

The Capital Market Implications of Climate Risk Disclosure

Jiang Luo

Konstantinos Stathopoulos

Avanidhar Subrahmanyam

Xiaoxia Ye

Ran Zhao

September 2, 2024

Abstract

Corporate climate risk (CR) disclosures have become increasingly widespread in recent years. Based on a simple theoretical model, we hypothesize that increased CR disclosure allows a firm to appeal to a larger set of institutional investors, and that this, in turn, implies an increased supply of lendable shares, less binding short-selling constraints, and improved market quality. We consider a difference-in-differences setting to test our implications, using the publication of the [SEC \(2010\)](#) guidance on CR disclosure as our DiD event. We find empirical evidence consistent with all of our hypotheses. Our study identifies CR disclosures as a novel source of ownership breadth, and, ultimately, financial market liquidity and efficiency. We also show that socially responsible mutual funds are particularly important in channeling CR disclosures' positive effects on financial markets.

Keywords: Climate risk, Disclosure, Breadth of ownership, Stock liquidity, Price efficiency

JEL: G14, G20, G30, Q54

Luo (luojiang@ntu.edu.sg) is with Nanyang Business School, Nanyang Technological University, Stathopoulos (k.stathopoulos@manchester.ac.uk) is with Alliance Manchester Business School, The University of Manchester, Subrahmanyam (asubrahm@anderson.ucla.edu) is with UCLA Anderson School of Management, Ye (x.ye@exeter.ac.uk) is with University of Exeter Business School, and Zhao (rzhao2@sdsu.edu) is with San Diego State University. We thank Marie Dutordoir and Alex Kostakis for their helpful comments on early versions of this paper.

The Capital Market Implications of Climate Risk Disclosure

September 2, 2024

Abstract

Corporate climate risk (CR) disclosures have become increasingly widespread in recent years. Based on a simple theoretical model, we hypothesize that increased CR disclosure allows a firm to appeal to a larger set of institutional investors, and that this, in turn, implies an increased supply of lendable shares, less binding short-selling constraints, and improved market quality. We consider a difference-in-differences setting to test our implications, using the publication of the [SEC \(2010\)](#) guidance on CR disclosure as our DiD event. We find empirical evidence consistent with all of our hypotheses. Our study identifies CR disclosures as a novel source of ownership breadth, and, ultimately, financial market liquidity and efficiency. We also show that socially responsible mutual funds are particularly important in channeling CR disclosures' positive effects on financial markets.

Keywords: Climate risk, Disclosure, Breadth of ownership, Stock liquidity, Price efficiency

JEL: G14, G20, G30, Q54

1 Introduction

Recent years have witnessed strong growth in public awareness of climate risk (CR). This growth in CR awareness has coincided with a significant increase in the flow of funds to sustainable investment (Pástor, Stambaugh and Taylor (2022)). Policy makers have responded to this heightened interest in CR by introducing policies intended to enhance the quality of CR-related corporate information.¹ These regulatory moves, in turn, have led to debates on costs of compliance (Tett (2024)), as well as on the effect of CR disclosures on firm values (Flammer, Toffel and Viswanathan (2021)). However, little is known about the capital market implications of CR disclosure. This study fills this gap. Specifically, we build a simple theoretical framework that considers the impact of CR disclosures on breadth of ownership, and in turn, on market liquidity and price efficiency, and test implications arising from our setting.

Edmans (2023) proposes that firms can enhance their appeal to institutional investors by increasing the transparency of CR disclosures. This is because such high-quality disclosures enable investors to better assess the resilience of a firm's business model to climate change. Kim, Wang and Wu (2022) show that CR disclosures increase firms' climate risk mitigation activities, which could increase firms' appeal to a broader set of investors. Indeed, Ilhan et al. (2023) find that institutional investors prefer to hold stocks of firms with more informative CR disclosures.² Still, the implications of this increased institutional ownership for firms' stock market liquidity and price efficiency are not clear-cut, and leave room for new analysis, as we argue below.

First, several lines of thought suggest CR disclosure can increase ownership breadth.

¹ Recent regulatory 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).

² Ilhan et al. (2023) propose that their reported correlation between CR disclosure and ownership by climate-conscious institutions could be due to two effects: an influence effect where climate-conscious institutions actively engage firms to produce such information, and a selection effect, where climate-conscious institutions prefer to invest in firms with better CR disclosures. While Ilhan et al. (2023)'s tests support the influence effect, our analysis finds complementary evidence for the selection effect.

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 an unprecedented increase in socially responsible investment (SRI), to the point where it now represents one-third of the \$51 trillion assets under management in the U.S. ([US-SIF \(2020\)](#)). These arguments all suggest a positive impact of CR disclosures on breadth of ownership. In turn, this increased breadth should lead to greater trading activity and 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 \(forthcoming\)](#)).

Alternatively, 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 despite the politicization of the issue ([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 impact of block ownership on market quality ([Brockman, Chung and Yan \(2009\)](#)). Thus, the relation between CR disclosures and firm ownership structure is an empirical question, that deserves an answer.

Establishing a clean directional linkage from CR disclosures to institutional ownership

dispersion is difficult, however. For instance, confounding factors such as environmentally conscious management could contribute to both CR disclosures and ownership structures. Furthermore, there may be reverse causality from ownership structure to disclosure policy, (e.g., via board activism), as proposed by [Ilhan et al. \(2023\)](#). To address these issues, we extend [Kim, Wang and Wu \(2022\)](#)'s study and perform a difference-in-differences (DiD) analysis using SEC's publication of the [2010 Commission Guidance Regarding Disclosure Related to Climate Change](#), which advised public companies on climate change disclosures.³ This is the earliest regulatory intervention on CR disclosures that we could find in the U.S. The event allows for sufficiently long post- and pre-event periods that allow us to reliably study its impact on ownership structures and, in turn, on market liquidity and price efficiency. We identify our treatment group as firms that changed their CR disclosure behavior around the issuance of the guidance and the control group as firms that did not. Our DiD approach helps us identify the effect of CR disclosure on firms' ownership structure and financial market quality by ruling out the impact of (unobservable) changes in other firm characteristics correlated with ownership structure.

Consistent with our inferences and our theory, the DiD analysis confirms that firms which increase CR disclosure post-SEC-guidance experience increased ownership breadth relative to the control group. Specifically, the treatment firms experience an increase in the number of institutions as well as a lowered value of the Herfindahl–Hirschman concentration index. The empirical results are robust to various regression specifications, alternative CR disclosure measures, and commonly used controls. Further, we show that SRI drives the increase in institutional ownership and the reduction in ownership concentration. It is noteworthy that mutual funds exhibit the most robust response to positive CR disclosure changes. This highlights their pivotal contribution to the improvement of market quality. To our knowledge, we are the first to report causal evidence on the conjecture that better quality CR disclosures improve the breadth of ownership in financial markets.

³ Although 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.

Our 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 increased CR disclosure have higher stock lendable supplies and lower borrowing costs. Further, such firms have higher liquidity (lower bid-ask spreads) and improved pricing efficiency as proxied by variance ratios and the delay measure of [Hou and Moskowitz \(2005\)](#). These findings highlight the mediating role of ownership breadth in channeling CR disclosures' positive effects on liquidity and pricing efficiency. Overall, our findings highlight a new advantage of increased CR disclosure, namely, an improvement in market quality, which adds perspective to the evolving debate on global sustainability reporting standards and regulations ([Ilhan et al. \(2023\)](#), [Christensen, Hail and Leuz \(2021\)](#)).

Our study contributes to two major facets of the literature. First, we add to the fast-growing body of work on climate finance and its disclosure. Our evidence that CR disclosures increase ownership breadth accords with the idea that increasing CR transparency enhances the appeal of the firm to socially conscious investors ([Berk and van Binsbergen \(forthcoming\)](#)). In a comprehensive review, [Christensen, Hail and Leuz \(2021\)](#) summarize the proposed economic effects of CSR disclosures. Several of the reviewed studies (e.g., [Barth et al. \(2017\)](#), [Grewal, Hauptmann and Serafeim \(2021\)](#), [Cho, Lee and Pfeiffer Jr \(2013\)](#)) provide important correlational evidence on the relevant mechanisms. [Ramadorai and Zeni \(forthcoming\)](#) argue that firms' current responses to carbon emission regulatory events have economic implications for future corporate decisions and outcomes. By documenting a novel causation flowing from CR disclosures to ownership dispersion, and, in turn, to market quality, we shed new light on how environmental disclosures affect financial markets.

Second, we contribute to the literature on liquidity and market efficiency. Our work builds on many other liquidity studies. 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 impacts 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 greater liquidity for firms with greater transparency in their disclosures.

In other work directly related to sustainability issues, [Wang et al. \(2023\)](#) show that ESG performance is positively associated with firms' stock liquidity within China.⁴ [Krueger et al. \(forthcoming\)](#) provide correlational evidence showing a positive relation between ESG disclosure mandates and stock liquidity across countries, supporting a link between disclosure regulation and the quality of the information environment. Citing [Christensen, Hail and Leuz \(2021\)](#), [SEC \(2024\)](#) also 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 \(2021\)](#), however, point out 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 effect of CR disclosures on 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

⁴ [Chen et al. \(2023\)](#) and [He, Feng and Hao \(2023\)](#) present additional evidence from China supporting positive relationships between ESG performance/ratings and stock liquidity. [Roy, Rao and Zhu \(2022\)](#) demonstrate that Indian firms adhering to a mandated corporate social responsibility regulation experience significantly increased stock liquidity.

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, which they attribute to SRI’s ESG preferences and limited attention. We add to this literature by demonstrating a pathway from CR disclosures to ownership dispersion, and, in turn, to lower short-selling constraints and greater pricing efficiency. To our knowledge, we are the first to establish this pathway.

2 The Model

In this section, we present a simple model that serves as the basis for our empirical tests. The model examines the impact of disclosing information about a specific source of uncertainty, that we term climate risk, on ownership dispersion and market quality.

2.1 The economic setting

We use a setting with two dates, denoted as 0 and 1. Investors trade at Date 0, and consume at Date 1.

2.1.1 Assets

There is a risky stock. At Date 1, 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 . The second, c , represents the component of cash flows that is exposed to climate change (or simply, the CR cost). We assume that the mean cost is negative; and specifically, that $c \sim N(\bar{c}, v_c)$, with $\bar{c} > 0$. 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.

2.1.2 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_{m1} and seeks to maximize the expectation of a standard exponential utility function: $U(W_{m1}) = -\exp(-\gamma W_{m1})$, 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 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 has a belief that the CR cost c is drawn from a normal distribution with mean $c_m \equiv \bar{c} + \lambda_m/\eta$ and variance v_c , where $\lambda_m \sim N(0, v_\lambda)$. 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 2.1.3 below. 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. They can be viewed as large institutions trading on their own account or 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 $U(W_{n1}) = -\exp(-\gamma W_{n1})$, given final wealth W_{n1} .

Third, there is a group of *noise traders*, separated into noise buyers and noise sellers. At Date 0, 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 $\ell_H > 0$. 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.

2.1.3 Information and disclosure

At Date 0, a public signal is available about θ , $\phi = \theta + \zeta$, where $\zeta \sim N(0, v_\zeta)$. There is also a public disclosure of the firm's climate exposure via the variable η , which influences each active investor's subjective mean $\bar{c} + \lambda_m/\eta$. 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 $\eta \rightarrow \infty$, the CR disclosure moves active buyers' assessment of the mean of c more and 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 (Kim, Wang and Wu (2022)). Thus, η is an exogenous parameter in our setting, and represents the quality of the firm's CR disclosure.

2.2 The equilibrium

Before we proceed to the equilibrium, we describe some pre-ambls that allow the derivation of the equilibrium in analytic form. Denote $v_\phi = v_\theta + v_\zeta$, $\tau = v_\theta/v_\phi$, and $\Gamma = \gamma[v_\theta(1 - \tau) + v_c]/\sqrt{v_\lambda}$. We impose the following parameter restrictions:

$$\ell_H < Q - \max\left(\frac{M}{\Gamma\eta\sqrt{2\pi}}, \rho N\right) \text{ and } \rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma\eta}. \quad (1)$$

Assumption (1) implies that the demands from noise buyers (i.e., $\ell \in (0, \ell_H]$) and sellers (i.e., $s = -\rho MB$) are not too large. If these demands are mainly from retail investors, this assumption is consistent with the notion that retail investors' long or short holdings represent only a small fraction of the firm.

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. To describe the equilibrium price, 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:⁵

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 a function of ℓ , specified in Equation (2). Further, $dP(\phi, \ell)/d\eta < 0$.

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, $-(\kappa(\ell)/\eta)\sqrt{v_\lambda}$, captures the effect of CR disclosure (i.e., η) on the price.

We now discuss the result in Theorem 1 that $dP(\phi, \ell)/d\eta < 0$. We show in the proof of the theorem (see Equation (A.1)) 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 extent; this puts an upward pressure on the price. Since in equilibrium more optimistic

⁵All proofs appear in Appendix A.

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 decrease 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 downward price pressure.

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 the ownership breadth, given ℓ , as:

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

We obtain the following result:

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

As previously shown (see Theorem 1), as CR disclosure (η) increases, the price offers a 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.

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, $E[|s(\ell)|]$, is increasing in the level of CR disclosure (η).*

From Proposition 1, 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.

We next turn to illiquidity in this market. Note that the total noise demand is given by $z(\ell) \equiv \ell + s(\ell)$. It can be shown that $dP(\phi, \ell)/dz(\ell) > 0$. We measure expected illiquidity by $E[dP(\phi, \ell)/dz(\ell)]$, and obtain the following result:

Proposition 3 *The expected illiquidity measure, $E[dP(\phi, \ell)/dz(\ell)]$, 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 (i.e., a higher $E[|s(\ell)|]$; 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. We measure the informational efficiency of the stock price using the inverse of the variance ratio $\text{Var}[V - P(\phi, \ell)]/\text{Var}(V)$. This ratio serves as a proxy for the ratio of return variances over short and long horizons. We obtain the following result:

Proposition 4 *The variance ratio $\text{Var}[V - P(\phi, \ell)]/\text{Var}(V)$ decreases (prices become more efficient) when there is an increase in CR disclosure (i.e., a rise in η).*

The above proposition is a direct consequence of Proposition 3. Specifically, 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.

2.3 Testable 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) Enhanced CR disclosure increases ownership breadth.
2. (Proposition 2) Enhanced CR disclosure implies a greater supply of lendable shares.
3. (Proposition 3) Enhanced CR disclosure reduces the price impact of trades (increases stock market liquidity).
4. (Proposition 4) Enhanced CR disclosure increases price efficiency.

We test these implications on stock ownership and market quality in Section 4, after describing our data in Section 3.

3 Data and variable construction

3.1 Data sources

We select U.S. public firms in Compustat with fiscal years from 2005 to 2014. This timeframe aligns with the study by [Kim, Wang and Wu \(2022\)](#). We also explore an alternative, extended sample period in Section 4.5. 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.

3.2 Climate risk disclosure in 10-K statements

We follow [Kim, Wang and Wu \(2022\)](#) and extract CR keywords as specified in Table B1 in the Appendix B of the firms' 10-K reports. We consider the firm to have a CR disclosure

when at least one of the keywords in Table B1 is presented in the 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 4.5.⁶

In the main regression analysis, we control for the logarithm of the total number of words in the 10-K report. This quantity proxies for the readability of the report. We approximate the disclosure specificity using the number of unique words divided by the total number of words in the financial statement. We 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 net sentiment as the difference between the number of positive and negative words divided by the total number of words.

We map the CR disclosure data to firm fundamentals, including the firm's age and logarithm of the return-on-assets, and stock data, including the stock return, the logarithm of market capitalization, stock price, and stock volatility. The selection of the control variables follows Grullon, Kanatas and Weston (2004).

3.3 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

⁶ The measure, termed *Earnings call based CR disclosure*, is the variable defined as the frequency of the climate change related bigrams shown in the earnings call transcripts. The data are publicly available at: <https://osf.io/fd6jq/>.

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).

3.4 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 (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 the individual stock return on the current and lagged four weeks' market portfolio return ([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 are estimated at an annual level for each stock. We provide detailed definitions of the variables in Table 1.

3.5 Descriptive analysis

Table 2a summarizes the basic statistics for the breadth of ownership, lendable supply, stock liquidity, price efficiency, and control variables.⁷ The average firm has 51.7% of shares owned by institutions, 42 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 4.2 basis points. The average value of the Variance Ratio measure (i.e., 3.67) suggests that the market is not fully efficient, as the Variance Ratio is expected to be one under the efficient market hypothesis. 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 Table 2a. 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)) 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. Conse-

⁷ Variables 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. The statistics are presented for these annual versions.

quently, the institutional ownership sample split by category is smaller than the baseline sample. We present summary statistics by category in Table 2b. 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 Table 3a. In Table 3b, we replace the last nine rows (comprised of controls) of Table 3a 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 Empirical results on ownership

We employ a quasi-natural experiment to investigate the causal effect of CR disclosure. For our policy event, we use SEC (2010)'s CR-disclosure guidance (Kim, Wang and Wu (2022)). In particular, we perform a DiD analysis around the SEC guidance announcement.

4.1 Event year and treatment definition

In February 2010, the SEC published SEC (2010), reinforcing the standards for public companies' CR disclosures.⁸ This publication provided guidance for disclosure of key climate change matters, including regulatory, physical, and other related business risks.

⁸ The 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 SEC chair Gary Gensler makes references to the SEC (2010) guidance and mentions requirements on disclosing material climate risks that are related to scope 1 and 2 emissions. These rules will have much wider impact on firms that are not traditionally recognized as climate related, as all firms need energy to run and scope 2 emissions look at the energy sources for all firms.

Although the standards mainly apply to 10-K filings,⁹ the document also mentions their relevance and implications for voluntary disclosures (for example, earnings calls).¹⁰ Therefore, the guidance is an exogenous policy shock to both mandatory disclosures (such as 10-K reports) as well as voluntary ones (such as earnings call transcripts). As a result, the guidance provides a reliable way to investigate the effect of improved CR disclosures on financial markets.

There also 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".¹¹ The speech included pointers that the introduction of SEC (2010) was imminent.

To address the possible pre-announcement effect of the SEC guidance, we propose a rank-based, data-driven approach for the treatment group definition. In this definition, given an event year, to be classified in the treatment 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)¹² comparing the 10-K based CR disclosure measures in the year before the event year relative to those in the year after becomes 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 should be higher than that in the year before; and (3) the value of the firm's 10-K based CR disclosure

⁹ Kim, Wang and Wu (2022) find that the guidance significantly increased firms disclosing CR in 10-Ks. The percentage of CR-reporting firms increases by 8% in the first 10-K filing after the guidance was published.

¹⁰ The details can be found in Section B.3 on pages 8 to 9 of SEC (2010).

¹¹ The 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.'

¹² The 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.

in the year after the event year should be 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.

We apply the above definition to the period 2005-2012 and plot the percentage of identified firms over this period in Figure 1. We find that this percentage peaks in 2009 at 15% (nearly 9% more than that in 2005 and 5% more than that in 2012), 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 treatment group to be the firms meeting the three conditions in 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) & $\overline{\text{Condition (2)}}$ & $\overline{\text{Condition (3)}}$. 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 from our control group. All other non-treated 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. Therefore, they comprise our control group.¹³

4.2 Difference-in-differences analysis of the impacts of CR disclosures

We aim to establish causal evidence on the impacts of CR disclosure using a DiD analysis. We expect SEC (2010) to influence firms' climate risk disclosures but not to directly impact variables such as breadth of ownership, lendable equity, market liquidity, or price efficiency. Therefore, if we observe changes in treatment firms' financial market environment that

¹³ We follow Kim, Wang and Wu (2022) and also use firms that never disclose CR information as an alternative control group. In results not tabulated for brevity, we find that our conclusions remain broadly unchanged.

differ from those of control firms pre- versus post-SEC (2010), we can indeed attribute these changes to CR disclosures.

For control variables in our DiD we largely follow Grullon, Kanatas and Weston (2004) and Lang and Stice-Lawrence (2015). Specifically, we use firm age, past stock returns, ROA, market capitalization, nominal share price, return volatility, controls for general informativeness of financial disclosure (i.e., number of Words, count of unique words, and net sentiment).

4.2.1 DiD regressions and results

We specify our DiD regression as follows:

$$\begin{aligned} \text{Dependent}_{i,t} = & a_0 + a_1 \text{Treatment}_i \times \text{Post} + a_2 \text{Treatment}_i \\ & + \text{Controls}_{i,t} + \text{Industry and Year Fixed Effects} + \varepsilon_{i,t}, \end{aligned} \quad (6)$$

where $\text{Treatment}_i \times \text{Post}$ is our DiD term, Post is the time dummy variable which equals one for years after 2009 (including 2009) and zero otherwise, Controls are those described in Section 4.2, and the $\text{Industry Fixed Effects}$ are based on firms' 3-digit SIC codes. The DiD is estimated at the firm-year level, and results for breadth of ownership, lendable equity, liquidity, and price efficiency are shown in Table 4.¹⁴ Panel (a) of Table 4 shows the DiD results with the control variables, and Panel (b) of Table 4 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 DiD coefficients in the first three columns of Table 4a show that breadth of ownership significantly changes due to firms' policy on CR disclosure: both $\text{InstOwn}\%$ and InstOwn log\# increase while InstOwn HHI decreases. Specifically, the DiD coefficients of $\text{InstOwn}\%$ and InstOwn log\# are 0.03 (t -statistic = 3.25) and 0.17 (t -statistic = 3.03),

¹⁴The 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.

respectively, and are significant at the 1% level. The DiD coefficient of InstOwn HHI is -0.01 with t -statistic = -3.12 and significant at the 1% level. In economic terms, after 2009, the treatment 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 2a, than the control group's. For InstOwn HHI, the treatment group is, on average 0.01 lower than the control group, which is 8% of InstOwn HHI's sample standard deviation of 0.10 as in Table 2a. The positive DiD coefficients of InstOwn% and InstOwn log# accord with the notion that institutional investors prefer holding stocks of firms with more informative CR disclosure. This is what Ilhan et al. (2023) call the *selection effect*. The negative coefficient of InstOwn HHI is our novel result that enhanced CR disclosures increase ownership breadth.

Using lendable equity data, we next test the effect of CR disclosure on both the supply and demand sides of equity lending (our Implication 2). Given the positive impact of CR disclosure on ownership breadth, we expect that treated 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 DiD 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 treatment group's Lendable Supply (Borrow Cost Score) is, on average, 0.01 higher (0.08 lower) than the control group's. These magnitudes are respectively 8% and 21% of the standard deviations for the two variables (Table 2a).

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 DiD coefficient for Lendable Demand is insignificant, indicating that investors generally do not consider CR disclosure as an adverse signal. As Lendable Demand does not exhibit significance in the DiD, we do not

consider it further.

Using data on the bid-ask spread, we examine the effect of CR disclosure on stock liquidity (our Implication 3). Specifically, we propose that CR disclosure can improve liquidity due to increased ownership breadth (Dixon, Fox and Kelley (2021), Dixon (2021)). The negative DiD coefficients for BA Spread in Table 4a confirm the effect of CR disclosure on liquidity. Specifically, the DiD coefficient of the BA Spread is -0.01 (t -statistic = -4.28) and significant at the 1% level. In economic terms, after 2009, the treatment group's BA Spread is, on average, 0.01 lower than the control group's, which is 14% of the spread's 0.06 standard deviation as in Table 2a.

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), Dixon (2021)). It is therefore natural to expect that CR disclosure to also have a positive effect on price efficiency (our last theoretical implication). Using the variance ratio and delay data, we next test this notion. We find significantly negative DiD coefficients for Variance Ratio and Delay in the last two columns in Table 4a. More concretely, the DiD 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 2a, and suggest that market efficiency increases in the treatment group post-2009 relative to the control group. The results offer causal evidence that firms with better quality CR disclosures tend to have better stock price efficiency (inversely) measured by Variance Ratio and Delay.

In Table 4b, we conduct the DiD regressions without the control variables. Not surprisingly, we find greater significance. For instance, the t -statistic of the DiD coefficient for InstOwn HHI is -4.31, which is 1.4 times larger in magnitude compared to that in Table 4a. Similarly, Lendable Supply's DiD coefficient exhibits a significant increase in t -statistic from 3.13 in Table 4a to 4.66 in Table 4b. The magnitude of its estimate also increases from

0.01 to 0.017. This implies that, in comparison to the control group, the treatment group's Lendable Supply is, on average, 14% Lendable Supply's sample standard deviation higher in Table 4b as opposed to 8% in Table 4a. Overall, the consistency between Table 4a and Table 4b underscores the robustness of our DiD regression findings.¹⁵

4.2.2 Parallel trends assumption

We next check the robustness of our DiD coefficients to the parallel trends assumption. 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 treated and control groups 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 dummy variables and run the following panel regression:

$$\begin{aligned} \text{Dependent}_{i,t} = & b_0 + b_1 \text{Treatment}_i + \delta_{-3} \text{TY-3}_i + \delta_{-2} \text{TY-2}_i + \delta_{+1} \text{TYpost}_i \\ & + \text{Industry and Year Fixed Effects} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where Treatment_i is the treatment dummy variable for the DiD regression, $\text{TY-3}_i = \text{Treatment}_i \times Y_{-3}$ and Y_{-3} is one for 2006 (= 2009 - 3) and zero otherwise, $\text{TY-2}_i = \text{Treatment}_i \times Y_{-2}$ and Y_{-2} is one for 2007 (= 2009-2) and zero otherwise, $\text{TYpost}_i = \text{Treatment}_i \times \text{Post}$, and Industry and Year Fixed Effects are the same as those in eq. (6). Since the regression includes a constant term, the year dummy 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 2.

¹⁵ All DiD results are also robust to replacing the year-fixed effect with the Post dummy. The results without a year-fixed effect are available upon request.

The results in Figure 2 are encouraging. The significance of all DiD 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 DiD coefficients (InstOwn%, InstOwn log#, Lendable Supply, Borrow Cost Score, Variance Ratio, and Delay) remain significant even when the post-treatment 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-treatment trend in the bid/ask spread is significant for sufficiently large values of M . Put together, our overall DiD 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 3. We do this exercise separately for the treatment and control samples. The trend time series includes four years before and five years after 2009. We present the two trends in the left panel, Figure 3a. Take Lendable Supply as an example. While we see that the treatment group and the control group start at the same level, the treatment group's Lendable Supply diverges from the control 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, Figure 3b. Notably, the divergence becomes evident after 2009, as highlighted in Figure 3b.

4.3 Breadth of ownership mediating the effect of CR disclosures

The evidence thus far implies that CR disclosures have an impact along multiple dimensions, namely, breadth of ownership, supply of lendable equity, stock liquidity, and price efficiency. 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

address the extent to which the evidence supports the above pathway.

Specifically, we check the correlations between InstOwn HHI and the other outcome variables of the treated firms. We compute the difference between the average value before and after 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 InstOwn HHI reduction and the other variables' reduction/increase. We find that among the treated firms the InstOwn HHI reduction is significantly and positively correlated with the increase in Lendable Supply (0.17***) and the reductions in Borrow Cost Score (0.20***), BA Spreads (0.18***), and Delay (0.23***). The only insignificant correlation is for the Variance Ratio reduction (-0.02).

The preceding correlations appear to be consistent with the main thrust of our argument. Firms which 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. [Krueger, Sautner and Starks \(2020\)](#) also find 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 is consistent with earlier evidence that socially

conscious institutional investors tend to engage more with their investee firms over ESG concerns (Dimson, Karakaş 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 that we observe for treated firms. Indeed, SRI assets have grown to \$17 trillion at the end of 2020, representing one-in-three dollars of the \$51 trillion US 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.

First, we distinguish between SRI and Non-SRI InstOwn% and SRI and Non-SRI InstOwn log#. Specifically, we rerun the DiD regression of eq. (6) with the dependent variables SRI and Non-SRI InstOwn% or SRI and Non-SRI InstOwn log#. The results are presented in Table 5a. 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 Table 5a. The DiD 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 2b), while the coefficient of Non-SRI InstOwn% is -0.004 and insignificant. Although the DiD 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# we observe in Table 4.

Table 5a establishes an SRI channel via which the quality of CR disclosure impacts 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 DiD regression of eq. (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 Table 5b. We find that SRI can explain the negative effect of CR disclosure on

InstOwn HHI. Specifically, the coefficient of DiD in the Nonzero SRI subsample is -0.011 and significant at the 1% level (t -statistic = -5.49). In contrast, the coefficient of DiD in the Zero SRI subsample is 0.01 and insignificant. Importantly, the coefficient of DiD 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.

To further investigate how the institutional SRI influences the other financial market measures, we augment the DiD estimation in eq. (6) with two cross-terms. These are $\text{DiD} \times \text{High SRI}$ and $\text{DiD} \times \text{Low SRI}$, where High SRI (Low SRI) is a dummy variable that is one for firms with institutional SRI higher (lower) than the industry median of the year, and zero otherwise. The results of this exercise are presented in Table 6. For InstOwn%, InstOwn log#, and Lendable Supply, the coefficients of $\text{DiD} \times \text{High SRI}$ and $\text{DiD} \times \text{Low SRI}$ are significant and of opposite signs. Only the signs of the coefficients for $\text{DiD} \times \text{High SRI}$ align consistently with those observed in Table 4. Further, the responses from High SRI firms tend to dominate overall, as evidenced by the findings in Table 4. In the case of InstOwn HHI, Borrow Cost Score, BA Spread, and Delay, only the coefficients of $\text{DiD} \times \text{High SRI}$ exhibit significance, and their signs consistently align with the observations in Table 4. For Variance Ratio, the coefficients of both $\text{DiD} \times \text{High SRI}$ and $\text{DiD} \times \text{Low SRI}$ are significant and consistent with those observed in Table 4. In most cases (except InstOwn% and Lendable Supply), the coefficients of $\text{DiD} \times \text{High SRI}$ are of higher magnitude and more significant than those of $\text{DiD} \times \text{Low SRI}$. All in all, the results in Tables 5 and 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 largest institutional investor type in terms of ownership stakes in US public firms in our data. Indeed, average mutual fund ownership stands at 46.3%, which is the highest among all institutional ownership types by a large margin (see Table 2b).

One would expect mutual funds to play a large role in driving the findings reported in this paper so far. 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. \(2020\)](#) examine investor ideology estimated through proxy voting records. They find that the largest mutual funds are "money-conscious," that is, they tend oppose social- and environment-friendly proposals that could financially cost shareholders. At the same time, though, [Nofsinger and Varma \(2014\)](#) report that total net assets in US domestic SRI equity mutual funds grew 5 times as much as assets in non-SRI equity mutual funds in recent years.

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 DiD regression of eq. (6) with the dependent variable, in turn, being Banks, Mutual, Pension, and Other InstOwn% or the respective InstOwn log#. We present the results in Table 7a. If mutual fund ownership drives the results of InstOwn# and InstOwn log# in Table 4, we expect the most significant results for Mutual compared to other categories from the same DiD regression. This expectation is indeed confirmed in Table 7a. The DiD 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 2b). In contrast, the DiD coefficients of the other three categories (Banks, Pension, and Other) are insignificant. Only the DiD 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 Table 7a confirms mutual funds' ownership as the primary force driving the results of InstOwn# and InstOwn log# we observe in Table 4.

To further explore whether Mutual InstOwn% mediates CR disclosure's effect on the overall InstOwn HHI, we rerun the DiD regression of eq. (6) with InstOwn HHI as the dependent variable on two subsamples, High and Low, for each type of institutional

ownership. The High (Low) subsample includes firms with InstOwn% in each type of institutional ownership higher (lower) than its median InstOwn% in each year. If a type of institutional ownership influences CR disclosure's effect on the overall InstOwn HHI, we should expect to find a significant DiD coefficient in the High InstOwn% subsample for that type. We should observe the opposite in the two subsamples if a type of institutional ownership does not mediate CR disclosure's effect on the overall InstOwn HHI as institutional ownership tends to be less concentrated (i.e., smaller InstOwn HHI) in the Low subsample.¹⁶ The results are presented in Table 7b. We find that mutual fund ownership does influence the negative effect of CR disclosure on InstOwn HHI observed in Table 4. Specifically, the coefficient of DiD in the High Mutual subsample is -0.01 and significant at the 1% level (t -statistic = -3.65) while the coefficient of DiD in the Low Mutual subsample is -0.007 and insignificant. The coefficient of DiD 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 DiD 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.

4.5 Robustness checks

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 treatment group to include firms that substantially changed their earnings-call-based CR disclosure behavior in 2009. Thus, in addition to the three 10-K based conditions applied to treated firms (Section 4.1), our revised treatment group also includes firms meeting the

¹⁶ This pattern can be verified by the negative correlations between different types of InstOwn% and the overall InstOwn HHI and the positive correlations among different types of InstOwn% in Table 3b.

same three conditions for earnings-call-based CR disclosure measures in the treatment year. Further, our revised control group excludes firms that change CR disclosure behavior, measured by earnings-call-based CR disclosure, significantly and negatively (around 2.6% of the sample).

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

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 of the DiD regression of eq. (6) based on 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 Conclusions

Recent years have witnessed heightened media coverage and growing awareness of climate-related issues. 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 simple model to show that improved climate disclosures allow investors to assess better

the resilience of a business to climate change (Edmans (2023)), and thus increase breadth of ownership. Our theoretical analysis further shows that this decreased concentration of ownership leads to enhanced market liquidity and efficiency.

To empirically examine our theoretical arguments, we use a DiD analysis around the issuance of the SEC (2010) guiding document on CR disclosures. We find that firms whose disclosures align with the guidance experience an increase in breadth of ownership and lendable equity supply. These firms also exhibit enhanced market liquidity and price efficiency. We thus identify increased CR disclosure as a novel source of enhanced financial market quality. Our work complements the finding of Ilhan et al. (2023) that enhanced CR disclosure increases institutional ownership. We also underscore the crucial role played by SRI mutual funds in the positive effects of CR disclosures on financial market quality.

Integration of climate risk awareness and financial markets research remains an important issue, and ours is but one contribution. There is room for more research on the connections between media-driven public awareness, institutional investor influence, and proactive corporate climate risk disclosures. For example, CR disclosures could feed back to real investment via their impact on market price efficiency. They could also affect risk perceptions and have a direct impact on the costs of capital. Analysis of such issues is left for the future.

References

- Albuquerque, Rui (2012) “Skewness in stock returns: Reconciling the evidence on firm versus aggregate returns,” *Review of Financial Studies*, 25 (5), 1630–1673.
- Amihud, Yakov (2002) “Illiquidity and stock returns: Cross-section and time-series effects,” *Journal of Financial Markets*, 5 (1), 31–56.
- Asquith, Paul, Parag Pathak, and Jay Ritter (2005) “Short interest, institutional ownership, and stock returns,” *Journal of Financial Economics*, 78 (2), 243–276.
- Avramov, Doron, Si Cheng, Abraham Lioui, and Andrea Tarelli (2022) “Sustainable investing with ESG rating uncertainty,” *Journal of Financial Economics*, 145 (2), 642–664.
- Barth, Mary, Steven F Cahan, Li Chen, and Elmar Venter (2017) “The economic consequences associated with integrated report quality: Capital market and real effects,” *Accounting, Organizations and Society*, 62, 43–64.
- Berk, Jonathan and Jules van Binsbergen (forthcoming) “The impact of impact investing,” *Journal of Financial Economics*.
- Biasi, Barbara and Heather Sarsons (2022) “Flexible wages, bargaining, and the gender gap,” *Quarterly Journal of Economics*, 137 (1), 215–266.
- Bodnaruk, Andriy, Tim Loughran, and Bill McDonald (2015) “Using 10-K text to gauge financial constraints,” *Journal of Financial and Quantitative Analysis*, 50 (4), 623–646.
- Boehmer, Ekkehart and Juan Wu (2013) “Short selling and the price discovery process,” *Review of Financial Studies*, 26 (2), 287–322.
- Bolton, Patrick, Tao Li, Enrichetta Ravina, and Howard Rosenthal (2020) “Investor ideology,” *Journal of Financial Economics*, 137 (2), 320–352.
- Brockman, Paul, Dennis Chung, and Xuemin Sterling Yan (2009) “Block ownership, trading activity, and market liquidity,” *Journal of Financial and Quantitative Analysis*, 44 (6), 1403–1426.
- Cao, Jie, Sheridan Titman, Xintong Zhan, and Weiming Zhang (2023) “ESG preference,

- institutional trading, and stock return patterns," *Journal of Financial and Quantitative Analysis*, 58 (5), 1843–1877.
- Chen, Joseph, Harrison Hong, and Jeremy Stein (2002) "Breadth of ownership and stock returns," *Journal of Financial Economics*, 66 (2-3), 171–205.
- Chen, Meng-Tao, Da-Peng Yang, Wei-Qi Zhang, and Qi-Jun Wang (2023) "How does ESG disclosure improve stock liquidity for enterprises—Empirical evidence from China," *Environmental Impact Assessment Review*, 98:106926.
- Chen, Yong, Zhi Da, and Dayong Huang (2022) "Short selling efficiency," *Journal of Financial Economics*, 145 (2), 387–408.
- Cho, Seong, Cheol Lee, and Ray Pfeiffer Jr (2013) "Corporate social responsibility performance and information asymmetry," *Journal of Accounting and Public Policy*, 32 (1), 71–83.
- Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam (2008) "Liquidity and market efficiency," *Journal of Financial Economics*, 87 (2), 249–268.
- Christensen, Dane, George Serafeim, and Anywhere Sikochi (2022) "Why is corporate virtue in the eye of the beholder? The case of ESG ratings," *Accounting Review*, 97 (1), 147–175.
- Christensen, Hans, Luzi Hail, and Christian Leuz (2021) "Mandatory CSR and sustainability reporting: Economic analysis and literature review," *Review of Accounting Studies*, 26 (3), 1176–1248.
- D'Avolio, Gene (2002) "The market for borrowing stock," *Journal of Financial Economics*, 66 (2-3), 271–306.
- Diamond, Douglas and Robert Verrecchia (1987) "Constraints on short-selling and asset price adjustment to private information," *Journal of Financial Economics*, 18 (2), 277–311.
- Dimson, Elroy, Oğuzhan Karakaş, and Xi Li (2015) "Active ownership," *Review of Financial Studies*, 28 (12), 3225–3268.
- Dixon, Peter (2021) "Why do short selling bans increase adverse selection and decrease

- price efficiency?" *Review of Asset Pricing Studies*, 11 (1), 122–168.
- Dixon, Peter, Corbin Fox, and Eric Kelley (2021) "To own or not to own: Stock loans around dividend payments," *Journal of Financial Economics*, 140 (2), 539–559.
- Edmans, Alex (2023) "The end of ESG," *Financial Management*, 52 (1), 3–17.
- Efron, Bradley (1982) *The Jackknife, the Bootstrap and Other Resampling Plans*: Society for Industrial and Applied Mathematics.
- Flammer, Caroline, Michael Toffel, and Kala Viswanathan (2021) "Shareholder activism and firms' voluntary disclosure of climate change risks," *Strategic Management Journal*, 42 (10), 1850–1879.
- Gibson Brandon, Rajna, Simon Glossner, Philipp Krueger, Pedro Matos, and Tom Steffen (2022) "Do responsible investors invest responsibly?" *Review of Finance*, 26 (6), 1389–1432.
- Glosten, Lawrence (1989) "Insider trading, liquidity, and the role of the monopolist specialist," *Journal of Business*, 211–235.
- Goyal, Amit, Avandhar Subrahmanyam, and Bhaskaran Swaminathan (2023) "Illiquidity and the cost of equity capital: Evidence from actual estimates of capital cost for US data," *Review of Financial Economics*, 41 (4), 364–391.
- Grewal, Jody, Clarissa Hauptmann, and George Serafeim (2021) "Material sustainability information and stock price informativeness," *Journal of Business Ethics*, 171 (3), 513–544.
- Griffin, John, Patrick Kelly, and Federico Nardari (2010) "Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets," *Review of Financial Studies*, 23 (8), 3225–3277.
- Grullon, Gustavo, George Kanatas, and James Weston (2004) "Advertising, breadth of ownership, and liquidity," *Review of Financial Studies*, 17 (2), 439–461.
- Hair, Joseph, William Black, Barry Babin, and Rolph Anderson (2009) *Multivariate data analysis*: Prentice Hall.
- Harris, Theodore (1960) "A lower bound for the critical probability in a certain percolation process," in *Mathematical Proceedings of the Cambridge Philosophical Society*, 56, 13–20,

Cambridge University Press.

- He, Feng, Yaqian Feng, and Jing Hao (2023) "Corporate ESG rating and stock market liquidity: Evidence from China," *Economic Modelling*, 129:106511.
- Hou, Kewei and Tobias Moskowitz (2005) "Market frictions, price delay, and the cross-section of expected returns," *Review of Financial Studies*, 18 (3), 981–1020.
- Huang, Jing-Zhi, Nan Qin, and Ying Wang (forthcoming) "Breadth of ownership and the cross-section of corporate bond returns," *Management Science*.
- Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura Starks (2023) "Climate risk disclosure and institutional investors," *Review of Financial Studies*, 36 (7), 2617–2650.
- Karolyi, Andrew, Kuan-Hui Lee, and Mathijs Van Dijk (2012) "Understanding commonality in liquidity around the world," *Journal of Financial Economics*, 105 (1), 82–112.
- Kim, Jeong-Bon, Bing Li, and Zhenbin Liu (2019) "Information-processing costs and breadth of ownership," *Contemporary Accounting Research*, 36 (4), 2408–2436.
- Kim, Jeong-Bon, Chong Wang, and Feng Wu (2022) "The real effects of risk disclosures: Evidence from climate change reporting in 10-Ks," *Review of Accounting Studies*, 1–48.
- Krueger, Philipp, Zacharias Sautner, and Laura Starks (2020) "The importance of climate risks for institutional investors," *Review of Financial Studies*, 33 (3), 1067–1111.
- Krueger, Philipp, Zacharias Sautner, Dragon Yongjun Tang, and Rui Zhong (forthcoming) "The effects of mandatory ESG disclosure around the world," *Journal of Accounting Research*.
- Lang, Mark, Karl Lins, and Mark Maffett (2012) "Transparency, liquidity, and valuation: International evidence on when transparency matters most," *Journal of Accounting Research*, 50 (3), 729–774.
- Lang, Mark and Lorien Stice-Lawrence (2015) "Textual analysis and international financial reporting: Large sample evidence," *Journal of Accounting and Economics*, 60 (2-3), 110–135.
- Loughran, Tim and Bill McDonald (2011) "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *Journal of Finance*, 66 (1), 35–65.

Mann, Henry and Donald Whitney (1947) "On a test of whether one of two random variables is stochastically larger than the other," *Annals of Mathematical Statistics*, 50–60.

Mech, Timothy (1993) "Portfolio return autocorrelation," *Journal of Financial Economics*, 34 (3), 307–344.

Ng, Lilian, Fei Wu, Jing Yu, and Bohui Zhang (2016) "Foreign investor heterogeneity and stock liquidity around the world," *Review of Finance*, 20 (5), 1867–1910.

Nofsinger, John and Abhishek Varma (2014) "Socially responsible funds and market crises," *Journal of Banking and Finance*, 48, 180–193.

Ortega-Egea, José Manuel, Nieves García-de Frutos, and Raquel Antolín-López (2014) "Why do some people do "more" to mitigate climate change than others? Exploring heterogeneity in psycho-social associations," *PLoS One*, 9 (9), e106645.

Pástor, L'uboš, Robert Stambaugh, and Lucian Taylor (2022) "Dissecting green returns," *Journal of Financial Economics*, 146 (2), 403–424.

Porras Prado, Melissa, Pedro Saffi, and Jason Sturgess (2016) "Ownership structure, limits to arbitrage, and stock returns: Evidence from equity lending markets," *Review of Financial Studies*, 29 (12), 3211–3244.

Ramadorai, Tarun and Federica Zeni (forthcoming) "Climate regulation and emissions abatement: Theory and evidence from firms' disclosures," *Management Science*.

Rambachan, Ashesh and Jonathan Roth (2023) "A more credible approach to parallel trends," *Review of Economic Studies*, 90 (5), 2555–2591.

Roy, Partha, Sandeep Rao, and Min Zhu (2022) "Mandatory CSR expenditure and stock market liquidity," *Journal of Corporate Finance*, 72:102158.

Saffi, Pedro and Kari Sigurdsson (2011) "Price efficiency and short selling," *Review of Financial Studies*, 24 (3), 821–852.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang (2023) "Firm-level climate change exposure," *Journal of Finance*, 78 (3), 1449–1498.

Schwartzkopff, Frances (2024) "BlackRock's ESG fund business is soaring despite attacks

by the GOP,” <https://www.bloomberg.com/news/articles/2024-02-13/blackrock-is-global-leader-in-esg-thanks-to-passive-funds>, *Bloomberg L.P.*

SEC (2010) “Commission guidance regarding disclosure related to climate change,” *Securities and Exchange Commission*, Release Nos. 33-9106; 34-61469.

——— (2024) “The enhancement and standardization of climate-related disclosures for investors,” *Securities and Exchange Commission*, Release Nos. 33-112755; 34-99678.

Lopez-de Silanes, Florencio, Joseph McCahery, and Paul Pudschedl (2020) “ESG performance and disclosure: A cross-country analysis,” *Singapore Journal of Legal Studies* (Mar 2020), 217–241.

Tett, Gillian (2024) “Green audits are coming for a company near you,” <https://www.ft.com/content/1686c16e-78a2-46fa-875d-de6543a7665e>, *FT.com*.

US-SIF (2020) “Report on US sustainable and impact investing trends,” *US SIF and US SIF Foundation*.

Wang, Kai, Tingting Li, Ziyao San, and Hao Gao (2023) “How does corporate ESG performance affect stock liquidity? Evidence from China,” *Pacific-Basin Finance Journal*, 80:102087.

Figure 1. Percentage of Firms with Significant Improvement in CR Disclosure Over 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.

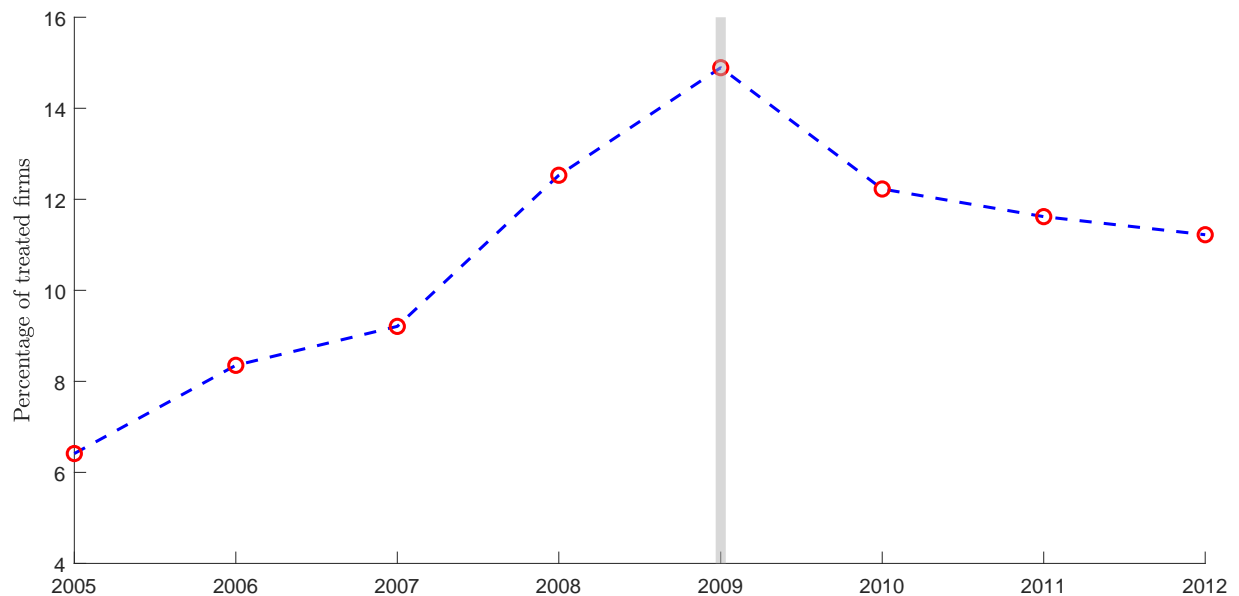


Figure 2. Robust Confidence Intervals Analysis of DiD Coefficients

The panels in this figure show robust 90% confidence intervals for the DiD coefficients on InstOwn%, InstOwn log#, InstOwn HHI, Lendable Supply, Borrow Cost Score, BA Spread, Variance Ratio, and Delay. 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.

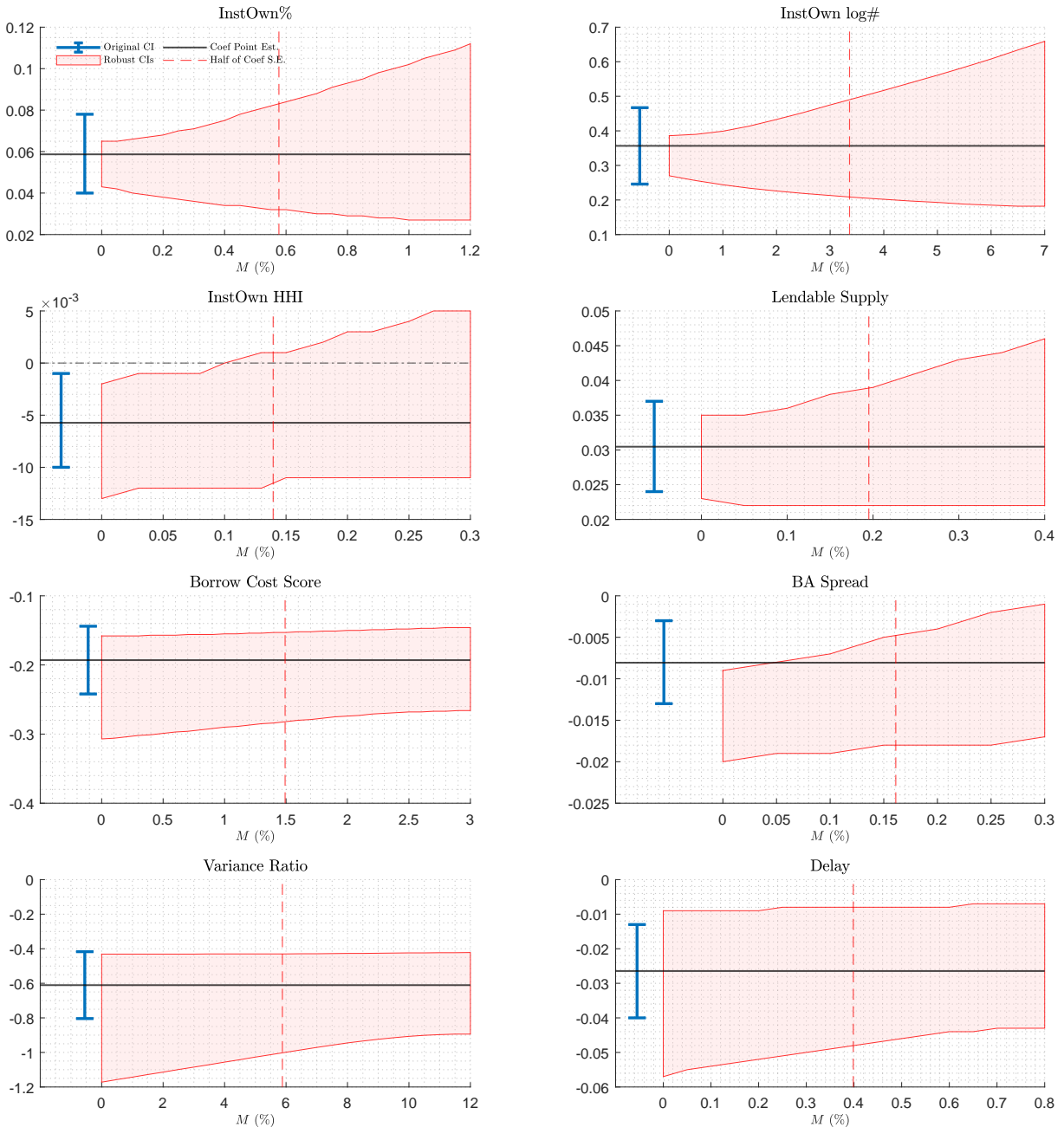


Figure 3. Treatment Group vs Control Group Average Trends Comparison

Panel (a) in this figure contains time series plots of the average values of the treatment group's eight dependent variables in the four categories (solid blue line) versus that of the control group (dashed red line). Panel (b) contains time series plots of the difference between the dependent variables of the treatment group and the control group (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 from 2005 to 2014.

(a) Trends

(b) Difference in Trends

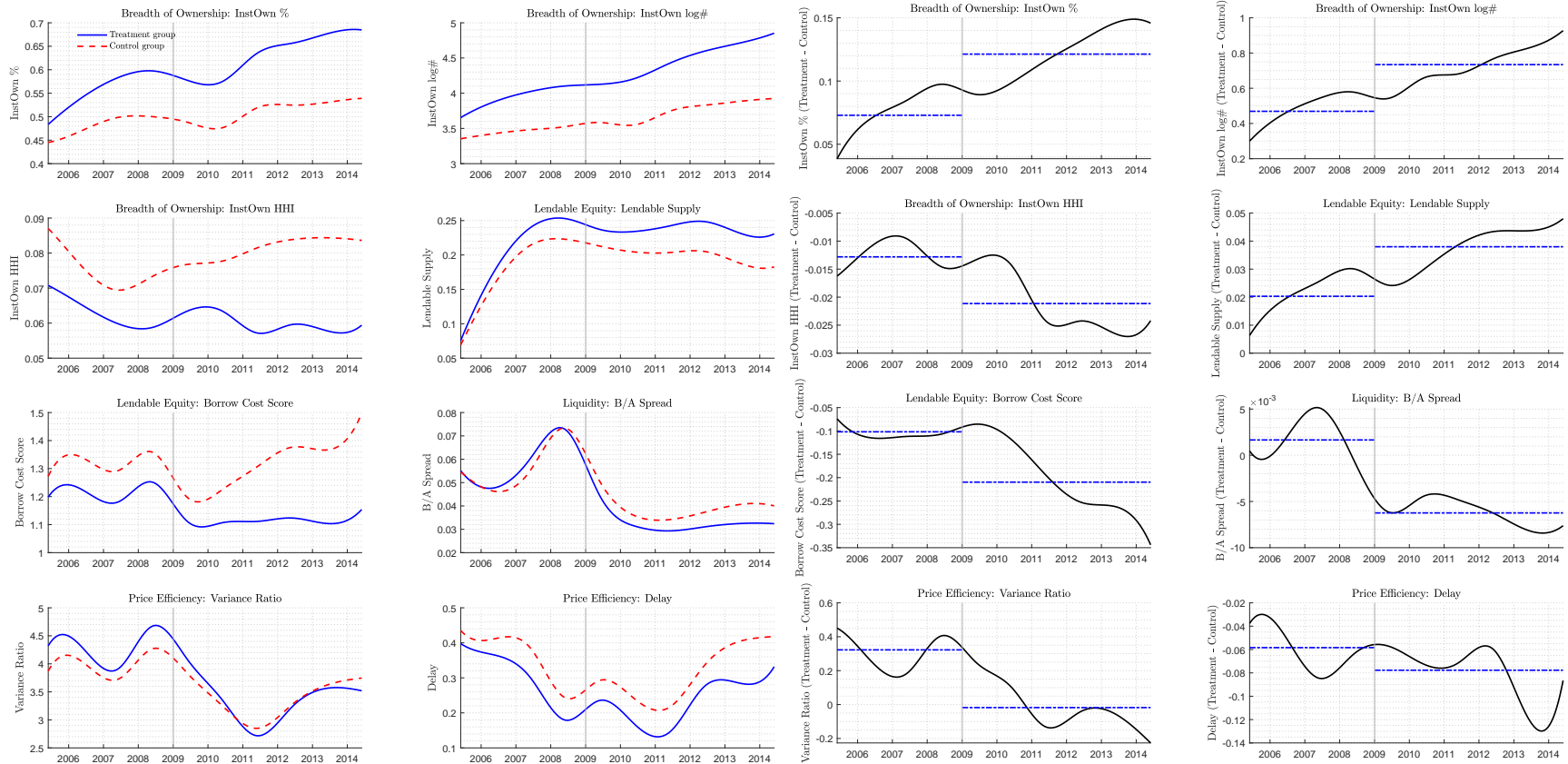


Table 1. Variable Definitions

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, Glossner, Krueger, Matos and Steffen \(2022\)](#). Quarterly values of all ownership variables are aggregated up to an annual basis.

(a) Main Dependent and Independent Variables

Variable	Definition
InstOwn%	The fraction of the common shares owned by the institutional investors.
InstOwn log#	Logarithm of the number of institutional investors owning the common shares of the underlying firm plus one.
InstOwn HHI	The Herfindahl-Hirschman Index of the institutional ownership.
Lendable Supply	The average value of relative stock inventory available to lend ('LendableValue' in the Markit data scaled by market capitalization) over the year.
Lendable Demand	The average value of the relative 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 on an annual basis.
BA Spread	Difference between the bid and ask quotes of the stock scaled by their midpoint, in percentage. This daily measure is aggregated on 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 $r_{i,t} = a_i + b_1 r_{m,t} + \sum_{n=1}^4 \delta_n^{-n} r_{m,t-n} + \varepsilon_{i,t}$, 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 $1 - R^2_{\delta_n^{-n}=0, \forall n \in [1,4]} / R^2$, where $R^2_{\delta_n^{-n}=0, \forall n \in [1,4]}$ 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 the climate change related bigrams in the firm's transcripts of earnings calls.
10-K based CR disclosure	The frequency of the climate change risk bigrams scaled by the total number of words in the 10-K reports.
Average CR disclosure	The average frequency of the climate change risk bigrams over the total number of words in the transcripts of earnings calls and 10-K reports.
Stock Return	The individual stock 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 market capitalization over the year.
1/(Share Price)	The reciprocal of the average 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 net number of positive and negative sentiment words over the total number of words in the Form 10-K report.

Table 1. Variable Definitions (contd.)**(b) Categorical Institutional Ownership Variables**

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

Table 2. Summary Statistics

Panel (a) presents the summary statistics on 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.

(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
Earning calls 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.)**(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 Table 3b, we replace the last nine rows (comprised of controls) of Table 3a 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.

(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) Earning calls 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.)

(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) Earning calls 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 DiD Results

This table presents the primary results for the effect of CR disclosure on dependent variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency. The dependent 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 independent variable is the DiD term defined as $Treatment_i \times Post$. The sample is from 2005 to 2014. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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.

(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
DiD	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)
Treatment	-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. R2	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

(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
DiD	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)
Treatment	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. R2	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. Socially Responsible Investor DiD Results

This table presents the effect of CR disclosure on the Breadth of Ownership for SRI and Non-SRI separately. The dependent variables in Panel (a) are InstOwn % and InstOwn log#, calculated for SRI and Non-SRI. The dependent variable in Panel (b) is InstOwn HHI, and the regressions are conducted on two subsamples: Nonzero SRI and Zero SRI, where the former are the firms with nonzero SRI InstOwn% and the latter are those with zero SRI InstOwn% in each year. The SRI group is defined as the ownership by the United Nations Principle of Responsible Investment signatories. The key independent variable is the DiD term defined as $Treatment_i \times Post$. 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. The sample is from 2005 to 2014. Regression coefficients are followed by robust *t*-statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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.

(a) InstOwn% and InstOwn log#

	SRI IO		Non-SRI IO	
	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#
DiD	0.020*** (6.52)	0.092*** (6.00)	-0.004 (-0.62)	0.060** (3.23)
Treatment	-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. R2	0.70	0.87	0.42	0.78
Controls	Yes	Yes	Yes	Yes

(b) InstOwn HHI

	Nonzero SRI	Zero SRI
	InstOwn HHI	InstOwn HHI
DiD	-0.011*** (-5.49)	0.010 (0.17)
Treatment	0.002 (0.59)	0.010 (1.33)
Obs.	20,235	2,532
Adj. R2	0.33	0.53
Controls	Yes	Yes

Table 6. Socially Responsible Investor Channel Results

This table presents the effect of CR disclosure on dependent variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, conditioned on the SRI ownership. The dependent 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. The key independent variable is the DiD term multiplied by the high or low SRI ownership dummy. The high (low) SRI group is defined as the firms with SRI ownership higher (lower) than the industry median for the year. The SRI group is defined as the ownership by the United Nations Principle of Responsible Investment signatories. The sample is from 2005 to 2014. Regression coefficients are followed by robust *t*-statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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
DiD * High SRI	0.062*** (6.68)	0.071*** (3.66)	-0.017*** (-5.01)	0.037*** (10.19)	-0.083*** (-3.18)	-0.017*** (-6.04)	-0.267*** (-2.90)	-0.028*** (-3.61)
DiD * Low SRI	-0.070*** (-5.02)	-0.059*** (-2.63)	-0.000 (-0.04)	-0.037*** (-6.23)	-0.072 (-1.58)	0.001 (0.34)	-0.225** (-1.99)	-0.006 (-0.60)
Treatment	-0.001 (-0.09)	0.009 (0.51)	0.002 (0.52)	0.001 (0.19)	-0.008 (-0.31)	0.008** (2.34)	0.220** (2.27)	0.006 (0.80)
Obs.	22,807	22,807	22,807	22,578	22,594	22,807	21,797	22,807
Adj. R2	0.42	0.86	0.34	0.46	0.18	0.26	0.13	0.33
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Institutional Ownership Types Results

This table presents the effect of CR disclosure on the Breadth of Ownership for banks, mutual funds, pension funds, and other types, separately. The dependent variables in Panel (a) are InstOwn % and InstOwn log#, calculated separately by type of institutional ownership. The dependent variable in Panel (b) is InstOwn HHI, and the regressions are conducted on two subsamples: High and Low, for each type of institutional ownership. The High (Low) subsample includes firms with InstOwn % in each type of institutional ownership higher (lower) than its median InstOwn % in each year. The key independent variable is the DiD term defined as $Treatment_i \times Post$. 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. The sample is from 2005 to 2014. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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.

(a) InstOwn% and InstOwn log#

	Banks		Mutual		Pension		Others	
	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#	InstOwn%	InstOwn log#
DiD	-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)
Treatment	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. R2	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

(b) InstOwn HHI

	Banks		Mutual		Pension		Others	
	High	Low	High	Low	High	Low	High	Low
DiD	-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)
Treatment	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. R2	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 DiD Results: 10-K and Earnings Call Treatment Group

This table presents results for the effect of CR disclosure on dependent variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, based on the treatment group defined using both 10-K and earnings call CR disclosure measures. The dependent 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 independent variable is the DiD term defined as $Treatment_i \times Post$. The sample is from 2005 to 2014. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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.

(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
DiD	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)
Treatment	-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. R2	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

(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
DiD	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)
Treatment	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. R2	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 DiD Results: Extended Data Timeframe

This table presents results for the effect of CR disclosure on dependent variables in four categories: Breadth of Ownership, Lendable Equity, Liquidity, and Price Efficiency, based on an alternative, extended timeframe from 2003 to 2016. The dependent 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 independent variable is the DiD term defined as $Treatment_i \times Post$. Regression coefficients are followed by robust t -statistics (in parentheses) based on standard errors clustered by the 3-digit SIC code. *, **, and *** indicate the 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.

(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
DiD	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)
Treatment	-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. R2	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

(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
DiD	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)
Treatment	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. R2	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

Appendix A: Proofs

Proof of Theorem 1: (a) Denote $\tau = v_\theta/v_\phi$ 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 $c \sim N(\bar{c} + \lambda_m/\eta, v_c)$. Denote the stock price as P , and write the active buyer's wealth at Date 1 as $W_{m1} = W_{m0} + x_m(V - P) = W_{m0} + x_m(\theta - c - P)$. The buyer chooses the demand x_m to maximize

$$\begin{aligned} & \hat{E}_m [U(W_{m1})|\phi] \\ &= \hat{E}_m [-\exp[-\gamma W_{m0} - \gamma x_m(\theta - c - P)]|\phi] \\ &= -\exp \left[-\gamma W_{m0} - \gamma x_m \left[\bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \frac{\lambda_m}{\eta} - P \right] + 0.5\gamma^2 x_m^2 [v_\theta(1 - \tau) + v_c] \right], \end{aligned}$$

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.¹⁷ 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 $\kappa = -\eta p/\sqrt{v_\lambda}$ and $\Gamma = \gamma[v_\theta(1-\tau) + v_c]/\sqrt{v_\lambda}$. 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 $\kappa = -\eta p/\sqrt{v_\lambda}$. 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 still need to show that given ℓ , Equation (A.5) specifies a unique $\kappa > 0$. Define a function of κ :

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

¹⁷In 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

$$\frac{dH(\kappa)}{d\kappa} = MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > N - \Gamma\eta\rho Mf(0) \propto \frac{N}{M} - \frac{\Gamma\eta}{\sqrt{2\pi}}\rho > 0 \quad (\text{A.6})$$

where the last inequality obtains because $\rho < \frac{N}{M} \frac{\sqrt{2\pi}}{\Gamma\eta}$ from Assumption (1). Therefore, $H(\kappa) = 0$ or, equivalently, Equation (A.5), specifies a unique κ . Further,

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

where the second inequality follows from $\ell \leq \ell_H$, and the last inequality obtains because $\ell_H < Q - \frac{M}{\Gamma\eta\sqrt{2\pi}}$ from Assumption (1). Therefore, we have $\kappa > 0$.

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

$$P(\phi, \ell) = \bar{\theta} + \tau(\phi - \bar{\theta}) - \bar{c} - \frac{\kappa(\ell)}{\eta} \sqrt{v_\lambda}. \quad (\text{A.7})$$

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

$$\frac{d\kappa(\ell)}{d\eta} = \frac{\Gamma[Q - \ell + \rho MF(\kappa)]}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} \propto Q - \ell + \rho MF(\kappa) > Q - \ell \geq Q - \ell_H > 0, \quad (\text{A.8})$$

where the \propto obtains because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.6), the second inequality follows from $\ell \leq \ell_H$, and the last inequality obtains because $\ell_H < Q$ from Assumption (1).

It then follows from Equation (A.7) that

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

where the first equality follows from Equation (A.8), the third \propto obtains because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.6), and the second equality follows from Equation (A.5). This completes the proof of the theorem. \square

Proof of Proposition 1: For $E[B(\ell)]$ to increase in η , it suffices to show that $B(\ell)$ increases in η . From the expression of $B(\ell)$ in Equation (4), it follows immediately that

$$\frac{dB(\ell)}{d\eta} \propto \frac{d\kappa(\ell)}{d\eta} > 0, \tag{A.9}$$

where the inequality follows from Equation (A.8). This completes the proof of this proposition. \square

Proof of Proposition 2: For $E[|s(\ell)|]$ to increase in η , it suffices to show that $|s(\ell)|$ increases in η . From the expression of $s(\ell)$ in Equation (5), it follows immediately that

$$\frac{d|s(\ell)|}{d\eta} \propto \frac{dB(\ell)}{d\eta} > 0,$$

where the inequality follows from Equation (A.9). This completes the proof of the proposition. \square

Proof of Proposition 3: From the specification of $\kappa(\ell)$ in Equation (2), we have

$$\frac{d\kappa(\ell)}{d\ell} = -\frac{\Gamma\eta}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)} < 0 \tag{A.10}$$

because $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.6). It follows that

$$\frac{dP(\phi, \ell)}{d\ell} = -\frac{d\kappa(\ell)}{d\ell} \frac{\sqrt{v_\lambda}}{\eta} = \frac{\Gamma\sqrt{v_\lambda}}{MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa)}.$$

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

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

where the second equality follows from Equation (A.10). It follows that

$$\frac{dP(\phi, \ell)}{dz(\ell)} = \frac{dP(\phi, \ell)/d\ell}{dz(\ell)/d\ell} = \frac{\Gamma\sqrt{v_\lambda}}{MF(\kappa) + N} > 0.$$

Since κ increases in η from Equation (A.8), it follows that $dP(s, \ell)/dz(\ell)$ decreases in η .

This completes the proof. \square

Proof of Proposition 4: From Theorem 1,

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

and the variance ratio

$$\frac{\text{Var}[V - P(\phi, \ell)]}{\text{Var}(V)} = \frac{v_\theta(1 - \tau) + v_c + v_\lambda \text{Var}(K)}{v_\theta + v_c},$$

where $K \equiv \kappa(\ell)/\eta$. For $\text{Var}[V - P(\phi, \ell)]/\text{Var}(V)$ to decrease in η , it suffices 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 $\text{Cov}(K, dK/d\eta) < 0$. Note that both $K = \kappa(\ell)/\eta$ and $dK/d\eta$ depend on the random variable ℓ . Further, it follows from Equation (A.10) that

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

Next, observe that $\kappa(\ell) > 0$ from the proof of Theorem 1, and that

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

where the \propto follows from Equation (A.8), and the first inequality obtains because $\ell \leq \ell_H$, $\ell_H < Q - \rho N$ from Assumption (1), and $MF(\kappa) + N - \Gamma\eta\rho Mf(\kappa) > 0$ from Equation (A.6).

We then have

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

From the Harris (1960) inequality, we then obtain that $\text{Cov}(K, dK/d\eta) < 0$. This completes the proof of the proposition. \square

Appendix B: Technical Details for Climate Risk Disclosures

Table B1. Bigrams of Climate Risk Disclosures in 10-Ks

This table lists 64 CR-related keywords that [Kim, Wang and Wu \(2022\)](#) identify from the risk factor disclosures in 10-Ks. This is the same table as [Kim, Wang and Wu \(2022, Table 12\)](#).

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)	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	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	regulation(s) related to climate change	weather pattern(s)