The Network Origins of the Carbon Risk Premium*

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April 2026

Abstract

Carbon risk is shaped not only by firms' own emissions but also by their position in production networks. We develop a general-equilibrium asset-pricing framework with input–output linkages, carbon emissions, and aggregate regulatory risk, and derive a sufficient-statistic characterization of the carbon risk premium in terms of direct exposure γ and indirect network exposure χ. Empirically, χ dominates γ in the cross-section of expected returns and accounts for roughly 85% of the total carbon risk premium. Using a Carbon Regulatory Index constructed from textual sources, we show that high-χ firms contract sharply in valuations, investment, and earnings during regulatory-risk episodes. The incidence is strikingly asymmetric: "network-brown" firms—low direct emissions but high network exposure—produce under 2% of aggregate Scope 1 emissions yet bear about 27% of the aggregate carbon risk premium. In a networked economy, emissions are governed by γ, but carbon-policy risk is governed by $\gamma + \chi$.

Keywords: Carbon Risk Premium, Production Networks, Input–Output Linkages, Climate Policy, Network Exposure.

JEL Classification: G12, G1, Q5, Q54, E2, L1

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*For very helpful comments, we thank Zhuo Chen, Max Croce, Bing Han, Xianling Long, Jincheng Tong, and Jun Pan, and conference participants at SED (2025), MRS (2025), CICF (2025), SFS Asian-Pacific (2025), Suzhou Finance Conference (2025). Kai Li acknowledges the financial support from National Natural Science Foundation of China (Project Number: 72525005) and Theme-based Research Scheme T31-603/21-N from Hong Kong University Grants Committee (RGC). Minghao Li acknowledges the financial support from National Natural Science Foundation of China (Project Number: 72203010). Wu Zhu acknowledges financial support from Tsinghua University Initiative Scientific Research Program (No.2022Z04W02016) and Tsinghua University School of Economics and Management Research Grant (No.2022051002). All errors are our own.

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1. INTRODUCTION

Climate transition policies and climate-related regulatory uncertainty are reshaping risk exposures across firms and sectors. A basic macro question remains unresolved: *who ultimately bears carbon transition risk?* The standard intuition is that the burden falls on high-emission ("brown") producers. In a networked economy, however, carbon risk need not stay where emissions occur. Firms are connected through input–output linkages, and carbon-related shocks can propagate across supply chains, so that firms with modest direct emissions may nonetheless be highly exposed through their trading partners. This paper studies how production networks redistribute carbon risk across firms and sectors, how this redistribution is reflected in asset prices, and how it maps into firms' real responses to climate-policy shocks.

Our central premise is simple. Carbon risk is transmitted through input–output linkages, and the dominant channel runs from downstream customers to upstream suppliers. When climate regulation tightens—or when broader carbon-related risks intensify—downstream sectors experience adverse cash-flow shocks and reduce their demand for intermediate inputs. These demand contractions transmit upstream through supply chains, lowering suppliers' cash flows and raising their exposure to carbon risk even when their own direct emissions are modest. Emissions identify where carbon is *produced*; networks identify where carbon risk is *borne*.

We formalize this idea in a tractable general-equilibrium asset-pricing framework that combines input–output linkages with carbon emissions and an aggregate regulatory-risk shock. The model yields a sharp characterization of the cross-sectional carbon risk premium in terms of two sufficient statistics: a firm's direct exposure γ, proportional to its own emission intensity, and its indirect exposure χ, capturing network propagation through the Leontief structure of the economy. The ranking of expected returns across firms is determined entirely by $\gamma + \chi$. This decomposition clarifies why empirical studies that focus solely on direct emissions can miss a substantial component of carbon risk: a firm's position in the production network can amplify or dampen its overall exposure beyond what emissions alone reveal.

The theoretical result translates directly into an empirical procedure. Using firm-level emissions from Trucost, input–output tables from the U.S. Bureau of Economic Analysis, and financial data from CRSP and Compustat, we construct firm- and industry-level measures of both γ and χ. Our indirect exposure is not a relabeling of Scope 3 emissions accounting. Scope 3 measures reported upstream emissions; χ measures the economic exposure of a firm's cash flows to carbon-related shocks transmitted through the network, which is the object that matters for pricing. Empirically, χ and γ carry distinct information: their cross-sectional correlation averages 0.34 and ranges from 0.16 to 0.43 across years.

Our first set of empirical results establishes that indirect exposure is first-order for cross-sectional pricing. Using the implied cost of capital (ICC) as an ex-ante measure of expected returns, firms in the top quintile of χ earn an annualized ICC that is 2.24% higher than firms in the bottom quintile, while direct exposure γ alone does not generate a statistically significant spread. Panel regressions and Fama–MacBeth estimates confirm that a one-standard-deviation increase in χ raises annualized ICC by about 1.2 percentage points, that the effect is robust to standard controls, to alternative emissions measures (Scopes 1–3), to reporting lags, to a generalized CES production specification, and to subsample splits, and that χ dominates γ in explaining the cross-section. A decomposition attributes roughly 85% of the total carbon premium to indirect exposure—of which the cross-industry component accounts for about two-thirds—and only 15% to direct exposure, driven almost entirely by the within-industry component. A factor-model analysis reinforces these findings: augmenting the CAPM with γ and χ factors substantially improves the model's ability to price portfolios sorted on carbon exposure.

To provide direct evidence on the risk mechanism, we construct a Carbon Regulatory Index (CRI) from a large-language-model analysis of *Wall Street Journal* articles and extract unexpected changes in regulatory risk as innovations from an AR(1) process. High-χ firms experience disproportionately large declines in returns, revenues, investment, and net income following unexpected increases in regulatory risk, while high-γ firms exhibit only muted responses once network exposure is controlled for. This evidence is consistent with the network-propagation mechanism that underlies the theoretical framework.

We then connect these cross-sectional pricing estimates to the macro question that motivates the paper. Decomposing the aggregate carbon risk premium across firm types, we find that firms with low direct emissions but high network exposure—what we call "network-brown" firms—account for roughly 20% of aggregate market capitalization but absorb about 27% of the aggregate carbon risk premium, more than the share attributable to firms with high direct emissions and low network exposure. The same group absorbs a disproportionate share of realized market-wide wealth losses during episodes of heightened climate-regulatory risk, and reduces investment most sharply during those episodes. Yet these firms produce less than 2% of aggregate Scope 1 emissions. Carbon-policy risk in a networked economy is distributed very differently from the emissions that generate it.

We interpret this asymmetry as a systematic misalignment between two distinct objects. The distribution of emissions is the margin relevant for correcting the externality, for instance through Pigouvian taxation. The distribution of carbon-policy risk incidence is the margin relevant for a different set of questions: the financial-stability monitoring of transition risk, the design of transition-support and adjustment policies, and ex-post distributional analysis. In a horizontal economy without input–output linkages these two distributions coincide, but in a networked economy they do not: the first is governed by γ alone, while the second is governed by $\gamma + \chi$. Our estimates quantify the gap between the two and suggest that exposure assessments based on emissions accounting—including common implementations of climate stress tests and disclosure-based metrics—can substantially understate the breadth of firms and capital affected by climate-policy risk.

Although we develop the framework around carbon regulatory risk, its logic is not specific to carbon. Any aggregate shock that maps into firm-level cash flows through a sector-specific exposure—shifts in consumer preferences toward "green" firms, changes in the probability of climate-related physical disasters, technology shocks that favor or penalize particular sectors, or trade-policy shocks that raise the cost of inputs from specified origins—can be accommodated by reinterpreting γ_j as the relevant sectoral exposure. The sufficient-statistic result then carries over: cross-sectional expected returns are governed by the sum of a firm's direct exposure and its network exposure through the Leontief structure. The network channel documented in this paper, and the wedge it generates between emissions-based and exposure-based measures, should therefore be relevant for a broader class of aggregate-risk pricing questions.

Our paper makes three contributions. First, we develop a tractable general-equilibrium asset-pricing framework that integrates carbon emissions, input–output linkages, and aggregate regulatory risk, and we derive a sufficient-statistic characterization of the cross-sectional carbon risk premium in terms of direct and indirect exposures. Second, we provide a measurement tool that goes beyond existing emissions-based accounting: our χ captures the economic exposure of firms' cash flows to carbon risk as transmitted through the production network, which is the object that matters for pricing. Empirically, we show that indirect exposure is the dominant priced component, a finding that reconciles mixed evidence in the prior literature on whether direct emissions are associated with higher expected returns. Third, we use the pricing estimates to produce an incidence accounting of who bears carbon transition risk in the aggregate, document a systematic misalignment between emissions and risk exposure, and connect these ex-ante patterns to the cross-sectional distribution of ex-post wealth losses and real-side responses during regulatory shocks.

Related Literature. **Carbon risk and the cross-section of returns.** A large body of work examines whether firms with higher carbon emissions earn higher expected returns. Bolton and Kacperczyk (2021, 2023); Hsu et al. (2023); Atilgan et al. (2024); Lioui and Misra (2023) document a positive carbon premium in realized returns, whereas Pástor et al. (2022); Zhang (2025); Eskildsen et al. (2024) argue that realized-return evidence is fragile or reflects ex-post shocks rather than ex-ante risk compensation. These studies focus almost exclusively on direct emissions. Our contribution is to show, theoretically and empirically, that the cross-sectional carbon risk premium is governed by a sufficient statistic that combines direct and network-based exposures, and that the network component is the dominant driver. Our measurement approach also offers a partial reconciliation of the mixed prior evidence: once χ is incorporated, the role of γ in explaining expected returns becomes consistent and modest.

Production networks and asset pricing. A literature beginning with Ahern (2013); Herskovic (2018); Richmond (2019); Gofman et al. (2020); Yang and Zhu (2020) studies how network position and concentration shape risk premia in equity and currency markets. Our paper complements this work by introducing a specific aggregate risk—carbon regulatory risk—and by tracing its propagation through input–output linkages to firm-level profits and expected returns. The associated general-equilibrium analysis rests on the foundational treatments of production networks in Carvalho (2010);

Acemoglu et al. (2012); Carvalho and Gabaix (2013); Acemoglu et al. (2015); Carvalho et al. (2021).

Supply-chain exposure to carbon risk. Sautner et al. (2023b) and De Angelis et al. (2023) emphasize that firms are exposed to climate risk through supply chains and financial networks, but do not embed this exposure in a general-equilibrium asset-pricing framework. Aghion et al. (2025) considers green transition technologies along supply chains in a general equilibrium model, whereas we focus on regulatory risks and premia. Pastor et al. (2024) construct a "carbon burden" object that aggregates Scope 1, 2, and 3 emissions into a present-value measure, and show that for the vast majority of U.S. firms Scope 1 emissions alone materially understate exposure. Our χ differs conceptually from this construct: it is not a present value of embodied emissions but a covariance-based risk measure derived from a GE model in which aggregate regulatory shocks propagate through the network. The two objects are complementary—one characterizes the level of embedded carbon, the other characterizes the pricing-relevant exposure to carbon *risk*.

Climate policy uncertainty and regulatory risk. Theoretical and empirical work has emphasized the role of regulatory uncertainty in shaping carbon risk premia (Nordhaus, 2019; Ilhan et al., 2021; Sautner et al., 2023a; Hsu et al., 2023; Gasparini, 2023; Hong et al., 2019). Related evidence comes from green-bond markets (Larcker and Watts, 2020; Baker et al., 2022; Zerbib, 2022; Giglio et al., 2025). Our paper contributes by providing a general-equilibrium account of how such regulatory shocks transmit through production networks, and by documenting that the cross-section of responses to identified regulatory-risk shocks lines up closely with the theoretical χ. Methodologically, our Carbon Regulatory Index builds on recent work that applies large language models to textual sources in economics and finance (Bybee, 2023; Chen et al., 2023; Cong et al., 2024).

Roadmap. Section 2 develops the general-equilibrium model and derives the sufficient-statistic characterization of expected returns. Section 3 constructs the empirical counterparts of direct and indirect exposures. Section 4 tests the cross-sectional pricing implications using portfolio sorts, panel regressions, Fama–MacBeth estimates, and a within- versus cross-industry decomposition. Section 5 constructs the Carbon Regulatory Index and examines firm-level responses to identified regulatory shocks. Section 6 evaluates carbon-risk factor models against competing specifications. Section 7 translates the pricing estimates into macro and policy objects, quantifying the incidence of carbon risk across firm types and the misalignment between emissions and risk exposure. Section 8 concludes.

2. Theoretical Framework

This section develops a tractable general equilibrium asset pricing framework in which carbon risk propagates through production networks. The key result is that cross-sectional variation in expected stock returns is governed by a sufficient statistic, $\gamma_j + \chi_j$, where γ_j captures direct exposure through a firm's own emissions and χ_j captures indirect exposure transmitted through input-output linkages.

Carbon regulation affects firms both directly and through their trading partners: when regulation tightens, downstream firms reduce demand for intermediate inputs, transmitting shocks upstream along the supply chain. As a result, firms with low emissions may nonetheless bear substantial carbon risk if they are closely connected to carbon-intensive sectors. Formally, this framework combines production with input-output linkages, carbon taxes, and a representative household that determines the stochastic discount factor.

2.1 Model Setup

Production and Networks. Time is discrete with two periods, $t = 0, 1$, where period 0 represents the planning stage prior to the realization of shocks. The economy consists of N industries, each producing a distinct good. Within each industry, a continuum of perfectly competitive firms operates.

Firms in industry j produce output according to

$$Y_{jt} = \xi_j X_{jt}^{\eta_j}, \tag{1}$$

where Y_{jt} denotes output, X_{jt} is a composite of intermediate inputs, and $\eta_j \in (0, 1)$ is the share of the composite input. The term $\xi_j = \eta_j^{\eta_j} \prod_{k=1}^{N} a_{jk}^{a_{jk}}$ is a normalization constant, where a_{jk} is defined in Equation (2). Decreasing returns to scale generate positive profits, which are distributed to households.[1]

The composite input X_{jt} is aggregated from intermediate inputs sourced from all industries via the economy's input-output linkages:

$$X_{jt} = \prod_{k=1}^{N} X_{jkt}^{a_{jk}}, \tag{2}$$

where X_{jkt} denotes the quantity of good k used by industry j, and $a_{jk} \geq 0$ is the corresponding input share, with $\sum_{k=1}^{N} a_{jk} = 1$. The matrix $\boldsymbol{A} = [a_{jk}]_{N\times N}$ summarizes the input–output structure of the economy.

The Cobb–Douglas specification in (2) yields sharp closed-form solutions. However, it implies that input shares are constant and carbon-tax shocks propagate only directly to upstream sectors. In Appendix A.1, we extend the model to a constant-elasticity-of-substitution (CES) aggregator that allows for endogenous input substitution and bidirectional propagation of shocks. Following a carbon tax increase, firms substitute toward lower-cost inputs, typically sourced from less carbon-intensive industries. Section 4.5 shows that our main results remain quantitatively robust when this substitution channel is introduced.

Carbon Emissions. We assume that producing one dollar of output in industry j releases γ_j units of carbon, where γ_j denotes the emission intensity. The government imposes a tax τ_t per unit of

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[1] This can be interpreted as reflecting a fixed factor of production—such as capital or managerial input—that absorbs residual profits; for example, $Y_{jt} = \xi_j Z_{jt} \overline{K}^{1-\eta_j} X_{jt}^{\eta_j}$, where $\overline{K}$ denotes fixed capital.

emissions, implying an effective tax rate $\tau_{jt} = \gamma_j \tau_t$ for industry j. Firms in industry j thus earn after-tax revenue of $(1 - \tau_{jt})P_{jt}Y_{jt}$, where P_{jt} is the output price. Carbon tax revenues are rebated to households as lump-sum transfers.

An alternative approach to modeling emissions is based on firms' input usage (Shapiro and Walker, 2018).[2] We adopt the revenue-based specification for two reasons. First, it provides a parsimonious measure of exposure and aligns with empirical studies of carbon risk premia that use revenue-adjusted emission intensity (Engle et al., 2020; Ilhan et al., 2021; Zhang, 2025). Second, detailed firm-level input data are often unavailable, limiting the empirical feasibility of input-based approaches. Appendix A.2 shows that, under mild conditions, the two approaches are theoretically equivalent.

Over longer horizons, firms may adjust production in response to regulation—for example, by adopting cleaner technologies or substituting toward low-carbon inputs (Acemoglu et al., 2012; Martin et al., 2014; Cullen and Mansur, 2017; Xiang, 2023). Our focus, however, is on short-run asset pricing implications using monthly or annual data. Over these horizons, it is reasonable to treat production technologies as fixed. Nonetheless, in the empirical analysis, we allow the input–output matrix A to evolve over time to capture gradual changes in the production structure.

Aggregate Risk. In period 1, carbon regulatory risk materializes. The uniform tax rate τ_1 is drawn from a distribution with mean $\overline{\tau}$, variance σ_τ^2, and support on $(0, 1)$. This tax shock is the sole source of aggregate uncertainty. Because firms differ in emission intensity, their exposure to this shock varies, generating cross-sectional dispersion in risk premia. For simplicity, we normalize $\bar{\tau} = 0$.

Households. The economy is populated by a continuum of identical households with time-separable preferences:

$$U = \mathbb{E}_0 \sum_{t=0}^{1} \log C_t, \tag{3}$$

where C_t is an aggregate consumption bundle composed of N goods:

$$\log C_t = \sum_{j=1}^{N} \alpha_j \log \left(\frac{C_{jt}}{\alpha_j} \right).$$

Here, C_{jt} denotes consumption of good j, and α_j is its expenditure share, with $\sum_{j=1}^{N} \alpha_j = 1$. The corresponding aggregate price index is $P_t = \prod_{j=1}^{N} P_{jt}^{\alpha_j}$, and normalize $P_0 = P_1 = 1$.

Financial markets are complete. In period 0, households trade a risk-free bond with gross return R_1^f and purchase equity claims on firms. Let B_1 denote bond holdings, $\vartheta_1 \leq 1$ the share of equity held, and V_1 the equity price. Let Π_{jt} denote profits in industry j. The household's flow budget constraints

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[2] For example, emissions from firm i can be written as $\sum_{j=1}^{N} \gamma_j P_j X_{ij}$, where γ_j denotes emissions per dollar of input j.

are given by

$$
\begin{aligned}
C_0 + B_1/R_1^f + \vartheta_1 V_1 &\le B_0 + \sum_{j=1}^{N} \Pi_{j0}, \\
C_1 &\le B_1 + \vartheta_1 \sum_{j=1}^{N} \Pi_{j1} + \sum_{j=1}^{N} \gamma_j \tau_1 P_{j1} Y_{j1}.
\end{aligned}
\tag{4}
$$

Equilibrium. A competitive equilibrium consists of goods prices $\{P_{jt}\}_{j=1}^N$, the risk-free rate R^f, the equity price V_1, intermediate inputs $\{X_{jkt}\}_{j,k=1}^N$, final outputs $\{Y_{jt}\}_{j=1}^N$, and final consumption $\{C_{jt}\}_{j=1}^N$ such that:

1. Households maximize expected utility (3) subject to the budget constraints (4).

2. Firms maximize profits by choosing the intermediate inputs $\{X_{jkt}\}$,

$$
\max_{\{X_{jkt}\}_{k=1}^N} (1 - \tau_{jt}) P_{jt} Y_{jt} - \sum_{k=1}^{N} P_{kt} X_{jkt}, \;\; t = 0, 1, \tag{5}
$$

   where Y_{jt} is given by expression (1).

3. The bond market clears: $B_1 = 0$, the stock market clears: $\vartheta_1 = 1$, and goods markets clear for all j and t,

$$
C_{jt} + \sum_{k=1}^{N} X_{kjt} = Y_{jt}, \;\; t = 0, 1, \tag{6}
$$

Discussion. The model introduces carbon regulatory risk through the tax τ_{jt}, but the framework readily accommodates a broader class of carbon-related aggregate risks. For example, shifts in consumer preferences toward low-emission firms or changes in the likelihood of climate-related disruptions can be represented as shocks that differentially affect firms based on their carbon intensity. In such cases, the term $\tau_{jt} P_{jt} Y_{jt}$ captures the relative revenue loss of high-emission ("brown") firms compared to low-emission ("green") firms.[3] More generally, the framework applies to any aggregate shock that loads on firms differentially and propagates through production networks.

2.2 Preview: Network Transmission of Carbon Risk

Before solving for the carbon risk premium, we consider three simple network structures to build intuition for how carbon shocks propagate through production networks.

Example 1: Horizontal network. Consider an economy with no input–output linkages, where each industry produces using only a fixed factor and households consume all goods (Figure 1, panel (a)). In this case, carbon taxation affects firms solely through their own emissions. Firms with higher emission

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[3] We follow standard terminology in referring to high-emission firms as “brown” and low-emission firms as ”green”.

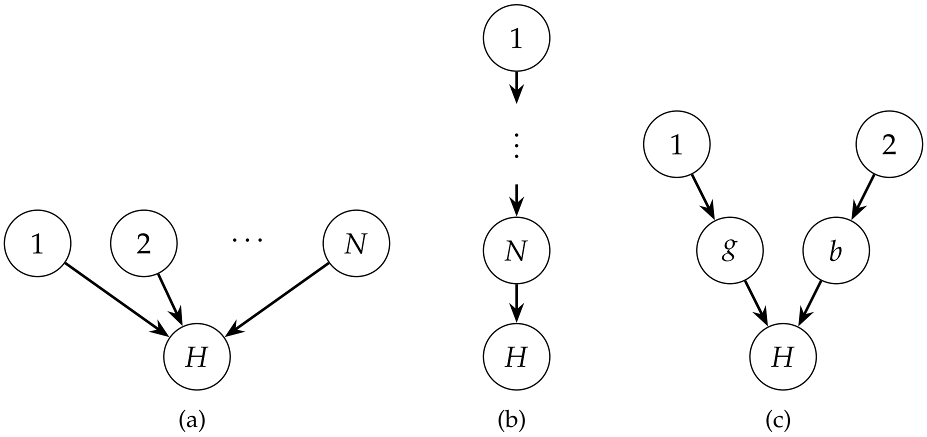

Figure 1: Network Examples

intensity experience larger profit declines, while firms with lower emissions are less affected. There is no propagation of shocks across industries.

Example 2: Vertical network. Now consider a vertical production chain, where each industry supplies inputs to the next (Figure 1, panel (b)). A carbon tax reduces demand in downstream industries, which in turn reduces demand for inputs from upstream suppliers. As a result, shocks propagate upstream along the supply chain. Firms that are farther upstream are exposed to the cumulative effect of downstream shocks, even if all industries have identical emission intensity.

Example 3: Centrality and trading partners. Finally, consider two firms with identical emissions but different trading partners (Figure 1, panel (c)). Firm 1 supplies a carbon-intensive industry b, while firm 2 supplies a cleaner industry g. A carbon tax reduces demand more strongly in the carbon-intensive sector, leading to a larger decline in sales for its suppliers. As a result, the first firm is more exposed to carbon risk despite having identical direct emissions.

These examples illustrate that carbon risk depends not only on a firm's own emissions, but also on how shocks propagate through the production network. The next sections formalize this intuition and characterize firm-level exposure in general equilibrium. We revisit these examples in Section 2.5 after solving for the carbon risk premium.

2.3 Expected Stock Returns

We characterize expected stock returns in the model using a standard consumption-based asset pricing framework. The key result is that cross-sectional variation in expected returns is summarized by a sufficient statistic that combines direct emissions with a network-based measure of indirect exposure.

To establish this result, we proceed in three steps. First, we derive the expression for the Domar weight, a central concept that links firm-level profits to aggregate consumption. Second, we characterize how carbon regulation affects both firms' profits and aggregate consumption growth. Third, we combine these results to express expected returns in terms of the covariance between firm profits and the stochastic discount factor.

2.3.1 Domar Weight

The Domar weight of industry j in period t is defined as its pre-tax revenue relative to GDP:

$$S_{jt} = \frac{\Psi_{jt}}{P_t C_t},$$

where $\Psi_{jt} = P_{jt} Y_{jt}$ denotes industry j's pre-tax revenue.

Domar weights summarize how industry-level shocks affect aggregate outcomes. In a networked economy, they depend on both direct and indirect input–output linkages.

To derive the expression for S_{jt}, combining firms' and households' optimality conditions with market clearing yields

$$S_{jt} = \alpha_j + \sum_{k=1}^{N} (1 - \gamma_k \tau_t) \eta_k a_{kj} S_{kt}.$$

In vector form,

$$\boldsymbol{S}_t = \boldsymbol{\alpha} + \boldsymbol{A}' \boldsymbol{D}_\eta (I - \boldsymbol{D}_\gamma \tau_t) \boldsymbol{S}_t, \tag{7}$$

which implies the closed-form solution

$$\boldsymbol{S}_t = \left[I - \boldsymbol{A}' \boldsymbol{D}_\eta (I - \boldsymbol{D}_\gamma \tau_t) \right]^{-1} \boldsymbol{\alpha}, \tag{8}$$

where $\boldsymbol{D}_\gamma = \text{diag}(\gamma_1, \gamma_2, ..., \gamma_N)$ and $\boldsymbol{D}_\eta = \text{diag}(\eta_1, \eta_2, ..., \eta_N)$.

This expression highlights that an industry's Domar weight is a general equilibrium object: S_{jt} depends not only on industry j's own characteristics, but also on the carbon emission intensities, returns to scale, and consumers' expenditure shares of all other industries. In particular, carbon shocks in downstream industries affect upstream sectors through input demand, generating interdependence across industries. These interdependencies arise from input-output linkages and vanish only when the input-output matrix $\boldsymbol{A}$ is diagonal.

Linearization and Network Exposure. Let $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_N)'$ denote the vector of emission intensities, and let $\boldsymbol{D}_S = \text{diag}(S_{10}, S_{20}, \ldots, S_{N0})$ denote period-0 Domar weights. Linearizing equation (7) around values in period 0 yields the following lemma.

Lemma 1. *The growth rates of Domar weights are given by*

$$\Delta \log \boldsymbol{S_t} = -\boldsymbol{\chi} \tau_t, \tag{9}$$

where

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1} (I - \boldsymbol{A}' \boldsymbol{D}_\eta)^{-1} \boldsymbol{A}' \boldsymbol{D}_\eta \boldsymbol{D}_S \boldsymbol{\gamma} > 0, \tag{10}$$

and $\boldsymbol{\chi} = (\chi_1, \chi_2, \ldots, \chi_N)'$.

The vector $\boldsymbol{\chi}$ is the key object in our analysis. We will show that it measures the total exposure of each industry to carbon risk transmitted through the production network. Unlike emission intensity γ_j, which captures direct exposure, χ_j aggregates all indirect exposures arising from input–output linkages.

Economic Interpretation. To build intuition, expression (9) can be written in a recursive structure capturing all propagation paths in the network,

$$\Delta \log S_{jt} = -\frac{1}{S_{j0}}[\sum_{k=1}^{N} a_{kj}\eta_k S_{k0}\gamma_k\tau_t + \sum_{k=1}^{N}\sum_{\ell=1}^{N}\eta_k\eta_\ell a_{k\ell}a_{\ell j}S_{\ell 0}\gamma_\ell\tau_t + \sum_{k=1}^{N}\sum_{\ell=1}^{N}\sum_{m=1}^{N}\eta_k\eta_\ell\eta_m a_{k\ell}a_{\ell m}a_{mj}S_{m0}\gamma_m\tau_t \ldots] \quad (11)$$

How does the carbon regulatory risk τ_t affect industry j's Domar weight? An unexpected tightening of carbon policy (i.e., a positive shock to τ_t) reduces industry k' demand for inputs as long as $\gamma_k > 0$. These reductions propagate upstream: the first term captures industry j's exposure to its immediate downstream customers, the second term captures the exposure to customers of those customers, and higher-order terms capture longer production chains. All of these cascading effects are succinctly summarized in the closed-form expression (9), by the sufficient statistic χ_j.

2.3.2 Profits

Firms choose intermediate inputs to maximize profits. The first-order condition implies the optimal demand for inputs from industry k:

$$X_{jkt} = \frac{(1-\gamma_j\tau_t)\eta_j a_{jk} Y_{jt} P_{jt}}{P_{kt}}. \quad (12)$$

Substituting into the firm's profit function yields:

Lemma 2. *Profits in industry j are proportional to pre-tax revenue,*

$$\Pi_{jt} = (1-\eta_j)(1-\gamma_j\tau_t)\Psi_{jt} = (1-\eta_j)(1-\gamma_j\tau_t)S_{jt}C_t. \quad (13)$$

Equation (13) shows that profits are a constant fraction of after-tax revenue. The term $(1-\gamma_j\tau_t)$ captures the direct effect of carbon taxation, while $S_{jt}C_t$ reflects general equilibrium effects through changes in revenue shares and aggregate demand.

To characterize the response of profits to carbon risk, we linearize (13) around period 0:

Proposition 1. *Profits in industry j satisfy*

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0}\left(\phi_{\pi j}\tau_t + \Delta \log C_t\right), \quad (14)$$

where

$$\phi_{\pi j} = -\gamma_j - \chi_j < 0. \quad (15)$$

In vector form,

$$\boldsymbol{\Pi}_t = \boldsymbol{\Pi}_0 + \boldsymbol{D}_{\Pi_0} \left(\boldsymbol{\phi}_\pi \tau_t + \mathbf{1} \Delta \log C_t \right), \tag{16}$$

where $\boldsymbol{D}_{\Pi_0} = \text{diag}(\Pi_{10}, \ldots, \Pi_{N0})$ *and* $\boldsymbol{\phi}_\pi = (\phi_{\pi 1}, \ldots, \phi_{\pi N})'$.

Proposition 1 delivers a simple decomposition of carbon risk exposure. The term $-\gamma_j$ captures the direct effect of carbon taxation on a firm's profit through its own emissions. The term $-\chi_j$ captures the indirect network effect: firms are exposed to carbon risk through their customers' demand for inputs, with shocks propagating upstream through production linkages. Hence, A firm's total exposure to carbon risk is given by $\gamma_j + \chi_j$, which will play a central role in determining expected returns.

2.3.3 Aggregate Consumption Growth

The following proposition characterizes the effect of carbon taxation on aggregate consumption growth.[4]

Proposition 2. *Aggregate consumption growth is given by*

$$\Delta \log C_t = \phi_C \tau_t, \tag{17}$$

where

$$\phi_C = -\boldsymbol{\alpha}' \boldsymbol{\Omega} (\boldsymbol{D}_\eta^{-1} - I) \boldsymbol{\gamma} - \boldsymbol{\alpha}' \boldsymbol{\Omega} \boldsymbol{\chi} < 0, \tag{18}$$

and $\boldsymbol{\Omega} = (I - \boldsymbol{D}_\eta \boldsymbol{A})^{-1} (I - \boldsymbol{D}_\eta)$.

The inequality $\phi_C < 0$ implies that carbon taxation reduces aggregate consumption growth. Intuitively, the tax introduces wedges in production, leading to misallocation and a decline in aggregate output.

To see the underlying forces, note that $\log C_t = \boldsymbol{\alpha}' \log \boldsymbol{\Psi}_t - \boldsymbol{\alpha}' \log \boldsymbol{S}_t$. A higher carbon tax reduces firms' revenues $\boldsymbol{\Psi}_t$, lowering consumption. At the same time, it reduces Domar weights $\boldsymbol{S}_t$, which partially offsets this effect by reallocating expenditure across industries. Proposition 2 shows that the revenue effect dominates: carbon taxation unambiguously reduces consumption growth.

Importantly, the term $\boldsymbol{\alpha}' \boldsymbol{\Omega} \boldsymbol{\chi}$ reflects the role of production networks in shaping aggregate outcomes: network propagation amplifies the impact of carbon shocks on consumption by transmitting distortions across industries.

2.3.4 Expected Stock Returns

We characterize expected returns using a standard consumption-based asset pricing framework. With log utility, the stochastic discount factor is given by $(1 - \Delta \log C_t)$ under a log-linear approximation.

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[4] See Appendix A.3.4 for the proof.

The value of a firm in industry j satisfies

$$V_{jt} = \frac{\mathbb{E}(\Pi_{jt})}{R_t^f} - \mathrm{Cov}(\Delta \log C_t, \Pi_{jt}). \tag{19}$$

Using $\mathbb{E}(\Pi_{jt}) = \Pi_{j0}$ and rearranging yields the expected net return:

$$\mathbb{E}r_{jt} = r_t^f + \frac{\mathrm{Cov}(\Delta \log C_t, \Pi_{jt})}{\Pi_{j0}}. \tag{20}$$

Substituting the expressions for $\Delta \log C_t$ and Π_{jt} from (17) and (14), we obtain:

Proposition 3. *Expected returns satisfy*

$$\mathbb{E}r_{jt} = r_t^f + \phi_{\pi j}\phi_C\sigma_\tau^2 + \mathrm{Var}(\Delta \log C_t), \tag{21}$$

where $\phi_{\pi j} = -\gamma_j - \chi_j < 0$ *and* $\phi_C < 0$.

Proposition 3 implies that expected excess returns are increasing in: (i) the variance of the aggregate consumption growth, (ii) the volatility of regulatory shocks, (iii) the responsiveness of aggregate consumption growth to these shocks, and (iv) the sensitivity of firm profits to the shocks. Since the first three terms are common across industries, cross-sectional variation in expected returns is entirely governed by firm-level exposure $\phi_{\pi j}$.

Theorem 1. *For any industries j and k, if $\gamma_j + \chi_j > \gamma_k + \chi_k$, then $\mathbb{E}r_{jt} > \mathbb{E}r_{kt}$.*

Theorem 1 shows that $\gamma_j + \chi_j$ is a sufficient statistic for ranking expected returns. The term γ_j captures direct exposure to carbon risk, while χ_j captures indirect exposure through production networks. This result implies a decoupling between where carbon is produced and where carbon risk is borne. As a result, expected returns depend not only on where emissions occur, but also on how carbon risk propagates across firms in general equilibrium.

This result guides the empirical analysis that follows. We construct empirical counterparts of γ_j and χ_j and test the model's predictions using panel regressions, portfolio sortings, and Fama–MacBeth regressions. We find that firms with higher $\gamma_j + \chi_j$ exhibit higher expected returns and higher implied cost of capital, with the network component χ_j accounting for the majority of the variation.

Connection to Existing Literature. The existing literature typically relates expected returns to firms' own emissions or emission intensity (Bolton and Kacperczyk (2021); Aswani et al. (2024a); Zhang (2025)). The following proposition provides sufficient conditions under which this approach is valid.

Proposition 4. *Suppose that for industries j and k: (i) $a_{hj} = a_{hk}$ for all h, and (ii) $\alpha_j = \alpha_k$. Then, $\mathbb{E}r_{jt} > \mathbb{E}r_{kt}$ if and only if $\gamma_j > \gamma_k$.*

Proposition 4 shows that emissions alone are sufficient only when all industries have identical input–output structures. In this case, firms face identical network exposure, and expected returns depend solely on emission intensity. In practice, however, the input-output matrix exhibits substantial heterogeneity across industries, implying that network structure plays a first-order role in explaining variation in expected returns.

2.4 Additional Testable Implications

We derive additional implications that clarify the channels underlying the carbon risk premium. These predictions are tested empirically in Section 4.4. We begin with two definitions.

Definition 1. *The Leontief inverse is defined as* $\boldsymbol{L} = [\ell_{jk}] = (I - \boldsymbol{D}_\eta \boldsymbol{A})^{-1}$.

The element ℓ_{jk} measures the importance of industry k as a direct or indirect supplier to industry j. This concept is closely related to the notion of network centrality, as formalized below.

Definition 2. *The* ***carbon-adjusted centrality*** *of industry j is defined as*

$$\vartheta_j = \sum_{k=1}^{N} \omega_k \ell_{kj}, \tag{22}$$

where $\omega_k = e_k / \sum_{h=1}^{N} e_h$ is industry k's share of total emissions.

In vector form, $\boldsymbol{\vartheta}' = \boldsymbol{\omega}'\boldsymbol{L}$. This measure is a weighted analogue of Bonacich centrality, which assigns equal weight to all industries. By contrast, ϑ_j places greater weight on connections to carbon-intensive industries. As a result, it captures a firm's exposure to carbon risk through its position in the production network.

Proposition 5. *Suppose $\Psi_{i0} = \Psi_{j0}$. Then $\mathbb{E}r_{it} > \mathbb{E}r_{jt}$ if and only if $\vartheta_i > \vartheta_j$.*

Proposition 5 shows that, holding size fixed, carbon-adjusted centrality is sufficient to rank expected returns. Firms that are exposed to more carbon-intensive sectors experience larger declines in demand following a carbon tax increase and therefore command higher risk premia.

Proposition 6. *Suppose $\vartheta_i = \vartheta_j$. Then $\mathbb{E}r_{it} > \mathbb{E}r_{jt}$ if and only if $\Psi_{i0} < \Psi_{j0}$.*

Proposition 6 shows that, holding network exposure fixed, smaller industries have higher expected returns. This reflects the larger proportional impact of shocks on firms with lower baseline revenue.

2.5 Examples revisited.

We now revisit the three examples in Section 2.2 and relate them to the sufficient statistic characterized in Theorem 3. The theorem shows that a firm's exposure to carbon risk is given by $\gamma_j + \chi_j$, where γ_j captures direct exposure and χ_j captures indirect exposure through production networks.

Example 1: Horizontal network. In the absence of input–output linkages, carbon shocks do not propagate across industries. As a result, $\chi_j = 0$ for all j, and exposure is fully determined by direct emissions γ_j. Expected returns are therefore increasing in emission intensity, consistent with a setting in which only direct exposure matters.

Example 2: Vertical network. In the vertical network, carbon shocks propagate upstream along the supply chain. From equation (11), the network exposure satisfies the recursion

$$S_{j-1,0}\chi_{j-1} = \eta_j S_{j,0}\chi_j + \eta_j S_{j,0}\gamma_j, \tag{23}$$

with boundary condition $\chi_N = 0$. This expression captures the cumulative effect of downstream demand reductions on upstream industries.

To isolate the role of network position, suppose $S_{j0} = S_0$, $\eta_j = \eta$, and $\gamma_j = \gamma$ for all j. Then

$$\chi_j = \frac{\eta(1-\eta^{N-j})}{1-\eta}\gamma.$$

Thus, upstream industries have larger χ_j and therefore higher expected returns. Even with identical emissions, firms differ in risk exposure due to their position in the production network.

Example 3: Centrality and trading partners. Assume $S_{j0} = S_0$ and $\eta_j = \eta$ for all j, and that upstream industries have identical emission intensity ($\gamma_1 = \gamma_2$). The downstream industries differ, with $\gamma_b > \gamma_g$.

From equation (11),

$$\chi_1 = \eta\gamma_b, \quad \chi_2 = \eta\gamma_g.$$

Since $\gamma_b > \gamma_g$, it follows that $\chi_1 > \chi_2$, and hence $\mathbb{E}r_1 > \mathbb{E}r_2$. Although industries 1 and 2 have identical emissions, industry 1 bears greater carbon risk because it supplies a more carbon-intensive sector.

This example illustrates that expected returns are shaped not only by a firm's own emissions, but also by the emissions of its trading partners. In particular, firms that are more central suppliers to carbon-intensive industries command higher risk premia.

Summary. Taken together, these examples illustrate that production networks possibly decouple emissions from risk exposure, as firms' carbon risk depends on both their own emissions and their position in the network, where χ_j provides a parsimonious summary of network-based exposure. Combined with γ_j, it fully characterizes how carbon risk is transmitted to firms in general equilibrium.

3. CONSTRUCTING DIRECT AND INDIRECT EXPOSURES

Guided by our theoretical framework, in this section, we construct the empirical measure of the direct and indirect carbon exposure (γ and χ) at both firm and industry level. We then offer an anatomy of the indirect exposure along the production network. We begin by describing the data we use and how we construct the key variables. More details are provided in Appendix B.

3.1 Data

Our empirical analysis leverages several data sources: firm-level carbon emissions from the Trucost dataset, input-output linkages from the U.S. Bureau of Economic Analysis (BEA) tables, stock returns from CRSP, and implied cost of capital (ICC) and standard financial variables from Compustat.

To measure direct carbon emissions and direct carbon emission intensity (γ), we follow the procedure in Bolton and Kacperczyk (2021) using the Trucost dataset. Additionally, recent research (Zhang, 2025) highlights that emission disclosures are typically released approximately 10 months after earnings reports. To account for this lag, we perform a robustness check by aligning the emission disclosures with the appropriate time periods following the approach in Zhang (2025).

Input-output linkages are constructed using data from the BEA's detailed industry tables. The BEA provides comprehensive input-output tables for 405 industries every five years, as well as annual tables for a more aggregated set of 71 industries, covering the period from 1997 to 2021. To exploit more time variations, we utilize the BEA's 71-industry annual tables.

We follow the approach proposed by Hou et al. (2012) to construct the annual implied cost of capital (ICC) using the data from Compustat. Tables OB.2 and OB.3 detail the construction of the control variables. Following Bolton and Kacperczyk (2021), we winsorize carbon-emission-related variables at the 2.5% level and apply a 1.0% winsorization to control variables.

3.2 Constructing Direct and Indirect Carbon Exposures

This subsection develops our empirical measures of carbon exposure at both the firm and industry levels. We construct four complementary exposure measures that distinguish between *direct* emissions intensity and *indirect* exposure arising from input-output linkages: (i) firm-level direct exposure, (ii) industry-level direct exposure, (iii) industry-level indirect exposure, and (iv) firm-level indirect exposure.

Our approach proceeds in three steps. We first define direct exposure using standard emissions intensity measures. We then leverage the input-output structure of the economy to construct industry-level indirect exposure based on the propagation mechanism characterized in Lemma 1. Finally, we map these industry-level exposures to the firm level using segment-level sales data. This framework allows us to capture both firms' own emissions and their exposure to carbon risk embedded in upstream production networks.

Direct carbon exposure. A firm's direct carbon exposure, denoted by γ, is defined as its carbon emissions intensity, i.e., total carbon emissions scaled by firm revenue. This measure is standard in the literature and captures the firm's own contribution to carbon emissions.

We aggregate firm-level direct exposure to the industry level by computing a sales-weighted average across firms within each industry.

Industry-level indirect exposure. We construct industry-level indirect carbon exposure based on the network propagation formula derived in equation (10):

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma}.$$

Here, $\boldsymbol{A}$ denotes the input-output matrix, $\boldsymbol{D}_\eta$ is the diagonal matrix of intermediate input shares, $\boldsymbol{D}_S$ contains Domar weights, and $\boldsymbol{\gamma}$ is the vector of industry-level direct carbon intensities.[5]

This formulation captures how carbon exposure propagates through production networks, reflecting not only an industry's own emissions but also its exposure to upstream carbon-intensive inputs.

Firm-level indirect exposure. We map industry-level indirect exposure to the firm level using Compustat segment data. Let $\text{sale}_{ij,t-1}$ denote firm i's sales in segment j at the end of fiscal year $t-1$, and let $\chi_{j,t}$ denote the indirect exposure of industry j in year t. We define firm-level indirect exposure as:

$$\chi_{i,t} = \sum_j \frac{\text{sale}_{ij,t-1}}{\sum_k \text{sale}_{ik,t-1}} \chi_{j,t}. \tag{24}$$

This construction ensures that each segment contributes proportionally to the firm's overall exposure based on its economic importance.[6]

We next describe the construction of the key inputs $\boldsymbol{A}$, $\boldsymbol{D}_\eta$, $\boldsymbol{D}_S$, and $\boldsymbol{\gamma}$.

Input-output matrix $\boldsymbol{A}$. The matrix $\boldsymbol{A}$ is an $N \times N$ input-output matrix, where element a_{jk} denotes the share of industry j's intermediate expenditure allocated to inputs from industry k. We construct $\boldsymbol{A}$ using BEA input-output tables, following Pasten et al. (2017). Detailed procedures are provided in Appendix B.

Intermediate input share matrix $\boldsymbol{D}_\eta$. We define $\boldsymbol{D}_\eta = \text{diag}(\eta_1, \eta_2, \ldots, \eta_n)$, where η_j captures the share of intermediate inputs in total output for industry j. At the firm level, we estimate:

$$\eta_{ijt} = \frac{COGS_{ijt}}{Revenue_{ijt}},$$

where $COGS_{ijt}$ denotes cost of goods sold. We then aggregate to the industry level by averaging across firms within each industry-year. As a robustness check, we also compute revenue-weighted and market-value-weighted averages, yielding similar results. Figure OA.4 presents the cross-industry distribution of η_j averaged over 2002–2020.

Domar weight matrix $\boldsymbol{D}_S$. We construct $\boldsymbol{D}_S = \text{diag}(s_1, s_2, \ldots, s_n)$, where s_j denotes the Domar weight of industry j, defined as the ratio of industry output to aggregate output. We compute these

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[5] For interpretability, we rescale $\boldsymbol{\gamma}$ by dividing each element by 1,000, such that units correspond to tons per thousand USD of revenue. This normalization does not affect any results, as $\boldsymbol{\chi}$ scales proportionally.

[6] This approach follows a growing literature combining segment-level data with industry characteristics to construct firm-level exposures (e.g., Hoberg and Phillips (2016); Shi et al. (2020); Cong et al. (2024)).

weights using BEA make tables. Domar weights capture an industry's systemic importance in the production network, independent of its emissions intensity.

Figure OA.5 reports average Domar weights across industries from 2002 to 2020. Notably, industries with the largest Domar weights (e.g., Housing, Wholesale Trade, and Construction) differ substantially from those with the highest carbon exposure, highlighting the distinction between economic centrality and carbon intensity.

Given these inputs, we construct the four carbon exposure measures described above, which form the basis of our empirical analysis.

3.3 Empirical Results and Validation

This subsection provides validation and economic interpretation of our carbon exposure measures. We establish four key results. First, direct exposure (γ) and indirect exposure (χ) are only weakly correlated, implying that production networks generate substantial independent variation in carbon risk. Second, we show that χ is fundamentally a network object by decomposing it into contributions from different layers of the input-output structure. Third, we provide a case study illustrating how supply-chain linkages generate large wedges between γ and χ. Finally, we demonstrate that χ is conceptually and empirically distinct from Scope 3 emissions, and contains independent asset pricing information.

3.3.1. How correlated are γ and χ?

A natural question is whether indirect exposure simply mirrors direct emissions intensity. We find that this is not the case. The correlation between γ and χ is modest, ranging from 0.16 to 0.43 over time, with an average of 0.34. This relatively low correlation implies that production networks introduce substantial reallocation of carbon risk across firms and industries.

Importantly, industries with high direct exposure do not necessarily exhibit high indirect exposure, and vice versa. Table 1 shows that *Utilities* have the highest γ but only moderate χ, while industries such as *Oil and Gas Extraction* and *Pipeline Transportation* exhibit among the highest χ despite only moderate γ. These patterns highlight that focusing solely on direct emissions can lead to a distorted view of carbon risk exposure.

3.3.2. Where does χ come from? Network depth decomposition

To understand the economic origin of χ, we decompose it along the depth of the production network:

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1} \sum_{l=1}^{\infty} (\boldsymbol{A}' \boldsymbol{D}_\eta)^l \boldsymbol{D}_S \boldsymbol{\gamma} = \sum_{l \geq 1} \boldsymbol{\chi}_l, \tag{25}$$

where $\boldsymbol{\chi}_l := \mathcal{L}_l \boldsymbol{\gamma}$ and $\mathcal{L}_l = \boldsymbol{D}_S^{-1} (\boldsymbol{A}' \boldsymbol{D}_\eta)^l \boldsymbol{D}_S$ captures the contribution from the l-th layer of upstream linkages.

We define the *link matrix*:

$$\mathcal{L} = \sum_{l \geq 1} \mathcal{L}_l = \boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S,$$

where $\mathcal{L}_{jk}$ measures how direct exposure in *contributor* industry k propagates to *receiver* industry j through all possible production paths.

Figure 2 shows that indirect exposure is primarily driven by shallow network layers: the first layer accounts for the largest share, followed by the second layer, while contributions beyond the fourth layer are negligible. This result indicates that χ is not driven by arbitrarily long chains, but instead reflects economically meaningful, local supply-chain linkages.

Moreover, Panel B shows substantial dispersion in χ conditional on γ, reinforcing that indirect exposure captures distinct variation beyond direct emissions.

3.3.3. A case study: Pipeline Transportation vs. Utilities

We next illustrate the mechanism using two representative industries. Figure 3 decomposes:

$$\chi_j = \sum_k \mathcal{L}_{jk}\, \gamma_k.$$

Panel A shows that the high indirect exposure of *Pipeline Transportation* is driven by strong linkages to a small set of highly carbon-intensive upstream industries, notably *Utilities* and *Petroleum and Coal Products*. Although Pipeline Transportation is not itself highly emission-intensive, it is deeply embedded in a carbon-intensive supply chain.

In contrast, Panel B shows that the *Utilities* sector, despite having the highest direct exposure, exhibits only moderate indirect exposure. This is because its production structure is relatively self-contained, with less reliance on other carbon-intensive industries.

Figure 4 further visualizes these patterns. The results highlight a key economic insight: *carbon risk is not only about how much a firm emits, but also about where it sits in the production network*. This network position generates large wedges between γ and χ.

3.4 χ Is Not Scope 3 Emissions

A natural comparison is between χ and firm-level Scope 3 emissions. While both measures propagate upstream emissions through input-output linkages, they differ fundamentally in both conceptual foundation and empirical content.

Conceptually, Scope 3 emissions are an accounting-based measure of *embodied carbon quantities*. They aggregate physical emissions through the supply chain using engineering-style attribution weights. By contrast, χ is a *general equilibrium object* derived from our model. It captures the covariance between firm cash flows and aggregate carbon shocks, reflecting how carbon policy risk propagates through production networks in equilibrium. Accordingly, χ is constructed using Domar weights—

which are revenue-based and equilibrium-relevant—rather than physical emissions flows.

Empirically, the two measures are only weakly related. We find that the cross-sectional correlation between firm-level χ and Scope 3 emissions is only 0.11 (0.14 at the industry level), indicating that the two measures capture economically distinct dimensions of carbon exposure.

More importantly, χ contains independent asset-pricing information beyond emissions accounting measures. To directly discriminate between the two concepts, we augment the baseline ICC specification with firm-level Scope 3 emissions.

Discriminating χ from Scope 3 emissions.. A natural concern is whether χ simply reflects Scope 3 (upstream embodied) emissions in a different metric. Section 3.4 documents that the firm-level cross-sectional correlation between χ and Scope 3 is only 0.11. We further test this by adding firm-level Scope 3 emissions as a control in equation (26). Column (6) of Table 4 reports the result. The coefficient on χ remains economically and statistically stable at 1.27 (relative to 1.25 in the baseline specification), while Scope 3 emissions enter with a small and statistically insignificant coefficient (0.027, $t = 0.614$). These results indicate that the pricing-relevant network exposure is captured by χ, rather than by conventional emissions accounting measures. We therefore include this horse-race specification in the main ICC results reported in Table 4.

The distinction between emissions and risk exposure also appears in the aggregate decomposition exercises in Section 7. Firms with relatively low direct emissions but high χ account for 11.64% of total Scope 3 emissions, yet bear 26.80% of the aggregate carbon risk premium (Panel J versus Panel F). This wedge highlights that carbon emissions and carbon risk exposure are not equivalent objects: firms that are not major emitters can nevertheless be highly exposed to equilibrium carbon-transition risk through their network position.

Taken together, these results validate our measurement approach and demonstrate that indirect exposure χ captures economically meaningful and pricing-relevant variation in carbon risk that is not subsumed by traditional emissions measures.

4. Direct and Indirect Carbon Risk Exposure and Premium

Building on the construction and validation of our carbon exposure measures in Sections 3.2 and 3.3, we now turn to their asset pricing implications. The previous sections show that indirect exposure χ captures substantial variation in carbon risk that is distinct from direct emissions γ, and reflects firms' positions within the production network. These findings raise a central question: *is this network-based carbon exposure priced in financial markets?*

This section empirically examines the risk premium implications of our theoretical model. We investigate whether firms with high carbon risk exposure deliver higher expected returns. A key challenge in linking carbon risk exposure to expected returns lies in the ongoing debate about whether observed stock returns are reliable proxies for expected returns. Pástor et al. (2022) argue that observed stock returns reflect realized returns rather than expected returns associated with risk premium, introducing potential bias. Furthermore, the existing literature provides mixed evidence on the relationship between carbon emissions and stock returns. For instance, Bolton and Kacperczyk (2021) find that high carbon emissions are associated with higher stock returns, whereas Zhang (2025) report the opposite, linking high carbon emissions to lower stock returns.

Two important considerations emerge from this discussion. First, prior research predominantly focuses on the empirical relationship between stock returns and firms' direct carbon emissions, neglecting the indirect exposure arising from input-output network effects. This omission may lead to a significant mischaracterization of the relationship between carbon risk and returns. Second, previous literature argues that observed stock returns capture realized outcomes, where green stocks witnessed a series of positive shock, rather than expected returns associated with risk (Pástor et al., 2022; Eskildsen et al., 2024; Gasparini, 2023; Atilgan et al., 2024), offering an explanation for the observed negative relationship between carbon emission intensity and stock returns.

To address these challenges, our primary analysis employs the implied cost of capital (ICC) as the ex-ante expected return measure, following the methodology of Gordon and Gordon (1997) and Hou et al. (2012) . This approach avoids the controversies surrounding the use of realized returns. As a robustness check, we also provide supporting evidence using stock returns, presented in the Appendix OB.11.

4.1 Portfolio Sorting and Firm Characteristics

This subsection presents summary statistics and portfolio-sorting evidence on the pricing of carbon risk exposure. We proceed in two steps. First, we describe the distribution of key variables, including our measures of direct exposure (γ) and indirect exposure (χ). Second, we examine whether these exposures are associated with differences in expected returns using portfolio sorts. The main finding is that indirect exposure χ plays a central role in explaining cross-sectional variation in expected returns, whereas direct exposure γ has limited explanatory power.

Summary statistics.

Table 2 reports summary statistics for the main variables used in the analysis. Panel A presents firm-level outcome variables, including the implied cost of capital (ICC), stock returns, and changes in revenue, investment, and net income. ICC (annualized) serves as our primary proxy for expected returns, while realized stock returns are used for robustness (Appendix OB.11). The real-side variables are used to study firms' responses to carbon regulatory shocks (Section 5).

Panel B summarizes the key explanatory variables: direct exposure (γ), indirect exposure (χ), and total exposure ($\gamma + \chi$). Panel C reports standard firm characteristics commonly used as controls in the literature, including firm size, book-to-market ratio, profitability, leverage, Tobin's Q, market concentration (HHI), financial constraints (KZ index), and employment (Bolton and Kacperczyk, 2023; Atilgan et al., 2024; Zhang, 2025). Detailed variable definitions and data construction are provided in

Table OB.2. The final sample contains 2,698 firms, with the sample selection procedure reported in Table OB.4.

Portfolio sorting methodology.

To assess the pricing of carbon risk exposure, we sort firms annually into quintile portfolios based on total exposure ($\gamma + \chi$), indirect exposure (χ), and direct exposure (γ). For each sorting variable, we compute the difference in ICC between the highest and lowest quintiles (top-minus-bottom portfolios). Statistical inference is based on Newey–West standard errors with 12 lags to account for autocorrelation in portfolio returns.

Main results.

Table 3 reports the portfolio-sorting results. We find a strong and economically meaningful return spread for total and indirect exposure. Firms in the highest quintile of total exposure earn ICCs that are 2.13 percentage points higher than those in the lowest quintile. The spread is even larger for indirect exposure, at 2.24 percentage points. Both differences are statistically significant at conventional levels.

In contrast, direct exposure alone does not generate a significant return spread. The difference in ICC between high-γ and low-γ firms is small and statistically insignificant. This result indicates that direct emissions intensity, by itself, is not sufficient to explain cross-sectional variation in expected returns.

Economic interpretation.

The return spreads are primarily driven by differences in the lowest quintiles. While high-exposure firms exhibit similar ICCs across sorting variables, firms in the lowest indirect exposure quintile have substantially lower ICCs than those in the lowest direct exposure quintile.

This pattern reflects the fact that some firms classified as low-γ nonetheless have high indirect exposure due to their position in the production network. As a result, sorting solely on direct exposure misclassifies these firms as "low risk," compressing the return spread. In contrast, sorting on χ better isolates firms with genuinely low exposure to carbon risk.

Taken together, these findings provide strong evidence that indirect exposure χ captures the economically relevant component of carbon risk that is priced in expected returns, whereas direct exposure γ does not.

4.2 Regression Analysis

This subsection examines the pricing implications of carbon risk exposure using regression-based approaches. We first estimate panel regressions that control for firm-level heterogeneity and aggregate shocks, and then implement Fama–MacBeth regressions as a complementary specification. Across both approaches, we find consistent evidence that indirect exposure χ is strongly priced, whereas direct exposure γ and emissions-based measures play a limited role.

Panel Regression. Our baseline specification takes the form:

$$y_{it} = \alpha + \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \tag{26}$$

where y_{it} denotes the implied cost of capital (ICC) for firm i at month t, and $\boldsymbol{X}_{it}$ includes standard firm characteristics. All specifications include firm and month fixed effects. Standard errors are clustered at the industry level. All exposure measures are standardized to facilitate interpretation.

We begin by estimating a restricted specification that imposes a common premium on total exposure $(\chi + \gamma)$ (Columns (1) and (4) of Table 4). This serves as a benchmark motivated by the model, which treats direct and indirect exposure symmetrically. In Column (1), a one-standard-deviation increase in total exposure is associated with a 0.512 percentage-point increase in annualized ICC. After introducing the full set of controls in Column (4), the coefficient increases to 0.779 percentage points and remains statistically significant. This increase suggests that standard firm characteristics absorb variation negatively correlated with carbon exposure, revealing a stronger underlying pricing effect once controls are included.

We next relax this restriction by allowing χ and γ to enter separately (Columns (2), (3), (5), and (6)). A clear pattern emerges. Across all specifications, the coefficient on indirect exposure χ is large, positive, and highly significant. In Column (2), a one-standard-deviation increase in χ is associated with a 1.169 percentage-point increase in ICC, and this effect remains stable at 1.249 percentage points in Column (5) after controlling for firm characteristics.

In contrast, the effect of direct exposure γ is economically small and statistically fragile. While Column (3) shows a modest positive coefficient (0.126), the estimate becomes only marginally significant once controls are included (Column (5)), and loses significance when jointly estimated with indirect exposure (Column (6)). Taken together, these results indicate that the pricing of carbon risk is primarily driven by indirect, network-based exposure rather than firms' own emissions intensity.

We further examine the role of carbon emissions, which are commonly used in the literature as a proxy for carbon risk. Due to high collinearity between emissions, firm size, and direct exposure, we replace γ with emissions (Columns (3) and (6)). The results show that emissions have a small and statistically insignificant effect on ICC once firm fixed effects are included. Importantly, the coefficient on χ remains stable in both magnitude and statistical significance. This pattern indicates that indirect exposure captures a dimension of carbon risk that is largely orthogonal to the emissions-based channel studied in prior work.

Overall, the panel regression results provide strong evidence that indirect exposure χ is the dominant driver of cross-sectional variation in expected returns.

Fama–MacBeth Regression. We next implement Fama–MacBeth regressions to provide a complementary perspective based purely on cross-sectional variation. In each month, we estimate cross-sectional regressions and average the coefficients over time. Standard errors are computed using Newey–West corrections with 12 lags to account for serial correlation.

Table 5 reports the results. Columns (1)–(3) mirror the baseline specifications by examining total exposure, indirect exposure, and direct exposure separately. Consistent with the panel results, total exposure is positively associated with ICC, and the magnitude increases after including standard firm controls (Column (4)), rising from 0.613 to 0.813.

Allowing for differential effects again highlights the dominant role of indirect exposure. In Column (5), a one-standard-deviation increase in χ is associated with a 1.29 percentage-point increase in annualized ICC, while the coefficient on γ remains small and statistically weak.

Column (6) replaces direct exposure with carbon emissions. The coefficient on emissions is close to zero and statistically insignificant, whereas the effect of χ remains stable in both magnitude and statistical significance.

Taken together, the Fama–MacBeth results closely mirror the panel evidence and reinforce the conclusion that indirect exposure χ—rather than direct emissions or emissions levels—is the primary component of carbon risk that is priced in expected returns.

4.3 Within vs Across Industry Decomposition

A natural concern with indirect exposure χ is whether it merely relabels industry heterogeneity. If χ primarily reflects differences across industries, then its pricing effect may simply proxy for industry fixed effects rather than capturing economically meaningful firm-level variation. This subsection addresses this concern by decomposing both γ and χ into within- and cross-industry components, and quantifying their respective contributions to the carbon risk premium.

We implement a two-step decomposition procedure. In the first step, we estimate the following regression:

$$Exposure_{ijt} = \alpha + Industry\ FE_j + \varepsilon_{ijt} \tag{27}$$

where $Exposure_{ijt}$ represents the direct or indirect exposure of firm i in industry j at period t. This specification decomposes each firm's exposure into a cross-industry component, captured by the industry fixed effect, and a within-industry component, captured by the residual. Specifically, we take the following decomposition for the indirect exposure

$$\chi_{ijt} = \textit{Cross-industry}_{\chi,jt} + \textit{Within-industry}_{\chi,it} = \tilde{\chi}_{jt} + \tilde{\chi}_{it} \tag{28}$$

and similar decomposition for the direct exposure,

$$\gamma_{ijt} = \textit{Cross-industry}_{\gamma,jt} + \textit{Within-industry}_{\gamma,it} = \tilde{\gamma}_{jt} + \tilde{\gamma}_{it} \tag{29}$$

In the second step, we estimate the following regression:

$$y_{ijt} = \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} + \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \tag{30}$$

where $\beta_{\chi,within}$ and $\beta_{\chi,cross}$ capture the premium associated with the within- and cross-industry components of indirect exposure, respectively, and $\beta_{\gamma,within}$ and $\beta_{\gamma,cross}$ are defined analogously for direct exposure. $\boldsymbol{X}_{ijt}$ includes standard control variables.

Table 6 reports the results. We focus on variation-adjusted coefficients to account for differences in dispersion across components. Specifically, for each component, we compute $\beta \times$ *STD(component)* to capture the effect of a one-standard-deviation increase. To evaluate the relative importance of each component, we normalize the variation-adjusted coefficients. For example, for $\tilde{\chi}_{jt}$, we compute its relative importance as:

$$\frac{\beta_{\chi,cross} \times STD(\tilde{\chi}_{jt})}{\beta_{\chi,cross} \times STD(\tilde{\chi}_{jt}) + \beta_{\chi,within} \times STD(\tilde{\chi}_{it}) + \beta_{\gamma,cross} \times STD(\tilde{\gamma}_{jt}) + \beta_{\gamma,within} \times STD(\tilde{\gamma}_{it})}.$$

The results reveal a sharp contrast between indirect and direct exposure. Indirect exposure χ accounts for approximately 85% of the total premium, with 66.98% arising from cross-industry variation and 18.40% from within-industry variation. In contrast, direct exposure γ contributes only about 15% in total, with the majority coming from within-industry variation (11.32%) and only a small fraction from cross-industry differences (3.30%).

These findings highlight that the sources of the premium differ fundamentally across the two measures. For indirect exposure, the premium is primarily driven by cross-industry variation, whereas for direct exposure, the premium is largely driven by within-industry heterogeneity.

These results yield three important implications. First, χ is not a relabeling of industry fixed effects. The within-industry component of χ alone accounts for 18.40% of the total premium, indicating that the segment-based firm-level construction of χ contains independent information beyond industry averages.

Second, the premia associated with γ and χ arise from structurally different sources. The premium for γ reflects within-industry firm heterogeneity—i.e., differences in firms' own emissions intensity—whereas the premium for χ reflects cross-industry differences in firms' positions within the production network.

Third, this pattern is consistent with the theoretical mechanism. As shown in Theorem 1, indirect exposure χ is determined by the propagation of shocks through the input-output matrix $\boldsymbol{A}$, implying that its variation is inherently tied to inter-industry linkages. This theoretical structure naturally gives rise to a dominant cross-industry component in the pricing of χ.

As a robustness check, we further examine the incremental contribution of each component to the regression R^2. Specifically, we start from a regression only with standard control variables as in Equation (30). we then incrementally include $\tilde{\chi}_{jt}$, $\tilde{\gamma}_{jt}$, $\tilde{\chi}_{it}$, and $\tilde{\gamma}_{it}$ into the regression specified in Equation (30), we calculate the incremental contribution to the R-square as

$$R^2\textit{(including component c) - }R^2\textit{(without component c)}$$

We then calculate the relative incremental R^2 of component c, which is defined as the absolute incremental contribution normalized by the total sum of incremental contributions from the four components: the within- and cross-industry components of the direct and indirect exposures.

The results confirm the same pattern as above: indirect exposure, particularly its cross-industry component, dominates the explanatory power for the carbon risk premium, while direct exposure contributes primarily through within-industry variation.

One potential concern is that the measurement of incremental R^2 could depend on the inclusion order of each component. As a robustness check, we confirm that the results are highly robust to the inclusion order of the components.

An alternative approach is to independently include each of the four components in Equation (30) and compute their incremental R^2 relative to a baseline regression with only control variables. The resulting decomposition yields consistent conclusions.

Taken together, these findings demonstrate that indirect exposure χ captures economically meaningful and independently priced variation that cannot be attributed solely to industry-level heterogeneity.

4.4 Testing Additional Model Predictions

We finally empirically test the model predictions in Section 2.4 . Specifically, we estimate the following panel regression model:

$$ICC_{it} = \beta_1 S_{i,t-1} + \beta_2 \vartheta_{it} + \beta_3 \gamma_{it} + \beta_4 Z_{it} + \lambda_t + \varepsilon_{it},$$

where ICC_{it} denotes the implied cost of capital for the firm i at time t, and $S_{i,t-1}$ represents the lagged revenue of the firm. The key explanatory variable, ϑ_{it}, is the carbon-adjusted centrality at the firm level, constructed by aggregating the value of the centrality at the industry level ϑ_{jt} using the revenue share of the firm i in each industry j as weights: $\vartheta_{it} = \sum_j w_{ijt} \vartheta_{jt}$, where w_{ijt} is the fraction of the revenue of the firm i derived from the industry j at time t. The variable γ_{it} captures the direct carbon intensity of firm i, while Z_{it} includes a set of standard control variables consistent with those used in our baseline regression. The term λ_t represents time fixed effects, which absorb macroeconomic trends and time-varying factors common to all firms.

Table 7 presents the regression results. In all specifications, the carbon adjusted centrality coefficient ϑ_{it} is positive and statistically significant, with magnitudes ranging from 0.022 to 0.031, while the lagged revenue coefficients are negatively and significantly associated with the implied capital cost. These results are consistent with Proposition 5, which predicts that - conditional on firm size - greater carbon adjusted centrality leads to higher implied cost of capital; and conditional on the carbon adjusted centrality of firms - larger firms face lower implied cost of capital.

In contrast, the coefficients for direct exposure to carbon risk γ_{it} and carbon emissions are statistically insignificant in all specifications. This result is consistent with the prediction that, once both firm size and carbon-adjusted centrality are controlled, direct emissions provide limited incremental information about firm carbon risk exposure.

4.5 Robustness

The dominance of indirect exposure χ over direct exposure γ in explaining cross-sectional variation in expected returns is robust across a wide range of specifications. We summarize these robustness checks along several dimensions. First, the results hold under alternative aggregation schemes at the industry level, including both value-weighted and equal-weighted ICC. Second, they are robust to alternative assumptions on production technology, including a general CES specification with varying elasticity of substitution. Third, the findings are insensitive to reporting lags in emissions and financial data. Fourth, controlling for alternative emissions measures (Scope 1, 2, and 3) and real-side variables does not affect the estimated premium on χ. Fifth, the results are stable across subsamples and time periods. Finally, the same qualitative patterns hold when using realized stock returns instead of ICC, despite known limitations of realized returns as proxies for expected returns.

Robustness Results on ICC. We begin by examining the robustness of our ICC-based results. Table OB.6 reports alternative specifications of the baseline regression. Across all specifications, firms with higher total exposure ($\chi + \gamma$) consistently exhibit higher ICC, even after controlling for firm and month fixed effects.

At the industry level, Tables OB.7 and OB.8 construct ICC using value-weighted and equal-weighted averages, respectively. The results are highly consistent across both approaches: industries with higher total exposure exhibit higher ICC.

We further decompose total exposure into direct and indirect components at the industry level. Tables OB.9 and OB.10 report results using value-weighted and equal-weighted ICC, respectively. Across all specifications, indirect exposure χ consistently exhibits a stronger and more significant association with ICC than direct exposure γ, confirming that our main findings are not driven by aggregation choices.

Results with General CES Specification. As discussed in Section 2.1 and detailed in Appendix A.1, we relax the Cobb–Douglas assumption in (2) by adopting a general CES aggregator with elasticity of substitution θ. Closed-form expressions for the direct and indirect exposures under this framework are provided in (A.15). We construct empirical counterparts $\widehat{\gamma}_j^{\theta}$ and $\widehat{\chi}_j^{\theta}$ for $\theta \in [0.75, 1.5]$.[7]

We then re-estimate the baseline regression (26), replacing $\{\widehat{\chi}_j^1\}$ with $\{\widehat{\chi}_j^{\theta}\}$.[8] Across all values of θ, the coefficient on indirect exposure remains statistically significant and quantitatively stable,

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[7] We explore $\theta \in [0.75, 1.5]$ for two reasons. First, our analytical solutions arise from linearizing the equilibrium around $\theta = 1$. Second, empirical estimates of substitution elasticities vary widely across data frequencies and aggregation levels; centering the range around 1 ensures empirical relevance.

[8] Figure OA.6 plots the correlation between $\{\widehat{\chi}_j^{\theta}\}$ and $\{\widehat{\chi}_j^1\}$.

confirming that the pricing of χ is not sensitive to assumptions about input substitutability.

Figure 5 plots the estimated coefficients on total exposure $\widehat{\chi}_j^\theta + \widehat{\gamma}_j^\theta$. Across the full range of θ, the estimated coefficients remain statistically and economically significant.

To further separate the roles of indirect and direct exposure, Figures OA.7 and OA.8 plot the estimated coefficients on $\widehat{\chi}_j^\theta$ and $\widehat{\gamma}_j^\theta$, respectively. The coefficient on χ remains positive and significant across all values of θ, with an inverted-U pattern reflecting the interaction between substitution flexibility and dispersion in network exposure. By contrast, the coefficient on γ remains substantially smaller and exhibits a U-shaped pattern. These results reinforce the conclusion that indirect exposure is the primary driver of the carbon risk premium.

Robustness Results on Stock Returns. We next examine whether our findings extend to realized stock returns. Prior literature documents mixed evidence on the relationship between carbon exposure and realized returns, partly due to the distinction between realized and expected returns.

Table OB.11 reports firm-level regressions of stock returns on carbon exposure. Following Zhang (2025), we incorporate a 10-month lag to account for delayed disclosure of emissions data. Columns (1)–(6) show that firms with higher total exposure earn higher realized returns, with a one-unit increase in total exposure associated with approximately 0.21% higher monthly returns (about 2.6% annually). Column (7) shows that this effect is primarily driven by indirect exposure χ, consistent with our ICC-based results.

We further examine robustness to alternative controls. Table OB.12 includes various emissions measures (log emissions, Scope 1, Scope 2, and Scope 3), following Aswani et al. (2024b) and Atilgan et al. (2024). The coefficient on χ remains stable, indicating that indirect exposure captures a dimension of carbon risk largely orthogonal to emissions-based measures.

Table OB.13 adds controls for sales and revenue growth, with no material impact on the results. Table OB.15 examines alternative return horizons using lags from 6 to 36 months. The results remain robust across all specifications except the 36-month lag. A dynamic specification measuring returns between disclosure dates yields similar conclusions.

Table OB.16 examines subsample stability. Consistent with Zhang (2025), the return premium weakens in the post-2015 period, in line with Pástor et al. (2022), which argues that realized returns may diverge from expected returns in recent years. Excluding high-tech firms—where emissions are known to be under-reported—does not affect the results, confirming that our findings are not driven by measurement bias.

Concluding Remarks on Robustness. Taken together, these robustness checks provide consistent evidence that indirect exposure χ is the primary driver of the carbon risk premium. The results are stable across alternative aggregation methods, model specifications, control variables, sample definitions, and return measures. This robustness reinforces the interpretation that carbon risk is priced through firms' positions in production networks rather than their own emissions alone.

5. Empirical Tests for Carbon Regulatory Risk

We have thus far provided empirical evidence suggesting that firms or industries with high direct or indirect carbon risk exposure deliver higher expected returns, as measured by the ICC. Our theoretical framework posits that an increase in carbon emission regulatory risk constitutes a negative shock to firms. If indirect exposure from supply chains is priced, we would expect firms with high indirect exposure to experience a larger decline in realized stock returns when regulatory risk increases, compared to their low-exposure counterparts. Similarly, firms with high indirect exposure are likely to experience more severe deteriorations in financial and real economic activities (Pástor et al., 2021; Hartzmark and Shue, 2022; Broccardo et al., 2022; Gormsen et al., 2023; De Angelis et al., 2023). One challenge in this analysis is to measure regulatory risk associated with carbon emissions.

5.1 Proxy for Carbon Regulatory Risk

We first screen the full set of *Wall Street Journal* articles using a set of energy-related keywords, including "carbon," "renewable," "drilling," "fossil," "oil and gas," "emission," "solar," and "pipeline" following Acharya et al. (2025). This procedure identifies articles potentially related to the energy sector, yielding a final sample of 50,360 articles from 1996 to 2023. For the filtered articles, leveraging the textual classification and analysis capabilities of large language models, we use ChatGPT-4o-mini to classify whether *Wall Street Journal* articles indicate that carbon-emission regulatory risk is "going up," "going down," or "unknown."

We design the prompt to make the classification transparent, disciplined, and replicable. First, the prompt explicitly instructs the model to reason step by step and to base its answer solely on the information contained in the article, without relying on external knowledge or assumptions. The model is also required to provide a brief explanation for each answer, which helps discipline the classification and reduces the scope for hallucinated or unsupported labels. Second, we frame the task as a narrow classification exercise with pre-specified answer categories and require the model to return a structured JSON object. This structure facilitates automated parsing and limits discretionary interpretation in the construction of the index. Third, the prompt follows a sequential design: it first asks whether the article is about the energy sector, then asks whether the article discusses regulations or regulatory risks affecting that sector, and finally asks whether the regulatory-risk signal is increasing, decreasing, or unclear. This stepwise structure separates sector relevance, regulatory relevance, and directional content, thereby reducing the chance that the model infers regulatory risk from articles that are not directly relevant.[9]

The full prompt is reported in Appendix OC. To enhance replicability, we set the temperature parameter to zero throughout the classification exercise, making the model output as deterministic as possible conditional on the model version, prompt, and input text. We then retain the model's most

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[9] This procedure follows similar prompt methodologies adopted in recent studies by Bybee (2023); Chen et al. (2023); Cong et al. (2024); Acharya et al. (2025).

likely response as the final classification, one with the highest probability.

For each month, we first construct a carbon regulatory index (CRI_t), measured as the difference between the percentage of news articles reporting "going up" and those reporting "going down."

To proxy for unexpected changes in carbon regulatory risk, we model CRI_t as a highly persistent state variable following a first-order autoregressive process, consistent with standard practice in modeling macro-financial state variables (e.g., Campbell et al. (1998), Cochrane (2009)):

$$CRI_t = \alpha + \rho \cdot CRI_{t-1} + \varepsilon_t,$$

where $\hat{\varepsilon}_t$ represents the carbon regulatory shock (CRS_t). A large positive CRS_t indicates a significant and unexpected rise in the carbon regulatory risk, while a large negative CRS_t suggests a significant and unexpected decline in the carbon regulatory risk.

The estimated coefficient of the AR(1) process is 0.30, which is statistically significant at the 1% level, with a z-statistic of 7.70. Figure 7 illustrates the monthly time series of the Carbon Regulatory Index (CRI) and the Carbon Regulatory Shock (CRS). The solid blue line represents the CRS, while the red dashed line indicates the CRI.

5.2 Validation for the Proxy

We evaluate the validity of our proxy from several perspectives. First, we randomly sample nine news articles, with three from each category classified by ChatGPT-4o-mini as indicating regulatory risk on carbon emissions "going down," "going up," and "unknown." Table OB.18 and OB.19 in the Appendix present these examples. A quick manual review of the titles and abstracts suggests that ChatGPT-4o-mini performs well in accurately classifying the news articles.

For instance, ChatGPT correctly classifies the news *"**Title:** L.I. Utility Seals Wind Farm Deal **Abstract:** UNIONDALE, N.Y. – The Long Island Power Authority finalized an agreement Wednesday to build New York state's first offshore wind farm 30 miles east of Montauk, N.Y., the latest effort by the industry."* as indicating the regulatory risk is "going down." Similarly, it correctly classifies the news *"**Abstract:** Underpinning China's lead-poisoning epidemic is a tension between the government's goals for economic growth and its efforts to curb environmental degradation,"* as indicating the regulatory risk is "going up."

To further validate our measure of the Carbon Regulatory Index (CRI), Figure 7 presents the time series of CRI and the Carbon Regulatory Shock (CRS). The shaded regions indicate significant events related to carbon regulation, as detailed in Table OB.17. Observing the figure, we find that CRI experiences substantial increases during these periods, aligning with major regulatory developments.

Sautner et al. (2023a) employ earnings conference calls and textual analysis to measure firm-level exposure to carbon regulatory risk, capturing topic mentions at both quarterly and annual frequencies. In contrast, our measure—the Carbon Regulatory Index (CRI)—is constructed at a monthly frequency using Wall Street Journal (WSJ) articles to proxy for aggregate regulatory risk.

To assess the validity of our measure, we aggregate the firm-level exposure data from Sautner et al.

(2023a), which includes variables such as climate change exposure, climate change risk, regulatory exposure, and regulatory risk, to the macro-level market data at annual and quarterly frequencies. We then compare our Carbon Risk Index (CRI) with this aggregated data. The correlation coefficients between CRI and the aggregated variables are reported in Table OB.20, showing relatively high correlations that are statistically significant at the 1% level, particularly for regulatory risk. We further compare the CRI with the aggregated regulatory risk in figure OA.9, where panels A and B depict the time series of our CRI alongside the aggregated regulatory risk measure from Sautner et al. (2023a) at the annual and quarterly levels, respectively.

Panel A shows that CRI exhibits strong co-movement with the firm-level regulatory risk index on an annual basis, with a correlation coefficient of 0.753. Similarly, Panel B demonstrates a high degree of correlation at the quarterly level, with a coefficient of 0.456. Notably, both indices display a strong alignment in the timing of peaks and troughs, further reinforcing the credibility of CRI as a valid proxy for aggregate carbon regulatory risk.

5.3 Stock Return, Real Performance, and Carbon Regulatory Shock

To examine the heterogeneous responses of firms to CRS_t, we sort firms into five groups each month based on their indirect carbon risk exposure (χ) at the end of the previous fiscal year. For each group, the following regression is estimated:

$$y_{git} = \alpha_g + \beta_{\text{CRS},g} \cdot \text{CRS}_t + \boldsymbol{X}'_{git}\beta_{gx} + \varepsilon_{git},$$

where y_{git} denotes the financial performance or stock return of firm i within group g at time t, CRS_t is the carbon regulatory shock, and $\boldsymbol{X}_{git}$ includes standard control variables.

Table 8 presents our main findings, where stock return, change in revenue, change in investment, and change in net income are used as dependent variables. For each variable of interest, we report the heterogeneous reactions of firms with varying levels of indirect carbon risk exposure to CRS_t, both with and without standard controls.

The results consistently show that firms with higher indirect carbon risk exposure are significantly more negatively responsive to carbon regulatory shocks across all metrics: returns, change in revenue, change in investment, and change in net income. The magnitudes of these effects are substantial and statistically significant at the 1% level, highlighting the heightened vulnerability of firms with greater indirect exposure to changes in carbon regulatory risk.

5.4 Carbon Regulatory Shock and Firm Performance

This section further examines how firms with varying levels of carbon risk exposure react to carbon regulatory shocks. We employ the following regression specification:

$$y_{it} = \alpha + \beta_{\text{CRS}} \times \text{CRS}_t + \beta_{\text{CRS},\chi} \times \chi_{it} \times \text{CRS}_t + \beta_{\text{CRS},\gamma} \times \gamma_{it} \times \text{CRS}_t + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \quad (31)$$

where y_{it} represents the stock return or a real performance variable of interest for firm i at time t. The coefficient β_{CRS} measures the direct effect of the carbon regulatory shock (CRS_t), while $\beta_{\text{CRS},\chi}$ captures the interaction between the indirect exposure (χ_{it}) and the carbon regulatory shock. Similarly, $\beta_{\text{CRS},\gamma}$ reflects the interaction between the direct exposure (γ_{it}) and the carbon regulatory shock.

The vector $\boldsymbol{X}_{it}$ includes standard control variables, such as direct exposure, indirect exposure, and other relevant firm-specific characteristics documented in the literature. Fixed effects for firms and industries are included as specified to control for unobservable heterogeneity. Robust standard errors are used to account for potential heteroskedasticity and serial correlation in the error term ε_{it}.

Table 9 reports our main findings. Panels A, B, C, and D show the difference-in-difference results for stock returns, changes in revenue, changes in investment, and changes in net income. For stock returns, our observation is at the firm-month level, while firm performance and activities (changes in revenue, investment, and net income) are analyzed at the firm-year level.

Panel A demonstrates that an increase in the Carbon Regulatory Shock (CRS), indicative of unexpected heightened regulatory risk associated with carbon emissions, is significantly associated with lower contemporaneous stock returns. This dampening effect is particularly pronounced for firms with high indirect exposure stemming from their supply chains. In contrast, the negative effect of direct exposure is much smaller and becomes statistically insignificant after controlling for industry or firm fixed effects.

In Panel B, we investigate the interaction between carbon risk exposure and the carbon regulatory shock on firms' revenue growth over the next two periods. After accounting for firm fixed effects and time-varying control variables, the coefficient for the interaction term (Indirect Exposure × CRS) is significantly negative. This finding suggests that firms with high indirect exposure experience a substantial decline in revenue growth in subsequent periods after an unexpected increase in carbon regulatory risk. Similarly, Panels C and D show that these firms also suffer significant declines in investment growth and net income growth.

In contrast, for firms with high direct exposure, the effects of an unexpected rise in carbon regulatory risk are limited in terms of both stock returns and financial performance, including revenue growth, investment growth, and net income growth.

Taken together, our evidence underscores that indirect exposure to carbon risk through supply chain linkages exerts a more significant and dominant impact than direct carbon risk exposure due to a firm's own carbon emissions, especially during periods of rising unexpected carbon regulatory risk. This heterogeneous response likely arises because firms can more readily adjust their own carbon emissions but face greater difficulty in mitigating indirect carbon risk exposure from their supply chains.

6. EVALUATING CARBON-RISK FACTOR MODELS

A central question is whether carbon-risk exposures contain priced information beyond standard sources of systematic risk. Following the asset-pricing diagnostic framework of Fama and French (1992) and Fama and French (1993), we evaluate whether portfolios sorted on carbon exposures are correctly priced by competing factor models and whether the resulting pricing errors are absorbed by carbon-related risk factors.

Test portfolio construction and design. Because carbon emissions are disclosed at an annual frequency, we follow the standard portfolio-formation convention in the asset-pricing literature and rebalance portfolios once per year. Specifically, at the end of each December, after firms have released their annual emissions information, we independently sort all stocks into quintiles based on their direct and indirect carbon exposures, γ and χ. This procedure generates a 5×5 set of 25 value-weighted test portfolios. The portfolios are formed at the end of December and held for the subsequent 12 months, from January through December of the following year. Portfolio returns are computed at the monthly frequency.

The factor sample spans 2002–2023, yielding 252 monthly portfolio-return observations. The resulting portfolios, reported in Figure 6, provide a transparent cross-sectional representation of carbon exposure and serve as the main test assets in our factor-model evaluation.

Factor construction. We construct the carbon-risk factors using univariate exposure sorts, consistent with the definition of the test assets. At the end of each December, all firms are sorted into quintiles based on γ and, separately, into quintiles based on χ. The γ factor is defined as the return on a zero-cost portfolio that is long the value-weighted portfolio of firms in the highest γ quintile and short the value-weighted portfolio of firms in the lowest γ quintile:

$$\gamma\text{-MKT}_t = R_t^{Q5_\gamma} - R_t^{Q1_\gamma}.$$

The χ factor is constructed analogously:

$$\chi\text{-MKT}_t = R_t^{Q5_\chi} - R_t^{Q1_\chi}.$$

All leg returns are value-weighted. The factors are rebalanced annually at the end of December and held from January through December of the following year, matching the timing convention used for the test portfolios.

Factor models and pricing evaluation. We compare two specifications. The first is the CAPM, which includes only the market excess return. The second augments the CAPM with the two carbon-risk factors, γ-MKT and χ-MKT:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}\left(R_{M,t} - R_{f,t}\right) + \beta_{i,\gamma}\gamma\text{-MKT}_t + \beta_{i,\chi}\chi\text{-MKT}_t + \varepsilon_{i,t}.$$

For each test portfolio, model-implied expected returns are computed using estimated time-series factor loadings multiplied by the sample means of the factors. Figure 6 plots realized average returns against model-implied expected returns under both specifications.

Empirical results and model fit. The CAPM exhibits substantial cross-sectional misspecification. As shown in Figure 6, portfolios with high γ and high χ exposures earn realized average returns that are systematically above their CAPM-implied values, whereas low-exposure portfolios tend to earn returns below the model predictions. This pattern indicates that the market factor alone does not span the systematic variation associated with carbon exposures.

By contrast, augmenting the CAPM with γ-MKT and χ-MKT substantially improves the cross-sectional fit. The realized and fitted returns move closer to the 45-degree line, and the systematic pricing errors at the extremes of the carbon-exposure distribution largely disappear. This evidence is consistent with the sufficient-statistic characterization in Theorem 3: expected returns vary monotonically with the combined exposure $\gamma + \chi$, and a factor structure spanned by these exposures captures the relevant cross-sectional variation in expected returns.

Formal model comparison. We formally compare the two specifications using the pricing-error test of Gibbons et al. (1989). The test is applied to the 25 carbon-sorted portfolios over the monthly sample period 2002–2023, with $T = 252$ monthly observations. Under the CAPM, we strongly reject the null that all pricing errors are jointly zero:

$$F_{25,\,226} = 4.6, \qquad p < 0.01.$$

This rejection confirms that the market factor alone leaves economically and statistically large pricing errors across the carbon-exposure portfolios.

Under the augmented CAPM with the γ-MKT and χ-MKT factors, the pricing errors decline sharply and are no longer jointly significant:

$$F_{25,\,224} = 1.18, \qquad p = 0.25.$$

The contrast between the two specifications indicates that the carbon-risk factors absorb the pricing errors that the market factor alone cannot explain. In economic terms, portfolios with high direct and indirect carbon exposures are not simply earning anomalous returns relative to the CAPM; rather, their returns reflect compensation for systematic carbon-related risks.

Because the GRS test relies on strong distributional assumptions, including i.i.d. multivariate normal residuals, we also report Shanken-corrected cross-sectional pricing-error tests. Specifically, we estimate the second-stage pricing regression using factor loadings from the first-stage time-series regressions and compute standard errors adjusted for the errors-in-variables problem in estimated betas following Shanken (1992). The CAPM is rejected under the Shanken correction, with a pricing-error Wald statistic of

$$\chi^2(25) = 61.3, \qquad p < 0.01.$$

In contrast, the augmented CAPM with the γ-MKT and χ-MKT factors is not rejected:

$$\chi^2(25) = 27.8, \qquad p = 0.32.$$

Thus, both the GRS test and the Shanken-corrected cross-sectional tests lead to the same conclusion: carbon-exposure factors materially reduce the joint pricing errors of the 25 test portfolios and substantially improve the model's ability to price the cross-section.

7. AGGREGATE AND POLICY IMPLICATIONS

The preceding sections establish two core facts. First, network exposure χ is a sufficient statistic for the cross-sectional pricing of carbon risk. Second, firms with higher χ exhibit stronger financial and real responses to regulatory-risk shocks. We now use these estimates to answer the macro question that motivates the paper: who ultimately bears carbon transition risk in a networked economy, and how does this distribution compare with the distribution of emissions?

We organize the analysis around four facts. First, we decompose the aggregate carbon risk premium across firm types ex ante. Second, we show that the same firms absorb disproportionate losses when regulatory risk materializes. Third, we compare these risk shares to the distribution of emissions and document a systematic misalignment. Fourth, we connect this financial incidence to real outcomes and show that network-exposed firms account for a disproportionate share of investment adjustment.

The central takeaway is that production networks create a wedge between the source of carbon emissions and the incidence of carbon risk. Financial institutions, regulators, and policymakers seeking to assess the incidence of climate-policy risk must account for how shocks propagate through production networks. Carbon policy does not stop where emissions occur; it is transmitted along supply chains, redistributing risk across firms and shaping aggregate investment.

7.1 Network-Brown Firms Bear a Large Share of the Ex-Ante Carbon Risk Premium

We begin by quantifying which firms are compensated ex ante for bearing carbon risk. Our starting point is the baseline cross-sectional specification relating the implied cost of capital (ICC) to direct and indirect exposures:

$$ICC_{i,t} = \alpha + \beta_\chi \chi_{i,t} + \beta_\gamma \gamma_{i,t} + X'_{i,t-1}\delta + \lambda_t + \varepsilon_{i,t}. \tag{32}$$

We define firm i's carbon risk premium as the fitted contribution of these exposures,

$$\hat{\pi}_{i,t}^{carbon} = \hat{\beta}_{\chi}\chi_{i,t} + \hat{\beta}_{\gamma}\gamma_{i,t},$$

which captures the portion of required return that compensates investors for exposure to climate-policy risk through both direct emissions and supply-chain linkages. Aggregating using market-capitalization weights $w_{i,t} = MCAP_{i,t}/\sum_j MCAP_{j,t}$ yields the aggregate premium

$$\Pi_t^{carbon} = \sum_i w_{i,t}\hat{\pi}_{i,t}^{carbon}.$$

We then sort firms each period into a 2×2 grid based on direct emissions γ and network exposure χ. For any group G, its incidence share is

$$Share_{G,t}^{carbon} = \frac{\sum_{i \in G} w_{i,t}\hat{\pi}_{i,t}^{carbon}}{\Pi_t^{carbon}}.$$

The decomposition reveals two facts. First, firms with low direct emissions but high network exposure are economically large (Table 10, Panel A and B). They account for about 20% of aggregate market capitalization, comparable to the share held by high-emission firms.

Second, consistent with our previous findings, required returns increase sharply with network exposure, even holding emissions fixed (Table 10, Panel C and D). Low-γ, high-χ firms face an implied cost of capital of 0.60%, nearly three times that of low-γ, low-χ firms at 0.23%. Indirect exposure through production networks thus substantially raises the cost of capital, even for firms that appear clean based on their own emissions.

These differences translate directly into risk incidence (Table 10, Panel E and F). Low-γ, high-χ firms account for roughly 27% of the aggregate carbon risk premium, compared with 17.32% for firms with high emission but low network exposure (high-γ, low-χ group). The economic incidence of carbon-policy risk is therefore not confined to high-emission producers. A substantial share is borne by firms that appear clean on their own balance sheets but are deeply embedded in carbon-intensive supply chains.

7.2 The Same Firms Lose When Regulatory Risk Materializes

The ex-ante decomposition identifies the firms that are compensated for bearing carbon risk in equilibrium. We now verify that these same firms absorb losses when regulatory risk materializes.

We focus on months in which the Carbon Regulatory Shock (CRS) measure, constructed in Section 5, indicates a sharp increase in regulatory risk. Let T^{shock} denote the set of such months. Firm-level abnormal returns during these episodes are defined relative to a benchmark as

$$AR_{i,\tau} = R_{i,\tau} - R_{i,\tau}^{bench}.$$

Aggregating across firms using lagged market-capitalization weights yields the market-wide revaluation in month τ,

$$L_\tau = \sum_i w_{i,\tau-1} AR_{i,\tau}.$$

For each group G, we compute its share of aggregate losses as the average contribution to total revaluation across shock months,

$$Share_G^{loss} = |T^{shock}|^{-1} \sum_{\tau \in T^{shock}} L_{G,\tau}/L_\tau.$$

The results closely mirror the ex-ante evidence (Table 10, Panel G and H). Low-γ, high-χ firms experience the largest declines in returns during shock months, −2.62%, and account for a disproportionate share of aggregate wealth losses during these episodes, 16.43%.

This alignment between ex-ante premia and ex-post losses provides a key discipline check on our framework: the firms that are compensated for bearing carbon risk are precisely those that incur losses when that risk is realized. The incidence pattern is therefore not merely a fitted-return decomposition; it is reflected in actual market revaluations during regulatory-risk episodes.

7.3 Emissions Are Not Exposure: Reconciling Risk Incidence with Emissions Accounting

Sections 7.1 and 7.2 characterize the distribution of carbon-policy risk in the economy. The natural next question is how this distribution compares with the distribution of emissions, which is the object targeted by standard climate policy.

For each group G, we compute its share of aggregate emissions as

$$Share_G^{emissions} = \sum_{i \in G} Emissions_i / \sum_j Emissions_j,$$

and these shares for Scope 1 emissions are reported in Panel I and J of Table 10.

The contrast is stark. Low-γ, high-χ firms account for less than 2% of total emissions, yet they bear roughly 27% of the aggregate carbon risk premium and a substantial share of realized losses during regulatory shocks. Firms that contribute little to emissions nonetheless bear a large share of the risk generated by policies targeting those emissions.

We interpret this as a systematic misalignment between emissions and risk incidence. These two objects capture distinct margins of the economy. The distribution of emissions is the relevant margin for correcting the externality through Pigouvian taxation. The distribution of carbon-policy risk incidence is the relevant margin for financial stability, transition policy, and distributional analysis. In a horizontal economy without input–output linkages, the two coincide: direct emissions fully characterize exposure. In a networked economy, they do not. Emissions are governed by γ, while risk exposure is governed by $\gamma + \chi$.

This distinction has important implications. First, emissions-based measures—such as disclosure metrics, portfolio alignment scores, and standard climate stress tests—may substantially understate the breadth of firms and capital exposed to climate-policy risk. Second, policies aimed at managing transition risk—such as targeted support, financial-stability interventions, or sectoral adjustment programs—are better guided by network-based exposure than by direct emissions alone.

Importantly, this does not imply that emissions-based policies are misguided. Pigouvian taxation remains the appropriate instrument for internalizing the externality. Rather, our results imply that the incidence of carbon-policy risk is broader than the set of firms that generate emissions, and that understanding this incidence requires accounting for the propagation of shocks through production networks.

7.4 Real Adjustment Runs Through the Network

Finally, we connect the incidence results to real outcomes. The previous facts show that low-γ, high-χ firms bear a substantial share of carbon-policy risk in financial markets. We now ask whether this financial incidence also maps into real adjustment.

The answer is yes. Section 5 shows that firms with greater network exposure reduce investment more sharply when regulatory risk rises. At the group level, this pattern is concentrated among low-γ, high-χ firms (Table 10, Panel *I* and *J*). During regulatory shock periods, these firms reduce investment by 3.25%, the largest contraction among the four groups, and experience a 1.07% decline in net income. Thus, firms that appear clean based on direct emissions account for a disproportionate share of the real adjustment to carbon-policy shocks.

A simple aggregation illustrates the macro relevance of this pattern. Using value weights, the aggregate investment response to a regulatory shock can be approximated by

$$\frac{\Delta I_{agg}^{shock}}{I_{agg}^{base}} \approx \hat{\theta}_1 \sum_i w_i \chi_i + \hat{\theta}_2. \tag{33}$$

This expression maps the estimated firm-level investment elasticities into an aggregate response. Because a substantial share of the risk-bearing mass is concentrated among low-γ, high-χ firms, the aggregate contraction in investment is driven to a large extent by firms that are not themselves major emitters.

We interpret this calculation as a reduced-form aggregation of the estimated micro elasticities rather than a structural counterfactual, and leave a fully structural quantification to future work. Its purpose is to show that the incidence documented above is not only a financial-market phenomenon: network-based exposure also shapes the allocation of real adjustment across firms and contributes to aggregate investment responses.

8. CONCLUSION

This paper studies how production networks redistribute carbon risk across firms and sectors, and how that redistribution is reflected in asset prices and real responses to climate-policy shocks. We develop a tractable general-equilibrium asset-pricing framework that embeds input–output linkages, carbon emissions, and aggregate climate-regulatory risk, and we derive a sufficient-statistic characterization of the cross-sectional carbon risk premium in terms of direct exposure γ and indirect network exposure χ. The result makes precise the intuition that in a networked economy, carbon risk is transmitted from downstream customers to upstream suppliers: a firm's position in the production network can amplify or dampen its overall exposure beyond what its own emissions reveal.

Guided by the theory, we construct firm- and industry-level measures of γ and χ from Trucost, BEA, CRSP, and Compustat, and show that indirect exposure is the dominant priced component of the carbon risk premium. A one-standard-deviation increase in χ raises the annualized implied cost of capital by roughly 1.2 percentage points; indirect exposure accounts for about 85% of the cross-sectional premium, with the cross-industry component doing most of the work. An augmented factor model that includes γ and χ improves the pricing of carbon-sorted portfolios relative to the CAPM. Using a Carbon Regulatory Index constructed from textual sources, we further document that high-χ firms exhibit sharper contractions in valuations, investment, and earnings during identified regulatory-risk episodes, providing direct evidence for the network-propagation mechanism.

Translated into an incidence accounting, these pricing estimates reveal a systematic asymmetry between where carbon is emitted and where carbon-policy risk is borne. Firms with low direct emissions but high network exposure—"network-brown" firms—produce less than 2% of aggregate Scope 1 emissions yet absorb about 27% of the aggregate carbon risk premium and a comparable share of wealth losses during regulatory shocks. In a networked economy, emissions are governed by γ alone, but carbon-policy risk is governed by $\gamma + \chi$. This distinction matters for assessments of exposure to climate-policy risk—including climate stress tests, portfolio alignment metrics, and disclosure-based frameworks—which rely primarily on emissions accounting and may therefore understate the breadth of firms and capital affected.

The framework developed here is not specific to carbon. The same sufficient-statistic logic applies to any aggregate shock that transmits through sector-specific exposures: shifts in consumer preferences toward "green" producers, changes in the probability of climate-related physical disasters, technology shocks that favor particular sectors, or trade-policy shocks that raise the cost of inputs from specified origins. In each case, cross-sectional expected returns are governed by the sum of a firm's direct exposure and its network exposure through the Leontief structure, and the wedge between direct and network-based measures is pricing-relevant. We leave a fuller exploration of these extensions, together with a structural welfare analysis of the emissions–exposure asymmetry documented in this paper, to future work.

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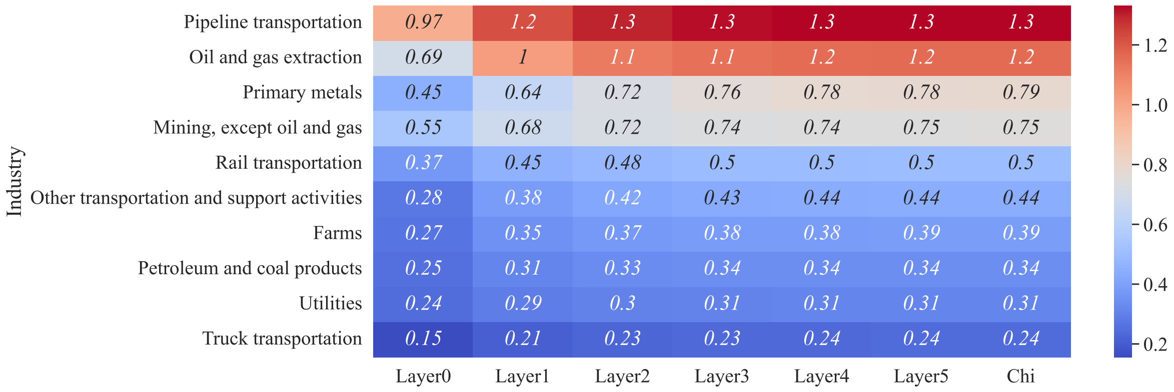
9. Figures and Tables

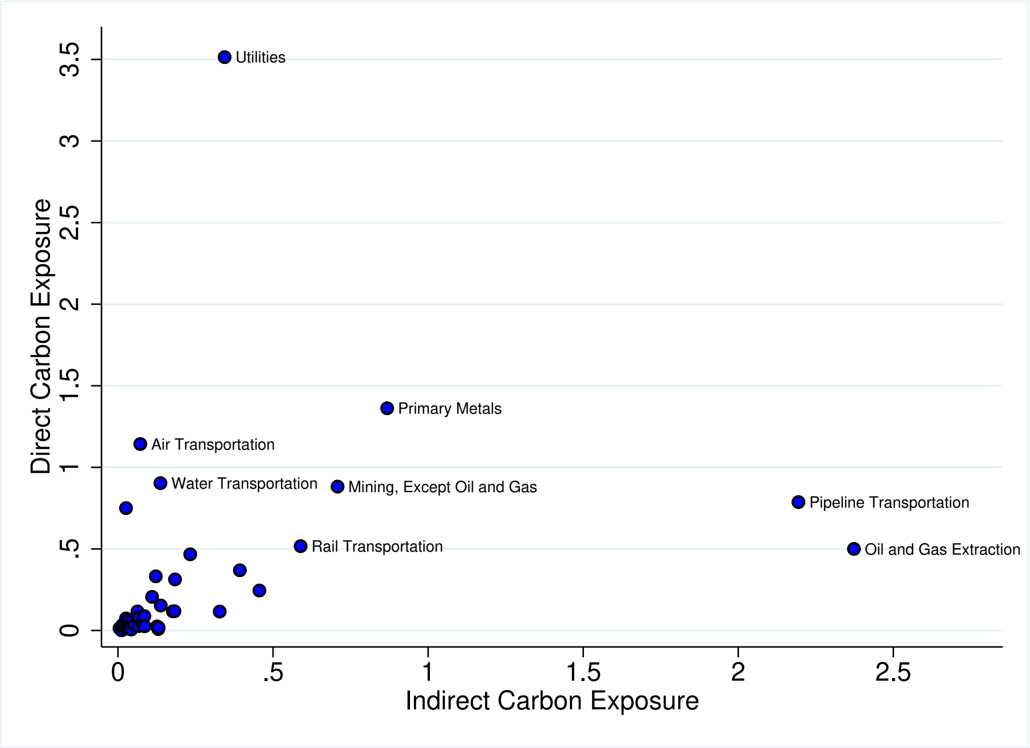
Figure 2: Effect of Network Depth on χ Measurement

Panel A: Top 10 Industries Ranked by χ



Industry	Layer0	Layer1	Layer2	Layer3	Layer4	Layer5	Chi
Pipeline transportation	0.97	1.2	1.3	1.3	1.3	1.3	1.3
Oil and gas extraction	0.69	1	1.1	1.1	1.2	1.2	1.2
Primary metals	0.45	0.64	0.72	0.76	0.78	0.78	0.79
Mining, except oil and gas	0.55	0.68	0.72	0.74	0.74	0.75	0.75
Rail transportation	0.37	0.45	0.48	0.5	0.5	0.5	0.5
Other transportation and support activities	0.28	0.38	0.42	0.43	0.44	0.44	0.44
Farms	0.27	0.35	0.37	0.38	0.38	0.39	0.39
Petroleum and coal products	0.25	0.31	0.33	0.34	0.34	0.34	0.34
Utilities	0.24	0.29	0.3	0.31	0.31	0.31	0.31
Truck transportation	0.15	0.21	0.23	0.23	0.24	0.24	0.24

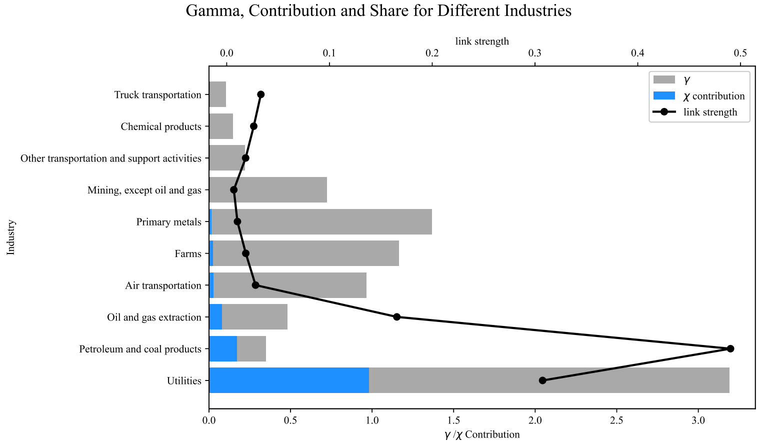
Panel B: Scatterplot of Indirect (χ) vs Direct (γ) Carbon Risk Exposure



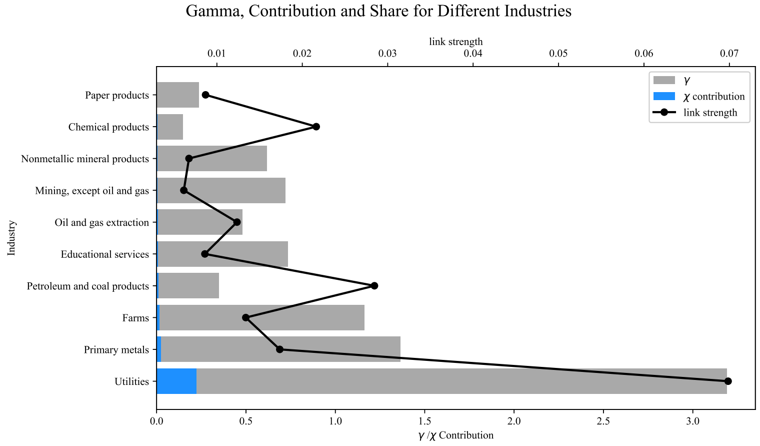
Panel A illustrates how network depth shapes the measurement of indirect carbon exposure (χ). The figure reports the top ten industries ranked by their total χ values. The y-axis lists industries, while the x-axis plots χ computed using networks of increasing depth (layers 0 through 5). Indirect exposure rises sharply within the first three layers and converges thereafter, indicating that most network effects originate from nearby upstream and downstream connections. Panel B presents a scatter plot of direct (γ) versus indirect (χ) carbon exposure, averaged across years. Even conditional on direct exposure, industries exhibit substantial dispersion in χ, underscoring the significant heterogeneity in network-driven carbon risk.

Figure 3: Decomposition of χ: A Case Study

Panel A: Pipeline Transportation

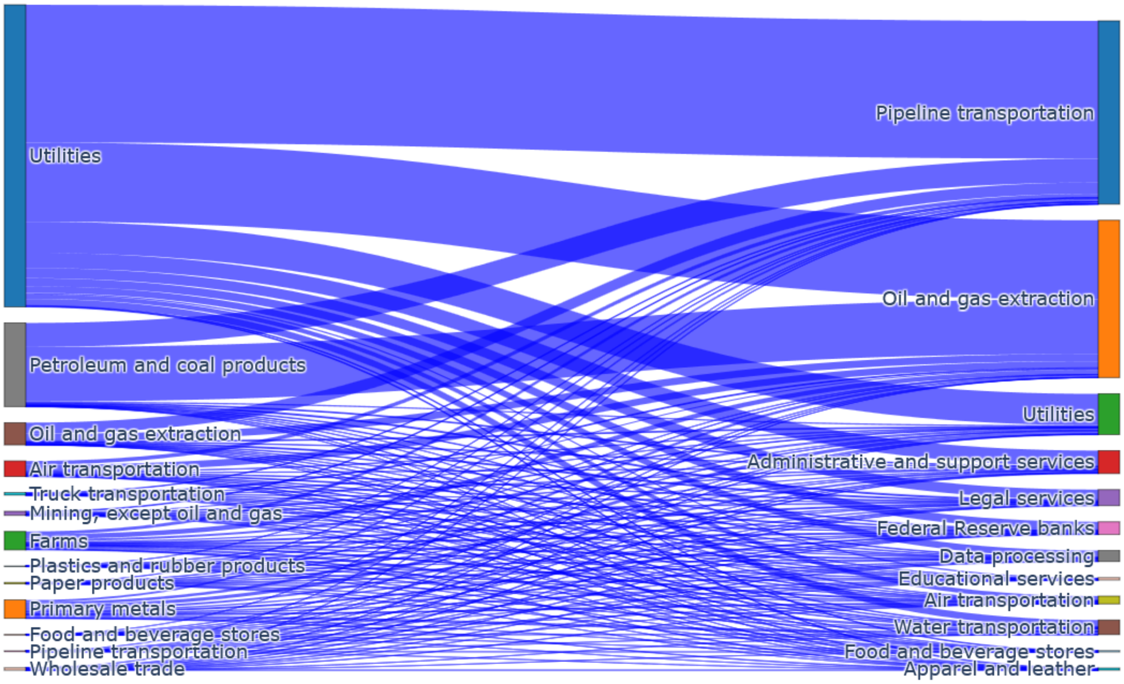


Panel B: Utilities



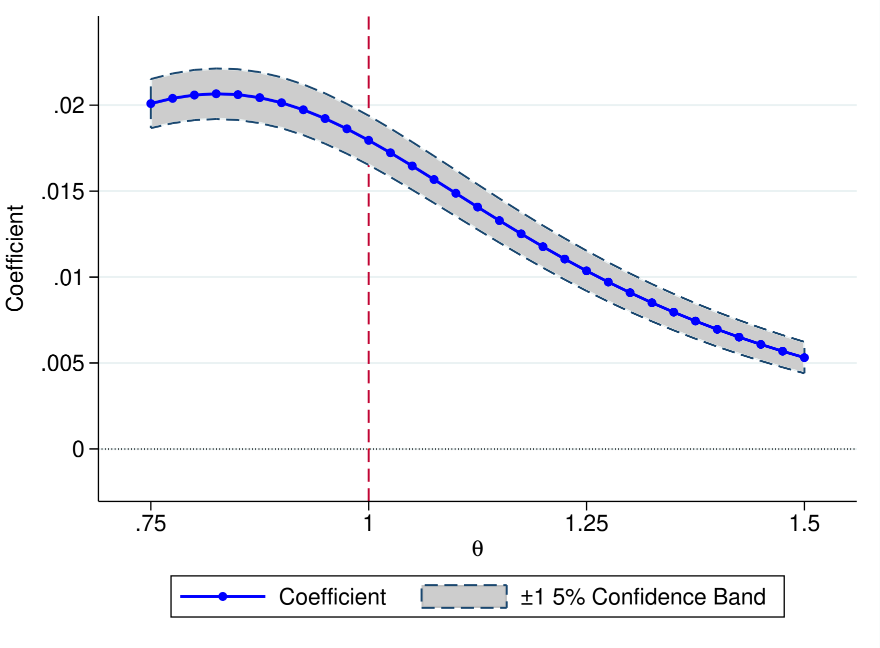
This figure decomposes the sources of an industry's indirect exposure (χ) into its link strength with other sectors and the direct exposure (γ) of those linked industries. The gray bars represent the direct exposure of the linked industries, the black solid line indicates link strength, and the blue bars measure the total contribution of each linked industry to the industry's indirect exposure. Panel A illustrates the pipeline transportation industry, and Panel B focuses on the utilities industry, both of which exhibit relatively high χ values compared to their own γ, indicating substantial exposure to downstream industries.

Figure 4: Decomposition of χ in the Network: Sankey Diagram



This figure depicts a Sankey diagram illustrating how the direct carbon exposure of contributing industries (*contributors*) flows into the indirect carbon exposure of receiving industries (*receivers*). The left axis lists the contributors while the right lists the receivers. The heights of the bars on the left and right axes represent contributors' direct exposure and receivers' indirect exposure, respectively. The width of each link captures the magnitude of the contributor's contribution to the receiver's indirect exposure. The diagram highlights, for example, that the indirect exposure of *Pipeline Transportation* is driven primarily by *Utilities*, followed by *Petroleum and Coal Products*, and that *Utilities* also substantially influence the indirect exposure of *Oil and Gas Extraction*. For clarity, the figure displays only industries with large gaps between direct and indirect exposure (as listed in Table OB.5).

Figure 5: Coefficients of $\chi^{\theta} + \gamma$ Estimated Using CES Production Function



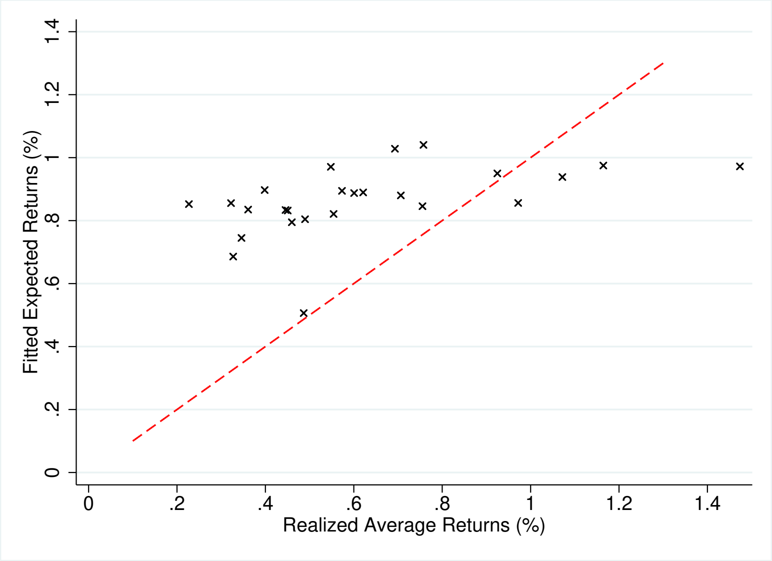
This figure shows the estimated coefficients of $\chi^{\theta} + \gamma$ from the following specification:

$$ICC_{it} = \alpha_i + \beta_{\chi+\gamma} \left(\chi_{it}^{\theta} + \gamma_{it}\right) + \boldsymbol{X}_{it}' \beta_x + \varepsilon_{it},$$

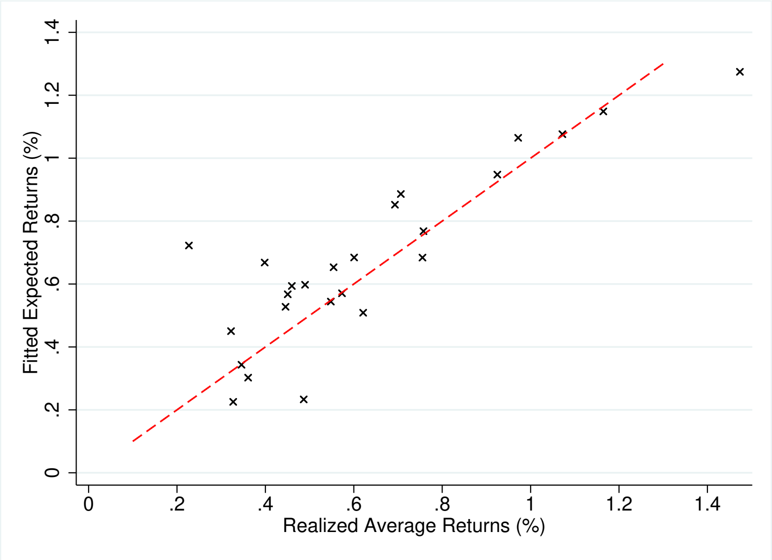
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the indirect carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. The control variables $\boldsymbol{X}_{it}$ are consistent with those in the baseline regression. The blue dots plot the estimated coefficients $\beta_{\chi+\gamma}$ across different values of θ, while the shaded gray area depicts the corresponding 95% confidence intervals. This analysis examines how the relationship between firms' carbon exposures and their implied cost of capital varies with the elasticity of substitution in the CES production framework.

Figure 6: Realized versus Model-Predicted Portfolio Returns

Panel A: CAPM Model

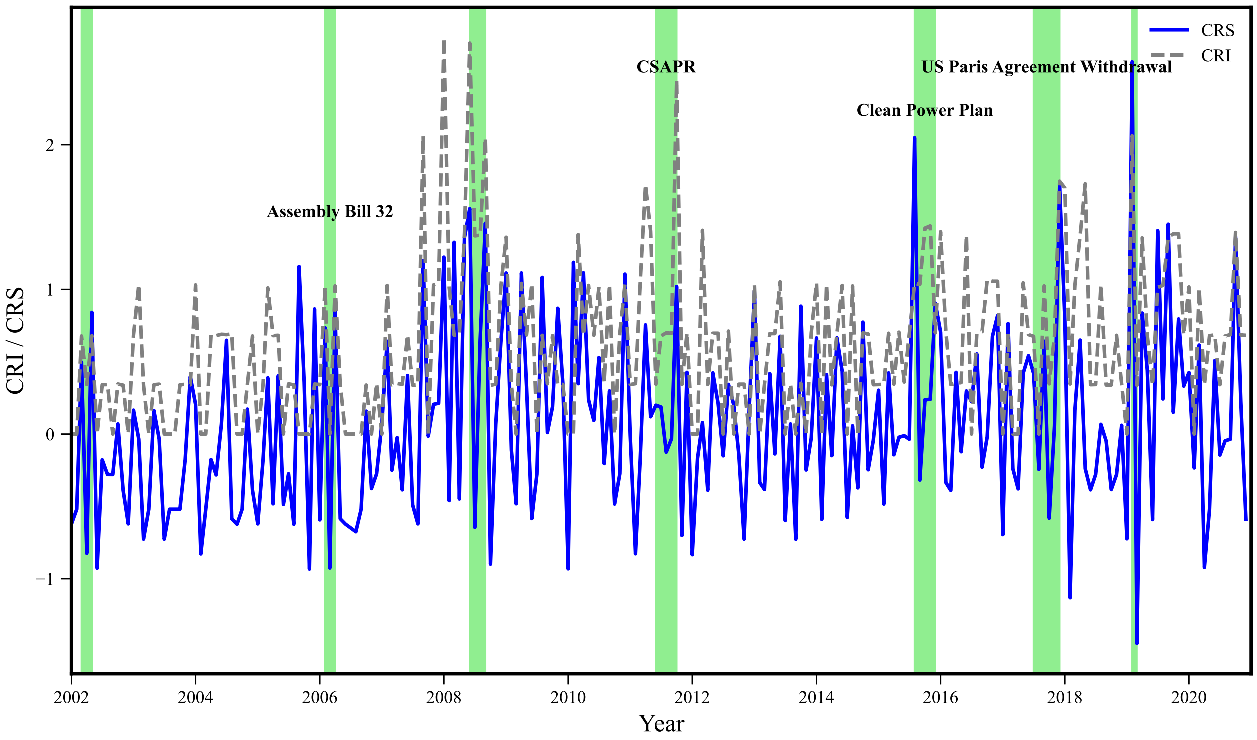


Panel B: Extended CAPM with χ and γ Factors



This figure compares realized returns of 25 portfolios—constructed from unconditional 5 × 5 sorts on direct (γ) and indirect (χ) carbon risk exposures—with returns predicted by two asset pricing models. Each portfolio corresponds to a quintile combination of γ and χ, where the first quintile reflects the lowest exposure and the fifth the highest. Panel A reports results from the standard CAPM, while Panel B presents results from an extended model that augments the market factor with γ and χ factors. The γ and χ factor returns are computed monthly as the return spread between the highest and lowest exposure quintiles. The x-axis plots realized average returns, and the y-axis plots model-implied returns; points closer to the 45-degree line indicate stronger explanatory power for cross-sectional variation in returns.

Figure 7: Time Series of CRI and CRS



This figure illustrates the time series of the Carbon Regulatory Shock (CRS) and the Carbon Regulatory Index (CRI) for the period from 2002 to 2020, based on the *Wall Street Journal*. The blue solid line represents CRS, while the gray dashed line represents CRI. The CRI, constructed using ChatGPT classifications, is based on the monthly proportion of articles reporting carbon-emission regulatory risk as "going up" minus those reporting it as "going down". CRS is computed as the residual from an AR(1) regression of the CRI time series. The green shading in the figure corresponds to periods of significant changes and uncertainty in carbon regulatory policies, with event labels matching those in Table OB.17.

Table 1: Direct (γ) and Indirect (χ) Carbon Risk Exposure across Industries

This table reports the average values of direct exposure (γ), indirect exposure (χ), and total exposure ($\gamma + \chi$), averaged across years. All exposure measures are expressed in tons per thousand U.S. dollars. Industry identifiers correspond to BEA sector codes.

BEA Code	Industry Description	χ	γ	$\chi + \gamma$
22	Utilities	0.344	3.514	3.859
486	Pipeline Transportation	2.194	0.787	2.981
211	Oil and Gas Extraction	2.373	0.500	2.873
331	Primary Metals	0.868	1.362	2.230
212	Mining, Except Oil and Gas	0.708	0.882	1.591
481	Air Transportation	0.072	1.143	1.215
482	Rail Transportation	0.589	0.517	1.107
483	Water Transportation	0.137	0.903	1.040
324	Petroleum and Coal Products	0.393	0.369	0.762
61	Educational Services	0.026	0.75	0.76
487OS	Other Transportation and Support Activities	0.456	0.245	0.701
327	Nonmetallic Mineral Products	0.233	0.467	0.700
322	Paper Products	0.184	0.313	0.498
111CA	Farms	0.122	0.332	0.455
213	Support Activities for Mining	0.328	0.116	0.444
313TT	Textile Mills and Textile Product Mills	0.110	0.206	0.316
484	Truck Transportation	0.182	0.118	0.300
332	Fabricated Metal Products	0.177	0.117	0.294
325	Chemical Products	0.138	0.153	0.290
3364OT	Other Transportation Equipment	0.063	0.117	0.180
326	Plastics and Rubber Products	0.085	0.088	0.173
42	Wholesale Trade	0.126	0.025	0.151
333	Machinery	0.131	0.018	0.149
485	Transit and Ground Passenger Transportation	0.066	0.078	0.144
5411	Legal Services	0.13	0.009	0.14
334	Computer and Electronic Products	0.065	0.063	0.129
323	Printing and Related Support Activities	0.078	0.048	0.126
113FF	Forestry, Fishing, and Related Activities	0.084	0.031	0.115
335	Electrical Equipment, Appliances, and Components	0.086	0.026	0.112
23	Construction	0.046	0.058	0.104
315AL	Apparel and Leather and Allied Products	0.026	0.074	0.101
311FT	Food, Beverage, and Tobacco Products	0.035	0.065	0.100
523	Securities, Commodity Contracts, and Other Financial Investments	0.067	0.027	0.094
541	Professional, Scientific, and Technical Services	0.053	0.036	0.089
561	Administrative and Support and Waste Management and Remediation Services	0.021	0.043	0.065
62	Health Care and Social Assistance	0.030	0.035	0.065
337	Furniture and Related Products	0.035	0.026	0.061
441	Motor Vehicle and Parts Dealers	0.031	0.029	0.061
3361MV	Motor Vehicles, Bodies and Trailers, and Parts	0.037	0.015	0.052
511	Publishing Industries, Except Internet (Includes Software)	0.043	0.006	0.050
531	Real Estate	0.014	0.033	0.047
339	Miscellaneous Manufacturing	0.031	0.014	0.046
4A0	Other Retail	0.033	0.012	0.045
81	Other Services (Except Public Administration)	0.019	0.023	0.042
512	Motion Picture and Sound Recording Industries	0.024	0.015	0.039
72	Accommodation and Food Services	0.014	0.025	0.039
445	Food and Beverage Stores	0.010	0.023	0.033
71	Arts, Entertainment, and Recreation	0.011	0.015	0.026
452	General Merchandise Stores	0.010	0.013	0.024
92	Public Administration	0.005	0.013	0.018
521CI	Federal Reserve Banks, Credit Intermediation, and Related Activities	0.012	0.001	0.012
514	Data Processing, Internet Publishing, and Other Information Services	0.010	0.004	0.011

Table 2: Summary Statistics

This table presents summary statistics for the variables used in the empirical analysis. After matching the Trucost and Compustat data, the sample size is reduced from 312,544 to 299,139 observations, which are used for regression analysis both with and without control variables. The table is organized into three panels: Panel A provides the summary statistics for the independent variables, Panel B presents the carbon risk exposure variables, and Panel C summarizes the control variables. All variables are reported in consistent units: firm size (Size) is measured in millions of U.S. dollars; employment (Employee) is measured in thousands of employees; carbon emissions (Emission) are measured in tons per million U.S. dollars of revenue; and the carbon risk metrics γ and χ are measured in tons per thousand U.S. dollars. For the variable definition, see OB.3 in the Appendix.

Panel A: Dependent Variables

	Obs	Mean	SD	Min	p25	p50	p75	Max
Return (%, annualized)	299139	9.11	59.59	-96.93	-25.12	2.82	30.47	1163.86
ICC (%, annualized)	299139	7.02	17.01	0.00	2.65	4.60	7.48	1623.29

Panel B: Carbon Risk Exposure

	Obs	Mean	SD	Min	p25	p50	p75	Max
χ (industry)	299139	0.15	0.26	0.00	0.05	0.09	0.13	2.63
χ (firm)	299139	0.14	0.24	0.00	0.06	0.08	0.12	2.63
γ (industry)	299139	0.20	0.39	0.00	0.01	0.02	0.06	3.66
γ (firm)	299139	0.18	0.58	0.00	0.01	0.03	0.06	3.66

Panel C: Control Variables

	Obs	Mean	SD	Min	p25	p50	p75	Max
Ln(Size)	287862	5.12	2.27	0.03	3.43	5.10	6.84	10.08
BM	287862	2.27	3.00	0.03	0.52	1.11	2.48	18.16
ROA	287862	-0.19	0.18	-0.80	-0.29	-0.15	-0.05	0.12
Leverage	287862	0.65	0.47	-0.07	0.30	0.50	0.93	2.53
Tobin's Q	287862	2.64	1.06	0.86	1.84	2.51	3.29	6.52
HHI	287862	0.21	0.10	0.04	0.13	0.17	0.28	0.71
KZINDE	287862	-4.72	14.34	-736.17	-4.76	-1.80	0.57	155.78
Employee	287862	4.44	3.57	0.05	2.18	3.51	5.97	33.80
Emission (Scope1)	299139	271924.70	763918.30	0.00	4363.81	24281.95	126931.20	5752388.00
Emission (Scope2)	299139	270878.70	1075978.00	0.00	6446.14	32486.00	133846.50	31500000.00
Emission (Scope3)	299139	1480812.00	6459104.00	0.30	31282.09	185532.20	833817.90	229000000.00

Table 3: Summary Statistics for Firms Sorted by Carbon Risk Exposure

This table presents the summary statistics for the ICC of firms. ICC is calculated as the annualized return on a monthly basis, expressed as a percentage. The stocks are sorted into quintiles based on: $\chi + \gamma$, χ, and γ. For each panel, the table shows the mean and standard error of ICC for the different groups (Low, 2, 3, 4, and High), as well as the difference between the High and Low groups (H-L).

Panel A: Stocks Sorted by $\chi + \gamma$

Group	Low	2	3	4	High	H-L
Mean	6.15***	6.35***	6.93***	7.62**	8.28**	2.13**
Standard Error	1.69	1.44	2.35	3.25	3.24	1.05

Panel B: Stocks Sorted by χ

Group	Low	2	3	4	High	H-L
Mean	6.24***	6.04***	6.93***	7.36**	8.48***	2.24***
Standard Error	1.51	1.89	2.19	3.02	2.84	0.89

Panel C: Stocks Sorted by γ

Group	Low	2	3	4	High	H-L
Mean	8.11***	6.66***	6.21***	5.47***	8.28***	0.16
Standard Error	3.09	1.82	1.92	1.78	2.65	1.17

Table 4: Implied Cost of Capital and Carbon Risk Exposure (Panel Regression)

This table examines the effect of direct and indirect carbon risk exposure on ICC:

$$y_{it} = \beta_{\chi}\chi_{it} + \beta_{\gamma}\gamma_{it} + \boldsymbol{X}'_{it}\beta_{x} + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} is the ICC of firm i at month t, β_{χ} captures the effect of indirect exposure arising from network effects, β_{γ} captures the effect of direct exposure due to a firm's own carbon emissions, and $\boldsymbol{X}$ includes standard control variables commonly used in the literature Bolton and Kacperczyk (2021). Emissions is defined as the company's annual scope 1 carbon emissions in tons. t-statistics are reported in parentheses, and all standard errors are robust, clustered at the BEA industry level. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) *ICC*	(2) *ICC*	(3) *ICC*	(4) *ICC*	(5) *ICC*	(6) *ICC*
Total exposure ($\chi + \gamma$)	0.512***			0.779**		
	(4.801)			(2.063)		
Indirect exposure (χ)		1.169***			1.249***	1.266***
		(6.584)			(12.201)	(10.981)
Direct exposure (γ)			0.126**		0.163*	
			(2.193)		(1.723)	
Ln(Size)				-8.518***	-8.521***	-8.527***
				(-5.414)	(-5.364)	(-5.364)
Ln(BM)				1.905***	1.904***	1.903***
				(5.320)	(5.323)	(5.328)
Roa				0.032	0.028	0.028
				(0.571)	(0.516)	(0.516)
Leverage				-0.029	-0.027	-0.025
				(-0.835)	(-0.837)	(-0.776)
Tobin's Q				-0.034	-0.037	-0.031
				(-0.679)	(-0.727)	(-0.613)
HHI				-0.145	-0.216	-0.253
				(-0.253)	(-0.365)	(-0.415)
KZ Index				0.047	0.125	0.193
				(0.137)	(0.323)	(0.448)
Ln(Employee)				-0.286	-0.225	-0.161
				(-0.564)	(-0.464)	(-0.331)
Emissions						0.219
						(0.522)
Scope3						0.027
						(0.614)
Month Fixed Effects	Y	Y	Y	Y	Y	Y
R-squared	0.025	0.028	0.023	0.081	0.085	0.085

Table 5: Implied Cost of Capital and Carbon Risk Exposure (Fama-MacBeth Regression)

This table examines the effect of carbon risk exposure on ICC using Fama-Macbeth regression,

$$y_{it} = \alpha + \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \varepsilon_{it},$$

where y_{it} is the standardized ICC of firm i at time t, β_χ represents the effect of the indirect exposure (χ), β_γ represents the effect of the direct exposure (γ), and $\boldsymbol{X}$ includes additional control variables. Emissions refers to the firm's annual Scope 1 carbon emissions in tons. Standard errors are Newey-West adjusted with a lag of 12 periods. t-statistics are reported in parentheses, and the coefficients marked with *, **, and *** are significant at the levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ICC	*ICC*	*ICC*	*ICC*	*ICC*	*ICC*
Total exposure ($\chi + \gamma$)	0.613**			0.829***		
	(2.390)			(3.401)		
Indirect exposure (χ)		1.308***			1.292***	1.329***
		(2.877)			(3.257)	(3.056)
Direct exposure (γ)			0.400**		0.261***	
			(2.357)		(3.615)	
Ln(Size)				-1.649***	-1.634***	-1.624***
				(-4.613)	(-4.610)	(-4.606)
Ln(BM)				8.531***	8.519***	8.523***
				(4.633)	(4.648)	(4.632)
Roa				0.002	-0.290	-0.377
				(0.010)	(-0.649)	(-0.738)
Leverage				-1.528	-0.881	-0.882
				(-1.050)	(-0.739)	(-0.736)
Tobin's Q				0.175	-1.378	-1.820
				(0.421)	(-0.912)	(-0.962)
HHI				0.079	0.184	0.172
				(0.487)	(0.922)	(0.843)
KZ Index				-0.118	-0.139	-0.101
				(-1.018)	(-1.102)	(-1.206)
Ln(Employee)				0.391***	0.436***	0.413***
				(4.845)	(5.609)	(6.040)
Emissions						0.001
						(0.006)
Newey lag 12	Y	Y	Y	Y	Y	Y
Observations	287,862	287,862	287,862	287,862	287,862	287,862
R-squared	0.003	0.012	0.001	0.135	0.141	0.142

Table 6: The Effect of Within and Cross-industry Direct and Indirect Exposure on ICC

This figure examines the effect of within- and cross-industry indirect and direct exposures on the ICC premium. The regression specification is given by:

$$\begin{aligned} y_{ijt} &= \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} \\ &+ \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \end{aligned} \tag{34}$$

where $\tilde{\chi}_{it}$, $\tilde{\chi}_{jt}$, $\tilde{\gamma}_{it}$, and $\tilde{\gamma}_{jt}$ represent within-industry indirect exposure, cross-industry indirect exposure, within-industry direct exposure, and cross-industry direct exposure, respectively, as defined in subsection 4.3. Panel A reports the results without control variables, while Panel B includes standard control variables. Panel C shows the explanatory power of different sources of risk exposure on ICC (see subsection 4.3 for details). Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Cross-industry		**Within-industry**	
	χ	γ	χ	γ
Panel A: Without Controls				
β	5.53***	-0.39***	4.18***	0.43***
Standard error	0.13	0.05	0.36	0.06
Panel B: With Controls				
β	5.45***	0.11**	4.10***	0.47***
Standard error	0.13	0.05	0.33	0.06
Panel C: Explanatory Power				
$\beta \times$ *standard deviation of component*	66.98%	3.30%	18.40%	11.32%
Relative incremental R^2 (incremental inclusion)	88.42%	0.12%	8.10%	3.35%
Relative incremental R^2(independent inclusion)	94.10%	1.78%	1.52%	2.61%

Table 7: Implied Cost of Capital and Carbon-Adjusted Centrality

This table presents the estimation results for the relationship between the implied cost of capital (ICC) and carbon-adjusted centrality. The model specification is:

$$ICC_{it} = \alpha_i + \beta_1 S_{i,t-1} + \beta_2 \vartheta_{it} + \beta_3 \gamma_{it} + \beta_4 Z_{it} + \varepsilon_{it},$$

where ICC_{it} is the implied cost of capital for firm i at month t, $S_{i,t-1}$ represents the revenue of firm i in the previous year, ϑ_{it} is the carbon-adjusted centrality (as defined in Appendix A.1), γ_{it} represents direct carbon risk exposure, and Z_{it} are control variables. t-statistics are reported in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) *ICC*	(2) *ICC*	(3) *ICC*	(4) *ICC*
ϑ	0.022*	0.031*	0.022*	0.031*
	(1.633)	(1.704)	(1.624)	(1.681)
γ	-0.005***	0.002		
	(-8.541)	(0.965)		
Emission			0.002	-0.015
			(0.815)	(-1.121)
Revenue	-0.039***	-0.044***	-0.038***	-0.042***
	(-4.307)	(-5.314)	(-3.425)	(-5.244)
Month Fixed	N	Y	N	Y
Controls	Y	Y	Y	Y
Observations	287,862	287,862	287,862	287,862
R-squared	0.492	0.484	0.452	0.491

Table 8: Interaction of Indirect Carbon Risk Exposure and Carbon Regulatory Shock (Portfolio Level)

This table examines how firms with varying levels of indirect carbon risk exposure (χ) respond to the carbon regulatory shock (CRS_t) using the specification:

$$y_{git} = \alpha_g + \beta_{\text{CRS},g}\text{CRS}_t + \boldsymbol{X}'_{git}\beta_{gx} + \varepsilon_{git},$$

where firms are sorted annually into five groups based on their indirect carbon risk exposure (χ). y_{git} denotes the financial performance or stock return of firm i within group g at time t, CRS_t is the carbon regulatory shock, and $\boldsymbol{X}_{git}$ includes standard control variables. Panel A shows results for returns, Panel B for changes in revenue (ΔRevenue), Panel C for changes in investment (ΔInvestment), and Panel D for changes in net income (ΔNet Income). Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns

Group	1	2	3	4	5
Without Controls					
$\beta_{\text{CRS},g}$	-0.140***	-0.263***	-0.088*	-0.318***	-0.435***
With Controls					
$\beta_{\text{CRS},g}$	-0.131**	-0.291***	-0.019	-0.272***	-0.403***

Panel B: ΔRevenue

Group	1	2	3	4	5
Without Controls					
$\beta_{\text{CRS},g}$	-15.482**	-18.636***	-14.190***	-8.711**	-92.744***
With Controls					
$\beta_{\text{CRS},g}$	-19.329***	-20.816***	-18.996***	-18.237***	-85.423***

Panel C: ΔInvestment

Group	1	2	3	4	5
Without Controls					
$\beta_{\text{CRS},g}$	-1.797	-3.117***	-2.228***	-2.362***	-10.810***
With Controls					
$\beta_{\text{CRS},g}$	-1.948*	-3.268***	-2.921***	-2.962***	-12.540***

Panel D: ΔNet Income

Group	1	2	3	4	5
Without Controls					
$\beta_{\text{CRS},g}$	2.362	-2.530	5.253	-9.670***	-17.184***
With Controls					
$\beta_{\text{CRS},g}$	3.898	-9.067***	1.359	-9.736***	-16.054***

Table 9: Interaction of Carbon Regulatory Shock and Carbon Risk Exposure (Firm Level)

This table examines the heterogeneous reaction of firms with varying levels of carbon risk exposure to the carbon regulatory shock (CRS_t). The regression specification is:

$$y_{it} = \alpha + \beta_{\text{CRS}} \times \text{CRS}_t + \beta_{\text{CRS},\chi} \times \chi_{it} \times \text{CRS}_t + \beta_{\text{CRS},\gamma} \times \gamma_{it} \times \text{CRS}_t + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} represents the dependent variables of interest, including stock return, change in revenue, change in investment, and change in net income for firm i at time t. β_{CRS} measures the effect of the carbon regulatory shock, $\beta_{\text{CRS},\chi}$ captures the interaction between indirect exposure (χ_{it}) and the carbon regulatory shock, and $\beta_{\text{CRS},\gamma}$ reflects the interaction between direct exposure (γ_{it}) and the carbon regulatory shock. $\boldsymbol{X}$ includes standard control variables. Fixed effects for firms and industries are included as specified. Robust standard errors are reported in parentheses, and coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns

	(1) *Return*	(2) *Return*	(3) *Return*	(4) *Return*	(5) *Return*
CRS	-0.235***	-0.188***	-0.168***	-0.168***	-0.181***
	(-9.395)	(-6.765)	(-6.014)	(-3.541)	(-3.309)
Indirect exposure × CRS		-0.166***	-0.171***	-0.173***	-0.109**
		(-3.005)	(-3.092)	(-3.505)	(-2.370)
Direct exposure × CRS		-0.075*	-0.081*	-0.064	-0.049
		(-1.702)	(-1.822)	(-0.864)	(-0.774)
Controls	N	N	Y	Y	Y
Industry Fixed Effects	N	N	N	Y	N
Firm Fixed Effects	N	N	N	N	Y
Observations	1,110,492	1,110,492	1,110,492	1,110,492	1,110,492

Panel B: ΔRevenue

	(1) *t+1*	(2) *t+1*	(3) *t+1*	(4) *t+2*	(5) *t+2*	(6) *t+2*
CRS	-11.714***	-8.375**	0.750	-7.034	-7.924	5.055
	(-3.425)	(-2.406)	(0.097)	(-1.644)	(-1.255)	(0.411)
Indirect exposure × CRS	-66.174***	-70.941***	-83.276***	-33.059***	-54.217***	-59.026***
	(-8.115)	(-8.618)	(-6.527)	(-3.625)	(-4.046)	(-4.289)
Direct exposure × CRS	-13.717**	-14.884**	-6.728	-12.441*	-24.714**	-17.764
	(-2.347)	(-2.544)	(-0.569)	(-1.838)	(-2.497)	(-1.083)
Controls	N	Y	Y	N	Y	Y
Firm Fixed Effects	N	N	Y	N	N	Y
Observations	14,890	14,890	14,890	14,890	14,890	14,890

Table 9: Interaction of Carbon Regulatory Shock and Carbon Risk Exposure (Firm Level, Continued)

This table examines the heterogeneous reaction of firms with varying levels of carbon risk exposure to the carbon regulatory shock (CRS_t). The regression specification is:

$$y_{it} = \alpha + \beta_{\text{CRS}} \times \text{CRS}_t + \beta_{\text{CRS},\chi} \times \chi_{it} \times \text{CRS}_t + \beta_{\text{CRS},\gamma} \times \gamma_{it} \times \text{CRS}_t + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} represents the dependent variables of interest, including stock return, change in revenue, change in investment, and change in net income for firm i at time t. β_{CRS} measures the effect of the carbon regulatory shock, $\beta_{\text{CRS},\chi}$ captures the interaction between indirect exposure (χ_{it}) and the carbon regulatory shock, and $\beta_{\text{CRS},\gamma}$ reflects the interaction between direct exposure (γ_{it}) and the carbon regulatory shock. $\boldsymbol{X}$ includes standard control variables. Fixed effects for firms and industries are included as specified. Robust standard errors are reported in parentheses, and coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel C: ΔInvestment

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	*t+1*	*t+1*	*t+2*	*t+2*	*t+2*
CRS	-0.681	-1.048**	-1.096	0.334	-0.721	-1.412
	(-1.448)	(-2.199)	(-1.317)	(-0.428)	(-0.862)	(-1.398)
Indirect exposure × CRS	-18.470***	-19.119***	-21.126***	-15.435***	-20.308***	-19.253***
	(-16.844)	(-17.254)	(-13.189)	(-9.418)	(-11.604)	(-10.601)
Direct exposure × CRS	1.410*	1.603**	3.027**	-2.664**	-2.472*	1.059
	(-2.347)	(-2.544)	(-0.569)	(-2.186)	(-1.908)	(-0.749)
Controls	N	Y	Y	N	Y	Y
Firm Fixed Effects	N	N	Y	N	N	Y
Observations	14,890	14,890	14,890	14,890	14,890	14,890

Panel D: ΔNet Income

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	*t+1*	*t+1*	*t+2*	*t+2*	*t+2*
CRS	-2.868	-1.744	1.009	-1.503	-1.303	1.434
	(-1.506)	(-0.910)	(0.483)	(-0.574)	(-0.496)	(0.566)
Indirect exposure × CRS	-9.804**	-9.147**	-13.744***	-0.894	-3.986	-11.013***
	(-2.350)	(-2.167)	(-3.629)	(-0.174)	(-0.767)	(-3.293)
Direct exposure × CRS	-3.980	-4.541	0.123	-4.174	-5.799	-1.056
	(-1.324)	(-1.509)	(0.027)	(-1.088)	(-1.507)	(-0.250)
Controls	N	Y	Y	N	Y	Y
Firm Fixed Effects	N	N	Y	N	N	Y
Observations	14,890	14,890	14,890	14,890	14,890	14,890

Table 10: Integrated Summary of Carbon Risk Incidence and Real Effects Across Direct Emissions and Network Exposure

Notes: This table provides an integrated summary of carbon-risk incidence and associated real effects across firm groups defined by direct emissions (γ) and network exposure (χ). Firms are sorted into Low/High bins of γ and χ. Panels A–B report firm counts and market-capitalization shares. Panels C–D report fitted implied cost of capital (ICC) and its cross-sectional share. Panels E–F report the carbon risk premium implied by the asset-pricing decomposition and its share across groups. Panels G–H report average abnormal returns during climate policy shock months (CRS) and the share of aggregate losses borne by each group. Panels I–J report shares of Scope 1 and Scope 3 emissions. Panels K–L report average investment and net income growth. Cell shading highlights the Low-γ/High-χ group to emphasize firms with low direct emissions but high network exposure.

Panel A. Firm Count

		χ	
		L	H
γ	L	601	493
	H	483	499

Panel B. Market Capitalization Share

		χ	
		L	H
γ	L	24.13%	20.04%
	H	25.22%	30.60%

Panel C. Fitted ICC

		χ	
		L	H
γ	L	0.23%	0.60%
	H	0.34%	1.93%

Panel D. Share of Fitted ICC

		χ	
		L	H
γ	L	7.34%	19.28%
	H	11.04%	62.24%

Panel E. Carbon Risk Premium

		χ	
		L	H
γ	L	0.24%	1.92%
	H	1.24%	3.78%

Panel F. Share of Carbon Risk Premium

		χ	
		L	H
γ	L	3.30%	26.80%
	H	17.32%	52.60%

Panel G. Policy-Shock Return

		χ	
		L	H
γ	L	0.16%	-2.62%
	H	-0.84%	-3.33%

Panel H. Share of Policy-Shock Return

		χ	
		L	H
γ	L	1.63%	16.43%
	H	15.91%	66.03%

Panel I. Scope 1 Emissions Share

		χ	
		L	H
γ	L	1.92%	1.76%
	H	36.72%	59.60%

Panel J. Scope 3 Emissions Share

		χ	
		L	H
γ	L	15.36%	11.64%
	H	28.26%	44.73%

Panel K. Investment Growth

		χ	
		L	H
γ	L	0.21%	-3.25%
	H	-0.55%	-1.76%

Panel L. Net Income Growth

		χ	
		L	H
γ	L	0.06%	-1.07%
	H	-0.33%	-0.46%

Appendix

The Network Origins of the Carbon Risk Premium

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December 2025

A. THEORY APPENDIX

A.1 Non-Cobb-Douglas Production Function

In this section, we relax the assumption of the Cobb-Douglas Production function and assume that the elasticity of substitution between intermediate inputs is not equal to one. This specification allows the regulatory shock to transmit *directly* from upstream to downstream sectors, while in our baseline, it only transmits from upstream to downstream sectors through the general equilibrium effect. We derive the expression for the carbon risk premium, consisting of the direct and indirect effects.

In particular, we assume that the composite input X_{jt} is aggregated from intermediate inputs purchased from other industries through the economy's input-output network:

$$X_{jt} = \left(\sum_{k=1}^{N} a_{jk}^{\frac{1}{\theta}} X_{jkt}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

where X_{jkt} represents the quantity of industry k's output used by industry j, and a_{jk} denotes the share of good k as an intermediate input in the production of good j. Constant returns to scale implies that $a_{jk} \geq 0$ and $\sum_{k=1}^{N} a_{jk} = 1$ for all j. The input-output linkages across industries are captured by the matrix $\boldsymbol{A} = [a_{jk}]$.

The first-order condition of firms' profit optimization problem in industry j yields the optimal demand for intermediate inputs produced by firms in industry k,

$$X_{jkt} = (1 - \gamma_j \tau_t) \eta_i a_{jk} Y_{jt} \frac{P_{jt}}{Q_{jt}} \left(\frac{P_{kt}}{Q_{jt}} \right)^{-\theta}, \tag{A.1}$$

where

$$Q_{jt} = \left(\sum_{s=1}^{N} a_{js} P_{st}^{1-\theta} \right)^{\frac{1}{1-\theta}}$$

is the price index of the intermediate inputs bundle X_{jt}.

Deriving $\Delta \log \boldsymbol{S}_t$. The market clearing condition is given by

$$C_{jt} + \sum_{k=1}^{N} X_{kjt} = Y_{jt}, \quad t = 0, 1, \tag{A.2}$$

Multiplying P_{jt} to both sides of the market clearing condition, replacing $P_{jt} X_{kjt}$ from firms' first-order condition (A.1) and $P_{jt} C_{jt}$ from households' first-order condition $P_{jt} C_{jt} = \alpha_j P_t C_t$, and dividing both sides by $P_t C_t$ we obtain the following expressions for $j = 1, 2, \ldots, N$,

$$S_{it} = \alpha_j + \sum_{k=1}^{N} (1 - \gamma_k \tau_t) \eta_k a_{kj} \left(\frac{P_{jt}}{Q_{kt}} \right)^{1-\theta} S_{kt}. \tag{A.3}$$

Denote j's input share from k as

$$\lambda_{jkt} = \frac{P_{kt} X_{kjt}}{P_{jt} Y_{jt}} = (1 - \gamma_j \tau_t) \eta_j a_{jk} \left(\frac{P_{kt}}{Q_{jt}} \right)^{1-\theta} \tag{A.4}$$

Equation (A.3) can be written as

$$S_{jt} = \alpha_j + \sum_{k=1}^{N} \lambda_{kjt} S_{kt} \tag{A.5}$$

Log-linearizing equation (A.5) yields the following expression,

$$\Delta \log S_{jt} = \frac{1}{S_{j0}} \sum_{k=1}^{N} \sum_{h=1}^{N} S_{k0} \lambda_{kh} \ell_{hj} \Delta \log \lambda_{kht}, \tag{A.6}$$

where the Leontief inverse is given by $L = (I - D_\eta \boldsymbol{A})^{-1}$ and ℓ_{hk} is the (h, k)th element of matrix L.

Next, we log-linearize the expression (A.4) and obtain

$$\Delta \log \lambda_{kht} = -\gamma_k \tau_t + (1 - \theta) \left(\Delta \log P_{ht} - \sum_{m=1}^{N} a_{km} \Delta \log P_{mt} \right) \tag{A.7}$$

Substituting equation (A.7) into equation (A.6) we have

$$\Delta \log S_{jt} = -\frac{1}{S_{j0}} \sum_{h=1}^{N} \sum_{k=1}^{N} S_{k0} \eta_k \gamma_k a_{kh} \ell_{hj} \tau_t + \frac{1 - \theta}{S_{j0}} \sum_{h=1}^{N} \sum_{k=1}^{N} S_{k0} \eta_k \gamma_k a_{kh} \ell_{hj} \left(\Delta \log P_{ht} - \sum_{m=1}^{N} a_{km} \Delta \log P_{mt} \right). \tag{A.8}$$

Here we impose the steady-state condition that $\lambda_{kh} = \eta_k a_{kh}$. We then express the above equation in vector form,

$$\Delta \log \boldsymbol{S}_t = -D_S^{-1} L' A' D_\eta D_S \boldsymbol{\gamma} \tau_t + (1-\theta) \underbrace{D_S^{-1} L' \left(\text{diag}(A' D_\lambda D_\eta \mathbf{1}) - A' D_S A\right)}_{\Phi_P} \Delta \log \boldsymbol{P}_t, \tag{A.9}$$

where diag(x) denotes a diagonal matrix with diagonal entries given by vector x. We define

$$\Phi_P = D_S^{-1} L' \left(\text{diag}(A' D_\lambda D_\eta \mathbf{1}) - A' D_S A\right).$$

Profits. The profits of firms in industry i are given by

$$\Pi_{jt} = (1 - \gamma_i \tau_t) P_{jt} Y_{jt} - \sum_{k=1}^{N} P_k X_{jkt}$$

Substituting equation (12) into this equation we have

$$\Pi_{jt} = (1 - \gamma_j \tau_t) \left(1 - \sum_{k=1}^{N} \eta_j a_{jk} (P_{kt}/Q_{kt})^{1-\theta}\right) P_{jt} Y_{jt}$$

Log-linearizing around the steady-state we have

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0} \left[-\gamma_j \tau_t + \Delta \log S_{jt} + \Delta \log C_t - (1-\theta)(I - D_\eta)^{-1} D_\eta A (I - A) \Delta \log \boldsymbol{P}_t\right] \tag{A.10}$$

Deriving $\Delta \boldsymbol{P}_t$. Since we aim to obtain a first-order approximation of S_{jt} and Π_{jt} around $\theta - 1$ and note that the coefficient before $\Delta \boldsymbol{P}_t$ is multiplied by $(1-\theta)$ in equation (A.9). Hence, it is sufficient to derive $\Delta \boldsymbol{P}_t$ under the Cobb-Douglas assumption ($\theta = 1$).

Under the Cobb-Douglas assumption, substituting firms' input demand into the production function, we have

$$P_{jt} Y_{jt} = P_{jt} \prod_{k=1}^{N} \left(\frac{(1 - \gamma_j \tau_t) P_{jt} Y_{jt}}{P_{kt}}\right)^{\eta_j a_{jk}} \tag{A.11}$$

After log-linearization we can show that

$$\Delta \log \boldsymbol{P}_t = (I - D_\eta \boldsymbol{A})^{-1} \boldsymbol{\gamma} \tau_t + (I - D_\eta \boldsymbol{A})^{-1} (I - D_\eta) \Delta \log \boldsymbol{S}_t + (I - D_\eta \boldsymbol{A})^{-1} (I - D_\eta) \mathbf{1} \Delta \log C_t \tag{A.12}$$

Deriving Expected Returns. Substituting equation (A.12) into (A.9) we have

$$\Delta \log \boldsymbol{S}_t = \underbrace{[(1-\theta)\Phi_P L \boldsymbol{\gamma} - D_S^{-1} L' A' D_\eta D_S \boldsymbol{\gamma}]}_{\Phi_\tau} \tau_t + (1-\theta)\Phi_P L (I - D_\eta) \Delta \log \boldsymbol{S}_t$$
$$+ (1-\theta)\Phi_P L (I - D_\eta) \mathbf{1} \Delta \log C_t,$$

Where we define $\Phi_\tau = (1-\theta)\Phi_P L\boldsymbol{\gamma} - D_S^{-1} L' A' D_\eta D_S \boldsymbol{\gamma}$. Rearranging the expression above yields

$$\Delta \log \boldsymbol{S}_t = \left[I - (1-\theta)\Phi_P L(I - D_\eta)\right]^{-1} \Phi_\tau \tau_t + (1-\theta)\left[I - (1-\theta)\Phi_P L(I - D_\eta)\right]^{-1} \Phi_P L(I - D_\eta)\mathbf{1}\Delta \log C_t \tag{A.13}$$

Substituting equation (A.13) and (A.12) into (A.10) we obtain the expression for profit

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0}\left[-\gamma_j \tau_t + (\Psi_{s\tau} + (\theta - 1)\Psi_{\pi p}\Psi_{p\tau})\tau_t + h(\Delta \log C_t)\right]$$

where we define

$$\begin{aligned}
\Psi_{s\tau} &= \left[I - (1-\theta)\Phi_P L(I - D_\eta)\right]^{-1} \Phi_\tau, \\
\Psi_{\pi p} &= (I - D_\eta)^{-1} D_\eta A(I - A), \\
\Psi_{p\tau} &= (I - D_\eta \boldsymbol{A})^{-1}\boldsymbol{\gamma} + (I - D_\eta \boldsymbol{A})^{-1}(I - D_\eta)\Psi_{s\tau},
\end{aligned}$$

and $h(\Delta \log C_t)$ is a linear function of $\Delta \log C_t$.

We can then calculate the expected return,

$$r_{jt} = r_t^f + \frac{\text{Cov}\left(\Delta \log C_t, \Pi_{jt}\right)}{\Pi_{j0}}. \tag{A.14}$$

It is straightforward to show that the direct effect is $\boldsymbol{\gamma}$ and the indirect effect is

$$\boldsymbol{\chi} = \Psi_{s\tau} + (\theta - 1)\Psi_{\pi p}\Psi_{p\tau}. \tag{A.15}$$

From this equation, it is obvious that equation (A.15) reduces to the equation in our baseline specification when $\theta = 1$. The additional terms reflect the input substitution channel.

A.2 Input-based and Revenue-based Emission: An Equivalence Result

The model specification is identical to Section 2.1, except that we consider the following specification for carbon emissions. Suppose that the production process releases $\widetilde{\gamma}_k$ units of carbon when one dollar-valued good k is used as an intermediate input. Firms' total carbon emissions in industry j is given by

$$\widetilde{e}_j = \sum_{k=1}^{N} \widetilde{\gamma}_k P_{kt} X_{jkt}.$$

Denoting $e_j = \gamma_j P_{jt} Y_{jt}$ as the emission in our baseline specification, we have

$$\frac{\widetilde{e}_j}{e_j} = \frac{\sum_{k=1}^{N} \widetilde{\gamma}_k P_{kt} X_{jkt}}{\gamma_j P_{jt} Y_{jt}}$$

$$= \frac{\eta_j \sum_{k=1}^{N} a_{jk} \widetilde{\gamma}_k}{\gamma_j}, \tag{A.16}$$

where the second equality holds by substituting into the input demand $P_{kt} X_{jkt} = \eta_j a_{jk} P_{jt} Y_{jt}$.

Equation (A.16) implies that for any specification $\{\widetilde{\gamma}_k\}_{k=1}^{N}$, there exists a unique set of $\{\gamma_k\}_{k=1}^{N}$ such that for any industry j, $\widetilde{e}_j = e_j$. Put differently, under the assumptions in Section 2.1, the two specifications are equivalent in modeling carbon emissions.

A.3 Proofs of Lemmas and Propositions

A.3.1 Proof of Lemma 1

The market clearing condition in the main text implies that

$$\boldsymbol{S}_t = \boldsymbol{\alpha} + \boldsymbol{A}'\boldsymbol{D}_\eta (I - \boldsymbol{D}_\gamma \tau_t)\boldsymbol{S}_t.$$

Approximating this equation around the period-0 equilibrium up to first-order yields

$$\boldsymbol{S}_t - \boldsymbol{S}_0 = \boldsymbol{A}'\boldsymbol{D}_\eta(\boldsymbol{S}_t - \boldsymbol{S}_0) - \boldsymbol{A}'\boldsymbol{D}_\eta \boldsymbol{D}_S \boldsymbol{V}_\gamma \tau_t$$

which can be further simplified to

$$\Delta \log \boldsymbol{S_t} = \log \boldsymbol{S_1} - \log \boldsymbol{S_0} = -\left[\boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}\boldsymbol{A}'\boldsymbol{D}_\eta \boldsymbol{D}_S \boldsymbol{\gamma}\right] \tau_t.$$

which is equation (9) in the main text.

A.3.2 Proof of Lemma 2

The profits of firms in industry i are given by

$$\Pi_{it} = (1 - \gamma_i \tau_t) P_{it} Y_{it} - \sum_{j=1}^{N} P_j X_{ijt}$$

Substituting equation (12) into this equation we have

$$\begin{aligned}\Pi_{it} &= (1 - \gamma_i \tau_t) P_{it} Y_{it} - (1 - \gamma_i \tau_t)\eta_i (\sum_{j=1}^{N} a_{ij}) P_{it} Y_{it} \\ &= (1 - \eta_i)(1 - \gamma_i \tau_t)\Psi_{it},\end{aligned}$$

which is equation (13) in the main text.

A.3.3 Proof of Proposition 1

Taking logs on both sides of equation (13) gives

$$\log \Pi_{it} = \log\big(1 - \eta_i\big) + \log(1 - \gamma_i \tau_t) + \log S_{it} + \log C_t$$

Differencing between period t and period 0 and approximating up to first order we obtain

$$\begin{aligned}\Pi_{it} &= \Pi_{0t} + \Pi_{i0}(-\gamma_i \tau_t + \Delta \log S_{it} - \Delta \log C_t) \\ &= \Pi_{0t} - \Pi_{i0}(\gamma_i + \chi)\tau_t + \Pi_{i0}\Delta \log C_t,\end{aligned}$$

which is equation (14) in the main text.

A.3.4 Proof of Proposition 2

To derive the expression for aggregate consumption growth, we first derive the expression for revenue.

Revenue. Substituting the first order condition (12) into the production function of firms in industry j (1) we obtain

$$\Psi_{jt} = P_{jt} \prod_{k=1}^{n} \left(\frac{(1 - \gamma_j \tau_t)\Psi_{jt}}{P_{kt}} \right)^{\eta_j a_{jk}} . \tag{A.17}$$

Taking logs and rearranging this expression yields the following lemma.

Lemma A.1. *The log revenue of firms in industry j is given by:*

$$\log \Psi_{jt} = \frac{\eta_j}{1 - \eta_j} \log\big(1 - \gamma_j \tau_t\big) + \frac{1}{1 - \eta_j} \left(\log P_{jt} - \eta_j \sum_{k=1}^{N} a_{jk} \log P_{kt} \right). \tag{A.18}$$

Industry j's log revenue is negatively affected by the carbon tax τ_t. Everything else equal, a firm benefits from the higher price of its output P_{jt} and lower prices of its intermediate inputs $\{P_{kt}\}_{k=1}^{N}$. Finally, we can re-write equation (A.18) in vector form, up to first order:

$$\log \boldsymbol{\Psi}_t = (I - \boldsymbol{D}_\eta)^{-1} \left[-\boldsymbol{D}_\eta \gamma \tau_t + \big(I - \boldsymbol{D}_\eta \boldsymbol{A}\big) \log \boldsymbol{P}_t \right] . \tag{A.19}$$

Aggregate Consumption Growth. With Lemma A.1, we are ready to derive the expression for the aggregate consumption growth. Based on the definition of Domar weights, the log aggregate consumption can be expressed as:

$$\mathbf{1} \log C_t = \log \boldsymbol{\Psi} - \log \boldsymbol{S}_t, \tag{A.20}$$

where $\mathbf{1} = (1, 1, ..., 1)'$. Substituting equation (8) and (A.19) into (A.20) we have the following expression:

$$\mathbf{1} \log C_t = (I - \boldsymbol{D}_\eta)^{-1} \left[-\boldsymbol{D}_\eta \boldsymbol{\gamma} \tau_t - (1 - \boldsymbol{D}_\eta) \log \boldsymbol{S}_t + \left(I - \boldsymbol{D}_\eta \boldsymbol{A}\right) \log \boldsymbol{P}_t \right]$$

Let us denote $\boldsymbol{\Omega} = \left(I - \boldsymbol{D}_\eta \boldsymbol{A}\right)^{-1} (I - \boldsymbol{D}_\eta)$. Multiplying $\boldsymbol{\alpha}'\boldsymbol{\Omega}$ to both sides, using the normalization $\boldsymbol{\alpha}' \log \boldsymbol{P}_t = 0$ and noting that $\boldsymbol{\alpha}'\boldsymbol{\Omega}\mathbf{1} = 1$, we obtain the expression for the aggregate consumption

$$\log C_t = -\boldsymbol{\alpha}' \left(I - \boldsymbol{D}_\eta \boldsymbol{A}\right)^{-1} \boldsymbol{D}_\eta \boldsymbol{\gamma} \tau_t - \boldsymbol{\alpha}' \boldsymbol{\Omega} \log \boldsymbol{S}_t. \tag{A.21}$$

Differencing equation (A.21) between period 1 and period 0 yields the expression for the aggregate consumption growth in Proposition 2.

B. DATA CONSTRUCTION

Trucost data on Carbon Emission. Consistent with Bolton and Kacperczyk (2021), we utilize the Trucost dataset for firm-specific carbon emissions analysis. Trucost compiles its emissions data from various public disclosures, including financial reports (annual reports, 10-K/20-F filings), environmental reports (CSR, sustainability reports), and regulatory filings (Carbon Disclosure Project (CDP), Environmental Protection Agency (EPA)). Additionally, it incorporates information from authoritative sources like the Intergovernmental Panel on Climate Change, the Food and Agriculture Organization, the U.S. Energy Information Agency, and the International Energy Agency. For firms not voluntarily disclosing emissions, Trucost employs an environmentally extended input-output (EEIO) model that integrates industry-specific environmental data with macroeconomic indicators to trace inter-sectoral goods and services flow. Trucost's model assesses over 800 metrics across the full operational range of companies, including raw material usage and electricity procurement.

Emissions are quantified according to the Greenhouse Gas (GHG) protocol and are expressed in tons of CO2 annually, categorized into three scopes:

- Scope 1 covers direct emissions from sources that a firm owns or controls, such as emissions from internal combustion engines.
- Scope 2 includes externally produced emissions from purchased energy, like electricity or steam.
- Scope 3 involves indirect emissions not directly owned or controlled by the firm but related to its broader operational activities, including supply chain and downstream user consumption. For example, emissions from an aircraft are considered "scope 1" for the airline operating it but "scope 3" for the manufacturer.

It's crucial to note that much of Trucost's data, particularly regarding scope 2 and 3 emissions, is estimated rather than directly reported by the firms. "Scope 3" typically represents the most comprehensive portion of a firm's emissions profile due to its broad inclusion of indirect activities. Descriptive statistics for these emission scopes are presented in Table 2.

Guided by our theoretical framework, we focus on "Scope 1" as a measure of direct carbon emissions and use its ratio to company revenue to measure carbon emission intensity within the same fiscal year. Zhang (2025) document that emissions disclosures are typically released roughly 10 months after the earnings report; accordingly, we align emissions disclosures with subsequent return months in our regression analysis.

Our preference for "Scope 1" is also reinforced by the findings of Busch et al. (2022), who demonstrate its superior reliability across various data providers. In their comparative analysis of carbon emission data from several sources, including Bloomberg, CDP, ISS Ethix, Trucost, MSCI, Sustainalytics, and Thomson Reuters, Busch et al. (2022) reveal that "Scope 1" emission correlations among these entities approximate 0.99. Nonetheless, the correlation for "Scope 3" emissions significantly decreases to 0.58, which is attributed to the lack of detailed input-output linkages between companies. Moreover, they categorize carbon emission data into two segments: company-reported and third-party estimated. For company-reported data, the average Pearson correlation for Scope 1, Scope 2, and Scope 3 emissions is 0.99, 0.98, and 0.58, respectively. In contrast, for third-party estimated data, the mean Pearson correlations for Scope 1, Scope 2, and Scope 3 emissions are 0.79, 0.63, and 0.15, respectively, highlighting the challenges of accurately estimating indirect emissions.

Figure OA.1 shows annual carbon emissions averaged across firms within each year. The box shows average Scope 1 emissions, and the red line shows average Scope 1 emissions intensity averaged across years. Two points are worth noting. First, both average emissions and emissions intensity decline over time due to changes in sample coverage: early years disproportionately contain firms with high emissions and intensity, while lower-emission firms enter later. Second, due to a jump in firm coverage, there is a significant drop in emissions and intensity in 2016. To mitigate concerns that our empirical results are driven by Trucost coverage changes, we aggregate emissions to the industry level and scale by firm sales to measure industry-level emissions and emissions intensity.

Figure OA.3 shows Scope 1 carbon emission intensity at the BEA industry level averaged across years. There is substantial variation in direct carbon emission intensity across industries, ranging from more than 3,500 tons of CO2 per million dollars in Utilities to near-zero emissions in Legal Services. The five industries with the highest carbon emission intensity are Utilities, Mining (except Oil and Gas), Air Transportation, Water Transportation, and Pipeline Transportation.

Input-Output Data. Our input-output table is derived from the Bureau of Economic Analysis (BEA)'s detailed industry relationships. The BEA regularly publishes these data, offering comprehensive insights across a broad spectrum of industries. Specifically, it provides data on 405 sectors every five years and on a more aggregated basis for 71 sectors annually, spanning from 1997 to 2021. Our study utilizes the annual data for the 71 sectors based on two main considerations: (i) The 405-sector tables, which are updated every five years, demonstrate considerable changes in industry classifications and coverage, potentially impacting the consistency of our analysis; (ii) Our dataset on carbon emissions covers the period from 2002 to 2020, during which only three updates (2007, 2012, and 2017) of the 405-sector tables were released. The infrequent updates of these comprehensive tables limit the temporal variability critical for our empirical analysis.

The Bureau of Economic Analysis (BEA) aligns its 71 industries with the North American Industry Classification System (NAICS) codes, varying from 2-digit to 4-digit levels of specificity. Our study has methodically aligned these BEA industries with the corresponding three-digit NAICS sectors. This alignment reveals that 53 of the BEA industries match with firms represented in our carbon emission dataset. Industries not included, as highlighted — such as wood products and the federal general government—predominantly fall outside the scope of manufacturing as shown in the Table

OB.1. Figure OA.2 shows the number of BEA industries that can be matched with our Trucost data over years.

Construction of $\boldsymbol{A}$. The input-output Matrix $\boldsymbol{A}$ is a $k \times k$ matrix capturing the input-output relationship between industries. Its element a_{ij} is the expenditure percentage of industry i on intermediate goods in the industry j to i's total intermediate expenditure.

We use the input-output tables by BEA to construct the matrix $\boldsymbol{A}$. BEA provides the annual input-output table at the level of 71 sectors spanning from 2002 to 2020. Two things worth mentioning are the differences between the input-output matrix in theory and its counterparts in the data.

- Product Uniqueness and Representation: In our theoretical model, each industry comprises firms producing a distinct, homogeneous product, and we symbolize the entire industry by a single representative firm. Consequently, each industry corresponds uniquely to its product. However, the real-world data presents a more intricate picture. Even if categorized under one industry, companies like Google or Amazon have operations spanning multiple industries. Simply aggregating firms' production within a sector might not accurately represent sectoral production. Addressing this complexity, the BEA introduces a "make" table. Represented as the matrix **MAKE**, each entry (i, j) captures the proportion of products from sector i attributed to sector j.
- Product Consumption across Sectors: Parallel to the "make" table, the BEA offers a "use" table, capturing inter-sectoral consumption. Symbolized as $\boldsymbol{USE}$, an entry (i, j) in this table reveals the fraction of intermediate goods consumed by sector i originating from sector j.

To handle the gap between the input-output matrix in theory and its empirical counterpart, we follow the method proposed by Pasten et al. (2017) to construct the empirical counterpart of the matrix $\boldsymbol{A}$.

Other Datasets. We measure firm returns using two primary metrics: the implied cost of capital (ICC) and stock returns. The use of stock returns to measure the expected returns associated with carbon emission risk is subject to significant controversy, particularly due to its potential misalignment with forward-looking measures (Pástor et al., 2022; Eskildsen et al., 2024). To address this concern, we adopt the implied cost of capital approach, following the method proposed by Gordon and Gordon (1997); Hou et al. (2012), to approximate finite-horizon expected returns. As a robustness check, we confirm that our main findings remain consistent when stock returns are used as a proxy for expected returns.

Our return data primarily originates from the Center for Research in Security Prices (CRSP), complemented by delisting-adjusted return data from Compustat for a subset of delisted firms. To mitigate the influence of extreme observations, we exclude returns exceeding 100%.

Control variables are constructed as follows: $LOGSIZE_{i,t}$ represents the natural logarithm of firm i's market capitalization, calculated as the product of share price and shares outstanding, at year-end t; $B_{i,t}/M_{i,t}$ is the book-to-market ratio, where the market value of equity (MVE) is computed as the stock price per share multiplied by the number of outstanding shares; LEVERAGE denotes the book leverage ratio of the firm; $ROE_{i,t}$ measures earnings performance as the net income of firm i divided by its book value of equity; $MOM_{i,t}$ captures momentum as the average return of stock i over the 12 months preceding month $t-1$; $INVEST/A$ represents the ratio of capital expenditures to the book value of assets; HHI is the Herfindahl-Hirschman Index, reflecting market concentration based on revenue across business segments; LOGPPE is the natural logarithm of the firm's property, plant, and equipment value; $BETA_{i,t}$ is the market beta of firm i in year t, estimated using daily returns; and $VOLAT_{i,t}$ represents return volatility, computed as the standard deviation of monthly returns over the past 12 months.

To address outlier concerns, we winsorize B/M, LEVERAGE, and $INVEST/A$ at the 2.5% level, and MOM and $VOLAT$ at the 0.5% level.

C. VARIABLE CONSTRUCTION FOR IMPLIED COST OF CAPITAL

We construct the implied cost of capital (ICC) following Hou et al. (2012). This appendix describes the key variables and the forecasting procedure used to estimate expected future earnings.

C.1 Step 1: Forecast One-Year-Ahead Earnings

We first estimate one-year-ahead expected earnings using a cross-sectional earnings forecasting model. For each year t, we estimate the following regression:

$$IB_{i,t+1} = \alpha_t + \beta_{1,t}AT_{i,t} + \beta_{2,t}DVC_{i,t} + \beta_{3,t}DD_{i,t} + \beta_{4,t}IB_{i,t} + \beta_{5,t}NE_{i,t} + \beta_{6,t}ACCRUAL_{i,t} + \varepsilon_{i,t+1}, \quad \text{(C.1)}$$

where $IB_{i,t+1}$ denotes income before extraordinary items for firm i in year $t+1$. The explanatory variables are measured at year t: $AT_{i,t}$ is total assets; $DVC_{i,t}$ is dividends paid to common or ordinary shareholders; $DD_{i,t}$ is the dividend payout indicator or payout ratio; $IB_{i,t}$ is income before extraordinary items; $NE_{i,t}$ is net equity issuance; and $ACCRUAL_{i,t}$ denotes accruals.

The fitted value from this regression provides the forecast of firm i's one-year-ahead earnings, denoted by $\widehat{IB}_{i,t+1}$. This forecast serves as the first input in the ICC calculation.

C.2 Step 2: Compute the Implied Cost of Capital

Following Gordon and Gordon (1997), we compute the implied cost of capital (ICC) from expected earnings and dividend-related variables. The ICC calculation incorporates assumptions on future earnings growth and payout ratios.

We use accounting variables from Compustat Annual and monthly size information based on the monthly market value. The Compustat Annual variables include `IB` (income before extraordinary items), `CEQ` (common/ordinary equity), `AT` (total assets), and `DVC` (dividends paid to common/ordinary shareholders).

We construct accruals as follows:

$$\begin{aligned} ACCRUAL_{i,t} = &(ACT_{i,t} - ACT_{i,t-1}) - (CHE_{i,t} - CHE_{i,t-1}) - (LCT_{i,t} - LCT_{i,t-1}) \\ &+ (DLC_{i,t} - DLC_{i,t-1}) + (TXP_{i,t} - TXP_{i,t-1}) - DP_{i,t}. \end{aligned} \quad \text{(C.2)}$$

Beginning in 1988, we use the cash-flow-statement approach to construct accruals, following **?**. Specifically,

$$ACCRUAL_{i,t} = IBC_{i,t} - (OANCF_{i,t} - XIDOC_{i,t}), \quad \text{(C.3)}$$

where `IBC` is income before extraordinary items and discontinued operations from the cash-flow statement, `OANCF` is net operating cash flow, and `XIDOC` is extraordinary items and discontinued operations from the cash-flow statement.

C.3 Sample Filters

We restrict the sample to ordinary common shares listed on NYSE, NASDAQ, or AMEX. In CRSP, this corresponds to observations with exchange codes `exchcd` equal to 1, 2, or 3, and share codes `shrcd` equal to 10 or 11. To avoid look-ahead bias, we impose a three-month reporting lag when matching annual accounting variables to market data.

To reduce the influence of extreme observations, we winsorize level-based financial variables, including total assets, earnings, and dividends, at the 1st and 99th percentiles within each year.

Negative ICC estimates are set to missing. We further winsorize the estimated ICC within each year to limit the influence of outliers.

Online Appendix

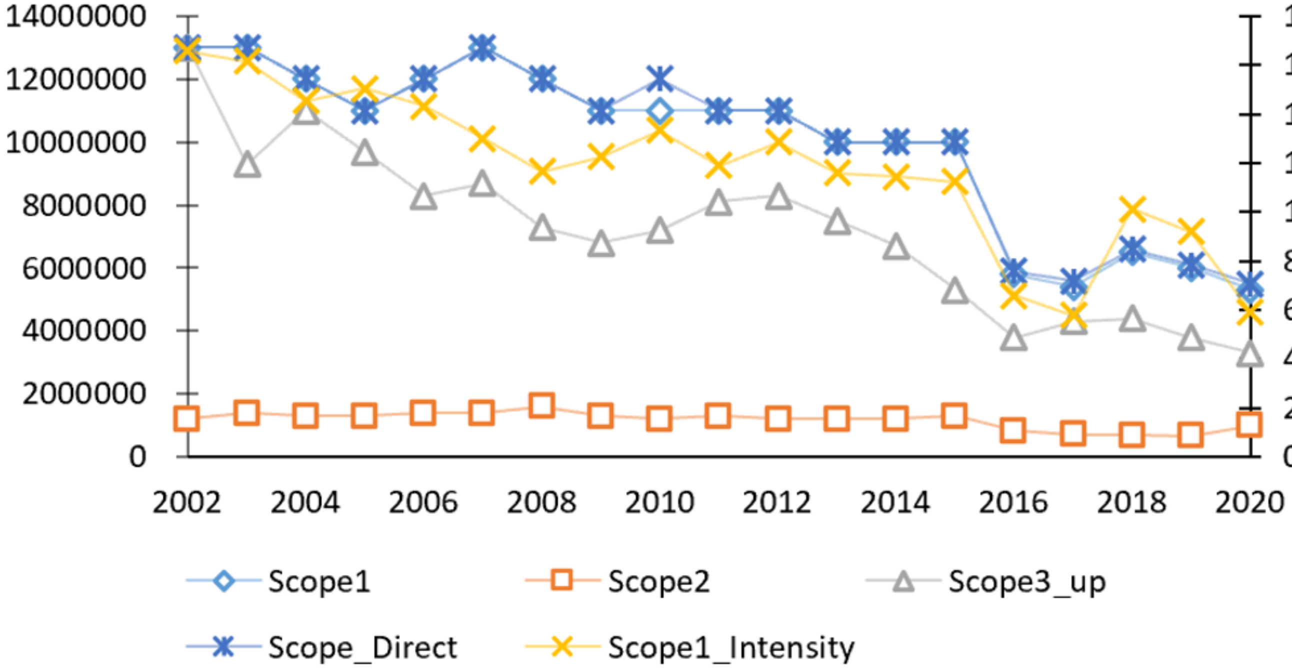
The Network Origins of the Carbon Risk Premium

Shubo Kou   Kai Li   Minghao Li   Wu Zhu

December 2025

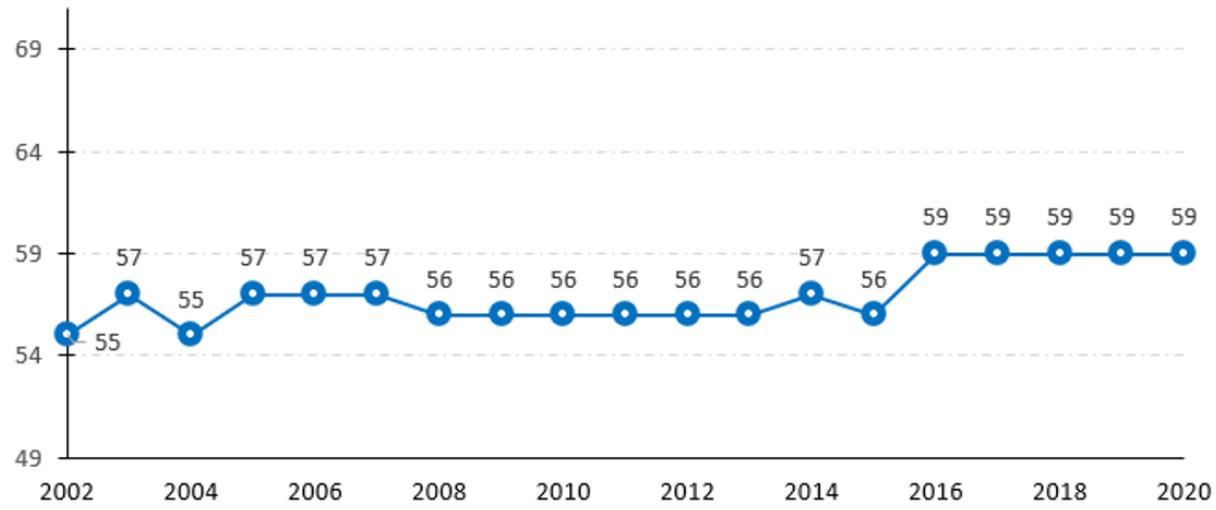
OA. ADDITIONAL FIGURES

Figure OA.1: Carbon Emission and Intensity



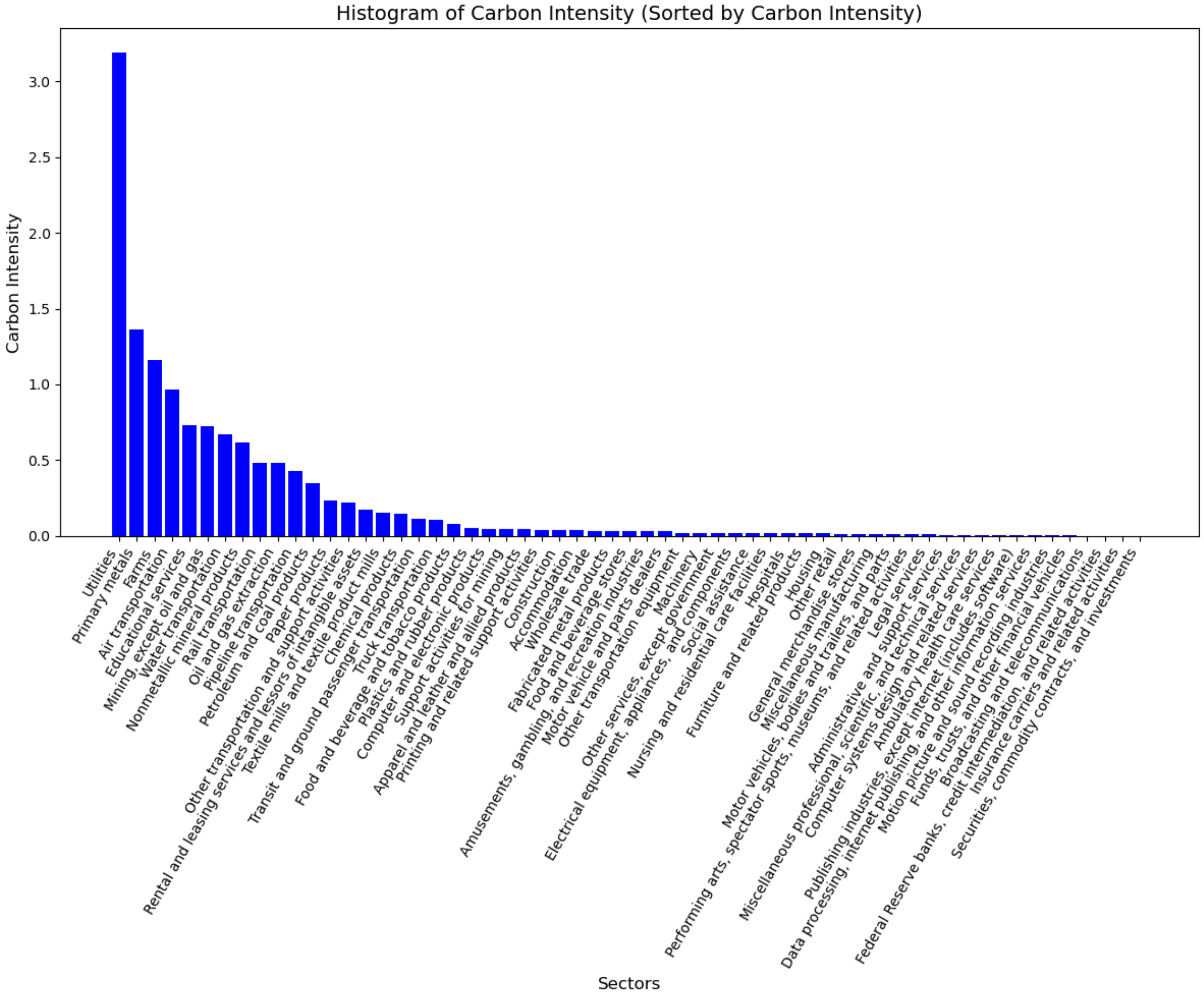
This figure shows the time trend of carbon emissions for "Scope 1", "Scope 2", and "Scope 3".

Figure OA.2: The Number of Industries Matched over Years



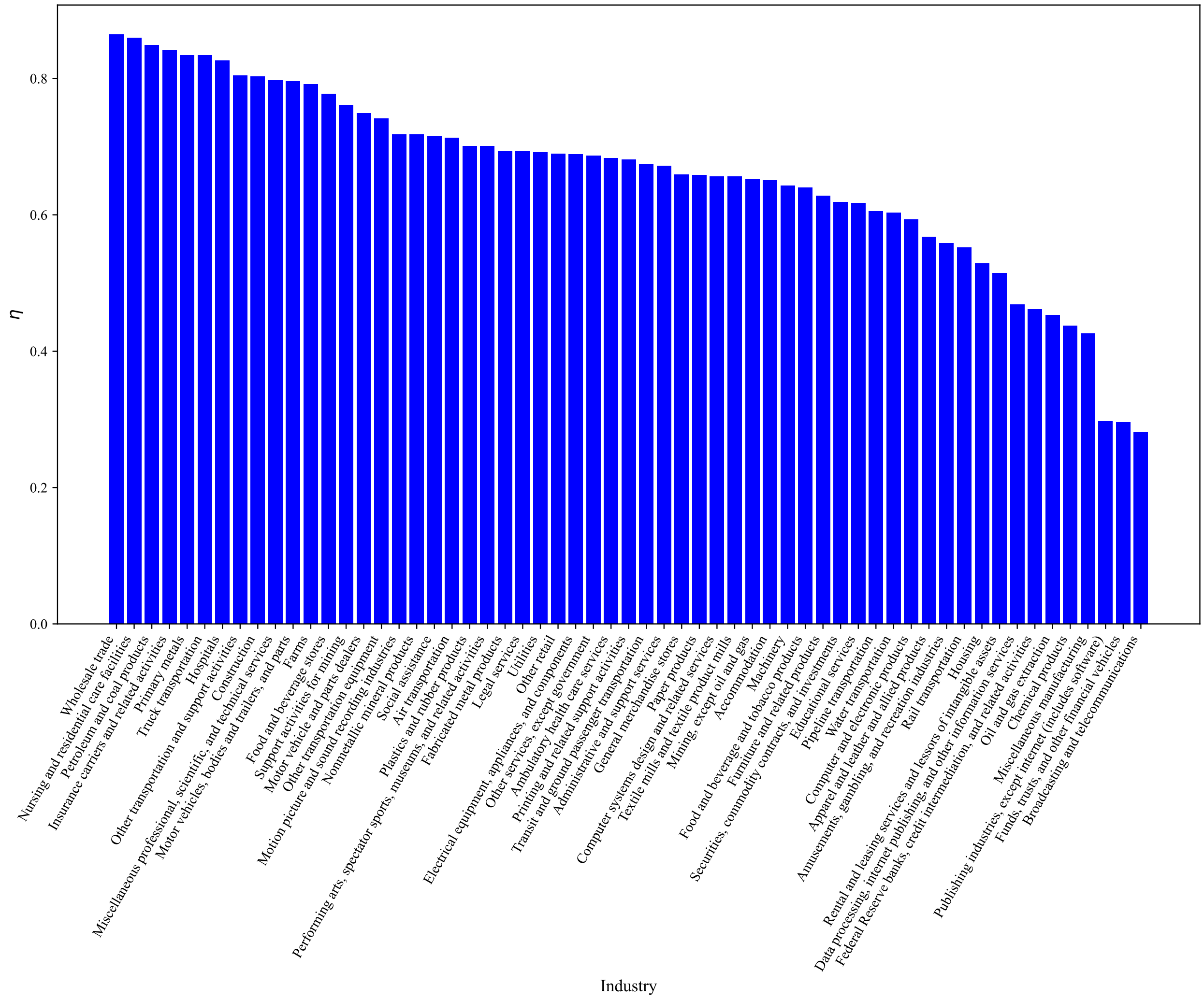
This figure plots the number of BEA industries covered by the samples we analyze each year. As the number of firms covered by Trucost increases, the number of industries is also increasing. However, the variability in the number of industries is small, which does not affect the balance of panel data too much.

Figure OA.3: The Carbon Emission Intensity at the BEA Industry Level



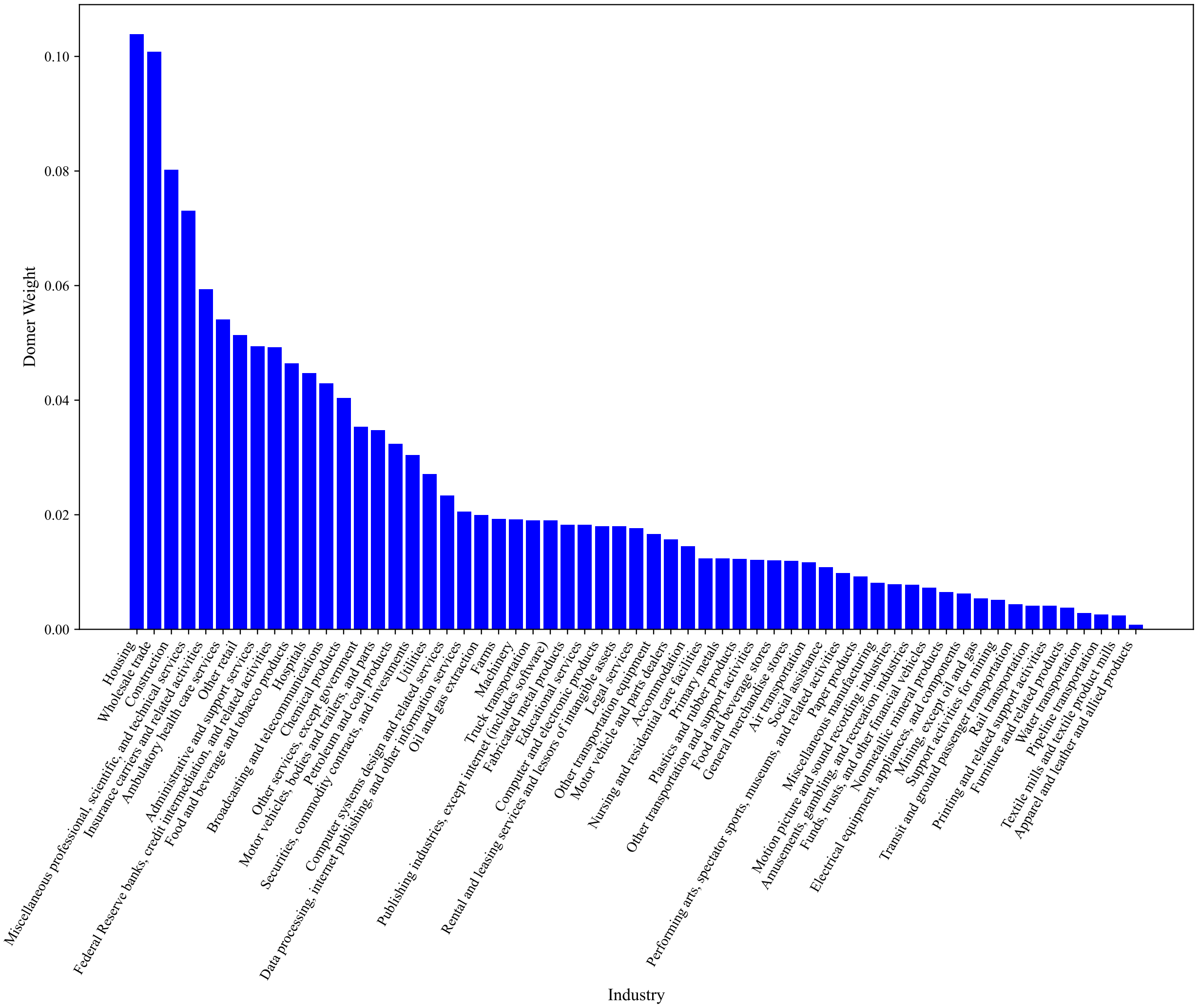
This figure depicts the annual average carbon emission intensity at the BEA industry level. From 2002 to 2020, the industry's average carbon emission intensity is 236.22 (tons per million dollars). There is substantial variation in direct carbon emissions across industries. The top five industries with the highest carbon emission intensity include Utilities, Air Transportation, Mining (except Oil and Gas), Water Transportation, and Primary Metals.

Figure OA.4: The Ratio of Composite Intermediate Input (η_i) at the BEA Industries Level



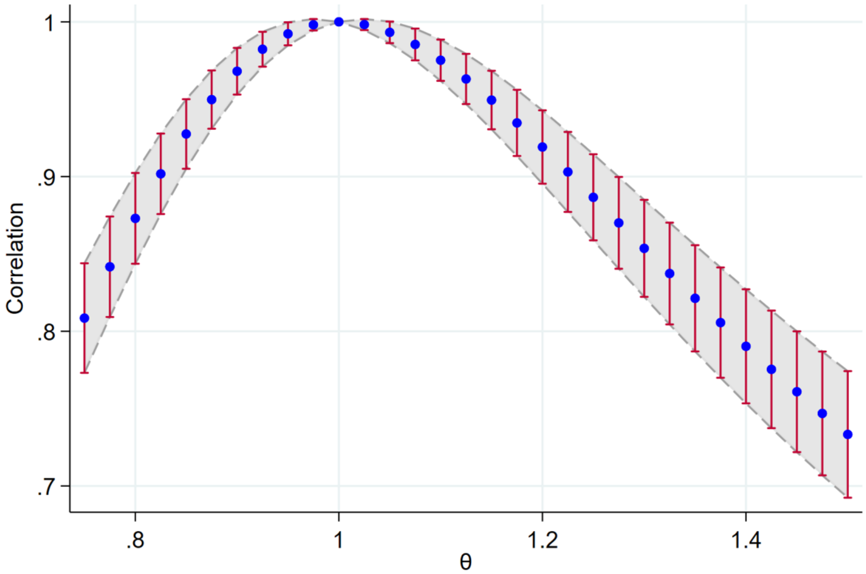
This figure shows the annual average ratio of composite intermediate input, η, at the BEA industry level.

Figure OA.5: The Industrial Domar Weights



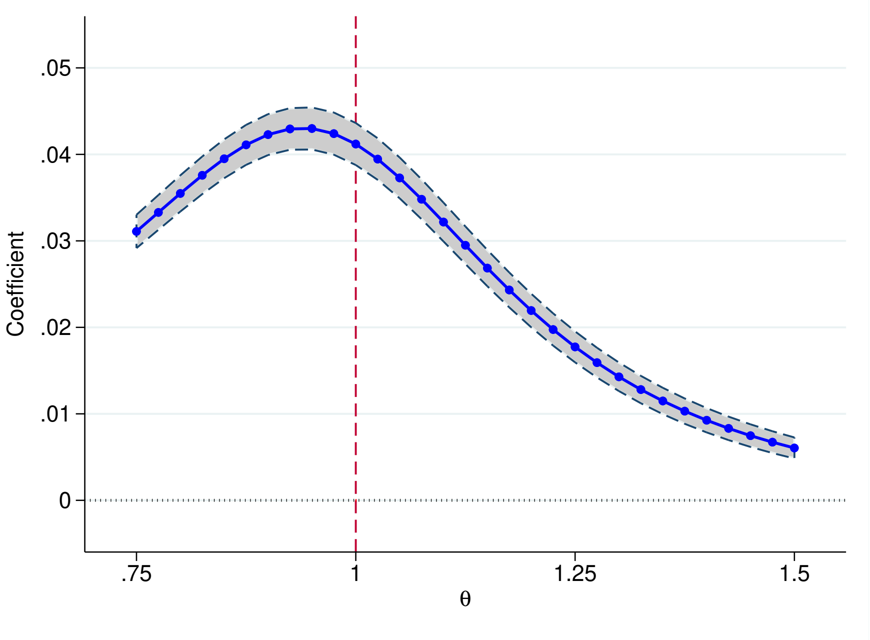
This figure shows the annual Domar weight at the BEA industry level averaged across years from 2002 to 2020. Over the sample period, the top five industries with the highest average Domar weight are Housing, Wholesale Trade, Construction, Scientific and Technical Services, and Insurance Services.

Figure OA.6: Indirect Carbon Emission Exposure (χ) under the CES Production Setting



This figure illustrates the estimated values of Indirect Carbon Emission Exposure (χ) under the CES production function for different values of θ. The blue dots represent the correlation coefficient of χ when both χ and θ are equal to 1, and the red vertical lines indicate the 95% confidence interval of the correlation coefficient.

Figure OA.7: Coefficients of χ^θ Estimated Using CES Production Function

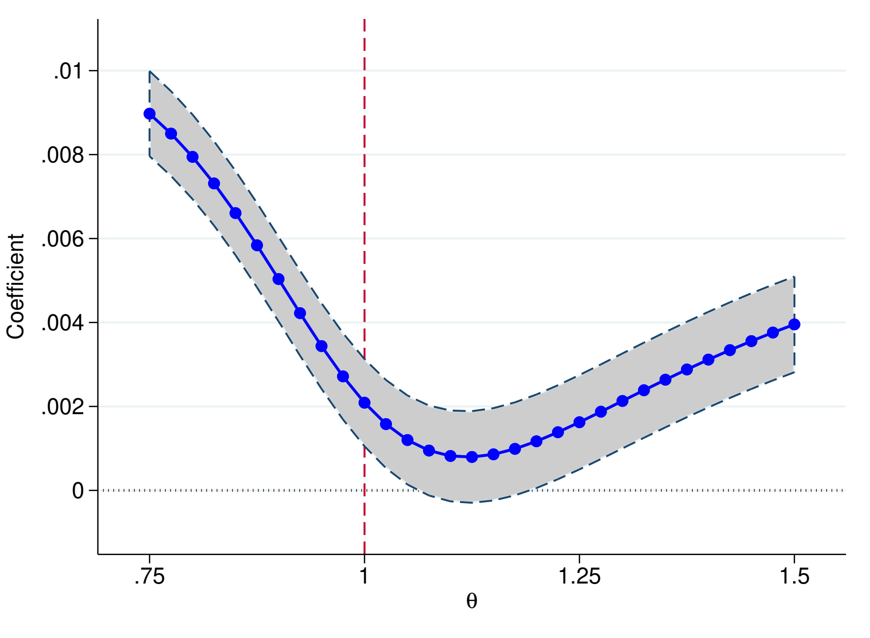


This figure presents the estimated coefficients of χ^θ from the following specification:

$$ICC_{it} = \alpha_i + \beta_\chi \chi_{it}^\theta + \beta_\gamma \gamma_{it} + \boldsymbol{X}_{it}' \beta_x + \varepsilon_{it},$$

where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^θ represents the indirect carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. The control variables $\boldsymbol{X}_{it}$ are consistent with those in the baseline regression. The blue dots plot the estimated coefficients β_χ across different values of θ, while the shaded gray area depicts the corresponding 95% confidence intervals. This analysis examines how the relationship between indirect carbon risk exposure and firms' implied cost of capital varies with the elasticity of substitution in the CES production framework.

Figure OA.8: Coefficients of γ Estimated Using CES Production Function



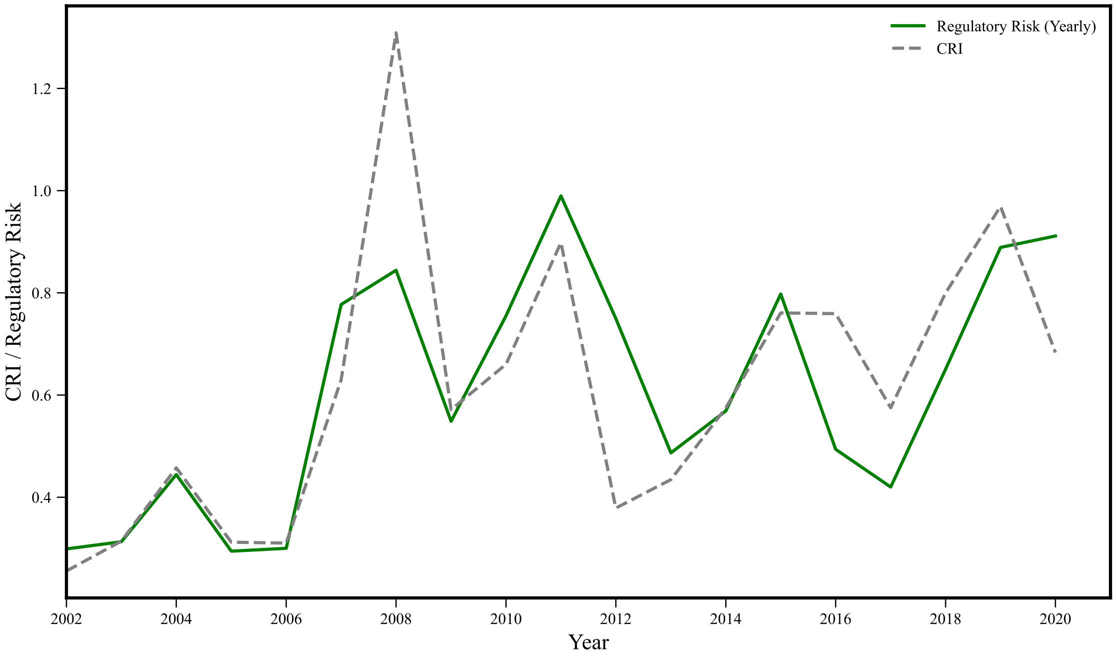
This figure presents the estimated coefficients of γ from the following specification:

$$ICC_{it} = \alpha_i + \beta_\chi \chi_{it}^{\theta} + \beta_\gamma \gamma_{it} + \boldsymbol{X}_{it}' \beta_x + \varepsilon_{it},$$

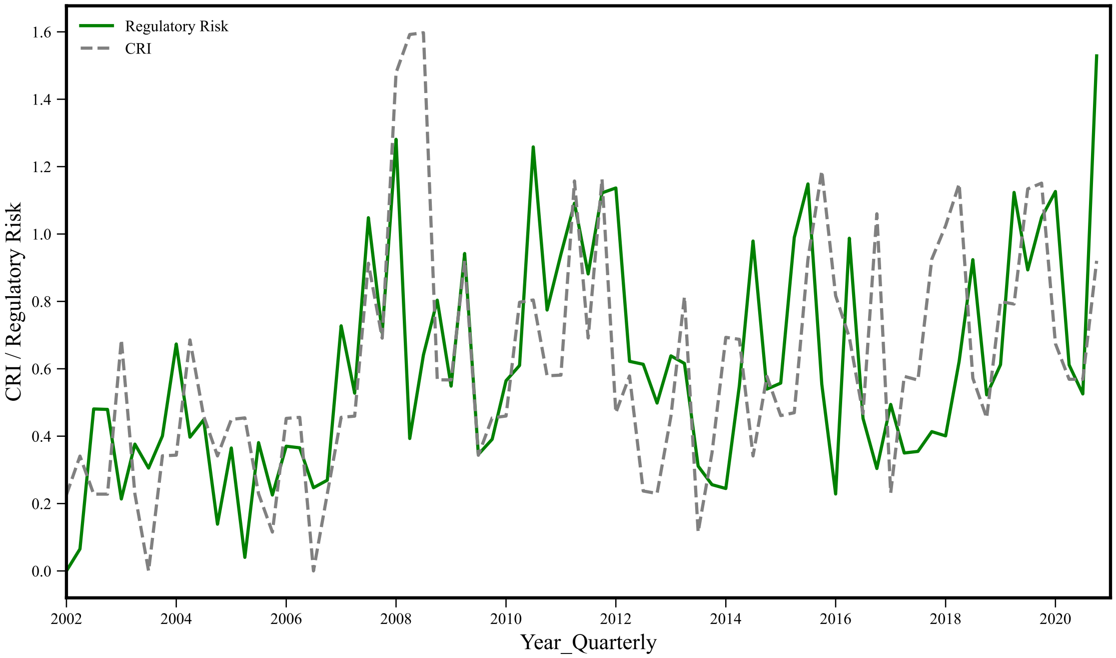
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the indirect carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. The control variables $\boldsymbol{X}_{it}$ are consistent with those in the baseline regression. The blue dots plot the estimated coefficients β_γ across different values of θ, while the shaded gray area depicts the corresponding 95% confidence intervals. This analysis examines how the relationship between direct carbon risk exposure and firms' implied cost of capital varies with the elasticity of substitution in the CES production framework.

Figure OA.9: Time Series of CRI and Regulatory Risk (Sautner et al., 2023a)

Panel A: Annual Time Series of CRI and Regulatory Risk



Panel B: Quarterly Time Series of CRI and Regulatory Risk



This figure presents the time series of the Carbon Regulatory Index (CRI) and regulatory risk, the latter aggregated from firm-level climate regulatory risk as calculated by Sautner et al. (2023a). Panel A shows the annual series, and Panel B shows the quarterly series. The correlation between CRI and regulatory risk is 0.753 annually and 0.456 quarterly, both statistically significant at the 1% level. The green solid line represents the aggregated regulatory risk, and the gray dashed line represents the CRI.

OB. ADDITIONAL TABLES

Table OB.1: BEA Codes Unmatched with NAICS Codes

This table lists the industries in the BEA classification system that cannot be matched with the corresponding NAICS codes. The table provides the BEA code and the corresponding industry description. These industries represent unique sectors that are not directly comparable to NAICS categories.

BEA Code	**Industry Description**
321	Wood products
493	Warehousing and storage
ORE	Other real estate
562	Waste management and remediation services
722	Food services and drinking places
GFGD	Federal general government (defense)
GFGN	Federal general government (nondefense)
GFE	Federal government enterprises
GSLG	State and local general government
GSLE	State and local government enterprises

Table OB.2: Definition of Variables

This table provides the definitions of the variables used in the empirical analysis, along with the sources and construction of the variables. Panel A presents variables related to carbon emissions sourced from Trucost. Panel B includes financial data from Compustat, while Panel C shows stock price variables from CRSP. The table also includes abbreviations for each variable and the treatment of outliers, where applicable.

Panel A: Emission variables (from Trucost)

Variable	Winsorized	Description
Carbon Emissions Scope 1	2.5%	Scope 1 emissions are greenhouse gas emissions from sources that are owned or controlled by the company (tons CO2e).
Carbon Emissions Scope 2	2.5%	Scope 2 emissions are greenhouse gas emissions from consumption of purchased electricity, heat or steam by the company (tons CO2e).
Carbon Emissions Scope 3	2.5%	Scope 3 emissions are other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc (tons CO2e).
Carbon Emissions_Direct	2.5%	Carbon Emissions_Direct are greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company (tons CO2e).
Carbon Intensity_Scope 1	2.5%	Greenhouse gas (GHG) emissions from sources that are owned or controlled by the company (categorized by the Greenhouse Gas Protocol) divided by the company's revenue (tons CO2e/$Billion).

Panel B: Cross-sectional firm variables (from compustat)

Variable	Winsorized	Description
ln(size)	1.0%	The natural logarithm of market capitalization (the total amount outstanding for the bond) at the end of June (million dollars).
BM	1.0%	The book equity for the fiscal year ending in calendar year t-1 divided by the market equity at the end of December of year t-1. The book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit if available, minus the book value of preferred stock.
RDTA	1.0%	R&D expenditures divided by sale.
ROA	1.0%	Operating income before depreciation as a fraction of average total assets based on most recent two periods.
PPETA	1.0%	Total tangible assets (Property, Plant, and Equipment) divided by total assets.
Leverage	1.0%	Total debt divided by the book value of equity.
CAPEXTA	1.0%	Capital expenditures divided by total assets.
HINDEX	1.0%	Herfindahl index of 4-digit SIC industry j where firm i belongs.
Tobin' Q	1.0%	The ratio of the market value of assets (market cap of equity plus book value of debt) divided by the book value of assets.
KZINDEX	1.0%	The KZ index (Kaplan and Zingales, 1997) is a relative measure of a company's dependence on external financing. KZ Index = -1.001909 x Cash flows / Property, Plant, and Equipment(PPE) + 0.2826389 x Tobin' Q + 3.139193 x Debt / Total capital + -39.3678 x Dividends / PPE + -1.314759 x Cash / PPE
Ln(Age)	1.0%	The natural logarithm of the number of years since the IPO year.

Table OB.3: Definition of Variables (continued)

Panel C: Cross-sectional return variables (from CRSP)

Variable	Winsorized	Description
ICC (%, annualized)	no	The implicit cost of capital of the firm at month t
Return (%, annualized)	1.0%	The holding period stock return in the month t
Prior return	1.0%	The holding period stock return in the previous month t-1
Vol	1.0%	The stock return volatility based on the past 60 monthly returns.
Ivol	no	The idiosyncratic volatility based on the Fama-French 3 factor model using the past 60 monthly returns.
Amihud	no	Amihud Illiquidity measure is calculated as the absolute price change scaled by the volume.
Momentum	no	The cumulative holding period stock returns from month t-12 to t-2 preceding the quarterly earnings announcement month.
Beta	no	The stock market beta is estimated for each stock from the time-series regressions of individual stock excess returns on the CRSP value-weighted market index excess returns using a 36-month rolling window.
Beta_SMB	no	The SMB beta is estimated for each stock from the time-series regressions of individual stock excess returns on the SMB portfolio return using a 36-month rolling window, after controlling for the stock market excess return and HML portfolio return.
Beta_HML	no	The HML beta is estimated for each stock from the time-series regressions of individual stock excess returns on the SMB portfolio return using a 36-month rolling window, after controlling for the stock market excess return and SMB portfolio return.

Table OB.4: Sample Selection of Firms in Trucost

This table outlines the process and criteria used to select firms from Trucost's North America database. The initial sample comprises 4,038 firms. Firms are progressively excluded based on the following filters: firms outside the continental United States, non-US incorporated firms, firms without GVKEY/CUSIP identifiers, firms not matched with Compustat and CRSP, and firms missing stock returns or emissions data. This process results in a final sample of 2,698 firms.

Filters	*Excluded Firms*	*Remaining Firms*
Firms in Trucost North America database	(0)	4,038
Less: Firms outside the continental US	(549)	3,489
Less: Non-US incorporated firms (S&P US firms)	(620)	2,869
Less: Firms missing GVKEY/CUSIP	(81)	2,788
Less: Firms not matched with COMPUSTAT and CRSP	(53)	2,735
Less: Firms missing stock returns or emissions data	(37)	2,698
Final Sample		**2,698**

Table OB.5: Rank Changes in High Chi and Gamma Cases

This table presents the rank changes for firms with high χ and high γ exposures. Panel A lists industries where χ ranks are high relative to γ, while Panel B lists industries with high γ and low χ. The rank change represents the difference between the γ and χ ranks, illustrating the relative positioning of firms based on these two exposures.

Panel A: High χ Cases

BEA Code	**Industry**	γ **Rank**	χ **Rank**	**Rank Change**
486	Pipeline transportation	11	***1***	10
211	Oil and gas extraction	10	***2***	8
561	Administrative and support services	48	***12***	36
5411	Legal services	47	***19***	28
521CI	Federal Reserve banks, credit intermediation, and related activities	57	***21***	36
514	Data processing, internet publishing, and other information services	53	***25***	28

Panel B: High γ Cases

BEA Code	**Industry**	γ **Rank**	χ **Rank**	**Rank Change**
22	Utilities	***1***	9	-8
481	Air transportation	***4***	33	-29
61	Educational services	***5***	50	-45
483	Water transportation	***7***	20	-13
315AL	Apparel and leather and allied products	***24***	49	-25
445	Food and beverage stores	***30***	52	-22

Table OB.6: Implied Cost of Capital and Total Carbon Risk Exposure

This table examines the effect of total carbon risk exposure on the Implied Cost of Capital (ICC) using the specification,

$$y_{it} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} is the ICC of firm i at month t, $\beta_{\chi+\gamma}$ captures the effect of the total carbon risk exposure, including indirect carbon risk exposure (χ_{it}) due to network effects and direct carbon risk exposure (γ_{it}) associated with a firm's own carbon emissions. $\boldsymbol{X}$ includes standard control variables commonly used in the literature. Fixed effects are included in various setups to examine the drivers of the total carbon risk premium. t-statistics are reported in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) *ICC*	(2) *ICC*	(3) *ICC*	(4) *ICC*
Total exposure ($\chi + \gamma$)	0.600***	0.900***	1.200***	2.000**
	(17.701)	(29.818)	(25.576)	(2.333)
Ln(Size)		-2.200***	-2.200***	-8.500***
		(-72.154)	(-72.106)	(-5.309)
Ln(BM)		2.800***	2.800***	1.900***
		(95.059)	(94.938)	(4.873)
Roa		-0.100***	-0.100***	0.000
		(-4.282)	(-4.201)	(0.320)
Leverage		0.100**	0.100**	-0.000
		(2.302)	(2.228)	(-1.245)
Tobin's Q		-0.100***	-0.200***	-0.000
		(-4.879)	(-5.190)	(-0.600)
HHI		-0.400***	-0.400***	-0.200
		(-11.773)	(-10.958)	(-1.190)
KZ Index		0.400***	0.400***	0.200
		(12.379)	(10.321)	(1.148)
Ln(employee)		0.400***	0.400***	0.000
		(11.692)	(12.057)	(0.113)
Emissions			-0.400***	-0.200
			(-8.586)	(-1.014)
Month Fixed Effects	N	N	N	Y
Firm Fixed Effects	N	N	N	Y
Observations	287,862	287,862	287,862	287,862
R-squared	0.006	0.061	0.061	0.463

Table OB.7: Industry Level Implied Cost of Capital and Carbon Risk Exposure - Value Weighted

This table examines the effect of total carbon risk exposure on the implied cost of capital (ICC) at the industry level. The industry-level ICC is calculated as the value-weighted average of each firm's ICC within the industry. We consider the following specification:

$$y_{it} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} is the ICC of BEA industry i at month t, calculated as the value-weighted average ICC of the firms within the industry. $\beta_{\chi+\gamma}$ captures the effect of total carbon risk exposure, which includes indirect carbon risk exposure (χ_{it}) arising from network effects and direct carbon risk exposure (γ_{it}) associated with a firm's own carbon emissions. $\boldsymbol{X}$ represents standard control variables commonly used in the literature. Fixed effects are included in various setups to analyze the drivers of the total carbon risk premium. t-statistics are reported in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Value Weighted					
	ICC	*ICC*	*ICC*	*ICC*	*ICC*	*ICC*
Total exposure ($\gamma + \chi$)	0.547***	0.581***	0.487***	0.532***	1.955***	1.620***
	(17.133)	(17.237)	(11.310)	(10.610)	(9.149)	(8.895)
Ln(Size)		-0.538***	-0.521***	-0.486***	-0.591***	-0.506***
		(-12.277)	(-11.815)	(-10.853)	(-9.566)	(-7.754)
Ln(BM)		0.067**	0.072**	0.082***	0.104***	0.114***
		(2.166)	(2.318)	(7.188)	(6.829)	(9.628)
Roa		0.070**	0.074**	0.068**	0.089***	0.075**
		(2.135)	(2.248)	(2.245)	(2.617)	(2.446)
Leverage		0.168***	0.168***	0.050	0.135***	0.064*
		(5.305)	(5.325)	(1.522)	(4.704)	(1.734)
Tobin's Q		-0.182***	-0.178***	-0.109***	-0.075***	-0.010
		(-5.536)	(-5.397)	(-5.595)	(-3.728)	(-0.503)
HHI		-0.297***	-0.301***	-0.261***	0.054	0.263*
		(-9.149)	(-9.225)	(-7.842)	(0.331)	(1.802)
KZ Index		0.142***	0.242***	0.159***	-0.260	-0.688***
		(3.166)	(4.553)	(4.666)	(-1.603)	(-6.651)
ln(Employee)		0.312***	0.298***	0.343***	-1.027***	-0.284**
		(9.332)	(8.809)	(17.273)	(-4.439)	(-2.393)
Emissions			0.180***	0.075*	-0.930***	-1.021***
			(3.486)	(1.765)	(-6.733)	(-10.263)
Month Fixed	N	N	N	Y	N	Y
Industries Fixed	N	N	N	N	Y	Y
Observations	7,987	7,987	7,987	7,987	7,987	7,987
R-squared	0.035	0.093	0.095	0.316	0.326	0.541

Table OB.8: Industry Level Implied Cost of Capital and Carbon Risk Exposure - Equal Weighted

This table examines the impact of total carbon risk exposure on the ICC at the industry level, using an equal-weighted approach. The specification is as follows:

$$y_{it} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} represents the ICC of the BEA industry i at month t, calculated as the equal-weighted average ICC of firms within the industry. $\beta_{\chi+\gamma}$ captures the effect of total carbon risk exposure, including both indirect carbon risk exposure (χ_{it}) from network effects and direct carbon risk exposure (γ_{it}) tied to a firm's own emissions. The vector $\boldsymbol{X}$ contains standard control variables. Fixed effects are included to account for industry- and time-specific variations. t-statistics are shown in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Equal Weighted					
	ICC	*ICC*	*ICC*	*ICC*	*ICC*	*ICC*
Total exposure ($\gamma + \chi$)	0.587***	0.419***	0.349***	0.277**	1.643***	0.623*
	(9.425)	(6.289)	(4.092)	(2.349)	(3.658)	(1.900)
Ln(Size)		-0.591***	-0.579***	-0.762***	-0.346*	-0.963***
		(-6.821)	(-6.630)	(-8.929)	(-1.927)	(-7.571)
Ln(BM)		0.027	0.030	0.074**	0.005	0.055
		(0.434)	(0.491)	(2.139)	(0.114)	(1.338)
Roa		0.097	0.100	0.100***	0.020	0.010
		(1.490)	(1.532)	(2.937)	(0.442)	(0.283)
Leverage		0.083	0.083	-0.116*	0.104**	-0.041
		(1.322)	(1.328)	(-1.854)	(2.247)	(-0.585)
Tobin's Q		-0.346***	-0.343***	-0.207***	-0.347***	-0.205***
		(-5.316)	(-5.255)	(-9.338)	(-5.972)	(-4.491)
HHI		-0.934***	-0.936***	-0.976***	-0.345	-0.811***
		(-14.531)	(-14.494)	(-13.613)	(-0.892)	(-4.044)
KZ Index		-0.111	-0.036	-0.121*	0.290	-0.201
		(-1.245)	(-0.343)	(-1.901)	(1.045)	(-1.383)
ln(Employee)		0.125*	0.114*	0.150***	-0.843**	-0.263**
		(1.894)	(1.708)	(5.764)	(-2.523)	(-1.991)
Emissions			0.135	0.245**	-0.818***	-0.186
			(1.319)	(2.482)	(-3.343)	(-1.396)
Month Fixed	N	N	N	N	Y	Y
Industries Fixed	N	N	N	N	N	Y
Observations	7,987	7,987	7,987	7,987	7,987	7,987
R-squared	0.011	0.046	0.046	0.287	0.165	0.401

Table OB.9: Industry-Level ICC, Direct and Indirect Exposure - Value Weighted

This table examines the effect of direct and indirect carbon risk exposure on the implied cost of capital (ICC) at the industry level. Specifically, we consider the following industry-level regression:

$$y_{it} = \alpha + \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} is the ICC of BEA industry i at month t, calculated as the value-weighted average ICC of firms within the industry. β_χ represents the effect of indirect carbon risk exposure from network effects, β_γ captures the direct carbon risk exposure associated with a firm's own carbon emissions, and $\boldsymbol{X}$ includes standard control variables commonly used in the literature. Fixed effects are included in various setups to examine the drivers of the indirect carbon risk premium. t-statistics are reported in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Value-Weighted				
	ICC	*ICC*	*ICC*	*ICC*	*ICC*
Indirect exposure (χ)	0.171***	0.208***	0.214***	0.193***	0.693***
	(4.996)	(5.809)	(5.963)	(3.700)	(4.205)
Direct exposure (γ)	0.468***	0.470***	0.373***	0.460***	1.266***
	(13.661)	(13.926)	(7.842)	(20.580)	(7.168)
Ln(Size)		-0.535***	-0.521***	-0.484***	-0.502***
		(-12.207)	(-11.821)	(-10.615)	(-7.402)
Ln(BM)		0.069**	0.072**	0.082***	0.114***
		(2.231)	(2.325)	(7.182)	(9.644)
ROA		0.071**	0.074**	0.067**	0.075**
		(2.145)	(2.239)	(2.215)	(2.446)
Leverage		0.180***	0.172***	0.063*	0.066*
		(5.602)	(5.324)	(1.882)	(1.838)
Tobin's Q		-0.179***	-0.177***	-0.107***	-0.010
		(-5.440)	(-5.376)	(-5.555)	(-0.453)
HHI		-0.300***	-0.302***	-0.263***	0.269*
		(-9.230)	(-9.241)	(-7.951)	(1.875)
KZ Index		0.137***	0.232***	0.123***	-0.684***
		(3.047)	(4.164)	(5.142)	(-6.422)
Ln(Employee)		0.305***	0.297***	0.340***	-0.278**
		(9.067)	(8.772)	(17.534)	(-2.363)
Emissions			0.165***	-0.922***	-1.028***
			(2.861)	(-6.668)	(-10.136)
Month Fixed Effects	N	N	Y	N	Y
Industry Fixed Effects	N	N	N	Y	Y
Observations	7,987	7,987	7,987	7,987	7,987
R-squared	0.094	0.095	0.316	0.326	0.541

Table OB.10: Industry Level ICC, Direct and Indirect Exposure - Equal Weighted

This table examines the effect of indirect and direct carbon risk exposure on the implied cost of capital (ICC) at the industry level using an equal-weighted method. Specifically, we consider the industry-level regression

$$y_{it} = \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where y_{it} represents the ICC of the BEA industry i at month t, calculated as the equal-weighted average ICC of the firms within the industry. β_χ represents the effect of indirect carbon risk exposure from network effects, β_γ captures the direct carbon risk exposure associated with a firm's own carbon emissions, and $\boldsymbol{X}$ includes standard control variables commonly used in the literature. Fixed effects are included to examine the drivers of the indirect carbon risk premium. t-statistics are reported in parentheses, and all standard errors are robust. Coefficients marked with *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
			Equal Weighted		
	ICC	*ICC*	*ICC*	*ICC*	*ICC*
Indirect exposure (χ)	0.633***	0.579***	0.603***	0.238	-0.391
	(9.482)	(8.210)	(4.130)	(0.572)	(-1.035)
Direct exposure (γ)	0.134**	0.027	-0.397***	1.880***	1.311***
	(2.004)	(0.409)	(-5.701)	(6.746)	(6.503)
Ln(Size)		-0.608***	-0.775***	-0.338*	-0.932***
		(-7.026)	(-9.156)	(-1.900)	(-7.161)
Ln(BM)		0.015	0.069*	0.005	0.056
		(0.244)	(1.957)	(0.115)	(1.356)
Roa		0.095	0.113***	0.022	0.010
		(1.464)	(3.312)	(0.493)	(0.278)
Leverage		0.010	-0.222***	0.118**	-0.022
		(0.163)	(-3.101)	(2.360)	(-0.308)
Tobin's Q		-0.363***	-0.224***	-0.340***	-0.198***
		(-5.588)	(-7.481)	(-5.919)	(-4.518)
HHI		-0.917***	-0.960***	-0.324	-0.749***
		(-14.296)	(-13.819)	(-0.847)	(-4.011)
KZ Index		-0.081	0.174***	0.341	-0.163
		(-0.911)	(3.447)	(1.231)	(-1.079)
ln(employee)		0.167**	0.170***	-0.824**	-0.205
		(2.518)	(6.557)	(-2.451)	(-1.466)
Emissions			0.710***	-0.844***	-0.246*
			(8.837)	(-3.436)	(-1.888)
Month Fixed	N	N	Y	N	Y
Industries Fixed	N	N	N	Y	Y
Observations	7,987	7,987	7,987	7,987	7,987
R-squared	0.015	0.050	0.295	0.166	0.402

Table OB.11: Carbon Risk Exposure and Stock Returns

This table examines the effect of indirect and direct carbon risk exposure on expected stock returns. Specifically, we consider the following specification,

$$r_{i,t+10} = \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}$$

and

$$r_{i,t+10} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it},$$

where $r_{i,t+10}$ denotes the stock return for firm i at time t, measured 10 months following the earnings announcement. Given that carbon emissions disclosures typically occur approximately 10 months after the release of financial reports, we adjust for this reporting lag to mitigate any look-ahead bias, in line with the methodology outlined by Zhang (2025). β_χ and β_γ represent the effects of indirect and direct carbon risk exposure, respectively, $\beta_{\chi+\gamma}$ captures the effect of the total carbon risk exposure, while $\boldsymbol{X}_{it}$ includes a vector of standard control variables . Time and industry fixed effects are included to account for both temporal and industry-specific variations. t-statistics are presented in parentheses, with all standard errors adjusted for robust . Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) r_{t+10}	(2) r_{t+10}	(3) r_{t+10}	(4) r_{t+10}	(5) r_{t+10}	(6) r_{t+10}	(7) r_{t+10}
Total exposure ($\chi + \gamma$)	0.108***	0.116***	0.111***	0.344***	0.042**	0.208***	
	(5.94)	(5.28)	(5.01)	(7.39)	(1.97)	(5.20)	
Indirect Exposure (χ)							0.156***
							(4.95)
Direct Exposure (γ)							0.078***
							(3.22)
Ln(Size)		-0.191***	-0.198***	-0.205***	-0.206***	-0.220***	-0.210***
		(26.37)	(22.41)	(30.11)	(23.62)	(26.57)	(25.45)
Ln(BM)		0.036***	0.040***	0.035***	0.025***	0.029***	0.031***
		(6.03)	(4.83)	(6.28)	(3.14)	(4.34)	(5.05)
Roa		-4.363***	-6.084***	1.162***	0.961**	-0.647***	-0.045***
		(-19.05)	(-15.19)	(4.62)	(2.31)	(-13.08)	(-9.87)
Leverage		-0.553***	-0.908***	-0.204***	-0.748***	-0.521***	-0.604***
		(-10.413)	(-9.591)	(-3.978)	(-8.792)	(-6.82)	(-7.40)
Tobin's Q		-0.942***	-1.250***	0.050	-0.174**	-0.073***	-0.387***
		(-24.759)	(-21.755)	(1.07)	(-2.445)	(-14.65)	(-18.67)
HHI		0.000***	0.000	0.000***	0.000***	0.000***	0.000***
		(4.50)	(0.73)	(4.62)	(6.50)	(4.27)	(4.48)
KZ Index		0.000***	0.000***	0.000**	0.000***	0.000***	0.000***
		(7.19)	(9.45)	(2.30)	(3.26)	(5.53)	(5.28)
ln(Employee)		0.039***	0.085***	0.010	0.069***	0.039***	0.046***
		(8.22)	(7.24)	(1.16)	(5.62)	(4.45)	(5.56)
Emission Growth			-0.486***	-0.483***	0.050	0.060	-0.292
			(-11.56)	(-11.09)	(1.22)	(1.34)	(-1.03)
Month Fixed Effects	N	N	N	N	Y	Y	Y
Industry Fixed Effects	N	N	N	Y	N	Y	Y
Observations	1,108,249	888,722	888,722	888,722	888,722	888,722	888,722
R-squared	0.000	0.000	0.000	0.000	0.130	0.130	0.045

Table OB.12: Robustness Test - Alternative Measure of Carbon Emissions

This table examines the relation between expected stock returns and carbon risk exposure. Specifically, we explore how carbon risk exposure—both indirect and direct—affects stock returns, while incorporating carbon emissions at different levels (total, Scope 2, and Scope 3) as additional control variables. The model is specified as follows:

$$r_{i,t+10} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}$$

where $r_{i,t+10}$ denotes the stock return for firm i in the tenth month following the earnings announcement, measured at time $t + 10.\chi$ and γ represent indirect and direct carbon risk exposure, respectively. The model includes control variables ($\boldsymbol{X}_{it}$), time, and industry fixed effects. All standard errors are adjusted for heteroskedasticity and clustered at the industry level. t-statistics are presented in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) r_{t+10}	(2) r_{t+10}	(3) r_{t+10}	(4) r_{t+10}	(5) r_{t+10}
Total Exposure ($\chi + \gamma$)	0.226***	0.244***	0.199***	0.241***	0.209***
	(5.56)	(5.95)	(4.86)	(5.91)	(5.20)
ln(Emissions)		-0.042**			
		(-2.253)			
Emissions			0.003***		
			(5.72)		
Scope 2				0.013***	
				(5.33)	
Scope 3					0.002***
					(7.34)
Controls	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y
Observations	888,722	888,722	888,722	888,722	888,722
R-squared	0.126	0.127	0.127	0.127	0.127

Table OB.13: Robustness Test - Control for Sale Growth

This table examines the relation between expected stock returns and carbon risk exposure, while incorporating revenue-related indicators as additional control variables to mitigate concerns about the high correlation between carbon emissions and firm revenue. Column (2) reports the results after excluding financial firms from the sample, and columns (3) through (5) further introduce sales, sales growth, revenue, and revenue growth as control variables. The model is specified as follows:

$$r_{i,t+10} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}$$

where $r_{i,t+10}$ denotes the stock return for firm i in the tenth month following the earnings announcement, measured at time $t+10$. χ and γ represent indirect and direct carbon risk exposure, respectively. The model includes control variables ($\boldsymbol{X}_{it}$), time, and industry fixed effects. All standard errors are adjusted for heteroskedasticity and clustered at the industry level. t-statistics are presented in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) r_{t+10}	(2) r_{t+10}	(3) r_{t+10}	(4) r_{t+10}	(5) r_{t+10}
Total Exposure ($\chi + \gamma$)	0.226***	0.201***	0.215***	0.224***	0.211***
	(5.56)	(5.60)	(5.32)	(5.52)	(5.22)
Sales			-0.097***		
			(-5.110)		
Revenue				-0.177***	
				(-5.982)	
Revenue_growth					-0.409***
					(-3.710)
Controls	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y
Observations	888,722	743,623	888,722	888,722	888,722
R-squared	0.126	0.119	0.126	0.126	0.126

Table OB.14: Robustness Test - Control for Other Network Effects

This table examines the relation between expected stock returns and carbon risk exposure, while incorporating additional control variables to address potential omitted-variable concerns. Specifically, columns (2) through (5) introduce the industry-level upstreamness of the firm's sector, the firm's sensitivity to changes in network sparsity (β_S), and the firm's sensitivity to changes in network concentration (β_C) as control variables. The upstreamness measure follows Gofman et al. (2020), while the measures of network sparsity and network concentration sensitivities follow Herskovic (2018). The model is specified as follows:

$$r_{i,t+10} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}$$

where $r_{i,t+10}$ denotes the stock return for firm i in the tenth month following the earnings announcement, measured at time $t+10$. χ and γ represent indirect and direct carbon risk exposure, respectively. The model includes control variables ($\boldsymbol{X}_{it}$), time, and industry fixed effects. All standard errors are adjusted for heteroskedasticity and clustered at the industry level. t-statistics are presented in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) r_{t+10}	(2) r_{t+10}	(3) r_{t+10}	(4) r_{t+10}	(5) r_{t+10}
Total Exposure ($\chi + \gamma$)	0.226***	0.228***	0.225***	0.225***	0.224***
	(5.56)	(5.60)	(5.41)	(5.51)	(5.34)
Upstreamness		-0.011			
		(-0.625)			
β_C			0.024		0.032
			(0.533)		(0.451)
β_S				0.089	0.071
				(0.628)	(0.576)
Controls	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y
Observations	888,722	888,722	888,722	888,722	888,722
R-squared	0.126	0.126	0.126	0.126	0.126

Table OB.15: Robustness Test - Considering Return under Different Time Lags

This table examines the relation between expected stock returns and carbon risk exposure. Specifically, we explore how carbon risk exposure—both indirect and direct—affects stock returns, while changing the time lag for different returns (6, 12, 24 and 36 months) to serve as proxies for expected returns. The model is specified as follows:

$$r_{i,t+k} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \mathit{Fixed\ Effects} + \varepsilon_{it}$$

where $r_{i,t+k}$ denotes the stock return for firm i at time $t + k$, with k representing different time horizons (6, 12, 24 and 36 months). r_{adjust} is the monthly return between two carbon emission disclosure times, serving as the dependent variable for the carbon risk exposure constructed from the previous carbon emission data. χ and γ represent indirect and direct carbon risk exposure, respectively. The model includes control variables ($\boldsymbol{X}_{it}$), time, and industry fixed effects. All standard errors are adjusted for heteroskedasticity and clustered at the industry level. t-statistics are presented in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	r_{t+6}	r_{t+12}	r_{t+18}	r_{t+24}	r_{adjust}	r_{t+36}
Total Exposure ($\chi + \gamma$)	0.172***	0.237***	0.237***	0.219***	0.269**	0.088
	(4.54)	(5.77)	(6.14)	(5.26)	(2.41)	(1.46)
Controls	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	888,722	888,722	888,722	888,722	888,722	888,722
R-squared	0.126	0.126	0.127	0.127	0.127	0.127

Table OB.16: Robustness Test - Considering Different Subsamples

This table examines the relation between expected stock returns and carbon risk exposure, considering three different subsamples. Column (1) and (2) use data from after 2009, following Zhang (2025), to focus on the quality of carbon emission disclosure. Column (3) and (4) consider the effect of the Paris Agreement, which was signed in 2015 and officially implemented in 2016. Column (5) and (6) exclude high-tech firms with insufficient carbon emission disclosure information.
The model is specified as follows:

$$r_{i,t+10} = \beta_{\chi+\gamma}(\chi_{it} + \gamma_{it}) + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}$$

where $r_{i,t+10}$ denotes the stock return for firm i in the tenth month following the earnings announcement, measured at time $t+10$. r_{adjust} is the monthly return between two carbon emission disclosures, serving as the dependent variable for the carbon risk exposure constructed from the previous carbon emission data. χ and γ represent indirect and direct carbon risk exposure, respectively. The model includes control variables ($\boldsymbol{X}_{it}$), time, and industry fixed effects. All standard errors are adjusted for heteroskedasticity and clustered at the industry level. t-statistics are presented in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Year>2009		Year>2015		Exclude High-Tech	
	r_{t+10}	r_{adjust}	r_{t+10}	r_{adjust}	r_{t+10}	r_{adjust}
Total Exposure ($\chi+\gamma$)	0.118**	0.103**	-0.041	0.005	0.218***	0.209***
	(2.44)	(2.47)	(0.69)	(0.09)	(4.42)	(3.76)
Controls	Y	Y	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	730,291	730,291	437,681	437,681	812,432	812,432
R-squared	0.126	0.126	0.127	0.127	0.127	0.127

Table OB.17: Key Regulatory and Legislative Events Related to Carbon Emission Policies

This table outlines key regulatory and legislative events related to carbon emission policies. It includes the timeframes of these events, a brief description of each, and the associated labels for reference. These events highlight critical milestones in U.S. environmental and carbon emissions policy, reflecting a period of significant uncertainty and shifting dynamics in the regulation of carbon emissions.

Time	Event Description	Label
2002.3-5	SEC issued guidance on ESG disclosures; the Sarbanes-Oxley Act was being developed.	Sarbanes-Oxley Act
2006.2-4	The California Global Warming Solutions Act (AB 32) was drafted, with the core goal of reducing greenhouse gas emissions to 1990 levels by 2020.	Assembly Bill 32
2008.6-9	The Lieberman-Warner Climate Security Act was debated in the Senate but failed due to concerns raised by the financial crisis over increased regulatory risks.	Lieberman-Warner Climate Security Act
2011.6-10	EPA finalized the Cross-State Air Pollution Rule (CSAPR). The EPA and NHTSA also issued GHG emissions standards for medium- and heavy-duty engines and vehicles.	CSAPR
2015.8-12	The EPA unveiled the Obama administration's Clean Power Plan. Around 195 countries reached the Paris Climate Agreement.	Clean Power Plan
2017.7-12	President Trump announced the U.S. withdrawal from the Paris Climate Agreement.	U.S. Paris Agreement Withdrawal
2019.2-3	Alexandria Ocasio-Cortez and Senator Ed Markey introduced the Green New Deal Resolution in Congress, aiming for net-zero carbon emissions within ten years.	Green New Deal Resolution

Table OB.18: Examples of News Classified by the ChatGPT-3.5

Carbon Emission Regulatory	**Month**	**Content**
going down	2008-09	**Title:** World News: U.K. Data Suggest Easing Inflation **Abstract:** It suggested that lower oil prices also may help ease price pressures in other leading economies.
going down	2017-01	**Title:** L.I. Utility Seals Wind Farm Deal **Abstract:** UNIONDALE, N.Y. – The Long Island Power Authority finalized an agreement Wednesday to build New York state's first offshore wind farm 30 miles east of Montauk, N.Y., the latest effort by the industry.
going down	2021-09	**Title:** Car Makers Shift Toward Eco-Friendly Steel **Abstract:** BERLIN – Auto makers are racing to find cleaner steel to build their cars. The industry's approach ranges from low-tech – using more recycled steel – to less-proven methods, including trying to sou.
going up	1984-12	**Title:** Sun Co. Canadian Unit To Spend $500 Million On Plant Expansion **Abstract:** Suncor Inc., a 75%-owned unit of Sun Co., said it will spend about $500 million (Canadian) over the next five years to increase capacity at its Fort McMurray, Alberta, oil sands plant.
going up	2011-10	**Title:** World News: Shanghai Closes Plants That Use Lead **Abstract:** "Underpinning China's lead-poisoning epidemic is a tension between the government's goals for economic growth and its efforts to curb environmental degradation," says the June report, which is based on ...
going up	2018-01	**Title:** Business News: Energy Pipeline Projects Follow Familiar Path **Abstract:** Some of North America's biggest new pipeline projects are already in the ground. As environmentalists and local activists make it extraordinarily difficult to build new oil and gas lines, energy company.

Table OB.19: Examples of News Classified by the ChatGPT-4o-mini (Continued)

Carbon Emission Regulatory	**Month**	**Content**
unknown	2005-12	**Title:** Ask Dow Jones **Abstract:** A: What I wrote is correct. You're probably thinking of the general time limit for filing amended returns. But there's a different rule for worthless securities. To take a deduction for a worthless se.
unknown	2007-02	**Title:** Signing Off: Online edition **Abstract:** For the first time in YEARS, I'm not checking email until I get back to Boston. We're talking FIVE DAYS. I'm not gonna lie, it drove me nuts this morning . . . but now I'm feeling OK. The withdrawals.
unknown	2011-07	**Title:** India's Reserve Bank Shouldn't Drive Blind **Abstract:** [Financial Analysis and Commentary] India's policy makers are getting worried about the poor quality of economic data that forces multiple revisions to key numbers and can befuddle investors.

Table OB.20: Correlation Matrix for CRI and Climate Risks

This table reports the correlation matrix for the Carbon Risk Index (CRI) and the climate exposures and risks calculated at the firm level using data from Sautner et al. (2023a). These variables, including Climate Change Exposure, Climate Change Risk, Regulatory Exposure, and Regulatory Risk, are aggregated from the firm level to the overall market at the quarterly and annual levels. Panel A presents the correlations for the annual data, while Panel B shows the correlations for the monthly data. Statistical significance is indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Annual Data

	CRI	Climate Exposure	Climate Risk	Regulatory Exposure
Climate Exposure	0.628***			
Climate Risk	0.624***	0.979***		
Regulatory Exposure	0.603***	0.864***	0.880***	
Regulatory Risk	0.753***	0.737***	0.782***	0.807***

Panel B: Monthly Data

	CRI	Climate Exposure	Climate Risk	Regulatory Exposure
Climate Exposure	0.504***			
Climate Risk	0.484***	0.958***		
Regulatory Exposure	0.459***	0.828***	0.808***	
Regulatory Risk	0.456***	0.592***	0.635***	0.683***

OC. Prompt on Carbon Regulatory Risk

Prompt for Identifying Energy-Sector Regulatory Risk.

You are an expert in analyzing news articles to identify sector-specific content and regulatory risks. Carefully read the following article and answer the questions using step-by-step reasoning based solely on the provided content. Avoid assumptions or external knowledge.

News Article:

`"""{fulltext}"""`

Please answer the following questions:

Question 1: Is this article specifically about the **energy sector**?
Options:

(a) Yes

(b) No

→ Provide a brief explanation for your answer (max 100 words).

Question 2: If your answer to Question 1 is **Yes**, does the article discuss any **regulations or regulatory risks** affecting the energy sector?
Options:

(a) Yes

(b) No

→ Provide a brief explanation (max 100 words), and describe the nature of the regulatory risk if applicable.

Question 3: Based on your analysis, does the article suggest that **regulatory risk** in the energy sector is:

(a) Increasing (going up)

(b) Decreasing (going down)

(c) Unclear

→ Provide a brief explanation for your answer (max 100 words).

Format your response as a JSON object like below:

```
{   “Q1_answer”:  “<a or b>”,
“Q1_explanation”:  “...”,
“Q2_answer”:  “<a or b>”,
“Q2_explanation”:  “...”,
“Q3_answer”:  “<a, b, or c>”,
“Q3_explanation”:  “...”  }
```

OD. Proofs of Theorems and Propositions

OD.1 Proof of Lemma