U.S. Banks' Exposures to Climate Transition Risks

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Abstract

We propose a new approach to estimate banks' credit exposures to transition risks that combines sectoral effects of climate policies from general equilibrium (GE) models with historical information on loans' default risks. At worst, estimated exposures reach 14% of bank loan portfolio values. Accounting for historic loan payoff structures reduces exposures to 0.5%–2%. Exposures can increase by 3–5 percentage points due to aggregate economic shocks. Analyses surrounding climate transition events suggest our estimates can serve as an upper bound on banks' transition risk exposures. Highlighting our measure's novelty, emissions explain at most 60% of variation in banks' exposures.

JEL classification: G21, H23, Q54

Keywords: Banks climate risk exposures, climate transition risks, NGFS scenarios

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I Introduction

Researchers and policymakers are increasingly interested in understanding the potential impact of climate transition risks 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 for financial stability by assessing the exposure of U.S. banks to transition policies.

Transition policies, such as carbon taxes, can affect banks through their loan portfolios. By altering borrowers' production costs and profitability, transition policies can change borrowers' default risk, and in turn, the value of banks' credit claims. Losses in the banking sector may have broader real economic implications through reductions in credit supply. Assessing banks' exposures to transition risks has proven difficult because it requires understanding how borrowers and, more generally, the economy respond to transition policies. To date, attempts to measure banks' exposures have tackled this challenge by building on measures of borrowers' carbon emissions. We take a different approach and leverage findings from the literature that has investigated the effects of transition policies on the U.S. economy.

[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.

We start from forward-looking general equilibrium (GE) estimates of how climate transition policies affect industry-level output or profits. We then map these industry-level responses to loan payoffs, either through stylized assumptions or by estimating this relationship in the data, to quantify the impact of transition policies on bank loan values. Finally, we aggregate these loan-level effects using banks' loan portfolio compositions to measure banks' exposures to transition risk.

We build on GE estimates of industry-level responses to climate transition policies from Jorgenson, Goettle, Ho, and Wilcoxen (2018), Goulder and Hafstead (2018) and NGFS (2022a). We use the three models because they are based on different assumptions and methodologies.[2] For this reason, we focus on comparisons of banks' exposures to different policies within the same model. Nonetheless, comparing results across the three models helps mitigate concerns about model risk inherent in GE-based estimates.

We combine the industry-level estimates from the three models with commercial and industrial (C&I) loan data for large U.S. banks from the Federal Reserve's Y-14 collection to estimate banks' exposures to transition policies. This data is ideal for our investigation because it provides granular loan-level information as well as borrower characteristics, including industry classification. Further, the data not only covers publicly listed and large private borrowers but also medium-sized businesses.

We follow the standard stress testing approach of assuming that banks maintain a static portfolio of credit exposures (Hirtle and Lehnert, 2015).[3] Accordingly, we take

[2]Appendix A details the main differences between the three models.

[3]More generally, we assume the industry shares of banks' loan portfolios remain the same over time. Although banks may endogenously change their loan composition as transition risk increases, modeling it requires an additional set of assumptions and is therefore typically abstracted from in stress tests. See Parlatore and Philippon (2023) for example.

banks' loan portfolio as of year t and investigate how loan values will be affected due to the changes in industry-level output or profits over the time horizon of the GE models.[4]

Finally, we consider three approaches to translate changes in industry-level output into changes in the value of banks' credit claims on borrowers in those industries. The baseline approach assumes a one-to-one relationship between industry output effects and loan values. Under this approach, if the industry's output (or profits) declines by $x\%$ as a result of the transition policy, we assume that the value of the bank's claims on borrowers in that industry decreases by the same $x\%$. The second approach imposes a severe stress scenario under which loans to the industries most affected by the policy lose their entire value. The third approach captures the nonlinear relationship between borrowers' performance and loan payoffs by incorporating historical information on the probability of default (PD) and loss given default (LGD).

Under the baseline approach, estimated bank exposures to transition risk are economically meaningful across scenarios. According to Jorgenson et al. (2018), the average bank's exposure to transition risk varies between 0.5% and 3.5% as of 2023. For Goulder and Hafstead (2018), the average bank's exposure varies between about -1.5% and about 1% as of 2023. For the NGFS (2022a) model, the average bank's exposure varies between about 2% and 6.4% as of 2023. Differences in the estimated exposures across GE models reflect differences in underlying assumptions and policy scenarios, highlighting the usefulness of considering multiple models.

Turning to the severe stress scenario, the estimated exposures are higher by

[4] Note that financial frictions can affect the implications of transition risks (Carattini, Heutel, and Melkadze, 2021). However, given that GE models typically do not include a financial sector, the models we use do not consider those effects.

construction, as this exercise is intended to provide an upper bound. Under the assumption that loans to industries most adversely affected by the transition policy lose their entire value, banks' average exposure to transition risk ranges between 6% and 14%, depending on the GE model used. For reference, banks projected a 7% loss rate on the C&I loans under the severely adverse scenario considered in the Federal Reserve Stress Test conducted in 2023.

When incorporating historical information on PD and LGD to account for loans' nonlinear payoff structure, the estimated exposures are lower, ranging from about 0.5% to 2%, but in line with ECB's climate stress test results (European Central Bank, 2023).[5] The use of historical loan default data allows us to capture the nonlinearity of loans' payoffs. However, it may yield downward biased estimates of banks' exposures to transition risk because the historical data does not fully reflect the effects of carbon tax programs or the economic conditions at the time these programs are implemented, which can have meaningful implications.

We examine the potential amplification effects induced by both adverse sectoral and aggregate economic shocks. We find that a sectoral shock similar to the 2014–2016 oil price shock has limited effects, increasing banks' exposures by only about one percentage point. By contrast, an aggregate shock similar to the Global Financial Crisis (GFC) has a much larger effect, increasing banks' exposures by 3–5 percentage points.

We undertake several additional extensions to deepen our understanding of banks'

[5]The ECB reported median predicted bank losses ranging from 0.7% to 0.9% relative to total credit exposure in all scenarios. In our baseline scenario, average bank losses for the NGFS estimates (which resemble ECB's scenarios) range from about 2% to 6.4%. When we factor in loans' PDs and LGDs, our estimated losses in the most severe NGFS scenario is about 1%, which is similar to the ECB's estimate.

transition risk exposures. The first extension addresses the fact that not all industries lose from transition policies; green industries may actually benefit. In a subset of GE models that feature benefiting industries, we evaluate the importance of bank lending to these industries. We find that banks' exposures increase by about one percentage point when banks are unable to benefit from improved performance of green industries following transition policies.

Given that emissions are often used as a proxy for banks' exposures to transition risk, we compare our exposure measures with bank-level emissions funding. We find that banks' emissions funding explains only up to 60% of the variation in our exposure measure, suggesting that emissions alone may not fully capture transition risks. In other words, our exposure measure based on GE model estimates accounts for additional factors beyond emissions, such as forward-looking risks and industry spillovers.

Finally, we evaluate the assumption that banks maintain a static portfolio of credit exposures. Assessing this assumption is important because portfolio reallocation in response to climate-related shocks could attenuate or amplify the exposures we measure. Using difference-in-differences analyses, we find mixed evidence across GE models. Highly exposed banks reduce lending to the brownest industries after the Paris Agreement under some models, while responses are muted under others; a similar pattern holds for banks that sign the Net-Zero Banking Alliance. At the same time, borrowers in the brownest industries disproportionately switch to non-signatory banks, suggesting that observed changes in exposures reflect banks' management of transition risks. Taken together, our results offer some support for the static portfolio assumption. More generally, our evidence showing that banks' responses operate mainly through reductions in lending to brown industries suggests that our bank exposure estimates can be interpreted as an upper bound on banks' exposures to transition risks.

Our paper is related to the emerging literature on the vulnerability of the financial system (e.g., Clerc, Bontemps-Chanel, Diot, Overton, Soares de Albergaria, Vernet, and Louardi, 2021, European Central Bank, 2023, Jung, Engle, and Berner, 2025), in particular banks (Arseneau, Kara, and Kotidis, 2022, Battiston, Mandel, Monasterolo, Schütze, and Visentin, 2017, Martini, Sautner, Steffen, and Theunisz, 2024) to climate transition risks. Like this literature, we too find that banks' exposures to transition risk are meaningful. In contrast to this literature, which primarily relies on emissions-based or market-implied proxies for transition risk, we build on GE estimates of economic effects from transition policies to develop a novel measure of banks' exposures to transition risk. This difference matters because emissions are backward-looking and are only one dimension that will be affected in a transition to a low-carbon economy. GE estimates are forward-looking by construction and should capture many different facets that will be affected in that transition.[6] As we show, emissions explain only a portion of the GE estimated effects of transition policies. Further, GE estimates allow us to investigate and compare a wide range of different carbon tax policy implementations, including different tax levels and tax redistribution mechanisms.

Our paper is also related to the literature on banks' responses to climate transition policies/risks (e.g., Antoniou, Delis, Ongena, and Tsoumas, 2021, Delis, de Greiff, de Greiff, Iosifidi, and Ongena, 2019, Ivanov, Kruttli, and Watugala, 2022, Laeven and Popov, 2022). Like these studies, which find weak bank responses, we too find that U.S.

[6] van Binsbergen and Brøgger (2022) offer a forward-looking approach to consider carbon emissions.

banks' responses to the Paris Agreement and the signing of the Net Zero Alliance were limited.[7] Also, the response appears to be focused on a reduction in their exposure to borrowers in brown industries.

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 III presents our results on banks' exposures to transition risks, as well as the results of a set of robustness tests we carry out. Section IV examines whether banks are managing their transition risk exposures. Section V concludes with some final remarks.

II Data, Methodology, and Sample Characterization

A Data Sources

Our main data sources are (i) the Federal Reserve's Y-14 and Y-9C databases, (ii) the industry estimates associated with climate transition policies 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 quarterly information on various asset classes, capital components, and income components for a subset of bank holding companies (BHCs) and intermediate holding companies (IHCs). These include any top-tier BHC or IHC that has $50 billion or more in total consolidated assets, as well as any other bank

[7]This is in line with investors' mixed responses to transition risks. While studies of the options market (Ilhan, Sautner, and Vilkov, 2021) and bond market (Seltzer, Starks, and Zhu, 2022) suggest that investors factor in climate change risks, studies of the stock market (e.g., Bolton and Kacperczyk, 2021, 2023, Hsu, Li, and Tsou, 2023, Sautner, Van Lent, Vilkov, and Zhang, 2023) find mixed evidence on the pricing of climate policy risks. Krueger, Sautner, and Starks (2020) documents that institutional investors believe transition risks will materialize in the near-term, and Engle, Giglio, Kelly, Lee, and Stroebel (2020) argue these risks are hedgeable.

that is or has ever been subject to the Federal Reserve's stress tests.[8]

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: 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).[9] Overall, the loans reported in the data account for about two thirds of all C&I lending volume.

We focus on loans originated between 2012:Q3 and 2023:Q1 across 42 unique banks. We consider both drawn and undrawn commitments in our analysis. We complement this data with bank-level data, including bank assets and total C&I lending, from Y-9C reports.

The data on industry effects of climate transition policies come from three 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).[10] The second source 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 is 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

[8]The size cutoff is based on the bank's total consolidated assets in the four most recent quarters reported in FR Y-9C. Since 2020:Q2, the respondent panel is comprised of any top-tier BHC or IHC with $100 billion or more in total consolidated assets.

[9]It is possible that carbon taxes could have an impact on banks' portfolios beyond C&I loans, such as their mortgage holdings. However, the GE models do not provide estimates of how each carbon tax would impact the savings of heterogeneous households.

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

(NGFS). While there exist other GE models examining the economic effects of climate transition risk, such as that in Golosov et al. (2014), we focus on Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a) because they provide industry-level information. We provide more detail on each of these models in section III.

Our last data source is Trucost data on carbon emissions. 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 for three different categories based on the Greenhouse Gas Protocol.[11] We focus on scope 1 emissions, which are the direct emissions from establishments controlled by the company.[12]

We use industry-level scope 1 emissions, computed for the average firm in the industry (weighted by the firm's total assets from Compustat).[13] 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 Classification System (NAICS) industry classification. We also estimate bank emission intensity, which we calculate as bank emissions funding scaled by bank total assets.

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

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

[13] Results are broadly similar when we use either industry total emissions from Trucost or CDP disclosed emissions in Trucost.

B Methodology

We use industries' estimates of changes induced by climate-related policies from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a) to measure banks' exposures to transition risks. Each of these sources provides information on the expected reduction in industries' profits or output generated by GE models.[14] Next, we match the industry-level estimates with bank loans in the Y-14 based on the crosswalks provided in Tables B.1, B.2 and B.3.[15]

We then use the data to evaluate banks' exposures to transition risks. Towards that end, we compute the decrease in the value of bank loan portfolios that would occur if loan values were to drop by the reduction in output or profits from the GE model estimates:

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

$Exposure_{b,t}^{P}$ is the exposure of bank b to transition risk at time t under policy scenario P. $Markdown_{j}^{P}$ is the expected percentage drop in output or profits for industry j under policy P. For simplicity, in our baseline analysis we assume that loan values will decline proportionally to the drop in the expected output or profits of the borrower's industry. Lastly, $w_{b,j,t}$ is the share of bank $b's$ outstanding credit at time t granted to industry j.

Note that because we build on the GE estimates of transition policies, our approach does not capture individual firms' responses to those policies.[16] Also, following the

[14]The industry estimates we use abstain from the potential effects of policies in the rest of the world.

[15]While the G-Cubed provides results for 20 industries, the available mapping here only includes 12 industries. Our main results pertain to the 12 industries version, but in the Appendix we report results that include all 20 industries.

[16]Firms' responses are, in fact, ex-ante unclear; for instance, Shue and Hartzmark (2023) find that

standard approach of stress testing (e.g., Hirtle and Lehnert, 2015), we assume that the industry composition of a bank's loan portfolio is constant over time. This implicitly assumes that when a loan matures, the bank will either refinance it, or extend a loan to another borrower in the same industry. $Exposure^{P}_{b,t}$ can therefore be interpreted as the percentage drop in the value of a bank's loan portfolio if a climate transition policy is enacted, conditional on the allocation of loans by industry at time t.[17]

Our baseline measure is intentionally simple, making it easy to interpret, but it abstracts from several features that are useful to consider in richer settings. We therefore extend it along three dimensions. First, we put greater weight on industries most adversely affected by transition risks by assuming an extreme case in which loans to the most exposed industries lose their entire value (Section 3.2.1). Second, because our baseline measure allows banks to benefit from improved performance in green industries, we construct a variant that shuts down this upside channel to isolate the losses from adversely affected industries (Section 3.2.2). Third, we incorporate nonlinearities in banks' loan exposures by drawing on supervisory Y-14 data on expected losses from default to derive a more refined bank exposure measure (Section 3.2.3).

Another source of nonlinearity not captured in the general equilibrium model estimates we rely upon are economy wide shocks that could cause default risk to rise disproportionately. We ascertain the importance of these shocks building on the 2008 global financial crisis and the 2014–2016 oil price shock (Section 3.3). We also undertake

sustainable investing that directs capital away from brown firms toward green firms can make brown firms *more* brown.

[17] Our measure implicitly assumes that loan values change at the time the policy is enacted. In Figure B.6 we show results of banks' exposures over the transition path.

several exercises to establish the soundness of our exposure estimates. For example, we investigate to what extent our exposure estimates are driven by banks' contemporaneous funding of carbon emissions to assess the benefits of relying on the GE economic estimates of transition policies (Section 3.4.4). Finally, we build on the Paris Agreement and the signing of the Net-Zero Alliance to ascertain banks' constant loan portfolio composition assumption (Section 4).

C Sample Characterization

After we merge the Y-14 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. Table 1 reports summary statistics, with variable descriptions provided in Table B.4. 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 carbon 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.

III Banks' Exposure to Transition Risks

In this section, we first describe the GE models used to estimate banks' exposures to transition risks, and examine the time series of those exposures. Next, we investigate how banks' exposures vary with some assumptions we make in our baseline analysis. After that, we investigate the implications of the economic conditions at the time when transition policies are introduced. We end the section with some robustness tests.

A Banks' Transition Risk Exposures: Baseline Analysis

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 frequency and plot the time series of the average bank's exposure.[18]

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

Our first analysis of banks' exposures to transition risks uses the results of the IGEM-N provided in Jorgenson et al. (2018).[19] The authors produce estimates of the impact of carbon taxes on output for 36 industries for several initial tax levels, annual tax growth rates, and methods of recycling the income back into the economy.[20] Their policies aim at implementing the carbon trajectory necessary to meet the Paris Agreement goals or the U.S. EPA projections under scenarios developed by the Mcfarland et al. (2018). The estimated adverse impact of their policies on GDP is economically significant, ranging from

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

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

[20]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.

0.7% to 2%. Under their policies, 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 focus on output change estimates for different initial tax levels and annual tax growth rates, where the income is recycled as a lump sum redistribution.[21] As we can see from Figure 1, banks' exposures based on Jorgenson et al. (2018) are persistent over time. The $50 initial tax rate and 5% growth rate scenario, where both the initial tax and growth rate are the highest, has the largest estimated exposure. Here, we expect that the loan portfolio of the average bank would lose about 3.5% of its value. Figure B.1 plots the time series evolution of the average bank's exposure based on a second set of policies (lump sum redistribution, capital tax cut, and labor tax cut).[22]

2 Building on Goulder and Hafstead (2018) Carbon Taxes

We use Goulder and Hafstead (2018) to obtain our second estimates of banks' exposures to climate transition risk. Goulder and Hafstead (2018) uses the E3 model to examine how alternative ways to redistribute carbon tax revenues affect firms and households. Like IGEM-N, it is a multiperiod GE model. However, it is not possible to directly compare banks' exposures under the two models. 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. Additionally, while Jorgenson et al. (2018) provides estimates of changes in industry

[21] Output estimates for these scenarios are provided in Table 8 of Jorgenson et al. (2018), which is reproduced in Table B.5.

[22] Industry estimates for these scenarios are reproduced in Table B.6.

performance from 2015 until 2050, Goulder and Hafstead (2018) provides estimates over an 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 that, the tax increases in real terms by 4% annually until 2048 when it reaches $60 per ton.

We build on Goulder and Hafstead (2018) estimates of changes in U.S. profits for 35 industries from the carbon tax.[23] Figure 2, which plots the time series evolution of the average bank's exposure, also shows little variation in banks' exposure over time. The exposure estimates based on the Goulder and Hafstead (2018) model are especially low. The loan portfolio value for the average bank 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 (-1.5%), meaning that the average bank would benefit from the policy, largely because profits increase for 20 out of the 35 industries.

3 Building on NGFS (2022a) scenarios

Last, we use the G-Cubed model industry-level estimates of the NGFS (2022a) scenarios. The G-Cubed is a GE model that provides information on both macroeconomic and environmental outcomes in the context of the transition to a net zero economy. We consider estimates from the G-Cubed U.S. 12 sector-model. (NGFS, 2022b).[24]

[23] Industry estimates are provided in Table 5.4 of Goulder and Hafstead (2018), which is reproduced in Table B.7. 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 5.9% of the loans in the sample in 2023:Q1.

[24] Estimates are provided in Table B.8 (`https://cama.crawford.anu.edu.au/cama-publications/g-cubed-modelling-results-ngfs-climate-scenarios`). 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.

In NGFS (2022a), the carbon tax is endogenously estimated to achieve different climate goals by 2050. In one scenario, current policies remain in place (modeled as a \$3.72 carbon tax instated in 2021 that grows nonlinearly to \$26.50 in 2050). In another scenario, there is an "orderly transition", with the adoption of the necessary policy mix to achieve net-zero carbon emissions by 2050. Here, a \$16.75 carbon tax is implemented in 2021 that grows nonlinearly to \$119.14 in 2050, with tax proceeds used to invest in infrastructure and pay down government debt. Finally, there is a "delayed transition" scenario, where the policy is adopted in 2031 to limit the end-of-century temperature rise to below 2 degrees. For this scenario, no carbon tax is in place until 2030. At that time, a \$31.52 carbon tax is enacted that grows nonlinearly to \$121.97 in 2050, and the proceeds are paid to households as a lump sum dividend.

Figure 3 plots the time series of the average bank's exposure under the three scenarios described above. 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%. 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. Banks' exposures are highest (lowest) under the disorderly (current) policy scenarios, respectively.[25] The idea that more stringent policies generate higher bank

[25] Note these results rely on the publicly available mapping, which only identifies 12 industries. Figure B.2 displays results from the 20 industry G-Cubed model.

exposures is also present in the other models and confirmed in regression analysis.[26]

B Understanding Banks' Baseline Risk Exposures

In this subsection, we present three variations to our baseline exposure measure. This will allow us to better understand our baseline measure, as well as the importance of different assumptions made to construct it.

1 Banks' Exposures to the Most Brown Industries

There may be nonlinear effects of transition risks on bank payoffs. For instance, brown industries could be disproportionally affected in the transition. To this end, we consider a stress scenario in which loans to the most adversely affected industries lose their entire value. For all other industries, losses are assumed to be proportional to declines in the borrower's industry output (or sales).[27] The bank's exposure under stress is defined as:

$$\begin{aligned} &\textit{Exposure Under Stress}^{P}_{b,t} = \\ &\sum_{j \in J} w_{b,j,t}\, \mathbb{1}\left(\textit{Markdown}^{P}_{j} > x\right) + \sum_{j \in J} w_{b,j,t} \mathbb{1}\left(\textit{Markdown}^{P}_{j} \leq x\right) \cdot \textit{Markdown}^{P}_{j}, \end{aligned} \tag{2}$$

where $\textit{Exposure Under Stress}^{P}_{b,t}$ is the exposure for bank b at time t under policy P. We define the industries most exposed to transition risks (i.e., the most brown industries) as those in the top-one or top-two deciles of transition risk distribution across industries.

The time series of banks' exposures to the most brown industries are displayed in

[26] This is apparent in Figures 1 through 3, and in regression analysis reported in Tables B.9 and B.10.

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

Figure 4. Panel (a) displays the results for the Jorgenson et al. (2018) model. The estimates are considerably higher using the *Exposure Under Stress* than with the baseline *Exposure* measure. The expected drop in bank loan portfolio values increases by about 4.5 percentage points when assuming that the top-decile of the industries lose all of their value, and an additional 6 percentage points when assuming that the top-two deciles of industries lose all of their value. Note that these estimates have declined by 1–3 percentage points over the past 10 years, consistent with banks gradually reducing their exposures to the most brown industries.

Panel (b) shows that the *Exposure Under Stress* is about 2 percentage points higher than the baseline exposure when the top-decile industry loses all of its value under Goulder and Hafstead (2018), and by an additional 2 percentage points when assuming the top-two deciles lose all of their value. For the NGFS model, we see from panel (c) that the *Exposure Under Stress* measure is almost identical to the baseline when assuming the two most brown industries default in the "disorderly transition" scenario.[28] This similarity reflects the fact that the NGFS scenarios already imply losses comparable in magnitude to those assumed in our severe scenario. In the NGFS disorderly scenario, output in gas extraction and utilities (the most brown industry) falls by 100% by 2050, and output in coal (the second most brown industry) falls by about 96%, leaving little additional loss to be projected under our *Exposure Under Stress* measure. When we assume the top-3 ranked industries lose their entire value, banks' loan portfolio values are expected to decline by an additional 1 percentage point as of 2023.

[28]These results rely on the publicly available mapping, which only identifies 12 industries. Panel (b) of Figure B.3 displays the results with all 20 industries for the G-Cubed model.

These results show that banks' loan portfolios in 2023 would drop by about 14% under the extreme assumption that 20% of the industries most affected by climate transition risks according to Jorgenson et al. (2018) completely lose their value, although they are smaller under Goulder and Hafstead (2018) and NGFS (2022a).[29] Overall, these exposures have decreased by about 2–4 percentage points since 2012, further suggesting that banks have been reducing their exposure to the most brown industries.

2 Evaluating the Benefits of Green Industries' Exposures

Our baseline exposure measure allows banks to benefit from improved performance in green industries following the implementation of transition policies. In this subsection, we consider a variant that shuts down this channel. Specifically, when constructing the exposure measure, we bound the increase in industry output or profits at zero. This variant both isolates the role of gains from green industries and reflects the asymmetric nature of loan payoffs, which limits banks' ability to benefit from upside realizations.

Figure 5 shows the time series of banks' exposure without any benefit from green industries. In the Goulder and Hafstead (2018) and NGFS (2022a) models, exposures increase by about 1 percentage point once banks no longer benefit from lending to green borrowers.[30] No change is observed for the Jorgenson et al. (2018) model because there is no sector that greatly benefits from transition policies in their model, which highlights how different model assumptions can drive exposure estimates. Overall, our results suggest that

[29] Note that the *Exposure Under Stress* outside the GE framework we used in our baseline analysis. For this reason, we are unable to observe how the rest of the economy would respond to the scenario where the most brown industries lose all their value, and consequently account for spillover effects between the industries.

[30] We observe a larger effect when we consider the NGFS 20 sector model (Figure B.3.)

gains from green industries matter but are quantitatively modest, especially relative to the risk exposure coming from brown industries.

3 Banks' Exposures Accounting for Nonlinearity in Loan Payoffs

Section 1 provides a simple way to account for banks' nonlinear exposure to default risk across industries. There, we assume complete losses on loans to the most exposed industries to highlight the potential magnitude of exposure under a severe scenario. In this section, we complement the previous analysis by using expected loss estimates to directly capture the nonlinear effect of transition risks on loans' payoffs.

Since bank loan payoffs are typically nonlinearly related to a borrower's performance, we use the Y-14's data on loss given default (LGD), probability of default (PD) and borrower sales to estimate the relationship between expected loan losses and sales for each industry. Specifically, we begin by sorting expected loan losses (PD$\times LGD$) into sales deciles, within industry, where the industries are defined according to the GE model. Next, we run the following regression, separately for each industry j and year t.

$$Losses_i = \alpha_{j,t} + \sum_{k=1}^{10} \beta_{j,t}^{d} \mathbb{1}(d_i = k), \tag{3}$$

where $Losses_i$ represent the expected losses for loan i, and d_i is equal to 1 if the borrower for loan i was in sales decile k in year t. Whenever possible we run regressions within 3-digit NAICS industries for each year. If this is not possible, we run regressions within 2-digit NAICS industries for each year.[31] Otherwise, we run regressions within the broad

[31]Note that as some 2- and 3-digit NAICS include multiple broad industries as defined for each GE model, we run the regressions separately for the subset of each NAICS industry included in each GE industry.

industries used by the GE model. We cap losses for bank i at one, ensuring that losses do not exceed the full value of the loan portfolio. While we do not have information on borrowers' leverage ratios, and therefore cannot rely on them to identify nonlinearities in default, we still account for the possibility that defaults become more likely for risky borrowers by assuming a default probability of one for loans with an above-average PD. For all other loans, losses are computed using the expected loss estimates from equation (3).

Finally, we combine the estimated relationship above with the GE model estimates of decline in sales for each scenario to compute $NLExposure$, the exposure accounting for the nonlinear relationship between borrower sales and loan losses:

$$NLExposure_{b,t}^{P} = \sum_{j \in J} w_{b,j,t} \hat{Losses}_i, \tag{4}$$

where $w_{b,j,t}$ represents the share of loan amount made by bank b to industry j in quarter t, and $\hat{Losses}_i$ estimates come from (3).

Figure 6 shows banks' exposures adjusted for the nonlinearity of loans' payoffs. The exposures are similar across models, ranging between 0.5% and 2% as of 2023. As of 2023, at worst exposures adjusted for loans' payoffs nonlinearity are about the same as baseline exposures (for the same model), and at best are up to 4 percentage points lower. This is because banks typically do not lose the full value of a loan upon default in historical realizations.

Assuming that loan losses following transition policies resemble historical default outcomes provides a natural benchmark for estimating the impact of those policies. However, that impact may underestimate the full implementation of transition policies.

Further, it may also depend on the economic conditions at the time the policies are implemented, a possibility we explicitly consider next.

C Sensitivity of Banks' Exposures to Shocks

The stress scenario exercise in which loans to the most adversely affected industries lose their entire value, while arguably extreme, highlights the importance of nonlinear effects on banks' transition risk exposures. An additional dimension of nonlinearity arises from state dependence; as shown in Nagel and Purnanandam (2020), shocks can interact with adverse aggregate conditions, causing default risk to rise disproportionately in bad states of the economy. In light of this mechanism, the adverse effects of transition policies can be amplified during economic downturns.

To capture this state-dependent nonlinearity, we consider two types of shocks to the economy: an economy-wide shock and a shock specific to the energy sector. For the former, we use the 2008 global financial crisis because it represents a sharp deterioration in aggregate economic conditions. For the latter, we use the 2014–2016 oil price shock. Between mid-2014 and early 2016, oil prices fell by roughly 70 percent, marking one of the three largest oil price declines since World War II and the most persistent since the supply-driven collapse of 1986 (World Bank, 2018). The prolonged and sector-specific nature of this episode makes it a natural laboratory for sustained stress in the energy sector.[32]

To assess how bank exposures would change if transition policies were implemented

[32]While oil prices fell more sharply during COVID-19, that episode reflected an aggregate global demand collapse with extensive policy intervention, making the 2014–2016 shock a cleaner setting for our analysis.

during a downturn, we construct a counterfactual increase in default risk calibrated to the crisis episodes described above. Specifically, for each industry (6-digit NAICS-level), we compute the change in the PDs over each shock episode.[33] We then apply these changes to loan-level PDs in the Y-14 to estimate counterfactual bank exposures under crisis-like conditions.

For the GFC, we define the shock period based on the trough-to-peak in the aggregate default risk, which corresponds to 2007:Q2 to 2009:Q1. We take this approach because PDs, rather than business-cycle dating per se (e.g., NBER recessions), are the relevant state variable for bank loan losses. For the energy-sector shock, we define the shock period using the peak-to-trough decline in Brent Crude Oil index, which spans 2014:Q2 to 2016:Q1.[34] While one could calibrate the shock using default-probability changes for a preselected set of affected industries, the oil price collapse did not impact all industries uniformly, making such a selection unclear ex ante. We, therefore, anchor the shock directly in the observed oil price decline.

Figure 6 reports the estimated exposure to transition risk under the aggregate shock (solid red line). An economy-wide downturn increases banks' (nonlinearity-adjusted) exposures by roughly 3–5 percentage points, based on 2023 loan portfolios, with exposures reaching up to 11% in 2020 under the NGFS (2022a) framework. This reflects both the amplification of transition-related losses in highly exposed sectors and broader increases in default risk across less transition-exposed industries.

[33] Because the Y-14 data begin in 2012, we use one-year expected default probabilities from Moody's KMV CreditMark to measure changes in default risk in GFC exercise. Although Y-14 data are available for the oil-price shock, we use KMV CreditMark for consistency; results are similar when changes in default probabilities are instead computed using Y-14 data.

[34] Source: `https://fred.stlouisfed.org/graph/?g=ko34`.

The effects of the sectoral shock are shown by the green line. With an energy-sector shock, exposures rise by about 1 percentage point relative to the nonlinearity-adjusted baseline. Unlike the aggregate shock, the oil price collapse did not increase default risk uniformly across industries. While transition-exposed sectors experienced higher default risk, other sectors, including some green industries, benefited from lower energy costs, muting the overall impact on exposure.

Overall, these results suggest that banks' exposures to transition risk can be amplified when transition policies coincide with adverse aggregate economic conditions. Sectoral shocks during the transition, by contrast, have relatively smaller effects on banks' exposures.

D Robustness Analysis and Extensions

In this section, we present a set of robustness analyses and extensions to deepen our understanding of banks' exposures to transition risk.

1 Within-Industry Heterogeneity

In constructing our exposure measure we assume that bank selection of borrowers within an industry is random relative to the borrower's transition risk. To examine this assumption, we use granular industry-level emissions data, at the 4-digit NAICS level, which allows us to examine heterogeneity in banks' lending to high and low emission industries, within each sector of the GE models. To do this, we identify the highest and lowest emitting industries within each modeled sector and calculate the following ratio:

$$P(Lending_{it}^{Low}) = \frac{Lending_{it}^{Low}}{Lending_{it}^{Low} + Lending_{it}^{High}}, \quad (5)$$

where $Lending_{it}^{Low}$ is lending to the lowest-emitting borrowers in the GE sector and $Lending_{it}^{High}$ is lending to the highest-emitting borrowers in the GE sector.[35] We regress this measure on bank fixed effects for each quarter in the sample.

The R^2 of these regressions based on the Jorgenson et al. (2018) industries are plotted in Figure B.4. 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. Also, the fitted line through the R^2's is flat, suggesting that banks are not increasingly sorting into browner or greener borrowers within each industry over time. The red line, which displays the R^2 from a regression of $P(Lending_{it}^{Low})$ on both bank and industry fixed effects, shows similar results.

2 Exposure Relative to Bank Capital

The results reported thus far show banks' exposures to transition risk scaled by their assets. Given that leverage plays an important role in determining banks' vulnerability, we also scale exposures by bank capital. Figure B.5 displays the results scaling the exposure measure by bank capital for all three models. As expected, scaling by bank capital yields larger exposures, but it does not change the relative impact of the various policies.

[35] 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 $Lending_{it}^{High}$.

3 Banks' Exposures over the Transition Path

Our baseline estimates report the long-run impact of transition policies as of the final year in the model horizon—that is, a snapshot of the final outcome. However, one may also be interested in understanding how exposures evolve along the transition path. While most GE models we rely on do not report intermediate outcomes, the G-Cubed model provides industry-level estimates over time. We, therefore, use the G-Cubed transition paths to trace the evolution of banks' exposures under each scenario.

The resulting exposure paths using the G-Cubed scenarios are shown in Figure B.6. Based on our baseline measure, while the exposures under the current policy and orderly policy are realized gradually over time, the exposure of banks under the disorderly scenario is zero until 2030. At that point, the exposure under the disorderly scenario increases more rapidly than in the other two scenarios. By contrast, when assuming the top-1, -2 and -3 most affected industries lose their entire value, exposures are realized much more quickly than in the baseline measure.

4 Banks' Emissions Funding and Exposure to Transition Risk

Finally, thus far we have not considered carbon emissions, which are commonly used to proxy for climate transition risks. Therefore, one may wonder how our findings compare to banks' exposures had we relied on carbon emissions. To this end, we regress our estimates on banks' exposures on banks' carbon emission funding and carbon emissions intensity for each policy scenario, and report the R^2 of these regressions in Table 2.

Depending on the model and the scenario used, the R^2 is at least 30%, and at most

60%. Overall, it is reassuring to observe a positive correlation between our GE based exposures and bank emissions funding; after all industries with high emissions are expected to be more affected by the transition policies.[36] However, it is notable that at least 40% of the variation in our exposure measures is *not* explained by carbon emissions alone. Additionally, we examine the relationship between the industry-level emissions and industry-level exposures in Table B.11, and find that the R^2 estimates are even lower.

IV Do Banks Manage Transition Risks' Exposures?

Our approach assumes that banks' loan portfolio compositions remain constant following the implementation of carbon tax policies, consistent with standard stress-testing frameworks. Evaluating this assumption is important because portfolio reallocation in response to climate-transition policies could either attenuate or amplify the exposures we measure. Because a carbon tax has not been implemented in the U.S., we instead examine this assumption by exploiting banks' responses to two important climate-related events: the Paris Agreement and banks' signing of Net-Zero Banking Alliance. If banks adjust their portfolios in response to these events, the direction and magnitude of the adjustment will help assert whether our baseline estimates are closer to a lower or an upper bound.

A Paris Agreement

We begin by investigating banks' responses to the Paris Climate Accord. On December 12, 2015, 196 nations adopted the Paris Agreement. By doing so, they agreed to

[36] Tables B.12 and B.13 show that banks are more exposed to stricter policies when they fund higher emissions.

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 would likely have disproportionately negative effects for industries exposed to transition risk.[37]

We empirically examine whether banks with significant lending portfolios to industries exposed to transition risk changed their lending policies after the Paris Agreement. To do this, we first identify the most affected banks as the ones with high exposure to the most brown industries before the Paris Agreement. Next, we run the following regression:

$$Exposure_{it} = \alpha + \beta \; \textit{Pre-Paris Exposure}_i \times Post_t + \Gamma X_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{6}$$

where $\textit{Pre-Paris Exposure}_i$ is the 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.[38] We include bank-level controls ($X_{i,t}$), as well as bank and time fixed effects (γ_i, δ_t). The exposure is policy-specific, and is computed based on equation (1). The sample period is from 2012:Q3 to 2019:Q4 to isolate the effect coming from the other important event, signing of Net-Zero Banking Alliance, which occurred in 2021. 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

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

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

disorderly transition for the NGFS (2022a) model. We expect a negative β if the affected banks reduced their exposures (compared to the control group) following the Paris Agreement.

Panel A of Table 3 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. The results are mixed. The negative coefficients in Columns (1) and (3) indicate that banks reduced their exposures following the Paris Agreement. In the specification based on the Goulder and Hafstead (2018) model (Column 2), the coefficient is also negative but not statistically significant. When exposure is measured using emissions, the coefficient turns positive, although it is not statistically significant.

In order to understand which margin—reducing brown exposure and/or increasing green exposures—banks adjust, we analyze the shares of loans to the "most brown" and "most green" industries separately. We identify the former industries as those in the top-two deciles of exposure and the latter industries as those in the bottom-two deciles of exposure.[39] Panel B of Table 3 shows that the affected banks reduced lending to the most brown industries, and panel C shows that they increased lending to the most green industries, relative to the control group, following the Paris Agreement. Overall though, the change in exposure appears more driven by the decline in browner lending than an increase in greener lending.

Although the mixed evidence on portfolio rebalancing following the Paris Agreement offers some support for the static balance sheet assumption one may wonder to

[39]Note that in the case of the NGFS (2022a) we instead define the most brown industries as top-three ranked industries and the most green industries as bottom-three ranked industries given the relatively smaller number of industries in the model.

what extent it derives from the declining oil prices which overlapped with the Paris Agreement. To help isolate banks' management of their exposures to climate transition risks, we examine banks' responses to their signing of the Net-Zero Banking Alliance.

B 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 for a suitable setting to test whether banks are adjusting their lending in response to concerns with transition risks. We define the treated group as the 11 banks in the Y-14 that signed the Alliance in 2021:Q1. We focus on the sample period 2017:Q2 to 2023:Q1 to isolate the effect of the Net-Zero Banking Alliance signing. This design narrows the post-time window, and therefore, the results should be interpreted with this caveat in mind. 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 dummy variable, *Post*:

$$Exposure_{it} = \alpha + \beta\ Signatory_i \times Post_t + \Gamma X_{i,t} + \gamma_i + \kappa_t + \varepsilon_{i,t} \quad (7)$$

where $Signatory_i$ takes a value of 1 if the bank signed the Net-Zero Banking 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 if the signatory banks reduced their exposures relative to other banks after signing the Alliance.

Similar to our previous analysis, the results are mixed. Table 4 shows that signatory banks reduced their exposures relative to non-signatory banks after signing the Net-Zero Banking Alliance, based on the Jorgenson et al. (2018) and the NGFS (2022a) models. The results based on the emissions measure and Goulder and Hafstead (2018) are not statistically significant. The signs of coefficients in Panels B and C are consistent with the decline in exposure being driven by banks reducing lending to the most brown industries rather than increasing lending to the most green industries. However, the coefficients are statistically significant only under the NGFS (2022a) model.

The results on signatory banks' responses align with our findings from the Paris Agreement, suggesting that to the extent they are undertaking any risk-exposure management it is limited to a reduction in their exposures to brown industries. To further ascertain whether these changes are bank-driven we investigate borrowers' decisions to switch between signatory and non-signatory banks in the next subsection.

C Borrowers' Switches between Banks

We begin by computing the probability of non-signatory banks' borrowers switching to signatory banks, and the probability of signatory banks' borrowers switching to non-signatory banks. Next, 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. A higher odds ratio indicates borrowers were relatively more likely to switch to non-signatory banks. We compute the odds ratio separately for the most brown industries and the most green industries before and after the alliance. The most brown and most green industries are defined the same as in the above analysis.

Figure 7 reports the odd ratios. Panel A, which is based on the Jorgenson et al. (2018) model, shows that the odds ratio of the most brown industries increased (from 4.6 to 6.4) after the signing of the alliance. The odds ratio of the most green industries increased, but by relatively less (from 4.1 to 4.3) after signing the alliance. Panels B, C, and D, which are based on Goulder and Hafstead (2018), NGFS (2022a), and emission funding, respectively, show similar results.[40] This evidence indicates that relative to the most green industries, bank-borrower relationships moved from signatory to non-signatory for the most brown industries.

Table B.14 shows consistent results based on a similar exercise comparing borrowing from highly-exposed and less-exposed banks around the Paris Agreement. Together with our previous findings on lending volume, these results on borrowers' switches show some evidence of banks' responses although limited to a reduction in their exposures to brown industries.

In sum, the evidence on banks' responses to the Paris Agreement and the signing of the Net Zero Alliance offers some, arguably mixed, support for the static balance sheet assumption we made in our estimates of banks' exposures to transition risk. However, the fact that banks' responses were by in large limited to a reduction in exposures to brown industries suggests that our bank exposure estimates can be viewed as an upper bound of

[40]Results are presented in table form in Table 5.

banks' exposures to transition risks.

V Conclusion

There is growing interest 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 with GE sectoral estimates of changes in the U.S. economy following different transition policy scenarios. In contrast to carbon emissions, which are backward-looking, our estimates are forward-looking, and because they are computed from GE models, they capture a wider range of effects induced by policies to promote the transition to a low-carbon economy.

Our results show that banks' exposures to transition risks are at their highest 14% of their loan portfolios under the most severe scenario; however, they are about 0.5%–2% when accounting for historical loans' PDs and LGDs. We estimate that exposures are up to 5 percentage points higher if the transition policy is implemented at the time of an economic downturn, with a relatively smaller effect if the policy coincides with a sectoral shock. Our results also show that a commonly used metric, past carbon emission, is unable to explain at least 40% of the bank exposures estimated from general equilibrium models. Finally, while we find some evidence that U.S. banks are managing their exposures to transition risks, this effect is primarily driven by reduced lending to brown borrowers.

Our paper suggests some several fruitful areas for future research in the nexus between financial stability and climate change risks. For example, 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. Given that we focused on transition risks, it would be worthwhile to expand our 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' ability to access funding going forward.

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-output reduction estimated in Jorgenson et al. (2018). Plots show the average exposure measures across banks, weighted by a bank's total assets. Bank-level exposures are computed using the Y14 loan-level data. All scenarios assume the carbon tax is redistributed as a lump sum. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency and are from 2012 until 2023.

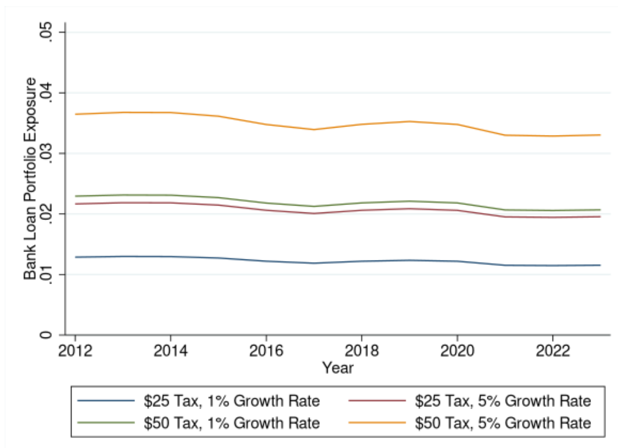


Figure 2: Differences in Exposure to Transition Risks from Goulder and Hafstead (2018) by Redistribution

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-profits reduction estimated by Goulder and Hafstead (2018). Plots show the average exposure measures across banks, weighted by a bank's 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.

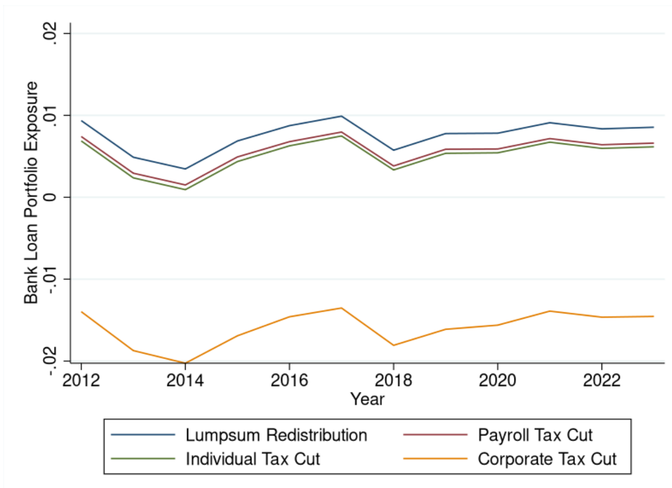


Figure 3: Differences in Exposure to Transition Risks from the G-Cubed Scenarios

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-output reduction estimated by NGFS (2022a). Plots show the average exposure measures across banks, weighted by a bank's total assets. Bank-level exposures are computed using the Y14 loan-level data. Industries are as defined by the G-Cubed. Data are smoothed at the annual frequency, and are from 2012 until 2023.

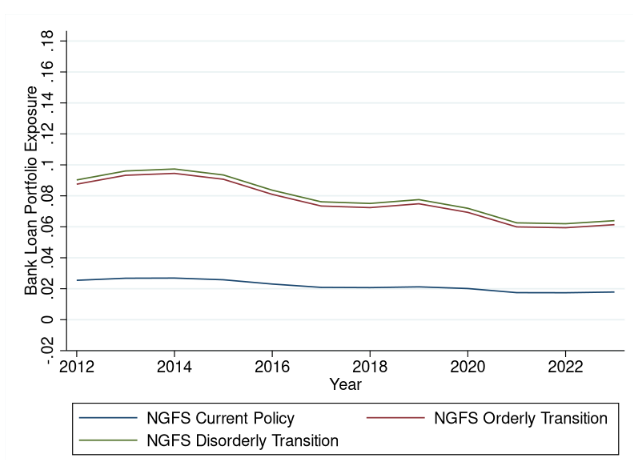
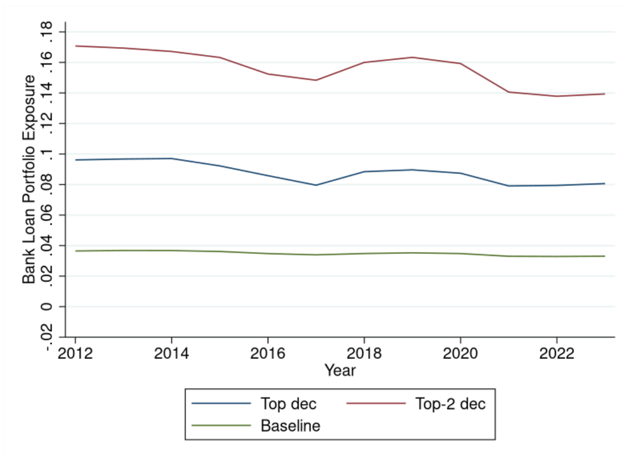


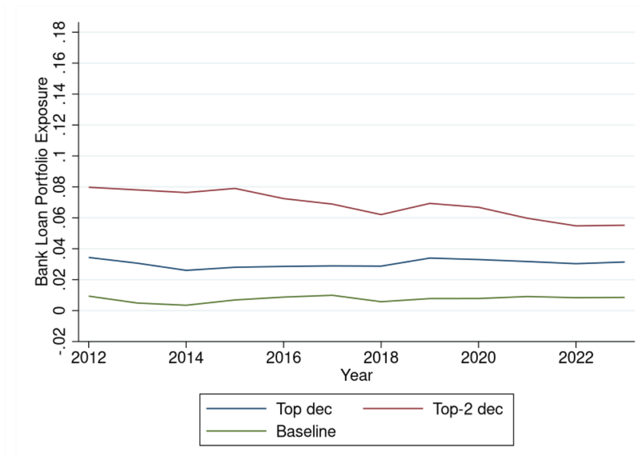
Figure 4: Exposures to Transition Risks for the Most Brown Industries

Shows exposures to transition risks for the most brown 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 most brown 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 most brown industries are those in the top-two deciles of exposure to transition risks, and for NGFS (2022), the most brown 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.

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



(b) Goulder and Hafstead (2018) lump sum redistribution



(c) G-Cubed Disorderly Transition

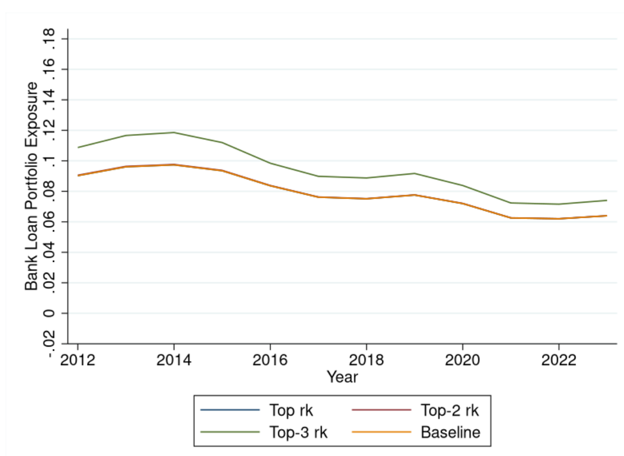
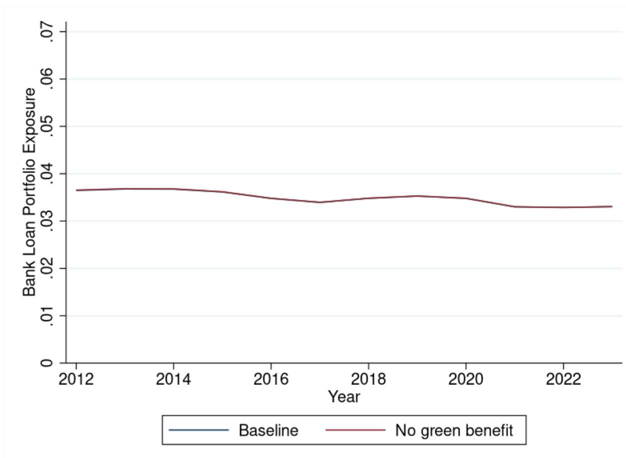


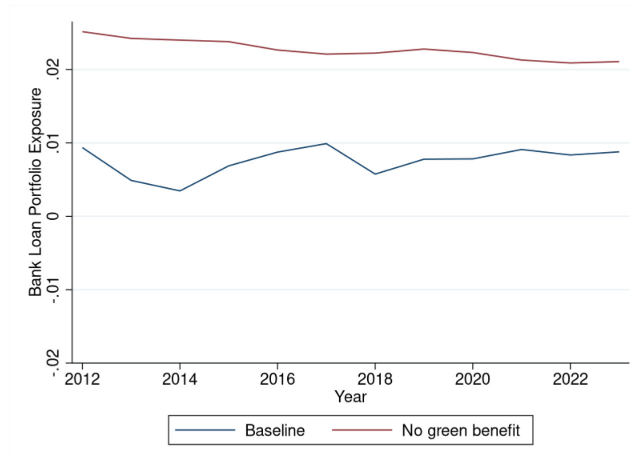
Figure 5: Exposures to Transition Risks When There is No Benefit to Lending to Green Borrowers

Shows exposures to transition risks from model-estimates of industry-level exposures from Jorgenson et al. 2018, Goulder and Hafstead 2018 and NGFS (2022) over time. Loan exposures are calculated as described above. We cap loan balances so they cannot increase above their current day value. Exposures are adjusted so banks cannot benefit from improved performance by green industries following 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.

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



(b) Goulder and Hafstead 2018 lump sum redistribution



(c) G-Cubed Disorderly Transition

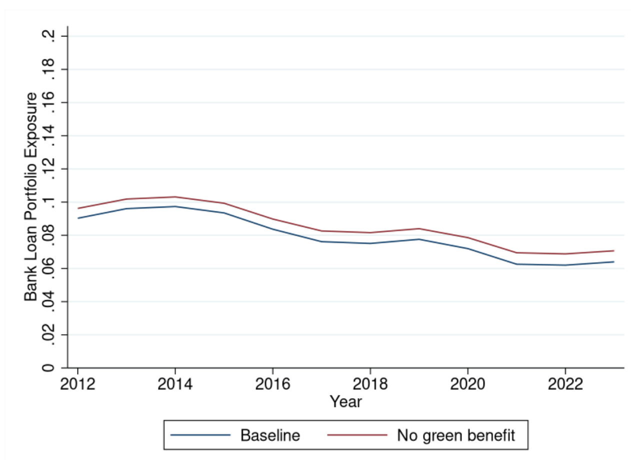
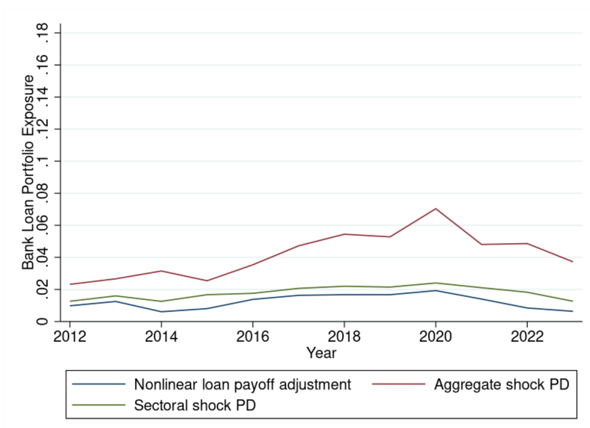


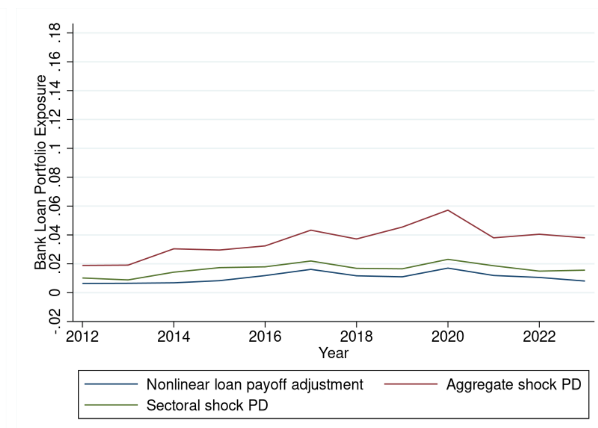
Figure 6: Exposures to Transition Risks Accounting for Nonlinearities

Shows exposures to transition risks adjusted for nonlinearities in the payoff structure from model-estimates of industry-level 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 all loans with an above average probability of default eventually default. For the industries that default, we adjust by the loss given default in the Y-14, and for all other industries we adjust by the total loss as estimated from a regression of borrower expected loss on sales decile indicators. For Jorgenson et al. (2018) and Goulder and Hafstead (2018), the most brown industries are those in the top-two deciles of exposure to carbon taxes, and for NGFS (2022), the most brown industries are the three industries most exposed to climate policy. To capture the effect of a major aggregate shock, we add the rise in industry-level probabilities of default that occurred during the 2008 financial crisis (2007:Q2–2009:Q1) to the loan-level probabilities of default in the Y-14, and to capture the effect of a sectoral shock, we add the change in industry-level probabilities of default that occurred from the peak in oil prices to their bottom (i.e., 2014:Q2 until 2016:Q1) to the loan-level probabilities of default in the Y-14. Industries are defined by the authors of the referenced paper. Data are smoothed at the annual frequency, and are from 2012 until 2023.

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



(b) Goulder and Hafstead (2018) lump sum redistribution



(c) G-Cubed Disorderly Transition

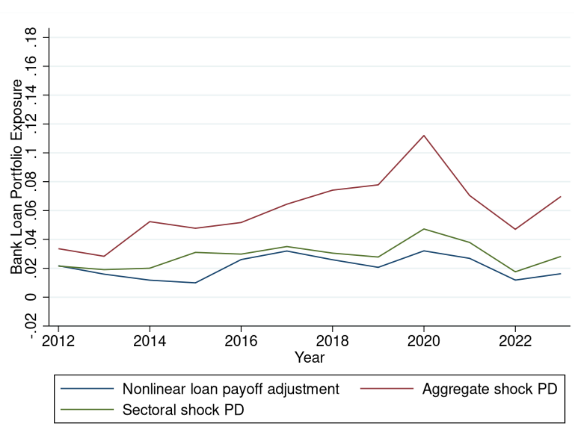
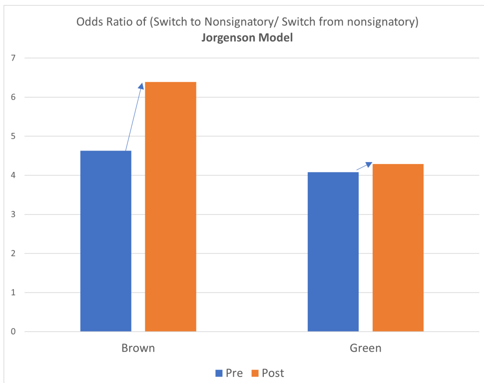


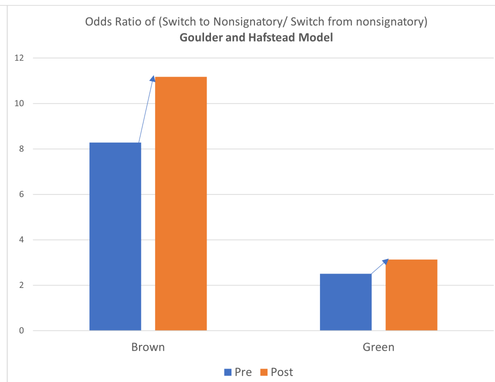
Figure 7: Likelihood of Switching Lenders After the Net-Zero Banking Alliance

Shows the change in odds ratios of likelihood of switching to signatory-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.

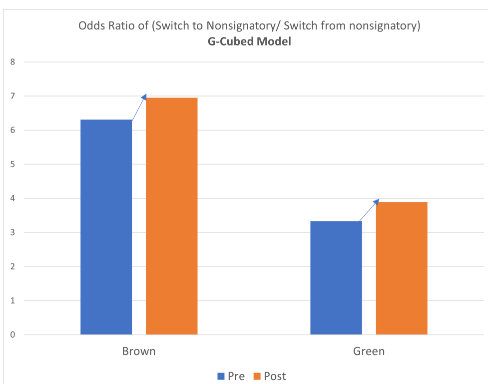
(a) Jorgenson et al. (2018)



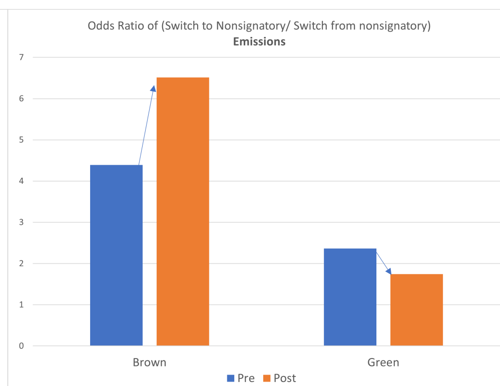
(b) Goulder and Hafstead (2018)



(c) G-Cubed



(d) Emissions



Tables

Table 1: Summary Statistics

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.

	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	0.00	0.06	-0.02	0.02	0.02	1,340
Goulder Payroll Tax Cut	0.00	0.06	-0.02	0.02	0.02	1,340
Goulder Individual Tax Cut	0.00	0.06	-0.02	0.02	0.02	1,340
Goulder Corporate Tax Cut	-0.02	0.06	-0.05	-0.00	0.00	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	1130.00
Emission Intensity	0.04	0.05	0.00	0.02	0.07	1122.00
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					

Table 2: Explanatory Power of Emissions for Exposures

Shows the R^2's of regressions of bank-exposure measures on banks' emission funding. 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 intensities are calculated as bank emission funding scaled by bank total assets. Data are quarterly and from 2013:Q1 until 2021:Q4.

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	0.297	0.297	0.297	0.297
Emissions Intensity R2	0.117	0.116	0.117	0.118
	Panel D: G-Cubed Scenarios			
	Current Policy	Disorderly Transition	Orderly Transition	
Emissions R2	0.496	0.411	0.416	
Emission Intensity R2	0.254	0.207	0.208	

Table 3: Changes in Banks' Exposures or Emissions Funding After the Paris Agreement Based on Initial Exposures

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 most brown industries, or the percentage of a bank's lending portfolio to the most green industries based on their exposures prior to the Paris Agreement, after the Paris Agreement was announced. Data are quarterly from 2012:Q3 until 2019:Q4.

Panel A: Banks' Exposures

	(1) Exposure	(2) Exposure	(3) Exposure	(4) Emissions
Pre-Paris IGEM Exposure × Post Paris	-0.140***			
	(-3.22)			
Pre-Paris Goulder Exposure × Post Paris		-0.090		
		(-1.59)		
Pre-Paris NGFS Exposure × Post Paris			-0.175***	
			(-3.00)	
Pre-Paris Emissions × Post Paris				0.046
				(0.75)
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	0.081	0.061	0.163	0.014
Observations	897	897	897	841

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

Panel B: Lending to the Most Brown Industries

	(1) Pr(Brown Lending)	(2) Pr(Brown Lending)	(3) Pr(Brown Lending)	(4) Pr(Brown Lending)
Pre-Paris IGEM Exposure × Post Paris	-2.266***			
	(-3.02)			
Pre-Paris Goulder Exposure × Post Paris		-0.044		
		(-0.41)		
Pre-Paris NGFS Exposure × Post Paris			-0.261***	
			(-2.78)	
Pre-Paris Emissions × Post Paris				-0.003***
				(-4.59)
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	0.129	0.101	0.153	0.094
Observations	897	897	897	841

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

Table 3 — Continued

Panel C: Lending to the Most Green Industries

	(1) Pr(Green Lending)	(2) Pr(Green Lending)	(3) Pr(Green Lending)	(4) Pr(Green Lending)
Pre-Paris IGEM Exposure × Post Paris	-0.042			
	(-0.04)			
Pre-Paris Goulder Exposure × Post Paris		0.231***		
		(3.55)		
Pre-Paris NGFS Exposure × Post Paris			0.381***	
			(3.28)	
Pre-Paris Emissions × Post Paris				-0.001
				(-0.27)
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	0.092	0.051	0.149	0.068
Observations	897	897	897	841

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

Table 4: Changes in Banks' Exposures or Emissions Funding for Signatories After the Net-Zero Banking Alliance

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 most brown industries, or the percentage of a bank's lending portfolio to the most green 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 2017:Q2 until 2023:Q1.

Panel A: Banks' Exposures

	(1) Exposure	(2) Exposure	(3) Exposure	(4) Emissions
Signatory × Post Alliance	-0.001*	0.002	-0.011*	-0.908
	(-1.81)	(0.41)	(-2.01)	(-1.18)
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	0.103	0.111	0.202	0.028
N	594	594	594	471

Panel B: Lending to the Most Brown Industries

	(1) Pr(Brown Lending)	(2) Pr(Brown Lending)	(3) Pr(Brown Lending)	(4) Pr(Brown Lending)
Signatory × Post Alliance	-0.006	-0.005	-0.009*	-0.015
	(-0.58)	(-0.99)	(-1.88)	(-1.45)
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	0.104	0.065	0.152	0.013
N	594	594	594	471

Panel C: Lending to the Most Green Industries

	(1) Pr(Green Lending)	(2) Pr(Green Lending)	(3) Pr(Green Lending)	(4) Pr(Green Lending)
Signatory × Post Alliance	-0.012	-0.002	0.016	0.028
	(-0.36)	(-0.17)	(0.85)	(1.20)
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	0.095	0.012	0.288	0.074
N	594	594	594	471

Table 5: Switches Between Lenders for Signatories and Non-Signatories

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 2017:Q2 until 2023:Q1.

Panel A: Jorgenson et al. (2018)

	Switch to Signatory	Switch to non-signatory	Odds ratio
Most Brown Pre-Alliance	0.095	0.44	4.632
Most Green Pre-Alliance	0.088	0.359	4.080
Most Brown Post-Alliance	0.093	0.594	6.387
Most Green Post-Alliance	0.09	0.386	4.289

Panel B: Goulder and Hafstead (2018)

	Switch to Signatory	Switch to non-signatory	Odds ratio
Most Brown Pre-Alliance	0.065	0.538	8.277
Most Green Pre-Alliance	0.116	0.291	2.509
Most Brown Post-Alliance	0.063	0.704	11.175
Most Green Post-Alliance	0.106	0.332	3.132

Panel C: G-Cubed

	Switch to Signatory	Switch to non-signatory	Odds ratio
Most Brown Pre-Alliance	0.096	0.606	6.313
Most Green Pre-Alliance	0.098	0.327	3.337
Most Brown Post-Alliance	0.099	0.688	6.949
Most Green Post-Alliance	0.091	0.354	3.890

Panel D: Emissions

	Switch to Signatory	Switch to non-signatory	Odds ratio
Most Brown Pre-Alliance	0.1	0.439	4.390
Most Green Pre-Alliance	0.126	0.298	2.365
Most Brown Post-Alliance	0.064	0.417	6.516
Most Green Post-Alliance	0.130	0.227	1.746

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Internet Appendix

Appendix A Additional Information on the General Equilibrium Models

Table A.1: Comparison of General Equilibrium Models

Model	Jorgenson et al (2018)	Goulder and Hafstead (2018)	G-Cubed
Number of industries	36	35	12
Endogenous financial sector in the model	No	No	No
Assumptions about sectoral adaptation	The model includes a "biased technical change" component, which allows for an approximation of energy-saving due to technological change.	Sectors are able to obtain energy from non-fossil electricity generation.	Sectors are able to obtain energy from renewable energy technologies. The G-Cubed also makes exogenous allowances for deployment of negative emissions technologies.
Variation in policy	Tax level and redistribution	Redistribution	Policy Goal
Model time horizon	2015-2050	Infinite (in present value terms)	2020-2050
Renewable energy source	No	Yes	Yes
Metric for estimates	Output	Profits	Output
Most unfavorable policy for banks	\$50 tax/5% growth rate	Lumpsum redistribution	Disorderly Scenario
Maximum carbon tax rate in the most unfavorable policy for banks	\$216.10 per ton as of 2050	\$60 per ton in 2048	\$121.97 per ton in 2050
Main beneficiary from the most unfavorable policy for banks	Education Services (.7% increase)	Non-fossil electricity generation (62.7% increase)	Services (1.22% increase)
Main loser from the most unfavorable policy for banks	Coal mining (33.8% decrease)	Coal-fired electricity generation (74.7% decrease)	Gas Extraction and Utilities (100% decrease)

We use estimates from three general equilibrium models to estimate how bank loan values are affected by climate transition policies. These models are from Jorgenson et al. (2018), Goulder and Hafstead (2018) and NGFS (2022a). The table above highlights some of the differences in the assumptions and specifications of the three models. As is typical in general equilibrium models, simplifying assumptions are necessary in order to obtain tractable results. For instance, none of these models contain a financial sector, which forces us to assume that the balance sheets of financial institutions are static. Additionally, while the Goulder and Hafstead (2018) and NGFS (2022a) models have a renewable energy sector, Jorgenson et al. (2018) does not.

Of course, these simplifying assumptions expose us to the model risk that is inherent in any general equilibrium analysis. However, by using these three models in combination, we are able to vary the assumptions and examine how that changes the results. In this way, combining these three models in our analysis helps to mitigate the model risk.

Appendix B Appendix Tables and Figures

Appendix Figures

Figure B.1: 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-output 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 a bank's 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.

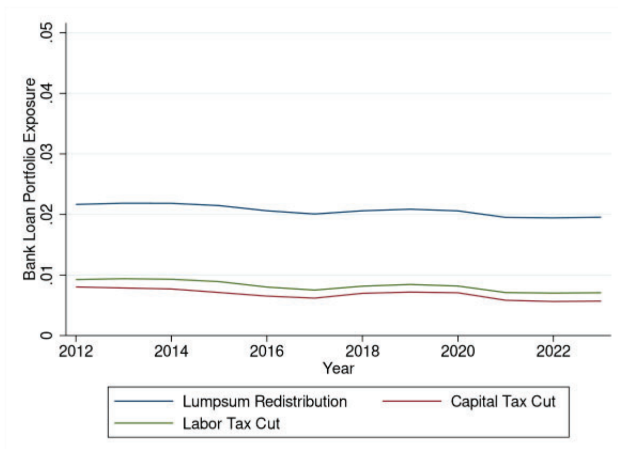


Figure B.2: Differences in Exposure to Transition Risks from the NGFS Scenarios with a 20 Industry Mapping

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.

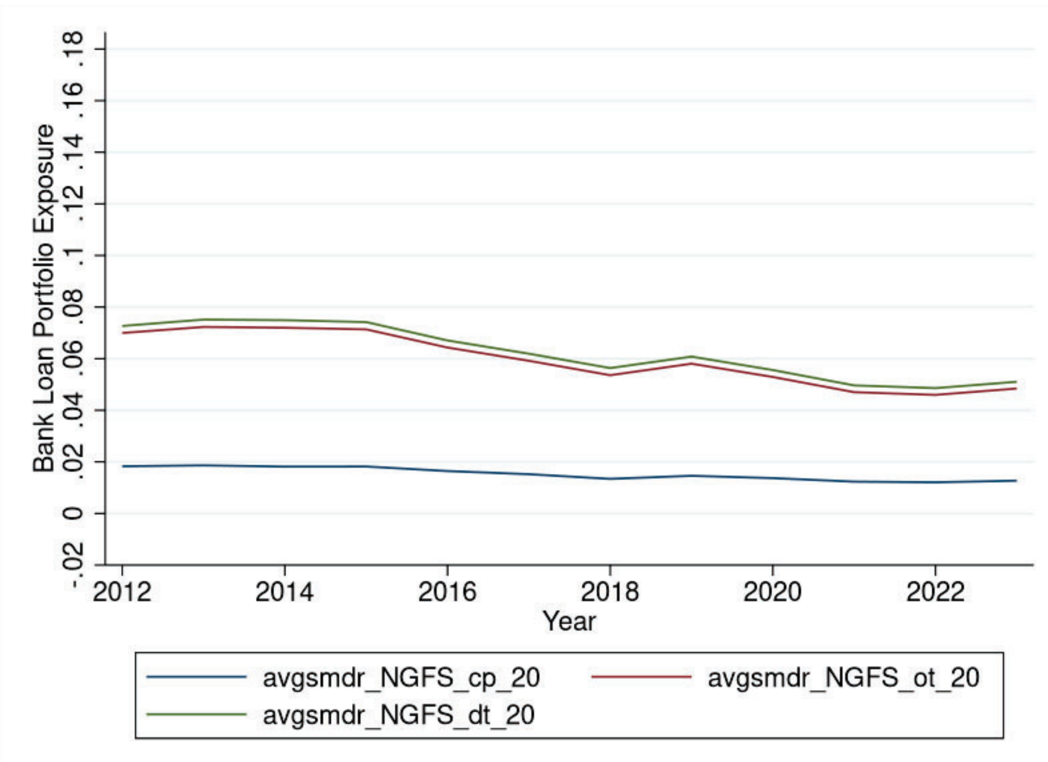
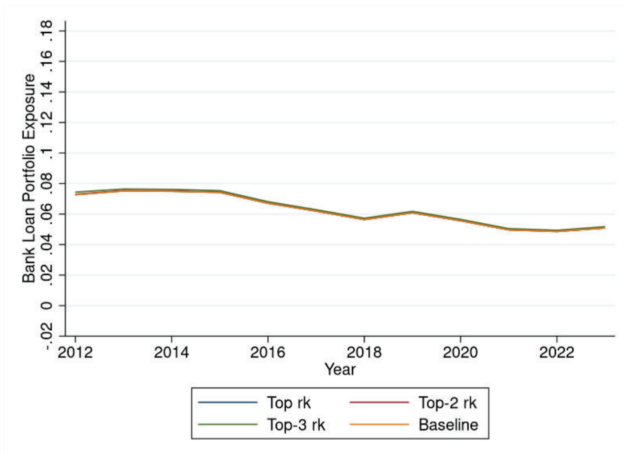


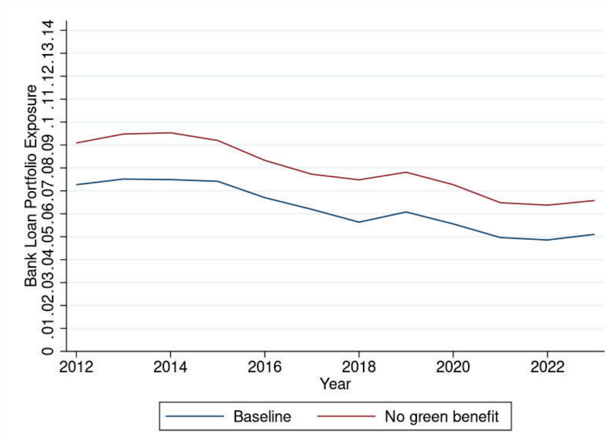
Figure B.3: Alternative Exposure Measures Using the 20 Industry NGFS Results

Shows exposures to transition risks adjusted for nonlinearities in loan payoffs, and exposures to transition risks for the most brown 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 most brown 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.

(a) Exposure to Most Brown Industries



(b) No Benefit for Green Lending



(c) Exposure Accounting for Nonlinearities

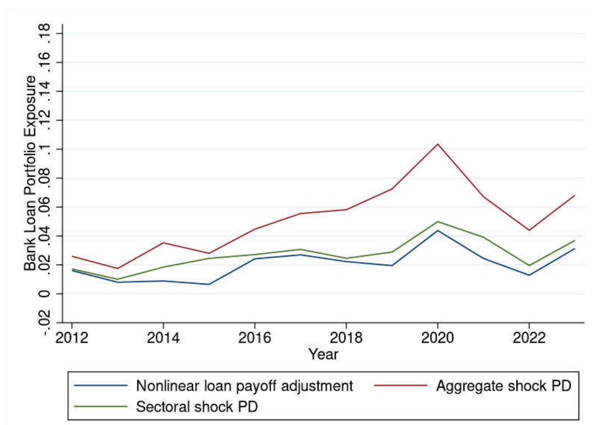


Figure B.4: Examining Bank Sorting Within Industry

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.

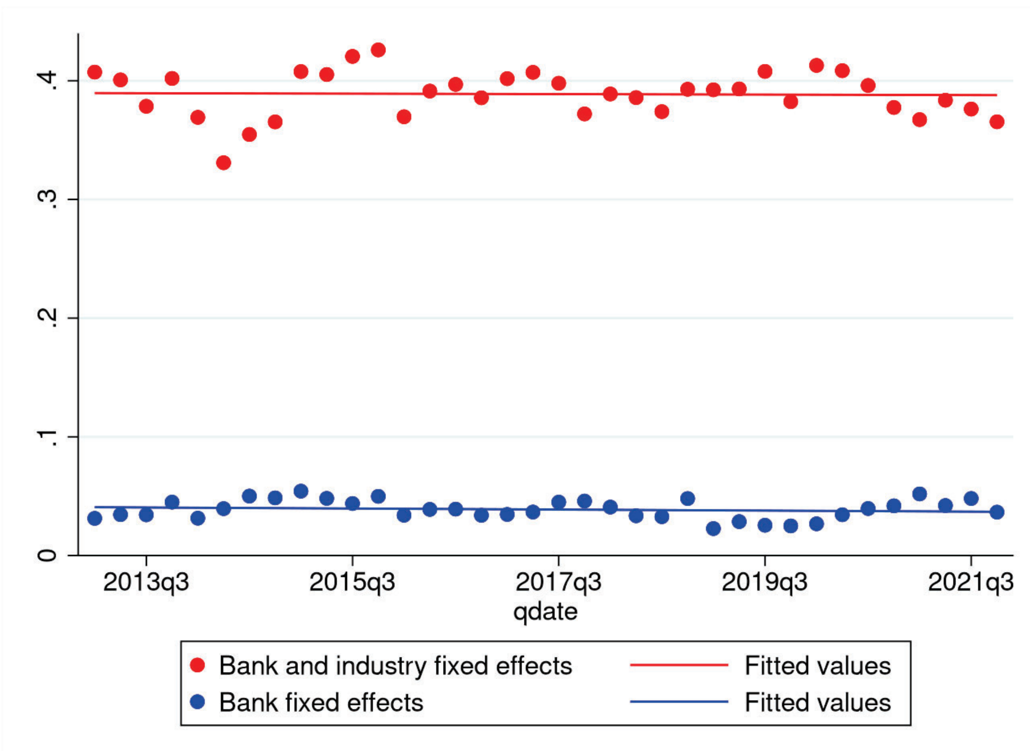
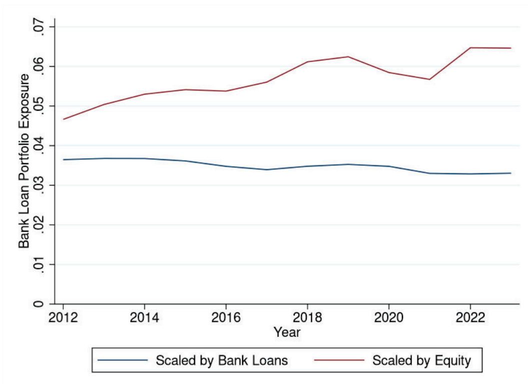


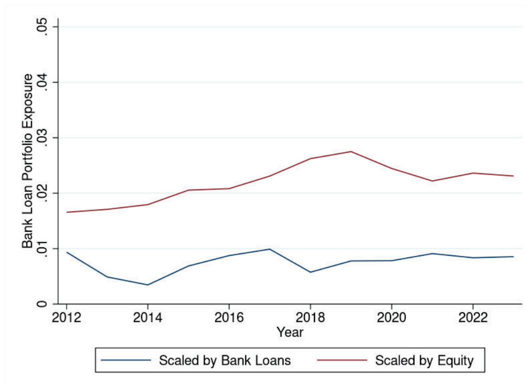
Figure B.5: Exposures to Transition Risks Relative to Bank Capital

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 most brown 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.

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



(b) Goulder and Hafstead (2018) lump sum redistribution



(c) G-Cubed Disorderly Transition

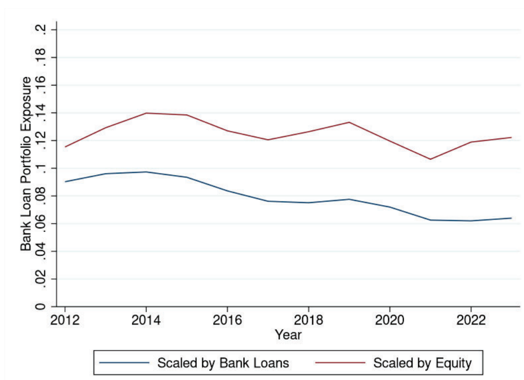
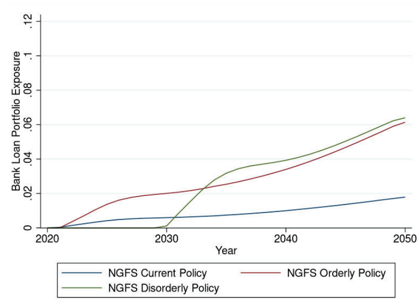


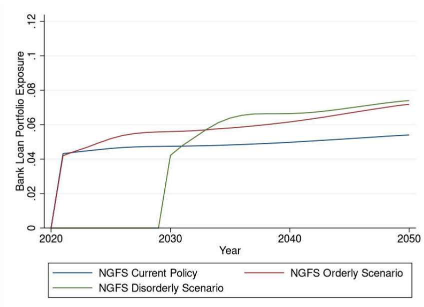
Figure B.6: Path of Exposure to Transition Risks from the G-Cubed Scenarios

Shows expected exposure to transition risks from model estimates of industry-level exposures to climate policy from the G-Cubed scenarios based on the G-Cubed 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-output 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 a bank's total assets. Y14 loan data as of 2023 is used.

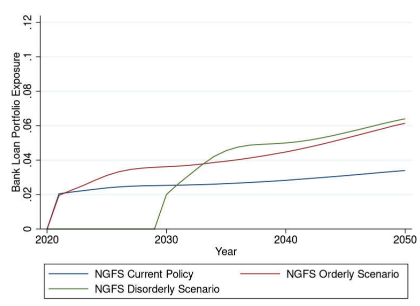
(a) Baseline Measure



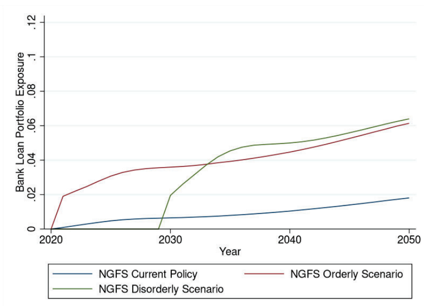
(b) Top-3 Ranked Bankrupt



(c) Top-2 Ranked Bankrupt



(d) Top-1 Ranked Bankrupt



Appendix Tables

Table B.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 intermediates; Leasing	Real estate (ex owner-occupied)	531
	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 B.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 B.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

[B.1] The Exposure metric is calculated as follows:

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

$Exposure_{b,t}^{P}$ is the exposure of bank b to transition risk at time t under policy scenario P. $Markdown_{j}^{P}$ 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 the drop in the expected output or profits of the borrower's industry. Lastly, $w_{b,j,t}$ is the share of bank $b's$ outstanding credit at time t granted to industry j, where we obtain information on the size of each outstanding loan in bank $b's$ portfolio in dollars from the y14.

Table B.4: Variable Definitions

Variable	Source	Definition
Exposure	Calculated by authors from y14 and GE models	The average decrease in the value of bank loan portfolios occurring if loan values drop by the reduction in output or profits provided by the estimates from the general equilibrium models.[B.1]
Jorgenson 25d Tax, 1p Growth	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario of a \$25 growing at 1% annually from Jorgenson et al. (2018).
Jorgenson 25d Tax, 5p Growth	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario of a \$25 growing at 5% annually from Jorgenson et al. (2018).
Jorgenson 50d Tax, 1p Growth	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario of a \$50 growing at 1% annually from Jorgenson et al. (2018).
Jorgenson 50d Tax, 5p Growth	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario of a \$50 growing at 5% annually from Jorgenson et al. (2018).
Jorgenson Lumpsum	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as a lumpsum dividend from Jorgenson et al. (2018).
Jorgenson Capital Tax Cut	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as a cut in capital taxes from Jorgenson et al. (2018).
Jorgenson Labor Tax Cut	Jorgenson et al. (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as a cut in labor taxes from Jorgenson et al. (2018).
Goulder Lumpsum	Goulder and Hafstead (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as lumpsum dividend from Goulder and Hafstead (2018).
Goulder Payroll Tax Cut	Goulder and Hafstead (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as cut in payroll taxes from Goulder and Hafstead (2018).
Goulder Individual Tax Cut	Goulder and Hafstead (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as cut in individual taxes from Goulder and Hafstead (2018).
Goulder Corporate Tax Cut	Goulder and Hafstead (2018), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the scenario where carbon tax proceeds are paid out as cut in corporate taxes from Goulder and Hafstead (2018).
NGFS Current Policy	NGFS (2022a), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the current policy scenario NGFS (2022a).
NGFS Orderly Transition Policy	NGFS (2022a), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the orderly transition scenario NGFS (2022a).
NGFS Disorderly Transition Policy	NGFS (2022a), y14	Banks' exposure to transition risk, as calculated in footnote A.1, for the disorderly transition scenario NGFS (2022a).
Emissions (MM Tons)	Trucost, y14	Bank scope 1 emissions funding, in millions of tons. Calculated as average emissions for all the borrowers with loans from a bank, weighted by the size of the loan in dollars. We use the emissions for the average firm in the industry that a borrower belongs to, where we use the finest-digit NAICS industry available.
Emission Intensity	Trucost, y14	Bank scope 1 emissions funding, in millions of tons. Calculated as the bank's emissions, as defined above, scaled by bank total assets in billions of dollars. We use the emissions for the average firm in the industry that a borrower belongs to, where we use the finest-digit NAICS industry available.
Ln(Assets)	y9c	The natural log of bank total assets.
Loans/Assets	y9c	Total commercial and industrials loans for a bank scaled by the bank's total assets.
ROA	y9c	The bank's return on assets, measured as the quarterly net income scaled by the total assets.
Leverage	y9c	The bank's total liabilities scaled by the bank's total assets.
Deposits/Assets	y9c	The bank's total deposits, scaled by the bank's total assets.
Loan Loss Reserves/Loans	y9c	The bank's loan loss reserves, scaled by the bank's total assets.
Non-Interest Income/Net Income	y9c	The bank's quarterly non-interest income scaled by the bank's quarterly net income.

Table B.5: Drop in Industry Output for Carbon Tax and Growth Rate Scenarios in Jorgenson et al. (2018)

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.

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

Table B.6: Drop in Industry Output for Redistribution Scenarios in Jorgenson et al. (2018)

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.

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

Table B.7: Drop in Industry Sales for Redistribution Scenarios in Goulder and Hafstead (2018)

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.

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

Table B.8: Drop in Industry Sales from G-Cubed Scenarios

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

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

Table B.9: Comparing Exposure Measures by Policy

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 lump sum 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 G-Cubed scenarios. Standard errors are clustered at the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1.

	(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			-0.02***	
			(-77.79)	
Payroll Tax Cut			-0.00***	
			(-158.20)	
Individual Income Tax Cut			-0.00***	
			(-43.42)	
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)	(1.25)	(-0.40)
Loans/Assets	-0.01*	-0.02*	0.13*	-0.05
	(-1.75)	(-1.86)	(1.90)	(-1.09)
ROA	-0.09	-0.12	0.61	-0.66
	(-0.81)	(-0.98)	(0.51)	(-0.98)
Leverage	-0.07	-0.09*	0.68	-0.38
	(-1.51)	(-1.79)	(1.32)	(-1.44)
Deposits/Assets	-0.00	-0.00	0.03	-0.01
	(-0.33)	(-0.18)	(0.52)	(-0.21)
Loan Loss Reserves/Loans	-0.00	-0.01	0.22	-0.05
	(-0.00)	(-0.23)	(0.58)	(-0.13)
Non-Interest Income/Net Income	0.00	0.00	0.00	0.00
	(0.26)	(0.15)	(0.74)	(0.40)
Model	Jorgenson	Jorgenson	Goulder and Hafstead	NGFS
Policy Lever	Tax	Redistribution	Redistribution	Transition
Adjusted R2	0.66	0.60	0.27	0.38
Observations	5,328	3,996	5,328	3,996

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

Table B.10: Comparing Exposure Measures by Policy – with Bank and Time Fixed Effects

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 lump sum 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 G-Cubed scenarios. Standard errors are clustered at the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1.

	(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			-0.02***	
			(-77.48)	
Payroll Tax Cut			-0.00***	
			(-157.58)	
Individual Income Tax Cut			-0.00***	
			(-43.25)	
Orderly Transition				0.05***
				(10.41)
Disorderly Transition				0.06***
				(10.87)
Ln(Assets)	-0.00	-0.00	0.01	0.00
	(-0.75)	(-0.67)	(1.23)	(0.22)
Loans/Assets	-0.02***	-0.01***	0.12***	-0.08**
	(-4.23)	(-4.28)	(3.28)	(-2.65)
ROA	0.04	0.04	-0.21*	0.48***
	(1.54)	(1.52)	(-1.78)	(2.94)
Leverage	0.00	0.00	0.01	0.04
	(0.23)	(0.34)	(0.23)	(0.30)
Deposits/Assets	0.00	0.00	0.04	0.04
	(1.49)	(1.57)	(1.38)	(1.42)
Loan Loss Reserves/Loans	-0.00	0.00	-0.26	-0.33*
	(-0.10)	(0.23)	(-1.41)	(-1.82)
Non-Interest Income/Net Income	0.00*	0.00*	-0.00	0.00
	(1.83)	(1.69)	(-0.96)	(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	0.37	0.65
Observations	5,328	3,996	5,328	3,996

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

Table B.11: Explanatory Power of Industry-Emissions for Industry-Exposures

Shows the R^2's of regressions of industry-exposure measures on industry-level emissions. The exposure is taken directly from 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.

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	0.019	0.019	0.019	0.020
	Panel D: G-Cubed Scenarios			
	Current Policy	Disorderly Transition	Orderly Transition	
Emissions R2	0.283	0.269	0.268	

Table B.12: Heterogeneity in Effects of Policy on Exposure by Bank Emissions

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.

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

Table B.13: Heterogeneity in Effects of Policy on Exposure by Bank Emissions – with Fixed Effects

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.

	(1) exposure	(2) exposure	(3) exposure	(4) 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
Bank Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
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
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: Switches Between Lenders for More and Less Exposed Banks After Paris Agreement

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.

Panel A: Jorgenson et al. (2018)

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Most Brown Pre-Alliance	0.172	0.248	1.442
Most Green Pre-Alliance	0.146	0.148	1.014
Most Brown Post-Alliance	0.155	0.239	1.542
Most Green Post-Alliance	0.196	0.151	0.770

Panel B: Goulder and Hafstead (2018)

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Most Brown Pre-Alliance	0.076	0.506	6.658
Most Green Pre-Alliance	0.129	0.303	2.349
Most Brown Post-Alliance	0.069	0.547	7.928
Most Green Post-Alliance	0.116	0.209	1.802

Panel C: G-Cubed

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Most Brown Pre-Alliance	0.117	0.595	5.085
Most Green Pre-Alliance	0.125	0.207	1.656
Most Brown Post-Alliance	0.166	0.482	2.904
Most Green Post-Alliance	0.182	0.179	0.984

Panel D: Emissions

	Switch to Low Exposed Bank	Switch to High Exposed Bank	Odds ratio
Most Brown Pre-Alliance	0.174	0.356	2.046
Most Green Pre-Alliance	0.192	0.236	1.229
Most Brown Post-Alliance	0.19	0.249	1.311
Most Green Post-Alliance	0.197	0.196	0.995