Climate Transition Risks of Banks*

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Abstract

We develop a bottom-up measure of U.S. banks' exposures to climate transition risks from the carbon footprint of their syndicated loan portfolios. Transition risk exposures have declined over time, especially since the Paris Agreement. This decline results from a re-balancing of bank loan portfolios, with more lending to low-emission borrowers rather than a reduction in lending to high-emission borrowers. Banks with higher transition risk provide more climate-related disclosures in their earnings calls only when probed by analysts, but not voluntarily in their Form 10-Ks. Banks engage in more anti-climate lobbying after their risk exposures increased. Our measure of transition risk correlates with bank-level climate betas, which reflect the sensitivity of bank returns to the returns of a stranded asset index.

Keywords: Climate transition risks; banks; syndicated loans; disclosure; lobbying
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"It is not for us supervisors to tell banks who they should or should not lend to. However, we will continue insisting that banks actively manage the risks as the economy decarbonises. And banks cannot do this without being able to accurately identify transition risks and how they evolve over time."

Frank Elderson, 23 January 2024, Executive Board Member, European Central Bank
Co-Chair, Task Force on Climate-related Financial Risks, Basel Committee

I. Introduction

Banks face climate change risks by lending to firms vulnerable to physical or transition risks. Physical risks involve climate-related shocks, while transition risks arise from regulatory changes or climate-related litigation. Both risks increase a borrower's likelihood to default and thereby also the riskiness of bank lending portfolios. These risks are difficult to identify, price, and hedge due to their systematic nature, insufficient firm disclosures, and a lack of hedging instruments (Krueger et al., 2020). Consequently, central banks now treat climate change as a potential source of systemic risk and incorporate this risk in their regular stress tests.[1] Shareholders are pressuring banks to implement climate risk transition plans to align with global carbon reduction targets (Mooney and Williams, 2023) and recent climate disclosure mandates, such as the SEC's proposals and similar rules in Europe, the UK, Japan, and New Zealand, also require public companies, including banks, to disclose their climate risk exposures.

Overall, the evolving regulatory environment increases the scrutiny as to banks' (reported) exposures to climate change, and banks face elevated litigation and reputation risks regarding these exposures. This heightened focus might force them to be more cautious in both public disclosures (annual reports, earnings calls) and lobbying efforts to avoid amplifying their perceived climate risk exposures and potential legal challenges associated with them. As the introductory quote by Frank Elderson suggests, quantifying bank-level, time-varying measures of climate risk exposure is thus crucial for regulators and market participants to understand the implications of stricter climate policies for the banking sector. This is the main focus of this paper.

[1] Central banks are increasingly acknowledging the risk climate change poses on financial stability and the importance of addressing this risk within their mandates (see, e.g., Network for Greening the Financial System, 2021). In January 2024, the European Central Bank (ECB) released a comprehensive report, highlighting the risks associated with the possible misalignment between banks' financing practices and key climate policy objectives (ECB, 2024).

Our first contribution is to develop a novel time-varying measure of a bank's exposure to climate transition risk, which is constructed as a bottom-up metric based on the carbon footprint of a bank's borrowers.[2] We construct this measure for the syndicated loan portfolios of U.S. banks (worth about $2 trillion) over the 2002-2021 period and label it "Climate Transition Risk Exposure" (CTRE). The CTRE measure has an intuitive interpretation: it captures the weighted average Scope 1 emissions of all firms in a bank's syndicated loan book, expressed in kilotons (kt) of CO_2-equivalent. A higher score indicates higher exposure to climate transition risks.[3]

Our sample includes 34 major U.S. banks for which we can construct the CTRE measure, including Bank of America, Citigroup, Goldman Sachs, JPMorgan Chase, and Morgan Stanley. The bank with the lowest average CTRE score is Silicon Valley Bank, which reflects the bank's focus on venture capitalists and tech startups (i.e., borrowers that typically generate few carbon emissions). The bank with the largest average CTRE score is Huntington Bancshares. As the bank is based in Ohio, its high exposure likely reflects significant lending to local customers in Ohio, known for its history of coal mining and industrial minerals extraction. The banks in our sample constitute a significant part of the U.S. banking system. By 2021, they represent 82% of total assets and 76% of the total market capitalization of all listed banks. The sampled syndicated loans constitute 72% of the banks' outstanding loan volume in 2021, and those with matched emissions data 39% of that volume. Relative to all U.S. lenders, the sampled loan portfolios with emissions data make up 20% of the total lending volume as of 2021.

Our syndicated loan data are sourced from the Refinitiv LoanConnector database, which allows us to carefully track loan amendments over time and to compute a bank's outstanding exposure to a borrower at any point in time. Importantly, we take into account that lenders sell off some (or all) of their commitments after primary syndication. We use the approach developed by Blickle et al. (2022) that approximates the share of a loan that is retained by the syndicating lenders. Notably, banks have exposure to transition risks also for non-retained loans, as participation in a syndicate can lead to reputation costs, due to naming-and-shaming campaigns, and legal risks if the loan is

[2] Research struggles with a data gap on banks' exposure to climate risks (Acharya et al., 2023). Due to borrower-level data challenges, past work relies on market-based approaches using equity data (Battiston et al., 2017; BIS, 2020; Jung et al., 2021; Boungou and Urom, 2023). These methods, while system-wide, lack granularity for individual bank risk assessment.

[3] A mounting concern is that firms "reduce" emissions through the divestment of polluting assets, thereby essentially replacing direct Scope 1 emissions by supplier-produced upstream Scope 3 emissions. To understand whether such a substitution affects our conclusions, we compute for robustness banks' CTRE scores based on Scope 1 and 3 upstream emissions

misaligned with public climate statements ("greenwashing").

Armed with a comprehensive measure of bank-level transition risk we can ask: What steps are U.S. banks actively taking to comply with the Paris Agreement and to facilitate a decarbonization of the economy? We investigate this question by analyzing four dimensions: i) the time-series change in CTRE of banks and its drivers; ii) cross-sectional differences across banks exposed to climate transition risk; iii) disclosure practices; and iv) active anti-climate lobbying by banks.

Since 2011, U.S. banks have shown a gradual decrease in transition risk exposure, with a notable decline following the Paris Agreement in 2015. However, this reduction slowed after 2017, coinciding with President Donald Trump's announcement that the U.S. would withdraw from the Paris Agreement.[4] There are two primary, non-mutually exclusive channels through which CTRE scores may have declined: Banks may have reallocated credit toward low-emission borrowers (loan book re-balancing channel), or the emissions of banks' (fixed) portfolios of borrowers may have fallen (emission reductions channel).

We establish that the decline in the average bank's CTRE score since the Paris Agreement originates primarily from loan book re-balancing. In fact, the aggregate Scope 1 and Scope 3 emissions of the average borrower *increased* after 2015, though not enough to counter the re-balancing effect. The decarbonization associated with the re-balancing was achieved primarily by initiating new lending relationships with low-emission borrowers, rather than by terminating loans with high-emitters. Most of the re-balancing occurred *within* borrower industries (in particular within Transportation and Utilities). These results suggest that the decarbonization of bank portfolios does not necessarily translate into lower emissions in the economy.

We dissect the heterogeneity in banks' transition risk exposures by exploring the relationship between CTRE scores and underlying bank characteristics. Two striking results emerge. First, banks with higher risk exposures are larger and more leveraged; this effect is not mechanical as the CTRE score is normalized by the value of a bank's loan book. These findings indicate potential vulnerabilities in the financial system following future climate-related regulatory tightening (as large and highly leveraged banks—which are of central concern for financial stability—will be affected the most). Second, banks with a higher share of female board members have lower exposures to transition risks, in line with evidence highlighting a positive relationship between gender diversity and environmental performance (Liu, 2018; Atif et al., 2021).

[4] We verify that the downward trend is not caused by composition effects related to a change in emissions data coverage in Trucost (the data provider we use for emissions data).

Our results raise the question of whether CTRE scores are reflected in banks' stock returns. Our evidence suggests that this is the case, particularly when climate transition risks materialize. We document a positive correlation between banks' CTRE scores and their return sensitivities (or betas) to the return of a stranded asset index (Jung et al., 2021). In other words, banks with higher exposure to transition risks have returns that co-vary to a greater extent with stocks prone to devalue when transition risks materialize.

Regulators and policymakers argue that poor disclosure practices by banks on climate-related risks may undermine financial stability (Carney, 2015)—if disclosures are insufficient, market participants may be unable to locate where transition risks accumulate in the system. This raises the question of whether and how the CTRE scores are reflected in banks' climate-related disclosures. When we contrast banks' disclosures in Form 10-K filings with those in earnings conference calls, we observe remarkable differences across disclosure channels. High-CTRE banks appear relatively hesitant to disclose their exposures in 10-K reports, potentially due to concerns surrounding reputation, regulatory scrutiny, or negative market reactions. During earnings calls, however, analysts challenge these banks, with management in turn disclosing more on climate-related risks. The divergence in disclosures may explain why the SEC recently proposed rules to enhance and standardize climate-related disclosures in 10-Ks (SEC, 2022).

The disclosure results indicate an inconsistency between banks' exposures to climate transition risks and their disclosures in Forms 10-K. According to anecdotal evidence, a further inconsistency exists regarding banks' climate commitments and their anti-climate lobbying practices. For example, many banks made public commitments to combat climate change, for example, via the Glasgow Financial Alliance for Net Zero (GFANZ), while at the same time conducting anti-climate lobbying (Schwartzkopff and Marsh, 2023; Ceres, 2023) or maintaining memberships in industry groups lobbying against climate policies (InfluenceMap, 2022). Using data on banks' anti-climate lobbying expenses, we demonstrate that one driver motivating banks' anti-climate lobbying activities is their exposure to climate transition risk. We estimate that a 1% increase in CTRE scores implies 20% higher anti-climate lobbying expenditures.

Overall, returning to our initial question, we find that the sampled banks—through their lending activities—do not actively reduce aggregate carbon emissions in the economy. In fact, they tend to disclose less information if they have significant exposures to climate transition risks and actively lobby against stricter climate policies. Consequently, the current role of banks in decarbonizing the economy appears to be limited. At the same time, financial markets respond to banks' transition risk exposures.

Related literature. Our paper contributes to several strands of the literature. First, it extends the literature on the nexus between climate risks and bank lending by introducing a bank-level measure of climate transition risk exposure. Prior work shows that banks started to take firms' climate risk profiles into account when making lending decisions (Goss and Roberts, 2011; Altavilla et al., 2023; Correa et al., 2023; Ivanov et al., 2024; Meisenzahl, 2023). There is also evidence that post-2015, the pricing of syndicated loans began to reflect climate transition risks (Ehlers et al., 2022; Degryse et al., 2023; Delis et al., 2024), and European banks shifted lending away from polluting firms (Reghezza et al., 2022). Mueller and Sfrappini (2022) and Benincasa et al. (2023) show that banks reallocate capital based on the stringency of local climate change policies.

Other studies find mixed evidence on the impact of banks' individual climate commitments on credit volume and borrowers' investment behavior. On the one hand, Kacperczyk and Peydró (2022) reveal a decrease in syndicated bank credit to high-polluting firms following their lenders' green commitments. Green and Vallee (2024) analyze the coal industry and demonstrate the effectiveness of banks' exit policies in reducing coal firms' emissions, largely due to their limited options to switch to other financial institutions or markets. On the other hand, Giannetti et al. (2024) provide evidence on strategic bank disclosures, documenting that banks that emphasize sustainability in their credit policies lend more to brown borrowers. Likewise, Sastry et al. (2024) finds that European banks in the Net Zero Banking Alliance do not significantly divest from brown assets compared to other banks. While this literature mostly focuses on whether and how climate risks affect bank lending volumes at the firm level, our paper shifts the focus to measuring the overall environmental impact of banks' loan portfolios at the bank level. This approach facilitates a novel analysis of aggregate portfolio adjustments over time, and their associations with stock market pricing, bank disclosures, and lobbying activities.

Our paper also connects to the literature on climate stress testing (Roncoroni et al., 2021; Nguyen et al., 2023; Jung et al., 2024). A challenge when analyzing banks' resilience to climate risks is the lack of granular exposure data (Baudino and Svoronos, 2021; Financial Stability Board and NGFS, 2022). As such, previous research mostly relies on top-down market-based approaches (Battiston et al., 2017; Boungou and Urom, 2023; Jung et al., 2021), with some exceptions. Battiston et al. (2020) combine a top-down approach of climate scenarios with loan-level data to estimate the transition risk exposure of Austrian banks, and Reinders et al. (2023) assess the resilience of Dutch banks' equity market value and debt instruments to the impact of a carbon tax. Jourde and Moreau (2024) estimate whether climate risks generate contagion effects in the European banking sector. Jung et al. (2024) develop a measure of climate transition risk exposures using estimated industry-level effects of climate transition policies from general equilibrium models. Jung et al. (2021) validate their top-down measure using data on U.S. banks' loan portfolios. In line with Acharya et al. (2023), we argue that climate stress tests should consider bottom-up metrics.

In passing, we relate to the literature on environmental lobbying. Existing studies highlight the impact of lobbying on climate policy outcomes and corporate strategies.[5] We expand this literature by considering climate lobbying by banks with different exposures to climate risks, demonstrating that banks increase lobbying as the carbon footprints of their loan books rise.

II. Sample Construction and Data Sources

Bank loan-level exposures. Our analyses use data on outstanding loan volumes at the lender-borrower-year level. The sample construction starts with the universe of *transactions* covered by the most recent Refinitiv LoanConnector DealScan database, which provides detailed information on syndicated loan transactions.[6] We exclude loans from non-U.S. lenders and—following Schwert (2018)—loans granted to financial borrowers (SIC codes 6000–6999).

Next, we link the lender identifiers from DealScan to Compustat GVKEYs.[7] The matched lenders include bank holding companies as well as non-banks. We restrict the sample to lenders with SIC codes 60 "Depository Institutions" (not 601 "Central Banks"), 61 "Non-Depository Credit Institutions" (not 614-615 "Personal or Business Credit Institutions"), and 6211 "Security Brokers." This implies that PE firms as well as other non-bank lenders are excluded from the sample. Our final sample consists of 34 major U.S. bank holding companies. For simplicity, we refer to bank holding companies as "banks." The 34 banks have loan exposures to 29,471 unique borrowers from 2002 to 2021.

We consider loans to both domestic as well as foreign (non-U.S.) borrowers. Tracing the global lending portfolio is important. First, it enables us to also capture emissions associated with loans financed outside of the United States. If some banks, for example,

[5] See Meng and Rode (2019), An et al. (2023), Heitz et al. (2023), Kwon et al. (2023), Lantushenko and Schellhorn (2023), Rendina et al. (2023), and Leippold et al. (2024).

[6] In 2021, DealScan revamped its database structure and updated its identification system. A major benefit of the new database structure is that it allows users to track loan amendments and refinancings.

[7] We first map the "new" DealScan identifiers to the "legacy" DealScan identifiers via the WRDS linking table. Then, we connect the legacy identifiers to the corresponding GVKEYs via the linking file from Schwert (2018).

were merely shifting their lending from domestic to foreign fossil fuel firms, the accompanying carbon emissions would still be included in our data (Benincasa et al., 2023; Laeven and Popov, 2023). Second, some countries may introduce carbon taxes or related regulations to which U.S. banks will be exposed through borrowers operating in these countries.

Firm carbon emissions. To compute the carbon footprint of a bank's loan portfolio, we merge the loan portfolio data with annual data from S&P Global's Trucost on each borrower's carbon emissions using i) the GVKEY-linking table from Chava and Roberts (2008), and ii) a conservative name-matching approach.[8] Following Kacperczyk and Peydró (2022), we center our analysis on Scope 1 carbon emissions (expressed in kilotons of CO_2 equivalent), which constitute "direct" greenhouse gas (GHG) emissions produced at sources within the control of a firm. We focus on Scope 1 emissions to preempt potential concerns about double counting. Specifically, two firms may include the same emissions in their inventories, leading to an overestimation of financed emissions in a bank's climate change exposure measure. This is particularly important when aggregating bottom-up company data (Fahlenbrach and Jondeau, 2023).[9] In robustness tests, we examine firms' Scope 2 and Scope 3 emissions, finding trends in banks' climate change exposures that are similar to those of the Scope 1-focused analyses. Reflecting the coverage period of the Trucost database, our sample period begins in 2002 and ends in 2021 (last full year with significant data coverage in Trucost).

Bank characteristics. We use the GVKEY-linking table from Schwert (2018) to add data on banks' stock returns and financial characteristics from CRSP and Compustat. Bank characteristics include, among others, bank size (total assets), the leverage ratio (debt over total assets), bank profitability (net income over assets), the loan ratio (net loans over assets), and the market-to-book ratio. Data on female board membership and political connections are from BoardEx. Data on lobbying are from Leippold et al. (2024). Table A1 provides detailed variable definitions and reports the respective data sources.

Sample representativeness. How representative are our data on syndicated loan portfolios for the overall loan portfolio of our banks? To answer this question, we compare in Figure 1 the loan volumes (in $ billion) in our sample with bank balance sheet data from Compustat. In the figure, the blue dashed line represents the aggregate balance-sheet-based loan volume of banks in our sample. The red dotted line below reflects the

[8] The firms sampled by Trucost represent approximately 95% of the global equity market capitalization.

[9] For instance, Scope 3 emissions of one firm may be considered as Scope 1 emissions of another firm, resulting in double counting. This concern is particularly relevant in the energy sector, where emissions from power generation facilities may be counted both as Scope 1 emissions for the power plant and as Scope 2 emissions for industrial companies using the generated electricity.

syndicated loan amounts issued by the same lenders according to DealScan data. Finally, the green solid line shows the syndicated loan amounts if we further restrict the sample to borrowers with Scope 1 emission data.

Figure 1 shows that syndicated lending represents roughly two-thirds of our banks' balance-sheet-based loan volumes. When we impose the emission data restriction, the sample's loan coverage starts with one-fifth of the banks' balance sheet volume in 2002. This fraction increases over time, with more borrowers disclosing emissions and Trucost increasing data coverage. Across all years, our sample with matched emissions data covers 45% of syndicated lending by our banks. The volume that we capture is sizeable: the emission-matched sample includes loans worth more than $2 trillion in 2021.[10]

III. Climate Transition Risk Exposure: Methodology and Statistics

A. *Construction of CTRE Scores*

To compute each bank's climate transition risk exposure (CTRE), we aggregate the carbon emissions of a bank's corporate borrowers. We normalize the loan amounts by the value of the overall syndicated loan book of a bank at the year-end to account for the varying sizes of banks. This provides us with a size-adjusted exposure score that is comparable across banks and over time. Specifically, we calculate each bank b's CTRE score in year t by multiplying the Scope 1 emissions of each borrowing firm in a bank's syndicated loan book by the fraction of the loan weight of the borrower in the loan book of the bank:

$$CTRE_{b,t} = \sum_{i=1}^{N_{b,t}} (w_{i,b,t} \cdot Scope\,1\,Emissions_{i,t}), \tag{1}$$

where $Scope\,1\,Emissions_{i,t}$ refers to the Scope 1 emissions of borrower i covering year t, and $w_{i,b,t}$ represents the weight of borrower i in the loan book of bank b in year t (relative

[10] Figure IA1 compares the industry composition of the loan volumes in DealScan with our emission-matched sample. Our sample exhibits a high degree of industry balance. First, the industry ranking across the two samples is similar, with the Manufacturing sector accounting for the largest share of the aggregate loan volume in both samples, and Agriculture, Forestry, and Fishing representing the smallest share. Second, we do not observe large deviations in the volume-based shares of the industries. The largest deviation is for the Non-Classified sectors (4% of our sample compared to 0.7% in DealScan). Overall, the data restrictions imposed by our methodology do not appear to introduce significant industry selection bias.

to the total loan volume):

$$w_{i,b,t} = \frac{Outstanding\,Loan\,Amount_{i,b,t}}{Total\,Outstanding\,Loan\,Amount_{b,t}} \tag{2}$$

To calculate *Outstanding Loan Amount*, we transform the syndicated loan data to *outstanding* loan volumes in year t using the lender-specific loan shares reported in DealScan. Importantly, we account for the fact that lenders often sell off their original loan commitments to institutional investors after syndication. In particular, we follow the approach from Blickle et al. (2022) and estimate the actual share of loans retained after origination. In line with Gropp et al. (2019), we transform these loan-level holding estimates into outstanding loan volumes at the lender-borrower-year level based on the loans' maturity dates, carefully taking into account loan amendments and refinancings while these loans are outstanding. As transition risks arise due to banks' outstanding (term) loans as well as lending commitments through credit lines, we include both loan types in our calculation of the CTRE measure.

Intuitively, the CTRE score is a proxy for the weighted average Scope 1 emissions of all firms in a bank's syndicated loan book, expressed in kilotons (kt) of CO_2-equivalent. A higher CTRE score indicates higher exposure to climate transition risks.[11] Some of our analyses use a standardized CTRE score, $Z\_CTRE_{b,t}$, constructed to have a mean of zero and a standard deviation of one. This standardization approach allows for a more meaningful interpretation of the regression coefficients and ensures that the results are not driven solely by the magnitude of the CTRE score (the score exhibits large differences between the minimum and maximum values and a high standard deviation). We require that a given bank has lending relationships with at least five borrowers in a year to ensure that the CTRE scores reflect a minimum degree of variation in emissions among borrowers. We further include in the sample only banks with at least five CTRE observations (this implies that our sample of 34 banks is constructed after dropping one bank, SouthTrust Bank).

[11] The approach of scaling and conditioning on emissions data is similar to Hwang et al. (2021) and Cao et al. (2023), who construct the carbon footprint of institutional investor portfolios. Conditioning the score construction on emissions data is also similar to how Morningstar calculates Globes or Low Carbon Designations for mutual funds—it includes only those holdings for which Sustainalytics ESG scores or emissions are available (Hartzmark and Sussman, 2019; Ceccarelli et al., 2023).

B. *Descriptive Statistics of CTRE Scores*

B.1. *CTRE Scores: Cross-Sectional Variation*

Table 1 presents bank-level summary statistics of the (unstandardized) CTRE score, calculated over the 2002 to 2021 period, with banks ranked in alphabetical order.[12] The mean CTRE score ranges from 14.6kt CO_2 (Silicon Valley Bank) to 11,199kt (Huntington Bancshares), indicating significant cross-sectional heterogeneity in exposures to climate transition risk.[13] This heterogeneity reflects the diverse nature of banks' business models. For example, Silicon Valley Bank has the lowest exposure to transition risk given its focus on venture capitalists and tech-startups that typically generate fewer carbon emissions. On the other hand, Huntington Bancshares, the bank with the largest average exposure, is based in Ohio and the high exposure likely reflects significant lending relationships with customers located in the state of Ohio, known for its history of coal mining and industrial minerals extraction. The standard deviation of the CTRE score for some banks is higher than their average CTRE score. This indicates significant variation in the financed carbon emissions over time, even *within* banks, and it underscores the need to explore the time-series to understand how banks reacted to climate-related events.

B.2. *CTRE Scores: Time-Series Variation*

Figure 2 reports the evolution of the transition risk exposure for our sample banks. We calculate an annual average CTRE score across banks and show the evolution of this average from 2002 to 2021 (with 95% confidence intervals). We also report key climate policy-related events during the period (red vertical lines). Following 2011, banks' average transition risk exposure gradually decreased, particularly after the Paris Agreement in 2015; this is consistent with a progressive reduction in banks' exposures to carbon-related risks. Interestingly, however, the reduction in carbon emissions slowed down starting in 2017, that is, since President Donald Trump took office and announced the intention to withdraw from the Paris Agreement. After the U.S. formally withdrew in 2020, there is an increase in the average transition risk exposure among U.S. banks.[14]

[12] The number of observations per bank can be smaller than the total number of sample years due to bank acquisitions or closures. For example, Marshall & Ilsley Corporation has only ten data points as it was acquired in 2011 by the Bank of Montreal. We account for mergers and acquisitions by carrying over the historical loan portfolios of the target banks to the acquiring banks.

[13] To illustrate these exposures, the 11,199.6 kt, or 11 megatons (mt), CO_2 for Huntington Bancshares compare with 28mt CO_2 emitted by Denmark in 2021, or 51mt CO_2 by Royal Dutch Shell in 2022.

[14] Figure IA2 illustrates similar aggregate trends when factoring in Scope 2 and Scope 3 upstream emissions, or when considering Scope 1 intensities instead of absolute emissions. Incorporating Scope 2

In Figure 3a, we plot the time-series of the six largest U.S. lenders' CTRE scores (as well as a yearly average CTRE score across the six banks). At the onset of the sample period, there is substantial variation in the banks' exposures to transition risk. After the Paris Agreement in 2015, banks' CTRE scores converge substantially, suggesting a collective effort to reduce the carbon footprint of their lending portfolios. Consistent with the aggregate dynamics in Figure 2, there is a gradual increase in CTRE scores after 2017.[15]

Figure 3b plots average CTRE scores over time across three size groups (terciles of average lending volume over the sample period). Most of the pre-2015 CTRE decline occurs at large banks, which started reducing their exposures earlier than small or medium banks. From 2015 onwards, the exposures of large and medium banks converge. There is a decline in transition risk exposures across all bank types from 2014 to 2017; however, this decline levels off and exposures begin to rise again after the 2017 announcement to withdraw from the Paris Agreement.

B.3. CTRE Scores: Sample Composition Effects over Time

A potential concern is that the downward trend in CTRE scores is driven by a change in the set of firms covered by Trucost over time. As Trucost covers an increasing number of firms over the years, including newly added entities with lower emissions could mechanically reduce the calculated average CTRE scores. To address this concern, we adopt a similar approach as Bolton and Kacperczyk (2023) and maintain a consistent set of Trucost firms to then regenerate new versions of Figure 2. That is, through 17 iterations, we fix all firms to those present in Trucost before each year from 2003 to 2019, and then recalculate 17 times the CTRE scores for the 2002-2021 period. This iterative process generates 17 distinct time series, representing subsamples with consistent firm compositions. By exclusively considering Trucost firms present prior to each year, the recalculated average CTRE scores are unaffected by newly added firms as we maintain a consistent firm composition. This enables us to exclude the influence of newly added entities from changes in the carbon footprint of banks' lending portfolios.

Figure 4 shows that fixing the sample to Trucost firms present in the database from

emissions elevates the trend line, but the downward CTRE trend persists. Additionally including Scope 3 emissions raises the trend line further, possibly reflecting some degree of double-counting. Again, we continue to observe a downward trend. Even when utilizing the Scope 1 intensity, calculated as absolute Scope 1 emissions scaled by a firm's revenues, the downward trend line holds a comparable pattern.

[15] Figure IA3 and Figure IA4 show that the downward trend in average CTRE scores can be attributed, to a large degree, to banks' reduced exposures to borrowers from the Transportation and Utilities sector, especially since 2015 (this sector remains responsible for the post-2015 decline when we use a static sample of firms present in Trucost before 2015, that is, we are not merely picking up compositional effects).

2004 onward largely preserves the average trend until the year 2015 (for all sample iterations). Since 2015, we observe a sustained higher average CTRE score for the iterated samples. That is, samples that include Trucost firms, which have been added after 2015, exhibit lower average CTRE scores, which impacts the pattern in Figure 2. Importantly, our key conclusion remains intact: even after excluding the impact of newly added firms, there is a gradual decline in CTRE scores, particularly since the Paris Agreement, then a slowdown in the pace of this decline after 2017, and an increase after 2020.

IV. Decomposition of Changes in CTRE Scores

There are two primary ways through which U.S. banks may have reduced their exposures to climate transition risk, especially after the Paris Agreement in 2015. First, banks may have decreased their loan exposures to borrowers with significant emissions, reallocating credit toward borrowers with lower emissions ("loan book re-balancing" channel). Second, banks may have achieved a CTRE reduction through emission changes at the borrower level; borrowers may have reduced their emissions by shifting their business practices toward more environmentally friendly approaches ("emission reductions" channel). This could involve adopting greener technologies, processes, and strategies. Such changes at the borrower level would ultimately result in lower CTRE scores at the bank level, even without banks actively changing their lending behavior.[16]

A. Quantifying Loan Book Re-Balancing vs. Emission Reductions

We use a two-pronged approach to quantify the extent to which the two channels drive the change in banks' transition risk exposures. This approach pins down changes in banks' CTRE scores originating from two components of a bank's CTRE score in Eq. (1): i) changes in outstanding loan book amounts ($LA_{i,b,t}$ for short); and ii) changes in borrowers' Scope 1 emissions ($EM_{i,t}$).[17] As a first step, we derive the components' contributions to changes in the CTRE scores by multiplying each component's change from $t-1$ to t with the first-order derivative of the CTRE score with respect to that component. This enables us to interpret the contribution consistently with the direction of its impact on the CTRE score, allowing only one of the components to change over time (while treating

[16] Banks may have contributed to borrowers' emission reductions by financing the underlying changes.

[17] A similar approach is adopted by Gropp et al. (2024) to decompose the changes in banks' capital ratios, and by Atta-Darkua et al. (2023) to examine portfolio decarbonizations by institutional investors.

the other components as constants).[18]

$$\Phi_{i,b,t}^{LoanAmount} = \Delta LA_{i,b,t-1,t} \cdot \frac{\partial CTRE_{b,t}}{\partial LA_{i,b,t}} \\ = \Delta LA_{i,b,t-1,t} \cdot \frac{\sum_{j \neq i}^{N_{b,t}} (EM_{i,t} - EM_{j,t}) \cdot LA_{j,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} \tag{3}$$

$$\Phi_{i,b,t}^{Scope\,1\,Emissions} = \Delta EM_{i,t-1,t} \cdot \frac{\partial CTRE_{b,t}}{\partial EM_{i,t}} \\ = \Delta EM_{i,t-1,t} \cdot \frac{LA_{i,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} \tag{4}$$

Intuitively, Eq. (3) indicates that when a bank adjusts its outstanding loan amount to a specific borrower i, the change in the bank's CTRE score is influenced by the emission of borrower i relative to other borrowers j in the portfolio, weighted by their loan amounts. Similarly, Eq. (4) demonstrates that the effect of emission reductions at the borrower level on the bank's CTRE score is determined by the weight of the borrower in the bank's loan portfolio.

To understand the channels through which banks reduced their average CTRE scores over time, we aggregate $\Phi_{i,b,t}^{LoanAmount}$ and $\Phi_{i,b,t}^{Scope\,1\,Emissions}$ at the bank-year level by summing across all borrowers i of bank b in year t. We then average these bank-year-level measures across five time periods (which we explain in detail below).

In a second step, we ensure that the final contributions sum up to the empirical difference in average CTRE scores. Therefore, we calculate the percentage contribution by scaling each contribution with respect to the total contributions:

$$\Psi^{LoanAmount} = \frac{\Phi^{LoanAmount}}{|\Phi^{LoanAmount} + \Phi^{Scope\,1\,Emissions}|} \tag{5}$$

$$\Psi^{Scope\,1\,Emissions} = \frac{\Phi^{Scope\,1\,Emissions}}{|\Phi^{LoanAmount} + \Phi^{Scope\,1\,Emissions}|} \tag{6}$$

We then multiply the shares with the empirical differences in average CTRE scores:

$$\omega^{LoanAmount} = \Psi^{LoanAmount} \cdot |\Delta CTRE| \tag{7}$$

$$\omega^{Scope\,1\,Emissions} = \Psi^{Scope\,1\,Emissions} \cdot |\Delta CTRE| \tag{8}$$

[18] Internet Appendix B details the computation of the first-order derivatives.

Both quantities have intuitive interpretations. $\omega^{LoanAmount}$ quantifies the extent to which banks are altering their loan amounts to adjust their exposures to carbon transition risk. For instance, banks might strategically tilt their loan books away from borrowers with high emissions. In contrast, $\omega^{Scope\,1\,Emissions}$ reflects the extent to which changes in average CTRE scores can be attributed to borrowers lowering their emissions.

B. Relative Importance of Loan Book Re-Balancing vs. Emission Reductions

Figure 5 displays the decomposition of the CTRE scores for five time periods: i) 2002 to 2009 (before the Copenhagen Climate Change Summit); ii) 2010 to 2015 (after Copenhagen and before the Paris Agreement); iii) 2016 to 2017 (after Paris the Agreement and before the U.S. withdrawal announcement); iv) 2018-2020 (after the announcement and before formal withdrawal; and v) the year 2021 (after the withdrawal). For each period, we report averages of $\omega^{LoanAmount}$ and $\omega^{Scope\,1\,Emissions}$.

From 2002 to 2009, the average bank reduced its CTRE score by 24kt of CO_2-equivalent, from 5,519kt in 2002 to 5,495kt in 2009. This total change originates from a decline in emissions of 481kt that can be attributed to loan book re-balancing (towards less-emitting firms), which is partially offset by a 457kt increase in emissions at existing borrowers. Between 2010 and 2015, a period during which the average CTRE score declined substantially, banks re-balanced their loan books away from heavily-polluting borrowers, resulting in a gross reduction of 1,276kt in the average CTRE score. As borrowers simultaneously decreased their emissions (by 349kt), the net reduction in banks' CTRE scores from 2010 to 2015 amounted to 1,625kt (=3,870-5,495kt).[19]

After the Paris Agreement in 2015, the primary driver of the CTRE reduction remains loan book re-balancing, accounting for a gross reduction of 831kt. In contrast, after the U.S. announced to withdraw from the Paris Agreement in 2017, banks re-balanced their portfolios towards more polluting firms, leading to an average *increase* of 264kt in their CTRE scores. At the same time, cuts to firm-level emission lowered the CTRE scores by 673kt (potentially reflecting efforts by non-U.S. borrowers unaffected by the withdrawal announcement). Consequently, the total decrease in the average CTRE score from 2018 to 2020 amounts to only 409kt. Following the U.S. withdrawal from the Paris Agreement in 2020, banks continued to lend to more polluting firms, resulting in a gross CTRE increase of 135kt. At the same time, the emissions share by borrowing firms also contributed *positively*, reflecting a post-2020 increase in emissions at some financed firms.[20]

[19] The net reduction is equivalent to cutting the yearly emissions of 353,260 cars.

[20] Figure IA5 shows that these findings are robust to analyzing a static sample of firms present in the

C. Substitution of Scope 1 for Scope 3 Emissions

A mounting concern is that firms "reduce" emissions through the divestment of polluting assets, thereby essentially replacing direct Scope 1 emissions by supplier-produced upstream Scope 3 emissions (Bartram et al., 2022; Berg et al., 2023; Dai et al., 2024; Duchin et al., 2024). To understand whether such a substitution affects our conclusions, we compute banks' CTRE scores based on Scope 1 and 3 upstream emissions, and then repeat the CTRE decomposition. This analysis is important. For example, if borrowers are reducing their Scope 1 emissions by shifting the production of CO_2-intensive products along the supply chain, we would not expect to observe negative CTRE contributions from the emission reductions channel.

Figure 6 reports the outcomes of the resulting CTRE decomposition. While the overall decline in average CTRE scores and the underlying channels align with the decomposition based on Scope 1 emissions alone, notable differences emerge in specific subperiods. Between 2010 and 2015, we still observe a negative contribution to banks' average CTRE scores from borrower-level emissions reductions (390kt), albeit to a lesser extent than when accounting solely for Scope 1 emissions.[21]

In the 2016-2017 period, changes in combined Scope 1 and 3 upstream emissions led to a *positive* increase in banks' transition risk exposures, contrary to the decrease observed when focusing on Scope 1 emissions only in Figure 5. This evidence indicates that between 2016 and 2017, firms were indeed diminishing Scope 1 emissions while augmenting Scope 3 emissions, consistent with the outsourcing of carbon emissions to (foreign) suppliers as documented by Berg et al. (2023), Dai et al. (2024), and Duchin et al. (2024). Consequently, we observe a positive impact on banks' average exposure to climate transition risks from borrower-level emission changes when accounting for both Scope 1 and 3 emissions. Nevertheless, the main conclusions remain the same: the primary channel of reducing exposures is the loan book re-balancing, not firm-level emission reductions, which reverses after 2017 when president Trump announced the withdrawal from the Paris Agreement.

2015 Trucost legacy dataset (i.e., results are unaffected by the inclusion of new entities in Trucost).

[21] This finding is consistent with Bartram et al. (2022), who find that the 2013 California cap-and-trade program led firms to shift emissions to less regulated regions. Specifically, over the 2010-2015 period, emission reductions contributed 19.3% when considering both Scope 1 and 3 emissions in Figure 6, which is less than the 21.5% when accounting solely for Scope 1 emissions in Figure 5.

D. *Margins of Loan Book Re-Balancing*

To better understand how banks decarbonize loan books, we examine whether the re-balancing (as quantified by $\Phi^{LoanAmount}_{i,b,t}$) stems from the intensive or extensive margins. Specifically, we quantify the extent to which three lending strategies contribute to the total changes in CTRE scores: i) loans for a given borrower are reduced but not fully stopped; ii) relationships are terminated entirely; and iii) new lending relationships with low-emitters are initiated. Two variables differentiate the impact of changes in loan amounts across the extensive margins: $Entry_{i,b,t}$ equals one when a firm newly enters a bank's loan book, and $Exit_{i,b,t}$ equals one when a firm ceases to exist within a bank's loan book. Both variables equal zero for firms that remain on a bank's loan book (intensive margin borrowers).[22] We use these measures to estimate the following regression for bank b, firm i, and year t:

$$\Phi^{LoanAmount}_{i,b,t} = \beta_1 Entry_{i,b,t} + \beta_2 Exit_{i,b,t} + \mu_b + \mu_t + \mu_i + \epsilon_{i,b,t}, \tag{9}$$

where $\Phi^{LoanAmount}_{i,b,t}$ represents the change in the CTRE score of bank b between $t-1$ and t caused by adjustments in the loan amounts to firm i. $Entry_{i,b,t}$ and $Exit_{i,b,t}$, as described above, each equal one if a firm enters or exits a bank's loan book. Note that the estimated CTRE score changes are calculated relative to the average reduction stemming from intensive margin borrowers (our reference group). We seek identification from within-bank estimates and include bank fixed effects (μ_b). We also add year (μ_t) and borrower-industry (μ_i) fixed effects (SIC4 level) to account for heterogeneity across years and industries that could affect loan allocations. Standard errors are clustered at the bank-firm level.

Estimates of Eq. (9) are presented in Table 2, Panel A (for the five time periods from Figure 5). Across most time periods, banks primarily decarbonize loan books by initiating new lending relationships with low-emitters, rather than by cutting ties with high-emitters. For instance, the estimate in column 2 (2010-2015 period) indicates that these new lending relationships contribute to an average decrease in CTRE scores of 5.8kt, over the average change stemming from intensive margin borrowers. The effect of exits from existing bank relationships is statistically insignificant in that period. In column 3, for the years after the Paris Agreement (2016-2017), the main driver through which banks decarbonize loan books is credit to new firms with relatively lower emissions. The effect

[22] Summary statistics of these variables are reported in Table IA1. Note that $\Phi^{Scope\,1\,Emissions}_{i,b,t}$ is always equal to zero for firms entering or exiting, as a firm's emissions reduction initiatives do not influence a bank's CTRE score when they are in the process of joining or departing from the loan portfolio.

of new entrants on a bank's CTRE score is equivalent to an average reduction of 3.6kt per borrower.[23] These dynamics essentially stop in columns 4 for the post-2017 period after President Trump's announcement to withdraw from the Paris Agreement: we observe a decline in both the magnitude and statistical significance of the $Entry_{i,b,t}$ estimate. In column 5, the effect becomes statistically insignificant after the official Paris Accord withdrawal, plausibly reflecting reduced pressure to undertake initiatives to decarbonize the loan book when transition risks are less pressing.[24]

E. Across- vs. Within-Industry Loan Book Re-Balancing

Are banks re-balancing across borrower-industries or within borrower-industries? To answer this question, we re-estimate Eq. (9) while saturating the model with bank-by-industry ($\mu_b \times \mu_i$) and industry-by-year ($\mu_i \times \mu_t$) fixed effects. The bank-by-industry fixed effects allow us to identify within-bank-and-industry changes in CTRE contributions due to changes in loan amounts along the extensive margins, keeping everything else constant (e.g., time-varying industry-specific credit demand as modelled via industry-by-year fixed effects). Hence, we estimate the following regression for bank b, firm i, and year t:

$$\Phi^{LoanAmount}_{i,b,t} = \beta_1 Entry_{i,b,t} + \beta_2 Exit_{i,b,t} + \mu_b \times \mu_i + \mu_i \times \mu_t + \epsilon_{i,b,t} \tag{10}$$

Regression estimates are reported in Table 2, Panel B.[25] Interestingly, we find no statistically significant effects along the extensive margins adjustments, except for the years 2016 and 2017, the period after the Paris Agreement and before the withdrawal announcement (column 3). The negative coefficient implies that banks actively decarbonize loan books by establishing new relationships with low-emitters operative within the same industry. Quantitatively, this leads to an average decrease in CTRE score of 3.5kt per borrower, over and above the average reduction from intensive margin borrowers. This

[23] This result is consistent with evidence that the pricing of syndicated loans began reflecting firms' exposures to climate transition risks after the Paris Agreement (Degryse et al., 2023; Delis et al., 2024). More favorable loan terms can incentivize low-emitters to seek new bank credit. The finding also aligns with lending discrimination based on environmental performance and capital reallocation toward more environmentally conscious firms (Ehlers et al., 2022; Kacperczyk and Peydró, 2022; Reghezza et al., 2022; Altavilla et al., 2023). We obtain similar patterns when utilizing CTRE scores derived from both Scope 1 and Scope 3 upstream emissions. Hence, banks adjust portfolios toward *new* borrowers with lower emissions across Scope 1 and Scope 3 upstream categories.

[24] We obtain similar results when fixing the set of firms to those in Trucost prior to 2015 (Table IA2).

[25] Across all columns, the sample size decreases compared to Panel A because singleton groups are dropped from the regression sample. This means that estimation is based on bank-industry groups with at least two borrower-observations within the group.

result suggests that banks are gravitating towards new, lower-emitting clients within the same industry and highlights the importance of assessing banks' exposure to transition risks using firm-level emission data rather than industry-level estimates.

V. Climate Transition Risk Exposure and Bank Characteristics

We examine the relationship between banks' CTRE scores and their underlying characteristics to assess which bank traits predict higher or lower levels of emission financing. The goal is not to establish causal effects but instead to establish novel correlations. We consider five sets of bank characteristics: i) asset-side features; ii) liability-side features; iii) market-based characteristics; iv) regulation-related characteristics; and v) board diversity.

Regarding the asset side, we examine the role of bank size (total assets), profitability (return on assets), and the loan ratio (net loans to assets). More profitable banks may be inclined to provide more financing to carbon-intensive firms as their profits imply a larger risk buffer (Reghezza et al., 2022). The loan ratio serves as a proxy for a bank's business model, allowing us to investigate the correlation between a bank's lending focus and the financing of carbon emissions. For the liability side, we examine the link between a bank's debt ratio (total liabilities to assets) and its exposure to climate transition risk. This relationship offers insights into the vulnerability of more leveraged banks, which likely face larger general financial stability issues, to the challenges posed by transition risks. We incorporate the market-to-book ratio to gauge the relationship between market sentiment and banks' transition risk exposures. We consider a bank's Tier 1 capital ratio to assess the association between a bank's shock absorber (capital buffer) and its risk exposure. We include a measure of board gender diversity, the proportion of women on the board of directors, as prior studies have highlighted a positive relationship between gender diversity and environmental performance (Liu, 2018; Atif et al., 2021; Gambacorta et al., 2022).

Using these measures, we estimate the following regression for bank b and year t:

$$Z\_CTRE_{b,t} = \beta_1 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \tag{11}$$

where $Z\_CTRE_{b,t}$ is the standardized CTRE score for bank b in year t, $X_{b,t-1}$ is a vector of bank characteristics, and $\mu_b + \mu_t$ represent fixed effects. We include two sets of fixed effects to identify effects either from variation across banks in a year (year and state-fixed effects) or from variation within banks over time (bank fixed effects). Standard errors are adjusted to account for heteroskedasticity. As we use a standardized dependent variable, the regression coefficients can be interpreted as the change in the CTRE score's standard deviation associated with a one-unit increase in the regressor.

In Table 3, we provide different estimates of Eq. (11). In columns 1 and 3, we identify effects from the cross-section—regressions differ based on the governance variables included (they are missing for some banks). Banks with higher exposure to transition risks are larger, more leveraged, exhibit smaller loan ratios, and have a smaller share of female board directors. That banks with greater exposure to climate transition risks are larger and more leveraged is important: it indicates potential vulnerabilities in the financial system after a climate-related regulatory tightening. The estimated effects are large, with *Debt Ratio* and *Log Total Assets* having the biggest effects. In column 3, a one-standard-deviation increase in the debt ratio (2.3pp) is associated with a 0.24 standard-deviations-increase in the CTRE score, indicating that banks with higher debt ratios in the cross-section tend to finance a greater volume of carbon emissions. Similarly, a one-standard-deviation increase in the logarithm of bank size (1.4pp) is associated with a 0.15 standard-deviation increase in the CTRE score, equivalent to an increase of 537kt of CO_2.

In columns 2 and 4, when examining variation within banks, some differences emerge. Bank size now shows a statistically insignificant association, suggesting that an increase in a bank's balance sheet does not necessarily lead to increased financing of emissions. Moreover, gender diversity emerges as an influential factor. In column 4, a one-standard-deviation increase in female board membership corresponds to less involvement in loans with high-emitters, leading to a decrease of about 619kt in a bank's CTRE score.

VI. Climate Transition Risk Exposure and Stock Market Pricing

A. Estimating Stranded Assets Betas

We investigate how banks' stock returns are influenced by their climate transition risk exposures, thereby assessing whether CTRE scores are contained in market participants' price information. Instead of considering unconditional pricing effects, which are hard to detect, we identify CTRE pricing at times when aggregate climate transition risks are realized. Such realizations may impair the ability of high carbon emitters to repay their loans, thereby affecting the credit risk exposure of banks; such changes in credit risk should affect the returns of banks. The realizations may also shift banks' reputation and legal risks.

To test whether this relation holds true in the data, we follow Jung et al. (2021) and estimate banks' return sensitivities to a monthly market-wide proxy for climate transition risks (or "climate risk factor"). Following Jung et al. (2021) and Jung et al. (2023), the climate risk factor is constructed as the return of a "Stranded Assets Portfolio" that consists of a long position in the Energy Select Sector SPDR ETF (30% weight) and the VanEck Vectors Coal ETF (70% weight), along with a short position in the SPDR S&P 500 ETF Trust. This portfolio is *inversely* correlated with climate transition risks as it represents significant holdings in coal and other fossil fuel firms.[26] We incorporate the return on the Stranded Assets Portfolio into standard asset pricing models to estimate each bank's return sensitivity to this index. For each bank, we run 12-month rolling regressions of the bank's excess returns on monthly observations of the climate risk factor utilizing three asset pricing models: i) the 3-Factor Model; ii) the 5-Factor Model; and iii) an augmented 6-Factor model (5-Factor Model plus Momentum). Hence, we estimate variants of the following model for each bank b and month t:

$$\begin{aligned} Excess\,Return_{b,t} = &\alpha_{b,t} + \beta_1 Climate\,Risk\,Factor_t + \beta_2 Market_t + \\ &+ \beta_3 SMB_t + \beta_4 HML_t + \beta_5 RMW_t + \beta_6 CMA_t + \beta_7 MOM_t + \epsilon_{b,t}, \end{aligned} \tag{12}$$

where $Excess\,Return_{b,t}$ is the return of bank b over the risk-free rate (1-month Treasury yield) in year-month t. $Climate\,Risk\,Factor_t$ is the return of the Stranded Assets Portfolio. The other variables represent the Fama-French factors, that is, the market factor ($Market_t$), small minus big (SMB_t), high minus low (HML_t), robust minus weak (RMW_t), conservative minus aggressive (CMA_t), as well as the Carhart momentum factor (MOM_t) (Carhart, 1997; Fama and French, 2015). Our coefficient of interest is β_1, the "stranded asset beta," which reflects the return sensitivity of an individual bank b to the climate risk factor.

Figure 7 displays the estimated stranded assets betas—the estimates are obtained from the 6-Factor Model (we report values for 2019). The numbers indicate significant heterogeneity in the extent to which banks' returns co-vary with the stranded assets index, and the betas align with those found by Jung et al. (2021).[27]

[26] This analysis is confined to 2008-2019 as the VanEck Vectors Coal ETF only went public in 2008 and closed down before the end of 2020.

[27] The number of banks is less than 34 as two banks were acquired in 2019. There is significant variation even among the largest lenders. Some banks, such as Citigroup or Goldman Sachs, exhibit positive return correlations with the stranded assets return, suggesting that these banks' returns decrease when the performance of stranded assets deteriorates. Silicon Valley Bank has a negative beta, implying that the bank's returns improve when the performance of stranded assets declines.

B. CTRE Scores and Estimated Stranded Assets Betas

Constituting the core of the pricing analysis, we assess how the CTRE score correlates with the estimated stranded assets betas ($\hat{\beta}_1$). As the CTRE score is computed on an annual frequency, we focus on the correlation with time-averaged monthly stranded assets betas at the quarter-end month of a year t (Jung et al., 2021). We estimate the following model for bank b in year t:

$$Stranded\,Assets\,Beta_{b,t} = \beta_1 Z\_CTRE_{b,t} + \beta_2 X_{b,t} + \mu_b + \mu_t + \epsilon_{b,t} \tag{13}$$

where $Stranded\,Assets\,Beta_{b,t}$ is the beta for bank b, measured as the average quarter-end month beta in year t and estimated according to Eq. (12). $Z\_CTRE_{b,t}$ is the standardized CTRE score for bank b in year t. We control for year and bank fixed effects as well as time-varying bank controls. To account for autocorrelation, we employ Driscoll and Kraay (1998) standard errors with four-year lags (results are similar with three- or two-year lags).

We present different variants of Eq. (13) in Table 4. Columns 1–2 use the 3-Factor (3FM), 3–4 the 5-Factor (5FM), and 5–6 the 6-Factor (6FM) Model. We report results with and without bank controls and bank fixed effects. Across all columns, we observe a positive correlation between banks' CTRE scores and their return sensitivities to the stranded assets index. This finding implies that banks with higher exposure to carbon emissions tend to have returns that co-vary to a greater extent with stocks that are prone to devalue with climate transition risks. The most saturated estimation in column 6 suggests that a one-standard-deviation increase in the (standardized) CTRE score raises the stock price co-movement with transition risks by 12.6pp. These results suggest that our CTRE measure is a valid approximation of banks' exposure to climate transition risk, and that markets started to care about the risk.

VII. Climate Transition Risk Exposure and Bank Disclosure

A. Climate-related Disclosure Measures

We investigate whether and how the CTRE measure correlates with two text-based metrics capturing banks' climate-related disclosures. Understanding these relationships is crucial given the ongoing debate about the financial materiality of climate-related risks and their inclusion in corporate reports.[28] There are also concerns that disclosures may

[28] The SEC, for instance, recently proposed rules to enhance and standardize climate-related disclosures, suggesting that current policies are inadequate (SEC, 2022).

be greenwashed, with firms overstating their environmental efforts by omitting or downplaying transition risks. Alternative disclosure channels, such as earnings calls, might provide more comprehensive information on climate-related risks, potentially serving as substitutes.

We construct two variables to address these issues. First, we create a text-based climate disclosure measure for banks' Form 10-K filings (10-*K Disclosure*). Using climate change bigrams from Sautner et al. (2023), we count their occurrences in 10-K filings and scale this count by the number of words in the filing. Second, we measure the relative frequency of these bigrams in banks' earnings calls, utilizing the annual climate change exposure measure from Sautner et al. (2023) (*Earnings Call Disclosure*). For both measures, we exclude keywords related to physical climate risks and calculate moving averages over the previous three years and the current year because issues addressed in prior years may not be reiterated or receive less attention in the current year.

B. Disclosures in Forms 10-K vs. Earnings Conference Calls

We evaluate the relationships between the two disclosure metrics and banks' CTRE scores in two ways. First, we run a regression at the bank-year level:

$$Y_{b,t} = \beta_1 Z\_CTRE_{b,t-1} + \beta_2 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \tag{14}$$

where $Y_{b,t}$ is one of the two disclosure metrics for bank b in year t and $Z\_CTRE_{b,t-1}$ is the standardized CTRE score for bank b in $t-1$. We introduce a one-year lag in the CTRE variable to avoid look-ahead bias (to ensure that the metrics accurately reflect the information contained in the CTRE score). We control for time-varying differences between banks by including bank fundamentals ($X_{b,t-1}$). The variables μ_b and μ_t reflect bank and time fixed effects, respectively.

Second, we address that the impact of a one-standard-deviation increase in the CTRE score may differ between the least (low CTRE scores) and the most exposed banks (high CTRE scores). Therefore, we estimate effects linearly within CTRE score quartiles using a spline regression. In this way, the relationship between CTRE and the disclosure variable is estimated separately for the different parts of the CTRE distribution:

$$Y_{b,t} = \sum_{k=1}^{4} \beta_k Z\_CTRE_{b,k,t-1}^{Quart=k} + \beta_5 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \tag{15}$$

where $Z\_CTRE^{Quart=k}_{b,k,t-1}$ represents the value of $Z\_CTRE_{b,t-1}$ below quartile k of the Z_CTRE distribution across all years so that β_k measures the slope for the interval k. As before, we include time-varying bank controls, bank fixed effects, and year fixed effects. For both specifications, we estimate Poisson fixed effects models as we use dependent variables with only positive values and a high concentration of values at zero (Cohn et al., 2022). Hence, the coefficients should be interpreted as a $(e^{\beta \times SD} - 1) \times 100$ percent change in the original text-based metric for a one-standard-deviation increase in the CTRE score.

Regression results are reported in Table 5.[29] Columns 1–4 provide estimates for 10-K disclosures and columns 5–8 estimates for earnings call disclosures.[30] In column 1–2, we find a significantly positive association between CTRE scores and climate-related disclosures in 10-Ks, indicating that banks increase climate change-disclosure as they finance more carbon emissions. When dividing banks into CTRE-quartile splines in columns 3–4, where coefficients measure slopes within each quartile, this relationship is particularly pronounced for banks with small (first CTRE quartile) and large risk exposures (fourth quartile), while insignificant for the second and third quartiles. This pattern seems consistent with less-exposed banks proactively disclosing their exposures to signal to the market that transition risks are not a concern, and more-exposed banks fulfilling their duty to report on material financial risks (large risk exposures). Accounting for quartile-specific standard deviations, we find that banks with the highest risk exposure are less inclined to disclose changes in transition risks, compared to the less-exposed banks (recall that we estimate within-bank effects). In column 4, for banks in the first quartile, a one-standard-deviation increase of just 0.1 in the standardized CTRE score is associated with a significant 27% rise in 10-K disclosures. In contrast, for banks in the top quartile, despite a larger absolute increase in exposure (standard deviation of 1), the corresponding increase in 10-K disclosures is only 25%. This suggests that banks with higher exposures are less transparent about their transition risks, compared to banks with the lowest risk exposures.

Turning to earnings calls, CTRE scores remain positively associated with climate-related disclosures. In columns 7–8, this relationship is again driven by banks in the bottom and top CTRE quartile. In column 8, a one-standard-deviation rise in the CTRE score at banks in the first CTRE quartile (0.1) is associated with a 14% disclosure increase, while a similar increase at the fourth quartile (1.0) is associated only with a 10%

[29] In Table IA4, we report summary statistics which cover the overall sample and sample splits based on CTRE quartiles. Panel A presents statistics for the 10-K analysis, while Panel B reports the same statistics for the earnings call sample. The samples slightly differ due to data availability reasons.

[30] Positive or higher coefficients indicate higher levels of disclosure (and hence more transparency), while negative or lower coefficients suggest less disclosure (and hence less transparency).

increase. Hence, also for earnings calls, the disclosure sensitivity to changes in CTRE scores is lower for the most exposed banks (compared to the least exposed ones). In the next subsection, we dig deeper to better understand this gap.

C. Greenwashing Incentives: Presentations vs. Q&A in Earnings Calls

The contrasting results between low- and high-exposure banks may be attributed to greenwashing incentives of high-exposure lenders. Specifically, such banks may appear relatively more hesitant to disclose their exposures (albeit their disclosures are not zero), potentially due to concerns about reputation effects, regulatory scrutiny, or market reactions. A specific feature of earnings calls allows us to evaluate this conjecture. During earnings calls, market participants can challenge bank management and raise climate-related issues because these calls consist of two parts: a presentation by bank management—which may be largely silent about transition risks—and a subsequent Q&A. In the second part, analysts can actively seek risk information by probing questions (Sautner et al., 2024). To analyse this possibility, we calculate the level of disclosure separately for both parts (*Earnings Call Presentation* and *Earnings Call Q&A*).

Table 6 bears out our conjecture. The estimates for the presentation part in columns 1–4 show a statistically significant and positive effect between CTRE scores and climate-related disclosures only among banks with the lowest risk exposures. This finding reaffirms our earlier observation, highlighting that banks with minimal exposure proactively communicate their exposures to signal to the market that transition risks are of negligible concern to them. In contrast, in columns 5–8, where we zoom in on disclosures during the Q&A, the effect is concentrated among the most exposed banks. Our results are consistent with greenwashing incentives. High-CTRE banks are somewhat hesitant to disclose their exposures in earnings-call presentations compared to low-CTRE banks. Analysts, however, continue to raise questions about banks' actual climate change exposure, compelling the banks' managers to more extensively disclose the respective risks.

VIII. Climate Transition Risk Exposure and Anti-Climate Lobbying

The prior section shows that banks with high exposure to climate change avoid publicly disclosing them. In this section, we investigate whether banks—in an attempt to avoid amplifying their perceived transition risk and potential legal challenges—actively lobby against stricter climate policies. While most U.S. banks have pledged to align activities with the Paris Agreement, many maintain memberships in industry groups lobbying against climate policies (InfluenceMap, 2022). A driver of banks' anti-climate lobbying activities may be the exposure to climate transition risk, with lobbying efforts aiming to delay or avoid regulations that may impair the value of carbon-intense lending portfolios.[31]

To investigate this possibility, we use a quarterly measure of anti-climate lobbying expenses developed by Leippold et al. (2024). We aggregate each bank's quarterly anti-climate lobbying expenses to an annual level and normalize the sum by the bank's total assets. We then relate anti-climate lobbying expenses of bank b in year t to changes in the bank's CTRE score:

$$Climate\,Lobby\,Intensity^{Anti}_{b,t} = \beta_1 \Delta CTRE_{b,t} + \beta_2 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \qquad (16)$$

where the dependent variable refers to the scaled anti-climate lobbying expenses of bank b in year t and $\Delta CTRE_{b,t}$ is the percentage change in a bank's CTRE score from $t-1$ to t. Following prior literature, $X_{b,t-1}$ includes *Log Total Assets*, *Debt Ratio*, *ROA*, and lobbying-related control variables. The lobbying controls include i) a bank's political orientation (*Political Stance*), calculated as Democratic-leaning lobbying contributions scaled by total lobbying expenditures (in %); ii) total lobbying expenditures scaled by total assets (*Total Lobbying Amount*); iii) political connectedness of the board (*Political Connections*); and iv) bank founding dates (*Age*) (e.g., Duchin and Sosyura, 2012; Lambert, 2019).[32] Summary statistics are reported in Table IA5. μ_b and μ_t represent year- or bank-fixed effects (we estimate either of them). Given the skewness of the outcome variable, we again employ Poisson regressions. This implies that the estimation is restricted to fixed-effects groups with at least one non-zero value. The sample size, in turn, shrinks significantly, but we identify effects from variation that is most informative (within-year or within-bank). Standard errors are adjusted for heteroskedasticity.

Table 7 presents the regression results. All estimates on $\Delta CTRE$ indicate that banks that increase lending towards more carbon-intensive firms subsequently spend more on anti-climate lobbying.[33] This holds true when estimating effects across banks within a

[31] A Bloomberg article documents the misalignment between the Glasgow Financial Alliance for Net Zero (GFANZ) signatories' climate commitments and their political lobbying (Schwartzkopff and Marsh, 2023). Similarly, Ceres reports that 13 of the largest U.S. banks push back pro-climate policies while publicly stating the need for combating climate change (Ceres, 2023).

[32] We lag the lobbying-related control variables to avoid reverse causality (anti-climate lobbying expenses feed into total lobbying amounts and correlate with the general direction of lobbying expenses).

[33] In unreported results, we obtain insignificant effects for CTRE score levels. Hence, more-exposed banks do not routinely lobby more against climate policies. Rather, banks' recent lending to carbon-intensive borrowers (changes in CTRE scores) motivate more anti-climate lobbying. Further, banks' pro-climate lobbying expenses are unrelated to CTRE score changes.

year (columns 1–4) or from within-bank changes (columns 5–8). For instance, in column 4, a 1% increase in CTRE scores implies 20% higher anti-climate lobbying expenses. In column 8, the effect is smaller but still economically large (10% increase in anti-climate lobbying for the same CTRE score change). Further, we find at least suggestive evidence that an increase in politically connected board members is associated with a decrease in anti-climate lobbying expenses (column 8). This finding aligns with existing studies documenting that different forms of political influence might serve as substitutes for one another (Blau et al., 2013; Correia, 2014; Bertrand et al., 2014; Albuquerque et al., 2020). Specifically, politically connected board members have direct access to policymakers, allowing them to advocate directly for their company's interests, thereby reducing the need for formal lobbying. Overall, our results highlight an important link between the carbon footprint of banks' lending practices and their anti-climate lobbying activities.

IX. Conclusion

Climate change and the transition to a low-carbon economy have the potential to affect financial stability and banks' role as intermediaries. To assess the impact of climate transition risks on banks, we propose a bottom-up approach that utilizes loan portfolio data to measure banks' exposures to climate transition risks through their syndicated loan books.

Using this novel measure of transition risk for 34 major U.S. lenders, we examine which steps banks take to facilitate the decarbonization of the economy. We break this bigger question down by analyzing four dimensions: i) the time-series change in transition risk exposures and its drivers; ii) cross-sectional differences in bank and return characteristics based on transition risk exposures; iii) disclosure practices; and iv) active anti-climate lobbying by banks.

Our findings reveal significant cross-sectional and time-series variations in banks' transition risk exposures. For instance, the average exposure in the U.S. banking system significantly declined after the ratification of the Paris Agreement in 2015. The exposure reduction was achieved primarily by initiating new lending relationships with low-emission borrowers, rather than by terminating loans with high-emission borrowers. Transition risk exposure is larger at bigger and more leveraged banks, and at banks with fewer female directors on the board. Contrary to less-exposed banks, banks with high risk exposures appear hesitant to present their exposures in 10-K reports and earnings conference calls.

Overall, we conclude that the sampled banks do not actively reduce carbon emissions in the economy. They tend to disclose relatively less information if they have significant exposure to climate transition risks and actively lobby against stricter climate policies. Consequently, the current role of banks in decarbonizing the economy appears to be limited. At the same time, stock markets appear to care about banks' transition risk exposures. Our proposed measure can serve as a potential tool for regulators, practitioners, and academics to assess transition risks across banks and over time.

Appendix A

Table A1: **Variable Definitions and Data Sources**

Variable Name	Definition and Source
$Age_{b,t}$	The difference between year t and the founding date of a bank, retrieved from banks' official webpages. *Source: Self-constructed.*
$Board\,Gender\,Diversity_{b,t}$	The fraction of female members among the board of directors of a given bank in a given year (in %). *Source: BoardEx.*
$Climate\,Lobby\,Intensity^{Anti}_{b,t}$	Annual anti-climate lobbying expenses scaled by total assets (in USD million) from Leippold et al. (2024). This measure tracks a bank's spending on anti-climate lobbying by analyzing data from OpenSecrets' lobbying reports. Authors extract climate-related lobbying expenses from reports by examining issue descriptions and associated bills. They determine the lobbying direction (anti- or pro-climate) by considering executives' and lobbyists' campaign contributions to the Republican or Democratic Party.
CMA_t	Monthly Conservative-Minus-Aggressive factor from Fama and French (2015). *Source: Kenneth French's data library.*
$CTRE_{b,t}$	Climate transition risk exposure of a given bank in a given year. The measure represents the weighted average Scope 1 greenhouse gas emissions of all borrowers in a bank's syndicated loan book (in kilotons of CO_2 equivalent). *Source: Self-constructed.*
$Z\_CTRE_{b,t}$	Standardized climate transition risk exposure of a given bank in a given year. Constructed to have a mean of zero and standard deviation of one. *Source: Self-constructed.*
$Debt\ Ratio_{b,t}$	Ratio of total debt to total assets (in %) of a given bank in a given year. *Source: Compustat Bank.*
$Earnings\,Call\ Disclosure_{b,t}$	Annual climate change disclosure measure based on textual analyses of the quarterly earnings call transcripts of a given bank in a given year. The measure is defined as the relative frequency with which bigrams related to (non-physical) climate change risks from Sautner et al. (2023) occur in the transcripts of analyst conference calls. We multiply the measure by 100,000. *Source: Firm-level Climate Change Exposure Repository (OSF).*
$Earnings\,Call\ Presentation_{b,t}$	Annual climate change disclosure measure based on textual analyses of the presentation part of quarterly earnings call transcripts of a given bank in a given year. The measure is defined as the relative frequency with which bigrams related to (non-physical) climate change risks from Sautner et al. (2023) occur in the presentation part of analyst conference calls. We multiply the measure by 100,000. *Source: Self-constructed.*
$Earnings\,Call\ Q\&A_{b,t}$	Annual climate change disclosure measure based on textual analyses of the Q&A part of quarterly earnings call transcripts of a given bank in a given year. The measure is defined as the relative frequency with which bigrams related to (non-physical) climate change risks from Sautner et al. (2023) occur in the Q&A part of analyst conference calls. We multiply the measure by 100,000. *Source: Self-constructed.*
$Entry_{i,b,t}$	Binary variable that equals one if a firm enters a bank's loan book in a given year, and zero for firms that remain on a bank's loan book (i.e., intensive margin borrowers). *Source: Self-constructed.*
$Exit_{i,b,t}$	Binary variable that equals one if a firm exits a bank's loan book in a given year, and zero for firms that remain on a bank's loan book (i.e., intensive margin borrowers). *Source: Self-constructed.*
HML_t	Monthly High-Minus-Low factor from Fama and French (1993). *Source: Kenneth French's data library.*
$Loan\ Ratio_{b,t}$	Ratio of net loans to total assets (in %) of a given bank in a given year. *Source: Compustat Bank.*
$Log\,Total\ Assets_{b,t}$	Natural logarithm of total assets (in USD million) of a given bank in a given year. *Source: Compustat Bank.*

Variable Name	Definition and Source
$Market\ Return_t$	Monthly Market factor from Fama and French (1993). *Source: Kenneth French's data library.*
$Market\text{-}to\text{-}Book_{b,t}$	Total market value of equity to the book value of equity of a given bank in a given year. *Source: Compustat Bank.*
MOM_t	Monthly Momentum factor from Carhart (1997). *Source: Kenneth French's data library.*
$Outstanding\ Loan\ Amount_{b,t}$	Outstanding loan amount from a given lender to a given bank in a given year (in USD equivalents). The measure is constructed based on loan origination data from *Refinitiv Dealscan*. We follow the approach from Blickle et al. (2022) and estimate the actual share of loans retained by the lenders after origination. We consider amendments and refinancings over time and otherwise assume that loans remain outstanding until their original maturity date. *Source: Self-constructed.*
$Political\ Connections_{b,t}$	Share of board members (executive and supervisory) with simultaneous or former work experience at a government agency (e.g., Congress, government departments, or regulatory agencies), as defined by the BoardEx database (in %). *Source: BoardEx.*
$Political\ Stance_{b,t}$	The proportion of Democratic-leaning annual lobbying contributions scaled by total lobbying expenditures of a given bank in a given year (in %) from Leippold et al. (2024).
RMW_t	Monthly Robust-Minus-Weak factor from Fama and French (2015). *Source: Kenneth French's data library.*
$ROA_{b,t}$	Ratio of net income to total assets (in %) of a given bank in a given year. *Source: Compustat Bank.*
$Scope\ 1\ Emissions_{i,t}$	Absolute Scope 1 greenhouse gas emissions of a given firm in a given year (in kilotons of CO_2 equivalent. Trucost data item *Absolute: GHG Scope 1* scaled by 1/1,000. *Source: S&P Global.*
SMB_t	Monthly Small-Minus-Big factor from Fama and French (1993). *Source: Kenneth French's data library.*
$Stock\ Price_{b,t}$	Daily stock prices (*PRC*) of a given bank. *Source: CRSP.*
$Stranded\ Asset\ Factor_t$	Monthly Stranded Asset Factor from Jung et al. (2021), which serves as a proxy for the market's expectations on future climate transition risk. The factor is composed of a 70% long position in VanEck Vectors Coal ETF (KOL), a 30% long position in Energy Select Sector SPDR ETF (XLE), and a short position in SPDR S&P 500 ETF Trust (SPY). *Source: Self-constructed.*
$Tier\ 1\ Capital\ Ratio_{b,t}$	Ratio of regulatory Tier 1 capital to total risk-weighted assets (in %) of a given bank in a given year. *Source: Compustat Bank.*
$Total\ Lobbying\ Amount_{b,t}$	Total lobbying expenditures (in USD) scaled by total assets (in USD million) from Leippold et al. (2024).
$Total\ Outstanding\ Loan\ Amount_{b,t}$	Total outstanding loan amount from a given bank to all borrowers in a given year (in USD equivalents). The measure is constructed based on loan origination data from *Refinitiv DealScan*. We follow the approach from Blickle et al. (2022) and estimate the actual share of loans retained by the lenders after origination. We consider amendments and refinancings over time and otherwise assume that loans remain outstanding until their original maturity date. *Source: Self-constructed.*
$10\text{-}K\ Disclosure_{b,t}$	Annual climate change disclosure measure based on textual analyses of the 10-K report of a given bank in a given year. The measure is defined as the relative frequency with which bigrams related to (non-physical) climate change risk from Sautner et al. (2023) occur in lenders' 10-K reports. We count the number of such bigrams and divide by the total number of words in the reports. We multiply the measure by 100,000. *Source: Self-constructed.*
$\Phi^{LoanAmount}_{i,b,t}$	Loan amount share that quantifies the change in the CTRE score of a given bank between $t-1$ and t that is caused by adjustments in outstanding loan amounts to firm i, and originates from a bank's loan book re-balancing.*Source: Self-constructed.*

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Figure 1: **Loan Volume Representativeness**

This figure displays the total loan volume of the U.S. lenders included in our sample from 2002 to 2021, expressed in USD billion. The blue dashed line reflects the total net loan amounts on banks' balance sheets (net of total allowances for loan losses) retrieved from Compustat Bank. The red dotted line reflects the net loan amounts issued by the same lenders based on the DealScan database. The green solid line shows the net loan amounts after conditioning on the availability of borrowers' Scope 1 emissions data.

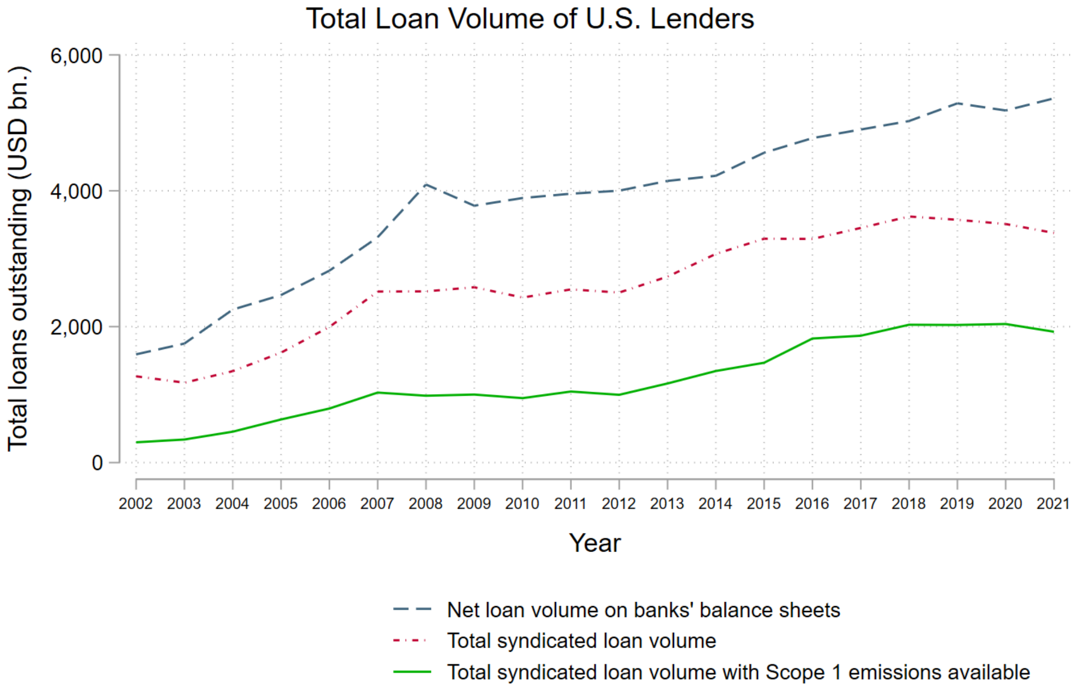


Figure 2: **Average CTRE Scores Over Time**

The figure displays the average CTRE scores of the U.S. banking system from 2002 to 2021, with 95% confidence interval. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The red vertical lines represent some key climate policy-related events: the 2009 Copenhagen UN climate change conference, the 2015 Paris Agreement, the 2017 announcement of the U.S. to withdraw from the Paris Agreement, and the formal U.S. withdrawal in 2020.

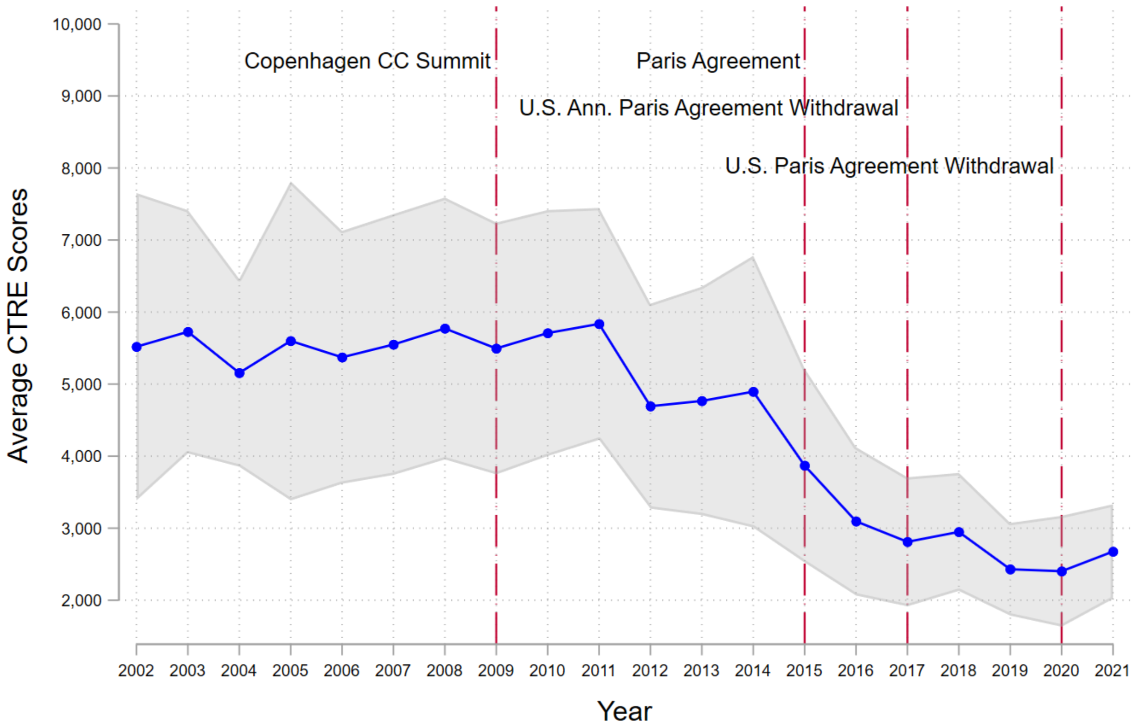
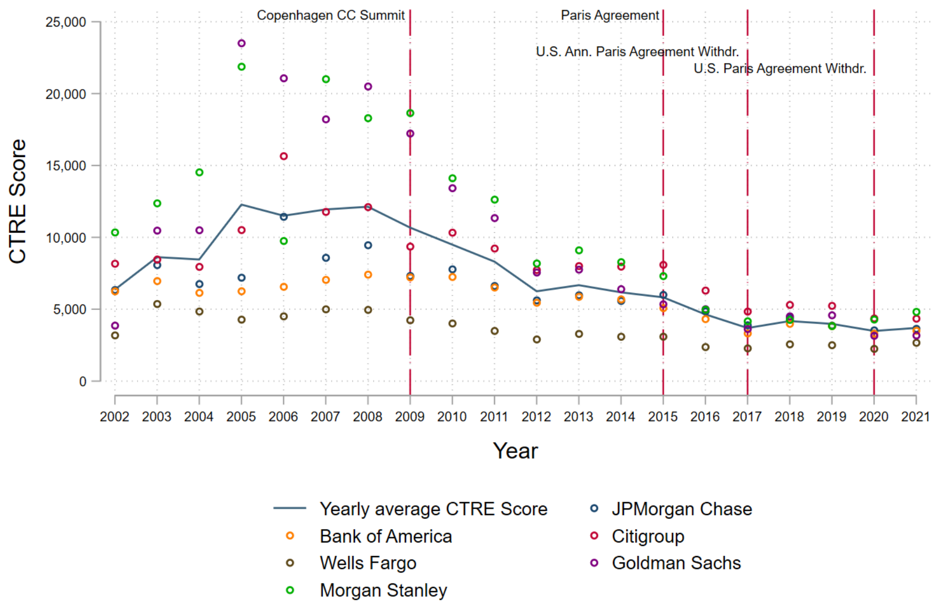


Figure 3: **CTRE Scores Over Time By Size**

These figures show the time-series development in the CTRE scores from 2002 to 2021. Figure (a) shows the CTRE scores of the six largest U.S. lenders, with the blue line showing the average of their CTRE scores. Figure (b) shows the average CTRE scores across three size groups based on terciles of banks' average outstanding lending volumes during the sample period with cutoff points at USD 12.897 billion and USD 64.628 billion. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The red vertical lines represent some key climate policy-related events: the 2009 Copenhagen UN climate change conference, the 2015 Paris Agreement, the 2017 announcement of the U.S to withdraw from the Paris Agreement, and the formal U.S. withdrawal in 2020.

(a) CTRE Scores of the Six Largest U.S. Lenders



(b) CTRE Scores by Size Groups

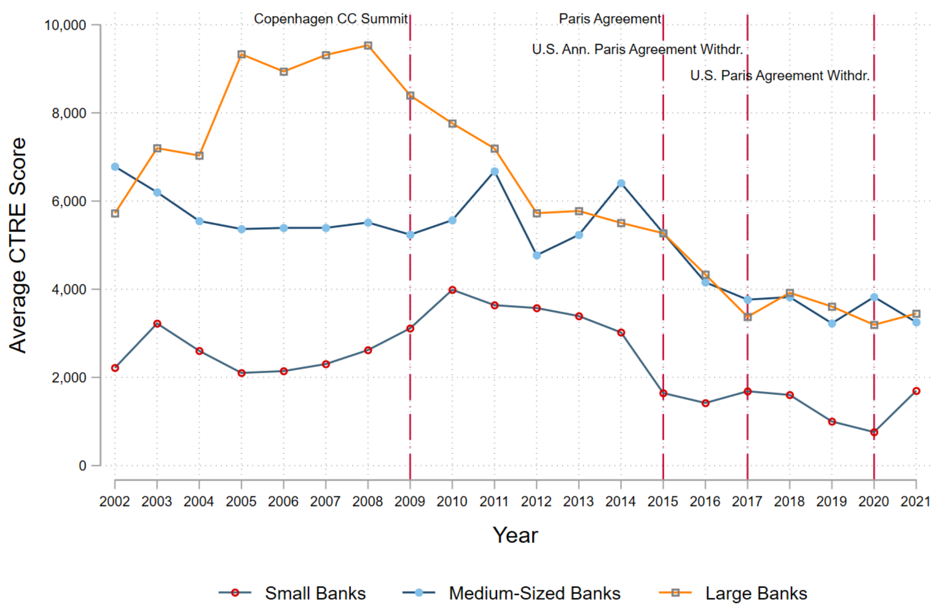


Figure 4: **Average CTRE Scores Over Time: Trucost Legacy Samples**

This figure displays the average CTRE score of the U.S. banking system from 2002 to 2021, depicted by the blue line (replication of the CTRE trend illustrated in Figure 2). In addition, the figure presents the average CTRE scores computed using Trucost's "legacy samples", represented as scattered lines in shades of grey. These scores are calculated based on subsamples for which all firms remain fixed to those existing in Trucost prior to each year, ranging from 2003 to 2019. This approach ensures that the average CTRE scores remain unaffected by the inclusion of newly added firms in the Trucost database. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

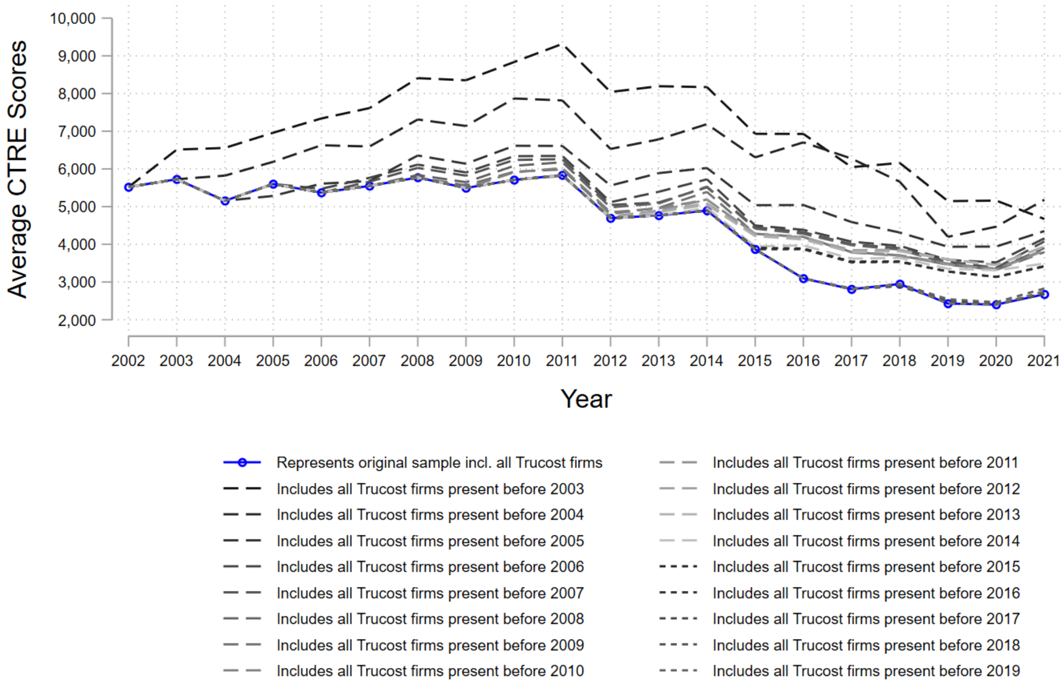


Figure 5: **Loan Book Re-Balancing vs. Emission Reductions**

This figure shows the decomposition of the changes in banks' climate transition risk exposures (CTRE scores) over five different time periods: i) the period from 2002 to 2009, which falls before the Copenhagen UN climate change conference; ii) the period from 2009 to 2015, which follows the conference and precedes the Paris Agreement, iii) the period from 2015 to 2017, which comes after the Paris Agreement and before the U.S. announcement to withdraw from the Paris Agreement, iv) the period from 2017-2020, which follows the withdrawal announcement and precedes the formal withdrawal, and v) 2020-2021, which is the period after the U.S. formally withdrew from the Paris Agreement. We report in grey bars the levels of average CTRE scores for the years 2002, 2009, 2015, 2017, 2020, and 2021, respectively. We also report the corresponding average CTRE values above the bars. Next to the reported levels, we report in red or green bars the changes in average CTRE scores between the six different years (red bars indicate an increase and green bars a decrease in CTRE scores). The changes in the CTRE scores originate either from a loan book re-balancing channel, measured using the loan amount share $\omega^{Loan Amount}$, or an emission reduction channel, as indicated by the Scope 1 emission share $\omega^{Scope\,1\,Emissions}$. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2equivalent).

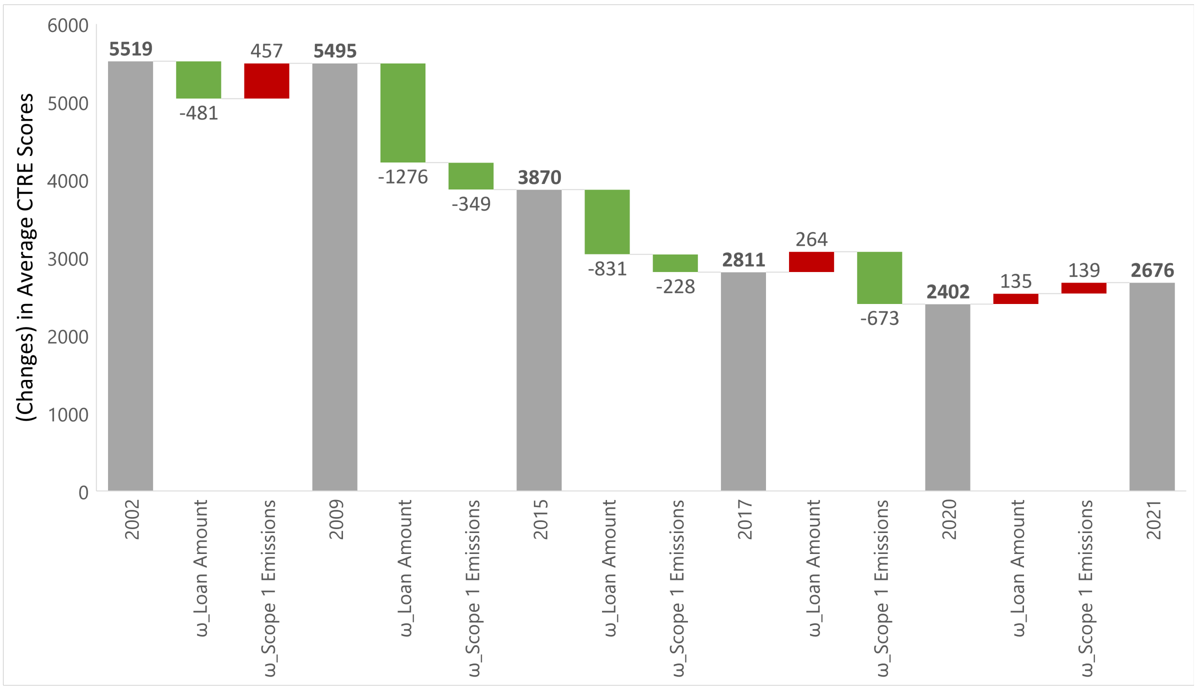


Figure 6: **Decomposition of CTRE Scores Using Scope 1 + Scope 3 Emissions**

This figure shows the decomposition of the changes in banks' climate transition risk exposures (CTRE scores) computed using borrowers' absolute Scope 1 *and* Scope 3 emissions. We report the decomposition for five periods: i) the period from 2002 to 2009, which falls before the Copenhagen UN climate change conference; ii) the period from 2009 to 2015, which follows the conference and precedes the Paris Agreement, iii) the period from 2015 to 2017, which comes after the Paris Agreement and before the U.S. announcement to withdraw from the Paris Agreement, iv) the period from 2017-2020, which follows the withdrawal announcement and precedes the formal withdrawal, and v) 2020-2021, which is the period after the U.S. formally withdrew from the Paris Agreement. We report in grey bars the levels of average CTRE scores for the years 2002, 2009, 2015, 2017, 2020, and 2021, respectively. We also report the corresponding average CTRE values above the bars. Next to the reported levels, we report in red or green bars the changes in average CTRE scores between the six different years (red bars indicate an increase and green bars a decrease in CTRE scores). The changes in the CTRE scores originate either from a loan book re-balancing channel, measured using the loan amount share $\omega^{Loan Amount}$, or an emission reduction channel, as indicated by the Scope 1 + 3 emission share $\omega^{Scope\,1+3\,Emissions}$. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

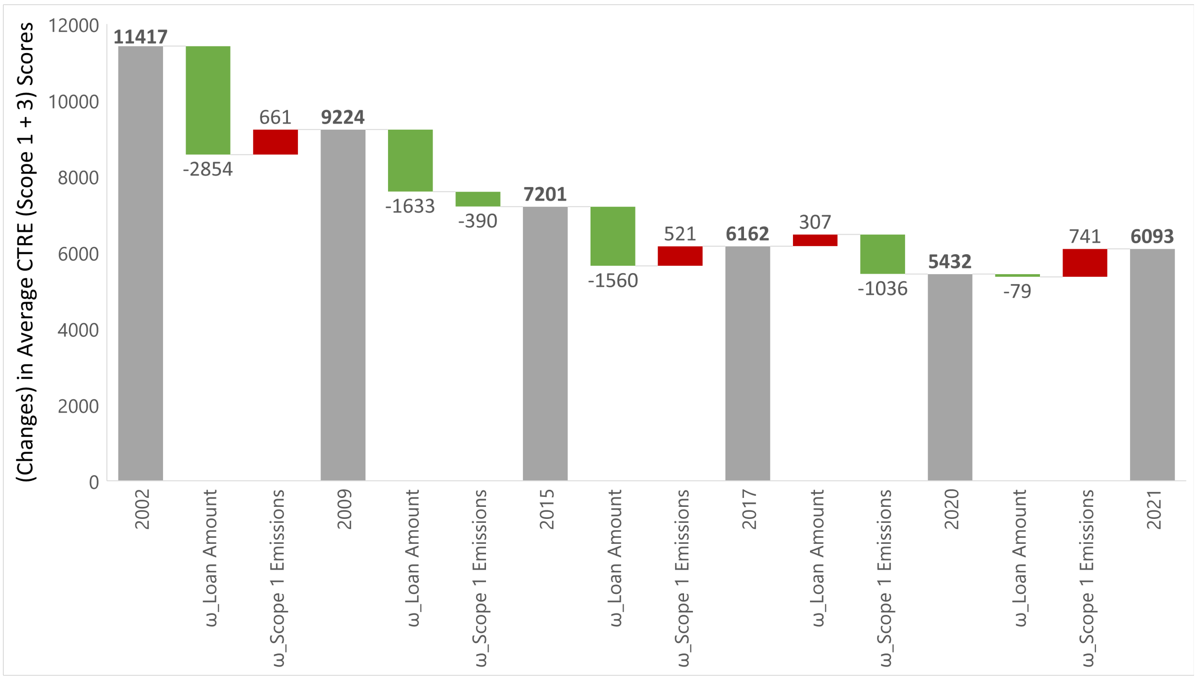


Figure 7: **Climate Betas by U.S. Lenders: Stranded Assets Betas**

This figure displays banks' stranded assets betas estimated using the 6-Factor model reported in Eq. (12) for the year 2019 across the U.S. banks in our sample. The number of banks listed in the figure is less than 34 as two banks left the sample by 2019 due to acquisitions or closures. We use banks' monthly returns over the past 12 months, with at least 10 monthly observations available, to estimate time-varying stock return sensitivities.

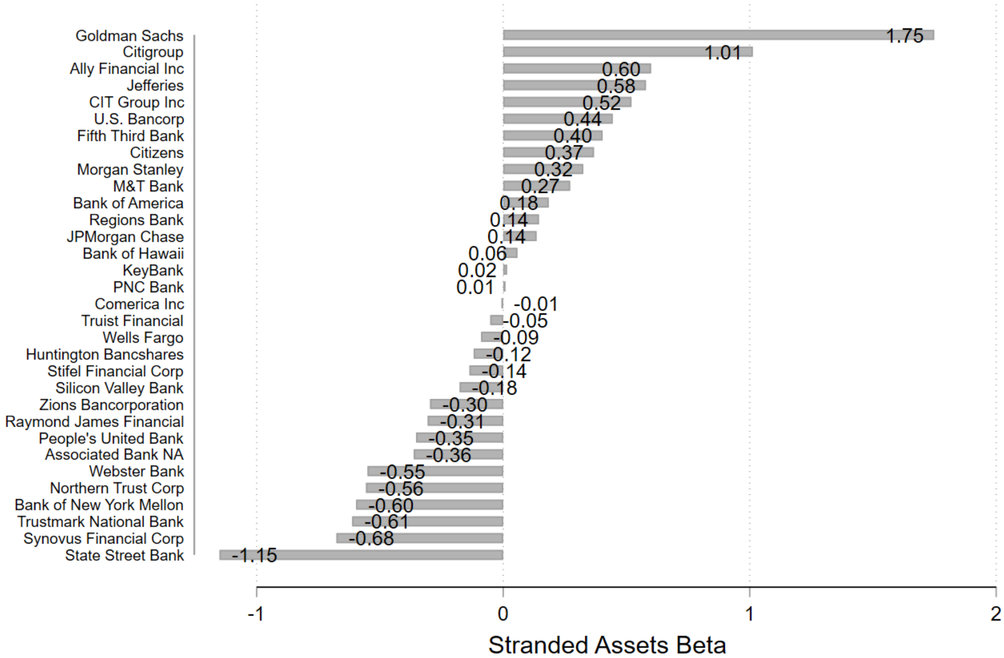


Table 1: **Summary Statistics: CTRE Scores by Bank**

This table reports summary statistics of CTRE scores at the bank-year level for the sampled banks over the 2002-2021 period. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The sample covers 34 U.S. banks with loan exposures to 7,447 unique borrowers with emissions data available. The number of bank-year observations can be smaller than the total number of sample years due to bank acquisitions or closures.

Bank Name	Mean	SD	Min	Max	Bank-Year Obs.
Ally Financial Inc	2,242.6	3,215.2	186.2	12,187.3	16
Associated Bank NA	2,617.4	1,676.2	702.3	7,314.1	17
Bank of Hawaii	1,077.4	864.2	262.2	3,211.3	20
Bank of New York Mellon	7,389.1	1,625.4	5,335.6	10,676.3	20
Bank of America	5,606.1	1,416.2	3,306.4	7,418.6	20
CIT Group Inc	3,081.4	1,647.0	1,104.1	7,488.6	20
Citigroup	8,294.5	2,881.6	4,354.5	15,658.0	20
Citizens	1,996.7	1,712.5	304.6	5,490.4	20
Comerica Inc	2,482.0	478.7	1,481.2	3,552.8	20
Fifth Third Bank	5,012.4	3,491.6	1,653.4	16,582.8	20
Goldman Sachs	10,069.2	6,690.6	3,163.4	23,513.7	20
Hibernia Corp	481.6	161.1	309.4	772.1	8
Huntington Bancshares	11,199.6	6,246.5	3,834.6	22,607.1	20
JPMorgan Chase	6,352.8	2,081.9	3,540.9	11,440.4	20
Jefferies	303.4	120.8	196.3	526.7	10
KeyBank	8,206.6	2,786.9	4,347.6	12,735.6	20
M&T Bank	3,465.5	2,301.6	1,085.4	8,884.2	20
Marshall & Ilsley Corp	2,508.8	481.7	1,842.2	3,311.9	10
Morgan Stanley	10,645.7	5,857.1	3,840.2	21,881.2	20
Northern Trust Corp	4,805.9	1,909.8	1,919.7	9,533.8	20
PNC Bank	4,344.1	1,212.7	2,273.3	6,650.6	20
People's United Bank	531.0	447.0	66.3	1,359.1	12
Raymond James Financial	627.9	344.1	214.3	1,524.6	16
Regions Bank	3,499.6	1,114.4	2,078.6	6,194.0	20
Silicon Valley Bank	14.6	2.4	11.1	19.2	9
State Street Bank	6,997.4	5,595.0	1,460.1	17,471.9	20
Stifel Financial Corp	473.8	418.9	230.3	1,467.9	8
Synovus Financial Corp	1,697.6	2,379.1	511.0	7,962.9	9
Truist Financial	3,297.6	756.2	2,198.6	4,807.6	20
Trustmark National Bank	1,378.0	1,028.4	658.0	3,377.9	6
U.S. Bancorp	3,898.2	858.4	2,992.0	6,224.4	20
Webster Bank	3,597.1	4,036.2	215.1	12,638.8	19
Wells Fargo	3,552.3	1,020.1	2,256.1	5,375.4	20
Zions Bancorporation	1,092.6	928.9	409.4	3,910.0	17
Total	4,417.0	4,140.1	11.1	23,513.7	577

Table 2: **Decomposition of CTRE: Margins of Loan Book Re-Balancing**

This table reports regressions at the bank-firm-year level across five distinct periods: i) 2002 to 2009 (pre-Copenhagen Climate Change Summit); ii) 2010 to 2015 (post-Copenhagen and pre-Paris Agreement); iii) 2016 to 2017 (post-Paris Agreement and pre-withdrawal announcement); iv) 2018-2020 (post-announcement and pre-withdrawal; and v) 2021 (post-withdrawal). The dependent variable $\Phi^{LoanAmount}_{i,b,t}$ measures the change in CTRE score of bank b between $t-1$ and t that is caused by adjustments in outstanding loan amounts to firm i. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The variables of interest are $Entry_{i,b,t}$ and $Exit_{i,b,t}$, which equal one if a firm enters or exits a bank's loan book, respectively, and zero for firms that remain on a bank's loan book (intensive margin borrowers). Variables are defined in Appendix Table A1. Summary statistics are provided in Table IA1. Standard errors, reported in parentheses, are clustered at the bank-firm level. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Within-Bank Estimates					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
			$\Phi^{LoanAmount}_{i,b,t}$		
$Entry_{i,b,t}$	-2.920	-5.814**	-3.551***	-1.228*	.972
	(2.798)	(2.493)	(.721)	(.644)	(3.234)
$Exit_{i,b,t}$	9.327***	2.571	2.270**	-.347	2.367
	(3.348)	(2.145)	(.975)	(2.025)	(2.515)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.007	.005	.023	.018	.045
Obs.	39,278	42,249	22,926	36,604	12,586
Model	OLS	OLS	OLS	OLS	OLS

Panel B: Within-Bank-and-Industry Estimates					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
			$\Phi^{LoanAmount}_{i,b,t}$		
$Entry_{i,b,t}$	.345	-2.917	-3.485***	-.660	.405
	(3.373)	(2.929)	(.640)	(.905)	(2.116)
$Exit_{i,b,t}$	5.396	-.581	1.293	-2.141	-.530
	(4.102)	(2.744)	(1.105)	(2.290)	(3.102)
Bank × Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.089	.094	.278	.182	.358
Obs.	38,914	41,820	22,579	35,972	9,904
Model	OLS	OLS	OLS	OLS	OLS

Table 3: **CTRE Scores and Bank Characteristics**

This table reports regressions at the bank-year level. Regressions run on data from 2002 to 2021. The dependent variable $Z\_CTRE_{b,t}$ is the standardized CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's syndicated loan portfolio (expressed in kt of CO_2-equivalent). The measure is standardized to have zero mean and unit variance. Variables are defined in Appendix Table A1. Summary statistics are provided in Table IA3. Standard errors, reported in parentheses, are adjusted for heteroskedasticity. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)
	$Z\_CTRE_{b,t}$			
$Log\,Total\ Assets_{b,t-1}$	.100**	.087	.106**	-.118
	(.045)	(.148)	(.047)	(.161)
$ROA_{b,t-1}$	.031	.046	.037	.064
	(.064)	(.094)	(.066)	(.102)
$Loan\ Ratio_{b,t-1}$	-.010**	-.008	-.010**	-.002
	(.004)	(.008)	(.005)	(.009)
$Debt\ Ratio_{b,t-1}$	.100***	.053**	.103***	.057**
	(.023)	(.022)	(.023)	(.022)
$Market\text{-}to\text{-}Book_{b,t-1}$	-.156	-.078	-.181	-.051
	(.144)	(.164)	(.158)	(.176)
$Tier\ 1\ Capital\ Ratio_{b,t-1}$	-.001	.008	.003	.012
	(.027)	(.024)	(.028)	(.023)
$Board\,Gender\ Diversity_{b,t-1}$			-.007	-.019***
			(.005)	(.006)
State fixed effects	Yes	No	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	No	Yes	No	Yes
R^2	.524	.615	.526	.625
Obs.	470	470	454	454
Model	OLS	OLS	OLS	OLS

Table 4: **CTRE Scores and Stranded Assets Betas**

This table reports regressions at the bank-year level. The dependent variable is the *Stranded Assets Beta* obtained from estimating either the 3-Factor Fama-French Model (3FM), the 5-Factor Fama-French Model (5FM), or the 6-Factor Model (6FM). The regressions run on data from 2008 to 2019. The variable of interest is Z_CTRE, which is the standardized CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The measure is standardized to have zero mean and unit variance. Bank controls include *Log Total Assets*, *ROA*, *Loan Ratio*, *Debt Ratio*, and *Market-to-Book* (not reported). Variables are defined in Appendix Table A1. Standard errors, reported in parentheses, are Driscoll and Kraay (1998) standard errors with 4-year lags. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Stranded Assets Beta$_{b,t}$					
	3FM	3FM	5FM	5FM	6FM	6FM
$Z\_CTRE_{b,t}$	.040***	.060*	.068***	.094**	.070***	.126**
	(.011)	(.031)	(.020)	(.041)	(.019)	(.046)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	Yes	No	Yes	No	Yes
Bank controls	No	Yes	No	Yes	No	Yes
(Within) R^2	.302	.356	.268	.330	.193	.255
Obs.	292	292	292	292	292	292
Model	OLS	OLS	OLS	OLS	OLS	OLS

Table 5: **CTRE Scores and Climate Risk Disclosures**

This table reports regressions at the bank-year level. All regressions run on data from 2003 to 2021. In columns 1–4, the dependent variable is a bank's climate change disclosure score based on Form 10-K filings ($10\text{-}K\ Disclosure_{b,t}$). In columns 5–8, the dependent variable is a bank's climate change disclosure score from Sautner et al. (2023), which is based on earnings conference calls ($Earnings\ Call\ Disclosure_{b,t}$). For both measures, we focus on non-physical climate change risks and consider moving averages over a four-year period $[t-3;t]$. The variable of interest is $Z\_CTRE_{b,t-1}$, which is the one-year lagged CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The measure is standardized to have zero mean and unit variance. $Z\_CTRE_{b,t-1}^{Quart=k}$ denote CTRE levels within quartile k of the standardized CTRE score distribution and computed using spline regressions. Bank controls include *Log Total Assets*, *Debt Ratio*, and *ROA* (not reported, lagged by one year). Summary statistics are provided in Table IA4. Variables are defined in Appendix Table A1. Standard errors, reported in parentheses, are adjusted for heteroskedasticity. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$10\text{-}K\ Disclosure_{b,t}$				$Earnings\ Call\ Disclosure_{b,t}$			
$Z\_CTRE_{b,t-1}$	.235***	.250***			.096***	.095**		
	(.041)	(.042)			(.036)	(.039)		
$Z\_CTRE_{b,t-1}^{Quart=1}$			1.876***	2.417***			1.228***	1.337***
			(.436)	(.398)			(.431)	(.445)
$Z\_CTRE_{b,t-1}^{Quart=2}$			-.162	-.369			-.398	-.495*
			(.271)	(.276)			(.282)	(.282)
$Z\_CTRE_{b,t-1}^{Quart=3}$			.124	.242			.151	.197
			(.178)	(.172)			(.144)	(.148)
$Z\_CTRE_{b,t-1}^{Quart=4}$			.234***	.222***			.107**	.096**
			(.055)	(.058)			(.046)	(.048)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	.342	.347	.347	.354	.555	.559	.559	.563
Obs.	499	499	499	499	504	504	504	504
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Table 6: **CTRE Scores and Earnings Call Disclosure: Presentation vs. Q&A**

This table reports regressions at the bank-year level. All regressions run on data from 2003 to 2021. In columns 1–4, the dependent variable is a bank's climate change disclosure score based on the presentation parts of earnings conference calls ($Earnings\,Call\,Presentation_{b,t}$). In columns 5–8, the dependent variable is a bank's climate change disclosure score which is based on the Q&A parts of earnings conference calls ($Earnings\,Call\,Q\&A_{b,t}$). For both measures, we focus on non-physical climate change risks and consider moving averages over a four-year period $[t-3;t]$. The variable of interest is $Z\_CTRE_{b,t-1}$, which is the one-year lagged CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The measure is standardized to have zero mean and unit variance. $Z\_CTRE^{Quart=k}_{b,t-1}$ denote CTRE levels within quartile k of the standardized CTRE score distribution and computed using spline regressions. Bank controls include *Log Total Assets*, *Debt Ratio*, and *ROA* (lagged by one year, not reported). Summary statistics are provided in Table IA4. Variables are defined in Appendix Table A1. Standard errors, reported in parentheses, are adjusted for heteroskedasticity. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Earnings\,Call\,Presentation_{b,t}$				$Earnings\,Call\,Q\&A_{b,t}$			
$Z\_CTRE_{b,t-1}$	.056	.069			.192***	.173**		
	(.046)	(.050)			(.066)	(.074)		
$Z\_CTRE^{Quart=1}_{b,t-1}$			1.374***	1.410***			.993	1.024
			(.532)	(.539)			(.719)	(.740)
$Z\_CTRE^{Quart=2}_{b,t-1}$			-.772**	-.806**			.143	.088
			(.345)	(.355)			(.352)	(.353)
$Z\_CTRE^{Quart=3}_{b,t-1}$			.282	.317			.021	.038
			(.192)	(.199)			(.212)	(.220)
$Z\_CTRE^{Quart=4}_{b,t-1}$			.057	.062			.219***	.193**
			(.059)	(.061)			(.076)	(.083)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	No	Yes	No	Yes	No	Yes	No	Yes
Pseudo R^2	.467	.468	.474	.475	.623	.625	.624	.626
Obs.	504	504	504	504	504	504	504	504
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Table 7: **CTRE Scores and Anti-Climate Lobbying**

This table reports regressions at the bank-year level. The dependent variable refers to the scaled anti-climate lobbying expenses of bank b in year t. The regressions run on data from 2003 to 2021. The variable of interest is $\Delta CTRE$, which is the percentage change in the CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). Bank controls include *Log Total Assets*, *Debt Ratio*, and *ROA* (lagged by one year, not reported). Summary statistics are provided in Table IA5. Variables are defined in Appendix Table A1. Standard errors, reported in parentheses, are adjusted for heteroskedasticity. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Climate\ Lobby\ Intensity^{Anti}_{b,t}$							
$\Delta CTRE_{b,t}$	.035*	.095***	.187***	.186***	.046***	.176***	.117**	.095**
	(.020)	(.030)	(.059)	(.055)	(.012)	(.055)	(.046)	(.043)
$Political\ Stance_{b,t-1}$			-.083*	-.084			-.018	-.003
			(.043)	(.052)			(.013)	(.018)
$Total\ Lobbying\ Amount_{b,t-1}$			-.248	-.259			.283	.627**
			(.614)	(.468)			(.474)	(.297)
$Political\ Connections_{b,t-1}$				.006				-.240**
				(.084)				(.106)
$Age_{b,t}$		-.024***	-.002	-.002		-1.025***	-.599	-.782
		(.008)	(.021)	(.020)		(.238)	(.883)	(.770)
Year fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Bank fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Bank controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Pseudo R^2	.414	.722	.763	.761	.301	.688	.687	.702
Obs.	67	65	55	53	95	94	68	70
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Internet Appendix

for

Climate Transition Risks of Banks

Internet Appendix A

Additional Material

Figure IA1: **Sample Industry Shares**

This figure displays borrower industry loan shares of the sampled U.S. lenders over the period 2002 to 2021. The industry classifications are based on borrowers' Standard Industrial Classification (SIC) codes, which we obtain from DealScan. The dark gray bars represent industry loan shares in the unrestricted DealScan sample, whereas the light gray bars represent industry loan shares if we restrict the sample to those borrowers with available Scope 1 emissions data.

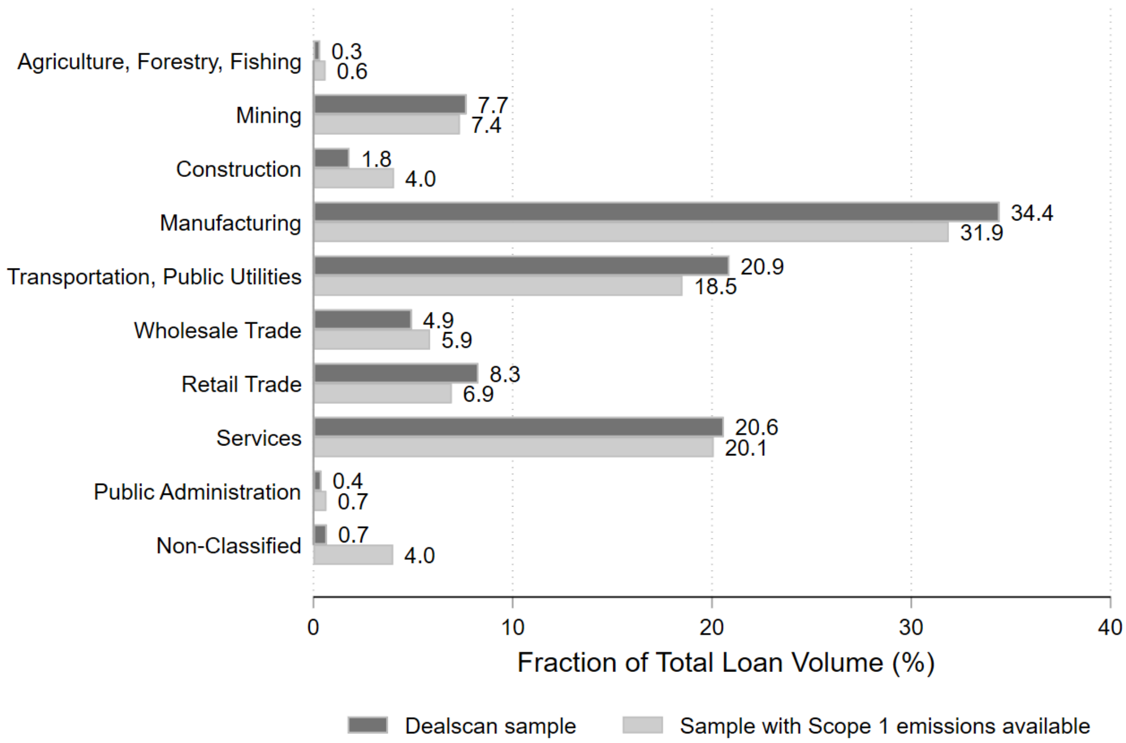


Figure IA2: **Average CTRE Scores Over Time: Other Carbon Emission Metrics**

This figure displays the average CTRE scores of the U.S. banking system from 2002 to 2021, computed using different carbon emission metrics. On top of absolute Scope 1 emissions, we consider absolute Scope 1 + Scope 2 emissions, absolute Scope 1 + Scope 2 + Scope 3 emissions, and Scope 1 emission intensity which is absolute Scope 1 emissions scaled by a firm's revenues. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio. The red vertical lines represent key climate policy-related events: the 2009 Copenhagen UN climate change conference, the 2015 Paris Agreement, the 2017 announcement of the U.S. to withdraw from the Paris Agreement, and the formal U.S. withdrawal in 2020.

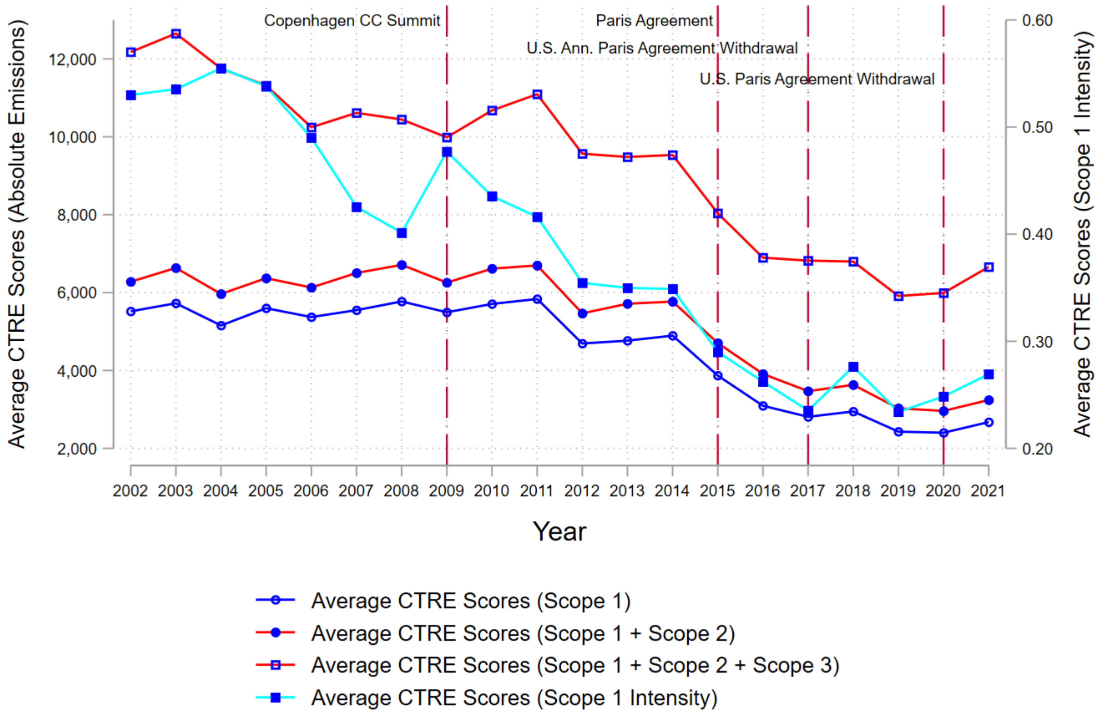


Figure IA3: **CTRE Contributions Over Time by Industry**

This figure shows the time-series development in the CTRE scores by borrower industry from 2002 to 2021. Borrower industry classifications are based on Standard Industry Classification (SIC) codes reported in DealScan. Bar heights indicate the absolute fraction of banks' total CTRE score that a given borrower industry accounts for in a given year. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

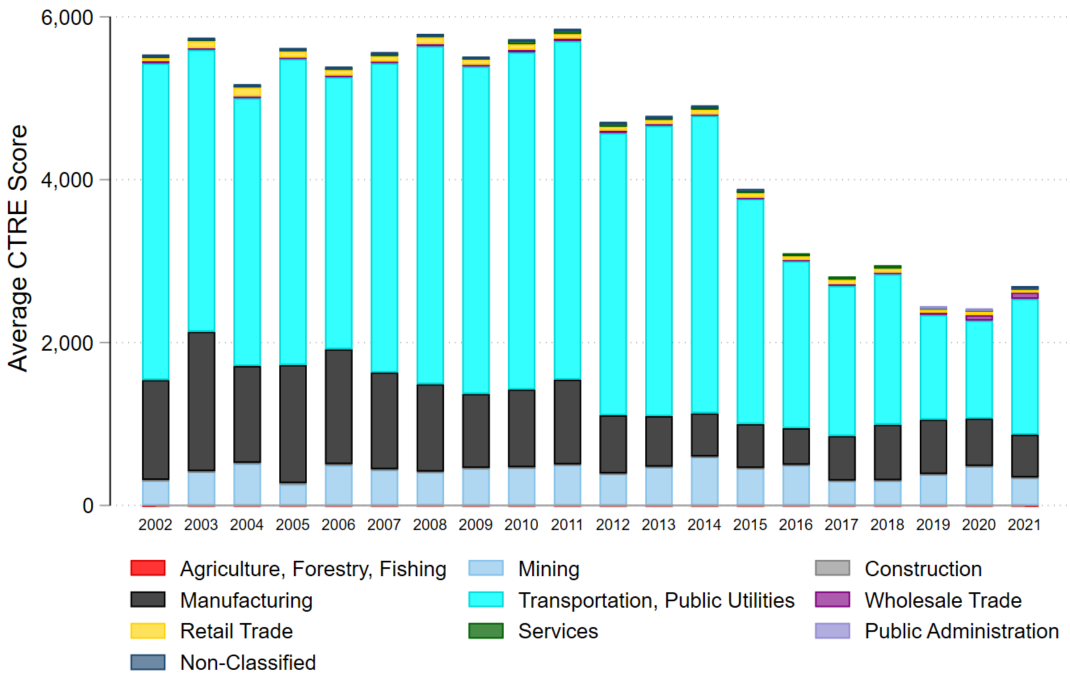


Figure IA4: **CTRE Contributions Over Time by Industry Share**

This figure shows the time-series development in the CTRE scores by borrower industry from 2002 to 2021. Borrower industry classifications are based on Standard Industry Classification (SIC) codes reported in DealScan. Bar heights indicate the relative fraction of banks' total CTRE score that a given borrower industry accounts for in a given year. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

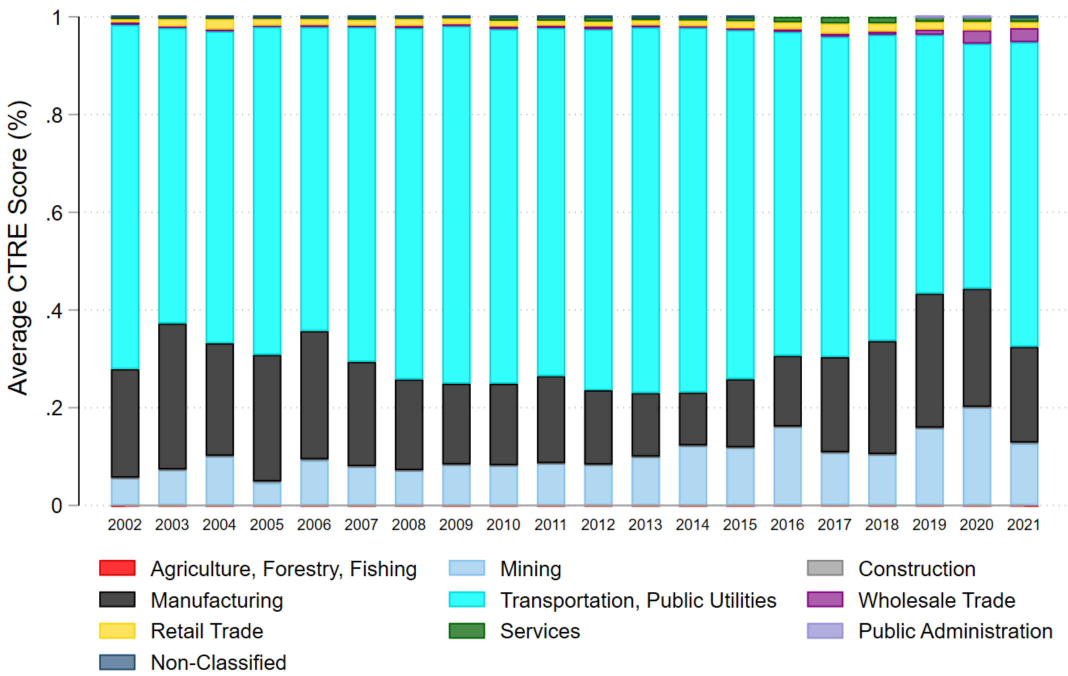


Figure IA5: **Decomposition using the 2015 Trucost Sample**

This figure shows the decomposition of the changes in banks' climate transition risk exposures (CTRE scores) computed using Trucost's "legacy sample" of 2015. This means that the computation is based on the fixed sample of firms present in Trucost before 2015, ensuring that the average CTRE scores remain unaffected by the inclusion of newly added firms in the Trucost database. We report the decomposition for five periods: i) 2002 to 2009 (pre-Copenhagen Climate Change Summit); ii) 2009 to 2015 (post-Copenhagen and pre-Paris Agreement); iii) 2015 to 2017 (post-Paris Agreement and pre-withdrawal announcement); iv) 2017-2020 (post-announcement and pre-withdrawal; and v) 2020-2021 (post-withdrawal). We report in grey bars the levels of the average CTRE scores for the years 2002, 2009, 2015, 2017, 2020, and 2021, respectively. We also report the corresponding average CTRE values above the bars. Next to the reported levels, we report in red or green bars the changes in the average CTRE scores between the six different years (red bars indicate an increase and green bars a decrease in CTRE scores). The changes in the CTRE scores originate either from a loan book re-balancing channel, measured using the loan amount share $\omega^{Loan\,Amount}$, or an emissions reduction channel, as indicated by the Scope 1 emissions share $\omega^{Scope\,1\,Emissions}$. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

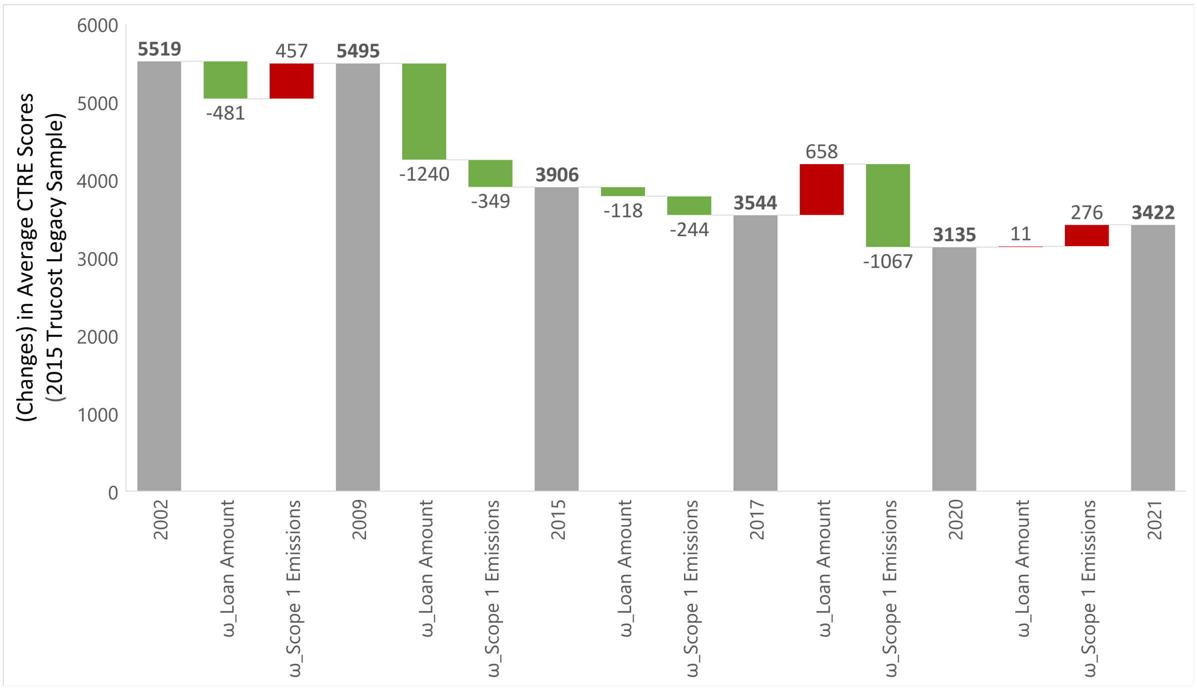


Table IA1: **Decomposition of Changes in CTRE Scores: Summary Statistics**

This table presents summary statistics at the bank-firm-year level of the variables used in the analysis reported in Table 2. Variables are defined in Appendix Table A1.

	Sample Period	Mean	SD	Obs.
$\Phi_{i,b,t}^{Loan\,Amount}$	2002-2009	-0.5	152.9	39,278
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2002-2009	0.6	63.9	39,278
$Entry_{i,b,t}$	2002-2009	15.7%		39,278
$Exit_{i,b,t}$	2002-2009	7.8%		39,278
$\Phi_{i,b,t}^{Loan\,Amount}$	2010-2015	-0.7	127.8	42,249
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2010-2015	-0.2	29.8	42,249
$Entry_{i,b,t}$	2010-2015	12.2%		42,249
$Exit_{i,b,t}$	2010-2015	9.4%		42,249
$\Phi_{i,b,t}^{Loan\,Amount}$	2016-2017	-0.8	34.7	22,926
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2016-2017	-0.2	37.2	22,926
$Entry_{i,b,t}$	2016-2017	22.7%		22,926
$Exit_{i,b,t}$	2016-2017	8.4%		22,926
$\Phi_{i,b,t}^{Loan\,Amount}$	2018-2020	0.2	51.5	36,604
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2018-2020	-0.4	12.2	36,604
$Entry_{i,b,t}$	2018-2020	12.6%		36,604
$Exit_{i,b,t}$	2018-2020	10.9%		36,604
$\Phi_{i,b,t}^{Loan\,Amount}$	2021	0.4	56.7	12,586
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2021	0.4	10.3	12,586
$Entry_{i,b,t}$	2021	12.9%		12,586
$Exit_{i,b,t}$	2021	15.5%		12,586

Table IA2: **Margins of Loan Book Re-Balancing: 2015 Trucost Sample**

This table reports regressions at the bank-firm-year level across five distinct periods: i) 2002 to 2009 (pre-Copenhagen Climate Change Summit); ii) 2010 to 2015 (post-Copenhagen and pre-Paris Agreement); iii) 2016 to 2017 (post-Paris Agreement and pre-withdrawal announcement); iv) 2018-2020 (post-announcement and pre-withdrawal; v) the year 2021 (post-withdrawal). The underlying sample is Trucost's "legacy sample" as of 2015. This means that the computation is based on the fixed sample of firms present in Trucost before 2015, ensuring that the CTRE scores remain unaffected by the inclusion of newly added firms in the Trucost database. The dependent variable $\Phi_{i,b,t}^{LoanAmount}$ measures the change in the CTRE score of bank b between $t-1$ and t that is caused by adjustments in outstanding loan amounts to firm i. The CTRE score is a bottom-up measure of a bank's climate transition risk, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The variables of interest are $Entry_{i,b,t}$ and $Exit_{i,b,t}$, which equal one if a firm enters or exits a bank's loan book, respectively, and zero for firms that remain on a bank's loan book (intensive margin borrowers). Variables are defined in Appendix Table A1. Standard errors, reported in parentheses, are clustered at the bank-firm level. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
			$\Phi_{i,b,t}^{LoanAmount}$		
$Entry_{i,b,t}$	-2.920	-5.762**	-4.361*	-3.389	7.649
	(2.798)	(2.525)	(2.364)	(2.465)	(16.212)
$Exit_{i,b,t}$	9.327***	2.584	3.864**	-1.280	-.610
	(3.348)	(2.145)	(1.650)	(4.373)	(8.540)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.007	.005	.024	.023	.057
Obs.	39,278	42,149	15,770	21,697	6,703
Model	OLS	OLS	OLS	OLS	OLS

Table IA3: **CTRE Scores and Bank Characteristics: Summary Statistics**

This table presents the summary statistics at the bank-year level of the variables used in the analysis reported in Table 3. Variables are defined in Appendix Table A1.

	Mean	SD	Min	Max	Obs.
$CTRE_{b,t}$	4,288.6	3,621.5	11.1	22,607.1	470
$Z\_CTRE_{b,t}$	-0.0	1.0	-1.2	5.1	470
$Log\,Total\ Assets_{b,t-1}$	11.7	1.4	9.2	15.0	470
$ROA_{b,t-1}$	0.9	0.8	-6.0	3.1	470
$Loan\ Ratio_{b,t-1}$	53.2	17.8	4.3	78.7	470
$Debt\ Ratio_{b,t-1}$	89.6	2.3	76.0	94.8	470
$Market\text{-}to\text{-}Book_{b,t-1}$	1.5	0.8	0.3	5.0	470
$Tier\ 1\ Capital\ Ratio_{b,t-1}$	11.4	2.6	6.8	29.5	470
$Board\,Gender\ Diversity_{b,t-1}$	20.4	9.0	0.0	55.6	454

Table IA4: **CTRE Scores and Climate Disclosure Metrics: Summary Statistics**

This table presents summary statistics at the bank-year level of the variables used in the analysis reported in Table 5. Variables are defined in Appendix Table A1.

	Overall Sample		Quartile 1		Quartile 2		Quartile 3		Quartile 4	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
$10\text{-}K\ Disclosure_{b,t}$	2.3	2.6	2.7	2.6	2.2	2.1	1.9	1.6	2.3	3.8
$CTRE_{b,t-1}$	4,723.2	4,311.3	683.5	454.1	2,672.6	532.6	4,917.1	857.9	10,667.4	4,183.9
$Z\_CTRE_{b,t-1}$	-0.0	1.0	-0.9	0.1	-0.5	0.1	0.0	0.2	1.4	1.0
$Log\,Total\ Assets_{b,t-1}$	11.9	1.5	10.5	0.8	11.8	1.2	12.6	1.3	12.6	1.4
$Debt\ Ratio_{b,t-1}$	89.3	4.1	87.5	6.9	89.1	2.4	89.9	1.8	90.9	2.3
$ROA_{b,t-1}$	0.9	1.1	1.0	1.1	0.8	1.7	1.0	0.5	0.6	0.9
Obs.	499		125		125		125		124	
$Earnings\,Call\ Disclosure_{b,t}$	26.8	28.4	30.0	35.2	34.3	39.7	23.2	13.4	19.9	11.5
$Earnings\,Call\ Presentation_{b,t}$	24.3	26.6	27.0	32.5	33.0	36.2	18.7	12.1	18.7	13.9
$Earnings\,Call\ Q\&A_{b,t}$	24.5	34.3	27.6	41.9	31.2	47.3	22.6	21.9	16.6	11.4
$CTRE_{b,t-1}$	4,702.2	4,283.4	691.4	456.1	2,659.3	527.0	4,899.7	851.2	10,558.2	4,194.5
$Z\_CTRE_{b,t-1}$	-0.0	1.0	-0.9	0.1	-0.5	0.1	0.0	0.2	1.4	1.0
$Log\,Total\ Assets_{b,t-1}$	11.9	1.5	10.5	0.8	11.8	1.2	12.5	1.3	12.6	1.4
$Debt\ Ratio_{b,t-1}$	89.6	2.7	88.4	3.4	89.1	2.4	89.8	1.8	90.9	2.3
$ROA_{b,t-1}$	0.9	1.1	1.0	0.8	0.8	1.7	1.1	0.5	0.6	0.9
Obs.	504		126		126		126		126	

Table IA5: **CTRE Scores and Anti-Climate Lobbying: Summary Statistics**

This table presents summary statistics at the bank-year level of the variables used in the analysis reported in Table 7. Variables are defined in Appendix Table A1.

	Mean	SD	Min	25%	Median	75%	95%	Max	Obs.
$Climate\ Lobby^{Anti}_{b,t}$	6,139.9	39,460.2	0.0	0.0	0.0	0.0	19,125.0	365,000.0	95
$Climate\ Lobby\ Intensity^{Anti}_{b,t}$	0.0	0.2	0.0	0.0	0.0	0.0	0.0	1.4	95
$CTRE_{b,t}$	5,297.5	2,523.7	2,078.6	3,578.5	4,515.5	6,502.7	10,518.4	15,658.0	95
$\Delta CTRE_{b,t}$	-0.1	20.3	-43.4	-14.9	-0.8	10.3	40.3	58.8	95
$Log\ Total\ Assets_{b,t-1}$	13.3	1.2	10.8	12.4	13.2	14.5	14.7	15.0	95
$Debt\ Ratio_{b,t-1}$	89.7	2.1	85.8	87.9	89.9	91.3	92.7	94.8	95
$ROA_{b,t-1}$	0.9	0.8	-3.8	0.7	1.0	1.4	1.8	2.5	95
$Age_{b,t}$	121.1	74.8	5.0	40.0	153.0	166.0	218.0	222.0	95
$Political\ Stance_{b,t-1}$	36.3	40.7	0.0	0.0	16.1	74.2	100.0	100.0	84
$Total\ Lobbying\ Amount_{b,t-1}$	2.3	3.6	0.0	0.3	0.8	2.8	11.3	18.0	86
$Political\ Connections_{b,t-1}$	28.6	18.1	0.0	14.3	23.1	41.2	58.3	83.3	94

Internet Appendix B

Computation of the First-Order Derivatives in Eq. (3) and Eq. (4)

We derive the first-order derivatives of bank's CTRE score in Eq. (1) with respect to $Outstanding\,Loan\,Amount_{i,b,t}$ and $Scope\,1\,Emissions_{i,t}$, respectively. For conciseness, we relabel $Outstanding\,Loan\,Amount_{i,b,t}$ as $LA_{i,b,t}$ and $Scope\,1\,Emissions_{i,t}$ as $EM_{i,t}$ such that Eq. (1) becomes:

$$CTRE_{b,t} = \frac{LA_{1,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} \cdot EM_{1,t} + \frac{LA_{2,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} \cdot EM_{2,t} + \ldots + \frac{LA_{N,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} \cdot EM_{N,t}$$

where we can denote $w_{i,b,t} = \frac{LA_{i,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} = \frac{LA_{i,b,t}}{LA_{1,b,t}+LA_{2,b,t}+LA_{3,b,t}+\ldots+LA_{N,b,t}}$

B.1 Derivation w.r.t. Outstanding Loan Amount

After applying the chain rule, we get:

$$\frac{\partial CTRE_{b,t}}{\partial LA_{i,b,t}} = \sum_{j=1}^{N_{b,t}} \frac{\partial CTRE_{b,t}}{\partial w_{j,b,t}} \cdot \frac{\partial w_{j,b,t}}{\partial LA_{i,b,t}}$$

Then, by the quotient rule, we get:

$$\begin{aligned} \frac{\partial CTRE_{b,t}}{\partial w_{j,b,t}} &= EM_{j,t} \\ \frac{\partial w_{i,b,t}}{\partial LA_{i,b,t}} &= \frac{LA_{j,b,t} + \ldots + LA_{N,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} \\ \frac{\partial w_{j,b,t}}{\partial LA_{i,b,t}} &= \frac{-LA_{j,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} \end{aligned}$$

Substituting these derivatives into $\frac{\partial CTRE_{b,t}}{\partial LA_{i,b,t}}$, we get:

$$\begin{aligned} \frac{\partial CTRE_{b,t}}{\partial LA_{i,b,t}} &= EM_{i,t} \cdot \frac{LA_{j,b,t} + \ldots + LA_{N,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} + \ldots + EM_{N,t} \cdot \frac{-LA_{N,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} \\ &= \frac{\sum_{j\neq i}^{N_{b,t}} (EM_{i,t} - EM_{j,t}) \cdot LA_{j,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2} \end{aligned}$$

For example, for j = 1,2,3 :

$$\frac{\partial CTRE_{b,t}}{\partial LA_{1,b,t}} = \frac{(EM_{1,t} - EM_{2,t}) \cdot LA_{2,b,t} + (EM_{1,t} - EM_{3,t}) \cdot LA_{3,b,t}}{(LA_{1,b,t} + LA_{2,b,t} + LA_{3,b,t})^2}$$

B.2 Derivation w.r.t. Scope 1 Emissions

$$\frac{\partial CTRE_{b,t}}{\partial EM_{i,t}} = w_{i,b,t} = \frac{LA_{i,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}}$$