The Financial Instability Contribution Scores: Theory and Application

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Abstract

Carbon taxation is a central instrument for mitigating climate change, but it may impact financial stability as high-emission, debt-intensive sectors face heightened default risks. This paper introduces the *Financial Instability Contribution Scores* (FICS), a metric that quantifies sectoral contributions to financial instability under carbon taxation. FICS combine default probabilities, leverage, and tax-induced demand effects within a structural model of heterogeneous firms and bank exposures that are linked through input-output linkages. Applying the framework to U.S. data, we find that utilities, agriculture, and transport pose the greatest risk for financial stability under a $75/ton carbon tax.

Keywords: carbon tax, default, transition risk, input-output.

JEL classifications: G21, G33, H23, Q54, Q58.

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1 Introduction

Carbon taxation is widely regarded as a cornerstone policy for reducing greenhouse gas emissions and mitigating climate change. Yet, while such policies are effective in reshaping incentives for firms and consumers, they may also create unintended risks for financial stability. In particular, carbon taxes can amplify solvency risks in highly leveraged, emission-intensive sectors, where disruptions to profitability and pricing may lead to elevated default rates and, in turn, systemic vulnerabilities in the banking sector. Understanding these risks is critical for ensuring that climate policies align with broader goals of financial resilience.

This paper introduces the *Financial Instability Contribution Scores* (FICS), a novel metric designed to quantify the extent to which different sectors contribute to banking fragility under carbon taxation. Unlike aggregate indicators, the FICS framework accounts for sector-specific default risks, balance sheet structures, and inter-industry linkages, providing a granular and comprehensive measure of financial vulnerability. By enabling comparisons across sectors, FICS offer policymakers and regulators a practical tool to identify where carbon taxes may generate disproportionate risks for the financial system. A further advantage of the methodology is its reliance on readily accessible inputs, such as sectoral balance-sheet data and tools like the Carbon Price App (Guilhoto et al., 2024), which facilitates replication and policy implementation.

The construction of FICS builds on a static model with heterogeneous sectors, each differing in their input-output structure, emissions intensity, and exposure to default risk. The score reflects the marginal effect of a sector-specific carbon tax on the expected profits of a representative bank, capturing three critical dimensions: (i) the probability of default, modeled as exposure to idiosyncratic shocks to profitability;

(*ii*) sectoral leverage, proxied by the debt-to-asset ratio; and (*iii*) demand effects, which stem from other sectors' responses to price adjustments induced by the tax. Together, these components provide an intuitive decomposition of why certain sectors may amplify financial instability more than others.

We apply this framework to the United States, one of the world's largest emitters with a highly interconnected financial system. Using Compustat firm-level data over the period 2010–2024, aggregated at the sectoral level, we estimate sector-specific FICS under a hypothetical carbon tax of $75 perton of carbon. The results are twofold. First, all industries exhibit negative FICS, suggesting heightened vulnerability to instability. Second, there is substantial heterogeneity in sectors' contribution to financial instability, with sectors such as utilities, land transport, and air transport emerging as particularly destabilizing due to their high leverage, debt-servicing burdens, and exposure to demand shocks.

Our findings highlight the importance of complementing climate policy design with financial stability considerations. A one-size-fits-all carbon tax risks generating unintended systemic consequences if applied uniformly across sectors with divergent financial structures. The FICS framework provides a replicable, data-driven approach that allows policymakers to balance the twin imperatives of emissions reduction and financial resilience. In doing so, this study contributes to the growing literature on climate-finance interactions, while also responding to international policy initiatives such as the G20's Data Gaps Initiative (DGI-3), which emphasizes the need for better measurement of climate-related financial risks.

Literature review. The literature on carbon taxation and financial stability has expanded rapidly over the past decade, reflecting growing concerns about how climate policy may interact with systemic risk in the financial sector. Early contributions such as Guth et al. (2021) examine the impact of carbon pricing in Austria by combining an input–output model of sectoral price changes with an insolvency model to assess sector-specific default probabilities. Their results show that disorderly implementations of carbon taxes can significantly raise default risks in emission-intensive sectors such as agriculture and transport, thereby challenging banking stability. Nonetheless, they conclude that the Austrian financial system, in aggregate, retains sufficient resilience, albeit at higher costs. Our paper complements this line of work by introducing a unified, model-based approach that quantifies each sector's contribution to instability, thereby enabling systematic cross-country comparisons.

Building on this, D'Orazio, Hertel, and Kasbrink (2024) estimate the exposure of the German banking sector to climate transition risks using the Climate Policy Relevant Sectors (CPRS) classification of Battiston et al. (2017). They demonstrate that banks with concentrated loan exposures to carbon-intensive industries—particularly energy, transportation, and manufacturing—are most vulnerable to transition shocks. Their study underscores the systemic importance of transition risks, particularly for larger banks with less diversified portfolios. Similarly, Evdokimova and Millischer (2025) highlight the heterogeneous effects of carbon pricing on firm valuations, showing that highly carbon-intensive firms suffer disproportionate losses unless they adapt via allowances or cost pass-through. This heterogeneity is critical for understanding how risks materialize for banks lending to these firms.

A complementary strand of literature focuses on stress-testing financial systems against abrupt climate policy changes. Reinders, Schoenmaker, and Dijk (2025), for example, propose a conceptual framework for climate risk stress testing under "abrupt transitions," where sudden policy tightening induces rapid shifts in market conditions. Their framework helps identify how such transitions could elevate default risk in vulnerable sectors and propagate instability across the banking sector. Similar concerns are raised in regional studies: the World Bank (2024) finds that Philippine banks currently face limited transition risk, but warns of large potential losses if carbon policies tighten abruptly. Jung, Santos, and Seltzer (2024) provide a parallel assessment for the United States, estimating that roughly 14% of bank loans are exposed to transition risk, with risks highly concentrated in carbon-intensive sectors. These findings highlight the importance of sectoral concentration in amplifying systemic risk.

Network-based approaches also play a prominent role in this literature. Battiston et al. (2017) introduce the CPRS methodology to trace how climate risks propagate through inter-industry linkages, a framework further developed in studies such as Campiglio et al. (2018) and Reinders, Schoenmaker, and Dijk (2025). These contributions emphasize that indirect exposures can be as important as direct ones: even sectors not directly taxed may suffer financial strain through their reliance on carbon-intensive inputs. The conceptual foundation for this research can be traced back to Carney (2015), whose speech on the "tragedy of the horizon" highlighted the failure of markets to adequately price long-term climate risks, motivating central banks and regulators to incorporate transition risk into their mandates.

Overall, these studies converge on three insights: (i) transition risks are highly sector-specific, with emission-intensive and highly leveraged industries particularly vulnerable; (ii) disorderly or abrupt implementations of climate policy significantly amplify systemic risk; and (iii) network effects and inter-sectoral linkages are essential for capturing the true scope of exposures. Yet, despite these advances, the literature still lacks a unified, quantifiable metric that can compare sector-specific contributions to financial instability across contexts. By developing the *Financial Instability Contribution Score* (FICS), our paper fills this gap. FICS provide a data-driven, decomposable measure that explicitly incorporates default risk, leverage, and demand effects while embedding sectors within an input–output framework. This approach extends existing stress-testing methodologies by offering a transparent and replicable tool to identify sectors most at risk of destabilizing the financial system under carbon taxation.

Roadmap. The remainder of this paper is structured as follows. Section 2 introduces the structural model underpinning the FICS. Section 3 derives the mathematical formulation of FICS and discusses its interpretation. Section 4 presents the empirical application to U.S. sectors. Section 5 concludes with policy recommendations and outlines avenues for future research.

2 Model

In this section, we present the structural model used to derive sectoral Financial Instability Contribution Scores (FICS). The model is static and stylized, but it captures the key channels through which the implementation of a carbon tax can affect firms, their default probabilities, and ultimately the stability of the banking sector.

2.1 Environment overview

The economy consists of $n + 1$ agents: n representative firms (one for each sector) and a representative bank that lends to them. The overarching idea is to embed a Merton-type model of firm default into a multisector input–output economy with explicit emissions intensity. This approach allows us to capture both the direct effects of a carbon tax (through higher sectoral costs) and the indirect effects that arise from sectoral interdependencies. While the model abstracts from dynamic adaptation, market valuation effects, or changes in technology, it provides a tractable framework that isolates the short-run financial stability implications of carbon taxation.

A number of simplifying assumptions are required to keep the model analytically tractable. First, production technologies are static in the short run such that firms cannot immediately substitute away from carbon-intensive inputs or adopt new technologies; their technical coefficients remain fixed. This means that the static quality of the model is okay to explain the short-run impact of implementing a carbon tax. Second, firms' reliance on credit D_i is fixed ex ante. That is, debt structures do not adjust instantly in response to taxation. This isolates the effect of taxation on default probability without conflating it with financial restructuring. Third, the only channel through which carbon taxes affect default risk is via prices and costs. Other channels, such as changes in firm valuations in capital markets or shifts in investor expectations, are excluded here but could be incorporated in future work.

These assumptions are restrictive, but they align with the goal of developing a transparent and tractable baseline model. The framework should be interpreted as a first step, with future work relaxing each of these assumptions.

2.2 Firms

Production. There are n sectors, each indexed by $i = 1, \ldots, n$. Each sector has a representative firm that produces a final good y_i. Following standard input–output economics, we assume a Leontief production structure:

$$y_i = \min\left(\frac{x_{1i}}{a_{1i}}, \ldots, \frac{x_{ni}}{a_{ni}}, \frac{g_i}{a_i^g}\right), \tag{1}$$

where x_{ji} denotes the input from sector j into sector i, and a_{ji} are the corresponding technical coefficients. The last term includes greenhouse gas emissions g_i scaled by a_i^g, the emissions coefficient.

This production function reflects two important features. First, inputs are used in fixed proportions: firms cannot substitute across inputs in the short run. Second, emissions enter production directly, so that output is tied to pollution intensity. These features are stylized but realistic in the short run, when technological substitution and abatement options are limited.

The cost-minimizing input demand is then straightforward:

$$x_{ji} = a_{ji} y_i,$$

which means inputs are proportional to output. Defining vectors $a_i = (a_{1i}, \ldots, a_{ni})$ and $x_i = (x_{1i}, \ldots, x_{ni})$, one can write the production relationship compactly. In this specification, sector i may even use its own output as an intermediate input.

Profits. Firm i's profits are given by revenues net of production costs, taxes, and idiosyncratic shocks:

$$\begin{aligned}
\pi_i &= p_i y_i - \sum_{j=1}^{n} p_j x_{ji} - \tau_i g_i - \varepsilon_i \\
&= p_i y_i - \sum_{j=1}^{n} p_j a_{ji} y_i - \tau_i a_i^g y_i - \varepsilon_i \\
&= \left(p_i - \sum_{j=1}^{n} p_j a_{ji} - \tau_i a_i^g \right) y_i - \varepsilon_i .
\end{aligned}$$

Here p_i is the output price, τ_i the carbon tax per unit of emissions, and ε_i a random shock with distribution $N(\mu_i, \sigma_i^2)$. The shock captures uncertainty in demand, productivity, or other factors not explicitly modeled.

The quantity y_i itself is determined by the sum of intermediate demands:

$$y_i = \sum_{j=1}^{n} a_{ij} y_j.$$

This makes profits depend both on sector i's own conditions and on the interconnected structure of the economy.

Default risk. Each firm carries debt D_i at interest rate r_i. If realized profits fall short of debt repayments, the firm defaults. Formally, default occurs if $\pi_i < (1+r_i)D_i$.

Define the non-stochastic component of profit as

$$E_i = p_i y_i - \sum_{j=1}^{n} p_j a_{ji} y_i - \tau_i a_i^g y_i.$$

The probability of default is then

$$\begin{aligned} PD_i &= \Pr[\pi_i < (1 + r_i)D_i] \\ &= \Pr[E_i - \varepsilon_i < (1 + r_i)D_i] \\ &= 1 - \Phi_i(E_i - (1 + r_i)D_i), \end{aligned}$$

where Φ_i is the cumulative distribution function of the normal distribution with mean μ_i and variance σ_i^2.

This setup is deliberately close to the Merton (1974) model of corporate default, with one key difference: here, the stochastic element applies to profits rather than asset values. This is appropriate given the emphasis on profitability shocks induced by taxation.

Effects of a carbon tax. A carbon tax affects firms in two ways. First, there is a direct effect. The tax increases the costs of firms proportional to their emissions intensity. This directly reduces profits and raises default probabilities. Second, there is an indirect effect: through the input–output network, a tax on one sector increases costs for its customers in other sectors. This propagates shocks throughout the economy, affecting even low-emission sectors.

To model these effects, we adopt a cost-push price system. Baseline prices satisfy

$$\mathbf{p} = A\mathbf{p} + V,$$

where A is the input–output matrix, $\mathbf{p}$ the vector of prices, and V is value added as measured in input-output tables. When a carbon tax is implemented, value added increases by ΔV, so the new price vector is

$$\mathbf{p} = A\mathbf{p} + (V + \Delta V).$$

Solving yields

$$\mathbf{p} = (I - A)^{-1}(V + \Delta V).$$

This structure makes the propagation of carbon taxes transparent. Even a tax on a single sector changes the price vector economy-wide, with linear effects due to the Leontief structure.

2.3 Representative Bank

The final agent is the representative bank, which lends to all sectors. The bank's profits Π are the sum of repayments from each sector, conditional on default. The distribution of Π is Poisson binomial, so its mean and variance are tractable:

$$\mathbb{E}[\Pi] = \sum_i r_i D_i (1 - PD_i),$$
$$Var(\Pi) = \sum_i (r_i D_i)^2 (1 - PD_i) PD_i.$$

To measure financial stability, we use the bank's z-score:

$$z = \frac{\mathbb{E}[\Pi] + E}{\sqrt{Var(\Pi)}},$$

where $E = \sum_i D_i$ is bank equity. The z-score is widely used in financial stability analysis. Intuitively, it compares expected returns plus equity buffers to the volatility of returns. A high z indicates resilience; a low z signals fragility.

2.4 Discussion

This model provides a clean link from sectoral taxation to banking instability. Its strengths are clarity and tractability: every assumption is transparent, and the mechanics are easy to interpret. However, its simplicity comes at a cost. The static nature of the model excludes dynamic adaptation, technological substitution, or feedback effects from credit supply. Similarly, assuming independent shocks across firms abstracts from correlated risks that are likely important in practice.

Despite these limitations, the model is well suited to the purpose of constructing FICS. By holding other factors constant, it isolates the pure effect of carbon taxation on sectoral default probabilities and their implications for the banking system. Extensions could incorporate correlated shocks, valuation effects, or dynamic investment behavior, but these would build on rather than replace the framework outlined here.

3 The Financial Instability Contribution Scores

Definition. The Financial Instability Contribution Score (FICS) measures the marginal effect of a sector-specific carbon tax on the stability of the banking system. The procedure is straightforward: first, compute the z-score of the representative bank in the benchmark economy with no carbon tax, denoted z. Second, impose a carbon tax exclusively on sector i and recompute the bank's z-score, denoted z_i. The FICS for industry i is then defined as:

$$\text{FICS}_i = \frac{z_i}{z} - 1$$

This relative measure provides a standardized way of assessing how much a given sector's exposure to a carbon tax amplifies or mitigates systemic risk.

The interpretation of the FICS is intuitive. A score of zero implies neutrality: the imposition of a tax on sector i does not alter the resilience of the banking system relative to the no-tax baseline. A negative FICS indicates that the post-tax z-score is lower than the benchmark, meaning that the introduction of the carbon tax in that sector reduces bank stability. In economic terms, sector i has become a destabilizing channel through which the policy shock transmits to the financial system. Conversely, a positive FICS suggests that taxing sector i improves stability, either by lowering default probabilities in that sector (perhaps by shifting its cost structure or rebalancing its reliance on debt) or by redistributing risk in a way that strengthens the banking system overall.

From a regulatory and policy perspective, the FICS allows us to go beyond aggregate measures of stability. It provides a *sector-specific lens* through which policymakers can identify "systemic amplifiers" of instability. This is especially important in transition-risk scenarios, where climate policies may have uneven effects across industries.

4 Application to the USA

In this section, we apply the FICS methodology to the case of the USA. We find that the sectors with the lowest FICS, i.e. those most likely to contribute to financial instability upon the implementation of a carbon tax, are (1) electricity, gas, steam and air conditioning supply, (2) land transport and transport via pipelines, and (3) water supply, sewerage, waste management and remediation activities.

4.1 Data

Compustat sample and cleaning. We construct a cross-sectional dataset for fiscal year 2024 from Compustat. Nominal values are deflated to 2022 USD using the CPI (annual average), and firms with missing or clearly erroneous totals are excluded. Industries are harmonized by mapping 4-digit SIC to a 2-digit SIC and then to a 45-sector ICIO-consistent taxonomy used in the OECD inter-industry tables. The final sample covers 19,000 firms and yields sectoral aggregates for the full set of private industries; telecommunications is dropped due to extreme outliers in leverage and interest expense in 2024.

Variables and sectoral aggregation. From Compustat we retain current assets (ACT), total debt (DT), interest expense (XINT), gross profits (GP), and net sales (SALE). For each sector i, we compute sales-weighted aggregates: debt D_i, assets A_i, the effective interest expense $XINT_i$, and the distribution of profits summarized by a sales-weighted mean μ_i and standard deviation σ_i. We then form leverage D_i/A_i and an effective interest rate $r_i = XINT_i/D_i$, setting $r_i = 0$ if $D_i = 0$. Figures 1 through 4 summarize the sector-specific debt, interest rates, mean profits and standard deviation of profits. There is substantial cross-sector dispersion in leverage, financing costs, and profit risk. These moments are the inputs to sectoral default probabilities in the FICS computation.

Figure 1: Distribution of debt, by sector

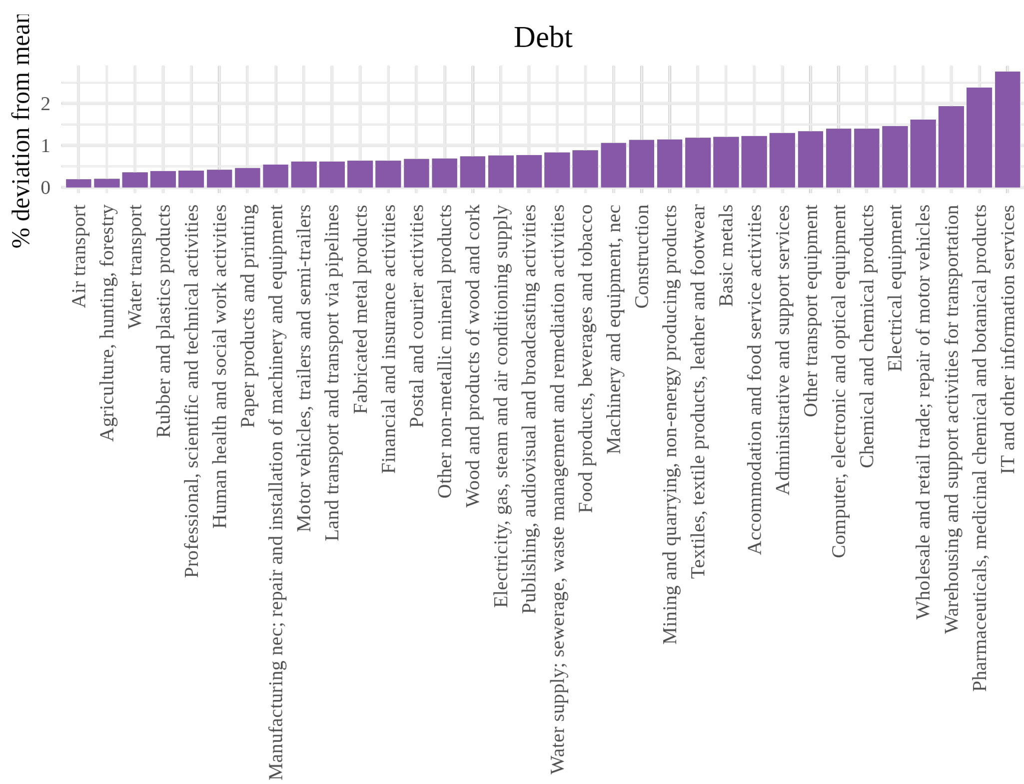
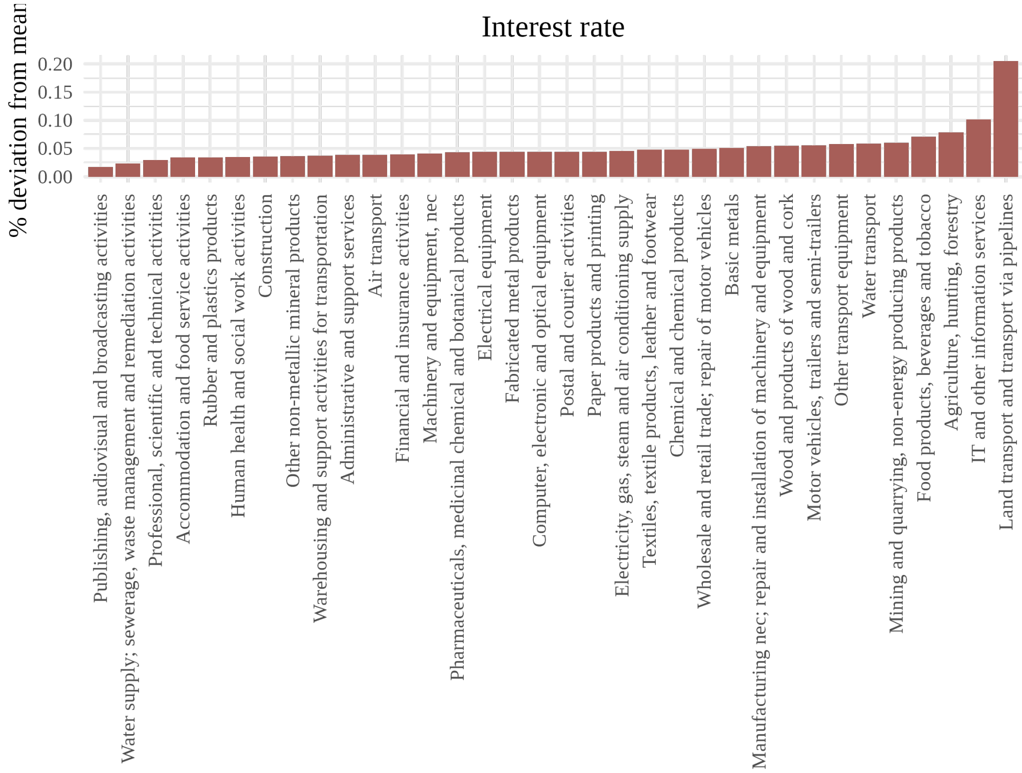


Figure 2: Distribution of interest rate on debt, by sector

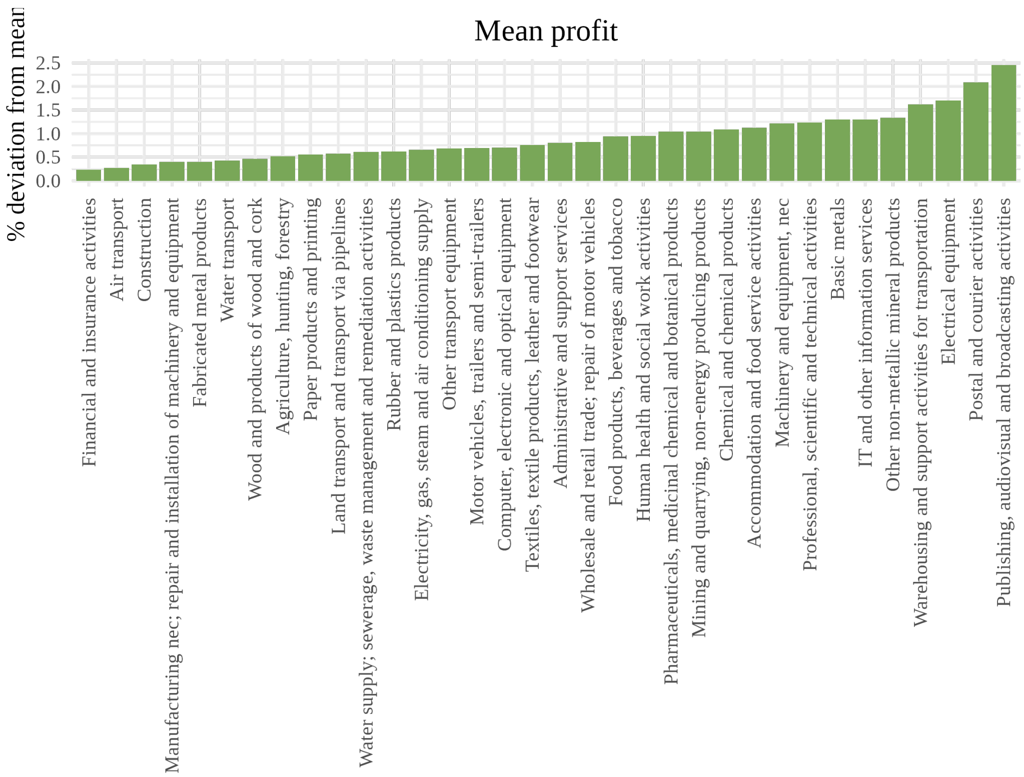


Input-output and emissions data. To quantify price and demand spillovers from carbon taxation, we use the OECD ICIO 2023 release. We extract the 2020 USA domestic block to obtain the technical-coefficients matrix and the industry output vector, together with industry greenhouse-gas emissions that determine the tax base. This pairing—2024 balance sheets and 2020 IO linkages—anchors the micro risk distribution in the latest firm data while using the most recent consistent IO structure for price pass-through.

4.2 Results

Figure 5 plots the estimated scores across sectors. Three findings emerge. First, all sectors exhibit negative FICS: a sector-specific carbon tax reduces the banking z-

Figure 3: Distribution of mean profit, by sector

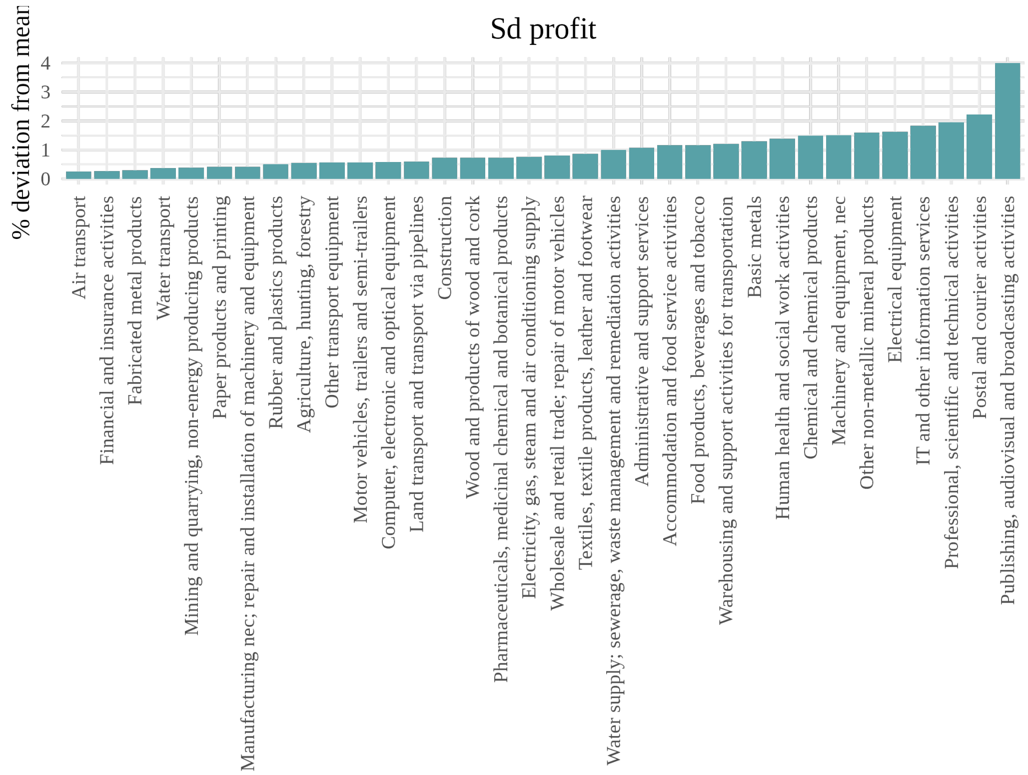


score relative to the no-tax benchmark. This reflects both direct cost increases in the taxed sector and indirect pass-through via input–output linkages that raise default probabilities in exposed borrowers.

Second, the magnitudes vary widely. Utilities (electricity, gas, steam and air conditioning supply) and land transport (including pipelines) are the most destabilizing: a \$75/ton tax on utilities reduces the z-score by roughly 75% (i.e., FICS ≈ -0.75), and on land transport by about 60% (FICS ≈ -0.60). Water supply, sewerage, waste management and remediation activities also post strongly negative scores, placing them among the top three contributors to instability.

Third, sectors with large negative FICS combine (i) higher leverage and non-trivial interest burdens, (ii) thinner or more volatile profit buffers, and (iii) central positions

Figure 4: Distribution of standard deviation of profit, by sector



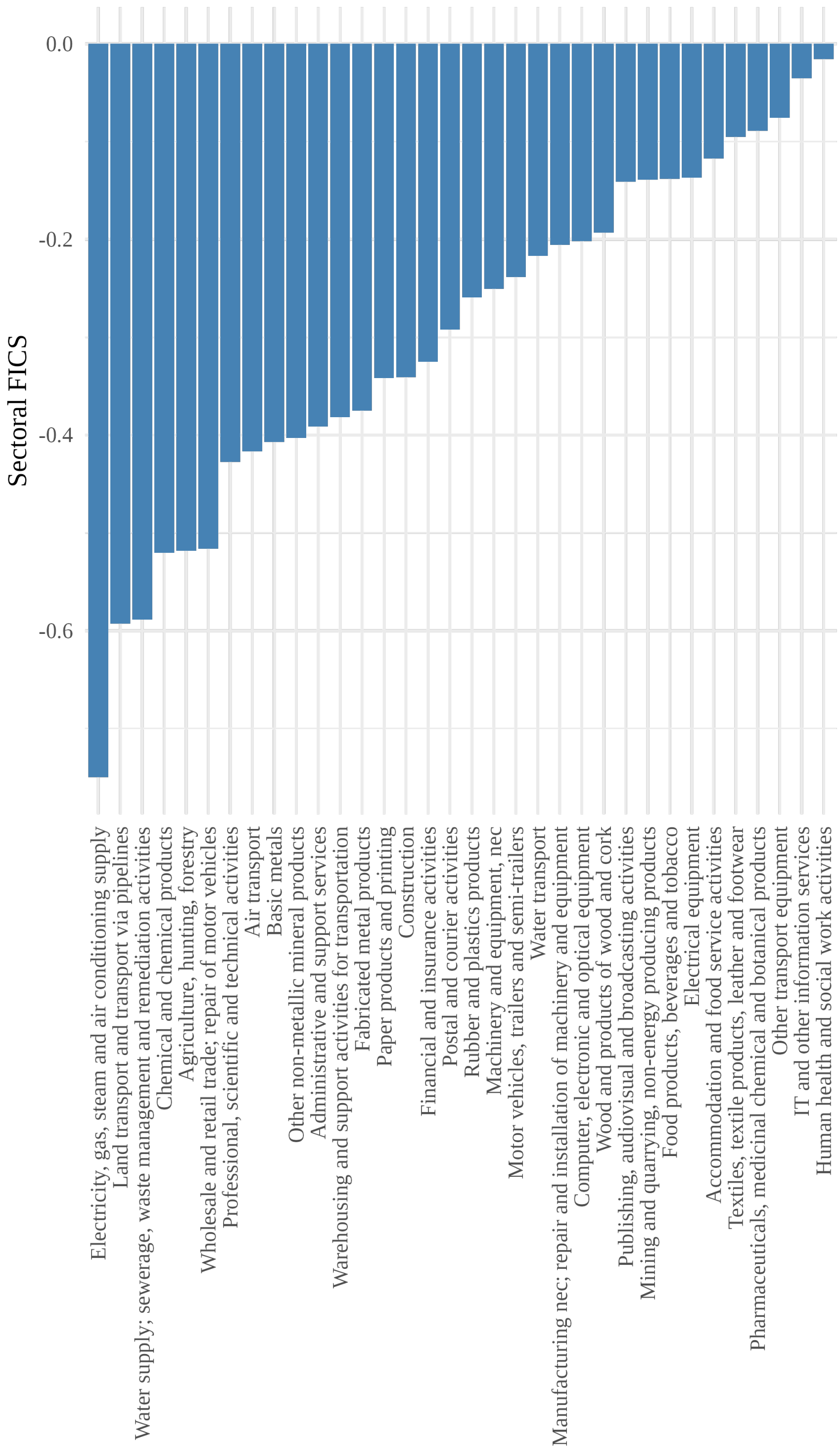
in the production network that amplify cost pass-through. The summary figures corroborate these features: utilities and transport display above-average leverage and meaningful profit risk, consistent with elevated model-implied default probabilities when taxed.

5 Conclusion

This paper developed the Financial Instability Contribution Scores (FICS), a tractable metric linking carbon taxation to systemic risk. By combining sectoral default probabilities, leverage, and input–output linkages, FICS provide policymakers with a transparent and replicable way to identify fragile sectors.

Applying the framework to the United States shows that utilities and transport pose

Figure 5: Estimated FICS across sectors



outsized risks under carbon taxation. Policymakers should therefore consider complementary measures: phased or differentiated taxes, prudential buffers for banks with concentrated exposures, and coordination between climate and financial regulators.

Future research could extend FICS into dynamic settings with technological substitution, correlated shocks, and endogenous firm exit. Comparative studies across countries would also illuminate how different industrial structures mediate transition risks. Finally, the structure of the FICS makes it possible to distinguish between financial instability coming from foreign countries and transmitted through input-output linkages. Those are several future research avenues which would contribute to the implementation of sustainable carbon taxation on industries.

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