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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.

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

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[1] *Transition risks* are associated with the losses resulting from a transition of production and consumption toward 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.

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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 article, 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.

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 (2017), and Bertram, Boirard, Edmonds, Fernando, Gayle, Hurst, Liu, McKibbin, Payerols, Richters, and Schets (2022). 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,

[2]Appendix A in the Supplementary Material 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 (2025), for example.

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we take 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 (2017), the average bank's exposure varies between about −1.5% and about 1% as of 2023. For the Bertram et al. (2022) 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 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

[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.

[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.

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the 2014–2016 oil price shock has limited effects, increasing banks' exposures by only about 1 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' 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 1 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 nonsignatory 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 article 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), and 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

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

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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 article is also related to the literature on banks' responses to climate transition policies/risks (e.g., Antoniou, Delis, Ongena, and Tsoumas (2026), Delis, de Greiff, de Greiff, Iosifidi, and Ongena (2019), Ivanov, Kruttli, and Watugala (2024), and Laeven and Popov (2023)). Like these studies, which find weak bank responses, we too find that U.S. 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 article 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 (2017) and Bertram et al. (2022), 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 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: 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.

[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 (2026)) 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) document 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.

[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.

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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 (2017), 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 (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 (2017), and Bertram et al. (2022) 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 nondisclosing firms when possible. Trucost reports emissions for three different categories based on the Greenhouse Gas Protocol (https://ghgprotocol.org/). We focus on scope 1 emissions, which are the direct emissions from establishments controlled by the company.[11]

We use industry-level scope 1 emissions, computed for the average firm in the industry (weighted by the firm's total assets from Compustat).[12] 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.

B. Methodology

We use industries' estimates of changes induced by climate-related policies from Jorgenson et al. (2018), Goulder and Hafstead (2017), and Bertram et al. (2022) to measure banks' exposures to transition risks. Each of these sources provides information on the expected reduction in industries' profits or output

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

[11]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.

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

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generated by GE models.[13] 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 in the Supplementary Material.[14]

We then use the data to evaluate banks' exposures to transition risks. Toward 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:

$$Exposure^{P}_{b,t} = \sum_{j \in J} w_{b,j,t} Markdown^{P}_{j}. \tag{1}$$

$Exposure^{P}_{b,t}$ is the exposure of bank b to transition risk at time t under policy scenario P. $Markdown^{P}_{j}$ 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.[15] Also, following the 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.[16]

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 III.B.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 III.B.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 III.B.3).

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

[14]While the G-Cubed provides results for 20 industries, the available mapping here (https://www.sensiblepolicy.com/Manuals2021/GGGv20JManual/sectmap.htm) includes only 12 industries. Our main results pertain to the 12-industry version, but in the Supplementary Material we report results that include all 20 industries.

[15]Firms' responses are, in fact, ex ante unclear; for instance, Hartzmark and Shue (2023) find that sustainable investing that directs capital away from brown firms toward green firms can make brown firms *more* brown.

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

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Another source of nonlinearity not captured in the GE model estimates we rely upon is economy-wide shocks that could cause default risk to rise disproportionately. We ascertain the importance of these shocks building on the 2008 GFC and the 2014–2016 oil price shock (Section III.C.). We also undertake 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 III.D.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 IV).

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 1340 observations from 2012:Q3 until 2023:Q1. Table 1 reports summary statistics, with variable descriptions provided in Table B.4 in the Supplementary Material. 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 (2017) model, a corporate tax cut seems to be the most favorable tax redistribution scheme for banks. Finally, in the Bertram et al. (2022) 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.

TABLE 1

Summary Statistics

Table 1 shows summary statistics from Y14 loan-level data, which are aggregated to the bank level. Data are quarterly and from 2012:Q3 until 2023:Q1

	Mean	Std. 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 lump sum	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 lump sum	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	1,130
Emission intensity	0.04	0.05	0.00	0.02	0.07	1,122
ln(assets)	19.42	1.06	18.33	19.05	21.36	1,332
Loans/assets	0.48	0.21	0.14	0.54	0.71	1,332
ROA	0.00	0.00	0.00	0.00	0.00	1,332
Leverage	0.89	0.03	0.86	0.89	0.92	1,332
Deposits/assets	0.63	0.19	0.32	0.70	0.81	1,332
Loan loss reserves/loans	0.01	0.01	0.00	0.01	0.02	1,332
Noninterest income/net income	2.66	8.65	0.92	1.82	5.31	1,332
No. of obs.	1,340					

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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.[17]

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).[18] 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.[19] 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 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.[20] 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 in the Supplementary Material 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).[21]

2. Building on Goulder and Hafstead (2017) Carbon Taxes

We use Goulder and Hafstead (2017) to obtain our second estimates of banks' exposures to climate transition risk. Goulder and Hafstead (2017) use the E3 model

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

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

[19]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.

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

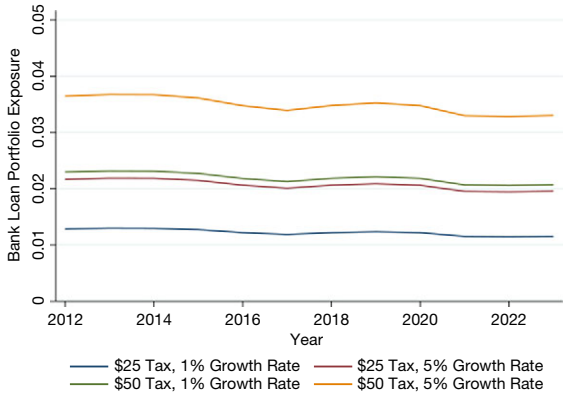
[21]Industry estimates for these scenarios are reproduced in Table B.6 in the Supplementary Material.

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FIGURE 1

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

Figure 1 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.



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 (2017) includes a nonfossil electricity generation sector which benefits from carbon taxes. Additionally, while Jorgenson et al. (2018) provide estimates of changes in industry performance from 2015 until 2050, Goulder and Hafstead (2017) provide 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 (2017) estimates of changes in U.S. profits for 35 industries from the carbon tax.[22] 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 (2017) 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.

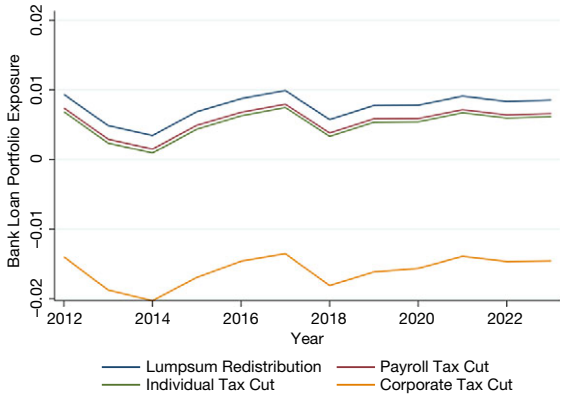
[22]Industry estimates are provided in Table 5.4 of Goulder and Hafstead (2017), which is reproduced in Table B.7 in the Supplementary Material. E3-industries are mapped to the Y14 by NAICS, forcing us to drop loans that do not map to an E3 industry. This exclusion amounts to 5.9% of the loans in the sample in 2023:Q1.

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FIGURE 2

Differences in Exposure to Transition Risks from Goulder and Hafstead (2017) by Redistribution

Figure 2 shows exposure to transition risks based on model estimates from Goulder and Hafstead (2017) 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 (2017). 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.



3. Building on Bertram et al. (2022) Scenarios

Last, we use the G-Cubed model industry-level estimates of the Bertram et al. (2022) 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.[23]

In Bertram et al. (2022), 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 from Bertram et al. (2022). Exposures are much higher than the estimates based on Jorgenson et al. (2018) and Goulder and Hafstead (2017). In the orderly transition, the average bank's loan value decreases by about 6% as of 2023, and in

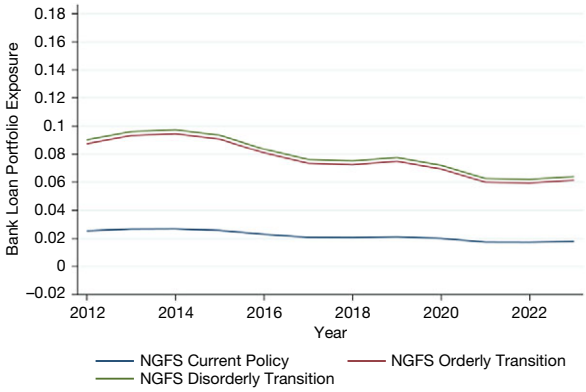
[23]Estimates are provided in Table B.8 in the Supplementary Material. NGFS industries are mapped to the Y14 by NAICS, forcing us to drop loans that do not map to an NGFS industry. This exclusion amounts to 3.6% of the loans in the sample in 2023:Q1.

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FIGURE 3

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

Figure 3 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 Bertram et al. (2022). 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.



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.[24] The idea that more stringent policies generate higher bank exposures is also present in the other models and confirmed in regression analysis.[25]

B. Understanding Banks' Baseline Risk Exposures

In this section, 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

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

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

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assumed to be proportional to declines in the borrower's industry output (or sales).[26] The bank's exposure under stress is defined as:

$$(2)\quad Exposure\ Under Stress^{P}_{b,t} = \sum_{j\in J} w_{b,j,t}\,\mathbb{1}\left(Markdown^{P}_{j} > x\right) + \sum_{j\in J} w_{b,j,t}\,\mathbb{1}\left(Markdown^{P}_{j} \le x\right)\cdot Markdown^{P}_{j},$$

where $Exposure\ Under Stress^{P}_{b,t}$ 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 Figure 4. Graph 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 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.

Graph 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 (2017), 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 Graph 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.[27] 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 three ranked industries lose their entire value, banks' loan portfolio values are expected to decline by an additional 1 percentage point as of 2023.

These results show that banks' loan portfolios in 2023 would drop by about 14% under the extreme assumption that the 20% of 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 (2017) and Bertram et al. (2022).[28] Overall, these exposures have decreased by about 2–4 percentage

[26]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.

[27]These results rely on the publicly available mapping, which only identifies 12 industries. Graph B of Figure B.3 in the Supplementary Material displays the results with all 20 industries for the G-Cubed model.

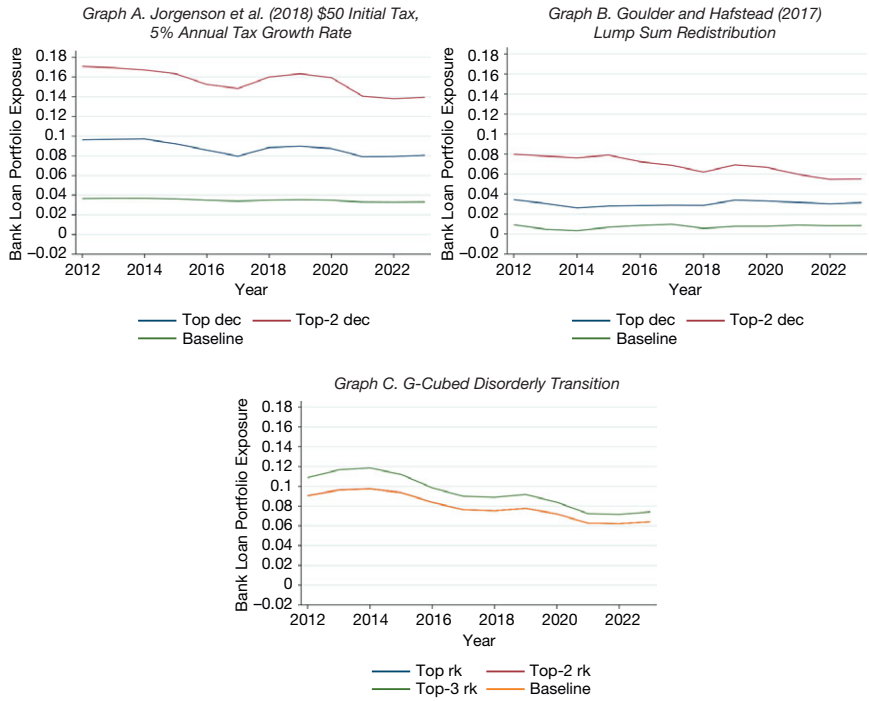
[28]Note that the *Exposure Under Stress* outside the GE framework we used in our baseline analysis. For this reason, we are unable to observe how the rest of the economy would respond to the scenario where the most brown industries lose all their value, and consequently account for spillover effects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

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FIGURE 4

Exposures to Transition Risks for the Most Brown Industries

Figure 4 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 over time. Estimates from Jorgenson et al. (2018), Goulder and Hafstead (2017), and Bertram et al.(2022) are shown in Graphs A, B, and C respectively. 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 (2017), the most brown industries are those in the top two deciles of exposure to transition risks, and for Bertram et al. (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.



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 section, 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.

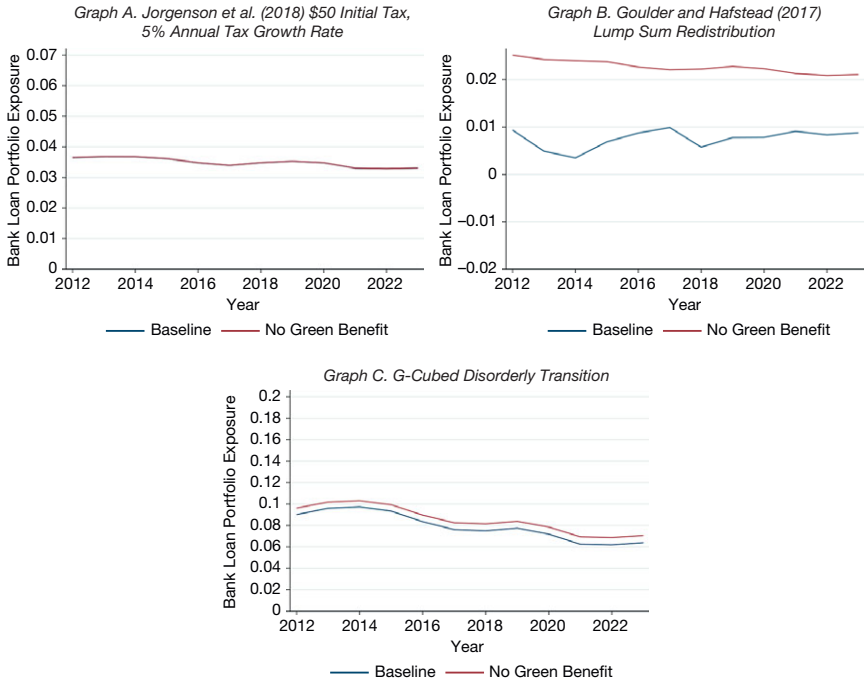
Figure 5 shows the time series of banks' exposure without any benefit from green industries. In the Goulder and Hafstead (2017) and Bertram et al. (2022) models, exposures increase by about 1 percentage point once banks no longer

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FIGURE 5

Exposures to Transition Risks When There Is No Benefit to Lending to Green Borrowers

Figure 5 shows exposures to transition risks from model estimates of industry-level exposures over time. Estimates from Jorgenson et al. 2018, Goulder and Hafstead (2017) and Bertram et al. (2022) are shown in Graphs A, B, and C respectively. Loan exposures are calculated as described in section III.B.2. 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.



benefit from lending to green borrowers.[29] 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 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 III.B.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.

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

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Since bank loan payoffs are typically nonlinearly related to a borrower's performance, we use the Y-14's data on LGD, 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.[30] Otherwise, we run regressions within the broad industries used by the GE model. We cap losses for bank i at 1, 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 1 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 computed using equation (3) 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:

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

where $w_{b,j,t}$ represents the share of loan amount made by bank b to industry j in quarter t, and $\widehat{Losses}_i$ 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' payoff 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.

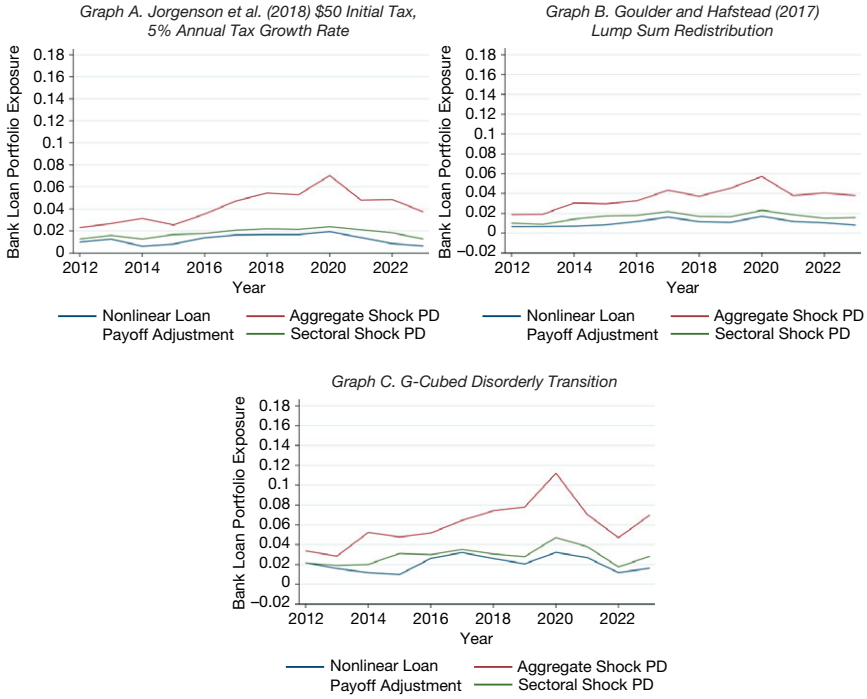
[30]Note that as some 2- and 3-digit NAICS include multiple broad industries as defined for each GE model, we run the regressions separately for the subset of each NAICS industry included in each GE industry.

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FIGURE 6

Exposures to Transition Risks Accounting for Nonlinearities

Figure 6 shows exposures to transition risks adjusted for nonlinearities in the payoff structure from model estimates of industry-level exposures over time. Estimates from Jorgenson et al. (2018), Goulder and Hafstead (2017), and Bertram et al. (2022) are shown in Graphs A, B, and C respectively. 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 (2017), the most brown industries are those in the top two deciles of exposure to carbon taxes, and for Bertram et al. (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.



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 GFC because it represents a sharp deterioration in

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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.[31]

To assess how bank exposures would change if transition policies were implemented during a downturn, we construct a counterfactual increase in default risk calibrated to the crisis episodes described in the above paragraph. Specifically, for each industry (6-digit NAICS-level), we compute the change in the PDs over each shock episode.[32] 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 the Brent Crude Oil index, which spans 2014:Q2 to 2016:Q1 (https://fred.stlouisfed.org/graph/?g=ko34). 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 Bertram et al. (2022) 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.

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.

[31]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.

[32]Because the Y-14 data begin in 2012, we use 1-year expected default probabilities from Moody's KMV CreditMark to measure changes in default risk in the 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.

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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:

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

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.[33] 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 in the Supplementary Material. 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 $P\left(Lending_{it}^{Low}\right)$ is not explained by bank behavior. Also, the fitted line through the R^2s 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 $P\left(Lending_{it}^{Low}\right)$ 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 in the Supplementary Material 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.

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,

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

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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 in the Supplementary Material. 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 one, two, and three 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.[34] 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 in the Supplementary Material 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 United States, we instead examine this assumption by exploiting banks' responses to two important climate-related events: the Paris Agreement and banks' signing of the 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 Dec. 12, 2015, 196 nations adopted the Paris Agreement. By doing so, they agreed to enact national action plans limiting end-of-century temperature rise to at most 1.5

[34]Tables B.12 and B.13 in the Supplementary Material show that banks are more exposed to stricter policies when they fund higher emissions.

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TABLE 2

Explanatory Power of Emissions for Exposures

Table 2 shows the R^2s 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 R^2	0.572	0.577	0.582	0.588
Emission intensity R^2	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 R^2	0.577	0.595	0.577	
Emissions intensity R^2	0.269	0.297	0.262	
Panel C. Goulder and Hafstead (2017) Redistribution Scenarios				
	Lump Sum Redistribution	Corporate Tax Cut	Payroll Tax Cut	Individual Income Tax Cut
Emissions R^2	0.297	0.297	0.297	0.297
Emissions intensity R^2	0.117	0.116	0.117	0.118
Panel D. G-Cubed Scenarios				
	Current Policy	Disorderly Transition	Orderly Transition	
Emissions R^2	0.496	0.411	0.416	
Emission intensity R^2	0.254	0.207	0.208	

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.[35]

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:

$$(6) \qquad Exposure_{it} = \alpha + \beta\ Pre\text{-}Paris\ Exposure_i \times Post_t + \Gamma X_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}$$

where $Pre\text{-}Paris Exposure_i$ is the exposure for bank i as of the quarter before the Paris Agreement (2015:Q3) and $Post_t$ is a dummy variable which takes a value of 1 if t is after the Paris Agreement, and 0 otherwise.[36] 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 the Net-Zero Banking Alliance, which occurred in 2021. We consider the most severe

[35]See Seltzer et al. (2026) for more details on the Paris Agreement.

[36]Results are similar when we define $Pre\text{-}Paris Exposure_i$ using the exposure at the beginning of the sample period.

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policy from each model to compute the exposure, that is 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 (2017) model, and the disorderly transition for the Bertram et al. (2022) 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 (2017) 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.[37] 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 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 a suitable setting to test whether banks are adjusting their lending in response to concerns about 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

[37]Note that, in the case of the Bertram et al. (2022), we instead define the most brown industries as the top three ranked industries and the most green industries as the bottom three ranked industries, given the relatively smaller number of industries in the model.

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TABLE 3

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

Table 3 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. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Banks' Exposures

	Exposure	Exposure	Exposure	Emissions
	1	2	3	4
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 R^2	0.081	0.061	0.163	0.014
No. of obs.	897	897	897	841

Panel B. Lending to the Most Brown Industries

	Pr(Brown Lending)	Pr(Brown Lending)	Pr(Brown Lending)	Pr(Brown Lending)
	1	2	3	4
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 R^2	0.129	0.101	0.153	0.094
No. of obs.	897	897	897	841

Panel C. Lending to the Most Green Industries

	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)
	1	2	3	4
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)

(continued on next page)

TABLE 3 (continued)

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

Panel C. Lending to the Most Green Industries (continued)

	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)
	1	2	3	4
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 R^2	0.092	0.051	0.149	0.068
No. of obs.	897	897	897	841

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 between 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 nonsignatory banks after signing the Net-Zero Banking Alliance, based on the Jorgenson et al. (2018) and the Bertram et al. (2022) models. The results based on the emissions measure and Goulder and Hafstead (2017) 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 Bertram et al. (2022) 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 reducing their exposure to brown industries. To further ascertain whether these changes are bank-driven, we investigate borrowers' decisions to switch between signatory and nonsignatory banks in the next section.

C. Borrowers' Switches Between Banks

We begin by computing the probability of nonsignatory banks' borrowers switching to signatory banks, and the probability of signatory banks' borrowers switching to nonsignatory banks. Next, we compute the odds ratios by dividing the percentage of borrowers that switched to nonsignatories by the percentage of borrowers that switched to signatories. A higher odds ratio indicates borrowers

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TABLE 4

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

Table 4 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 nonsignatories. Late signers of the Alliance are excluded from the analysis. Data are quarterly from 2017:Q2 until 2023:Q1.

Panel A. Banks' Exposures

	Exposure	Exposure	Exposure	Emissions
	1	2	3	4
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 R^2	0.103	0.111	0.202	0.028
N	594	594	594	471

Panel B. Lending to the Most Brown Industries

	Pr(Brown Lending)	Pr(Brown Lending)	Pr(Brown Lending)	Pr(Brown Lending)
	1	2	3	4
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 R^2	0.104	0.065	0.152	0.013
N	594	594	594	471

Panel C. Lending to the Most Green Industries

	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)	Pr(Green Lending)
	1	2	3	4
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 R^2	0.095	0.012	0.288	0.074
N	594	594	594	471

were relatively more likely to switch to nonsignatory 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 analysis described in section IV.A.

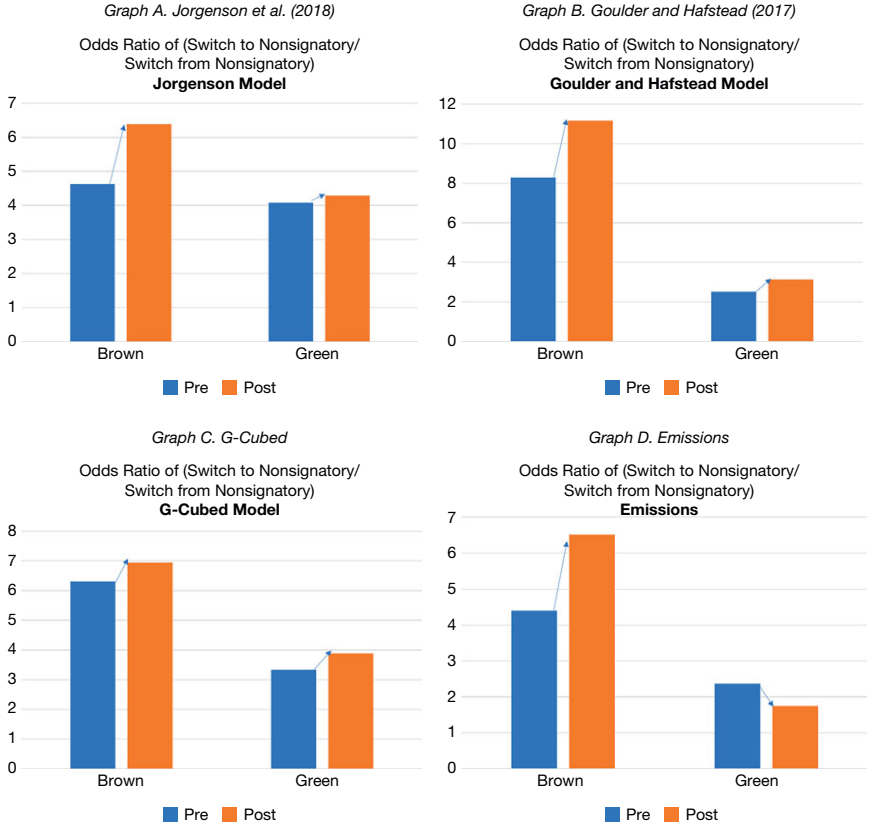
Figure 7 reports the odds ratios. Graph A, which is based on the Jorgenson et al. (2018) model, shows that the odds ratio of the most brown industries increased (from 4.6 to 6.4) after the signing of the Alliance. The odds ratio of the most green industries increased, but by relatively less (from 4.1 to 4.3) after signing the Alliance. Graphs B–D, which are based on Goulder and Hafstead (2017), Bertram

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FIGURE 7

Likelihood of Switching Lenders After the Net-Zero Banking Alliance

Figure 7 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. Graph A shows results from Jorgenson et al (2018), Graph B shows results from Goulder and Hafstead (2017), Graph C shows results from Bertram et al. (2022), and Graph D shows results using carbon emissions. The odds ratio is calculated as the portion of borrowers who switched from a nonsignatory to a signatory, scaled by the portion of borrowers who switched from a signatory to a nonsignatory.



et al. (2022), and emission funding, respectively, show similar results.[38] This evidence indicates that relative to the most green industries, bank–borrower relationships moved from signatory to nonsignatory for the most brown industries.

Table B.14 in the Supplementary Material 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

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

TABLE 5

Switches between Lenders for Signatories and Nonsignatories

Table 5 compares switches of lenders from nonsignatories to signatories, to switches of lenders from signatories to nonsignatories 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 nonsignatories 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.

	Switch to Signatory	Switch to Nonsignatory	Odds Ratio
Panel A. Jorgenson et al. (2018)			
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 (2017)			
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			
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			
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

balance sheet assumption we made in our estimates of banks' exposures to transition risk. However, the fact that banks' responses were largely limited to a reduction in exposures to brown industries suggests that our bank exposure estimates can be viewed as an upper bound of 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 article, 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 emissions, is unable to explain at least 40% of the bank exposures estimated from GE models. Finally, while we find some evidence that U.S. banks

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are managing their exposures to transition risks, this effect is primarily driven by reduced lending to brown borrowers.

Our article suggests 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.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109026103226.

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