Emissions Reduction Potential and Early-Stage Capital*

Abstract

This paper examines how the positive climate impact of startup innovation affects venture capital (VC) investment decisions. We build a novel dataset that quantifies the emissions reduction potential (ERP) of climate-tech startups and merge it with VC investment records across North America and Europe. We find that startups with higher ERPs attract larger investments. To establish causality, we conduct a field experiment in collaboration with the UN Women climate-tech Accelerator, angel investor networks, and VC firms. The results suggest that investors show greater interest in startups with higher ERPs and that both financial and non-pecuniary motives influence funding decisions.

JEL Classification: G24, Q54, Q55, L26.
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1. Introduction

A transition to a low-carbon economy requires an unprecedented technological development and large-scale capital deployment. The International Energy Agency (IEA) estimates that roughly 40% of the emissions reductions needed to reach net-zero by mid-century depend on technologies that are not yet commercially available (International Energy Agency, 2020, 2023). Climate-tech companies are central to developing these mitigation technologies and reducing firms' negative environmental impacts (Creutzig, Hilaire, Nemet, Müller-Hansen, & Minx, 2023; Thomas, Williams, Surana, & Edwards, 2025). Yet, investments in climate technologies remain insufficient: of the US$4.5 trillion the IEA projects is needed to limit warming to 1.5°C, only US$1.8 trillion has been deployed, leaving a US$2.7 trillion financing gap (International Energy Agency, 2023). Venture capital (VC)—with its mandate to fund high-risk, high-growth innovation—is therefore essential to closing the gap and accelerating the green transition (Aghion, Bergeaud, De Ridder, & Van Reenen, 2024; Lerner & Nanda, 2020).

Unlike typical startup investments, climate-tech ventures often pursue multiple objectives, combining social and environmental benefits with financial returns (Geczy, Jeffers, Musto, & Tucker, 2021). Understanding whether early-stage investors account for the long-term positive environmental impact of the innovations they fund is essential, as these impacts are central to achieving global climate goals.

The existing literature primarily examines investors' responses to firms' ESG risks or their carbon emissions, with a particular focus on public companies and stock market returns (e.g., Cheng, Ioannou, & Serafeim, 2014; Hartzmark & Sussman, 2019; Krueger, Sautner, & Starks, 2020; Bolton & Kacperczyk, 2023). Far less is known about how the prospective environmental benefits of companies' innovations—typically long-term and far-reaching—shapes investors' decisions. In this paper, we address this gap and provide the first systematic evidence—both descriptive and causal, via a field experiment—on whether VCs and angel investors respond to the emissions reduction potentials (ERPs) of startups' climate technologies. We also examine the mechanisms through which the ERP information translates into funding outcomes.

Measuring the potential environmental and social benefits of startups, especially at scale and with consistency, remains a significant challenge (Edmans, Gosling, & Jenter, 2024). We address this difficulty by leveraging a new and standardized measure: ERP per unit. ERP captures the percentage reduction in greenhouse-gas (GHG) emissions that a new product or process can achieve relative to a prevailing baseline, based on harmonized life-cycle-assessment

(LCA) analysis.[1] We collect the ERP data from Rho Impact. The dataset covers more than 5,000 climate technologies and maps to individual startups via large-language-model (LLM) classification. To our knowledge, this is the first study to measure ERP at the firm level, enabling a systematic assessment of climate benefit potential. Notably, this exercise is more tractable and less noisy for startups than for publicly traded companies, as early-stage firms typically concentrate on a single product or service, making ERP attribution more straightforward and precise.

We combine this firm-level ERP data with historical deal-level investment records from PitchBook for climate-tech startups founded in North America and Europe between 2010 and 2023. Our analysis examines the relation between ERP and the size of investment from VC and other early-stage investors.[2] Our regression analysis shows that climate startups with higher ERP per unit receive significantly larger VC investment size: a one-standard-deviation increase in ERP per unit (34%) is associated with a 4% increase in deal size. These results are robust to alternative model specifications and sample restrictions.

Causal interpretation of the ERP–investment relation is complicated by standard selection and omitted variable concerns. Startups with high ERP may differ systematically from others in ways unrelated to emissions impact—for example, they may be better managed, better funded ex-ante, operate in more active venture segments, be more capital intensive, or more focused on impact over profitability. These concerns are exacerbated by data limitations: for many early-stage startups, detailed financial and operational information is unavailable, even years after initial funding. Moreover, information on startups that fail or are rejected by investors at early stages is typically not observable, introducing further selection bias.

To address these challenges and provide evidence closer to a causal interpretation, we conduct a field experiment in partnership with the UN Women climate-tech Accelerator, two angel investor networks (the ABC Network and the Women's Angel Investment Network), and 21 VC firms, involving a total of 70 investors. The experiment follows a within-subject design: each investor evaluates the pitch materials of 17 climate-tech startups, which are randomly allocated to a control group with no ERP information in the pitch or to a treatment group in which ERP information is added, distinguishing between low and high ERP. We test whether

[1] The life-cycle-assessment or LCA is a method for evaluating the environmental impact of a product or service throughout all the stages of its life cycle.

[2] Climate-tech is defined as any new business model or technology focused on mitigating the impacts and drivers of global GHG emissions. We follow the PitchBook taxonomy, which includes nine segments: clean energy generation, clean grid technology, electric transportation, mobility solutions, food systems, land use, clean industry tech, the built environment, and carbon tech. See Section 3 for details.

providing ERP information alters investors' stated interest in pursuing an investment. The results show that investors express significantly stronger interest in startups with higher ERP values, suggesting that the potential for positive climate impact influences their investment decisions.

We next investigate several non–mutually exclusive channels through which ERP may matter to early-stage investors—financial return, risk, and impact motive. First, because VCs (including impact funds) are largely profit-driven (Geczy et al., 2021; Jeffers, Lyu, & Posenau, 2024), a natural interpretation of the ERP–investment relation is that investors view high-ERP startups as more likely to succeed financially. VCs can potentially realize both direct financial returns from climate-tech ventures and indirect returns via the monetization of carbon credits. Startups with higher ERP are also well positioned to benefit from rapidly expanding markets for sustainable products and services. Consistent with this view, using the PitchBook data, we find that higher ERP per unit is associated with higher startup valuations.

Second, risk considerations may shape the ERP–investment link. Revenue streams for climate-tech firms—through product sales and carbon credits—often depend on supportive public policies (e.g., subsidies, procurement mandates, or carbon pricing). This dependence exposes high-ERP startups to elevated political and regulatory risk. While such firms may benefit from stringent climate policy (Engle, Giglio, Kelly, Lee, & Stroebel, 2020), they face greater downside amid policy uncertainty or weak regulatory regimes. Using the Pitchbook data, we test whether the impact of ERP is related to policy risk, exploiting the first presidential term of Donald Trump in the U.S. as a negative policy shock in a difference-in-differences framework. The results show that the relation between ERP per unit and deal size is negative and statistically significant during periods of negative policy shocks relative to the rest of the sample. These results suggest that policy uncertainty and risk are key factors linking ERP to investment size.

Third, non-pecuniary motives can also contribute to the positive relation between ERP and investment. Using the PitchBook data, we find that startups with higher ERP are more likely to receive funding from impact investors—a group known to incorporate environmental and social impact alongside financial performance. Consistent with this pattern, our field experiment shows that investors who rate ERP as more important than other common investment criteria—such as the startup's value proposition, founding team, or market size—are significantly more likely to express interest in high-ERP startups. Investor experience also appears to matter: those with less familiarity in using ERP-related information exhibit stronger responsiveness to high-ERP startups, suggesting that salience and novelty may amplify the perceived value of environmental impact in early-stage investment decisions.

Finally, we compared investors' attention to ERP with that of other stakeholders in the climate-tech ecosystem, including scientists and academics, corporate executives, and government/NGO officers. In collaboration with NetZero Insights—a platform like Pitchbook but specialized in climate tech—we experimentally manipulate the subject line of one of their newsletters and add an ERP section to the content of the newsletter. Analyzing email opening rate and clicking behavior across newsletter sections (conditional on opening the email), we find evidence suggesting that investors pay more attention to ERP than other stakeholders.

Collectively, our study employs a novel, state-of-the-art measure of startups' ERP to examine whether the expected environmental benefits of innovations in climate-tech firms influence investor decision-making. Both descriptive and experimental evidence indicate that higher ERP is associated with larger investment sizes and greater willingness to invest, and this is seemingly driven by both financial and non-pecuniary channels. Further, we document that investors seem more attentive to ERP information than other stakeholders. These insights are relevant to investors, startups, and policymakers. Startups should prioritize innovations that generate greater positive environmental and social outcomes to attract more investment. In addition, providing credible ERP information can help channel capital toward the most impactful technologies and accelerate the green transition.

This paper contributes to the growing literature on how investors respond to firms' environmental and social impacts. Most prior work examines how investors price firms' own climate and ESG risk exposures—that is, risks borne by the firms themselves—such as carbon footprints, transition/physical risk metrics, or composite ESG ratings, primarily in public equity markets (See, for example, Aswani, Raghunandan, and Rajgopal (2024); Bolton and Kacperczyk (2021, 2023); Hartzmark and Sussman (2019); Krueger et al. (2020); Li (2025); Lu, Serafeim, Xu, and Awada (2024); Zhang (2025)).[3] In contrast, we shift the focus from climate risk exposure of firms to the forecasted environmental benefit of the firm's climate innovations—the positive external impact generated by the technologies they develop. We study early-stage private markets to assess whether—and how—venture capital and angel

[3]One notable exception is Lu, Riedl, Xu, and Serafeim (2024), which uses LLMs to quantify the extent to which U.S. public firms utilize climate solution products and services by counting relevant sentences in the 10-K filings. While it also aims to shed light on firm-level climate innovation, our approach differs in several important respects. First, we rely on a direct, quantitative measure of the expected emissions reduction potential of a firm's technology—the ERP—rather than indirect textual proxies. Second, whereas Lu, Riedl, et al. (2024) focus on the pricing implications of climate solution exposure in public markets, we analyze how startups' ERP influences funding decisions in private markets, particularly venture capital.

investors respond to startups' ERP. This focus is especially relevant given the importance of climate innovation and the increasingly important role that private capital plays in advancing climate innovation.

Emphasizing ERP offers several advantages: unlike historical emissions data—which are backward-looking and often confounded by macroeconomic cycles and policy shifts—ERP captures the forward-looking environmental potential of a startup's technology. In addition, while net-zero pledges of companies are forward-looking by design, they are voluntary, non-binding, and often decoupled from firms' actual investment or operational choices (Sastry, Verner, & Ibanez, 2024). In contrast, startups' ERP provides a product- and technology-specific measure of emissions impact grounded in engineering estimates rather than aspirational corporate disclosure.

This paper also contributes to the entrepreneurial finance literature studying the process through which early-stage investors select the companies that they fund (Bernstein, Giroud, & Townsend, 2016; Fried & Hisrich, 1994; Kerr, Lerner, & Schoar, 2014). Startup firms lack tangible assets, face information problems, and thus are uncertain and difficult to finance (Hall & Lerner, 2010). While previous papers focus on intangible assets such as founder characteristics and innovation capabilities (Bernstein, Korteweg, & Laws, 2017; Goldstein, Doblinger, Baker, & Anadón, 2020; Puri & Robinson, 2013), this paper provides evidence and implications on the influence of an alternative intangible asset, i.e., social and environmental benefits of startups.

Lastly, our work relates to the growing literature on the role of VC in the development of climate technologies. Several studies examine the financial returns to VC investors from climate-focused investments (Barber, Morse, & Yasuda, 2021; Cornelli, Frost, Gambacorta, & Merrouche, 2023; Gaddy, Sivaram, Jones, & Wayman, 2017; van den Heuvel & Popp, 2023). Other work investigates external drivers of VC investment in climate startups, including climate regulation and environmental policy uncertainty (Noailly, Nowzohour, & van den Heuvel, 2021, 2022). We contribute to this literature by providing evidence on how firm-level characteristics of climate-tech ventures—such as the emissions reduction potential of their innovations—affect VCs and shape investment decisions.

The remainder of the paper is organized as follows. Section 2 develops a conceptual framework outlining how positive climate impact may influence investment decisions. Section 3 describes the data, measurement, and empirical methodology. Section 4 examines the relationship between ERP and investment size using historical data. Section 5 details the design and findings of the field experiment. Section 6 explores the underlying mechanisms. Section 7 provides evidence that investors place greater emphasis on ERP relative to other stakeholders. Section 8 concludes.

2. Climate Impact and Early-stage Investment — A Conceptual Framework

2.1. Monetization Mechanisms

From the perspective of private capital markets, it is critical to understand how climate-tech startups can generate financial returns to attract VCs and other early-stage investors. An important monetization mechanism involves tapping into new markets and opportunities using innovative technologies. For instance, startups developing hydrogen solutions, energy storage systems, and small modular reactors are addressing the growing demand for clean energy. Companies producing electric vehicles are meeting rising consumer demand for green transportation. Likewise, providers of organic farming solutions can improve livestock feed efficiency and reduce methane emissions, a major source of greenhouse gases. In addition, climate-tech companies that focus on adaptation and resilience—rather than mitigation—help prevent property damage from climate-related events. This, in turn, may reduce insurance and financing costs while enhancing real estate values.

Climate-tech startups can also realize additional revenue by participating in carbon markets. Because many of these startups directly or indirectly reduce GHG emissions, their technologies often qualify to generate carbon credits under established regulatory or voluntary carbon market frameworks. These credits can be sold to companies and institutions seeking to offset their own emissions, thereby creating a recurring revenue stream. Beyond direct revenue, carbon markets may also offer strategic value. The ability to create tradable credits can help startups forge partnerships with corporations aiming to meet net-zero commitments, thereby expanding their customer base and improving long-term growth prospects.

2.2. Financial Return, Risk, and Impact

The prior section details the mechanism through which startups can monetize their emission-reduction technologies and products, directly via entering new markets, and indirectly via carbon credit markets. In this section, we examine whether startups that generate greater climate benefits—by offering solutions with higher emissions reduction potential—attract more early-stage investment. In particular, trade-offs among financial return, risk, and impact—conceptualized as a three-dimensional efficient frontier—can complicate investment decisions (Flammer, Giroux, & Heal, 2025; Pedersen, Fitzgibbons, & Pomorski, 2021).

2.2.1. Impact and Financial Return

On the one hand, a higher positive climate impact may be associated with superior future performance. As discussed, startups with high ERP are often well-positioned to benefit from the rapidly expanding markets for sustainable products and services. In this context, ERP can serve as a proxy for a startup's capacity to develop solutions to pressing environmental problems, potentially leading to competitive advantages, faster revenue growth, and higher long-term valuations. Moreover, startups with high ERP may exhibit other favorable characteristics—such as strong founding teams, advanced technological capabilities, or forward-looking strategic orientations—that can further improve their performance and investment prospects. Thus, for profit-maximizing investors, a high ERP could serve as a signal of the firm's ability to capture profitable opportunities in fast-growing green markets.

On the other hand, there could be a trade-off between impact and financial returns. Higher ERP may reflect a founder's emphasis on social or environmental goals over profit—an approach that some investors may view unfavorably (Geczy et al., 2021; Jeffers et al., 2024). If investors suspect that founders are more focused on impact than on maximizing profits, they might perceive a greater risk of moral hazard and become less willing to invest.

2.2.2. Impact and Risk

All else equal, climate-tech startups with higher positive climate impacts may entail greater risk. Technologies with high ERPs often require substantial R&D investment in intangible assets, which are inherently risky. For example, hydrogen production and carbon capture and storage typically demand significantly larger upfront investments and involve greater R&D uncertainty than more incremental innovations such as energy-efficiency improvements—even though the high-ERP solutions promise greater positive impact. Investors may respond to financing risk by shifting their focus toward startups with lower ERPs (Nanda & Rhodes-Kropf, 2017).

Moreover, the revenue streams highlighted in Section 2.1—both product sales and carbon credits—often depend on supportive public policies (such as subsidies, procurement mandates, or carbon pricing). This dependence exposes high-ERP startups to substantial political and regulatory risk. The success of these companies hinges on robust growth in clean energy markets and sustained high carbon prices. While high-ERP firms may benefit from stringent climate policies (Engle et al., 2020), they also face heightened risks amid political uncertainty or under weaker regulatory regimes.

2.2.3. Other Considerations

Market inefficiencies might prevent ERP metrics from being fully factored into investment decisions. A growing body of literature documents pricing anomalies related to climate risk and ESG factors. For example, researchers have identified mispricing of drought exposure (Hong, Li, & Xu, 2019), abnormal temperatures (Cuculiza, Kumar, Xin, & Zhang, in press; Pu, 2023), ESG practices (Glossner, 2021), and flood risk (Rizzi & Lewis, 2025). These findings suggest that even if climate impact is financially relevant, it may not be promptly or fully incorporated into investor behavior—especially in private markets and startup investments, where historical information is scarce and uncertainty is high.

Taken together, although a greater positive climate impact may yield financial benefits, it can also entail elevated risk. Consequently, it remains an open question whether early-stage investors systematically favor climate-tech startups with higher ERPs.

3. Data and Methodology

3.1. Measuring Climate Impact

The positive environmental and social impacts of climate solutions can often be qualitatively assessed by informed audiences for a limited number of firms, but quantifying these impacts at scale remains challenging. To address this issue, we use data from Rho Impact to measure the ERP of various solutions developed by climate-tech startups.[4] One of Rho Impact's data products, Koi, translates authoritative energy and environmental research into impact forecasts across a broad range of technologies.

The calculation of the ERP of a technology solution is based on two components: GHG emissions data from incumbent technologies and from the proposed climate solution. *Incumbent technology data* refers to the existing or projected systems that serve as the baseline for comparison. Koi identifies relevant data on incumbent technology impacts, industry scenarios (e.g., from the IEA, European Commission, U.S. Energy Information Administration, or industry reports), and industry-level de-carbonization targets (e.g., EU Taxonomy, Science Based Targets Initiative, One Earth Climate Model). These datasets typically provide macroscopic views of the industry and are often dynamic, reflecting expected changes over time. Forecasts are based on historical trends or aspirational pathways, such as the IEA's Net Zero Emissions Scenario. *Solution technology data* refers to the anticipated life cycle impacts of emerging technologies. Koi translates, transforms, and contextualizes findings from

[4] `https://rhoimpact.com`.

peer-reviewed publications and LCA databases. Its models provide product- and process-level views of a solution's potential impact, considering and distinguishing between relevant value chain phases. These impacts are compared against a suitable baseline product or process to generate a unit ERP. Koi utilizes LLMs to generate qualitative information on the solution and baseline, a model framework, and quantitative estimates for the GHG intensities of baseline and solution technologies for the climate-tech startups in our sample.[5]

For example, a battery-electric delivery vehicle integrates a high-efficiency electric motor, power electronics, and regenerative braking with a modular lithium-ion battery to provide propulsion and recover braking energy. The incumbent technology is a diesel light commercial truck, which emits approximately 0.4 kg COe per ton-kilometer (t-km) in 2035. The solution technology—a battery-electric delivery vehicle—emits about 0.08 kg COe per t-km in 2035. This estimate includes life-cycle emissions from electricity use, battery and vehicle manufacturing, maintenance, charging infrastructure, and end-of-life recycling. The difference between the baseline and the solution, 0.32 kg COe per t-km, represents the emissions reduction potential when the electric vehicle displaces the diesel alternative.

Different climate technologies have different units to measure their ERPs (e.g., CO_2 tonnes per hectare in agriculture, CO_2 tonnes per mile in travel/mobility, etc.). To ensure comparability across startups, we construct the unit change of ERP in the baseline as:

$$\text{ERP per Unit Change} = \frac{\text{Unit Emissions}_{\text{Incumbent}} - \text{Unit Emissions}_{\text{Climate Tech.}}}{\text{Unit Emissions}_{\text{Incumbent}}}, \quad (1)$$

where Unit $\text{Emissions}_{\text{Incumbent}}$ represents the per unit emissions of the most used technology that the startup would replace. The Unit $\text{Emissions}_{\text{Climate Tech.}}$ represents the per unit emissions of the technology utilized by the climate-tech startup under consideration.

We focus on ERP per unit change as the primary independent variable in the baseline, rather than total emission reduction potential. This choice is driven by several conceptual and empirical advantages that make ERP per unit more appropriate for analyzing early-stage climate-tech investment. First, ERP per unit change is more interpretable and transparent for both researchers and practitioners. It quantifies the emission reduction associated with one unit of a product or service (e.g., per battery, ton of fertilizer, or square meter of insulation), offering a more intuitive and direct measure of technological impact. Second, ERP per unit change is inherently technology-specific, capturing the intrinsic efficiency or impact of the

[5] Further methodological details are provided at `https://docs.koi.eco/docs/data-and-methodology/overview`

product or process without requiring assumptions about market size, adoption rates, and the pace of technological diffusion. In contrast, for total emission reductions, the difference between incumbent and the solution scales with firm output or market size, making it difficult to disentangle emissions impact from size-related effects.

At the same time, ERP per unit change data have their own limitations. First, there are inherent uncertainties in the ERPs predicted by engineering and climate models for both incumbent and proposed technologies. Nevertheless, the Koi ERP data represents the best available data for estimating startups' future ERP. Second, while per unit ERP change data rely on fewer assumptions such as market penetration, total GHG emissions are more directly tied to future global warming impact. In additional analysis, we also utilize projected Total Annual ERP (in tonnes of CO_2) as an alternative measure:

$$\begin{aligned}\text{Total Annual ERP} = (&\text{Unit Emis.}_{\text{Incumbent}} - \text{Unit Emis.}_{\text{Climate Tech.}}) \\ &\times \text{Market Size} \times \text{Market Capture}\,,\end{aligned} \tag{2}$$

where Market Size represents the estimated market size for one specific technology in 2035. Market capture represents the estimated adoption rate of the solution technology. The total annual ERP measure necessarily relies on additional assumptions about market size and adoption dynamics, which may introduce measurement error.

Koi is a relatively recent product, made available to interested parties in 2024. However, it can be applied retroactively to estimate the ERP of startups with deals dating back to 2010, which aligns with the coverage of our PitchBook data. As a result, our ERP measure should be interpreted as a proxy for the type of ERP measure that informed investors may have developed or accessed in the past.

The matching between climate solutions and startups is performed by Rho Impact using information from the startups' official websites. Specifically, we provided Rho Impact with a list of startups and their corresponding URLs. Rho Impact then ran its Koi engine on this list to generate ERP estimates, which were subsequently shared with us.

The strengths of the ERP data we use lie in its broad technology coverage and fine-grained level of detail, which is estimated based on company-specific climate solutions. However, the data is not without limitations. For example, although Koi covers more than 5,000 climate solutions, it does not always allow for a perfect match with the specific technologies developed by the climate-tech companies in our sample. Nonetheless, the team employs the best available methods for matching, including manual checking on selected samples.

3.2. *Deal-level Data*

We collect deal-level data for climate-tech startups founded in North America and Europe from PitchBook and match it with the ERP data from Koi.[6] The PitchBook definition of climate-tech is broad and encompasses any new business model and technology with a core focus to mitigate the impacts and drivers of global GHG emissions. It includes nine segments: clean energy generation, clean grid technology, electric transportation, mobility solutions, food systems, land use, clean industry tech, built environment, and carbon tech.

The deal-level data include information on company characteristics such as founding year, number of employees, headquarters location, industry, company description, and patent applications. It also contains deal-specific information, such as deal size and deal stage, which is categorized as seed round, early-stage VC, or later-stage VC. In addition, the dataset includes investor characteristics, such as whether an investor is classified by PitchBook as an impact investor.

We focus on deal size as our primary outcome variable for a couple of reasons. First, ERP is time-invariant, which precludes a standard panel analysis of deal likelihood over time. Second, the PitchBook data contains limited and sporadic information on valuations and financial multiples, which constrains broader valuation-based analysis.[7] Third, investment size is often interpreted as a proxy for perceived startup quality and is positively correlated with startup valuation, and has been widely used in the literature (Castiglia, 2025; Gompers & Lerner, 2000; Guzman & Kacperczyk, 2019; Lerner & Leamon, 2023).

3.3. *Methodology*

We estimate correlations between a startup's ERP per unit change and the size of the deals at the startup-deal-year level. The OLS regression model is specified as follows:

$$y_{i,d,t} = \beta ERP_i + \gamma X_{i,d,t} + \rho_{j,t} + \omega_{c,t} + \delta_d + \varepsilon_{i,d,t}\,, \tag{3}$$

where d represents the deal in year t for startup i operating in industry j and country c. $\rho_{j,t}$ represents industry-year fixed effects, $\omega_{s,t}$ represents country-year fixed effects, and δ_d represents deal-stage fixed effects, respectively.

The dependent variable y is the natural logarithm of deal size. We run this model separately with the ERP per Unit Change (Equation (1)) as the main explanatory variable in the baseline

[6]We focus on North America and Europe as Koi's current model does not perform as well with non-English websites of startups.

[7]We conduct additional tests using startup valuations as the dependent variable and find consistent results.

and Total Annual ERP (Equation (2)) in the additional analysis. Standard errors are clustered at the country level.[8]

The vector of control variables X includes the natural logarithm of patent count, startup age, and employees measured at the time of deal. We use the log-link formulation because of the non-negative and highly skewed nature of these count-based variables. The inclusion of control variables mitigates the possibility that the findings are driven by some startup-year-level omitted variables. For example, it could be that startups with stronger technology capabilities may attract more capital (Conti, Thursby, & Rothaermel, 2013; Hsu & Ziedonis, 2013). Controlling for startups' patent count addresses this potential confounding influence (Guzman & Kacperczyk, 2019; Silverman, 1999; Snellman & Solal, 2023). Similarly, other controls such as the startups' age and number of employees account for differences in experience and size that may correlate with the size of the investment.

4. ERP and Investment Size

4.1. Summary Statistics

Our sample includes all deals of climate-tech companies founded between 2010 and 2023.[9] We drop companies without ERP information. The final sample includes 2,805 startups and a total of 7,849 deals. Table 1 provides summary statistics for the variables used in the analysis. The correlation matrix is available in Table A1 of Appendix A.

Figure 1 presents the average and total deal sizes of climate-tech startups by year and by ERP per unit change bins (terciles). The figure shows that the average deal size generally increased from 2010 to 2023, while total deal size rose steadily until 2021 before declining in 2022 and 2023. Based on the ERP per unit change bins, it is difficult to discern a clear relationship between ERP levels and deal size.

Figure 2 illustrates the average and total deal sizes by year, industry, region, and deal stage.[10] Although the average deal size in the Financial Services industry is high, the number of deals and total investment in this sector are relatively small. In contrast, the Energy and Materials industries have smaller average deal sizes but account for the largest total investment volumes. On average, North America has larger average deal sizes; however, the region experienced a decline in total investment in 2022 and 2023.

[8]We also cluster the standard errors at industry-year and country-year level and the results are robust, as shown in Table A.2 of Appendix A.

[9]We begin our sample period from 2010 to remove the impact of the financial crisis. In addition, there were very few climate-tech firms funded before 2010.

[10]We utilize Pitchbook industry classification.

4.2. Baseline Results

Table 2 reports the results of the baseline regression reported in Equation (3) with various fixed effects specifications. The results show a positive and statistically significant relation between deal size and ERP per Unit Change across all specifications. Specifically, a one-standard-deviation increase in ERP per Unit (34%) is associated with a 4% (11.7% $\times$ 34%) increase in deal size on average. In addition, when using indicator variables instead of a continuous measure (column (4)), the results suggest that startups in the highest quintile of ERP per Unit (quintile 5) raise significantly larger capital per deal compared to those in lower quintiles.

In addition, we use Total Avoided Emissions instead of ERP per Unit as the outcome variable, and conduct similar analysis. As shown in Table A3 of Appendix A, the results are qualitatively similar: there is a positive and statistically significant relation between deal size and annual total avoided emissions. As reported in Table A2 of Appendix A, the results are qualitatively similar when transforming the ERP per Unit Change using the inverse hyperbolic sine, when clustering the standard error at the country-year and industry-year levels, and when using the natural logarithm of the deal size over employees as the outcome variable.

The analysis above suggests that climate startups with higher ERPs receive larger investment. While documenting this correlation with historical data is valuable, the analysis is not without complications. First, we cannot examine the relation between ERP and the likelihood of receiving investment, as the PitchBook dataset does not include climate-tech startups that failed or were rejected at early stages. Second, the ERP coefficient may be affected by endogeneity bias. For example, firms with higher environmental impact may also possess superior human capital or other firm-level capabilities. This omitted variable concern is compounded by the lack of financial and operational data for many startups, even years after their initial funding rounds. To address these limitations, we conduct a field experiment, described below.

5. Field Experiment

We conduct a field experiment to examine how ERP influences investor behavior. The core experimental manipulation involves randomly including or omitting ERP information in the pitch materials of early-stage climate-tech startups. This design enables us to (i) identify the causal effect of ERP disclosures on investors' investment interest, and (ii) explore the mechanisms through which ERP shape decision-making. The findings shed light on whether and how sustainability metrics affect investor behavior in early-stage venture contexts.

The experiment was embedded in the *UN Women climate-tech Accelerator*, which featured 17 early-stage climate-tech startups founded in Southeast Asia, each with at least one woman on the founding team. As part of the program, these startups were introduced to potential investors to seek funding. We leveraged this setting to implement the ERP information treatment.

The participating startups span a diverse range of climate technology solutions, including smart water management systems, regenerative agriculture platforms, electric boat propulsion, marine biotech, and sustainable aquaculture. For example, one startup offers Internet-of-Things-enabled clean water distribution in Indonesia, another develops biochar-based soil enhancers to boost crop yields in Thailand, while others create energy-efficient home technologies, natural disinfectants, or circular economy solutions such as fruit preservation coatings and chopstick recycling. This diversity reflects the broad innovation landscape within the UN Women climate-tech Accelerator and illustrates the varied channels through which early-stage companies aim to reduce emissions.

Our investor sample includes 70 total individuals that are investors—33 angel investors and 37 venture capitalists—recruited through partnerships with two prominent Southeast Asian angel networks, the "ABC Network" and the "Women's Angel Investment Network" (names are changed to preserve anonymity), as well as 21 VC firms. These investors are experienced, having invested in an average of 35 startups. More than one-third of them write checks exceeding US$250,000. These investors reviewed all 17 startup pitches and indicated their investment interest, allowing us to observe variation in responses across randomized ERP disclosure conditions.

5.1. Experimental Design and Randomization

The experiment was designed in October–November 2024, and investor evaluations took place between mid-December 2024 and the end of January 2025. The study received approval from the Research Ethics Committee at the authors' institution (anonymized for blind review) and was pre-registered in the AEA RCT Registry (AEARCTR-0014943). Startup founders signed informed consent forms acknowledging their participation in academic research on investor behavior. Investors were not informed in advance, but were fully debriefed following the study.

We employed a within-subject experimental design: each investor evaluated all 17 startups, which were randomly assigned to the control and the two treatment groups: 7 startups in control, 5 in low ERP treatment, and 5 in high ERP treatment (we explain the treatments below). This within-subject design enhances statistical power and ensures that each startup is equally represented across conditions. To mitigate order or fatigue effects, we implemented complete counterbalancing. Using the *Block Randomizer* feature in Qualtrics, we treated each startup as a separate block and generated all orderings consistent with the 7/5/5 control–low–high ERP allocation.[11] When an investor launched the survey, Qualtrics randomly selected one of these pre-generated sequences and displayed the corresponding startup pages in that exact order. Because (i) each startup appears equally often in every ordinal position, and (ii) ERP conditions are orthogonal to those positions, any systematic learning, anchoring, or fatigue effects are purged from the treatment contrast. Observed differences in investment intent can thus be attributed to the ERP manipulation rather than presentation order.

Our treatments modify a standard pitch template that ABC Angel Investment Network uses to provide the basic information that is necessary to assess investment intent. This template is approximately one page long divided into four sections. The *first section of the template*, titled "Pitch", consists of a 10- to 15-lines paragraph describing the startup, the problem it is tackling, the solution or product that it is proposing or executing, a link to the startup website, the accomplishments of the startup (e.g., volume of business already attained), and other information. This paragraph was written by the startups.

The *second section of the template* is titled "Emissions reduction potential" and contains a paragraph with two sentences. The first sentence is fixed and reads: "ERP is measured by Rho Impact as a percentage decrease in per unit CO_2 emissions generated by the startup's technology relative to those produced by the baseline technology used currently in the market."[12] The second sentence was modified experimentally. We randomized across three versions: one control sentence and two treatment sentences. The control version reads: "Due to the nature of the technology and company activities, it is difficult to estimate the ERP, and the information is currently unavailable." This means ERP information is absent in the control condition.

The two treatment versions provide ERP signals. In the "low ERP" condition, the sentence reads: "This startup is below the median ERP across all the startups evaluated in this program." In the "high ERP" condition, it reads: "This startup is above the median ERP across all the startups evaluated in this program." This design allows us to compare the absence of ERP information (control) versus any ERP signal (pooled treatments), and high versus low ERP signals.

[11] Qualtrics assigns respondents to block sequences with equal probability, so each ordering is expected to be shown the same number of times across our sample.

[12] A hyperlink to Rho Impact's website was added to its name.

Because ERP group assignment is randomized, the treatment label is "accurate" only half the time—some startups labeled as "high ERP" fall below the true median, and vice versa. The control condition, while stating that ERP is unavailable, is technically always inaccurate (as the information by Rho Impact is available for the 17 startups). This deliberate imprecision mimics the early-stage uncertainty of climate impact metrics and relies on the perceived credibility of third-party estimates from Rho Impact. We took care of the ethical considerations of this choice[13], document that a potential bias that stems from this choice likely did not happen[14], and discarded experimental designs that did not involve inaccuracy as they would produce omitted variable bias.[15]

The *third section of the template* is titled "Global market size" and it provides the information that Rho Impact collects and uses to estimate the market size. This information is expressed in the relevant units of the startup (e.g., kilograms of crop for a startup that improves water usage in agriculture). The *fourth section* is titled "Founders" and displays the name of the founders with hyperlinks to their LinkedIn profiles.

We conducted the experiment using an online Qualtrics survey, which was distributed via email to investors. Each investor was required to review all 17 startups (for a total of 1,184 investor-startup observations; 17 startups × 70 investors), and before proceeding to the next one, they had to answer a question capturing our main outcome of interest (described in the following paragraph). After completing all 17 evaluations, investors were directed to an exit survey containing additional questions. The responses from this exit survey are used in the heterogeneous treatment analyses; we detail these moderators below.

Our primary outcome of interest is investors' interest in investing in a given startup. After reviewing each startup's pitch, investors were asked: "Would you consider investing in this

[13]Given our within-subject design, all startups end up receiving the same proportion of control and treatment sentence, and thus, all startups are expected to be incorrect/correct in the same proportion. Startups were informed ahead of the experiment of this situation and were given the option to opt-out. Investors were debriefed at the end of the experiment, where the potential harm was flagged (but no transaction was executed in the experiment, so investors can rectify).

[14]A question arises to what bias this inaccuracy might produce. It is possible that if there are investors that are savvy about ERP, then they would discount the information we gave, and thus, a downward bias in our coefficients might occur (i.e., the informed group does not react and the estimated coefficient is depressed). However, in our exit survey we find a positive strong correlation between an investor's prior use or collection of ERP and the trust they placed in the ERP information we provided. Further, it is likely that for early stage startups, information is inherently uncertain, and thus investor adjust accordingly.

[15]Other experimental designs that would not involve inaccurate information were discarded. Any type of between-subject design (e.g., randomly assigning high or low ERP startups to investors) cannot randomly affect high and low ERP without inaccuracy and obtain an unbiased estimated (as high and low ERP would be correlated with other startup characteristics). Similarly, a within-subject design that randomly assigns the control condition but maintains accuracy in high/low ERP when not randomized to control, also brings up the problem that high/low ERP may be systematically correlated with other startup characteristics.

startup?" They responded using a continuous slider scale ranging from 1 to 5, where 1 was labeled "definitely not," 2 "probably not," 3 "I don't know," 4 "probably yes," and 5 "definitely yes." This measure provides a granular, investor-level assessment of interest across the 1,184 investor–startup observations. The mean response across all evaluations was 2.68, with a standard deviation of 0.93, reflecting a moderate degree of interest and meaningful variation across startups and investors.

To assess the statistical power of our experimental design, we calculate the minimal detectable effect (MDE) for this outcome. Based on the use of both startup and investor fixed effects—made possible by our within-subject design—we conservatively assume a 35% reduction in residual variance relative to the raw outcome. With 1,184 observations, power set at 0.8, and a two-sided significance level of 5%, this implies an MDE of approximately 10.4% of a standard deviation. This threshold guides the interpretation of the treatment effects reported in later sections.[16]

5.2. Investor Sample and Descriptive Characteristics

We begin by outlining the demographic and professional background of our 70 investors to contextualize later treatment effects. Table 3 provides summary statistics for these participants; this data comes from an exit survey that investors responded after evaluating all 17 startups. Investors display a wide range of prior experience—on average having invested in 35 startups—and vary substantially in typical check size. Nearly 60% of the sample are women, and the table further illustrates variation across investors in familiarity with ERP metrics, their reported use of ERP in decision making, and their motivations for investing, whether commercial, environmental, or ethical. These characteristics are later used in our heterogeneous treatment effect analysis.

5.3. Average Effect of ERP on Investors' Investment Interest

We estimate the average effect of providing ERP information—both presence of ERP information and strength of ERP—on investors' stated interest in funding startups. We estimate the following regression model:

$$Invest_{i,j} = \beta_0 + \beta_1 ERP_{i,j} + \beta_2 ERP_{i,j} \times High\,ERP_{i,j} + \mu_i + \delta_j + \varepsilon_{i,j}\,, \tag{4}$$

[16] In our pre-registration, we reported an MDE of 16%, based on an expected sample of 21 startups and 25 investors. Regarding startups, two dropped out, and two opted out from the experimental design. Regarding investors, we increased the number of investors to 70.

where $Invest_{i,j}$ measures investor j's interest in investing on startup i. $ERP_{i,j}$ is a binary indicator equal to one if the startup's pitch included ERP information (either high or low ERP) and zero otherwise (i.e., control condition). $High\,ERP_{i,j}$ is a binary indicator equal to one if the ERP information indicated that the startup is above the median in emissions reduction potential, and zero otherwise. Because ERP and $High\,ERP$ are randomly assigned across startups within investors, we include both startup fixed effects (μ_i) and investor fixed effects (δ_j), thereby exploiting within-investor and within-startup variation.

Table 4 presents the results from estimating the effect of providing ERP information. Columns (1) through (3) progressively add investor and startup fixed effects. Across all specifications, we find no statistically significant effect of merely providing ERP information on investment interest. That is, the presence or absence of ERP data alone does not meaningfully influence whether investors express greater interest in a given startup. This result implies that generic sustainability disclosures, absent additional signals about quality or magnitude, may not be sufficient to shift investor behavior. In a setting where investors are exposed to multiple pitches, basic ERP inclusion appears insufficient to draw attention or differentiate startups.

Next, we examine whether the content of the ERP information matters. Table 4 in columns (4) to (6) reports results for the interaction between ERP provision and whether the ERP of the startup is above the median. In the model with interaction term, the coefficient of ERP is interpreted as the effect of receiving information indicating that the startup is below the median in emissions reduction potential.[17]

We find that receiving low ERP information is negatively associated to investment interest (as compared to not receiving information), but this effect is not statistically significant. The coefficient on the interaction term ($ERP \times High\,ERP$) is positive and statistically significant at the 10% level ($p < 0.1$) in specifications including both investor and startup fixed effects. This means that in comparison to receiving low ERP information, receiving a high ERP signal significantly increases investor investment intentions. The magnitude of this coefficient is 0.097, which corresponds to 10.4% of the standard deviation in the outcome variable (mean = 2.64, SD = 0.93)—a value that matches the minimal detectable effect (MDE). Overall, the results suggest that when ERP signals are not only present but framed as relatively strong (i.e., above-median performance), they become salient enough to affect investor behavior.

[17] We define $Low\ ERP$ analogously as $High\ ERP$ but for below the median startup. Given that $ERP = High\ ERP + Low\ ERP$ it is easy to show that Equation (4) can be expressed as follows: $Invest_{i,j} = \beta_0 + \beta_1 Low\ ERP_{i,j} + (\beta_1 + \beta_2) High\,ERP_{i,j} + \mu_i + \delta_j + \varepsilon_{i,j}$.

This pattern is consistent with theories of bounded attention or signal threshold effects: investors may filter or ignore sustainability information unless it reaches a threshold that signals standout performance. Alternatively, investors may rely on ERP disclosures only when they believe the startup is exceptionally impactful, and otherwise defer to traditional decision criteria.

Regarding inference, and in line with Robinson (2020) and Abadie, Athey, Imbens, and Wooldridge (2023), we note that clustering of standard errors is not required purely on the basis of experimental design. However, for purposes of generalization, we also report standard errors clustered at both the investor and startup levels in Appendix A. As shown in Table A4, clustering at the investor level increases the p-value on the $High\,ERP$ interaction to 0.14 (two-tailed test) or 0.07 (one-tailed test), whereas clustering at the startup level results in statistical significance at the 5% level.

Taken together, these results indicate that simply including ERP data may not be enough to influence investment interest—investors respond only when the ERP signal crosses a threshold. This underscores the importance of not only disclosing sustainability metrics but also emphasizing their relative strength to make them decision-relevant. To understand which types of investors respond to ERP signals and why, we next examine heterogeneous treatment effects across investor characteristics.

5.4. Heterogeneous Effects of ERP Disclosure Across Investor Characteristics

We explore whether investors' responsiveness to ERP information varies systematically by investor characteristics. To examine this, we estimate the following model:

$$\begin{aligned} Invest_{i,j} = {} & \beta_0 + \beta_1 ERP_{i,j} + \beta_2 (ERP_{i,j} \times High\,ERP_{i,j}) \\ & + \beta_3 (ERP_{i,j} \times M_j) + \beta_4 (ERP_{i,j} \times High\,ERP_{i,j} \times M_j) \\ & + \mu_i + \delta_j + \varepsilon_{i,j} \end{aligned} \tag{5}$$

where $Invest_{i,j}$, $ERP_{i,j}$ and $High\,ERP_{i,j}$ are defined as before. The variable M_j denotes investor-level moderators measured via an exit survey that investor responded after evaluating all 17 startups. As before, we include startup fixed effects μ_i and investor fixed effects δ_j to control for baseline differences in investment behavior across investors. The error term $\varepsilon_{i,j}$ captures idiosyncratic unobserved variation. The investor-level moderator variables fall into five categories displayed below.[18]

General investor characteristics: These include gender (binary), investor type (angel or VC), typical check size (coded as a binary indicator for above median), number of prior startup investments (also indicator for above median), and prior experience in investing in climate-tech startups (also indicator for above median).

ERP importance: We include two measures of how much importance the investor placed on ERP. One is a rank-based measure of how ERP compared to other evaluation criteria (e.g., founder quality, market size), and the other is a direct slider rating (1–5) on ERP importance. Both are coded as binary indicators for above median.

ERP expertise: We measure prior familiarity with ERP (yes/no), self-reported use of ERP in investment decisions (slider, converted to binary using the median), and whether the investor had previously collected ERP data (yes/no). These proxies allow us to distinguish between experienced and novice ERP users.

Investment motivation: We include two continuous slider questions capturing the importance of commercial returns and environmental impact (which are dichotomized based on the median), as well as a forced-choice binary variable indicating whether the investor viewed ERP primarily as a return-based or duty-based criterion.

ERP trust: We include a slider rating (1–5) capturing the investor's trust in the ERP information presented in the experiment, converted into a binary indicator for above-median trust.

Table 5 presents the moderation results. For transparency, we display the moderation across all our exit survey variables. These results are exploratory as statistical power is reduced in interaction analysis and we did not stratified our experiment by any moderator. We find several moderators influence the differential effect of high versus low ERP ($ERP \times High\, ERP$). First, investors' perceptions of ERP importance play a meaningful role. We find that investors who rank ERP as more important (among other investment criteria) are significantly more responsive to high ERP signals (interaction coefficient: 0.268, $p < 0.05$). In contrast, investors who assign lower importance to ERP exhibit a negative response ($High\, ERP$ coefficient is negative), but this is not statistically significant. This finding highlights the importance of aligning information with investors' stated priorities. It also suggests that ERP disclosures are most effective when they resonate with the criteria investors already care about.

ERP expertise also moderates the effect. Investors with lower ERP familiarity, less prior

[18] Table A5 provides variable details, question wordings, and coding decisions. Correlations and descriptive statistics appear in Table A6.

use of ERP in decision making, or no history of collecting ERP data exhibit stronger responses to the high ERP treatment. Compared to the average treatment effect of 0.097 in Table 4 (10.4% of a standard deviation), these subgroups show larger coefficients in their investment interest, namely 0.164, 0.174, and 0.145, respectively (all $p < 0.05$) (these are the coefficients associated with $High\ ERP$). The interaction between $High\ ERP$ and the three experience variables are all negative and large (-0.145, -0.135, and -0.224), only the latter being statistically significant ($p < 0.1$). An immediate concern of these results is that maybe experienced investors are not responsive because they do not value ERP as a signal, either because they distrust the signal we gave them or because, via their direct experience, they do not see the value of ERP. The correlation patterns in Table A6 suggest that this is not the case: investors with ERP experience are significantly more likely to view ERP as an important performance metric for startups and to trust the ERP data we provided. We speculate that a reason that can explain this result is that experienced investors might have their own ways of assessing ERP (and do not consider external inputs), and rely on this data in later stages in the investment cycle. This would lead them to be less reactive to our treatment than unexperienced investors (even though they may react in latter stages, after their own ERP analysis.)

Taken together, the evidence highlights the nuanced role that investor heterogeneity plays in shaping the effectiveness of ERP information. Investors who rank environmental impact high in decision making factors are more responsive to high ERP information. Also, investors with less experience with ERP appear more open to the signal and are more likely to increase their interest in startups labeled as high ERP. For these investors, the ERP label may act as a credible shortcut or heuristic in the absence of strong internal evaluation tools. In contrast, investors with a history of ERP engagement do not respond to the same signal, likely because they are equipped to independently assess ERP through their own methods or prefer relying on proprietary diligence processes.

6. Why does ERP Matter to Investors?

As discussed in Section 2, investors might be interested in startups with high positive environmental impact for both financial and non-pecuniary considerations. In the following sections, we explore different mechanisms and discuss the results. We first explore financial and non-pecuniary motivation using the PitchBook data. We then discuss evidence from the field experiment.

6.1. *Financial Performance Considerations*

First, a high ERP may signal a startup's ability to develop scalable solutions that address critical environmental challenges, potentially translating into competitive advantages, stronger revenue growth, and higher profits. Hence, investors might be willing to pay a premium, i.e., higher valuations, for startups with higher ERPs.[19] In Table 6, we examine the relation between ERP and company valuations and find that valuations are positively correlated with higher ERP per unit change. Specifically, a one-standard-deviation increase (34%) in ERP per unit is associated with a 8% (34% $\times$ 23%) increase in a company's valuation. Furthermore, as shown in column (4), companies in the highest quintile of ERP per unit change are associated with a 14.4% higher valuation, indicating that the effect is concentrated among firms with the highest ERPs. The results suggest that the expected future financial performance is one of the channels linking ERP to investors' decision making.

6.2. *Policy Risk Considerations*

A high ERP may also serve as a hedge against regulatory risks and market shifts. In the context of increasingly stringent climate policies, startups aligned with these trends are better positioned to succeed in a changing policy landscape. Conversely, when investors anticipate less stringent carbon regulations, they may be less responsive to ERPs due to higher risks. For instance, the U.S. government under the first term of the Trump administration (2017–2020) was less supportive of climate mitigation policies, likely reducing the perceived need for investors to hedge against regulatory risks during that period. The unexpected nature of Trump's first-term victory provides a quasi-exogenous shock that we exploit using a difference-in-differences approach.

Specifically, we define deals that took place in the U.S. during the 2017–2020 period as treated deals and U.S. deals both before and after this window and non-U.S. deals as controls. In Table 7, we show that investors were less likely to invest in U.S. startups with higher ERPs during the Trump administration ($p < 0.01$), compared to the rest of deals. The negative coefficient on the interaction term ERP per Unit Change $\times$ 1(Trump Pres.) in column (1) ($p < 0.01$) indicates that during the Trump administration, the relation between ERP and deal size decreased by 106% ($-0.151/0.142 = -1.06$). This difference-in-differences specification allows us to account for time-invariant startup characteristics through startup

[19] Higher valuations may also reflect the climate-risk hedge provided by assets whose cash flows are positively correlated with climate risk (Pástor, Stambaugh, & Taylor, 2021, 2022). Disentangling the relative contributions of profitability and climate-risk hedging to valuation is beyond the scope of this study.

fixed effects. Results reported in column (2) show that the impact of ERP for U.S. startups during this period is statistically lower than for the control group, accounting for startup time-invariant characteristics. The results are qualitatively similar when using an indicator for the highest quintile of ERP per unit (columns (3) and (4)). These findings suggest that investors' responses to ERP are shaped, at least in part, by expectations of regulatory risk, which may alter perceptions of future financial returns.

6.3. Non-pecuniary Considerations

Beyond financial considerations, some investors may be morally motivated to support companies that generate social and environmental impact. To further investigate this non-pecuniary mechanism, we examine whether firms with higher ERPs are more likely to attract impact investors. Because impact investors prioritize social and environmental impact—sometimes even at the expense of financial returns—they are expected to invest more in climate deals with higher ERPs. We test this hypothesis by estimating the model specified in Equation (3), with the outcome variable being an indicator for the participation of an impact investor in the deal. We utilize PitchBook's classification to identify impact investors.

As shown in Table 8, our results indicate that a one-standard-deviation increase (34%) in ERP per Unit is associated with a 2% (34% $\times$ 5.7%) increase in the likelihood of impact investor participation in climate-tech deals. Furthermore, deals in the highest quintile of ERP per unit change are most likely to attract impact investors (column (4)). Overall, this evidence suggests that non-pecuniary motives may be one of the channels driving the larger deal sizes observed for high-ERP startups.

6.4. Motivation Moderators in the Field Experiment

In Table 5 we explored three variables associated with the motivation around ERP, namely the importance of commercial returns and environmental impact individually considered, and the forced-choice between duty and return. None of these variables meaningfully moderate the effect of high ERP. This suggests that both types of motivation—financial and moral—may coexist in driving responses to sustainability information, such that neither of them takes primacy in boosting the investment intentions in high startups.

7. Do Investors Care About ERP more than Other Stakeholders?

Our baseline results suggest that investors are more likely to invest in, and commit more funding to, climate-tech startups with higher ERP. However, it is unclear whether investors care about ERP more than other stakeholders. To address this question, we collaborated with NetZero Insight (N0i) and conducted a second experiment that moves beyond a sole focus on investors. N0i is a platform similar to PitchBook but specialized in climate-tech startups. We compared investor behavior to that of other key stakeholders in the climate-tech space, including scientists and academics, corporate executives, and government/NGO officials. Specifically, we examined whether investors are more drawn to or engaged with ERP-related content in newsletters sent by N0i compared to other stakeholders. This enables us to develop a more nuanced understanding of investor behavior related to ERP.

Details of the experimental design and results are presented in Appendix B. In summary, we do not find that investors are more likely than other stakeholders to open newsletters with ERP-focused subject lines. However, among those who do open the newsletter, investors are significantly more likely to click through and engage with the ERP section of the newsletter (in this analysis we use fixed effects for newsletter recipient and ERP section). These findings suggest that while investors may not initially exhibit greater interest, they show deeper engagement with ERP content once exposed—indicating a potentially stronger underlying interest in ERP information compared to other stakeholders.

8. Conclusion

To the best of our knowledge, this study is the first attempt to examine how the expected environmental impact of innovations developed by startups—measured by ERP—influences early-stage investment decisions. Unlike investors' response to firms' ESG or climate risks (e.g., Cheng et al., 2014; Hartzmark & Sussman, 2019; Krueger et al., 2020; Bolton & Kacperczyk, 2023), little is known about how the environmental benefits of companies' innovations—typically long-term and far-reaching—influences investors' decisions. This is due to lack of data on startups' social and environmental impact, as well as endogeneity problems due to omitted unobservable startup characteristics.

In this paper, we compile novel data to quantify the ERP of various climate-tech startups based on their specific technology innovations. We combine these ERP estimates with historical investment records of climate-tech companies in North America and Europe, and find that startups with higher unit ERPs tend to attract larger investments. To identify a causal relationship, we conduct a randomized field experiment to test whether VCs and angel investors are more likely to invest in startups with high ERPs. We find that investors respond positively to ERP levels. We also document that investors seem more attentive to ERP information than other stakeholders (e.g., corporate executives, government officials).

Together, our results indicate that the level of positive environmental impact of innovations plays a causal role in the funding of early-stage climate-tech firms. Furthermore, we explore the underlying mechanisms and provide evidence that the relationship between ERP and investment is driven by expected financial performance, policy risk, and non-pecuniary considerations.

This paper contributes to the sustainable finance literature by examining how the environmental benefit from innovations of startups, rather than firms' ESG risks or their own carbon emissions, influences investor decision-making and outcomes. It also contributes to the entrepreneurship finance literature by highlighting the importance of an alternative type of intangible asset—environmental and social impact—for startup success.

This study also carries practical implications. First, because environmental impact is important to both investors and society, it is essential to improve the measurement of ERP—and other impact metrics—and to enhance the transparency of this information. Second, since venture capitalists and angel investors tend to invest more in firms with higher ERPs, this pattern incentivizes startups to prioritize innovation and generate greater positive environmental and social outcomes. Finally, the effectiveness of ERP depends not only on the content of the information but also on the audience's prior beliefs, familiarity with the topic, and perceptions of the source's credibility. Entrepreneurs and intermediaries seeking to influence investor behavior through sustainability metrics should therefore consider how such information is framed and communicated. Increasing transparency regarding the underlying methodology and obtaining validation from credible third parties may further strengthen the effectiveness and adoption of these metrics.

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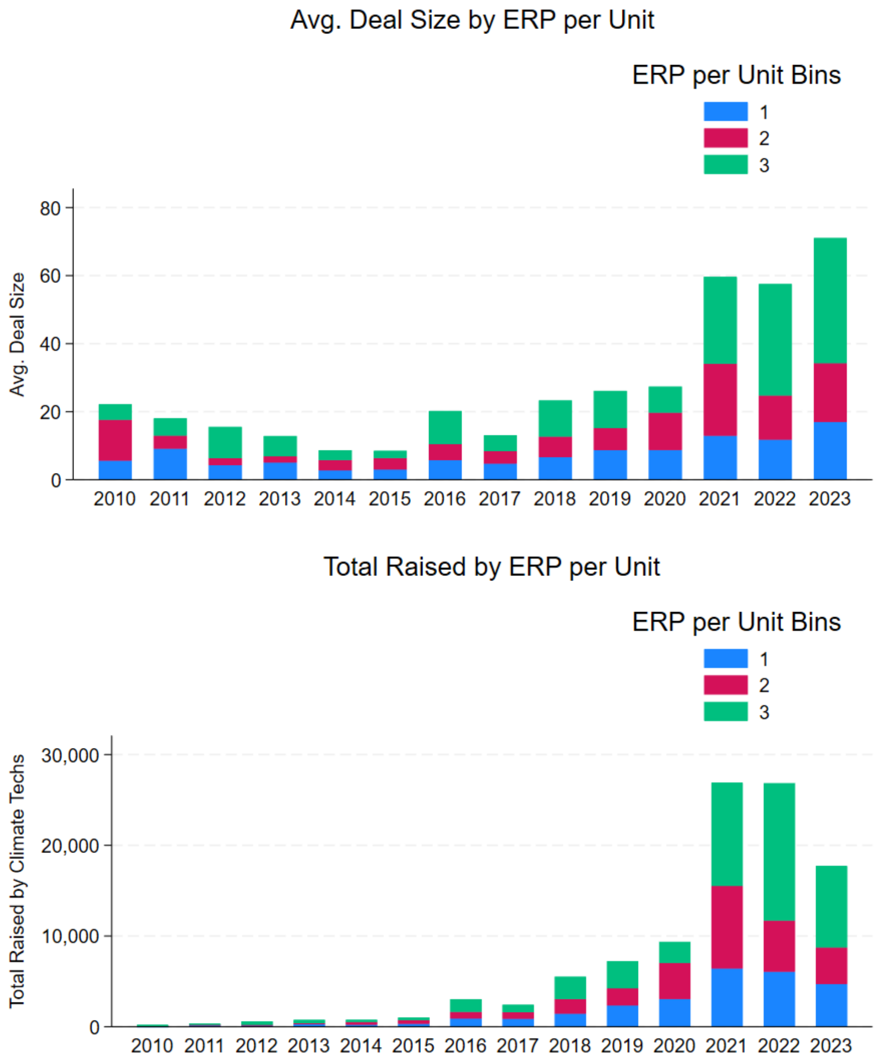
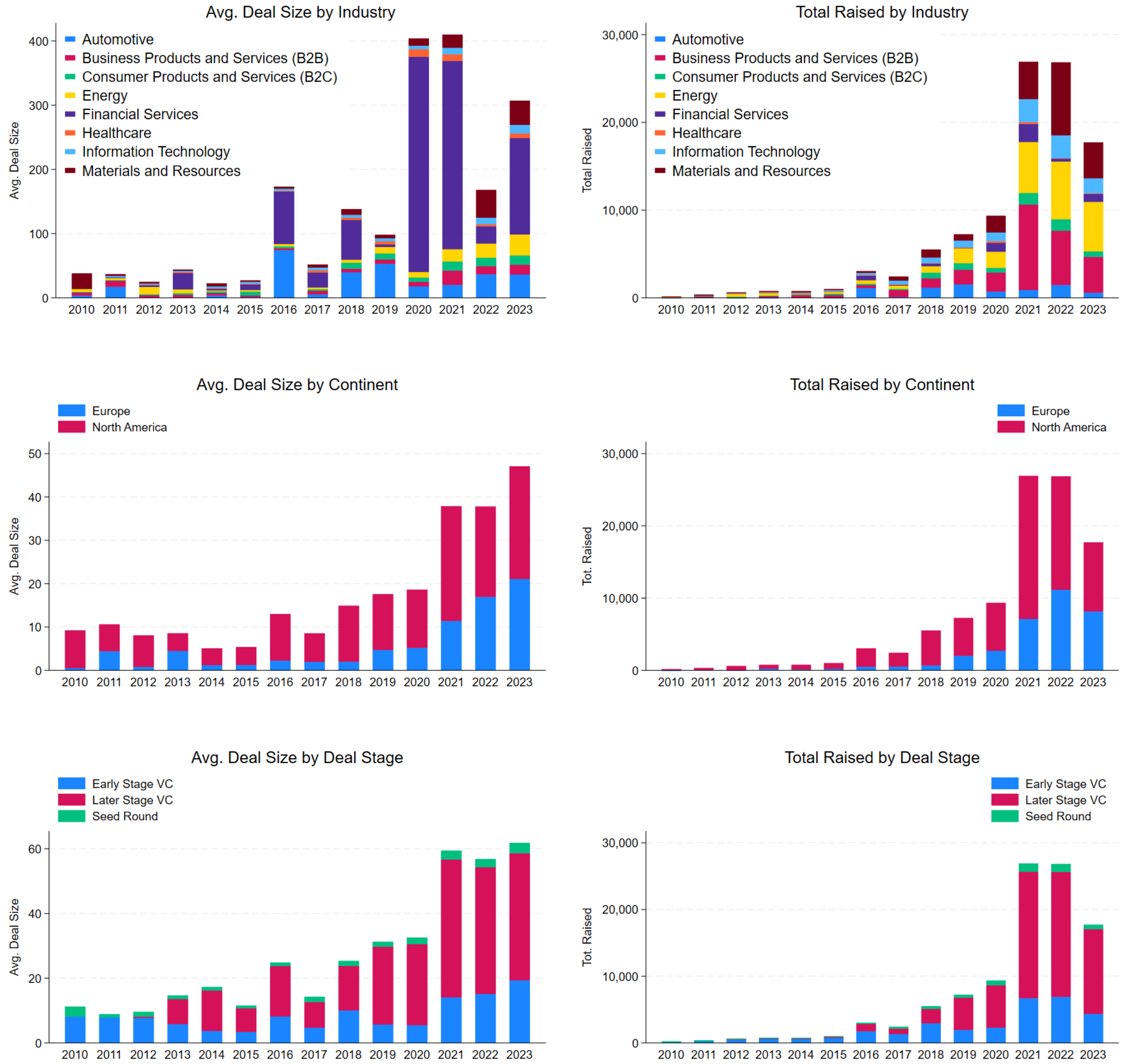
Figure 1: Investment Amount and ERP per unit



This figure reports the average deal size and total amount raised in $M per year by ERP per unit bins for climate-tech startups deals. Startups are sorted into terciles based on ERP per unit, with tercile 1 comprising those with the lowest ERP per unit. The sample includes climate-tech startups funded in North America and Europe between 2010 and 2023.

Figure 2: Industry, Continent, and Deal Stage Break Down



This figure reports the average deal size and total amount raised in $M per year by industry, continent and deal stage. The industry are defined following the definitions from PitchBook. The sample includes climate-tech startups funded in North America and Europe between 2010 and 2023.

Table 1: Summary Statistics

Variable	Obs.	Mean	Median	St. Dev.
Deal Size (ln)	8,110	1.34	1.05	1.22
ERP per Unit	8,110	0.31	0.18	0.34
Startup Age	8,110	3.85	3.00	2.82
Employees (ln)	7,855	3.10	3.04	1.15
Patents (ln)	8,110	1.31	0.00	1.60
Impact Investors	4,730	0.12	0.00	0.32
Valuation (ln)	3,646	2.91	2.73	1.46

This table reports the summary statistics for the variables used to analyze the relationship between ERP and deal size. Impact Investor represents an indicator variable equal to 1 for deal that have at least one impact investor in the syndicate. Investors are defined as “impact“ following PitchBook’s definition.

Table 2: Deal Size and ERP per Unit Change

	(1)	(2)	(3)	(4)
ERP per Unit	0.119***	0.117***	0.117***	
	(3.46)	(3.42)	(3.50)	
Startup Age	-0.027**	-0.029**	-0.028**	-0.028**
	(-2.26)	(-2.49)	(-2.60)	(-2.50)
Employees (ln)	0.479***	0.489***	0.490***	0.488***
	(8.22)	(8.35)	(8.51)	(8.42)
Patents (ln)	0.070***	0.072***	0.072***	0.073***
	(3.00)	(2.99)	(2.91)	(2.97)
1(Q5 ERP per Unit)				0.074***
				(3.77)
Country F.E.	Y	N	N	N
Year F.E.	Y	N	N	N
Industry F.E.	Y	Y	N	N
Deal Stage F.E.	Y	Y	Y	Y
Country-Year F.E.	N	Y	Y	Y
Industry-Year F.E.	N	N	Y	Y
Observations	7,849	7,801	7,795	7,795
R^2	0.500	0.511	0.517	0.516

This table reports the OLS regression estimates with deal size (ln) as the dependent variable. ERP per Unit represents the emission reductions per unit change (%) of startup i. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 ERP per Unit is an indicator equal to 1 for startups in the ERP quintile 5 (highest ERP) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Summary Statistics for Investor-Level Variables in Field Experiment

Variable	Obs.	Mean	Median	St. Dev.
Female	70	0.60	1.00	0.49
Angel Investor	70	0.47	0.00	0.50
Check Size: $0–10k	70	0.24	0.00	0.42
Check Size: $10–25k	70	0.21	0.00	0.40
Check Size: $25–50k	70	0.03	0.00	0.17
Check Size: $50–100k	70	0.04	0.00	0.21
Check Size: $100–250k	70	0.12	0.00	0.32
Check Size: $250k+	70	0.37	0.00	0.48
Investment Experience (# of Startups)	70	34.87	13.00	65.25
Prior climate-tech Investment (0-No, 1-Yes)	70	0.68	1.00	0.47
ERP Rank (1-Most Important, 5-Least Important)	70	3.74	4.00	1.11
ERP Importance (1-Least, 5-Most)	70	3.51	4.00	0.96
ERP Familiarity (0-No, 1-Yes)	70	0.50	0.50	0.50
ERP in Decision Making (1-Least, 5-Most)	70	2.85	3.00	1.32
Previously Collected ERP (0-No, 1-Yes)	70	0.24	0.00	0.42
Commercial Motivation (1-Least, 5-Most)	70	3.83	4.00	0.70
Environmental Motivation (1-Least, 5-Most)	70	3.48	3.00	0.84
Duty over Return on Investment (0-No, 1-Yes)	70	0.59	1.00	0.49
Trust in ERP Info (1-Least, 5-Most)	70	2.99	3.00	0.87

This table reports the summary statistics of the investor-related variables for the field experiment on investors' investment interest in climate-tech startups.

Table 4: Main Effects of ERP and High ERP on Investors Considering Investing in Startups

	ERP Only			ERP × High ERP		
	(1)	(2)	(3)	(4)	(5)	(6)
ERP	0.0051	0.0081	0.015	-0.040	-0.038	-0.034
	(0.059)	(0.049)	(0.049)	(0.068)	(0.057)	(0.057)
ERP × High ERP				0.090	0.093*	0.097*
				(0.065)	(0.055)	(0.055)
Investor FEs	No	Yes	Yes	No	Yes	Yes
Startup FEs	No	No	Yes	No	No	Yes
Observations		1,184			1,184	
Adj. R^2	0.00	0.33	0.37	0.00	0.34	0.37
Mean (st. dev)			2.64 (0.93)			

This table presents regression estimates of ERP effects on investor interest in startups. Columns (1)-(3) report the main effects of ERP with incremental inclusion of fixed effects. Columns (4)-(6) add an interaction with High ERP (above-median ERP indicator). All models use the same sample. Robust standard errors are provided in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Interaction Table for Investors Considering Investing in Startups

	i) General Investor Characteristics					ii) ERP Importance		iii) ERP Expertise			iv) Investment Motivation			v) Trust in ERP
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ERP	0.002	-0.013	-0.081	-0.053	0.042	-0.120	0.001	-0.021	-0.102	-0.087	-0.062	0.051	0.051	-0.142
	(0.090)	(0.078)	(0.088)	(0.090)	(0.101)	(0.093)	(0.092)	(0.082)	(0.086)	(0.066)	(0.121)	(0.211)	(0.091)	(0.115)
High ERP	0.083	0.056	0.147*	0.144*	-0.030	-0.091	0.034	0.164**	0.174**	0.145**	0.179	0.134	0.109	0.168
	(0.085)	(0.074)	(0.083)	(0.084)	(0.097)	(0.107)	(0.088)	(0.077)	(0.082)	(0.063)	(0.115)	(0.200)	(0.085)	(0.109)
ERP × Moderator	-0.060	-0.048	0.089	0.020	-0.105	0.124	-0.056	-0.019	0.118	0.240*	0.036	-0.093	-0.134	0.141
	(0.115)	(0.113)	(0.116)	(0.122)	(0.121)	(0.097)	(0.116)	(0.114)	(0.113)	(0.134)	(0.137)	(0.218)	(0.116)	(0.131)
High ERP × Moderator	0.024	0.088	-0.096	-0.037	0.180	0.268**	0.101	-0.145	-0.135	-0.224*	-0.105	-0.040	-0.029	-0.095
	(0.110)	(0.108)	(0.110)	(0.116)	(0.117)	(0.133)	(0.111)	(0.108)	(0.108)	(0.128)	(0.130)	(0.207)	(0.110)	(0.125)
Evaluator FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Startup FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moderator	Gender (Female)	Angel Investor	Check Size	Experience	Prior Climate Invest.	ERP Rank	ERP Importance	ERP Familiarity	ERP in Decision	ERP Data Coll.	Comm. Motivation	Env. Motivation	Duty over ROI	Trust in ERP
Observations	1,184	1,184	1,156	1,020	1,156	1,173	1,184	1,156	1,184	1,156	1,184	1,184	1,156	1,184
Adjusted R^2	0.319	0.319	0.317	0.322	0.318	0.319	0.319	0.318	0.320	0.319	0.319	0.319	0.318	0.320

This table presents interaction effects between ERP treatments and investor-level moderators on the continuous measure of investment interest. Each column displays the regression estimate for one moderator. Evaluator fixed effects are included in all specifications. Robust standard errors are provided in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Valuation and ERP per Unit Change

	(1)	(2)	(3)	(4)
ERP per Unit	0.220***	0.233***		
	(0.038)	(0.041)		
Startup Age	0.010	0.005	0.006	0.007
	(0.021)	(0.019)	(0.019)	(0.018)
Employees (ln)	0.598***	0.613***	0.609***	0.610***
	(0.031)	(0.026)	(0.026)	(0.028)
Patents (ln)	0.081***	0.083***	0.085***	0.086***
	(0.014)	(0.012)	(0.012)	(0.013)
1(Q5 ERP per Unit)			0.140***	0.144***
			(0.038)	(0.037)
Country F.E.	Y	N	N	N
Year F.E.	Y	N	N	N
Industry F.E.	Y	Y	N	N
Deal Stage F.E.	Y	Y	Y	Y
Country-Year F.E.	N	Y	Y	Y
Industry-Year F.E.	N	N	Y	Y
Observations	3,579	3,551	3,551	3,541
R^2	0.631	0.644	0.643	0.649

This table reports the OLS regression estimates with valuation (ln) as the dependent variable. ERP per Unit represents the emission reductions per unit change (%) of startup s. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 ERP per Unit is an indicator equal to 1 for startups in the ERP quintile 5 (highest ERP) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Deal Size and ERP per Unit Change - Negative Policy Shock

	(1)	(2)	(3)	(4)
ERP per Unit	0.142***			
	(0.032)			
1(Trump Pres.) × ERP per Unit	-0.151***	-0.110***		
	(0.036)	(0.018)		
Startup Age	-0.028**		-0.028**	
	(0.011)		(0.011)	
Employees (ln)	0.490***		0.488***	
	(0.058)		(0.058)	
Patents (ln)	0.072***		0.073***	
	(0.025)		(0.025)	
1(Q5 ERP per Unit)			0.092***	
			(0.020)	
1(Q5 ERP per Unit) × 1(Trump Pres.)			-0.131***	-0.059***
			(0.023)	(0.012)
Country-Year F.E.	Y	Y	Y	Y
Industry-Year F.E.	Y	Y	Y	Y
Deal Stage F.E.	Y	Y	Y	Y
Startup F.E.	N	Y	N	Y
Observations	7,795	6,927	7,795	6,927
R^2	0.517	0.759	0.516	0.759

This table reports the OLS regression estimates with deal size as the dependent variable. ERP per Unit represents the emission reductions per unit change (%) of startup s. Trump Pres. is an indicator equal to 1 for deals of U.S. Startups in the years of the first U.S. presidency of Donald Trump (2017-2020). Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 ERP per Unit is an indicator equal to 1 for startups in the ERP quintile 5 (highest ERP) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Impact Investor Involvement and Emission Reduction per Unit Change

	(1)	(2)	(3)	
ERP per Unit	0.056***	0.056**	0.057**	
	(0.020)	(0.020)	(0.021)	
Startup Age	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Employees (ln)	0.020***	0.021***	0.021***	0.021***
	(0.003)	(0.003)	(0.003)	(0.003)
Patents (ln)	-0.009*	-0.008*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.005)
1(Q5 ERP per Unit)				0.056***
				(0.018)
Country F.E.	Y	N	N	N
Year F.E.	Y	N	N	N
Industry F.E.	Y	Y	N	N
Deal Stage F.E.	Y	Y	Y	Y
Country-Year F.E.	N	Y	Y	Y
Industry-Year F.E.	N	N	Y	Y
Observations	4,647	4,603	4,594	4,594
R^2	0.060	0.085	0.096	0.097

This table reports the OLS regression estimates with likelihood of impact investor involvement as the dependent variable. An investor is defined as "impact" following the PitchBook classification. ERP per Unit represents the emission reductions per unit of startup s. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 ERP per Unit is an indicator equal to 1 for startups in the ERP quintile 5 (highest ERP) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A for

Early Stage Climate Investors and Climate Impact

Table A1: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Deal Size (ln)	1.00					
(2) ERP per Unit	0.02	1.00				
(3) Tot. Avoided Emissions 2035 (asinh)	0.02	0.12	1.00			
(4) Age	0.36	-0.01	0.03	1.00		
(5) Employees (ln)	0.45	-0.02	0.03	0.24	1.00	
(6) Patents (ln)	0.19	-0.03	0.07	0.24	0.25	1.00

This table reports the correlation matrix for the variables from the PitchBook dataset and Koi used in the historical data analysis.

Table A2: Robustness Tests

Dependent variable	Deal size			Deal size / Empl.	
	(1)	(2)	(3)	(4)	(5)
ERP per unit (asinh)	0.130***				
	(3.48)				
ERP per Unit		0.117***	0.117***	0.041***	0.041***
		(3.80)	(2.76)	(5.87)	(5.21)
Startup Age	-0.028**	-0.028***	-0.028***	-0.009*	-0.009*
	(-2.60)	(-3.06)	(-3.39)	(-1.76)	(-1.83)
Employees (ln)	0.490***	0.490***	0.490***	-0.036***	-0.036***
	(8.51)	(14.93)	(20.04)	(-3.94)	(-4.01)
Patents (ln)	0.072***	0.072***	0.072***	0.017*	0.017*
	(2.91)	(6.06)	(9.27)	(2.00)	(1.95)
S.E. Cluster	Country	Country-Year	Industry-Year	Country	Country
Deal Stage F.E.	Y	Y	Y	Y	Y
Industry F.E.	N	N	N	Y	N
Country-Year F.E.	Y	Y	Y	Y	Y
Industry-Year F.E.	Y	Y	Y	N	Y
Observations	7,795	7,795	7,795	7,801	7,795
R^2	0.517	0.517	0.517	0.305	0.315

This table reports the OLS regression estimates with deal size (ln) (columns (1)-(3)) and ratio of deal size and employees (ln) (columns (4)-(5)) as the dependent variables. ERP per Unit (asinh) represents the emission reductions per unit change of startup i transformed using the inverse hyperbolic sine function. ERP per Unit represents the emission reductions per unit of startup s. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the different levels. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Deal Size and Total Avoided Emissions

	(1)	(2)	(3)	(4)
Tot. Avoided Emissions 2035	0.012**	0.011**	0.011**	
	(2.42)	(2.18)	(2.18)	
Startup Age	-0.026**	-0.028**	-0.028**	-0.027**
	(-2.16)	(-2.39)	(-2.49)	(-2.46)
Employees (ln)	0.478***	0.488***	0.489***	0.488***
	(8.19)	(8.31)	(8.47)	(8.46)
Patents (ln)	0.071***	0.073***	0.073***	0.073***
	(3.05)	(3.05)	(2.97)	(2.97)
1(Q5 Tot. Avoided Emissions 2035)				0.047*
				(1.81)
Country F.E.	Y	N	N	N
Year F.E.	Y	N	N	N
Industry F.E.	Y	Y	N	N
Deal Stage F.E.	Y	Y	Y	Y
Country-Year F.E.	N	Y	Y	Y
Industry-Year F.E.	N	N	Y	Y
Observations	7,849	7,801	7,795	7,795
R^2	0.500	0.511	0.516	0.516

This table reports the OLS regression estimates with deal size (ln) as the dependent variable. Tot. Avoided Emissions 2035 represents the annual total avoided emissions of startup i up to 2035. This variable is transformed using the inverse hyperbolic sine function. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 ERP per Unit is an indicator equal to 1 for startups in the ERP quintile 5 (highest ERP) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Main Effects of ERP and High ERP on Investors Considering Investing in Startups - SE Robustness

	(1)	(2)	(3)
Panel A: SEs Clustered by Investor Level			
ERP	0.0051	0.0081	0.015
	(0.044)	(0.045)	(0.048)
ERP	-0.040	-0.038	-0.034
	(0.049)	(0.051)	(0.051)
ERP × High ERP	0.090	0.093	0.097
	(0.067)	(0.069)	(0.066)
Panel B: SEs Clustered by Startup Level			
ERP	0.0051	0.0081	0.015
	(0.070)	(0.052)	(0.050)
ERP	-0.040	-0.038	-0.034
	(0.074)	(0.059)	(0.052)
ERP × High ERP	0.090	0.093**	0.097**
	(0.066)	(0.043)	(0.033)
Fixed Effects and Model Info			
Investor fixed effects	No	Yes	Yes
Startup fixed effects	No	No	Yes
Observations	1,184	1,184	1,184
R^2 (ERP Model/ERP x High ERP Model)	0 / 0.0017	0.33 / 0.34	0.37 / 0.37
Mean (st. dev)		2.64 (0.93)	

This table presents regression estimates of ERP effects on investor interest in startups. Columns (1)-(3) report the main effects of ERP with incremental inclusion of fixed effects. Standard errors (provided in parentheses) are clustered by investor level in Panel A and by startup level in Panel B. All models use the same sample. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Variable Descriptions for Investor Moderators

Type	Name	Details
Investor general characteristics	Gender	Manually collected based on names. Dummy value that takes the value of 1 if gender is female, and 0 if male.
	Angel	Manually collected. Dummy that takes the value of 1 if the investor is an angel investor and 0 if it is part of venture capital firm.
	Check size	From the exit survey. Question: What is your typical investment check size (in USD)? Answers: "0 -10,000", "10,000 - 25,000", "25,000 - 50,000", "50,000 - 100,000", "100,000 - 250,000", and "250,000+". Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.
	Experience	From the exit survey. Question: In total, how many companies have you invested in? Answers: open. Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.
Importance of ERP	Prior Climatech investment	From the exit survey. Question: Have you invested in climate-tech startups before? Answers: "Yes", "No". We created a dummy that takes the value of 1 if answer is "Yes".
	ERP rank	From the exit survey. Question: Please rank order which information about the startup influenced your investment interest decision the most: i) startup description, ii) company website, iii) ERP, iv) Founding team, v) Market size info. Answer: If ranked first, we assign a 1, second a 2, and so on to last a 5. Measure: We create a dummy that took the value of 1 if below or equal to the median, and 0 otherwise.
	ERP importance	From the survey. Question: Do you think ERP data is an important performance metric for a startup? Answers: continuous slider from 1 to 5 with labels at 1 ("definitively not"), 2 ("probably not"), 3 ("I don't know"), 4 ("Probably"), and 5 ("definitively yes"). Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.

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Type	Name	Details
Expertise with ERP	ERP familiarity	From the exit survey. Question: Before this evaluation, were you familiar with the concept of Emissions Reduction Potential (ERP)? Answers: “Yes”, “No”. We created a dummy that takes the value of 1 if answer is “Yes”.
	ERP prior use	From the exit survey. Question: Do you take ERP data into account when making investment decisions? Answers: continuous slider from 1 to 5 with labels at 1 (“definitively not”), 2 (“probably not”), 3 (“I don’t know”), 4 (“Probably”), and 5 (“definitively yes”). Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.
	ERP data collection	From the exit survey. Question: In your previous investment evaluations of climate-tech startups, did you regularly collect information on the ERP of startups? Answers: “Yes”, “No”, “Not applicable. I have not previously evaluated climate-tech startups before”. Measure: We created a dummy that takes the value of 1 if answer is “Yes”.
Motivation for investment	Commercial motivation	From the exit survey. Question: How much did the startups’ commercial potential influence your answers? Answers: Continuous slider from 1 to 5 with labels at 1 (“Not at all”), 2 (“barely”), 3 (“it mattered but wasn’t the most important”), 4 (“it was one of the most important factors”), and 5 (“it was the single most important factor”). Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.

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Type	Name	Details
	Environmental motivation	From the exit survey. Question: How much did the startups' environmental impact influence your answers? Answers: Continuous slider from 1 to 5 with labels at 1 ("Not at all"), 2 ("barely"), 3 ("it mattered but wasn't the most important"), 4 ("it was one of the most important factors"), and 5 ("it was the single most important factor"). Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.
	Duty (over return)	From the exit survey. Question: When considering ERP in your investment decision, which statement do you agree with more? Answers: either "In a world where carbon-equivalent emissions will be priced, higher ERP means that the expected return on investment increases" or "Given climate change and the expected problems it will generate, it is the investor's duty to consider ERP, independent of the return on investment it can have." We create a dummy that took the value of 1 respondent chose the second sentence.
Trust in ERP	Trust in ERP information provided	From the exit survey. Question: Did you trust the ERP information that was provided? Answers: continuous slider from 1 to 5 with labels at 1 ("definitively not"), 2 ("probably not"), 3 ("I don't know"), 4 ("Probably yes"), and 5 ("definitively yes"). Measure: We create a dummy that took the value of 1 if above the median, and 0 otherwise.

Table A6: Correlation Matrix with Means and Standard Deviations of Investor-Level Variables

Variables	N	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Female	70	0.600	0.493	1.000													
(2) Angel Investor	70	0.471	0.503	0.187	1.000												
(3) Check Size	68	0.559	0.500	-0.116	-0.942***	1.000											
(4) Experience	70	0.586	0.496	-0.213	-0.484***	0.551***	1.000										
(5) Prior Climatech Investment	68	0.676	0.471	-0.240**	-0.419***	0.462***	0.484***	1.000									
(6) ERP Rank	69	0.594	0.495	0.038	-0.178	0.220*	0.134	0.060	1.000								
(7) ERP Importance	70	0.629	0.487	0.217*	-0.044	0.032	-0.073	0.167	-0.094	1.000							
(8) ERP Familiarity	68	0.500	0.504	0.210*	-0.295***	0.355***	0.149	0.189	0.000	0.182	1.000						
(9) ERP in Decision Making	70	0.571	0.498	0.118	0.008	-0.014	-0.084	0.019	-0.070	0.529***	0.118	1.000					
(10) ERP Data Collection	68	0.235	0.427	0.096	-0.245**	0.283**	0.128	0.235	-0.099	0.365***	0.347***	0.423***	1.000				
(11) Commercial Motivation	70	0.786	0.413	-0.071	-0.134	0.099	0.197	0.011	0.065	-0.041	-0.035	-0.101	0.044	1.000			
(12) Environmental Motivation	70	0.929	0.259	0.227	0.151	-0.250**	-0.233	-0.074	-0.231	0.361***	0.169	0.208	0.156	-0.010	1.000		
(13) Duty (Over ROI)	68	0.588	0.496	0.176	0.011	0.039	-0.117	0.060	-0.032	0.080	0.120	-0.021	0.041	-0.301	-0.007	1.000	
(14) Trust in ERP Info	70	0.757	0.432	0.014	-0.066	0.034	0.020	0.036	-0.267**	0.185	-0.034	0.317***	0.320***	-0.052	0.360***	0.000	1.000

This table displays Pearson correlation coefficients along with descriptive statistics, including observations (N), mean, and standard deviation (SD) for investor-level characteristics. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Valuation and Total Avoided Emissions

	(1)	(2)	(3)	(4)
Tot. Avoided Emissions 2035	0.243***	0.257***		
	(0.042)	(0.046)		
Startup Age	0.010	0.005	0.006	0.007
	(0.021)	(0.019)	(0.020)	(0.019)
Employees (ln)	0.598***	0.613***	0.609***	0.610***
	(0.031)	(0.026)	(0.025)	(0.028)
Patents (ln)	0.081***	0.083***	0.086***	0.087***
	(0.014)	(0.012)	(0.013)	(0.013)
1(Q5 Tot. Avoided Emissions 2035)			0.079***	0.080**
			(0.027)	(0.028)
Country F.E.	Y	N	N	N
Year F.E.	Y	N	N	N
Industry F.E.	Y	Y	N	N
Deal Stage F.E.	Y	Y	Y	Y
Country-Year F.E.	N	Y	Y	Y
Industry-Year F.E.	N	N	Y	Y
Observations	3,579	3,551	3,551	3,541
R^2	0.631	0.644	0.642	0.649

This table reports the OLS regression estimates with valuation (ln) as the dependent variable. Tot. Avoided Emissions 2035 represents the annual total avoided emissions of startup s up to 2035. This variable is transformed using the inverse hyperbolic sine function. Startup Age represents the years from the founding year. Employees (ln) represents the natural logarithm of employees. Patents (ln) represents the natural logarithm of one plus patent counts. Q5 Tot. Avoided Emissions 2035 is an indicator equal to 1 for startups in the Tot. Avoided Emissions 2035 quintile 5 (highest Tot. Avoided Emissions) and zero otherwise. Columns (1) through (4) progressively introduce various fixed effects. Standard errors are clustered at the country level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B
Net0Insight Field Experiment

We designed a second field experiment to assess whether investors respond more strongly to ERP signals than other types of climate-tech stakeholders. While the main experiment isolates the causal effect of ERP information on investors' stated investment interest, this additional experiment shifts focus to an upstream behavioral channel: *attention*.

We partnered with *NetZero Insight (N0i)*, a platform similar to PitchBook that focuses on a climate-tech startups, which distributes a monthly newsletter to over 2,600 subscribers. We randomized the subject line of the July 2024 newsletter (issue #68) and analyzed both open rates (a behavioral proxy for attention) and click behavior on the newsletter content (which had a section on ERP). Of the 2,600 recipients, 585 were investors, with the remainder comprising corporate employees (605), startup founders (245), academics (110), and government or NGO officials (90).

A. Experimental Design and Randomization

This subsection details the subject-line treatment embedded in the July 2024 newsletter and outlines how recipients were randomly assigned. We conducted a field experiment embedded in issue #68 of the *NetZero Insight* (N0i) newsletter, which was distributed on July 17, 2024. The study was pre-registered in the AEA RCT Registry (AEARCTR-0013616). The experimental manipulation was implemented through the subject line of the email delivering the newsletter. Recipients in the treatment group received an email with the subject: *"Which climatech technology reduces emissions the most? — Net0i #68"*. The control group received the standard subject line used by N0i for that edition, which read: *"H1 2024: Are There Reasons for Optimism? — Net0i #68"*. Our main outcome of interest is the email open rate—a behavioral proxy for attention—and we specifically test whether investors respond more strongly than other types of recipients.

Randomization was stratified by both the recipient's stakeholder type and whether they were a paying customer of N0i. Approximately 110 subscribers were paying customers, including roughly 45 investors, 30 corporate executives, and 10 government/NGO officials.[1]experiment replaced an earlier version pre-registered in May 2024 and implemented via newsletter #66. Due to a miscommunication during execution, the treatment subject line used the acronym

"ERP" instead of spelling out "emissions reduction potential," which was likely unfamiliar to recipients. This resulted in unusually low open rates in the treatment group (under 7%, compared to N0i's typical 30% average). To address this, we abandoned the May version and re-ran the experiment in July using revised language. All updates were documented in the AEA RCT Registry. We also accounted for the initial treatment assignment (control, treatment 1, and treatment 2) from the failed May experiment in the new randomization.

To assess statistical power, we calculated the minimum detectable effect (MDE) for the email open rate, using historical open rate data from previous N0i newsletters. The average open rate is approximately 28%, with a standard deviation of 44.9%. Given a total sample size of 2,600 recipients, the MDE is about 11% of a standard deviation (roughly 5 percentage points). For the investor subgroup (N = 585), the corresponding MDE is 25% of a standard deviation (about 11 percentage points). Incorporating baseline data from the June 2024 newsletter (issue #67) into a difference-in-differences design improves power: the MDE for investors drops to 21% of a standard deviation, or approximately 9.5 percentage points.

The content of the newsletter itself was held constant across treatment and control groups. Both versions included a featured section on ERP. To complement our open-rate analysis, we also examine whether investors—among those who opened the email—were more likely than other stakeholder types to click on the ERP section. This analysis is observational and leverages fixed effects for both recipient type and newsletter section to isolate differential engagement.

B. Data and Variables

We describe the unit of analysis and outcome variables for the open-rate and click-behavior analyses, along with key covariates used in the regression models. Our analysis combines experimental and observational data from recipients of the July 2024 edition of the *NetZero Insight* (N0i) newsletter. For the open-rate analysis, the unit of observation is the individual email recipient ($N = 2,626$), and the primary outcome is a binary variable equal to one if the email was opened. Key covariates include treatment assignment (ERP-framed subject line), stakeholder type (e.g., investor, corporate, academic), and their interaction. For the click-rate analysis, the unit of observation is the "recipient and newsletter section" pair, and the outcome variables are both a binary indicator for whether any click occurred on a given section (extensive margin) and the total number of clicks per section (intensive margin).

C. ERP-Framed Subject Lines and Email Open Rates by Stakeholder Type

We begin by assessing whether investors, relative to other stakeholder groups, are more likely to open emails when the subject line highlights emissions reduction potential. A simple t-test comparing treated and control recipients shows no significant difference: the mean open rate for the treatment group was 0.088, compared to 0.082 for the control group, yielding a p-value of 0.601 (see second row of Table B2) . Thus, we do not reject the null hypothesis of no difference in open rates.

We then estimate the following regression models to explore heterogeneity in treatment response by recipient type:

$$Open_{ij} = b_0 + b_1 Treatment_i + \delta_j + e_i \tag{6}$$

$$Open_{ij} = b_0 + b_1 Treatment_i + b_2 Treatment_i \times Investor_j + \delta_j + e_i \tag{7}$$

In these models, $Open_{ij}$ is a binary variable equal to 1 if recipient i opened the newsletter, and 0 otherwise. The variable $Treatment_i$ indicates assignment to the ERP-framed subject line. $Investor_j$ is a dummy for investor recipients, and δ_j captures recipient type fixed effects (e.g., investor, corporate, academic). The coefficient b_1 measures the average difference in open rates between treatment and control across all recipient types, while b_2 captures the differential treatment effect for investors relative to non-investors—our main parameter of interest.

As shown in Table B1, we find no statistically significant difference in open rates between treatment and control overall, nor do we find evidence that investors were more responsive to the ERP-framed subject line compared to other recipient groups.

To further probe treatment effects, we implement a difference-in-differences (DiD) analysis using newsletter #67 (June 2024) as a baseline and newsletter #68 (July 2024) as the post-treatment period. Table B2 presents the raw mean open rates for each group in both periods. While no significant difference emerges in newsletter #68 (“After”), the baseline newsletter #67 (“Before”) shows a statistically significant difference of 0.027 in open rates between the groups, with a p-value ¡ 0.1.

To account for these pre-treatment differences, we estimate the following DiD models:

$$Open_{it} = b_0 + b_1 Treatment_i + b_2 Treatment_i \times Post_t + \gamma_i + \tau_t + e_{it}\,; \tag{8}$$

$$\begin{aligned} Open_{it} = b_0 + b_1 Treatment_i + b_2 Treatment_i \times Post_t + \\ b_3 Treatment_i \times Post_t \times Investor_j + b_4 Post_t \times Investor_j + \gamma_i + \tau_t + e_{it}. \end{aligned} \tag{9}$$

Here, t indexes time (June or July), $Post_t$ is a dummy equal to 1 for the July newsletter, γ_i denotes recipient fixed effects, and τ_t captures time fixed effects. The coefficient b_3 is the key interaction term, capturing whether investors responded differently to the ERP subject line in the post-treatment period, relative to other recipient types.

The results, shown in Table B3, confirm our earlier findings: there is no evidence that investors were more likely than other recipients to open the ERP-framed email. Notice, however, that in this DiD specification the treatment subject line increases the likehihood of opening the email. Taken together, these analyses suggest that while an ERP focused subject seems to attract the attention of newsletter recipients, it does so equally across investors and non-investors.

D. Descriptive Evidence on ERP Content Engagement by Stakeholder Type

We next examine whether, conditional on opening the newsletter, investors were more likely than other stakeholder types to engage with ERP-related content. The July 2024 newsletter contained five main sections: (1) "What is Emissions Reduction Potential (ERP) and why it matters," (2) "Optimistic climate-tech funding outlook," (3) "Last Call to the State of climate-tech Webinar," (4) "Must attend conferences," and (5) "Latest climate-tech Deals."

While this analysis is non-experimental, we observe clicking behavior of a recipient across many areas of the newsletter and thus were are able to plug newsletter recipient fixed effects, controlling for time invariant unobservable characteristics of the recipients.

In the treatment group, the ERP section appeared first, aligning with the ERP-focused subject line. In the control group, due to formatting constraints imposed by N0i—which requires the first section of the newsletter to match the subject line—the "Optimistic climate-tech funding outlook" section appeared first, and the ERP section appeared fourth. This variation in content placement allows us to explore whether investor engagement with ERP is driven primarily by the subject line "priming" the topic, or reflects broader organic interest regardless of presentation order. Because section position varies systematically across treatment arms—and we do not randomize section content independently—this analysis should be interpreted as descriptive of engagement behavior, not causal.

Click behavior serves as a proxy for attention or interest allocation. We measure engagement on two margins: the extensive margin (whether a section received any clicks) captures initial interest, while the intensive margin (total number of clicks) reflects depth of engagement.

To assess whether investors engaged more with ERP-related content than other types of recipients, we estimate the following regression model using only recipients of the July newsletter:

$$Click_{is} = b_0 + b_1 Investor_j \times ERPsection_s + \gamma_i + \epsilon_s + e_{is} \tag{10}$$

Here, $Click_{ijs}$ denotes clicks made by recipient i (which is a stakeholder type j) on newsletter section s. The coefficient of interest, b_1, captures whether investors are more likely than other recipients—such as corporate employees, startup founders, academics, or government/NGO representatives—to engage with the ERP section. We include recipient fixed effects γ_i to control for individual-level variation in clicking behavior and section fixed effects ϵ_s to account for average differences across sections.

Table B4 reports the results. In the first two columns, we restrict the sample to recipients who opened the newsletter in either the control or treatment group. We find that investors are significantly more likely to engage with the ERP section than other stakeholder types, particularly on the intensive margin, where the estimated coefficient is statistically significant at the 10% level. The magnitude of the effect is substantial—comparable to the average number of clicks per section overall, and slightly above the ERP section mean.

Columns 3 and 4 present robustness checks using the full sample of openers, regardless of treatment assignment. The positive association between investor status and ERP engagement persists, though the significance level declines. This suggests that investor interest in ERP is not driven solely by the ERP-themed subject line, but reflects broader curiosity or relevance of the topic.

Importantly, effect sizes are larger among recipients who opened the ERP-framed email. This supports the interpretation that ERP priming may amplify attention among investors already predisposed to care about the topic, highlighting the role of selective attention in shaping downstream engagement.

Table B1: Opening Rate Regression Analysis

	(1)	(2)
Treatment	0.006 (0.011)	0.011 (0.012)
Treatment × Investor		-0.023 (0.029)
Strata FE	Yes	Yes
R-squared	0.0129	0.0132
Observations	2,626	2,626
Mean	0.0849	0.0849

This table presents OLS regressions estimating the effect of receiving a treatment version of the newsletter on whether recipients opened the email. Column (2) includes an interaction term for investor recipients. Robust standard errors are provided in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B2: Mean Opening Rate Between Treatment and Control, Before and After

	Before	After
Control	0.219 (1,312)	0.082 (1,312)
Treatment	0.193 (1,307)	0.088 (1,307)

This table restricts the sample to recipients who received both Newsletter #67 (June 2024) and Newsletter #68 (July 2024). Numbers in parentheses indicate the number of observations. The table compares mean open rates for control and treatment groups before and after the intervention. The difference in pre-treatment open rates is statistically significant at $p<0.1$.

Table B3: Difference-in-Difference Regression Analysis

	(1)	(2)
Post	-0.137*** (0.012)	-0.136*** (0.013)
Treatment × Post	0.032** (0.016)	0.032** (0.016)
Treatment × Post × Investor		0.005 (0.041)
Investor × Post		-0.007 (0.029)
Recipient FE	Yes	Yes
R-squared	0.66	0.66
Observations	5,238	5,238
Mean	0.146	0.146

This table reports a difference-in-differences specification assessing whether treatment recipients increased their likelihood of opening emails after the intervention, relative to control. Robust standard errors are provided in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table B4: Click Behavior on ERP Newsletter Section

	Full Sample		Treatment Only		Control Only	
	Dummy Click	# Clicks	Dummy Click	# Clicks	Dummy Click	# Clicks
ERP Section × Investor	0.040 (0.051)	0.147* (0.088)	0.065 (0.087)	0.192 (0.153)	0.026 (0.053)	0.116 (0.098)
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes
Newsletter Section FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Opened Email		Treatment Group		Control Group	
R-squared	0.20	0.22	0.21	0.25	0.19	0.20
Observations	1,115	1,115	575	575	540	540
Mean Dep. Var.	0.096	0.146	0.110	0.165	0.081	0.126
Mean ERP Section	0.094	0.126	0.139	0.182	0.046	0.065

This table analyzes whether investors clicked on the ERP section in the email. Results are broken down by overall sample, treatment group, and control group. Columns include both binary and count outcomes. Robust standard errors are provided in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.