Carbon Risk in Production Networks[*]

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Abstract

This paper shows that carbon risks are shaped not only by firms' own emissions but also by their position in production networks. We develop a tractable general equilibrium model that incorporates input-output linkages, carbon emissions, and climate regulatory risks. Analytically, we demonstrate that the carbon risk premium is captured by two sufficient statistics: direct and indirect carbon risk exposure, the latter capturing the propagated network effect. Guided by the model, we empirically measure both direct and indirect exposures and demonstrate a significant cross-sectional carbon risk premium after accounting for firms' indirect carbon risk exposure. Through a decomposition, we quantify that indirect carbon risk exposure accounts for the majority of the premium, surpassing the impact of direct carbon emissions. Firms with higher indirect exposure also experience larger real effects following increases in climate regulatory risk, consistent with the model's network mechanism.

Keywords: Carbon Risk Premium, Production Networks, Environmental Regulatory Risks, Risk Exposure

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1. INTRODUCTION

Understanding how carbon-related risks are transmitted across firms and ultimately priced in financial markets is increasingly central to both macroeconomics and finance. A large and growing literature studies how firms' carbon emissions affect expected returns, typically focusing on a firm's own exposure to regulatory, technological, or transition risks. Yet a defining feature of modern economies is that firms operate in deeply interconnected production networks, where shocks to one sector propagate throughout the supply chain and shape aggregate outcomes. In such an environment, a firm's exposure to carbon risk arises not only from its own emissions, but also—and often predominantly—from the emissions of the industries it buys from and sells to.

This paper shows that carbon risk is fundamentally a network-propagated phenomenon, and that ignoring production linkages dramatically understates both firm-level exposure and the aggregate carbon risk premium. We develop a tractable general equilibrium framework embedding carbon emissions into an input–output economy, derive two sufficient statistics—direct carbon exposure (γ) and indirect, network-propagated exposure (χ)—and show theoretically and empirically that indirect exposure accounts for the vast majority of the cross-sectional carbon risk premium.

Our paper makes two key contributions. First, we develop a tractable consumption-based general equilibrium asset pricing model with production networks, incorporating carbon emissions in the production process and aggregate risks in carbon regulation. The model analytically decomposes firms' stock returns into two components: (1) the direct effect of aggregate risks on firms' profits, driven by their own carbon emissions, and (2) the indirect effect, capturing the general equilibrium transmission of carbon risk through supply chains. This framework informs an empirical procedure to measure direct and indirect carbon risk exposures. Second, we empirically measure these two components and demonstrate that the indirect effect accounts for most of the cross-sectional variation in firms' stock returns. Moreover, this term captures variations in stock returns beyond any direct measure of firms' carbon emissions.

In our theoretical framework, we develop a tractable two-period general equilibrium model in which firms are linked via input-output linkages, and the production process involves emitting CO_2. In the second period, the government imposes a uniform carbon tax on the quantity of firms' carbon emissions. In the first period, firms face uncertainty about the tax rate, which follows a random variable with zero mean and finite variance. This uncertainty serves as the aggregate regulatory risk in the economy. In our multi-sector framework, firms' carbon emission intensity—defined as units of carbon emitted to produce goods worth one dollar—varies across sectors. As a result, firms are subject to different exposures to this aggregate regulatory risk, which we refer to as sector-specific carbon risk exposures. The carbon tax creates a wedge in firms' input choices, influencing aggregate consumption growth and firms' profits, both of which are jointly determined in general equilibrium.

Our theoretical findings highlight that the carbon risk premium is succinctly captured by two sufficient statistics: direct carbon risk exposure (γ) and indirect carbon risk exposure (χ). Within our consumption-based framework, a firm's stock return is proportional to the covariance between aggregate consumption growth and the firm's profit. A firm's profit is negatively related to its total taxes paid and positively correlated with its pre-tax revenues. The direct carbon risk exposure (γ) reflects the covariance between aggregate consumption growth and sector-specific taxes paid, which are proportional to a firm's own carbon emissions. In contrast, the indirect carbon risk exposure (χ) captures the covariance between aggregate consumption growth and firms' pre-tax revenues, reflecting the transmission of carbon risk through production networks. Importantly, the direct carbon risk exposure is still a result of general equilibrium outcomes, as aggregate consumption growth is endogenously determined by carbon regulatory risks and the primitives of the production network.

We demonstrate that aggregate consumption growth moves negatively with the carbon tax rate, and a greater direct carbon risk exposure results in lower profits for firms. Consequently, a firm's direct carbon risk exposure increases with its own carbon emissions. However, this does not necessarily imply that the carbon risk premium hypothesis holds, as the sign of the indirect carbon risk exposure depends on the carbon emissions of other sectors and general equilibrium allocations. This observation clarifies why it is crucial to incorporate input-output linkages when measuring carbon risk. We further show that the difference in expected returns between two stocks is independent of is linearly proportional to the variance of the carbon tax rate, which is unobservable, and the coefficient is determined by observable sector-level parameters: the input-output (IO) table, economies of scale, carbon emission intensity, the Domar weight (defined as the ratio of revenue to aggregate GDP), and the expenditure share in households' total spending. This feature allows us to empirically measure these parameters.

Guided by our theoretical results, we initiate our empirical analysis by constructing the empirical counterparts of the direct and indirect carbon exposures. To do so, We combine and use several data sources: the firm-level carbon emission data from the Trucost dataset, input-output (IO) tables from the U.S. Bureau of Economic Analysis (BEA), stock returns from the CRSP dataset and balance sheet information from the Compustat. Specifically, we aggregate firm-level carbon emissions to obtain the sector-level carbon emissions. To link industries in the IO table with firms in the Trucost dataset, we employ our manually constructed concordance between the BEA industry classification and the NAICS industry codes, and map individual firms to BEA industries. We further utilize our compiled data set to construct the following variables at the sector level — the IO table, the measure of economy of scale, the Domar weights and the consumption expenditure shares — to finally obtain the empirical measure of firms' direct and indirect exposures, using our analytical formulas.

Informed by our general equilibrium model with network-based production, we empirically construct direct and indirect carbon risk exposures at both the firm and industry levels. Direct carbon exposure (γ) is measured as a firm's carbon emission intensity (carbon emissions scaled by revenue), while indirect carbon exposure (χ) captures the network effect through input-output linkages, reflecting how a firm's exposure is influenced by the carbon emissions of its suppliers and customers. We find that indirect exposure (χ) differs significantly from direct exposure (γ), with their correlation ranging from 0.16 to 0.43 across years (average of 0.34), underscoring the importance of accounting for network effects when measuring carbon risk.

We further examine the risk premium implications of carbon risk exposure, focusing on whether firms with higher exposure deliver higher expected returns. Using implied cost of capital (ICC) as a proxy for expected returns, we conduct portfolio sorting and regression analyses. Firms in the highest quintile of total carbon risk exposure ($\gamma + \chi$) earn an average annual return that is 2.13% higher than those in the lowest quintile. The indirect exposure (χ) drives most of this premium, with firms in the highest quintile of (χ) earning 2.24% higher returns, while direct exposure (γ) does not generate a significant premium. Regression analyses confirm that indirect exposure has a stronger and more statistically significant effect on ICC compared to direct exposure. A return decomposition reveals that indirect exposure accounts for 85.4% of the total premium, with the cross-industry component contributing 66.98% and the within-industry component contributing 18.40%. In contrast, direct exposure contributes only 14.6%, primarily driven by within-industry effects. These findings highlight the critical importance of accounting for input-output linkages when measuring carbon risk and understanding its premium.

We further examine additional cross-sectional predictions of our model by linking ICC to firms' position in the production network. We construct a firm-level, carbon-adjusted centrality measure that weights industry-level network centrality by each firm's revenue shares across industries, and estimate how this measure relates to ICC after controlling for firm size, direct carbon intensity, and standard firm characteristics. Consistent with the theory, we find that more carbon-central firms face higher required returns, whereas larger firms—conditional on their carbon-adjusted centrality— face lower required returns. By contrast, once we control for size and carbon-adjusted centrality, direct emissions no longer explain variation in ICC. These results reinforce our central message that it is a firm's network-embedded carbon risk, rather than its standalone emissions, that is priced in expected returns.

We subject our main findings to an extensive battery of robustness checks to ensure their validity and generality. We verify that the carbon premium persists across alternative portfolio constructions, industry weighting schemes, and regression specifications, and show that our results are robust to incorporating different measures of carbon emissions (Scopes 1–3), alternative lag structures reflecting reporting delays, and additional controls such as revenue growth. We further demonstrate that the dominance of indirect exposure holds under a generalized CES production framework that relaxes Cobb–Douglas assumptions, and that the premiums are stable across subsamples, including periods that exclude low-emission or high-tech industries. Taken together, these analyses confirm that our central conclusion— that network-propagated carbon risk is the primary priced component of firms' carbon exposure—is highly robust across data choices, model specifications, and empirical designs.

Finally, to provide a risk-based explanation consistent with our general equilibrium model, we investigate how firms with varying levels of carbon risk exposure respond to carbon regulatory shocks. Using a novel Carbon Regulatory Index (CRI) constructed from textual analysis of Wall Street Journal articles, we find that firms with higher indirect exposure experience more significant declines in stock returns, revenue, investment, and net income following an unexpected increase in regulatory risk. For example, firms in the highest quintile of indirect exposure experience a 92.74% decline in revenue growth after a regulatory shock, compared to a 15.48% decline for firms in the lowest quintile. This evidence aligns strongly with our theoretical predictions.

The remaining paper is structured as follows. Section 2 develops a tractable general equilibrium model that incorporates carbon emissions and regulatory risks, providing the theoretical foundation for the study. Section 3 constructs empirical measures of direct and indirect carbon risk exposures at both the firm and industry levels. Section 4 empirically tests the implications of these exposures for asset pricing, demonstrating that indirect carbon risk exposure, driven by production networks, accounts for most of the cross-sectional variation in firms' stock returns and implied cost of capital (ICC). Finally, Section 5 investigates how firms with varying levels of carbon risk exposure respond to carbon regulatory shocks, using a novel Carbon Regulatory Index (CRI) constructed from textual analysis of Wall Street Journal articles. The paper concludes with a discussion of the broader implications of these findings for understanding the pricing of carbon risk in financial markets.

Related Literature. The pricing of carbon risk is a central issue in asset pricing, with extensive research indicating that firms with higher carbon emissions require higher expected returns. For instance, (Bolton and Kacperczyk, 2021a, 2023; Lioui and Misra, 2023; Atilgan et al., 2024) have all demonstrated this relationship. However, prior studies primarily focus on direct carbon emissions, ignoring the broader network effects that shape carbon risk exposure. Our research extends this literature by incorporating both direct and indirect exposure into a firm's carbon risk profile and showing that these risks are priced in expected returns, particularly under policy uncertainty.

Empirical evidence supports the existence of a carbon premium, where firms with higher emissions earn higher average returns (Bolton and Kacperczyk, 2023; Pástor et al., 2022; Eskildsen et al., 2024). However, Eskildsen et al. (2024) replicated the carbon premium based on a wide set of greenness measures based on realized returns and found that the evidence is not robust. Unlike existing work, our study moves beyond static firm-level emissions to examine how network position influences a firm's exposure to carbon risk and return dynamics. Our study finds that the majority of the carbon premium is captured by indirect carbon exposure, which can only be captured through the production network.

While most research considers firm-level emissions, recent studies highlight that firms are exposed to carbon risk through supply chains and financial networks including Sautner et al. (2023b); De Angelis et al. (2023), among others. However, these works neither investigate the asset-pricing implications nor embed carbon risk in a general-equilibrium framework. Indirect exposure through interconnected firms leads to mispricing if investors fail to account for these spillover risks. Our study builds on this idea by explicitly modeling carbon risk propagation in networks, demonstrating that firms embedded in carbon-intensive networks face greater carbon-related costs, even with low direct emissions. To our knowledge, this network-based carbon exposure has not been fully accounted for in existing empirical tests of the carbon premium.

Climate policy uncertainty plays a critical role in carbon risk pricing. Theoretical work emphasizes the role of regulatory risk (Hsu et al., 2023). Firms with greater exposure to regulatory risks, as measured by climate-related discussions in earnings calls, exhibit higher option-implied expected returns (Sautner et al., 2023b; Gasparini, 2023). Carbon-intensive firms also experience higher downside protection costs in options markets, reinforcing the view that investors demand additional compensation for policy risks (Nordhaus, 2019; Ilhan et al., 2021; Bolton and Kacperczyk, 2023). Policy-driven risk differentials are further reflected in the pricing of green bonds, which attract ESG-conscious investors and may lower financing costs (Larcker and Watts, 2020; Baker et al., 2022; Zerbib, 2022; Giglio et al., 2025). However, prior research has not studied how such risk can propagate through supply chain linkages and affect firm valuations, a gap that our study aims to fill.

This paper is also closely related to the literature that investigate the asset pricing implications when firms operating within production networks. Prior studies examine how network centrality affects stock returns (Ahern, 2013), the role of network concentration in shaping risk premia (Herskovic, 2018), and the impact of trade network centrality on currency risk premia (Richmond, 2019). Others analyze risk propagation in vertical production networks (Gofman et al., 2020) and the amplification of economic shocks through network linkages (Yang and Zhu, 2020). Our paper complements these studies in an extended framework focusing on the transmission of carbon risk premium.[1] In this framework, we introduce aggregate environmental regulatory risk and show that it leads to reduced aggregate consumption, output, investment,revenue, and firms' profits. This framework enables us to empirically measure firms' direct and indirect exposure to regulatory risk and quantify their contributions to the carbon risk premium. We demonstrate that the different exposures to this aggregate risk can explain variations in the cross-sectional expected stock returns, both theoretically and empirically. To the best of our knowledge, our paper is the first to study asset pricing implications of carbon emissions in production networks.

Recent evidence from Pastor et al. (2024) substantiates the view that direct (Scope 1) emissions provide an incomplete picture of firms' carbon risk exposure. Their novel construct of the "carbon burden"—the present value of the social costs of future emissions—reveals that for 77% of U.S. firms, total carbon burdens (Scope 1+2+3) exceed market capitalization, compared to only 13% when considering Scope 1 emissions alone. Particularly striking is the financial sector, where Scope 1 carbon burdens are negligible, yet Scope 3 emissions—reflecting financed and value-chain-related emissions—imply carbon burdens over 17 times market value. These findings highlight that significant carbon externalities

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[1] Seminal contributions to the literature on production networks in economics and finance include Carvalho (2010), Acemoglu et al. (2012), Carvalho and Gabaix (2013), Acemoglu et al. (2015) and Carvalho et al. (2021).

are embedded in inter-firm relationships, upstream suppliers, and downstream customers, none of which are captured in firm-level direct emissions. The study also shows that decarbonization efforts are highly concentrated: just 30 firms are expected to account for the entire projected reduction in U.S. corporate emissions by 2050, underscoring the central role of network hubs in shaping systemic carbon risks. Collectively, these results emphasize the necessity of adopting a production-network perspective when assessing corporate carbon exposure, as traditional approaches based solely on Scope 1 emissions materially underestimate both firm-level and systemic carbon risks.

2. Theoretical Framework

We develop a general equilibrium model that features both carbon emissions and input-output linkages. Carbon regulatory risk arises as government imposes taxes on firm-level emissions. This framework allows us to connect firms' expected stock returns with their carbon emissions, and characterize the key determinants of the carbon-risk premium.

2.1 Model Setup

Network-based Production. There are two periods, indexed by $t = 0, 1$. Period 0 represents the planning stage without shocks. The economy is comprised of N industries, each producing a distinct good. Within each industry, a continuum of perfectly competitive firms operates. The production function for firms in industry j at period t is given by

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

where Y_{jt} denotes output, X_{jt} is a composite of intermediate inputs, $\eta_j \in (0,1)$ is the share of the composite input, and $\xi_j = \eta_j^{\eta_j} \prod_{k=1}^{N} a_{jk}^{a_{jk}}$ is a normalization constant, with α_{jk} defined in Equation 2. The production function exhibits decreasing returns to scale, yielding positive profits.[2] These profits are distributed to households, who own all firms.

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} represents the quantity of good k used by industry j, and a_{jk} denotes the corresponding input share. Constant returns to scale implies that $a_{jk} \geq 0$ and $\sum_{k=1}^{N} a_{jk} = 1$ for all j. 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 demand shocks propagate only directly to upstream sectors. In

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[2] This can be interpreted as reflecting a fixed factor of production—such as capital or management—absorbing 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.

Appendix A.1, we relax this assumption by adopting a general constant-elasticity-of-substitution (CES) aggregator, which permits input shares to adjust endogenously and shocks to propagate both upstream and downstream. We solve and characterize the model analytically. Section 4.5 shows that our main results remain quantitatively robust.

Carbon Emissions. We assume that producing one dollar of output in industry j releases γ_j units of carbon, that is, γ_j denotes the industry's carbon emission intensity. The government imposes a tax of τ_t per unit of emissions, implying an effective revenue tax rate of $\tau_{jt} = \gamma_j \tau_t$ for industry j. This formulation captures the industry's exposure to carbon regulatory risks. Firms in industry j thus earn after-tax revenue of $(1 - \tau_{jt})P_{jt}Y_{jt}$, where P_{jt} denotes the output price. Carbon tax revenues are rebated to households as lump-sum transfers.

An alternative approach to modeling firms' emissions is based on their input usage (Shapiro and Walker, 2018).[3] We adopt a revenue-based specification for two main reasons. First, it provides a parsimonious way to capture emissions and aligns with recent empirical studies of carbon risk premia that measure firm emissions using revenue-adjusted carbon 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. Nevertheless, Appendix A.2 shows that under mild assumptions, the two approaches are theoretically equivalent.

Relatedly, recent studies document that firms adjust their production functions over the medium to long run in response to regulatory shocks—e.g., by adopting green technologies or substituting toward cleaner inputs (Acemoglu et al., 2012; Martin et al., 2014; Cullen and Mansur, 2017; Xiang, 2023). By contrast, our focus is on the short-run asset pricing implications of regulatory risk, using monthly or annual data. Over such horizons, it is reasonable to treat production functions as fixed. Nonetheless, we allow for annual updates in the input–output matrix A in our empirical analysis to capture gradual changes in the production structure.

Aggregate Shock. In period 1, the carbon regulation 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 constitutes the aggregate source of uncertainty in the model. Because firms differ in their carbon emission intensities, their exposures to this shock vary, generating cross-sectional dispersion in risk premia. For simplicity, we assume that $\overline{\tau} = 0$.

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

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

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

where C_t denotes 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} is 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 $P_t = \prod_{j=1}^{N} P_{jt}^{\alpha_j}$. We normalize $P_0 = P_1 = 1$.

Financial markets are complete. At period 0, households trade a risk-free bond that pays one unit of the final good in period 1, with gross return R_1^f. Bond holdings are denoted by B_1. Households also purchase equity shares in firms, with $\vartheta_1 \leq 1$ denoting the share held and V_1 the price per unit. Let Π_{jt} denote total profits in industry j at time t. The household's flow budget constraints are given by

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

Equilibrium. A competitive equilibrium consists of good prices $\{P_{jt}\}_{j=1}^{N}$, risk-free interest rate R^f, stock 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 in (4).

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

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

   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 $i = 1, 2, \dots, N$ and $t = 0, 1$,

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

Discussion. The central innovation of this paper is the introduction of carbon regulatory risk, captured by τ_{jt}. Yet, our framework extends beyond regulatory risk and accommodates a broader class of carbon-related aggregate shocks. For instance, shifts in consumer preferences toward "green" firms or an increased likelihood of climate-related disasters can be interpreted within our framework. In such cases, the term $\tau_{jt} P_{jt} Y_{jt}$ represents the potential revenue loss of "brown" firms relative to "green" firms.[4] Our model can thus be readily extended to analyze these alternative risks and their

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[4] Following standard terminology, we refer to high-emission firms as "brown" and low-emission firms as "green."

propagation to equity prices through production linkages.

2.2 Expected Stock Returns

In this section, we derive an analytical expression for expected stock returns. The framework builds on the consumption-based capital asset pricing model (CCAPM), where expected returns are proportional to the covariance between firms' profits and the aggregate consumption growth. Both are shaped by the carbon regulatory risk and network structure.

We begin by deriving the expression for Domar weights, which play a central role in linking firm-level profits and aggregate consumption growth.

2.2.1 Domar Weight

The Domar weight of industry j at period t is defined as industry j's pre-tax revenue relative to GDP:

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

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

To derive the expression for S_{jt}, multiply both sides of the market-clearing condition (6) by P_{jt}, substitute $P_{jt} X_{jkt}$ using the firm's first-order condition (13), and replace $P_{jt} C_{jt}$ with $\alpha_j P_t C_t$ using the household's first-order condition. Dividing both sides by $P_t C_t$ yields,

$$S_{jt} = \alpha_j + \sum_{k=1}^{N} (1 - \gamma_k \tau_t) \eta_k a_{kj} S_{kt}. \tag{7}$$

In vector form,

$$\boldsymbol{S}_t = \boldsymbol{\alpha} + \boldsymbol{A}' \boldsymbol{D}_\eta (I - \boldsymbol{D}_\gamma \tau_t) \boldsymbol{S}_t, \tag{8}$$

where $\boldsymbol{D}_\gamma = \text{diag}(\gamma_1, \gamma_2, ..., \gamma_N)$ and $\boldsymbol{D}_\eta = \text{diag}(\eta_1, \eta_2, ..., \eta_N)$. Solving yields the closed-form expression:

$$\boldsymbol{S}_t = \left[I - \boldsymbol{A}' \boldsymbol{D}_\eta (I - \boldsymbol{D}_\gamma \tau_t) \right]^{-1} \boldsymbol{\alpha}. \tag{9}$$

This expression shows that an industry's Domar weight depends not only on its industry-specific parameters but also on all other industries' carbon emission intensities, returns to scale, and consumers' expenditure shares. These interdependencies arise from input-output linkages and vanish only when the input-output matrix $\boldsymbol{A}$ is diagonal.[5]

Denote the vector of carbon emission intensities by $\boldsymbol{V}_\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_N)'$, and the diagonal matrix of period-0 Domar weights by $\boldsymbol{D}_S = \text{diag}(S_{10}, S_{20}, \ldots, S_{N0})$. Linearizing equation (8) around values in period 0 and rearranging terms yields the following result.

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[5] If $\boldsymbol{A}$ is diagonal, equation (9) implies that S_{jt} depends only on industry j's own parameters.

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

$$\Delta \log \boldsymbol{S_t} = \log \boldsymbol{S}_1 - \log \boldsymbol{S}_0 = -\boldsymbol{\chi}\tau_t, \tag{10}$$

where

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1}(I - \boldsymbol{A'}\boldsymbol{D}_\eta)^{-1}\boldsymbol{A'}\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{V}_\gamma > 0, \tag{11}$$

and $\boldsymbol{\chi} = (\chi_1, \chi_2, \ldots, \chi_N)'$.[6]

To build intuition, we represent expression (10) in a recursive structure capturing all the direct and indirect effects along the network linkages,

$$\Delta \log S_{jt} = -\frac{1}{S_{j0}}[\sum_{k=1}^{N} a_{kj}\eta_k S_{0k}\gamma_k\tau_t + \sum_{k=1}^{N}\sum_{\ell=1}^{N}\eta_k\eta_\ell a_{k\ell}a_{\ell j}S_{0\ell}\gamma_\ell\tau_t + \sum_{k=1}^{N}\sum_{\ell=1}^{N}\sum_{m=1}^{N}\eta_k\eta_\ell\eta_m a_{k\ell}a_{\ell m}a_{mj}S_{0m}\gamma_m\tau_t \ldots] \tag{12}$$

How does the carbon regulatory risk τ_t affect industry j's Domar weight? Consider an unexpected tightening of carbon policy (i.e., a positive shock to τ_t). Firms in industry k respond by reducing their demand for intermediate inputs as long as $\gamma_k > 0$. This reduction transmits to industry j if it serves as a direct or indirect supplier to industry k. The first term in (12) captures the direct exposure of industry j to demand reductions from its immediate downstream customers. The second term reflects effects from the customers of those customers, and the third term captures effects from customers three steps downstream, and so on. All of these cascading effects are succinctly summarized in the closed-form expression (10).

2.2.2 Profit

The first-order condition from the profit optimization problem of a firm in industry j yields the optimal demand for intermediate inputs from industry k,

$$X_{jkt} = \frac{(1-\gamma_j\tau_t)\eta_j a_{jk} Y_{jt} P_{jt}}{P_{kt}}, \tag{13}$$

leading to the following lemma.

Lemma 2. *Firms' profits in industry j are proportional to their pre-tax revenue $\Psi_{jt} = S_{jt}C_t$,*

$$\Pi_{jt} = (1-\eta_j)(1-\gamma_j\tau_t)\Psi_{jt} = (1-\eta_i)(1-\gamma_j\tau_t)S_{jt}C_t. \tag{14}$$

In equation (14), the term $(1-\gamma_j\tau_t)\Psi_{jt}$ captures the after-tax revenue, of which a fraction η_j is paid to intermediate input suppliers, with the remainder accruing as profit.

An increase in the carbon tax τ_t directly reduces profits through the term $(1-\gamma_j\tau_t)$. Indirect effects arise via changes in firms' revenue Ψ_{jt}, which depends on the Domar weight S_{jt} and aggregate consumption C_t, both determined in general equilibrium.

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[6] A vector is positive if its elements are all positive real numbers.

Taking first-order differences of (14) between periods 1 and 0, we obtain the following proposition:

Proposition 1. *The profit of a firm in industry j is approximated by the following expression*

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0}(\phi_{\pi j}\tau_t + \Delta \log C_t), \tag{15}$$

where

$$\phi_{\pi j} = -\gamma_j - \chi_j < 0. \tag{16}$$

In vector form,

$$\boldsymbol{\Pi}_t = \boldsymbol{\Pi}_0 + \boldsymbol{D}_{\Pi_0}(\boldsymbol{\phi}_\pi \tau_t + \mathbf{1}\Delta \log \boldsymbol{C}_t), \tag{17}$$

where $\boldsymbol{D}_{\Pi_0} = diag(\Pi_{10}, \Pi_{20}, ..., \Pi_{N0})$ and $\boldsymbol{\phi}_\pi = (\phi_{\pi 1}, \phi_{\pi 2}, ..., \phi_{\pi N})'$.

The effect of a carbon tax on firm profits in industry j thus can be decomposed into a direct channel, $-\gamma_j$, and an indirect network channel, $-\chi_j$.

2.2.3 Aggregate Consumption Growth

The following proposition characterizes the effect of the carbon tax on aggregate consumption growth.[7]

Proposition 2. *The aggregate consumption growth in the economy is given by*

$$\Delta \log C_t = \phi_C \tau_t, \tag{18}$$

where

$$\phi_C = -\boldsymbol{\alpha}'\boldsymbol{\Omega}(\boldsymbol{D}_\eta^{-1} - I)\boldsymbol{V}_\gamma - \boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{\chi} < 0, \tag{19}$$

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

The inequality $\phi_C < 0$ implies that an increase in the carbon tax τ_t reduces aggregate consumption growth. Intuitively, the tax introduces wedges between the equilibrium allocation and the efficient one, generating misallocation and depressing aggregate consumption.

From another perspective, note that $\log C_t = \boldsymbol{\alpha}' \log \boldsymbol{\Psi}_t - \boldsymbol{\alpha}' \log \boldsymbol{S}_t$. On average, the carbon tax reduces firms' revenues $\boldsymbol{\Psi}_t$, which lowers consumption. However, it also depresses the Domar weights $\boldsymbol{S}_t$, which partially offsets this decline. Proposition 2 establishes that the revenue effect dominates: carbon taxation unambiguously reduces consumption growth.

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[7] Please refer to Appendix A.4.4 for the proof.

2.2.4 Expected Stock Returns

Given the pricing kernel $(1 - \Delta \log C_t)$ and gross risk-free rate R_{ft}, the value of stocks in industry j is given by:[8]

$$V_{jt} = \frac{\mathbb{E}(\Pi_{jt})}{R_t^f} - \text{Cov}\left(\Delta \log C_t, \Pi_{jt}\right). \tag{20}$$

The expected gross return of firms in industry j at period t is

$$\mathbb{E}R_{jt} = \frac{\mathbb{E}\Pi_{jt}}{V_{jt}} = \frac{\Pi_{j0}}{V_{jt}},$$

where we use the fact that $\mathbb{E}\Pi_{jt} = \Pi_{j0}$. Rearranging and approximating equation (20) yields the expression for the expected net return $\mathbb{E}r_{jt}$:

$$\mathbb{E}r_{jt} = r_t^f + \frac{\text{Cov}\left(\Delta \log C_t, \Pi_{jt}\right)}{\Pi_{j0}}, \tag{21}$$

where r_t^f is the net risk-free rate. Substituting the expressions for $\Delta \log C_t$ and Π_{jt} from (18) and (15), we obtain the following characterization.

Theorem 1. *The expected net return on stocks in industry j is given by*

$$\mathbb{E}r_{jt} = r_t^f + \phi_{\pi j}\phi_C \sigma_\tau^2 + Var(\Delta \log C_t). \tag{22}$$

where $\phi_{\pi j} = -\gamma_j - \chi_j < 0$ (with $\chi_j > 0$ as defined in (11)) and $\phi_C < 0$ is given in (19).

Theorem 1 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 governed entirely by the firm-level exposure $\phi_{\pi j}$, as stated in the following proposition.

Proposition 3. *For any industry j and industry k, if $\gamma_j + \chi_j > \gamma_k + \chi_k$, then $\mathbb{E}r_{jt} > \mathbb{E}r_{kt}$.*

Proposition 3 implies that $\gamma_j + \chi_j$ serves as a sufficient statistic for ranking expected stock returns. The term γ_j captures direct exposure to regulatory shocks, while χ_j reflects indirect exposure through general equilibrium effects along the supply chain—a channel largely overlooked in the existing literature, which typically emphasizes firms' own emissions.

This result guides the empirical analysis that follows. In Section 3, we construct empirical counterparts of γ_j and χ_j, and in Section 4 we test the model's predictions. Using panel regressions, portfolio sorting, and Fama–MacBeth analysis, we find that firms with higher $\gamma_j + \chi_j$ face higher implied cost of capital (ICC) and higher expected returns, both at the firm and industry level. The

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[8] The pricing kernel is given by $(C_t/C_{t-1})^{-1} \approx 1 - \Delta \log C_t$ under the log-linear approximation.

indirect component χ_j emerges as the dominant driver. Section 5 further shows that high-$\gamma_j + \chi_j$ firms exhibit greater exposure to aggregate regulatory risk

Connection to Existing Literature. The existing literature seeks to explain cross-sectional variation in expected stock returns using firms' carbon emissions or emission intensity (Bolton and Kacperczyk (2021a); Aswani et al. (2024a); Zhang (2025)). In Appendix A.3, we derive a sufficient condition under which this approach is valid—namely, when expected returns are determined solely by emission intensity. This condition requires that all columns of the input–output matrix A are identical, i.e., $A(:, j) = A(:, k)$ for all industries j and k. In other words, all firms must sell to the same customers in identical proportions. Empirically, however, the IO matrix exhibits substantial heterogeneity across columns, underscoring the importance of production network structure in explaining variation in equity returns.

2.3 Additional Testable Implications

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

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

Consistent with standard network theory, the element ℓ_{jk} captures the importance of industry k as a direct or indirect input supplier to industry j. This concept is closely related to the notion of network centrality, as formalized below.

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

$$\vartheta_j = \sum_{k}^{N} \omega_k \ell_{kj}, \tag{23}$$

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

In vector form, equation (23) becomes $\boldsymbol{\vartheta}' = \boldsymbol{\omega}' \boldsymbol{L}$, where $\boldsymbol{\omega} = (\omega_1, \ldots, \omega_N)'$. This measure modifies the Bonacich centrality, a widely used network metric defined recursively as $\vartheta_j^B = 1/N + \sum_{k=1}^{N} a_{kj} \eta_k \vartheta_k^B$, or equivalently, $\vartheta_j^B = \sum_{k=1}^{N} \ell_{kj}/N$.[9] The central idea is that an agent is more central if she is connected to other central agents.

The carbon-adjusted centrality in (23) extends this concept by replacing the uniform weights $1/N$ with emission shares ω_k. Since ℓ_{kj} captures the importance of j as a supplier to k, this adjustment gives greater weight to connections with carbon-intensive industries

Proposition 4. *Suppose* $\Psi_{i0} = \Psi_{j0}$*. Then* $\mathbb{E} r_{it} > \mathbb{E} r_{jt}$ *if and only if* $\vartheta_i > \vartheta_j$.

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[9] In vector notation: $\boldsymbol{\vartheta}^B = (I - \boldsymbol{A}' \boldsymbol{D}_\eta)^{-1} \mathbf{1}$.

Proposition 4 shows that carbon-adjusted centrality suffices to rank expected returns across industries of equal size (measured by time-0 revenue). The intuition is that firms with greater centrality suffer larger profit losses following an increase in the carbon tax, as they serve more carbon-intensive industries.

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

Proposition 5 shows that, holding centrality constant, smaller industries have higher expected returns. This reflects the greater proportional impact of profit shocks on smaller firms.

2.4 Illustrative Examples

We conclude by presenting three examples that further illustrate the key forces shaping stock returns in the model.

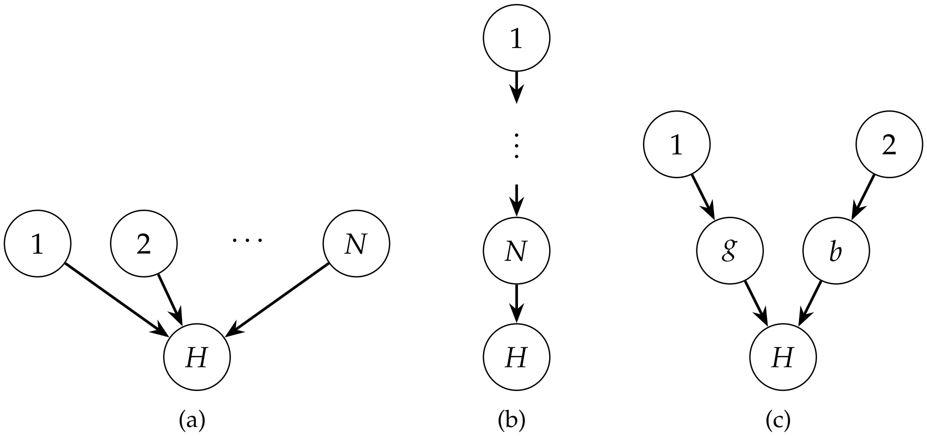

Figure 1: Network Examples

Example 1 (horizontal network). Consider the horizontal production network in Figure 1, panel (a), where the fixed factor is the sole input, there are no input–output linkages, and households—denoted by vertex H—consume output from all industries. In this setting, the carbon tax τ_t affects profits only through direct exposure, without propagation through supply chains. By Theorem 1, expected stock returns are increasing in carbon emission intensity γ_j.

Example 2 (Vertical Network). Consider the vertical production network shown in Figure 1, panel (b). In this setting, each industry j supplies the sole intermediate input for industry $j+1$; industry 1 relies only on the fixed factor, and final consumption by households H is limited to goods produced in industry N.

Equation (12) implies that the indirect effect χ_j can be expressed recursively as

$$S_{j-1,0}\chi_{j-1} = \eta_j S_{j,0}\chi_j + \eta_j S_{j,0}\gamma_j, \tag{24}$$

with the boundary condition $\chi_N = 0$. This formulation is intuitive: carbon taxes induce cumulative demand effects that propagate upstream along the supply chain.

To further distill the role of network position, suppose all industries share the same size ($S_{j0} = S_0$), identical returns-to-scale parameter ($\eta_j = \eta$), and equal carbon emission intensity ($\gamma_j = \gamma$). Under these assumptions, equation (24) yields

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

Thus, profits of more upstream industries exhibit stronger responses to aggregate shocks, resulting in higher expected stock returns.

Example 3 (carbon-adjusted centrality). This example illustrates the concept of carbon-adjusted centrality: industries earn higher expected stock returns if they are more important suppliers to industries with higher carbon emissions.

Consider the network depicted in Figure 1, panel (c), where households consume goods produced by industries g and b. Industry 1 is the sole supplier to industry g, and industry 2 is the sole supplier to industry b. For simplicity, assume all industries have the same size ($S_{j0} = S_0$) and identical degrees of decreasing returns to scale ($\eta_j = \eta$). Industries 1 and 2 have the same carbon emission intensity ($\gamma_1 = \gamma_2$), but the downstream industries differ: industry b ("brown") emits more carbon than industry g ("green"), so $\gamma_b > \gamma_g$.

An immediate application of equation (12) implies that

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

Since $\gamma_b > \gamma_g$, it follows that $\chi_1 > \chi_2$, and thus expected return $\mathbb{E}r_1 > \mathbb{E}r_2$. This occurs because industry 1's profits are more negatively impacted by aggregate carbon regulatory risk, given its direct supply relationship with the higher-emitting "brown" industry.

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 (2021a) 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 (2021a), 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

Our empirical analysis is conducted at both the firm and industry level, we therefore construct four measures of carbon exposure: 1) firm-level direct exposure, 2) industry-level direct exposure, 3) firm-level indirect exposure and 4) industry-level indirect exposure.

A firm's direct carbon exposure γ is defined as its carbon emission intensity, or its total carbon emissions scaled by its revenue. The existing literature typically focuses on this measure, and we follow the standard approach to construct it. We construct the industry-level direct carbon exposure by calculating a sales-weighted average of firms' direct exposure.

We construct the industry-level indirect carbon exposure based on equation (11) in Lemma 1,

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

Recall that $\boldsymbol{A}$ is the input-output matrix, $\boldsymbol{D}_\eta$ is the return-to-scale diagonal matrix, $\boldsymbol{D}_S$ is the Domar-weight diagonal matrix, and $\boldsymbol{V}_\gamma$ is a vector of carbon emission intensity.[10]

Leveraging Compustat segment data, we measure each firm's indirect carbon exposure as the sales-weighted average of the indirect exposures of the industries in which it operates. Specifically, 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 industry j's indirect exposure in year t. We define firm i's indirect exposure as

$$\chi_{i,t} \;=\; \sum_j \frac{\text{sale}_{ij,t-1}}{\sum_k \text{sale}_{ik,t-1}}\,\chi_{j,t}\,. \tag{25}$$

This formulation ensures that each business segment contributes to the firm's overall exposure in

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[10] To better interpret the result, we scale each element in the $\boldsymbol{V}_\gamma$ vector by dividing the original carbon intensity by 1,000, adjusting the unit to tons per thousand USD. This will not affect our results since $\boldsymbol{\chi}$ and $\boldsymbol{\gamma}$ are scaled proportionally.

proportion to its relative sales. [11]

In what follows, we construct the empirical counterpart for matrices $\boldsymbol{A}$, $\boldsymbol{D}_\eta$, $\boldsymbol{D}_S$, and $\boldsymbol{V}_\gamma$, and the four carbon risk exposures are immediately obtained.

Construction of $\boldsymbol{A}$ matrix. $\boldsymbol{A}$ is a $N \times N$ matrix capturing the input-output relationship between industries. Its element a_{jk} is the expenditure percentage of industry j on intermediate goods in the industry k to j's total intermediate expenditure. We use the input-output tables by BEA and follow the procedure proposed by Pasten et al. (2017) to construct the matrix $\boldsymbol{A}$. For details on the construction, please refer to Pasten et al. (2017) and the Appendix B.

Construction of $\boldsymbol{D}_\eta$. To measure the concept of composite intermediate input ratios within industries, we define the diagonal matrix $\boldsymbol{D}_\eta = \text{diag}(\eta_1, \eta_2, ..., \eta_n)$, where each η_j represents the proportion of composite intermediate expenditure relative to the total value of the final product in industry j. Practically, this ratio is estimated by comparing the total expenditure on intermediate goods to the total revenue for a given firm i within industry j during year t, expressed as:

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

Here, $COGS_{ijt}$ denotes the cost of goods sold. To calculate η_{jt} for each industry, we average the η_{ijt} values across all firms i within industry j. For robustness, we also compute a weighted average of η_{ijt}, utilizing the firm's revenue or market value as weights, and confirm that our findings remain robust. Figure OA.4 shows the distribution of the η_j across industries averaged over years between 2002 and 2020.

Construction of $\boldsymbol{D}_S$ (Domar Weights). We then constructs the empirical counterpart of $\boldsymbol{D}_S$ with $\boldsymbol{D}_S = \text{diag}(s_1, s_2, ..., s_n)$. s_j is *Domar weight* of industry j measured as the ratio of industry revenue to the aggregate GDP. We use the annual BEA's make table to construct the *Domar weight*. Specifically, the Domar weight of industry j is measured as the j's output to the aggregate output across all industries in BEA. Figure OA.5 shows the Domar weights at the BEA industry level averaged across years between 2002 and 2020. Domar weight of an industry capture its systemic role in the input-output network but not its systemic role in carbon emission due to gaps in emission intensity and the associated network effect. Figure OA.5 shows the Domer weights industry averaged over years between 2002 and 2020. The top five industries with highest Domar weights are Housing, Wholesale Trade, Construction, Scientific and Technical Services, and Insurance Services that are significantly different from the top industries with highest carbon-emission exposure as shown in the table OA.5.

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[11] A number of studies construct firm-level measures by combining segment-level data with industry-level variables, enabling a more nuanced assessment of firm-specific exposures within broader industry contexts (e.g., Hoberg and Phillips (2016), Shi et al. (2020), Cong et al. (2024)).

3.3 Empirical Results and Validations

This subsection provides additional empirical evidence to validate our measures of direct and indirect exposure, denoted as γ and χ. We demonstrate that neglecting indirect exposure through production networks could potentially lead to a significant misunderstanding of a firm's overall carbon risk exposure.

Effect of Network Depth on χ Measurement. To provide further intuition, we examine the underlying structure of the indirect exposure along the supply chain. Specifically, we decompose χ as:

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1} \sum_{l=1}^{\infty} (\boldsymbol{A}'\boldsymbol{D}_\eta)^l \boldsymbol{D}_S \boldsymbol{V}_\gamma = \boldsymbol{D}_S^{-1} \boldsymbol{A}'\boldsymbol{D}_\eta \boldsymbol{D}_S \boldsymbol{V}_\gamma + \boldsymbol{D}_S^{-1} (\boldsymbol{A}'\boldsymbol{D}_\eta)^2 \boldsymbol{D}_S \boldsymbol{V}_\gamma + \ldots, \tag{26}$$

where the first term captures the indirect exposure from direct upstream and downstream connections, while the second term captures the indirect exposure from the second layer of neighbors. More generally, the term $\boldsymbol{\chi}_l := \boldsymbol{\mathcal{L}}_l \boldsymbol{V}_\gamma$, with $\boldsymbol{\mathcal{L}}_l = \boldsymbol{D}_S^{-1}(\boldsymbol{A}'\boldsymbol{D}_\eta)^l \boldsymbol{D}_S$ and $l \geq 1$, represents the indirect exposure originating from the l-th layer of neighbors along the input-output linkages.

We define $\boldsymbol{\mathcal{L}} = \sum_{l \geq 1} \boldsymbol{\mathcal{L}}_l = \boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1} \boldsymbol{A}'\boldsymbol{D}_\eta \boldsymbol{D}_S$ as the *Link Matrix*. For convenience, let $\mathcal{L}_{jk}$ denote the *link strength* between industry j and industry k. The value $\mathcal{L}_{jk}$ captures how one unit of direct exposure from a ***contributor***—industry k—propagates to the indirect exposure of a ***receiver***—industry j—through all possible paths within the supply chain. Furthermore, $\mathcal{L}_{jk}\gamma_k$ represents the contribution of the direct exposure from the ***contributor***, industry k, to the indirect exposure of the ***receiver***, industry j.

Figure 2 illustrates the effect of network depth on χ measurement. Panel A presents the top 10 industries with the highest indirect exposure (χ), while Panel B shows the scatterplot of direct and indirect exposure. In Panel A, the column "Layer L" indicates the cumulative effect, $\sum_{l \leq L} \boldsymbol{\chi}_l$, while the final column "chi" represents the total indirect exposure, χ, combining all the effects of the network. In general, we find that the first layer contributes predominantly to the indirect exposure, followed by the second layer. Contributions beyond the fourth layer are negligible. Panel B shows us that there can be a large variation in the indirect exposure even conditional on the direct exposure.

An Illustration of γ, χ, and $\gamma + \chi$. Several points are worth highlighting. First, indirect carbon emission exposure (χ) can differ significantly from direct carbon emission exposure (γ) due to network effects arising from the supply chain. The correlation between the γ and χ exhibits substantial variation over time, ranging from approximately 0.16 to 0.43, with an average value of 0.34. This indicates that, overall, the correlation between direct and indirect exposures is relatively low.

Second, industries with high direct exposure may exhibit relatively low indirect exposure, and conversely, industries with high indirect exposure may have low direct exposure. For instance, Table 1 provides the average direct, indirect, and total exposure of each industry between 2002 and 2020. The "Utilities" industry displays the highest direct exposure but only modest levels of indirect exposure.

Conversely, the "Oil and Gas Extraction" and "Pipeline Transportation" industries demonstrate the highest indirect exposure while exhibiting only moderate levels of direct exposure.

Figure 3 decomposes the indirect exposure of selected receiving industries (*receivers*) into contributions from contributing industries (*contributors*). We focus on two representative receivers: *Pipeline Transportation*, which exhibits the second-highest level of indirect exposure, and *Utilities*, which features high direct exposure but relatively modest indirect exposure. The decomposition follows:

$$\chi_j = \sum_k \mathcal{L}_{jk}\,\gamma_k, \qquad j \in \{\text{“Pipeline Transportation”}, \text{“Utilities”}\},$$

where $\mathcal{L}_{jk}$ denotes the link strength from contributor k to receiver j, and γ_k is the direct exposure of contributor k.

Panel A shows that the elevated indirect exposure of *Pipeline Transportation* is primarily driven by strong supply-chain linkages with two highly carbon-intensive contributors: *Utilities* and *Petroleum and Coal Products*. The gray bars display the direct exposure of contributors, the black solid line plots their link strengths $\mathcal{L}_{jk}$, and the blue bars represent each contributor's final contribution to χ_j. These components together reveal that a small number of carbon-intensive upstream industries account for most of *Pipeline Transportation*'s indirect exposure.

Panel B demonstrates that the relatively modest indirect exposure of the *Utilities* sector arises largely from feedback loops within the industry itself. Although *Utilities* have high direct exposure, their indirect exposure remains limited because the sector is less dependent on other carbon-intensive industries.

Figure 4 provides a complementary visualization using a Sankey diagram. The bars on the left axis represent contributors' direct exposure, while the bars on the right axis represent receivers' indirect exposure. The width of each flow captures the magnitude of a contributor's contribution to a receiver's indirect exposure. The diagram highlights that the indirect exposure of *Pipeline Transportation* is dominated by contributions from *Utilities*, followed by *Petroleum and Coal Products*. It also shows that *Utilities* substantially contribute to the indirect exposure of *Oil and Gas Extraction*. For clarity, only industries exhibiting large discrepancies between direct and indirect exposure are displayed in the figure.

4. Direct and Indirect Carbon Risk Exposure and Premium

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 (2021a) 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

Table 2 presents the summary statistics for the variables used in our empirical analysis. Specifically, Panel A provides the summary statistics for ICC (annualized return), stock returns, changes in revenue, investment, and net income. The ICC will be employed as the main dependent variable in our primary analysis, while stock returns will be used for robustness checks (see Appendix OB.11). Changes in revenue, investment, and net income will be used to assess the real impact of firms facing tightening of carbon regulatory shocks (see Section 5 for details).

Panel B summarizes the key variables that measure direct exposure (γ), indirect exposure (χ), and total exposure ($\gamma + \chi$) to carbon risk. Finally, Panel C presents the summary statistics for standard control variables widely used in the literature Bolton and Kacperczyk (2023) , Atilgan et al. (2024) and Zhang (2025) , including the logarithm of firm size (ln(Size)), book-to-market ratio (BM), return on assets (ROA), leverage ratio (Leverage), Tobin's Q, HHI index, KZ index (KZIndex), and logarithm of employment ($\ln(\text{Employees})$).

For further details on the construction, definitions, and winsorization of the control variables, please refer to Table OB.2. The final data set comprises 2,698 companies, and Table OB.4 outlines the sample selection procedure.

Our first set of empirical tests examines whether firms with higher carbon risk exposure earn higher expected returns. Table 3 reports portfolio differences in implied cost of capital (ICC) based on sorts of total exposure ($\chi + \gamma$), indirect exposure (χ), and direct exposure (γ). For each measure, firms are sorted annually into quintiles ranging from the lowest 20% to the highest 20%.

Panel A reports results for portfolios sorted on total exposure, Panel B sorts on indirect exposure, and Panel C sorts on direct exposure. Firms in the top quintile of total exposure earn an average annual ICC that is 2.13% higher than firms in the bottom quintile, a difference that is statistically significant at the 5% level. Panel B shows an even larger spread: firms with the highest indirect exposure earn 2.24% higher ICCs than those with the lowest indirect exposure. By contrast, Panel C reveals no statistically meaningful difference in ICCs between firms with the highest and lowest direct exposure.

The long–short return differences in Panels A–C are driven almost entirely by the bottom quintiles. While the top quintile portfolios yield similar ICCs across all three exposure measures, Panels A and B exhibit substantially lower ICCs for the bottom quintile than Panel C. This pattern arises because some firms in the lowest direct-exposure quintile nonetheless possess high indirect exposure, which elevates their ICCs. In addition, firms with low χ tend to earn lower ICCs than firms with low γ. Consequently, the lowest quintile based on total exposure includes more firms from low-χ industries than the lowest quintile based on direct exposure. Taken together, these results highlight the important role of indirect exposure in explaining cross-sectional variation in the carbon risk premium.

4.2 Regression analysis

Panel Regression. This subsection further examines the premium implication from the perspective of regression, which allows us to control for more heterogeneity across firms with various carbon risk exposures. Our baseline specification takes the form of

$$y_{it} = \alpha + \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \tag{27}$$

where y_{it} is the implied cost of capital (ICC) for firm i at month t, β_χ captures the effect of indirect exposure arising from network effects, β_γ captures the effect of direct carbon risk exposure associated with a firm's own carbon emissions, and $\boldsymbol{X}_{it}$ are standard control variables commonly used in the literature, including logarithm of firm size (measured as the lagged market value), logarithm of the book-to-market ratio, ROA, Leverage, Tobin's Q, HHI index, KZ index, logarithm of employment, and Carbon emissions. Finally, we include the month and firm fixed effect to control for the common time-varying factors and unobservable firm specific characteristics.

To facilitate interpretation and ensure comparability between coefficients, we normalize the indirect exposure to carbon risk (χ_{it}), direct carbon risk exposure (γ_{it}), and total exposure ($\chi_{it} + \gamma_{it}$) by demeaning each variable and dividing by its standard deviation over the entire sample period.

Table 4 reports panel regressions linking firms' ICC to their direct and indirect carbon risk exposures. All specifications include month fixed effects to absorb aggregate time-varying conditions. Columns (4)–(6) further incorporate an extended set of firm-level control variables commonly used in the literature, allowing us to assess the robustness of the exposure–ICC relationship after accounting for standard determinants of expected returns.

Columns (1) and (4) estimate the effect of total exposure, $\chi + \gamma$, implicitly imposing a common premium for indirect and direct exposure. This restriction serves as a useful benchmark, consistent with our theoretical framework in which both components enter symmetrically. In Column (1), a one-standard-deviation increase in total exposure is associated with a 0.512 percentage-point increase in annualized ICC, significant at the 1% level. After introducing the full set of standard firm-level control variables in Column (4), the coefficient rises to 0.779 percentage points and remains statistically significant at the 5% level. The substantial increase in magnitude suggests that these controls absorb variation correlated with total exposure—such as firm size, valuation ratios, and other characteristics—revealing a stronger underlying relationship between carbon risk exposure and expected returns once conventional determinants of ICC are accounted for.

Columns (2), (3), (5), and (6) relax the equality restriction by estimating the effects of indirect exposure χ and direct exposure γ separately. Across all specifications, the coefficient on indirect exposure 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 annualized ICC. When the full set of standard firm-level controls is included in Column (5), the coefficient on χ remains strong at 1.249 percentage points and highly significant. The magnitude and stability of these estimates across specifications indicate that indirect, network-driven carbon exposure is a primary driver of cross-sectional variation in expected returns.

Direct exposure γ, by contrast, exhibits a much weaker association with ICC. Column (3) reports a small but statistically significant coefficient of 0.126 percentage points, while Column (5) produces an only marginally significant coefficient of 0.163 percentage points after adding standard controls. In Column (6), where indirect exposure and emissions are included jointly, the coefficient on emissions becomes statistically insignificant. These results suggest that a firm's own emissions contain far less information about expected returns than the carbon intensity transmitted through its supply-chain network.

The control variables behave as expected and align with prior findings: smaller firms, higher book-to-market firms, and firms with lower Tobin's Q earn higher ICCs, consistent with Hartzmark and Shue (2022); Eskildsen et al. (2024). Overall, the regression evidence suggests the dominant role of indirect exposure in explaining the carbon risk premium, consistent with the central prediction of our general-equilibrium framework that carbon risk propagates through production networks rather than being driven primarily by firms' own emissions.

The literature usually uses carbon emissions rather than emission intensity (γ) to capture the effects of carbon exposure, leading to mixed results. For example, Bolton and Kacperczyk (2021a) and Atilgan et al. (2024) document that high carbon emissions are associated with higher stock returns, whereas Zhang (2025) and Karolyi et al. (2023) find contrasting evidence, suggesting that high carbon emissions imply lower stock returns. Here, we reexamine the effect of carbon emissions in terms of ICC. Columns 3 and 6 present the results when examining the joint effects of indirect exposure and carbon emissions. Direct exposure is excluded due to the high collinearity between size, emissions, and direct exposure. The findings show that the effect of carbon emissions is small, and the coefficient is comparable to the effect associated with direct exposure, becoming statistically insignificant after including firm fixed effects. In contrast, as shown in column 6, the indirect exposure exhibits a robust and positive effect on ICC, both economically and statistically significant. Besides, the coefficient and t-statistics for indirect carbon risk exposure remain stable when we replacing the direct exposure with carbon emissions, further suggesting that our measure of indirect exposure is nearly conditional orthogonal to the carbon emission channel documented in prior literature.

Fama–MacBeth Regression. While our baseline panel regressions incorporate month fixed effects and a comprehensive set of standard control variables, they may still be sensitive to time–series correlation in the residuals. Such serial dependence can arise from persistent shocks or gradual trends in firms' exposures, potentially biasing standard errors downward and overstating statistical significance. To address this concern, we conduct a robustness analysis using the two–step Fama–MacBeth procedure (Fama and MacBeth, 1973). In this approach, we estimate cross-sectional regressions in each month and then average the coefficients over time, computing standard errors that explicitly adjust for serial correlation. By relying solely on cross-sectional variation at each point in time, the Fama–MacBeth method provides an alternative and complementary perspective on the relationship between carbon risk exposures and ICC, strengthening the robustness of our inference.

Table 5 presents the Fama-MacBeth regression results at the firm level. Column 1 examines the total exposure ($\gamma + \chi$), Column 2 focuses exclusively on the indirect exposure (χ), while Column 3 examines the direct exposure (γ).

In Column 4, we include all control variables commonly documented in the literature that could influence carbon emission disclosure, such as firm size, book-to-market ratio, ROA, leverage, and Tobin's Q. After accounting for these controls, the coefficient for the total exposure ($\chi + \gamma$) increases from 0.613 to 0.813, reflecting nearly a 30% increase in magnitude.

Column 5 examines the effects of direct and indirect exposures by allowing differentiation in the premium. Consistent with the results in Table 4, two key findings emerge. First, indirect carbon risk exposure (χ) consistently dominates direct exposure (γ) to explain the cross-sectional variation in ICC. Specifically, a one standard deviation increase in indirect exposure is associated with a 1.29% annual increase in ICC. Second, the coefficient for direct carbon risk exposure (γ) is smaller and less significant, highlighting the limited role of direct exposure.

Column 6 replaces direct exposure (γ) with carbon emissions, a measure commonly used in the literature Bolton and Kacperczyk (2021a) and Aswani et al. (2024b). The coefficient for carbon emissions is nearly zero and insignificant both statistically and economically, consistent with previous findings that the effect of emissions is highly fragile. In contrast, the coefficient and t-statistics associated with indirect exposure (χ) remain stable, further confirming that indirect exposure arising from network effects is conditionally orthogonal to the carbon emission channel.

4.3 Within vs Across Industry Decomposition

In our theoretical and empirical construction, the indirect exposure captures the risk exposure to the trading partners through the input and output linkage, thus, a large variation in the indirect exposure should be attributed to the cross-industry rather than the within-industry variation. Our previous analysis in the panel regression including the industry-fixed effect obscures the relative contribution to the premium arising from the within- and between-industry component. This subsection takes a two-step regression. In the first step, we consider the following specification:

$$Exposure_{ijt} = \alpha + Industry\ FE_j + \varepsilon_{ijt} \tag{28}$$

where the $Exposure_{ijt}$ represents the direct or indirect exposure of firm i in industry j at period t. This fixed effect regression allows us to separate a firm's exposure into two components: cross-industry, captured by the term associated with *Industry FE*, and within-industry component captured by the estimated residual. Specifically, we take the following decomposition for the indirect exposure

$$\chi_{ijt} = Cross\text{-}industry_{\chi,jt} + Within\text{-}industry_{\chi,it} = \tilde{\chi}_{jt} + \tilde{\chi}_{it} \tag{29}$$

and similar decomposition for the direct exposure,

$$\gamma_{ijt} = Cross\text{-}industry_{\gamma,jt} + Within\text{-}industry_{\gamma,it} = \tilde{\gamma}_{jt} + \tilde{\gamma}_{it} \tag{30}$$

We then consider the following regression:

$$y_{ijt} = \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} + \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \tag{31}$$

where $\beta_{\chi,within}$ and $\beta_{\chi,cross}$ capture the premium associated with the indirect exposure (χ) attributed to within-industry and cross-industry components, respectively. Similarly, $\beta_{\gamma,within}$ and $\beta_{\gamma,cross}$ reflect the premium associated with the direct exposure (γ) attributed to within-industry and cross-industry components. $\boldsymbol{X}_{it}$ includes a set of standard control variables.

Table 6 presents our main results for the risk premium with within- and cross-industry decomposition. Panel A shows the results without including standard control variables, while Panel B includes standard control variables. Panels A and B reveal an interestingly contrasting pattern in the effects of within- and cross-industry components for direct and indirect exposures. Specifically, we find that an increase of one unit in the inter-industry component of indirect exposure is associated with a 5.45% increase in ICC, which is greater than the effect of the inter-industry component. In contrast, the premium for direct exposure primarily arises from the within-industry component rather than the cross-industry component.

The magnitude of β associated with the components within and between industries can reveal the relative variation of each component. For example, the cross-industry variation for indirect exposure dominates the within-industry variation, whereas for direct exposure, the opposite holds true, with within-industry variation being the primary driver.

Panel C accounts for differences in the variation of the four components, which are combinations of cross- and within-industry with indirect and direct carbon risk exposures. Specifically, for each component, we calculate the variation adjusted β to capture the effect of a one-standard deviation increase, which is given by $\beta \times$ *STD(component)*, where β represents the coefficient of each component in the regression (31) and *STD(component)* is the standard deviation of each component. To evaluate the relative importance of each component, we normalize the variation-adjusted β. For example, for $\tilde{\chi}_{jt}$, we compute its relative importance as:

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

This normalization allows us to assess the proportional contribution of each component to the total premium, accounting for differences in variation across components.

The first row of Panel C presents the relative importance of variation-adjusted β. Two key findings emerge: First, indirect exposure (χ) is the dominant contributor to the premium, accounting for nearly 85.4% (= 66.98% + 18.40%), while direct exposure (γ) contributes only approximately 14.6% (= 3.30% + 11.32%). Second, within indirect exposure (χ), the cross-industry effect dominates the within-industry effect (66.98% vs. 18.40%). In striking contrast, for direct exposure (γ), the within-industry effect significantly outweighs the cross-industry effect (11.32% vs. 3.3%). These findings highlight the striking differential roles of cross- and within-industry components in explaining the risk premium associated with indirect and direct carbon exposures.

We further examine the incremental contribution of each component to the R-squre. Specifically, we start from a regression only with standard control variables as in Equation (31). we then incrementally include $\tilde{\chi}_{jt}$, $\tilde{\gamma}_{jt}$, $\tilde{\chi}_{it}$, and$\tilde{\gamma}_{it}$ into the regression specified in Equation (31), 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 second row in Panel C presents the relative importance of incremental R^2. Consistent with the findings from variation-adjusted β, the results reveal a clear and consistent pattern: the effect of indirect exposure is predominantly driven by the cross-industry component, while the effect of direct exposure is primarily attributed to the within-industry component. Furthermore, indirect exposure substantially dominates the total contribution to the premium.

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 to address concerns regarding the inclusion order is to independently include each of the four components in Equation (31) in the regression and calculate their respective incremental R^2 relative to a baseline regression that only includes standard control variables. We then compute the relative importance of each component by scaling its incremental R^2 by the sum of the four incremental R^2 values. The third row in Panel C presents the results.

In summary, our findings highlight two key insights. First, the effect of indirect exposure significantly dominates the contribution to the total premium. Second, the sources of the premium differ between indirect and direct exposures. For indirect exposure, its effect on the premium primarily arises from the cross-industry component. In contrast, for direct exposure, its effect is predominantly driven by the within-industry component.

4.4 Testing Additional Model Predictions

We finally empirically test the model predictions in Section 2.3 . 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 4, 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

This subsection discusses the robustness of our main results and alternative setups. We start by analyzing ICC across industries using both value-weighted and equal-weighted approaches, ensuring our results capture variations in industry weighting methods. We then explore the relationship between carbon risk exposure and expected stock returns, extending our Cobb-Douglas production technology to a general CES specification and considering various lag times to adjust for reporting delays in financial and emissions data. Our robustness tests are further strengthened by including different measures of carbon emissions (Scope 1, 2, and 3) and revenue growth as control variables. Additionally, we assess the consistency of the carbon premium over different time periods and in sub-samples excluding low-emission sectors like high-tech. These robustness checks confirm the validity of our empirical results and their alignment with our theoretical predictions.

Robustness Results on ICC. Table OB.6 in the Appendix examines different specifications to test the effect of total exposure on the premium. Consistent with our theoretical predictions, we find that firms with high total exposure consistently deliver high ICC, even after controlling for firm and month fixed effects.

At the industry level, Tables OB.7 and OB.8 show consistent results. Table OB.7 presents findings where the industry ICC is constructed as the value-weighted ICC of firms within the industry, while Table OB.8 uses equal weights. In both cases, industries with high total exposure deliver higher ICC.

Tables OB.9 and OB.10 examine the premium for direct and indirect exposure at the industry level. Table OB.9 reports results using value-weighted ICC, and Table OB.10 reports results with equal weights. Across all setups, indirect exposure consistently contributes more significantly to the premium than direct exposure.

Results with General CES Specification. As discussed in Section 2.1 and detailed in Appendix A.1, we relax the Cobb–Douglas specification 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 appear in (A.15). We then construct the empirical analogues $\widehat{\gamma}_j^{\theta}$ and $\widehat{\chi}_j^{\theta}$ for θ ranging from 0.75 to 1.5.[12] Next, we re-estimate the baseline regression (27), replacing $\{\widehat{\chi}_j^{1}\}$ with $\{\widehat{\chi}_j^{\theta}\}$.[13] Across all values of θ, the coefficient on indirect exposure remains statistically significant and quantitatively similar, confirming the robustness of our main finding that indirect carbon exposure is a key driver of cross-sectional variation in expected returns.

Figure 5 plots the estimated coefficients on the composite exposure term $\widehat{\chi}_j^{\theta} + \widehat{\gamma}_j^{\theta}$ for varying values of θ. Blue markers denote the point estimates of $\beta_{\chi+\gamma}$, and shaded gray bands indicate the 95% confi-

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[12] 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 the substitution elasticity between intermediate inputs vary substantially: using annual data, Carvalho et al. (2021) report $\theta \approx 1.18$ across narrowly defined industries; Boehm et al. (2019) find $\theta \in [0.2, 0.62]$ at quarterly frequency; and Peter et al. (2023) document $\theta \in [4.7, 8]$ over multi-year aggregates. Centering our range on 1 ensures relevance across monthly and annual horizons.

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

dence intervals. Across the entire range of θ, $\beta_{\chi+\gamma}$ remains statistically significant and economically significant, confirming the robustness of the relationship between the total carbon exposure of firms and their implied cost of capital, regardless of the assumptions of input substitutability.

To further disentangle the effect of indirect and direct carbon risks, Figure OA.7 and Figure OA.8 examine the estimated coefficients on $\widehat{\chi}_j^{\theta}$ and $\widehat{\gamma}_j^{\theta}$, respectively, using equation (27). In Figure OA.7, the coefficient β_{χ} remains statistically significant and economically meaningful for all values of θ, and the premium associated with the indirect exposure displays an inverted-U relationship.[14] Figure OA.8 shows the effect of direct carbon intensity (β_{γ}), by contrast, displaying a U relationship. The estimated coefficient is much smaller compared to that of the indirect exposure, consistent with our estimation in the Cobb-Douglas setup.

Robustness Results on Stock Returns. Prior literature (Hong et al., 2019; Larcker and Watts, 2020; Giglio et al., 2021; Ilhan et al., 2021; Pástor et al., 2022; Lioui and Misra, 2023; Gasparini, 2023; Chen et al., 2023; Lontzek et al., 2023; Karolyi et al., 2023; Zhang, 2025; Giglio et al., 2025) documents mixed findings regarding the premium associated with expected returns ,with some studies defining this premium as the realized return spread between high- and low-carbon emission portfolios over different time periods. Table OB.11 presents firm-level results on the effect of total, direct, and indirect exposure on stock returns. Following Zhang (2025), we account for the typical 10-month lag in carbon emission disclosure relative to financial disclosure to avoid information leakage. Columns 1-6 show that firms with high total exposure consistently deliver higher expected returns, with a one-unit increase in total exposure resulting in approximately a 0.21% monthly return, an equivalent 2.6 percent of annual return. Column 7 examines the direct and indirect components, confirming that indirect exposure dominates direct exposure in driving the premium, consistent with ICC results.

Table OB.12 tests robustness by including various measures of carbon emissions (e.g., logarithm of emissions, Scope 1, Scope 2, and Scope 3 emissions) as control variables (see Appendix B for details on the definition of "Scope 1","Scope 2", and "Scope 3" emissions), following Aswani et al. (2024b) and Atilgan et al. (2024). Results remain robust, indicating that our measure of carbon risk exposure is almost conditionally orthogonal to the channels documented in previous literature (Pástor et al., 2022; Bolton and Kacperczyk, 2021a,b, 2023; D'Amico et al., 2023; Zhang, 2025). Additionally, Table OB.13 incorporates multiple measures of sales or revenue growth, with no substantial changes to our findings.

Table OB.15 explores robustness by examining returns with different lags, including 6, 12, 18, 24, and 36 months after the fiscal year-end. Our results remain consistent and statistically significant, except for the 36-month lag. We also consider a dynamic approach where returns are measured monthly between two emission disclosures; findings on premiums remain robust.

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[14] The inverted-U relationship can be understood through two limiting cases. First, when the production function is Leontief ($\theta = 0$), firms cannot adjust input quantities in response to tax shocks. This rigidity increases variation in χ, resulting in smaller coefficients. Second, when the production function is linear ($\theta = \infty$), firms concentrate input demand in a single sector that earns unbounded profits, while all other sectors earn none. This extreme specialization leads to large dispersion in χ, again producing small coefficients.

Table OB.16 investigates subsamples using stock returns as a proxy for the premium. Consistent with Zhang (2025), we find that the positive premium disappears for the post-2015 subsample, aligning with arguments by Pástor et al. (2022) that realized returns diverge from expected returns in recent periods. Columns 5 and 6 exclude high-tech firms, which are known to under-report carbon emissions (Giglio et al., 2021; Iovino et al., 2021; Downar et al., 2021; Edmans et al., 2022; Bolton et al., 2023; De Angelis et al., 2023). The results remain robust, confirming that the findings are not driven by under-reporting biases.

Concluding Remarks on Robustness. The robustness tests validate the consistency of our findings across various specifications, datasets, and methodologies. Notably, the dominance of indirect exposure in driving the premium is a robust phenomenon, observable across ICC and realized stock returns. Moreover, the distinction between cross-industry and within-industry components of indirect and direct exposures further highlights the nuanced ways in which carbon risk is priced in financial markets. These results reinforce the credibility and generalizability of our findings, providing a solid foundation for future research on carbon risk and its implications for asset pricing.

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

Leveraging the advanced textual analysis capabilities of large language models, we design a prompt instructing ChatGPT-3.5 to analyze the titles and abstracts of **Wall Street Journal** articles. The model is tasked with determining whether the news indicates that carbon emission regulatory risk is "going up," "going down," or "unknown." This procedure follows similar prompt methodologies adopted in recent studies by Bybee (2023); Chen et al. (2023); Cong et al. (2024). 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 using an AR(1) process:

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

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 level 1%, 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-3.5 as indicating regulatory risk on carbon emissions "going down," "going up," and "unknown." Table OB.19 in the Appendix presents these examples. A quick manual review of the titles and abstracts suggests that ChatGPT-3.5 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:

$$y_{it} = \alpha + \beta_{\text{CRS}} \times \text{CRS}_t + \beta_{\text{CRS},\chi} \times \chi_{it} \times \text{CRS}_t + \beta_{\text{CRS},\gamma} \times \gamma_{it} \times \text{CRS}_t + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \quad (32)$$

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 the stock return, change in revenue, change in investment, and change in net income. For the stock return, our observation is month-firm level, while for the firm performance and activties including change in revenue, investment and net income are year-firm level analysis.

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

Following the asset-pricing tradition established by Jagannathan and Wang (1996), we assess whether our carbon-risk exposure measures help explain the cross-section of expected returns. We begin by forming portfolios sorted on firms' direct (γ) and indirect (χ) carbon-risk exposures and examine whether augmenting the traditional CAPM with carbon-related factors improves the model's explanatory power. This exercise provides a transparent, model-free way to evaluate whether carbon-risk exposures are systematically linked to return differences that the market factor alone fails to capture.

At the beginning of each month, we independently sort all stocks into quintiles based on their current γ and χ exposures, forming a 5×5 set of portfolios. These portfolios are rebalanced monthly following the updated exposure estimates. We compute the time-series average realized returns for the 25 portfolios. To construct the γ and χ factors, each month we take the return spread between the highest and lowest exposure quintiles, consistent with standard factor-portfolio construction. Using these factors, we estimate two models—the CAPM and an extended specification that augments the market factor with the γ and χ factors—and obtain model-implied expected returns for each of the 25 portfolios. Figure 6 plots realized portfolio returns against model-predicted returns, allowing us to visually assess each model's ability to account for cross-sectional variation.

The results show a clear improvement when the γ and χ factors are incorporated. Relative to the CAPM, the extended model produces fitted returns that lie much closer to the 45-degree line, indicating substantially stronger explanatory power. Portfolios with high carbon-risk exposures are systematically mispriced under the CAPM but are well captured once carbon-related factors are included. These patterns demonstrate that carbon-risk exposure contains priced information beyond the market factor and that our γ and χ measures help explain economically meaningful differences in portfolio returns.

7. CONCLUSION

In this paper, we develop a tractable two-period general equilibrium model that incorporates input-output linkages, carbon emissions, and aggregate regulatory risks. We revisit the carbon risk premium and demonstrate that it is captured by two key components: direct carbon risk exposure and indirect carbon risk exposure.

This framework provides a basis for empirically measuring direct and indirect carbon risk exposures. Based on the model, we empirically measure these components and demonstrate that the indirect effect accounts for most of the cross-sectional variation in firms' stock returns, capturing variations beyond any direct measure of firms' carbon emissions.

Our framework is not limited to studying carbon regulatory risks. It can potentially be generalized to other scenarios. For instance, future changes in consumer preferences towards "green" firms or an increased probability of climate disasters could cause revenue losses for "brown" firms compared to "green" firms. We leave the exploration of these directions to future research.

References

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The environment and directed technical change. *American economic review 102*(1), 131–166.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic risk and stability in financial networks. *American Economic Review 105*(2), 564–608.

Ahern, K. R. (2013). Network centrality and the cross section of stock returns. *Available at SSRN 2197370*.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024a). Are carbon emissions associated with stock returns? *Review of Finance 28*(1), 75–106.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024b). Are carbon emissions associated with stock returns? *Review of Finance 28*(1), 75–106.

Atilgan, Y., K. O. Demirtas, A. Edmans, and A. D. Gunaydin (2024). Does the carbon premium reflect risk or mispricing? *FEB-RN Research Paper* (03).

Baker, M., D. Bergstresser, G. Serafeim, and J. Wurgler (2022). The pricing and ownership of us green bonds. *Annual review of financial economics 14*(1), 415–437.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake. *Review of Economics and Statistics 101*(1), 60–75.

Bolton, P. and M. Kacperczyk (2021a). Do investors care about carbon risk? *Journal of financial economics 142*(2), 517–549.

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *The Journal of Finance 78*(6), 3677–3754.

Bolton, P. and M. T. Kacperczyk (2021b). Carbon disclosure and the cost of capital. *Available at SSRN 3755613*.

Bolton, P., M. T. Kacperczyk, and M. Wiedemann (2023). The co2 question: Technical progress and the climate crisis. *Available at SSRN 4212567*.

Broccardo, E., O. Hart, and L. Zingales (2022). Exit versus voice. *Journal of Political Economy 130*(12), 3101–3145.

Busch, T., M. Johnson, and T. Pioch (2022). Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology 26*(1), 350–363.

Bybee, J. L. (2023). The ghost in the machine: Generating beliefs with large language models. *arXiv preprint arXiv:2305.02823*.

Carvalho, V. and X. Gabaix (2013). The great diversification and its undoing. *American Economic Review 103*(5), 1697–1727.

Carvalho, V. M. (2010). Aggregate fluctuations and the network structure of intersectoral trade.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Chen, J., G. Tang, G. Zhou, and W. Zhu (2023). Chatgpt, stock market predictability and links to the macroeconomy. *Available at SSRN 4660148*.

Chen, X., L. Garlappi, and A. Lazrak (2023). Responsible consumption, demand elasticity, and the green premium. Technical report, Working Paper.

Cong, L. W., T. Liang, X. Zhang, and W. Zhu (2024). Textual factors: A scalable, interpretable, and data-driven approach to analyzing unstructured information. Technical report, National Bureau of Economic Research.

Cong, L. W., Y. Lu, H. Shi, and W. Zhu (2024). Automation-induced innovation shift. *Available at SSRN 5049949*.

Cullen, J. A. and E. T. Mansur (2017). Inferring carbon abatement costs in electricity markets: A revealed preference approach using the shale revolution. *American Economic Journal: Economic Policy 9*(3), 106–133.

D'Amico, S., J. Klausmann, and N. A. Pancost (2023). The benchmark greenium. *Available at SSRN 4128109*.

De Angelis, T., P. Tankov, and O. D. Zerbib (2023). Climate impact investing. *Management Science 69*(12), 7669–7692.

Downar, B., J. Ernstberger, S. Reichelstein, S. Schwenen, and A. Zaklan (2021). The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies 26*(3), 1137–1175.

Edmans, A., D. Levit, and J. Schneemeier (2022). *Socially responsible divestment*. Centre for Economic Policy Research.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020). Hedging climate change news. *The Review of Financial Studies 33*(3), 1184–1216.

Eskildsen, M., M. Ibert, T. I. Jensen, and L. H. Pedersen (2024). In search of the true greenium. *Available at SSRN*.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy 81*(3), 607–636.

Gasparini, M. (2023). Are financial markets pricing the net zero carbon transition? a reconsideration of the carbon premium. Technical report, Institute for New Economic Thinking at the Oxford Martin School, University . . . .

Giglio, S., B. Kelly, and J. Stroebel (2021). Climate finance. *Annual review of financial economics 13*(1), 15–36.

Giglio, S., M. Maggiori, J. Stroebel, Z. Tan, S. Utkus, and X. Xu (2025). Four facts about esg beliefs and investor portfolios. *Journal of Financial Economics 164*, 103984.

Gofman, M., G. Segal, and Y. Wu (2020). Production networks and stock returns: The role of vertical creative destruction. *The Review of Financial Studies 33*(12), 5856–5905.

Gordon, J. R. and M. J. Gordon (1997). The finite horizon expected return model. *Financial Analysts Journal 53*(3), 52–61.

Gormsen, N. J., K. Huber, and S. Oh (2023). Climate capitalists. *Available at SSRN 4366445*.

Hartzmark, S. M. and K. Shue (2022). Counterproductive sustainable investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

Herskovic, B. (2018). Networks in production: Asset pricing implications. *The Journal of Finance 73*(4), 1785–1818.

Hoberg, G. and G. Phillips (2016). Text-based network industries and endogenous product differentiation. *Journal of political economy 124*(5), 1423–1465.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of econometrics 208*(1), 265–281.

Hou, K., M. A. Van Dijk, and Y. Zhang (2012). The implied cost of capital: A new approach. *Journal of Accounting and Economics 53*(3), 504–526.

Hsu, P.-h., K. Li, and C.-y. Tsou (2023). The pollution premium. *The Journal of Finance 78*(3), 1343–1392.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *The Review of Financial Studies 34*(3), 1540–1571.

Iovino, L., T. Martin, and J. Sauvagnat (2021). Corporate taxation and carbon emissions. *Available at SSRN 3880057*.

Jagannathan, R. and Z. Wang (1996). The conditional capm and the cross-section of expected returns. *The Journal of finance 51*(1), 3–53.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The quarterly journal of economics 112*(1), 169–215.

Karolyi, G. A., Y. Wu, and W. W. Xiong (2023). Understanding the global equity greenium. Technical report, Working paper, Cornell University. Available at.

Larcker, D. F. and E. M. Watts (2020). Where's the greenium? *Journal of Accounting and Economics 69*(2-3), 101312.

Lioui, A. and S. Misra (2023). Carbon pricing confusion: The origin and a simple solution. *Available at SSRN 4613025*.

Lontzek, T., W. Pohl, K. Schmedders, M. Thalhammer, and O. Wilms (2023). Asset pricing with disagreement about climate risks. In *Proceedings of the EUROFIDAI-ESSEC Paris December Finance Meeting*.

Martin, R., M. Muûls, L. B. De Preux, and U. J. Wagner (2014). Industry compensation under relocation risk: A firm-level analysis of the eu emissions trading scheme. *American Economic Review 104*(8), 2482–2508.

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review 109*(6), 1991–2014.

Pasten, E., R. Schoenle, and M. Weber (2017). Price rigidity and the origins of aggregate fluctuations. Technical report, National Bureau of Economic Research.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2021). Sustainable investing in equilibrium. *Journal of Financial Economics 142*(2), 550–571.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2022). Dissecting green returns. *Journal of financial economics 146*(2), 403–424.

Pastor, L., R. F. Stambaugh, and L. A. Taylor (2024). Carbon burden. Technical report, National Bureau of Economic Research.

Peter, A., C. Ruane, et al. (2023). The aggregate importance of intermediate input substitutability. Technical report, National Bureau of Economic Research.

Richmond, R. J. (2019). Trade network centrality and currency risk premia. *The Journal of Finance 74*(3), 1315–1361.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023a). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023b). Pricing climate change exposure. *Management Science 69*(12), 7540–7561.

Shapiro, J. S. and R. Walker (2018). Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade. *American economic review 108*(12), 3814–3854.

Shi, Y., R. Townsend, and W. Zhu (2020). Tiered intermediation in business groups and targeted sme support.

Xiang, W. (2023). Clean growth and environmental policies in the global economy. *Available at SSRN 4619717*.

Yang, Y. and W. Zhu (2020). Networks, business cycles, and asset pricing. *Business Cycles, and Asset Pricing (October 26, 2020)*.

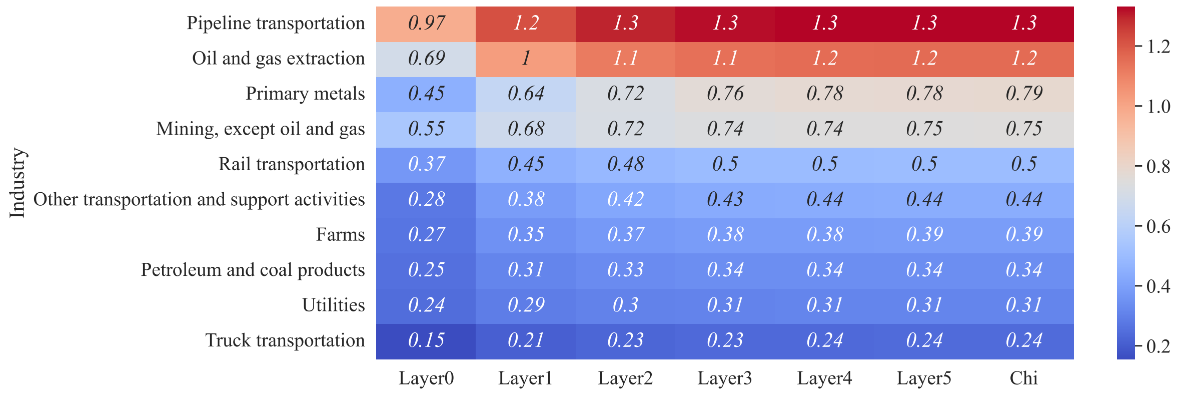
Zerbib, O. D. (2022). A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. *Review of Finance 26*(6), 1345–1388.

Zhang, S. (2025). Carbon returns across the globe. *The Journal of Finance 80*(1), 615–645.

8. FIGURES AND TABLES

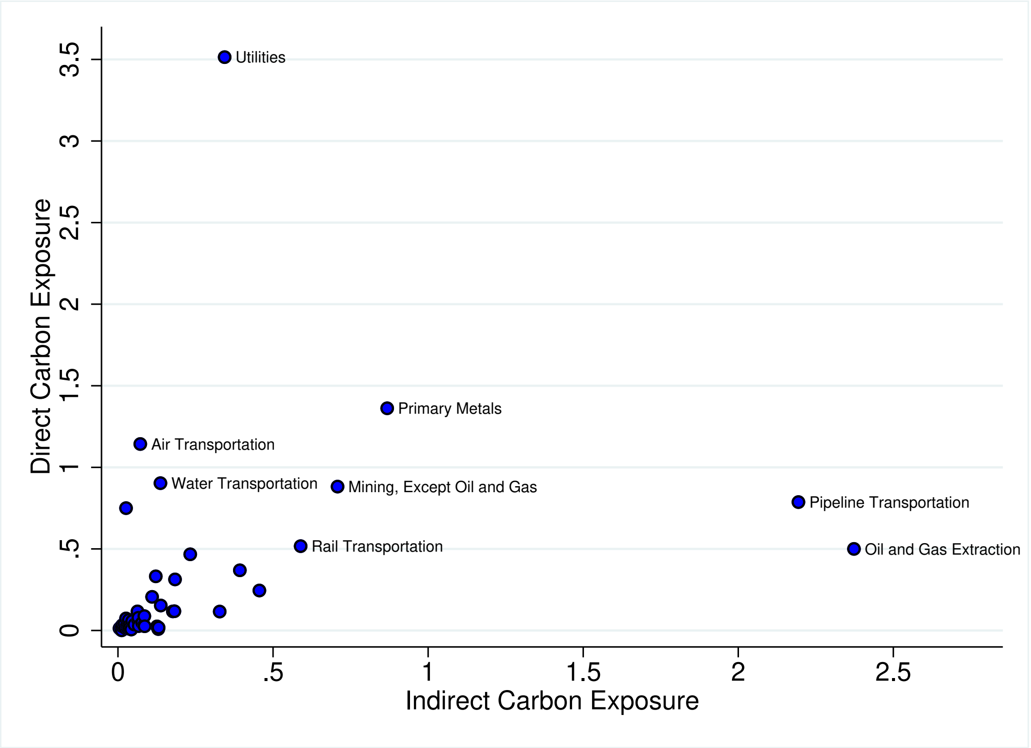
Figure 2: Effect of Network Depth on χ Measurement

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

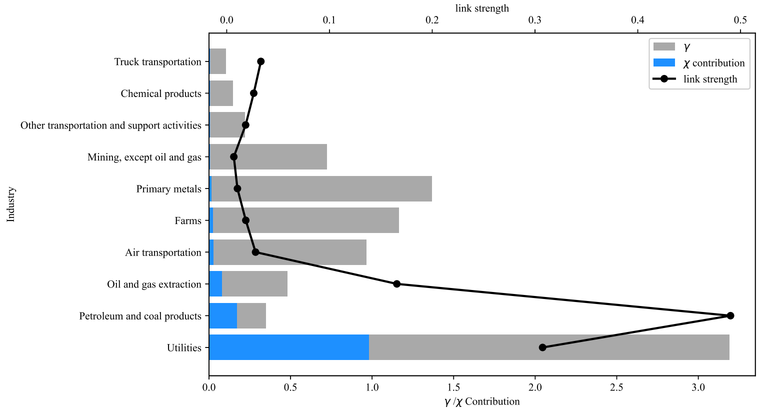


Panel A illustrates how network depth shapes the measurement of indirect carbon exposure (χ). The figure reports the top ten industries ranked by their total χ values. The y-axis lists industries, while the x-axis plots χ computed using networks of increasing depth (layers 0 through 5). Indirect exposure 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

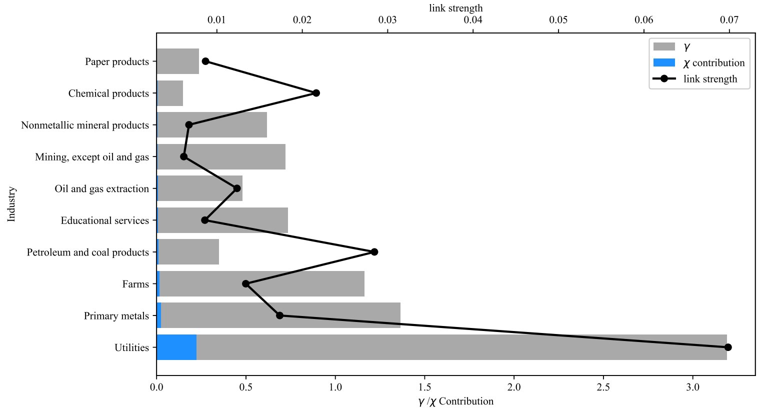
Panel A: Pipeline Transportation

Gamma, Contribution and Share for Different Industries



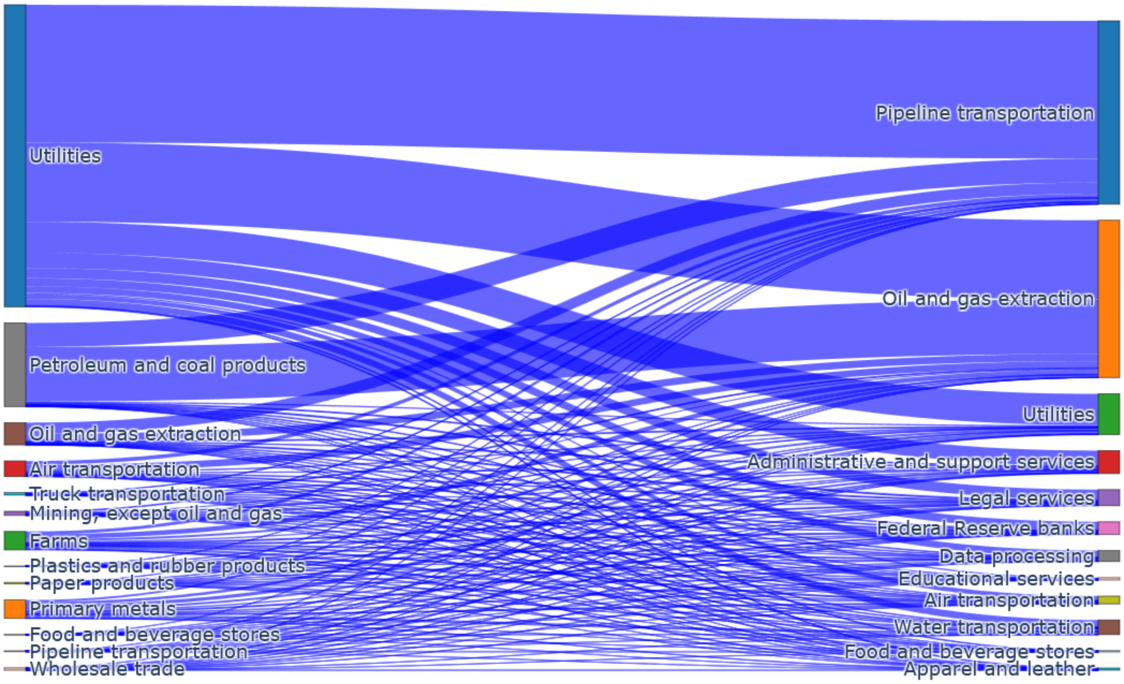
Panel B: Utilities

Gamma, Contribution and Share for Different Industries



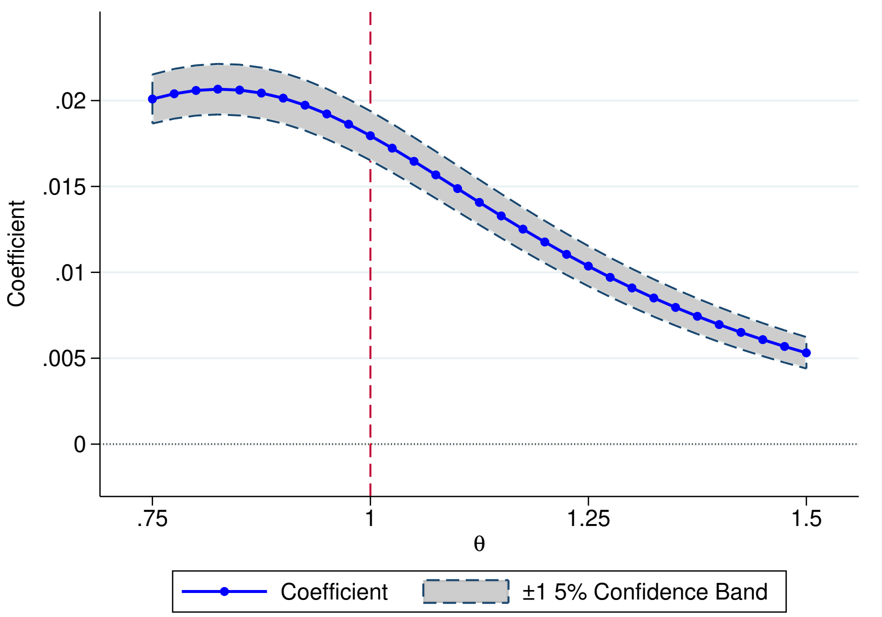
This figure decomposes the sources of an industry's indirect exposure (χ) into its link strength with other sectors and the direct exposure (γ) of those linked industries. The gray bars represent the direct exposure of the linked industries, the black solid line indicates link strength, and the blue 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



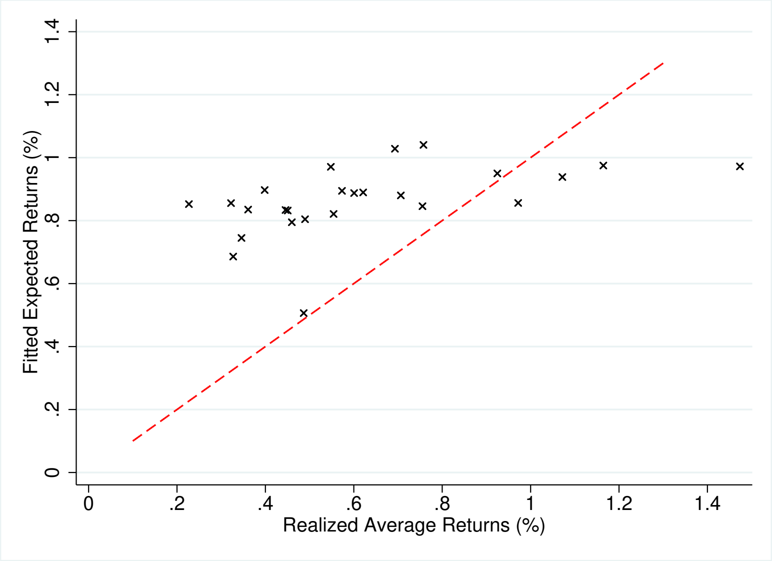
This figure shows the estimated coefficients of $\chi^{\theta} + \gamma$ from the following specification:

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

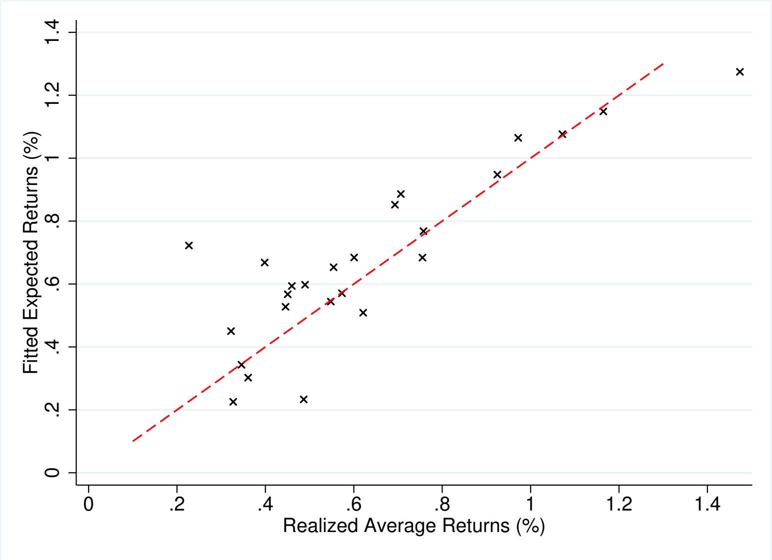
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the indirect carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. The control variables $\boldsymbol{X}_{it}$ 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

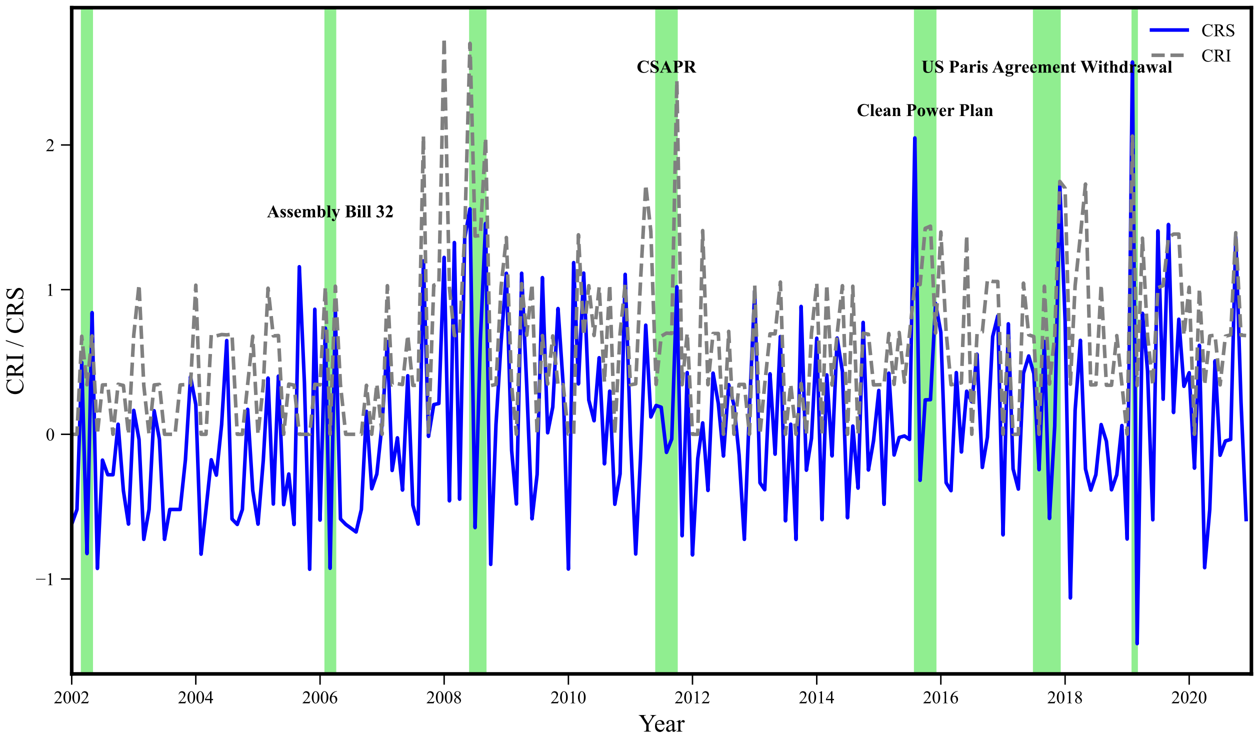


Panel B: Extended CAPM with χ and γ Factors



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 WSJ. The blue solid line represents CRS, while the gray dashed line represents CRI. The CRI, constructed by ChatGPT, is based on the monthly proportion of Wall Street Journal 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 (2021a). 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)
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) *ICC*	(2) *ICC*	(3) *ICC*	(4) *ICC*	(5) *ICC*	(6) *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:

$$\begin{aligned} y_{ijt} &= \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} \\ &\quad + \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \end{aligned} \tag{33}$$

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

Appendix

Carbon Risk in Production Networks

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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

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

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 Leontif 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,

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

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 (13) 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

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

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

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

Where we define $\Phi_\tau = (1-\theta)\Phi_P L V_\gamma - D_S^{-1} L' A' D_\eta D_S V_\gamma$. 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

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

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

We can then calculate the expected return,

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

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

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

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

$$\begin{aligned}
\frac{\widetilde{e}_j}{e_j} &= \frac{\sum_{k=1}^{N} \widetilde{\gamma}_k P_{kt} X_{jkt}}{\gamma_j P_{jt} Y_{jt}} \\
&= \frac{\eta_j \sum_{k=1}^{N} a_{jk} \widetilde{\gamma}_k}{\gamma_j},
\end{aligned} \tag{A.16}$$

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 Emission Intensity and Expected Returns: A Sufficient Condition

This section presents a sufficient condition under which expected returns depend solely on emission intensity. We begin with the following definition:

Definition A.1. *Industries j and k are downstream symmetric if $a_{hj} = a_{hk}$ for all h and $\alpha_j = \alpha_k$.*

That is, downstream-symmetric industries sell to the same set of customers in identical proportions. Recalling equation (A.3), $S_{i0} = \alpha_i + \sum_{k=1}^{N} \eta_j a_{ki} S_{k0}$, it follows that downstream-symmetric industries have identical period-0 Domar weights: $S_{i0} = S_{j0}$.

Proposition A.1. *Suppose that industry i and industry j are downstream symmetric. Then, $\mathbb{E}r_{it} > \mathbb{E}r_{jt}$ if and only if $\gamma_i > \gamma_j$.*

Proposition A.1 characterizes the conditions under which higher carbon emission intensity is associated with higher expected stock returns—that is, when the *carbon risk premium* hypothesis discussed in existing literature holds. While this hypothesis has received considerable empirical attention, the evidence remains mixed. Our framework shows that in the presence of production networks, "brown" firms earn higher expected returns than "green" firms only when the two are downstream symmetric. As we demonstrate in Section 3, this condition is not supported by the data. Heterogeneity in downstream linkages plays a critical role in shaping the cross-section of expected returns.

A.4 Proofs of Lemmas and Propositions

A.4.1 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

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

which is equation (10) in the main text.

A.4.2 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 (13) 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 (14) in the main text.

A.4.3 Proof of Proposition 1

Taking logs on both sides of equation (14) 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 (15) in the main text.

A.4.4 Proof of Prosposition 2

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

revenue. Substituting the first order condition (13) 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:

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

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 (9) and (A.19) into (A.20) we have the following expression:

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

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

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

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 (2021a), 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.

Navigated by our theoretical framework, we focus on "Scope 1" as a measure of direct carbon emissions and its ratio to company revenue to measure carbon emission intensity within the same fiscal year. Zhang (2025) documents that the emission disclosure is usually released by roughly 10 month after th release of the earning report, we follow their approach to make an adjust to make a time match in 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 reduces 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's 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 the annual carbon emission averaged across firms within the year. The box shows the average carbon emission of scope 1 and the read line shows the aveage carbon emission intensity of scope 1 averaged across years. There are two things worth mentioning: first, both the average carbon emission and intensity decline over years due to the selection bias of the sample. At the early stage, only firms with high carbon emission and intensity are included in the sample, and firms with low carbon emission or intensity are covered recently. Second, due to a jump in the firms coverage, there is a significant drop in the carbon emission and intensity in 2016. To mitigate the concern that the empirical results are driven the selection bias of Trucost coverage, we aggregate the carbon emission at the industry level and scaled by the corresponding firm's sale to measure the industry-level carbon emission and intensity.

Figure OA.3 shows the carbon emission intensity of "scope 1" at the BEA industries level averaged across years. There is a large variation in the direct carbon emission intensity between industries from more than 3,500 tons of CO2 per million dollars in the Utilities industry to near 0 emission in Legal Services. The top five industries with highest carbon emission intensity are Utilities, Mining, 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 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 $\mathbf{MAKE}$, 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. Summary statistics for all variables are presented in Table 2.

C. VARIABLE CONSTRUCTION FOR IMPLIED COST OF CAPITAL CALCULATION

To compute the Implied Cost of Capital (ICC) as outlined by Hou et al. (2012), the following steps and dataset definitions are used:

C.1 Step 1: Compute the One-Year Ahead Expected Earnings

The one-year ahead expected earnings are estimated using a cross-sectional regression model. The dependent variable, IB_{t+1}, is the income before extraordinary items at time $t+1$, and the independent variables are as follows:

$$\text{Model:} \quad IB_{t+1} = \alpha + \beta_1\text{AT} + \beta_2\text{DVC} + \beta_3\text{DD} + \beta_4\text{IB} + \beta_5\text{NE} + \beta_6\text{ACCRUAL} + \varepsilon$$

Where:

- IB_{t+1}: Income Before Extraordinary Items at $t+1$
- AT: Total Assets
- DVC: Dividends to Common/Ordinary Shareholders
- DD: Dividend Payout Ratio
- IB: Income Before Extraordinary Items
- NE: Net Equity
- $ACCRUAL$: Accruals

C.2 Step 2: Compute the Implied Cost of Capital (ICC)

Following Gordon and Gordon (FAJ, 1997), the implied cost of capital is derived from the expected earnings and dividend-related variables. Specifically, the formula for the ICC incorporates the assumptions about growth rates and payout ratios.

C.3 Input Dataset

The following dataset is utilized:

- **Compustat Annual:**
  - `IB`: Income Before Extraordinary Items
  - `CEQ`: Common/Ordinary Equity (Total)
  - `AT`: Total Assets

- `DVC`: Dividends to Common/Ordinary Shareholders
- `ACCRUAL`: Calculated as follows:

  $$\text{accrual} = (ACT-L\_ACT)-(CHE-L\_CHE)-(LCT-L\_LCT)+(DLC-L\_DLC)+(TXP-L\_TXP)-DP$$

  For accrual calculations starting from 1988, the cash flow statement method is used (Hribar and Collins, JAR, 2002, Page 109). Specifically:

  accrual = Earnings Before Extraordinary Items and Discontinued Operations (IBC)−(Operating Cash F

  Where:

  - `IBC`: Income Before Extraordinary Items (Cash Flow)
  - `OANCF`: Operating Activities Net Cash Flow
  - `XIDOC`: Extraordinary Items and Discontinued Operations (Cash Flow)
- **Retmonthly**: This dataset includes monthly size data.

C.4 Filter Criteria

- Only include observations where:
  - `exchcd` = 1, `exchcd` = 2, or `exchcd` = 3 (denoting the NYSE, NASDAQ, and AMEX exchanges)
  - `shrcd` = 10 or `shrcd` = 11 (denoting ordinary shares)
- Apply a 3-month lag in financial reporting.

C.5 Data Treatment

- Annually winsorize all level-based financial variables (such as total assets, earnings, dividends, etc.) at the 1st and 99th percentiles to mitigate the impact of extreme outliers.

C.6 Handling Negative ICC Estimates

If the estimated Implied Cost of Capital (ICC) is negative, it is set as missing.

Additionally, the estimated ICC is winsorized annually to ensure robustness and limit the influence of outliers.

Online Appendix

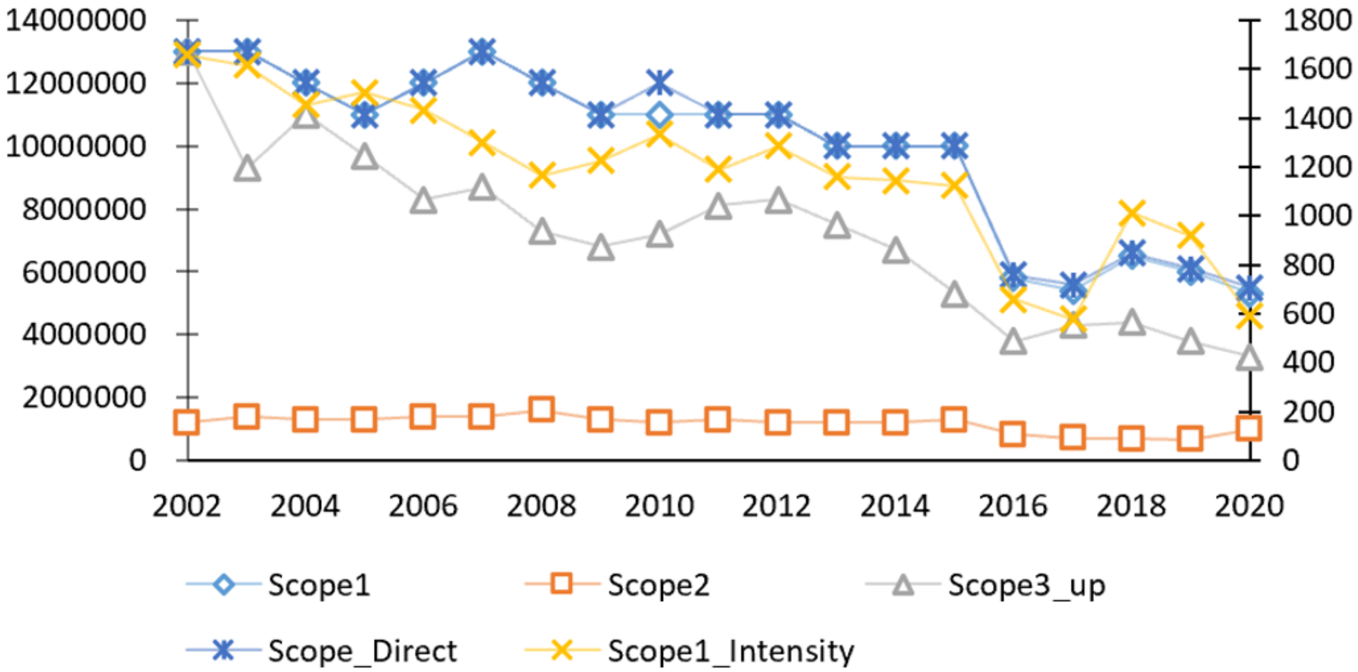
Carbon Risk in Production Networks

Shubo Kou Kai Li Minghao Li Wu Zhu

December 2025

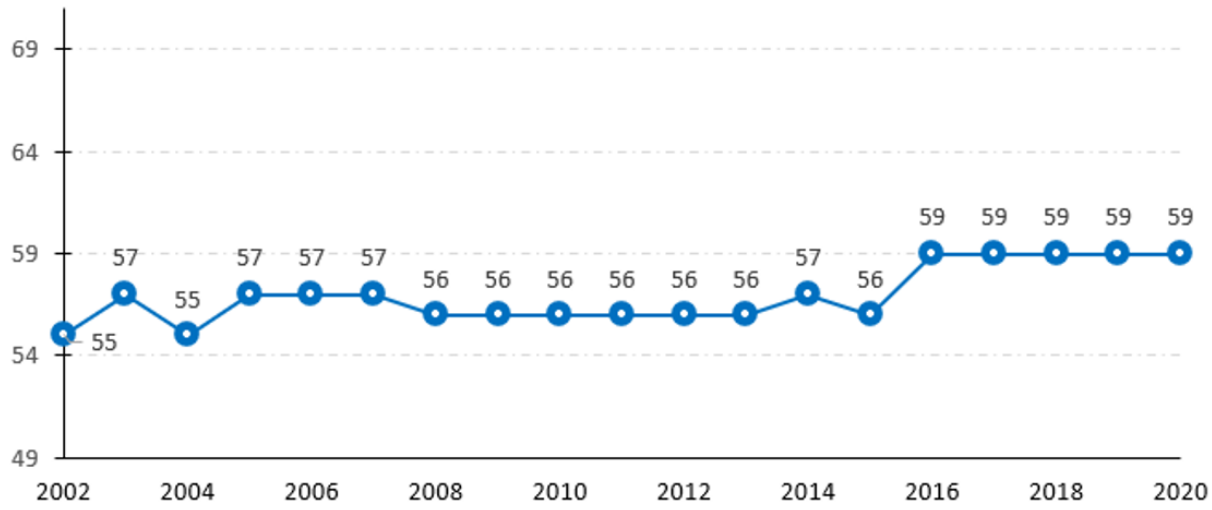
OA. ADDITIONAL FIGURES

Figure OA.1: Carbon Emission and Intensity



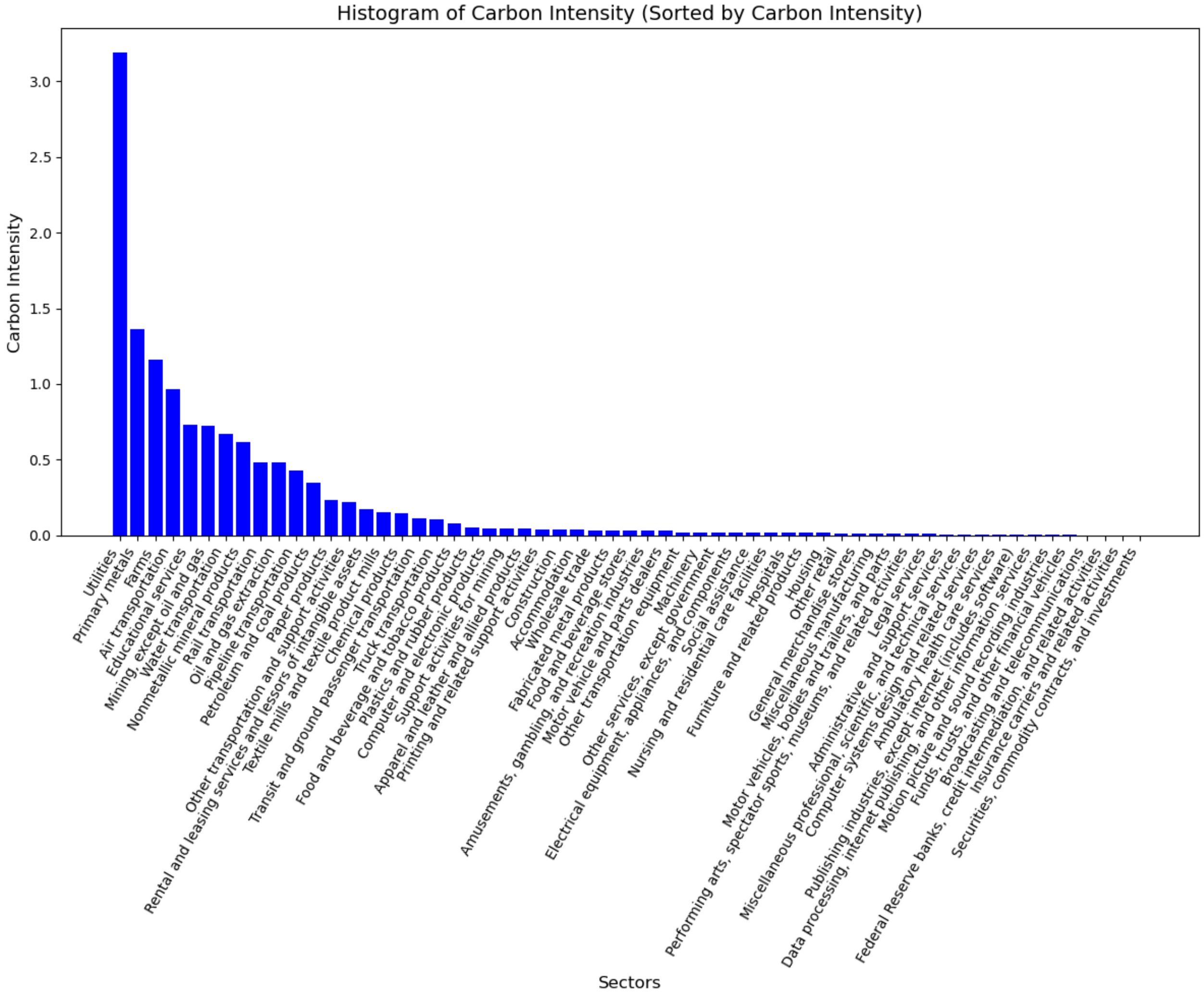
This figure shows the time trend of carbon emission of "scope 1", "scope 2", "scope 3".

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



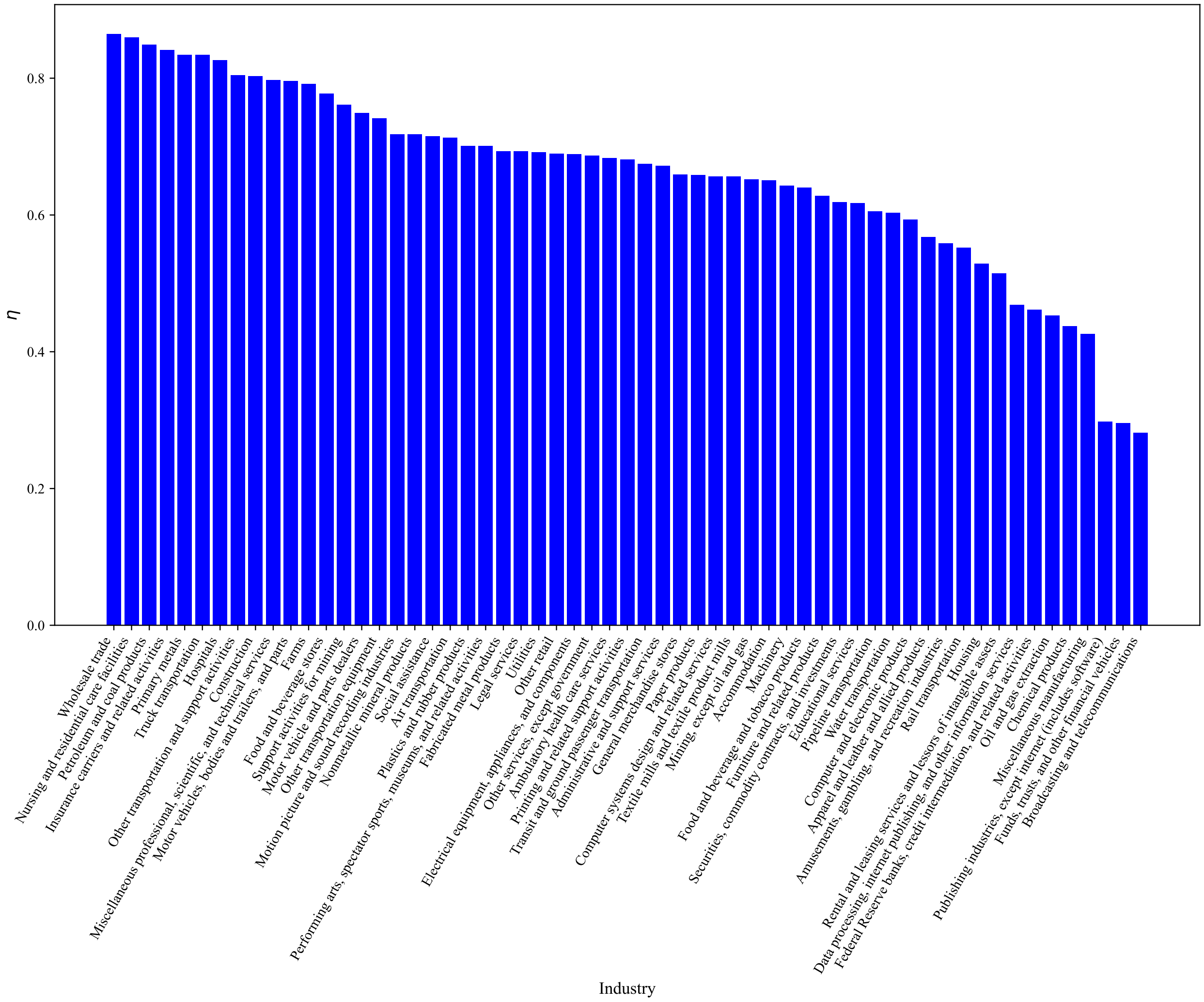
This figure plots the number of BEA industries covered by the samples we analyze each year. As the number of firms covered by Trucost increases, the number of industries is also increasing. However, the variability in the number of industries is small, which does not affect the balance of panel data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

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



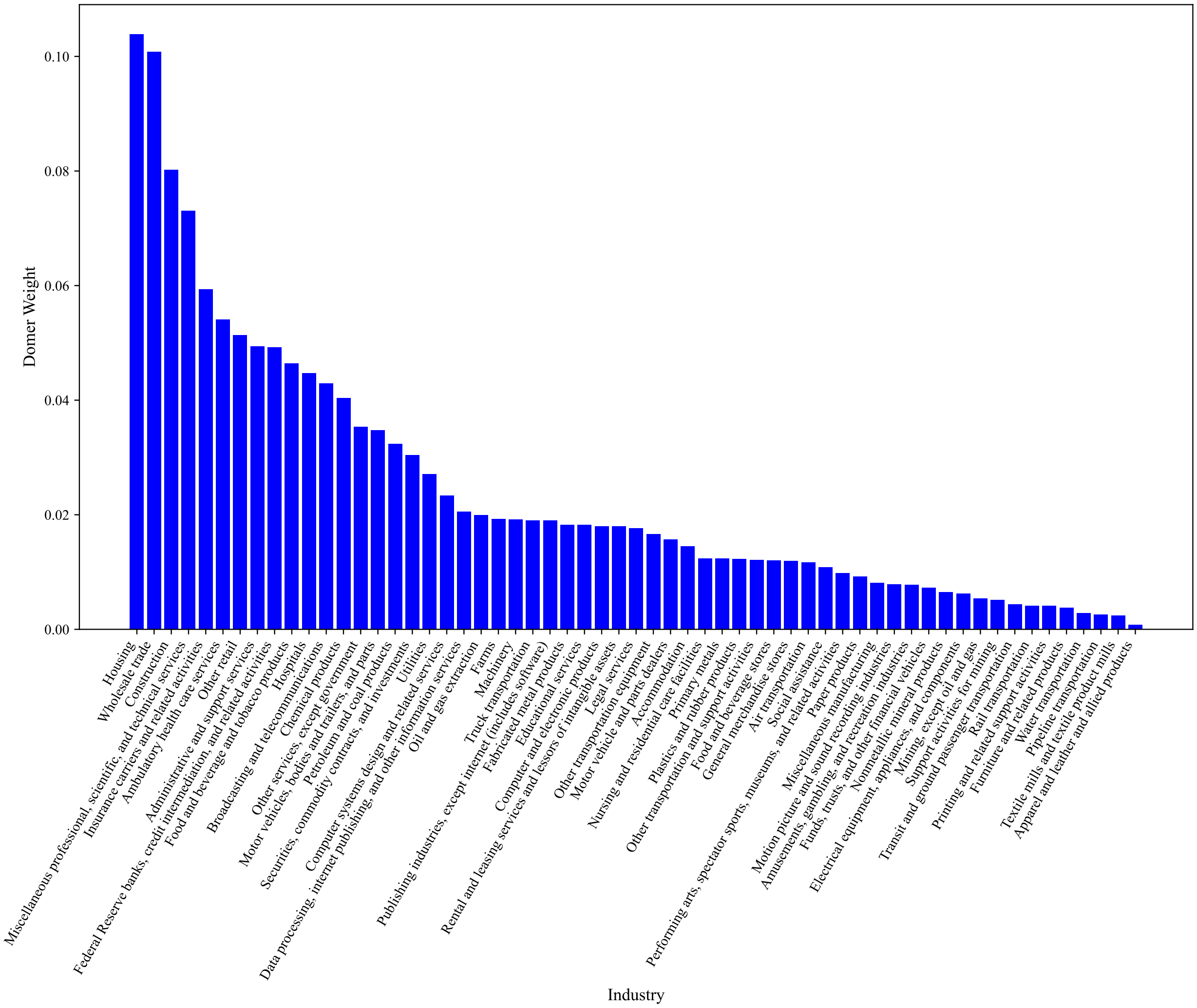
This figure depicts the annual average carbon emission intensity at the BEA industry level.From 2002 to 2020, the industry's average carbon emission intensity is 236.22(tons per million dollars). After data matching, there are an average of 53 industries each year. There are a large variation in the direct carbon emission across industries. The top five industries with highest carbon emssion 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



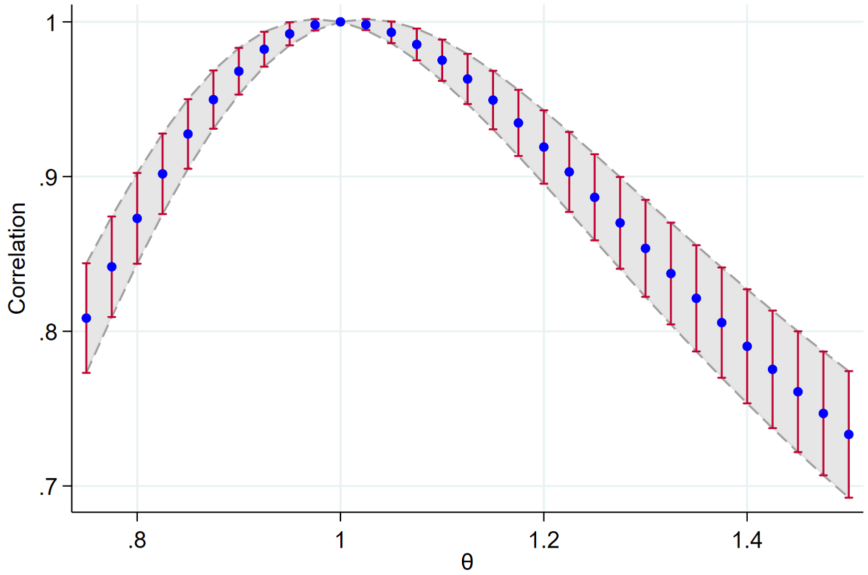
This figure shows the annual average ratio of composite intermediate input, η, at the BEA industry level.

Figure OA.5: The Industrial Domar Weights



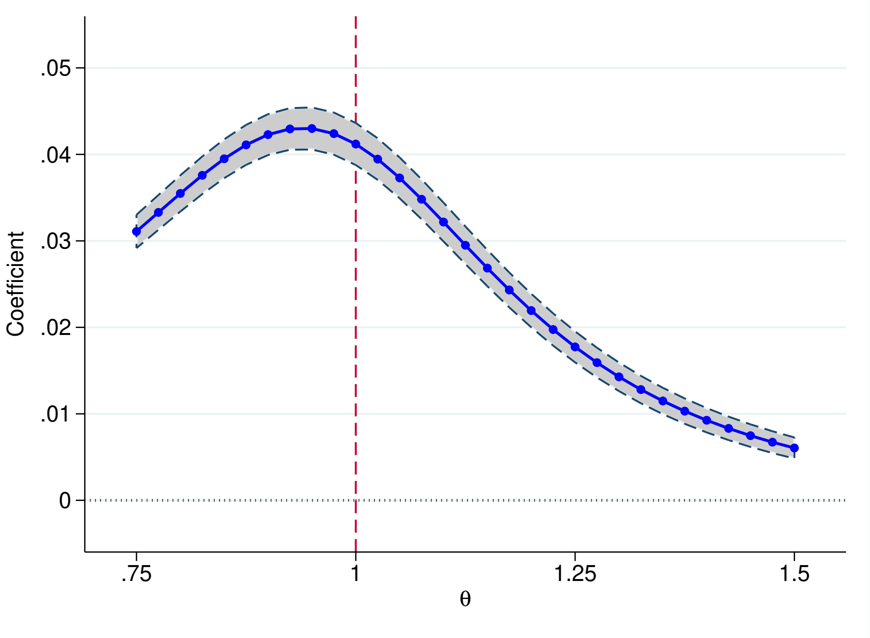
This figure shows the annual Domar weight at the BEA industry level averaged across years from 2002 to 2020. Over the sample period, the top five industries with highest average Domar weight are Housing, Wholesale Trade, Construction,Scientific and Technical Services, and Insurance Services.

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

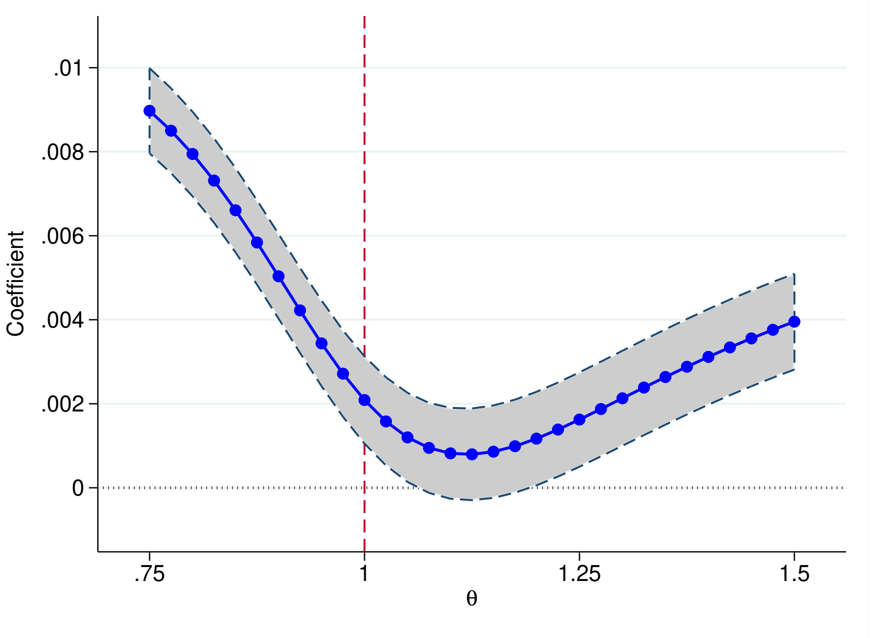


This figure presents the estimated coefficients of χ^{θ} from the following specification:

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

where ICC_{it} denotes the firm's implied cost of capital, χ^{θ}_{it} 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



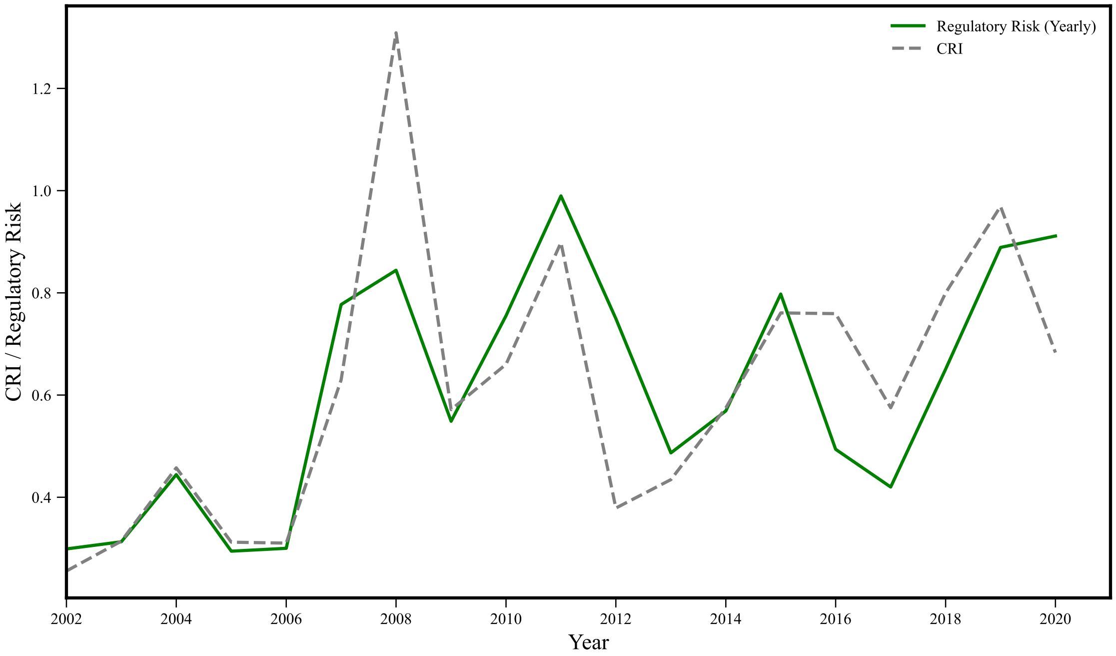
This figure presents the estimated coefficients of γ from the following specification:

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

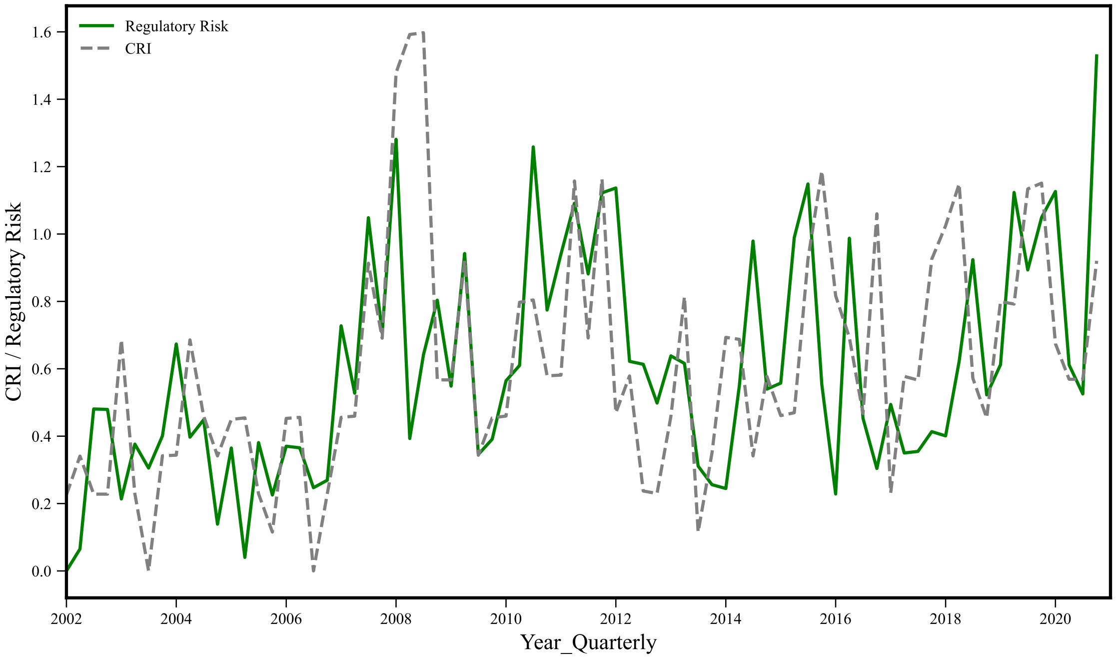
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the indirect carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. The control variables $\boldsymbol{X}_{it}$ 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 csrp)

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 returnse. 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)	(2)	(3)	(4)	(5)	(6)	(7)
	r_{t+10}	r_{t+10}	r_{t+10}	r_{t+10}	r_{t+10}	r_{t+10}	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 $t + 10$.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***	0.244***	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)	(2)	(3)	(4)	(5)
	r_{t+10}	r_{t+10}	r_{t+10}	r_{t+10}	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:

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

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-3.5 (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***