}{d\eta} > 1$ from Equation (A.13), the second $\propto$ obtains because $\frac{d\kappa}{d\eta} > 0$ from Equation (A.9), and the second inequality obtains because $\ell \leq \ell_H$, and the last inequality obtains for sufficiently high $Q - \ell_H$.

Next, note that $\frac{dP(\phi, \ell)}{d\eta} < 0$ from Theorem 1. In what follows, we show that $\frac{d}{dv_\lambda} \left(\frac{dP(\phi, \ell)}{d\eta} \right) < 0$.

From Equation (A.5), the implicit derivative

$$\frac{d\kappa}{dv_\lambda} = \frac{d\Gamma}{dv_\lambda} \eta \frac{Q - \ell + \rho MF(\kappa)}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} = \frac{d\Gamma}{dv_\lambda} \frac{\eta}{\Gamma} \frac{d\kappa}{d\eta}, \tag{A.15}$$

where the last equality follows from Equation (A.9). From Theorem 1, we have

$$\begin{aligned}
\frac{d}{dv_\lambda} \left[\frac{dP(\phi, \ell)}{d\eta} \right] &\propto \kappa - \eta \frac{d\kappa}{d\eta} + 2v_\lambda \left[\frac{d\kappa}{dv_\lambda} - \eta \frac{d}{v_\lambda} \left(\frac{d\kappa}{d\eta} \right) \right] \\
&= \kappa - \eta \frac{d\kappa}{d\eta} + 2v_\lambda \left[\frac{d\Gamma}{dv_\lambda} \frac{\eta}{\Gamma} \frac{d\kappa}{d\eta} - \eta \frac{d\Gamma}{dv_\lambda} \frac{1}{\Gamma} \left[\frac{d\kappa}{d\eta} + \eta \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) \right] \right] \\
&= \kappa - \eta \frac{d\kappa}{d\eta} - 2v_\lambda \frac{d\Gamma}{dv_\lambda} \frac{\eta^2}{\Gamma} \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) < \kappa - \eta \frac{d\kappa}{d\eta} \\
&= \kappa - \eta \frac{\Gamma[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} \\
&\propto \kappa [MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)] - [M[f(\kappa) + \kappa F(\kappa)] + N\kappa] \\
&\propto -\kappa\Gamma\eta\rho Mf(\kappa) - Mf(\kappa) < 0,
\end{aligned}$$

where the first equality follows from Equation (A.15), the first inequality obtains because $\Gamma = \frac{\gamma[v_\theta(1-\tau) + v_c]}{\sqrt{v_\lambda}}$ decreases in v_λ and $\frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) < 0$ from Equation (A.14), the third equality follows from Equation (A.9), the second $\propto$ follows from Equation (A.5) and $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ (see Equation (A.7)), and the last inequality obtains because $\kappa > 0$.

We now prove the proposition.

(i) Note that $\frac{dE[B(\ell)]}{d\eta} > 0$ from Proposition 1. We need to show that for a sufficiently high Q , $\frac{d}{dv_\lambda} \left[\frac{dE[B(\ell)]}{d\eta} \right] > 0$; it suffices to show that $\frac{d}{dv_\lambda} \left[\frac{dB(\ell)}{d\eta} \right] > 0$.

It follows from the expression $B(\ell) = F(\kappa(\ell))$ that

$$\begin{aligned} \frac{d}{dv_\lambda} \left[\frac{dB(\ell)}{d\eta} \right] &= \frac{d}{dv_\lambda} \left[f(\kappa) \frac{d\kappa}{d\eta} \right] = f(\kappa) \frac{d}{d\eta} \left(\frac{d\kappa}{dv_\lambda} \right) - \kappa f(\kappa) \frac{d\kappa}{dv_\lambda} \frac{d\kappa}{d\eta} \\ &= f(\kappa) \frac{d\Gamma}{dv_\lambda} \frac{1}{\Gamma} \left[\frac{d\kappa}{d\eta} + \eta \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) \right] - \kappa f(\kappa) \frac{d\Gamma}{dv_\lambda} \frac{\eta}{\Gamma} \left(\frac{d\kappa}{d\eta} \right)^2 \\ &\propto \frac{d\kappa}{d\eta} \left(\eta \kappa \frac{d\kappa}{d\eta} - 1 \right) - \eta \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) \\ &> 0, \end{aligned}$$

where the third equality follows from Equation (A.15), the $\propto$ obtains because $\Gamma = \frac{\gamma[v_\theta(1-\tau) + v_c]}{\sqrt{v_\lambda}}$ decreases in v_λ , and the inequality obtains because $\frac{d\kappa}{d\eta} > 0$ from Equation (A.9), $\eta \kappa \frac{d\kappa}{d\eta} > 1$ from Equation (A.13), and $\frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) < 0$ from Equation (A.14).

(ii) Note that $\frac{dE[|s(\ell)|]}{d\eta} > 0$ from Proposition 2. We need to show that for a sufficiently high Q , $\frac{d}{dv_\lambda} \left[\frac{dE[|s(\ell)|]}{d\eta} \right] > 0$; it suffices to show that $\frac{d}{dv_\lambda} \left[\frac{d|s(\ell)|}{d\eta} \right] > 0$. Since $s(\ell) = -\rho MB(\ell)$ from Equation (5), $E[|s(\ell)|]$ has the same monotonic property in η and v_λ as that of $E[B(\ell)]$. It follows from Part (i) that $\frac{d}{dv_\lambda} \left[\frac{d|s(\ell)|}{d\eta} \right] > 0$.

(iii) Note that $\frac{dE[\alpha(\phi, \ell)]}{d\eta} < 0$ from Proposition 3. We need to show that for a sufficiently high Q , $\frac{d}{dv_\lambda} \left[\frac{dE[\alpha(\phi, \ell)]}{d\eta} \right] < 0$; it suffices to show $\frac{d}{dv_\lambda} \left[\frac{d\alpha(\phi, \ell)}{d\eta} \right] < 0$. It follows from

Equation (A.12) that

$$\begin{aligned}
\frac{d}{dv_\lambda} \left[\frac{d \alpha(\phi, \ell)}{d\eta} \right] &\propto - \frac{-\kappa f(\kappa)[F(\kappa) + N/M]^2 - [f(\kappa)]^2 2[F(\kappa) + N/M]}{[F(\kappa) + N/M]^4} \frac{d\kappa}{dv_\lambda} \frac{d\kappa}{d\eta} \\
&\quad - \frac{f(\kappa)}{[F(\kappa) + N/M]^2} \frac{d}{dv_\lambda} \left(\frac{d\kappa}{d\eta} \right) \\
&\propto - \frac{-\kappa[F(\kappa) + N/M] - 2f(\kappa)}{F(\kappa) + N/M} \frac{d\kappa}{dv_\lambda} \frac{d\kappa}{d\eta} - \frac{d}{dv_\lambda} \left(\frac{d\kappa}{d\eta} \right) \\
&= - \frac{-\kappa[F(\kappa) + N/M] - 2f(\kappa)}{F(\kappa) + N/M} \frac{d\Gamma}{dv_\lambda} \frac{\eta}{\Gamma} \left(\frac{d\kappa}{d\eta} \right)^2 \\
&\quad - \frac{d\Gamma}{dv_\lambda} \frac{1}{\Gamma} \left[\frac{d\kappa}{d\eta} + \eta \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) \right] \\
&\propto \frac{-\kappa[F(\kappa) + N/M] - 2f(\kappa)}{F(\kappa) + N/M} \eta \left(\frac{d\kappa}{d\eta} \right)^2 + \left[\frac{d\kappa}{d\eta} + \eta \frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) \right] \\
&< -\eta \kappa \left(\frac{d\kappa}{d\eta} \right)^2 + \frac{d\kappa}{d\eta} \propto -\eta \kappa \frac{d\kappa}{d\eta} + 1 < 0,
\end{aligned}$$

where the equality follows from Equation (A.15), the third $\propto$ obtains because $\frac{d\Gamma}{dv_\lambda} < 0$, the first inequality obtains because $\frac{d}{d\eta} \left(\frac{d\kappa}{d\eta} \right) < 0$ from Equation (A.14), the last $\propto$ obtains because $\frac{d\kappa}{d\eta} > 0$ from Equation (A.9), and the last inequality obtains because $\eta \kappa \frac{d\kappa}{d\eta} > 1$ from Equation (A.13). This completes the proof. $\square$

Appendix B: Technical Details for Climate Risk Disclosures

Table B1. Keywords corresponding to climate risk disclosures in 10-Ks

We list the keywords that [Kim, Wang, and Wu \(2023\)](#) use to isolate CR disclosures in 10-Ks. This is the same table as their Table 12.

Adverse weather	Climate control initiative(s)	Extreme climate(s)	Regulatory initiative(s)
cap and trade	climate initiative(s)	extreme temperature(s)	regulatory risk(s) from climate change
carbon dioxide	climate legislation(s)	extreme weather	rising temperature(s)
changing climate(s)	climate registr(y) (ies)	GHG(s) (abbreviation for greenhouse gas(es))	Sea level(s)
clean air act	climate regulation(s)	global warming	tailoring rule
climate challenge(s)	climate risk(s)	greenhouse gas emissions legislation(s)	Title V
climate change	climate statute(s)	greenhouse gas(es)	United Nations Framework Convention on Climate Change
climate change laws	climate-change	indirect effect(s)	unseasonably warm weather
climate change legislation(s)	climate-change proposal(s)	indirect regulatory risks	unusual weather
climate change registr(y) (ies)	climate-related initiative(s)	indirect risks from climate change	volatility in seasonal temperature(s)
climate change regulation(s)	CO ₂ (carbon dioxide)	Kyoto protocol	warm weather
climate change risk(s)	controls on emission(s)	methane	warmer than normal winter(s)
climate change statute(s)	cooler than normal summer(s)	physical risk(s) from climate change	warmer weather
climate change treat(y)(ies)	emission(s) initiative(s)	reduction(s) of the emission(s)	warming of the climate
climate condition(s)	emission(s) standard(s)	regulation risk(s) from climate change	weather concern(s)
climate control	EU ETS (European Union Emissions Trading System)	regulation(s) related to climate change	weather pattern(s)

Internet Appendix for
The Capital Market Implications of Climate Risk Disclosure

IA.1: A Model with a Public Signal about CR Costs

In the main paper (Section 1), we assume that the firm's CR disclosure effectively mitigates the scale of the active buyers' optimism or pessimism about CR costs, and draws buyers closer to a Bayesian. Here, we consider an alternative setting in which the firm's CR disclosure reveals a public signal about the variable representing CR costs, c . In this variant; while active buyers still hold heterogeneous prior beliefs about CR costs, they interpret the public signal rationally, and update based as Bayesians. We will show that the main results of our paper still hold.

Specifically, buyer m believes c is drawn from a normal distribution with mean $c_m = \bar{c} + \lambda_m$ and variance v_c , where $\lambda_m \sim \mathcal{N}(0, v_\lambda)$. CR disclosure reveals a public signal of the firm's climate exposure, $\psi = c + \xi$ where ξ follows a normal distribution with mean zero and variance $1/\eta$. $\eta > 0$ is an exogenous parameter representing the quality of the firm's CR disclosure. The rest of the setting remains the same as in Section 1 of the main paper.

Denote $\tau \equiv \frac{v_\theta}{v_\theta + v_\zeta}$ and $\iota \equiv \frac{v_c}{v_c + 1/\eta}$, and redefine $\Gamma \equiv \frac{\gamma}{\sqrt{v_\lambda}} \left(v_\theta \frac{1-\tau}{1-\iota} + v_c \right)$. Also define a function for noise buying ℓ , $\kappa(\ell)$, according to the following specification:

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma[Q - \ell + \rho MF(\kappa)] = 0. \quad (\text{IA.1})$$

The condition below then suffices for uniqueness:

$$\rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma}. \quad (\text{IA.2})$$

The following result obtains:³¹

Theorem IA.1 *The equilibrium stock price is given as follows:*

$$P(\phi, \ell) = \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \iota(\psi - \bar{c}) - \kappa(\ell)(1 - \iota)\sqrt{v_\lambda},$$

where $\kappa(\ell)$ is specified in Equation (IA.1).

Again, we define ownership breadth as the fraction B of active buyers who go long in equilibrium. We show in the proof of Theorem IA.1 that the m 'th active buyer goes long

³¹All proofs appear in at the end of this section.

(i.e., $x_m > 0$) only if the investor is not too pessimistic. We can then compute the ownership breadth given ℓ as:

$$B(\ell) = F(\kappa(\ell)). \quad (\text{IA.3})$$

We obtain the following result, similar to Proposition 1 of the main paper:

Proposition IA.1 *Expected ownership breadth, $E[B(\ell)]$, increases in the level of CR disclosure, η .*

Note that by assumption noise sellers' demand s is proportional to the mass of utility-maximizing buyers who go long. Given a realization of noise buying ℓ , this demand is given by:

$$s(\ell) = -\rho MB(\ell). \quad (\text{IA.4})$$

We obtain the following result, similar to Proposition 2 of the main paper:

Proposition IA.2 *Expected short interest, $E[|s(\ell)|]$, increases in the level of CR disclosure, η .*

We next turn to illiquidity in this market. Let the total noise demand be given by $z(\ell) \equiv \ell + s(\ell)$. Denote

$$\alpha(\phi, \ell) \equiv \frac{dP(\phi, \ell)}{dz(\ell)}.$$

We measure expected illiquidity by $E[\alpha(\phi, \ell)]$, and obtain the following result, similar to Proposition 3 of the main paper:

Proposition IA.3 *The expected illiquidity measure, $E[\alpha(\phi, \ell)]$ (where $\alpha(\phi, \ell) > 0$), decreases when there is an increase in CR disclosure (i.e., a rise in η).*

Proofs:

Proof of Theorem IA.1: (a) Denote $\tau \equiv \frac{v_\theta}{v_\theta + v_\zeta}$ and $\iota \equiv \frac{v_c}{v_c + 1/\eta}$. The m 'th buyer believes that $\theta|\phi \sim N(\bar{\theta} + \tau(\phi - \bar{\theta}), v_\theta(1 - \tau))$ and $c|\psi \sim N(\bar{c} + \lambda_m + \iota(\psi - \bar{c} - \lambda_m), v_c(1 - \iota))$. Denote the stock price as P , and write the active buyer's Date 2 wealth as $W_{m2} = W_{m1} + x_m(V - P) =$

$W_{m1} + x_m(\theta - c - P)$, where W_{m1} is the wealth at Date 1. The buyer chooses the demand x_m to maximize

$$\begin{aligned}\hat{E}_m[U(W_{m2})|\phi, \psi] &= \hat{E}_m[-\exp[-\gamma W_{m1} - \gamma x_m(\theta - c - P)]|\phi, \psi] \\ &= -\exp[-\gamma W_{m1} - \gamma x_m[\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \lambda_m - \iota(\psi - \bar{c} - \lambda_m) - P] \\ &\quad + 0.5\gamma^2 x_m^2[v_\theta(1 - \tau) + v_c(1 - \iota)]] ,\end{aligned}$$

where $\hat{E}_m(\cdot)$ indicates expectations based on the buyer's belief. The first-order condition with respect to x_m and the short-selling constraint (i.e., $x_m \geq 0$) imply that the optimal demand is

$$\begin{aligned}x_m &= \frac{\max(0, \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \lambda_m - \iota(\psi - \bar{c} - \lambda_m) - P)}{\gamma[v_\theta(1 - \tau) + v_c(1 - \iota)]} \\ &= \frac{\max(0, -\lambda_m(1 - \iota) - p)}{\gamma[v_\theta(1 - \tau) + v_c(1 - \iota)]},\end{aligned}\tag{IA.5}$$

where $p = P - [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \iota(\psi - \bar{c})]$.

(b) The mass N of arbitrageurs believe that $\theta|\phi \sim N(\bar{\theta} + \tau(\phi - \bar{\theta}), v_\theta(1 - \tau))$ and $c|\psi \sim N(\bar{c} + \iota(\psi - \bar{c}), v_c(1 - \iota))$. We can use a similar derivation as that in Part (a) to show that the n 'th such arbitrageur's optimal demand is

$$y = \frac{\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \iota(\psi - \bar{c}) - P}{\gamma[v_\theta(1 - \tau) + v_c(1 - \iota)]} = \frac{-p}{\gamma[v_\theta(1 - \tau) + v_c(1 - \iota)]}.\tag{IA.6}$$

(c) The market-clearing condition requires

$$M \int_{-\infty}^{\infty} x_m dF\left(\frac{\lambda_m}{\sqrt{v_\lambda}}\right) + Ny + \ell + s = Q,\tag{IA.7}$$

where x_m and y are given in Equations (IA.5) and (IA.6), respectively.

Equation (IA.5) implies that $x_m > 0$ only if $\lambda_m < -p/(1-\iota)$. Thus, from Equation (IA.7),

$$\begin{aligned} M \int_{-\infty}^{-p/(1-\iota)} \frac{-\lambda_m(1-\iota) - p}{\gamma[v_\theta(1-\tau) + v_c(1-\iota)]} dF\left(\frac{\lambda_m}{\sqrt{v_\lambda}}\right) \\ + N \frac{-p}{\gamma[v_\theta(1-\tau) + v_c(1-\iota)]} - (Q - \ell - s) &= 0, \\ M \left[(1-\iota)\sqrt{v_\lambda} f\left(-\frac{p}{(1-\iota)\sqrt{v_\lambda}}\right) - pF\left(-\frac{p}{(1-\iota)\sqrt{v_\lambda}}\right) \right] \\ - Np - \gamma[v_\theta(1-\tau) + v_c(1-\iota)](Q - \ell - s) &= 0. \end{aligned}$$

Denote $\kappa \equiv -\frac{p}{(1-\iota)\sqrt{v_\lambda}}$ and $\Gamma \equiv \frac{\gamma[v_\theta(1-\tau) + v_c(1-\iota)]}{(1-\iota)\sqrt{v_\lambda}} = \frac{\gamma}{\sqrt{v_\lambda}} \left(v_\theta \frac{1-\tau}{1-\iota} + v_c \right)$. It follows that

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma(Q - \ell - s) = 0. \quad (\text{IA.8})$$

Because $x_m > 0$ only if $\lambda_m < -p/(1-\iota)$, the fraction of active buyers who go long is computed as

$$B = \int_{-\infty}^{-p/(1-\iota)} 1 dF\left(\frac{\lambda_m}{\sqrt{v_\lambda}}\right) = \int_{-\infty}^{\kappa\sqrt{v_\lambda}} 1 dF\left(\frac{\lambda_m}{\sqrt{v_\lambda}}\right) = F(\kappa),$$

where the second equality obtains from $\kappa = -\frac{p}{(1-\iota)\sqrt{v_\lambda}}$. It follows from the assumption $s = -\rho MB$ that $s = -\rho MF(\kappa)$; thus, Equation (IA.8) becomes

$$M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma[Q - \ell + \rho MF(\kappa)] = 0, \quad (\text{IA.9})$$

which is Equation (IA.1).

We need to show that given ℓ , Equation (IA.9) specifies a unique κ . Define a function of κ :

$$H(\kappa) \equiv M[f(\kappa) + \kappa F(\kappa)] + N\kappa - \Gamma[Q - \ell + \rho MF(\kappa)].$$

It is straightforward to show that $H(-\infty) < 0$, $H(\infty) > 0$, and

$$\frac{dH(\kappa)}{d\kappa} = MF(\kappa) + N - \Gamma\rho Mf(\kappa) > N - \Gamma\rho Mf(0) \propto \frac{N}{M} - \frac{\Gamma}{\sqrt{2\pi}}\rho > 0 \quad (\text{IA.10})$$

where the last inequality obtains because $\rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma}$ from Assumption (IA.2). Therefore, Equation (IA.9) specifies a unique κ .

Note that $p = P - [\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \iota(\psi - \bar{c})]$ and $\kappa = -\frac{P}{(1-\iota)\sqrt{v_\lambda}}$. Further, κ is a function of ℓ ; denoted $\kappa(\ell)$. The price takes the form

$$P(\phi, \ell) = \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \iota(\psi - \bar{c}) - \kappa(\ell)(1-\iota)\sqrt{v_\lambda}. \quad (\text{IA.11})$$

This completes the proof. $\square$

Proof of Proposition IA.1: Note that $\iota = \frac{v_c}{v_c + 1/\eta}$ increases in η ; $\Gamma = \frac{\gamma}{\sqrt{v_\lambda}} \left(v_\theta \frac{1-\tau}{1-\iota} + v_c \right)$ increases in ι ; and from Equation (IA.9), the implicit derivative

$$\frac{d\kappa}{d\Gamma} = \frac{Q - \ell + \rho MF(\kappa)}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)} \propto Q - \ell + \rho MF(\kappa) > Q - \ell \geq Q - \ell_H > 0, \quad (\text{IA.12})$$

where the $\propto$ obtains because $MF(\kappa) + N - \Gamma \rho Mf(\kappa) > 0$ from Equation (IA.10), and the second and third inequalities obtain because $\ell \leq \ell_H < Q$ by assumption. It follows that $d\kappa/d\eta > 0$. It follows from the expression of $B(\ell)$ in Equation (IA.3) that

$$\frac{dB(\ell)}{d\eta} \propto \frac{d\kappa}{d\eta} > 0. \quad (\text{IA.13})$$

This completes the proof. $\square$

Proof of Proposition IA.2: Note that $s(\ell) = -\rho MB(\ell)$ from Equation (IA.4); it follows that $E[|s(\ell)|]$ has the same monotonic property in η as that of $E[B(\ell)]$ (as given in Proposition IA.1). This completes the proof. $\square$

Proof of Proposition IA.3: From Equation (IA.9), the implicit derivative

$$\frac{d\kappa}{d\ell} = -\frac{\Gamma}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)} < 0 \quad (\text{IA.14})$$

because $MF(\kappa) + N - \Gamma \rho Mf(\kappa) > 0$ from Equation (IA.10). We then have

$$\frac{dP(\phi, \ell)}{d\ell} = -\frac{d\kappa}{d\ell}(1-\iota)\sqrt{v_\lambda} = \frac{\Gamma(1-\iota)\sqrt{v_\lambda}}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)} = \frac{\gamma[v_\theta(1-\tau) + v_c(1-\iota)]}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)}$$

because $\Gamma = \frac{\gamma}{\sqrt{v_\lambda}} \left(v_\theta \frac{1-\tau}{1-\iota} + v_c \right)$.

From Equations (IA.3) and (IA.4), $s(\ell) = -\rho MB(\ell) = -\rho MF(\kappa(\ell))$; thus,

$$z(\ell) = \ell + s(\ell) = \ell - \rho MF(\kappa(\ell)).$$

It follows that

$$\begin{aligned} \frac{dz(\ell)}{d\ell} &= 1 - \rho Mf(\kappa) \frac{d\kappa}{d\ell} = 1 + \rho Mf(\kappa) \frac{\Gamma}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)} \\ &= \frac{M(\kappa) + N}{MF(\kappa) + N - \Gamma \rho Mf(\kappa)}, \end{aligned}$$

where the second equality follows from Equation (IA.14).

Thus, we have that

$$\alpha(\phi, \ell) \equiv \frac{dP(\phi, \ell)}{dz(\ell)} = \frac{dP(\phi, \ell)/d\ell}{dz(\ell)/d\ell} = \frac{\gamma[v_\theta(1 - \tau) + v_c(1 - \iota)]}{MF(\kappa) + N} > 0.$$

Note that $\iota = \frac{v_c}{v_c + 1/\eta}$ increases in η , and $\frac{d\kappa}{d\eta} > 0$ from the proof of Proposition IA.1. It follows that $\frac{dE[\alpha(\phi, \ell)]}{d\eta} < 0$. This completes the proof. $\square$

IA.2: Parallel trends analysis

We investigate parallel trends in outcome variables across CRD-increasing firms and the other firms in the sample. For this purpose, we follow [Biasi and Sarsons \(2022, online appendix\)](#) and adopt [Rambachan and Roth \(2023\)](#)'s smoothness restrictions test. This test consists of constructing a set of possible deviations from the parallel trends assumption and estimating the confidence intervals associated with these deviations. Denote the difference in trends between CRD-increasing firms and other firms by δ . [Rambachan and Roth \(2023\)](#) introduce a parameter $M \geq 0$ which governs the amount by which the slope of δ can change between consecutive periods.

To implement [Rambachan and Roth \(2023\)](#)'s test, we introduce annual indicator variables and run the following panel regression:

$$\begin{aligned} \text{Dependent}_{i,t} = & b_0 + b_1 \text{CRDInc}_i + \delta_{-3} \text{TY-3}_i + \delta_{-2} \text{TY-2}_i + \delta_{+1} \text{TYpost}_i \\ & + \text{Industry and Year Fixed Effects} + \varepsilon_{i,t}, \end{aligned} \tag{IA.15}$$

where CRDInc_i is the CRDInc indicator variable for the interaction regression, $\text{TY-3}_i = \text{CRDInc}_i \times Y_{-3}$ and Y_{-3} is one for 2006 (= 2009 - 3) and zero otherwise, $\text{TY-2}_i = \text{CRDInc}_i \times Y_{-2}$ and Y_{-2} is one for 2007 (= 2009-2) and zero otherwise, $\text{TYpost}_i = \text{CRDInc}_i \times \text{Post}$, and Industry and Year Fixed Effects are the same as those in eq. (6). Since the regression includes a constant term, the year indicator 2008 (one year before the event year) is omitted. Following [Biasi and Sarsons \(2022\)](#), we set M to range from zero (linear pre-trends) to the standard error of the coefficient of interest (δ_{+1}) and plot the 90% confidence intervals for deviations defined by M s in Figure [IA.1](#).

The results in Figure [IA.1](#) are encouraging. The significance of all interactive coefficients is robust to linear violations of parallel trends ($M = 0$). More importantly, it is also robust to various degrees of nonlinear violations ($M > 0$). Specifically, six out of the eight interactive coefficients (InstOwn%, InstOwn log#, Lendable Supply, Borrow Cost Score, Variance Ratio, and Delay) remain significant even when the post-guidance trends deviate nonlinearly for M up to their standard errors. The significance of InstOwn HHI is robust for M up to 40% of the standard error. The post-guidance trend in the bid/ask spread is significant for

sufficiently large values of M . Put together, our overall analysis is robust to violations of the parallel trends assumption.

We plot trends in the cross-sectional averages of the dependent variables and the difference between them in Figure [IA.2](#). We do this exercise separately for the CRD-increasing firms and other firms. The trend time series includes four years before and five years after 2009. We present the two trends in the left panel of Figure [IA.2](#). Take Lendable Supply as an example. While we see that the CRD-increasing group and the other firm group start at the same level, the former group's Lendable Supply diverges from the latter group's post-2009. Similarly, examining InstOwn HHI, we observe close-to-parallel trends before 2009, followed by diverging trajectories after. This pattern extends to other dependent variables. The difference between the two trends is presented in the right panel of Figure [IA.2](#). Notably, the divergence becomes evident after 2009, as highlighted in this panel.

Figure IA.1. Robust Confidence Intervals Analysis of Interaction Coefficients

The panels in this figure show robust 90% confidence intervals for the interaction coefficients on InstOwn%, InstOwn log#, InstOwn HHI, Lendable Supply, Borrow Cost Score, BA Spread, Variance Ratio, and Delay. The interaction variable is $CRDInc_i \times Post$, where $CRDInc_i$ denotes an indicator for CRD-increasing firms following publicization of the [SEC \(2010\)](#) guidance, and $Post$ denotes the post-publicization period. We construct the intervals using the Smoothness Restrictions approach of [Rambachan and Roth \(2023\)](#). The error bar on the left is the original OLS confidence interval, which is only valid if the parallel trends assumption holds exactly. Moving to the right, the shaded area represents the confidence interval for different values of M with $M = 0$ corresponding to linear violations of parallel trends, and larger values of M allowing for larger deviations from linearity. The solid horizontal lines indicate the point estimates of the coefficients, and the dashed vertical lines indicate half of the coefficient standard errors.

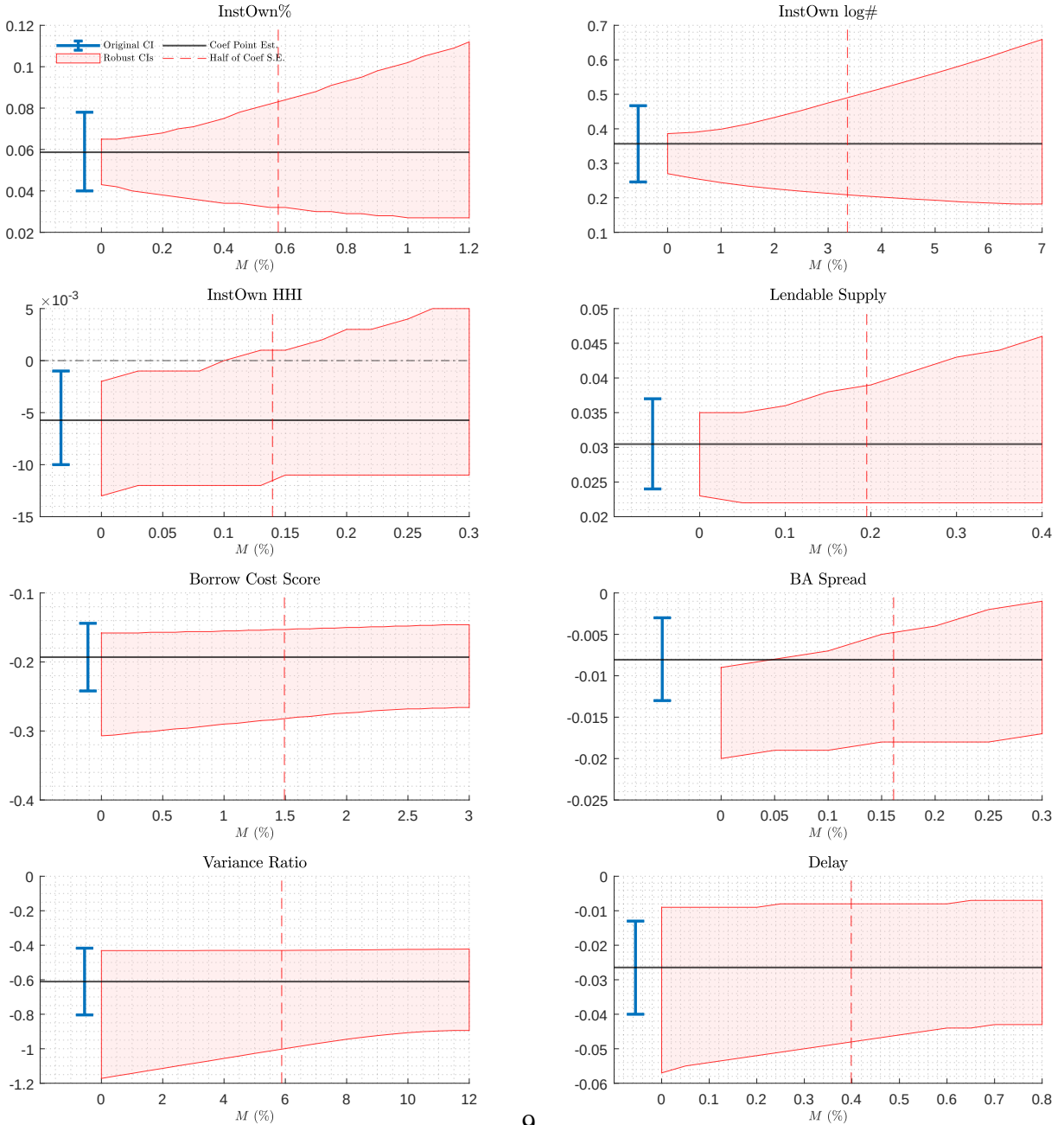
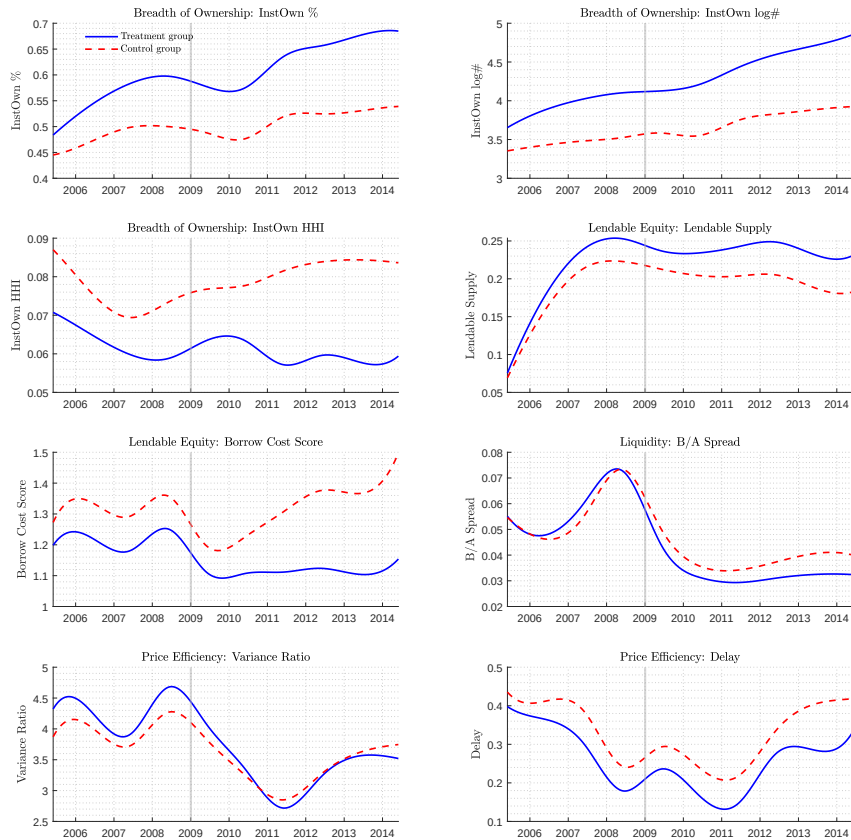


Figure IA.2. CRD-Increasing Group vs. Other Firms - Average Trends Comparison

Panel A of this figure contains time series plots of the average values of the CRD-increasing group's eight dependent variables in the four categories (solid blue line) versus that of other firms (dashed red line). The CRD-increasing group consists of those firms that materially increased their climate risk disclosure following publicization of SEC (2010). Panel B contains time series plots of the difference between the dependent variables of the CRD-increasing group and other firms (solid black line) as well as the level of the differences (dashed blue line) between and after the year 2009. The three variables in the Breadth of Ownership category are InstOwn %, InstOwn log#, and InstOwn HHI; the two variables in the Lendable Equity category are Lendable Supply and Borrow Cost Score; the variable in the Liquidity category is B/A Spread; and the two variables in the Price Efficiency category are Variance Ratio and Delay. The plotted trends are smoothed versions of yearly figures.

(a) Trends



(b) Difference in Trends

