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Abstract

We find that banks' credit exposures to transition risks are modest. We build on the estimated sectoral effects of climate transition policies from general equilibrium models. Even when we consider the strictest policies or the most adverse scenarios, exposures do not exceed 14 percent of banks' loan portfolios. We also find that commonly used carbon emissions can explain at most 60 percent of bank exposures estimated off general equilibrium models. Moreover, we find evidence of bank management of transition risk exposures. Banks that signed the Net-Zero Alliance have reduced their exposures compared to non-signatories, mainly by cutting lending to the riskiest industries.

Key words: banks' climate risk exposures, climate transition risks, NGFS scenarios

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1 Introduction

Growing evidence of climate change has heightened policymakers' interest in understanding the potential impact climate transition risks may have on the financial system.[1] For example, the 2021 Financial Stability Oversight Council (FSOC) report notes "... the economic effects associated with transitions may be transmitted through the financial sector, and the economy in ways that weaken the resilience of financial institutions or the financial sector." A 2021 European Central Bank (ECB) report notes "The financial system is exposed to transition risk arising, for example, from exposures to firms with high carbon emissions throughout their value chains." In this paper, we investigate the importance of transition risks to financial stability by assessing the impact of transition policies on U.S. banks, including those that have joined the Net-Zero Banking Alliance.

Understanding the answer to this question is important because there are growing concerns that financial institutions may be underestimating their exposures to climate transition risk. It also helps us ascertain the implications of alternative policies/paths toward a low-carbon economy for the banking sector. Additionally, it tells us whether U.S. banks have started to adjust their lending policies in response to them joining the Net-Zero Banking Alliance.

Evaluating banks' exposures to transition risks is challenging because it requires, among other things, understanding borrowers' responses to policies that aim at fostering the transition. To date, attempts to ascertain these exposures have tackled this challenge by building on measures of borrowers' carbon emissions. We take a different approach and leverage insights from the literature that has investigated the effects of transition policies on the U.S. economy. Specifically, we build on the sectoral estimates of transition policies generated by Jorgenson et al. (2018), Goulder and Hafstead (2018), and the G-Cubed model estimates of the Network for Greening the Financial System (NGFS)

[1] *Transition risks* are associated with the losses resulting from a transition of production and consumption towards methods and products that are compatible with a net-zero economy while *Physical risks* are the damages to facilities, operations, and assets caused by climate change-induced hazards.

scenarios (NGFS, 2022a).[2] A distinct, and important, feature of these studies is that they all derive their estimates of the policies' effects from general equilibrium models.[3]

Jorgenson et al. (2018) report industry-level estimates of output effects from different carbon taxes and redistribution mechanisms computed off their Intertemporal General Equilibrium Model (IGEM).[4] Goulder and Hafstead (2018), in turn, report industry-level estimates of profit effects from carbon taxes generated from their Environment-Energy-Economy (E3) model. Lastly, NGFS (2022a) estimate industry-level effects using the G-Cubed model for the U.S. from the three alternative climate scenarios adopted by NGFS. Given that each of these models is based on different assumptions and distinct methodologies, we will focus on comparing banks' exposures for different policy scenarios generated by the same model, rather than across models.

We combine the industry-level estimates from these exercises with loan-level data from the Federal Reserve's Y-14 data collection to estimate banks' exposures to the various transition policies. Since 2011, large banks with more than $50 billion in assets are required to report detailed information on most types of commercial and industrial (C&I) loans on their balance sheet with a commitment of $1 million or more. This data is ideal for our investigation because, in addition to reporting information on the loan, it also contains information on the borrower, including its sector of activity. Also, the data collection not only covers publicly listed and large private borrowers but also medium-sized businesses.

We assume that banks maintain a static portfolio of credit exposures.[5] In other words, we take these exposures as of year t and investigate how they will be impacted

[2]Another valuable approach involves exploiting prior implementations of transition policies, such as cap-and-trade (e.g., Kumar and Purnanandam, 2022; Ivanov et al., 2022). It is worth noting, however, that challenges associated with external validity may be present.

[3]Note that the outputs of these models are conditional on realizations of specific climate transition policies and do not factor in the uncertainties surrounding which policy would be implemented. We use the terms "climate risk" and "realizations of climate risk" interchangeably, as is commonly done in the climate finance literature.

[4]See Jorgenson et al. (2013) for more details on IGEM Model.

[5]More generally, we assume the industry shares of banks' loan portfolios remain the same over time.

given the change in industries' valuations by 2050 generated by the model from Jorgenson et al. (2018) and NGFS (2022a).[6] In the case of the model from Goulder and Hafstead (2018), we consider the model's estimates of the present value of the industries' changes over the infinite horizon induced by the transition policies.

This brings us to the last challenge we need to address: how do changes in industries' output and profits affect the value of the credit claims banks have on the borrowers in these industries? We consider three alternative approaches to tackle this problem. The first approach assumes a one-to-one relationship between industry effects and bank exposures. Under this approach, if the industry's output (profit) declines by $x\%$ as a result of the transition policy, we assume the value of the bank's claims on borrowers in that industry will decline by the same $x\%$. The second approach adjusts banks' exposures by factoring in historical information on the probability of default (PD) and loss given default (LGD). Finally, the third approach assumes banks' exposures to the top decile (or top two deciles) of the industries most affected by the policy lose their entire value. In this way, we measure banks' exposure to highly-exposed industries.

Our analysis yields three important findings. First, U.S. banks' exposures to transition risks while nonnegligible, are modest.[7] The average bank's exposure to transition risks as of 2023 does not exceed 14% of their loan portfolios under all of the scenarios we consider. For reference, banks projected a 7% C&I loss rate under the 2023 Stress Test severely adverse scenario. However, we find significant variation in banks' exposures across transition policies. According to Jorgenson et al. (2018), the average bank's exposure to transition risks varies between 0.5% and 3.5% as of 2023 with the latter emerging when we consider the policy that sets an initial carbon tax of $50 which

[6]Note that while financial frictions can affect the implications of transition risks (Carattini et al., 2021), the models we use do not consider those effects.

[7]This finding aligns with the ECB's climate stress test results (European Central Bank, 2023), especially when assessing the NGFS scenarios, which closely resemble the ECB's scenarios. The ECB reported median predicted bank losses ranging from 0.7% to 0.9% relative to total credit exposure across scenarios. In our baseline scenario, average bank losses range from 1.8% to 6.4%. Yet, when factoring in loans' PDs and LGDs to align with the ECB's methodology, our estimated losses range between 0.5% and 1.3%, close to the ECB's estimate.

grows at 5% per year. For Goulder and Hafstead (2018), the average bank's exposure varies between -1% and about 1% as of 2023, with the latter induced by a $20 initial carbon tax, which grows at 4% per year. Finally, for the NGFS (2022a) model, the average bank's exposure varies between about 2% and 6.4% as of 2023, with the latter occurring in the disorderly transition scenario.

Banks' exposures also vary with the type of arrangement considered to redistribute the carbon tax revenue with the lump sum dividend being the least favorable for banks. Banks' exposures decline when we factor in historical information on loans' PDs and LGDs. On the other hand, they increase when we assume large devaluations in loans to the riskiest industries. For instance, when examining the Jorgenson et al. (2018) model and assuming that loans to the riskiest industries lose their entire value, the average bank exposure reaches 12%-14% as of 2023, up from the 0.5%-3.5% baseline.[8] These results are based on projections of changes in output occurring by 2050, and therefore, are not informative if sudden changes occur along the transition trajectory. Yet, we can estimate the impact of such changes using NGFS (2022a), the only model providing estimates of changes in industry output *along the paths*. Under NGFS' disorderly scenario, banks face no exposure up until 2029, but the shock from the implementation of policies in 2030 leads to at most a 4% immediate decline in the value of banks' loan portfolio.

Second, we find that banks' emissions are unable to explain a substantial portion of their transition risks exposures computed of the estimated industry effects from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a). Emissions explain at most 60% of our measures of bank exposures to transition risks. Despite that, our results show that the effects of more stringent policies on banks' exposures to transition risks are strongest for high-emitting banks, pointing to the value of relying on the general equilibrium estimates of climate change policies to compute banks' exposures to transition risks.

[8]The magnitude of these changes implies that the savings from a potential preemptive divestment by banks from the riskiest industries would likely be modest, suggesting that, in a way, the static portfolio assumption is not critical.

Finally, we find evidence of a downward trend in banks' exposures to transition risks. This evidence appears to derive from banks' management of transition risks and not from a decline in the demand for bank loans by borrowers in the riskiest industries. Difference-in-differences analyses show that since the Paris Agreement highly-exposed banks reduced lending to the riskiest industries. Similarly, we find that since the Net-Zero Banking Alliance, signatories of the alliance reduced lending to the riskiest industries. Another reason is that we see evidence of borrowers in the riskiest industries disproportionately switching to non-signatory banks while borrowers in industries most prone to benefit in the transition disproportionately migrating to signatory banks.

Our paper is related to the emerging literature on financial system vulnerabilities to climate transition risks.[9] Arseneau et al. (2022) document that about one-third of US banks' corporate loans in the Y14 data are exposed to carbon emitting industries as captured by EPA data on plant-level CO2 emissions.[10] However, when they factor in the relative emissions of each industry they find that the average emissions intensity for their sample banks in 2020 is only 1.63, suggesting that for each $1 billion of credit outstanding banks fund 1.6 million metric tons of emissions. Using an environmental stress test, Battiston et al. (2017) also document that banks' direct exposure to the fossil fuel sector is small, although the exposure to all high-carbon sectors increases substantially when they account for the indirect exposure via financial counterparties. Jung et al. (2021) find that transition risk currently does not seem to pose a threat to the U.S. financial system using a market-based approach to measuring banks' exposure to transition risk. European Central Bank (2023) finds that the expected losses of European banks' credit portfolios are minimal, around 0.7% of the total loan exposure under both the accelerated and the delayed transition scenarios, and 0.9% under the

[9] A related strand of literature examines the role of commitment in bank lending in relation to transition risk. For example, Kacperczyk and Peydro (2022) and Bolton and Kacperczyk (2021b) examine the role of commitments made by firms and banks. Giannetti et al. (2023) document disconnect between environmental disclosures and bank lending. There is also a growing literature focusing on physical risks, including Blickle et al. (2021a) and Meisenzahl (2023). See Acharya et al. (2023) for a review of the literature.

[10] EPA covers CO2 emissions for all plants in the US that emit over 25,000 metric tons of CO2 equivalent per year.

late push scenario.

Consistent with this limited evidence of banks' exposures to transition risks, researchers have found mixed evidence as to whether banks factor in these risks in their lending policies.[11] Ivanov et al. (2022) show that banks responded to the California cap-and-trade bill by increasing interest rates and shortening loan maturities for high-emitting firms, and Laeven and Popov (2022) document that banks respond to the introduction of a carbon tax in the domestic market by reducing their fossil fuel lending at home and increasing their fossil lending abroad. However, Antoniou et al. (2021) document that, likely contrary to the goal of EU phase III Emission Trading System, banks lowered loan spreads, particularly to firms that proactively stored pollution permits while they were still traded at a low price. Also, Delis et al. (2019) find weak evidence that banks price climate risks in their corporate loans while looking at borrowers' exposure to transition risks as captured by the borrower's fossil fuel reserves.

Our paper is closer to the studies on banks' potential vulnerabilities to climate transition risks, but it differs from them in one important way. Existing studies capture banks' exposures to transition risks by considering the level of CO2 emissions of borrowers (industries) they have granted loans to. By contrast, we capitalize on general equilibrium industry-level estimates of the effects of different policies aimed at promoting the transition toward a net-zero economy. This difference matters for several reasons. Emissions are backward-looking and are only one of the dimensions that will be affected in a transition to a low-carbon economy. By contrast, general equilibrium estimates are forward-looking by construction and expected to capture *all* of the different facets that will be affected in that transition.[12] Indeed, as we show, emissions explain only

[11] Research in other financial markets also yields mixed evidence. Studies of the stock market (e.g. Sautner et al. (2023), Bolton and Kacperczyk (2023), Hsu et al. (2023), and Bolton and Kacperczyk (2021a)) find mixed evidence on the pricing of climate policy risks, while survey evidence indicates that institutional investors believe transition risks will materialize in the near-term (Krueger et al., 2020). Further strategies in Engle et al. (2020) and Alekseev et al. (2022) imply this risk is hedgeable. Additionally, studies of the options market (Ilhan et al., 2021) and bond market (Seltzer et al., 2022), suggest that investors in these markets factor in climate change risks.

[12] van Binsbergen and Brøgger (2022) provide a potential forward-looking approach to consider carbon emissions. In contrast, our approach does not rely on the use of carbon emissions.

a portion of the general equilibrium estimated effects of transition policies. Further, general equilibrium estimates allow us to investigate a wide range of policies that may be implemented in conjunction with carbon taxes on corporations and which might not affect corporations proportionally to their emissions such as carbon taxes on households or different redistribution policies.

On the other hand, relying on general equilibrium estimates exposes us to the usual model risk. Also, general equilibrium estimates are only available at the industry level, which precludes us from doing any borrower-level analysis and may raise concerns with banks' sorting within industries. However, our focus is on banks' overall exposures to transition risks, and differences across industries are likely more important than across borrowers within industries, particularly when defined with the level of granularity used by the general equilibrium models we consider. Further, we do not find evidence suggestive of banks' within-industry sorting of borrowers based on emissions.

The rest of the paper is organized as follows. The next section presents our data sources and describes our methodology. That section also characterizes our sample. Section 3 presents our results on banks' exposures to transition risks. This section also presents the results of a set of robustness tests we carry out. Section 4 investigates how exposures to alternative policies vary across banks depending on their current emissions funding. Section 5 examines whether banks are managing their transition risk exposures. Section 6 concludes with some final remarks.

2 Data Sources, Methodology, and Sample Characterization

2.1 Data Sources

Our main data sources are (i) the Fed's Y14 and Y9C databases, (ii) the industry estimates associated with climate transition risks from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a), and (iii) Trucost data on carbon emissions.

The FR Y-14Q data contains detailed quarterly information on various asset classes, capital components, and income components for a subset of bank holding companies (BHC) and intermediate holding companies (IHC). These include any top-tier BHC or IHC that has $50 billion or more in total consolidated assets, as well as any other bank that is or has ever been subject to the Federal Reserve's stress tests.[13]

We use the corporate loan schedule (H.1) which contains loan-level information on loans with a commitment of $1 million or more issued by the reporting bank. We include four types of loans, defined by their line numbers on schedule HC-C of the FR Y-9C reports filed by all BHCs: commercial and industrial (C&I) loans to U.S. addresses (Y-9C item 4.a), loans secured by owner-occupied nonfarm nonresidential properties (Y-9C item 1.e(1)), loans to finance agricultural production (Y-9C item 3), and other leases (Y-9C item 10.b).[14] Overall, the loans reported in the data account for a little less than two thirds of all C&I lending volume.

In comparison to other commonly used loan-level datasets (such as DealScan or the Shared National Credit (SNC) program), which are dominated by syndicated loans, the FR Y-14 includes both syndicated and non-syndicated loans. This provides an opportunity to consider loans to small and medium-sized corporations as well. Further, in contrast to DealScan which reports information only at loan origination and does not contain comprehensive information on syndicate participants' loan shares, Y-14 provides us with complete information on banks' loan portfolios at each point in time.

We focus on loans originated between 2012:Q3 and 2023:Q1 across 42 unique banks.[15] We consider both drawn and undrawn commitments in our analysis. We

[13]The size cutoff is *based on: (i) the average of the firm's total consolidated assets in the four most recent quarters as reported quarterly on the firm's Consolidated Financial Statements for Holding Companies (FR Y-9C); or (ii) if the firm has not filed an FR Y-9C for each of the most recent four quarters, then the average of the firm's total consolidated assets in the most recent consecutive quarters as reported quarterly on the firm's FR Y-9Cs.* Since 2020Q2, the respondent panel is comprised of any top-tier BHC or IHC with $100 billion or more in total consolidated assets.

[14]It is possible that carbon taxes could have an impact on banks' portfolios beyond C&I loans, such as their mortgage holdings. However, the general equilibrium models do not provide estimates of how each carbon tax would impact the savings of heterogeneous households. Thus, we focus on C&I loans as we can leverage the sectoral effects of carbon policies estimated by the models.

[15]Given that the majority of banks only report data after 2012:Q3, we drop observations prior to 2012:Q3.

complement this data with bank-level data, including bank assets and total C&I lending, from the consolidated financial statements for bank holding companies (Y-9C).

The data for our forward-looking proxies of climate transition risks come from three different sources. The first source is Jorgenson et al. (2018) who estimate industry-level changes in output from carbon taxes using the Intertemporal General Equilibrium Model (IGEM).[16] The second one is Goulder and Hafstead (2018) who estimate industry-level changes in profits induced by carbon taxes using the Environment-Energy-Economy (E3) model. The third source are the industry-output estimates for the U.S. generated by the G-Cubed model from the climate scenarios adopted by the Network for Greening the Financial System (NGFS). We provide more detail on each of these models in section 3.

Our last data source is Trucost data on carbon emissions, which is available from 2013:Q1 until 2021:Q4. Trucost provides information on greenhouse gas emissions (in millions of tons), which it collects from a variety of sources including annual reports, and firm disclosures in the Carbon Disclosure Project (CDP). Trucost also estimates emissions for non-disclosing firms when possible. Trucost reports emissions in three different categories based on the Greenhouse Gas Protocol.[17] We focus on scope 1 emissions, which are direct emissions from establishments controlled by the company.[18]

We use industry-level scope 1 emission, computed for the average firm in the industry (weighted by the firm's total assets from Compustat).[19] To address time variation in the availability of data on carbon emissions, we follow Ilhan et al. (2021) and restrict the sample to firms in the S&P 500. We compute bank carbon emissions funding as the average of each borrower's industry-level emissions, weighted by the amount of lending to that borrower. We use the finest feasible North American Industry Classifica-

[16]The authors refer to this iteration of the model as the IGEM-N, as the industries are based on NAICS-codes.

[17]`https://ghgprotocol.org/`

[18]Scope 2 emissions are indirect emissions from the purchase of electricity, steam, heat, or cooling. Finally, scope 3 emissions are indirect emissions in the supply chain that are not included in scope 2 emissions.

[19]Results are broadly similar when instead using either industry total emissions from Trucost, CDP disclosed emissions in Trucost, or industry-emissions computed from the EPA facility-level emissions data.

tion System (NAICS) industry classification. We also estimate bank emission intensity, which we calculate as bank emissions funding scaled by bank total assets.

2.2 Measuring Banks' Exposures to Transition Risk

We measure banks' exposures to transition risks, building on estimates of changes in the economic performance of different industries following the implementation of different climate policies. We begin by collecting data on climate transition risks from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a). Each of these sources provides information on the expected reduction in profits or output due to transition risks at the industry level, generated by general-equilibrium models, that vary according to different policy scenarios.[20] Next, we match the industry-level estimates from the general equilibrium models with bank loans in the Y14 based on the crosswalks provided in Tables A.1, A.2 and A.3.[21]

We then use the data to evaluate banks' exposures to transition risk. Towards that end, we compute the decrease in the value of bank loan portfolios that would occur if loan values drop by the expected reduction in output or profits provided by these proxies:

$$Exposure_{b,t}^{P} = \sum_{j \in J} w_{b,j,t} \; Markdown_{j}^{P}, \tag{1}$$

where $Exposure_{b,t}^{P}$ is the exposure of bank b to transition risk at time t under policy scenario P; $w_{b,j,t}$ is the share of bank b's loans made to industry j at time t; and $Markdown_{j}^{P}$ is the expected percentage drop in output or profits for industry j under policy P. For simplicity, we assume that loan values will be impaired proportionally to

[20] While it is important to consider the issue of international leakage in assessing carbon tax policies, the model does not account for changes in emissions in the rest of the world. Therefore, our analysis inherits this limitation.

[21] While the G-Cubed provides results for 20 industries, the mapping provided here only includes 12 industries. For our main results, we rely on the mapping with the 12 industries produced by the NGFS (2022a) authors, but in the Appendix, we report results that include all 20 industries, mapped with the Y14 using a hand-constructed mapping.

the drop in the expected output or profits of the borrower's industry.

Note that due to the general equilibrium nature of this measure, our approach captures how industries adjust their levels of production in response to transition policies.[22] However, our approach assumes that the industry composition of a bank's lending portfolio is constant over time. This implicitly assumes that when a loan matures, the bank will either refinance the loan, or extend a loan to another borrower in that industry.[23] $Exposure^{P}_{b,t}$ can therefore be interpreted as the percentage drop in the value of a bank's loan portfolio if a modeled climate policy is enacted, conditional on the allocation of loans by industry at time t.[24]

While the simplicity of our measure is appealing, we note that due to the payoff structure of loans, bank loan values are especially exposed to downside risks. As a result, it is possible that banks may be reducing their exposures to the riskiest industries, while not changing exposures to other industries. We also note that the value of bank loans may not decrease proportionally to the value of output, as banks can recover some portion of their loan balance in the event of loan default. We attempt to account for these issues by modifying our bank exposure measure, for example by factoring in historical information on loans' probability of default and loss given default.

Finally, given the frequent use of carbon emissions to assess transition risks, in the last part of our paper, we investigate to what extent our estimates of banks' exposures to transition risks are driven by their contemporaneous funding of carbon emissions.

[22]It is worth noting, however, that these models do not capture how firms in each industry may endogenously change their business models in response to those policies. Those responses are, in fact, ex-ante unclear; for instance, Shue and Hartzmark (2023) find that sustainable investing that directs capital away from brown firms and toward green firms can make brown firms *more* brown.

[23]Blickle et al. (2021b) document that banks "specialize" in industries by concentrating their lending disproportionately into one industry due to information friction. This suggests that finding a lending opportunity in a different industry would be costly.

[24]The measure also implicitly assumes that bank exposure is immediately incorporated into bank loan values at the time the policy is passed. We consider an alternative approach in subsubsection 3.3.4, which marks down the loan values gradually over a longer horizon.

2.3 Sample Characterization

After we merge the Y14 data with carbon emissions' data with the industry-level effects of climate policy measures we are left with a bank-quarterly panel with 1,340 observations from 2012:Q3 until 2023:Q1.[25]

Summary statistics are displayed in Table 1. As one would expect banks' exposures vary across the three models we consider and, within each model, across the policy scenarios. Looking at the Jorgenson et al. (2018) measures, we see that banks are more exposed to policies with higher tax rates, and higher tax growth rates. In the Goulder and Hafstead (2018) model, a corporate tax cut seems to be the most favorable tax redistribution scheme for banks. Finally, in the NGFS (2022a) model, the orderly and disorderly transition scenarios have higher exposures for banks than the current policy. We take a close look at banks' exposures to transition risks as captured by these models in the next section.

3 Banks' Exposure to Transition Risks

In this section, we first introduce our climate transition risk proxies, and examine the bank exposure measures from Equation 1 in the time series. Next, we investigate the distributions of each of these measures to understand cross-bank variation over time. Finally, we investigate the sensitivity of banks' exposures to some of the underlying assumptions we adopted.

3.1 Time Series of Banks' Transition Risk Exposures

We begin by computing each bank's exposure measure for each policy scenario explored by the three models at the quarterly level. Next, we smooth the measures at an annual

[25]Note the composition of banks varies by year.

frequency and plot the average bank's exposure in the time series.[26]

3.1.1 Building on Jorgenson et al. (2018) Carbon Taxes

Our first analysis of banks' exposures to transition risks builds on the version of the IGEM-N provided in Jorgenson et al. (2018).[27] Jorgenson et al. (2018) structure the economy around 36 industries, which are based on the NAICS.[28] The authors use that general equilibrium model to produce industry-level estimates of the impact of carbon taxes for a variety of initial tax levels, annual tax growth rates, and methods of recycling the income back into the economy. In each scenario, the tax is instated in 2020, and grows from 2020 until 2050, so the exposure measure can be seen as the reduction in the value of a bank's loan portfolio from time t until 2050.

We use two sets of estimates from Jorgenson et al. (2018). The first set provides changes in output for different initial tax levels and annual tax growth rates, while keeping the form of income recycling constant as a lump sum redistribution. Estimates for these scenarios are provided in Table 8 of Jorgenson et al. (2018), which is reproduced in Table A.4. The second set of estimates varies the form of income recycling used, while keeping the initial tax level constant at $25 and the annual tax growth rate constant at 5%. Estimates in these scenarios are provided in Table 9 of Jorgenson et al. (2018), which is reproduced in Table A.5.[29] Their results show that higher taxes and growth rates lead to larger decreases in industry output, and that carbon intensive industries, such as coal mining, face the largest decreases in output. They also show that tax cuts tend to have relatively lower decreases in industry output than a lump sum redistribution.

Figure 1 plots the time series evolution of the average bank's exposure to tran-

[26] Bank exposures are weighted by bank total assets in calculating the average bank's exposure.

[27] Note Jorgenson et al. (2018) builds on previous work from Jorgenson et al. (2013).

[28] IGEM-industries are mapped to the Y14 by NAICS, forcing us to drop loans which do not map to an IGEM-industry. This exclusion amounts to 1.2% of the loans in the sample in 2023:Q1.

[29] Both sets of estimates give percent changes in domestic industry output from 2015 until 2050 by scenario, although the estimates are transformed to show the percent decrease in the domestic output instead of the percent change.

sition risks based on the first set of policies (carbon tax rates), and shows that the exposures are stable over time for all four tax rate policies. This suggests that, on average, banks' loan portfolio composition with respect to the industry classification of Jorgenson et al. (2018) is persistent over time. Comparing across policies, we see that the \$50 initial tax rate and 5% growth rate scenario, where both the initial tax and growth rate are the highest, has the highest estimated exposure. Here, we expect the loan portfolio of the average bank would lose about 3.5% of its value. Figure A.1 presents the 10th and 90th percentile range of exposure for each point in time and suggests that there is limited cross-sectional variation in the exposure across banks.

Figure 2 plots the time series evolution of the average bank's exposure based on the second set of policies (lump sum redistribution, capital tax cut, and labor tax cut). The average bank loses about 2% of its value with a lump sum redistribution policy. On the other hand, a capital tax cut or a labor tax cut only reduces the bank's loan value by approximately 0.5%. Figure A.2 suggests that there is little cross-sectional variation in the exposure across banks; the range between 10th and 90th percentile is at most about 1.5% for all three policies.

3.1.2 Building on Goulder and Hafstead (2018) Carbon Taxes

We use Goulder and Hafstead (2018) to obtain our second estimate of banks' exposures to climate transition risk. Goulder and Hafstead (2018) uses the E3 model to examine how different climate policies (carbon taxes and alternative ways to redistribute the tax revenue) affect firms and households. Like IGEM-N, the model is multiperiod and general equilibrium.

However, it is not possible to readily compare banks' exposures from the E3 model with those from the IGEM-N because the two models differ in important ways. For instance, while Jorgenson et al. (2018) does not include a renewable energy industry, Goulder and Hafstead (2018) includes a non-fossil electricity generation sector which benefits from carbon taxes. This also allows industries to endogenously change their energy mix in response to changes in climate transition policy. Additionally, while Jorgenson et al. (2018) provides estimates of changes in industry performance from 2015 until 2050, Goulder and Hafstead (2018) provides estimates over an infinite time horizon, so we can interpret this exposure as the reduction in the value of a bank's loan portfolio from time t over the infinite time horizon. Their estimates assume that an unanticipated carbon tax is enacted in 2017, which grows to \$20 per ton of carbon emissions by 2019. After 2019, the tax is increased in real terms by 4% annually until 2048 when it reaches \$60 per ton.

We use the estimates on changes in US industry profits for 35 industries from the carbon tax provided in Table 5.4 of Goulder and Hafstead (2018), which is reproduced in Table A.6.[30] Figure 3 plots the time series evolution of the average bank's exposure based on Goulder and Hafstead (2018) model. Once again, there is little time-series variation, suggesting that banks' average bank's loan portfolio composition is persistent. However, the exposure estimates are especially low based on Goulder and Hafstead (2018) model. The average bank's loan value is expected to fall by around 1% under the first three scenarios (a lump sum redistribution, a payroll tax cut, and an individual income tax cut). Interestingly, when a corporate tax cut is introduced, the exposure is negative (-1%), meaning that the average bank would benefit from the policy. This is primarily because according to Goulder and Hafstead (2018), profits actually increase for 20 out of the 35 industries given the combination of a carbon tax and a corporate tax cut. For example, when the carbon tax revenue is recycled through a corporate tax cut, profits in the oil industry increase by 6.8%. Like exposure measures based on Jorgenson et al. (2018), Figure A.3 suggests that there is little cross-sectional variation in the exposure across banks in recent years.

[30] E3-industries are mapped to the Y14 by NAICS, forcing us to drop loans which do not map to an E3-industry. This exclusion amounts to 6.9% of the loans in the sample in 2023:Q1.

3.1.3 Building on NGFS (2022a) scenarios

Last, we use the NGFS (2022a) industry-level estimates of the impact of climate policies. Specifically, we use the G-Cubed model estimates of the NGFS scenarios. The G-Cubed is a general equilibrium model that provides information on both macroeconomic and environmental outcomes in the context of the transition to a net zero economy, (NGFS, 2022a). A set of the results from the G-Cubed model are presented on an online dashboard, which includes sectoral-level results for 12 sectors within the U.S. (NGFS, 2022b).[31] The estimates we use are included in Table A.7.[32]

NGFS (2022a) is unique in that the scenarios are designed to match specific climate goals. The G-Cubed model endogenously estimates what carbon tax is needed to achieve that goal. The first scenario is that current policies remain in place, which are insufficient to achieve net-zero emissions. For this scenario, a \$3.72 carbon tax is instated in 2021, that grows nonlinearly to \$26.50 in 2050. The second one is an "orderly transition", where the necessary policy mix to achieve net-zero carbon emissions by 2050 is adopted. For this scenario, a \$16.75 carbon tax is instated in 2021 that grows nonlinearly to \$119.14 in 2050. The proceeds of this tax are used to invest in infrastructure and pay down government debt. The third scenario is a delayed transition where a policy to limit end-of-century temperature rise to below 2 degrees is adopted in 2031, requiring more stringent policies than would otherwise be needed. For this scenario, no carbon tax is in place until 2030, at which point a \$31.52 carbon tax that grows nonlinearly to \$121.97 in 2050. The proceeds of this tax are used to pay a lump sum dividend to households.

We compute banks' exposures to climate policies based on NGFS (2022a) using the percentage decline in industry output for 12 industries from 2020 until 2050 for the

[31] `https://cama.crawford.anu.edu.au/cama-publications/g-cubed-modelling-results-ngfs-climate-scenarios`

[32] NGFS-industries are mapped to the Y14 by NAICS, forcing us to drop loans that do not map to an NGFS-industry. This exclusion amounts to 3.6% of the loans in the sample in 2023:Q1.

three scenarios described above. Therefore, our exposure measure captures the reduction in the value of a bank's loan portfolio from time t to 2050. Note that while this measure is useful due to its unique way of considering policy mixes, one caveat is the industry descriptions are very coarse since there are only twelve industries.

Figure 4 plots the time series evolution of the average bank's exposure based on NGFS (2022b). We find that the exposures are much higher than the estimates based on Jorgenson et al. (2018) and Goulder and Hafstead (2018). In the orderly transition, the average bank's loan value decreases by about 6% as of 2023, and in the disorderly transition, it decreases by about 6.5%. Moreover, exposures based on the two scenarios have fallen by about 3 percentage points since 2014, primarily driven by increased lending to the "services" sector, which benefits from the transition according to the model. On the other hand, the exposure is about 2% under the current policy scenario based on banks' loan portfolios as of 2023. The ordering of exposures across the three scenarios is consistent with the climate stress test results of central banks, where the highest exposure is under the disorderly scenario and the lowest exposure is under the current policy.[33] Figure A.5 presents the range between 10th and 90th percentiles, which tends to be larger for the disorderly and orderly scenarios than for the current policy.

3.2 Comparing Exposures by Policy Scenarios – Regression Analysis

The analysis above provides initial evidence of the differences in banks' exposures across transition policies/scenarios. In this section, we use regression analysis to more formally analyze how banks' exposures vary under different policies. To do this, we construct a

[33]Note these results rely on the publicly available mapping, which only identifies 12 industries. Figure A.4 displays results with all 20 industries for the G-Cubed model.

bank-by-policy-by-quarter level dataset and implement the following regression:

$$Exposure_{b,p,t} = \sum_{p \in P} \beta_p \mathbb{1}(Policy{=}p) + \Gamma X_{b,t} + \epsilon_{b,p,t}, \tag{2}$$

where $Exposure_{b,p,t}$ is the transition risk exposure for bank b under policy p at time t and $X_{b,t}$ is a vector of bank-by-quarter level controls. We include the natural log of total bank assets, loan-to-assets ratio, the bank return on assets, the bank leverage ratio, the bank deposit ratio, the loan-loss-reserves ratio, and the ratio of non-interest income to net income as controls in our regressions.

Each $\mathbb{1}(Policy{=}p)$ is an indicator variable equal to one if $Exposure_{b,p,t}$ is constructed for policy p. For each of these specifications, we only include observations for the general-equilibrium model that $Exposure_{b,p,t}$ is from. For instance, when examining the effect of the \$50 initial carbon tax at a 5% annual tax growth rate from Jorgenson et al. (2018) on bank exposure, we are comparing to the estimates for the other Jorgenson et al. (2018) initial tax and annual growth rate policies.

In general, we expect a positive β_p for stricter policies. For example, increasing the initial tax or annual growth rates in the Jorgenson et al. (2018) model, and applying the orderly or disorderly scenarios from NGFS (2022a), should result in higher transition risk exposures. On the other hand, it is theoretically unclear which method of redistribution of carbon taxes should result in higher exposure to transition risk.

Regression results are displayed in Table 2. Column (1) displays findings when examining the scenarios in Jorgenson et al. (2018) that vary the initial tax levels and annual tax growth rates of carbon taxes, while holding the type of redistribution used constant. The omitted scenario assumes a \$25 initial carbon tax at a 1% annual tax growth rate, which is the most lenient policy modeled in Jorgenson et al. (2018).

Looking at tax policies we see that a \$50 initial tax results in a bank exposure that is 1% higher than with a \$25 initial tax. Similarly, a 5% annual tax growth rate results in a 1% higher bank exposure than a 1% annual tax growth rate. Additionally, the coefficient on the interaction of these two policies is positive and statistically significant, indicating that bank exposure is higher when these two policies are used together than in isolation. These effects are intuitive: higher taxes can be interpreted as stricter policy, and bank exposures are higher in stricter policy scenarios.

Column (2) tells us that under Jorgenson et al. (2018) both capital tax cuts and labor tax cuts result in lower banks' exposures to climate transition risks than a lump sum redistribution. Column (3) displays results from Goulder and Hafstead (2018) which vary the method of redistribution while holding the level and growth rate of the tax constant. Regardless of whether a corporate, payroll, or individual income tax cut is used, the coefficient is negative. Together, these findings provide evidence that banks' exposures tend to be lower when income is recycled as a tax cut rather than as a lump sum redistribution, in line with the findings reported in column (2).

Lastly, column (4) shows that banks' exposures are about 5% higher in the NGFS' orderly transition and 6% higher in the disorderly transition than in the current policy scenario. Together with the findings from column (1), this provides evidence that stricter climate policies increase banks' exposures to transition risk. To understand if bank characteristics or time trends could contaminate the results, we next repeat the analyses by controlling for bank and time fixed effects. As we can see from Table 3 this does not affect our results.

In sum, the results from this subsection show that banks' exposures to transition risks induced by carbon taxes as modeled by Jorgenson et al. (2018) and Goulder and Hafstead (2018) are modest, with the average exposures ranging from -1% to 4% and declining even further when we account for capital and/or labor policies to redistribute the carbon tax revenue. By contrast, banks' exposures to transition risks are somewhat meaningful, reaching about 9% as of 2023 of their loan portfolios under the orderly and disorderly scenarios from NGFS (2022a). In the next subsection, we investigate to what extent our assumptions drive the relatively modest magnitude of banks' exposures to transition risks that we unveiled.

3.3 Robustness tests

The findings we reported above were computed under the assumption that bank loan values decrease proportionally to drops in output or profit. In this subsection, we examine how adjusting this assumption affects the findings. We begin by investigating what happens when we adjust the exposures to factor in the payoff structure of loans. Next, we investigate how our bank exposure measure changes under extreme scenarios where the riskiest industries lose their entire value in the transition. After that, we investigate whether our exposure measure might be biased because banks sort to borrowers with different risk, and what happens to our measure along the transition path. We finish this section by looking at the magnitudes of banks' exposures relative to their capital.

3.3.1 Adjusting Exposures for the Loan Payoff Structure

The previous results were computed under the assumption that the values of bank loans decrease proportionally to drops in output or profit. Now, we adjust the bank exposure measure to better capture bank loan payoff structures. Specifically, we calculate the bank's loss $Loss_{l,t}$ as the product of the loss given default and the probability of default found in the Y14. Then, for each industry, we implement a regression to estimate how a percentage change in output or profits is expected to affect $Loss_{l,t}$:[34]

$$Loss_{l,t} = \alpha_j + \beta_j log(Sales_{l,t}) + \epsilon_{l,t}. \tag{3}$$

Using this procedure, we can estimate the expected loss from loan l in time t as $\hat{\alpha_j} + \hat{\beta_j} Markdown_j^P$. We also identify borrowers likely to default on their loans by sorting industries based on their exposures to transition risks, and based on the model used find

[34] Results from this estimation are not reported for brevity, but are available upon request.

either the rank or decile of each industry. We match these industry-level proxies and rankings to information on bank loans, and assume these loans face defaults. We then compute the following measure of banks' exposures to climate transition risks adjusted for loan loss:

$$AdjExposure^P_{b,t} = \sum_{j \in J} w_{b,j,t}\ \mathbb{1}(Markdown^P_j > x)(\hat{\alpha}_j + \hat{\beta}_j Markdown^P_j) \\ + \sum_{j \in J} w_{b,j,t} \mathbb{1}\left(Markdown^P_j \leq x\right)(\hat{\alpha}_j + \hat{\beta}_j Markdown^P_j) Markdown^P_j, \qquad (4)$$

where $AdjExposure^P_{b,t}$ is the exposure of bank b to transition risk at time t under policy P, $Markdown^P_j$ is the modeled change in output for industry j under policy P, and x is a threshold level of the change in output to determine the severity of stress, where if the change in output is above x we assume that the loan's value goes to zero. $\hat{\alpha}_j$ and $\hat{\beta}_j$ are estimated from the above regression. We use deciles or ranks to designate the threshold level of the change in output, where the top-ranked and top-decile industries are the ones exposed to the greatest transition risk.

For the Jorgenson et al. (2018) and Goulder and Hafstead (2018) measures, we define industries as highly exposed to transition risk if they are either in the top-decile or top-two deciles of transition risk. For NGFS (2022a), due to the relatively smaller number of sectors, we define either the top-exposed industry, top-two exposed industries, or top-three exposed industries as highly exposed to transition risk. After estimating the measures at the bank-by-quarter level, we smooth them at the annual frequency. We then compute the aggregate time series as the average exposure across banks, weighted by bank total assets. As we're especially interested in observing the payoff structure of loans when default is more likely, we focus on the most severe scenarios.

We plot the exposures adjusted for loan payoff structures plotted in Figure 5. Panel (a) displays the plots for the most severe scenario from Jorgenson et al. (2018) (\$50 initial tax and 5% annual growth rate). Relative to the baseline measure, banks are expected to lose about 3% less of the loan portfolio as of 2023 when accounting for the loan payoff structure. Panel (b) displays the measure based on the Goulder and Hafstead (2018) lump sum redistribution scenario and provides estimates of the exposures adjusted for loan payoff structure, which are about 1% lower than the baseline. Finally, panel (c) shows the results with the NGFS disorderly scenario. Here, adjusting for loan payoff structures reduces the expected decrease in loan portfolios by about 5%. Thus, the difference is starker in the NGFS than in other two models.[35]

Overall, these results show that adjusting for bank loan payoff structures reduces bank exposures by between 1% and 5%. In all models, bank loan portfolios are expected to drop by about 1–2% after adjusting for loan payoff structures as of 2023. This seems to corroborate our previous insight that banks' exposures to transition risks are relatively modest. Of course, it is possible that the adjustments related to the loan payoff structures are too conservative, in particular, because they are based on historical loss given default and probability of default data. For that reason, in the next subsection, we examine banks' exposures when there is a severe decrease in loan values triggered by the transition policies.

3.3.2 Banks' Exposures to the Riskiest Industries

We consider what is arguably an extreme scenario and assume that loans to the industries most affected by transition risks would lose their entire value in line with the idea that these industries will become completely obsolete and banks will be unable to recover any of their loans. With regards to the remaining loans, we continue to assume they are affected in proportion to the decline in output or sales as in the industry of the borrower.[36]

To implement this approach, we compute an exposure where we assume that the

[35] Note these results rely on the publicly available mapping, which only identifies 12 industries. Panel (a) of Figure A.6 displays results with all 20 industries for the G-Cubed model.

[36] We also considered an alternative approach which assumes the remaining industries are unaffected by transition risks. This does not affect the results in a meaningful way.

value of bank loans to industries most adversely affected by transition risk goes to zero:

$$\begin{aligned}&\textit{Exposure Under Stress}^{P}_{b,t} = \\ &\sum_{j\in J} w_{b,j,t}\, \mathbb{1}\left(\textit{Markdown}^{P}_{j} > x\right) + \sum_{j\in J} w_{b,j,t} \mathbb{1}\left(\textit{Markdown}^{P}_{j} \leq x\right) \cdot \textit{Markdown}^{P}_{j}, \qquad (5)\end{aligned}$$

where $\textit{Exposure Under Stress}^{P}_{b,t}$ is the exposure for bank b at time t under policy P. Highly-exposed industries are those in the top- or top-two deciles of transition risk as in subsubsection 3.3.1. After estimating the measures at the bank-by-quarter level, we smooth them at the annual frequency. We then calculate the aggregate time series as the average exposure across banks, weighted by bank total assets. Similar to when examining the bank's loan exposure adjusted for the loan payoff structure, we focus on the most severe scenario from each model.

The time series of banks' exposures to the riskiest industries are displayed in Figure 6. Panel (a) displays results for the Jorgenson et al. (2018) model. The estimates are considerably higher using the *Exposure Under Stress* than with the continuous *Exposure*. Assuming that the top-decile of industries lose all their value increases the expected drop in bank loan portfolio value by about 4.5%, and assuming that the top-two deciles of industries lose all their value increases the exposure by an additional 6% based on loan portfolios as of 2023. Interestingly, both of these estimates have declined by at least 1% and as much as 3% over the past 10 years, consistent with banks gradually reducing their exposures to the industries most exposed to climate transition risks.

However, panel (b) shows that *Exposure Under Stress* are only about 1% higher than the baseline exposure when the top-decile industry loses all its value under Goulder and Hafstead (2018). The *Exposure Under Stress* increases by an additional 2% when assuming the top-two deciles lose all their value. For the NGFS model, we see from panel (c) that the *Exposure Under Stress* measure is identical to the baseline, with an average bank exposure of about 6.4% as of 2023, when the top-exposed industries default in the "disorderly transition" scenario.[37] This is because the NGFS scenarios assume that output for the top exposed industry (gas extraction and utilities) will drop by 100% by 2050. While the *Exposure Under Stress* is not identical when assuming the top-two industries lose all their value, it is extremely close since output for the second-most exposed industry (coal) is expected to decrease by about 96% by 2050. Therefore, while the values are different for the continuous measure and the *Exposure Under Stress* measure assuming the top-two industries lose all their value, the difference is within 0.01% as of 2023. When assuming the top-3 ranked industries go bankrupt, banks are expected to lose an additional 1% of their loan portfolio as of 2023.

These results add further support to the idea that banks have limited exposures to transition risks. For example, banks' loan portfolios in 2023 would drop by about 14% even when 20% of the industries most affected by climate transition risks according to Jorgenson et al. (2018) completely lose their value. The exposures are even smaller under Goulder and Hafstead (2018) and NGFS (2022b) (5% and 7%, respectively).[38] It is possible that our measures, in particular those for the most recent years, mask exposures to transition risks because banks, for example, have been increasingly sorting to borrowers with different risk exposures within each industry. To the extent that this has been happening only within the riskiest industries, it will not affect our insights when we assume the riskiest industries lose their entire value. We nonetheless investigate this concern in the next subsection.

3.3.3 Understanding within-industry variation in exposure

The source of the variation in our exposure measures comes from differences in exposures from the industries included in the general equilibrium models. A key assumption to

[37]These results rely on the publicly available mapping, which only identifies 12 industries. Panel (b) of Figure A.6 displays results with all 20 industries for the G-Cubed model.

[38]Note that while the baseline estimates were estimated in general equilibrium, the measure in this section is outside of that framework. In particular, this exercise is based on assumptions we made, outside of the general equilibrium models. For this reason, we are unable to observe how the rest of the economy would respond to the scenario where highly-exposed industries lose all their value, and consequently account for spillover effects between the industries.

interpret these exposures is that bank selection of borrowers within an industry is random relative to the borrower's transition risk. This would be especially worrying if banks are reducing their exposures by increasing their investments in the highest-emitting borrowers, within overall safer sectors. If this assumption is violated, the measure will be biased.

To validate this assumption, we use granular industry-level emissions data, at the 4-digit NAICS level. This provides an opportunity to examine heterogeneity in banks' lending to high and low emission industries, within each sector of the general equilibrium models. To do this, we identify the highest and lowest emitting industries within each modeled sector, and calculate the following ratio:

$$P(Lending_{it}^{Low}) = \frac{Lending_{it}^{Low}}{Lending_{it}^{Low} + Lending_{it}^{High}}, \tag{6}$$

where $Lending_{it}^{Low}$ is lending to the lowest-emitting borrowers in the general equilibrium sector and $Lending_{it}^{High}$ is lending to the highest-emitting borrowers in the general equilibrium sector.[39] We regress this measure on bank fixed effects for each quarter in the sample. If the R^2 of these regressions are increasing over time, this would indicate that banks are strategically investing more in higher-emitting borrowers within each sector.

The R^2 of these regressions based on the Jorgenson et al. (2018) industries are plotted in Figure 7. The blue line displays the trend in the R^2 from each of these regressions over time. At most, the R^2 is 5%, indicating that most of $P(Lending_{it}^{Low})$ is not explained by bank behavior. Nonetheless, the fitted line through the R^2's is flat, so banks are not increasingly sorting into riskier or safer borrowers within each industry over time. One concern is that banks may be doing this type of sorting more within higher risk industries. To examine this concern, the red line displays R^2 from a regression of $P(Lending_{it}^{Low})$ on both bank and industry fixed effects. While including industry fixed

[39]In this test, we limit the sample to cases where a bank lends to more than one 4-digit NAICS within a given IGEM industry in a quarter, as this allows us to identify distinct $Lending_{it}^{Low}$ and $Lending_{it}^{High}$.

effects increases the R^2 by about 35%, the fitted line is still flat. Therefore, even when looking within industry, banks do not appear to be sorting more into riskier borrowers in high-risk industries over time.[40]

3.3.4 Banks' Exposures over the Transition Path

All of the results we reported thus far are based on projections of changes in output occurring by 2050, and as a result, are not informative of banks' exposures along the transition paths. Even though our findings show banks have relatively low exposures to transition risks, the impact of these risks depends on how quickly they materialize. Addressing this issue requires observing information on the industries' paths under each scenario. That information is not available for either Jorgenson et al. (2018) or Goulder and Hafstead (2018). However, the G-Cubed model provides estimates of changes in output on an annual basis, which allows us to better understand the path of the transition and how this affects banks. Using the loan portfolio values from the Y14 as of 2023, we construct the path of the bank exposures based on the estimates from the G-Cubed model. Results are displayed in Figure 8.

Panel (a) displays the exposures based on Equation 1. For all scenarios, the decrease in bank loan values appears to be gradual. Looking at the specific policies, exposures for the orderly scenario are higher than those for the current policy. Banks face no exposure to the disorderly policy when examining changes in industry output from 2020 until 2029, but there is a steep increase in exposure after the policy is enacted in 2030.

We conducted a similar analysis for the exposures to the riskiest industries in Panels (b), (c) and (d), where we assume loans to the top-3, top-2 and top-1 exposed industries as of 2050 lose all their value.[41] The changes in exposure are much more

[40]Furthermore, untabulated results show that a regression of $P(Lending_{it}^{Low})$ on bank fixed effects interacted with a high risk industry dummy variable produce R^2 almost identical to those in Figure 7, further supporting that banks are not sorting more into riskier borrowers in high-risk industries over time.

[41]For the disorderly scenario we layer this assumption starting in 2030, when the policy is assumed to be put in place.

sudden using this approach, but they are not particularly large. Looking at the case where the top-3 riskiest industries lose their entire value (panel b), more than half of the decrease in bank loan values can be expected to occur immediately for the current policy and orderly scenarios. For the disorderly scenario, there is a sharp increase in exposures in 2030. In either case, however, the "shock" leads to less than a 5% decline in the value of banks' portfolio of values, arguably not a very large shock to banks.

3.3.5 Exposures relative to bank capital

One final concern with our investigation is that we calculated banks' exposures to transition risks as the expected decrease in bank loan portfolio values relative to the total bank loan portfolio. However, this could understate the true bank exposure because banks will start to experience distress before losing the entirety of the bank loan portfolio value. To address this concern, we construct an alternative exposure measure, where we instead scale the expected decrease in loan portfolio values by total bank capital:

$$CapitalExposure^{P}_{b,t} = \sum_{j \in J} w^{Capital}_{b,j,t} \; Markdown^{P}_{j}, \tag{7}$$

where $w^{Capital}_{b,j,t}$ is total lending by bank b to sector j at time t, scaled by bank b's total equity at time t.[42]

The time series of $CapitalExposure^{P}_{b,t}$ for the most severe scenario from each model are displayed in Figure 9. In each figure, the exposure measure calculated in Equation 1 is also shown for comparison. As expected, bank exposures are higher when scaling by capital than when scaling by bank loan portfolios. Further, for 2023, the year with the largest difference, the exposures when scaled by capital are about twice as large as those measured when scaled by loan portfolios. However, despite the large increase, their magnitudes do not reach very large values in absolute terms: 12% for

[42]When using total tier 1 risk-based capital in place of total bank equity, results look similar.

NGFS (2022b); 6% for Jorgenson et al. (2018) and 3% for Goulder and Hafstead (2018) as of 2023. In other words, constructing exposures scaled by bank capital yields higher results but does not change our key insight that banks are modestly exposed to climate transition risks.

4 Banks' Emissions Funding and Transition Risk Exposures

In the previous section, we assessed banks' exposures to transition risks building off effects estimated from general equilibrium models. General equilibrium estimates have the advantage of being tied to specific policies/scenarios, being forward looking, and factoring in the responses of the entire economy to those policies/scenarios. On the other hand, general equilibrium models are simplified versions of the entire economy that need to rely on a wide array of assumptions. It is reassuring to see that the results we derived from the three different models we considered were not very different. Nonetheless, one may wonder how our findings compare to banks' exposures had we relied on carbon emissions, which are commonly used to proxy for climate transition risks.

That is the purpose of this section. We begin by investigating what portion of banks' exposures to transition risks computed off the general equilibrium models is explained by their carbon emissions funding. Next, we investigate whether banks that fund more carbon emissions are also more exposed to stricter climate transition policies.

4.1 How Much Does Carbon Emission Funding Explain Banks' Exposures?

To address this question, we begin by regressing banks' exposures on banks' carbon emission funding and carbon emissions intensity for each policy scenario that we considered.

The R^2 of these regressions are reported in Table 4. Panels A and B display

R^2 from the regressions using the scenarios from Jorgenson et al. (2018). Across each scenario, about 57%-60% of the variation in banks' exposures is explained by banks' funding of carbon emissions. Panel C shows that the R^2 from Goulder and Hafstead (2018) are somewhat lower at about 26%. Finally, Panel D displays R^2 when using the NGFS scenarios, which are about 40%–50%. Overall, it is not surprising to find that the correlation is positive, because industries with high emissions are expected to be more affected by the transition policies. However, it is notable that at least 40% of the variation in our exposure measures is not explained by carbon emissions alone.

It is possible that results using banks' emission funding could be driven by banks' sizes. Ilhan et al. (2021) documents that financially constrained firms find it more difficult to adapt to climate regulations, suggesting smaller banks may have more difficulty responding to climate policies. Also, Bolton and Kacperczyk (2021a) find that although carbon emission intensities are not priced in equity returns, emission intensities do motivate divestment decisions by institutional investors. For this reason, we also assessed the explanatory power of banks' carbon intensities, defined as banks' emission funding scaled by bank total assets, in relation to our exposure measures. For all policy scenarios, the R^2 is at most about half the size as when using banks' emission funding. Additionally, we examined the relationship between the industry-level emissions and industry-level exposures in Table A.8, and we find that the R^2 estimates are even lower.

Overall, our results indicate that at least 40% of the variation in the banks' exposures to transition risk is no explained by banks' emission funding. This highlights the value of using forward-looking measures of transition risks derived from general equilibrium models.

4.2 Emissions Funding and Transition Policies' Exposures

Although banks' emissions funding only explains up to two thirds of their exposures to climate transition risks, given that they are positively related this gives us a further opportunity to do a "sanity" test on our findings computed off the general equilibrium estimates of transition policies. Specifically, we would expect banks that grant more credit to high carbon emission borrowers to be relatively more exposed to stricter climate transition risk policies. To investigate this hypothesis, we consider the following model:

$$\begin{aligned} Exposure_{b,p,t} = &\sum_{p \in P} \beta_{1p} \mathbb{1}(Policy{=}p) + \sum_{p \in P} \beta_{2p} \mathbb{1}(Policy{=}p) \cdot Emissions_{b,t} \\ &\beta_3 Emissions_{b,t} + \Gamma X_{b,t} + \epsilon_{b,p,t}, \end{aligned} \tag{8}$$

where $Emissions_{b,t}$ are the bank-level carbon emissions funding for bank b in quarter t, where bank emissions funding is computed as the emissions to the average borrower from a bank based on industry emissions at the finest NAICS-industry available. We also consider results using bank-level carbon emission intensity, where the bank emission intensity is defined as bank emission funding scaled by bank total assets.

The coefficient of interest in this regression is β_{2p}, which is the sensitivity of bank exposures to the interaction between policy p and bank emissions $Emissions_{b,t}$. We expect β_{2p} to be positive for stricter policy p because it is natural to hypothesize that stricter policy options should more severely affect higher-emitting banks. In this exercise, we focus on Jorgenson et al. (2018) tax rates and NGFS (2022a) scenarios. In particular, we should expect that higher initial levels and annual growth rates of carbon taxes in Jorgenson et al. (2018), and the orderly and disorderly transition policies in NGFS (2022a), should increase exposures to transition risks more for higher-emitting banks.[43]

Results from the interaction regressions are displayed in Table 5. Column (1) displays regression results examining how changes to carbon tax levels and growth rates from Jorgenson et al. (2018) affect exposure to transition risks across bank-funded emis-

[43] We do not consider redistribution scenarios because they can affect banks in ways other than their exposure to carbon emissions. For example, redistribution through labor tax will depend not only on carbon emissions but also on borrowers' employment.

sions. Firstly, note that when controlling for the bank emissions and the interaction of the policies with emissions, the coefficients on the policies are still positive and statistically significant. This highlights that differences in the different policies capture variation in transition risks that cannot be observed when simply using bank emissions to measure transition risk. Of particular note are the coefficients on the interactions between each policy and bank emissions funding. When examining these coefficients, it is clear that high initial taxes and annual tax growth rates both increase exposure to transition risks more as bank emissions increase. This finding is consistent with the hypothesis that an increase in the funding of carbon emissions increases the bank's exposure to transition risk.

Column (2) shows results varying the policy scenarios from NGFS (2022a). Recall that without considering banks' emissions funding, the disorderly and orderly transition scenarios result in higher levels of transition risk exposures for banks. Consistent with higher bank emissions leading to greater sensitivity of exposures to policy stringency, we see that banks' exposures increase more from these policies when they lend more to higher-emitting borrowers.

These results are robust to alternative specifications of this test. For instance, columns (3) and (4) display results using bank emission intensity in place of bank emission funding, and the results are consistent with stricter policies increasing exposures more for banks with more emissions. Additionally, Table A.9 displays regression results using bank and time fixed effects, which are qualitatively similar.

Given that higher carbon emitting borrowers will naturally be more adversely affected by the transition, it is reassuring to see that high-emitting banks are more exposed to more stringent climate policies that aim at promoting the transition to a net-zero economy. Further, these findings are robust to using fixed effects, as well as using either bank's emission funding or bank emission intensity. On the other hand, banks' emissions are unable to explain a substantial portion of their transition risks exposures computed of the estimated industry effects from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a), which points to the value of relying on general equilibrium estimates of transition policies.

5 Are U.S. Banks Managing their Transition Risks' Exposures?

While our previous results show that U.S. banks do not appear to have large exposures to transition risks, it is still important to understand whether they have been managing these risks. We attempt to answer this question in this section. We begin by investigating banks' exposure to the riskiest industries over time. We capitalize on two important events – the Paris Climate Accord and U.S. banks' signing of the Net-Zero Banking Alliance – that drew significant attention to the importance of climate transition risks. To assess the impact of each event, we first identify the most affected banks ("treated group"), and compare the changes in bank exposure (or share of lending made to the riskiest industries) to the control group, following the event.

5.1 Paris Agreement

We first examine whether and how banks' lending behavior changed after the Paris Agreement. On December 12, 2015, 196 nations adopted the Paris Agreement. By doing so, they agreed to enact national action plans limiting end of century temperature rise to at most 1.5 degrees Celsius above pre-industrial levels. These national action plans would require policy actions such as carbon pricing or regulation, that should have disproportionately negative effects for industries exposed to transition risk.[44]

Therefore, we empirically examine whether banks with significant lending portfolios to industries exposed to transition risk changed their behavior after the Paris Agreement. To do this, we identify the most affected banks as the ones with high ex-

[44] See Seltzer et al. (2022) for more detail on the Paris Agreement.

posure to the riskiest industries before the Paris Agreement.[45] Specifically, we run the following regression:

$$Exposure_{it} = \alpha + \beta\ \textit{Pre-Paris Exposure}_i \times Post_t + \Gamma X_{i,t} + \gamma_i + \varepsilon_{i,t} \tag{9}$$

where $\textit{Pre-Paris Exposure}_i$ is bank-level exposure for bank i as of the quarter before the Paris Agreement (2015:Q3) and $Post_t$ is dummy variable which takes a value of 1 if t is after the Paris Agreement and 0 otherwise.[46] We include bank-level controls denoted $X_{i,t}$ and bank fixed effects denoted γ_i. The exposure is policy-specific, and it is computed based on (2). The sample period is from 2012:Q3 to 2023:Q1. We consider the most severe policy from each model to compute the exposure, i.e. the \$50 tax growing at 5% annually for the Jorgenson et al. (2018) model, carbon tax policy with lump sum redistribution for the Goulder and Hafstead (2018) model, and the disorderly transition for the NGFS (2022a) model. The key coefficient is β, which we expect to be negative if the affected banks reduced the exposure (compared to the control group) following the Paris Agreement.

Panel A of Table 6 reports the results. Columns (1)-(3) are based on the aforementioned climate models and column (4) examines the effect on the bank-level emission funding. Consistent with the hypothesis, the coefficients are negative and significant although only for the Jorgenson et al. (2018) and the NGFS (2022a) models.

In order to understand whether riskier loans are falling or safer loans are rising, we analyze the share of riskier loans and the share of safer loans separately. To identify the riskiest and safest industries, we sort industries by exposures for each policy. We identify the "riskiest" industries as those in the top-two deciles of exposure and the

[45] One could also consider examining the cross-section of banks in terms of whether they signed the Net-Zero Banking Alliance or not. However, because the Net-Zero commitments were made later in time, and therefore Paris Agreement can affect banks' decision to join the Net-Zero banking alliance, we identify the most affected banks based on their pre-existing exposure.

[46] Results are similar when defining $\textit{Pre-Paris Exposure}_i$ using the exposure at the beginning of the sample period.

"safest" industries as those in the bottom-two deciles of exposure.[47] Panel B of Table 6 shows that the affected banks reduced lending to the riskiest industries and panel C shows that they increased lending to the safest industries, relative to the control group, following the Paris Agreement. Overall though, the change in exposure appears more driven by the decline in riskier lending than an increase in safer lending.

These results suggest that U.S. banks started to adjust their loan portfolio composition following the Paris Agreement. Nevertheless, a potential concern arises regarding the possible confounding impact of the decline in oil prices around the Paris Agreement. To address this concern, we examined another setting, the signing of Net-Zero Banking Alliance in the following subsection.

5.2 Signing of Net-Zero Banking Alliance

In 2021:Q1, an international coalition of banks created the Net-Zero Banking Alliance "committed to financing ambitious climate action to transition the real economy to net-zero GHG emissions by 2050". This provides a suitable setting to estimate the effect of signing the Net-Zero Banking Alliance on banks' credit portfolios. We define the treated group the 11 banks in the y14 that signed the Alliance in 2021:Q1. We exclude from the sample the seven banks that signed the Alliance later. Unlike the previous analysis focusing on the Paris Agreement, what matters in this exercise is whether banks joined the Alliance or not, rather than the pre-shock exposure. This is because highly exposed banks are not really affected unless they sign the commitment.

To examine the effect of making the commitments, we regress exposure on the interaction of a bank-level variable, *Signatory* and a time variable, *Post*:

$$Exposure_{it} = \alpha + \beta \; Signatory_i \times Post_t + \Gamma X_{i,t} + \gamma_i + \kappa_t + \varepsilon_{i,t} \tag{10}$$

[47] Note for the NGFS (2022a) estimates we instead define the riskiest industries as top-three ranked industries and the safest industries as bottom-three ranked industries given the relatively smaller number of industries in the model.

where $Signatory_i$ takes a value of 1 if the bank signed the Net-Zero Alliance, and 0 otherwise, and $Post_t$ is a time dummy variable that takes a value of 1 if it was after the initial signing in 2021:Q1. We expect to find negative β to the extent that the signatory banks reduced their exposures relative to other banks after signing the Alliance.

Table 7 reports the results. We find that signatory banks reduced their exposures relative to non-signatory banks after signing the Net-Zero Alliance, based on the Jorgenson et al. (2018) and the NGFS (2022a) models. Panels B and C indicate that this is primarily driven by banks reducing lending to the riskiest industries rather than increasing lending to the safest industries. It is reassuring to see the parallels between the results we unveiled based on the Paris Accord and the signing of the Net Zero Alliance. Further, the results that signatory banks changed relative to non-signatory banks add further support to the idea that these changes are bank-driven and not the result of a change in loan demand. To look further into this possibility, in the next subsection, we investigate borrowers' switch decisions between signatory and non-signatory banks.

5.3 Borrowers' Switches between Signatory and Non-signatory Banks

If the adjustment in lending, including the reduction in lending to the riskiest industries, by Net-Zero signatory banks that we unveiled in the previous section was indeed bank driven this should be reflected in borrowers' decisions to switch banks. To examine this, we compute two probability measures, the probability of borrowers from the non-signatory banks switching to signatory banks, and the probability of borrowers from the signatory banks switching to non-signatory banks. Then we compute the odds ratios by dividing the percentage of borrowers that switched to non-signatories by the percentage of borrowers that switched to signatories. We compute the odds ratio separately for the riskiest industries and the less risky industries before and after the alliance. The riskiest and safest industries are defined the same as in the above analysis.

Figure 10 reports the odd ratios. Panel A is based on the Jorgenson et al. (2018)

model, and it shows that the odds ratio of the riskiest industries increased (from 5.2 to 6.1) after the signing of the alliance. In contrast, the odds ratio of the safest industries fell (from 4.5 to 3.8) after signing the alliance. Panel B, C, and D are based on Goulder and Hafstead (2018), NGFS (2022a), and emission funding, respectively, and the results are consistent.[48] This evidence indicates that the bank-borrower relationships tend to move from signatory to non-signatory for the riskiest industries, while it moved from non-signatory to signatory for the safest industries.

While we focus on the banks' signing of the Net Zero alliance as the main exercise because of cleaner identification of treated banks, Table A.10 shows consistent results based on a similar exercise comparing borrowing from highly-exposed and less-exposed banks around the Paris Agreement. The results indicate that the borrowers in the riskiest industries switched away from highly-exposed banks after the Paris Agreement.

Together with our previous findings on lending volume, these results on borrowers' switches add support to the idea of signatory banks tightening their lending standards to riskiest borrowers while easing them to safe borrowers after they signed the Net-Zero Alliance.

6 Conclusion

Policymakers are increasingly interested in assessing the impact of transition risks on financial stability. However, most previous studies proxy transition risks using carbon emissions. In this paper, we take a different approach. We combine loan-level data from the Y-14 with the general equilibrium sectoral estimates for the US economy of transition policies and scenarios produced by Jorgenson et al. (2018), Goulder and Hafstead (2018), and NGFS (2022a). In contrast to carbon emissions, which are backward-looking, these estimates are forward-looking, and because they are computed from general equilibrium

[48] Results are presented in table form in Table 8.

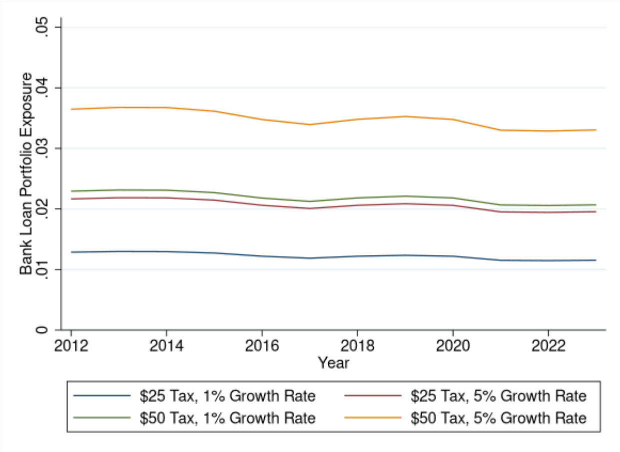
models, they capture a wider range of effects induced by the transition to a low-carbon economy. They also give us the opportunity to assess the implications of alternative transition policies.

Our key finding is that banks' exposures to transition risks, while nonnegligible, are not very large. This holds even when we consider the strictest transition policies or the most adverse scenarios. Our results also indicate that commonly used emissions are unable to explain about 40% of bank exposures estimated off general equilibrium models. Further, the effect of more strict policies on banks' exposures is stronger for banks with higher emissions, adding support to our approach of relying on the general equilibrium sectoral estimates to compute banks' exposures to transition risk. Finally, we find some evidence that U.S. banks are managing their exposures to transition risks. For example, banks that signed the Net-Zero Alliance have reduced their exposures to transition risks when compared to non-signatory banks. This reduction derived from banks mainly by cutting lending to industries likely to be adversely impacted by the transition. Consistent with this insight, we find evidence of borrowers in those industries disproportionately switching to non-signatory banks while borrowers in industries most prone to benefit in the transition disproportionately migrate to signatory banks.

Our paper suggests several fruitful areas for future research in the nexus between financial stability and climate risks. It would be useful to expand the analysis to asset managers and insurance companies given they retain substantial exposures to the same set of borrowers we considered. Similarly, given we focused on transition risks, it would be worthwhile to expand the analysis to include physical risks. Finally, as we develop a better understanding of borrowers' exposures to climate risks it would be worthwhile to investigate how this exposure affects borrowers' access to funding going forward, whether their financial claims fully reflect these risks, and where these securities end up landing in the financial system.

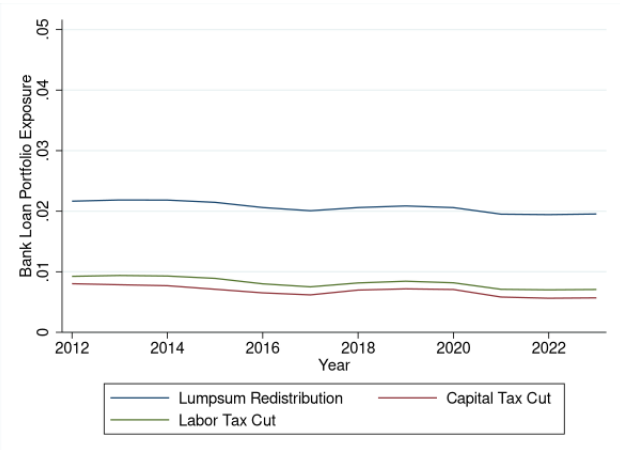
Figures

Figure 1: Differences in Exposure to Transition Risks from Jorgenson et al (2018) by Initial Tax and Annual Tax Growth Rate



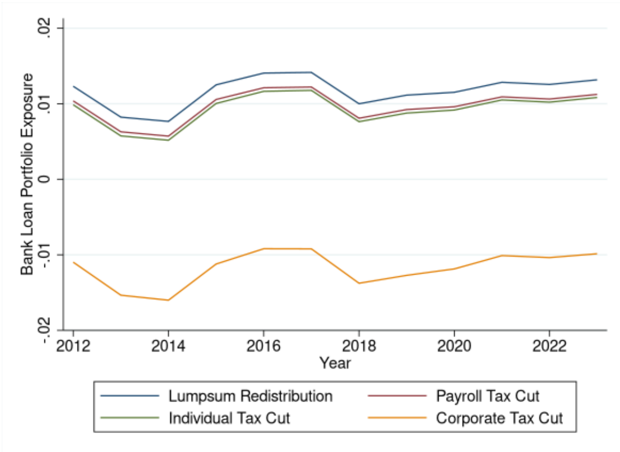
Shows exposure to transition risks based on model estimates from Jorgenson et al (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated in Jorgenson et al (2018). Plots show the average exposure measures across banks, weighted by bank total assets. Bank-level exposures are computed using the Y14 loan-level data. All scenarios assume the carbon tax is redistributed as a lumpsum. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency and are from 2012 until 2023.

Figure 2: Differences in Exposure to Transition Risks from Jorgenson et al (2018) by Redistribution



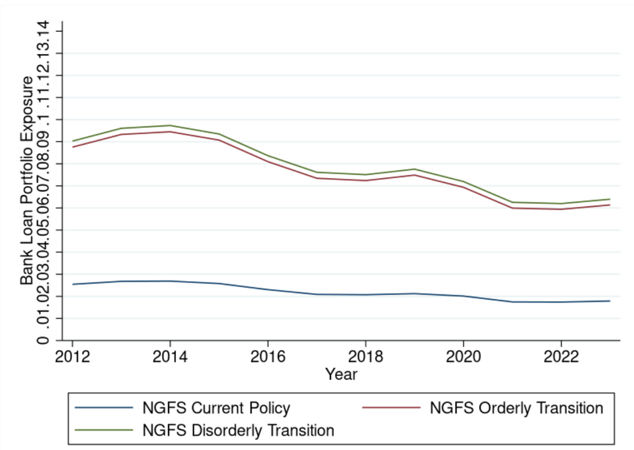
Shows exposure to transition risks based on model estimates from Jorgenson et al (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated in Jorgenson et al (2018). Bank-level exposures are computed using the Y14 loan-level data. Plots show the average exposure measures across banks, weighted by bank total assets. All scenarios assume a $25 initial tax and 5% annual tax growth rate. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Figure 3: Differences in Exposure to Transition Risks from Goulder and Hafstead (2018) by Redistribution



Shows exposure to transition risks based on model estimates from Goulder and Hafstead (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by Goulder and Hafstead (2018). Plots show the average exposure measures across banks, weighted by bank total assets. Bank-level exposures are computed using the Y14 loan-level data. All scenarios assume a \$20 initial tax and 4% annual tax growth rate. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

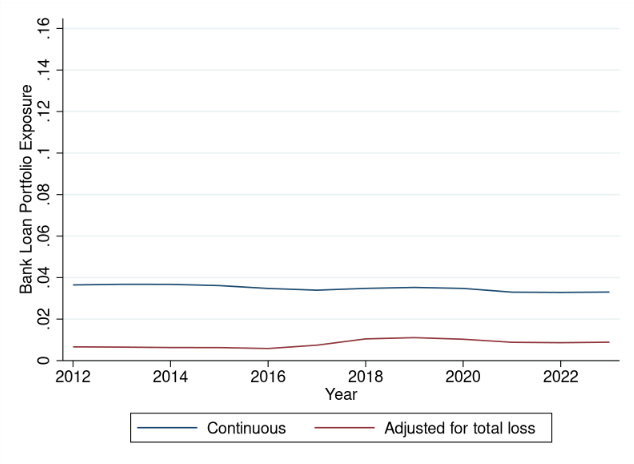
Figure 4: Differences in Exposure to Transition Risks from the G-Cubed Scenarios



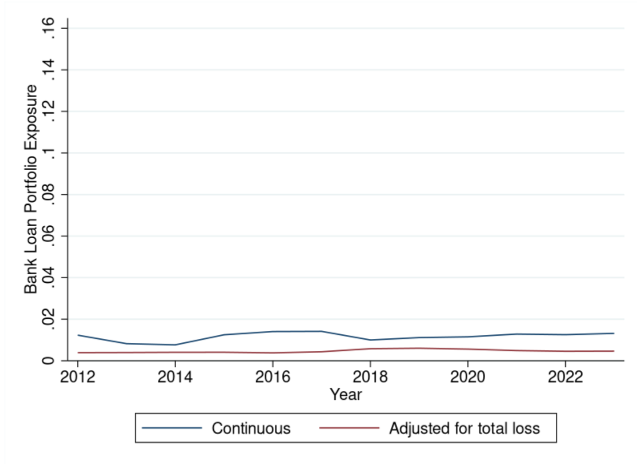
Shows exposure to transition risks based on model estimates from G-Cubed over time.The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by NGFS (2022a). Plots show the average exposure measures across banks, weighted by bank total assets. Bank-level exposures are computed using the Y14 loan-level data. Industries are as defined by the NGFS. Data are from 2012 until 2023.

Figure 5: Exposures to Transition Risks Adjusted for Payoff Structure

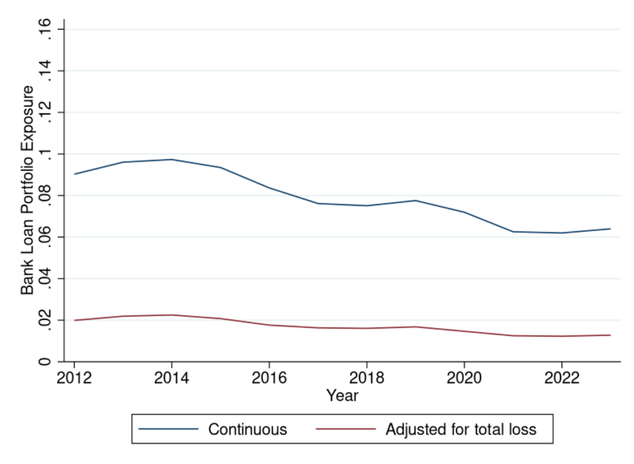
(a) Jorgenson et al (2018) $50 initial tax, 5% annual tax growth rate



(b) Goulder and Hafstead (2018) Lumpsum redistribution



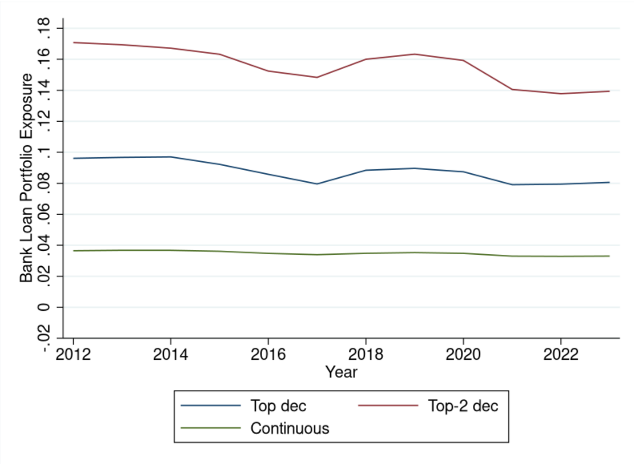
(c) NGFS Disorderly Transition



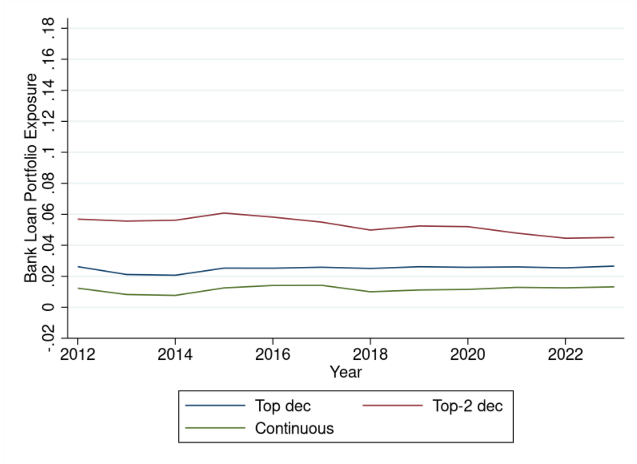
Shows exposures to transition risks adjusted for payoff structure from model-estimates of industry-level exposures to carbon taxes for the scenarios yielding the highest exposures from Jorgenson et al (2018), Goulder and Hafstead (2018) and NGFS (2022) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if we assume that all loans to the riskiest industries eventually default, and output for borrowers in all the other industries decreased by the same amount as the output reduction in the appropriate model. For the industries that default, we adjust by the loss given default and probability of default in the Y14. For Jorgenson et al (2018) and Goulder and Hafstead (2018), the riskiest industries are those in the top-two deciles of exposure to carbon taxes, and for NGFS (2022), the riskiest industries are either the top-ranked, top-two ranked or top-three ranked exposed to climate policy. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Figure 6: Exposures to Transition Risks for the Riskiest Industries

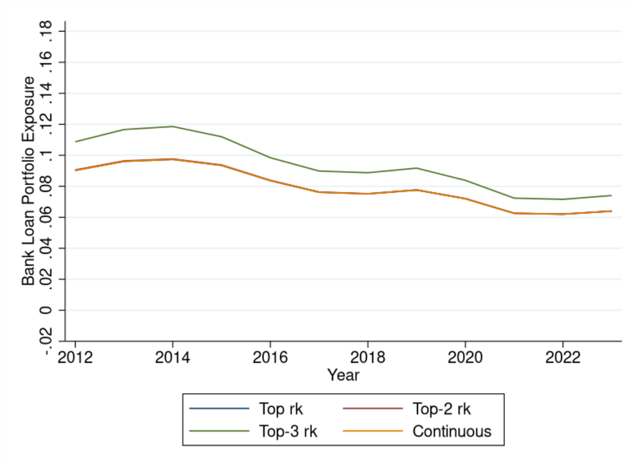
(a) Jorgenson et al (2018) \$50 initial tax, 5% annual tax growth rate



(b) Goulder and Hafstead (2018) Lumpsum redistribution

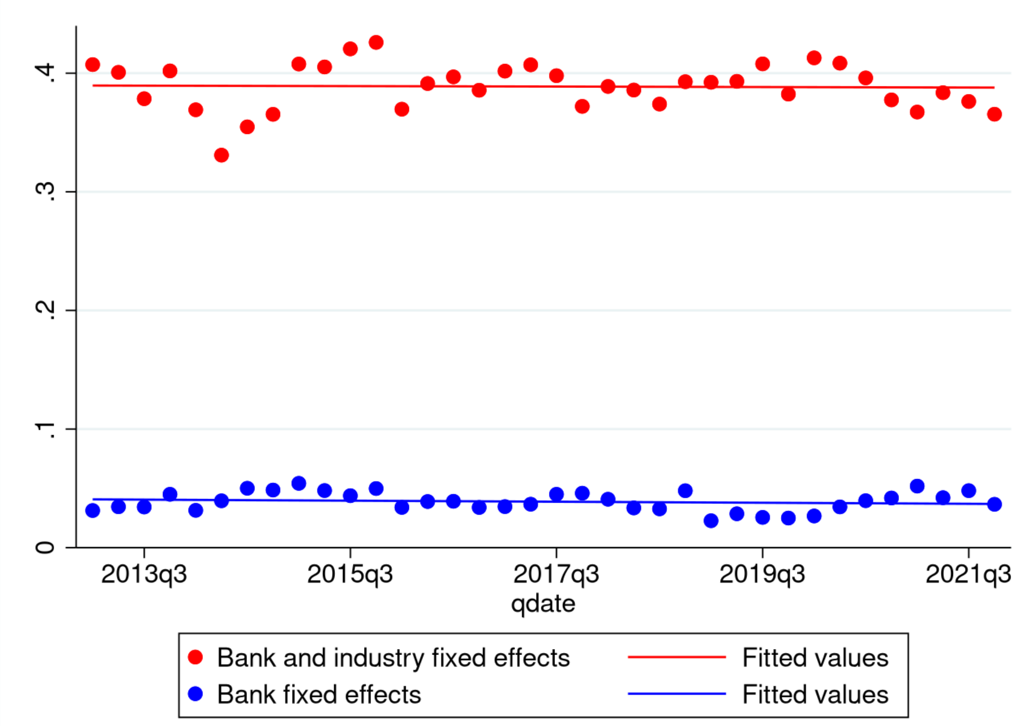


(c) NGFS Disorderly Transition



Shows exposures to transition risks for the riskiest industries from model-estimates of industry-level exposures to transition risks for the scenarios yielding the highest exposures from Jorgenson et al (2018), Goulder and Hafstead (2018) and NGFS (2022) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values for all loans to the riskiest industries had zero value, and loans to all the other industries decreased by the same amount as the output reduction in the appropriate model. For Jorgenson et al (2018) and Goulder and Hafstead (2018), the riskiest industries are those in the top-two deciles of exposure to transition risks, and for NGFS (2022), the riskiest industries are either the top-ranked, top-two ranked or top-three ranked exposed to transition risks. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

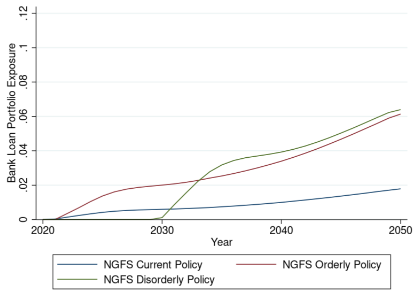
Figure 7: Examining Bank Sorting Within Industry



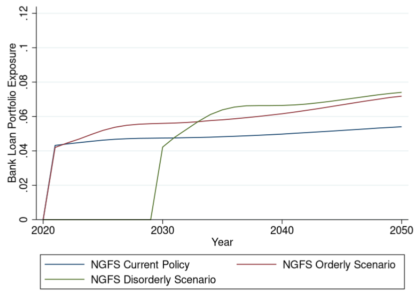
Shows the R^2 of cross-sectional regressions of regressions of the percentage of lending to borrowers in low-emitting 4-digit NAICS industries, relative to high-emitting borrowers, within a Jorgenson et al (2018) sector on bank fixed effects. Results based on 2021:Q1 data.

Figure 8: Path of Exposure to Transition Risks from the NGFS Scenarios

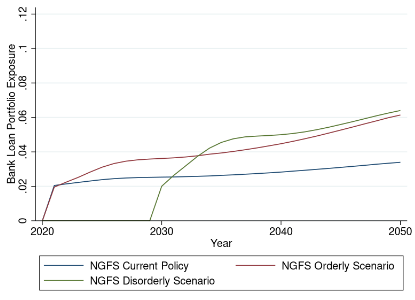
(a) Continuous Measure



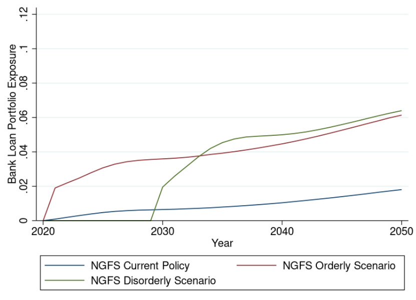
(b) Top-3 ranked bankrupt



(c) Top-2 ranked bankrupt



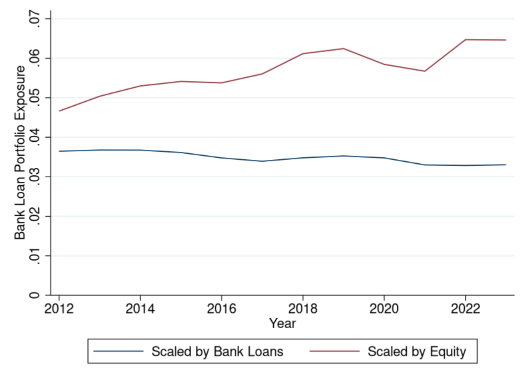
(d) Top-1 ranked bankrupt



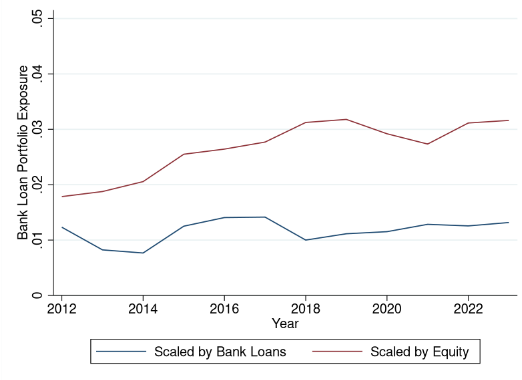
Shows expected exposure to transition risks from model estimates of industry-level exposures to climate policy from the NGFS scenarios based on the NGFS horizon. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by NGFS (2022). In panels (b) through (d), industry-rankings as of 2050 are used. Plots show the average exposure measures across banks, weighted by bank total assets. Y14 loan data as of 2023 is used.

Figure 9: Exposures to Transition Risks Relative to Bank Capital

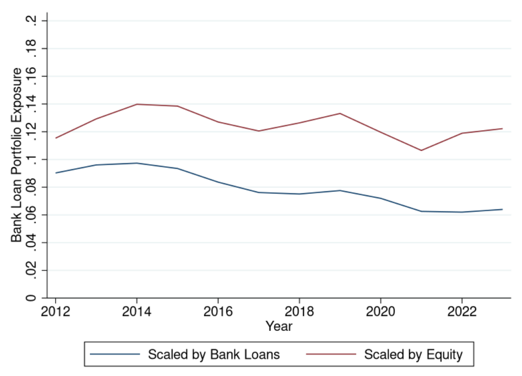
(a) Jorgenson et al (2018) \$50 initial tax, 5% annual tax growth rate



(b) Goulder and Hafstead (2018) Lumpsum redistribution



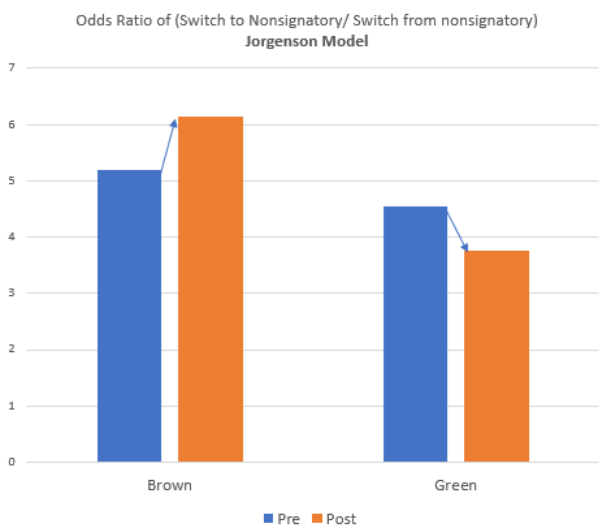
(c) NGFS Disorderly Transition



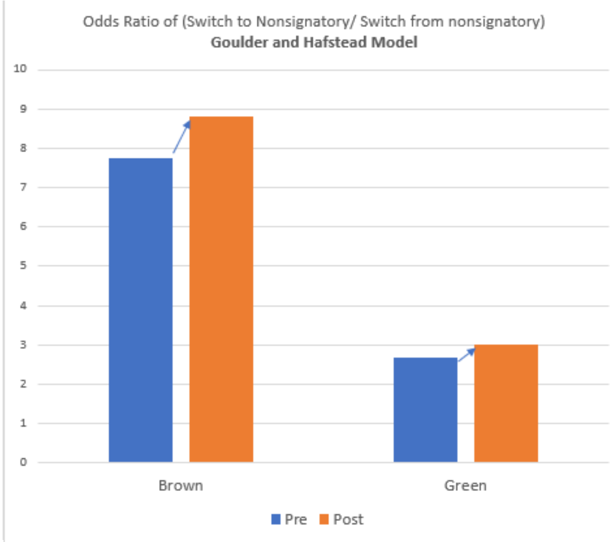
Shows exposures to transition risks from Jorgenson et al (2018), Goulder and Hafstead (2018) and NGFS (2022) over time when scaling by bank capital instead of bank loan portfolios. The exposure is calculated as the percentage decrease in a bank capital if loan values for all loans to the riskiest industries had zero value, and loans to all the other industries decreased by the same amount as the output reduction in the appropriate model. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Figure 10: Likelihood of Switching Lenders After the Net-Zero Banking Alliance

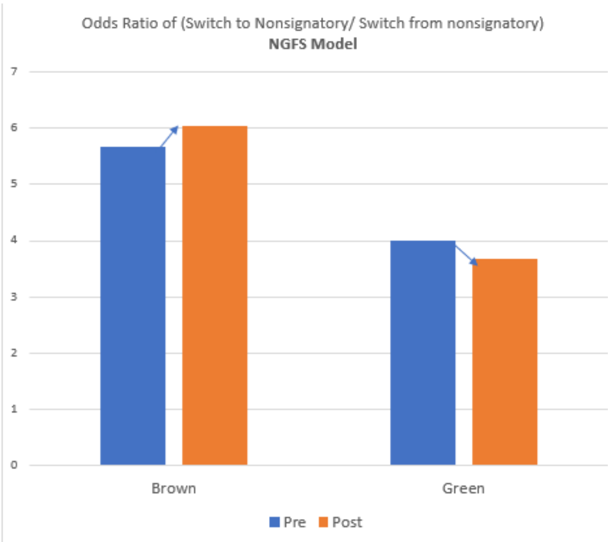
(a) Jorgenson et al (2018)



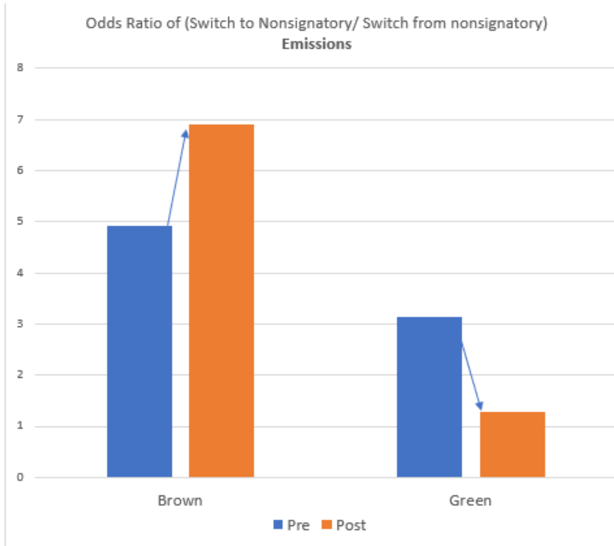
(b) Goulder and Hafstead (2018)



(c) NGFS



(d) Emissions



Shows the change in odds ratios of likelihood of switching to lenders after the Net-Zero Banking Alliance for brown borrowers relative to green borrowers, where brown and green are classified based on various model scenarios. The odds ratio is calculated as the portion of borrowers who switched from a non-signatory to a signatory, scaled by the portion of borrowers who switched from a signatory to a non-signatory.

Tables

Table 1: Summary Statistics

	Mean	St.Dev.	10P	50P	90P	Count
Jorgenson 25d Tax, 1p Growth	0.01	0.00	0.01	0.01	0.02	1,340
Jorgenson 25d Tax, 5p Growth	0.02	0.01	0.02	0.02	0.03	1,340
Jorgenson 50d Tax, 1p Growth	0.02	0.01	0.02	0.02	0.03	1,340
Jorgenson 50d Tax, 5p Growth	0.04	0.01	0.03	0.03	0.04	1,340
Jorgenson Lumpsum	0.02	0.01	0.02	0.02	0.03	1,340
Jorgenson Capital Tax Cut	0.01	0.01	0.00	0.01	0.01	1,340
Jorgenson Labor Tax Cut	0.01	0.01	0.00	0.01	0.01	1,340
Goulder Lumpsum	0.01	0.06	-0.00	0.02	0.03	1,340
Goulder Payroll Tax Cut	0.01	0.06	-0.00	0.02	0.03	1,340
Goulder Individual Tax Cut	0.01	0.06	-0.00	0.02	0.03	1,340
Goulder Corporate Tax Cut	-0.01	0.06	-0.03	-0.00	0.01	1,340
NGFS Current Policy	0.02	0.01	0.01	0.02	0.04	1,340
NGFS Orderly Transition	0.08	0.05	0.02	0.07	0.14	1,340
NGFS Disorderly Transition	0.08	0.05	0.02	0.08	0.14	1,340
Emissions (MM Tons)	5.96	5.66	1.78	4.60	11.15	1,130
Emission Intensity	0.04	0.05	0.00	0.02	0.07	1,122
Ln(Assets)	19.42	1.06	18.33	19.05	21.36	1,332
Loans/Assets	0.48	0.21	0.14	0.54	0.71	1,332
ROA	0.00	0.00	0.00	0.00	0.00	1,332
Leverage	0.89	0.03	0.86	0.89	0.92	1,332
Deposits/Assets	0.63	0.19	0.32	0.70	0.81	1,332
Loan Loss Reserves/Loans	0.01	0.01	0.00	0.01	0.02	1,332
Non-Interest Income/Net Income	2.66	8.65	0.92	1.82	5.31	1,332
Observations	1,340					

Data are from the Y14 loan-level data, which are aggregated to the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1.

Table 2: Comparing Exposure Measures by Policy

	(1) exposure	(2) exposure	(3) exposure	(4) exposure
50 dollar tax	0.01***			
	(25.58)			
5pp growth rate	0.01***			
	(26.73)			
50 dollar tax and 5pp growth rate	0.00***			
	(28.84)			
Capital Income Tax Cut		-0.01***		
		(-57.68)		
Labor Income Tax Cut		-0.01***		
		(-71.82)		
Corporate Income Tax Cut			-0.06***	
			(-12.30)	
Payroll Tax Cut			-0.00***	
			(-10.66)	
Individual Income Tax Cut			0.00	
			(0.59)	
Orderly Transition				0.05***
				(10.47)
Disorderly Transition				0.06***
				(10.93)
Ln(Assets)	-0.00	-0.00	0.01	-0.00
	(-1.26)	(-1.07)	(0.73)	(-0.40)
Loans/Assets	-0.01*	-0.02*	0.05	-0.05
	(-1.75)	(-1.86)	(0.48)	(-1.09)
ROA	-0.09	-0.12	1.63	-0.66
	(-0.81)	(-0.98)	(0.71)	(-0.98)
Leverage	-0.07	-0.09*	0.66	-0.38
	(-1.51)	(-1.79)	(0.75)	(-1.44)
Deposits/Assets	-0.00	-0.00	0.02	-0.01
	(-0.33)	(-0.18)	(0.18)	(-0.21)
Loan Loss Reserves/Loans	-0.00	-0.01	1.17*	-0.05
	(-0.00)	(-0.23)	(1.70)	(-0.13)
Non-Interest Income/Net Income	0.00	0.00	0.00	0.00
	(0.26)	(0.15)	(1.47)	(0.40)
Model	Jorgenson	Jorgenson	Goulder and Hafstead	NGFS
Policy Lever	Tax	Redistribution	Redistribution	Transition
Adjusted R2	0.66	0.60	0.06	0.38
Observations	5,328	3,996	21,312	3,996

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shows the results of a regression of bank-exposure measures on dummies equal to one if the measure is for a given policy. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction in the respective scenario. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the industry classification used in the referenced paper. Column (1) includes exposure measures from Jorgenson et al (2018), where a lumpsum redistribution is used and both the initial tax and annual tax growth rates vary. Column (2) includes exposure measures from Jorgenson et al (2018), where a \$25 initial tax and 5% annual tax growth rate is used, but the redistribution varies. Column (3) includes exposure measures from Goulder and Hafstead (2018), where a \$20 initial tax and 4% annual tax growth rate are used and the redistribution varies. Column (4) includes exposure measures from the NGFS scenarios. Standard errors are clustered at the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1.

Table 3: Comparing Exposure Measures by Policy – with Bank and Time Fixed Effects

	(1) exposure	(2) exposure	(3) exposure	(4) exposure
50 dollar tax	0.01***			
	(25.48)			
5pp growth rate	0.01***			
	(26.62)			
50 dollar tax and 5pp growth rate	0.00***			
	(28.72)			
Capital Income Tax Cut		-0.01***		
		(-57.38)		
Labor Income Tax Cut		-0.01***		
		(-71.45)		
Corporate Income Tax Cut			-0.06***	
			(-12.29)	
Payroll Tax Cut			-0.00***	
			(-10.65)	
Individual Income Tax Cut			0.00	
			(0.59)	
Orderly Transition				0.05***
				(10.41)
Disorderly Transition				0.06***
				(10.87)
Ln(Assets)	-0.00	-0.00	0.00	0.00
	(-0.75)	(-0.67)	(0.06)	(0.22)
Loans/Assets	-0.02***	-0.01***	-0.09*	-0.08**
	(-4.23)	(-4.28)	(-1.84)	(-2.65)
ROA	0.04	0.04	0.64**	0.48***
	(1.54)	(1.52)	(2.33)	(2.94)
Leverage	0.00	0.00	-0.20	0.04
	(0.23)	(0.34)	(-1.46)	(0.30)
Deposits/Assets	0.00	0.00	0.05	0.04
	(1.49)	(1.57)	(1.22)	(1.42)
Loan Loss Reserves/Loans	-0.00	0.00	-0.62***	-0.33*
	(-0.10)	(0.23)	(-2.71)	(-1.82)
Non-Interest Income/Net Income	0.00*	0.00*	0.00**	0.00
	(1.83)	(1.69)	(2.12)	(0.85)
Model	Jorgenson	Jorgenson	Goulder and Hafstead	NGFS
Policy Lever	Tax	Redistribution	Redistribution	Transition
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Within-R2	0.89	0.90	0.04	0.65
Observations	5,328	3,996	21,312	3,996

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shows the results of a regression of bank-exposure measures on dummies equal to one if the measure is for a given policy. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction in the respective scenario. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the industry classification used in the referenced paper. Column (1) includes exposure measures from Jorgenson et al (2018), where a lumpsum redistribution is used and both the initial tax and annual tax growth rates vary. Column (2) includes exposure measures from Jorgenson et al (2018), where a $25 initial tax and 5% annual tax growth rate is used, but the redistribution varies. Column (3) includes exposure measures from Goulder and Hafstead (2018), where a $20 initial tax and 4% annual tax growth rate are used and the redistribution varies. Column (4) includes exposure measures from the NGFS scenarios. Standard errors are clustered at the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1.

Table 4: Explanatory Power of Emissions for Exposures

Model Scenario	I	II	III	IV
	Panel A: Jorgenson et al (2018) Tax and Growth Rate Scenarios			
	\$25 Tax, 1% Growth Rate	\$25 Tax, 5% Growth Rate	\$50 Tax, 1% Growth Rate	\$50 Tax, 5% Growth Rate
Emissions R2	0.572	0.577	0.582	0.588
Emission Intensity R2	0.270	0.269	0.272	0.272
	Panel B: Jorgenson et al (2018) Redistribution Scenarios			
	Lump Sum Redistribution	Capital Tax Cut	Labor Tax Cut	
Emissions R2	0.577	0.595	0.577	
Emissions Intensity R2	0.269	0.297	0.262	
	Panel C: Goulder and Hafstead (2018) Redistribution Scenarios			
	Lump Sum Redistribution	Corporate Tax Cut	Payroll Tax Cut	Individual Income Tax Cut
Emissions R2	0.257	0.257	0.257	0.258
Emissions Intensity R2	0.092	0.091	0.092	0.093
	Panel D: NGFS Scenarios			
	Current Policy	Disorderly Transition	Orderly Transition	
Emissions R2	0.496	0.411	0.416	
Emission Intensity R2	0.254	0.207	0.208	

Shows the results of a regression of bank-exposure measures on dummies equal to one if the measure is for a given policy. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction in the respective scenario. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the industry classification used in the referenced paper. Bank emissions funding is calculated as the emissions to the average borrower from a bank. Bank emission intensity are calculated as bank emission funding scaled by bank total assets. Data are quarterly and from 2013:Q1 until 2021:Q4.

Table 5: Heterogeneity in Effects of Policy on Exposure by Bank Emissions

	(1) exposure	(2) exposure	(3) exposure	(4) exposure
50 dollar tax	0.01***		0.01***	
	(25.29)		(20.52)	
5pp growth rate	0.01***		0.01***	
	(26.16)		(21.48)	
50 dollar tax and 5pp growth rate	0.00***		0.00***	
	(32.93)		(23.80)	
Orderly Transition		0.03***		0.05***
		(5.34)		(8.12)
Disorderly Transition		0.04***		0.05***
		(5.70)		(8.56)
Emissions (MM Tons) * 50 dollar tax	0.00***			
	(7.10)			
Emissions (MM Tons) * 5pp growth rate	0.00***			
	(6.83)			
Emissions (MM Tons) * 50 dollar tax and 5pp growth rate	0.00***			
	(10.20)			
Emissions (MM Tons) * Orderly Transition		0.00***		
		(6.69)		
Emissions (MM Tons) * Disorderly Transition		0.00***		
		(6.51)		
Emission Intensity * 50 dollar tax			0.03**	
			(2.54)	
Emission Intensity * 5pp growth rate			0.02**	
			(2.50)	
Emission Intensity * 50 dollar tax and 5pp growth rate			0.01***	
			(3.02)	
Emission Intensity * Orderly Transition				0.27***
				(3.78)
Emission Intensity * Disorderly Transition				0.27***
				(3.81)
Emissions (MM Tons)	0.00***	0.00***		
	(6.89)	(4.64)		
Emission Intensity			0.04**	0.15**
			(2.38)	(2.24)
Model	Jorgenson	NGFS	Jorgenson	NGFS
Policy Lever	Tax	Transition	Tax	Transition
Controls	Yes	Yes	Yes	Yes
Adjusted R2	0.84	0.61	0.74	0.51
Observations	4,488	3,366	4,488	3,366.

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shows the results of a regression of bank-exposure measures on dummies equal to one if the measure is for a given policy, interacting with either bank emissions funding or bank emission intensity. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction in the respective scenario. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the industry classification used in the referenced paper. Bank emissions funding is calculated as the emissions to the average borrower from a bank. Bank emission intensity are calculated as bank emission funding scaled by bank total assets. Standard errors are clustered at the bank level. Data are quarterly and from 2013:Q1 until 2021:Q4.

Table 6: Changes in Banks' Exposures or Emissions Funding After the Paris Agreement Based on Initial Exposures.

Panel A: Banks' Exposures

	(1) Exposure	(2) Exposure	(3) Exposure	(4) Emissions
Pre-Paris IGEM Exposure × Post Paris	-0.141***			
	(-3.87)			
Pre-Paris Goulder Exposure × Post Paris		0.004		
		(0.11)		
Pre-Paris NGFS Exposure × Post Paris			-0.202***	
			(-2.80)	
Pre-Paris Emissions × Post Paris				0.029
				(0.56)
Model	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Within-R2	0.096	0.017	0.164	0.021
Observations	1,331	1,331	1,331	1,122

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Lending to the Riskiest Industries

	(1) Pr(Brown Lending)	(2) Pr(Brown Lending)	(3) Pr(Brown Lending)	(4) Pr(Brown Lending)
Pre-Paris IGEM Exposure × Post Paris	-2.260**			
	(-2.63)			
Pre-Paris Goulder Exposure × Post Paris		0.018		
		(0.27)		
Pre-Paris NGFS Exposure × Post Paris			-0.304**	
			(-2.53)	
Pre-Paris Emissions × Post Paris				-0.003***
				(-4.80)
Model	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Within-R2	0.138	0.030	0.153	0.119
Observations	1,331	1,331	1,331	1,122

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Lending to the Safest Industries

	(1) Pr(Green Lending)	(2) Pr(Green Lending)	(3) Pr(Green Lending)	(4) Pr(Green Lending)
Pre-Paris IGEM Exposure × Post Paris	-0.767			
	(-0.87)			
Pre-Paris Goulder Exposure × Post Paris		0.099*		
		(1.95)		
Pre-Paris NGFS Exposure × Post Paris			0.361***	
			(2.82)	
Pre-Paris Emissions × Post Paris				-0.002
				(-0.79)
Model	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Within-R2	0.064	0.077	0.236	0.070
Observations	1,331	1,331	1,331	1,122

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shows the results of difference-in-differences regressions comparing either the change in bank's exposure, the percentage of a bank's lending portfolio to the riskiest industries, or the percentage of a bank's lending portfolio to the safest industries based on their exposures prior to the Paris Agreement, after the Paris Agreement was announced. Data are quarterly from 2012:Q3 until 2023:Q1.

Table 7: Changes in Banks' Exposures or Emissions Funding for Signatories After the Net-Zero Banking Alliance.

Panel A: Banks' Exposures

	(1) Exposure	(2) Exposure	(3) Exposure	(4) Emissions
Signatory × Post Alliance	-0.002***	-0.000	-0.016***	-0.917
	(-2.92)	(-0.14)	(-2.81)	(-1.22)
Measure	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Within-R2	0.093	0.014	0.143	0.019
N	1,102	1,102	1,102	931

Panel B: Lending to the Riskiest Industries

	(1) Pr(Brown Lending)	(2) Pr(Brown Lending)	(3) Pr(Brown Lending)	(4) Pr(Brown Lending)
Signatory × Post Alliance	-0.008	-0.010*	-0.013*	-0.009
	(-0.68)	(-1.80)	(-1.80)	(-0.93)
Measure	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Within-R2	0.093	0.041	0.092	0.065
N	1,102	1,102	1,102	931

Panel C: Lending to the Safest Industries

	(1) Pr(Green Lending)	(2) Pr(Green Lending)	(3) Pr(Green Lending)	(4) Pr(Green Lending)
Signatory × Post Alliance	-0.004	-0.004	0.017	0.012
	(-0.11)	(-0.51)	(1.16)	(0.41)
Measure	Jorgenson	Goulder and Hafstead	NGFS	Emissions
Scenario	50d tax, 5p growth	Lump Sum	Disorderly Transition	N/A
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Within-R2	0.068	0.080	0.249	0.064
N	1,102	1,102	1,102	931

Shows the results of difference-in-differences regressions comparing either the change in bank's exposure, the percentage of a bank's lending portfolio to the riskiest industries, or the percentage of a bank's lending portfolio to the safest industries after the Net-Zero Banking Alliance was announced, for signatories relative to non-signatories. Late-signers of the Alliance are excluded from the analysis. Data are quarterly from 2012:Q3 until 2023:Q1.

Table 8: Switches Between Lenders for Signatories and non-Signatories.

Panel A: Jorgenson et al (2018)

	Switch to Signatory	Switch to non-signatory	Odds ratio
Riskiest Pre-Alliance	0.090	0.467	5.189
Safest Pre-Alliance	0.081	0.368	4.543
Riskiest Post-Alliance	0.094	0.577	6.138
Safest Post-Alliance	0.099	0.373	3.768

Panel B: Goulder and Hafstead (2018)

	Switch to Signatory	Switch to non-signatory	Odds ratio
Riskiest Pre-Alliance	0.090	0.698	7.756
Safest Pre-Alliance	0.120	0.323	2.692
Riskiest Post-Alliance	0.068	0.600	8.824
Safest Post-Alliance	0.103	0.310	3.010

Panel C: NGFS

	Switch to Signatory	Switch to non-signatory	Odds ratio
Riskiest Pre-Alliance	0.119	0.674	5.664
Safest Pre-Alliance	0.088	0.352	4.000
Riskiest Post-Alliance	0.108	0.651	6.027
Safest Post-Alliance	0.097	0.357	3.680

Panel D: Emissions

	Switch to Signatory	Switch to non-signatory	Odds ratio
Riskiest Pre-Alliance	0.104	0.513	4.933
Safest Pre-Alliance	0.114	0.357	3.132
Riskiest Post-Alliance	0.056	0.387	6.911
Safest Post-Alliance	0.171	0.220	1.287

Compares switches of lenders from non-signatories to signatories, to switches of lenders from signatories to non-signatories for brown and green borrowers, before and after the Net-Zero Banking Alliance. Odds ratios are calculated as the percentage of borrowers that switched to non-signatories divided by the percentage of borrowers that switched to signatories. Late signers of the Net-Zero Banking Alliance are excluded from the sample. Data are quarterly from 2012:Q3 until 2023:Q1.

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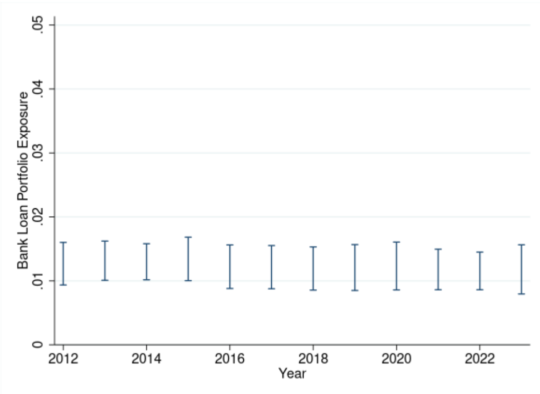
Internet Appendix

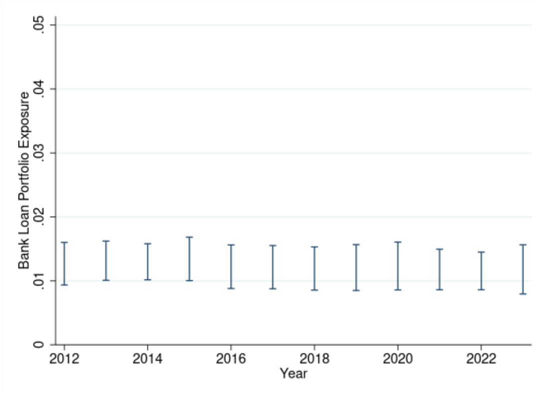
Appendix Figures

Figure A.1: Cross-Sectional Variation in Exposure to Transition Risks by Initial Tax and Annual Tax Growth Rate from Jorgenson et al (2018)

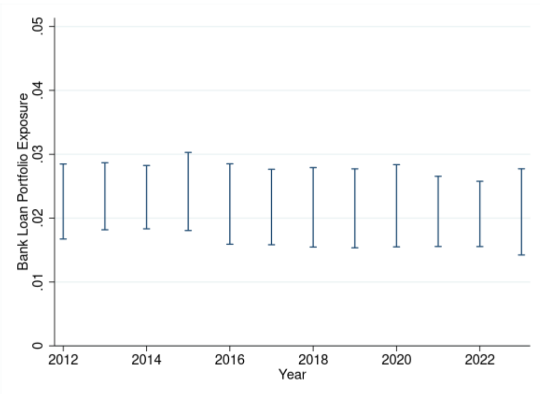
(a) $25 initial tax, 1% annual tax growth rate



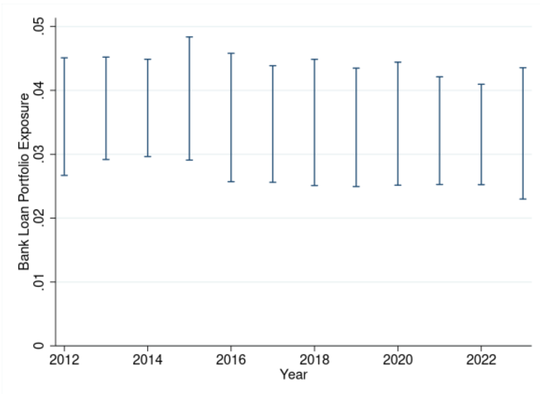
(b) $25 initial tax, 5% annual tax growth rate



(c) $50 initial tax, 1% annual tax growth rate



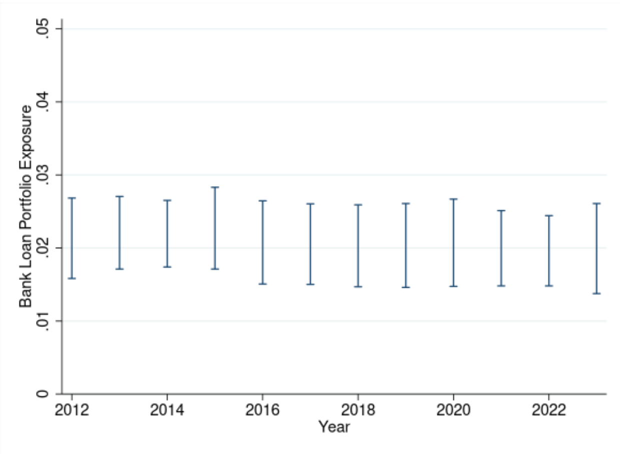
(d) $50 initial tax, 5% annual tax growth rate



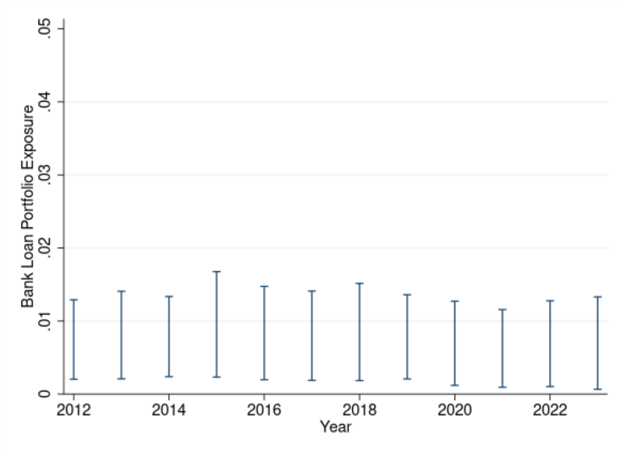
Shows the 10th and 90th percentiles in expected exposure to transition risks from model estimates of industry-level exposures to carbon taxes from Jorgenson et al (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated in Jorgenson et al (2018). The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to Jorgenson et al (2018) industries. All scenarios assume the carbon tax is redistributed as a lumpsum. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Figure A.2: Cross-Sectional Variation in Exposure to Transition Risks by Redistribution from Jorgenson et al (2018)

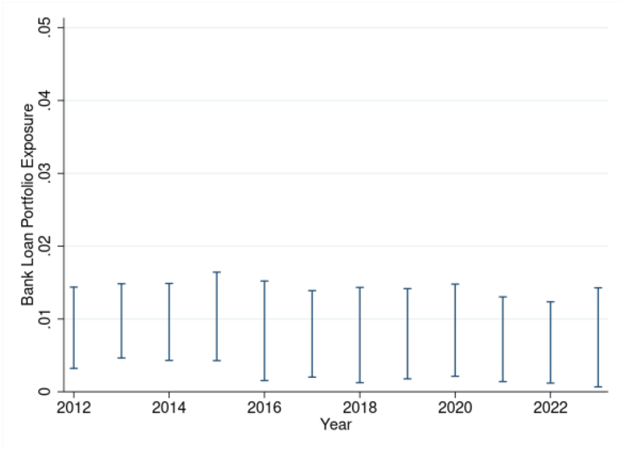
(a) Lumpsum redistribution



(b) Capital tax cut



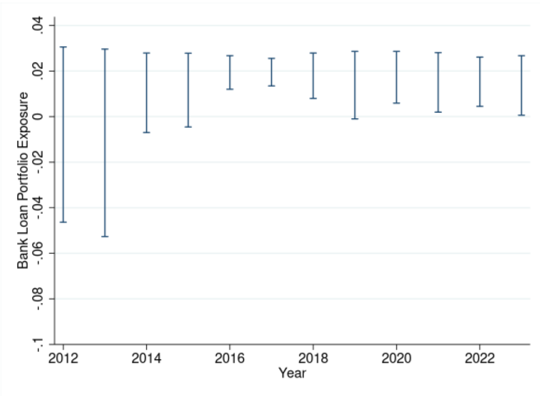
(c) Labor tax cut



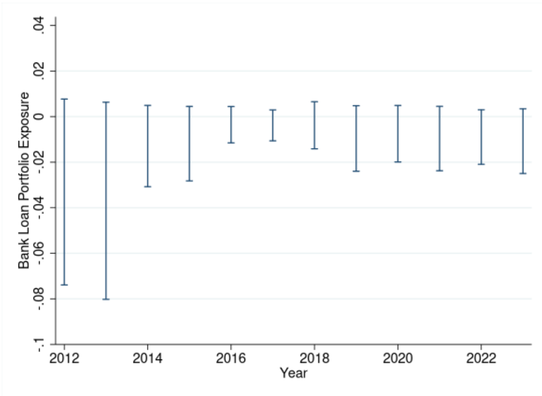
Shows the 10th and 90th percentiles in expected exposure to transition risks from model estimates of industry-level exposures to carbon taxes from Jorgenson et al (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by Jorgenson et al (2018). The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to Jorgenson et al (2018) industries. All scenarios assume a \$25 initial tax and 5% annual tax growth rate. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Figure A.3: Cross-Sectional Variation in Exposure to Transition Risks by Redistribution from Goulder and Hafstead (2018)

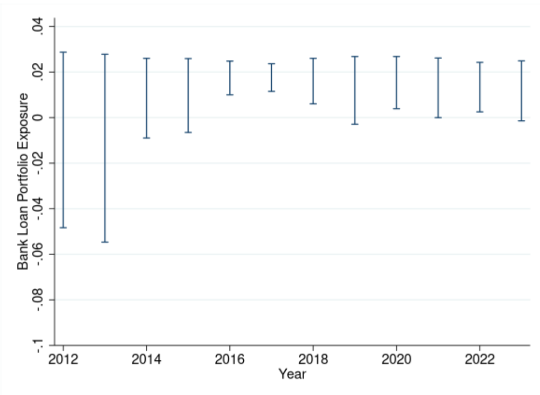
(a) Lump sum redistribution



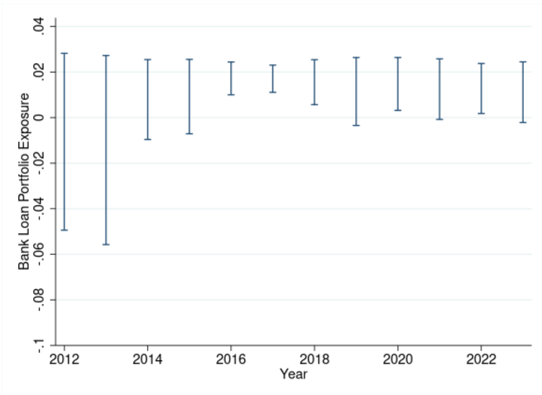
(b) Corporate tax cut



(c) Payroll tax cut

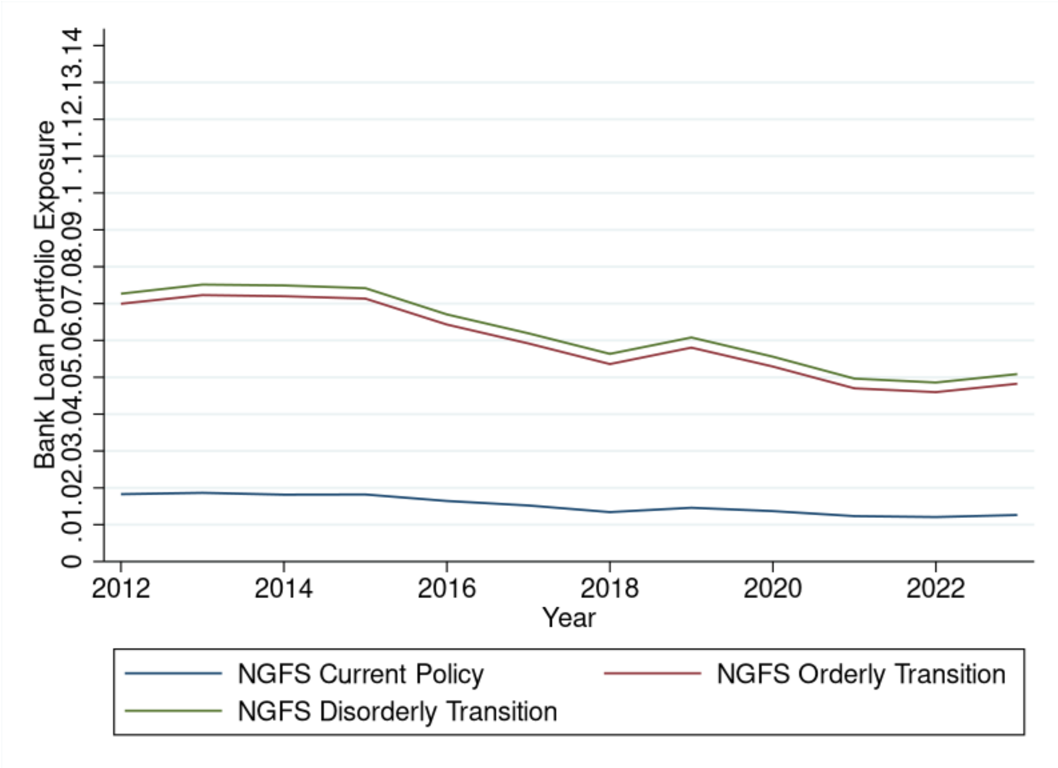


(d) Individual tax cut



Shows the 10th and 90th percentiles in expected exposure to carbon taxes from model estimates of industry-level exposures to carbon taxes from Goulder and Hafstead (2018) over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by Goulder and Hafstead (2018). The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to their Goulder and Hafstead (2018) industries. All scenarios assume a $20 initial tax and 4% annual tax growth rate. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

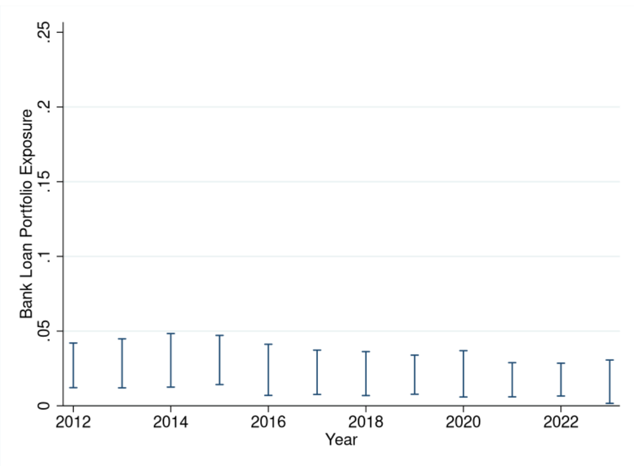
Figure A.4: Differences in Exposure to Transition Risks from the NGFS Scenarios with a 20 Industry Mapping



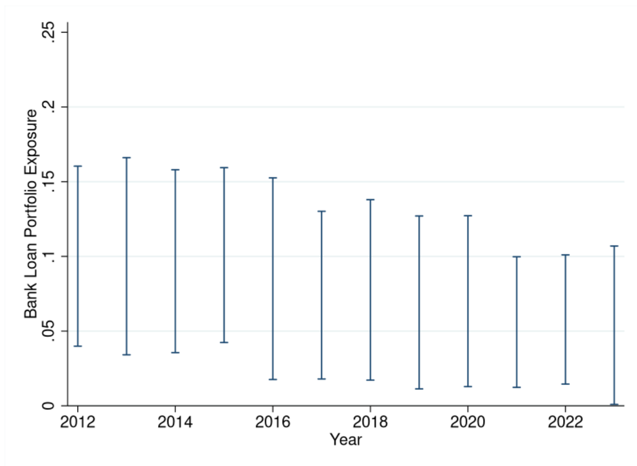
Shows expected exposure to transition risks from model estimates of industry-level exposures to climate policy from the NGFS scenarios over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by NGFS (2022a), using the version of model estimates done for 20 industries. Plots show the average exposure measures across banks, weighted by bank total assets. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the NGFS industries. This set of results relies on a mapping to the G-Cubed 20 sectors which we constructed by hand. Data are from 2012 until 2023.

Figure A.5: Cross-Sectional Variation in Exposure to Transition Risks by the NGFS Scenarios

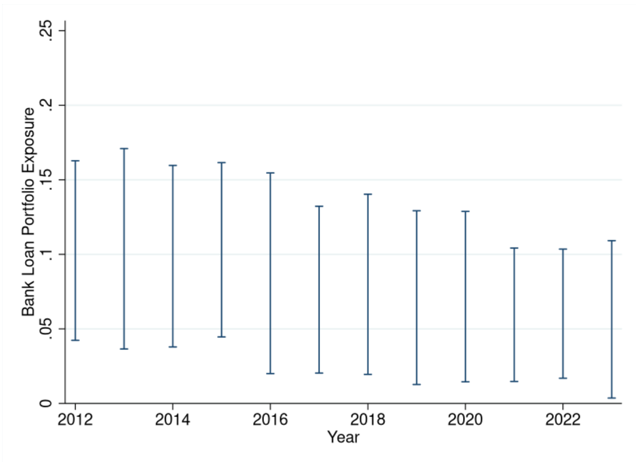
(a) Current Policy



(b) Orderly Transition



(c) Disorderly Transition

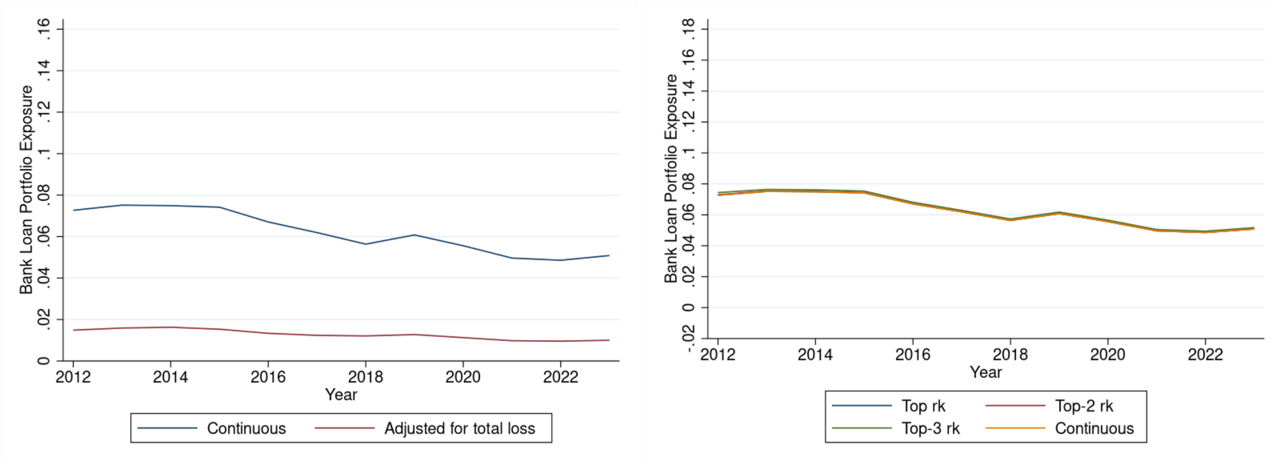


Shows the 10th and 90th percentiles in expected exposure to transition risks from model estimates of industry-level exposures to climate policy from the NGFS scenarios over time. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction estimated by NGFS (2022a) The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the NGFS industries. Industries are as defined by the NGFS. Data are from 2012 until 2023.

Figure A.6: Alternative Exposure Measures Using the 20 Industry NGFS results

(a) Exposure for Loan Payoff Structure

(b) Exposure to Riskiest Industries



Shows exposures to transition risks adjusted for loan payoff structure, and exposures to transition risks for the riskiest industries from model-estimates of industry-level exposures to carbon taxes for the scenarios yielding the highest exposures from and NGFS (2022) using the results for 20 industries over time. The riskiest industries are either the top-ranked, top-two ranked or top-three ranked exposed to climate policy. This set of results relies on a mapping to the G-Cubed 20 sectors which we constructed by hand. Data are smoothed at the annual frequency, and are from 2012 until 2023.

Appendix Tables

Table A.1: Mappings between NAICS codes and Jorgenson et al. (2018) Industries

IGEM-N Industries	NAICS	NAICS Code
Agriculture	Farms	111:112
	Forestry and related activities	113:115
Oil mining	Oil and gas extraction	2111 (Crude)
Gas mining	Oil and gas extraction	2111 (Gas)
Coal mining	Coal mining	2121
Non-energy mining and support	Mining except oil, gas, coal	212 (ex 2121), 213
Electric utilities (pvt+govt)	Utilities: Electric	2211
Natural gas distribution	Utilities: Natural gas distribution	2212
Water and sewage	Utilities: Water, Sewage	2213
Construction	Construction	23
Wood and paper products	Wood products; Paper Mfg.	321; 322
Nonmetallic mineral products	Nonmetallic mineral products	327
Primary metals	Primary metal mfg	331
Fabricated metal products	Fabricated metal product mfg	332
Machinery	Machinery	333
Information technology equipment	Computer and electronic prod	334
Electrical equipment	Electrical equipand components	335
Motor vehicles and parts	Motor vehicle and parts mfg	3361:3363
Other transportation equipment	Other transportation equipment	3364:3369
Miscellaneous manufacturing	Furniture and related products	337
	Miscellaneous manufacturing	339
Food, beverage and tobacco products	Food, beverage and tobacco	311; 312
Textile, Apparel, Leather	Textile mills	313:314
	Apparel, leather and allied	315
Printing and related support activities	Printing and related activities	323
Petroleum and coal products	Petroleum and coal products	324
Chemicals, rubber, plastic	Chemical mfg	325

	Plastics and rubber products	326
Wholesale Trade	Wholesale Trade	
Retail Trade	Retail Trade	
Transportation and warehousing	Air transportation 481	
	Rail transportation	482
	Water transportation	483
	Truck transportation	484
	Transit, ground psngr transp.	485
	Pipelines	486
	Other transportation	487, 488, 492
	Warehousing and storage	493
Publishing, Recording, Broadcasting	Publishing (ex software)	511 (ex5112)
and telecomunications	Motion picture	sound 512
	Broadcasting and telecom	515; 517
Software and information	Software publishers	5112
technology services	Information and data processing	518; 519
Finance and Insurance	Banks and credit intermediation	521:522
	Securities and investments	523
	Insurance	524
	Funds, trusts	525
Real Estate (rental); OOH	Real estate (ex owner-occupied)	531
intermediates; Leasing	Rental and leasing	532:533
Business Services	Legal services	5411
	Computer systems design	5415
	Misc. professional, scientific	541 (ex5411, 5415)
	Management of companies	551
	Administrative services	561
	Waste management	562
Educational services (pvt + gov)	Educational services	61
Health care and social assistance (pvt+gov)	Ambulatory health care services	621

	Hospitals and nursing	622, 623
	Social assistance	624
Accommodation and Other services	Performing arts, sports	711:712
	Amusements and recreation	713
	Accommodation	721
	Food services and drinking	722
	Other services except govt	81
Government (ex elec health edu)	Federal general government	92
	Federal government enterprises	92
	State and general government	92
	State and local government enterprises	92
Household capital	Owner-occupied rental imputation	531

Table A.2: Mappings between NAICS codes and Goulder and Hafstead (2018) Industries

E3 Industry	2007 NAICS Codes
Air transportation	481
Chemicals, plastics, and rubber	32412–32419
Chemicals, plastics, and rubber	325
Chemicals, plastics, and rubber	326
Coal mining	2121
Coal-fired electricity generation	2211
Communication and information	511
Communication and information	512
Communication and information	513
Communication and information	514
Construction	23
Electric transmission and distribution	2211
Fabricated metal products	332
Farms, forestry and fishing	1111–1123
Farms, forestry and fishing	113–115
Federal electric utilities	n/a
Food and beverage	311–312
Machinery and misc. manufacturing	333
Machinery and misc. manufacturing	334
Machinery and misc. manufacturing	335
Machinery and misc. manufacturing	3364–3369
Machinery and misc. manufacturing	337
Machinery and misc. manufacturing	339
Mining support activities	2131
Motor vehicles	3361–3363
Natural gas distribution	2212
Natural gas extraction	211
Nonfossil electricity generation	2211
Nonmetallic mineral products	327

Oil extraction	211
Other mining	2122–2123
Other transportation and warehousing	487–488, 492
Other transportation and warehousing	493
Other-fossil electricity generation	2211
Paper and printing	322
Paper and printing	323
Petroleum refineries	32411
Pipeline transportation	486
Primary metals	331
Railroad transportation	482
Real estate and owner-occupied housing	531
Real estate and owner-occupied housing	531
Services	521–522
Services	523
Services	524
Services	525
Services	532–533
Services	5411
Services	5415
Services	5412–5414,5416–5419
Services	55
Services	561
Services	562
Services	61
Services	621
Services	622
Services	623
Services	624
Services	711–712

Services	713
Services	721
Services	722
Services	81
Services	n/a
Services	n/a
State and local electric utilities	n/a
Textile, apparel, leather	313–314
Textile, apparel, leather	315–316
Trade	42
Trade	441
Trade	445
Trade	452
Trade	442,446,451,453
Transit and ground passenger transportation	485
Truck transportation	484
Water transportation	483
Water utilities	2213
Wood products	321

Table A.3: Mappings between SIC codes and NGFS (2022a) Industries

GGG12	US SIC Code	1987 US SIC
Electric Utilities	491	Electric Services
Gas Extraction and Utilities	492	Natural Gas Transmission
Petroleum refining	29	Petroleum and coal products
Coal mining	12	Coal mining
Crude oil extraction	13	Oil and gas extraction
Construction	15	Building construction–general contractors and operative builders
Mining	10	Metal mining
	14	Nonmetallic minerals, except fuels
Agriculture, Forestry, Fishing and Hunting	1	Agricultural production- crops
	2	Agricultural production- livestock
	7	Agricultural services
	9	Fishing, hunting, and trapping
	8	Forestry
	241	Logging
	242	Lumber
Durable manufacturing	331, 332	Iron and Steel
	324	Hydraulic Cement
	327	Concrete and Concrete Products
	35	Industrial machinery and equipment
	36	Electronic and other electric equipment
	38	Instruments and related products
	44	Transportation equipment
	24x	Lumber and wood products, except 241 and 242
	33x	Primary metal industries, except 331 and 332
	34	Fabricated metal products

	25	Furniture and fixtures
	32x	Stone, clay, and glass products, except 324
	39	Miscellaneous manufacturing industries
Non-durable manufacturing	28	Chemicals and allied products
	22	Textile mill products
	26	Paper and allied products
	19	bovine cattle, sheep and goat, horse meat products
	21	Tobacco products
	23	Apparel and other textile products
	27	Printing and publishing
	30	Rubber and miscellaneous plastics products
	31	Leather and leather products
Transportation	40	Railroad transportation
	41	Local and interurban passenger transportation
	42	Motor freight transportation and warehousing
	44	Water transportation
	45	Transportation by air
	46	Pipelines, except natural gas
	47	Transportation services
Services	50	Wholesale trade - durable goods
	51	Wholesale trade - nondurable goods
	52	Building materials, hardware, garden supply, and mobile home
	53	General merchandise stores
	55	Automotive dealers and gasoline service stations

	56	Apparel and accessory stores
	57	Home furniture, furnishings, and equipment stores
	58	Eating and drinking places
	59	Miscellaneous retail
	48	Communications
	60	Depository institutions
	49x	Electric, Gas and Sanitary Services, except 491 and 492
	61	Nondepository credit institutions
	62	Security and commodity brokers, dealers, exchanges, and services
	63	Insurance carriers
	64	Insurance agents, brokers, and services
	65	Real estate
	67	Holding and other investment offices, except trusts
	70	Hotels, rooming houses, camps, and other lodging places
	72	Personal services
	73	Business services
	75	Automotive repair, services, and parking
	76	Miscellaneous repair services
	78	Motion pictures
	79	Amusement and recreation services
	80	Health services
	81	Legal services
	82	Educational services
	83	Social services
	84	Museums, art galleries, and botanical and zoological gardens

	86	Membership organizations
	87	Engineering, accounting, research, management, and related services
	89	Services, not elsewhere classified

Table A.4: Drop in Industry Output for Carbon Tax and Growth Rate Scenarios in Jorgenson et al (2018)

IGEM Industry	**$25 tax, 1% growth rate**	**$25 tax, 5% growth rate**	**$50 tax, 1% growth rate**	**$50 tax, 5% growth rate**
Agriculture	0.009	0.016	0.017	0.028
Oil mining	0.026	0.045	0.049	0.079
Gas mining	0.059	0.097	0.103	0.157
Coal mining	0.163	0.237	0.252	0.338
Nonenergy mining	0.016	0.028	0.028	0.046
Electric utilities	0.047	0.077	0.082	0.124
Gas utilities	0.049	0.087	0.092	0.154
Water and wastewater	0.016	0.026	0.028	0.046
Construction	0.010	0.018	0.018	0.030
Wood and paper	0.015	0.026	0.027	0.045
Nonmetal mineral products	0.022	0.039	0.040	0.068
Primary metals	0.022	0.038	0.040	0.066
Fabricated metal products	0.013	0.022	0.023	0.037
Machinery	0.014	0.024	0.025	0.040
Information technology equipment	0.008	0.013	0.013	0.022
Electrical equipment	0.009	0.015	0.015	0.025
Motor vehicles and parts	0.014	0.024	0.025	0.040
Other transportation equipment	0.006	0.011	0.012	0.019
Miscellaneous manufacturing	0.010	0.017	0.017	0.029
Food, beverage and tobacco	0.006	0.011	0.012	0.019
Textiles, apparel and leather	0.010	0.017	0.019	0.031
Printing and related activities	0.004	0.007	0.008	0.012
Petroleum and coal products	0.042	0.070	0.077	0.123
Chemicals, rubber and plastics	0.012	0.020	0.022	0.035
Wholesale trade	0.006	0.011	0.011	0.018
Retail trade	0.008	0.013	0.013	0.022
Transportation and warehousing	0.027	0.046	0.048	0.079
Publishing, broadcasting, telecommunications	0.005	0.009	0.010	0.015
Software & information technology services	0.008	0.014	0.014	0.023
Finance and insurance	0.006	0.010	0.011	0.017
Real estate and leasing	0.008	0.013	0.015	0.022
Business services	0.008	0.014	0.015	0.024
Educational services	-0.002	-0.004	-0.004	-0.007
Health care and social assistance	0.003	0.006	0.006	0.010
Accommodation and other services	0.007	0.011	0.012	0.020
Other government	0.001	0.001	0.001	0.002

Estimates of decreases in industry output from Table 8 in Jorgenson et al (2018). All scenarios here assume that the income from the tax is recycled as a lump sum dividend. Estimates are of decrease in industry output from 2015 until 2050.

Table A.5: Drop in Industry Output for Redistribution Scenarios in Jorgenson et al (2018)

IGEM Industry	Lump Sum	Capital Tax Cut	Labor Tax Cut
Agriculture	0.0155	0.0077	0.00
Oil mining	0.0447	0.0416	0.0382
Gas mining	0.0965	0.0936	0.0919
Coal mining	0.2366	0.2215	0.2326
Nonenergy mining	0.0276	0.00	0.0156
Electric utilities	0.0765	0.0716	0.0664
Gas utilities	0.0865	0.0797	0.0786
Water and wastewater	0.0263	0.024	0.0143
Construction	0.0182	-0.01	0.0061
Wood and paper	0.0256	0.0091	0.0141
Nonmetal mineral products	0.0386	0.0186	0.0281
Primary metals	0.0381	0.0129	0.0276
Fabricated metal products	0.022	0.00	0.0106
Machinery	0.0243	-0.01	0.0125
Information technology equipment	0.0132	-0.01	0.0031
Electrical equipment	0.0152	-0.01	0.004
Motor vehicles and parts	0.0242	0.00	0.0115
Other transportation equipment	0.0113	-0.01	0.0036
Miscellaneous manufacturing	0.0173	-0.01	0.0034
Food, beverage and tobacco	0.0107	0.0077	-0.01
Textiles, apparel and leather	0.0173	0.0087	0.00
Printing and related activities	0.0072	0.00	0.00
Petroleum and coal products	0.0704	0.0649	0.061
Chemicals, rubber and plastics	0.0201	0.0036	0.0073
Wholesale trade	0.0109	0.00	0.00
Retail trade	0.013	0.00	0.00
Transportation and warehousing	0.0455	0.0337	0.0333
Publishing, broadcasting, telecommunications	0.0091	0.00	0.00
Software & information technology services	0.0143	-0.01	0.0029
Finance and insurance	0.0099	0.0019	0.00
Real estate and leasing	0.0132	-0.01	0.0068
Business services	0.014	0.0017	0.0015
Educational services	0.00	0.00	-0.01
Health care and social assistance	0.0056	0.0064	-0.01
Accommodation and other services	0.0111	0.0113	0.00
Other government	0.0009	0.0001	0.00

Estimates of decreases in industry output from Table 9 in Jorgenson et al (2018). All scenarios here assume that a $25 initial tax is put in place, growing at 5% per year. Estimates are of decrease in industry output from 2015 until 2050.

Table A.6: Drop in Industry Sales for Redistributions Scenario in Goulder and Hafstead (2018)

Industry	**Lump-sum Rebates**	**Cuts in Employee Payroll Taxes**	**Cuts in Individual Income Taxes**	**Cuts in Corporate Income Taxes**
Oil extraction	0.001	0.001	0.001	-0.068
Natural gas extraction	0.235	0.234	0.233	0.203
Coal mining	0.459	0.458	0.457	0.457
Electric transmission and distribution	0.079	0.077	0.076	0.055
Coal-fired electricity generation	0.747	0.746	0.746	0.750
Other-fossil electricity generation	0.185	0.183	0.183	0.148
Nonfossil electricity generation	-0.627	-0.630	-0.634	-0.661
Natural gas distribution	0.084	0.082	0.081	0.057
Petroleum refining	0.063	0.062	0.061	0.032
Pipeline transportation	0.072	0.071	0.070	0.033
Mining support activities	0.055	0.053	0.049	0.005
Other mining	0.032	0.030	0.028	0.002
Farms, forestry, fishing	0.018	0.016	0.016	-0.013
Water utilities	0.010	0.008	0.008	-0.012
Construction	0.023	0.021	0.018	-0.005
Wood products	0.020	0.019	0.017	-0.007
Nonmetallic mineral products	0.023	0.022	0.020	-0.005
Primary metals	0.033	0.032	0.031	0.008
Fabricated metal products	0.021	0.019	0.018	-0.002
Machinery and misc. manufacturing	0.019	0.017	0.016	-0.008
Motor vehicles	0.016	0.014	0.013	-0.007
Food and beverage	0.016	0.014	0.014	-0.013
Textile, apparel, leather	0.017	0.014	0.014	-0.017
Paper and printing	0.018	0.016	0.016	-0.002
Chemicals, plastics, and rubber	0.027	0.025	0.024	0.002
Trade	0.016	0.014	0.014	-0.011
Air transportation	0.028	0.026	0.026	0.004
Railroad transportation	0.036	0.035	0.034	-0.003
Water transportation	0.024	0.023	0.022	0.002
Truck transportation	0.020	0.018	0.018	-0.001
Transit and ground passenger transportation	0.012	0.010	0.010	-0.014
Other transportation and warehousing	0.018	0.017	0.017	-0.008
Communication and information	0.011	0.009	0.009	-0.017
Services	0.012	0.010	0.010	-0.004
Real estate and owner-occupied housing	0.011	0.009	0.009	0.004

Estimates of decreases in industry sales from Table 5.4 in Goulder and Hafstead (2018). All scenarios here assume that a $20 initial tax is put in place, growing at 4% per year. Estimates are of the present value of decreases in industry sales over an infinite time.

Table A.7: Drop in Industry Sales from NGFS Scenarios

NGFS Industry	**Current Policy**	**Disorderly Transition**	**Orderly Transition**
Electricity Generation & Delivery	0.1133	0.3040	0.3052
Gas Extraction & Utilities	0.1946	1.0000	1.0000
Petroleum Refining	0.0935	0.4066	0.3978
Coal Mining	0.7039	0.8961	0.9587
Crude Oil Extraction	0.1182	0.5603	0.5423
Construction	0.0233	0.0711	0.0694
Other Mining	0.0565	0.1801	0.1723
Agriculture	0.0152	0.0489	0.0463
Durable Manufacturing	0.0262	0.0790	0.0768
Non-durable Manufacturing	0.0114	0.0374	0.0362
Transportation	0.0313	0.1257	0.1237
Services	-0.0022	-0.0112	-0.0139

Estimates of decreases in domestic industry output from the NGFS scenarios. Estimates are of decreases in industry sales from 2020 until 2050.

Table A.8: Explanatory Power of Industry-Emissions for Industry-Exposures

Model Scenario	I	II	III	IV
	Panel A: Jorgenson et al (2018) Tax and Growth Rate Scenarios			
	\$25 Tax, 1% Growth Rate	\$25 Tax, 5% Growth Rate	\$50 Tax, 1% Growth Rate	\$50 Tax, 5% Growth Rate
Emissions R2	0.131	0.166	0.160	0.206
	Panel B: Jorgenson et al (2018) Redistribution Scenarios			
	Lump Sum Redistribution	Capital Tax Cut	Labor Tax Cut	
Emissions R2	0.160	0.207	0.160	
	Panel C: Goulder and Hafstead (2018) Redistribution Scenarios			
	Lump Sum Redistribution	Corporate Tax Cut	Payroll Tax Cut	Individual Income Tax Cut
Emissions R2	0.050	0.049	0.050	0.051
	Panel D: NGFS Scenarios			
	Current Policy	Disorderly Transition	Orderly Transition	
Emissions R2	0.283	0.269	0.268	

Shows the results of a regression of industry-exposure measures on industry-level emissions. The exposure is taken directly from the the referenced paper. Industry-emissions are calculated as the emissions to the average firm in an industry in millions of tons based on the finest level of industry emissions available. Data are quarterly and from 2013:Q1 until 2021:Q4.

Table A.9: Heterogeneity in Effects of Policy on Exposure by Bank Emissions – with Fixed Effects

	(1)	(2)	(3)	(4)
	exposure	exposure	exposure	exposure
50 dollar tax	0.01***		0.01***	
	(25.19)		(20.44)	
5pp growth rate	0.01***		0.01***	
	(26.05)		(21.39)	
50 dollar tax and 5pp growth rate	0.00***		0.00***	
	(32.80)		(23.70)	
Orderly Transition		0.03***		0.05***
		(5.32)		(8.08)
Disorderly Transition		0.04***		0.05***
		(5.67)		(8.52)
Emissions (MM Tons) * 50 dollar tax	0.00***			
	(7.08)			
Emissions (MM Tons) * 5pp growth rate	0.00***			
	(6.81)			
Emissions (MM Tons) * 50 dollar tax and 5pp growth rate	0.00***			
	(10.16)			
Emissions (MM Tons) * Orderly Transition		0.00***		
		(6.66)		
Emissions (MM Tons) * Disorderly Transition		0.00***		
		(6.47)		
Emission Intensity * 50 dollar tax			0.03**	
			(2.53)	
Emission Intensity * 5pp growth rate			0.02**	
			(2.49)	
Emission Intensity * 50 dollar tax and 5pp growth rate			0.01***	
			(3.01)	
Emission Intensity * Orderly Transition				0.27***
				(3.76)
Emission Intensity * Disorderly Transition				0.27***
				(3.79)
Emissions (MM Tons)	-0.00**	-0.00***		
	(-2.28)	(-3.05)		
Emission Intensity			-0.00	-0.07**
			(-1.05)	(-2.27)
Model	Jorgenson	NGFS	Jorgenson	NGFS
Policy Lever	Tax	Transition	Tax	Transition
Controls	Yes	Yes	Yes	Yes
Adjusted R2	0.96	0.89	0.94	0.86
Observations	4,488	3,366	4,488	3,366

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Shows the results of a regression of bank-exposure measures on dummies equal to one if the measure is for a given policy, interacting with either bank emissions funding or bank emission intensity. The exposure is calculated as the percentage decrease in a bank's loan portfolio if loan values drop the same amount as the industry-sales reduction in the respective scenario. The Y14 loan-level data are used to calculate the exposure at the bank level, where loans outstanding are aggregated at the bank-by-industry level according to the industry classification used in the referenced paper. Bank emissions funding is calculated as the emissions to the average borrower from a bank. Bank emission intensity are calculated as bank emission funding scaled by bank total assets. Standard errors are clustered at the bank level. Data are quarterly and from 2013:Q1 until 2021:Q4.

Table A.10: Switches Between Lenders for More and Less Exposed Banks After Paris Agreement.

Panel A: Jorgenson et al (2018)

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Riskiest Pre-Paris	0.171	0.255	1.491
Safest Pre-Paris	0.164	0.158	0.963
Riskiest Post-Paris	0.159	0.207	1.302
Safest Post-Paris	0.204	0.153	0.750

Panel B: Goulder and Hafstead (2018)

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Riskiest Pre-Paris	0.057	0.684	12.000
Safest Pre-Paris	0.132	0.316	2.394
Riskiest Post-Paris	0.066	0.778	11.788
Safest Post-Paris	0.098	0.268	2.735

Panel C: NGFS

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Riskiest Pre-Paris	0.113	0.590	5.221
Safest Pre-Paris	0.128	0.209	1.633
Riskiest Post-Paris	0.169	0.531	3.142
Safest Post-Paris	0.173	0.185	1.069

Panel D: Emissions

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Riskiest Pre-Paris	0.174	0.362	2.080
Safest Pre-Paris	0.196	0.242	1.235
Riskiest Post-Paris	0.192	0.225	1.172
Safest Post-Paris	0.191	0.183	0.958

Compares switches of lenders with below median exposures to those with above median exposures, to switches of lenders with above median exposure to below median exposure for brown and green borrowers, before and after the Paris Agreement. Odds ratios are calculated as the percentage of borrowers that switched to non-signatories divided by the percentage of borrowers that switched to signatories. Data are quarterly from 2012:Q3 until 2017:Q4.