The Propagation of Environmental Risk Through Production Networks: Borrowing Cost Effects

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Abstract

We study how environmental risks shape corporate borrowing costs through production networks. We develop a general equilibrium model with rigid input choices and default in which both production outcomes and interest rates are determined endogenously. The model introduces a network-based measure of borrowing costs and shows that climate shocks propagate along input-output linkages, amplifying default risk and premia. Brown firms face higher costs because of transition exposure, while even low-emission firms are penalized when they depend on brown suppliers, as upstream risks are transmitted through the supply chain. Using U.S. firm-level data matched with EPA sectoral emissions and input-output linkages, we find that lenders account for both direct and network-adjusted exposures. Evidence around the Paris Agreement confirms the relevance of these mechanisms. The results highlight how transition risk operates systemically through networks and motivate prudential tools that incorporate production linkages in credit markets.

JEL Codes: E44, G32, Q54, L14.
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1 Introduction

Firms are subject to climate physical risks, or losses due to natural disasters, and transition risks, due to regulation, reputation damages and technological obsolescence, as shown by Bolton and Kacperczyk (2021). Transition risks have been affecting significantly firms' profitability Bartram and Sehoon (2022) and have also been found to tighten credit conditions for brown firms Ivanov et al. (2023).

The question of how climate risks, transition and physical, are transmitted into financial markets is now central to both policy debates and academic research. In particular, there is growing evidence that firms with larger carbon footprints face higher borrowing costs. This finding has been taken as an indication that credit markets begin to internalize physical as well as transition risks, that we label environmental risks. Yet the existing evidence remains essentially reduced-form and partial: it interprets climate risk as a firm-level attribute, proxied by direct emissions, and studies its correlation with observed spreads. Such an approach neglects two essential aspects. First, firms do not operate in isolation but are embedded in complex input-output networks, where shocks originating in one sector propagate to others. Second, interest rates are not exogenously given risk premia, but equilibrium outcomes that result from the interaction of production, financing, and default risk. A proper understanding of climate risks versus finance interactions requires a framework that makes these mechanisms explicit.

This paper develops such a framework. Building on recent advances in the theory of production networks, we construct a static general equilibrium model with three types of agents: firms, consumers, and banks. Firms are heterogeneous in their environmental exposure. Green firms are subject only to physical risks, while brown firms, by their nature, are also exposed to transition risks. In the absence of shocks, brown firms are more productive than green ones, as is known from several empirical studies, but their production is subject to additional stochastic shocks. Crucially, firms must decide ex ante on inputs and labor without being able to adjust to the realized state. This rigidity, reflecting real-world irreversibilities in production and employment, generates the possibility of default when shocks realize ex post.

Shocks do not stop at the firm level. Because production uses intermediate goods, shocks propagate through input-output linkages. The Leontief inverse provides the natural tool to characterize this propagation: the primitive shocks to productivity are transformed into network-adjusted shocks that affect all downstream firms. Hence, a firm's effective exposure is determined not only by its own environmental risk but also by that of its suppliers.

Banks operate under perfect competition, are risk-neutral, and finance firms' liabilities. They are residual claimants, paid only after workers and suppliers, and are therefore directly exposed to default risk. Interest rates are set so that banks break even in expectation. This zero-profit condition delivers a simple but powerful characterization: the interest rate applied to any firm depends exclusively on the distribution of its normalized shocks, both the total shocks affecting its own output and the weighted shocks inherited from its suppliers. Productivity differences between green and brown firms do not directly affect borrowing costs; only risk does.

The model yields several implications. First, firm borrowing costs increase not only with direct exposure but also with the exposures of upstream suppliers. Thus even firms with low direct emissions may face high interest rates if they are embedded in brown supply chains, because primitive shocks to brown firms are greater than those to green firms. Second, interest rates on brown firms are weakly higher if the network is uniform, if links between the two subnetworks are weak, or if the two networks are separated (brown sells to brown, green to green). Third, if green and brown networks are separated and there are no physical shocks, the interest rate on green sectors is zero. These results show how systemic risk, network propagation, and endogenous pricing jointly determine the allocation of credit.

We bring these mechanisms to the data by combining U.S. firm-level balance sheet and borrowing cost information with sectoral emissions from the Environmental Protection Agency and input-output linkages from national accounts. The analysis documents that borrowing costs are higher for brown firms and, crucially, that lenders price not only direct emissions but also network-adjusted emissions that capture embodied carbon exposure. As a further step, we exploit the 2016 Paris Agreement as a quasi-natural experiment: after its adoption, interest rates rose disproportionately for firms embedded in brown supply chains, even when their own emissions remained low. This pattern is consistent with lenders responding to transition shocks transmitted through production networks.

Taken together, the theory and evidence demonstrate that climate risk is priced in credit markets as a systemic and forward-looking phenomenon. Borrowing costs are not just a reflection of a firm's own emissions, but of its position in the production network and its inherited exposure to upstream risks. The paper thus provides both a new theoretical foundation and empirical support for the view that transition risk operates through production networks and is internalized by credit markets.

Our contribution is threefold. First, we develop a network-based general equilibrium model with rigidities and default that endogenizes firm-specific borrowing costs as a function of direct and propagated environmental shocks, clarifying why brown firms face higher debt costs and why network position matters. Second, we validate the model using U.S. firm-level borrowing costs merged with EPA sectoral emissions and input-output linkages, constructing a network-adjusted exposure that lenders systematically price into credit spreads. Third, exploiting the 2016 Paris Agreement in a difference-in-differences design, we show that borrowing costs rose disproportionately for firms embedded in brown supply chains, even when their own emissions were low. Together, these results demonstrate that climate-finance interactions are systemic, operate through supply chains, and are amplified by production networks.

In sum, we extend the frontier of production network theory to climate finance by offering the first theoretical framework that links environmental risk, network propagation, and borrowing costs. At the same time, we empirically validate the relevance of these mechanisms for U.S. credit markets and provide causal evidence that the structure of supply chains plays a central role in the pricing of green versus brown debt.

The remainder of the paper is structured as follows. Section 2 develops the theoretical model, introducing rigid production, stochastic shocks, and competitive banks, and derives the main results on how environmental risk and network position shape borrowing costs. In Section 3 we outline the empirical methodology and explain how we bring the model's predictions to the data, including the use of the Paris Agreement as a quasi-natural experiment. Section 4 concludes with a discussion of the broader implications for credit markets and the transition to a low-carbon economy.

Literature. Our theoretical contribution draws on the literature on production networks, notably Acemoglu et al. (2012), which we extend by incorporating environmental shocks and default. We build on the frameworks of Como et al. (2025) and Pellet and Tahbaz-Salehi (2023), who introduce rigidities in input contracting. Since investments and production inputs must be ordered before shocks to production realize—as we witnessed during the Covid-19 pandemic and recent disruptions from wars—firms suffer losses and may even default. Relative to those papers, here we distinguish green and brown firms based on the risks they suffer and the productivity they enjoy. These elements allow us to explain how sector-level environmental shocks propagate through supply chains and influence firm-specific borrowing costs, even for firms that do not directly increase emissions.

A foundational theoretical channel for the pricing of green versus brown assets is provided by Pedersen et al. (2021) and Pastor et al. (2021). They model investor utility that includes a preference for green assets ("taste for higher ESG"), leading some investors to accept lower returns on green assets, thus explaining lower interest rates for green relative to brown firms. To our knowledge, there is no existing literature studying the role of transition shocks in determining the price of debt for green and brown sectors. We claim to be the first in developing a model which incorporates this feature and thus provide a mechanism explaining how brown sectors end up being priced more than green ones, *ceteris paribus*.

Empirically, a growing body of literature shows that environmental performance affects corporate financing. In credit markets, Delis et al. (2024) find that after the Paris Agreement, banks began pricing climate policy risk into syndicated loans, especially for firms with large fossil fuel reserves. In equity markets, Bolton and Kacperczyk (2021) uncover a "carbon premium" in US markets: high-emission firms tend to produce higher expected returns, consistent with risk-based compensation for carbon exposure. Bolton and Kacperczyk (2022) extend the result to 77 countries: higher carbon emission firms trade at a discount and face higher costs of capital.

Adding depth in the banking context, Altavilla et al. (2023) demonstrate that euro-area banks charge higher interest rates to firms with greater carbon emissions and lower rates to firms committing to emissions reductions, even after controlling for default risk. These effects are more pronounced among banks publicly committed to decarbonisation. Restrictive monetary policy amplifies both credit risk premia and emission-related pricing premia, tightening credit more for brown firms than for green ones. Related evidence from Ehlers et al. (2022) shows that polluting firms began paying a "carbon premium" on syndicated loans after the Paris Agreement, while Reghezza et al. (2022) find that European banks reduced credit to polluting firms in the US after the US withdrawal from the Paris Agreement, suggesting reputation and public pressure channels.

More broadly, earlier studies had already established that firms with poor CSR or environmental records face higher borrowing costs. Goss and Roberts (2011) show that socially irresponsible firms pay a premium on bank loans, while Chava (2014) document higher loan spreads for environmentally controversial firms. In bond markets, a modest "greenium" has been identified: Zerbib (2019) and Baker et al. (2018) find that green bonds carry slightly lower yields relative to comparable conventional bonds, consistent with investor preference channels highlighted by Pastor et al. (2021). Finally, Gormsen and Huber (2023) show that since 2016 greener firms have enjoyed a structurally lower capital cost, roughly 1% lower than brown firms, reflecting both the equity and debt markets.

2 Theoretical Analysis

The theoretical model builds on Como et al. (2025).[1] We develop a static general equilibrium in a production network with three types of agents: firms, consumers, and banks. All decisions are taken at time 0, prior to the realization of uncertainty. At time 1, the stochastic shocks on production are realized, production occurs, consumers consume, and payments between agents are settled.Uncertainty in production is introduced by defining a complete probability space $(\Omega, \mathcal{F}, P)$, on which random shocks are realized. Agents make ex-ante decisions at time 0, while outcomes and transfers materialize ex-post at time 1.

2.1 Rigidity

Production processes in the real world are characterized by lags and irreversibilities. Orders of intermediate goods and investment in physical capital typically take time to be delivered, and therefore - even when there is uncertainty on future state of the economy - are planned in advance, without the possibility of being tailored to the the state of the world that will realize. When a specific state occurs, these decisions are often irreversible. Similarly, labour is often hired in advance and cannot promptly be dismissed, at least in some jurisdictions. These forms of *rigidity*, which have recently been introduced in the network literature (Pellet and Tahbaz-Salehi (2023)), may generate default, if firms are levered. If, in a specific state, the costs of orders for intermediate goods and labour hired, as well as the interest rates to banks, are not covered by revenues, default occurs. To model all of this, we assume that the decision of firms about intermediate goods and labour are not state dependent. They are characterized by ex ante or *nominal* quantities, constant across possible states.

2.2 Firms

There are n firms or sectors in the economy[2], $\mathcal{V} = 1, 2, .., n$, partitioned into two groups. The first n_1 firms are classified as *green*, while the remaining $n - n_1$ firms are classified as

[1] With respect to them, we consider only the case with imperfect information, or rigidity, and positive leverage. We add the distinction between green and bron firms based on productivity and risks.

[2] We use indifferently the term firm and sector because we assume that firms are perfect substitutes: each sector is made by homogeneous firms, and as one defaults it can be substituted by a perfectly equal one. This prepares the empirical part, since the US input-output matrix is available to us at the 5 digit sector and not at the individual firm level

brown. Brown firms are more risky than green, in that they can be hit by transition as well as physical shocks, but are more productive, all others equal. Transition shocks include in our view fines, penalties, and other regulatory risks, as well as technological obsolescence. Physical risks correspond to natural catastrophes and their consequences.

On the probability space $(\Omega, \mathcal{F}, P)$, we define two vectors of non-positive random variables: $\omega : \Omega \to \mathbb{R}^n_-$ and $\epsilon : \Omega \to \mathbb{R}^{n-n_1}_-$. These represent the *primitive production shocks*. Green firms are exposed only to ω, which captures physical risks. Brown firms are exposed to both ω and an additional transition shock ϵ. Let $\eta : \Omega \to \mathbb{R}^n_-$ denote the overall vector of primitive shocks. Its first n_1 components are equal to ω, while its remaining $n - n_1$ components are the sum of those in ω and ϵ. The previous assumptions on η are equivalent to stating that shocks to brown firms are larger in absolute value than those to green firms, or that *green shocks dominate brown ones in the sense of first-order stochastic dominance*. Let G_k be the cumulative distribution function of $|\eta_k|$: for any $b > n_1$ (brown) and $g \leq n_1$ (green),

$$G_b(x) \leq G_g(x) \quad \text{for all } x \in \mathbb{R}^n, \text{ with strict inequality for some } x, \tag{1}$$

When considering η_k instead of its absolute value, since shocks are non-positive, the inequality reverses:

$$F_b(x) \geq F_g(x), \quad \text{for all } x \in \mathbb{R}^n, \text{ with strict inequality for some } x, \tag{2}$$

where F_k denotes the cumulative distribution function of η_k. The definition of transition and physical risks translates into the following assumption: $\eta_g \geq \eta_b$ in the sense of first-order stochastic dominance. Considering the absolute value of the shocks, $-\eta_g \leq -\eta_b$: later on, we label this saying that *green shocks are smaller or less severe than brown*.

To capture the basic trade-off between productivity and risk, and anticipating on the empirical evidence, we assume that brown firms, in the absence of shocks, are more productive than green ones. Let $Z \in \mathbb{R}^n_+$ denote the vector of total factor productivities. We assume Z_k is higher for brown firms ($k > n_1$) and lower for green firms ($k \leq n_1$), reflecting a higher baseline output among brown firms that compensates for their greater environmental exposure [3].

[3] Bartram and Sehoon (2022) show that transition shocks lower brown firms' profits, while Ivanov et al. (2023) find they raise borrowing costs. These effects highlight that such shocks, specific to brown firms, add to the risks faced by all firms

Firms use a Cobb-Douglas technology to produce output:

$$y_k = Z_k e^{\eta_k} l_k^{\beta_k} \prod_{j \in \mathcal{V}} z_{jk}^{A_{jk}}, \quad \text{for } k = 1, \ldots, n, \tag{3}$$

where:

- y_k is the output of firm k,
- $Z_k > 0$ is the firm-specific productivity,
- l_k is labor employed,
- $\beta_k \geq 0$ is the labor share,
- z_{jk} is the input of good j used by firm k,
- $A_{jk} \geq 0$ reflects the *importance* of input j in the production of firm k.

We define $\alpha_k = \sum_{j \in \mathcal{V}} A_{jk}$ and assume constant returns to scale:

$$\alpha_k + \beta_k = 1. \tag{4}$$

Let c_k denote the consumption of good k.

We collect output, consumption, labor, and productivity in the vectors $y, c, l, Z \in \mathbb{R}^n_+$, and the input coefficients z_{jk} in a matrix $z \in \mathbb{R}^{n \times n}_+$. The production function of firm k can be compactly written as $y_k = F_k^{\eta_k}(z, l)$.

The market clearing conditions are:

1. Goods market clearing:
$$y = z\mathbf{1} + c, \tag{5}$$

2. Labor market clearing:
$$l'\mathbf{1} = 1. \tag{6}$$

We also collect the coefficients A_{jk} into a matrix $A \in \mathbb{R}^{n \times n}_+$. Under the mild assumption that the spectral radius of A be smaller than one, the matrix A defines a Leontief inverse:

$$L = (I - A')^{-1}, \tag{7}$$

which has non-negative entries and plays a central role in shock propagation throughout the network, as we show now.

We assume that shocks propagate proportionally through the network: if a firm is hit by a shock that reduces output by a fraction p, it also reduces its supply of intermediate goods equally across suppliers and its supply of final goods by the same fraction. Formally, for all k, j such that $A_{kj} > 0$,

$$\frac{\tilde{y}_k}{y_k} = \frac{\tilde{z}_{kj}}{z_{kj}} = \frac{\tilde{c}_k}{c_k}. \tag{8}$$

where the values with a tilde are the actual or post-shock ones, while the ones without the tilde are the ex ante or nominal ones. Como et al. (2025) show that, under this assumption, the actual shocks received by firms are not the primitive shocks η, but the network-amplified shocks $\rho = L\eta$. A shock η_h originating in node h affects firm k if $L_{kh} > 0$:

$$\rho_k = \sum_{j \in \mathcal{V}} L_{kj}\eta_j. \tag{9}$$

The vector ρ has non-positive entries, which represent the total shocks to the different sectors, opposite to the primitive ones in η. This highlights the core network effect: production shocks can be magnified or attenuated depending on the structure of interfirm linkages. A sufficient condition for the total shocks to brown firms to be greater than the ones of green ones - as it happened for primitive ones - is that the Leontief matrix separates the two networks, or $L_{kh} > 0$ when both firms are either green or brown ($k \le n_1, h \le n_1$ and $k > n_1, h > n_1$), but not in the mixed cases, when one is green and the other brown.

Lemma 1. *If $L_{kh} > 0$ for $k \le n_1, h \le n_1$ and $k > n_1, h > n_1$, $L_{kh} = 0$ otherwise, $\rho_g \ge \rho_b$ in the sense of first-order stochastic dominance.*

To complete the description of the firm side of the economy, we introduce

- w, unit cost of the employed labor (*wage*);
- p_k, unit price of the good produced by firm k.

Because of (8), the *actual* assets or revenues of firm k are

$$\mathcal{A}_k := p_k y_k^{\eta} = p_k e^{\rho_k} F_k^0((z_{jk})_j, l_k) \tag{10}$$

where $(z_{jk})_j$ is column k of the matrix z, which collects all the inputs to sector k.

On the other hand, its *actual* liabilities due to intermediate goods and labor are

$$\mathcal{L}_k := \sum_{j\in\mathcal{V}} p_j z^{\eta}_{jk} + wl_k = \sum_{j\in\mathcal{V}} p_j e^{\rho_j} z_{jk} + wl_k. \tag{11}$$

Firms raise debt from financiers, which we call banks, As we explain below, the bank finances a fraction θ_k of the liabilities, and either receives the full payment of it and its interests, $(1 + r_k)\theta_k\mathcal{L}_k$, or gets only a recovery out of it. In the second case the firm looses the complement of the recovery with respect to the full payment, $(1 + r_k)\theta_k\mathcal{L}_k$, as default costs. So the firm always pays $(1 + r_k)\theta_k\mathcal{L}_k$. Then, profits are:

$$\Pi_k((z_{jk})_j, l_k, \eta, p) := \mathcal{A}_k - (1 + r_k\theta_k)\mathcal{L}_k \tag{12}$$

Actual assets, liabilities, and profits can be expressed in terms of normalized quantities, as follows. Define the *normalized total shocks* as the total shocks which affect k, divided by their expectation under the measure P

$$\tau_k := \frac{e^{\rho_k}}{\mathbb{E}[e^{\rho_k}]}. \tag{13}$$

Define also the *normalized suppliers' shocks* as the normalized total shocks to the nodes who provide inputs to node k, weighted by their importance. Considering that log shocks to labor are zero by assumption and inputs to sector k include labor, with importance β_k, the suppliers' shocks are

$$\epsilon_k := \beta_k + \sum_{j\in\mathcal{V}} A_{jk}\tau_j. \tag{14}$$

Then, defining $s_k := \mathbb{E}[\mathcal{A}_{\|}]$

$$\mathcal{A}_k = s_k\tau_k \tag{15}$$

$$\mathcal{L}_k = s_k\frac{\epsilon_k}{1 + r_k\theta_k}. \tag{16}$$

2.3 Banks

Financiers form a continuum of risk-neutral banks operating under perfect competition. Each bank is randomly matched with a firm and provides financing to cover a fraction $\theta_k \in [0, 1]$ of the firm's liabilities. Banks are paid only after firms have settled payments to workers and suppliers. Because of that, they are exposed to the possibility of default, which arises endogenously from the realization of shocks.

Let us assume that banks recover the minimum between the amount due $((1 + r_k)\theta_k\mathcal{L}$ and the cash flow available to the firm after labour ad the other firms have been paid. This means that labour and providers of intermediate goods are senior to the bank, or that the former do not take any default risk, as stated, and that the bank recovers whatever is left after those are paid, up to its credit, which is $(1 + r)\theta_k\mathcal{L}_k$. The bank's profit from lending to firm k is:

$$\mathcal{I}_k = \min(\max(\mathcal{A}_k - (1-\theta)\mathcal{L}, 0), (1+r)\theta_k\mathcal{L}_k) - \theta_k\mathcal{L}_k \tag{17}$$

$$= \min(\max(\mathcal{A}_k - \mathcal{L}, -\theta_k\mathcal{L}_k), r_k\theta_k\mathcal{L}_k). \tag{18}$$

Because banks operate competitively and are risk-neutral, they choose the interest rate r_k so as to break even in expectation. The zero-profit condition is:

$$\mathbb{E}[\mathcal{I}_k] = 0 \tag{19}$$

To simplify matters, in what follows we consider only the case in which liabilities are totally financed by debt, or $\theta = 1$. In that case, the condition that determines the interest rate for sector k becomes

$$\mathbb{E}\left[\min(\mathcal{A}_k - \mathcal{L}_k, r_k\mathcal{L}_k)\right] = \frac{s_k}{1+r_k}\mathbb{E}\left[\min(\tau_k(1+r_k) - \epsilon_k, r_k\epsilon_k\right]. \tag{20}$$

$$\mathbb{E}\left[\frac{-\epsilon}{1+r} + \min(\tau_k, \epsilon_k)\right] = 0. \tag{21}$$

and finally, since $\mathbb{E}[\epsilon_k] = 1$

$$\mathbb{E}[\min(\tau_k, \epsilon_k)] = \frac{1}{1+r_k}. \tag{22}$$

Therefore, the interest rate applied to each firm depends exclusively on its exposure to environmental shocks, and not directly on its productivity Z. Even though brown firms are assumed to be more productive than green firms (i.e., $Z_i > Z_j$ for $i > n_1$ and $j \leq n_1$), the interest rate is determined only by its shocks. However, and consistently with the transmission of shocks from one firm to the other through the network, which may generate default cascades (see also Como et al. (2025)), the shocks that matter are not only the primitive ones, η, but the total ones, and specifically the total shocks to the sector and to its suppliers, τ and ϵ.

Interest rates are non negative, since $\mathbb{E}[\min(\tau_k, \epsilon_k)] \leq \mathbb{E}[\epsilon_k] = 1$.

2.4 Network effects on the cost of debt

In this section we study the relationship between risks and cost of debt. We show that, in equilibrium, the cost of debt on green firms is smaller than the one on brown ones in a number of cases. First, when the network linkages are uniform, in that all sectors have the same importance. Second, if the networks formed by green and brown firms are almost separated (brown firms are more important to brown, green to green) and third, or if the two subnetworks are separated. Let us consider first the case in which labour - which is riskless - is not more important for green than for brown firms and all the importance coefficients - contained in the matrix A - are the same, $A_{jg} = A_{jb}$ for all indices j, g, b. This is an economically interesting case not only because all intermediate goods are equally important, be them produced or purchased by green or brown firms. But also because the transmission of the shocks in the network occurs in a uniform way. A matrix A of this type indeed implies that the off-diagonal terms of the Leontief matrix are the same: transmission of the primitive shocks to any other sector occurs in the same, *uniform* way. It is not difficult to guess that, in such a "neutral" transmission environment, brown sectors, whose primitive shocks are more severe, but are affected in the same way as green sectors by the shocks of other sectors, remain more risky and therefore deserve a greater interest rate. Banks charge higher interest rates to brown firms in order to compensate for higher default risk. This is the content of the next Theorem.

Theorem 1 (Interest Rates with a uniform network)**.** *If green firms do not employ less labour than brown firms, i.e., $\beta_g \geq \beta_b$ for all $g \leq n_1$ and $b > n_1$, and $A_{jg} = A_{jb}$ for all indices j, g, b, then the interest rate applied to brown firms is weakly higher than that applied to green firms:*

$$r_b \geq r_g, \tag{23}$$

.

Proof. Recall that primitive shocks η to green firms dominate those to brown firms in first-order stochastic dominance. For brevity, write $\eta_g \geq \eta_b$. This implies:

$$P(\eta_g \leq x) \leq P(\eta_b \leq x) \quad \text{for all } x \tag{24}$$

where P is the probability on Ω. Since $\rho = L\eta$, the same dominance holds for total (network-propagated) shocks:

$$P(\rho_g \leq Lx) \leq P(\rho_b \leq Lx). \tag{25}$$

Applying monotonic transformations:

$$P\left(\exp(\rho_g) \leq \exp(Lx)\right) \leq P\left(\exp(\rho_b) \leq \exp(Lx)\right). \tag{26}$$

Dividing by $\mathbb{E}[\exp(\rho_b)]$ preserves the inequality:

$$P\left(\frac{\exp(\rho_g)}{\mathbb{E}[\exp(\rho_b)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right) \leq P\left(\frac{\exp(\rho_b)}{\mathbb{E}[\exp(\rho_b)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right). \tag{27}$$

Using the fact that first-order stochastic dominance implies $\mathbb{E}[u(\rho_g)] \geq \mathbb{E}[u(\rho_b)]$ for all non-decreasing functions u, and taking $u = \exp$, we also have:

$$P\left(\frac{\exp(\rho_g)}{\mathbb{E}[\exp(\rho_g)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right) \leq P\left(\frac{\exp(\rho_g)}{\mathbb{E}[\exp(\rho_b)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right) \tag{28}$$

and therefore

$$P\left(\frac{\exp(\rho_g)}{\mathbb{E}[\exp(\rho_g)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right) \leq P\left(\frac{\exp(\rho_b)}{\mathbb{E}[\exp(\rho_b)]} \leq \frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}\right). \tag{29}$$

for all values of x and therefore all non negative real values that obtain from $\frac{\exp(Lx)}{\mathbb{E}[\exp(\rho_b)]}$. This shows that normalized shocks to green firms dominate those to brown firms:

$$\tau_g \geq \tau_b. \tag{30}$$

If the conditions in the theorem are true, then:

$$\epsilon_g \geq \epsilon_b. \tag{31}$$

Since the min is weakly increasing in both arguments, it follows that:

$$\mathbb{E}[\min(\tau_g, \epsilon_g)] \geq \mathbb{E}[\min(\tau_b, \epsilon_b)], \tag{32}$$

which implies:

$$r_g = \frac{1}{\mathbb{E}[\min(\tau_g, \epsilon_g)]} - 1 \leq \frac{1}{\mathbb{E}[\min(\tau_b, \epsilon_b)]} - 1 = r_b. \tag{33}$$

for any brown firm $b > n_1$ and green firm $g \leq n_1$.

■

We conclude that the hypotheses of the theorem are sufficient for the normalized total shocks τ_k and supplier shocks ϵ_k to imply a weakly higher endogenous interest rate for brown firms. The theorem outcome results from the brown firms' higher exposure to both physical and transition risks, as a result of their direct - not network related - exposure.

The second circumstance we study is the one in which green firms not only are affected by less severe primitive shocks, but are also more exposed to shocks transmitted by other green firms, because the importance of brown firms for them is higher than the one of brown firms. Both groups are equally exposed to brown shocks, because the total importance of brown sectors to them is the same. The intuition is that the networks are *almost separated.*

Theorem 2 (Interest Rates with stronger linkages among brown vs green sectors)**.** *If green firms do not employ less labour than brown firms, i.e., $\beta_g \geq \beta_b$ for all $g \leq n_1$ and $b > n_1$, and green sectors are more important than brown ones in the production of green sectors, $\sum_{j \leq n_1} A_{gj} \geq \sum_{j \leq n_1} A_{bj}$ and $\sum_{j > n_1} A_{gj} = \sum_{j > n_1} A_{bj}$, $\beta_g \geq \beta_b$ for all indices $g \leq n_1, b > n_1$, then the interest rate applied to brown firms is weakly higher than that applied to green firms:*

$$r_b \geq r_g, \tag{34}$$

Proof. We established in the previous theorem that the first order stochastic dominance of the primitive shocks is preserved by the total shocks

$$\tau_g \geq \tau_b. \tag{35}$$

Call m the minimum of the support of the total shocks to green sectors, and M the same quantity for brown sectors,

$$M = \min_{j \leq n_1} \textbf{support}(\tau_\mathbf{j}) \tag{36}$$

$$m = \min_{j > n_1} \textbf{support}(\tau_\mathbf{j}) \tag{37}$$

and observe that

$$\sum_{j \le n_1} A_{gj}\tau_j \ge M \sum_{j \le n_1} A_{gj} \tag{38}$$

$$\sum_{j > n_1} A_{gj}\tau_j \ge m \sum_{j > n_1} A_{gj} \tag{39}$$

$$m \le M \tag{40}$$

$$\epsilon_g \ge M \sum_{j \le n_1} A_{gj} + m \sum_{j > n_1} A_{gj} + \beta_g \tag{41}$$

$$\epsilon_b \ge M \sum_{j \le n_1} A_{bj} + m \sum_{j > n_1} A_{bj} + \beta_b \tag{42}$$

If $\sum_{j \le n_1} A_{gj} \ge \sum_{j \le n_1} A_{bj}$ and $\sum_{j > n_1} A_{gj} = \sum_{j > n_1} A_{bj}$, $\beta_g \ge \beta_b$, then the lower bound for ϵ_g is greater than the one for $\ge \epsilon_b$ and therefore $min(\epsilon_g, \tau_g) \ge \min(\epsilon_b, \tau_b)$. The expectation follows the same inequality, and therefore $r_g \le r_b$.

■

The extreme case of the previous network separation is the one in which the networks are *completely separated*, which is described by the hypotheses of Lemma 1. This is the circumstance which would be most welcome, at least in Europe, by the regulatory authority, in order to have very favourable loan conditions for green firms (see for instance Commission (2024)). Based on the previous Theorem, it would give the minimum interest rate for green firms.

Corollary 1 (Interest Rates with separated networks)**.** *If green firms do not employ less labour than brown firms, i.e.,* $\beta_g \ge \beta_b$ *for all* $g \le n_1$ *and* $b > n_1$*, and the hypotheses of lemma 1 hold, then the interest rate applied to brown firms is weakly higher than that applied to green firms:*

$$r_b \ge r_g, \tag{43}$$

Proof. Under the assumptions of the lemma, $\sum_{j \le n_1} A_{bj} = 0$ and $\sum_{j > n_1} A_{gj} = 0$ for all indices $g \le n_1, b > n_1,$. The conclusion is straightforward. ■

As a further corollary, it is easy to prove that, if there are no physical risks, green firms deserve a zero interest rate, because they run no default risk at all.

Corollary 2 (Interest Rates with separated networks and no natural risks)**.** *If green firms do not employ less labour than brown firms, i.e.,* $\beta_g \ge \beta_b$ *for all* $g \le n_1$ *and* $b > n_1$*, the* *hypotheses of lemma 1 are satisfied and there are no natural risks ($\omega = 0$), then the interest rate on green sectors is zero.*

Proof. Under the stated assumptions, $\tau_g = 1, \epsilon_g = 1$. The conclusion is straightforward. ■

All these results prove that risk-adjusted interest rates arise endogenously and reflect primitive environmental uncertainty, but also the way in which it is transmitted through the network.

2.5 Consumers

Consumers form a continuum and are modeled as a representative price-taking agent endowed with preferences over the n consumption goods. Preferences are described by a Cobb-Douglas utility function:

$$U(c) = \prod_{k \epsilon \nu} c_k^{\gamma_k}, \tag{44}$$

where $\gamma_k \geq 0$ is the consumer's weight on good k, and, in vector notation, $\gamma' \mathbf{1} = 1$. Because the coefficients of the utility function can also be smaller for green sectors than for brown ones, or can be all equal, preferences do not take into account any specific preference for greenness.

Like firms, the representative consumer makes a *rigid* nominal consumption plan at time 0, before the realization of shocks. Let $c = (c_k)_{k=1}^n$ denote this vector of nominal consumption choices. Once the shocks η are realized, because of (8), the actual consumption is scaled by the total shock affecting each good:

$$c_k^\eta = e^{\rho_k} c_k. \tag{45}$$

The consumer maximizes expected utility over the distribution of shocks:

$$\max_c \ \mathbb{E}[U(c^\eta)] \tag{46}$$

subject to a state-dependent budget constraint. The consumer receives:

- wages w from labor,
- dividends Π_k from firms,
- and interest income $r_k \theta_k \mathcal{L}_k$ from lending via banks (recall that consumers own both firms and banks).

The total endowment is therefore:

$$E = w + \sum_{k \in \mathcal{V}} \Pi_k + \sum_{k \in \mathcal{V}} r_k \theta_k \mathcal{L}_k. \tag{47}$$

The consumer's budget constraint, accounting for the realized shock to consumption, is:

$$\sum_{k \in \mathcal{V}} e^{\rho_k} c_k p_k \leq E. \tag{48}$$

Finally, define the *(Bonacich) network centrality vector* as:

$$v = L' \gamma. \tag{49}$$

Each element v_k of this vector captures the relative importance of each sector in the network, weighted by consumer preferences and input-output linkages.

2.6 Theoretical Framework: Equilibrium

We now characterize the general equilibrium (GE) of the economy described above. Following Como et al. (2025), we can state that a rigid Walrasian equilibrium exists and is unique when banks competitively set interest rates to satisfy their zero-profit condition.

We first define it:

Definition 1 (Rigid Walrasian Equilibrium)**.** Consider a Cobb-Douglas economy $(\mathcal{V}, A, \beta, \gamma, Z)$ satisfying (4), with $\rho(A) < 1$, equipped with an interest rate vector r and a financing share vector θ. Given a distribution P over primitive log-productivity shocks η, a *rigid Walrasian equilibrium* is a tuple (y, z, c, l, p, w) such that:

(i) For every firm $k \in \mathcal{V}$, the labor l_k and input bundle $(z_{jk})_j$ maximize expected profits $\mathbb{E}[\Pi_k]$ given prices p, wage w, interest rates r, and financing shares θ.

(ii) The consumption bundle c maximizes expected utility $\mathbb{E}[U(c^\eta)]$, subject to the state-dependent budget constraint:

$$\sum_{k \in \mathcal{V}} e^{\rho_k} c_k p_k \leq E. \tag{50}$$

We also need some additional notation. First, define the cost of debt under continuous compounding, instead of discrete, as $\zeta_k = log(1 + r_k \theta_k)$. This reflect the cost of debt to the single firm k. Also, define the total cost of debt over the supply chain, as the sum of the costs over the chain, weighted by the corresponding Leontief coefficients:

$$\xi_k = \sum_{j \in V} L_{kj} \zeta_j \,. \tag{51}$$

Also, let us define the Leontief inverse obtained from the modified importance coefficients,

$$\bar{A}_{jk} := A_{jk} \tfrac{1}{1+r_k\theta_k}, \quad \bar{L} := (I - \bar{A}')^{-1}, \tag{52}$$

and the corresponding Bonacich vector, together with the sum of its components weighted by the labour coefficients

$$\begin{aligned} \bar{\beta}_k &:= \beta_k \tfrac{1}{1+r_k\theta_k} \\ v^\zeta &:= \tfrac{\bar{L}'\gamma}{\bar{\beta}'\bar{L}'\gamma}, \end{aligned} \tag{53}$$

The following result is adapted from Como et al. (2025):

Theorem 3 (Existence and Uniqueness)**.** *Consider a Cobb-Douglas economy* $(\mathcal{V}, A, \beta, \gamma, \zeta)$ *satisfying* (4)*. Then a unique rigid Walrasian equilibrium* (y, z, c, l, p, w) *exists, and satisfies:*

- ***nominal productions:***

$$y_k^0 = v_k^\zeta e^{-\xi_k}\,; \tag{54}$$

- ***nominal intermediate quantities:***

$$z_{jk}^0 = v_k^\zeta A_{jk} e^{-\zeta_k - \xi_j}; \tag{55}$$

- ***employed labor:***

$$l_k = v_k^\zeta \beta_k e^{-\zeta_k}; \tag{56}$$

- ***nominal household's consumption:***

$$c_k^0 = \frac{\gamma_k e^{-\xi_k}}{\bar{\beta}'\bar{L}'\gamma}; \tag{57}$$

- ***prices over wage:***

$$\frac{p_k}{w} = \frac{e^{\xi_k}}{\mathbb{E}[e^{\rho_k}]}\,; \tag{58}$$

So, the interest rates studied above are consistent with an equilibrium with environmental shocks.

3 Empirical Validation

In this section we study how carbon emissions influence the cost of debt financing by combining firm-level financial data with industry-level measures of environmental exposure. The motivation arises from the growing importance of climate-related risks in financial markets and the recognition among lenders and investors that environmental factors affect firm performance and creditworthiness.

The empirical analysis relies on a newly constructed panel covering the period 2012 to 2023, which merges Compustat Fundamentals Annual with emissions data from the U.S. Environmental Protection Agency's Greenhouse Gas Reporting Program (GHGRP). Firm-level financial variables include measures of capital structure, profitability, liquidity, and balance sheet composition, while emissions are aggregated to the five-digit NAICS sector level. Each firm-year observation is assigned an industry-specific measure of environmental exposure defined by total reported CO_2 emissions in the corresponding sector.[4]

We begin by providing a brief overview of the data used in our analysis.[5] Our sample covers sector-year level observations aggregated at the 5-digit NAICS classification from 2010 to 2023. We combine financial variables such as debt composition and interest payments with measures of environmental exposure based on CO_2 emissions.

Sectors with high environmental intensity are predominantly in heavy industry, utilities, and extractive activities, whereas service-oriented sectors contribute little to direct emissions. The sample is balanced across both groups, allowing comparisons between emission-increasing ("brown") and emission-reducing ("green") activities.

Interest rate measures show meaningful dispersion, suggesting that financial costs vary systematically with environmental exposure. Emissions data are right-skewed, confirming that a relatively small share of the economy accounts for most reported emissions. Productivity, measured as log TFP residuals from a standard production function, has a distribution centered near zero but with a heavy left tail.

[4]Firms are included in the sample only if they report a valid NAICS classification and provide non-missing values for key variables, including interest expense, total debt, and asset values. Observations in the top and bottom one percent of the distribution for financial ratios are excluded to mitigate the influence of extreme values. A full description of data construction is provided in Appendix A.

[5]Details on sample selection, data cleaning, and variable construction are reported in Appendix A.

Comparisons across green and brown sectors reveal that emission-increasing sectors tend to display slightly higher average productivity, though they are more exposed to extreme low-productivity outcomes. This pattern underscores the central result: TFP is systematically related to green versus brown sector dynamics, motivating the empirical focus that follows.

Our key variable of interest is the cost of debt, constructed at the industry-year level as the ratio of aggregated interest expenses to aggregated interest-bearing debt, expressed as a percentage. This measure reflects the effective borrowing rate faced by firms within a given sector and captures differences in credit market conditions that may stem from environmental risk. Formally, for each industry j and year t,

$$\text{Interest Rate}_{jt} = \frac{\sum_{i \in j} \texttt{xint}_{it}}{\sum_{i \in j}(\texttt{dltt}_{it} + \texttt{dlc}_{it})} \times 100, \tag{59}$$

where $\texttt{xint}_{it}$ denotes interest expense and $\texttt{dltt}_{it} + \texttt{dlc}_{it}$ corresponds to long-term and short-term debt. In Appendix A.4 we show robustness to an alternative definition using total liabilities as the denominator.

Summary statistics at the NAICS5-year level indicate that the average cost of debt is equal to 5.30 percent with a standard deviation of 1.87, while an alternative measure using total liabilities yields a mean of 2.50 percent. A detailed description of these summary statistics is given in Appendix A.6.

Descriptive comparisons highlight systematic differences between the emission-increasing and emission-reducing sectors. Sectors that increased emissions face slightly higher borrowing costs on average, 4.75 percent versus 4.48 percent, and display somewhat more symmetric variation in interest rates. In terms of productivity, emission-increasing sectors exhibit marginally higher mean log TFP, 0.63 compared to 0.47, but with a heavier left tail, suggesting greater downside risk. These patterns indicate that higher emissions are associated with modestly higher borrowing costs and that sectors with growing emissions are not less productive, though their productivity distribution reflects greater exposure to low-performing outcomes.

Overall, the evidence underscores the relevance of sectoral environmental exposure for credit market outcomes, motivates our focus on industry-level aggregates, and provides the empirical foundation for investigating how environmental shocks may propagate through production networks and influence financial conditions.

Network-Adjusted Emissions and Transition Risk Propagation. To deepen our understanding of how environmental risks affect corporate borrowing conditions, we adopt a network-based perspective on emissions exposure. In contrast to traditional Scope 1 emissions, which capture only the direct emissions generated by a firm's own operations, our network-adjusted approach accounts for the broader carbon footprint embedded within inter-industry production linkages. Specifically, we construct a sector-level measure of embodied emissions, To do this we compute network-adjusted (embodied) CO_2 emissions at the 3-digit NAICS level by combining observed sectoral emissions with input-output linkages across industries. First, we align inter-industry transaction data and CO_2 emissions to the 3-digit level. We then construct the technical coefficients matrix and its associated Leontief inverse, which captures both direct and indirect input dependencies across sectors. Multiplying the Leontief matrix by the vector of observed emissions yields network-adjusted emissions, reflecting the total embodied CO_2 associated with each sector's output. These sector-year measures form a panel dataset used in our subsequent analysis [6].

For each year, we obtain a vector of observed sectoral CO_2 emissions, denoted as $\mathbf{e}_t$, aligned with the 3-digit NAICS codes. The network-adjusted, or embodied, CO_2 emissions vector for that year, which we refer to as CO_2 Leontief emissions and denote as $\mathbf{e}_t^{\text{Leontief}}$, is computed by

$$\mathbf{e}_t^{\text{Leontief}} = \mathbf{L} \cdot \mathbf{e}_t. \tag{60}$$

This matrix multiplication propagates the direct emissions of each sector through the entire network of production, yielding the total embodied emissions that account for all upstream production dependencies. As a result, $\mathbf{e}^{\text{Leontief}}$ captures not only the emissions directly attributable to a given sector but also those inherited from upstream suppliers, reflecting the comprehensive carbon intensity of economic activity.

By comparing firms' exposure to Scope 1 versus network-adjusted emissions, we gain insight into how environmental transition risks propagate through supply chains. This distinction is particularly relevant when considering systemic risks and policy spillovers, as financial markets may react not only to a firm's direct emissions but also to the environmental performance of its suppliers. The network-adjusted approach thus enables a richer understanding of how climate-related risks are internalized in credit markets, especially in industries with complex and emission-intensive supply chains.

In what follows, we present a difference-in-differences (DiD) estimation strategy that

[6] See Appendix A.5 for a full description of the data processing steps and matrix operations used to compute $\mathbf{e}^{\text{Leontief}}$.

exploits variation in $\mathbf{e}^{\text{Leontief}}$ across sectors and over time to identify the causal impact of transition risk propagation on borrowing costs.

Empirical Strategy and Regression Framework. To examine how exposure to environmental risk influences the cost of corporate debt, we estimate a dynamic panel regression in which the dependent variable is the effective interest rate paid by firm i in year t. Our empirical strategy exploits time-series variation in sector-level carbon emissions, interacting this variation with firm-level borrowing outcomes, while controlling for firm fundamentals and persistent unobserved heterogeneity.

Our core regression specification is as follows:

$$\text{Interest Rate}_{it} = \beta_1 \cdot \Delta\%\text{CO2}_{jt-1} + \beta_2 \cdot X_{it-1} + \gamma_i + \delta_t + \varepsilon_{it}, \tag{61}$$

where $\Delta\%\text{CO2}_{jt-1}$ denotes the lagged Haltiwanger growth rate of CO_2 emissions in industry j, capturing recent environmental shocks experienced by firms in the same NAICS5 sector. This variable reflects both the intensity and the change in environmental exposure from one year to the next, thereby serving as a proxy for evolving perceptions of environmental risk. A higher value of $\Delta\%\text{CO2}_{jt-1}$ implies a significant year-over-year increase in emissions, potentially signaling heightened regulatory, reputational, or operational risk in the eyes of creditors.

The vector X_{it-1} includes lagged firm-level controls that account for observable characteristics known to influence borrowing costs. Specifically, we control for: (i) firm leverage, defined as total debt over total assets, which proxies for financial risk; (ii) firm size, measured as the logarithm of total assets, capturing scale effects and access to capital markets; and (iii) liquidity, proxied by the ratio of cash holdings to total assets, reflecting short-term solvency. We also include one- and two-period lags of the dependent variable to account for persistence in interest rates.

The model includes firm fixed effects (γ_i) and year fixed effects (δ_t). Firm fixed effects absorb time-invariant heterogeneity across firms, such as business models or managerial practices, while year fixed effects control for macroeconomic trends, credit market conditions, and regulatory changes that affect all firms simultaneously. Standard errors are clustered at the firm level to account for serial correlation in the residuals.

Table 1 presents the results across three core specifications. Column (1) reports a baseline regression with additonal controls, as suggested by the literature. We find that a one-unit increase in the Haltiwanger growth rate of CO_2 emissions is associated with a 0.4 percentage

Table 1: Main Regression Results: CO_2 Shocks and Interest Rates

	Interest Rate	Interest Rate
Δ % $CO_{2t\text{-}1}$	0.004	0.005
	(0.001)	(0.001)
$\text{Leverage}_{t\text{-}1}$	0.009	0.009
	(0.002)	(0.002)
$\text{Assets}_{\ t\text{-}1}$	0.247	0.226
	(0.057)	(0.057)
$\text{Liquidity}_{t\text{-}1}$	-0.104	-0.106
	(0.138)	(0.138)
$\text{Interest Rate}_{t\text{-}1}$	0.276	0.276
	(0.045)	(0.045)
Δ % Leontief $CO_{2t\text{-}1}$		0.006
		(0.002)
Fixed Effects	Sector & Year	Sector & Year
R-squared	0.729	0.730
N	6332	6332

Standard errors in parentheses

point increase in the firm's borrowing cost, significant at the 1% level.

In Column (2), our preferred specification, we include both the scope 1 and the network measure of CO2 emissions, firm-level controls, two lags of the interest rate, as well as firm and year fixed effects. Specifically, we regress $\Delta\%\mathbf{e}_{jt-1}^{\text{Leontief}}$ on $\Delta\%\text{CO2}_{jt-1}$ across industries and years, and retain the residual from this regression. This residual represents the portion of network emissions growth not explained by contemporaneous direct emissions growth, i.e., the network channel stripped of collinearity with Scope 1. We then include this residualized network term in the main regression specification. This reinforces the interpretation that environmental shocks-proxied by rapid increases in sector-level emissions are priced into corporate borrowing costs, even after accounting for financial fundamentals and macroeconomic confounders. We observe that the coefficient on Scope 1 emissions growth increase slightly to 0.005 (significant at the 5% level), while the residualized network-adjusted emissions term enters with a positive and statistically significant coefficient of 0.006. The economic magnitude of this network effect is larger than that of direct emissions, suggesting that creditors assign considerable weight to environmental risk transmitted through production linkages.

In other words, both Scope 1 and network emissions matter for credit pricing, but the latter appears to carry more explanatory power once we strip out overlap with direct emissions.

These results underscore that banks internalize not only a firm's own environmental footprint but also that of its upstream suppliers. Firms embedded in carbon-intensive value chains face a financial penalty in the form of higher borrowing costs, even if their own emissions remain constant. This highlights the systemic nature of climate-related financial risk and the importance of tracing carbon exposure through the full supply network. Overall, the inclusion of network-adjusted emissions appears to partially mediate the effect of direct emissions, implying that lenders may internalize not only a firm's own carbon output but also the embedded environmental risk from its production network. This result highlights the importance of systemic transition risk and the role of inter-industry linkages in shaping credit conditions.

These findings provide compelling evidence that both direct and indirect (network-adjusted) environmental risks are priced into corporate credit markets. Creditors appear increasingly attentive to firms' positions within carbon-intensive supply chains, reinforcing the role of finance in steering the low-carbon transition.

Causality: The Paris Agreement. In addition to the baseline panel regressions presented in the main analysis, we strengthen our empirical strategy by implementing a difference-in-differences framework that leverages the 2016 entry into force of the Paris Agreement as a quasi-natural experiment. This policy milestone represents a major shift in the global regulatory and institutional environment surrounding climate change, as it signaled an unprecedented international commitment to de carbonization and created tangible expectations about the tightening of climate-related policies over time. By exploiting this exogenous policy shock, we are able to move beyond documenting simple correlations and instead test for a causal relationship between firms' carbon exposure and the cost of borrowing. The intuition behind this approach is straightforward. We compare the evolution of borrowing cost trajectories for firms operating in carbon-intensive sectors with those in relatively cleaner industries, before and after the Paris Agreement. Our key treatment dimension is defined by network-adjusted emissions, which incorporate not only firms' own direct carbon intensity but also the embedded emissions transmitted through their supply chains. This allows us to capture the propagation of transition risk in a way that is consistent with the network-based framework developed in earlier sections. The difference-in-differences estimates therefore provide a powerful test of whether the tightening of climate commitments after 2016 causally altered credit market outcomes, above and beyond any pre-existing trends or sectoral heterogeneity. The results of this exercise, reported in Appendix A.5, provide clear support for a causal interpretation.[7] The magnitude of this effect is economically meaningful, and its statistical significance reinforces the conclusion that financial markets updated their perceptions of transition risk in direct response to the global policy shock. In other words, the observed increase in debt costs for emission-intensive firms cannot be dismissed as a spurious correlation driven by unobserved confounders, but instead reflects a genuine causal mechanism through which climate policy is transmitted into credit pricing. Taken together, the evidence from both the panel regressions and the difference-in-differences strategy yields two central insights. First, consistent with the broader literature, we show that firms with higher carbon intensity firms-systematically face higher borrowing costs relative to "green" firms. This finding confirms that lenders are increasingly attentive to environmental risks and incorporate them into credit market outcomes. Second, and more novel, our results highlight the amplification role of production networks: transition risks are not confined to the most carbon-intensive firms but propagate along supply chains, such that upstream emissions materially raise borrowing costs for downstream partners. The use of the Paris Agreement as a quasi-natural experiment allows us to establish the causal nature of this mechanism, thereby underscoring the systemic dimension of climate-related financial risk.

Formally, we estimate the following specification:

$$\text{Interest Rate}_{it} = \alpha + \beta_1 \cdot \mathbf{e}_s^{\text{Leontief}} + \beta_2 \cdot \text{Post}_t + \delta \cdot (\mathbf{e}_s^{\text{Leontief}} \times \text{Post}_t) + \mathbf{X}_{it}'\gamma + \varepsilon_{it}, \tag{62}$$

where Interest Rate_{it} denotes the borrowing cost of firm i in year t, $\mathbf{e}_s^{\text{Leontief}}$ represents the network-adjusted CO_2 emissions at the sector level s, Post_t is a post-treatment indicator equal to one from 2016 onward, and $\mathbf{X}_{it}$ includes firm-level controls such as size, leverage, and profitability. The coefficient of interest, δ, captures the differential change in borrowing costs for firms operating in more emission-intensive sectors relative to cleaner sectors after the policy shock.

This specification allows us to isolate the causal effect of embodied emissions on borrowing costs, conditional on a structural break in policy that reshaped climate risk expectations.

[7] Table 6 shows that, following the adoption of the Paris Agreement, firms in high-emission sectors experienced a statistically significant increase in borrowing costs of approximately 18.8 basis points relative to cleaner firms. This differential response indicates that lenders explicitly reassessed and repriced credit risk in light of the new policy environment.

Table 2: Difference-in-Differences Estimates: $\mathbf{e}^{\text{Leontief}}$ and Borrowing Costs

	Scope 1 (1)	Network (2)
Brown x Post	0.201	0.310
	(0.048)	(0.033)
Post 2016	0.000	0.000
	(.)	(.)
Brown	-0.229	-0.223
	(0.040)	(0.025)
Fixed Effects	Sector & Year	Sector & Year
R-squared	0.757	0.758
N	7875	7875
Col (2) > Col (1): p-value	.	0.0023

Standard errors in parentheses

Standard errors clustered at the firm level in Model (2).

We estimate two variants of this regression: the first includes firm-level controls only, while the second introduces firm and year fixed effects to absorb unobserved heterogeneity and macroeconomic shocks.

Table 6 presents the results. In column (1), which looks at the causal impact of brown sectors defined as scope 1 emissions, the interaction term $\mathbf{e}^{\text{Leontief}} \times \text{Post}$ is positive and highly significant ($\hat{\delta} = 0.201$, $p < 0.01$), indicating that firms in high-emission sectors faced a 20 basis point increase in borrowing costs after the Paris Agreement. In column (2), which studies brown sectors defined as a network, the estimated effect increases to 31 basis points and remains statistically significant at the 1% level.

Overall, our findings contribute to the growing understanding of how environmental shocks are internalized in credit markets and demonstrate that network linkages are a critical channel through which climate policy impacts the financial system. Consistent with a causal repricing after the Paris Agreement, the DiD estimates (columns (1)-(2)) show that the Brown $\times$ Post coefficient rises from 0.201 (0.048) under Scope 1 to 0.310 (0.033) under the network treatment, a difference of 0.109 p.p. ($\approx$ 11 bps; one-sided $p = 0.0023$), indicating that upstream carbon exposure amplifies the transition risk premium.

4 Conclusion and Further Research

This paper has developed a theoretical framework that explains how environmental risks are transmitted into credit markets. Building on the theory of production networks, we constructed a static general equilibrium model with heterogeneous firms, consumers, and competitive banks. Firms are exposed to both physical and transition risks, and must commit to input and labor allocations before shocks realize, which generates the possibility of default. Because production relies on intermediate goods, shocks do not stop at the firm level but propagate through supply chains. The Leontief inverse provides the natural representation of this mechanism: primitive shocks are transformed into network-adjusted shocks that affect all downstream firms. Banks, being residual claimants, set interest rates so as to break even in expectation. This mechanism implies that borrowing costs emerge endogenously as an equilibrium outcome of direct and inherited exposures, independent of productivity differences. The model shows that even firms with low direct emissions face higher interest rates when embedded in brown supply chains, and that borrowing costs for brown firms are systematically higher, consistent with greater transition risk. In particular, the model clarifies how systemic risk, network propagation, and endogenous pricing jointly determine the allocation of credit.

We then validated these predictions empirically using U.S. data. Combining firm-level borrowing costs and balance sheet information from Compustat with sectoral CO_2 emissions from the Environmental Protection Agency and input-output linkages from national accounts, we documented that increases in emissions translate into statistically and economically significant increases in interest rates. These effects are strongest in carbon-intensive sectors and persist after controlling for firm fundamentals, time trends, and alternative measures of debt. Importantly, we showed that lenders systematically price not only direct emissions but also network-adjusted emissions, confirming that environmental shocks propagate through supply chains and are internalized in credit markets. To establish causality, we exploited the 2016 Paris Agreement as a quasi-natural experiment. The difference-in-differences results demonstrated that borrowing costs rose disproportionately for firms embedded in brown supply chains, even when their own emissions remained low. This provides direct evidence that transition shocks are transmitted through the production network in a manner consistent with the mechanism highlighted by our model.

Together, our contributions are theoretical and empirical. Theoretically, we provide the first general equilibrium model of climate-related credit risk that embeds transition shocks into a production network framework with default. Empirically, we demonstrate that credit markets in the U.S. already internalize environmental risks, pricing not only firm-level emissions but also upstream exposures, and we provide causal evidence that transition risks are amplified by supply chains.

The broader implication is that environmental risk is systemic and not idiosyncratic. Borrowing costs depend as much on the greenness of a firm's network as on its own emissions. This finding supports recent policy initiatives, such as the European Commission's Corporate Sustainability Due Diligence Directive Commission (2024), which explicitly accounts for supply chain-related risks. Moreover, our results suggest that market-based incentives can reinforce climate policy: by penalizing brown firms with higher capital costs and rewarding greener firms and supply chains, credit markets can accelerate the reallocation of resources toward a low-carbon economy.

Finally, this research also provides a foundation for the design of policy interventions. In an extension of the model, in Appendix B, we introduce a central bank facility with collateralized loans based on haircuts. We show that optimally chosen haircuts on brown-sector collateral can reduce the variance of financial risk without distorting real allocations by redistributing exposures between private banks and the central bank. This result highlights how prudential policy can be designed to internalize the network-amplified transition risk and stabilize the financial system. By linking production networks, environmental shocks, and monetary intermediation, our framework thus opens the way for future research on the effectiveness of green credit policies and their role in fostering a more resilient and sustainable economy.

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Appendix

A Empirical Analysis

A.1 EPA Greenhouse Gas Emissions Data

The environmental exposure variable is derived from the EPA's Greenhouse Gas Reporting Program (GHGRP), which publishes annual data on greenhouse gas (GHG) emissions reported by large facilities across the United States. The GHGRP dataset primarily captures **Scope 1 emissions**, which are direct emissions from owned or controlled sources. In certain cases, it may also include a subset of **Scope 2 emissions**, reflecting indirect emissions resulting from purchased electricity generation. For our purposes, emissions data are aggregated at the 5-digit North American Industry Classification System (NAICS) level to facilitate consistent matching with firm-level data.

A.2 Compustat Firm-Level Financial Data

Firm-level financial variables are obtained from the Compustat Fundamentals Annual database, covering publicly listed U.S. firms. Observations span the years 2012 to 2023. Firms are included in the analysis only if they report valid NAICS codes and have non-missing entries for interest expense and debt-related variables.

The key financial variables used in our analysis include:

- `xint`: Interest expense
- `dltt`: Long-term debt obligations
- `dlc`: Short-term debt (due within one year)
- `lt`: Total liabilities
- `at`: Total assets
- `che`: Cash and equivalents
- `ebit`: Earnings before interest and taxes
- `ppent`: Net property, plant, and equipment

- `ceq`, `mkvalt`: Variables used to compute market-to-book ratios

A.3 Measuring the Cost of Debt

A central variable in our empirical analysis is the firmâs cost of debt, which we construct at the industry-year level by aggregating firm-level interest expenses and debt balances. The goal is to obtain a reliable and interpretable measure of the average effective interest rate faced by firms within a given sector and year. This aggregation accounts for the possibility that credit markets may price risk not only at the level of individual firms but also at the level of sectors that differ in terms of regulatory scrutiny, environmental footprint, or exposure to transition risks.

Our preferred measure of the cost of debt is defined as the ratio of total interest expense to total interest-bearing debt, expressed as a percentage. Formally, for each industry j and year t, we define:

$$\text{Interest Rate}_{jt} = \frac{\sum_{i \in j} \texttt{xint}_{it}}{\sum_{i \in j} (\texttt{dltt}_{it} + \texttt{dlc}_{it})} \times 100, \tag{63}$$

where $\texttt{xint}_{it}$ denotes the interest expense reported by firm i in year t, and $\texttt{dltt}_{it} + \texttt{dlc}_{it}$ corresponds to total interest-bearing debt, composed of long-term debt due beyond one year and current liabilities due within one year. By aggregating both the numerator and the denominator across all firms in a given NAICS5 industry, we obtain a sector-level estimate of the average borrowing cost per dollar of debt.

This specification captures the prevailing effective borrowing rate within an industry and is particularly useful in contexts where credit conditions may systematically vary across sectors due to differences in environmental risk. In Appendix A.4, we test the robustness of our results using an alternative specification in which the denominator is defined as total liabilities instead of interest-bearing debt. This alternative accounts for potential reporting inconsistencies or classification issues, particularly for firms with complex capital structures.

A.4 Quantifying CO_2 Shocks: The Haltiwanger Growth Rate

To quantify annual changes in firm-level CO_2 emissions in a manner that accommodates both the presence of zero values and the often volatile nature of environmental data, we adopt the Haltiwanger growth rate transformation [8]. This approach, originally developed in the context of firm dynamics, provides a robust alternative to conventional log differences when computing growth rates. Specifically, we define the annual CO_2 shock for firm j in year t as:

$$\Delta\%\mathrm{CO2}_{jt} = 2 \cdot \frac{\mathrm{CO2}_{jt} - \mathrm{CO2}_{jt-1}}{|\mathrm{CO2}_{jt}| + |\mathrm{CO2}_{jt-1}|}. \tag{64}$$

This measure yields a symmetric and bounded growth rate that lies within the interval $[-2, +2]$.

In our empirical implementation, this transformation is coded in Stata as follows:

```
gen dhw_CO2 = 2 * (D.CO2) / (abs(CO2) + abs(L.CO2))
```

Here, `D.CO2` refers to the first difference of emissions, while `L.CO2` denotes the lagged value. The absolute value in the denominator ensures numerical stability regardless of the sign or magnitude of emissions in any given year.

This symmetrized growth rate serves as our primary measure of firm-level environmental shocks throughout the analysis.

Alternative Measure of Cost of Debt. To ensure robustness, we compute an alternative interest rate using total liabilities:

$$\text{Interest Rate}^{\text{Alt}}_{jt} = \frac{\sum_{i\in j} \texttt{xint}_{it}}{\sum_{i\in j} \texttt{lt}_{it}} \times 100. \tag{65}$$

Although this specification may understate the cost of debt, it is less susceptible to mismeasurement in the case of missing or misclassified debt components.

A.5 Computation of Network-Adjusted CO_2 Emissions

To compute the network-adjusted level of CO_2 emissions in the manufacturing sector at the 3-digit NAICS level, we proceed through a structured sequence of data processing and matrix operations that capture both direct and indirect contributions of each sector to total emissions. We begin by obtaining an inter-industry transactions matrix, which

[8] These properties make the transformation particularly well-suited for empirical work with microdata, where firm-level emissions may be highly skewed, occasionally zero, or subject to large relative fluctuations. Unlike log changes, which are undefined at zero and prone to producing extreme values in the presence of small denominators, the Haltiwanger growth rate remains defined and stable across the full support of the data. .

quantifies the flow of goods and services between industries, and a corresponding set of industry codes. Since these codes often extend beyond the 3-digit level, we aggregate the matrix by truncating each industry code to its first three digits and summing the relevant rows and columns accordingly, ensuring consistency between the input-output data and the CO_2 emissions data, which are both aligned at the 3-digit NAICS level.

Following this aggregation, we calculate the technical coefficients matrix, denoted as $\mathbf{A}$, by first inverting the original transactions matrix to obtain

$$\mathbf{L}^{-1} = \text{inverse of the transactions matrix}, \tag{66}$$

and then calculating

$$\mathbf{A} = \mathbf{I} - \mathbf{L}^{-1}, \tag{67}$$

where $\mathbf{I}$ is the identity matrix. This matrix $\mathbf{A}$ reflects the direct input requirements for each sector. To incorporate the full spectrum of inter-industry dependencies, including both direct and indirect effects, we compute the Leontief inverse matrix as

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}. \tag{68}$$

This matrix $\mathbf{L}$ measures how the production of each sector relies on inputs from all other sectors across the entire industrial network.

For each year, we obtain a vector of observed sectoral CO_2 emissions, denoted as $\mathbf{e}_t$, aligned with the 3-digit NAICS codes. The network-adjusted, or embodied, CO_2 emissions vector for that year, which we refer to as CO_2 Leontief emissions and denote as $\mathbf{e}_t^{\text{Leontief}}$, is computed by

$$\mathbf{e}_t^{\text{Leontief}} = \mathbf{L} \cdot \mathbf{e}_t. \tag{69}$$

This matrix multiplication propagates the direct emissions of each sector through the entire network of production, yielding the total embodied emissions that account for all upstream production dependencies.

The outcome of this process is a series of vectors $\mathbf{e}_t^{\text{Leontief}}$ that quantify, for each year and for each 3-digit NAICS sector, the total network-adjusted CO_2 emissions associated with producing the output of that sector. These values are then reshaped into a long-format panel dataset that records, for each year and each sector, the network-adjusted CO_2 emissions. This dataset serves as a foundation for subsequent econometric and policy analyses focused on tracing the propagation of environmental impacts through the interconnected industrial structure.

A.6 Descriptive Statistics

Before presenting our empirical strategy, we summarize the key characteristics of the main variables used in the analysis, including interest rate measures, environmental exposure, and productivity. Table 3 reports descriptive statistics for sector-level variables aggregated at the NAICS5-year level over the period 2010–2023.

The average interest rate on debt, defined as interest expense over the sum of long-term and short-term debt (DLTT + DLC), is 5.30%, with a standard deviation of 1.87 and a right-skewed distribution (skewness = 0.78). An alternative measure, interest over total liabilities, yields a lower mean of 2.50% with less dispersion.

Environmental exposure is proxied by total CO_2 emissions and their year-over-year changes. The log of emissions averages 10.91 with relatively mild skewness, while the percentage change in emissions, computed via a symmetric Haltiwanger transformation, exhibits substantial variability (standard deviation = 15.84) and a slightly left-skewed distribution.

Finally, log TFP, calculated using five-factor residuals from the CES-NBER Manufacturing Database, has a mean close to zero (0.13), with a negatively skewed distribution (skewness = -1.89), suggesting that the left tail contains relatively more extreme low-productivity observations.

These statistics provide a snapshot of the underlying data structure and confirm the presence of meaningful variation across both financial and environmental dimensions.

Table 3: Descriptive Statistics of Main Variables

	Mean	SD	Min	Max	Skewness	Count
Interest Rate (DLTT + DLC)	5.47	2.33	1.87	18.40	1.60	1100
Interest Rate (Total Liabilities)	2.53	1.10	0.42	6.20	0.69	1098
Log CO2	10.91	0.93	7.82	13.60	0.54	1151
CO2 % Change	-2.18	15.84	-158.65	160.00	-0.48	1014
Log TFP	0.13	0.86	-4.75	1.68	-1.89	411

Distribution of CO_2 Emissions. To illustrate the concentration and structure of environmental risk in the economy, Figure 1 plots the distribution of sector-level CO_2 emissions aggregated at the 5-digit NAICS level. The histogram reveals a highly skewed distribution:

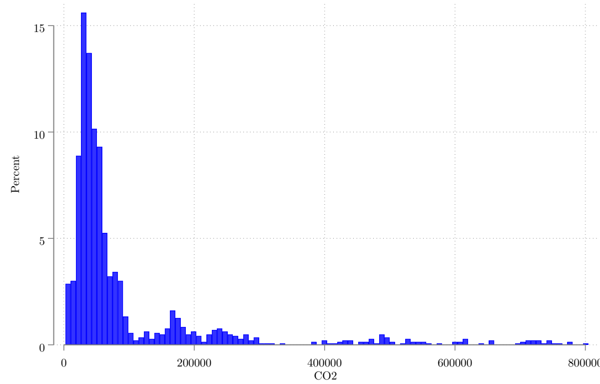

Figure 1: Distribution of Sectoral CO_2 Emissions (NAICS5)

Table 4: Interest Rates and CO2 Dynamics

	Mean	SD	Min	Max	Skewness	Count
Reduce CO2	4.51	1.54	1.90	18.40	2.57	4988
Increase CO2	4.78	1.63	1.87	16.60	1.85	5627

a small number of sectors primarily in heavy industry, utilities, and extractive activities account for a disproportionate share of reported emissions. In contrast, many service-oriented and knowledge-based sectors exhibit negligible direct emissions.

This heterogeneity underscores the importance of sectoral exposure in understanding climate-related financial risks. It also provides motivation for our focus on industry-level aggregates and supports a network-based perspective in which environmental shocks originating in upstream polluting sectors can propagate through production linkages and influence the financial conditions of downstream firms.

Green vs. Brown Sectors: Financial and Productivity Differences. Table 4 presents descriptive statistics comparing sectors that increased versus reduced their CO_2 emissions. We classify sectors based on whether their year-over-year emissions growth, computed using a symmetric Haltiwanger transformation, is positive or negative. The table focuses on the interest rate on debt, calculated as the ratio of interest expense to the sum of long-term and short-term debt (DLTT + DLC), aggregated at the NAICS5-year level.

On average, sectors that increased emissions face slightly higher borrowing costs, with a mean interest rate of 4.75%, compared to 4.48% for sectors that reduced emissions. This gap

Table 5: TFP and CO2 Dynamics

	Mean	SD	Min	Max	Skewness	Count
Reduce CO2	0.47	1.01	-4.75	2.18	-1.31	1819
Increase CO2	0.63	0.97	-7.69	2.16	-1.64	1616

comes with a modest increase in dispersion (standard deviation of 1.50 vs. 1.38), and a lower degree of right skewness (1.44 vs. 1.80), suggesting somewhat more symmetric variation in borrowing costs among emission-increasing sectors. The interest rate distribution is bounded within a comparable range across the two groups, with minimum values around 2.15% and maximums just above 11.3%. The number of sector-year observations is also balanced, with 4,948 observations for emission-reducing sectors and 5,557 for those with increasing emissions.

To complement the financial patterns, Table 5 reports summary statistics on total factor productivity (log TFP), again distinguishing between sectors that reduced versus increased CO_2 emissions. Firms that reduced emissions exhibit a slightly lower mean log TFP (0.47) relative to those that increased emissions (0.63), although the difference is modest. The standard deviation is also slightly higher for emission-reducing firms (1.01 vs. 0.97), and both distributions exhibit negative skewness, with emission-increasing sectors showing a more pronounced left tail (skewness of -1.64 vs. -1.31). This suggests that while emission-increasing sectors may display marginally higher productivity on average, their distribution is more heavily influenced by low-productivity outliers.[9]

Overall, the productivity differences are subtle, but may reflect underlying technological or operational trade-offs associated with emission-reducing efforts. Together, these patterns suggest that higher environmental impact may be associated with a small but systematic increase in borrowing costs, possibly reflecting lender sensitivity to sector-level environmental risk, and that emission-increasing sectors are not necessarily less productive, if anything, they appear slightly more productive, though at the cost of greater downside risk in the TFP distribution.

[9]TFP is constructed as a Solow residual using firm-level value added, labor, and capital inputs, with input elasticities sourced from the NBER CES Manufacturing database. Specifically, it is computed as `gen tfp = log(outputva) - (labsharelog(labor) + capsharelog(capital))`. The data are merged at the yearly level to align firm observations with the relevant sectoral elasticities.

A.7 Additional Results to the Motivating Evidence

Checking for different level of NAICS. To ensure that our results are not sensitive to the level of sectoral aggregation, we replicate our analysis using 2-, 3-, 4-, and 5-digit NAICS codes. Coefficients remain stable across these specifications.

	NAICS2	NAICS3	NAICS4	NAICS5
Δ % $CO_{2t\text{-}1}$	0.002^{***}	0.005^{***}	0.005^{***}	0.004^{***}
	(0.000)	(0.001)	(0.001)	(0.001)
R-squared	0.854	0.872	0.814	0.787
N	6421	6179	6224	6151

Standard errors in parentheses

Firm and year fixed effects included. SEs clustered at firm level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Difference-in-Differences Strategy. Our empirical strategy relies on a difference-in-differences (DiD) framework to estimate how sector-level network-adjusted CO_2 emissions influence borrowing costs for downstream firms, particularly in response to a salient environmental policy event: the 2016 implementation of the Paris Agreement. This international accord marked a turning point in global climate policy, committing signatory countries to reduce emissions and accelerate the transition to a low-carbon economy. As such, we treat 2016 as a quasi-natural experiment that shifted lenders' perceptions of transition risk, particularly for firms embedded in carbon-intensive production networks.

A key identification assumption of the DiD approach is that, in the absence of treatment, treated and control groups would have followed parallel trends in the outcome variable, in our case, firms' borrowing costs. To assess the validity of this assumption, we conduct a pre-trend test by comparing the average interest rates of "brown" (treated) and "green" (control) firms before and after the Paris Agreement. These groups are defined based on sectoral network-adjusted emissions, with brown firms operating in sectors above the median of the $\mathbf{e}^{\text{Leontief}}$ distribution and green firms below it.

Figure 2 displays the average interest rate trajectories of these two groups from several years before to several years after 2016. Prior to the Paris Agreement, both brown and green firms exhibit remarkably similar trends in borrowing costs, suggesting no systematic differences in their access to credit markets. This visual evidence supports the parallel

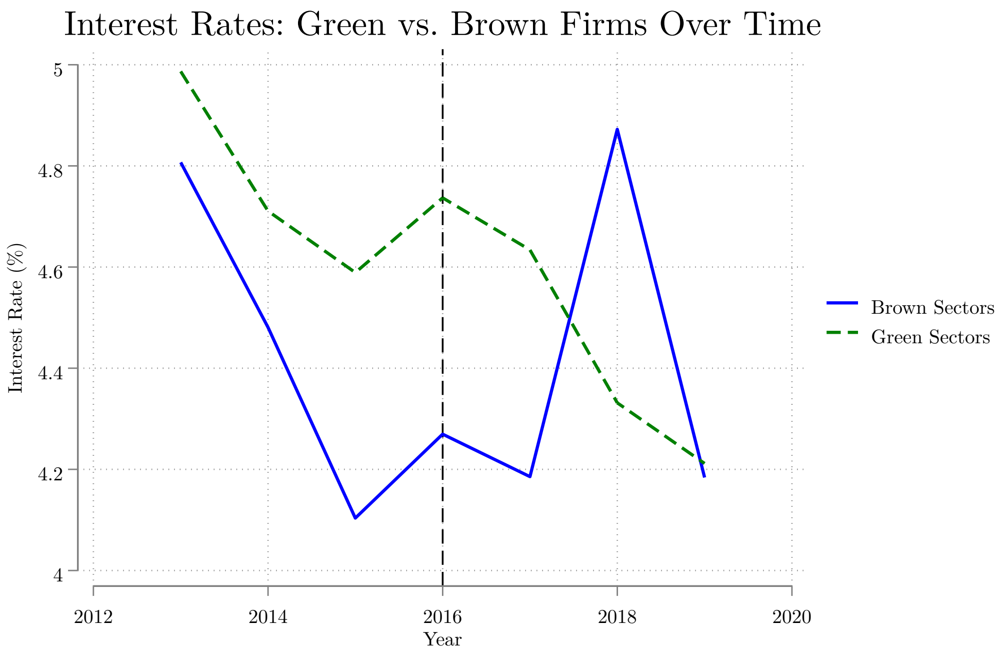

Figure 2: Parallel Trends in Interest Rates: Brown vs. Green Firms

trends assumption and lends credibility to our DiD design. Following 2016, a divergence emerges: borrowing costs for brown firms begin to rise, while those for green firms continue to decline. This divergence provides initial evidence that lenders started pricing in transition risks associated with embodied emissions after the Paris Agreement entered into force.

We leverage this empirical setting by exploiting within-sector variation in network-adjusted emissions at the 3-digit NAICS level, denoted as $\mathbf{e}^{\text{Leontief}}$. This variable, constructed as detailed in Appendix A.5[10], captures both direct and indirect CO_2 emissions embedded in the production of each sector, reflecting the propagation of environmental pressures through inter-industry input-output linkages. By accounting for the entire supply chain's emissions, $\mathbf{e}^{\text{Leontief}}$ aligns with recent advances in environmental input-output analysis and more comprehensively captures a firm's exposure to transition risks.

Formally, we estimate the following specification:

$$\text{Interest Rate}_{it} = \alpha + \beta_1 \cdot \mathbf{e}_s^{\text{Leontief}} + \beta_2 \cdot \text{Post}_t + \delta \cdot (\mathbf{e}_s^{\text{Leontief}} \times \text{Post}_t) + \mathbf{X}_{it}'\gamma + \varepsilon_{it}, \tag{70}$$

[10]See Appendix A.5 for a full description of the data processing and matrix calculations leading to the construction of the $\mathbf{e}^{\text{Leontief}}$ variable.

Table 6: Difference-in-Differences Estimates: $\mathbf{e}^{\text{Leontief}}$ and Borrowing Costs

	Scope 1 (1)	Network (2)
Brown x Post	0.201	0.310
	(0.048)	(0.033)
Post 2016	0.000	0.000
	(.)	(.)
Brown	-0.229	-0.223
	(0.040)	(0.025)
Fixed Effects	Sector & Year	Sector & Year
R-squared	0.757	0.758
N	7875	7875
Col (2) > Col (1): p-value	.	0.0023

Standard errors in parentheses

Standard errors clustered at the firm level in Model (2).

where Interest Rate$_{it}$ denotes the borrowing cost of firm i in year t, $\mathbf{e}_s^{\text{Leontief}}$ represents the network-adjusted CO_2 emissions at the sector level s, Post$_t$ is a post-treatment indicator equal to one from 2016 onward, and $\mathbf{X}_{it}$ includes firm-level controls such as size, leverage, and profitability. The coefficient of interest, δ, captures the differential change in borrowing costs for firms operating in more emission-intensive sectors relative to cleaner sectors after the policy shock.

This specification allows us to isolate the causal effect of embodied emissions on borrowing costs, conditional on a structural break in policy that reshaped climate risk expectations. We estimate two variants of this regression: the first includes firm-level controls only, while the second introduces firm and year fixed effects to absorb unobserved heterogeneity and macroeconomic shocks.

Table 6 presents the results. In column (1), which looks at the causal impact of brown sectors defined as scope 1 emissions, the interaction term $\mathbf{e}^{\text{Leontief}} \times \text{Post}$ is positive and highly significant ($\hat{\delta} = 0.201$, $p < 0.01$), indicating that firms in high-emission sectors faced a 20 basis point increase in borrowing costs after the Paris Agreement. In column (2), which studies brown sectors defined as a network, the estimated effect increases to 31 basis points and remains statistically significant at the 1% level.

We compare the post-2016 DiD effects from Scope 1 and network-adjusted treatments with firm-level clustering on the shared sample (sector and year FE; controls $\mathbf{X}_{it}$). The test

$$H_0: \ \beta_{\text{Net}} - \beta_{\text{S1}} \leq 0 \qquad \text{vs.} \qquad H_1: \ \beta_{\text{Net}} - \beta_{\text{S1}} > 0 \tag{71}$$

(using `lincom`) yields a difference of 0.109 p.p. (11 bps) with standard error of 0.039 ($z = 2.83$), for a one-sided $p = 0.0023$ (two-sided $p \approx 0.005$). Consistent with columns (1)-(2) of the table, the interaction estimate rises from 0.201 (0.048) under Scope 1 to 0.310 (0.033) under network treatment. We therefore reject H_0 and conclude that upstream exposure amplifies the transition risk premium. The one-sided p-value is reported beneath the coefficients.

Taken together, these findings provide strong evidence that lenders internalized network-propagated transition risks following the Paris Agreement. The parallel pre-treatment trends, the abrupt post-treatment divergence, and the robustness of our DiD estimates all support the conclusion that financial markets responded to environmental policy by increasing the cost of capital for firms more deeply embedded in carbon-intensive production structures.

B Theoretical Analysis: Central Banks and Collateral

We now extend the model to include the role of a central bank that intermediates liquidity provision through haircut-based collateralized lending. This extension preserves the core equilibrium logic of the model while enriching the structure of financial intermediation and allowing for the redistribution of default risk across institutions. It also lays the groundwork for policy design aimed at greening the financial system.

In the baseline model with $\theta = 1$, each firm k enters the period with a funding need equal to its liabilities $\mathcal{L}_k$. These liabilities must be financed up front at $t = 0$ in order to produce, and firms do not possess internal funds. In the benchmark case, banks directly supply this funding, bearing all the associated credit risk. In this extended setting, we introduce a central bank facility through which banks can refinance part or all of their lending using firm loans as collateral.

The key policy instrument of the central bank is the haircut parameter for sector k, denoted by $h_k \in [0, 1]$. The haircut determines the portion of a firm loan $\mathcal{L}_k$ that the central bank is willing to refinance. Green firms are totally re-financed, $h_g = 0$, while the haircut to brown firms h_b may be positive, and will be optimally chosen by the central bank to reduce systematic risk. A haircut of h implies that the central bank contributes $h \cdot \mathcal{L}_k$ toward the financing of firm k, while the remaining share, $(1-h) \cdot \mathcal{L}_k$, must be funded by the bank itself. Thus, the bank still performs the role of loan originator and underwriter, but the central bank becomes a co-financier.

At $t = 0$, each bank delivers the full loan amount $\mathcal{L}_k$ to the firm, as in the baseline model. However, it raises only part of this amount internally. The remainder is borrowed from the central bank against the collateral of the firm loan. This setup does not alter the real-side decisions of firms, they continue to operate under the same production technology and face the same shock vector. It does not affect the interest rate applied by banks, since their profit is

$$h_k \mathcal{I}_k \tag{72}$$

with $\mathcal{I}_k$ defined as in (17). Further, it does not affect the expectation of such profit, which remains zero. The set-up however affects the distribution of financial exposures across institutions.

At $t = 1$, firms realize their revenues $\mathcal{A}_k = p_k y_k^\eta$, which may fall short of liabilities due to productivity shocks. As in the baseline model, when firms cannot meet their obligations, lenders recover only a part of what they are owed.

The repayment flows to each intermediary are proportional to their share of the initial financing. Since the bank contributed a fraction $(1 - h_k)$ of the initial loan, it receives the same share of the recovery value. Similarly, the central bank receives the complementary fraction h_k. The bank's financial return from lending to firm k is thus given by:

$$h_k \mathcal{I}_k, \tag{73}$$

while the central bank's return is:

$$\mathcal{I}^{\mathrm{CB}} = \sum_{k \leq n_1} \mathcal{I}_k + \sum_{k > n_1} (1 - h_b)\mathcal{I}_k. \tag{74}$$

since the haircut is zero for green and h_b for brown sectors.

The total intermediation surplus from the loan therefore remains unchanged by the haircut. It merely reflects the overall gains or losses from financial intermediation and, for brown firms, is split between the central and the other banks.

In equilibrium, since expected profits from lending are zero for banks, they are zero also for the central bank:

$$\mathbb{E}[\mathcal{I}_k] = 0 \qquad \rightarrow \qquad \mathbb{E}[\mathcal{I}^{\mathrm{CB}}] = 0. \tag{75}$$

These conditions ensure that the full expected surplus from intermediation is passed through to households, in the form of higher consumption or lower interest rates, preserving the efficiency of the underlying allocation.

Importantly, the haircut does not distort firm-level incentives or resource allocation. Firms receive the full amount of their required funding $\mathcal{L}_k$ regardless of the value of h, and prices, wages, and production choices remain governed by the same equilibrium conditions. However, the haircut on brown firms plays a critical role in redistributing risk between intermediaries. A higher haircut shifts more risk to the central bank, reducing banks' exposure to firm default. Conversely, a lower haircut places more responsibility on banks to absorb losses, potentially leading to tighter credit conditions if banks become more risk-averse or capital-constrained.

Given its systemic role, the central bank may wish to set the haircut to manage its own risk exposure. One natural objective is to minimize the variance of its future cash flows, subject to maintaining efficiency and financial stability. The central bank's policy problem is thus:

$$\min_{h_b \in [0,1]} \mathrm{Var}\left(\mathcal{I}^{\mathrm{CB}}\right) \tag{76}$$

$$= \mathrm{Var}\left(\sum_{k \le n_1} \mathcal{I}_k\right) + \min_{h_b \in [0,1]} (1-h_b)^2 \mathrm{Var}\left(\sum_{k > n_1} \mathcal{I}_k\right) + 2(1-h_b)\mathrm{Covar}\left(\sum_{k \le n_1} \mathcal{I}_k, \sum_{k > n_1} \mathcal{I}_k\right) \tag{77}$$

where the summation reflects aggregate exposure across the economy.

The necessary and sufficient condition for this minimization handles the following optimal value for the haircut

$$1 - h_b = -\frac{\mathrm{Covar}\left(\sum_{k \le n_1} \mathcal{I}_k, \sum_{k > n_1} \mathcal{I}_k\right)}{\mathrm{Var}\left(\sum_{k > n_1} \mathcal{I}_k\right)} \tag{78}$$

where, since we are in the baseline model with $\theta = 1$, $\mathcal{I}_k = -\frac{\epsilon_k}{1+r_k} + \min(\tau_k, \epsilon_k)$.

Since the central bank profits inherit the volatility and correlation structure of the underlying shocks, including network amplification in τ, ϵ, this objective captures the central bank's desire to minimize macro-financial risk. This formulation also provides a natural foundation for green-oriented credit policy.