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Measuring Climate Transition Risk at the Regional Level with an Application to Community Banks[1]

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Abstract

We develop a measure of climate transition risk for regional economies in the U.S., based on the mix of firms that produce emissions in each region. To quantify transition risks, we consider the introduction of an emissions tax levied on companies emitting greenhouse gases and estimate changes in the market values of industries due to a carbon tax using Merton's (1974) model. We find that transition risks are highly concentrated in a few sectors and counties with heavy exposures to transition-sensitive sectors. The size and geographic concentration of the tax effects depend significantly on assumptions about the elasticity of demand for inputs in the production chain. When applying county-level estimates for transition risks to banks' deposit footprint, we find mild to moderate transition risks for community banks as a whole, although transition risks are high for a few banks.

Keywords: Greenhouse Gas Emissions, Transition Risk, Carbon Taxes, Regional Transition Risks, Bank Exposure

JEL Codes: R11, R15, Q21, Q51, Q54, C53

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I. Introduction

Many central banks around the world, including the Federal Reserve System, have initiated efforts to evaluate climate change risks to the economy and the financial system, in particular, the risks to banks. Most of the literature has adopted the same basic typology of climate risks: (i) the *physical risks* associated with an erosion of collateral and asset values of financial institutions due to extreme weather events; (ii) the *transition risks* associated with a reassessment of asset values due to changes in mitigation policies, technologies, and public sentiment. In this paper, we focus on the impact of transition risk. In particular, we introduce a quantitative approach to assess the transition risks of climate change (henceforth, "transition risks") for firms and regional economies then evaluate how these regional effects might impact small banks in the United States.[2]

We view our main contribution as providing a measure of regional transition risk in a production network setting. We model the effects of a permanent emissions tax levied on companies emitting greenhouse gases and link this measure of transition risk to small bank portfolios in the United States.[3] This approach is consistent with other researchers who also adopt the implementation of carbon taxation in the climate stress testing literature (e.g., Allen et al., 2020, Grippa and Mann, 2020, Reinders et al., forthcoming, Vermeulen et al., 2021). While we use an emissions tax as an example of government policies that could be implemented as a response to climate change, this approach can be applied to study other carbon mitigation policies that increase firms' costs of production in proportion to their emissions. Furthermore, our input-output methodology could be used to examine other sources of transition risk, for example, changing demand or technological changes.

We consider two carbon tax rates: $40 and $100 per metric ton of greenhouse gas emissions measured in carbon dioxide equivalent (CO_2 equivalent) units. Our choice of a $40 tax rate is based on recent carbon tax proposals, from which we take a midpoint across tax rates.[4] The $100 tax rate addresses the possibility of a more aggressive climate policy, driven by a major shift in

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[2] Our approach draws heavily on Reinders et al. (forthcoming), who conduct a transition risk stress test for large Dutch banks.

[3] We use the terms "carbon tax" and "emissions tax" interchangeably.

[4] See "What You Need to Know About a Federal Carbon Tax in the United States" by the School of International and Public Affairs at Columbia University.

policymakers' concerns about climate change. Our rates are broadly in line with the climate stress testing literature and the broader literature analyzing transition risk and its effect on the economy.[5]

The level of emissions is a key input for our measure of transition risks as they capture the exposure of firm profits and firm value to the carbon tax. We measure both *direct* and *embodied* emissions. Direct emissions refer to those emissions produced through a firm's production activities. Embodied emissions take account of the production structure of the economy. Consider an economy with two sectors, A and B. Sector A produces one-third of its goods for consumers, and two-thirds of its goods are used as inputs by sector B. Sector B produces all its goods for consumers. Assume sector A's direct emissions are 100 tons CO_2 equivalent and sector B's direct emissions are 100 tons CO_2 equivalent. Sector A's embodied emissions are 33 1/3 tons, while B's embodied emissions are 100 + 66 2/3 tons.[6]

While both measures of emissions may be of interest for several reasons, in our current exercise we use them to examine two polar assumptions about the incidence of the tax. Assume that the carbon tax is levied on the emissions at the point of production, and final goods producers face perfectly elastic demand from consumers.[7] In one polar case, the *no-pass-through* case, we assume that input demand is perfectly elastic, so the profits of the final goods producers fall one-for-one with the tax. In this case, there are no price effects along the production chain and the effect of the tax can be measured using direct emissions alone. In contrast, if we assume that input demand is perfectly inelastic, the *full-pass-through* case, we must take account of the price effects of the tax on each firm's inputs. For this exercise, we need to take account of the emissions embodied in these inputs. We discuss these polar cases below, but to avoid confusion: The two polar cases do not refer to different types of taxes. In both cases, we assume that firms are taxed on the emissions they generate in production; the polar cases reflect different assumptions about the incidence of the tax, driven by different assumptions about the input elasticity of demand.

[5] See, for example, Jung, Engle, and Berner (2023) and Conte, Desmet, and Rossi-Hansberg (2022).

[6] How do these measures of emissions compare to the measures in the Greenhouse Gas Initiative? Direct emissions are identical to Scope 1 emissions. However, embodied emissions do not involve the double counting of emissions that are included in the Scope 2 and Scope 3 measures. As our simple example illustrates (further, see Appendix A-3), in a closed economy, aggregate direct emissions equal aggregate embodied emissions, although the sectoral distributions will typically differ. See Section III.1 for a more formal derivation of the relationship between direct and embodied emissions.

[7] We do not make an attempt to model the elasticity of final demand. We discuss demand effects below.

Using data from EXIOBASE, we estimate direct and embodied emissions of industries at the 6-digit NAICS level and aggregate to the three-digit level. EXIOBASE is a publicly available, global input-output table, which has been extended to include data on greenhouse gas emissions. Like other researchers, we find that emissions are highly concentrated in a few sectors, notably Utilities, with the top-10 sectors contributing industries emitting 83 percent of direct emissions. When considering embodied emissions, we find that the sectoral concentration of emissions is still significant, but it declines considerably.

We then estimate the impact of the carbon taxes on firm values using Merton's (1974) model. Using measures of firm leverage and stock price volatility, we calculate the share of potential market value losses of firms relative to their asset value based on their industry-level carbon intensity. We aggregate these market value losses to the three-digit NAICS level and find that potential impacts are highly concentrated in a few industries with high emissions intensity. But the impact quickly drops as we move to industries with lower emission intensity. In the full-pass-through case, we find that the potential losses are less concentrated in just a few industries and significant tax effects occur for a broader range of industries.

With the industry-level losses at hand, we construct a measure of potential impacts at the regional level; in the current exercise, we take the county as the relevant regional unit. We calculate county-level losses as averages of losses across industries, weighted by county-level employment shares from the Quarterly Census of Employment and Wages (QCEW). In the no-pass-through case, potential county-level impacts are generally mild under a $40 carbon tax, yet they are sizable for a few geographic regions under a $100 carbon tax. Similar to our findings at the industry level, in the full-pass-through case, potential impacts are more widespread across counties. At the county level, agriculture and gas stations are major sources of emissions and county transition risk.

Our measure of the geographic exposure to a carbon tax is the focus of this exercise, but we also use this measure to take a preliminary step toward measuring transition risk for community banks. To do so, we use banks' deposit footprint together with the county-level impact due to the carbon tax. In this exercise, we take the view that shocks to the industries operating in a bank's market will affect all parts of the bank's loan portfolio.[8] In the no-pass-through case, we find a mild to

[8] We discuss this modelling choice in some detail when we present our results.

moderate degree of transition risks for community banks as a whole, while the impact is still concentrated at a small number of community banks. In the full-pass-through case, we find that the impact is more widespread across banks but still relatively small.

The rest of the paper proceeds as follows. In Section II, we discuss other estimates of the effects of transition risk change on banks. In Section III, we discuss our data and methodology for estimating emissions at the firm level and for estimating the effects of the carbon tax at the sectoral level. In Section IV, we construct our estimates of the transition risks at the regional level, which we then use to produce an estimate of the risks to community banks in Section V. We conclude in Section VI.

II. Literature Review

There is a growing literature on the effects of climate change on financial markets and institutions.[9] Here we focus on exercises that estimate the effect of climate transition risks for financial institutions, most of which have been carried out by economists working at central banks. Like most of the exercises, we model the source of transition risk as a scenario for increasing emissions taxes.[10] All of the preceding exercises have focused on large banks, most of them using European data.[11] Our focus on small U.S. banks' exposure to climate transition risk is unique in the literature. We discuss the challenges and limitations of this exercise in some detail below.

Similar to ACPR (2021) and Vermeulen et al. (2021), we derive our industry emissions estimates in an input-output setting.[12] This approach has several advantages. First, constructing estimates using an explicit production network permits the researcher to measure embodied emissions as well as direct emissions. In turn, we can take account of price effects of the emissions tax along

[9] Giglio et al. (2021) provide an excellent review of the literature on how climate change affects financial markets. See also Dennis (2022) for a recent survey of the literature on climate change and financial policy.
[10] We do not embed our estimates in an explicit macroeconomic model as in ACPR (2021) or Roncoroni et al. (2021).
[11] For example, see Battiston et al. (2017), Vermeulen et al. (2021), Grippa and Mann (2020), Reinders et al. (forthcoming), and Roncoroni et al. (2021). Jung, Engle, and Berner (2023) study large global banks in the U.S., the UK, Canada, Japan, and France. Arsenau et al. (2022) and Jung, Santos, and Seltzer (2023) examine large U.S. banks.
[12] In contemporaneous work, Krivorotov (2022) also estimates industry emissions in a production network, using elasticities from Atalay (2017). He doesn't address the regional incidence or the effects on banks.

the production chain in our full-pass-through case. The production network literature suggests that the input elasticity of substitution may be quite low (e.g., Atalay, 2017), so these price effects may be quantitatively important. ACPR (2021) explicitly models the elasticity of substitution using a CES production function, while we retain a Leontief production structure, which limits us to polar assumptions about tax incidence.[13] A second advantage of an explicit input-output structure is the flexibility to model different types of transition risks in addition to the effects of an emissions tax. For example, Vermeulen et al. (2021) consider the effects of technological adjustments to reduce emissions. Although we limit attention to the effects of an emissions tax in the current exercise, our methodology could be easily adapted to consider other types of transition risk.

Recently, Jung, Santos, and Seltzer (2023) investigate how transition risk affects large U.S. banks using alternative policies and scenarios (as generated by the models in Jorgenson et al. (2018), Goulder and Hafstead (2017), and the Network for Greening the Financial System (NGFS) (2022).[14] Industry losses are linked to bank losses via the industry composition of their C&I loan portfolio.[15] Along a similar line, a recent ongoing effort by the Federal Reserve (2023), the "Pilot Climate Scenario Analysis Exercise," intends to evaluate climate-related financial risks for the largest banking organizations.[16] The transition risk module will use the NGFS's current policy and Net Zero 2050 scenario and will evaluate their impact on the corporate and commercial real estate portfolio. Unlike these climate stress tests, we focus on the regional impact of carbon taxes, taking account of the sectoral linkages through the input-output production structure. While we do not explicitly calculate portfolio losses, we develop a measure of the risks to small banks operating in a region. Small banks are on average not very well geographically diversified, so the impact of transition risk will derive mostly from the impact of carbon taxes on the region where they operate.

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[13] But see Appendix A5 for a sensitivity test comparing our Leontief estimates to estimates from a production network similar to ACPR (2021).

[14] Jorgenson et al. (2018) report industry-level estimates of output effects from different carbon taxes computed off their Intertemporal General Equilibrium Model (IGEM). Goulder and Hafstead (2017), in turn, report industry-level estimates of profits effects from carbon taxes generated from their Environment-Energy-Economy (E3) model. NGFS (2022) estimates industry-level effects using the G-Cubed model for the U.S. from the three alternative climate scenarios adopted by NGFS.

[15] In a related article, Jung, Engle, and Berner (2023) take a market-based approach to measuring banks' exposure to transition risk capturing both market risk and credit risk channels and find that transition risk does not seem to pose a threat to the U.S. financial system.

[16] Six U.S. bank holding companies will participate: Bank of America, Citigroup, The Goldman Sachs Group, JP Morgan Chase & Co, Morgan Stanley, and Wells Fargo. Results will become available sometime before the end of 2023.

III. Assessing Transition Risks at the Industry Level

In this section, we quantify the transition risks of industries due to the implementation of a carbon tax. Our approach draws heavily on Reinders et al. (forthcoming).[17]

III.1 Direct and Embodied Emissions Estimates

We obtain emissions data from EXIOBASE, a publicly available, global, environmentally extended input-output table, which has been extended to include data on greenhouse gas emissions (GHG emissions).[18] It reports data for 44 countries (the U.S. is represented individually) and five rest-of-the-world regions, with a significant level of sectoral detail: 200 products and 163 industries. We collect 2019 data from the latest available version released in October 2021. EXIOBASE provides comprehensive up-to-date coverage of the global economy by providing data on input-output (I-O) transactions, labor inputs, energy supply and use, GHG emissions, material extraction, and land and water use as well as emissions to air, water, and soil.

EXIOBASE provides estimates of GHG emissions for each product defined by NACE code.[19] The estimates of emissions are provided for several greenhouse gases, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_20). For each product, we use the reported total measured in CO_2 equivalents, using a Global Warming Potential (GWP) of 100 years.[20]

When estimating industry-level emissions, we differentiate direct emissions and embodied emissions. A firm's direct emissions include only emissions generated in the production of a product; EXIOBASE reports direct emissions at the product level. For example, a steel manufacturer's direct emissions include only those generated in the production of steel, but do not take account of the emissions generated in the production of the firm's inputs, for example, iron ore, coal, and electricity used in steel production.

[17] Our implementation of the financial model is somewhat different from Reinder et al.'s (forthcoming). A more significant difference is that we use our estimates of transition risk for industrial sectors to develop a measure of transition risk for regions. For a geographically expansive country like the U.S., effects will vary across regions.
[18] Stadler et al. (2021) DOI 10.5281/zenodo.3583070. See the Appendix for a comprehensive description of EXIOBASE and emissions data.
[19] NACE is the classification of economic activities in the European Union. See details from the glossary provided by Eurostat.
[20] For example, Methane (CH_4) is estimated to have a GWP of 27 to 30 over 100 years. Nitrous oxide (N_2O) has a GWP 273 times that of CO_2 for a 100- year scale.

We use the EXIOBASE input-output table and its direct emissions estimates to calculate embodied emissions. Embodied emissions include both direct emissions in producing goods for final demand and the emissions that were generated in the production of the firm's inputs. In the steel production example, embodied emissions also include emissions generated by the mining sector in the production of iron and coal as well as emissions generated by the utilities in the production of electricity.[21] We calculate embodied emissions as follows. Let y denote the vector of final demand by product, f the vector of direct emissions, x the vector of output, A the input-output table, and $\mathrm{m}' = \mathrm{f}'\hat{\mathrm{x}}^{-1}(I - A)^{-1}$, where $\hat{x}^{-1}$is a diagonal matrix with the elements of the vector x^{-1} in the main diagonal and zeros everywhere else. Then, we can show that the vector of embodied emissions in final demand is $e_y = \widehat{m}y$. In Appendix A-3.2, we document how we use the input-output matrix and the direct emissions estimates from EXIOBASE to compute embodied emissions.[22]

Once we have our estimates of direct and embodied emissions at the product level, we use a concordance file provided by EXIOBASE to map emissions assigned under NACE products to industries defined by 2017 North American Industry Classification System (NAICS) codes.[23] To minimize potential biases, we allocate emissions according to employment shares at the 6-digit industry level from the U.S. Bureau of Labor Statistics (BLS) associated with each product[24,25] Then we aggregate emissions up to the three-digit industry level, which helps to maintain consistency of

[21] In a closed economy, direct and embodied emissions must be equal in aggregate. As we show below, they may differ quite significantly at the sector level.

[22] Direct emissions are identical to Scope 1 emissions following the Greenhouse Gas Protocol. Similar to Scope 2 and Scope 3 emissions, embodied emissions capture linkages along the production chain. However, as opposed to embodied emissions, the measurement of Scope 2 and Scope 3 emissions could result in double counting as they incorporate emissions of activities along the entire value chain.

[23] For each of the 200 EXIOBASE products, there is a list of corresponding 6-digit 2017 NAICS codes. Most of the environmental data in EXIOBASE derives from the International Energy Agency (IEA). The IEA energy balances are structured in matrices representing 63 energy products and 85 energy flows. These matrices show the supply and use of energy by different activities for each country.

[24] See Appendix A-3.3 for details.

[25] A drawback of using employment shares for this purpose (for EXIOBASE industries that map into more than one NAICS industry) is the possibility of underestimating emissions for a capital-intensive sub-industry with a low employment share. For example, the EXIOBASE product "Natural Gas Liquids" maps into NAICS codes 211 (Oil and gas extraction), and 213 (Support activities for mining). The BLS employment data results in 29.3 percent of emissions from "Natural Gas Liquids" allocated to NAICS 211 and the rest to NAICS 213. According to the BLS, in 2019, NAICS 211 is more capital intensive than NAICS 213 as their capital share equals 0.421 and 0.277, respectively. Data on capital levels by industry at a fine level of aggregation is not available but the evidence on capital shares suggests that using the distribution of capital could have resulted in a larger share of emissions from "Natural Gas Liquids" being allocated to NAICS 211 than the one that results from the employment distribution.

our emissions estimates with the financial and employment data we use below.[26] As a check on our methodology, we compare the distribution of our estimates for direct emissions to that of emissions reported by the U.S. Environmental Protection Agency (EPA), confirming that our estimates are broadly consistent with the reported emissions.[27]

It is important to note that aggregation of emissions at the three-digit level blurs some important differences between sub-industries within the same three-digit industry. For example, power plants are the largest source of greenhouse gas emissions in the United States.[28] At the three-digit level, emissions from power plants fall under Utilities (NAICS=221), which is a broad industry classification comprised of Electric Power Generation, Transmission and Distribution (NAICS=2211), Natural Gas Distribution (NAICS=2212), and Water, Sewage and Other Systems (NAICS=2213). Clearly, those sub-industries exhibit different emissions intensity (i.e., emissions relative to their outputs) and emit different levels of emissions. More importantly, we notice that the aggregation of emissions, even at the 5-digit level, can misrepresent the highly concentrated nature of emissions. In an extreme example, Electric Power Generation (NAICS=22111) includes both fossil fuel–based electric power plants (NAICS=221112) and other 6-digit sub-industries including Solar (NAICS=221114) and Wind Electric Power Generation (NAICS=221115), which generate essentially zero emissions.[29,30]

Table 1 lists the top-10 industries with the highest emissions from EXIOBASE, both in terms of direct and embodied emissions. Overall, our emissions estimates are sensible and broadly

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[26] Even at the 4-digit level, there are many industries that have missing data in Compustat, which we use to estimate the financial effect of the tax. In addition, the coverage of the reported county by industry employment (i.e., coverage in terms of the reported aggregate private-sector employment) drops sizably as we consider more disaggregated employment data (see more details about this below). References to Compustat herein refer to Compustat data from S&P Global Market Intelligence (2019) via Wharton Research Data Services (WRDS).

[27] We discuss the merits of using data on emissions from EXIOBASE relative to that from the U.S. EPA in Appendix A-2.

[28] Power plants account for more than one-quarter of all domestic GHG emissions in the United States according to the U.S. EPA. In addition, power plants account for about 59 percent of 2019 GHG emissions from facilities subject to the Greenhouse Gas Reporting Program (only facilities emitting over 25,000 metric tons of CO_2 equivalent per year are required to report).

[29] According to U.S. Energy Information Administration, about 61 percent of electricity generation (utility-scale) was from fossil fuels—coal, natural gas, petroleum, and other gases—in 2021.

[30] Based on our estimates from EXIOBASE, fossil fuel–based electric power plants (NAICS=221112) account for 35 percent and 5 percent of direct and embodied emissions, respectively. Their emissions account for a large proportion of direct emissions aggregated at the 5-digit (38 percent) and 3-digit level (46 percent). In contrast, their embodied emissions account for a relatively small proportion of embodied emissions relative to the aggregates, 19 percent, and 22 percent, respectively, at the 5- and 3-digit level.

consistent with estimates by others. We find that emissions are quite concentrated, significantly more so for direct emissions. Utilities generate nearly half of all direct emissions and the largest-10 emitting sectors generate 82.4 percent of total direct emissions. Embodied emissions are also quite concentrated. Utilities generate 19.9 percent of all embodied emissions, and the largest 10 emitters generate 69.1 percent of total embodied emissions.

Direct and embodied emissions can be quite different for industries. Apart from Utilities, one of the largest discrepancies arises for Animal Production and Aquaculture, which has a large share of direct emissions and a much smaller share of embodied emissions. In contrast, Food Manufacturing has a much larger share of embodied emissions than direct. These differences suggest that the estimated effects of an emissions tax may be quite sensitive to tax incidence, as we verify below.

III.2. Assessing Transition Risks at the Sectoral Level

To estimate the effects of the emissions tax at the sectoral level, we use Bharath and Shumway's (2008) implementation of the Merton (1974) model to estimate the effect of a permanent emissions tax on the value of firms' assets. For our current exercise, we estimate the effects of both a \$40 and a \$100 per metric ton of CO_2 emissions tax at the 3-digit NAICS level. In principle, we could estimate the effects of the tax at a more disaggregated industry level. Our current choice reflects tradeoffs and data limitations that we discuss in more detail in Section IV.[31]

As in Reinders et al. (forthcoming), we assume an instantaneous shock ξ_k to asset values of industry k, such that immediately after the shock the asset value of the average firm in industry k adjusts from V_k to V_k^*. That is, the shock induces a change in asset values to V_k^* where V_k^* is

$$V_k^* = (1 - \xi_k)\, V_k.$$

[31] The analysis in this paper can be generalized to other countries, as long as the country has emissions data from EXIOBASE, and input-output matrix and financial data are available. Each country has a different emission mix, and the supply chain differences may affect the estimates of the industrial level losses. The U.S. banking industry is also less concentrated than most countries in the world. Hence, when taking the analysis to the regional level, regional disparities in exposure estimates may not be as large for other countries dominated by a few large banks (e.g. Australia and Canada). These large banks would have deposits spread out over most if not all geographical locations, making the county-industry level shocks less important at the bank level.

The parameter ξ_k corresponds to a fraction of the asset valuation that is lost due to the discounted flow of losses arising from the carbon tax. More specifically, we let the net present value of carbon taxes in industry k be

$$NPV_{tax,k} \; = \; \sum_{t=0}^{T}(1-r_k)^{-t}\gamma_k\tau_t,$$

where γ_k captures the exposure of industry k to the carbon tax τ_t in period t, and r_k is the discount rate in industry k. This equation shows that our estimate of climate transition risk at the firm level—the decline in firm value associated with the emissions tax—is the present value of the firm's emissions tax payments discounted at the firm's cost of capital.[32] To estimate the industry-level shock, we average over all firms within a 3-digit industry. In our application, γ_k is calibrated using the level of emissions (in metric tons of CO_2 equivalent). That is, the exposure of an industry to the carbon tax (i.e., the tax base) is directly represented by its emission level.

We estimate current asset values using the Merton (1974) model and use the net present value of carbon taxes to estimate the fraction of the asset value of the firm that is lost due to carbon taxes as follows:

$$\xi_k \; = \; \frac{NPV_{tax,k}}{V_k}.$$

The estimate of ξ_k together with the estimates from the Merton model allows us to derive the losses in the market value of debt and equity for the average firm in industry k from which we compute the (leverage-weighted) average estimates of climate transition risk losses at the industry level denoted by λ_k.[33]

Our calibration of the Merton model follows Bharath and Shumway (2008). We work at the three-digit NAICS code level of aggregation.[34] We require estimates of the volatility of a firm's equity,

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[32] The methodology is flexible enough to permit adjustments by firms, for example, a shift away from fossil fuel use, although we do not consider adjustments in the current exercise. For example, Reinders et al. (forthcoming) make some preliminary estimates of the effects of technological adjustments to emissions taxes. They model these by adjusting the speed at which the tax is implemented and by making assumptions about technological change at the sectoral level. We do not consider changes to demand, technology, or general equilibrium effects (i.e., changes in r_k) that can have a multiplicative effect on losses for some industries, but those can be incorporated by analyzing changes to parameters in this equation.

[33] See Appendix A-4 for more details on the estimation of industry-level losses.

[34] Expanding to four or more digits reduces the sample size significantly or requires us to make assumptions about a large number of missing industries. Even at three digits, we face some data limitations, so when there are no data

the firm's market leverage ratio, the firm's cost of capital, and the risk-free rate. We calculate equity volatility using stock prices from CRSP from 2007 to 2019, a period that includes the stock price volatility of the global financial crisis.[35] We require that a firm has at least nine years of data and measure volatility by the annualized percent standard deviation of daily stock returns. A firm's market leverage ratio is measured using the market value of the firm's equity at the end of 2019 from CRSP and the face value of the firm's debt in 2019 from Compustat. Following Bharath and Shumway (2008), we measure the face value of the firm's debt by the value of its short-term debt plus one-half of the value of its long-term debt. The risk-free rate is computed using the average of the 1-year Treasury yield from 2007 to 2019.[36]

To derive the net present value of carbon taxes, we use our estimates of emissions discussed in the previous section. EXIOBASE emissions are reported at the product level, which we aggregate to the sector level. Note, when we aggregate emissions to the sector level, we are including both publicly traded and private firms. Thus, our subsequent estimates using data on public firms implicitly assume that private and public firms are identical. To calculate the present value of emissions tax payments, we use a 6 percent cost of capital and assume that public firms' share of sectors' emissions is proportional to public firms' share of those sectors' revenues. Firms' revenues are taken from Compustat, and the total sector revenues are from EXIOBASE. We provide estimates for two values of carbon taxes: \$40 and \$100 per ton of CO_2 equivalent. We note that there is evidence that small firms are less energy efficient than large firms (e.g., Bartram et al., 2022) and that private firms face a more significant transition shock from an emissions tax than public firms (Bartram et al., 2022, and Ivanov, 2024). Since our emissions estimates for an industrial sector include emissions by both public and private firms, this suggests that we have *overestimated* emissions intensities for our sample of public firms.[37]

available at this industry level, we use estimates from one level higher of aggregation. For example, there are no reporting firms for NAICS 55 (Management of Companies and Enterprises). To estimate the needed parameters for this industry, we take the average of equity volatility from industries with NAICS codes 51, 52, 53, 54, and 56.

[35] References to CRSP herein refer to data from CRSP US Stock Database (2019) from the Center for Research in Security Prices, LLC (CRSP) via WRDS.

[36] Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis [DGS1], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS1

[37] There is also bias in the opposite direction. Private firms are more volatile than public firms, so the true decline in asset value in response to an identical emissions tax will be larger than the decline measured for our sample of public firms. In practice, the size of a sector's emissions is the more important determinant of the effect of the tax.

We consider two polar assumptions concerning the incidence of the tax for estimating shocks to assets values. In both cases, we assume perfectly elastic final demand for all products, so consumers do not pay higher prices due to the emissions tax.[38] The first case, the *no-pass-through* case, assumes that input demand is perfectly elastic, so the tax does not lead to price effects along the production chain and it reduces each final goods producer's expected profits in proportion to its direct emissions. The second case, the *full-pass-through* case, assumes that input demand is perfectly inelastic, so the tax leads to a one-for-one price increase for all inputs in proportion to the input producer's emissions. In this case, each firm bears the tax not only on its direct emissions, but also on the emissions embodied in its inputs via the increase in input prices.

It is important to note that these two cases do not reflect different types of taxes. Both cases capture the effect of a tax on firms' direct emissions. The different effects on firms' expected profits depend solely upon our assumptions about input demand elasticities and, thus, the incidence of the tax. Our intention in considering these two polar cases is to make a preliminary attempt to gauge the importance of different assumptions about tax incidence on the sectoral and geographic effects of the emissions tax. While our exercise highlights the importance of the role of demand elasticities, further progress will require a more realistic description of the relevant elasticities.[39] [40]

Tables 2 and 3 present the estimated market value losses for the top-10 industries (when sorted by asset value losses) for the no-pass-through cases and full-pass-through cases, respectively. Table 2 shows that a carbon tax of $40 leads to nontrivial value losses for the most exposed industries, such as Air Transportation, Utilities, and Nonmetallic Mineral Product Manufacturing. These top-3 most exposed industries lost over 20 percent of their market value according to our estimates. If a higher carbon tax of $100 is implemented, then the losses are significantly larger. However, the

[38] Less elastic consumer demand would reduce the effects of the tax on firm profits and, thus, asset values, because consumer would bear some of the tax through higher prices.

[39] A recent literature has developed general equilibrium models with a particular attention to sectoral heterogeneity and understanding how shocks propagate through production chains while taking seriously sectoral elasticities of substitution of intermediate inputs. See, for example, Horvath (2000), Atalay (2017), or Baqaee and Farhi (2020). This approach is taken in Devulder and Lisack (2020), for the analysis of transition risk in France.

[40] In Appendix A5, we present a production network model with CES production functions and compare our results to two polar cases in terms of the elasticity of substitution of intermediate inputs. We relate the low elasticity case to the Full Pass-Through case and the high elasticity case to the No Pass-Through case. We find that our approach does a good job in capturing these two cases, as estimated losses are highly correlated. The appendix also discusses estimates for an intermediate value of the elasticity of demand. Results indicate that estimates scale (to an approximation) linearly with the value of the elasticity of substitution of intermediate inputs.

impact quickly drops as we move down to less exposed industries. For example, Oil and Gas Extraction is the 9th most exposed industry, and the market value loss is modest at 5.2 percent for a $40 carbon tax. Table 3 reports the results of a similar calculation taking account of price effects along the production chain. While the exact order of the most exposed industries changes, the main message remains the same: A carbon tax's impact is mostly concentrated in the few most exposed industries.

We do not present separate estimates of the changes in the value of equity and debt. We note that the effect of the carbon tax on the value of firms' debt alone is very small, as nearly all our measured effect is due to the fall in the value of equity.[41]

IV. Assessing the Transition Risks of Regional Economies

Our primary goal is to develop estimates of transition risk to regional economies. Although the precise mechanisms through which an emissions tax may affect the regional economy are complex, we take the simplifying view that the industrial mix of the firms operating in the region should be an important determinant of the regional effect of the tax. We expect that a negative shock to the expected profits of firms with operations in a region will lead to further effects, for example, a decline in employment or a decline in commercial real estate values. Although a full analysis of the regional effects of an emissions tax will take account of these mechanisms, in our preliminary analysis we construct a summary measure of the effect of the tax by the decline in the value of firms operating in the region. And because we will use this measure to get a sense of the risks to community banks, we carry out our analysis at the county level.

Let $emp_{k,c}$ be the number of employees for an industry k at a county c. To proxy for a county's exposure to each industry, we use the share of employment ($w_{k,c}$) calculated as $w_{k,c} = emp_{k,c}/\sum_j emp_{j,c}$. Then, we estimate county-level exposures to the emissions tax by combining a county's industrial exposure with our estimates for industry-level value losses. That is, denoting by Λ_k our estimate for the losses for an industry k, the transition risks for a county c (Λ_c) are a

[41] Our finding that the effects of an emissions tax on the value of firms' debt are relatively small is similar to the findings of Reinders et al. (forthcoming), as well as other researchers using different methodologies.

weighted average of industry-level losses, using the employment share of industries operating in each county as weights. Thus, for each county c, $\Lambda_c = \sum_k w_{k,c} \times \Lambda_k$.

While the QCEW provides disaggregated employment data up to the 6-digit NAICS code level, there are two reasons we use the three-digit NAICS code level. First, the coverage of reported industry employment drops sizably as we consider more disaggregated employment data. The total reported three-digit NAICS code-level employment over counties is about 120 million, which accounts for approximately 94 percent of the private-sector employment at the national level. This coverage reduces to 87 percent and 77 percent, respectively, as we move to the four- and 6-digit NAICS code level. Second, the coverage is particularly low for a few transition-sensitive industries. For example, electric utility sector produces more than half of greenhouse gas emissions, one of the most vulnerable sectors with respect to an emissions tax. But the electric utility sector exhibits relatively low coverage compared to other industries, since employment at utilities is relatively low and also because of nondisclosure policies associated with the QCEW data. Employment at electric utilities reported at the three-digit NAICS level for all counties accounts for 77 percent of the sector's national aggregate employment. At the four-digit level, the aggregate-reported employment at the sub-component industries falls to 31 percent of the sector's national aggregate employment.

Figures 1 and 2 display the geographic dispersion of our estimated losses for both the no-pass-through and full-pass-through cases. Each figure shows the results for a \$40 carbon tax (Panel A) and a \$100 carbon tax (Panel B). To complement these maps, Figure 3 provides the histograms of county-level impacts from carbon taxation in each case for a \$40 carbon tax (Panel A) and a \$100 carbon tax (Panel B). Our findings are twofold. First, we find that the potential impacts from the carbon tax are generally mild to moderate across counties in the no-pass-through case. For example, only 2 percent of counties—49 among 3,121 counties in our sample—experience larger than 2 percent market value losses under a \$40 carbon tax. The proportion of counties experiencing at least a 2 percent market value loss increases to 15 percent in the full-pass-through case under a \$100 carbon tax.

Second, in the full-pass-through case, we find broader geographical impacts. In the no-pass-through case, under a \$40 carbon tax, 30 percent of counties experience more than a 2 percent market value loss. About 91 percent of counties would experience larger than a 2 percent value loss under a \$100 carbon tax, and fully one-third of those counties would experience larger than a 5 percent loss.

Table 4 lists the 10 counties with the largest market value losses in the no-pass-through case. For each county, the fourth column reports its total private-sector employment. The next two columns report a county industries' market value losses due to a \$40 tax and a \$100 tax. The last column reports three-digit NAICS codes for the top-3 industries with the largest employment reported, along with the employment share of those industries in parentheses.

The highly impacted counties tend to have large exposures to the highly impacted industries. For example, many of the most affected counties have sizable employment in industries such as Air Transportation (NAICS=481), Utilities (NAICS=221), Nonmetallic Mineral Product Manufacturing (NAICS=327), Mining (except Oil and Gas) (NAICS=212), Support Activities for Mining (NAICS=213), and Specialty Trade Contractors (NAICS=238). Notice that the heavily impacted counties are relatively small. All the counties in the table have smaller employment than the median county (6,595).

Table 5 lists the 10 counties with the largest market value losses in the full-pass-through case. The number of counties experiencing significant losses are larger when we take account of the price effects along the production chain. Interestingly, the mix of industries generating large market losses are different in this case. We find larger market value losses both in small-sized counties having relatively large exposures to Gasoline Stations (NAICS=447), and in relatively large counties with significant employment in industries, such as Paper Manufacturing (NAICS=322) and Air Transportation (NAICS=481).

V. Assessing Transition Risks at Community Banks

We use our measures of transition risk at the regional level to produce preliminary estimates of transition risk at U.S. financial institutions. Related exercises have been carried out for large banks in the Netherlands (Reinders et al. (forthcoming), France (ACPR, (2021)), Mexico (Roncoroni et al. (2021)), Norway (Grippa and Mann (2020)), and the U.S. (Arsenau et al. (2022) and Jung, Engle, and Berner (2023)). By analogy to standard stress testing methodologies, these studies use loan-level data available to regulators to estimate shocks to bank portfolios from the imposition of a carbon tax.[42]

We take a somewhat different approach to take a step toward measuring transition risks at U.S. community banks, for which loan-level data are not available. To be clear, even if data on individual loans were available for small banks, there would be no simple mapping of our measure of sectoral transition risks to community bank portfolios, which are primarily composed of real estate loans, with only a modest share of C&I loans. And the borrowers in community banks' C&I portfolios are more likely to be dentist offices and local retailers, rather than the public firms that appear in Compustat. Nonetheless, a shock to the firms operating in a community bank's lending footprint is likely to have significant effects on the bank's health. As we argue above, declines in firms' expected profits within a region are likely to affect employment and local real estate markets, which will affect bank portfolios.[43] And since the vast majority of community banks operate in a single county or a small number of contiguous counties, the county is the relevant geographical unit for measuring community banks' lending footprints.[44]

Recognizing the limitations of our analysis, we proceed as follows:

To identify community banks for our empirical application in this section, we adopt the designation proposed by the Federal Deposit Insurance Corporation (FDIC) Community Banking Study (CBS) as of December 2019. The FDIC establishes standard requirements for lending and deposit gathering and for limits on the geographic scope of operations that a banking organization must meet to be designated as a community bank. See the CBS for details regarding criteria adopted by the FDIC.

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[42] Most of these papers are part of a growing literature and interest of central banks in analyzing the link between financial stability and climate change. Climate stress tests that evaluate transition risk have some important differences but are similar in spirit to standard stress tests (i.e., those with a primary focus on capital and liquidity levels during scenarios of stress) performed by macroprudential supervisors. The exercise we perform is not intended as a climate stress test, that is, we do not estimate a bank's portfolio losses or the probability that any bank's capital falls below the required level.

[43] We view the possible effects on local real estate markets as the most likely mechanism through which a carbon tax would directly affect community bank portfolios.

[44] Many small banks like community banks operate within a single county and the vast majority operate within a few counties clustered in a limited geographic area. For example, 35 percent of banks operate branches in one county, and 22 percent of banks operate branches in two counties, according to FDIC's Summary of Deposits. While our current exercise uses the county as the geographic unit, our methodology is easily modified to measure transition risks for broader regions.

To proxy for a bank's lending footprint, we use a bank's branch deposits obtained from the FDIC's Summary of Deposits as of June 2019.[45] Given our estimates for county-level transition risks, we calculate a bank-level estimate of the transition risks within its lending footprint. Specifically, let $dep_{i,b,c}$ be deposits of a bank i, which is held in a branch b located in a county c. Given a bank's branch-level deposits, we calculate a bank i's deposit exposure in a county c ($dep_{i,c}$) by summing up branch deposits located in the same county, $dep_{i,c} = \sum_b dep_{i,b,c}$. Then, a bank's exposures to counties with its branches are proxied by its deposit share ($w_{i,c}$) across counties with branch operation; that is, $w_{i,c} = dep_{i,c} / \sum_c dep_{i,c}$.

Our estimates for the bank-level transition-risks measures are calculated as weighted averages of county-level estimates for the transition risks, using banks' exposures to counties with branch operation as weights; that is, $\Lambda_i = \sum_c w_{i,c} \times \Lambda_c$.[46] To quantify the potential impacts on a community bank's operation, we multiply a bank-level estimate for the transition risks (Λ_i) by a bank's loans. We then express these losses as a percentage of either the bank's total assets or tier one capital.[47]

It is important to be clear that our measure of climate transition risk for community banks is *not* an estimate of expected portfolio losses due to an emissions tax. Instead, it is a preliminary attempt to get a sense of transition risks within the bank's lending footprint. We express the impact of the emissions tax as a percentage of bank assets or bank capital as a normalization.

Figure 4 plots a histogram of bank-level impacts from the tax (scaled by loan to assets). Since community banks generally have narrow geographic footprints, the histogram of bank exposure is similar to the histogram of county exposure. In the no-pass-through case, the shock to firms in banks' lending footprint are below 1 percent of assets for a \$40 carbon tax or 2 percent for a \$100 carbon tax when looking at direct emissions. The full-pass-through case with a \$100 tax reflects somewhat larger value losses but the losses are still moderate. In the aggregate, the carbon taxation would result in mild to moderate impacts on community banks' loan portfolios (Table 6). In the

[45] The FDIC's Summary of Deposits is the annual survey of branch office deposits as of June 30 for all FDIC-insured institutions, including insured U.S. branches of foreign banks. All institutions with branch offices are required to submit the survey; institutions with only a main office are exempt.
[46] We perform a sensitivity analysis using the commuting zone as the geographic unit and found that results are not affected by this choice.
[47] We measure a bank's maximum potential exposure by loans, rather than assets, because the value of securities and cash are not likely to be sensitive to local economic shocks.

no-pass through case, with a $40 carbon tax on direct emissions, community banks would experience losses that represent 0.3 percent of total assets and 2.7 percent of bank capital. We observe larger impacts from the higher carbon tax rate and in the full-pass-through case. However, even under the most severe case—$100 carbon tax on full pass-through case—the total loss accounts for 2.0 percent of total assets of community banking organizations.

V. Conclusion

This paper estimates potential climate transition risk at the industry, county, and small bank level. We construct a unique data set on emissions at the product/industry level. We find that the impact for some industries can be large (mostly due to high emissions intensity level) and that impacts at the sectoral level are quite sensitive to the incidence of the tax. However, the effects at the county and bank level appear to be relatively small.

In subsequent work, we intend to address some of the limitations of the current exercise. In particular, more realistic input and final demand elasticities for focusing on more disaggregated industries with significant emissions (direct or embodied) should improve our estimates. We can also extend our analysis to different forms of transition risk (e.g., demand shifts or technological developments). Finally, a serious look at transition risk at the regional level requires a more careful description of the mechanisms linking shocks to firms' profits to the regional economy.

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Tables and Figures

Table 1: List of industries with the highest emissions

	Direct Emissions				Embodied Emissions		
Rank	NAICS	Description	Emissions (% of total)	NAICS	Description	Emissions (% of total)
1	221	Utilities	43.0	221	Utilities	19.6
2	213	Support Activities for Mining	7.1	311	Food Manufacturing	8.4
3	112	Animal Production and Aquaculture	6.2	324	Petroleum and Coal Products Manufacturing	5.7
4	562	Waste Management and Remediation Services	6.2	531	Real Estate	4.2
5	481	Air Transportation	4.8	238	Specialty Trade Contractors	4.1
6	324	Petroleum and Coal Products Manufacturing	4.3	336	Transportation Equipment Manufacturing	3.9
7	115	Support Activities for Agriculture and Forestry	3.9	325	Chemical Manufacturing	2.7
8	325	Chemical Manufacturing	3.0	213	Support Activities for Mining	2.7
9	327	Nonmetallic Mineral Product Manufacturing	2.4	481	Air Transportation	2.5
10	311	Food Manufacturing	1.6	621	Ambulatory Health Care Services	1.9
Sub-total			82.4			55.8

Note: The column "Emissions (% of total)" reports each 3-digit NAICS industry's share of aggregate greenhouse gas emissions measured in CO_2 equivalent. We do not show the estimates of the "Public Administration" industries (2-digit NAICS 92) since there are no firms in Compustat to estimate the Merton (1974) model.

Table 2: List of the top-10 industries with the largest market value losses (no-pass-through)

Rank	NAICS	Description	Output	Emissions	Emission Intensity	Market Value Losses $40 tax	Market Value Losses $100 tax
1	481	Air Transportation	287	232	808	26.9%	77.9%
2	221	Utilities	627	2087	3,330	23.8%	60.0%
3	327	Nonmetallic Mineral Product Manufacturing	162	115	709	21.2%	52.3%
4	486	Pipeline Transportation	20	52	2,639	17.3%	43.2%
5	324	Petroleum and Coal Products Manufacturing	539	210	389	12.8%	32.1%
6	562	Waste Management and Remediation Services	181	300	1,658	8.7%	21.7%
7	212	Mining (except Oil and Gas)	81	56	690	6.5%	16.2%
8	213	Support Activities for Mining	321	343	1,069	6.3%	15.8%
9	211	Oil and Gas Extraction	53	59	1,118	5.2%	13.1%
10	315	Apparel Manufacturing	74	5	65	4.7%	11.6%

Note: Output is measured in billion USD, and emissions are in million metric tons of CO_2 equivalent. Emission intensity is measured in metric tons of CO_2 equivalent per million USD.

Table 3: List of the top-10 industries with the largest market value losses (full-pass-through)

Rank	NAICS	Description	Output	Emissions	Emission Intensity	Market Value Losses $40 tax	Market Value Losses $100 tax
1	324	Petroleum and Coal Products Manufacturing	539	303	562	18.6%	55.4%
2	481	Air Transportation	287	133	462	15.3%	38.9%
3	315	Apparel Manufacturing	74	13	176	12.5%	30.7%
4	221	Utilities	627	1045	1,667	11.9%	29.8%
5	447	Gasoline Stations	17	1	39	10.0%	24.2%
6	238	Specialty Trade Contractors	1090	221	202	9.1%	22.8%
7	486	Pipeline Transportation	20	26	1,304	8.5%	21.3%
8	311	Food Manufacturing	860	448	521	6.6%	16.4%
9	323	Printing and Related Support Activities	82	6	78	6.4%	16.1%
10	337	Furniture and Related Product Manufacturing	151	40	267	4.6%	11.6%

Note: Output is measured in billion USD, and emissions are in million metric tons of CO_2 equivalent. Emission intensity is measured in metric tons of CO_2 equivalent per million USD.

Table 4: List of the top-10 counties with the largest market value losses (no-pass-through)

				Market Value Losses	
Rank	State	County	Employment	$40 tax	$100 tax
1	Alaska	Lake and Peninsula Borough	1263	10.7%	30.4%
2	Tennessee	Stewart County	4282	10.5%	26.3%
3	California	Alpine County	127	10.0%	25.2%
4	Mississippi	Jefferson County	593	9.5%	24.0%
5	North Dakota	Mercer County	13284	9.2%	23.2%
6	Montana	Rosebud County	3268	7.5%	18.8%
7	Mississippi	Kemper County	628	7.4%	18.6%
8	Texas	Newton County	511	7.1%	17.8%
9	Illinois	Alexander County	509	6.8%	17.1%
10	Nevada	Esmeralda County	155	6.2%	15.5%

Note: Counties sorted by Market Value Losses under $40 carbon tax. In this case, the order is identical when sorting counties using Market Value Losses under the $100 carbon tax.

Table 5: List of the top-10 counties with the largest market value losses (full-pass-through)

				Market Value Losses	
Rank	State	County	Employment	$40 tax	$100 tax
1	Colorado	Kiowa County	226	8.4%	20.6%
2	Texas	Terrell County	111	8.0%	19.5%
3	Virginia	Charles City County	2267	6.6%	16.6%
4	Texas	Stonewall County	59	6.4%	16.1%
5	Alaska	Lake and Peninsula Borough	1263	6.4%	16.3%
6	Alaska	Aleutians East Borough	13558	6.3%	15.7%
7	Mississippi	Jefferson County	593	6.3%	15.6%
8	Missouri	Schuyler County	310	6.2%	15.2%
9	Montana	Rosebud County	3268	5.9%	14.8%
10	Georgia	Hancock County	56	5.9%	14.3%

Note: Counties are ordered by Market Value Loss under $40 tax. The same counties are included in the top-10 according to Market Value Losses under a $100 tax (the order is slightly different).

Table 6: Aggregate losses of the community banking organizations

	$40/ton		$100/ton	
	No pass-through	Full pass-through	No pass-through	Full pass-through
As a proportion of Aggregate Assets	0.31%	0.82%	0.80%	2.04%
As a proportion of Aggregate Equity	2.74%	7.22%	7.05%	18.04%

Figure 1a: County-level impact of $40 carbon tax (no-pass-through)

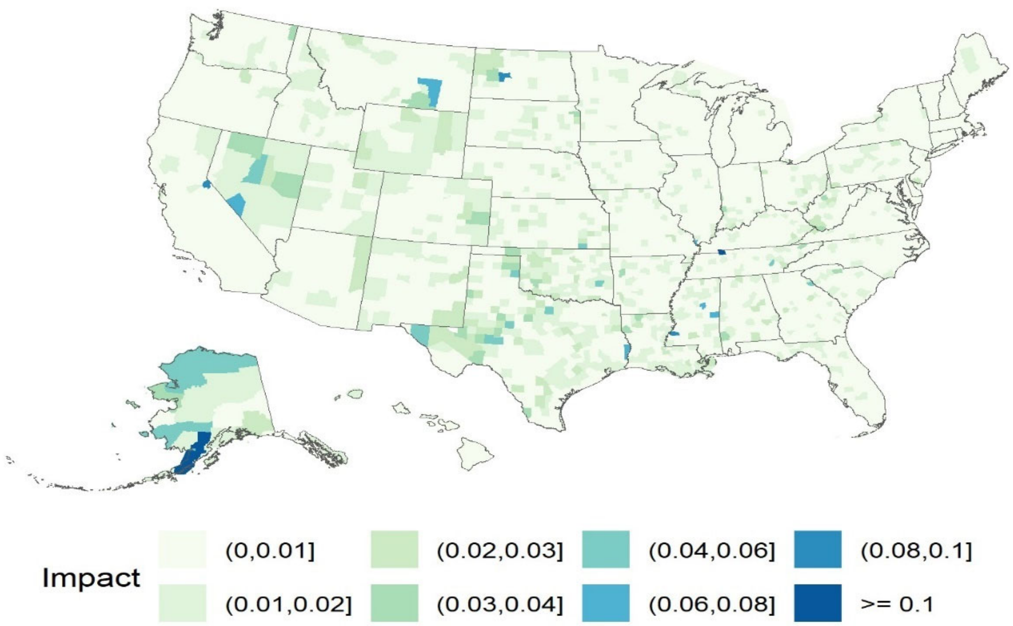


Figure 1b: County-level impact of $100 carbon tax (no-pass-through)

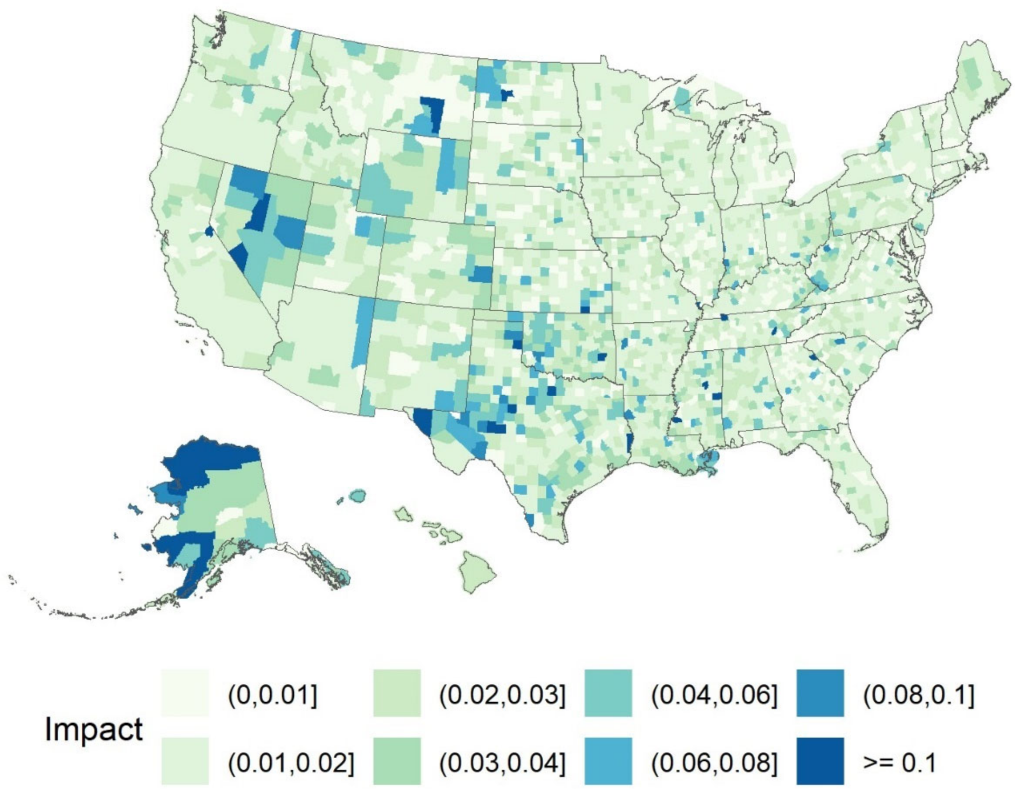


Figure 2a: County-level impact of $40 carbon tax (full-pass-through)

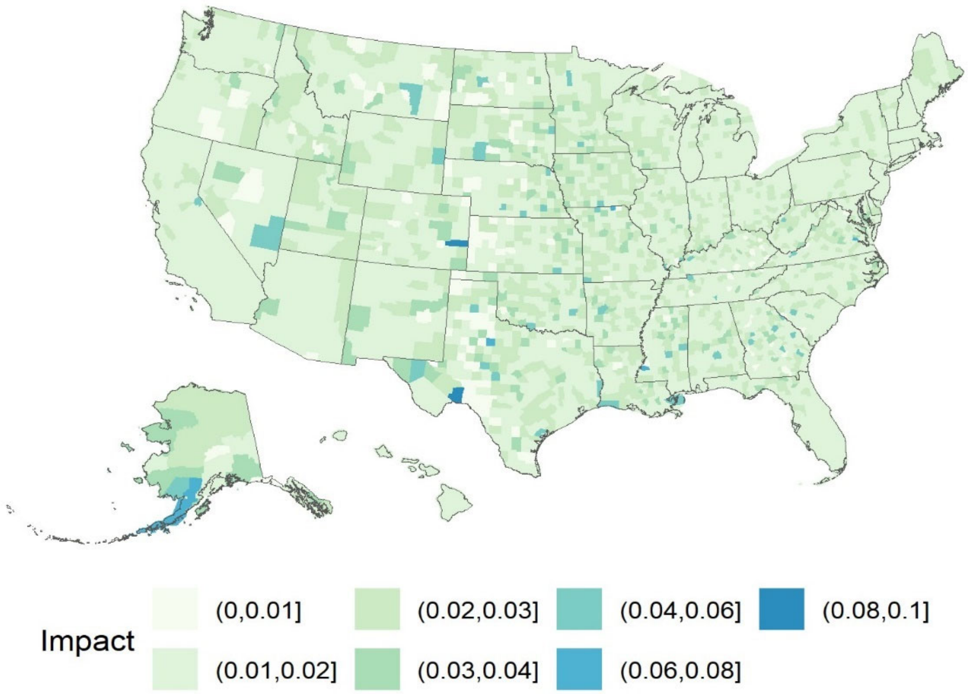


Figure 2b: County-level impact of $100 carbon tax (full-pass-through)

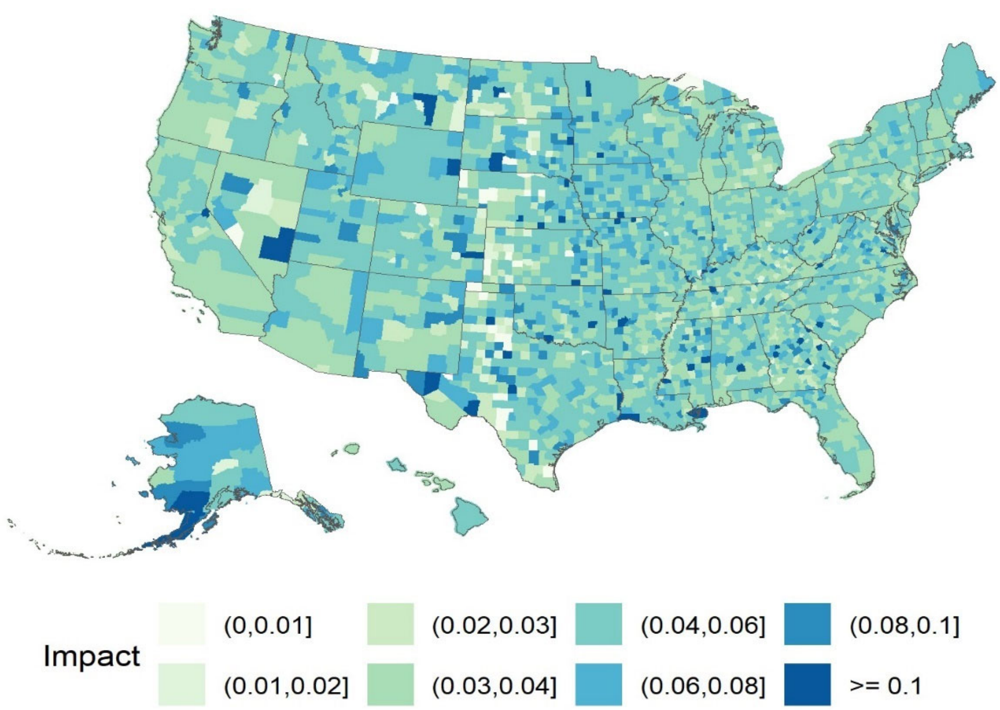
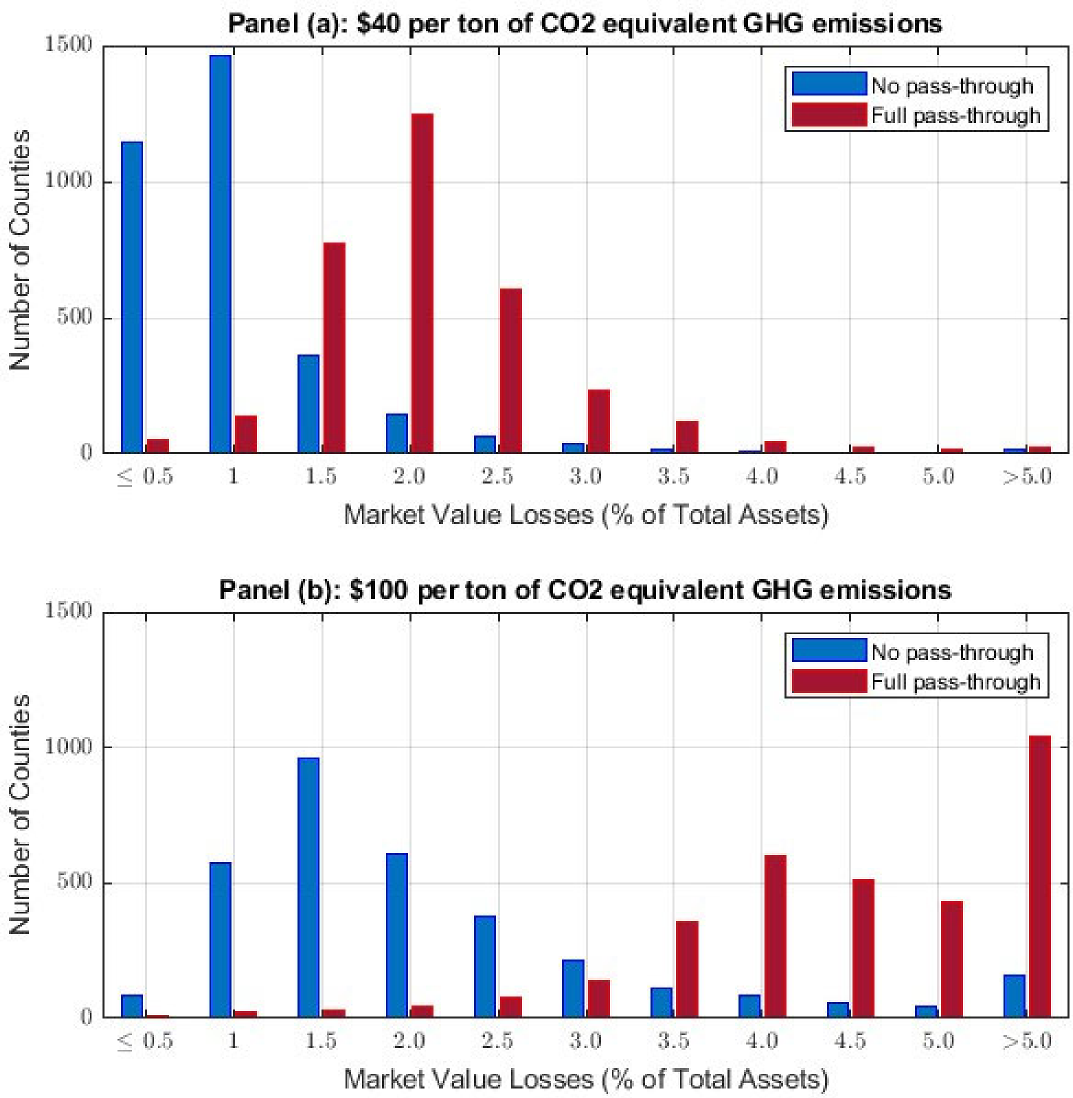
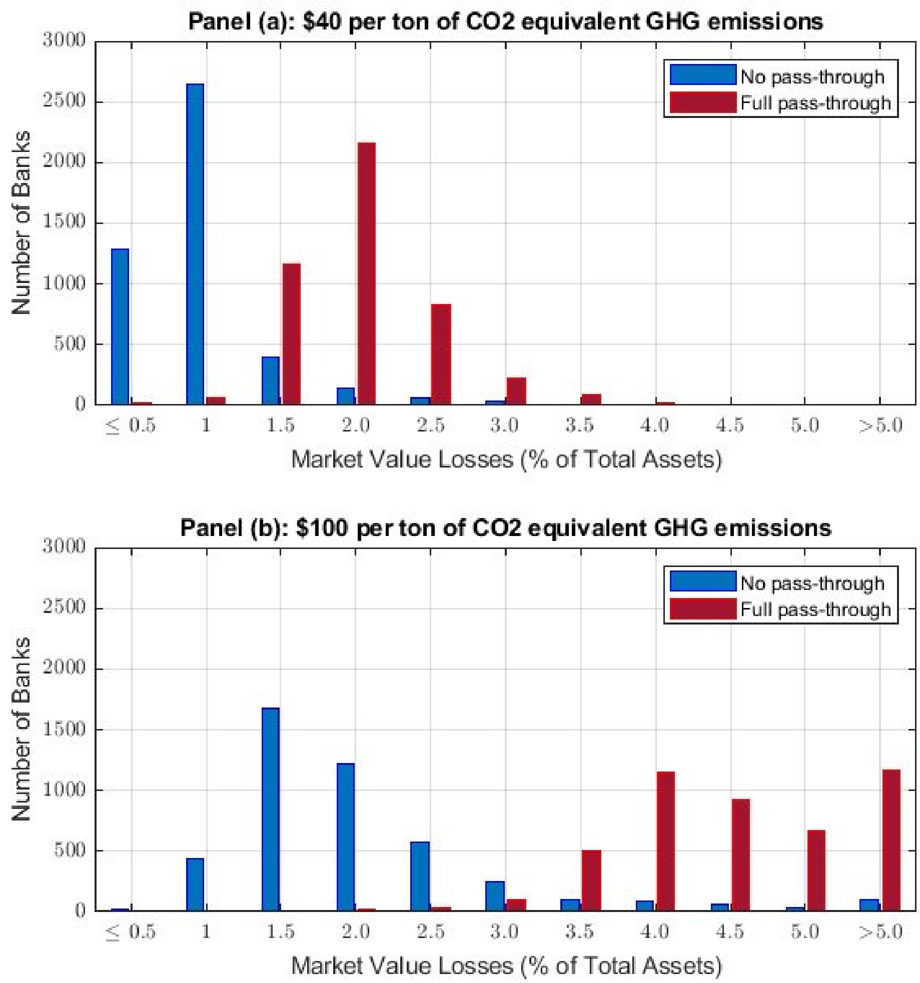


Figure 3: Distribution of market value losses across counties



Note: Each column includes the number of counties associated with corresponding market value losses (i.e., unweighted). The similar pattern is observed when the size of counties is considered (i.e., when bins are weighted by the size of counties proxied by their total reported private-sector employment).

Figure 4: Distribution of market value losses across banks (scaled by loans to assets)



Note: Each column includes the number of community banks associated with corresponding market value losses (i.e., unweighted). The similar pattern is observed when the size of banks is considered (i.e., when bins are weighted by the operation size proxied by banks' total assets).

Online Appendix: Measuring Climate Transition Risk at the Regional Level with an Application to Community Banks*

Mitchell Berlin Sung Je Byun Pablo D'Erasmo Edison Yu

A-1 Introduction

This appendix describes EXIOBASE, a global Input-Output table extended to include environmental information, and explains how we obtain direct emissions and embodied emissions in final demand at the industry level. We also describe the details of how we obtain the estimates of transition risk at the sectoral level. We also present the details of the general equilibrium production network model.

A-2 Description EXIOBASE

We obtain emissions data from EXIOBASE (see Stadler et al. (2021)). EXIOBASE is a global, detailed Multi-Regional Environmentally Extended Supply-Use Table (MR-SUT) and Input-Output Table (MR-IOT). EXIOBASE 3 (the latest version at the time we were writing the paper) was developed in the European Union Seventh Framework Program project DESIRE (Development of a System of Indicators for a Resource efficient Europe). It provides environmental information and features times-series data at a high level of product and industry detail as well as a physical representation of the world economy.[1]

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[1] More information about EXIOBASE can be found in their website (see also doi 10.5281/zenodo.3583070).

EXIOBASE reports data for 44 countries (the U.S. is represented individually) and 5 rest-of-the-world regions constructed on a 200-product and 163-industries resolution. It is built from several primary data sources (see Wood et al. (2015) for a full description of data sources). Industry and product output per country data were gathered from several national account databases (including the national accounts and national monetary supply-use tables (MSUTs)) and various international databases such as the Food and Agriculture Organization statistical database (FAOSTAT) and International Energy Agency's (IEA) energy balances.[2] The time series extends from 1995 to 2022 but some data is derived from "now-casts" (i.e., using technical coefficients combined with measures of output or consumption). We use the latest available version which is version 3.8.2 (released in October 2021).[3] In the particular case of the U.S., and for the version of the data we use, Supply-Use tables and Input-Output tables derive from data from the United Nations (UN) and the Bureau of Economic Analysis (BEA). This data is updated to 2018, with GDP and gross import/export projections from IMF after that. At a detailed level (product / industry), energy and energy-related emissions data are updated to 2015 using IEA energy balances (see link here for details on reports and available data from IEA). At an aggregate level, all CO2 fossil emissions are updated to 2019 based on the Edgar Database (see here for details on Edgar); all other GHG emissions are updated to 2017 using the PRIMAP-hist dataset (see Gütschow et al. (2016) and this link for a description on how the industry level estimates are obtained) with sectoral (Intergovernmental Panel on Climate Change (IPCC) based) emissions by gas available.[4] More recent data than those reported as end points are "now-casts".[5]

With data on input-output (I-O) transactions, labor inputs, energy supply and use, GHG emissions, material extraction, land and water use, as well as emissions to air, water, and soil, EXIOBASE provides a comprehensive up-to-date coverage of the global economy. It provides the first time series with adequate disaggregation of the agricultural, forestry, and mining sectors for proper consideration of the land, water, and material pressures related to these sectors, as well as a detailed division of energy extraction and transformation industries (see

[2]Stadler et al. (2018) provide detailed information on the sources (see the main text and Supplements S1 and S9).

[3]The data is publicly available and hosted in Zenodo. See link here. (version 3.8.2 October, 2021; link last accessed 2/4/2022)

[4]EDGAR is a multipurpose, independent, global database of anthropogenic emissions of greenhouse gases and air pollution on Earth. EDGAR provides independent emission estimates compared to what reported by European Member States or by Parties under the United Nations Framework Convention on Climate Change (UNFCCC), using international statistics and a consistent IPCC methodology.

[5]Land, material, and water related data are purely reliant on now-casts post 2011. In this version, there is a major update to the historical time-series of non-fuel combustion GHG emissions. Non-fuel combustion GHG emissions are now scaled to match the PRIMAP-hist dataset, with sectoral (IPCC based) emissions by gas available.

Wood et al. (2018)). This puts EXIOBASE in a unique position compared to other existing MRIO databases, such as Eora or WIOD (for a comparison of MRIO databases, see Tukker and Dietzenbacher (2013)).[6] The main benefit of using data with this structure is that it allows us to use information on "direct" emissions (i.e., what the Intergovernmental Panel on Climate Change calls the "Tier 1" or "default" method of calculating emissions) at the industry or product level but it also opens the possibility to derive "indirect" emissions or what environmental researchers call this a "life cycle" or "footprint" measure of emissions and international economists call it a "value chain" measure of emissions (see Shapiro (2021)).

Other data sets contain information on emissions. However, most of these other data sets, are not as detailed, complete, and methodologically consistent (see Stadler et al. (2018)). Importantly, as Shapiro (2021) describes, disaggregation to industry detail is EXIOBASE's focus as it tends to produce more accurate analysis of CO2 emissions (Steen-Olsen et al. (2014); de Koning et al. (2015)). In the US, the Environmental Protection Agency (EPA) provides data on emissions with different level of coverage and disaggregation. The more comprehensive data comes from the Inventory of U.S. Greenhouse Gas Emissions and Sinks (Inventory). The Inventory is a document prepared annually by EPA, for over 25 years, that estimates the total greenhouse gas emissions across all sectors of the economy using national-level data (see last report here). This includes estimates of greenhouse gas emissions from fossil fuel combustion, various industrial processes, and agricultural sources. The comprehensive greenhouse gas data presented in the Inventory comprise the official U.S. estimate of total national emissions that is submitted to the United Nations in accordance with the Framework Convention on Climate Change.[7] A drawback of this data for our analysis is that it is reported at a high level of aggregation (i.e., not very granular industry or product information is provided). An additional source of data that the EPA provides derives from the Greenhouse Gas Reporting Program (GHGRP). The GHGRP collects detailed emissions data from the largest greenhouse gas emitting facilities in the U.S. The GHGRP has collected data annually since 2010. These data can be used to compare facilities or industries at a very detailed level. However, the GHGRP includes most, but not all, U.S. emissions. In general, only large suppliers of greenhouse gas emitting products, or facilities that emit more than 25,000 metric tons of CO2 equivalent (CO2e) per year (roughly equivalent to the CO2 emitted from the burning of 136 rail cars of coal), are required to report their annual

[6]The Bureau of Economic Analysis (BEA) provides Input-Output information for the US at a level of disaggregation that is similar to 3-digit NAICS codes (71 industries).

[7]In preparing the annual emissions inventory report, EPA collaborates with hundreds of experts representing more than a dozen U.S. government agencies, academic institutions, industry associations, consultants and environmental organizations. EPA also collects greenhouse gas emissions data from individual facilities and suppliers of certain fossil fuels and industrial gases through the Greenhouse Gas Reporting Program.

greenhouse gas emissions. Some entire sectors, such as the agricultural and land-use sectors, are not required to report. When including suppliers these emissions cover approximately 85% of total emissions in the US. Without suppliers the number is closer to 50%. A drawback of the GHGRP data relative to EXIOBASE is that they do not allow to obtain estimates that go beyond "direct" emissions.

A-3 Emissions Data

This section describes how to use EXIOBASE to obtain measures of Greenhouse Gas (GHG) emissions. The public version of EXIOBASE is housed in Zenodo. We obtained the data (version 3.8.2, October 21, 2021) from here. There are files with data from 1995 to 2022. We focus on year 2019. We use the monetary transactions version of the data which among other things provides information on GHG emissions. We use data in file IOT_2019_pxp.zip. This file provides information by country and product which we link to 6 digits NAICS codes using a concordance file provided by EXIOBASE (see more details about this below). Table A.1 lists the files from EXIOBASE we use. We use lower-case bold letters for (column) vectors as in $\mathbf{x}$. We use upper-case bold letters for matrices as in $\mathbf{Z}$.

File Readme_3_8_1.txt (which can be found here) describes the different components and the end points of the data. EXIOBASE reports data for 44 countries and 5 rest-of-the-world regions constructed on a 200-product (P) and 163-industries (N) resolution. The US is represented individually in EXIOBASE. We denote the number of countries/regions by $C = 49$. There are also $K = 6$ Final Demand Sectors.

Table A.1: Variables EXIOBASE 3 (version 3.8.2)

Symbol	Description	Units	EXIOBASE File
	Industry Classification	-	"industries.txt"
	Product Classification	-	"products.txt"
$\mathbf{f}'$	Greenhouse Gas Emissions by country/product	kg CO_2-eq	"\impacts\F.txt"
$\mathbf{f}'_{\mathbf{hh}}$	Greenhouse Gas Emissions		
	by country/final demand sector	kg CO_2-eq	"\impacts\F_hh.txt"
$\mathbf{x}$	Output by country/product	M.EUR	"x.txt"
$\mathbf{v}$	Value Added	M.EUR	"\impacts\F.txt"
$\mathbf{Y}$	Final Demand	M.EUR	"Y.txt"
$\mathbf{y}$	Final Demand	M.EUR	derived from "Y.txt"
$\mathbf{A}$	Input-Output Matrix (Technical Coefficients)	M.EUR	"A.txt"
$\mathbf{Z}$	Input-Output Matrix	M.EUR	"Z.txt"
$\mathbf{m}'$	Emission Multiplier Vector	M.EUR	"\impacts\M.txt"

A-3.1 Direct Emissions

Direct emissions refer to emissions directly associated with a sector or product. The carbon footprint stressors available in EXIOBASE cover each industry/product across all countries/regions.The satellite and impact accounts contain the relevant information. All sources of emissions are included (following the Intergovernmental Panel on Climate Change (IPCC) categorization), including from agricultural production, but excluding those from the specific category of "land use, land use change and forestry," which are difficult to attribute to production sectors within a certain year.

The GHG footprint of a particular country/product or final demand sector is measured as the total emissions of GHG gases in kilograms of CO_2 equivalents (tCO_2-eq). It includes GHG, like CO_2, CH_4, and N_20 and calculates their Global Warming Potentials (GWP).[8]

- Variable "GHG emissions (GWP100) — Problem oriented approach: baseline (CML, 2001) — GWP100 (IPCC, 2007) kg CO2 eq.", that we take from the file "F.txt" in the "Impact" folder, provides the product level information for all countries and we extract the information for the US.[9]
- The file F.txt in the "satellite" folder provides a decomposition of the different GHG and different sources of emissions. It is possible to, for example, obtain detail emissions from CO2 combustion, CO2 non-combustion - cement production, CO2 - agriculture - peat decay.

We denote the (column) vector of direct emissions by $\mathbf{f}$. This is a vector of size $PC \times 1$ (i.e., each element corresponds to the value of direct emissions per product-country pair).

A-3.2 Embodied Emissions in Final Demand

In this subsection, we describe how to go from direct emissions to embodied emissions in final demand (see Hertwich and Wood (2018), Meng et al. (2018), and Yamano and Guilhoto (2020)). In order to do so, we first introduce some standard Input-Output table notation (e.g. Miller and Blair (2009)). For ease of exposition, the equations in this section correspond to a given country (closed economy) but can easily be extended to include more countries and/or regions (i.e., we work with vectors of size $P \times 1$ but the analysis can be extended

[8] The Global Warming Potential (GWP) was developed to allow comparisons of the global warming impacts of different gases. CO_2, by definition, has a GWP of 1 regardless of the time period used, because it is the gas being used as the reference. Methane (CH_4) is estimated to have a GWP of 28–36 over 100 years (see here). As most of the literature, we'll focus on CO_2 equivalent emissions using GWP 100.

[9] The IPCC manual with the corresponding categories can be found here (link last accessed February 3, 2022.

to use vectors of size $PC \times 1$ that include many countries/regions as well as imports and exports). We denote by x_i the total output (production) of sector i, by z_{ij} the value of a flow (in monetary units) from sector i to sector j (or the inter-industry sales by sector i to sector j), and y_i the total final demand for sector $i's$ product (y_i corresponds to the sum across the K final demand sectors). As before, we use lower-case bold letters for (column) vectors and capitalized bold letters for matrices. In compact form, we can represent the Input-Output as follows

$$\mathbf{x} = \mathbf{Z}\mathbf{i}_P + \mathbf{y}. \tag{A.3.1}$$

where $\mathbf{i}_P$ is a column vector of 1's of size P (use to add across columns). The vectors $\mathbf{x}$ and $\mathbf{y}$ are of size $P \times 1$ and the matrix $\mathbf{Z}$ is of size $P \times P$. The total (gross) output for a given industry can be calculated as the row sum of intermediate demand $\mathbf{Z}$ and final demand $\mathbf{y}$ for its output. More specifically, $x_i = \sum_{j=1}^{P} z_{ij} + y_i$. Each column in matrix $\mathbf{Z}$ represents the required inputs flows from other industries to produce a given amount of gross output. If we denote by $\mathbf{v}$ the vector of value added, gross output of sector j can also be calculated as the column sum of the inputs required to produce product j plus value added. That is $x_j = \sum_{i=1}^{P} z_{ij} + v_j$. Using this notation, Table A.2 presents a stylized Input-Output table with P sectors of production (still for a closed economy).

Table A.2: Stylized Input-Output Matrix

Sector	Sectors $1, 2, \ldots, P$	Final Demand	Total Gross Output
1 2 $\vdots$ P	$\mathbf{Z}$	$\mathbf{y}$	$\mathbf{x}$
Value Added	$\mathbf{v}'$		
Total Outlays	$\mathbf{x}'$		

Let $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-\mathbf{1}}$ denote the $P \times P$ matrix of technical coefficients where (as in Miller and Blair (2009)) a hat over a vector denotes a diagonal matrix with the elements of the vector along the main diagonal.[10] Then, equation (A.3.1) can be re-written as

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{y}, \tag{A.3.2}$$

so

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{y} = \mathbf{L}\mathbf{y}, \tag{A.3.3}$$

where $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}$ is known as the Leontief inverse or the total requirements matrix.

With estimates of direct emissions at hand (see Section A-3.1) and the corresponding Input-Output table, our objective is to compute embodied emissions in final demand which capture emissions associated with the production stage (i.e., they occur in the supply chain and are embodied in inputs from other sectors). The idea is to allocate direct emissions using the observed flows across sectors (i.e., obtain a simile Input-Output table for emission flows) to the corresponding sector. More specifically, the carbon footprint (or Total Gross Emissions) corresponds to the sum of direct emissions and the emissions embodied in the intermediate inputs of the process. Let f_j denote direct emissions in the production of sector/product j, m_i the emissions embodied per unit of output i, and m_j the emissions embodied per unit of input j. We also denote by f_{hh} direct emissions from Final Demand. Adding across rows, in matrix form, total gross emissions (or carbon footprint of total production) are

$$\mathbf{m}'\hat{\mathbf{x}} = \mathbf{f}' + \mathbf{m}'\mathbf{Z}. \tag{A.3.4}$$

Applying some simple algebra on equation (A.3.4) allows us to obtain an expression for $\mathbf{m}$.[11] More specifically, let $\mathbf{s}' = \mathbf{f}'\hat{\mathbf{x}}^{-\mathbf{1}}$, then

$$\mathbf{m}' = \mathbf{s}'(\mathbf{I} - \mathbf{A})^{-1}. \tag{A.3.5}$$

It is useful to note that from equation (A.3.1) we can also write (by pre-multiplying all terms by $\hat{\mathbf{m}}$)

$$\hat{\mathbf{m}}\mathbf{x} = \hat{\mathbf{m}}\mathbf{Z}\mathbf{i}_P + \hat{\mathbf{m}}\mathbf{y}. \tag{A.3.6}$$

[10] For example,

$$\hat{\mathbf{x}} = \begin{bmatrix} x_1 & 0 & 0 & \dots & 0 \\ 0 & x_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & x_P \end{bmatrix}.$$

[11] Right multiplying (A.3.4) by $\hat{\mathbf{x}}^{-\mathbf{1}}$ and replacing $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-\mathbf{1}}$ leads to equation (A.3.5).

From our graphical representation (and equation (A.3.6)), it is straightforward to see that the matrix that represents the embodied flows of emissions across production activities is

$$\mathbf{E_Z} = \hat{\mathbf{m}}\mathbf{Z}. \tag{A.3.7}$$

The way to interpret the coefficients of matrix $\mathbf{E_Z}$ is similar to the way we interpret the coefficients in matrix $\mathbf{Z}$. That is, the columns indicate the flow of emissions required from intermediate inputs and the rows the flow of emissions via sales to other sectors and to final demand.

The vector that represents the embodied flows of emissions in final demand is

$$\mathbf{e_y} = \hat{\mathbf{m}}\mathbf{y}. \tag{A.3.8}$$

This vector $\mathbf{e_y}$ is effectively the vector we want to estimate using data from EXIOBASE. It corresponds to the carbon footprint of the final demand. As Hertwich and Wood (2018) notes, $\mathbf{E_Z}$ includes emissions at multiple stages along the supply chain. $\mathbf{E_Z}$ shows the level of emissions that each industry has agency over along the full upstream supply chain. Total gross emissions $\mathbf{E_Z}\mathbf{i}_P + \mathbf{e_y}$ count each unique emission multiple times in the supply chain. Hence the sum of $\mathbf{E_z}$ is greater than $\mathbf{e_y}$ (or $\mathbf{f}$ that, by construction, the sum of its elements equals the sum of the elements of $\mathbf{e_y}$).

Note that like with the flow of transactions in Table A.2 where (by construction) total value added equals total final demand, the total embodied emissions in final demand $\sum_j m_j y_j + f_{hh}$ will equal total direct emissions $\sum_i f_i + f_{hh}$.

To gain more intuition, as in Meng et al. (2018), we can define the matrix $\mathbf{E_y}$ as follows

$$\mathbf{E_y} = \hat{\mathbf{m}}\hat{\mathbf{y}}. \tag{A.3.9}$$

This matrix provides estimates of the sector sources of emissions. A row in this matrix shows the distribution of emissions created from a sector across all sectors. That is, summing across all columns of this matrix (i.e., along a given row) we recover total direct emissions generated by the given sector and the matrix shows how each industry emissions are distributed to final demand. A column in this matrix provides an estimate of the sources of emissions involved in the production of a given product. That is the sum of a given column equals the corresponding element in vector $\mathbf{e_y}$ and decomposes the embodied emissions from the production of a given industry according to where intermediate inputs are produced.

A-3.2.1 A 2 Sector (closed-economy) Example

We use the input-output table of a given country with two sectors of production: Sector 1 and Sector 2. For ease of exposition, we assume that this is a closed economy. Table A.3 presents the monetary version of the input-output table.

Table A.3: Example: Input-Output Table (in M.$)

		To:			
		Sector 1	Sector 2	Final Demand	Total Gross Output
From:	Sector 1	15	50	35	100
	Sector 2	40	90	70	200
	Value Added	45	60	0	105
	Total	100	200	105	

In this example, $\mathbf{x} = \begin{bmatrix} 100 \\ 200 \end{bmatrix}$, $\mathbf{y} = \begin{bmatrix} 35 \\ 70 \end{bmatrix}$, and $\mathbf{Z} = \begin{bmatrix} 15 & 50 \\ 40 & 90 \end{bmatrix}$. Some simple algebra shows that $\mathbf{A} = \begin{bmatrix} 0.15 & 0.25 \\ 0.40 & 0.45 \end{bmatrix}$ and that $\mathbf{L} = \begin{bmatrix} 1.497 & 0.680 \\ 1.088 & 2.313 \end{bmatrix}$.

Let's assume that $\mathbf{f}' = [15\ 25]$ (i.e., direct emissions in Sector 1 equal 15 and in Sector 2 equal 25, respectively, both measured in metric tons of CO2-eq). Let's also assume that $f_{hh} = 0$. Representing the matrix flow of emissions for our simple example we obtain

		To:			
		Sector 1	Sector 2	Final Demand	Total Gross Emissions
From:	Sector 1	$m_1 z_{11}$	$m_1 z_{12}$	$m_1 y_1$	$m_1 x_1$
	Sector 2	$m_2 z_{21}$	$m_2 z_{22}$	$m_2 y_2$	$m_2 x_2$
	Direct Emissions	f_1	f_2	f_{hh}	$f_1 + f_2 + f_{hh}$
	Total	$m_1 x_1$	$m_2 x_2$	$m_1 y_1 + m_2 y_2 + f_{hh}$	

Solving for $\mathbf{m}$ we obtain that

$$\mathbf{m}' = \begin{bmatrix} 0.361 & 0.391 \end{bmatrix}.$$

This implies that there are 0.361 metric tons of CO2-eq embodied per unit of output (or inputs) of sector 1 and 0.391 metric tons of CO2-eq embodied per unit of output of sector 2. Table A.4 shows the matrix representation of embodied emissions or carbon footprint in our example.

Table A.4: Example: Emissions Input-Output Table (in metric tons of CO2-eq)

		To:			
		Sector 1	Sector 2	Final Demand	Total Gross Output
From:	Sector 1	5.41	18.03	12.62	36.05
	Sector 2	15.65	35.20	27.38	78.23
	Direct Emissions	15.00	25.00	0.00	40.00
	Total	36.05	78.23	40.00	

where it should be clear that

$$\mathbf{E_Z} = \begin{bmatrix} 5.41 & 18.03 \\ 15.65 & 35.20 \end{bmatrix}$$

and

$$\mathbf{e_y} = \begin{bmatrix} 12.62 \\ 27.38 \end{bmatrix}.$$

In addition, we find that $\mathbf{E_y} = \begin{bmatrix} 7.857 & 7.143 \\ 4.762 & 20.238 \end{bmatrix}$. The sum across rows in $\mathbf{E_y}$ equals the elements in $\mathbf{e_y}$. More specifically, $7.857 + 4.762 = 12.62$ and $7.143 + 20.238 = 27.38$.

A-3.2.2 Obtaining Embodied Emissions in EXIOBASE

Let P denote the number of products, C the number of countries, and K the number of final demand sectors. We follow the steps that we describe here

1. Obtain the vector of final demand by country/product

   - Load Y.txt (a matrix of size $(PC \times KC)$), sum across final demand sectors and countries to obtain vector $\mathbf{y}$ (a vector of size $(PC \times 1)$). This vector represents aggregate final demand by country/product.

2. Load the emission multiplier matrix. This corresponds to line "GHG emissions (GWP100) — Problem oriented approach: baseline (CML, 2001) — GWP100 (IPCC, 2007)" in M.txt (a vector of size $(1 \times PC)$). This corresponds to vector $\mathbf{m}'$.

- It is also possible to obtain $\mathbf{m}$ as follows $\mathbf{m}' = \mathbf{s}'(\mathbf{I}-\mathbf{A})^{-\mathbf{1}} = \mathbf{f}'\hat{\mathbf{x}}^{-1}(\mathbf{I}-\mathbf{A})^{-\mathbf{1}}$ where $\mathbf{f}$ is the vector of direct emissions, $\mathbf{x}$ is the vector of (gross) output, and $\mathbf{A}$ the matrix of requirements in the input output table. See A.1 for directions on where to find these files.

3. Compute (the vector of) embodied emissions in final demand

$$\mathbf{e_y} = \hat{\mathbf{m}}\mathbf{y}$$

where $\hat{\mathbf{m}}$ (a matrix of size $(PC \times PC)$) is the diagonalized version of $\mathbf{m}$. We use vector $\mathbf{e_y}$ when referring to embodied emissions.

A-3.3 Mapping Emissions at the EXIOBASE Product Level to NAICS (2017) codes

A final step in linking EXIOBASE data with other data from the US is to go from product level data in EXIOBASE to industry level data (as dictated by NAICS 2017 codes). This applies to the vector of direct emissions $\mathbf{f}$ and the vector of embodied emissions $\mathbf{e_y}$. We use a concordance file provided by EXIOBASE that links EXIOBASE products to NAICS 2017 codes.[12] This file maps each product to one or more NAICS codes. We combine this file with data on employment to allocate emissions to each NAICS code. In particular,

- Let $\tilde{e}_p$ denote emissions by product p where $p \in \{1, \ldots, P\}$. In our sample, we have $P = 200$. The vector $\tilde{e}_p$ can be equal to $\mathbf{f}$ or $\mathbf{e_y}$.

- The concordance table links product p with a particular set of NAICS codes. Let $I_{n,p}$ take value equal to 1 if the concordance table has a positive link between product p and NAICS code (6-digit level) n where $n \in \{1, \ldots, N\}$.

- We use employment level data from the Bureau of Labor Statistics (BLS). The Quarterly Census of Employment and Wages (QCEW) provides information at many levels of disaggregation. At this stage, we use National data at the 6-digit NAICS code level.[13] We obtain L_n which denotes total employment in NAICS code n. Let the employment weight (i.e., share of total employment) in NAICS code n be $s_n = L_n / \sum_{n=1}^{N} L_n$.

- We allocate emissions according to employment shares associated with each product. More specifically, let $\hat{s}_p = \sum_{n=1}^{N} I_{n,p} s_n$ and $w_{n,p} = (I_{n,p} s_n)/\hat{s}_p$. Then, total emissions by

[12] See link to concordance files here (link last accessed 2/4/2022).
[13] See here for the BLS data.

NAICS code n equals

$$e_n = \sum_{p=1}^{P} w_{n,p} \tilde{e}_p.$$

We implement this allocation method at the 6-digit level but it can be implemented at any level of aggregation.

A-4 Transition Risk At the Sectoral Level

We follow the finance approach of Reinders, Schoenmaker, and Van Dijk (2023) at the industry level to estimate potential market value losses from climate transition risk at the industry level. Losses across industries are heterogeneous due to their intrinsic likelihood of default but more importantly from the variation in their exposure to transition risk (measured using emissions).

A-4.1 Estimating Asset Value and Asset Volatility at the Industry Level

The asset market value and asset volatility are estimated using a variation of the Merton (1974) model proposed by Bharath and Shumway (2008). We follow the notation in Bharath and Shumway (2008). The Merton model stipulates that the equity value of a firm satisfies

$$E = V\mathcal{N}(d_1) - Fe^{-rT}\mathcal{N}(d_2) \tag{A.4.10}$$

where E is the market value of the firm's equity, F is the face value of firm's debt, r is the risk-free rate, $\mathcal{N}(\cdot)$ is the cumulative standard normal distribution function, d_1 is given by

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A.4.11}$$

and $d_2 = d_1 - \sigma_V\sqrt{T}$. Equation (A.4.10) is the well-known Black-Scholes-Merton equation that expresses the value of a firm's equity as a function of the value of the firm.[14] It is also possible to show that under Merton model's assumptions, the volatility of the firm and its

[14] A common alternative representation expresses the equity to asset value ratio E/V as a function of the leverage ratio $R = F/V$. More specifically $E/V = \mathcal{N}(d_1) - Re^{-rT}\mathcal{N}(d_2)$ so $d_1 = \frac{\ln(1/R)+(r+0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$.

equity are related by

$$\sigma_E = \left(\frac{V}{E}\right)\mathcal{N}(d_1)\sigma_V.\text{[15]} \tag{A.4.12}$$

To estimate asset volatility we first obtain directly from the data (at the industry level) the market value of equity (E), the volatility of stock returns (σ_E), the face value of debt (F), time to maturity T, and the risk free rate r.

Our estimate corresponds to the so called "Naive" approach in (Bharath and Shumway, 2008). This approach has been found to perform better than the standard Merton model. The volatility of firms debt is approximated with $\sigma_D^{\text{naive}} = 0.05 + 0.25 \times \sigma_E$. This leads to the total volatility of the firm being

$$\sigma_V^{\text{naive}} = \left(\frac{E}{E+F}\right)\sigma_E + \left(\frac{F}{E+F}\right)(0.05 + 0.25\sigma_E). \tag{A.4.13}$$

Then, with estimates of $\{E, F, r, \sigma_E\}$ and the value of σ_V from equation (A.4.13), we can estimate V by solving equation (A.4.10) (i.e., the main difference in the way we implement this approach is that we replace equation (A.4.12) with (A.4.13)).

A-4.1.1 Calibration Data Moments

We estimate moments at the firm level and use averages at the industry level. Averages are asset-weighted. While emission data is available at all levels of aggregation (2-digits, 3-digits, 6-digits), due to data limitations we estimate asset values and asset volatility only at the 2-digits and 3-digit level. There is a significant number of industries that do not meet our data requirements in Compustat (or that are directly not present in the data).[16] Even at the 3-digit level there is a number of industries with only a few firms with positive assets.

- Market equity volatility (by industry) : σ_E
  - We use daily stock returns. Source: CRSP.[17]
  - Volatility is computed as the annualized percent standard deviation of equity returns and is estimated from the prior year stock return data for each month (i.e., compute yearly stock return, average over month, compute standard deviation using prior 12 months)

[15] This expression can also be written as a function of the leverage ratio $\sigma_E = \left(\frac{1}{1-R}\right)\mathcal{N}(d_1)\sigma_V$ where we have used standard accounting rules so $V = F + E$.

[16] References to Compustat herein refer to Compustat data from S&P Global Market Intelligence (2019) via Wharton Research Data Services (WRDS).

[17] References to CRSP herein refer to data from CRSP US Stock Database (2019) from the Center for Research in Security Prices, LLC (CRSP) via WRDS.

- We use 12 years of data that ends in December of 2019. We only include firms that report stock prices and shares for at least 9 years. We use this 12 year period to include the variation caused by the global financial crisis in 2008 and 2009.

- Market value of equity (by industry): E
  - Source: CRSP
  - Market value of each firm's equity calculated as the product of share price at the end of the month and the number of shares outstanding
  - Data for December 2019. We include information for all firms with positive assets.

- Face value of Debt F
  - Source: Compustat (Annual)
  - As in Bharath and Shumway (2008) we use debt in current liabilities plus one-half of long term debt and set $T = 1$
  - Data for December 2019. We include information for all firms with positive assets.

- Risk free rate: r
  - Source: FRED. Constant Maturity Treasury, One year maturity.[18]
  - We use the average of 12 years of data that ends in December of 2017 (similar period as for σ_E).

- Leverage Ratios
  - Our base estimate corresponds to F/V.

When there is no data available at the industry level we use estimates from one level higher of aggregation. For example, there are no reporting firms for NAICS 55 (Management of Companies and Enterprises). In order to estimate V and σ_V for this industry, we take the average of $\{\sigma_E, E, F\}$ from industries with NAICS codes 51, 52, 53, 54, and 56. If there is no information for an industry at the 3-digit level we use the values at the 2-digit level.

[18]Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis [DGS1], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS1.

A-4.2 Estimating Climate Transition Losses

As in Reinders, Schoenmaker, and Van Dijk (2023), we will assume an instantaneous shock ξ (but that takes into account the full transition) on asset values such that immediately after the shock the asset value of the average firm in industry k adjusts from V_k to V_k^* where V_k^* is given by

$$V_k^* = (1 - \xi_k)V_k. \tag{A.4.14}$$

The parameter ξ_k is the asset valuation shock that we estimate by linking the discount flow of losses due to carbon taxes. More specifically, the net present value of carbon taxes in industry k is

$$NPV_{tax,k} = \sum_{t=0}^{T}(1 - r_k)^{-t}\gamma_k\tau_t \tag{A.4.15}$$

where γ_k denotes the exposure of industry k to the carbon tax τ_t in period t, and r_k is the discount rate in industry k. We associate γ_k with the level of emissions (in metric ton of CO2-eq). The particular application will determine whether we use direct or embodied emissions. Finally, the fraction of the market value of the firm lost due to carbon taxes is

$$\xi_k = \frac{NPV_{tax,k}}{\text{Total Asset Value}_k}. \tag{A.4.16}$$

With an estimate of ξ_k, we use the Merton model estimates (presented in the previous section) to derive the losses in the market value of debt and equity.Let D denote the market value of debt. D is given by

$$\begin{aligned}
D_k &= V_k - E_k \\
&= V_k - V_k\mathcal{N}(d_1) + F_k e^{-rT}\mathcal{N}(d_2) \\
&= V_k(1 - \mathcal{N}(d_1)) + F_k e^{-rT}(1 - \mathcal{N}(-d_2)) \\
&= V_k\mathcal{N}(-d_1) + F_k e^{-rT}(1 - \mathcal{N}(-d_2)) \\
&= F_k e^{-rT} - F_k e^{-rT}\mathcal{N}(-d_2) + V_k\mathcal{N}(-d_1),
\end{aligned}$$

where we have used the fact that $\mathcal{N}(x) = (1 - \mathcal{N}(-x))$.

Similarly, the market value of debt after the shock is

$$D_k^* = F_k e^{-rT} - F_k e^{-rT}\mathcal{N}(-d_2^*) + V_k^*\mathcal{N}(-d_1^*). \tag{A.4.17}$$

where d_1^* and d_2^* correspond to values of d_1 and d_2 evaluated using V_k^*.

Using these expressions we can obtain the ratio of the value of debt after the shock to the original value (which equals one minus the losses in the market value of debt) ϑ_D

$$\vartheta_{D,k} = \frac{D_k^*}{D_k} = \frac{F_k e^{-rT} - F_k e^{-rT}\mathcal{N}(-d_2^*) + (1-\xi_k)V_k\mathcal{N}(-d_1^*)}{F_k e^{-rT} - F_k e^{-rT}\mathcal{N}(-d_2) + V\mathcal{N}(-d_1)} \tag{A.4.18}$$

Using equations (A.4.10) and (A.4.14) we can also derive a similar ratio for the value of equity

$$\vartheta_{E,k} = \frac{E_k^*}{E_k} = \frac{(1-\xi_k)V_k\mathcal{N}(d_1^*) - F_k e^{-rT}\mathcal{N}(d_2^*)}{V\mathcal{N}(d_1) - F_k e^{-rT}\mathcal{N}(d_2)}. \tag{A.4.19}$$

We define the ratio of the firm post-shock market value to pre-shock market value as (i.e., the debt and equity post to pre-value ratios weighted according to the leverage ratio)

$$\overline{\vartheta}_k = \frac{F_k}{V_k}\vartheta_{D,k} + (1 - \frac{F_k}{V_k})\vartheta_{E,k}. \tag{A.4.20}$$

We define the market value loss as

$$\lambda_k = 1 - \overline{\vartheta}_k. \tag{A.4.21}$$

The industry level estimates of climate transition risk losses at the industry level we present in the paper (see Tables 2 and 3) and from where we derive the regional and bank level losses correspond to the estimated values of λ_k. The correlation between λ_k and ξ_k is above 0.99.

A-4.2.1 Calibration and Transition Scenarios

We present in this section the calibration of the transition risk scenarios.

- We assume that $\tau_t =$ can take two values \$40 and \$100 per ton of CO2 for all t.
  - The announcement of the tax is unexpected and the change lasts forever.
  - The exposure of each sector to the tax corresponds to our estimates of direct emissions or embodied emissions.
- We assume that the discount factor is equal to 6% as in Reinders, Schoenmaker, and Van Dijk (2023).
- We do not have information on the asset valuation of non-public firms but emissions correspond to total emissions at the sector/industry level, so we proceed as follows
  - Since we only know the total asset value (by industry) for public firms, we estimate emissions from public firms to then compute ξ_k. For every industry, we have

access to output per product from EXIOBASE. We can allocate output per product to NAICS as we do with emissions to then compute a measure of emissions per output (emission intensity) entirely from EXIOBASE. That is, letting y_k^{ex} denote total output in industry k from EXIOBASE, we can compute $\phi_k = e_k / y_k^{ex}$ where e_k denotes emissions (direct or embodied) in sector k (that is, the vector e_k corresponds to vector $\mathbf{f}$ in Section A-3.1 when we use directions and to the vector $\mathbf{e_y}$ in Section A-3.2 when we use embodied emissions).

– Then, using the estimated emission intensity by sector, we can compute total emissions for public firms as follows

$$\hat{e}_k = \phi_k y_k^{co},$$

where y_k^{co} denotes total output (sales) from Compustat in industry k. We can obtain Total asset value$_k$ by computing the total market value of firms in Compustat (denoted by $\overline{V}_k$) by using the estimated asset market value of the representative firm in industry k (V_k) times the number of firms in the industry.

$$\xi_k = \frac{\overbrace{\sum_{t=0}^{T}(1-r_k)^{-t}\hat{e}_k\tau_t}^{NPV_{tax,k}}}{\underbrace{\overline{V}_k}_{\text{Total Asset Value}_k}}. \tag{A.4.22}$$

Note that we are implicitly assuming that emissions and sales (or dividends) grow at the same rate.

- We will index the market value loss λ_k (see equation (A.4.21)) by the value of the tax $\tau \in \{\$40, \$100\}$ and the distribution of emissions $e \in \{\text{Direct}, \text{Embodied}\}$ used to compute the underlying shock ξ_k in equation (A.4.22).

A-5 A Simple Production Network Model

We present a simple production network model along the lines of Krivorotov (2022) and Devulder and Lisack (2020) and focus on carbon taxes on production that propagate to the rest of the economy via the endogenous input-output linkages.

A-5.1 Environment

Let $k \in \mathcal{C} = \{USA, ROW\}$ and $i \in \{1, \dots, N\}$ the number of industries. Each country has a representative firm for each industry and firms operate in a competitive market. The production technology is modeled as a nested Constant Elasticity of Substitution (CES):

$$y_{ik} = A_i \left(\mu_{ik}^{\frac{1}{\eta}} \ell_{ik}^{\frac{\eta-1}{\eta}} + \alpha_{X_{ik}}^{\frac{1}{\eta}} X_{ik}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{A.5.23}$$

where A_i is aggregate productivity, ℓ_{ik} represents labor demand in industry i in country k, and X_{ik} the demand of intermediate inputs for total production y_{ik}. The elasticity of substitution between labor and other inputs is η and $\mu_i k$ corresponds to the labor share in production for the industry with $\mu_{ik} + \alpha_{X_{ik}} = 1$. Firms in country k pay wages w_k.

Aggregate intermediate inputs are also aggregated using a CES function:

$$X_{ik} = \left(\sum_{l \in \mathcal{C}} \sum_{j=1}^{N} \left(\frac{\alpha_{ik}^{jl}}{\alpha_{X_{ik}}} \right)^{\frac{1}{\sigma}} \left(x_{ik}^{jl} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{A.5.24}$$

where x_{ik}^{jl} denotes input demand of product from industry j in country l from industry i in country k. σ captures the elasticity of substitutions across intermediate products and α_{ik}^{jl} the factor shares. That is parameters in the production function correspond to share of input j from country l in the production of good i in country k and satisfy

$$\sum_{l \in \mathcal{C}} \sum_{j=1}^{N} \alpha_{ik}^{jl} = \alpha_{X_{ik}}.$$

Prices for intermediate inputs from country l in industry j are denoted by p_{jl}. Firms pay production taxes $\tau_{ik} = \tau e_{ik}$ proportional to their production tax where τ is the corresponding carbon tax and e_{ik} is the emission intensity of industry i in country k.

The representative consumer in country k is endowed with $\bar{l}_k$ units of labor. Consumer preferences are $\nu_{k,-k} \frac{C_k^{1-\varphi} - 1}{1-\varphi}$ where C_k denotes aggregate consumption in country k, φ captures the curvature of the utility function, and $\nu_{k,-k}$ is a scale parameter. Aggregate consumption also take a CES form. In particular, aggregate consumption is

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

where c_{ikl} represents the consumption of good in industry i and country l from country k.

The parameter ρ captures the elasticity of substitution across consumption goods and γ_{ikl} the consumption shares with $\sum_{l\in\mathcal{C}}\sum_{i=1}^{N}\gamma_{ikl}=\nu_{k,-k},\ \forall k\in\mathcal{C}$. The representative consumer receives income from wages w_k, government lump-sum transfers, and firm profits.

The government collects taxes and transfers the proceeds to the representative household. Total transfers are $T_k=\sum_{i=1}^{N}\tau e_{ik}p_{ik}y_{ik}$.

A-5.2 Equilibrium

The household in country k solves

$$\max_{c_{ik},l_{ik}} \nu_{k,-k}\frac{\left(\sum_{l\in\mathcal{C}}\sum_{i=1}^{N}\left(\gamma_{ikl}^{\frac{1}{\rho}}c_{ikl}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}\right)^{1-\phi}-1}{1-\phi} \tag{A.5.25}$$

s.t.

$$\sum_{l\in\mathcal{C}}\sum_{i=1}^{N}p_{il}c_{ikl} = w_k\sum_{i=1}^{N}l_{ik}+\sum_{i=1}^{N}\Pi_{ik}+T_k, \tag{A.5.26}$$

$$\sum_{i=1}^{N}l_{ik} = \bar{l}_k. \tag{A.5.27}$$

The solution to this problem implies

$$c_k^{jl} = \gamma_k^{jl}\left(\frac{p_{jl}}{P_k}\right)^{-\rho}C_k. \tag{A.5.28}$$

The price index is

$$P_k = \left(\sum_{l\in\mathcal{C}}\sum_{j=1}^{N}\gamma_k^{jl}p_{jl}^{1-\rho}\right)^{\frac{1}{1-\rho}}\quad \forall\ k. \tag{A.5.29}$$

A firm in industry i in country k solves

$$\Pi_{ik}(p,\tau)\equiv\max_{y_{ik},\ell_{ik},x_{ik}^{jl}}\pi_{ik}=(1-\tau e_{ik})p_{ik}y_{ik}-w_k\ell_{ik}-\sum_{l\in\mathcal{C}}\sum_{j=1}^{N}p_{jl}x_{ik}^{jl} \tag{A.5.30}$$

s.t.

$$y_{ik}=A_i\left(\mu_{ik}^{\frac{1}{\eta}}\ell_{ik}^{\frac{\eta-1}{\eta}}+\alpha_{X_{ik}}^{\frac{1}{\eta}}X_{ik}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{A.5.31}$$

$$X_{ik} = \left(\sum_{l \in \mathcal{C}} \sum_{j=1}^{N} \left(\frac{\alpha_{ik}^{jl}}{\alpha_{X_{ik}}} \right)^{\frac{1}{\sigma}} \left(x_{ik}^{jl} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{A.5.32}$$

where p_{ik} is the price of the good k, l, e_{ik} emissions, ℓ_{ik} is employment, X_{ik} denote aggregate intermediate goods, and x_{ik}^{jl} intermediate inputs from industry j in country l used for production in industry i in country k.

The solution to problem (A.5.30) for each sector i in country k implies:

$$\ell_{ik} \quad : \quad \frac{\ell_{ik}}{y_{ik}} = \mu_{ik} \left(\frac{p_{ik}(1 - \tau e_{ik})}{w_k} \right)^{\eta} \tag{A.5.33}$$

$$X_{ik} \quad : \quad \frac{X_{ik}}{y_{ik}} = \alpha_{X_{ik}} \left(\frac{p_{ik}(1 - \tau e_{ik})}{P_{X_{ik}}} \right)^{\eta} \tag{A.5.34}$$

$$x_{ik}^{jl} \quad : \quad \frac{x_{ik}^{jl}}{X_{ik}} = \frac{\alpha_{ik}^{jl}}{\alpha_{X_{ik}}} \left(\frac{P_{X_{ik}}}{p_{jl}} \right)^{\sigma} \tag{A.5.35}$$

From cost minimization, obtain price aggregates for the CES basket of intermediates

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

Combining (A.5.34) and (A.5.35) we obtain the intermediate input demands

$$x_{ik}^{jl} \quad : \quad \frac{x_{ik}^{jl}}{y_{ik}} = \alpha_{ik}^{jl} \frac{(p_{ik}(1 - \tau e_{ik}))^{\eta}}{(p_{jl})^{\sigma}} P_{X_{ik}}^{\sigma-\eta} \tag{A.5.36}$$

In equilibrium, firms make zero profits. This implies that

$$(1 - \tau e_{ik}) p_{ik} = \left(\mu_{ik} w_k^{1-\eta} + \alpha_{X_{ik}} P_{X_{ik}}^{1-\eta} \right)^{\frac{1}{1-\eta}} \quad \forall \, \{i, k\}. \tag{A.5.37}$$

To complete the equilibrium, we also require market clearing

$$y_{ik} = \sum_{l \in \mathcal{C}} \sum_{j=1}^{N} x_{jl}^{ik} + \sum_{l \in \mathcal{C}} c_l^{ik}, \quad \forall \, \{i, k\} \tag{A.5.38}$$

$$L_k = \sum_{i=1}^{N} \ell_{ik}, \quad \forall \, \{k\}. \tag{A.5.39}$$

Aggregate consumption is given by

$$C_k = \frac{\sum_l \left(w_l L_l + \sum_j \tau e_{jl} y_{jl} \right)}{\sum_l \nu_{k,l} (P_k/P_l)^{1/\varphi} \left(\sum_m \sum_j \gamma_l^{jm} P_l^{\rho} p_{jm}^{1-\rho} \right)} \tag{A.5.40}$$

and government transfers satisfy $T_k = \sum_{i=1}^{N} \tau e_{ik} p_{ik} y_{ik}$.

A-5.3 Calibration

To provide a comparison with our baseline estimates we use EXIOBASE to calibrate the parameters of the model. The calibration requires the use of the full Input-Output table. For this reason, we work at the 2-digit level of disaggregation as mapping the EXIOBASE industry Input-Output table to 2-digit NAICS is straightforward. Constructing this mapping at the 3-digit level is not possible so we would have to restrict to EXIOBASE industries or use different sources for the baseline model and this exercise. We map the 163 industries to 2-digit NAICS codes using the mapping provided by EXIOBASE.

We assume that there are two countries, the US and the rest of the world (ROW). We set $A_i = 1$ and, in the baseline, we normalize all prices to 1 ($w_{USA} = p_{i,USA} = p_{i,ROW} = 1$). In the baseline, we set $\tau_{ik} = 0$.

The parameters α_{ijkl} can be calibrated using the ratio of intermediate expenditures to gross output. That is, from equation (A.5.36) when $p_{ik} = p_{jl} = 1$ and $\tau_{ik} = 0$

$$x_{ijkl} = \alpha_{ijkl} y_{ik} \quad \Rightarrow \alpha_{ijkl} = x_{ijkl}/y_{ik}.$$

The vector of parameters μ_{ik} can be calibrated using the ratio of value added to gross output. From the FOC with respect to l_{ik}

$$l_{ik} = \mu_{ik} y_{ik}$$

so, in the baseline where all other factors other than labor are intermediate inputs, μ_{ik} can be calibrated using the ratio of value added to total output

$$\mu_{ik} = \frac{l_{ik}}{y_{ik}} (w_k)^{\eta} = \frac{VA_{ik}}{y_{ik}},$$

where VA_{ik} corresponds to Value Added in industry i in country k. The consumption share parameters equal to consumption shares (ratio of consumption of good i of country l in country k to total consumption in country k)

$$\gamma_{ikl} = \frac{c_{ikl}}{C_k}.$$

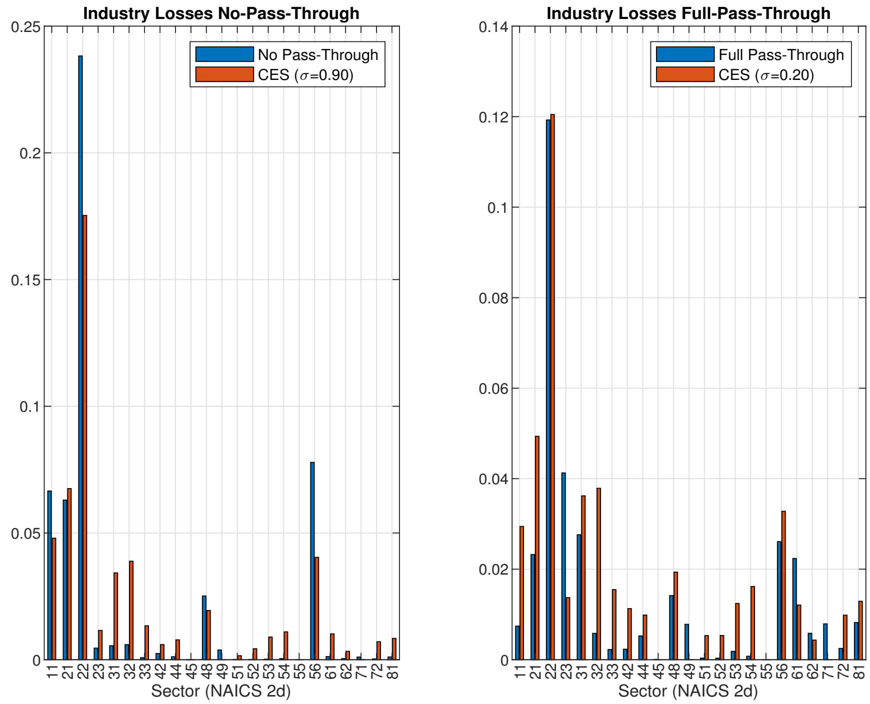
The preference parameters ρ and φ are set to standard parameters ($\rho = 0.90$ and $\varphi = 2$). The elasticity of labor and other inputs is set to a value commonly used in the literature $\eta = 0.80$ (e.g. Krivorotov (2022) and Devulder and Lisack (2020)). We evaluate different values of σ which captures different degrees of intermediate input substitution and thus implies different effects. We use two extreme values $\sigma \in \{0.20, 0.90\}$ to represent the case with a low elasticity of substitution (consistent with our Full Pass-through case) and a case with a high elasticity of substitution (consistent with the No Pass-Through case). We also present results for an intermediate value $\sigma = 0.55$.

We set e_{ik} using emission intensities (computed as the ratio of emissions to gross output). As described above, in the baseline, we set $\tau = 0$. As in our benchmark model we evaluate the introduction of a \$40 dollar and a \$100 dollar carbon tax (per ton of CO2 eq emissions).

A-5.4 Results

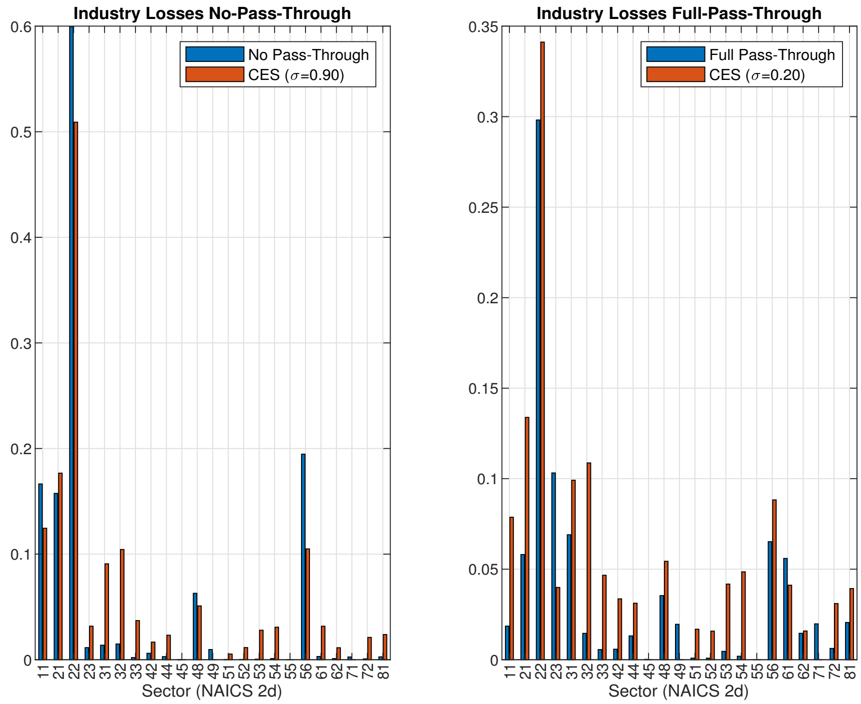
We solve the model described in this appendix for $\tau \in \{\$40, \$100\}$ and $\sigma \in \{0.20, 0.90\}$ and compare the results with our baseline estimates. Figure A.1 presents the results for the case when $\tau = \$40$ and Figure A.2 for the case when $\tau = \$100$. There is significant correlation across estimates. The correlation between the losses under the No Pass-Through case and losses when $\sigma = 0.90$ equals 0.9626 and the correlation between losses under the Full Pass-Through case and losses when $\sigma = 0.20$ equals 0.8841 (for both levels of τ). The production network model captures somewhat larger losses for the manufacturing and trade sectors (for low and high elasticity of substitution) than our baseline model. Estimates in the No Pass Through case appear to be larger in the Utilities sector (NAICS = 22) in our simple model than in the endogenous production network model but that difference disappears when we compare the Full Pass-Through case and the production model with $\sigma = 0.20$.

Figure A.1: Comparison Models: Industry Losses τ =\$40 per ton



Note: Estimates of industry losses (2-digit NAICS) across models. Full Pass-through and No Pass-through correspond to the results in our baseline model. CES ($\sigma \in \{0.20, 0.90\}$) correspond to results for $\sigma \in \{0.20, 0.90\}$ correspond to output losses derived from the production model presented in this appendix.

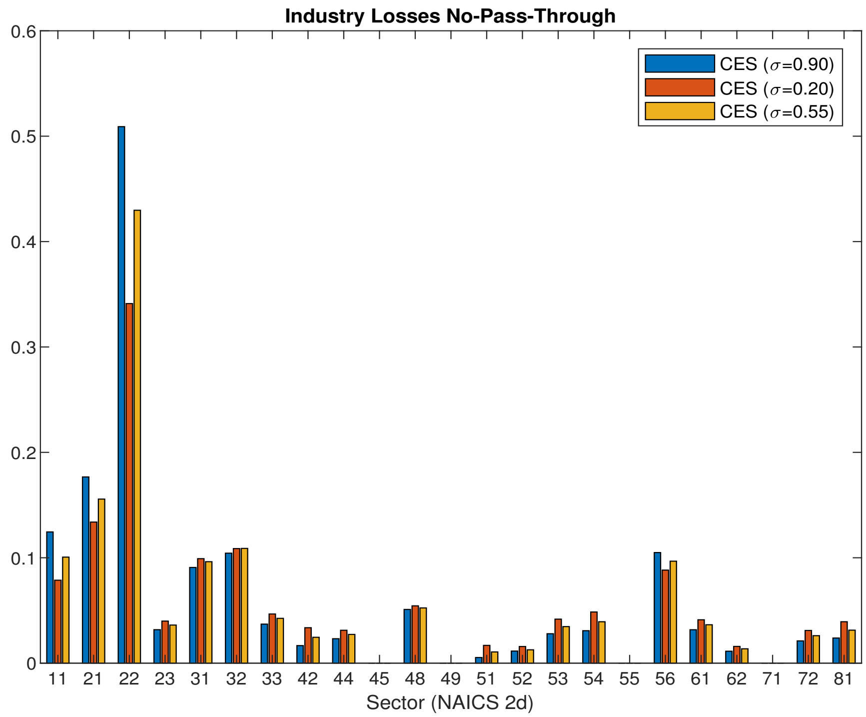
Figure A.2: Comparison Models: Industry Losses τ =\$100 per ton



Note: Estimates of industry losses (2-digit NAICS) across models. Full Pass-through and No Pass-through correspond to the results in our baseline model. Results for $\sigma \in \{0.20, 0.90\}$ correspond to output losses derived from the production model presented in this appendix.

We use the model to understand an intermediate case for the elasticity of substitution across intermediate inputs. We solve the model for $\sigma = 0.55$. Figure A.3 presents the results for the $\tau = \$100$ case. The results show that output losses scale almost linearly with changes in the elasticity. That is, $\sigma = 0.55 = \frac{(0.90+0.20)}{2}$ (i.e., the simple average of the two elasticity values previously considered) and output losses when $\sigma = 0.55$ are approximately the average of the losses for the case of $\sigma = 0.20$ and $\sigma = 0.90$. For example, output losses for Utilities (NAICS #21) when $\sigma = 0.55$ equals 15.57% while the average of the $\sigma = 0.20$ and $\sigma = 0.90$ equals 15.53%.

Figure A.3: Industry Losses τ =\$100 per ton for different values of σ

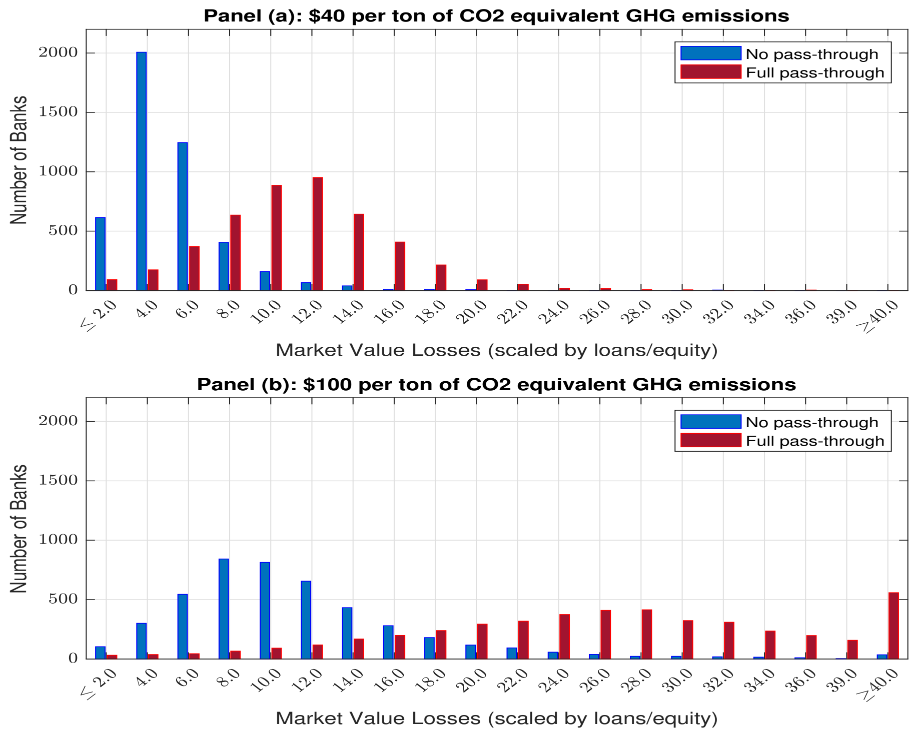


Note: Estimates of industry losses (2-digit NAICS). CES ($\sigma \in \{0.20, 0.55, 0.90\}$) correspond to results of the production network model presented in this Appendix for $\sigma \in \{0.20, 0.55, 0.90\}$.

A-6 Assessing Transition Risks at Community Banks

We complement the aggregate estimates presented in Table 6 and compute the distribution of market value losses at the bank level scaled by the loan to equity ratio. That is, we show the distribution of $\Lambda_i^e = \Lambda_i \frac{L_i}{E_i}$ which measures the impact of a carbon tax on the loan portfolio of a bank scaled by equity. Figure A.4 present the histogram for $\tau \in \{\$40, \$100\}$.

Figure A.4: Market Value Losses at the Bank Level (scaled by the loan /equity ratio) ($\tau \in \{\$40, \$100\}$



Note: Histogram of market value losses at the bank level scaled by the loan to equity ratio ($\Lambda_i^e = \Lambda_i \frac{L_i}{E_i}$) for $\tau \in \{\$40, \$100\}$. Each panel compares the No Pass-Through case with the Full Pass-Through case.

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