Sectoral Transition Risk in an Environmentally Extended Production Network Model

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Abstract

This paper analyzes sectoral transition risk in the US using a general equilibrium production network that captures the entire supply chain. Unlike prior approaches, this model contains sufficient granularity to separate key green and fossil fuel sectors through calibration on environmentally extended input-output tables from EXIOBASE. This allows for explicitly modeling the transition from non-green to green intermediates, as well as studying green subsidies. Carbon taxes cause substantial declines in fossil fuel-linked sectors and nonlinear increases in green-linked substitutes. Green subsidies are less effective than carbon taxes at shrinking high-emitting sectors due to incomplete pass-through. In both cases, magnitudes depend highly on the green vs. non-green elasticity of substitution. Finally, I examine to what extent emissions-based metrics such as scope 1, 2, and 3 can linearly approximate the economic impacts of a carbon tax.

Keywords: Production network; value chain; transition risk; climate risk; carbon tax; industry dynamics.
JEL Codes: C67, D57, H23, Q58

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1 Introduction

Transition risk from climate change mitigation policy is highly dependent on sector. Firms in certain sectors, such as those that burn fossil fuels directly, are inherently more exposed to policies such as carbon taxes or emissions cap and trade programs due to expenditures on offsets or taxes on their direct emissions.[1]

However, these directly emitting sectors typically form a relatively small portion of total output in advanced economies, which are instead dominated by lower emissions sectors such as the service sector. Figure 1 shows that over 90% of emissions in the US originate in sectors that constitute less than 25% of output. Even if an industry does not directly emit, this does not preclude its exposure to transition risk from climate change policies or imply that the sector is "climate-friendly" in any sense. Indeed, many low-emissions sectors are highly dependent on energy generated by burning fossil fuels. They could also be located upstream from emitting industries, supplying intermediate goods to sectors that would potentially shrink from a carbon tax. A prominent example would be coal mining in its relationship to electricity production from coal-fired power plants. This would also subject them to transition risk, as seen in the loss of employment in coal mining regions when these power plants shut down.

Consequently, a concept known as scope 3 emissions was developed, which refers to indirect emissions of a company or other entity along the entire length of their supply chain (both upstream and downstream). This contrasts with scope 1 emissions which refer only to direct fossil fuel burning and scope 2 emissions which refer only to emissions associated with immediate energy inputs. Many climate risk measurement exercises, such as those conducted at the Dutch Central Bank or European Central Bank, or prominent vendors

[1] This would similarly apply to a reduction in fossil fuel subsidies, prevalent throughout the world, which would map directly to carbon taxes. See Skovgaard and Van Asselt (2018) for context.

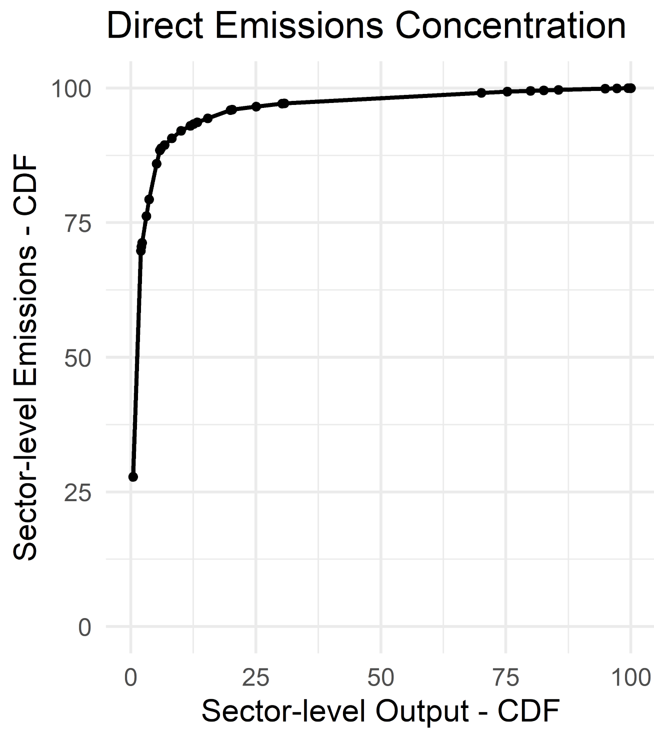

Figure 1: USA data.
Source: EXIOBASE 3, based on GWP100 standard of greenhouse gas weighting.

of ESG ratings, use scope 1+2+3 emissions as a major component of their measure of firm-level vulnerability to transition risk.[2]

However, the relative importance of the subcomponents of scope 1+2+3 emissions in determining transition risk is less well understood. This involves developing an understanding of the relative magnitude of indirect supply chain-related effects as opposed to effects arising from direct carbon taxes in determining either firm or sector-level transition risk.

A line of literature has started to examine this question, using production network models of the kind pioneered by Long and Plosser (1983), developed

[2]See Vermeulen et al. (2021), Battiston et al. (2017), and Alogoskoufis et al. (2021).

further theoretically in Acemoglu et al. (2012) and Baqaee and Farhi (2019), and examined empirically in Horvath (2000), Foerster et al. (2011) and Atalay (2017) among others. These papers primarily focus on understanding the effects of microeconomic shocks on the macroeconomy, but the framework also provides a useful tool to understand the propagation of carbon taxes. Some notable examples of papers in this realm are Devulder and Lisack (2020), Frankovic (2022) and Campiglio et al. (2022) who highlight the importance of forward and backward linkages from the entire input-output structure of the economy in determining sectors most at risk.[3] This paper continues in this line of literature, providing an estimate of the direct vs. indirect impacts of carbon tax propagation on a sector-by-sector basis using a "Leave One Covariate Out" or "LOCO"-style analysis. It finds that some highly-impacted sectors are affected almost entirely through indirect factors rather than a direct carbon tax. In addition to studying these direct vs. indirect impacts, this paper also introduces several modeling innovations that I will expand on next.

A key challenge in modeling the green transition in this framework is related to the data – the baseline input-output structure of any simulated economy needs to be calibrated to empirical input-output tables through sectoral share parameters in intermediate production and final consumption. However, these are not typically designed with modeling the green transition in mind. In these cases, key sectors associated with the green transition are lumped in with typically "dirty" sectors. For example, the World Input-Output Database (WIOD) that is used to empirically calibrate the models in Devulder and Lisack (2020), Frankovic (2022) and Campiglio et al. (2022) is based on the widely used ISIC Rev. 4 sectoral classification scheme.[4][5] However, this scheme, while extremely granular in some dimensions, does not differentiate between electricity from green sources and fossil fuel sources,

[3]These are also known as downstream and upstream effects.
[4]International Standard Industrial Classification
[5]For more information, see Timmer et al. (2015)

possibly the most important margin in this use case. This means that the green transition is only incompletely modeled in this context – its omission would mean that growth sectors, such as green energy and linked sectors, are not considered, and other policies such as green subsidies would be more difficult to capture.[6] In addition, estimates of aggregate value-added changes may be upwardly biased as a lack of substitutable low carbon-tax energy goods in the model would cause the entire simulated economy to shrink.

This paper solves this omission by using the EXIOBASE multi-regional environmentally extended input-output tables to calibrate share parameters and, thus, the baseline input-output structure of the simulated economy.[7] These tables were designed to provide a holistic view of the effect of the global economy on the environment through the entire supply chain. Crucially, the industry breakdown includes a detailed segmentation of the energy sector, including a differentiation between coal-fired plants, oil-fired plants, gas-powered plants, as well as all major renewable energy sectors such as solar photovoltaic, wind, geothermal, and nuclear power. They also provide an estimate of greenhouse gas emissions for all these industries, along with a host of other environmental impacts that are not considered in this paper. Using this database allows me to explicitly model the trade-off between green and fossil fuel energy in the transition to green and more accurately understand the winners, losers, and aggregate macroeconomic effects from this shift. In addition, I can explicitly model the impact of green subsidies, something not yet attempted in the literature. This also provides a link from the environmental economics literature, leveraging Long and Plosser (1983)-style models to estimate the sectoral dynamics of the transition, with the literature on environmentally extended input-output tables that provide a

[6]For example, this issue was noted in Battiston et al. (2017), motivating their reclassification of NACE.

[7]See Stadler et al. (2018). This database is licensed under the Creative Commons Attribution-ShareAlike 4.0 International license - see `https://creativecommons.org/licenses/by-sa/4.0/`. Changes were made by aggregating certain sectors and countries. Full crosswalk is available in an online appendix upon request.

holistic, but static view of industry-level environmental impacts.

With the baseline of the model set according to EXIOBASE, including sufficient granularity between green and non-green sectors, I now turn to dynamics. The critical factor is in understanding the ease of substitution to these green goods, both for producers in their use of intermediate goods and consumers in their consumption of final goods. Once again, the most material example is in the switch from fossil fuel energy to electricity from renewable sources – the ease in substitutability between these two industries in their use as intermediate and final goods would be a key parameter in determining the ease of the transition to green. If fossil fuel energy is easily substituted for renewable energy, then we would expect to see a much milder transition with sharper differences in outcomes between green and non-green sectors. This is in contrast to a situation where expensive, carbon-taxed fossil fuels would still need to be used in production due to difficulties in substitution to green. These considerations have been noted in other papers addressing transition risk. For example, sectoral input elasticity is listed as one of four key factors in determining a sector's transition risk in the classification scheme introduced in Battiston et al. (2022). However, this paper is the first to directly produce an estimate of the variability in economic impacts from this factor at the sector level.

Indeed, Long and Plosser-style production network models like the one used in this paper provide a valuable framework to examine this problem, made even more tractable when using functional forms flexible to non-unitary elasticities of substitution (EOS). Horvath (2000) introduced the use of Constant Elasticity of Substitution (CES) production functions in this framework when studying the propagation of sectoral shocks, and Devulder and Lisack (2020) and Campiglio et al. (2022) continue their usage in the context of carbon tax propagation. In contrast to those papers, by using a sectoral classification that includes a differentiation between green and non-green energy sources, I can explicitly examine the effects of varying the elasticity of substitution between green and non-green energy on the propagation of the carbon tax. I find that, corresponding to the intuition, this is key in determining the nature of the transition, with higher substitutability between energy factors leading to a milder transition on aggregate, but causing a sharper gradient in the sectoral incidence of the carbon tax. High-emissions and fossil fuel-linked sectors collapse sharply (15% - 40% declines depending on EOS and sector), and green energy-linked sectors grow rapidly (5% - 55% increase depending on EOS) in response to a relatively modest carbon tax of \$25/ton CO_2. This variation becomes even greater when assuming the same level of uncertainty in energy EOS on the consumer side as the producer side.

An additional analysis shows that common methods of approximating economic measures of transition risk from carbon taxes using emissions-based metrics such as scope 1, 2, or 3 have varying accuracy and rank-ordering ability depending on the EOS parameter. The relationship of any emissions-based factors to economic effects, as captured by the model, is nonlinear, so linear approximations tend to suffer poor accuracy, except if energy EOS is low. Scope 1 and 1+2 emissions also tend to have mediocre rank-ordering ability of economic effects, especially when substitution elasticities are assumed to be high and network dynamics are more complex. However, scope 1+2+3 emissions metrics rank-order negative economic impacts reasonably well, although they cannot, by definition, capture the positive impacts. These results provide conditions when certain simplified transition risk identification measures are suitable in the absence of complicated production network models.

A final question I answer is on the transmission of green subsidies through the economy. Previous studies using production network models have not adequately addressed this question due to the lack of differentiation between key green and non-green sectors. Indeed, this is an especially topical question as recent climate policies in the US have increasingly relied on subsidies to the clean energy sector rather than economy-wide carbon taxes. This includes the Inflation Reduction Act of 2022, which contains $369 billion in emissions-reducing climate and clean energy provisions at the federal level.[8] But, there are also numerous state and local policies such as clean energy tax credits, electric vehicle purchase incentives, and renewable energy certificate (REC) reimbursements.[9]

Green subsidies, unsurprisingly, have a direct and large effect on increasing real value-added in the renewable energy sector. But, on a per-dollar transfer basis, they are less effective in shrinking highly-emitting sectors. This is especially true if energy sources are not highly substitutable. Even if they are substitutable, large subsidies cannot reduce petroleum and fossil fuel electricity usage by more than the modest \$25/ton CO_2 tax studied earlier. This is due to incomplete pass-through even in the high EOS cases. However, as this model does not include some essential components in understanding sectoral dynamics in the long term, such as technological growth and R&D, this result is likely best interpreted as reflecting short-term effects. This finding is consistent with the insight in Borenstein (2012) that the imperfect elasticity between renewables and fossil fuels in generating electricity would lead to the reduced budgetary efficacy of renewable subsidies compared to carbon taxes.

The key role green vs. non-green EOS has in both results introduces a puzzle and potential gap in the literature. Elasticities of substitution between intermediate goods in final production have been estimated from typical input-output tables but usually outside the context of the green transition. Atalay (2017) uses military spending shocks as an instrument to estimate intermediate good elasticities of substitution and finds that they are reliably near 0, meaning that goods are, essentially, complements. However, this result relies on SIC and ISIC categorizations in BEA input-output tables and the World Input-Output Tables, which do not separate out green

[8]See Larsen et al. (2022) for an analysis of the Inflation Reduction Act of 2022.

[9]For an overview of state and local policies within the US, see the DSIRE database maintained by NC State University - Weissman and Gouchoe (2002).

energy. Papageorgiou et al. (2017) estimate elasticity parameters in a green growth context, using fuel-type use information in the World Input-Output Database to estimate a much higher elasticity of substitution between green and non-green intermediates - around 2 in the energy sector and 3 in the non-energy sector. However, the World Input-Output Database has limitations in the green transition context, and results are acknowledged to have potential endogeneity issues. This paper emphasizes the importance of finding accurate estimates behind these parameters in determining both aggregate and sectoral dynamics from transition risk.

The rest of the paper proceeds by introducing the model in section 2, describing the data, notably, the EXIOBASE tables, in section 3, presenting results from the simulated model in section 4, followed by a discussion and conclusion in section 5.

2 Model

2.1 Overview

I estimate a Long and Plosser (1983)-style general equilibrium production network model, with two countries, USA, and Rest of World or "ROW."[10]

- A representative consumer in each country has rational expectations, maximizing utility with respect to a consumption basket of differentiated goods and distributing their inelastic labor supply across industries.

- Representative firms for each country-industry maximize profit while hiring labor and buying intermediate goods to produce goods to sell on the international market.

[10] I do not focus on international supply chain dynamics per se but include a "ROW" mainly so that I can accurately model dynamics for sectors for which international imports comprise a major proportion of inputs.

- A government in each country levies carbon taxes proportional to emissions on firms and transfers them lump-sum back to consumers. [11]

2.2 Producers

I start by introducing the production structure of the economy. Let $k \in \mathcal{C} = \{\text{USA}, \text{ROW}\}$ be the set of countries in the world, and $i \in \{1, \ldots, N_E, \ldots, N\}$ be the set of industries, with the first N_E industries denoting the energy sector and the last $N - N_E$ industries denoting all other industries. Each country has a representative firm for each industry in the set, which solves the following profit maximization problem:

$$\Pi_{ik}(p, \tau_{ik}) = \max_{y_{ik}, l_{ik}, x_{ijk}} \pi_i = (1 - \tau_{ik}) p_{ik} y_{ik} - w l_{ik} - \sum_{l \in \mathcal{C}} \sum_{j=1}^{N} p_{jl} x_{ijkl}$$

s.t.

$$y_{ik} = A_i F_{ik}(l_{ik}, x_{i,1,k,\text{USA}}, ..., x_{i,N,k,\text{USA}}, x_{i,1,k,\text{ROW}}, ..., x_{i,N,k,\text{ROW}})$$

In other words, firms indexed by i, k take world prices p, and carbon taxes on production τ_{ik} as given and choose production levels y_{ik}, labor input l_{ik} , and intermediate inputs x_{ijkl} to maximize their profit.

Technology for production is determined by function $A_i F_{ik}$. We assume a constant elasticity of substitution (CES) functional form with several nested classes of goods. First, we have that

$$F_i(l_{ik}, x_{i1k}, ..., x_{iNk}) = \left(\mu_{ik}^{\frac{1}{\eta}} l_{ik}^{\frac{\eta-1}{\eta}} + \alpha_{X_{ik}}^{\frac{1}{\eta}} X_{ik}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

[11] This is not the only way to structure carbon taxes, but I assume all are borne by the firm and lump-sum transferred back for ease of analysis for the question at hand.

I.e., production in country k and industry i depends on a combination of X_{ik}, which denotes aggregated intermediate goods, and l_{ik}, labor. $\alpha_{X_{ik}}$ denotes the CES share parameter for intermediate production, which, in part, sets factor expenditure share for these goods, and μ_{ik} denotes the CES share parameter for labor, which similarly determines factor expenditure share for labor. In the context of input-output analysis, this would be associated with so-called "value-added."[12] These goods can be substituted between each other according to parameter η, which is the elasticity of substitution (EOS) between aggregated intermediate goods and labor.

The next level of CES nesting concerns intermediate goods, which are divided between energy goods E_{ik} and non-energy goods I_{ik}, as in Devulder and Lisack (2020).

$$X_{ik} = \left(\left(\frac{\alpha_{E_{ik}}}{\alpha_{X_{ik}}} \right)^{\frac{1}{\theta}} E_{ik}^{\frac{\theta-1}{\theta}} + \left(\frac{\alpha_{I_{ik}}}{\alpha_{X_{ik}}} \right)^{\frac{1}{\theta}} I_{ik}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

I index the first N_E and the last $N - N_E$ intermediate goods such that they denote industries that comprise energy goods E_{ik} and non-energy goods I_{ik} respectively. We also assign each class of goods its own within class EOS - σ for energy goods and ϵ for non-energy goods. We will pay specific attention to σ in later sections' counterfactuals. In summary, we have

$$E_{ik} = \left(\sum_{l \in \mathcal{C}} \sum_{j=1}^{N_E} \left(\frac{\alpha_{ijkl}}{\alpha_{E_{ik}}} \right)^{\frac{1}{\sigma}} x_{ijkl}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

and

$$I_{ik} = \left(\sum_{l \in \mathcal{C}} \sum_{j=N_E+1}^{N} \left(\frac{\alpha_{ijkl}}{\alpha_{E_{ik}}} \right)^{\frac{1}{\epsilon}} x_{ijkl}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$$

For each country $k \in \mathcal{C}$, the input matrix $\mathbf{X_k}$ can be visualized as [13]

[12] This would hold true in the case of production functions that are homogeneous of degree 1.

[13] For conciseness reasons I have not visualized the differentiation between energy and

$$
\begin{array}{c}
\begin{array}{ccc}
\overbrace{\hspace{4.5cm}}^{\substack{E_{i,USA}\text{:} \\ \text{US energy inputs}}} & \overbrace{\hspace{4.5cm}}^{\substack{I_{i,USA}\text{ :} \\ \text{US non-energy inputs}}} & \overbrace{\hspace{4.5cm}}^{\substack{X_{i,ROW}\text{ :} \\ \text{ROW intermediate inputs} \\ \text{(inc. energy and non-energy)}}}
\end{array} \\
\mathbf{X_k} = \begin{pmatrix}
x_{1,1,k,\text{USA}} & \cdots & x_{1,N_E,k,\text{USA}} & x_{1,N_E+1,k,\text{USA}} & \cdots & x_{1,N,k,\text{USA}} & x_{1,1,\text{ROW}} & \cdots & x_{1,N,k,\text{ROW}} \\
x_{2,1,k,\text{USA}} & \cdots & x_{2N_E,k,\text{USA}} & x_{2,N_E+1,k,\text{USA}} & \cdots & x_{2,N,k,\text{USA}} & x_{2,1,\text{ROW}} & \cdots & x_{2,N,k,\text{ROW}} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
x_{N,1,k,\text{USA}} & \cdots & x_{N,N_E,k,\text{USA}} & x_{N,N_E+1,k,\text{USA}} & \cdots & x_{N,N,k,\text{USA}} & x_{N,1,k,\text{ROW}} & \cdots & x_{N,N,k,\text{ROW}}
\end{pmatrix}
\begin{array}{l}
\text{Used to produce good 1} \\
\text{Used to produce good 2} \\
\\
\text{Used to produce good N}
\end{array}
\end{array}
$$

I also ensure industry share parameters sum to their class share parameters and subsequently to unity with the value-added share parameter. Thus, we have

$$
\left.
\begin{array}{l}
\sum_{l\in\mathcal{C}} \sum_{j=1}^{N_E} \alpha_{ijkl} = \alpha_{E_{ik}} \\
\sum_{l\in\mathcal{C}} \sum_{j=N_E+1}^{N} \alpha_{ijkl} = \alpha_{I_{ik}} \\
\alpha_{E_{ik}} + \alpha_{I_{ik}} = \alpha_{X_{ik}} \\
\mu_{ik} + \alpha_{X_{ik}} = 1
\end{array}
\right\} \forall i \in \{1,\ldots,N\}, k \in \mathcal{C}
$$

I introduce several terms from the producer side that will subsequently simplify derivations. Solving cost minimization problems to derive unit cost functions for intermediate goods gives

$$
P_{E_{ik}} = \left(\sum_{l\in\mathcal{C}} \sum_{j=1}^{N_E} \frac{\alpha_{ijlk}}{\alpha_{E_{ik}}} p_{jl}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}
$$

$$
P_{I_{ik}} = \left(\sum_{l\in\mathcal{C}} \sum_{j=N_E+1}^{N} \frac{\alpha_{ijlk}}{\alpha_{I_{ik}}} p_{jl}^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}
$$

$$
P_{X_{ik}} = \left(\frac{\alpha_{E_{ik}}}{\alpha_{X_{ik}}} P_{E_{ik}}^{1-\theta} + \frac{\alpha_{I_{ik}}}{\alpha_{X_{ik}}} P_{I_{ik}}^{1-\theta} \right)^{\frac{1}{1-\theta}}
$$

which are price aggregates for the CES baskets of nested goods.

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non-energy goods in ROW, but it should be noted that the nesting structure is identical for inputs from this "country" as well, with variable elasticities of substitution between energy and non-energy goods.

2.3 Consumers

Representative consumer in country $k \in \mathcal{C}$ takes prices p_{il}, wage w_k, firm profit Π_{ik}, and government transfers T_k as given. They maximize their aggregate consumption C_k, which consists of a CES consumption basket comprising differentiated goods of both domestic and foreign origin.

$$\max_{c_{i,k},l_{ik}} \nu_{k,-k} \frac{C_k^{1-\phi} - 1}{1-\phi}$$

s.t.

$$C_k = \sum_{l \in \mathcal{C}} \sum_{i=1}^{N} \left(\gamma_{ikl}^{\frac{1}{\rho}} c_{ikl}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

and

$$\sum_{l \in \mathcal{C}} \sum_{i=1}^{N} p_{il} c_{ikl} = w_k \sum_{i=1}^{N} l_{ik} + \sum_{i=1}^{N} \Pi_{ik} + T_k$$

In the consumption case, the CES aggregation is parametrized by a single EOS parameter, ρ, and parameters γ_{ikl}, denoting share of consumption within country k of good i originating from country l . $\nu_{k,-k}$ is an index denoting the ratio of consumptions between the countries.

$$\sum_{l \in \mathcal{C}} \sum_{j=1}^{N_E} \gamma_{ikl} = \nu_{k,-k} \quad \forall k \in \mathcal{C} \tag{1}$$

The consumer also chooses which firms in their country to allocate his/her fixed labor supply.

$$\sum_{i=1}^{N} l_{ik} = \bar{l}_k \tag{2}$$

We can also introduce the price index on the consumption side per country.

$$p_{C_k} = \left(\sum_{l \in \mathcal{C}} \sum_{j=1}^{N} \gamma_{ikl} p_{jl}^{1-\rho} \right)^{\frac{1}{1-\rho}} \tag{3}$$

2.4 Government

Governments in each country $k \in \mathcal{C}$ levy carbon taxes on sales of firms within their country and lump-sum transfer this back to consumers. While this is not necessarily a realistic modeling of fiscal policy, lump-sum transfers limit distortions to the consumer's problem and cause only a wealth effect, providing a cleaner analysis of substitution dynamics on the production side, the key margin of interest.

$$\sum_{i=1}^{N} \tau_{ik} p_i y_{ik} = T_k \tag{4}$$

Carbon taxes are proportional to empirical emission intensities, which I describe in section 3. I model green subsidies to be *only* falling on the renewable energy sector.

2.5 Market Clearing Conditions

I described labor market clearing conditions in section 2.3. Goods markets clear when production in each country-sector is equal to the sum of its use in final consumption and as intermediates across all country-sectors.

$$y_{ik} = \sum_{l \in \mathcal{C}} \sum_{j=1}^{N} x_{jilk} + \sum_{l \in \mathcal{C}} c_{ilk} \tag{5}$$

A visualization of the resulting input-output structure in matrix form (with country indices omitted) can be found below:

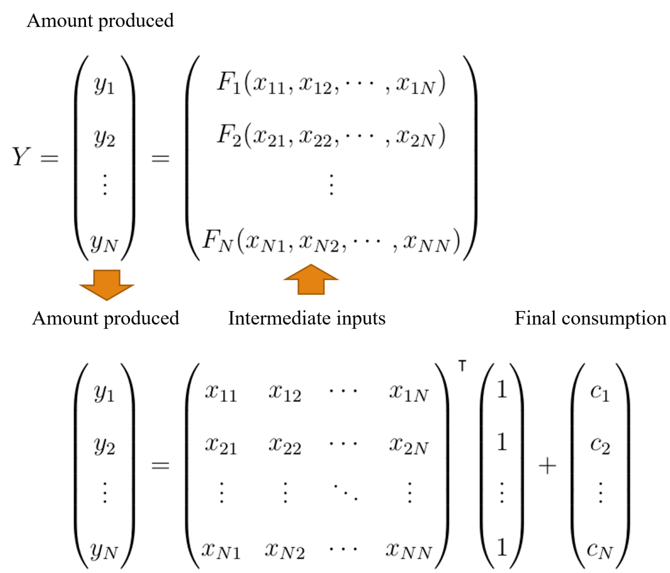

Figure 2: Input-output structure visualization

2.6 Solving for an Equilibrium

First-order conditions on the producer's side give

$$\{l_{ik}\}: \quad l_{ik} = \mu_{ik} F_{ik} \left(\frac{(1-\tau_{ik}) p_{ik} A_i}{w} \right)^{\eta} \tag{6}$$

$$\{X_{ik}\}: \quad X_{ik} = \alpha_{X_{ik}} F_{ik} \left(\frac{(1-\tau_{ik}) p_{ik} A_i}{P_{X_{ik}}} \right)^{\eta} \tag{7}$$

Solving the nested cost minimization problem to choose optimal CES aggregates gives

$$\{E_{ik}\}: \quad E_{ik} = \frac{\alpha_{E_{ik}}}{\alpha_{X_{ik}}} X_{ik} \left(\frac{P_{X_{ik}}}{P_{E_{ik}}}\right)^{\theta} \tag{8}$$

$$\{I_{ik}\}: \quad I_{ik} = \frac{\alpha_{I_{ik}}}{\alpha_{X_{ik}}} X_{ik} \left(\frac{P_{X_{ik}}}{P_{I_{ik}}}\right)^{\theta} \tag{9}$$

$$\{x_{ijkl}\}: \quad x_{ijkl} = \frac{\alpha_{ijkl}}{\alpha_{E_{ik}}} E_{ik} \left(\frac{P_{E_{ik}}}{p_{jl}}\right)^{\sigma} \qquad \text{for } j \in \{1, \dots, N_E\} \tag{10}$$

$$\{x_{ijkl}\}: \quad x_{ijkl} = \frac{\alpha_{ijkl}}{\alpha_{I_{ik}}} I_{ik} \left(\frac{P_{I_{ik}}}{p_{jl}}\right)^{\epsilon} \qquad \text{for } j \in \{N_E + 1, \dots, N\} \tag{11}$$

Iterating down the nesting structure by plugging in equations (8)-(11) sequentially into equation (7) we have

$$x_{ijkl} = \alpha_{ijkl} F_{ik} \frac{((1-\tau_{ik})p_{ik}A_i)^{\eta}}{p_{jl}^{\sigma}} P_{E_{ik}}^{\sigma-\eta} P_{X_{ik}}^{\eta-\theta} \qquad \text{for } j \in \{1, \dots, N_E\} \tag{12}$$

$$x_{ijkl} = \alpha_{ijkl} F_{ik} \frac{((1-\tau_{ik})p_{ik}A_i)^{\eta}}{p_{jl}^{\epsilon}} P_{I_{ik}}^{\epsilon-\eta} P_{X_{ik}}^{\eta-\theta} \qquad \text{for } j \in \{N_E + 1, \dots, N\} \tag{13}$$

I impose a zero profit condition on producers, which gives

$$\begin{aligned} (1-\tau_{ik})p_{ik}A_iF_{ik} &= wl_{ik} + p_{X_{ik}}X_{ik} \\ \implies (1-\tau_{ik})p_{ik} &= w\frac{l_{ik}}{F_{ik}} + p_{X_{ik}}\frac{X_{ik}}{F_{ik}} \end{aligned}$$

Plugging in equations (7) and (6), we have

$$(1-\tau_{ik})p_{ik}A_i = w\mu_{ik}\left(\frac{(1-\tau_{ik})p_{ik}A_i}{w}\right)^{\eta} + p_{X_{ik}}\alpha_{X_{ik}}\left(\frac{(1-\tau_{ik})p_{ik}A_i}{P_{X_{ik}}}\right)^{\eta}$$

Which gives the final form of the zero profit condition.

$$(1-\tau_{ik})p_{ik}A_i = \left(\mu_{ik}w^{1-\eta} + \alpha_{X_{ik}}p_{X_{ik}}^{1-\eta}\right)^{\frac{1}{1-\eta}} \tag{14}$$

Finally, we turn to the consumer side, where we solve the FOC for consumption and plug iteratively into the budget constraint, giving

$$\frac{C_{\text{k}}}{C_{\text{-k}}} = \nu_{k,-k} \left(\frac{P_{C_{\text{k}}}}{P_{C_{\text{-k}}}} \right)^{-\frac{1}{\phi}} \tag{15}$$

$$c_{ikl} = \frac{\gamma_{ikl}}{p_{il}^{\rho}} \frac{w_k \sum_{i=1}^{N} l_{ik} + T_k + \Pi_k}{\nu_{k,-k} \left(\frac{P_{C_{\text{k}}}}{P_{C_{\text{-k}}}} \right)^{-\frac{1}{\phi}} P_{C_k}^{\rho} \sum_{l \in \mathcal{C}} \sum_{j=1}^{N} \gamma_{jkl} p_{jl}^{1-\rho}} \tag{16}$$

2.7 Equilibrium Conditions

An equilibrium, is a bundle consisting of prices $\{p_{jk}\}_{j\in\{1,\dots,N\},k\in\mathcal{C}}$, wages $\{w_k\}_{k\in\mathcal{C}}$, and quantities $\{y_{jk}\}_{j\in\{1,\dots,N\},k\in\mathcal{C}}$ that satisfies the following conditions

- **Consumer demand** is set according to utility maximization problem: equations (15) and (16)
- **Producer intermediate good demand** is set according to profit maximization problem: equations (12) and (13)
- **Producer labor demand** is set according to profit maximization problem: equation (6)
- **Producers have zero profit**: equation (14)
- **Government transfers balance** : equation (4)
- **Goods and labor markets clear**: equations (5) and (2).

I set w_{USA} as the numeraire.

3 Data

3.1 Motivation

Let us set the baseline economy to be the one such that $\tau_{ik} = 0$. In this case, as is customary, I also normalize all prices to be equal to 1. This means that all units for quantities will be on an expenditure basis in the baseline. I also set $A_i = 1$ for the rest of the paper. Note from equations (12) and (12) in the producer's problem that this implies that

$$x_{ijkl}^{\text{base}} = \alpha_{ijkl} F_{ik}^{\text{base}} \tag{17}$$

Let us define the intermediate factor share of total production in baseline as

$$\hat{x}_{ijkl} := \frac{x_{ijkl}^{\text{base}}}{F_{ik}^{\text{base}}} \tag{18}$$

Note that this means that

$$\hat{x}_{ijkl} = \alpha_{ijkl} \tag{19}$$

This implies that the α_{ijkl} parameter sets the baseline input-output production structure of the economy. Similarly, we have that labor factor share of total production revenue, defined as

$$\hat{l}_{ik} := \frac{l_{ik}^{\text{base}}}{F_{ik}^{\text{base}}}$$

would be equal to μ_{ik}.

Finally, from equations (16), (1) and the consumer budget constraint, we have that

$$
\begin{aligned}
c_{ikl}^{\text{base}} &= \gamma_{ikl}(\sum_{i=1}^{N} l_{ik}^{\text{base}} + \sum_{i=1}^{N} \Pi_{ik}^{\text{base}} + T_k^{\text{base}}) \\
&= \gamma_{ikl} C_k^{\text{base}}
\end{aligned}
$$

Setting baseline consumption expenditure share as

$$\hat{c}_{ikl} \coloneqq \frac{c_{ikl}^{\text{base}}}{C_k^{\text{base}}}$$

we then have that

$$\hat{c}_{ikl} = \gamma_{ikl}$$

3.2 Input-Output Structure

To calibrate baseline consumption, intermediate good, and labor share parameters, we require an input-output database containing all these factors at a granularity that enables one to analyze the green transition meaningfully. In addition, we would also need consistent emissions intensity estimates at the same level of granularity to set a realistic carbon tax. As alluded to previously, typical input-output tables used in the literature, such as those from BEA, OECD, and WIOD lack the level of industry-level granularity in key sectors driving the green transition, such as the electricity sector.[14]

To address this issue, a literature focusing on the environmental impacts caused by within and between-country economic flows through the supply chain has formed, leading to the development of augmented input-output tables, known as "environmentally extended multi-region input-output databases" or EE MRIO. No central authority would have the scope to directly collect data on the breadth of topics that an EE MRIO is meant to cover. So by

[14]This is an issue that has been noted in Battiston et al. (2022) when motivating the construction of Climate Policy Relevant Sectors (CPRS). The classification I use here is intermediate in granularity between CPRS2 and CPRS Granular.

necessity, the numbers are estimates rather than direct observations. These augmented tables are meant to reconcile data from various countries' economic statistics services that hold inconsistent industry and sector classifications and fill that in with granular energy use, emissions, and other environmental impact data. Two of the most prominent are Eora26, described in Lenzen et al. (2013), and EXIOBASE3, described in.Stadler et al. (2018) I will leverage EXIOBASE 3 in this paper, primarily due to ease of access.

EXIOBASE 3, developed in 2018, is a refinement to the prior EXIOBASE 2 model, providing rectangular Supply-Use Tables (SUTs) for 44 countries (28 EU members plus 16 major economies) in a 163 industry by 200 product classification. It stands out as one that is compatible with the UN's System of Environmental-Economic Accounting (SEEA), meaning it fulfills certain requirements for bringing together economic and environmental information to measure the impact of the economy on the environment holistically.[15]

I construct a new sectoral aggregation system for this paper to reduce the 163 industries available by default to 31 industries. The reason is twofold. First, most available industries are not highly material when looking at the green transition as a whole and can be combined without the loss of a significant amount of information. Second, as EXIOBASE leverages model-based estimation and is not direct observation data, small sectors can be dominated by noise. The overall scheme ensures that meaningful sectors for the green transition are separated while ensuring sectoral size in terms of output is balanced. Importantly, we combine the many zero-emissions electricity sectors, such as solar photovoltaic, solar thermal, wind, nuclear, geothermal, and so on, into a single sector called "renewable electricity." Coal, natural gas, petroleum, and biomass-related energy sources are combined into the "fossil fuel electricity" sector. We also combine non-electricity-related energy sources into one sector, which includes natural gas provision, petroleum refining, and steam/hot water supply. A complete sector crosswalk is pro-

[15]See European Commission et al. (2014).

vided in an online appendix, available upon request. As this paper is focused on dynamics within the US, I set all non-US countries to be one aggregated sector known as "Rest of World" or "ROW."

I set α_{ijkl} equal to the ratio of intermediate expenditures to gross output in dollars as outlined in equation (19) and μ_{ik} similarly according to the ratio of value-added to gross output.[16]. Similarly, consumption share parameters are set according to EXIOBASE consumption shares. This sets the baseline input-output structure of the simulated economy, and we can check if essential features, such as forward and backward linkages, match between the simulated economy and the real world. To do this, I first define the total requirements matrix $\mathbf{L}$, and the direct requirements matrix, $\mathbf{D}$.

The intuition behind the direct requirements table would be that it represents the intermediate goods needed to produce one unit of output of a certain sector. This hinges on the assumption that goods are perfect complements, which means this concept is not directly mappable to the model in the paper unless I set $\sigma = \epsilon = \eta = \theta = 0$. However, it can be thought of as an approximation in the static baseline case. This means that

$$\mathbf{X} = \frac{1}{A_i} F_i^{-1}(\mathbf{Y}) \sim D\mathbf{Y} \tag{20}$$

Equation (18) implies that the direct requirements matrix is approximated in the model by

$$\mathbf{D}^{\text{model}} \sim \hat{\mathbf{X}} \tag{21}$$

The direct requirements table represents intermediate good requirements to the first order, but intermediate goods require yet more intermediate goods to produce themselves, and this repeats recursively along infinite steps of the entire supply chain. A classic example in the green energy context would be

[16]In a setting where production is homogeneous of degree 1, labor expenditure would capture all value-added

the coal required to fuel the electricity production to power an electric car. In addition, the mining needed to extract this coal would also require gasoline to fuel mining machinery and so on. The table that would capture these nth order effects in input-output analysis is known as the total requirements table. We derive it by plugging in equation (20) into the goods market clearing condition, equation (5) so that we have

$$\begin{aligned} Y &= \mathbf{D}Y + c \\ \implies c &\sim (1 - \mathbf{D})^{-1} Y \end{aligned}$$

The Leontief inverse matrix, or total requirements matrix, is defined as

$$\mathbf{L} = (1 - \mathbf{D})^{-1} \tag{22}$$

And consequently, in the model context, it would be

$$\mathbf{L}^{\text{model}} \sim (1 - \hat{\mathbf{X}})^{-1} \tag{23}$$

I confirm that the baseline model and empirical data have nearly identical Leontief matrices following calibration. The forward (upstream) and backward (downstream) linkages in the economy to each sector would be the column sums and row sums of the Leontief inverse matrix, respectively.[17]

3.3 Emissions

Direct emissions of each sector are also set according to the EXIOBASE database, aggregating carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) together using the Global Warming Potential 100 (GWP100) method. This weights gases to the extent they contribute to global warming

[17]One can also construct more targeted measures of linkages by weighting row/column sums appropriately.

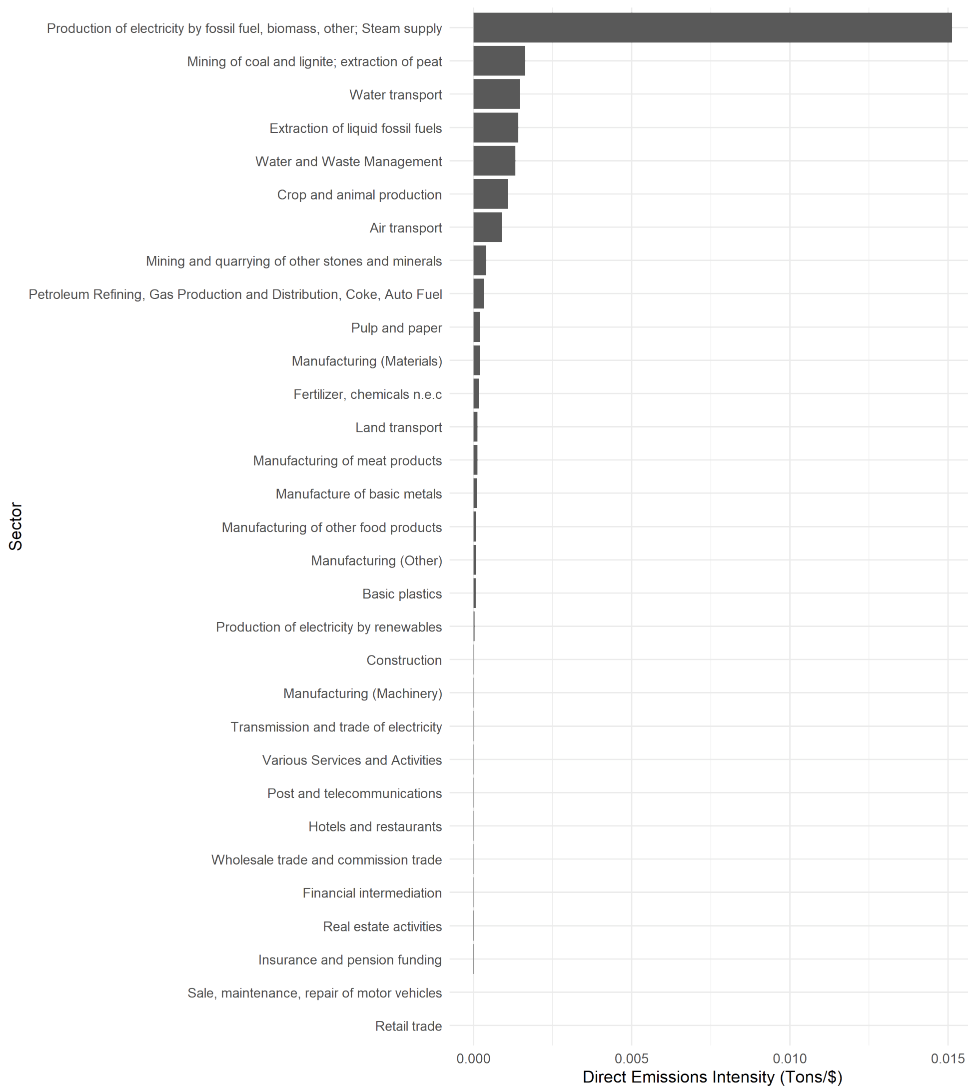

Figure 3: Direct Emissions Intensity .

over a 100-year horizon, with carbon dioxide weighted as 1.[18] This number, divided by gross output per industry, would correspond to emissions intensity and is how I calculate the carbon tax per sector. I combine direct emissions from the production of the good and consumption of the final good for each

[18]See US Environmental Protection Agency (2022)

industry and subsequently model all carbon taxes as being levied on the producer side, even for emissions that are produced during consumption. This primarily affects the *Petroleum Refining, Gas Production and Distribution, Coke, Auto Fuel* sector as consumers directly produce emissions primarily through heating and personal transportation. Emissions intensities are summarized in figure 3. Direct emissions are primarily concentrated in fossil fuel industries, transportation, crop and animal production, and mining.

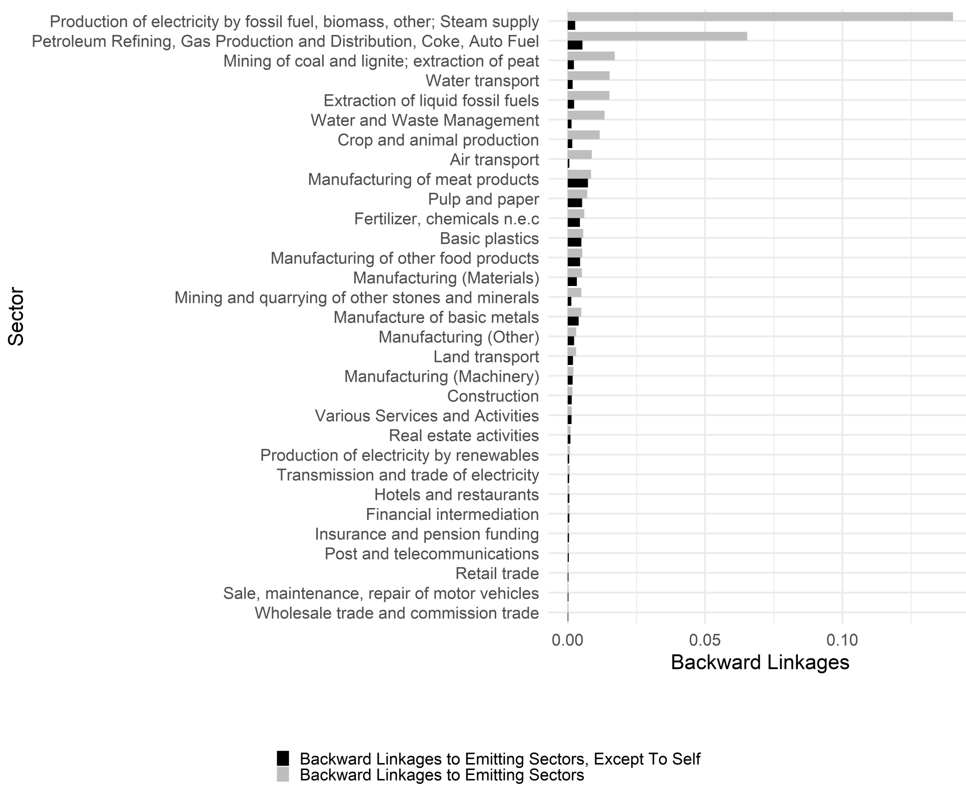

Figure 4: Backward Linkages to Emissions

Now I turn to forward and backward linkages to emissions, which would approximate the concept of scope 1+2+3 emissions as used as a standard measure of transition risk. Results are summarized in figure 4 and 5 for model-simulated results in baseline, which are almost identical to empirical

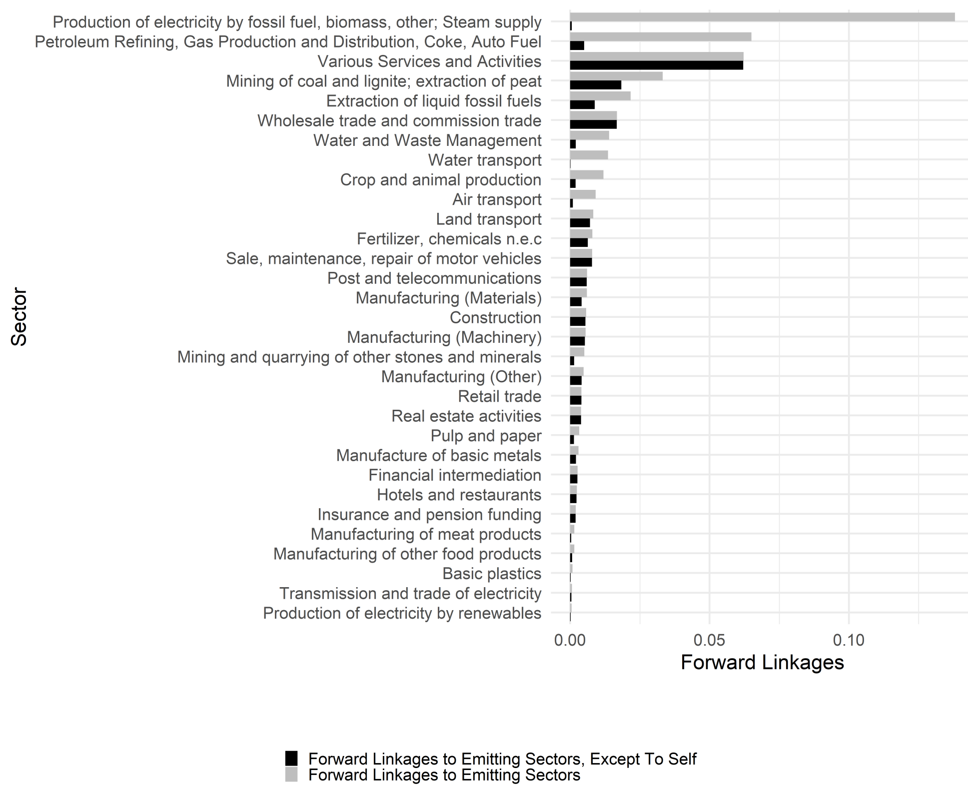

Figure 5: Forward Linkages to Emissions

results (available upon request). In both figures, I differentiate between direct and indirect exposure to emissions by calculating both the linkages to the emitting sectors and the linkages to the emitting sectors, minus self. This will separate the emission exposure that occurs purely through network effects.[19] It is evident that some of the most exposed sectors to emissions, such as fossil fuel electricity production, and petroleum/gas/auto fuel, are exposed primarily due to direct emissions. However, several sectors are primarily exposed indirectly. This would include *Manufacturing of meat products*, which

[19]The exposure through the network effects of emissions may still include exposure to self in this methodology. However, I have also calculated an indirect exposure measure that explicitly excludes any exposure to self, even through the supply chain, but the results are qualitatively similar.

is upstream from *Crop and animal production*, and *Various Services and Activities*, a large sector encompassing many service-related activities, which is downstream from energy sectors/utilities. Another major sector driven mainly by indirect supply-chain effects is the coal mining industry, as it is the major supplier for the fossil fuel electricity sector.

3.4 Elasticities

Now that the baseline is set, assumptions on elasticities would determine the magnitude and nature of reactions to taxes at the industry level. However, this parameter is not well-understood in the data. Atalay (2017) studies this in the context of the sectoral contribution to aggregate business cycle fluctuations using the BEA input-output tables. He uses defense spending as an exogenous instrument to consistently estimate that elasticities are near 0, with factor share expenditures moving almost 1 to 1 with price shocks. These results are cited and used subsequently in Baqaee and Farhi (2019) and Campiglio et al. (2022). However, as mentioned previously, the sectoral classification of BEA input-output tables is not well suited for studying the green transition, with key green and fossil fuel sectors combined. So it is unclear what conclusion to make for elasticities in this paper.

One paper of note, Papageorgiou et al. (2017), explicitly studies elasticities between green and non-green energy sources. He uses a panel from 26 countries for the period 1995-2009 derived from the World Input-Output Database and other inputs to estimate an elasticity of substitution parameter between clean and dirty energy between 2 and 3, which is much higher than the other estimates. However, the study acknowledges that it may be affected by endogeneity. In addition, it suffers from the same drawbacks of using the WIOD in studying the green transition, instead utilizing an energy addendum to estimate effects. Stern (2012) conducts a meta-analysis of the narrower case of inter-fuel substitutabilities, and finds a wide range of values, between 0 and 8 for elasticities between gas, oil, electricity, and so on.

However, it does not explicitly study green energy substitutability.

Given the wide range of potential estimates for this key parameter, I allow energy elasticity of substitution σ to vary between the range of potential estimates, from a low of 0.2, to a high of 4.7, and examine its effect on the distribution and magnitude of industry value-added changes. As for elasticities of other intermediate goods and labor value-added, I follow Atalay (2017) and Baqaee and Farhi (2019) in assuming they are, loosely speaking, complements and set $\eta = \theta = \epsilon = .1$. This adds the additional advantage that counterintuitive results, such as transportation industries substituting fuel for labor, would not occur. I set $\rho = 0.8$ following Baqaee and Farhi (2019) and Devulder and Lisack (2020). However, I conduct a robustness analysis in appendix A where I vary the energy EOS in consumption together with its elasticity in production, essentially assuming that energy types are similarly substitutable in final consumption as when they are used in intermediate inputs. Finally, I set $\phi = 2$ as a common value in the literature.[20]

Parameter	Description	Estimate
σ	Energy EOS	$0.2 - 4.7$
ϵ	Non-Energy EOS	0.1
η	Energy to non-Energy EOS	0.1
θ	Value-added to Intermediate Goods EOS	0.1
ρ	Consumption EOS	0.8
ϕ	Coefficient of Risk Aversion	2.0

[20]The primary margin ϕ would affect would be inter-country transfers, which are not a major focus of this paper.

4 Results

4.1 Carbon Tax

4.1.1 Sensitivity to Energy EOS

I impose varying levels of production carbon taxes upon the simulated economy, utilizing a range of assumptions for the energy elasticity of substitution in production. I initially focus on a $25/ ton CO_2 tax first in figure 6 since this is most relevant for a short to mid-term analysis, but results roughly scale proportionally for larger carbon taxes, as I will show later.[21][22] A modest $25/ton carbon tax may also be especially fitting to study within this framework since carbon tax policies will likely start incrementally and later ramp up, while this model, focused on comparative statics, does not include some features more important for long-term dynamics such as intertemporal investment decisions and technological change.

Sector-level losses in percentage terms are concentrated in highly emitting sectors such as *fossil fuel electricity* and *petroleum refining*, as well as moderate-emissions sectors that supply to these sectors, such as *coal mining*, and *extraction of liquid fossil fuels*. On the other hand, *renewable electricity* shows large increases in sector-level value-added. Sectors downstream from renewable electricity, such as *mining and quarrying of other stones and minerals*, *water transport*, and *basic plastics*, also show an increase. However, the magnitude largely depends on the elasticity of substitution between energy sources, with higher substitutability softening the impact on the aggregate economy, but more sharply impacting fossil fuel-related sectors.

This readily corresponds to intuition, in that an economy that has an easier time substituting from fossil fuel energy in the face of a carbon tax

[21] For imported goods from "ROW", I assume the same carbon tax as for domestic, US goods to ensure no arbitrage opportunities.

[22] I solve the series of nonlinear equations described in section 2.7 using the `fmincon` function in Matlab.

Figure 6: Percentage changes, varying energy EOS σ.

would be better off on aggregate, with a significant jump in value-added in the renewable energy sector. However, it would suffer large losses in emitting sectors that are quickly replaced by those renewables. On the other hand, when it is difficult to switch from fossil fuels, these industries suffer less. However, the entire economy drops in value-added as industries cannot avoid paying steep carbon taxes for dirty energy they cannot switch away from. At the same time, the renewable energy sector and related industries' rise is less pronounced, as it no longer takes up the same amount of slack in energy demand. This reinforces that the nature of transition risk, both at the sector level and on aggregate, is largely dependent on this key unknown parameter, which can be thought of intuitively as an "ease of transition."

In a robustness analysis shown in appendix A, I examine the extent to which changing energy EOS on the demand side at the same time as changing it on the production side modifies the results. This may be realistic as consumers may have a comparable willingness to substitute energy sources as firms do. However, the difference is not precisely estimated in the literature.[23] I find that qualitatively, the same results hold, with the effect magnified since consumers can more easily shift away in higher EOS situations. Indeed, in the modest carbon tax being studied, fossil fuel energy sources are almost 50% smaller in terms of real value-added under higher EOS assumptions. On the other hand, lower EOS assumptions for consumers predictably lead to even greater rigidity than before, with sectoral reshuffling being almost negligible. This highlights the importance of identifying the potential rich heterogeneity in this parameter.

When looking at total loss as opposed to percentage loss within sector in figure 7, the greatest impact is within the service sector. This may be surprising since emissions intensity in this sector is low and the percentage loss in this sector is relatively small. However, this sector holds by far the largest real value-added and output in the economy and is affected indirectly through supply-chain linkages. I will explicitly decompose the direct and indirect effects in section 4.1.2.

This introduces a second major insight of this paper, in that while transition risk is *concentrated* in fossil fuel-related industries, absolute levels of

[23] For a discussion of consumer elasticity of natural gas versus electricity, for example, see Bernstein and Griffin (2006).

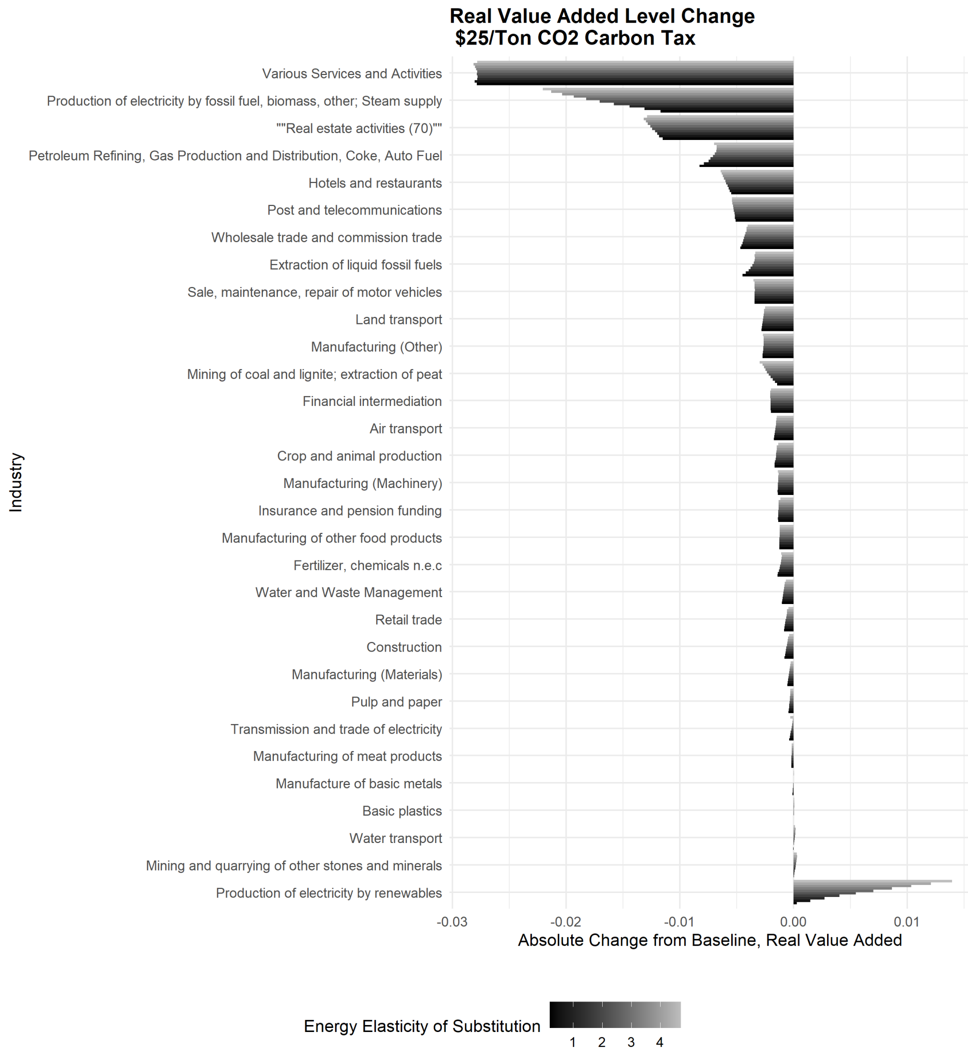

Figure 7: Absolute changes, varying energy EOS σ.

transition risk are highest in large sectors that are indirectly affected, and these sectors are the ones that drive the aggregate losses to the economy. Therefore, it is not enough to only look at emissions intensity when evaluating transition risk at the industry level, but also a measure that includes linkages.

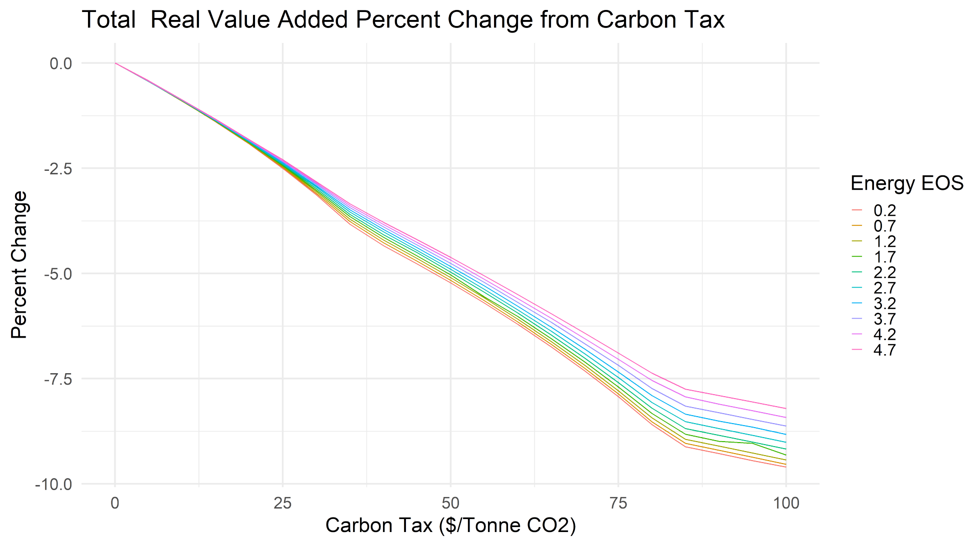

Figure 8: Aggregate changes, varying energy EOS σ.

In figure 8, one can see that when aggregating all sectors of the economy, the energy elasticity of substitution remains an important parameter - a higher substitutability between energy sources leads to a lower value-added drop. However, the difference is perhaps lower than might be expected since, in all scenarios of the EOS, the rise of green and decline of brown partially offset each other.

4.1.2 Direct vs. Indirect Decomposition

In the prior section, we observed that indirect effects can sometimes be more important in determining transition risk than direct emissions, an insight shared with Devulder and Lisack (2020) and Campiglio et al. (2022). Now I calculate the relative importance of these indirect effects to direct effects on the sector from its own carbon tax. To do this, I conduct a "LOCO" or "leave one covariate out"-style analysis, commonly used in machine learning feature importance analysis to assign variable contributions in a model. [24]

[24] See, for example, Molnar et al. (2018).

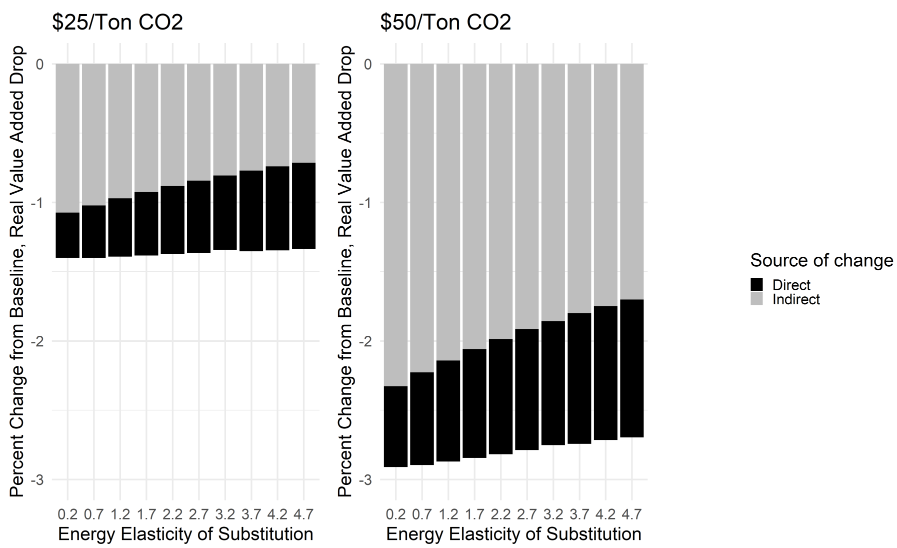

Figure 9: Decomposing aggregate changes.

For each sector, I calculate the value-added changes from taxing only that sector, which I denote as the direct effects of taxation. I then subtract this from the total value-added change in that sector from imposing a carbon tax on all sectors. This difference would represent the indirect effect of taxation, which would encapsulate the effects of the taxes from other sectors onto the sector in question. [25]

Results are pictured in figure 15 for a mid-range selection of energy elasticity, but results generalize. Certain sectors' value-added changes are almost entirely driven by indirect effects, such as *coal mining* and *extraction of liquid fossil fuels*. For some sectors, such as *petroleum refining* and *fossil fuel electricity* indirect effects go in the opposite way since taxes on sectors for which they substitute increase the demand for their own products. Another interesting example of direct and indirect effects going the opposite way is in the *water transport* sector, which is a supplier to the renewable electricity

[25] Shapley analysis has become a more dominant feature importance calculation methodology in the literature due to several useful axiomatic properties as described in Lundberg and Lee (2017), but LOCO is more directly interpretable in this context.

sector, but itself is subject to a carbon tax due to its direct emissions.

When looking at sectors by the level of real value-added change, as depicted in figure 16 in the appendix, one can again see that indirect effects dominate in key industries, such as in the service and real estate sectors. The aggregate effect is encapsulated in 9, which shows the outsize effect indirect effects have on aggregate value-added changes over and above the direct effects at the sector level from individual carbon taxes - around $2/3 - 4/5$ of aggregate value-added changes are indirect. Interestingly, these seem also to vary based on the elasticity of substitution, with higher complementarity causing a higher proportion of indirect effects due to the failure of the economy to easily adjust away from emitting goods.

4.1.3 Relationship with Emissions-based Proxy Measures

With the increasing demand for robust environmental disclosure, such as the ones outlined by the Task Force on Climate-Related Financial Disclosures (TCFD), there is a strong incentive for institutions of a wide variety of stripes to project transition-related risks.[26] Indeed, the Network for Greening the Financial System (NGFS) has also released principles recommending so-called "climate scenario analysis" for climate risk management purposes. Several sophisticated scenario analysis approaches at central banks such as Vermeulen et al. (2021) and Alogoskoufis et al. (2021) have used linear transformation of scope 1+2+3 emissions. However, one might expect institutions with less modeling expertise to use even more simplified measures, such as scope 1 or scope 1+2, especially considering the relative difficulty of acquiring data on firm-level scope 3 emissions. A key question would be how close these measures, or linear transformations of them, come to approximating the true economic damages, especially considering the potentially complex nonlinear dynamics outlined above.

To answer this question, I run linear regressions of sectoral scope 1, 1+2,

[26] For further context, see Pástor et al. (2022).

and 1+2+3 emissions on real value-added percentage change measures derived earlier. I then evaluate the accuracy in terms of R^2 and rank-ordering ability in terms of Somer's D. The measures of scope 1, 1+2, and 1+2+3 emissions are derived from EXIOBASE as earlier, with scope 1+2 derived using the direct requirements table and scope 1+2+3 emissions derived from the Leontief inverse matrix in the usual way.

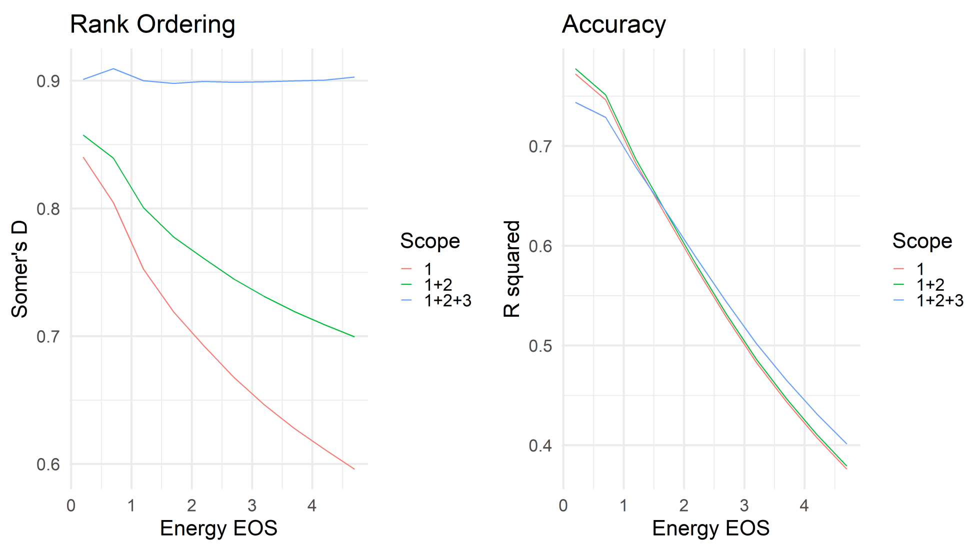

Figure 10: Accuracy/rank-ordering when regressing emissions-based measures on real value-added percentage change from model.

Accuracy and rank-ordering measures from the regressions are shown in figure 10 as they vary significantly based on assumptions regarding energy EOS. Accuracy tends to be relatively low except when high energy complementarity is assumed. This is because low energy EOS would dampen nonlinear dynamics from intermediate good substitution. The same holds for the rank-ordering ability of scope 1 and scope 1+2 as this is highly dependent on *both* downstream and upstream dynamics. For example, the coal mining sector is shown to have some of the highest transition risks of any sector, corresponding to intuition, but features only moderate scope 1 and scope 1+2 emissions. Indeed, its transition risk profile is primarily due to exposure to its high transition-risk customer, fossil fuel electricity. This exposure scales with the transition risk of its downstream customer, which in turn is proportional to energy EOS.

On the other hand, scope 1+2+3 emissions, while still relatively poor in accuracy under most EOS assumptions, is consistently high-performing in terms of rank ordering performance. This means that sectors with higher scope 1+2+3 emissions are consistently predicted to have higher transition risk in the model under any EOS assumption. This has implications for ESG ratings as it has been shown that many investors concentrate on rankings rather than levels, see Rzeźnik et al. (2021). However, it still falls significantly short as a measure for accurate linear prediction due to strong nonlinear dynamics - for visualization, see figure 17. In addition, it cannot predict to any degree the *upside* of transition risk, such as increases in the renewable energy and linked sectors.

4.2 Green Subsidy

We now analyze a "comparable" green subsidy to the modest carbon tax above. Mechanically, I set it proportional to sales in the renewable electricity sector and finance it through a lump-sum tax from consumers. First, I find the level of green subsidy that would cause the fossil fuel electricity sector to shrink by the same amount as the \$25/ton CO_2 tax studied earlier. As this model does not include components related to long-term dynamics such as investment and technological growth/R&D, a modest policy more likely to be implemented in the short to mid-term is the most appropriate to study, similar to the carbon tax discussed earlier.

In figure 11 it is apparent that even large subsidies to green have a relatively muted effect on fossil fuel electricity decline, even with high substitutability of energy inputs. Indeed, the real value-added percentage decline bottoms out at around 30% in this sector.[27] A subsidy of around 300% to

[27]The "bottoming-out" effect is due to the inelasticity of consumer demand. In robust-

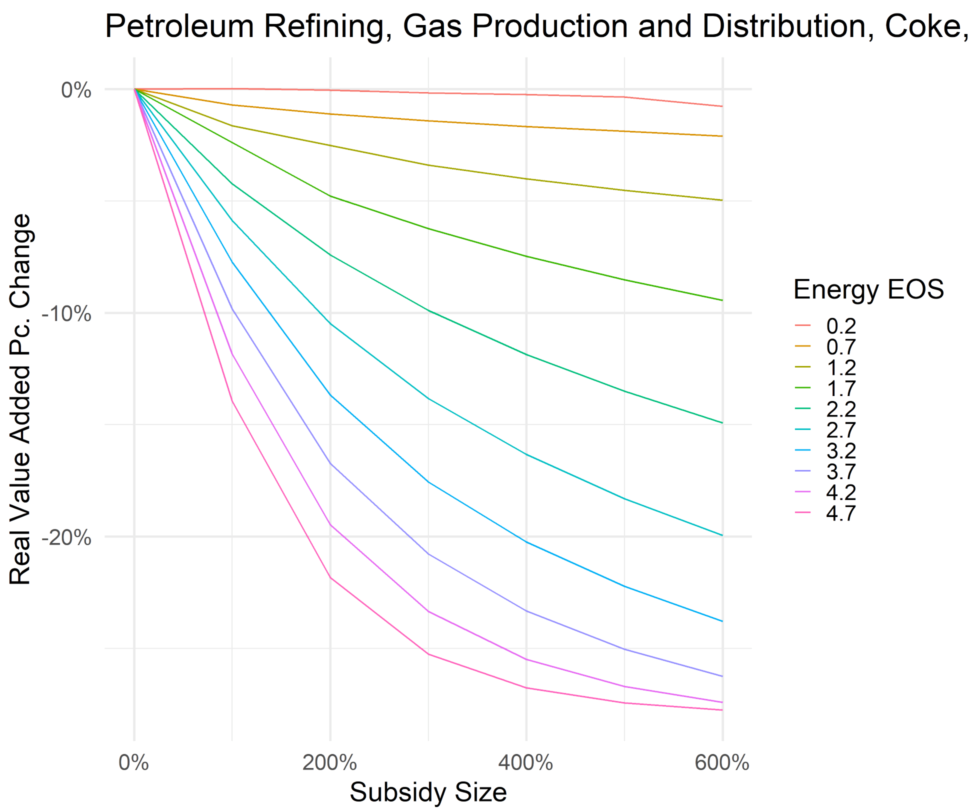

Figure 11: Sectoral real value-added percentage change by green subsidy size and energy EOS.

renewables causes a roughly similar decline as the \$25/ton CO_2 tax at high EOS in this sector, so I will focus on this level for a more detailed decomposition but results roughly scale. The full results are shown in figure **?**.

Again, results are highly dependent on energy EOS, with $120\% - 750\%$ increases in the renewable sector from the 300% subsidy. Indeed, this policy features mostly upside in terms of real value-added, with several green-linked

ness analysis similar to the one done for the carbon tax, when energy EOS on the demand side is adjusted at the same time as on the producer's side, green subsidies can cause a higher drop in real value-added for fossil fuel-linked industries. However, qualitatively, the results of this section hold and the carbon tax remains more effective per-dollar in causing this drop.

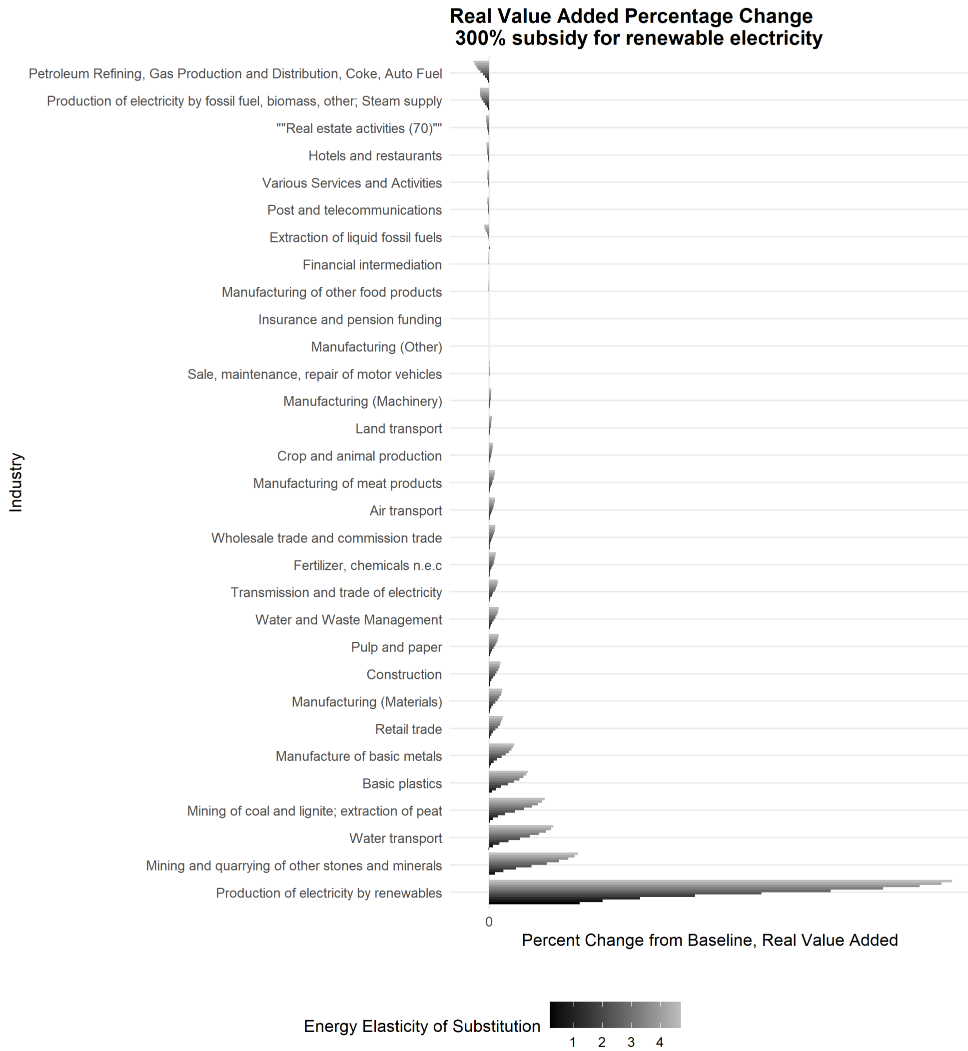

Figure 12: Percentage changes, varying energy EOS σ.

sectors increasing. This includes both upstream and downstream linkages, and sometimes both combined. Interestingly, when energy EOS is high, sectors downstream from petroleum such as *Air Transport* and *Water Transport* quickly switch to renewable electricity, which carries with it the potentially strong assumption that airplanes, ships, and vehicles can quickly electrify.

This may point to the usefulness of estimating custom elasticities of substitution at the fine sector level to capture these considerations. On the other hand, upstream sectors to renewable electricity also benefit, such as *Mining and quarrying of other stones and minerals*, which includes rare earth minerals essential for solar PV production and other materials necessary for clean energy power plants. Once again, this increase is highly contingent on energy EOS.

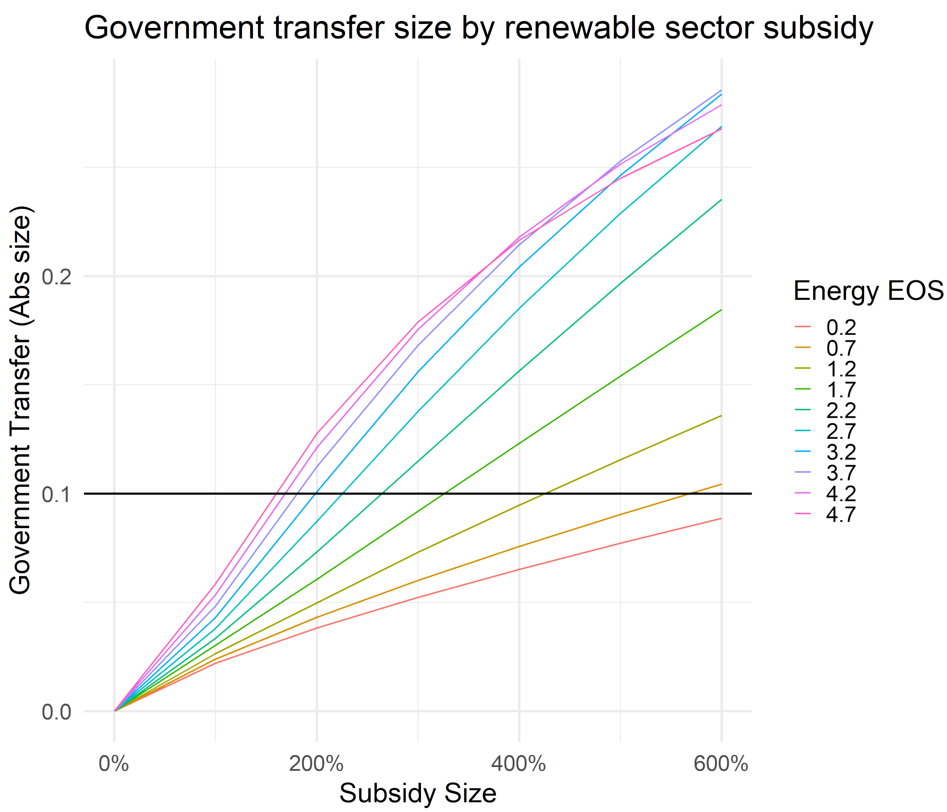

Figure 13: Absolute value of government transfer for green subsidy, varying energy EOS σ. Black line denotes $T_i = 0.1$, transfer for \$25/ton CO_2 tax under all EOS scenarios.

Clearly, this policy strongly boosts green energy-linked sectors and reduces the value-added of the high-emissions fossil fuel electricity sector by a similar degree to the \$25/ton CO_2 tax. However, one may ask whether it reduces this high-emissions sector as effectively on a per-dollar basis as the carbon tax. To do this, I compare the absolute value of government transfer T_i in the green subsidy vs. carbon tax case.

In figure 13, it is clear that government transfer sizes are generally *larger* in the subsidy case, with the \$25/ton CO_2 tax government transfer level denoted under the black line. The 300% subsidy transfer is around 70% higher in higher EOS cases where it is "equivalent" to the carbon tax. So, in a strictly budgetary sense, in this framework, the carbon tax is better at reducing value-added in the high EOS segments. This is perhaps unsurprising given the results in section 4.1.2 - despite the importance of indirect effects, direct effects still account for some portion of the comparative statics. Even in the higher energy EOS cases, there is not a 100% pass-through of the subsidy, thus leading to the dampened effect on the fossil fuel sectors. This provides macro-level evidence in line with empirical findings such as in Gugler et al. (2021), which supports the cost-effectiveness of carbon taxes over renewable subsidies.

However, it is important to keep in mind the caveats of these results. As mentioned earlier, this model is not designed to consider some critical factors that motivate clean energy subsidies, most notably R&D. Indeed, subsidies have been shown to be instrumental in spurring innovation and further maturing clean energy technologies. For example, solar photovoltaic energy costs have gone down by around 89% since 2010 - see Johnstone et al. (2010) and Gillingham et al. (2009) for a more detailed consideration of the topic. Hence, readers should interpret this result as most relevant for the short-to-mid term.

5 Conclusion

I study the effects of carbon taxes on the sectoral distribution of value in the economy, leveraging an empirically grounded dynamic model of input-output supply chain relationships. Crucially, this input-output structure contains the appropriate sectoral granularity to be able to meaningfully study the path of the green transition, with renewable electricity sources separated from fossil fuel sources. This allows me to explicitly model the primary path to net zero, the electrification of the economy to renewable sources, as well as study policies such as green subsidies, increasingly prominent in the US at both the federal and state/local level.

The results from this new sectoral classification enable me to pinpoint a key parameter upon which the transition hinges - the elasticity of substitution to green sources, most materially in the energy sector. As the literature identifying this parameter is still in the nascent stage, there is a large level of uncertainty as to the exact nature of the transition – whether it will be a rapid switch to renewables with a sharp rise in the renewable electricity-related sectors and a drop in fossil fuel-linked sectors, or a slower transition that features fewer sharp swings but an overall aggregate drop due to the failure to adjust.

This EOS parameter is closely tied to the concept known in popular parlance as the "green premium"- what the additional cost would be to switch over to green compared to the conventional source. An economy with higher green premiums across the board would likely be associated with more complementarity in its green vs. non-green intermediate and final goods.

It is important to keep in mind that the broad macro-based point of view taken in the paper would necessarily hide significant heterogeneity at a more granular level. For example, there is likely no "single" elasticity of energy substitution parameter, instead being highly context-dependent, especially in the case of renewable energy sources. Many areas have ample solar and wind resources and the appropriate infrastructure to transition to green quickly and cost-efficiently. In contrast, other locales may have significantly more difficulties or require investment in expensive infrastructure such as costly batteries or long-distance grid powerlines transporting renewable energy to where it is scarce. In addition, different green vs. non-green classes of goods likely have significantly different elasticities of substitution. For example, green substitutes for concrete are only in the early stages of research, while renewable electricity is a relatively mature technology. As such, identifying *elasticities* of substitution may be the most pertinent research task, as opposed to a single elasticity.

Several other caveats are worth mentioning. As the model is focused on the industrial sector as the unit of granularity, within-sector changes due to carbon tax imposition would not be examined here. For example, firms within an industry may take mitigating actions that would reduce emissions, even given the same mix of intermediate inputs through increased efficiency or changing production processes. This may soften the impact of the transition compared to what is calculated, but including this would require estimating a within-sector emissions response function that would respond in equilibrium to carbon taxes, which is not well-known in existing studies. This model is also necessarily more focused on short-term effects. This is because it does not include some features that would be important for long-term dynamics, such as intertemporal investment decisions and technological change, which has implications for the green subsidy analysis. In addition, there are likely other transition and climate-affected macroeconomic effects, such as would be captured in an Integrated Assessment Model, that are not considered here either.[28] In this sense, this model would not be a standalone "climate scenario analysis'" of the economy but would instead be a component of a larger framework. However, further research must be done to reconcile this model with higher and lower-level models within such a framework.

The production network approach taken in this paper exposes the oth-

[28]See Calvin et al. (2019) for an example of a prominent IAM.

erwise hidden magnitude of indirect effects, which in this paper comprise around $2/3 - 4/5$ of aggregate effects depending on the elasticity of substitution. This reinforces the results from other studies of carbon taxes in production networks, such as Devulder and Lisack (2020) and Campiglio et al. (2022), but with a novel "LOCO"-style approach in its calculation that differentiates the direct effect from a carbon tax on the single industry versus other, network effects. The work here suggests that climate scenario analyses that do not take the indirect effects of carbon taxes into account may not provide a good approximation to aggregate and sector-specific transition risk. We show that scope 3 emissions provides a relatively high rank-ordering of transition risk for downside risk (but not upside benefit), but misses in important regards with regards to accuracy when linearly projecting emissions to economic factors due to the nonlinear dynamics uncovered by this model. This is especially true when elasticities of substitution are high, providing conditions when reduced-form climate scenario analyses would best approximate a fully specified model.

While this paper takes a macro approach, the insights on the outsize importance of supply chain effects carry over to the firm level. Indeed, the results have direct implications for measuring commercial transition risk, but it is important to be aware of the potentially significant heterogeneity among firms. While sector-level considerations are perhaps the most significant margin along which firms vary, they may also be in significantly different stages of the transition compared to their peers. They may have fewer "stranded assets" and more adoption of green substitutes in their supply chains. This could be influenced by their regulatory environment, corporate governance, investor pressure, and other factors, such as, for example, a different ease of substitutability to green intermediates in their individual supply chains. In any case, another important task for future researchers would be to identify this parameter not only at the broad macro-level, but at a sector, geography, or even individual firm level.

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A Varying Energy EOS in Consumption

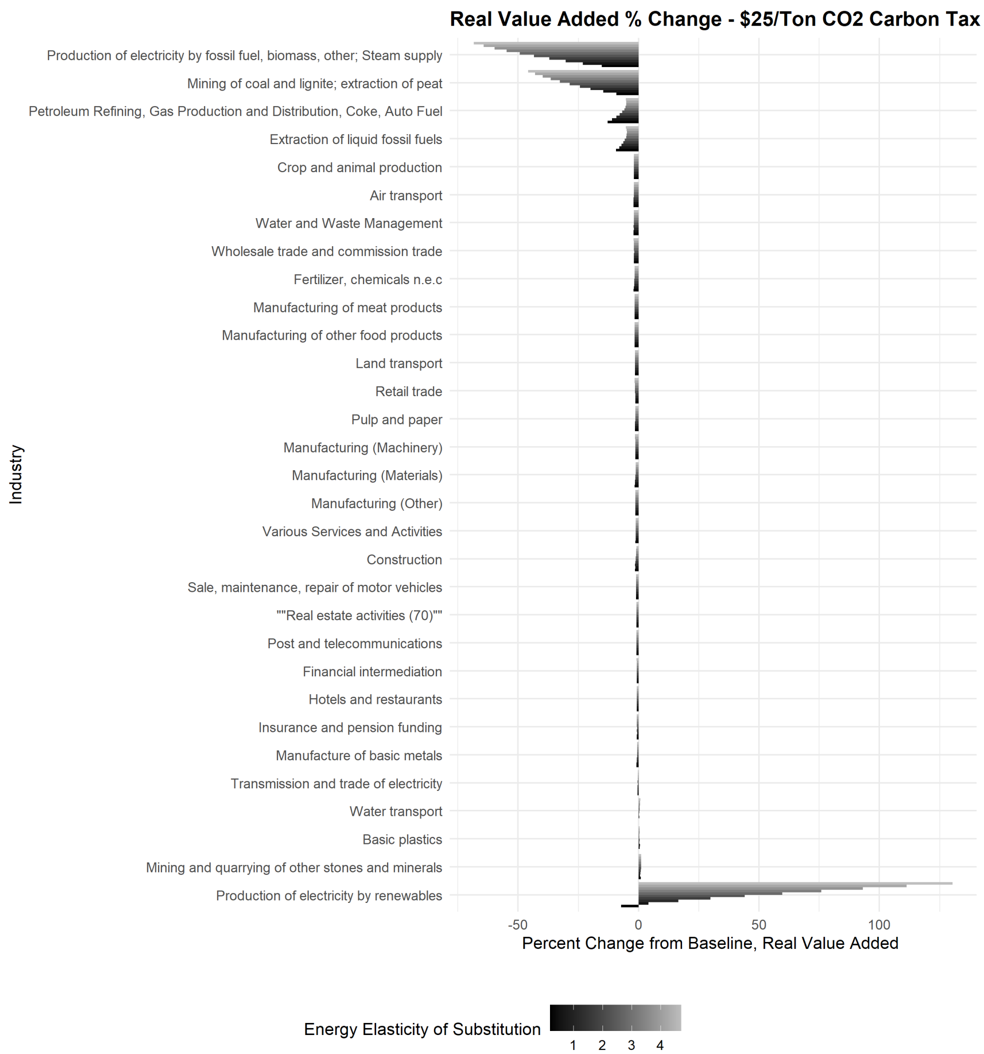

Figure 14: Percentage changes, varying energy EOS σ in both production and consumption.

B Additional Figures and Tables

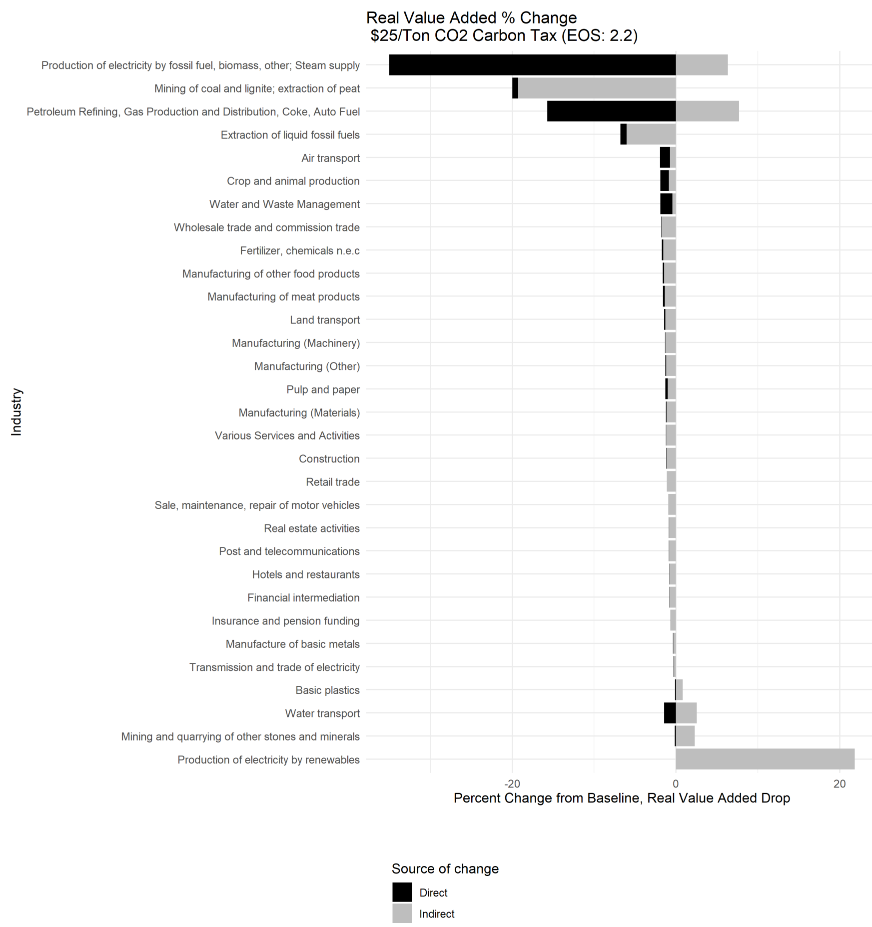

Figure 15: Percentage changes.

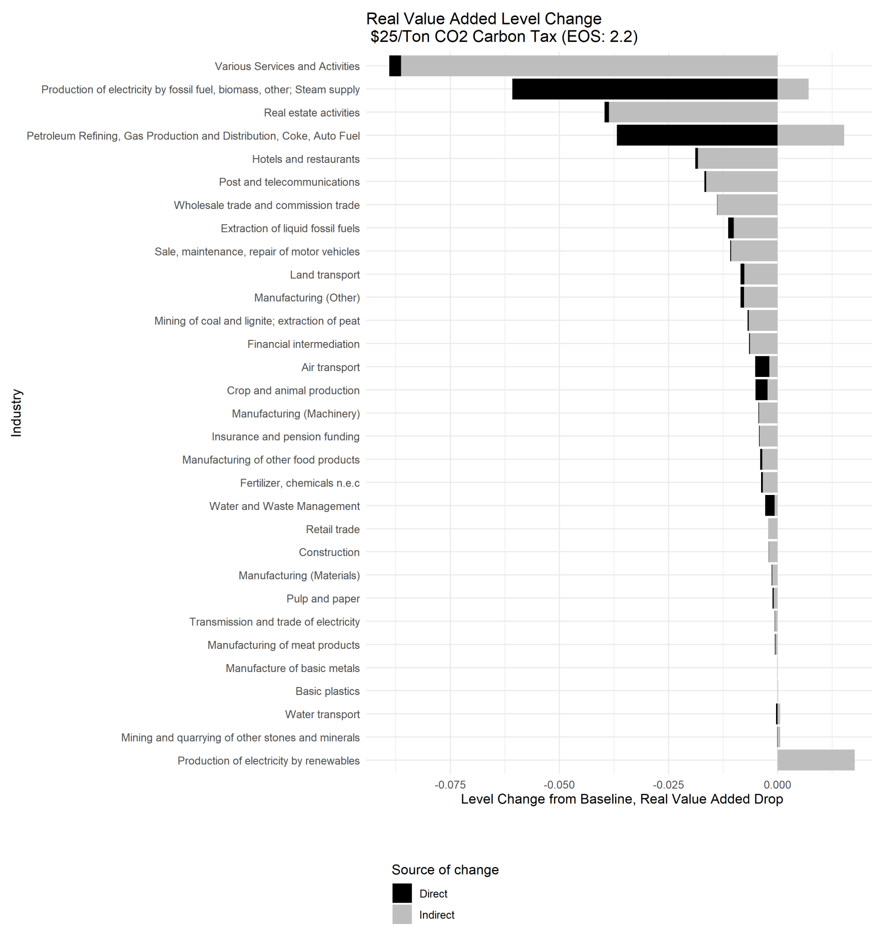

Figure 16: Absolute changes.

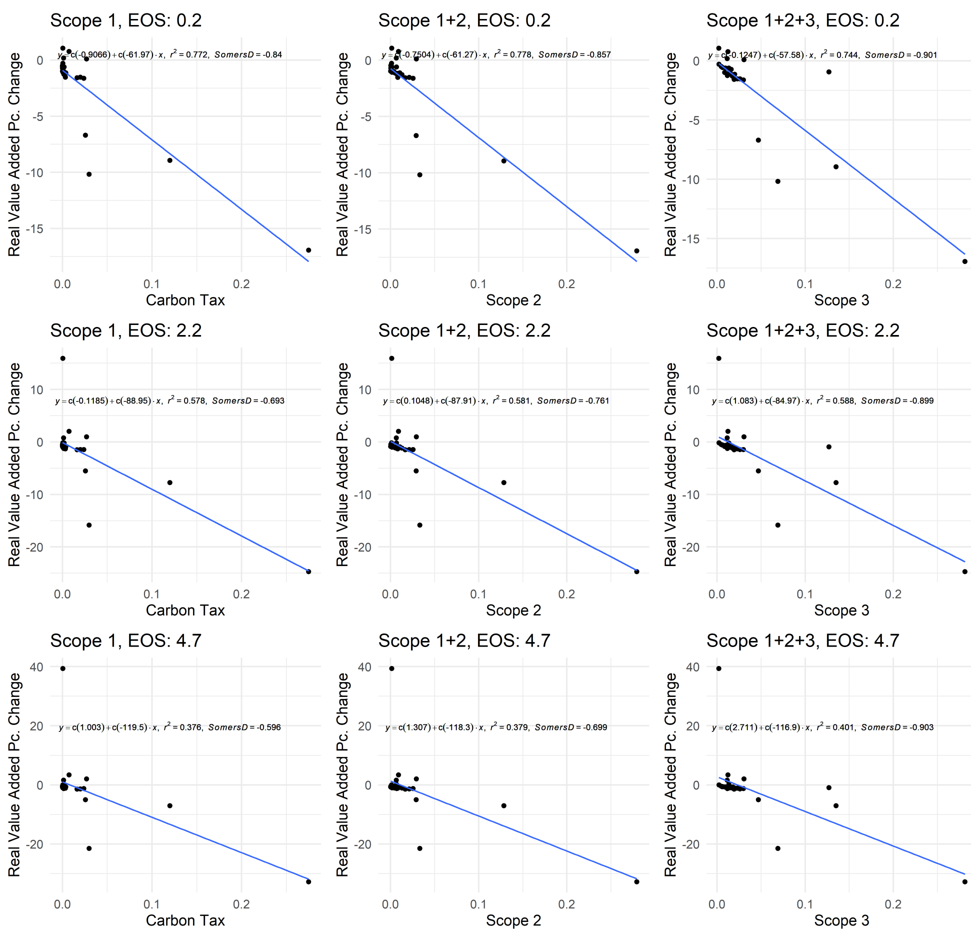

Figure 17: Accuracy/rank-ordering when regressing emissions-based measures on real value-added percentage change from model.