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**Carbon Pricing and
Corporate Biodiversity
Footprints: Environmental
Co-Benefits and Resource
Use Trade-Offs**

*By Pejman Abedifar, Soroush
Kamyab, Steven Ongena*

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Carbon Pricing and Corporate Biodiversity Footprints: Environmental Co-Benefits and Resource Use Trade-Offs

PEJMAN ABEDIFAR, SOROUSH KAMYAB, and STEVEN ONGENA *

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ABSTRACT

This paper examines how carbon pricing affects corporate biodiversity footprints using firm-level panel data from 2018–2024. Because such policies target greenhouse gas emissions, their broader biodiversity effects are theoretically ambiguous: cleaner production may reduce pollution and land use pressures, while the low-carbon transition may intensify resource extraction. Exploiting Washington State’s Cap-and-Invest Program as a quasi-experimental shock, we estimate difference-in-differences effects across biodiversity-pressure categories. We find that carbon pricing reduces firms’ overall biodiversity footprints by about 16.5%, driven by reductions in pressures associated with greenhouse gas emissions, land use, air pollution, and water pollution. In contrast, resource-related pressures increase, consistent with greater material demand during the transition. These reductions in biodiversity pressures are stronger among firms with higher pre-treatment emissions intensity, but weaker among rapidly growing firms. Overall, carbon pricing generates broad environmental co-benefits but also creates resource use trade-offs.

Keywords: *Biodiversity; Climate Change; Corporate Biodiversity Footprint; Carbon Pricing*

JEL Classification: G34; G38; Q56; Q58

* Pejman Abedifar (Corresponding author) is at the Tehran Institute for Advanced Studies, Khatam University, Iran, and Center for Responsible Banking and Finance, School of Management, University of St Andrews, Scotland, UK. Soroush Kamyab is at the Tehran Institute for Advanced Studies, Khatam University, Iran. Steven Ongena is at the University of Zurich, Swiss Finance Institute, KU Leuven, NTNU Business School, and CEPR. We sincerely appreciate Alexander Wagner for his helpful comments. We also thank Alexander Wagner and Thomas Rauter for their assistance in facilitating and arranging access to the biodiversity data. E-mail addresses: pa31@st-andrews.ac.uk (P. Abedifar); s.kamyab@teias.institute (S. Kamyab); steven.ongena@df.uzh.ch (S. Ongena).

I. Introduction

Environmental regulations play a crucial role in promoting environmental sustainability by influencing firms’ production choices and environmental externalities (OECD, 2011; IPCC, 2014). These regulations can be broadly categorized into two groups: (a) policies that target carbon emissions and global warming exclusively (hereinafter *carbon pricing* regulations); and (b) policies that take a broader environmental perspective, addressing multiple dimensions of ecological harm such as land use change, water pollution, and ecosystem degradation (hereinafter *biodiversity-oriented* regulations).

An important but underexplored question is the impact of carbon pricing regulations on biodiversity outcomes. Carbon pricing regulations may affect corporate biodiversity footprints through several distinct economic and technological mechanisms. On the one hand, these policies may reduce biodiversity pressures by increasing the relative cost of carbon-intensive production. Facing higher emissions costs, firms may respond by improving energy efficiency, reducing fossil fuel consumption, adopting cleaner production technologies, and optimizing operational processes (Martin et al., 2014; Calel and Dechezleprêtre, 2016). Because carbon-intensive activities are often jointly associated with other environmentally harmful externalities (Greenstone, 2003; Shapiro and Walker, 2018), these adjustments may generate spillover reductions in multiple biodiversity pressure components beyond greenhouse gas emissions alone. For example, lower fossil fuel combustion may simultaneously reduce sulfur dioxide, nitrogen oxides, particulate matter, and toxic emissions that contribute to air and water pollution (Fowlie, 2010). Similarly, improvements in production efficiency may reduce waste generation, material intensity, and environmental disturbance associated with extraction, transportation, and industrial processing (Berman and Bui, 2001; Copeland and Taylor, 2004). To the extent that firms substitute toward cleaner and more efficient technologies, carbon pricing may therefore generate broader ecological co-benefits and reduce aggregate corporate biodiversity footprints.

In addition, carbon pricing may induce organizational and strategic adjustments within firms that indirectly affect biodiversity outcomes. Regulatory pressure may incentivize firms to modernize production systems, redesign supply chains, improve environmental monitoring, and accelerate green innovation (Porter and Linde, 1995; Calel and Dechezleprêtre, 2016). Such adjustments may reduce environmental inefficiencies embedded in production networks and encourage the adoption of cleaner inputs and lower-impact operating practices. Financial markets and stakeholders may further reinforce these incentives by increasing scrutiny of firms’ environmental performance following climate policy adoption (Matsumura et al., 2014; Krüger, 2015), thereby amplifying firms’ incentives to reduce broader ecological impacts alongside carbon emissions (Flammer, 2021; Bolton and Kacperczyk, 2021).

On the other hand, the transition toward low-carbon production may itself generate new biodiversity pressures through input substitution and supply-chain reconfiguration. Compliance with carbon pricing regulations often requires increased deployment of renewable energy technologies, electrification systems, battery storage, and low-carbon infrastructure (IEA, 2021; Press et al., 2023), all of which rely heavily on the extraction of critical minerals and natural resources such as lithium, cobalt, nickel, copper, and rare earth elements. Expanding the production and processing of these materials may intensify mining activity, land use change, freshwater depletion, habitat fragmentation, and ecosystem degradation in resource-producing regions (Sonter et al., 2020).¹ These responses may increase biodiversity

¹ In addition, compliance with carbon pricing regulations may encourage firms to reorganize production net-

impacts associated with resource extraction, land disturbance, and upstream supply-chain activities even if direct emissions decline.

Importantly, these mechanisms may operate with different timing and intensity across environmental dimensions. Some responses—such as reductions in fossil fuel use, output adjustments, and improvements in energy efficiency leading to lower local pollution emissions—may emerge relatively quickly following policy enactment (Martin et al., 2014; Dechezleprêtre et al., 2022). In contrast, supply-chain restructuring, technological substitution, and material-intensive transition investments typically require longer planning horizons, capital turnover cycles, and infrastructure adjustment, and therefore tend to materialize more gradually over time (Fischer and Newell, 2008; Acemoglu et al., 2012; IEA, 2021).

Consistent with these mechanisms, our review of 10-K and 10-Q filings by firms indicates that many firms began evaluating compliance strategies shortly after the enactment of a carbon pricing regulation. These filings discuss a range of potential responses, including investments in energy efficiency, increased reliance on renewable energy sources, the purchase of emissions allowances and offsets, and broader operational adjustments to manage future compliance costs.² While some of these actions may reduce biodiversity pressures associated with greenhouse gas emissions and local pollution, others may increase pressures linked to resource extraction, land use, and supply-chain activities. Consequently, carbon pricing may simultaneously alleviate certain biodiversity pressures while exacerbating others, rendering its overall effect on corporate biodiversity footprints theoretically ambiguous and ultimately an empirical question.

Despite the global consensus on the urgency of addressing climate change—reinforced by the Paris Agreement (2015) and subsequent Conferences of the Parties—the biodiversity consequences of climate-focused regulations remain insufficiently understood. In the United States, several states and cities have maintained climate policy commitments across different political administrations. Washington State’s Cap-and-Invest Program, enacted under the Climate Commitment Act (CCA) in May 2021, represents one of the most ambitious state-level carbon pricing policies (Bohnet et al., 2026). This setting provides a useful opportunity to examine whether carbon pricing regulations reduce or unintentionally increase corporate biodiversity footprints.

The substantial decline in biodiversity over recent decades (WWF, 2024), and its potential adverse implications for ecosystems, economic activity, and financial stability (World Bank, 2020; IPBES, 2020; Garel et al., 2024), has led to growing recognition of the importance of biodiversity conservation. Global initiatives such as the Kunming Declaration (2021) and the Montreal Agreement (2022) reflect this increasing attention. However, it remains unclear whether carbon pricing policies are aligned with or in tension with these broader biodiversity objectives.

To study the effect of carbon pricing regulations on corporate biodiversity footprints, we

works or source carbon-intensive intermediate inputs from suppliers located in jurisdictions with less stringent environmental regulation, a phenomenon commonly referred to as carbon leakage (Cole, 2004; Copeland and Taylor, 2004; Levinson and Taylor, 2008; Dechezleprêtre and Sato, 2017; Dechezleprêtre et al., 2022).

² For example, in its Form 10-Q filed on November 2021, Avista Corporation stated: “The Climate Commitment Act signed into law in May 2021 requires natural gas distribution companies to reduce overall GHG emissions 45 percent below 1990 levels by 2030, 70 percent below 1990 levels by 2040 and 95 percent below 1990 levels by 2050, which may be achieved through increased energy efficiency and conservation measures, purchased emission allowances and offsets, and purchase of renewable natural gas. The Company has begun reviewing compliance options and expects the compliance costs for these legislated actions.” This disclosure indicates that firms began evaluating compliance strategies shortly after the enactment of the carbon pricing regulations by considering multiple options.

employ a difference-in-differences (DiD) design as our identification strategy, exploiting Washington State’s Cap-and-Invest Program as a quasi-natural experiment. Enacted under the Climate Commitment Act in May 2021, the program is one of the most ambitious U.S. state-level carbon pricing policies, aiming to reduce emissions 45 percent below 1990 levels by 2030 and achieve net-zero by 2050. It establishes a declining cap on greenhouse gas emissions and requires regulated entities emitting at least 25,000 metric tons of CO₂ equivalent annually to purchase emission allowances, covering sectors such as energy, transportation, manufacturing, and natural gas distribution. The policy operates through the Compliance Instrument Tracking System Service (CITSS),³ which identifies regulated market participants and tracks allowance holdings. Importantly, treatment assignment is plausibly exogenous, as the program follows California’s policy model and relies on pre-determined federal emissions reporting thresholds rather than firms’ biodiversity performance. Although implementation began in 2023, we use the 2021 legislative enactment as the policy shock to capture firms’ anticipatory responses, consistent with evidence that firms adjust investment and supply-chain decisions upon policy announcement. We identify treated firms using official CITSS registry data, defining treated firms as Covered Entities and Covered Sources subject to mandatory compliance under the Cap-and-Invest Program, supplemented by publicly listed firms headquartered in Washington that may be indirectly exposed to the regulation.

In this study, we adopt the corporate biodiversity footprint (CBF) framework developed by Iceberg Data Lab (IDL), which quantifies the annual impact of publicly listed firms on biodiversity at both global and local scales. The CBF captures multiple environmental pressure components, including greenhouse gas emissions, land use change, resource use, air pollution, water pollution, and invasive alien species.

To empirically examine the impact of carbon pricing regulation on corporate biodiversity outcomes, we construct a novel firm-level panel dataset by combining biodiversity impact metrics from IDL with financial statement information from Compustat. We merge these data with detailed firm-level financial characteristics such as size, leverage, profitability, liquidity, and market valuation. The resulting dataset forms an unbalanced panel covering the period 2018–2024 and includes 2,415 U.S. firms, yielding 12,292 firm-year observations after merging and cleaning.

To improve identification, we construct a matched control group of firms not subject to Washington State’s Cap-and-Invest Program using propensity score matching based on a rich set of financial characteristics. Each treated firm is matched to a number of control firms using nearest-neighbor matching with a caliper restriction to ensure similarity in estimated treatment propensity. The final estimation sample includes 247 firms, of which 74 are treated. This matching procedure substantially improves covariate balance and ensures that treated and control firms exhibit comparable observable characteristics, thereby strengthening the credibility of the difference-in-differences design. The final empirical framework compares dynamic changes in CBF outcomes between these two groups before and after the enactment of Washington State’s Cap-and-Invest Program in 2021, allowing us to estimate how carbon pricing regulation affects both total biodiversity impact and its underlying environmental pressure components.

Our baseline results suggest that carbon pricing regulation has meaningful but heterogeneous effects on corporate biodiversity outcomes. Following the enactment of Washington

³ These reports constitute the official registry of entities with active accounts in the Compliance Instrument Tracking System Service (CITSS), the administrative platform for the program. Each registered entity is assigned a unique CITSS identification number and categorized based on its regulatory status within the program.

State’s Cap-and-Invest Program, we observe a statistically significant decline in total corporate biodiversity footprints, driven primarily by reductions in greenhouse gas emissions, land use pressures, air pollution, and water pollution. These effects emerge shortly after policy enactment and are concentrated in the early post-treatment period. However, the response is not uniform across environmental dimensions. While most biodiversity pressure categories exhibit consistent declines, resource-related biodiversity impacts display a markedly different dynamic, with initial reductions followed by a reversal and a large increase in later years. Taken together, these findings suggest that carbon pricing regulations operate through multiple competing adjustment categories: while reductions in carbon-intensive production generate broad environmental co-benefits, low-carbon transition dynamics may simultaneously intensify upstream resource-related biodiversity pressures, likely reflecting increased demand for material-intensive technologies—such as electrification and renewable energy systems—induced by the Cap-and-Invest Program, particularly its revenue recycling and investment (i.e., “Invest”) component. Importantly, this increase in resource-related biodiversity pressures should be viewed as a potential by-product of the transition toward sustainability.

The heterogeneity analysis further shows that the effects of carbon pricing are shaped by firms’ initial environmental exposure and growth dynamics. Firms with higher pre-treatment GHG-related biodiversity footprints experience larger reductions in the GHG component after the policy, suggesting that the Cap-and-Invest Program generates stronger responses among firms with greater baseline carbon exposure. This pattern is consistent with a core carbon-pricing mechanism: firms with higher initial emissions-related biodiversity pressure have greater scope for abatement and face stronger incentives to reduce carbon-intensive activities once emissions become more costly. By contrast, faster-growing firms exhibit weaker GHG-related reductions after treatment. This suggests that expansion in assets, production capacity, facility activity, or input demand may partially offset the policy-induced decline in emissions-related biodiversity pressure. In other words, while carbon pricing encourages firms to reduce GHG-related impacts, growth-driven scale effects can dampen the magnitude of these improvements.

This research makes several important contributions to the environmental economics literature. First, while existing studies examine the effectiveness of carbon pricing regulations in reducing carbon emissions ([Greenstone, 2003](#); [Auffhammer and Kellogg, 2011](#); [Bushnell and Wolfram, 2012](#); [Bu and Shi, 2021](#); [Li et al., 2021](#)), as well as their effects on human well-being and firm performance ([Becker and Henderson, 2000](#); [Copeland and Taylor, 2004](#); [Bushnell and Wolfram, 2012](#); [Curtis, 2018](#)), we extend this literature by examining their spillover effects on corporate biodiversity footprint. Second, our findings suggest that the relationship between carbon pricing policy and biodiversity outcomes is heterogeneous across environmental pressure categories. While corporate biodiversity footprints associated with greenhouse gas emissions, land use, air pollution, and water pollution generally decline following carbon pricing regulation, resource use-related biodiversity pressure increases over time. This pattern is consistent with potential environmental trade-offs arising during the low-carbon transition, where decarbonization efforts may reduce some ecological pressures while simultaneously increasing demand for resource extraction and upstream material inputs required for cleaner technologies and supply chain [Sonter et al. \(2020\)](#). Importantly, this increase in resource-related biodiversity pressure should not necessarily be interpreted as evidence of reduced policy effectiveness, but rather as a potential by-product of the transition toward lower-carbon production systems, which may shift environmental pressures across categories rather than eliminating them uniformly. Third, while [Garel et al. \(2024\)](#) document the relationship between firm characteristics and corporate biodiversity footprints under baseline conditions,

we show how firms with different characteristics respond differentially to carbon pricing regulation, thereby identifying the firm-level margins along which biodiversity outcomes adjust to carbon pricing regulation.

Our findings also carry important policy implications. The evidence suggests that carbon pricing regulation can reduce multiple dimensions of firms’ environmental impacts, including both carbon emissions and several components of the corporate biodiversity footprint, although effects are not uniform across all environmental categories. The design of Washington State’s Cap-and-Invest Program—including its declining emissions cap, allowance auction mechanism, and targeted use of auction revenues for climate-related investments—offer useful lessons for other jurisdictions seeking to align climate mitigation with broader environmental objectives. However, our findings also indicate potential transition-related trade-offs, as we find that resource use-related corporate biodiversity footprints increase following regulation. This pattern suggests that carbon pricing policies alone may not fully internalize all environmental externalities associated with the low-carbon transition.

Complementary policies aimed at improving energy and material efficiency, supporting cleaner production technologies, and encouraging more resource-efficient deployment of renewable energy systems may help mitigate unintended biodiversity pressures arising from increased demand for upstream material inputs. Greater efficiency in resource use would reduce extraction requirements and improve the utilization of natural inputs, thereby strengthening the alignment between decarbonization objectives and biodiversity conservation outcomes and enhancing the overall environmental effectiveness of carbon pricing regulation. Combining carbon pricing with targeted subsidies or incentives that promote energy efficiency improvements (Acemoglu et al., 2012), material recycling, circular production processes, and technologies with lower material intensity may further reduce resource use-related biodiversity pressures without imposing additional regulatory burdens on firms or generating adverse spillover effects in other environmental categories, consistent with the heterogeneous responses documented in this study. Such complementary policies could help minimize unintended environmental trade-offs—particularly in resource use-related corporate biodiversity footprint—while preserving the emissions reduction benefits of carbon pricing, thereby improving policy efficiency and supporting broader sustainability objectives.

The remainder of the paper is organized as follows. Section II describes the institutional background and study setting, focusing on Washington State’s Cap-and-Invest Program. Section III details the data sources and matching procedure used to build the firm-level panel dataset. Section IV presents the identification strategy and empirical framework, including the difference-in-differences design and supporting assumptions. Section V reports the main results on the effects of carbon pricing regulation on corporate biodiversity footprints across multiple environmental pressure categories, along with the heterogeneous treatment effects according to firms’ characteristics. Section VI provides a series of robustness checks, including placebo tests and alternative matching specifications. Section VII concludes.

II. Study Setting

We use Washington State’s Cap-and-Invest Program as the setting for this study. Enacted as part of the Climate Commitment Act (CCA) on May 17, 2021, this program represents one of the most ambitious market-based approaches to reducing greenhouse gas emissions in the United States. The program aims to help Washington achieve its goal of reducing emissions to 45 percent below 1990 levels by 2030 and reaching net-zero emissions by 2050.

The regulation is modeled after successful cap-and-trade systems, particularly California’s, and establishes a declining cap on statewide emissions. Major emitters must purchase allowances for each ton of carbon dioxide they emit. However, unlike traditional cap-and-trade systems, Washington’s Cap-and-Invest Program directs revenue from allowance auctions to specific climate-related investments, including clean energy projects, public transportation improvements, and climate resilience programs. This targeted allocation reduces firms’ flexibility, as revenue cannot be used freely for other purposes but is instead dedicated to achieving broader environmental and social goals.

The program applies to firms emitting 25,000 metric tons or more of CO₂ equivalent annually, covering firms across key sectors: transportation (fuel distributors), energy production (electric utilities), industrial manufacturing (e.g., cement and steel plants), and natural gas distribution. Collectively, these firms account for nearly 70 percent of the state’s total greenhouse gas emissions, making this initiative a critical tool for addressing climate change at the state level. Small businesses and entities with emissions below the threshold are exempt from the program, ensuring its focus remains on the largest contributors to emissions.

A. Exogeneity

The treatment assignment in our setting is plausibly exogenous. Washington State enacted the CCA as part of a regional policy trend following California’s lead, not in response to firm-specific biodiversity outcomes. The 25,000 metric tons CO₂ emissions threshold is predetermined by existing federal reporting requirements under the Greenhouse Gas Reporting Program, reducing concerns about strategic threshold selection.

B. Treatment Timing

Although the Cap-and-Invest Program officially launched in January 2023, we treat the 2021 enactment date of the CCA as the policy shock for our difference-in-differences analysis. The CCA’s passage provided credible advance notice of future compliance obligations. Prior research demonstrates that firms begin adjusting environmental strategies—including capital investment, supply chain renegotiation, and compliance system development—upon policy announcement rather than implementation (Fowlie et al., 2016; Dechezleprêtre and Sato, 2017; Shapiro and Walker, 2018). Consistent with this view, our review of firms’ SEC filings (Forms 10-K and 10-Q) between 2021 and 2023 indicates that firms explicitly discussed the CCA, assessed its potential implications, and began evaluating compliance and mitigation strategies well before the program became operational. Moreover, using the enactment date allows us to capture these anticipatory responses, which would be missed if we treated 2023 as the start of treatment.

C. Treated Firms

For identifying treated firms, we rely on the Washington State’s Cap-and-Invest Program Quarterly CITSS Registrant Reports. These reports provide the official registry of entities holding active accounts in the Compliance Instrument Tracking System Service (CITSS), the platform used to administer the program. Each registrant is assigned a unique CITSS identification number and is classified according to its regulatory status under the program. Importantly, inclusion in the program is not restricted to firms headquartered in Washington State. Rather, the program covers entities that operate regulated facilities within Washington and whose greenhouse gas emissions exceed the applicable regulatory threshold. The

reports distinguish five categories of participants: (i) *Covered Entities* or *Covered Sources*, which exceed the emissions threshold for mandatory participation; (ii) *Opt-in Entities*, which voluntarily assume compliance obligations despite falling below the mandatory threshold; (iii) *General Market Participant-Organizations*, which participate in the allowance market without compliance obligations; (iv) *General Market Participant-Individuals*; and (v) *General Market Participant-Offset Only* entities, which are permitted to hold offset credits but face restrictions on allowance transactions.

Because the objective of this study is to evaluate the impact of carbon pricing regulation on firms directly subject to the program, as well as firms that may be indirectly affected through their location and economic exposure to Washington State, we define the treatment group to include (i) firms identified in the CITSS registry as Covered Entities/Covered Sources, which are subject to mandatory compliance obligations under the Cap-and-Invest Program, and (ii) publicly listed firms headquartered in Washington State that do not appear in the CITSS registry.⁴

III. Data

A. Data Sources

Our empirical analysis draws on two primary data sources: CBF metrics from IDL and financial statement data from Compustat. We merge these sources to construct a comprehensive panel dataset spanning years 2018 through 2024.

A.1. Iceberg Data Lab

IDL provides the CBF data to provide investors with a science-based indicator to help them measure and manage their investments' impact on biodiversity. Recent studies using IDL biodiversity data include Garel et al. (2024) and Coqueret et al. (2025). These studies provide a detailed discussion of the advantages of the IDL framework relative to alternative biodiversity measures, including disclosure-based and textual indicators derived from firms' 10-K statements. The CBF reflects the effects of multiple environmental pressures, such as land use, nitrogen deposition, emissions, or the release of toxic compounds, to quantify the biodiversity loss resulting from a firm's annual activities.

This measure aggregates biodiversity loss from a company's annual operations (encompassing both direct and indirect impacts),⁵ considering six impact categories: GHG emissions, land use, resource consumption, air pollution, water pollution, and invasive alien species.⁶

⁴ This broader definition is intended to capture both the direct regulatory effects on covered entities and the potential indirect exposure of locally headquartered firms to policy-induced changes in input costs, energy prices, and regional economic conditions. We do not classify Opt-in Entities as treated because their participation is voluntary rather than mandated by the regulation, making their participation potentially endogenous to firm characteristics. Likewise, General Market Participant-Organizations, General Market Participant-Individuals, and General Market Participant-Offset Only entities are excluded because they participate only in allowance or offset markets and are not subject to mandatory emissions compliance obligations under the Cap-and-Invest Program.

⁵ An example of a direct effect is mineral extraction by the same firm, while an indirect effect refers to purchasing renewable energy technologies from other companies, which in turn rely on the extraction of mineral materials for renewable energy production.

⁶ To measure this loss, the CBF uses the Mean Species Abundance (MSA) concept, which compares the abundance of native species in ecosystems to their abundance in undisturbed environments. The CBF expresses this loss in $\text{km}^2 \cdot \text{MSA}$. An area with an MSA of 0 percent has completely lost its native biodiversity (or is exclusively

Each channel is defined and operationalized as follows ([Iceberg Data Lab, 2023](#)):

- **CBF-GHG:** This channel captures biodiversity loss induced by climate change, to which corporate greenhouse gas (GHG) emissions (e.g., carbon dioxide, methane, and nitrous oxide) contribute. It includes emissions across Scope 1, Scope 2, and Scope 3. Scope 1 refers to direct emissions from owned or controlled sources, Scope 2 captures indirect emissions from purchased energy, and Scope 3 encompasses all other indirect emissions occurring along the value chain, including both upstream activities (e.g., purchased goods and services) and downstream activities (e.g., use and end-of-life treatment of sold products).
- **CBF-Land Use:** This channel quantifies biodiversity loss arising from the physical occupation, conversion, or artificialization of land resulting from a firm’s direct operations and value chain activities. Land use pressures include deforestation, agricultural expansion, urban development, mining, and infrastructure construction.
- **CBF-Resource Use:** This channel quantifies biodiversity loss associated with the extraction and consumption of natural resources beyond land occupation, including freshwater, minerals, timber, fisheries, and other biological or geological materials. Over-extraction reduces resource availability for native species, degrades habitat structure, and disrupts ecosystem processes. For example, excessive freshwater withdrawal depletes river flows and wetlands, while overharvesting of biological resources collapses food webs and reduces population resilience.
- **CBF-Air Pollution:** This channel measures biodiversity loss driven by the emission of airborne pollutants. Key contributors include sulfur dioxide and nitrogen oxides (precursors to acid rain, which damages forests, soils, and aquatic systems), particulate matter (which reduces photosynthetic capacity and contaminates leaf surfaces), and ground-level ozone (which causes phytotoxicity). Air pollution also alters nutrient deposition patterns, thereby shifting plant community composition and ecosystem function.
- **CBF-Water Pollution:** This channel accounts for biodiversity loss resulting from the discharge of pollutants into freshwater and marine ecosystems. Principal contaminants include industrial chemicals, heavy metals, excess nutrients (nitrogen and phosphorus from agricultural runoff or wastewater), and thermal pollution. These pollutants degrade water quality, induce eutrophication and hypoxic conditions, poison aquatic organisms, and impair critical habitats such as coral reefs, wetlands, and riparian zones.
- **CBF-Invasive Alien Species:** This channel captures biodiversity loss resulting from the introduction and spread of non-native species through corporate activities, such as shipping (ballast water and hull fouling), agricultural trade, or unintentional transport of organisms. Invasive alien species outcompete, predate upon, or transmit pathogens to native species, often leading to population declines, local extirpations, and irreversible alterations to ecosystem structure.

colonized by invasive species), whereas one with an MSA of 100 percent is considered equal in biodiversity to an ecosystem undisturbed by human activities and pressures. The CBF expresses a firm’s negative impacts on biodiversity in terms of square kilometers of “artificialized” or “denatured” land (i.e., $\text{km}^2 \cdot \text{MSA}$). For example, a CBF of -100 km^2 means that 10 percent of the original biodiversity has been lost in an area of $1,000 \text{ km}^2$ or that a proportionally smaller amount of biodiversity, 5 percent, has been lost in an area of $2,000 \text{ km}^2$. In this article, we multiply the CBF scores by -1 so that higher values indicate a more negative impact on biodiversity. For details on how CBF is computed please refer to [Garel et al. \(2024\)](#).

[Insert Figure 1 About Here]

For the period 2018 to 2024, IDL reports both the total CBF and channel-specific CBF for 9,510 publicly listed companies worldwide, including 2,415 U.S. firms. As the CBF is highly skewed, we use log-transformed of all CBF components, and winsorize at the 1st and 99th percentiles to mitigate the concern regarding the outliers in our analysis. Figure 1 decomposes the CBF by underlying pressure source for the U.S. firms. Land use is the largest single contributor at 44.2%, followed by GHG emissions (31%) and air pollution (15.8%); water pollution (7.5%) and resource use (1.6%) play comparatively minor roles. Land use and GHG emissions together account for nearly three-quarter of the classified footprint, indicating that land-intensive and carbon-intensive activities are the dominant sources of CBF.

A.2. Compustat

For the control variables, we follow the literature (e.g., Krüger, 2015; Bolton and Kacperczyk, 2021; Garel et al., 2024) and include a set of firm-level annual financial characteristics capturing size, valuation, profitability, capital structure, investment intensity, and firm’s growth. Specifically, we control for *Size*, *Book to Market*, *ROA*, *Leverage*, *Capex to Assets*, and *Asset Growth*. *Size* is defined as natural logarithm of the book value of total assets. *Book to Market* is computed as book equity divided by market equity. *ROA* is measured as net income scaled by total assets, capturing accounting profitability. *Leverage* is defined as total debt over total assets, where total debt is the sum of long-term debt and debt included in current liabilities. *Capex to Assets* is constructed as capital expenditures divided by total assets, capturing firm-level investment intensity. *Asset Growth* is defined as the annual percentage change in total assets. In addition to these, we include *Asset Turnover*, defined as sales divided by total assets, to capture operational efficiency in generating revenues from the firm’s asset base. We further control for *Cash Holdings*, measured as natural logarithm of the ratio of cash and short-term investments to total assets, to account for liquidity and internal financing capacity. This inclusion is motivated by Sonter et al. (2020), who show that firms’ cash holdings shape environmental performance.

For all 2,415 U.S. firms identified in the IDL dataset, we collect these variables from Compustat.⁷ To mitigate the influence of outliers, we winsorize all variables at the 1st and 99th percentiles. Because the IDL and Compustat datasets do not share a common numeric identifier (e.g., GVKEY or CIK) for all firms, we merge the two datasets using fuzzy string matching on company names. Specifically, we employ a Jaro-Winkler string distance algorithm (Jaro, 1989; Winkler, 1990). Since the CBF is not reported for all firms across the full 2018–2024 period, resulting in an unbalanced panel. Consequently, the final merged sample comprises 12,292 firm-year observations.

B. Matching and Covariate Balance

B.1. Matched Control Group

To construct the control group, we match U.S. firms that are not headquartered in Washington State and do not belong to the treated group (as defined in Subsection II.C) to treated firms

⁷ For firms subjected to Washington State’s Cap-and-Invest Program that are not covered in Compustat, we supplement financial information using Capital IQ.

using propensity score matching.⁸ We employ propensity score matching (PSM) to ensure that control firms are comparable to treated firms along observable financial characteristics. The matching covariates include the following firm-level variables: *Size*, *Book to Market*, *ROA*, *Leverage*, *Capex to Assets*, *Asset Growth*, *Asset Turnover*, and *Cash Holdings*.

We implement nearest-neighbor matching. Specifically, we specify a 5:1 matching ratio, reflecting the relatively small number of treated firms (70) compared with the large pool of potential control firms (2,174). Under this approach, each treated firm is matched with up to five control firms. Using multiple control matches improves the precision of the estimated treatment effects by reducing sampling variance while maintaining satisfactory covariate balance.⁹ To ensure high-quality matches, we follow the recommendation of Austin (2011) and impose a caliper equal to 0.2 of standard deviations of the logit of the propensity score. Consequently, control firms whose propensity scores differ from those of treated firms by more than this threshold are excluded from the matching procedure, thereby reducing the likelihood of poor matches and improving the comparability of the matched sample.¹⁰ This restriction ensures that matches are made only within a region of sufficient common support, thereby improving comparability between treated and control firms and reducing bias from dissimilar observations. The matching is performed without replacement, and common support is enforced to exclude observations with non-overlapping propensity score distributions. The final sample, comprising both treated and control firms, consists of 322 firms, of which 55 are treated.¹¹ This yields an average of approximately 4.85 control firms per treated firm, below the maximum 5:1 ratio due to the caliper restriction and common support enforcement.

[Insert Figure 2 About Here]

Figure 2 presents the density distributions of the estimated propensity scores for the treated and control groups. The distributions show adequate overlap across the range of propensity scores, particularly in the [0.01–0.10] interval. This overlap confirms that the common support assumption holds reasonably well, allowing for effective matching of treated firms with comparable control firms.

Table 1 presents summary statistics for the biodiversity footprint measures and firm characteristics used in the analysis (please refer to Table A1 for variable definitions). The total CBF exhibits substantial cross-sectional variation, with a mean of 3.998 (corresponding to approximately 54.5 km².MSA in biodiversity-equivalent loss) and a standard deviation of 3.291, indicating pronounced heterogeneity in firms' aggregate biodiversity impacts. The distribution ranges from −3.473 to 9.754,¹² with a median (4.078) close to the mean, suggesting a

⁸ Firms headquartered in Oregon are excluded from the pool of potential control firms because Oregon adopted significant climate-related regulations beginning with Executive Order 20–04 in 2020, which established statewide greenhouse gas reduction targets and initiated the development of emissions-control policies. Excluding Oregon firms helps avoid contamination of the control group by firms potentially exposed to environmental regulations similar in objective to Washington's Cap-and-Invest Program.

⁹ We identify 90 Covered Entities/Covered Sources in the Washington State's Cap-and-Invest Program registry. However, for 64 of these firms, CBF or financial data are unavailable in either the IDL dataset or Compustat (or Capital IQ), leaving 26 covered entities with usable data. Two of these covered entities are also publicly listed firms headquartered in Washington State. In addition, Compustat identifies 131 publicly listed firms headquartered in Washington State, but 85 of these firms do not have corresponding CBF data in the IDL dataset.

¹⁰ In Subsection VI.B, we implement several alternative matching specifications to assess the robustness of our findings. Specifically, we estimate the models using 5:1 nearest-neighbor matching with calipers of 0.1 and 0.3, as well as 10:1 nearest-neighbor matching with calipers of 0.1, 0.2, and 0.3.

¹¹ The number of treated firms decreases from 70 to 55 after matching because observations with missing values in one or more matching covariates are excluded from the propensity score estimation and matching procedure.

¹² A negative value indicates that the measured biodiversity loss is less than 1 km².MSA.

relatively balanced central tendency despite the wide dispersion.

[Insert Table 1 About Here]

The high mean value of CBF-ex-GHG (3.307) suggests that a substantial share of firms' biodiversity impacts arises from environmental pressure channels other than GHG emissions. Additionally, among the individual biodiversity footprint components, GHG emissions, land use, and air pollution exhibit the highest average biodiversity impacts, with mean values exceeding 2 on the log scale (corresponding to biodiversity loss greater than about 7.5 km².MSA), indicating that these pressures account for a relatively larger share of firms' biodiversity footprints than the remaining components. Specifically, CBF-GHG has a mean (median) value of 2.772 (2.829) with moderate variability (S.D. = 2.936), indicating that GHG-related biodiversity impacts are widespread but relatively less dispersed across firms. CBF-Land Use displays a mean (median) value of 1.983 (2.416) but the high standard deviation among components (S.D. = 4.074), together with a wide range (−9.185 to 9.049), reflecting substantial heterogeneity in land use-related ecological pressures across firms. CBF-Air Pollution shows a mean (median) value of 2.069 (2.220) and moderate dispersion (S.D. = 3.228), suggesting consistently material but uneven air pollution impacts across the sample.

Turning to the weaker components, water pollution and resource use exhibit lower mean contributions to firms' biodiversity footprints but still display substantial variation across firms. CBF-Water Pollution has a mean of 0.927 and a median of 1.268, with a standard deviation of 3.407, with a standard deviation of 3.306 and a wide range from −7.030 to 7.049, indicating that although average impacts are relatively limited, there is considerable dispersion driven by a subset of firms with very high water-related pressures. CBF-Resource Use has a negative average (−2.176) corresponding to 0.11 km².MSA biodiversity loss which suggests comparatively lower resource use-related impacts for most firms. However, its dispersion is even more pronounced (S.D. = 4.392), with values ranging from −13.225 to 6.115, reflecting strong dispersion.

The biodiversity footprint associated with invasive alien species is available for only 163 firm-year observations, reflecting substantial data limitations in coverage and reporting. Because of this limited sample size and concerns about representativeness, we exclude this measure from the main analysis. Consequently, we omit this component from the total CBF measure.

The summary statistics for firm-level financial characteristics indicate substantial heterogeneity across the sample. *Size* has a mean of 8.433 and a median of 8.383, with range spanning from 4.640 to 12.655, reflecting considerable cross-firm variation in firm size. *Book to Market* is low on average with a mean (median) value of 0.006 (0.002), with a relatively tight interquartile range, indicating that most firms in the sample are growth-oriented and their market value of equity substantially exceeds the book value, although some variation persists across the upper tail. Profitability, measured by *ROA*, exhibits a mean of 0.002 and a median of 0.035, with values ranging from −0.698 to 0.283, highlighting meaningful differences in firm performance, including a non-negligible share of loss-making firms. *Leverage* has a mean of 0.246 and a standard deviation of 0.158, with values ranging from 0 to 1.092,¹³ indicating moderate variation in capital structure across firms, while the majority of firms exhibit leverage levels below the mean. Investment intensity, captured by *Capex to Assets*,

¹³ The reported minimum and maximum values are calculated after winsorizing the continuous variables at the 1st and 99th percentiles. Leverage values slightly above one are possible when a firm's book debt exceeds its total assets, for example among highly levered or financially distressed firms.

has a mean of 0.037 and a median of 0.026, with relatively concentrated dispersion between 0.011 and 0.048. The majority of firms invest modestly, as the 75th percentile is only 0.048. However, the maximum value of 0.204 indicates that some firms undertake substantial capital investment. The average *Asset Growth* is 0.207, substantially higher than the median of 0.063, indicating a strong right-skewed distribution driven by a few high-growth firms. The standard deviation is considerable, 0.498, reflecting high volatility in growth rates. Operational efficiency, measured by *Asset Turnover*, has a mean of 0.908 and a median of 0.719, suggesting a right-skewed distribution. The standard deviation of 0.713 indicates significant variation in how efficiently firms utilize their assets to generate sales. The 25th percentile is 0.405, while the 75th percentile is 1.222, with a maximum of 3.009, showing that while many firms generate less than one dollar in sales per dollar of assets, a significant minority are highly efficient. *Cash Holdings*, measured by natural logarithm of the ratio of cash and short-term investments to total assets, has a mean of -2.071 (corresponding to about $e^{-2.071} = 0.126$) and a median of -1.976 .

B.2. Covariate Balance

An acceptable level of covariate balance between treated and control firms is essential to support the credibility of the identifying assumption that the two groups are also comparable along unobserved dimensions and to mitigate concerns about confounding. We follow the approach in [Imbens and Rubin \(2015\)](#) by employing three metrics to assess the overlap in covariate distributions including:

1) Normalized Difference: This statistic is defined as the difference in group means standardized by the pooled standard deviation, where the denominator is the square root of the average variance across the treated and control samples. It is expressed as:

$$\Delta_{c,t} = \frac{\mu_t - \mu_c}{\sqrt{(\sigma_t^2 + \sigma_c^2)/2}}$$

2) Dispersion Difference: This metric is computed as the logarithm of the ratio of the standard deviations of treated firms to control firms:

$$\Gamma_{c,t} = \log\left(\frac{\sigma_t}{\sigma_c}\right)$$

3) Coverage Frequency: This measure assesses the extent of distributional overlap between the treated and control groups by quantifying the share of observations in one group whose covariate values fall within the extreme tails of the corresponding distribution in the other group. It is formally defined as:

$$\pi_t^\alpha = F_t\left(F_c^{-1}\left(\frac{\alpha}{2}\right)\right) + \left(1 - F_t\left(F_c^{-1}\left(1 - \frac{\alpha}{2}\right)\right)\right)$$

For a specific value of α , π_t^α denotes the probability mass of the covariate's distribution in the sample of treated firms that lies outside the quantiles $1 - \alpha/2$ and $\alpha/2$ of that covariate in the sample of control firms. This measure verifies that the support of the covariate distributions overlaps across groups by checking whether the extreme values in one group remain within the range of those observed in the other group.

To assess overall covariate balance between the two samples, we estimate *P-Score* and the log-odds transformation (*Linearized P-Score*) using a logistic regression in which the treatment indicator is modeled as a function of a set of covariates, including *Size*, *Book to Market*,

ROA, *Leverage*, *Capex to Assets*, *Asset Growth*, *Asset Turnover*, and *Cash Holdings*. By computing overlap diagnostics—namely the standardized difference, dispersion ratio, and coverage frequency of the estimated propensity scores—we evaluate the degree of covariate balance between the treated and control groups.

[Insert Table 2 About Here]

Table 2 presents covariate balance statistics for both the full and matched samples. Prior to matching, the full sample exhibits substantial imbalance across several firm characteristics. The largest normalized differences are observed for *Cash Holdings* (Nor Dif = 0.487), *Leverage* (Nor Dif = −0.373), *Asset Turnover* (Nor Dif = 0.356), *Size* (Nor Dif = 0.254), *Asset Growth* (Nor Dif = 0.233), and *Capex to Assets* (Nor Dif = 0.217), all of which exceed the conventional 0.2 threshold in absolute value. By contrast, *Book to Market* (Nor Dif = −0.192) and *ROA* (Nor Dif = −0.052) show smaller differences in means before matching. The Log Ratio of STD further reinforces the presence of imbalance, with several variables displaying sizable differences in dispersion between treated and control firms, including *Size* (0.328), *Leverage* (−0.247), *Capex to Assets* (−0.312), *Asset Growth* (0.228), and *Asset Turnover* (0.221). These imbalances are also reflected in the propensity-score measures. Both the *P-Score* and *Linearized P-Score* display large pre-matching differences, with normalized differences of 0.600 and 0.824, respectively. This suggests that treated and control firms were drawn from noticeably different distributions of observable characteristics, underscoring the need for matching to mitigate selection bias.

The PSM procedure substantially improves covariate balance. After matching, all covariates have absolute normalized differences below 0.20, with most below 0.10. The largest remaining imbalance is observed for *ROA* (Nor Dif = −0.145), followed by *Book to Market* (Nor Dif = 0.090), *Asset Growth* (Nor Dif = 0.061), *Asset Turnover* (Nor Dif = 0.061), and *Leverage* (Nor Dif = 0.054). The improvement in balance is substantial across nearly all variables. In absolute terms, the normalized difference declines from 0.254 to 0.003 for *Size*; from 0.192 to 0.090 for *Book to Market*; from 0.373 to 0.054 for *Leverage*; from 0.217 to 0.040 for *Capex to Assets*; from 0.233 to 0.061 for *Asset Growth*; from 0.356 to 0.061 for *Asset Turnover*; and from 0.487 to 0.047 for *Cash Holdings*. The propensity-score balance also improves sharply: the normalized difference for the *P-Score* falls from 0.600 to 0.112, while the *Linearized P-Score* declines from 0.824 to 0.086.

The only covariate for which the normalized difference increases after matching is *ROA*, rising in absolute value from 0.052 to 0.145. However, this post-matching value remains below the conventional 0.20 threshold. The Log Ratio of STD also improves for most covariates, although it remains above 0.20 for *Book to Market* (0.254) and *Capex to Assets* (−0.376). Tail ratios ($\pi^{0.05}$), which capture the share of observations outside the opposite group’s quantile range, also generally move closer to the benchmark value of 5 percent after matching. Overall, these improvements indicate that the matching procedure substantially reduces observable differences between treated and control firms and produces a more comparable matched sample for the DiD analysis.

IV. Identification Strategy

We employ a difference-in-differences (DiD) design to estimate the causal effect of Washington State’s Cap-and-Invest Program on CBF. This approach allows us to compare changes in outcomes between treated firms and matched control firms before and after the policy shock.

By examining differential changes in outcomes over time, we can isolate the policy effect from other concurrent trends. The PSM approach (as described in Subsection III.B.1) further strengthens identification by ensuring that treated and control firms are comparable on observable characteristics, reducing potential selection bias. Our baseline DiD specification takes the following form:

$$y_{it} = \sum_{k \in K} \beta_k (\text{Treat}_i \times \mathbf{1}[t = k]) + \delta X_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where y_{it} denotes one of the seven CBF outcomes for firm i in year t : total CBF, CBF-ex-GHG, CBF-GHG, CBF-Land Use, CBF-Resource Use, CBF-Air Pollution, and CBF-Water Pollution; Treat_i takes value 1 for treated firms and zero for firms in the control group; K is the set of years including 2018, 2019, 2020, 2022, 2023, and 2024 (2021 is the omitted reference year); X_{it} is the vector of control variables; α_i and γ_t are firm and year fixed effects; and ε_{it} is the error term clustered at the state level, which accounts for serial and cross-sectional correlation in unobserved shocks among firms exposed to the same state-level regulatory environment, consistent with the fact that Cap-and-Invest is implemented as a single, state-level policy shock (Bertrand et al., 2004; Abadie et al., 2023).

Parallel trends is a central identifying assumption in the DiD framework, requiring that, absent the policy intervention, treated and control firms would have evolved along similar trajectories in corporate biodiversity footprints. The event-study specification allows us to assess whether treated and control firms exhibit any differential dynamics in the pre-policy period (2018–2020), relative to the omitted baseline year 2021, which would be indicative of pre-existing divergence. We also complement these diagnostics with placebo timing tests and alternative matching specifications in the robustness analysis (Section VI) to further examine whether the estimated effects are sensitive to spurious timing or sample construction. Taken together, this combination of design-based and empirical checks is intended to support the credibility of the parallel trends assumption and validity of our DiD analysis, which remains fundamental for causal interpretation of the estimated treatment effects.

A. Heterogeneous Treatment Effect

To further explore the underlying adjustment mechanisms and potential distributional responses to the Cap-and-Invest Program, we extend the baseline DiD framework to allow for heterogeneous treatment effects across firms. We test four hypotheses about how firms may respond differently to carbon pricing. These hypotheses focus on four moderators—pre-treatment CBF-GHG, firm size, internal liquidity, and asset growth—as follows:

Hypothesis 1 (H1): Baseline carbon exposure

Firms with higher pre-treatment CBF-GHG are expected to respond more strongly to carbon pricing because they enter the policy period with greater GHG-related biodiversity pressure. These firms are more exposed to the costs created by carbon pricing and therefore face stronger incentives to reduce emissions-intensive activities, improve energy efficiency, or substitute toward cleaner production processes. In addition, firms with higher baseline CBF-GHG likely have greater scope for abatement, since they may have more carbon-intensive operations or less efficient production technologies before the policy shock. By contrast, firms with lower pre-treatment CBF-GHG may already operate with relatively cleaner production processes, leaving less room for further reductions. Therefore, if the Cap-and-Invest Program works through the intended carbon-pricing channel, we expect treatment effects to be

stronger among firms with higher pre-treatment $\text{Ln}(\text{CBF-GHG})$.

Hypothesis 2 (H2): Firm size

The effects of a state-level policy may vary with firm size. Larger firms may operate through more geographically dispersed facilities and complex production networks, which can dilute the impact of the Cap-and-Invest Program on firm-wide biodiversity outcomes. Smaller firms, by contrast, may have more concentrated operations and fewer margins for geographic or organizational reallocation. Therefore, we expect treatment effects to be stronger among smaller firms.

Hypothesis 3 (H3): Financial flexibility

Firms with greater internal liquidity may respond differently from firms with limited cash holdings. Because the Cap-and-Invest Program allows firms to comply partly through financial channels, such as purchasing allowances, cash-rich firms may face less immediate pressure to change production processes. Firms with lower cash holdings may instead be pushed toward real operational adjustments. Therefore, we expect treatment effects to be stronger among firms with lower cash holdings.

Hypothesis (H4): Growth-driven expansion

Firms undergoing faster expansion may respond less strongly to the Cap-and-Invest Program because growth can create a scale effect that offsets environmental improvements. Expanding firms may increase production capacity, energy use, facility activity, or input demand, making it harder for policy-induced efficiency gains to translate into large reductions in biodiversity pressure. Therefore, we expect treatment effects to be weaker among firms with higher asset growth.

To formally test these hypotheses, we augment the baseline DiD specification by including a triple interaction term between the treatment indicator, event-year indicators, and the relevant firm-level moderator:

$$y_{it} = \sum_{k \in K} \beta_k (\text{Treat}_i \times \mathbf{1}[t = k]) + \sum_{k \in K} \theta_k (\text{Treat}_i \times Z_{it}^{(j)} \times \mathbf{1}[t = k]) + \delta X_{it} + \alpha_i + \gamma_t + \varepsilon_{it}. \quad (2)$$

where $Z_{it}^{(j)}$ denotes the moderator corresponding to hypothesis j . We estimate Equation (2) separately for each of the four moderators: pre-treatment $\text{Ln}(\text{CBF-GHG})$, *Size*, *Cash Holdings*, and *Asset Growth*. The coefficient θ_k captures how the treatment effect in event year k varies with the corresponding firm characteristic.

For *Size*, *Cash Holdings*, and *Asset Growth*, the moderator enters the triple interaction using its observed firm-year value. For the emissions-related moderator, however, we do not use the contemporaneous value of $\text{Ln}(\text{CBF-GHG})$. Since $\text{Ln}(\text{CBF-GHG})$ is itself one of the dependent variables in our outcome set, using its contemporaneous value as a moderator would mechanically place the same variable on both sides of the regression when the outcome is $\text{Ln}(\text{CBF-GHG})$. To avoid this problem, we construct a predetermined firm-level GHG moderator using the firm's average $\text{Ln}(\text{CBF-GHG})$ over the pre-treatment period:

$$Z_i^{GHG} = \frac{1}{T_0} \sum_{t \in \mathcal{T}_0} \text{Ln}(\text{CBF-GHG})_{it}$$

where $\mathcal{T}_0$ denotes the pre-treatment years and T_0 is the number of available pre-treatment observations for firm i . This variable captures firms' initial GHG-related biodiversity pressure

before the policy shock. In specifications using this moderator, $Z_{it}^{(j)}$ in Equation (2) is replaced by the time-invariant baseline measure Z_i^{GHG} .

The parallel trends assumption in the heterogeneous specification is assessed by testing whether the pre-treatment triple-interaction coefficients, θ_{2018} , θ_{2019} , and θ_{2020} , are jointly equal to zero. Failure to reject this null hypothesis indicates that the moderator does not predict differential pre-treatment trends between treated and control firms prior to the introduction of the policy.

V. Results

In this section, we discuss the results of estimation of Equation (1) for exploring the impact of Washington State’s Cap-and-Invest Program on seven CBF outcomes: total CBF, CBF-ex-GHG, CBF-GHG, CBF-Land Use, CBF-Resource Use, CBF-Air Pollution, and CBF-Water Pollution. The coefficients of interest are the interaction terms between treatment status and year dummies, with 2021 (the enactment year) as the omitted reference category. Pre-treatment coefficients (2018–2020) test the parallel trends assumption, while post-treatment coefficients (2022–2024) capture the dynamic treatment effects.

As presented in Table 3,¹⁴ the pre-treatment coefficients are small in magnitude and statistically insignificant across all specifications, providing support for the parallel trends assumption. This is further supported by formal Wald/F tests of joint significance of the pre-treatment coefficients (2018–2020). For Total CBF ($F = 0.75$, $p = 0.52$), CBF-ex-GHG ($F = 0.90$, $p = 0.44$), CBF-GHG ($F = 1.05$, $p = 0.37$), CBF-Land Use ($F = 0.35$, $p = 0.79$), CBF-Resource Use ($F = 0.93$, $p = 0.42$), CBF-Air Pollution ($F = 0.99$, $p = 0.40$), and CBF-Water Pollution ($F = 0.86$, $p = 0.46$), we fail to reject the null hypothesis that all pre-treatment coefficients are jointly equal to zero. This provides formal statistical support for the parallel trends assumption across these outcomes.

[Insert Table 3 About Here]

Following the 2021 enactment of the Climate Commitment Act, we observe significant reductions in firms’ overall biodiversity footprints. For total CBF (Column 1), the treatment effects are negative and statistically significant in all post-treatment years: 2022 (−0.19), 2023 (−0.16), and (−0.17), all significant at 1% level. These results indicate meaningful reductions in firms’ overall biodiversity footprint in the early post-treatment period. Consistent with these year-specific estimates, the aggregated post-treatment effect across 2022–2024, computed as the inverse-variance-weighted average of the corresponding yearly coefficients, is negative and highly statistically significant ($ATT = -0.18$, significant at 1% level), confirming a substantial overall reduction in total CBF following policy implementation. In economic terms, this corresponds to a decline from the pre-treatment mean of 35.9 km²·MSA to approximately 30.0 km²·MSA, implying an approximately 16.5% reduction in firms’ biodiversity footprints. While this represents a modest shift in distributional terms (approximately 0.05 standard deviations of CBF), it reflects a non-trivial contraction in environmental impacts following the implementation of the Cap-and-Invest Program.

¹⁴ The high adjusted R^2 values in the baseline specifications, ranging from 0.94 to 0.96, mainly reflect the inclusion of firm fixed effects. This interpretation is supported by an auxiliary specification in which firm fixed effects are replaced with a treated-group dummy while keeping year fixed effects, controls, and event-study interactions. In that specification, the adjusted R^2 falls substantially, ranging from 0.30 to 0.64 across outcomes. This comparison indicates that the high explanatory power of the baseline model is driven primarily by time-invariant firm heterogeneity.

The decomposition of total CBF into its underlying environmental components indicates that the observed aggregate decline is broadly driven by multiple pollution channels, with the exception of resource use. Starting with the aggregate decomposition, CBF-ex-GHG declines significantly following the policy (Column 2), with coefficients of -0.25 , -0.18 , and -0.23 in 2022, 2023, and 2024, respectively, all significant. This indicates that the reduction in overall biodiversity footprint is not solely attributable to GHG emissions but reflects broader improvements across non-carbon environmental dimensions. Consistent with this pattern, CBF-GHG itself declines by 0.17 (1% level) in 2022 and 0.11 (5% level) in 2023 (Column 3), indicating meaningful reductions in carbon-related environmental impacts.

Turning to the decomposition across non-GHG components, we observe widespread and statistically significant reductions. The land use-related CBF (Column 4) falls by 0.31 in 2022 (1% level) and 0.19 in 2023 (5% level), suggesting a pronounced contraction in firms' land use intensity in the immediate post-treatment period. One potential mechanism is that carbon pricing encourages firms to improve production efficiency and reduce the scale or intensity of carbon-intensive operations that also require substantial land occupation. Firms may respond by consolidating production, improving capacity utilization, retiring inefficient facilities, or shifting activity away from more land-intensive processes.

The air pollution-related CBF decreases by 0.23 in 2022 and 0.15 in 2023 (significant at 1% and 5% levels, respectively, as depicted in Column 6), with the effect remaining negative and statistically significant in 2024 (-0.66 , 1% level). This pattern is consistent with the idea that carbon abatement and air pollution abatement are often complementary. Reductions in fossil-fuel combustion, improvements in energy efficiency, and shifts toward cleaner inputs can lower not only GHG emissions but also local air pollutants generated by the same production activities. The persistence and strengthening of the air pollution effect in 2024 may reflect gradual adjustment, as firms implement operational changes, cleaner technologies, or compliance-related investments over time. Similarly, the water pollution-related CBF (Column 7) declines by 0.26 in 2022 (1% level) and 0.87 in 2024 (1% level), further confirming sustained reductions in water-related environmental impacts. This may reflect process-level adjustments that reduce waste streams, chemical discharge, or water-intensive production practices.

[Insert Figure 3 About Here]

Resource Use (Column 5) presents a notable deviation from the overall pattern. While the treatment effect is negative in 2022 (-0.29 , 1% level), it does not remain negative anymore in the subsequent years. Specifically, it becomes positive with 0.53 and 2.83 increase in 2023 and 2024, both significant at 1% level, indicating a substantial increase in resource use-related biodiversity pressures in the later post-treatment period. This sharp reversal differs markedly from the generally negative effects observed for the other biodiversity footprint components. Consistent with these dynamics, the aggregated post-treatment effect is positive and highly statistically significant ($ATT = 0.65$, significant at 1% level), suggesting that, on average, the policy is associated with an increase rather than a reduction in resource use-related biodiversity impacts. Additionally, Figure 3 indicates that this result is not driven by a small subset of firms. Rather, more than 60% of treated firms increase their resource use-related biodiversity pressures following the treatment, suggesting that the aggregate effect reflects a broad-based adjustment across the treated sample.

One possible interpretation is that compliance with the Cap-and-Invest Program induces substitution toward more material-intensive technologies and supply chains. In particular,

transitions toward electrification and renewable energy systems may increase demand for critical minerals such as lithium, cobalt, and rare earth elements, thereby raising upstream resource extraction pressures captured in this component. This interpretation is consistent with [Sonter et al. \(2020\)](#), which documents that mining activities associated with resource extraction can generate substantial biodiversity loss through land disturbance, habitat fragmentation, and ecosystem degradation. Importantly, this increase should be interpreted as a potential by-product of the low-carbon transition rather than evidence that the policy failed to reduce overall biodiversity footprints, which decline significantly across most other environmental dimensions.

Additional evidence supports this interpretation. When we examine firms’ Scope 3 upstream GHG emissions, we find no significant effect in 2022, but observe a positive and statistically significant effect in 2023 and 2024 (0.18 and 0.87, both significant at 1% level) as shown in Figure 4. Because Scope 3 upstream emissions capture environmental impacts embedded in purchased goods and services and firms’ supply chains, this result suggests that part of the adjustment to carbon pricing may occur through increased reliance on upstream inputs. Taken together with the increase in CBF-Resource Use, the evidence is consistent with a reallocation of environmental pressures toward upstream production stages associated with the low-carbon transition. Such a mechanism may arise from increased demand for renewable energy technologies, batteries, and other material-intensive inputs that require substantial resource extraction and processing.

[Insert Figure 4 About Here]

The control variables exhibit broadly expected relationships with CBF outcomes. Firm size is positively and significantly associated with all CBF components, with coefficients ranging from 0.81 to 1.04 (all significant at 1% level), indicating that larger firms have larger biodiversity footprints, consistent with [Garel et al. \(2024\)](#). Additionally, consistent with [Garel et al. \(2024\)](#), we find that *Asset Growth* is consistently negative and statistically significant across all CBF components, with coefficients ranging from approximately -0.20 to -0.34 (all significant at 1%). This pattern indicates that firms experiencing higher growth in total assets tend to exhibit lower biodiversity footprint measures. One plausible interpretation is that rapidly expanding firms may be allocating incremental capital toward more efficient production technologies, cleaner inputs, or improved environmental management systems, thereby decoupling growth from biodiversity-related externalities. Alternatively, this result may reflect a compositional effect, whereby high-growth firms are more likely to be younger, more dynamic organizations operating with newer capital stock that embeds stricter environmental standards relative to legacy assets.

Additionally, *ROA* is positively and significantly associated with all CBF measures (coefficients ranging from 1.24 to 1.78, significant only for CBF-ex-GHG, CBF-Land Use, and CBF-Air Pollution), consistent with evidence in [Garel et al. \(2024\)](#), [Konar and Cohen \(2001\)](#), and [Fujii et al. \(2013\)](#), which documents a positive association between firms’ profitability and environmental pressures or emissions in certain contexts. Leverage is also positively associated with biodiversity footprints, with coefficients ranging from 0.54 to 1.28 across CBF measures, suggesting that more highly leveraged firms tend to exhibit greater biodiversity-related pressures. Finally, the coefficient for operational efficiency measured by *Asset Turnover* is positive and statistically significant across all CBF components, with coefficients ranging from 0.77 to 0.87 (all significant at 1% level). This indicates that firms with higher revenue generated per unit of assets tend to exhibit higher CBF.

A. Heterogeneous Treatment Effects across Firm Characteristics

In this subsection, we test the four heterogeneity hypotheses developed in Subsection IV.A. Specifically, we examine whether treatment effects vary with firms' pre-treatment $\text{Ln}(\text{CBF-GHG})$, *Size*, *Cash Holdings*, and *Asset Growth*.

[Insert Table 4 About Here]

Table 4 show that among the 28 specifications reported, the joint pre-trend test fails to reject the null of no differential pre-treatment trends in only three cases: the CBF-GHG outcome interacted with pre-treatment $\text{Ln}(\text{CBF-GHG})$, *Asset Growth*, and *Cash Holdings*. Therefore, we interpret the remaining post-treatment coefficients with caution and do not assign them a *causal* interpretation.

The strongest support is for Hypothesis 1. For the CBF-GHG outcome, the pre-trend test for the pre-treatment $\text{Ln}(\text{CBF-GHG})$ moderator is statistically insignificant ($F = 1.54$, $p = 0.203$), while the post-treatment coefficient is negative and highly significant (-0.03 , significant at 1% level). This suggests that firms with higher baseline GHG-related biodiversity pressure experience larger reductions in the GHG component after the Cap-and-Invest Program. The result is consistent with the proposed carbon-exposure mechanism: firms with greater initial emissions-related pressure have more scope for abatement and stronger incentives to adjust when carbon emissions become costly.

The evidence does not support Hypothesis 2. For *Size*, the pre-trend test rejects the null of no differential pre-treatment trends for all seven CBF outcomes. Although several post-treatment coefficients are statistically significant, these estimates are difficult to interpret causally because larger and smaller firms were already following different biodiversity-footprint trajectories before the policy.

The evidence for Hypothesis 3 is also limited. For *Cash Holdings*, the pre-trend test does not reject parallel trends only for the CBF-GHG outcome ($F = 1.53$, $p = 0.205$). However, the corresponding post-treatment coefficient is not statistically significant (-0.03 , $p > 0.141$). Thus, although this specification satisfies the pre-trend diagnostic, we do not find evidence that firms' internal liquidity meaningfully shapes their GHG-related response to the policy. For the remaining CBF outcomes, the pre-trend tests reject the null, so the post-treatment estimates cannot be given a causal interpretation.

By contrast, Hypothesis 4 receives stronger support. For the CBF-GHG outcome, the pre-trend test for *Asset Growth* is statistically insignificant ($F = 0.98$, $p = 0.402$), while the post-treatment coefficient is positive and highly significant (0.48 , significant at 1% level). Given the standard deviation of *Asset Growth* (0.498), this implies approximately 27% higher CBF-GHG after the Cap-and-Invest Program for a one-standard-deviation increase in *Asset Growth*. Since the average treatment effect on CBF-GHG is negative, this positive heterogeneous effect indicates that faster-growing firms reduce their GHG-related biodiversity footprint less than firms with lower asset growth. This pattern is consistent with the growth-driven expansion mechanism: expansion in assets, production capacity, facility activity, or input demand may partially offset the emissions-related reductions induced by carbon pricing.

Overall, the heterogeneity analysis provides the clearest evidence for two mechanisms. First, firms with higher baseline GHG-related biodiversity pressure experience stronger GHG-related reductions, supporting the idea that carbon pricing has larger effects where initial abatement opportunities are greater. Second, faster-growing firms experience weaker GHG-related improvements, suggesting that expansion can offset part of the policy-induced reduction in emissions-related biodiversity pressure. In contrast, we do not find robust causal evi-

dence that firm size or internal liquidity significantly shapes the response once the pre-trend diagnostic is taken into account.

VI. Robustness Checks

A. Placebo Timing Test

We conduct a placebo timing test to assess the validity of our difference-in-differences identification strategy. Specifically, we re-estimate the baseline specification, as in Equation (1), by assigning a fictitious treatment year prior to the actual enactment of Washington State’s Climate Commitment Act and examine the dynamic treatment coefficients across all outcome variables. The objective of this exercise is to test whether the empirical model spuriously generates treatment effects in periods when no policy intervention has occurred.

In this placebo exercise, we set the false treatment timing to 2020, which precedes the actual policy enactment in 2021, and re-estimate the full event-study specification using the same dynamic structure as in the baseline model. This implies that 2018–2019 serve as pre-placebo periods, while 2021–2024 are treated as post-placebo periods, even though no real policy change occurred at the placebo date. A valid DiD design should exhibit no systematic or statistically significant effects in pre-treatment periods, as this would indicate that treated and control firms follow parallel trends prior to the policy shock. Moreover, under a correctly specified model, we should not observe economically meaningful or systematically significant treatment effects immediately following the placebo year (i.e., in 2021), since no actual regulatory intervention took place at that time. Instead, coefficients should remain statistically indistinguishable from zero in both pre-placebo periods and the immediate post-placebo year. Evidence of systematic pre-trends in the pre-placebo period or statistically significant effects immediately following the fictitious treatment year would cast doubt on the validity of our DiD design.

[Insert Figure 5 About Here]

As shown in Figure 5, the placebo estimates provide broadly supportive evidence for the validity of the identification strategy across most CBF outcomes. For the all of specifications, pre-placebo coefficients are statistically indistinguishable from zero and insignificant, consistent with the absence of differential pre-trends. In addition, the interaction term for 2021—corresponding to the first post-placebo period—remains statistically insignificant across all outcomes, indicating that no spurious treatment effects are detected immediately after the fictitious policy implementation date. This further supports the validity of the placebo design and reinforces the credibility of the parallel trends assumption underlying our baseline specification.

Overall, the placebo exercise provides supportive evidence for the validity of the design, with all outcomes showing no meaningful pre-trend behavior and treatment effects in the main specification emerging only in the actual post-policy period.

B. Alternative Matching Specifications

To assess the sensitivity of our baseline results to the matching procedure, we re-estimate the analysis employing several alternative propensity score matching configurations. These include 5:1 nearest-neighbor matching with calipers set to 0.1 and 0.3, alongside 10:1 nearest-neighbor matching with calipers of 0.1, 0.2, and 0.3. This battery of estimates serves as a

robustness check against dependence on the specific matching design. Should our findings be robust—rather than an artifact of the chosen parameters or arbitrary pairings—we would expect the treatment effects to retain their qualitative consistency across all specifications in terms of direction, temporal dynamics, and statistical significance.

[Insert Figure 6 About Here]

Figure 6 demonstrates that the results are highly consistent with the baseline findings across all CBF components, confirming the robustness of our main estimates. Across all outcomes, the pre-treatment coefficients (2018–2020) remain statistically insignificant, further supporting the parallel trends assumption. The only notable nuance is that for CBF-Air Pollution, the 2018 interaction term becomes significant under the 10:1 nearest-neighbor specifications, implying a more cautious interpretation of the primary results for this particular component. Furthermore, the post-treatment effects largely preserve the magnitude, direction, and timing observed in the baseline model. However, under the 10:1 matching (irrespective of the caliper value), the 2024 interaction term in CBF-Land Use specification becomes significant at 5% level for CBF-Land Use.

Overall, the alternative matching specifications confirms the robustness of our baseline results. Across nearly all outcomes and specifications, the estimated treatment effects exhibit remarkable consistency in terms of magnitude, timing, and statistical significance. The few nuances—particularly the significance for CBF-Air Pollution in 2018 and the additional significance of 2024 coefficients for CBF-Land Use under 10:1 matching—do not undermine the overall pattern, which clearly indicates a persistent and economically meaningful treatment effect. Given that the pre-trends remain flat and the post-treatment responses are stable across a wide range of matching designs, we interpret these results as strong evidence against the possibility that our findings are driven by matching parameter choices or arbitrary pairwise alignments.

VII. Conclusion

This paper examines the impact of a market-based carbon pricing regulation on corporate biodiversity outcomes. Using firm-level data on the corporate biodiversity footprint (CBF) from Iceberg Data Lab merged with financial statement information from Compustat, we study Washington State’s Cap-and-Invest Program as a quasi-experimental policy shock. Combining a difference-in-differences framework with propensity score matching, we estimate how regulated firms adjust their environmental impacts across multiple biodiversity pressure categories.

Our findings suggest that carbon pricing regulation has meaningful but heterogeneous effects on corporate biodiversity outcomes. Following the implementation of Washington State’s Cap-and-Invest Program, total CBF decline, driven primarily by reductions in greenhouse gas emissions, land use pressures, air pollution, and water pollution. These patterns suggest that carbon pricing policies can generate environmental benefits extending beyond their direct emissions reduction objective. However, the effects are not uniform across biodiversity dimensions. While most pressure categories improve following regulation, resource use-related biodiversity impacts increase over time, potentially reflecting greater demand for material-intensive inputs associated with the low-carbon transition, including electrification and renewable energy deployment. These findings suggest that carbon pricing policies oper-

ate through competing adjustment mechanisms, generating both environmental co-benefits and transition-related trade-offs.

The results also indicate that the effects of carbon pricing are not uniform across firms. The strongest heterogeneous responses are related to firms' initial GHG-related biodiversity exposure and growth dynamics. Firms with higher pre-treatment CBF-GHG experience larger reductions in the GHG component, suggesting that carbon pricing is more effective among firms with greater initial scope for abatement. However, faster-growing firms show weaker GHG-related improvements, consistent with the idea that expansion in assets, production capacity, or input demand can partially offset policy-induced emissions reductions. We do not find robust evidence that firm size or internal liquidity systematically shapes treatment effects once pre-treatment trends are taken into account. Overall, these findings suggest that carbon pricing can generate broad biodiversity co-benefits, but its effectiveness depends partly on firms' initial environmental exposure and whether growth-related scale effects counteract environmental improvements.

Our results carry important implications for environmental policy design. The evidence suggests that carbon pricing regulation can influence multiple dimensions of firms' environmental footprints, but carbon pricing alone may not fully internalize all environmental externalities associated with the transition toward a low-carbon economy. Complementary policies that improve energy and material efficiency, encourage cleaner production technologies, support recycling and circular production processes, and reduce material intensity may help mitigate unintended biodiversity pressures arising from increased upstream resource demand. Such policies may strengthen the alignment between decarbonization objectives and biodiversity conservation goals while preserving the emissions reduction benefits of carbon pricing.

Future research could extend this analysis in several directions. First, the current study is constrained by the limited time coverage of the CBF data. Extending the sample period would enable the study of other large-scale carbon pricing systems, such as California's cap-and-trade program enacted in 2013, which covers a broader set of firms and industries and offers richer variation in regulatory exposure. Second, future work could broaden the analysis to alternative forms of carbon pricing and environmental regulation, including carbon taxes, performance-based emissions standards, or hybrid regulatory systems combining price and quantity instruments. Such extensions would help clarify whether the observed biodiversity effects are specific to cap-and-invest designs or generalizable across policy regimes. Finally, more granular regulatory variation—such as differentiated thresholds, sector-specific compliance requirements, or incentive schemes for low-emission firms—could be exploited to better understand how specific design features shape biodiversity outcomes. Together, these extensions would help build a more comprehensive understanding of how climate policy interacts with biodiversity across institutional settings and regulatory architectures.

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TABLES

Table 1: Summary Statistics

	Mean	S.D.	Min	25%	50%	75%	Max	Obs.
Ln(CBF)	3.998	3.291	-3.473	1.619	4.078	6.466	9.754	1,672
Ln(CBF-ex-GHG)	3.307	3.569	-4.715	0.678	3.472	6.094	9.381	1,661
Ln(CBF-GHG)	2.772	2.936	-4.056	0.621	2.829	4.866	8.458	1,694
Ln(CBF-Land Use)	1.983	4.074	-9.185	-0.574	2.416	4.937	9.049	1,679
Ln(CBF-Resource Use)	-2.176	4.392	-13.225	-5.952	-1.958	1.286	6.115	1,488
Ln(CBF-Air Pollution)	2.069	3.228	-5.635	-0.311	2.220	4.534	7.841	1,694
Ln(CBF-Water Pollution)	0.927	3.407	-7.030	-1.453	1.268	3.519	7.049	1,684
Ln(CBF-Invasive Alien Species)	-0.352	4.829	-8.234	-4.223	-1.177	2.837	8.495	163
Size	8.433	1.871	4.640	7.011	8.383	9.765	12.655	1,696
Book to Market	0.006	0.010	-0.008	0.001	0.002	0.007	0.093	1,553
ROA	0.002	0.158	-0.698	-0.028	0.035	0.085	0.283	1,696
Leverage	0.246	0.198	0.000	0.077	0.219	0.363	1.092	1,686
Capex to Assets	0.037	0.039	0.000	0.011	0.026	0.048	0.204	1,696
Asset Growth	0.207	0.498	-0.352	-0.010	0.063	0.215	2.787	1,678
Asset Turnover	0.908	0.713	0.012	0.405	0.719	1.222	3.009	1,696
Cash Holdings	-2.071	1.281	-7.277	-2.793	-1.976	-1.021	-0.102	1,695

This table presents summary statistics at the firm-year level of the variables used in the returns analysis. The sample period spans from 2018 to 2024. Please refer to Table A1 for variable definitions.

Table 2: Covariate Balance Test

	Full Sample				Matched Sample (PSM)			
	Nor Dif	Log Ratio of STD	$\pi^{0.05}$		Nor Dif	Log Ratio of STD	$\pi^{0.05}$	
			Control	Treated			Control	Treated
Size	0.254	0.328	0.011	0.158	-0.003	0.158	0.0000	0.1064
Book to Market	-0.192	-0.142	0.085	0.018	0.090	0.254	0.0411	0.0530
ROA	-0.052	-0.091	0.112	0.018	-0.145	0.050	0.0679	0.0496
Leverage	-0.373	-0.247	0.118	0.053	0.054	-0.047	0.0220	0.0393
Capex to Assets	0.217	-0.312	0.230	0.000	-0.040	-0.376	0.1832	0.0035
Asset Growth	0.233	0.228	0.111	0.088	0.061	0.147	0.0551	0.0536
Asset Turnover	0.356	0.221	0.148	0.088	0.061	-0.020	0.0615	0.0532
Cash Holdings	0.487	0.078	0.098	0.088	0.047	-0.096	0.0920	0.0106
P-Score	0.600	0.916	0.155	0.140	0.112	0.182	0.0500	0.0687
Linearized P-Score	0.824	0.101	0.154	0.140	0.086	0.084	0.0500	0.0687

This table presents the overlap assessment of covariates between treated and control firms. The overlap measures include normalized differences (Nor Dif), dispersion differences (Log Ratio of STD), and coverage frequency ($\pi^{0.05}$). Propensity scores (P-Score) and linearized propensity scores (Linearized P-Score) are also reported. Please refer to Table A1 for variable definitions.

Table 3: Dynamic Treatment Effects Results

	(1) Total	(2) Ex-GHG	(3) GHG	(4) Land Use	(5) Res. Use	(6) Air Pol.	(7) Water Pol.
Interaction Terms							
Treat $\times$ Year (2018)	-0.11 (0.14)	-0.15 (0.14)	-0.03 (0.12)	0.09 (0.13)	-0.12 (0.22)	-0.17 (0.11)	-0.11 (0.19)
Treat $\times$ Year (2019)	-0.11 (0.09)	-0.14 (0.09)	-0.02 (0.08)	0.01 (0.09)	-0.14 (0.10)	-0.12 (0.08)	-0.07 (0.11)
Treat $\times$ Year (2020)	0.00 (0.08)	-0.03 (0.09)	0.05 (0.07)	0.08 (0.12)	-0.04 (0.13)	-0.03 (0.08)	0.06 (0.08)
Treat $\times$ Year (2022)	-0.19*** (0.04)	-0.25*** (0.04)	-0.17*** (0.03)	-0.31*** (0.05)	-0.29*** (0.10)	-0.23*** (0.04)	-0.26*** (0.05)
Treat $\times$ Year (2023)	-0.16*** (0.06)	-0.18*** (0.07)	-0.11*** (0.05)	-0.19*** (0.09)	0.53*** (0.11)	-0.15*** (0.06)	-0.09 (0.08)
Treat $\times$ Year (2024)	-0.17*** (0.07)	-0.23*** (0.07)	-0.07 (0.09)	-0.05 (0.08)	2.83*** (0.14)	-0.66*** (0.10)	-0.87*** (0.17)
Control Variables							
Size	0.84*** (0.11)	0.85*** (0.11)	0.81*** (0.12)	1.04*** (0.15)	0.99*** (0.13)	0.83*** (0.12)	0.81*** (0.13)
Book to Market	5.04 (7.91)	6.64 (7.96)	3.42 (7.76)	7.68 (7.49)	-0.91 (7.35)	4.23 (7.60)	8.51 (9.80)
ROA	1.31*** (0.35)	1.48*** (0.39)	1.24*** (0.33)	1.78*** (0.52)	1.54*** (0.57)	1.29*** (0.36)	1.54*** (0.51)
Leverage	0.82*** (0.27)	0.97*** (0.30)	0.54*** (0.24)	1.28*** (0.28)	0.84*** (0.28)	0.65*** (0.29)	0.83*** (0.43)
Capex to Assets	0.51 (1.03)	0.40 (0.90)	0.77 (1.21)	-0.04 (0.82)	0.22 (1.12)	0.54 (1.05)	0.85 (1.10)
Asset Growth	-0.20*** (0.04)	-0.23*** (0.04)	-0.20*** (0.04)	-0.30*** (0.06)	-0.34*** (0.08)	-0.20*** (0.04)	-0.27*** (0.03)
Asset Turnover	0.83*** (0.23)	0.83*** (0.24)	0.77*** (0.23)	0.87*** (0.25)	0.77*** (0.19)	0.79*** (0.25)	0.81*** (0.22)
Cash Holdings	-0.02 (0.02)	-0.01 (0.02)	-0.03 (0.03)	0.01 (0.04)	0.05 (0.05)	-0.02 (0.03)	-0.02 (0.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.96	0.96	0.96	0.95	0.96	0.96	0.94
# Obs.	1514	1504	1536	1521	1365	1536	1526

This table presents difference-in-differences estimates of the impact of Washington State's Cap-and-Invest Program on seven corporate biodiversity footprint (CBF) outcomes estimated from Equation (1). Columns (1) through (7) correspond to total CBF, CBF-ex-GHG, CBF-GHG, CBF-Land Use, CBF-Resource Use, CBF-Air Pollution, and CBF-Water Pollution, respectively. The coefficients of interest are interaction terms between Treat and year indicators, with 2021 as the omitted base year. Standard errors (in parentheses) are clustered at the state level. Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Please refer to Table A1 for variable definitions.

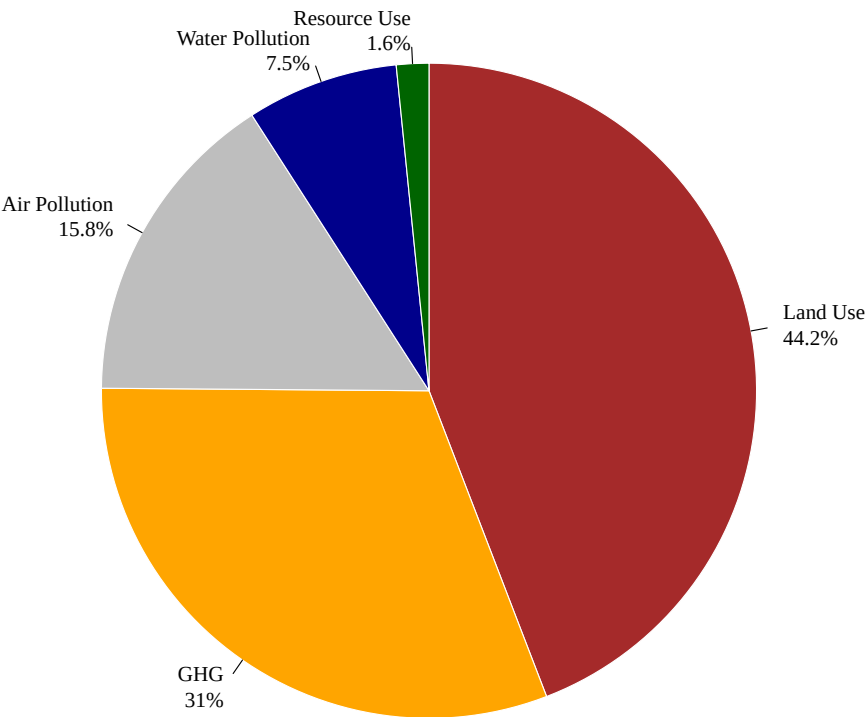
Table 4: Heterogeneous Treatment Effects Results

	Total		Ex-GHG		GHG		Land Use		Resource Use		Air Pol.		Water Pol.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
H1: Ln(CBF-GHG)	2.54*	-0.02***	4.99***	0.00	1.54	-0.03***	16.07***	0.01	11.59***	-0.55***	10.50***	0.01**	7.41***	0.07***
	(0.0550)	(0.0004)	(0.0019)	(0.8748)	(0.2028)	(0.0000)	(0.0000)	(0.1359)	(0.0000)	(0.0000)	(0.0000)	(0.0114)	(0.0001)	(0.0000)
H2: Size	4.52***	0.00	8.39***	0.03**	2.66**	-0.02**	7.28***	0.05***	6.11***	-1.50***	5.38***	0.06***	2.28*	0.12***
	(0.0037)	(0.8752)	(0.0000)	(0.0191)	(0.0468)	(0.0284)	(0.0001)	(0.0017)	(0.0004)	(0.0000)	(0.0011)	(0.0000)	(0.0773)	(0.0000)
H3: Cash Holdings	11.54***	-0.05***	16.17***	-0.09***	1.53	-0.03	16.58***	-0.12***	19.88***	-2.05***	3.52**	0.02	33.36***	-0.04
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.2049)	(0.1408)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0146)	(0.3579)	(0.0000)	(0.2546)
H4: Asset Growth	10.98***	0.47***	29.22***	0.47***	0.98	0.48***	80.55***	0.42***	35.97***	-4.56***	2.97**	2.22***	21.26***	1.36***
	(0.0000)	(0.0023)	(0.0000)	(0.0049)	(0.4023)	(0.0002)	(0.0000)	(0.0054)	(0.0000)	(0.0000)	(0.0308)	(0.0000)	(0.0000)	(0.0000)

This table presents heterogeneous treatment effects across firm-level variables for all CBF components, estimated from Equation (2). Column numbers index each Pre/Post pair by outcome. The *Pre* column reports the Wald/F test on the pre-treatment triple-interaction terms, testing whether the moderator predicts differential pre-treatment trends. The *Post* column reports the aggregated post-treatment effect across 2022–2024, computed as the inverse-variance-weighted average of the corresponding yearly triple-interaction coefficients. Values in parentheses are p-values. Statistical significance is denoted by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See Table A1 for variable definitions.

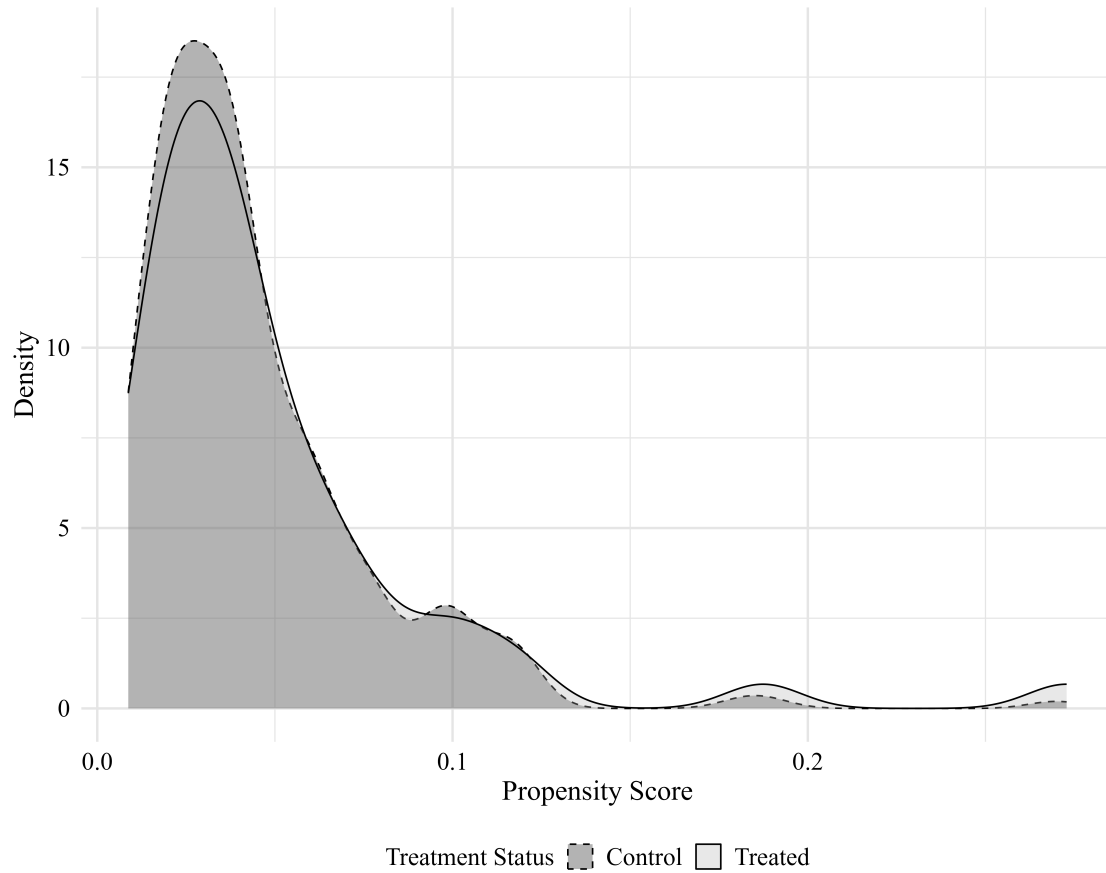
FIGURES

Figure 1: Source-based decomposition of the CBF—U.S. Firms



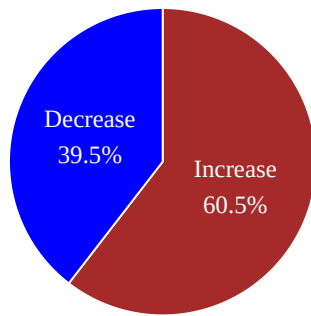
The pie chart shows the relative contribution of each environmental pressure category to the CBF of U.S. firms.

Figure 2: Propensity Score Matching Diagnostics

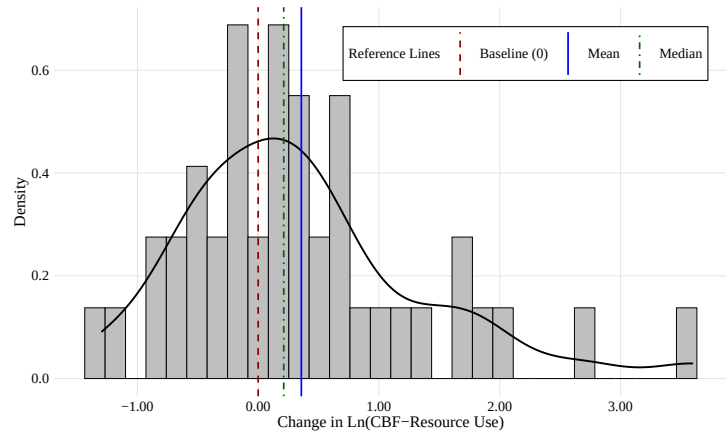


This figure displays the propensity score density distribution for treated (solid line, light gray) and control (dashed line, dark gray) firms.

Figure 3: Change in CBF-Resource Use Among Treated Firms Following the Policy



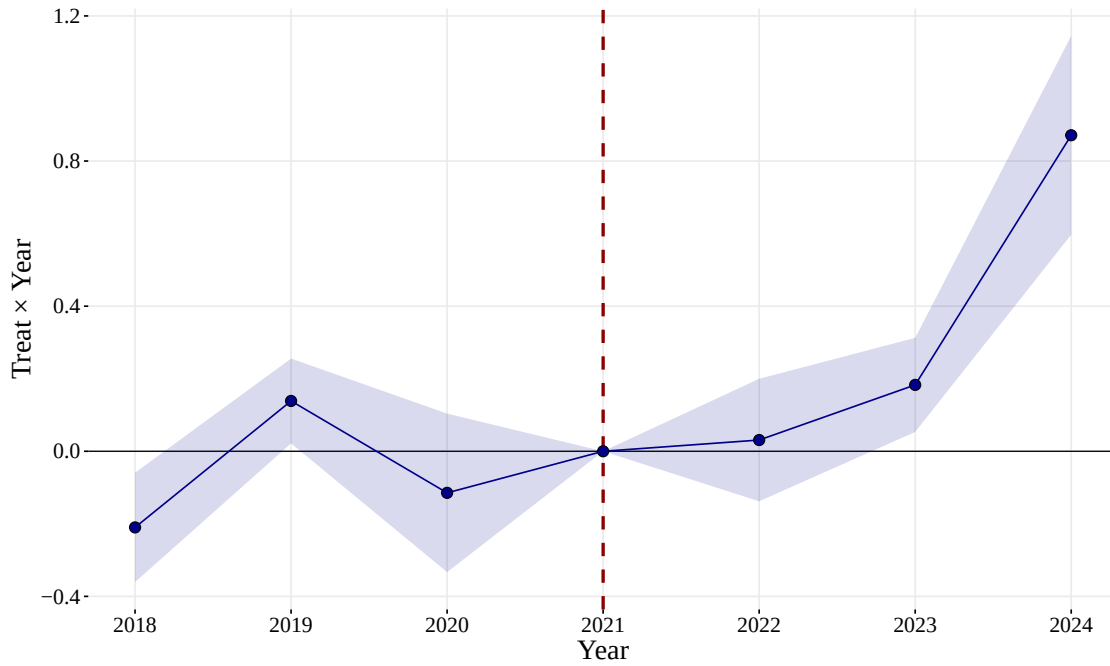
(a) Share of Firms



(b) Distribution of Firm-Level Changes

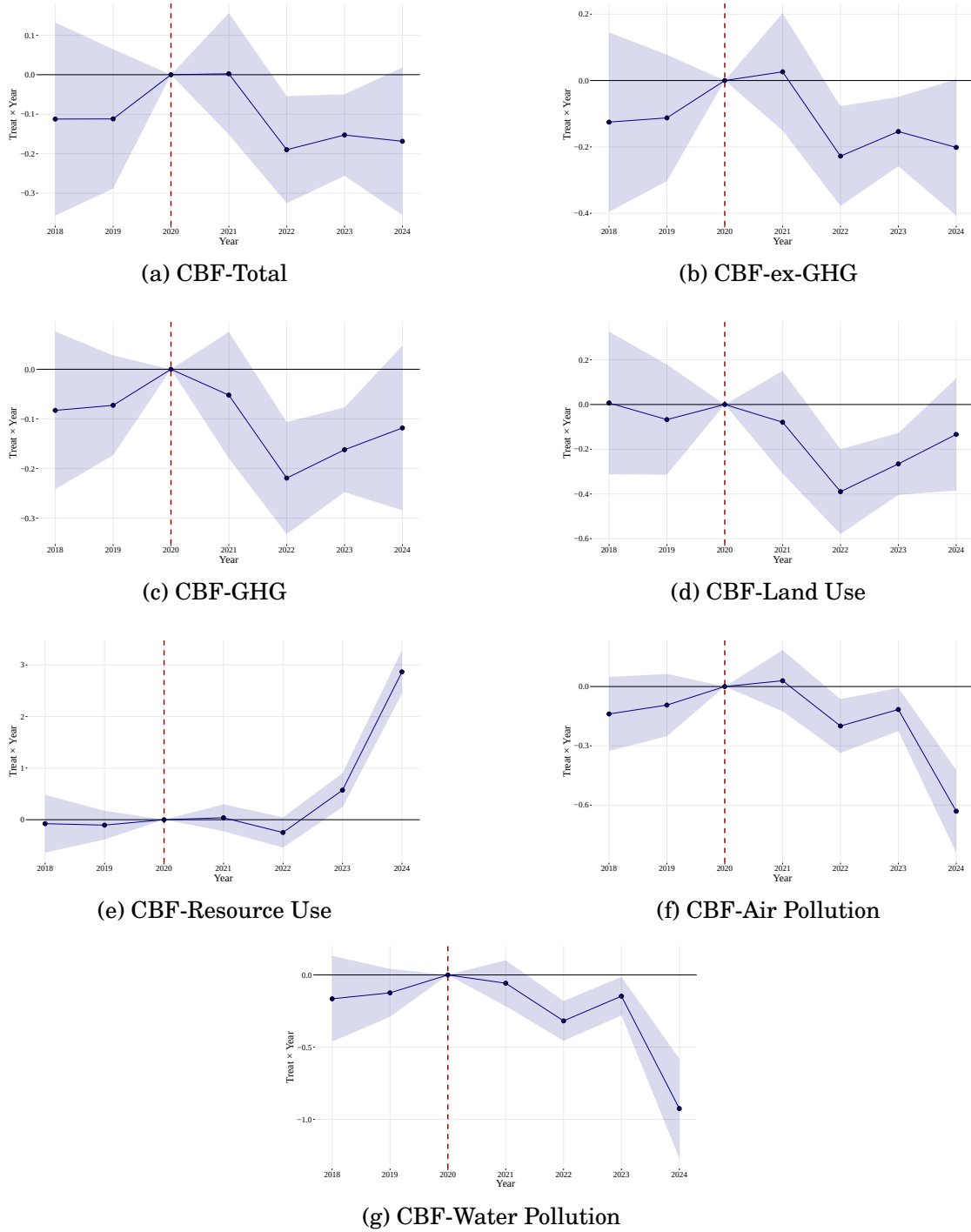
This figure illustrates changes in $\ln(\text{CBF-Resource Use})$ for treated firms following the introduction of Washington Cap-and-Invest Program. Panel (a) reports the share of treated firms that decrease or increase their CBF-Resource Use following the policy. Panel (b) presents the distribution of firm-level changes in $\ln(\text{CBF-Resource Use})$. The y-axis denotes density, and the x-axis shows the change in $\ln(\text{CBF-Resource Use})$. The vertical dashed line indicates zero (no change), the solid line indicates the mean change, and the dot-dashed line indicates the median change.

Figure 4: Dynamic Treatment Effects on CBF-GHG-Scope 3 Upstream



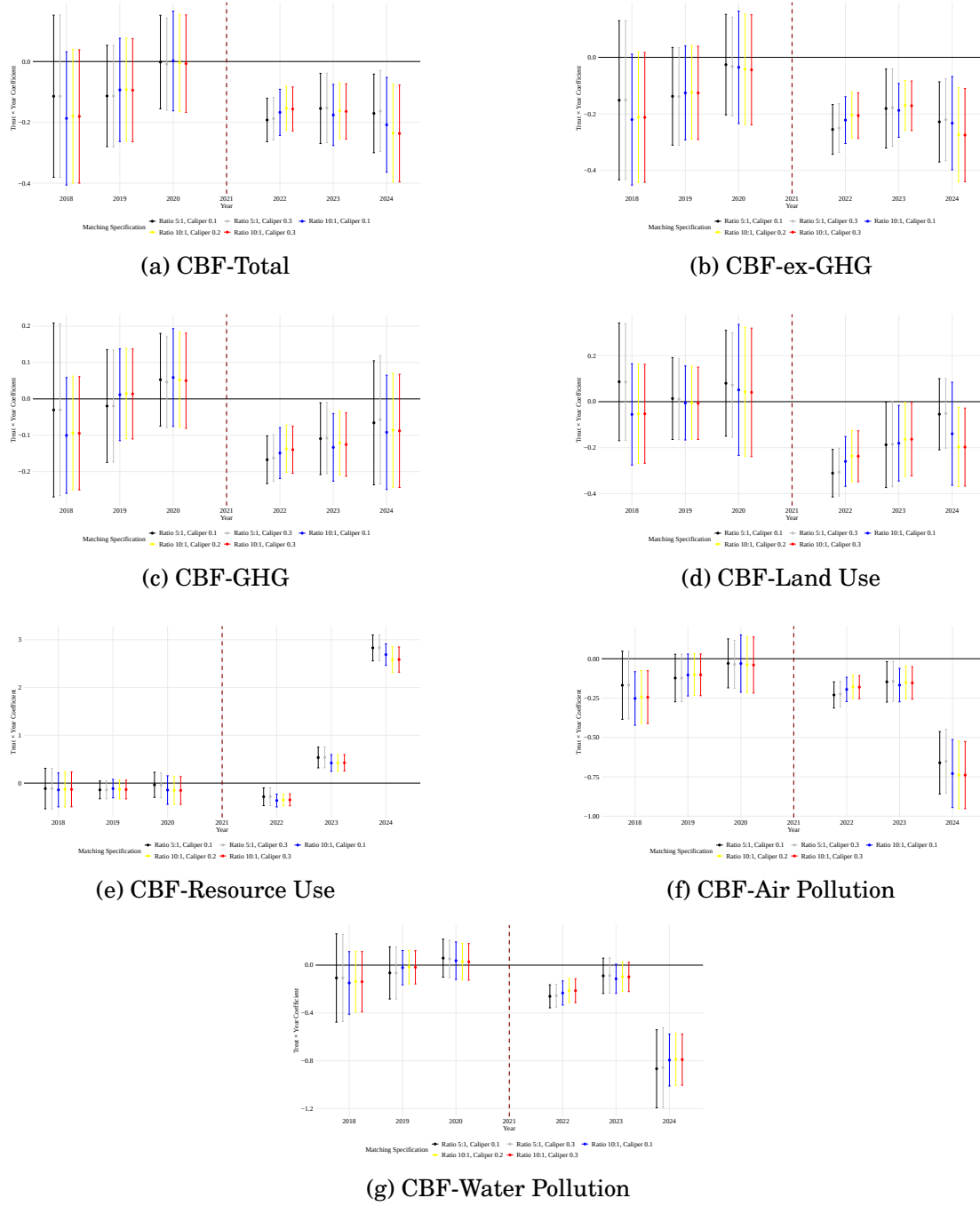
This figure displays the dynamic treatment effects for CBF-GHG-Scope 3 Upstream estimated using Equation (1). The coefficients correspond to interactions between the treatment indicator and year dummies, with 2021 serving as the omitted base year. The shaded areas represent 95% confidence intervals based on state-clustered robust standard errors. The vertical dashed line indicates the onset of the Washington State's Cap-and-Invest Program in 2021.

Figure 5: Dynamic Treatment Effects Under Placebo Treatment Timing



This figure reports dynamic treatment effects using a placebo treatment year set to 2020, which precedes the actual enactment of Washington State's Climate Commitment Act. The coefficients are estimated from Equation (1) and represent the interaction between the treatment indicator and year-specific dummies, with 2020 omitted as the base period. The vertical dashed line indicates the policy enactment year. The shaded areas represent 95% confidence intervals. The seven panels report results for (a) CBF-Total, (b) CBF-ex-GHG, (c) CBF-GHG, (d) CBF-Land Use, (e) CBF-Resource Use, (f) CBF-Air Pollution, and (g) CBF-Water Pollution.

Figure 6: Dynamic Treatment Effects Under Alternative Matching Specifications



This figure reports dynamic treatment effects using an alternative propensity score matching specifications with 5:1 nearest-neighbor matching with calipers of 0.1 and 0.3 (black and grey lines, respectively), as well as 10:1 nearest-neighbor matching with calipers of 0.1, 0.2, and 0.3 (blue, yellow, and red lines, respectively). The coefficients are estimated from Equation (1) and represent the interaction between the treatment indicator and year-specific dummies, with 2021 omitted as the base period. The vertical dashed line indicates the policy enactment year. For each specification, the point estimates and 95% confidence intervals are displayed. The seven panels report results for (a) CBF-Total, (b) CBF-ex-GHG, (c) CBF-GHG, (d) CBF-Land Use, (e) CBF-Resource Use, (f) CBF-Air Pollution, and (g) CBF-Water Pollution.

APPENDIX

Table A1: Variable Definitions

Variable	Definition
CBF-Total	Direct and indirect corporate biodiversity footprint covering all environmental impact channels, including emissions, land transformation, resource extraction, and pollution. It represents the overall firm-level biodiversity pressure across global supply chains and operational activities. Winsorized at the 1st and 99th percentiles.
CBF-ex-GHG	Corporate biodiversity footprint excluding the greenhouse gas emissions component, computed as CBF-Total net of CBF-GHG. It captures the aggregate biodiversity pressure attributable to non-climate channels, including land use, resource extraction, air pollution, and water pollution. Winsorized at the 1st and 99th percentiles.
CBF-GHG	Direct and indirect corporate biodiversity footprint attributable to greenhouse gas emissions, capturing climate-driven ecosystem degradation effects through radiative forcing and climate-related habitat disruption. Winsorized at the 1st and 99th percentiles.
CBF-GHG-Scope 3 Upstream	Component of the GHG-related biodiversity footprint attributable to upstream Scope 3 emissions embedded in purchased goods, services, and supply-chain inputs, as distinct from direct operational emissions (Scope 1) and purchased energy (Scope 2). This measure captures biodiversity pressure transmitted through a firm's upstream supply chain rather than its own production activities. Winsorized at the 1st and 99th percentiles.
CBF-Land Use	Direct and indirect corporate biodiversity footprint arising from land occupation, land transformation, and conversion of natural habitats into industrial, agricultural, or urban land. Winsorized at the 1st and 99th percentiles.
CBF-Resource Use	Direct and indirect corporate biodiversity footprint generated by extraction and consumption of natural resources (e.g., minerals, fossil fuels, biomass), including upstream supply-chain dependencies. Winsorized at the 1st and 99th percentiles.
CBF-Air Pollution	Direct and indirect corporate biodiversity footprint due to emissions of air pollutants (e.g., NOx, SOx, particulate matter), which affect ecosystem quality through atmospheric deposition and ecosystem toxicity. Winsorized at the 1st and 99th percentiles.
CBF-Water Pollution	Direct and indirect corporate biodiversity footprint associated with waterborne pollutants, including chemical discharges and nutrient loading affecting aquatic ecosystems. Winsorized at the 1st and 99th percentiles.
Treat	It is an indicator variable equal to one for firms in the treatment group and zero otherwise. The treatment group includes (i) firms identified in the CITSS registry as Covered Entities, Covered Sources, or Opt-in Entities that are subject to mandatory compliance obligations under Washington State's Cap-and-Invest Program, and (ii) publicly listed firms headquartered in Washington State that are not included in the CITSS registry.
Size	Natural logarithm of total book assets, capturing firm size and production scale. Winsorized at the 1st and 99th percentiles.
Book to Market	Book equity divided by market equity, commonly used as a valuation and distress-risk proxy. Winsorized at the 1st and 99th percentiles.
ROA	Return on assets, computed as net income divided by total assets, measuring accounting profitability. Winsorized at the 1st and 99th percentiles.
Leverage	Total debt divided by total assets, measuring the extent of asset financing through debt. Winsorized at the 1st and 99th percentiles.
Capex to Assets	Capital expenditures divided by total assets, capturing firm-level investment intensity. Winsorized at the 1st and 99th percentiles.
Asset Growth	Annual percentage change in total assets. Winsorized at the 1st and 99th percentiles.
Asset Turnover	Sales divided by total assets, to capture operational efficiency in generating revenues from the firm's asset base. Winsorized at the 1st and 99th percentiles.
Cash Holdings	Natural logarithm of the ratio of cash and short-term investments to total assets, to account for liquidity and internal financing capacity. Winsorized at the 1st and 99th percentiles.

This table defines all variables used in the empirical analysis.



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