The Network Incidence of Carbon Transition Risk*

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Abstract

Who bears the risk of the carbon transition? We show that production networks drive a wedge between where emissions occur and where transition risk is borne. In a general-equilibrium model, the sensitivity of firm profits to carbon-regulatory shocks is governed by direct carbon intensity γ and network exposure χ. In U.S. data, χ predicts higher expected returns and larger declines in valuations, investment, and earnings when carbon-regulatory risk rises unexpectedly, even controlling for direct and Scope 3 emissions. "Network-brown" firms—low direct emissions but high network exposure—produce less than 2% of Scope 1 emissions yet account for about 27% of the aggregate carbon risk premium. Carbon policy may target emissions where they occur, but its economic consequences are borne much more broadly through production networks.

Keywords: Carbon Transition Risk; Production Networks; Carbon Risk Premium; Asset Pricing; Risk Incidence; Carbon Regulation.

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1. Introduction

Who bears the economic risk associated with the carbon transition? A natural answer is the firms that emit the most carbon. Carbon regulation is imposed on emissions, and high-emission producers are therefore the most visible targets of transition policy. Yet this logic conflates two distinct economic objects: where an externality originates and where the costs and risks of policies designed to address that externality are ultimately borne.

Production networks can create a large wedge between the two. Firms buy from and sell to one another, so a carbon-policy shock to one sector changes the demand faced by its suppliers and, through higher-order production linkages, the cash flows of firms far removed from the original source of emissions. Consider a low-emission firm that supplies inputs to a carbon-intensive customer. When carbon regulation tightens, the customer faces a larger adverse shock and reduces its demand for intermediate inputs. The resulting demand contraction is transmitted upstream to the supplier even though the supplier itself produces little carbon. The same mechanism operates through customers of customers and higher-order production links. Two propagation forces are economically relevant. Because suppliers' sales are derived from downstream production, a contraction by carbon-intensive customers reduces their demand for intermediate inputs and transmits the shock upstream. When inputs are substitutable, carbon shocks also change relative input prices and input choices, creating a cost-push channel from upstream suppliers to downstream users. In our framework, the Cobb–Douglas benchmark isolates the first force, while the constant-elasticity-of-substitution (CES) extension allows both. Thus, emissions identify where carbon is *produced*; production networks help determine where carbon-policy risk is *borne*. This paper asks how production networks redistribute carbon-policy risk across firms, how markets price that exposure ex ante, and where the associated financial and real adjustment occurs ex post.Throughout the paper, by the economic incidence of transition risk we mean both who is compensated ex ante through a higher cost of capital and who absorbs ex-post valuation and real adjustment when regulatory risk rises.

We formalize this mechanism in a tractable general-equilibrium asset-pricing framework with input–output linkages, carbon emissions, and aggregate carbon-regulatory risk. The model delivers a simple characterization. A firm's exposure to the regulatory shock consists of two components: direct exposure γ, which is proportional to its own carbon intensity, and network exposure χ, which aggregates the effects of carbon-intensive downstream demand through all direct and indirect production paths. The cross-sectional ranking of expected returns is governed by the sufficient statistic $\gamma + \chi$. In an economy without production linkages, $\chi = 0$, and own emissions are sufficient to characterize carbon risk. With production networks, however, two firms with identical direct emissions can have very different exposures because they sell to different customers or occupy different positions in the production structure. The model therefore provides a precise sense in which the location of emissions and the incidence of carbon-policy risk become decoupled.

We bring this characterization to the data using firm-level emissions from Trucost, annual input–

output tables from the U.S. Bureau of Economic Analysis, and financial data from CRSP and Compustat. These data allow us to construct empirical counterparts of both γ and χ at the firm and industry levels. Although the model conditions on a predetermined network at a given date, our empirical measure does not impose a time-invariant network: we reconstruct the input–output matrix and χ each year using the corresponding annual BEA table. The measurement therefore incorporates observed evolution in production linkages over time, while abstracting from within-period rewiring caused by the contemporaneous shock. The two measures contain substantially different information: their average cross-sectional correlation is only 0.34. Network exposure is also conceptually different from Scope 3 emissions. Scope 3 is a physical-accounting object: it attributes quantities of emissions along the value chain, but is not designed to capture how relative prices, substitution elasticities, general-equilibrium feedback, or final-demand structure map those emissions into firm cash-flow exposure. By contrast, χ is a general-equilibrium exposure measure derived from the model and is the sufficient statistic for the network component of firms' sensitivity to carbon-policy shocks. Consistent with this distinction, the firm-level correlation between χ and Scope 3 emissions is only 0.11, and controlling for Scope 3 emissions leaves the pricing effect of χ essentially unchanged.

We first study whether network exposure is reflected in the ex-ante cost of capital. Firms in the highest quintile of χ have an annualized implied cost of capital (ICC hereafter) 2.24 percentage points higher than firms in the lowest quintile, whereas sorting on direct exposure alone generates no significant spread. In panel and Fama–MacBeth regressions, a one-standard-deviation increase in χ is associated with roughly a 1.2 percentage-point increase in annualized ICC. The result survives standard firm controls, alternative emissions measures including Scope 3, reporting-lag adjustments, alternative production elasticities, and different sample definitions. Importantly, the relation remains economically and statistically strong under the CES specification, where relative-price and substitution responses allow both downstream-to-upstream demand propagation and upstream-to-downstream cost transmission. A decomposition shows that network exposure provides the dominant variation-adjusted contribution to the pricing results, and most of that contribution comes from cross-industry differences in production-network position. Direct exposure, by contrast, contributes much less and operates primarily through within-industry variation in firms' own emission intensities. These patterns are consistent with the model's central distinction: the direct component is a firm attribute, whereas the network component is fundamentally a relationship between a firm and the rest of the production economy.

We next ask whether the firms priced as more exposed also perform worse when carbon-regulatory risk rises. We construct a Carbon Regulatory Index from *Wall Street Journal* coverage and use innovations in the index to capture unexpected changes in the regulatory-risk environment. Firms with higher χ experience significantly larger declines in contemporaneous stock returns and subsequent revenues, investment, and net income when regulatory risk unexpectedly increases. The corresponding response associated with direct exposure is substantially smaller once network exposure is taken

into account. This evidence provides an independent validation of the mechanism: the firms that require greater ex-ante compensation for carbon risk are also the firms whose market values and real activity are more sensitive when that risk materializes.

The difference between emissions and economic exposure becomes particularly stark when we aggregate these firm-level estimates. Firms with low direct exposure but high network exposure—what we call "network-brown" firms—account for about 20% of aggregate market capitalization and approximately 27% of the aggregate fitted carbon-risk premium. Yet they produce less than 2% of aggregate Scope 1 emissions. Thus, firms responsible for less than 2% of direct emissions bear more than one quarter of priced carbon-transition risk. The asymmetry also appears in ex-post market outcomes: network-brown firms bear a disproportionate share of losses when regulatory risk rises. Separately, the interaction evidence in Section 5 shows that high-χ firms reduce investment more when regulatory risk rises. In a production network, the economic incidence of transition risk can be distributed very differently from the emissions that motivate the policy in the first place.

This wedge does not imply that emissions-based carbon policy is incorrectly targeted. Emissions and risk incidence answer different policy questions. Direct emissions identify the margin relevant for internalizing the carbon externality and therefore remain the natural basis for Pigouvian taxation. Network exposure instead identifies the distribution of the financial and real consequences generated by that policy. It is therefore relevant for climate stress testing, financial-stability surveillance, transition-support and adjustment policies, and distributional analysis. In an economy without input–output linkages, these two objects coincide: the firms that emit carbon are also the firms exposed to policies that penalize those emissions. In a networked economy they need not coincide. The first is governed by γ; the second by $\gamma + \chi$. Our estimates show that the resulting wedge is quantitatively large and that emissions-based exposure measures can substantially understate the breadth of firms and capital affected by the transition.

Although our application is carbon regulation, the economic logic is broader. Whenever an aggregate shock affects sectors heterogeneously and propagates through production relationships, the location of the initial shock need not coincide with the location of its economic incidence. Carbon provides a particularly important setting in which to study this distinction because the source of the externality is directly observable, while the production network determines how the associated transition risk spreads across the economy.

Our analysis makes three main contributions. First, we provide a general-equilibrium characterization of the *incidence of carbon-transition risk through production networks*. The model shows that direct emissions alone are sufficient for measuring exposure only in the absence of economically meaningful production linkages. With such linkages, firm-level exposure is summarized by the sum of direct carbon intensity, γ, and network exposure, χ. This result links the production-network literature to a first-order question in climate economics: why the firms bearing transition risk need not be the firms generating the underlying emissions.

Second, we distinguish *emissions accounting from economic exposure*. Existing measures such as Scope 1 and Scope 3 attribute physical emissions to firms or value chains. Our χ instead measures the equilibrium sensitivity of firm cash flows to carbon-policy risk transmitted through production relationships. Empirically, this distinction is economically consequential: χ contains substantial pricing information beyond direct and Scope 3 emissions and helps explain why estimates of the carbon premium based only on firms' own emissions can be unstable or incomplete.

Third, we quantify the *aggregate financial incidence* of the carbon transition. The striking fact is not simply that network exposure is priced, but that its distribution is very different from the distribution of emissions. Network-brown firms generate less than 2% of Scope 1 emissions yet account for roughly 27% of the aggregate fitted carbon-risk premium, and these firms also experience substantial market revaluations when regulatory risk rises. This evidence shows that production networks can relocate the economic incidence of environmental policy well beyond the firms directly responsible for the externality.

Related Literature. Carbon risk and the cross-section of returns. Our paper first relates to the literature on carbon risk and asset prices. Bolton and Kacperczyk (2021, 2023); Hsu et al. (2023); Atilgan et al. (2024); Lioui and Misra (2023) study whether carbon-intensive firms command higher returns, while Pástor et al. (2022); Zhang (2025); Eskildsen et al. (2024) emphasize the distinction between realized green returns and ex-ante risk compensation. This literature largely measures carbon exposure using firms' own emissions. We show that this misses an economically important component of exposure arising from production relationships. Incorporating network exposure helps explain why direct-emissions measures alone provide an incomplete characterization of the carbon premium.

Production networks and asset pricing. Second, Ahern (2013); Herskovic (2018); Richmond (2019); Gofman et al. (2020); Yang and Zhu (2020) study how network position shapes risk premia in equity and currency markets. This literature builds on work establishing production linkages as a mechanism for shock propagation and aggregate fluctuations (Carvalho, 2010; Acemoglu et al., 2012; Carvalho and Gabaix, 2013). Empirical evidence documents effects on firms' operating outcomes and market values (Barrot and Sauvagnat, 2016; Carvalho et al., 2021), while related research examines financial-shock amplification (Bigio and La'O, 2020; Huremović et al., 2026), default contagion (Jacobson and von Schedvin, 2015; Acemoglu et al., 2015), and investment networks (vom Lehn and Winberry, 2022). We bring these insights to carbon-regulatory risk by characterizing how emission intensity and network position jointly shape cross-sectional differences in proportional profit responses and expected returns. This distinction connects the location of emissions to the broader financial incidence of carbon regulation.

Supply-chain exposure to carbon risk. Third, our paper relates to work emphasizing climate exposure beyond firms' own emissions. Sautner et al. (2023b) and De Angelis et al. (2023) study climate

exposure through supply chains and financial networks, while Aghion et al. (2025) analyzes green technology adoption along supply chains. Pastor et al. (2024) construct the "carbon burden," a present-value measure of the social cost associated with corporate emissions, including indirect emissions, while Croce et al. (2026) develop a network-based general equilibrium framework to measure Scope 3 and embodied emissions along global supply chains. Our object is different but complementary. These measures characterize the location and magnitude of emissions and their associated externalities; χ instead is an equilibrium incidence measure that captures how carbon-policy shocks affect a firm's cash flows through production relationships. This distinction between the location and magnitude of emissions and the location of transition-risk incidence is central to our analysis.

Climate policy uncertainty and regulatory risk. Finally , our regulatory-risk analysis also connects to work on climate-policy uncertainty and transition risk (Nordhaus, 2019; Ilhan et al., 2021; Sautner et al., 2023a; Hsu et al., 2023; Gasparini, 2023; Hong et al., 2019). Related evidence comes from green-bond markets (Larcker and Watts, 2020; Baker et al., 2022; Zerbib, 2022; Giglio et al., 2025). We contribute by showing that the cross-sectional response to changes in regulatory risk is systematically related to firms' ex-ante positions in the production network. Methodologically, the construction of our Carbon Regulatory Index builds on recent applications of large language models to textual data in economics and finance (Bybee, 2023; Chen et al., 2023; Cong et al., 2024).

Roadmap. Section 2 develops the production-network model and derives the sufficient-statistic characterization of carbon-risk exposure. Section 3 constructs the empirical measures of direct and network exposure. Section 4 studies their pricing implications, and Section 5 examines firms' financial and real responses to innovations in carbon-regulatory risk. Section 6 provides additional asset-pricing validation. Section 7 returns to the paper's motivating question and quantifies the aggregate financial incidence of carbon-transition risk relative to the distribution of emissions. Section 8 concludes.

2. Theoretical Framework

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

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

2.1 Model Setup

Production and Networks. Time is discrete with two periods, $t = 0, 1$, where period 0 represents the planning stage and uncertainty is resolved in period 1. The economy consists of N industries, each producing a distinct good. Each industry contains a fixed mass of perfectly competitive firms endowed with fixed factors of production.

Firms in industry j produce output according to

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

where Y_{jt} denotes output, X_{jt} is a composite of intermediate inputs, and $\eta_j \in [0, 1)$ is its output elasticity. The term $\xi_j = \eta_j^{\eta_j} \prod_{k=1}^{N} a_{jk}^{a_{jk}}$ is a normalization constant, where a_{jk} is defined in Equation (2). Decreasing returns to scale generate positive profits, which are distributed to households.[1] The common productivity factor Z_t reflects the resource costs of regulatory compliance and operating disruptions, whose process is specified below.

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

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

where X_{jkt} denotes the quantity of good k used by industry j, and $a_{jk} \geq 0$ is the corresponding input share, with $\sum_{k=1}^{N} a_{jk} = 1$. The matrix $\boldsymbol{A} = [a_{jk}]_{N \times N}$ summarizes the input–output structure of the economy. For tractability, the model treats $\boldsymbol{A}$ as predetermined within a date; however, this assumption does not require the empirical production network to be constant over time.

The Cobb–Douglas specification in (2) yields sharp closed-form solutions and fixes input expenditure shares. In this baseline, the direct network channel runs from carbon-exposed downstream customers to upstream suppliers through reductions in input demand. In Appendix A.1, we extend the model to a constant-elasticity-of-substitution (CES) aggregator. Endogenous input prices and substitution add an upstream-to-downstream input-cost channel, so carbon shocks can propagate directly in both directions through the production network. Section 4.5 shows that our main results remain quantitatively robust under this generalized specification.

Carbon Emissions. We assume that producing one dollar of output in industry j releases $\gamma_j \geq 0$ units of carbon, where γ_j denotes the emission intensity. The government imposes a tax τ_t per unit of emissions, implying an effective tax rate $\tau_{jt} = \gamma_j \tau_t$ for industry j. Firms in industry j thus earn after-tax revenue of $(1 - \tau_{jt}) P_{jt} Y_{jt}$, where P_{jt} is the output price. Carbon tax revenues are rebated to households as lump-sum transfers.

An alternative approach to modeling emissions is based on firms' input usage (Shapiro and Walker,

[1] These profits accrue to a fixed factor, such as capital or managerial input. For example, production can be written as $Y_{jt} = \xi_j Z_t \overline{K}_j^{1-\eta_j} X_{jt}^{\eta_j}$, with $\overline{K}_j^{1-\eta_j}$ absorbed into ξ_j.

2018).[2] We adopt the revenue-based specification for two reasons. First, it provides a parsimonious measure of exposure and aligns with empirical studies of carbon risk premia that use revenue-adjusted emission intensity (Engle et al., 2020; Ilhan et al., 2021; Zhang, 2025). Second, detailed firm-level input data are often unavailable, limiting the empirical feasibility of input-based approaches. In Appendix A.2, we relate the two emissions measures at the baseline allocation.

Over longer horizons, firms may adopt cleaner technologies or substitute toward low-carbon inputs (Acemoglu et al., 2012; Martin et al., 2014; Cullen and Mansur, 2017; Xiang, 2023). We focus on short-run asset pricing implications and hold η_j, γ_j, and a_{jk} fixed with respect to the contemporaneous shock, whereas in the empirical analysis, we allow the input–output matrix to vary across years to capture gradual changes in production structure.

Aggregate Risk. In period 1, carbon regulatory risk materializes. We interpret τ_1 as an innovation in the carbon-regulatory wedge around its baseline level $\tau_0 = 0$. We normalize $\mathbb{E}[\tau_1] = 0$, let $\mathrm{Var}(\tau_1) = \sigma_\tau^2$, and assume bounded support such that $1 - \gamma_j\tau_1 > 0$ and $\max_j\{\eta_j(1-\gamma_j\tau_1)\} < 1$ for all industries in every state. Positive realizations represent unexpected tightening and negative realizations unexpected easing.

This innovation is the sole source of aggregate uncertainty in the economy, and affects common productivity according to

$$Z_0 = 1, \qquad \log Z_1 = -\kappa\tau_1, \qquad \kappa > 0. \tag{3}$$

This common productivity component captures the short-run resource costs of regulatory compliance.[3] We represent these costs through $\log Z_1 = -\kappa\tau_1$, with $\kappa > 0$. Because firms differ in emission intensity and network position, their exposure to the aggregate risk varies, generating cross-sectional dispersion in risk premia.

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

$$U = \mathbb{E}_0 \sum_{t=0}^{1} \log C_t, \tag{4}$$

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

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

Here, C_{jt} denotes consumption of good j, and α_j is its expenditure share, with $\alpha_j \geq 0$ and $\sum_{j=1}^{N} \alpha_j = 1$. The corresponding aggregate price index is $P_t = \prod_{j=1}^{N} P_{jt}^{\alpha_j}$, and we normalize $P_0 = P_1 = 1$. Goods with $\alpha_j = 0$ receive no final expenditure and are omitted from the logarithmic consumption sum.

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

[3] Research shows that environmental regulation can divert productive inputs toward pollution abatement, as in Shapiro and Walker (2018), and increase production costs and reduce measured productivity (Gollop and Roberts (1983)).

We assume that every industry has strictly positive baseline revenue, and hence a positive baseline Domar weight.

Households are initially endowed with one unit of equity in each industry. In period 0, they trade industry equity claims and a risk-free bond. Let B_1 denote the bond payoff, R_1^f its gross return, h_{j1} the holding of industry j's equity, and V_{j0} its ex-dividend price in period 0. Each equity claim pays industry profits Π_{j1} in period 1. Households take prices and lump-sum transfers as given, and their flow budget constraints are

$$\begin{aligned} C_0 + \frac{B_1}{R_1^f} + \sum_j h_{j1} V_{j0} &\leq \sum_j \Pi_{j0} + \sum_j V_{j0}, \\ C_1 &\leq B_1 + \sum_j h_{j1} \Pi_{j1} + \sum_j \gamma_j \tau_1 P_{j1} Y_{j1}. \end{aligned} \tag{5}$$

Equilibrium. A competitive equilibrium consists of goods prices $\{P_{jt}\}$, the risk-free return R_1^f, equity prices $\{V_{j0}\}$, intermediate inputs $\{X_{jkt}\}$, outputs $\{Y_{jt}\}$, consumption $\{C_{jt}\}$, and household portfolios $\{h_{j1}\}$ such that:

1. Households maximize expected utility (4) subject to the budget constraints (5).

2. Firms choose intermediate inputs $\{X_{jkt}\}$ to maximize profits,

$$\max_{\{X_{jkt}\}_{k=1}^N} (1 - \gamma_j \tau_t) P_{jt} Y_{jt} - \sum_{k=1}^N P_{kt} X_{jkt}, \qquad t = 0, 1, \tag{6}$$

   with Y_{jt} given by (1).

3. Financial markets clear, $B_1 = 0$ and $h_{j1} = 1$ for every j, and goods markets clear:

$$C_{jt} + \sum_{k=1}^N X_{kjt} = Y_{jt}, \qquad t = 0, 1. \tag{7}$$

Discussion. The model introduces carbon regulatory risk through the tax rate τ_{jt}. Other carbon-related risks, such as shifts in consumer preferences toward low-emission firms or climate-related disruptions, may also propagate through production networks. Extending the model to these risks requires specifying how they affect preferences or technology and deriving the resulting equilibrium responses. However, as long as these shocks differentially affect firms based on their carbon intensity, our model provides a framework to accommodate a broader class of carbon-related aggregate risks. We therefore use the carbon-tax innovation as a parsimonious representation of carbon-regulatory risk and the model is not intended as an optimal-tax analysis.

2.2 Preview: Network Transmission of Carbon Risk

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

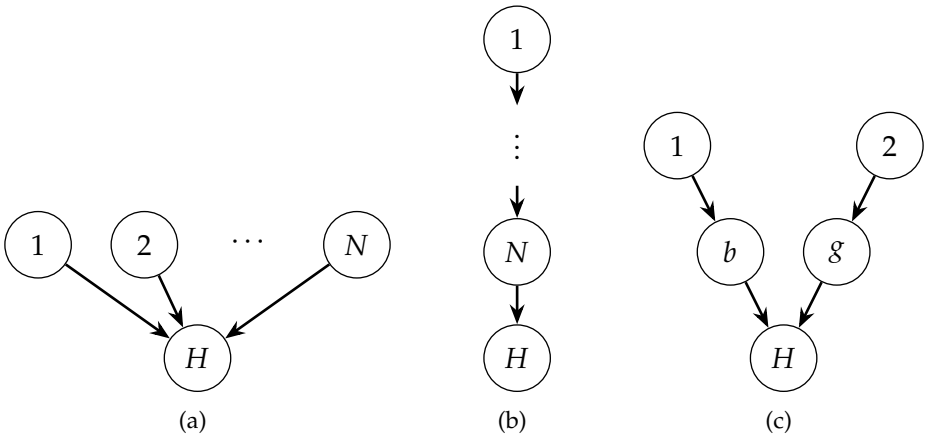

Figure 1: Network Examples

Example 1: Horizontal network. Suppose all industries produce using only fixed factors ($\eta_j = 0$), and households consume all goods (Figure 1, panel (a)). Regulatory tightening lowers productivity in every industry. With no input–output linkages, differences in profit responses depend only on firms' own emission intensities.

Example 2: Vertical network. Suppose industry 1 produces using only a fixed factor, each subsequent industry buys inputs from the preceding industry, and households consume the final good (panel (b)). Carbon taxes reduce downstream input spending and transmit the shock upstream. Industries farther upstream are exposed to the cumulative effect of downstream shocks, even if all industries have identical emission intensity.

Example 3: Centrality and trading partners. Industry 1 supplies the carbon-intensive industry b, while industry 2 supplies the cleaner industry g (panel (c)). Both upstream industries use only fixed factors and have identical direct emission intensities. Regulatory tightening reduces input spending more in b, giving industry 1 greater network exposure. Because tightening also lowers aggregate consumption, this greater exposure commands a higher risk premium.

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

2.3 Expected Stock Returns

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

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

2.3.1 Domar Weight

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

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

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

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

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

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

In vector form,

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

which implies the closed-form solution

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

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

This expression highlights that an industry's Domar weight is a general equilibrium object: S_{jt} depends not only on industry j's own characteristics, but also on the carbon emission intensities, returns to scale, and consumers' expenditure shares of all other industries. In particular, carbon shocks in downstream industries affect upstream sectors through input demand, generating interdependence across industries. Cross-industry propagation requires off-diagonal entries in $\boldsymbol{D}_\eta \boldsymbol{A}$.

Linearization and Network Exposure. Let $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_N)'$ denote the vector of emission intensities, and let $\boldsymbol{D}_S = \text{diag}(S_{10}, S_{20}, \ldots, S_{N0})$ denote period-0 Domar weights. Linearizing equation (8) around values in period 0 yields the following lemma.

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

$$\Delta \log \boldsymbol{S}_t = -\boldsymbol{\chi}\tau_t + O(\tau_t^2), \tag{10}$$

where

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

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

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

Economic Interpretation. To build intuition, expression (10) can be written in a recursive structure capturing all propagation paths in the network,

$$\Delta \log S_{jt} = -\frac{\tau_t}{S_{j0}}\left[\sum_k \eta_k a_{kj} S_{k0}\gamma_k + \sum_{k,\ell} \eta_k\eta_\ell a_{k\ell}a_{\ell j} S_{k0}\gamma_k + \sum_{k,\ell,m} \eta_k\eta_\ell\eta_m a_{k\ell}a_{\ell m}a_{mj} S_{k0}\gamma_k + \cdots\right] + O(\tau_t^2). \tag{12}$$

How does the carbon regulatory risk τ_t affect industry j's Domar weight? An unexpected tightening of carbon policy (i.e., a positive shock to τ_t) reduces industry k's demand for inputs as long as $\gamma_k > 0$. These reductions propagate upstream: the first term captures industry j's exposure to its immediate downstream customers, the second term captures the exposure to customers of those customers, and higher-order terms capture longer production chains. All of these cascading effects are succinctly summarized in the closed-form expression (10), by the sufficient statistic χ_j.

2.3.2 Profits

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

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

Substituting into the firm's profit function yields:

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

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

Equation (14) shows that profits are a constant fraction of after-tax revenue. The term $(1 - \gamma_j\tau_t)$ captures the direct effect of carbon taxation, while $S_{jt}C_t$ reflects general equilibrium effects through changes in revenue shares and aggregate demand.

To characterize the response of profits to carbon risk, we linearize (14) around period 0:

Proposition 1. *Profits in industry j satisfy*

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0}\left(\phi_{\pi j}\tau_t + \Delta \log C_t\right) + O(\tau_t^2), \tag{15}$$

where

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

In vector form,

$$\mathbf{\Pi}_t = \mathbf{\Pi}_0 + \boldsymbol{D}_{\Pi_0}\left(\boldsymbol{\phi}_\pi \tau_t + \mathbf{1}\Delta \log C_t\right) + O(\tau_t^2), \tag{17}$$

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

Proposition 1 decomposes the profit response into direct exposure, γ_j, network exposure, χ_j, and aggregate consumption growth. The network exposure captures the indirect network effect: firms are exposed to carbon risk through their customers' demand for inputs, with shocks propagating upstream through production linkages. Thus $\gamma_j + \chi_j$ summarizes cross-sectional variation in proportional profit responses, which will play a central role in determining expected returns.

2.3.3 Aggregate Consumption Growth

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

Proposition 2. *Aggregate consumption growth satisfies*

$$\Delta \log C_t = \phi_C \tau_t + O(\tau_t^2), \tag{18}$$

where

$$\phi_C = -\kappa \boldsymbol{\alpha}'(I - \boldsymbol{D}_\eta \boldsymbol{A})^{-1}\mathbf{1} = -\kappa \sum_{j=1}^{N} S_{j0} < 0. \tag{19}$$

The inequality $\phi_C < 0$ implies that carbon taxation reduces aggregate consumption growth. Regulatory tightening lowers productivity in every industry. Its effect on aggregate consumption is proportional to the sum of baseline Domar weights, reflecting the use of intermediate goods along supply chains.

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

2.3.4 Expected Stock Returns

With log utility, the stochastic discount factor is $M_1 = C_0/C_1$. Household optimality implies $\mathbb{E}_0[M_1] = 1/R_1^f$ and the valuation equation

$$V_{j0} = \mathbb{E}_0[M_1 \Pi_{j1}] = \frac{\mathbb{E}_0[\Pi_{j1}]}{R_1^f} + \mathrm{Cov}_0(M_1, \Pi_{j1}). \tag{20}$$

Define the gross equity return $R_{j1} = \Pi_{j1}/V_{j0}$ and net returns $r_{j1} = R_{j1} - 1$ and $r_1^f = R_1^f - 1$. Then

$$\mathbb{E}_0[r_{j1}] - r_1^f = -\frac{R_1^f}{V_{j0}} \mathrm{Cov}_0(M_1, \Pi_{j1}). \tag{21}$$

To characterize expected returns locally, write $\tau_1 = \sigma_\tau u$, where u has a fixed bounded distribution with zero mean and unit variance, and let $\sigma_\tau \to 0$. The first-order profit and consumption responses imply $M_1 = 1 - \phi_C \tau_1 + O(\tau_1^2)$, $R_1^f = 1 + O(\sigma_\tau^2)$, and $V_{j0} = \Pi_{j0} + O(\sigma_\tau^2)$. Substituting these expressions gives

$$\mathbb{E}_0[r_{j1}] - r_1^f = \frac{\mathrm{Cov}_0(\Delta \log C_1, \Pi_{j1})}{\Pi_{j0}} + o(\sigma_\tau^2). \tag{22}$$

Proposition 3. *Expected returns satisfy*

$$\mathbb{E}_0[r_{j1}] = r_1^f + \phi_{\pi j} \phi_C \sigma_\tau^2 + \mathrm{Var}_0(\Delta \log C_1) + o(\sigma_\tau^2), \tag{23}$$

where $\phi_{\pi j} = -\gamma_j - \chi_j \leq 0$, $\phi_C < 0$, *and* $\mathrm{Var}_0(\Delta \log C_1) = \phi_C^2 \sigma_\tau^2 + o(\sigma_\tau^2)$.

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

The coefficient on $\gamma_j + \chi_j$ is $-\phi_C \sigma_\tau^2 > 0$. Firms with greater direct and network exposure lose more cash flow when aggregate consumption is low and marginal utility is high. Investors therefore require higher expected returns to hold their equity.

Theorem 1. *For any industries j and k with $\gamma_j + \chi_j > \gamma_k + \chi_k$, expected returns satisfy $\mathbb{E}_0[r_{j1}] > \mathbb{E}_0[r_{k1}]$ for sufficiently small positive σ_τ.*

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

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

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

Proposition 4. *Suppose industries j and k satisfy (i) $a_{hj} = a_{hk}$ for all h and (ii) $\alpha_j = \alpha_k$. To leading order in shock variance, industry j has a higher expected return than industry k if and only if $\gamma_j > \gamma_k$.*

Proposition 4 provides sufficient conditions for emission intensity alone to rank the expected returns of two industries to leading order in shock variance. Equal downstream customer shares and final expenditure shares imply equal network exposure. These conditions are not necessary for equal network exposure and need not hold throughout the economy. More generally, differences in downstream connections can generate differences in network exposure.

2.4 Additional Testable Implications

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

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

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

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

$$\vartheta_j = \sum_{k=1}^{N} \omega_k \ell_{kj}, \tag{24}$$

where $\omega_k = e_{k0} / \sum_h e_{h0}$ is industry k's share of baseline emissions, $e_{k0} = \gamma_k \Psi_{k0}$, and total emissions satisfy $\sum_h e_{h0} > 0$.

In vector form, $\boldsymbol{\vartheta}' = \boldsymbol{\omega}' \boldsymbol{L}$. Carbon-adjusted centrality is a weighted analogue of Bonacich centrality, with weights proportional to total baseline emissions, $e_{k0} = \gamma_k \Psi_{k0}$. Using $\omega_k = 1/N$ gives the corresponding equal-weighted benchmark. Since the Leontief inverse includes each industry itself, ϑ_j reflects both industry j's own emissions and its connections to other emitting industries.

Proposition 5. *Suppose $\Psi_{i0} = \Psi_{j0}$. To leading order in shock variance, industry i has a higher expected return than industry j if and only if $\vartheta_i > \vartheta_j$.*

Proposition 5 shows that, among industries with the same baseline revenue, higher carbon-adjusted centrality implies greater total proportional exposure, $\gamma_j + \chi_j$, and higher expected returns to leading order in shock variance. This comparison includes both direct exposure through an industry's own emissions and network exposure through its customers.

Proposition 6. *Suppose $\vartheta_i = \vartheta_j > 0$. To leading order in shock variance, industry i has a higher expected return than industry j if and only if $\Psi_{i0} < \Psi_{j0}$.*

Proposition 6 shows that, holding positive carbon-adjusted centrality fixed, industries with lower baseline revenue have higher expected returns to leading order in shock variance. At a given centrality, lower revenue implies greater proportional exposure to the regulatory shock; network exposure χ_j need not be the same across industries.

2.5 Examples revisited

We now apply these results to the three networks in Section 2.2. In each case, the productivity response implies $\phi_C < 0$, and $\gamma_j + \chi_j$ determines cross-sectional differences in expected returns.

Example 1: Horizontal network. Set $\eta_j = 0$ for all industries. Then $\boldsymbol{L} = I$, $\boldsymbol{S}_0 = \boldsymbol{\alpha}$, and $\chi_j = 0$. The aggregate consumption response is $\phi_C = -\kappa$, and industry j's expected excess return is $\kappa\gamma_j\sigma_\tau^2 + \kappa^2\sigma_\tau^2 + o(\sigma_\tau^2)$. Cross-sectional differences therefore depend only on emission intensity.

Example 2: Vertical network. Industry 1 uses only a fixed factor, so $\eta_1 = 0$, and $a_{j,j-1} = 1$ and $\eta_j \in (0,1)$ for $j = 2, \ldots, N$. Households consume only the final good, with $\alpha_N = 1$ and $\alpha_j = 0$ otherwise. Baseline market clearing implies $S_{N0} = 1$ and $S_{j-1,0} = \eta_j S_{j0}$. Network exposure satisfies

$$S_{j-1,0}\chi_{j-1} = \eta_j S_{j0}(\chi_j + \gamma_j), \qquad \chi_N = 0. \tag{25}$$

Consequently,

$$\chi_j = \sum_{k=j+1}^{N} \gamma_k.$$

If $\gamma_j = \gamma > 0$ for every industry, then $\chi_j = (N-j)\gamma$. Industries farther upstream are exposed to more downstream wedges and command higher expected returns. If $\eta_j = \eta > 0$ for $j \geq 2$, then $S_{j0} = \eta^{N-j}$ and $\phi_C = -\kappa \sum_{j=1}^{N} \eta^{N-j} < 0$.

Example 3: Centrality and trading partners. Industries 1 and 2 use only fixed factors. Industry b buys inputs exclusively from industry 1, and industry g exclusively from industry 2. Set $\eta_b = \eta_g = \eta \in (0,1)$ and $\alpha_b = \alpha_g = 1/2$, with no final demand for goods 1 and 2. Then $S_{b0} = S_{g0} = 1/2$ and $S_{10} = S_{20} = \eta/2$. Industries b and g have no industrial customers, so $\chi_b = \chi_g = 0$, while

$$\chi_1 = \gamma_b, \qquad \chi_2 = \gamma_g.$$

For $\gamma_1 = \gamma_2$ and $\gamma_b > \gamma_g$, industry 1 has greater total exposure and commands higher expected returns. The aggregate consumption response is $\phi_C = -\kappa(1+\eta) < 0$.

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

3. Constructing Direct and Network Exposures

Guided by our theoretical framework, in this section, we construct the empirical measure of the direct and network carbon exposure (γ and χ) at both firm and industry level. We then offer an anatomy of the network 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. Throughout the paper, we refer to χ as "network exposure." We reserve "indirect" for propagation paths or effects rather than as the name of the exposure measure.

3.1 Data

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

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

Input-output linkages are constructed using data from the BEA's detailed industry tables. The BEA provides comprehensive input-output tables for 405 industries every five years, as well as annual tables for a more aggregated set of 71 industries, covering the period from 1997 to 2021. We use the 71-industry annual tables and reconstruct $\boldsymbol{A}_t$ and χ_t year by year. Thus, our empirical network exposure incorporates observed annual changes in input–output structure rather than imposing a fixed network throughout the sample.

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

3.2 Constructing Direct and Network Carbon Exposures

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

Our approach proceeds in three steps. We first define direct exposure using standard emissions intensity measures. We then leverage the input-output structure of the economy to construct industry-level network exposure based on the propagation mechanism characterized in Lemma 1. Finally, we map these industry-level exposures to the firm level using segment-level sales data. This framework allows us to capture both firms' own emissions and their exposure to carbon risk transmitted through production linkages. The baseline measure χ captures the downstream-to-upstream demand channel in the Cobb–Douglas model; the CES extension additionally allows upstream-to-downstream propagation through input prices and substitution.

Sample coverage. The Trucost database contains carbon-emissions information for 2,698 unique firms after our sample-selection and data-cleaning procedures. These firms are used to construct industry-level direct and network carbon exposures. The resulting industry-level exposure measures are then mapped to the universe of Compustat firms using segment-level sales shares, as described below. Consequently, the final regression sample is not restricted to firms with directly observed emissions. Instead, any Compustat firm with sufficient segment information can be assigned firm-level exposure measures through its industry composition, which substantially expands the empirical panel relative to the original emissions sample.

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

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

Industry-level network exposure. We construct industry-level network carbon exposure based on the network propagation formula derived in equation (11):

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

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

This baseline formulation captures how shocks to carbon-intensive downstream customers prop-

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

agate upstream through input demand. In the CES extension in Appendix A.1, endogenous input prices and substitution add an upstream-to-downstream channel, yielding a generalized network exposure with bidirectional propagation.

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

$$\chi_{i,t} = \sum_j \frac{\text{sale}_{ij,t-1}}{\sum_k \text{sale}_{ik,t-1}} \chi_{j,t}. \tag{26}$$

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

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

Input-output matrix $\boldsymbol{A}$. The matrix $\boldsymbol{A}$ is an $N \times N$ input-output matrix, where element a_{jk} denotes the share of industry j's intermediate expenditure allocated to inputs from industry k. We construct $\boldsymbol{A}$ using BEA input-output tables, following Pasten et al. (2017). In year t, the exposure measure uses the corresponding annual matrix $\boldsymbol{A}_t$; hence changes in observed customer–supplier expenditure shares feed directly into the year-t network exposure χ_t. Detailed procedures are provided in Appendix B.

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

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

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

Domar weight matrix $\boldsymbol{D}_S$. We construct $\boldsymbol{D}_S = \text{diag}(s_1, s_2, \ldots, s_n)$, where s_j denotes the Domar weight of industry j, defined as the ratio of industry output to aggregate output. We compute these weights using BEA make tables. Domar weights capture an industry's systemic importance in the production network, independent of its emissions intensity.

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

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

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

3.3 Empirical Results and Validation

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

3.3.1. How correlated are γ and χ?

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

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

3.3.2. Where does χ come from? Network depth decomposition

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

$$\boldsymbol{\chi} = \boldsymbol{D}_S^{-1} \sum_{l=1}^{\infty} (\boldsymbol{A}' \boldsymbol{D}_\eta)^l \boldsymbol{D}_S \boldsymbol{\gamma} = \sum_{l \geq 1} \boldsymbol{\chi}_l, \tag{27}$$

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

We define the *link matrix*:

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

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

Figure 2 shows that network exposure is primarily driven by shallow network layers: the first layer accounts for the largest share, followed by the second layer, while contributions beyond the fourth

layer are negligible. This result indicates that χ is not driven by arbitrarily long chains, but instead reflects economically meaningful, local supply-chain linkages.

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

3.3.3. A case study: Pipeline Transportation vs. Utilities

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

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

Panel A shows that the high network exposureof *Pipeline Transportation* is driven by strong linkages to a small set of highly carbon-intensive downstream sectors, notably *Utilities* and *Petroleum and Coal Products*. Although Pipeline Transportation is not itself highly emission-intensive, its revenues are exposed to demand from carbon-intensive customers through the production network.

In contrast, Panel B shows that the *Utilities* sector, despite having the highest direct exposure, exhibits only moderate network exposure. In the baseline measure, this reflects its downstream customer structure: the carbon intensity and strength of the sectors purchasing from Utilities generate less network-mediated demand exposure than Utilities' own direct emissions would suggest.

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

3.4 Scope 3 Accounting versus General-Equilibrium Network Exposure

A natural comparison is between χ and firm-level Scope 3 emissions. Both measures incorporate information beyond a firm's own direct emissions, but they answer different economic questions and are constructed differently.

Conceptually, Scope 3 is a physical-accounting measure: it attributes quantities of emissions along the value chain. Such accounting is not designed to capture how prices, substitution elasticities, general-equilibrium feedback, or final-demand structure transform a carbon-policy shock into firm-level cash-flow exposure. By contrast, χ is derived from the general-equilibrium model as the sufficient statistic for the network component of that exposure. In the Cobb–Douglas baseline, it reflects downstream customer demand transmitted to suppliers; in the CES extension, relative-price and substitution responses additionally transmit upstream cost shocks downstream. Accordingly, χ summarizes equilibrium exposure through the production network rather than physical emissions attribution.

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

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

Discriminating χ from Scope 3 emissions.. A natural concern is whether χ simply reflects Scope 3 (upstream embodied) emissions in a different metric. Section 3.4 documents that the firm-level cross-sectional correlation between χ and Scope 3 is only 0.11. We further test this by adding firm-level Scope 3 emissions as a control in equation (28). Column (6) of Table 4 reports the result. The coefficient on χ remains economically and statistically stable at 1.27 (relative to 1.25 in the baseline specification), while Scope 3 emissions enter with a small and statistically insignificant coefficient (0.027, $t = 0.614$). These results indicate that the pricing-relevant network exposure is captured by χ, rather than by conventional emissions accounting measures. We therefore include this horse-race specification in the main ICC results reported in Table 4.

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

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

4. Direct and Network Carbon Risk Exposure and Premium

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

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

report the opposite, linking high carbon emissions to lower stock returns.

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

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

4.1 Portfolio Sorting and Firm Characteristics

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

Summary statistics.

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

Panel B summarizes the key explanatory variables: direct exposure (γ), network exposure (χ), and total exposure ($\gamma + \chi$). Panel C reports standard firm characteristics commonly used as controls in the literature, including firm size, book-to-market ratio, profitability, leverage, Tobin's Q, market concentration (HHI), financial constraints (KZ index), and employment (Bolton and Kacperczyk, 2023; Atilgan et al., 2024; Zhang, 2025). Detailed variable definitions and data construction are provided in Table OB.2. The final sample contains 2,698 firms, with the sample selection procedure reported in Table OB.4.

Portfolio sorting methodology.

To assess the pricing of carbon risk exposure, we sort firms annually into quintile portfolios

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

Main results.

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

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

Economic interpretation.

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

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

Taken together, these univariate sorts show that network exposure χ generates a strong ICC spread, whereas direct exposure γ alone does not.

4.2 Regression Analysis

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

Panel Regression. Our baseline specification takes the form:

$$y_{it} = \alpha + \beta_\chi \chi_{it} + \beta_\gamma \gamma_{it} + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \tag{28}$$

where y_{it} denotes the implied cost of capital (ICC) for firm i at month t, and $\boldsymbol{X}_{it}$ includes standard firm characteristics. All specifications include month fixed effects, with firm characteristics included

as indicated in the table. Standard errors are clustered at the industry level. All exposure measures are standardized to facilitate interpretation.

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

We next relax this restriction by allowing χ and γ to enter separately (Columns (2), (3), and (5)). A clear pattern emerges. The coefficient on network exposure χ is large, positive, and highly significant. In Column (2), a one-standard-deviation increase in χ is associated with a 1.169 percentage-point increase in ICC, and this effect remains stable at 1.249 percentage points in Column (5) after controlling for firm characteristics. Direct exposure γ is positive but much smaller: Column (3) reports a coefficient of 0.126, and in the joint specification with χ and controls in Column (5), the coefficient on γ is 0.163 and only marginally significant. Column (6) instead controls for Scope 1 emissions and Scope 3 emissions; the coefficient on χ remains essentially unchanged, while the emissions measures are small and statistically insignificant. These results indicate that network exposure contains substantial pricing information beyond firms' own emissions intensity and conventional emissions measures.

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

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

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

Allowing for differential effects again highlights the larger economic magnitude of network exposure. In Column (5), a one-standard-deviation increase in χ is associated with a 1.29 percentage-point increase in annualized ICC. The coefficient on γ remains positive and statistically significant, but at 0.261 it is much smaller in magnitude.

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

statistical significance.

Taken together, the Fama–MacBeth results closely mirror the panel evidence: both components contain pricing information, but network exposure χ carries a substantially larger pricing magnitude than direct exposure γ or emissions levels.

4.3 Within vs Across Industry Decomposition

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

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

$$Exposure_{ijt} = \alpha + Industry\ FE_j + \varepsilon_{ijt} \tag{29}$$

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

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

and similar decomposition for the direct exposure,

$$\gamma_{ijt} = Cross\text{-}industry_{\gamma,jt} + Within\text{-}industry_{\gamma,it} = \tilde{\gamma}_{jt} + \tilde{\gamma}_{it} \tag{31}$$

In the second step, we estimate the following regression:

$$y_{ijt} = \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} + \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \tag{32}$$

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

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

relative importance as:

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

The results reveal a sharp contrast between network and direct exposure. In this variation-adjusted decomposition, network exposure χ accounts for approximately 85% of the total pricing contribution, with 66.98% arising from cross-industry variation and 18.40% from within-industry variation. Direct exposure γ accounts for the remaining roughly 15%, with the majority coming from within-industry variation (11.32%) and only a small fraction from cross-industry differences (3.30%).

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

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

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

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

As a robustness check, we further examine the incremental contribution of each component to the regression R^2. Specifically, we start from a regression only with standard control variables as in Equation (32). we then incrementally include $\tilde{\chi}_{jt}$, $\tilde{\gamma}_{jt}$, $\tilde{\chi}_{it}$, and $\tilde{\gamma}_{it}$ into the regression specified in Equation (32), 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 network exposures.

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

One potential concern is that the measurement of incremental R^2 could depend on the inclusion

order of each component. As a robustness check, we confirm that the results are highly robust to the inclusion order of the components.

An alternative approach is to independently include each of the four components in Equation (32) and compute their incremental R^2 relative to a baseline regression with only control variables. The resulting decomposition yields consistent conclusions.

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

4.4 Testing Additional Model Predictions

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

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

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

Table 7 presents the regression results. The coefficient on carbon-adjusted centrality, ϑ_{it}, is consistently positive across specifications, with estimates ranging from 0.022 to 0.031 and generally providing statistical support for a positive relation with the implied cost of capital. The coefficient on lagged revenue is consistently negative and statistically significant. These patterns are consistent with Proposition 5: conditional on firm size, firms with greater carbon-adjusted centrality tend to face a higher implied cost of capital, whereas, conditional on carbon-adjusted centrality, larger firms tend to face a lower implied cost of capital.

In contrast, the coefficients on direct carbon risk exposure, γ_{it}, and carbon emissions do not exhibit a consistent pattern across specifications, with their signs and statistical significance varying across different model specifications. This lack of a robust relationship is consistent with the prediction that, conditional on firm size and carbon-adjusted centrality, direct emissions contain limited incremental information about firms' exposure to carbon risk.

4.5 Robustness

The evidence for the importance of network exposure χ in explaining cross-sectional variation in expected returns remains broadly robust across a wide range of specifications. We summarize these robustness checks along several dimensions. First, the results continue to support a role for network exposure under alternative aggregation schemes at the industry level, including both value-weighted and equal-weighted ICC, although the relative strength of χ and direct exposure γ varies across specifications. Second, the results are robust to alternative assumptions about production technology, including a general CES specification with varying elasticities of substitution. Third, the findings are insensitive to alternative reporting lags in emissions and financial data. Fourth, controlling for alternative emissions measures (Scopes 1, 2, and 3) and real-side variables leaves the estimated relation between χ and expected returns broadly intact. Fifth, the results are stable across subsamples and time periods. Finally, the same qualitative patterns extend to realized stock returns, despite the well-known limitations of realized returns as proxies for expected returns.

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

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

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

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

We then re-estimate the baseline regression (28), replacing $\{\widehat{\chi}_j^1\}$ with $\{\widehat{\chi}_j^{\theta}\}$.[8] Across all values of θ, the coefficient on network exposure remains statistically significant and quantitatively stable, confirming that the pricing of χ is not sensitive to assumptions about input substitutability.

[7] We explore $\theta \in [0.75, 1.5]$ for two reasons. First, our analytical solutions arise from linearizing the equilibrium around $\theta = 1$. Second, empirical estimates of 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 empirical relevance across monthly and annual horizons.

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

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

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

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

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

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

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

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

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

5. Empirical Tests for Carbon Regulatory Risk

We have thus far provided empirical evidence suggesting that firms or industries with high direct or network 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 network exposure is priced, we would expect firms with high network exposure to experience a larger decline in realized stock returns when regulatory risk increases, compared to their low-exposure counterparts. Similarly, firms with high network exposure are likely to experience more severe deteriorations in financial and real economic activities (Pástor et al., 2021; Hartzmark and Shue, 2022; Broccardo et al., 2022; Gormsen et al., 2023; De Angelis et al., 2023). One challenge in this analysis is to measure regulatory risk associated with carbon emissions.

5.1 Proxy for Carbon Regulatory Risk

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

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

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

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

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

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

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

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

where $\hat{\varepsilon}_t$ represents the carbon regulatory shock (CRS_t). A large positive CRS_t indicates a significant and unexpected rise in carbon regulatory risk, while a large negative CRS_t suggests an unexpected decline. We refer to this innovation as a regulatory shock for brevity; because it is an innovation in a news-based risk index rather than an instrumented policy shock, we interpret it as an unexpected change in the regulatory-risk environment.

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

5.2 Validation for the Proxy

We evaluate the validity of our proxy from several perspectives. First, we randomly sample nine news articles, with three from each category classified by GPT-4o-mini as indicating regulatory risk on carbon emissions "going down," "going up," and "unknown." Table OB.18 and OB.19 in the Appendix present these examples. These examples provide a qualitative sanity check on the classification rather than a formal validation of classification accuracy.

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 annually into five groups based on their network 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 network carbon risk exposure to CRS_t, both with and without standard controls.

The responses are especially negative for the highest-χ group, most clearly for returns, revenue, and investment. Net-income responses are also more negative at high χ, although the pattern is less monotonic across quintiles. Overall, the portfolio evidence indicates that firms with greater network exposure are more vulnerable when the regulatory-risk index rises.

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:

$$y_{it} = \alpha + \beta_{\text{CRS}} \times \text{CRS}_t + \beta_{\text{CRS},\chi} \times \chi_{it} \times \text{CRS}_t + \beta_{\text{CRS},\gamma} \times \gamma_{it} \times \text{CRS}_t + \boldsymbol{X}'_{it}\beta_x + \textit{Fixed Effects} + \varepsilon_{it}, \quad (33)$$

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 network 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, network 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 report the interaction-regression results for stock returns, changes in revenue, changes in investment, and changes in net income. For stock returns, our observation is at the firm-month level, while firm performance and activities (changes in revenue, investment, and net income) are analyzed at the firm-year level.

Panel A demonstrates that an increase in the Carbon Regulatory Shock (CRS), indicative of unexpected heightened regulatory risk associated with carbon emissions, is significantly associated with lower contemporaneous stock returns. This dampening effect is particularly pronounced for firms with high network 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 (Network Exposure $\times$ CRS) is significantly negative. This finding suggests that firms with high network exposure experience a substantial decline in revenue growth in subsequent periods after an unexpected increase in carbon regulatory risk. Panel C shows a robust decline in investment growth. Panel D points in the same direction for net income, although the estimates are less uniform across horizons and specifications.

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, higher network exposure is associated with more adverse financial and real responses when regulatory risk rises, whereas the effects associated with direct exposure are generally smaller and less stable across specifications. This evidence is consistent with the network-transmission mechanism without requiring a particular adjustment-cost interpretation.

6. Evaluating Carbon-Risk Factor Models

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

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

The carbon-emissions sample spans 2002–2020. Because portfolios formed at the end of year t use emissions measured in year $t-1$, the corresponding portfolio-return sample spans January 2004 through December 2022, yielding 228 monthly portfolio-return observations. Accordingly, the portfolio-return sample begins in January 2004 even though the underlying carbon-emissions data begin in 2002. The resulting portfolios, reported in Figure 6, provide a transparent cross-sectional representation of carbon exposure and serve as the main test assets in our factor-model evaluation.

Factor construction. We construct the carbon-risk factors using univariate exposure sorts, consistent with the definition of the test assets. At the end of each December of year t, all firms are sorted into quintiles based on γ_{t-1} and, separately, into quintiles based on χ_{t-1}[10]. The γ factor is defined as the return on a zero-cost portfolio that is long the value-weighted portfolio of firms in the highest γ quintile and short the value-weighted portfolio of firms in the lowest γ quintile:

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

The χ factor is constructed analogously:

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

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

[10]Corporate carbon emission disclosures typically suffer from an approximate 10-month reporting lag before third-party vendors (e.g., Trucost, MSCI) process and release the finalized metrics. Aligning year $t-1$ emissions data (γ_{t-1} and χ_{t-1}) with the portfolio formation at the end of December in year t ensures a 12-month information lag, guaranteeing that all input variables were fully observable to market participants at the time of portfolio construction and strictly avoiding look-ahead bias.

the test portfolios.

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

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

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

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

By contrast, augmenting the CAPM with γ-MKT and χ-MKT substantially improves the cross-sectional fit. The realized and fitted returns move closer to the 45-degree line, and the systematic pricing errors at the extremes of the carbon-exposure distribution largely disappear. This evidence is consistent with the sufficient-statistic characterization in Theorem 1: expected returns vary monotonically with the combined exposure $\gamma + \chi$, and a factor structure spanned by these exposures captures the relevant cross-sectional variation in expected returns.

Formal model comparison. We formally compare the two specifications using the pricing-error test of Gibbons et al. (1989). The test is applied to the 25 carbon-sorted portfolios over the monthly sample period January 2002–December 2022, with $T = 252$ monthly observations. Under the CAPM, we strongly reject the null that all pricing errors are jointly zero:

$$F_{25,202} = 4.6, \qquad p < 0.01.$$

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

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

$$F_{25,200} = 1.18, \qquad p = 0.25.$$

The contrast between the two specifications indicates that the carbon-risk factors absorb the pricing errors that the market factor alone cannot explain. We interpret this exercise as an asset-pricing diagnostic: the improved fit is consistent with compensation for systematic carbon-related risks,

rather than independent identification of a new factor structure.

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

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

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

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

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

7. The Incidence of Carbon Transition Risk

The preceding sections establish that network exposure is reflected in firms' ex-ante cost of capital and is associated with stronger financial and real responses when carbon-regulatory risk rises. We now return to the question that motivates the paper: who bears carbon-transition risk in a networked economy? The answer requires distinguishing the location of emissions from the economic incidence of the transition. In this section, we focus on two financial margins of incidence: ex-ante compensation for bearing transition risk in capital markets and ex-post market revaluations when that risk rises.

We organize the analysis around three facts. First, we use the cross-sectional pricing estimates to decompose the aggregate fitted carbon-risk premium across firms with different direct and network exposures. Second, we examine how the same groups perform during episodes in which our regulatory-risk index rises unexpectedly. Third, we compare these financial-incidence shares with the distribution of Scope 1 and Scope 3 emissions.

The central result is a quantitative wedge between the source of the carbon externality and the incidence of transition risk. Firms can be minor emitters yet important bearers of priced risk because their customers expose them to carbon-intensive parts of the production network. This distinction—rather than a claim that emissions-based taxation is itself mis-targeted—is the main macro and policy implication of the paper.

7.1 Ex-Ante Incidence: Network-Brown Firms Bear a Large Share of Priced Transition Risk

We begin with an incidence accounting based on the ex-ante pricing estimates in Section 4. Our starting point is the baseline cross-sectional relation between the implied cost of capital (ICC) and direct and network exposures (Table 4, Column 5):

$$ICC_{i,t} = \alpha + \beta_\chi \chi_{i,t} + \beta_\gamma \gamma_{i,t} + X'_{i,t-1}\delta + \lambda_t + \varepsilon_{i,t}. \tag{34}$$

For this accounting exercise, we define firm i's fitted carbon-risk premium using the estimated baseline coefficients ($\hat{\beta}_\chi$ and $\hat{\beta}_\gamma$) and exposure variables entered in their raw units:

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

which captures the component of required returns associated with direct and network carbon exposure under the baseline specification. This exercise is an incidence accounting based on asset-pricing estimates, rather than a measure of social carbon damages or a structural welfare object. We define firm i's market-capitalization weight in month t as

$$w_{i,t} = \frac{MCAP_{i,t}}{\sum_j MCAP_{j,t}}.$$

The aggregate fitted carbon-risk premium in month t is therefore

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

We sort firms each period into a 2×2 grid based on direct exposure γ and network exposure χ, where High and Low bins are defined relative to their annual cross-sectional means. For each group G, we calculate its contribution to the aggregate fitted carbon-risk premium using the same market-capitalization weights $w_{i,t}$:

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

Thus, $\Pi^{carbon}_{G,t}$ measures group G's contribution to the aggregate fitted carbon-risk premium in month t, rather than the average premium of a representative firm within the group. By construction,

$$\Pi^{carbon}_t = \sum_G \Pi^{carbon}_{G,t}.$$

We then compute group G's share of aggregate priced carbon-risk incidence in each month and average this share over the sample period. Specifically,

$$Share^{carbon}_G = \frac{1}{T} \sum_{t=1}^{T} \frac{\Pi^{carbon}_{G,t}}{\Pi^{carbon}_t}.$$

This measure therefore captures the average monthly fraction of aggregate priced carbon-risk incidence borne by group G, allowing both the group's market-capitalization share and its fitted carbon-risk premium to vary over time.

Table 10 provides an integrated anatomy of carbon-risk incidence across direct and network exposure. The decomposition reveals that firms with low direct exposure but high network exposure—our "network-brown" firms—are economically important. They represent about 20% of aggregate market capitalization (Table 10, Panels A–B). Thus, network-brown firms are not a small collection of unusual firms; they constitute a substantial portion of the listed corporate sector.

Pricing also differs sharply by network exposure within the low-γ group. The fitted ICC reported in Table 10, Panels C–D, is 0.60% for low-γ, high-χ firms, compared with 0.23% for low-γ, low-χ firms. This comparison highlights the central empirical point: firms that appear similarly clean based on their own emissions can face substantially different priced transition risk because of their positions in the production network.

These differences translate into substantial differences in the incidence of aggregate priced transition risk (Table 10, Panels E–F). Network-brown firms account for 26.80% of the aggregate fitted carbon-risk premium, compared with 17.32% for high-γ, low-χ firms. Thus, more than one quarter of aggregate priced transition-risk incidence falls on firms with relatively low direct emissions but substantial exposure to carbon-intensive production networks.

7.2 Ex-Post Market Incidence When Regulatory Risk Rises

The ex-ante decomposition identifies where priced transition exposure is concentrated. We next ask whether network-brown firms also experience adverse revaluations during episodes in which our Carbon Regulatory Shock (CRS) measure records an unexpectedly large increase in regulatory risk. Because CRS is an innovation in a news-based risk index rather than an instrumented policy shock, we interpret this exercise as ex-post incidence evidence and a validation of the pricing mechanism.

Let T^{shock} denote the set of months in which CRS, constructed in Section 5, indicates a sharp increase in regulatory risk, defined as months where the monthly CRS index lies in the top 10% (i.e., at or above the 90th percentile) of its historical distribution. Firm-level abnormal returns are measured relative to the benchmark return as

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

Using lagged market-capitalization weights, the market-wide revaluation in month τ is

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

For each group G, we measure its relative share of abnormal return losses across shock months $\tau \in T^{shock}$ as:

$$Share_G^{loss} = \frac{1}{|T^{shock}|} \sum_{\tau \in T^{shock}} \frac{L_{G,\tau}}{L_\tau}, \tag{35}$$

where $L_{G,\tau} = |AR_{G,\tau}|$ is the absolute market-adjusted abnormal return of group G (computed using within-group market-capitalization weighting) in shock month τ, and $L_\tau = \sum_k L_{k,\tau}$ is the aggregate sum of weighted return losses across all firm groups.

The ex-post pattern is directionally consistent with the ex-ante incidence (Table 10, Panels G–H). Network-brown firms lose 2.62% on average in these episodes and account for 16.43% of the total aggregate return loss across groups.

The important point is therefore not a one-for-one mapping between ex-ante premium shares and ex-post loss shares. Rather, both exercises show that network exposure helps locate carbon-transition risk beyond the direct emitters. The fitted-premium decomposition is thus supported by an independent pattern in realized market revaluations when regulatory risk rises.

7.3 Emissions Are Not Exposure: The Incidence Wedge

The preceding exercises characterize where transition risk is priced and where market losses occur. We now compare these incidence measures with the distribution of emissions—the object relevant for the environmental externality itself.

For each group G, its share of aggregate emissions is

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

with Scope 1 and Scope 3 shares reported in Panels I and J of Table 10.

The contrast is stark. Network-brown firms produce only 1.76% of aggregate Scope 1 emissions, yet account for 26.80% of the aggregate fitted carbon-risk premium and 16.43% of market losses in regulatory-risk episodes. The difference is not simply an artifact of ignoring value-chain emissions: the same firms account for 11.64% of Scope 3 emissions, still far below their share of priced transition risk. Emissions accounting and economic incidence therefore identify different sets of firms.

We interpret this wedge as a systematic misalignment between emissions and risk incidence. The two objects answer different policy questions. Emissions identify the margin relevant for internalizing the carbon externality and therefore remain the natural basis for Pigouvian taxation. Network exposure identifies how the financial and real consequences of that transition are distributed across the production economy. In the model, the first object is governed by γ, while the second is governed by $\gamma + \chi$. The tax base and the incidence map are distinct objects.

The distinction matters whenever the policy objective is to measure or manage transition exposure rather than to price the environmental externality itself. Exposure assessments based only on firms' own emissions can miss low-emission firms whose cash flows depend heavily on carbon-intensive customers. Climate stress testing, transition-support programs, and distributional analyses may

therefore require network information in addition to emissions data if they aim to capture the breadth of firms affected by the transition.

The empirical message is therefore narrower, but also sharper, than a claim about optimal carbon taxation: the incidence of carbon-transition risk is substantially broader than the set of firms that directly generate emissions, and production linkages help explain where that risk lands.

8. Conclusion

This paper asks who bears carbon-transition risk in a networked economy. We develop a tractable general-equilibrium framework in which carbon-regulatory risk propagates through input–output linkages and show that a firm's exposure is summarized by two components: direct exposure γ, tied to its own carbon intensity, and network exposure χ, generated by its position in the production network. The sufficient statistic $\gamma + \chi$ makes precise the paper's central distinction: emissions identify where the carbon externality originates, while production networks help determine where the associated transition risk is borne.

Guided by the theory, we construct firm- and industry-level measures of γ and χ using Trucost, BEA, CRSP, and Compustat. Network exposure contains substantial pricing information beyond firms' own emissions and Scope 3 accounting: firms in the highest quintile of χ have an annualized implied cost of capital 2.24 percentage points higher than firms in the lowest quintile, and a one-standard-deviation increase in χ is associated with roughly a 1.2 percentage-point increase in annualized ICC. Firms with higher network exposure also respond more adversely when our carbon-regulatory-risk index rises unexpectedly. Most importantly, the aggregate financial incidence differs sharply from the distribution of emissions. Firms with low direct exposure but high network exposure—"network-brown" firms—produce less than 2% of aggregate Scope 1 emissions yet account for about 27% of the aggregate fitted carbon-risk premium; they also bear a substantial share of market losses relative to their small direct-emissions share. The firm-level evidence in Section 5 also shows that high-χ firms exhibit pronounced investment contractions when regulatory risk rises.

These results imply that emissions accounting and transition-risk incidence are distinct policy objects. Direct emissions remain the natural margin for internalizing the carbon externality, for example through Pigouvian taxation. Network exposure instead helps identify the firms and capital whose valuations and real activity are exposed to the transition, making it relevant for climate stress testing, financial-stability surveillance, transition-support policies, and distributional analysis. The broader lesson extends beyond carbon: production networks can separate the origin of an aggregate shock from the location of its economic incidence.

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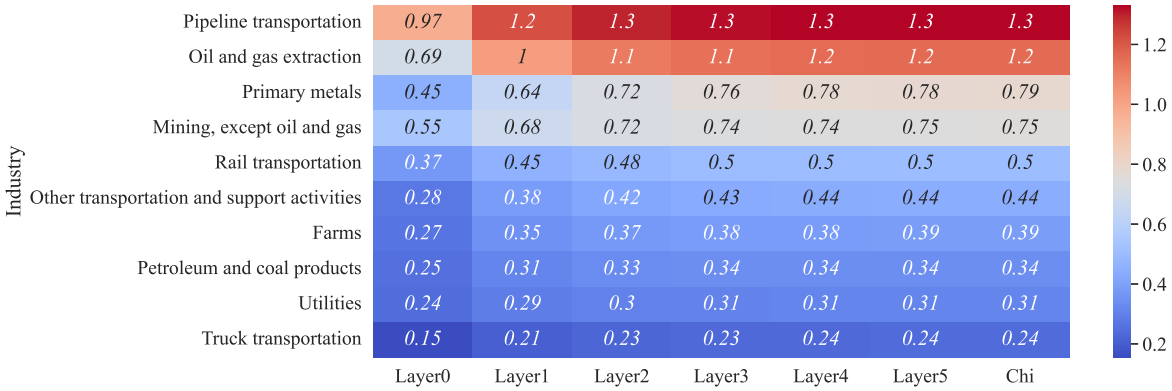
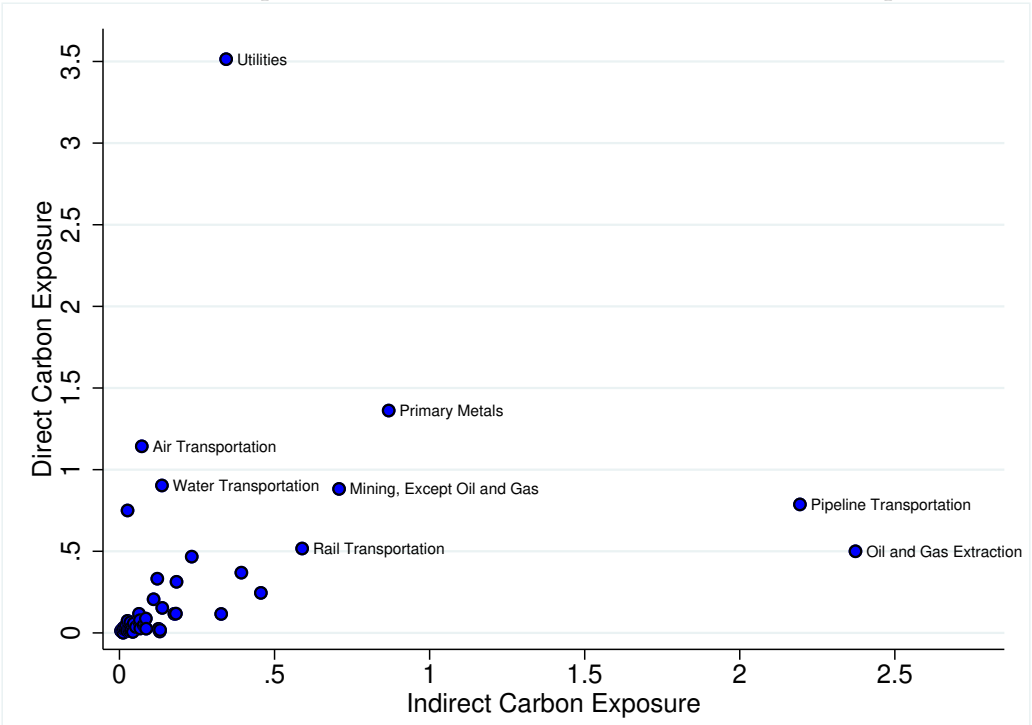
9. Figures and Tables

Figure 2: Effect of Network Depth on χ Measurement

Panel A: Top 10 Industries Ranked by χ

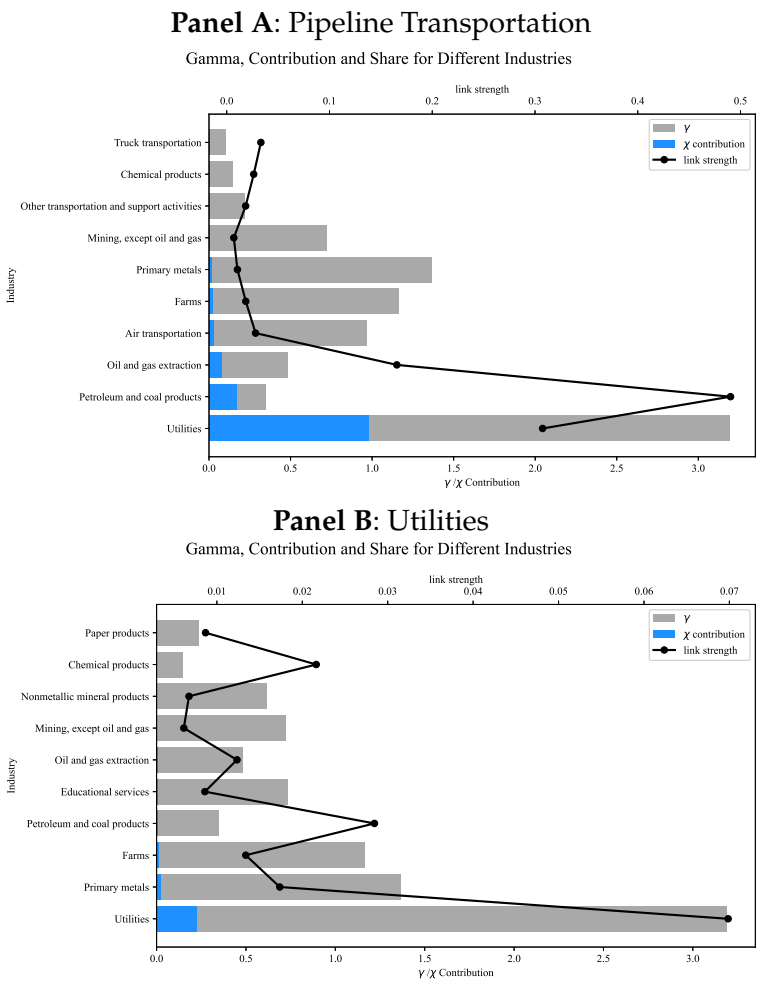


Panel B: Scatterplot of Network (χ) vs Direct (γ) Carbon Risk Exposure



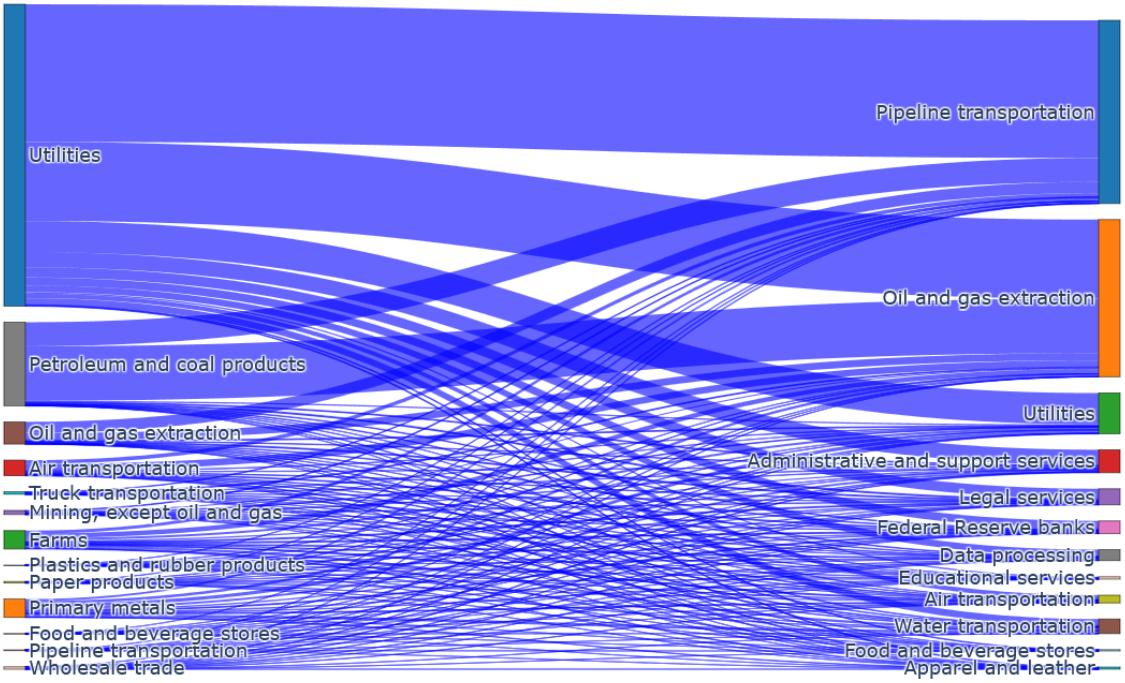
Panel A illustrates how network depth shapes the measurement of network carbon exposure (χ). The figure reports the top ten industries ranked by their total χ values. The y-axis lists industries, while the x-axis plots χ computed using networks of increasing depth (layers 0 through 5). Network exposure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



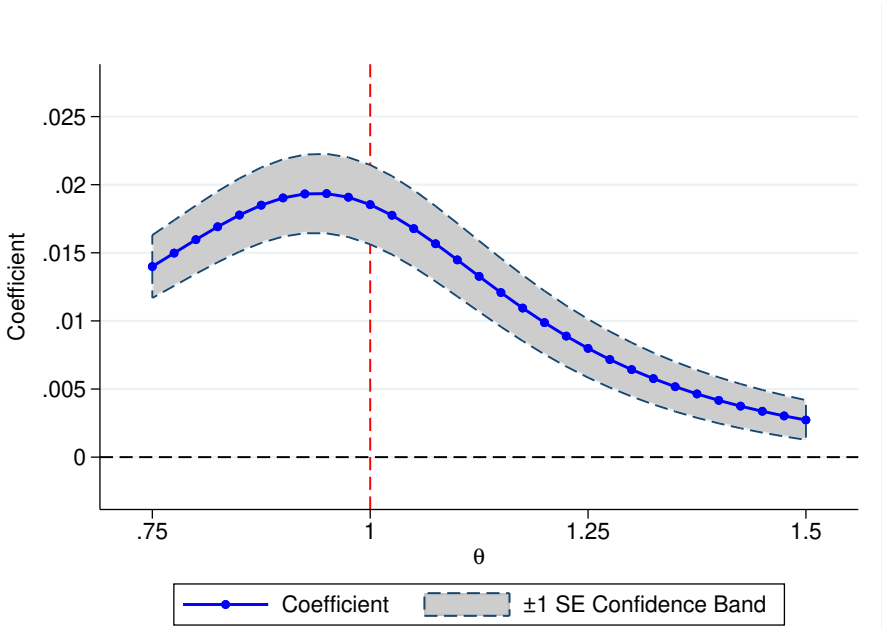
This figure decomposes the sources of an industry's network exposure (χ) into its link strength with other sectors and the direct exposure (γ) of those linked industries. The gray bars represent the direct exposure of the linked industries, the black solid line indicates link strength, and the blue bars measure the total contribution of each linked industry to the industry's network 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 network 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' network exposure, respectively. The width of each link captures the magnitude of the contributor's contribution to the receiver's network exposure. The diagram highlights, for example, that the network exposure of *Pipeline Transportation* is driven primarily by *Utilities*, followed by *Petroleum and Coal Products*, and that *Utilities* also substantially influence the network exposure of *Oil and Gas Extraction*. For clarity, the figure displays only industries with large gaps between direct and network exposure (as listed in Table OB.5).

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



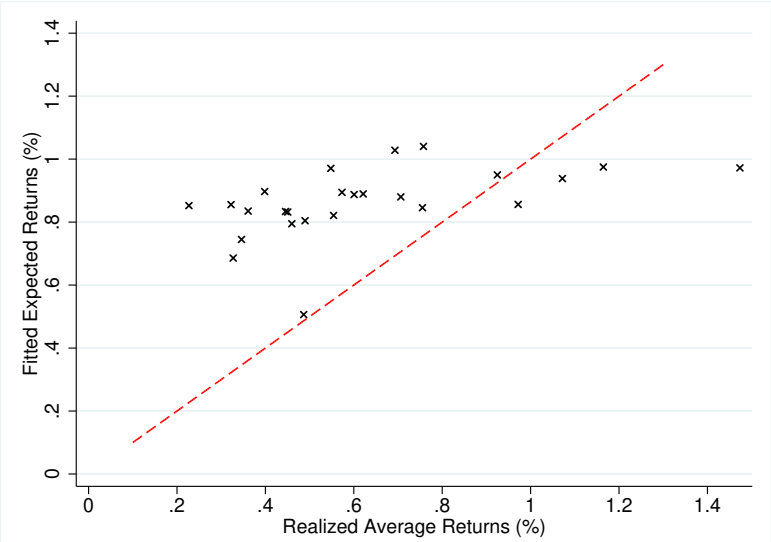
This figure shows the estimated coefficients of $\chi^{\theta} + \gamma$ from the following specification:

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

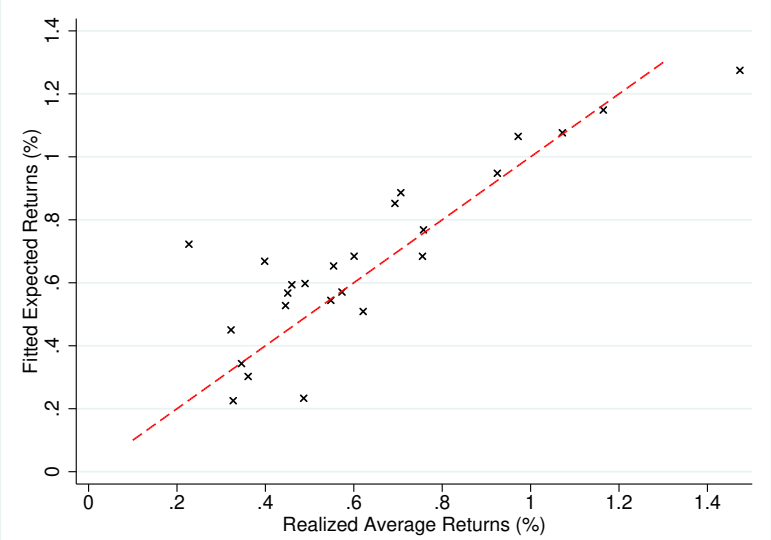
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the network carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. We set $\kappa = 4\%$ following the estimates in Greenstone et al. (2012). 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 one-standard-error bands. 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

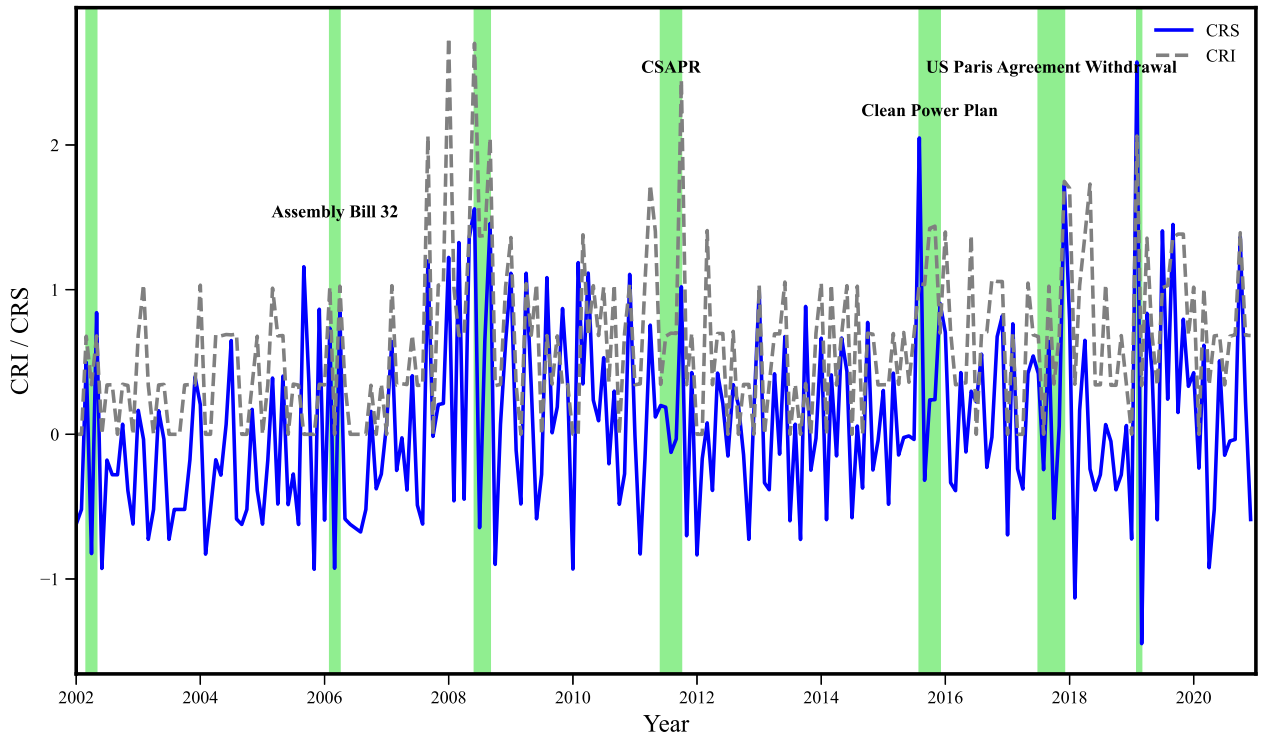


Panel B: Extended CAPM with χ and γ Factors



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

Figure 7: Time Series of CRI and CRS



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

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

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

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

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

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	ICC	*ICC*	*ICC*	*ICC*	*ICC*	*ICC*
Total exposure ($\chi + \gamma$)	0.613**			0.829***		
	(2.390)			(3.401)		
Network 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 Network Exposure on ICC

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

$$\begin{aligned} y_{ijt} = \alpha + \beta_{\chi,within} \times \tilde{\chi}_{it} + \beta_{\chi,cross} \times \tilde{\chi}_{jt} \\ + \beta_{\gamma,within} \times \tilde{\gamma}_{it} + \beta_{\gamma,cross} \times \tilde{\gamma}_{jt} + \boldsymbol{X}'_{ijt}\boldsymbol{\beta_x} + \varepsilon_{ijt}, \end{aligned} \tag{36}$$

where $\tilde{\chi}_{it}$, $\tilde{\chi}_{jt}$, $\tilde{\gamma}_{it}$, and $\tilde{\gamma}_{jt}$ represent within-industry network exposure, cross-industry network 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)	(2)	(3)	(4)
	ICC	*ICC*	*ICC*	*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 Network Carbon Risk Exposure and Carbon Regulatory Shock (Portfolio Level)

This table examines how firms with varying levels of network 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 network 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). t-statistics are reported in parentheses below the coefficients. 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***
	(-2.784)	(-3.912)	(-1.721)	(-4.256)	(-5.110)
With Controls					
$\beta_{\text{CRS,g}}$	-0.131**	-0.291***	-0.019	-0.272***	-0.403***
	(-2.105)	(-4.120)	(-0.482)	(-3.864)	(-4.935)
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***
	(-2.241)	(-3.105)	(-2.842)	(-2.018)	(-6.820)
With Controls					
$\beta_{\text{CRS,g}}$	-19.329***	-20.816***	-18.996***	-18.237***	-85.423***
	(-3.250)	(-3.481)	(-3.210)	(-3.095)	(-6.142)
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***
	(-1.352)	(-3.021)	(-2.684)	(-2.741)	(-5.390)
With Controls					
$\beta_{\text{CRS,g}}$	-1.948*	-3.268***	-2.921***	-2.962***	-12.540***
	(-1.815)	(-3.150)	(-2.981)	(-3.012)	(-5.925)
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***
	(1.120)	(-1.241)	(1.450)	(-3.215)	(-4.680)
With Controls					
$\beta_{\text{CRS,g}}$	3.898	-9.067***	1.359	-9.736***	-16.054***
	(1.412)	(-3.082)	(0.725)	(-3.240)	(-4.410)

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 network 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. Firm and industry fixed effects are included as specified. Robust t-statistics are reported in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Returns

	(1)	(2)	(3)	(4)	(5)
	Return	*Return*	*Return*	*Return*	*Return*
CRS	-0.235***	-0.188***	-0.168***	-0.168***	-0.181***
	(-9.395)	(-6.765)	(-6.014)	(-3.541)	(-3.309)
Network 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)	(2)	(3)	(4)	(5)	(6)
	t+1	*t+1*	*t+1*	*t+2*	*t+2*	*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)
Network 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 network 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. Firm and industry fixed effects are included as specified. Robust t-statistics are reported in parentheses, and *, **, and *** denote 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)
Network 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
	(1.677)	(2.051)	(2.173)	(-2.245)	(-1.731)	(1.452)
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)
Network exposure × CRS	-9.804**	-9.147**	-13.744***	-0.894	-3.986	-11.013***
	(-2.350)	(-2.167)	(-3.629)	(-0.174)	(-0.767)	(-3.293)
Direct exposure × CRS	-3.980	-4.541	0.123	-4.174	-5.799	-1.056
	(-1.324)	(-1.509)	(0.027)	(-1.088)	(-1.507)	(-0.250)
Controls	N	Y	Y	N	Y	Y
Firm Fixed Effects	N	N	Y	N	N	Y
Observations	14,890	14,890	14,890	14,890	14,890	14,890

Table 10: The Anatomy of Carbon Risk Incidence: Direct vs. Network Exposure

Notes: This table provides an integrated summary of carbon-risk incidence across firm groups defined by direct emissions (γ) and network exposure (χ). Firms are sorted into Low and High bins based on whether their γ or χ is below or above the cross-sectional mean, respectively. All group-level values are computed using market-capitalization weighting. Panels A–B report firm counts and market-capitalization shares. Panels C–D report fitted implied cost of capital (ICC, in monthly percentage points) and its cross-sectional share. Panels E–F report the carbon risk premium (in monthly percentage points) implied by the asset-pricing decomposition and its share across groups. Panels G–H report average abnormal returns during climate policy shock months (CRS) and the share of aggregate losses borne by each group. Panels I–J report shares of Scope 1 and Scope 3 emissions. Cell shading highlights the Low-γ/High-χ group to emphasize firms with low direct emissions but high network exposure.

Panel A. Firm Count

		χ	
		L	H
γ	L	601	493
	H	483	499

Panel B. Market Capitalization Share

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

Panel C. Fitted ICC

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

Panel D. Share of Fitted ICC

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

Panel E. Carbon Risk Premium

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

Panel F. Share of Carbon Risk Premium

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

Panel G. Policy-Shock Return

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

Panel H. Share of Policy-Shock Return

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

Panel I. Scope 1 Emissions Share

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

Panel J. Scope 3 Emissions Share

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

Appendix

THE NETWORK INCIDENCE OF CARBON TRANSITION RISK

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A. Theory Appendix

A.1 Non-Cobb-Douglas Production Function

This section replaces the Cobb–Douglas input aggregator with a CES specification. Production remains $Y_{jt} = \xi_j Z_t X_{jt}^{\eta_j}$, with $\log Z_t = -\kappa\tau_t$. We calibrate the aggregator to the Cobb–Douglas period-0 allocation, holding baseline input shares and industry productivity fixed across substitution elasticities. Let X_{jk0}, X_{j0}, and P_{k0} denote baseline inputs, composites, and prices. For industries with $\eta_j > 0$ and elasticity $\theta > 0$, define

$$X_{jt} = X_{j0}\left[\sum_{k:a_{jk}>0} a_{jk}\left(\frac{X_{jkt}}{X_{jk0}}\right)^{(\theta-1)/\theta}\right]^{\theta/(\theta-1)}. \tag{A.1}$$

The weights satisfy $a_{jk} = P_{k0}X_{jk0}/\sum_h P_{h0}X_{jh0}$ and $\sum_k a_{jk} = 1$. Since $X_{j0} = \prod_k X_{jk0}^{a_{jk}}$, the limit as $\theta \to 1$ is the Cobb–Douglas composite in (2). Industries with $\eta_j = 0$ produce $Y_{jt} = \xi_j Z_t$ and use no intermediate inputs, so input composites and input price indices are not defined for them. They enter the equilibrium system with zero input-expenditure shares. Their rows of $\boldsymbol{A}$ may be chosen arbitrarily subject to unit row sums, since these rows are multiplied by $\eta_j = 0$.

Let $\widehat{P}_{kt} = P_{kt}/P_{k0}$ and, for industries with $\eta_j > 0$, $\widehat{Q}_{jt} = Q_{jt}/Q_{j0}$ denote prices relative to the baseline, where $Q_{j0} = \sum_k P_{k0}X_{jk0}/X_{j0}$. The corresponding input price index is

$$\widehat{Q}_{jt} = \left(\sum_k a_{jk}\widehat{P}_{kt}^{1-\theta}\right)^{1/(1-\theta)}. \tag{A.2}$$

For industries with $\eta_j > 0$, cost minimization and profit maximization imply

$$X_{jkt} = (1 - \gamma_j \tau_t)\eta_j a_{jk} \frac{P_{jt} Y_{jt}}{P_{kt}} \left(\frac{\widehat{P}_{kt}}{\widehat{Q}_{jt}} \right)^{1-\theta}. \tag{A.3}$$

Input demand now responds to relative prices. At the baseline, expenditure on input k as a share of industry j's revenue equals $\eta_j a_{jk}$, including when goods prices differ across industries.

Deriving $\Delta \log \boldsymbol{S}_t$. Goods-market clearing remains

$$C_{jt} + \sum_k X_{kjt} = Y_{jt}. \tag{A.4}$$

Multiplying by P_{jt}, substituting (A.3) and household demand, and dividing by C_t yields

$$S_{jt} = \alpha_j + \sum_k (1 - \gamma_k \tau_t)\eta_k a_{kj} \left(\frac{\widehat{P}_{jt}}{\widehat{Q}_{kt}} \right)^{1-\theta} S_{kt}. \tag{A.5}$$

Define expenditure on input k as a share of industry j's pre-tax revenue:

$$\lambda_{jkt} = \frac{P_{kt} X_{jkt}}{P_{jt} Y_{jt}} = (1 - \gamma_j \tau_t)\eta_j a_{jk} \left(\frac{\widehat{P}_{kt}}{\widehat{Q}_{jt}} \right)^{1-\theta}. \tag{A.6}$$

Then

$$S_{jt} = \alpha_j + \sum_k \lambda_{kjt} S_{kt}, \qquad \lambda_{jk0} = \eta_j a_{jk}. \tag{A.7}$$

Let $\boldsymbol{s}_t$, $\boldsymbol{p}_t$, and c_t denote the first-order changes in $\log \boldsymbol{S}_t$, $\log \boldsymbol{P}_t$, and $\log C_t$, respectively. The systems below omit terms of order τ_t^2. With $\boldsymbol{L} = (I - \boldsymbol{D}_\eta \boldsymbol{A})^{-1}$ and $\boldsymbol{S}_0 = \boldsymbol{L}'\boldsymbol{\alpha}$, differentiating (A.7) gives

$$s_{jt} = \frac{1}{S_{j0}} \sum_{k,h} S_{k0} \eta_k a_{kh} \ell_{hj} \, \Delta \log \lambda_{kht}. \tag{A.8}$$

Changes in input shares are evaluated to first order, with zero baseline shares omitted. Differentiating (A.6) yields

$$\Delta \log \lambda_{kht} = -\gamma_k \tau_t + (1 - \theta) \left(p_{ht} - \sum_m a_{km} p_{mt} \right). \tag{A.9}$$

Substitution gives the vector system

$$\boldsymbol{s}_t = -\boldsymbol{\chi} \tau_t + (1 - \theta) \boldsymbol{\Phi}_P \boldsymbol{p}_t, \tag{A.10}$$

where $\boldsymbol{\chi}$ is the Cobb–Douglas exposure in (11), and

$$\boldsymbol{\Phi}_P = \boldsymbol{D}_S^{-1} \boldsymbol{L}' \left[\operatorname{diag}(\boldsymbol{A}' \boldsymbol{D}_\eta \boldsymbol{S}_0) - \boldsymbol{A}' \boldsymbol{D}_\eta \boldsymbol{D}_S \boldsymbol{A} \right]. \tag{A.11}$$

Since $\mathbf{\Phi}_P \mathbf{1} = 0$, a common proportional change in prices leaves relative input shares unchanged.

Profits. Within each input bundle, expenditure shares sum to one:

$$\sum_k a_{jk} \left(\frac{\widehat{P}_{kt}}{\widehat{Q}_{jt}} \right)^{1-\theta} = 1.$$

Total intermediate-input expenditure therefore equals $(1 - \gamma_j \tau_t)\eta_j P_{jt} Y_{jt}$, and profits satisfy

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

Consequently,

$$\frac{\Pi_{jt} - \Pi_{j0}}{\Pi_{j0}} = -\gamma_j \tau_t + s_{jt} + c_t + O(\tau_t^2). \tag{A.12}$$

Input substitution affects profits through revenues and Domar weights; profits remain a constant share of after-tax revenue.

Deriving $\Delta \log \boldsymbol{P_t}$. For industries with $\eta_j > 0$, profit maximization implies $Q_{jt} X_{jt} = (1 - \gamma_j \tau_t)\eta_j \Psi_{jt}$. Combining this condition with the production function and differentiating at the baseline gives the corresponding revenue response. For industries with $\eta_j = 0$, differentiating $Y_{jt} = \xi_j Z_t$ gives $s_{jt} + c_t = p_{jt} - \kappa \tau_t$. Combining the two cases yields

$$(I - \boldsymbol{D}_\eta)(\boldsymbol{s}_t + \mathbf{1} c_t) = -(\kappa \mathbf{1} + \boldsymbol{D}_\eta \boldsymbol{\gamma})\tau_t + (I - \boldsymbol{D}_\eta \boldsymbol{A})\boldsymbol{p}_t.$$

At the baseline, $\Delta \log Q_{jt} = \sum_k a_{jk} p_{kt}$ to first order for any fixed $\theta > 0$. Using $\mathbf{\Omega} = \boldsymbol{L}(I - \boldsymbol{D}_\eta)$ and $\mathbf{\Omega 1} = \mathbf{1}$, we obtain

$$\boldsymbol{p}_t = \boldsymbol{L}(\boldsymbol{D}_\eta \boldsymbol{\gamma} + \kappa \mathbf{1})\tau_t + \mathbf{\Omega} \boldsymbol{s}_t + \mathbf{1} c_t. \tag{A.13}$$

Deriving Expected Returns. Substituting (A.13) into (A.10) and using $\mathbf{\Phi}_P \mathbf{1} = 0$ gives a system in Domar weights. Define

$$\boldsymbol{H}_\theta = I - (1 - \theta)\mathbf{\Phi}_P \mathbf{\Omega}.$$

At a regular local equilibrium for which $\boldsymbol{H}_\theta$ is nonsingular,

$$\boldsymbol{s}_t = -\boldsymbol{H}_\theta^{-1} \left[\boldsymbol{\chi} - (1 - \theta)\mathbf{\Phi}_P \boldsymbol{L}(\boldsymbol{D}_\eta \boldsymbol{\gamma} + \kappa \mathbf{1}) \right] \tau_t. \tag{A.14}$$

The generalized network exposure is therefore

$$\boldsymbol{\chi}^\theta = \boldsymbol{H}_\theta^{-1} \left[\boldsymbol{\chi} - (1 - \theta)\mathbf{\Phi}_P \boldsymbol{L}(\boldsymbol{D}_\eta \boldsymbol{\gamma} + \kappa \mathbf{1}) \right]. \tag{A.15}$$

Direct exposure is $\boldsymbol{\gamma}$, and the Cobb–Douglas case gives $\boldsymbol{\chi}^1 = \boldsymbol{\chi}$. When $\theta \neq 1$, both revenue wedges and common productivity affect relative prices and input substitution. Network exposure

$\boldsymbol{\chi}^{\theta}$ therefore generally depends on κ and can be negative for some industries. Equation (A.15) is first order in the regulatory innovation. Expanding $\boldsymbol{H}_{\theta}^{-1}$ gives a local approximation around $\theta = 1$.

Holding the baseline allocation fixed, the first-order aggregate consumption response is independent of the substitution elasticity. To see this, note that

$$\boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{\Phi}_P = \mathbf{1}'\left[\operatorname{diag}(\boldsymbol{A}'\boldsymbol{D}_{\eta}\boldsymbol{S}_0) - \boldsymbol{A}'\boldsymbol{D}_{\eta}\boldsymbol{D}_S\boldsymbol{A}\right] = \mathbf{0}'.$$

Equation (A.10) therefore implies $\boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{s}_t = -\boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{\chi}\tau_t$. Applying the price normalization $\boldsymbol{\alpha}'\boldsymbol{p}_t = 0$ to (A.13) and using the cancellation established in the proof of Proposition 2 yields

$$c_t = -\kappa\boldsymbol{\alpha}'\boldsymbol{L}\mathbf{1}\,\tau_t = \phi_C\tau_t. \tag{A.16}$$

Substituting these responses into (A.12) gives the profit loading $-\gamma_j - \chi_j^{\theta} + \phi_C$. The pricing argument in the main text then implies

$$\mathbb{E}_0[r_{j1}] - r_1^f = \left[-\phi_C(\gamma_j + \chi_j^{\theta}) + \phi_C^2\right]\sigma_\tau^2 + o(\sigma_\tau^2). \tag{A.17}$$

Thus $\gamma_j + \chi_j^{\theta}$ ranks expected returns to leading order in shock variance. In the Cobb–Douglas limit, common productivity affects profits only through aggregate consumption, and network exposure reduces to (11).

A.2 Input-Based and Revenue-Based Emissions: Equivalence at the Baseline Allocation

This subsection relates input-based and revenue-based emissions at the baseline allocation. Suppose one dollar of good k used as an intermediate input releases $\widetilde{\gamma}_k$ units of carbon. At a given allocation, the two measures are

$$\widetilde{e}_{jt} = \sum_k \widetilde{\gamma}_k P_{kt} X_{jkt}, \qquad e_{jt} = \gamma_j P_{jt} Y_{jt}.$$

At the Cobb–Douglas baseline $(\tau_0, Z_0) = (0, 1)$, (13) gives $P_{k0}X_{jk0} = \eta_j a_{jk}\Psi_{j0}$. Therefore,

$$\widetilde{e}_{j0} = \eta_j\Psi_{j0}\sum_k a_{jk}\widetilde{\gamma}_k = e_{j0} \quad \text{if} \quad \gamma_j = \eta_j\sum_k a_{jk}\widetilde{\gamma}_k. \tag{A.18}$$

Equation (A.18) maps any nonnegative vector of input-based intensities into revenue-based intensities with the same baseline emissions. Away from the baseline, input-based emissions evaluated at the revenue-wedge equilibrium satisfy

$$\widetilde{e}_{jt} = (1 - \gamma_j\tau_t)\eta_j\Psi_{jt}\sum_k a_{jk}\widetilde{\gamma}_k.$$

A tax on input-based emissions would instead raise the effective input price to $P_{kt}(1+\widetilde{\gamma}_k\tau_t)$, changing firms' input demands. The equivalence in (A.18) is therefore an accounting relation at the baseline;

equilibrium tax responses and risk premia can differ across the two specifications. Direct emissions, Scope 3 emissions, and network exposure also remain distinct empirical measures.

A.3 Proofs of Lemmas and Propositions

A.3.1 Proof of Lemma 1

The input expenditure conditions and market clearing imply

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

Domar weights depend on revenue wedges and input expenditure shares. At $\tau_0 = 0$, $\boldsymbol{S}_0 = (I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}\boldsymbol{\alpha} = \boldsymbol{L}'\boldsymbol{\alpha}$. Differentiating around this baseline gives

$$\boldsymbol{S}_t - \boldsymbol{S}_0 = \boldsymbol{A}'\boldsymbol{D}_\eta(\boldsymbol{S}_t - \boldsymbol{S}_0) - \boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma}\tau_t + O(\tau_t^2).$$

Premultiplication by $\boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}$ yields

$$\Delta \log \boldsymbol{S}_t = -\boldsymbol{D}_S^{-1}(I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma}\tau_t + O(\tau_t^2),$$

which gives (10), with network exposure defined by (11).

A.3.2 Proof of Lemma 2

Using (13) and $\sum_k a_{jk} = 1$,

$$\begin{aligned}\Pi_{jt} &= (1 - \gamma_j\tau_t)\Psi_{jt} - \sum_k P_{kt}X_{jkt} \\ &= (1 - \gamma_j\tau_t)\Psi_{jt} - (1 - \gamma_j\tau_t)\eta_j\Psi_{jt} \\ &= (1 - \eta_j)(1 - \gamma_j\tau_t)\Psi_{jt}.\end{aligned}$$

Substituting $\Psi_{jt} = S_{jt}C_t$ gives (14) for any realization of Z_t.

A.3.3 Proof of Proposition 1

Taking logarithms of (14) gives

$$\log \Pi_{jt} = \log(1 - \eta_j) + \log(1 - \gamma_j\tau_t) + \log S_{jt} + \log C_t.$$

Taking changes from period 0 and applying Lemma 1,

$$\Delta \log \Pi_{jt} = -(\gamma_j + \chi_j)\tau_t + \Delta \log C_t + O(\tau_t^2).$$

Expanding the profit level gives

$$\Pi_{jt} = \Pi_{j0} + \Pi_{j0}\left[-(\gamma_j + \chi_j)\tau_t + \Delta \log C_t\right] + O(\tau_t^2),$$

which establishes (15). Common productivity affects profits through aggregate consumption.

A.3.4 Proof of Proposition 2

We derive industry revenue and aggregate consumption, then differentiate around $(\tau_0, Z_0) = (0, 1)$.

Revenue. Substituting (13) into the production function gives

$$\Psi_{jt} = \xi_j Z_t P_{jt} \prod_{k: a_{jk} > 0} \left[\frac{(1 - \gamma_j \tau_t)\eta_j a_{jk} \Psi_{jt}}{P_{kt}}\right]^{\eta_j a_{jk}}. \tag{A.19}$$

Let $b_j = \log \xi_j + \eta_j \log \eta_j + \eta_j \sum_k a_{jk} \log a_{jk}$, with the convention $0 \log 0 = 0$. For industries using only fixed factors, $b_j = \log \xi_j$.

Lemma A.1. *Industry revenue satisfies*

$$\log \Psi_{jt} = \frac{1}{1 - \eta_j}\left[b_j + \log Z_t + \eta_j \log(1 - \gamma_j \tau_t) + \log P_{jt} - \eta_j \sum_k a_{jk} \log P_{kt}\right]. \tag{A.20}$$

Taking logarithms of (A.19) establishes the lemma. In vector form,

$$\begin{aligned}(I - \boldsymbol{D}_\eta) \log \boldsymbol{\Psi}_t = \boldsymbol{b} + \mathbf{1} \log Z_t + \boldsymbol{D}_\eta \log(\mathbf{1} - \boldsymbol{\gamma}\tau_t) \\ + (I - \boldsymbol{D}_\eta \boldsymbol{A}) \log \boldsymbol{P}_t.\end{aligned} \tag{A.21}$$

The constants $\boldsymbol{b}$ determine revenue levels and cancel when taking changes.

Aggregate Consumption Growth. By the definition of Domar weights,

$$\mathbf{1} \log C_t = \log \boldsymbol{\Psi}_t - \log \boldsymbol{S}_t. \tag{A.22}$$

Let $\boldsymbol{L} = (I - \boldsymbol{D}_\eta \boldsymbol{A})^{-1}$ and $\boldsymbol{\Omega} = \boldsymbol{L}(I - \boldsymbol{D}_\eta)$. Since $\boldsymbol{A}\mathbf{1} = \mathbf{1}$, we have $\boldsymbol{\Omega}\mathbf{1} = \mathbf{1}$ and $\boldsymbol{\alpha}'\boldsymbol{\Omega}\mathbf{1} = 1$. Premultiplying (A.21) by $\boldsymbol{\alpha}'\boldsymbol{L}$, using (A.22) and the normalization $\boldsymbol{\alpha}' \log \boldsymbol{P}_t = 0$, gives the exact consumption equation

$$\begin{aligned}\log C_t = \boldsymbol{\alpha}'\boldsymbol{L}\boldsymbol{b} + \boldsymbol{\alpha}'\boldsymbol{L}\mathbf{1} \log Z_t \\ + \boldsymbol{\alpha}'\boldsymbol{L}\boldsymbol{D}_\eta \log(\mathbf{1} - \boldsymbol{\gamma}\tau_t) - \boldsymbol{\alpha}'\boldsymbol{\Omega} \log \boldsymbol{S}_t.\end{aligned} \tag{A.23}$$

Differencing from period 0 and using $\log Z_t = -\kappa\tau_t$ and Lemma 1 yields

$$\Delta \log C_t = \left[-\kappa \boldsymbol{\alpha}'\boldsymbol{L}\mathbf{1} - \boldsymbol{\alpha}'\boldsymbol{L}\boldsymbol{D}_\eta \boldsymbol{\gamma} + \boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{\chi}\right]\tau_t + O(\tau_t^2). \tag{A.24}$$

To simplify the last two terms, use $\boldsymbol{S}_0 = \boldsymbol{L}'\boldsymbol{\alpha}$, $\boldsymbol{\Omega} = \boldsymbol{L}(I - \boldsymbol{D}_\eta)$, and $\boldsymbol{L}(I - \boldsymbol{D}_\eta)\mathbf{1} = \mathbf{1}$ to obtain

$$\begin{aligned}\boldsymbol{\alpha}'\boldsymbol{\Omega}\boldsymbol{\chi} &= \boldsymbol{S}_0'(I - \boldsymbol{D}_\eta)\boldsymbol{D}_S^{-1}\boldsymbol{L}'\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma} \\ &= \mathbf{1}'(I - \boldsymbol{D}_\eta)\boldsymbol{L}'\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma} \\ &= \mathbf{1}'\boldsymbol{A}'\boldsymbol{D}_\eta\boldsymbol{D}_S\boldsymbol{\gamma} = \boldsymbol{S}_0'\boldsymbol{D}_\eta\boldsymbol{\gamma} = \boldsymbol{\alpha}'\boldsymbol{L}\boldsymbol{D}_\eta\boldsymbol{\gamma}. \end{aligned} \tag{A.25}$$

The equality $\mathbf{1}'\boldsymbol{A}' = \mathbf{1}'$ follows from the unit row sums of $\boldsymbol{A}$. Substituting into (A.24) yields

$$\Delta \log C_t = -\kappa\boldsymbol{\alpha}'\boldsymbol{L}\mathbf{1}\,\tau_t + O(\tau_t^2), \qquad \phi_C = -\kappa\sum_j S_{j0} < 0,$$

which proves Proposition 2. When $\kappa = 0$, the first-order consumption response is zero because the tax is fully rebated and the baseline allocation is undistorted. When $\kappa > 0$, the resource cost of regulation lowers aggregate consumption, while γ_j and χ_j determine cross-sectional exposure to revenue wedges.

A.3.5 Proof of Proposition 3

Write $\tau_1 = \sigma_\tau u$, where u has a fixed bounded distribution with zero mean and unit variance, and let $\sigma_\tau \to 0$ with other primitives fixed. Let $c_1 = \Delta \log C_1$. Propositions 1 and 2 imply

$$\begin{aligned} c_1 &= \phi_C\tau_1 + O(\sigma_\tau^2), \\ \frac{\Pi_{j1}}{\Pi_{j0}} &= 1 + \phi_{\pi j}\tau_1 + c_1 + O(\sigma_\tau^2), \end{aligned}$$

where the remainders are uniform over the bounded support of u. With log utility, the stochastic discount factor satisfies

$$M_1 = \frac{C_0}{C_1} = e^{-c_1} = 1 - c_1 + O(\sigma_\tau^2).$$

Since $\mathbb{E}_0[\tau_1] = 0$, we have $\mathbb{E}_0[c_1] = O(\sigma_\tau^2)$. Household optimality and (20) therefore give

$$R_1^f = \frac{1}{\mathbb{E}_0[M_1]} = 1 + O(\sigma_\tau^2), \qquad V_{j0} = \mathbb{E}_0[M_1\Pi_{j1}] = \Pi_{j0}\big[1 + O(\sigma_\tau^2)\big].$$

The first-order fluctuations in consumption and profits are of order σ_τ, so their covariances with the second-order remainders are of order σ_τ^3. Substituting the preceding expansions into the exact excess-return identity (21) yields

$$\begin{aligned}\mathbb{E}_0[r_{j1}] - r_1^f &= -\frac{R_1^f}{V_{j0}}\operatorname{Cov}_0(M_1, \Pi_{j1}) \\ &= \frac{\operatorname{Cov}_0(c_1, \Pi_{j1})}{\Pi_{j0}} + o(\sigma_\tau^2)\end{aligned}$$

$$= \phi_{\pi j} \operatorname{Cov}_0(c_1, \tau_1) + \operatorname{Var}_0(c_1) + o(\sigma_\tau^2).$$

Using the consumption expansion and $\operatorname{Var}_0(\tau_1) = \sigma_\tau^2$, we obtain

$$\operatorname{Cov}_0(c_1, \tau_1) = \phi_C \sigma_\tau^2 + o(\sigma_\tau^2), \qquad \operatorname{Var}_0(c_1) = \phi_C^2 \sigma_\tau^2 + o(\sigma_\tau^2).$$

Consequently,

$$\mathbb{E}_0[r_{j1}] = r_1^f + \phi_{\pi j}\phi_C \sigma_\tau^2 + \operatorname{Var}_0(\Delta \log C_1) + o(\sigma_\tau^2),$$

which is (23). The signs $\phi_{\pi j} = -\gamma_j - \chi_j \le 0$ and $\phi_C < 0$ follow from Propositions 1 and 2, completing the proof.

A.3.6 Proof of Proposition 4

Subtracting the market-clearing equations for industries j and k in (8) gives

$$S_{jt} - S_{kt} = \alpha_j - \alpha_k + \sum_{h=1}^{N} \eta_h (1 - \gamma_h \tau_t)(a_{hj} - a_{hk}) S_{ht} = 0,$$

where the last equality follows from $\alpha_j = \alpha_k$ and $a_{hj} = a_{hk}$ for every h. Thus $S_{jt} = S_{kt}$ in every state, including $S_{j0} = S_{k0} > 0$. Their proportional responses to the regulatory innovation are therefore identical. By Lemma 1, $\chi_j = \chi_k$.

For the expected-return comparisons, consider $\tau_1 = \sigma_\tau u$, where u has a fixed bounded distribution with zero mean and unit variance, and let $\sigma_\tau \to 0$. Subtracting (23) across the two industries, the common risk-free return and consumption-variance term cancel. Using $\phi_{\pi j} = -\gamma_j - \chi_j$ and $\chi_j = \chi_k$ yields

$$\mathbb{E}_0[r_{j1} - r_{k1}] = -\phi_C(\gamma_j - \gamma_k)\sigma_\tau^2 + o(\sigma_\tau^2).$$

Since $\phi_C < 0$, the coefficient on shock variance is positive if and only if $\gamma_j > \gamma_k$, and it is zero when $\gamma_j = \gamma_k$. This proves the proposition to leading order in shock variance.

A.3.7 Proof of Proposition 5

We first relate carbon-adjusted centrality to total exposure. Since $\boldsymbol{L}' = (I - \boldsymbol{A}'\boldsymbol{D}_\eta)^{-1}$, we have $\boldsymbol{L}'\boldsymbol{A}'\boldsymbol{D}_\eta = \boldsymbol{L}' - I$. Substituting this identity into (11) gives

$$\boldsymbol{\gamma} + \boldsymbol{\chi} = \boldsymbol{D}_S^{-1} \boldsymbol{L}' \boldsymbol{D}_S \boldsymbol{\gamma}.$$

Using $S_{h0} = \Psi_{h0}/C_0$ and $e_{h0} = \gamma_h \Psi_{h0}$, the component for any industry j is

$$\gamma_j + \chi_j = \frac{1}{S_{j0}} \sum_{h=1}^{N} \ell_{hj} S_{h0} \gamma_h = \frac{1}{\Psi_{j0}} \sum_{h=1}^{N} \ell_{hj} e_{h0}$$

$$= \frac{\sum_{h=1}^{N} e_{h0}}{\Psi_{j0}} \vartheta_j,$$

where the last equality follows from Definition 2. If $\Psi_{i0} = \Psi_{j0}$, subtracting (23) across industries and applying this identity yields

$$\mathbb{E}_0[r_{i1} - r_{j1}] = -\phi_C \sigma_\tau^2 \frac{\sum_{h=1}^{N} e_{h0}}{\Psi_{i0}} (\vartheta_i - \vartheta_j) + o(\sigma_\tau^2).$$

Baseline revenue and total baseline emissions are positive, and $\phi_C < 0$. Hence the coefficient on shock variance is positive if and only if $\vartheta_i > \vartheta_j$, and it is zero when the two centralities are equal. This proves the proposition.

A.3.8 Proof of Proposition 6

By the exposure identity established in the proof of Proposition 5, the assumption $\vartheta_i = \vartheta_j > 0$ implies

$$(\gamma_i + \chi_i) - (\gamma_j + \chi_j) = \left(\sum_{h=1}^{N} e_{h0} \right) \vartheta_i \left(\frac{1}{\Psi_{i0}} - \frac{1}{\Psi_{j0}} \right).$$

Substituting into the difference of expected returns in (23) gives

$$\mathbb{E}_0[r_{i1} - r_{j1}] = -\phi_C \sigma_\tau^2 \left(\sum_{h=1}^{N} e_{h0} \right) \vartheta_i \left(\frac{1}{\Psi_{i0}} - \frac{1}{\Psi_{j0}} \right) + o(\sigma_\tau^2).$$

Since $-\phi_C > 0$, $\sum_h e_{h0} > 0$, and $\vartheta_i > 0$, the coefficient on shock variance is positive if and only if $\Psi_{i0} < \Psi_{j0}$. It is zero when baseline revenues are equal. This proves the proposition to leading order in shock variance.

B. Data Construction

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

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

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

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

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

Our preference for "Scope 1" is also reinforced by the findings of Busch et al. (2022), who demonstrate its superior reliability across various data providers. In their comparative analysis of carbon emission data from several sources, including Bloomberg, CDP, ISS Ethix, Trucost, MSCI, Sustainalytics, and Thomson Reuters, Busch et al. (2022) reveal that "Scope 1" emission correlations among

these entities approximate 0.99. Nonetheless, the correlation for "Scope 3" emissions significantly decreases to 0.58, which is attributed to the lack of detailed input-output linkages between companies. Moreover, they categorize carbon emission data into two segments: company-reported and third-party estimated. For company-reported data, the average Pearson correlation for Scope 1, Scope 2, and Scope 3 emissions is 0.99, 0.98, and 0.58, respectively. In contrast, for third-party estimated data, the mean Pearson correlations for Scope 1, Scope 2, and Scope 3 emissions are 0.79, 0.63, and 0.15, respectively, highlighting the challenges of accurately estimating indirect emissions.

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

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

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

The Bureau of Economic Analysis (BEA) aligns its 71 industries with the North American Industry Classification System (NAICS) codes, varying from 2-digit to 4-digit levels of specificity. Our study has methodically aligned these BEA industries with the corresponding three-digit NAICS sectors. This alignment reveals that 53 of the BEA industries match with firms represented in our carbon emission dataset. Industries that are not included in the matched sample are listed in 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 input-output relationships across industries. Its element a_{ij} is the expenditure percentage of industry i on intermediate goods in the industry j to i's total intermediate expenditure.

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

- Product Uniqueness and Representation: In our theoretical model, each industry comprises firms producing a distinct, homogeneous product, and we symbolize the entire industry by a single representative firm. Consequently, each industry corresponds uniquely to its product. However, the real-world data presents a more intricate picture. Even if categorized under one industry, companies like Google or Amazon have operations spanning multiple industries. Simply aggregating firms' production within a sector might not accurately represent sectoral production. Addressing this complexity, the BEA introduces a "make" table. Represented as the matrix **MAKE**, each entry (i, j) captures the proportion of products from sector i attributed to sector j.

- Product Consumption across Sectors: Parallel to the "make" table, the BEA offers a "use" table, capturing inter-sectoral consumption. Symbolized as $\boldsymbol{USE}$, an entry (i, j) in this table reveals the fraction of intermediate goods consumed by sector i originating from sector j.

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

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

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

Control variables follow the definitions reported in Table OB.2. In particular, firm size is measured using market capitalization, book-to-market captures valuation, leverage captures capital structure, ROA measures operating profitability relative to assets, and the remaining controls cap-

ture investment, market concentration, financing constraints, employment, and standard return characteristics as used in the corresponding regressions.

Variable-specific outlier treatments are summarized in Table OB.2 and are applied consistently in the reported regressions.

C. Variable Construction for Implied Cost of Capital

We construct the implied cost of capital (ICC) following the empirical implementation of Hou et al. (2012). The construction proceeds in two steps. First, we estimate one-year-ahead expected earnings using a cross-sectional forecasting model. Second, we combine the forecasted annual earnings with contemporaneous market equity to construct the firm's implied cost of capital. The resulting ICC is an annualized measure that is updated monthly through changes in market equity. This appendix describes the forecasting procedure, accounting adjustments, timing convention, and sample filters required to replicate the ICC measure.

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

We estimate one-year-ahead expected earnings using the cross-sectional forecasting model of Hou et al. (2012). For each forecasting-year cohort t, the forecasting regression is estimated using observations from the current forecasting-year cohort and the preceding ten forecasting-year cohorts:

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

where $IB_{i,t+1}$ denotes income before extraordinary items for firm i in fiscal year $t+1$. All explanatory variables are measured using accounting information from fiscal year t. Specifically, $AT_{i,t}$ is total assets (`AT`); $DVC_{i,t}$ is common dividends (`DVC`); $DD_{i,t}$ is an indicator equal to one if $DVC_{i,t} > 0$ and zero otherwise; $IB_{i,t}$ is income before extraordinary items (`IB`); $NE_{i,t}$ is an indicator equal to one if $IB_{i,t} < 0$ and zero otherwise; and $ACCRUAL_{i,t}$ denotes operating accruals.

The estimation window is organized by forecasting-year cohorts rather than realized earnings years. For each forecasting-year cohort, accounting variables dated in year t are matched with realized earnings in year $t+1$ to estimate the forecasting coefficients. The estimated coefficients are then applied to accounting information from forecasting-year cohort t to obtain firm-level forecasts of one-year-ahead earnings.

To account for reporting delays in annual financial statements, fiscal years ending in January through March are assigned to the preceding forecasting-year cohort, whereas fiscal years ending from April through December are assigned to the corresponding calendar-year cohort. This convention ensures that accounting information is publicly available before it is used to forecast future earnings and subsequently matched to market values.

Prior to 1988, operating accruals are constructed using the balance-sheet approach:

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

where ACT denotes current assets, CHE cash and short-term investments, LCT current liabilities, DLC debt in current liabilities, TXP income taxes payable, and DP depreciation and amortization.

Beginning in 1988, following Hribar and Collins (2002), operating accruals are constructed from the statement of cash flows:

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

where IBC is income before extraordinary items and discontinued operations from the statement of cash flows, $OANCF$ is operating cash flow, and $XIDOC$ is extraordinary items and discontinued operations.

All level-based accounting variables (IB, IB_{t+1}, CEQ, AT, DVC, and $ACCRUAL$) are winsorized annually at the 1st and 99th percentiles within each forecasting-year cohort. The estimated coefficients are then applied to accounting variables from forecasting-year cohort t to obtain firm i's predicted one-year-ahead earnings, denoted by $\widehat{IB}_{i,t+1}$.

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

Following the empirical implementation of Hou et al. (2012), we construct the implied cost of capital using forecasted one-year-ahead earnings and contemporaneous market equity. This implementation is closely related to the valuation framework of Gordon and Gordon (1997). Under the simplified valuation assumption adopted in this implementation, the firm's expected cost of capital is approximated by the forecasted one-year-ahead earnings yield. Accordingly, the implied cost of capital is computed as

$$ICC_{i,t} = \frac{\widehat{IB}_{i,t+1}}{ME_{i,t}}, \tag{C.4}$$

where $ME_{i,t}$ denotes the market value of common equity. Market equity is computed from CRSP monthly data as the absolute stock price multiplied by shares outstanding. Because CRSP reports shares outstanding in thousands of shares, market equity is first expressed in thousands of dollars and subsequently divided by 1,000 so that both market equity and predicted earnings are measured in millions of dollars.

This implementation may be viewed as the zero-growth approximation to the Gordon and Gordon (1997) valuation framework. Rather than explicitly solving a multi-period valuation equation with terminal-value assumptions, the implementation uses the forecasted one-year-ahead earnings yield as the empirical proxy for the firm's implied cost of capital, consistent with the implementation of Hou et al. (2012).

When a firm (`PERMCO`) has multiple securities (`PERMNO`) outstanding in the same month, market equity is aggregated across all securities and assigned to the security with the largest individual market capitalization, thereby constructing a firm-level measure of market equity.

Predicted earnings based on forecasting-year cohort t are matched with monthly market equity from June of year $t+1$ through May of year $t+2$. Under this convention, the annual earnings forecast

remains fixed throughout the June–May matching period, while market equity is updated monthly. Consequently, the resulting ICC is an annualized measure whose value changes monthly through movements in market equity. Monthly updating therefore reflects changes in market valuation rather than a conversion from an annual expected return into a monthly expected return.

C.3 Sample Filters and Implementation Details

The sample is restricted to ordinary common shares listed on the NYSE, AMEX, or NASDAQ (CRSP exchange codes `exchcd`$\in \{1, 2, 3\}$ and share codes `shrcd`$\in \{10, 11\}$). The Compustat sample further requires nonmissing values for income before extraordinary items, common equity, total assets, common dividends, and operating accruals.

Observations with negative estimated ICC values ($ICC_{i,t} < 0$) are treated as missing. Valid ICC estimates are winsorized annually at the 1st and 99th percentiles to mitigate the influence of extreme observations.

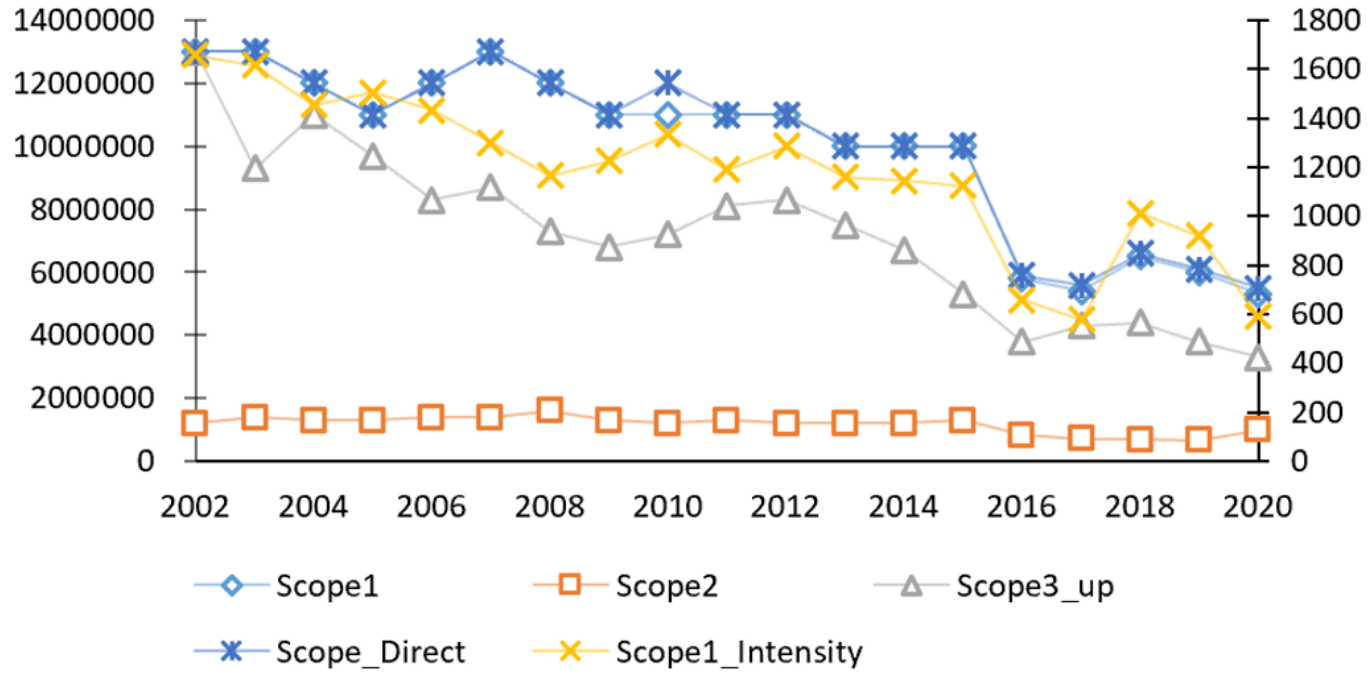
Online Appendix

The Network Incidence of Carbon Transition Risk

Shubo Kou Kai Li Minghao Li Wu Zhu

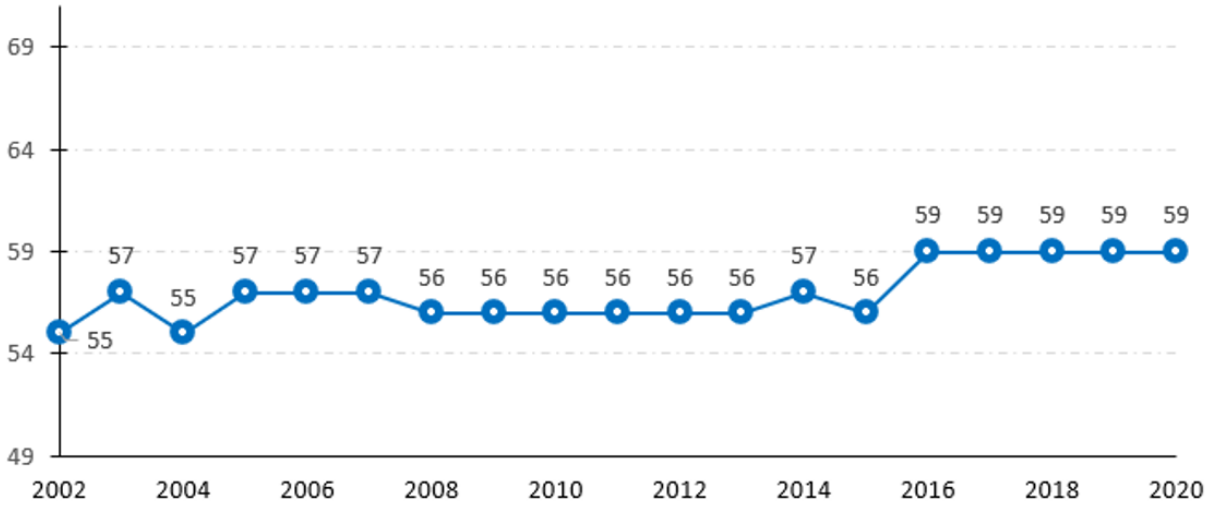
OA. Additional Figures

Figure OA.1: Carbon Emission and Intensity



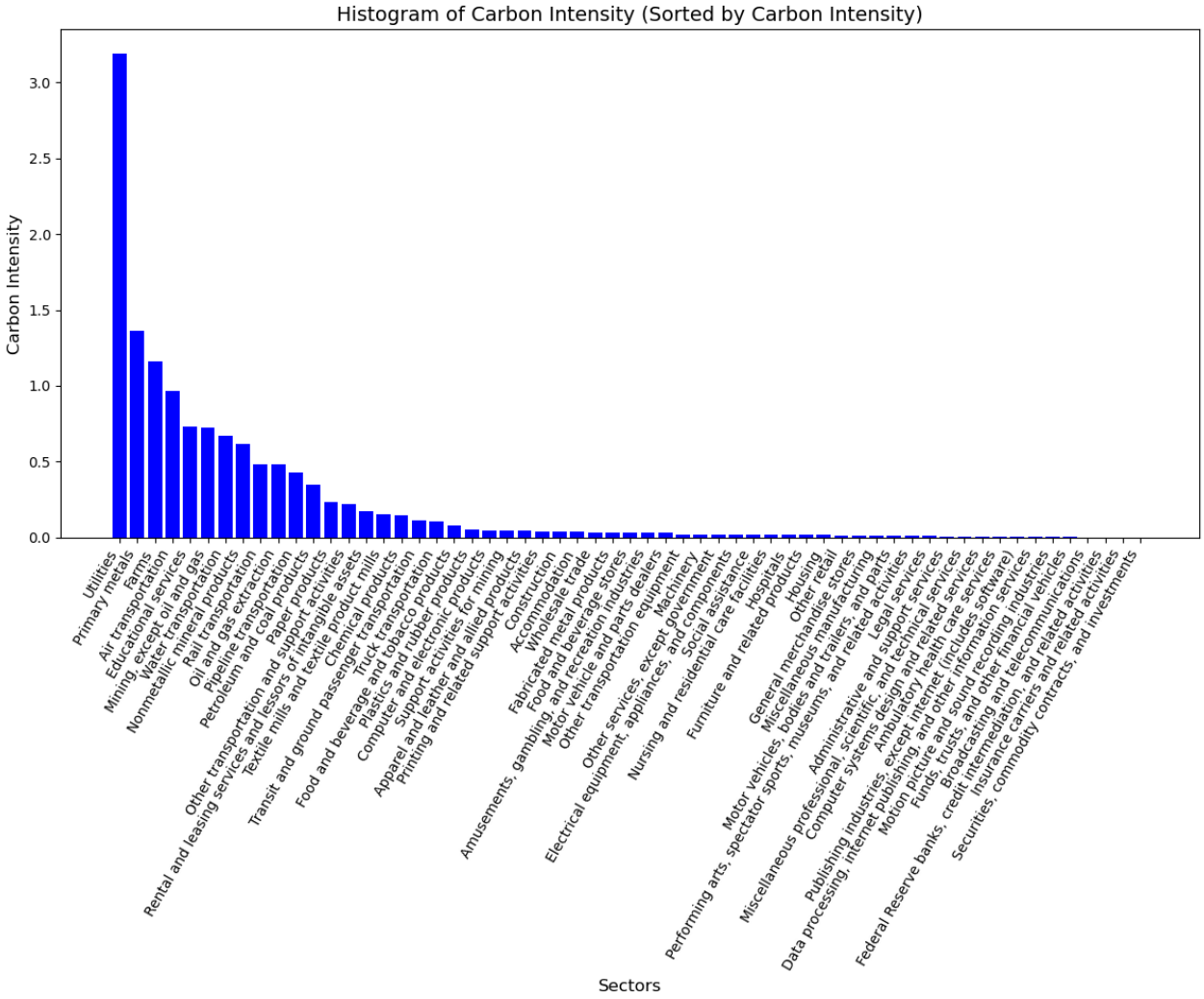
This figure plots the time series of selected carbon-emissions measures in the Trucost database. Specifically, Scope 3 emissions refer strictly to upstream emissions (`Scope3_up`), reflecting Trucost's focus on supply-chain inputs. Additionally, direct emissions (`Scope_Direct`) are reported as a distinct metric separate from standard Scope 1 emissions. The figure also includes standard Scope 1, Scope 2, and Scope 1 emissions intensity.

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



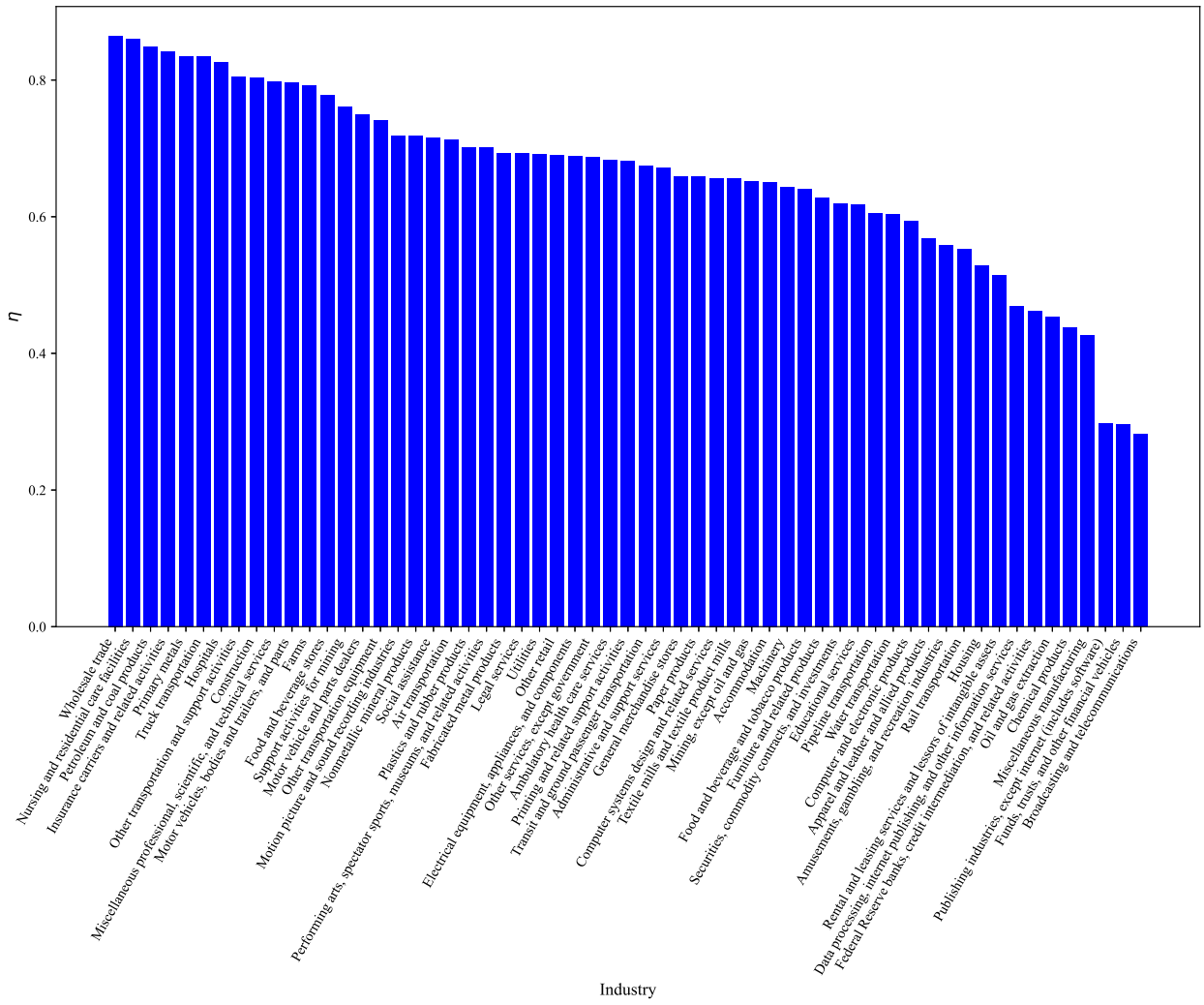
This figure plots the number of BEA industries represented in the matched Trucost sample for each individual year. While the annual count of matched industries ranges between 54 and 59 due to expanding Trucost firm coverage over time, a core set of 53 BEA industries remains continuously represented across all sample years.

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



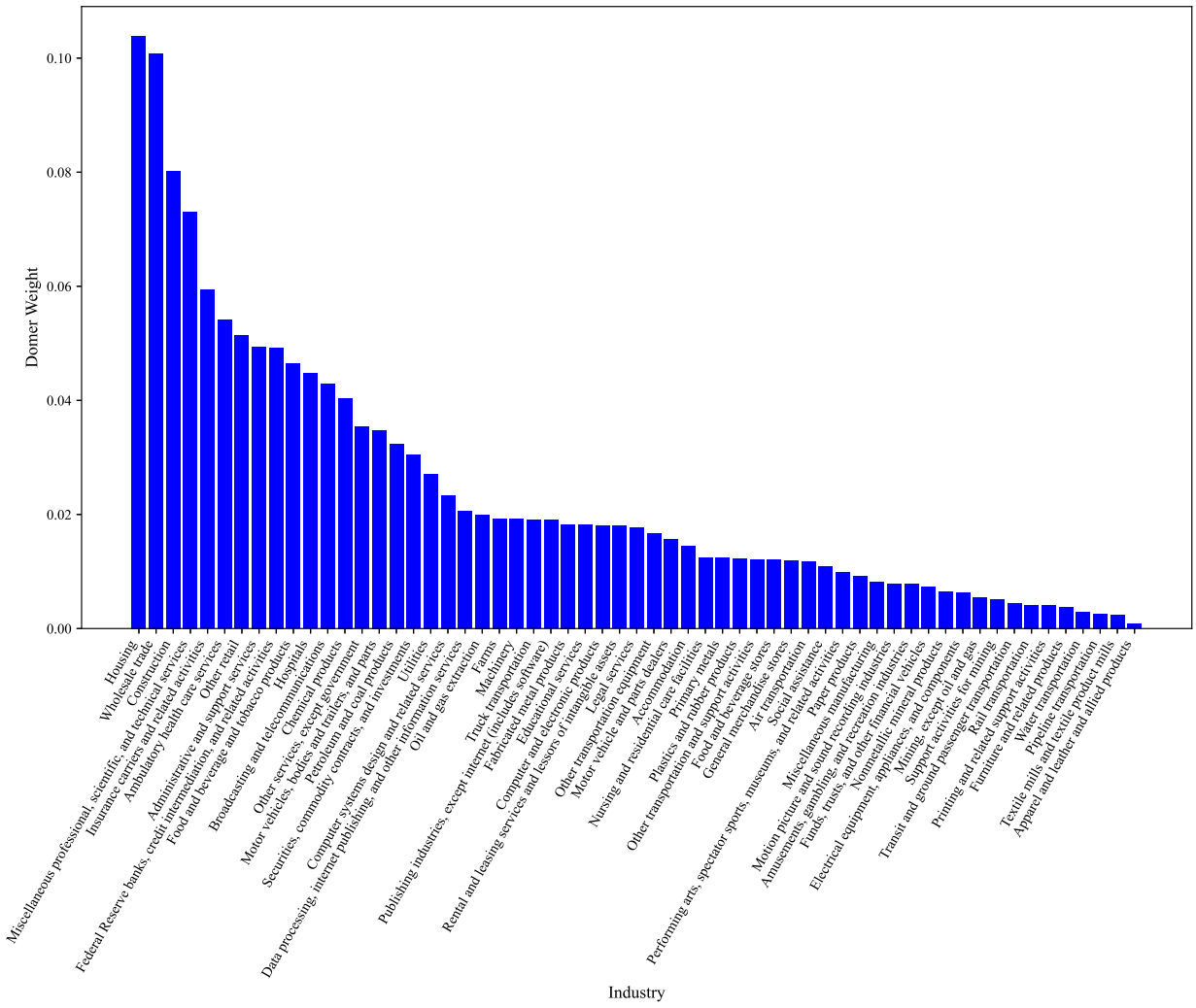
This figure depicts the annual average carbon emission intensity at the BEA industry level. From 2002 to 2020, the industry's average carbon emission intensity is 236.22 (tons per million dollars). There is substantial variation in direct carbon emissions across industries. The top five industries with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

Figure OA.4: The Ratio of Composite Intermediate Inputs (η_i) across BEA Industries



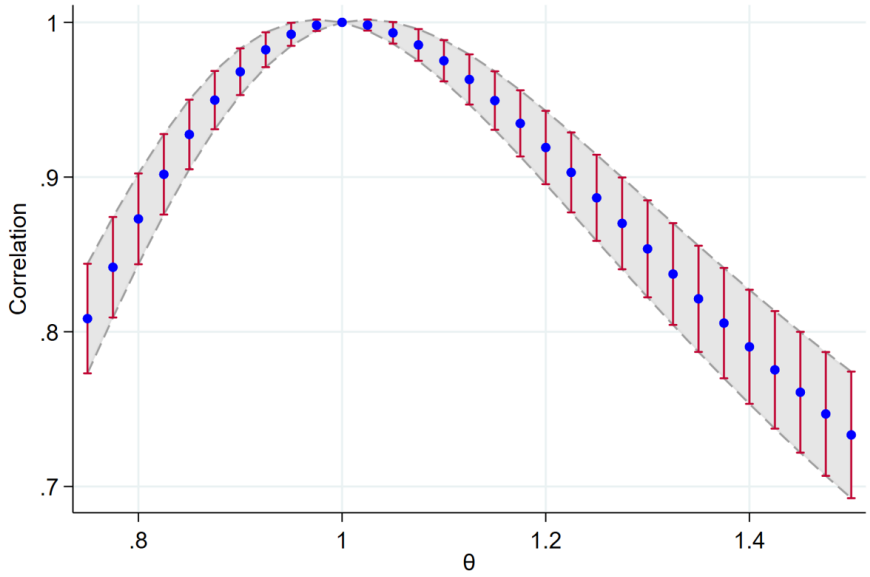
This figure shows the annual average ratio of composite intermediate input, η, at the BEA industry level.

Figure OA.5: The Industrial Domar Weights



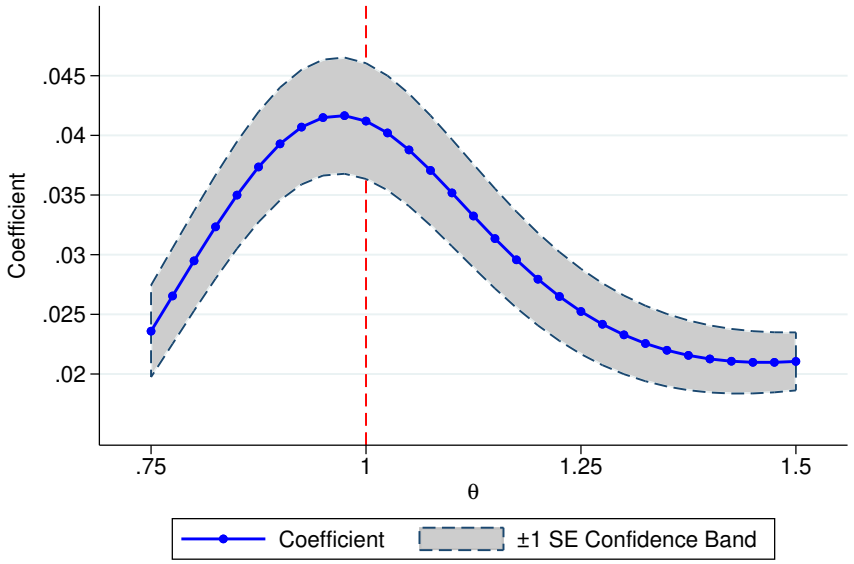
This figure shows the annual Domar weight at the BEA industry level averaged across years from 2002 to 2020. Over the sample period, the top five industries with the highest average Domar weight are Housing, Wholesale Trade, Construction, Scientific and Technical Services, and Insurance Services.

Figure OA.6: Network Exposure (χ^{θ}) under the CES Production Setting



This figure plots, for each elasticity parameter $\theta \in [0.75, 1.5]$, the cross-sectional correlation between the CES network-exposure measure χ^{θ} and the Cobb–Douglas benchmark $\chi^{\theta=1}$. We set $\kappa = 4\%$ following the estimates in Greenstone et al. (2012). The points report the correlations and the vertical bars report the corresponding one-standard-error bands.

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

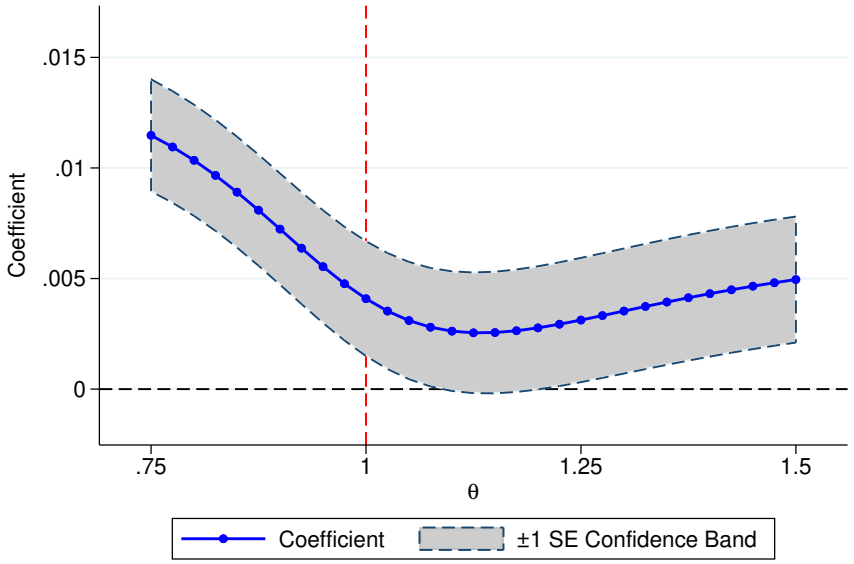


This figure presents the estimated coefficients of χ^{θ} from the following specification:

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

where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the network 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. We set $\kappa = 4\%$ following the estimates in Greenstone et al. (2012). 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 one-standard-error bands. This analysis examines how the relationship between network 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



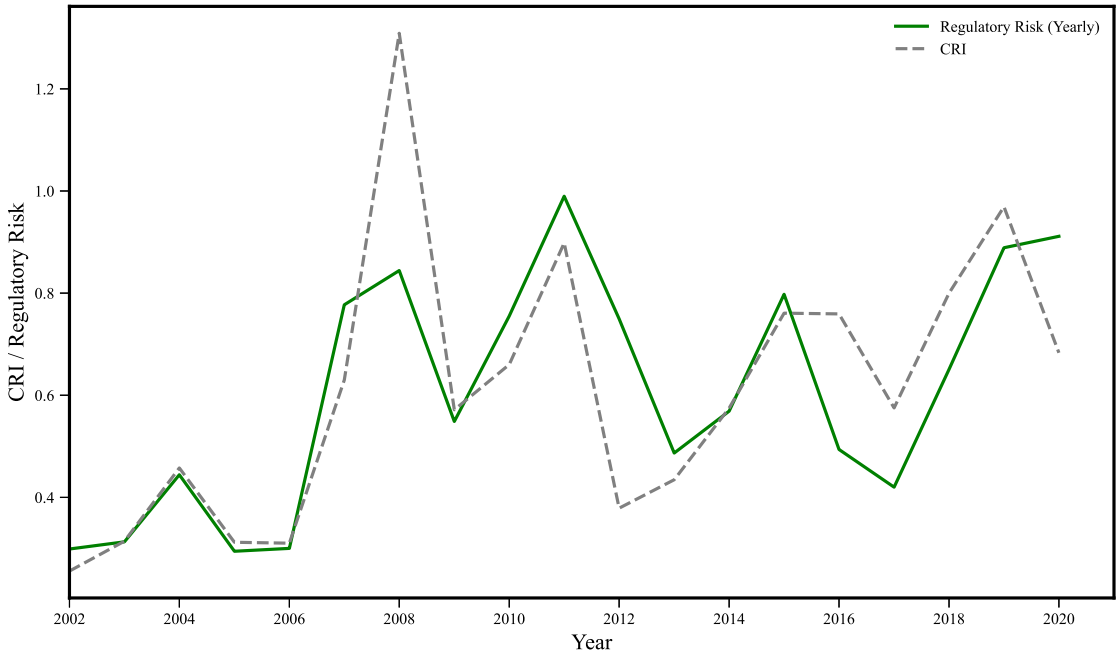
This figure presents the estimated coefficients of γ from the following specification:

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

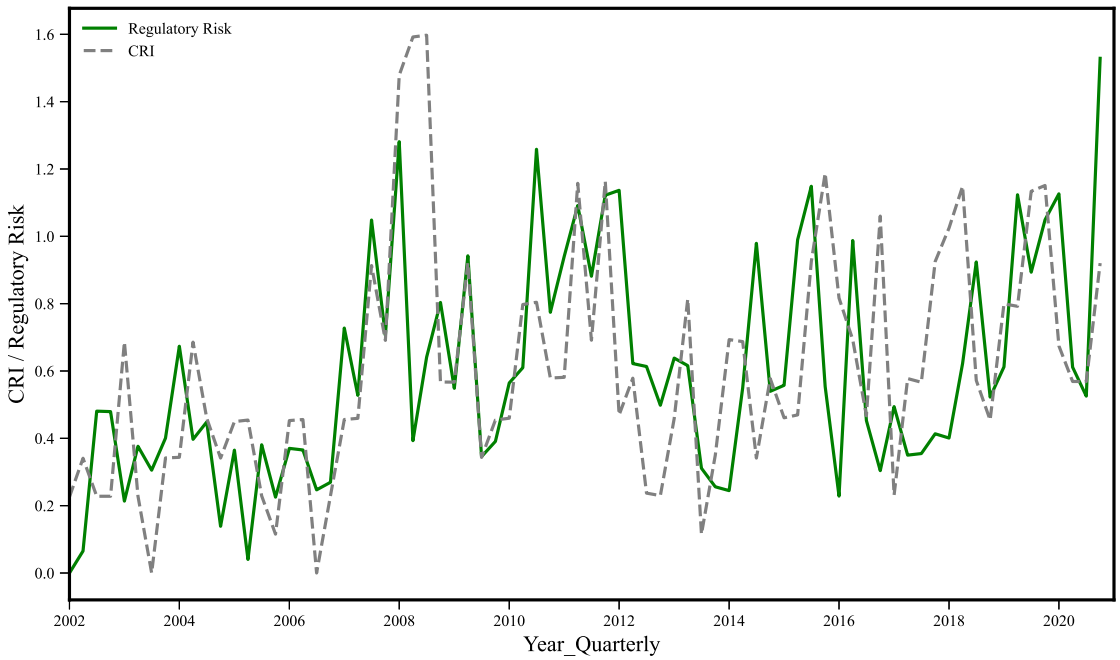
where ICC_{it} denotes the firm's implied cost of capital, χ_{it}^{θ} represents the network carbon risk exposure derived from a CES production function with elasticity parameter $\theta \in [0.75, 1.5]$, and γ_{it} is the firm's carbon emission intensity. We set $\kappa = 4\%$ following the estimates in Greenstone et al. (2012). 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 one-standard-error bands. 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 are the BEA industries excluded from the matched BEA–NAICS sample used in the empirical analysis.

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 equity market capitalization 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 sales.
ROA	1.0%	Operating income before depreciation as a fraction of average total assets based on most recent two periods.
PPETA	1.0%	Total tangible assets (Property, Plant, and Equipment) divided by total assets.
Leverage	1.0%	Total debt divided by the book value of equity.
CAPEXTA	1.0%	Capital expenditures divided by total assets.
HINDEX	1.0%	Herfindahl index of 4-digit SIC industry j where firm i belongs.
Tobin' Q	1.0%	The ratio of the market value of assets (market cap of equity plus book value of debt) divided by the book value of assets.
KZINDEX	1.0%	The KZ index (Kaplan and Zingales, 1997) is a relative measure of a company's dependence on external financing. KZ Index = -1.001909 x Cash flows / Property, Plant, and Equipment(PPE) + 0.2826389 x Tobin' Q + 3.139193 x Debt / Total capital + -39.3678 x Dividends / PPE + -1.314759 x Cash / PPE
Ln(Age)	1.0%	The natural logarithm of the number of years since the IPO year.

Table OB.3: Definition of Variables (continued)

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

Variable	Winsorized	Description
ICC (%, annualized)	1.0%	The implied cost of capital of the firm at month t.
Return (%, annualized)	1.0%	The monthly stock return in month t, annualized by multiplying by 12
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 time-series regressions of individual stock excess returns on the HML portfolio return using a 36-month rolling window, 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 Differences between Network and Direct Carbon Exposure

This table presents rank differences across industries based on network exposure χ and direct exposure γ. Panel A lists industries whose χ ranks are high relative to their γ ranks, while Panel B lists industries with high γ ranks and lower χ ranks. Rank change is the difference between the γ and χ ranks.

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 network 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)	(2)	(3)	(4)
	ICC	*ICC*	*ICC*	*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 network 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 network 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 Network Exposure - Value Weighted

This table examines the effect of direct and network 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 network carbon risk exposure, 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*
Network 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 Network Exposure - Equal Weighted

This table examines the effect of network 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 network carbon risk exposure, 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*
Network 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 relation between network and direct carbon risk exposure and realized stock returns. Specifically, we consider the following specification,

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

and

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

where $r_{i,t+10}$ denotes the stock return for firm i at time t, measured 10 months following the earnings announcement. Given that carbon emissions disclosures typically occur approximately 10 months after the release of financial reports, we adjust for this reporting lag to mitigate any look-ahead bias, in line with the methodology outlined by Zhang (2025). β_χ and β_γ represent the effects of network 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)	
Network 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 carbon risk exposure and realized stock returns while controlling for alternative emissions measures (total emissions, Scope 2, and Scope 3). 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 network 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***	0.244***	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 carbon risk exposure and realized stock returns while adding revenue-related controls to address concerns about the correlation between emissions and firm scale. 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 network 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 carbon risk exposure and realized stock returns while adding controls for alternative production-network characteristics. 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 network 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***	0.228***	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 robustness of the relation between carbon risk exposure and realized stock returns across alternative return-measurement lags (6, 12, 18, 24, and 36 months), as well as returns measured between consecutive emissions disclosures. 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 network 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 carbon risk exposure and realized stock returns across three subsamples. Column (1) and (2) use data from after 2009, following Zhang (2025), to focus on the quality of carbon emission disclosure. Columns (3) and (4) report the post-2015 subsample around the Paris Agreement. 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 network 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
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 Classifications

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	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 Classifications (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 correlations at the annual frequency, while Panel B presents correlations at the quarterly frequency. 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: Quarterly Data				
	CRI	Climate Exposure	Climate Risk	Regulatory Exposure
Climate Exposure	0.504***			
Climate Risk	0.484***	0.958***		
Regulatory Exposure	0.459***	0.828***	0.808***	
Regulatory Risk	0.456***	0.592***	0.635***	0.683***

OC. Prompt on Carbon Regulatory Risk

Prompt for Identifying Energy-Sector Regulatory Risk.

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

News Article:

```
"""{fulltext}"""
```

Please answer the following questions:

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

(a) Yes

(b) No

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

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

(a) Yes

(b) No

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

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

(a) Increasing (going up)

(b) Decreasing (going down)

(c) Unclear

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

Format your response as a JSON object like below:

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