Climate Transition Risks of Banks*

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Abstract

We develop a measure of U.S. banks' exposures to climate transition risks from the carbon footprint of their syndicated loans. The measure correlates with bank-level climate betas, reflecting the sensitivity of bank returns to a stranded asset index. Transition risk exposures have declined over time, especially since 2015. This decline results from re-balancing of loan portfolios, with more lending to low-emitters rather than cutting ties with high-emitters. Banks with higher risk exposures provide more climate-related disclosures when probed by analysts in earnings calls, but not voluntarily in Form 10-Ks. Banks lobby more against climate action after their risk exposures increase.

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

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. 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). Additionally, recent climate disclosure mandates, such as the SEC's proposals and similar rules in Europe, the UK, Japan, and New Zealand, require public companies, including banks, to disclose their climate risk exposures (SEC, 2024).

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

[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).

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.

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.[3] A higher score indicates higher exposure to climate transition risks. Consistent with Bolton and Kacperczyk (2023), we adopt a holistic perspective on climate transition risks. Beyond higher carbon-related credit risks, higher CTRE scores reflect increased litigation or reputational risk.

Our sample includes 33 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

[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., 2024; 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

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 DealScan database, which allows us to carefully track loan amendments over time and to compute a bank's outstanding exposure to a given borrower at any point in time. Importantly, we take into account that lenders sometimes 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 through 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 misaligned with public climate statements ("greenwashing").

CTRE scores are reflected in banks' stock returns, 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., 2024). 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. This finding is important as it corroborates the CTRE scores are a valid approximation of banks' exposure to climate transition risk, and that markets started to care about the risk.

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

Since 2011, U.S. banks' transition risk exposure have gradually declined, with a no-

table drop following the Paris Agreement in 2015. However, this decline 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.

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

[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) or by reduced economic growth, as it holds when using Scope 1 intensity (emissions scaled by revenues).

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 suggest an inconsistency between banks' exposures to climate transition risks and their disclosures in Forms 10-K. Anecdotal evidence also points to a further inconsistency between 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) find 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., 2024), 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. (2024) 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, which highlights the impact of lobbying on climate policy 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.

1. Sample Construction and Data Sources

Bank loan-level exposures. We 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—as in Schwert (2018)—loans 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 In-

[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 map the "new" DealScan identifiers to the "legacy" identifiers via the WRDS linking table. Then, we connect the legacy identifiers to the corresponding GVKEYs via Schwert (2018)'s linking file.

stitutions"), 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 33 major U.S. bank holding companies. For simplicity, we refer to bank holding companies as "banks." The 33 banks have loan exposures to 29,481 unique borrowers from 2002 to 2021.

We consider loans to both domestic as well as foreign (non-U.S.) borrowers. Tracing global lending portfolios is important. First, it enables us to also capture emissions associated with loans financed outside of the U.S. If some banks, for example, were merely shifting their lending from domestic to foreign fossil fuel firms, the accompanying 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 are exposed through borrowers operating abroad.

Borrower 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

[8]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.

exposures that are similar to those of Scope 1-focused analyses. Reflecting the coverage period of the Trucost database, our sample period starts in 2002 and ends in 2021 (last full year with significant data coverage in Trucost as of March 2024).

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. The dashed black line represents the aggregate balance-sheet-based loan volume of banks in our sample. The red dotted line below reflects the syndicated loan amounts issued by the same lenders according to DealScan data, and the solid blue line shows the syndicated loan amounts if we further restrict the sample to borrowers with Scope 1 emission data. The figure shows that syndicated lending represents two-thirds of our banks' balance-sheet-based loan volumes. With 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]

[10] Figure IA.A1 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

2. Climate Transition Risk Exposure: Methodology and Anatomy

2.1. 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. Specifically, to obtain a size-adjusted score that is comparable across banks and over time, we calculate bank b's CTRE score at the end of year t by multiplying the Scope 1 emissions of each borrower in the bank's syndicated loan book by the weight of the borrower in the loan book:

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

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 to the total loan volume and conditional on the availability of emissions data):[11]

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

To calculate $Outstanding\,Loan\,Amount_{i,b,t}$, we transform data on syndicated loan *transactions* to *outstanding* loan volumes in year t using the lender-specific loan shares and loan maturities in DealScan. As transition risks arise due to banks' outstanding (term) loans and commitments through credit lines, we include both loan types in the CTRE calculation. We address that lenders sometimes sell off their original loan commitments after syndication by following Blickle et al. (2022)'s approach on how to esti-

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, 0.7% in DealScan).

[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 investor portfolios. Conditioning on emissions data is also similar to how Morningstar calculates Low Carbon Designations for mutual funds (Hartzmark and Sussman, 2019; Ceccarelli et al., 2023).

mate the actual loan share retained after origination. In line with Gropp et al. (2019), we transform loan-level holding estimates into outstanding loan volumes at the lender-borrower-year level based on loan maturity dates, taking into account loan amendments and refinancings while loans are outstanding.

The CTRE score is a proxy for the weighted average Scope 1 emissions of firms in a bank's syndicated loan book, expressed in kilotons (kt) of CO_2. Higher scores indicate higher exposure to climate transition risks. In some tests we use a standardized score, $Z_CTRE_{b,t}$, constructed to have a mean of zero and a standard deviation of one. This allows for a more meaningful interpretation of regression coefficients and ensures that results are not solely driven by the magnitude of the CTRE score (the score exhibits large differences between the minimum and maximum). We require that a bank has lending relationships with at least five borrowers in a year. We include in the sample only banks with at least five CTRE observations.

2.2. Descriptive Statistics of CTRE Scores

2.2.1. 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 14kt CO_2 (Silicon Valley Bank) to 11,241kt CO_2 (Huntington Bancshares), indicating significant cross-sectional heterogeneity in risk exposures.[13] The heterogeneity reflects the diverse nature of banks' business models. For example, Silicon Valley Bank's low exposure is in line with its focus on venture capitalists and tech-startups that typically generate low emissions. On the other hand, the high exposure of

[12]The observations per bank can be smaller than the number of sample years due to bank restructurings, acquisitions or closures (e.g., Marshall & Ilsley Corporation has only eight data points as it was acquired in 2011 by 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 11,241kt, or 11.2 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.

Huntington Bancshares likely reflects significant lending relationships with firms in Ohio, where the bank's is based, known for its history of coal mining and industrial minerals extraction. The CTRE score's standard deviation for some banks is higher than their average scores, indicating significant time-series variation in financed emissions even *within* banks. In Internet Appendix B, we relate banks' CTRE scores to bank characteristics.[14]

2.2.2. CTRE Scores: Time-Series Variation

Figure 2 illustrates how banks' transition risk exposures evolved over time. We calculate an annual average CTRE score across banks and plot its progression from 2002 to 2021, including 95% confidence intervals. We also highlights key climate policy events (vertical lines) and plot the *Media Climate Change Concern Index* from Ardia et al. (2023) (red dotted line). In the first half of the sample period, banks' CTRE scores remained relatively flat. From around 2012, the scores began to decline, with a particularly steep drop after the Paris Agreement in 2015. The reduction in CTRE scores slowed down around 2017, coinciding with President Donald Trump's administration and his announcement to withdraw from the Paris Agreement. After the formal withdrawal from the agreement in 2020, average CTRE scores of U.S. banks increased. A comparison of the trend in CTRE scores with the *Media Climate Change Concern Index* reveals a strikingly negative correlation. This aggregate pattern suggests that banks reduced risk exposures in response to heightened climate change concerns. In Internet Appendix C, we show that the CTRE trends are not driven by emission measurement, sample composition effects, and short-maturity loans that exhibit lower risk exposures.

In Figure 3a, we plot the time-series of the six largest U.S. lenders' CTRE scores (as

[14]Two results emerge from this analysis. 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 CTRE scores.

well as a yearly average CTRE score across the six banks). At the onset of the sample, there is substantial variation in the banks' exposures to transition risk. After the Paris Agreement in 2015, CTRE scores converge substantially, suggesting a collective effort to reduce the carbon footprint of the lending portfolios. Consistent with the dynamics in Figure 2, there is a gradual increase in CTRE scores after 2017.[15]

In Figure 3b, we display average CTRE scores over time across three size groups based on terciles of average lending volumes. Most of the pre-2015 CTRE decline occurs at large banks, which started reducing their exposures earlier than other banks. Since 2015, the exposures of large and medium banks converge. There is a decline in risk exposures across all bank types from 2014 to 2017; this decline levels off and exposures begin to rise again after the Paris withdrawal announcement.

3. Climate Transition Risk Exposure and Stock Market Pricing

3.1. Estimating Stranded Assets Betas

We investigate how banks' stock returns are influenced by their climate transition risk exposures. This analysis also serves as a validation that CTRE scores are an approximation of banks' broader exposures to climate transition risk that the market cares about. Given that our scores are constructed for syndicated loan books only, this is a useful exercise. Instead of considering hard-to-detect unconditional pricing effects, 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 or legal risks.

[15] Figure IA.A2 and Figure IA.A3 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 in Trucost before 2015, i.e., we are not picking up compositional effects).

We follow Jung et al. (2024) and estimate banks' return sensitivities to a monthly market-wide proxy for climate transition risks (or "climate risk factor"). As in Jung et al. (2024) 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.[16] 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 models: i) the 3-factor; ii) the 5-factor; and iii) the 6-factor (5-factor model plus momentum) model. Hence, we estimate variants of the following model for each bank b and month t:

$$\begin{aligned} Excess\,Return_{b,t} =& \alpha_{b,t} + \beta_1 Climate\,Risk\,Factor_t + \beta_2 Market_t + \\ &+ \beta_3 SMB_t + \beta_4 HML_t + \beta_5 RMW_t + \beta_6 CMA_t + \beta_7 MOM_t + \epsilon_{b,t}, \end{aligned} \tag{3}$$

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), and the momentum factor (MOM_t) (Carhart, 1997; Fama and French, 2015). The coefficient of interest is β_1, the "stranded asset beta," which reflects the return sensitivity of bank b to the climate risk factor.

Figure 4 displays the estimated stranded assets betas (obtained from the 6-factor

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

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. (2024).[17]

3.2. CTRE Scores and Estimated Stranded Assets Betas

How do CTRE score correlate 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., 2024). We estimate the following model for bank b in year t:

$$Stranded\,Assets\,Beta_{b,t} = \beta_1 Z_CTRE_{b,t} + \beta_2 X_{b,t} + \mu_b + \mu_t + \epsilon_{b,t} \tag{4}$$

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. (3). $Z_CTRE_{b,t}$ 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 several variants of Eq. (4) in Table 2. Columns 1–2 use the 3-factor, columns 3–4 the 5-factor, and columns 5–6 the 6-factor model. We observe a positive correlation between banks' CTRE scores and their return sensitivities to the stranded assets index. Hence, banks with higher exposure to emissions have returns that co-vary to a greater extent with stocks prone to devalue with climate transition risks. In column 6 a one-standard-deviation increase in $Z_CTRE_{b,t}$ raises the stock price co-movement with transition risks by 12.5pp. Overall, the CTRE measure appears to be a valid ap-

[17] The number of banks is less than 33 as one bank left the sample due to an acquisition by 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, for example, has a negative beta, implying that the bank's returns improve when the performance of stranded assets declines.

proximation of banks' exposure to climate transition risk that investors care about.

4. Climate Transition Risk Exposure: Decomposition of Changes

There are two primary ways through which banks may have reduced their exposures to climate transition risk, as documented in Figure 2. First, banks may have decreased their loan exposures to high-emission borrowers, reallocating credit toward low-emission borrowers ("loan book re-balancing" channel). Second, banks may have achieved CTRE score reductions through changes at the borrower level, with borrowers reducing emissions by adopting greener technologies or changing operations ("emission reductions" channel); this may decrease CTRE scores without banks actively changing lending behavior.[18]

4.1. 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' CTRE scores. This approach pins down CTRE score changes to changes in 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' emissions ($EM_{i,t}$).[19]

As a first step, we derive the components' contributions to changes in 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 each component. This enables us to interpret the contribution consistently with the direction of its impact on the CTRE score, allowing only one of the

[18] Banks may still contribute to the emission reductions by financing the underlying changes or by pressuring borrowers to adopt more sustainable business practices.

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

components to change over time (while treating the other components as constants).[20]

$$\begin{aligned}\Phi_{i,b,t}^{LoanAmount} &= \Delta LA_{i,b,t-1,t} \cdot \frac{\partial CTRE_{b,t}}{\partial LA_{i,b,t}} \\ &= \Delta LA_{i,b,t-1,t} \cdot \frac{\sum_{j\neq i}^{N_{b,t}} (EM_{i,t} - EM_{j,t}) \cdot LA_{j,b,t}}{(\sum_{j=1}^{N_{b,t}} LA_{j,b,t})^2}\end{aligned} \tag{5}$$

$$\begin{aligned}\Phi_{i,b,t}^{Scope\,1\,Emissions} &= \Delta EM_{i,t-1,t} \cdot \frac{\partial CTRE_{b,t}}{\partial EM_{i,t}} \\ &= \Delta EM_{i,t-1,t} \cdot \frac{LA_{i,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}}\end{aligned} \tag{6}$$

Eq. (5) 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. Eq. (6) 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:

$$\Psi^{LoanAmount} = \frac{\Phi^{LoanAmount}}{|\Phi^{LoanAmount} + \Phi^{Scope\,1\,Emissions}|} \tag{7}$$

$$\Psi^{Scope\,1\,Emissions} = \frac{\Phi^{Scope\,1\,Emissions}}{|\Phi^{LoanAmount} + \Phi^{Scope\,1\,Emissions}|} \tag{8}$$

[20] Internet Appendix D details the computation of the first-order derivatives.

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

$$\omega^{LoanAmount} = \Psi^{LoanAmount} \cdot |\Delta CTRE| \tag{9}$$

$$\omega^{Scope\,1\,Emissions} = \Psi^{Scope\,1\,Emissions} \cdot |\Delta CTRE| \tag{10}$$

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 (e.g., 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.

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

Figure 5 displays the decomposition of the CTRE scores for five 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 the Paris Agreement and before the U.S. withdrawal announcement); iv) 2018-2020 (after the announcement and before the 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 104kt of CO_2, from 5,781kt to 5,677kt. This change originates from a decline in emissions by 1,388kt attributed to loan book re-balancing (towards less-emitting firms), which is partially offset by a 1,283kt emissions increase at existing borrowers. Between 2010 and 2015, a period when the average CTRE score declined substantially, banks re-balanced their loan books away from high-emission borrowers, resulting in a gross CTRE score reduction of 1,412kt. As borrowers simultaneously decreased their emissions (by 396kt), the net reduction in CTRE scores amounts to 1,808kt (=3,869-5,677kt). After the Paris Agreement, the pri-

mary driver of CTRE reduction remains loan book re-balancing, accounting for a gross reduction of 824kt. In contrast, after the U.S. announced to withdraw from the Paris Agreement, banks re-balanced their portfolios towards *more* polluting firms, leading to an average *increase* in CTRE scores by 249kt. At the same time, cuts to firm-level emission lowered the CTRE score by 667kt (potentially efforts by non-U.S. firms unaffected by the withdrawal). Consequently, the total CTRE score decrease from 2018 to 2020 is 418kt. Following the actual Paris withdrawal, banks continued to lend to more polluting firms, resulting in a gross CTRE increase of 134kt. The emissions share by borrowers simultaneously contributed *positively* to the CTRE scores (post-2020 emissions increase).[21]

4.3. Substitution of Scope 1 for Scope 3 Emissions

A mounting concern is that firms "reduce" emissions through the divestment of polluting assets, thereby replacing 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 repeat the CTRE decomposition. This analysis is important. For example, if borrowers are reducing their Scope 1 emissions by shifting 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 results. While the overall decline in average CTRE scores and the underlying channels align with the decomposition based on Scope 1 emissions, 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 (-477kt), albeit to a lesser extent than when accounting solely for Scope 1 emissions.[22] In

[21] Figure IA.A4 shows that these findings are robust to analyzing a static sample of firms present in the 2015 Trucost legacy dataset (i.e., results are unaffected by the inclusion of new entities in Trucost).

[22] 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,

the 2016-2017 period, changes in combined Scope 1 and 3 upstream emissions led to a *positive* increase in banks' risk exposures, contrary to the decrease observed when focusing on Scope 1 emissions. Hence, in 2016 and 2017, some firms reduced Scope 1 while increasing Scope 3 emissions, consistent with an emission outsourcing to (foreign) suppliers as documented by Berg et al. (2023), Dai et al. (2024), or Duchin et al. (2024). Consequently, we observe a positive impact on banks' average CTRE scores from borrower-level emission changes when accounting for Scope 1 and 3 emissions. Nevertheless, the primary channel of reducing exposures remains loan book re-balancing, not firm-level emission reductions, which reverses after 2017 when President Trump announced the Paris withdrawal.

4.4. Margins of Loan Book Re-Balancing

To understand how banks decarbonize loan books, we examine whether the documented re-balancing (as captured by $\Phi_{i,b,t}^{LoanAmount}$) stems from the intensive or extensive margins. We therefore quantify three possible lending strategies that may contribute to the CTRE score changes: i) reducing, but not fully stopping, loans for a given borrower; ii) entirely terminating lending relationships; and iii) initiating new lending relationships with low-emission borrowers. Two variables differentiate the impact of changes in loan amounts across the extensive margins: $Entry_{i,b,t}$ equals one when a borrower newly enters a bank's loan book, and $Exit_{i,b,t}$ equals one when a borrower leaves a bank's loan book. Both variables equal zero for borrowers that remain on a bank's loan book (intensive margin borrowers).[23] We use these measures to estimate for bank b, firm i, and year t:

$$\Phi_{i,b,t}^{LoanAmount} = \beta_1 Entry_{i,b,t} + \beta_2 Exit_{i,b,t} + \mu_b + \mu_t + \mu_i + \epsilon_{i,b,t}, \tag{11}$$

emission reductions contributed 20.5% when considering both Scope 1 and 3 emissions in Figure 6, which is less than the 21.9% when accounting solely for Scope 1 emissions in Figure 5.

[23] Summary statistics of these variables are reported in Table IA.A.1. Note that $\Phi_{i,b,t}^{Scope\,1\,Emissions}$ always equals 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.

where $\Phi_{i,b,t}^{LoanAmount}$ 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. $Entry_{i,b,t}$ ($Exit_{i,b,t}$) equals one if a firm enters (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 (the reference group). We seek identification from within-bank estimates with bank fixed effects (μ_b). We 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. (11) are presented in Table 3 (for the time periods in Figure 5). Across most periods, banks primarily decarbonize loan books by initiating new lending relationships with low-emitters, rather than by cutting ties with high-emission firms. For instance, the estimate in column 2 (2010-2015 period) indicates that new lending relationships contribute to an average decrease in CTRE scores of 5.9kt, over the average change stemming from intensive margin borrowers. The effect of exits from bank relationships is statistically insignificant in that period. In column 3, for the years after the Paris Agreement (2016-2017), the driver through which banks decarbonize loan books is credit to new firms with relatively lower emissions. The effect of new entrants on a bank's CTRE score is equivalent to an average reduction of 3.6kt per borrower.[24] These dynamics stop in columns 4 for the post-2017 period after President Trump's Paris withdraw announcement: 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 actual Paris withdrawal, plausibly reflecting reduced pressure to undertake initiatives to

[24]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-emission firms 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.

decarbonize the loan book when transition risks are less pressing.[25] In Internet Appendix E, we show that banks re-balance mostly towards new, lower-emitting clients within the same industry (not across industries).

5. Changes in CTRE Scores and Credit Supply Effects

Are increases (decreases) in CTRE scores associated with reductions (expansions) in credit supply to high-emission firms? We address this question by exploiting exogenous variation in CTRE scores stemming from the "emission reductions" channel. The logic is as follows: While overall CTRE changes are endogenous to banks' lending decisions, passive changes in banks' risk exposures—resulting from borrower-level emission changes—are plausibly orthogonal to banks' credit supply. If strategic climate risk management considerations affect lending—for example via fixed risk budgets—banks may compensate for *passive increases* in portfolio brownness with a contraction in lending to high-emission borrowers. Similarly, banks may respond to *passive reductions* in portfolio brownness by increasing credit to high-emission firms or by decreasing any planned scaling back of transition risk exposures. To disentangle credit supply from demand effects, we estimate differences in lending to the *same* high-emission borrower i across banks b with varying degrees of plausibly exogenous CTRE changes:

$$Y_{i,b,t} = \beta_1 Brown\,Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions} + \mu_i \times \mu_t + \mu_b \times \mu_t + \epsilon_{i,b,t}, \tag{12}$$

where $Y_{i,b,t}$ is the outstanding loan amount (in logs) of bank b to firm i in year t as defined for Eq. (2). $Brown\,Borrower_{i,t}$ equals one for firms with a one-year lagged Scope 1 intensity above the yearly industry (SIC4) average, and zero otherwise.[26] Exogenous changes in CTRE scores from firm-level emission changes are captured by $\Phi_{b,t}^{Scope\,1\,Emissions}$, which

[25] We obtain similar results when fixing the set of firms to those in Trucost prior to 2015 (Table IA.A.2).
[26] We require that at least five firms within an industry-year have available emission intensity data.

is defined in Eq. (6) and aggregated to the bank-year level (we sum across portfolio firms). To ease interpretability of β_1, we scale $\Phi_{b,t}^{Scope\,1\,Emissions}$ in these regressions by a bank's CTRE score.[27] We control for credit demand by including firm-by-time fixed effects ($\mu_i \times \mu_t$) and we control for other supply-side factors using bank-by-time fixed effects ($\mu_b \times \mu_t$). These fixed effects also absorb other time-varying firm and bank characteristics that affect lending decisions. Standard errors are clustered at the bank-firm level to account for serial correlation in loan exposures.

Estimates of Eq. (12) are reported in Table 4, Panel A, for the five time periods in Figure 5). Overall, we find no statistically significant credit supply effects. An exception is 2021, after the U.S. exited from the Paris Agreement, where the negative coefficient estimate can be interpreted in two ways: i) banks reduce lending to high-emission firms after experiencing exogenous increases in firm-level emissions; or ii) banks increase lending to high-emission firms after decreases in firm-level emissions. Both interpretations are possible as a symmetry is implied by the single slope β_1 in Eq. (12) (it captures the effects of increases or decreases in portfolio brownness).

To shed light on which interpretation holds, we amend Eq. (12) by including a triple interaction that distinguishes banks' lending adjustments based on the direction of the passive CTRE change. We introduce the dummy variable $Passive\,Decrease_{b,t}$, which identifies periods when a bank's portfolio brownness declines due to borrower-level emission reductions ($\Phi_{b,t}^{Scope\,1\,Emissions} \leq 0$). By interacting this variable with $Brown\,Borrower_{i,t}$ and $\Phi_{b,t}^{Scope\,1\,Emissions}$, we examine whether lending adjustments differ when portfolio brownness

[27] Hence, if a bank's CTRE score increases by 100% due to firm-level emission *increases* ($\Phi_{b,t}^{Scope\,1\,Emissions} > 0$), the bank exposure to high-emission firms adjusts by $\hat{\beta}_1 \times 100\%$ on average. Conversely, if the CTRE score decreases by 100% due to firm-level emission *reductions* ($\Phi_{b,t}^{Scope\,1\,Emissions} < 0$), the exposure to high-emission firms adjusts by $-\hat{\beta}_1 \times 100\%$, on average.

is increasing *versus* decreasing:

$$
\begin{aligned}
Y_{i,b,t} = {} & \beta_1 Brown\, Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions} \\
& + \beta_2 Brown\, Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions} \times Passive\, Decrease_{b,t} \\
& + \beta_3 Brown\, Borrower_{i,t} \times Passive\, Decrease_{b,t} + \mu_i \times \mu_t + \mu_b \times \mu_t + \epsilon_{i,b,t}.
\end{aligned} \tag{13}
$$

This regression evaluates whether portfolio adjustments have stronger, weaker, or symmetric effects on credit supply to high-emission firms depending on the direction of the passive CTRE change: $\hat{\beta}_1$ ($\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$) captures banks' average lending response to high-emission firms when CTRE scores increase (decrease).

Estimates of Eq. (13) are presented in Table 4, Panel B. Columns 4–5 show a statistically significant and negative relationship between passive CTRE changes and lending to high-emission firms, but only among banks experiencing an *increase* in portfolio brownness ($\hat{\beta}_1$). In column 5, an average increase in brownness of 4.1% leads to an average decrease in brown lending by 4.2%. As the sum of $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$ is never statistically significant, we find no evidence of lending adjustments towards polluting firms following a passive *decrease* in portfolio brownness. Hence, banks reduce lending to polluting firms only when their portfolios passively becomes browner (and only in the most recent past). This compensation effect aligns with strategic risk management considerations to maintain a target level of loan book transition risk exposure.[28]

6. Climate Transition Risk Exposure and Bank Disclosure

6.1. Climate-related Disclosure Measures

We investigate whether and how CTRE scores correlate with text-based metrics capturing banks' climate-related disclosures. Understanding these relationships is crucial given

[28] In Internet Appendix F, we provide findings pointing to a (modest) overall increase in high-CTRE banks' screening and monitoring efforts for high-emission firms.

the ongoing debate about the financial materiality of climate risks and their inclusion in corporate reports.[29] There are also concerns that disclosures may 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 risks, potentially serving as substitutes.

We construct two variables to address these issues. First, we create a text-based climate disclosure measure using 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. We 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.

6.2. 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 estimate 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 score to avoid look-ahead bias. We control for time-varying differences between banks by including bank fundamentals ($X_{b,t-1}$). μ_b and μ_t reflect bank and time fixed

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

effects, respectively. Standard errors are adjusted for heteroskedasticity.

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 $Z_CTRE_{b,k,t-1}^{Quart=k}$ is the value of $Z_CTRE_{b,t-1}$ below quartile k of the Z_CTRE distribution across all years, i.e., 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).

Results are reported in Table 5, with Columns 1–4 providing estimates for 10-K disclosures and columns 5–8 for earnings call disclosures.[30] Note that positive or higher coefficients indicate higher levels of disclosure (more transparency), while negative or lower coefficients suggest less disclosure (less transparency). In column 1–2, we find a significantly positive association between CTRE scores and 10-k disclosures, indicating that banks increase disclosures when they finance more 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); effects are insignificant for the second and third quartiles. This pattern is consistent with less-exposed banks proactively disclosing their exposures to signal to the market that transition risks are not a concern,

[30] In Table IA.A.3, 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.

and more-exposed banks fulfilling their duty to report on material financial risks. When we account for quartile-specific standard deviations, we find that high-exposure banks are less inclined to disclose changes in transition risks compared to low-exposure banks (recall that we estimate within-bank effects). In column 4, for banks in the first quartile, a standard-deviation increase in the standardized CTRE score (0.1) is associated with a 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 increase in 10-K disclosures is only 25%. Hence, banks with high exposures are not more transparent about their transition risks compared to banks with the low exposures.

CTRE scores remain positively associated with climate-related disclosures when we consider earnings calls. 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% 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.

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

Can the contrasting results between low- and high-exposure banks attributed to greenwashing incentives of high-exposure banks? High-exposure banks may be relatively hesitant to disclose their exposures 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, call 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 silent about transition risks—and a subsequent

Q&A in which analysts can actively seek information by asking probing questions (Sautner et al., 2024). To analyse this possibility, we calculate disclosures separately for both parts of a call (*Earnings Call Presentation* and *Earnings Call Q&A*).

Table 6 bears out our conjecture. The estimates for the presentation part (columns 1–4) show a significant and positive relationship between CTRE scores and climate-related disclosures only among low-exposure banks. This 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. In contrast, when we zoom in on Q&A disclosures (columns 5–8), the effect is concentrated among high-exposure banks. These 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, raise questions about banks' actual exposures, compelling management to more extensively disclose the respective risks.

7. Climate Transition Risk Exposure and Anti-Climate Lobbying

The prior section shows that banks with high exposure to climate change tend to avoid publicly disclosing them. In this section, we investigate whether banks—to avoid amplifying their perceived transition risks and potential legal challenges—lobby against stricter climate policies. Specifically, 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. To investigate this possibility, we use a quarterly measure of banks' anti-climate lobbying expenses developed by Leippold et al. (2024) that we aggregate to an annual level and normalize the sum by a bank's total assets. We then relate the scaled anti-climate lobbying expenses of bank b in year t to (i) changes in the bank's overall CTRE score, and (ii) the decomposition of CTRE changes into an active (from loan book re-balancing) and a

passive (from borrower-level emission changes) component:

$$Climate\,Lobby\,Intensity_{b,t}^{Anti} = \beta_1 \Delta CTRE_{b,t} + \beta_2 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \tag{16}$$

$$\begin{aligned} Climate\,Lobby\,Intensity_{b,t}^{Anti} = \beta_1 \Phi_{b,t}^{Loan\,Amount} + \beta_2 \Phi_{b,t}^{Scope\,1\,Emissions} \\ + \beta_3 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \end{aligned} \tag{17}$$

where $Climate\,Lobby\,Intensity_{b,t}^{Anti}$ are the scaled anti-climate lobbying expenses of bank b in year t. $\Delta CTRE_{b,t}$ is the percentage change in a bank's CTRE score from $t-1$ to t. $\Phi_{b,t}^{Loan\,Amount}$ refers to changes in CTRE scores attributed to active loan book rebalancing and $\Phi_{b,t}^{Scope\,1\,Emissions}$ to changes in CTRE scores stemming from firm-level emission changes. Both variables are defined in Eq. (5) and Eq. (6), respectively, and aggregated to the bank level by summing across portfolio firms (to ease the interpretability of the coefficients, both are scaled by a bank's CTRE score and expressed in percentages). $X_{b,t-1}$ includes $Log\,Total\,Assets$, $Debt\,Ratio$, ROA, and lobbying-related control variables (e.g., Duchin and Sosyura, 2012; Lambert, 2019). The lobbying controls include i) a bank's political orientation ($Political\,Stance$), calculated as Democratic-leaning lobbying contributions scaled by total lobbying expenditures; ii) total lobbying expenditures scaled by total assets ($Total\,Lobbying\,Amount$); iii) political connectedness of the bank's board members ($Political\,Connections$); and iv) the political preferences of banks' executives, calculated as the percentage of campaign contributions to the Democratic Party relative to their total campaign contributions ($Execs\,Political\,Preferences$).[31] μ_b and μ_t represent year- or bank-fixed effects (we estimate either of them). We employ Poisson regressions so 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

[31] 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).

are adjusted for heteroskedasticity.

Table 7 estimates of Eq. (16). In columns 1–5, all estimates on $\Delta CTRE$ indicate that increases in brownness of banks' loan portfolios are associated with more anti-climate lobbying.[32] This holds true when estimating effects using the pooled sample (columns 1–3), across banks within a year (column 4) or from within-bank changes (column 5). For instance, in column 4, a 1% increase in CTRE scores implies 10% higher anti-climate lobbying expenses. In column 5, the effect is smaller but still economically large (7% increase in anti-climate lobbying for the same CTRE score change). In columns 6–10, we present estimates of Eq. (17), which examine which component of the change in CTRE—loan book re-balancing or firm-level emission changes—is associated with increases in anti-climate lobbying expenses. Across all specifications, both channels are significantly positively related to lobbying, with the economic magnitude being largest for loan book re-balancing. In column 10, where identification relies on within-bank variation, an average increase in CTRE of 3.7% due to loan book re-balancing is associated with a 43% increase in bank-level lobbying expenses, compared to just 14% for an average increase stemming from firm-level emission changes. Hence, banks lobby against climate action both when their portfolios tilt more towards high-polluting firms and when portfolio firms themselves become browner, with more pronounced effects for the former. Overall, our results highlight an important link between the carbon footprint of banks' lending practices and their anti-climate lobbying activities.

8. 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 tran-

[32] 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.

sition 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 for 33 major U.S. banks, we examine which steps banks take to facilitate the decarbonization of the economy. We break this bigger question down by analyzing i) the time-series changes in transition risk exposures, its drivers, and financial market effects; ii) disclosure practices; and iii) anti-climate lobbying by banks.

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
$Board\,Gender\,Diversity_{b,t}$	The fraction of female members among the board of directors of a given bank in a given year (in %). *Source: BoardEx.*
$Climate\,Lobby\,Intensity_{b,t}^{Anti}$	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.*
$Market\,Return_t$	Monthly Market factor from Fama and French (1993). *Source: Kenneth French's data library.*

Variable Name	Definition and Source
$Market\text{-}to\text{-}Book_{b,t}$	Total market value of equity to the book value of equity of a given bank in a given year. *Source: Compustat Bank.*
$Media\ Climate\ Change\ Concerns\ Index_t$	Annualized and standardized ('Aggregate') *Media Climate Change Concerns Index* based on Ardia et al. (2023). *Source: Sentometrics.*
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. (2024), 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.*
$\Phi_{i,b,t}^{LoanAmount}$	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.*

Variable Name	Definition and Source
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	Scope 1 emissions share that quantifies the change in the CTRE score of a given bank between $t-1$ and t that is caused by firm-level adjustments in Scope 1 emissions, and originates from emission reductions channel. *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 black 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 outstanding loan amounts of the same lenders based on the DealScan database. The blue solid line shows the outstanding loan amounts after conditioning on the availability of borrowers' Scope 1 emissions data.

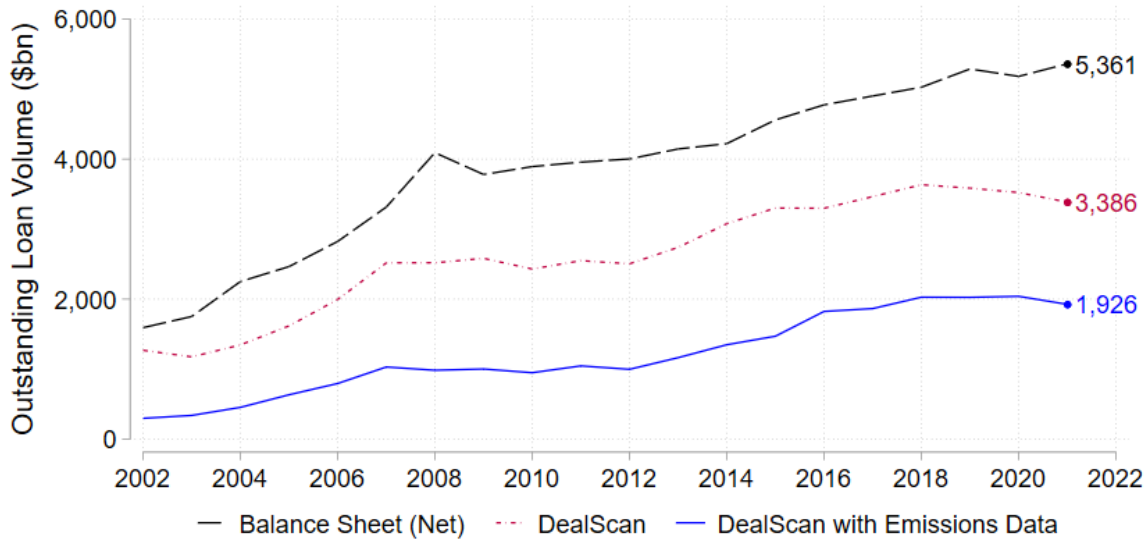


Figure 2: **Average CTRE Scores Over Time**

The figure displays the average CTRE scores of the U.S. banking system from 2002 to 2021 (solid blue line, plotted against the left-hand-side axis), with 95% confidence interval (shaded grey area). The CTRE score is a bottom-up measure of a bank's climate transition risk exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The dashed 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 withdrawal from the Paris agreement by the U.S. in 2020. The dashed red line, plotted against the right-hand-side axis, represents the standardized *Media Climate Change Concerns Index* based on Ardia et al. (2023).

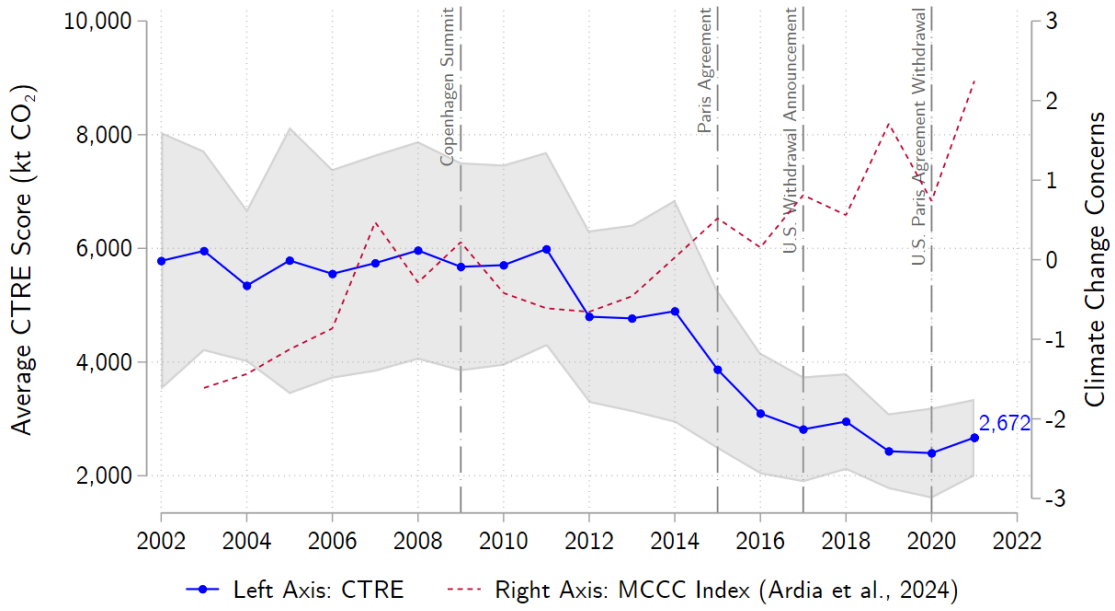
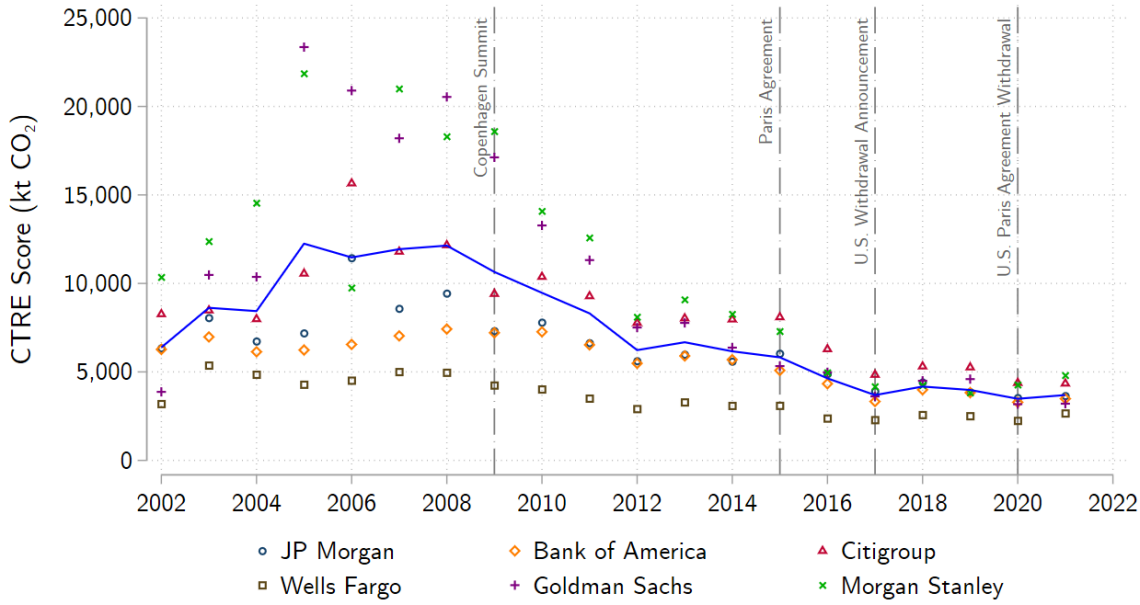


Figure 3: **CTRE Scores Over Time By Size**

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 solid 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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). The vertical dashed 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.

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



(b) CTRE Scores by Size Groups

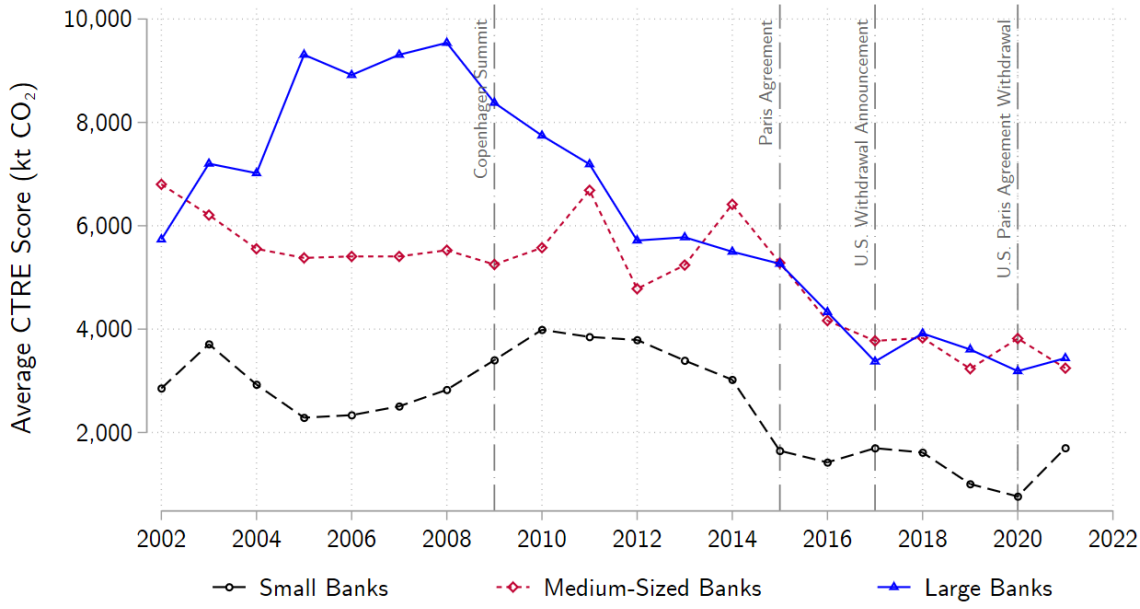


Figure 4: **Climate Betas by U.S. Lenders: Stranded Assets Betas**

This figure displays banks' stranded assets betas estimated using the 6-Factor model reported in Eq. (3) for the year 2019 across the U.S. banks in our sample. The number of banks listed in the figure is less than 33 as one bank left the sample by 2019. We use banks' monthly returns over the past 12 months, with at least 10 monthly observations available, to estimate time-varying stock return sensitivities.

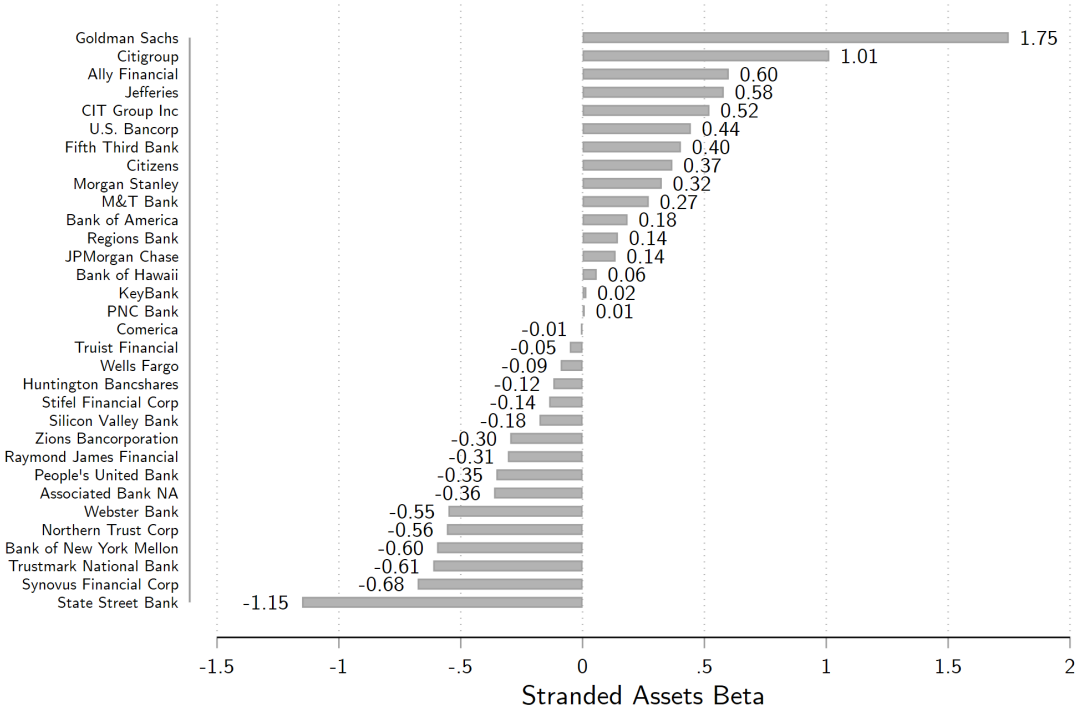


Figure 5: **Loan Book Re-Balancing vs. Emission Reductions**

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 $\omega^{LoanAmount}$, 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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2equivalent).

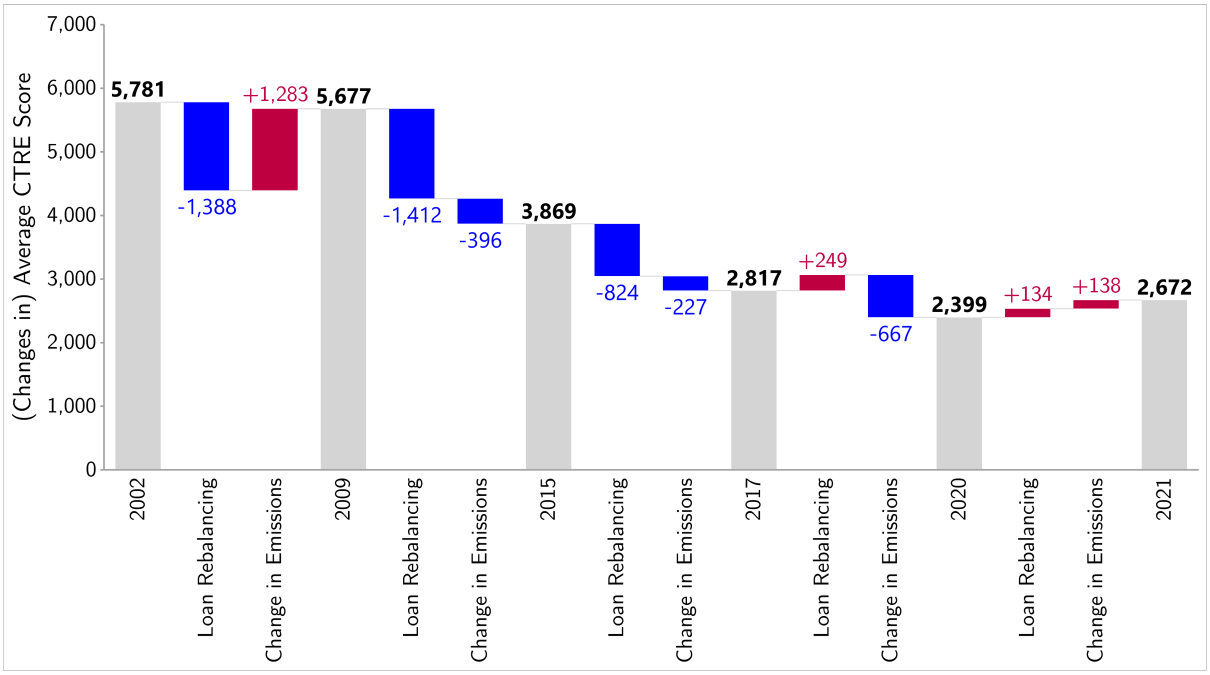


Figure 6: **Decomposition of CTRE Scores Using Scope 1 + Scope 3 Emissions**

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 $\omega^{LoanAmount}$, 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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

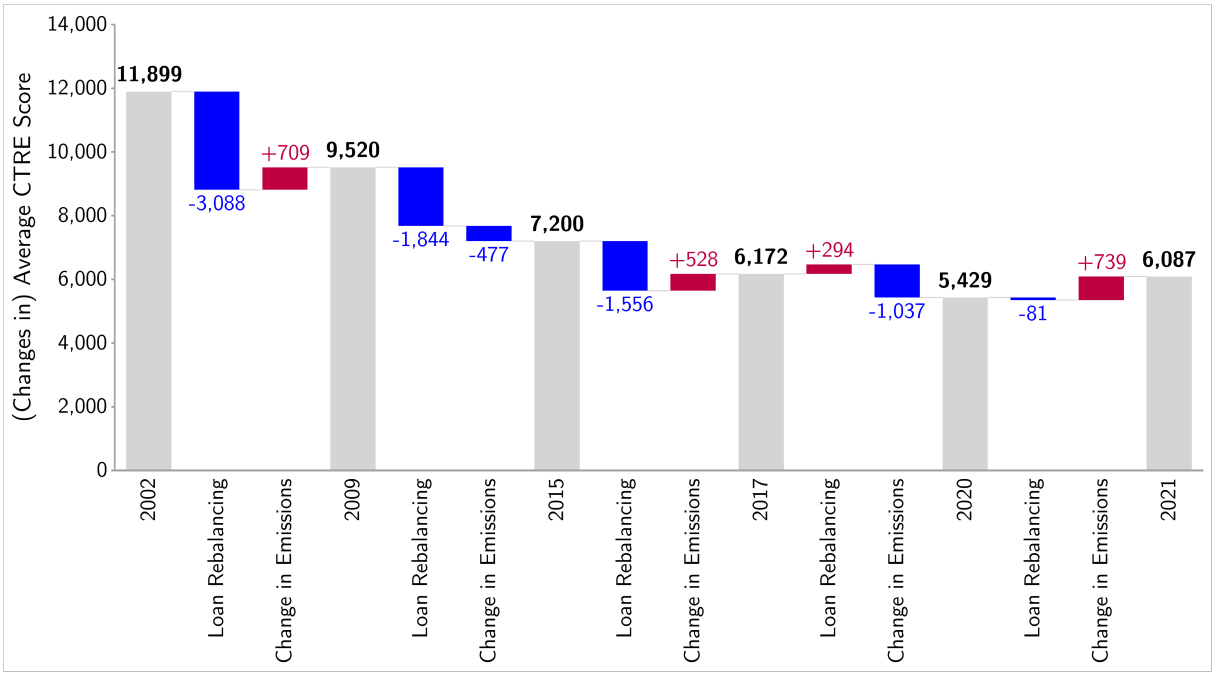


Table 1: **Summary Statistics: CTRE Scores by Bank**

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	2,245.8	3,218.2	186.2	12,187.3	16
Associated Bank	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	7,389.2	1,625.1	5,334.9	10,680.4	20
BofA Securities	5,603.3	1,419.5	3,288.1	7,424.6	20
CIT Group	3,083.1	1,647.0	1,104.1	7,488.6	20
Citi	8,311.3	2,890.0	4,344.8	15,655.7	20
Citizens	1,996.9	1,712.4	304.6	5,490.4	20
Comerica Inc	2,475.2	458.6	1,484.8	3,451.6	20
Fifth Third Bank	5,019.9	3,506.7	1,657.4	16,672.1	20
Goldman Sachs	10,024.2	6,652.9	3,175.9	23,355.1	20
Huntington Bancshares	11,240.5	6,241.5	3,838.1	22,639.3	20
JP Morgan	6,350.5	2,074.7	3,534.8	11,435.1	20
Jefferies	319.1	112.8	209.0	526.7	10
KeyBank	8,219.9	2,792.8	4,345.4	12,760.5	20
M&T Bank	3,479.1	2,295.7	1,085.4	8,884.2	20
Marshall & Ilsley	2,661.3	405.6	2,235.7	3,311.9	8
Morgan Stanley	10,624.3	5,856.1	3,829.0	21,860.7	20
Northern Trust	4,806.1	1,912.4	1,919.7	9,542.0	20
PNC Bank	4,340.6	1,214.2	2,260.5	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	3,504.8	1,111.3	2,092.4	6,196.5	20
Silicon Valley Bank	13.9	1.6	11.1	16.1	9
State Street Bank	7,000.2	5,595.9	1,460.1	17,471.9	20
Stifel Financial	473.5	419.1	229.0	1,467.9	8
Synovus Financial	1,697.6	2,379.1	511.0	7,962.9	9
Truist Financial	3,297.9	759.9	2,200.5	4,814.8	20
Trustmark National Bank	1,378.0	1,028.4	658.0	3,377.9	6
US Bancorp	3,901.0	858.3	2,983.2	6,218.3	20
Webster Bank	3,597.1	4,036.2	215.1	12,638.8	19
Wells Fargo	3,549.7	1,021.5	2,244.7	5,369.6	20
Zions Bancorporation	1,092.6	928.9	409.4	3,910.0	17
Total	4,482.6	4,145.1	11.1	23,355.1	567

Table 2: **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 exposure, 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***	.059*	.068***	.094**	.070***	.125**
	(.011)	(.032)	(.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
Observations	292	292	292	292	292	292
Model	OLS	OLS	OLS	OLS	OLS	OLS

Table 3: **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 $\Phi_{i,b,t}^{LoanAmount}$ 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 exposure, 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 IA.A.1. Standard errors, reported in parentheses, are clustered at the bank-firm level. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Within-Bank Estimates					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
	$\Phi_{i,b,t}^{LoanAmount}$				
$Entry_{i,b,t}$	-2.945	-5.921**	-3.505***	-1.259*	.940
	(2.816)	(2.494)	(.729)	(.643)	(3.234)
$Exit_{i,b,t}$	9.695***	2.251	2.279**	-.337	2.362
	(3.372)	(2.140)	(.977)	(2.013)	(2.519)
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	.004	.023	.018	.045
Obs.	39,040	42,194	22,854	36,485	12,543
Model	OLS	OLS	OLS	OLS	OLS

Table 4: **Changes in CTRE Scores and Credit Supply Effects**

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 $Log\,Outstanding\,Loan\,Amount_{i,b,t}$ measures the outstanding loan amount (in logs) of bank b to firm i in year t. $Brown\,Borrower_{i,t}$ equals one for firms with one-year lagged emission intensity (Scope 1 emissions scaled by revenues) higher than their yearly industry average (SIC4 level), and zero otherwise. $\Phi_{b,t}^{Scope\,1\,Emissions}$ measures the change in CTRE score that is caused by firm-level emission adjustments and is scaled by the bank's CTRE score. The CTRE score is a bottom-up measure of a bank's climate transition risk exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). $Passive\,Decrease_{b,t}$ equals one for periods when a bank's CTRE score declines due to borrower-level emission reductions, and zero otherwise. 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.

Panel A: Linear Response to Passive Changes in CTRE					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
	$Log\,Outstanding\,Loan\,Amount_{i,b,t}$				
$Brown\,Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions}$(scaled by CTRE)	-.097	-.134	.011	-.154	-.775**
	(.094)	(.186)	(.066)	(.120)	(.329)
Firm x Year fixed effects	Yes	Yes	Yes	Yes	Yes
Bank x Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.699	.697	.712	.754	.792
Obs.	32,662	36,915	17,275	30,394	10,574
Model	OLS	OLS	OLS	OLS	OLS
Mean $\Phi_{b,t}^{Scope\,1\,Emissions}$(scaled by CTRE)	.011	-.006	-.040	-.045	.041

Panel B: Asymmetries in Response to Passive Changes in CTRE					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
	$Log\,Outstanding\,Loan\,Amount_{i,b,t}$				
$Brown\,Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions}$(scaled by CTRE)	-.246	-.538	-.244	-.662*	-1.017**
	(.178)	(.401)	(.184)	(.372)	(.408)
$Brown\,Borrower_{i,t} \times \Phi_{b,t}^{Scope\,1\,Emissions}$(scaled by CTRE) $\times Passive\,Decrease_{b,t}$	.181	.656	.351	.673	4.074
	(.252)	(.550)	(.235)	(.470)	(6.290)
$Brown\,Borrower_{i,t} \times Passive\,Decrease_{b,t}$	-.023	.007	-.003	-.010	.012
	(.021)	(.027)	(.027)	(.019)	(.101)
Firm x Year fixed effects	Yes	Yes	Yes	Yes	Yes
Bank x Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.699	.697	.712	.754	.792
Obs.	32,662	36,915	17,275	30,394	10,574
Model	OLS	OLS	OLS	OLS	OLS
Mean $\Phi_{b,t}^{Scope\,1\,Emissions}$(scaled by CTRE)	.011	-.006	-.040	-.045	.041
$\hat{\beta}1+\,\hat{\beta}2+\,\hat{\beta}3$	-.087	.125	.104	.001	3.068

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-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 exposure, 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 IA.A.3. As we use Poisson regressions, the coefficient estimates 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. 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-K $Disclosure_{b,t}$				$Earnings\ Call\ Disclosure_{b,t}$			
$Z_CTRE_{b,t-1}$	.235***	.250***			.097***	.095**		
	(.041)	(.042)			(.036)	(.039)		
$Z_CTRE_{b,t-1}^{Quart=1}$			1.871***	2.409***			1.169***	1.277***
			(.436)	(.397)			(.426)	(.439)
$Z_CTRE_{b,t-1}^{Quart=2}$			-.158	-.363			-.386	-.486*
			(.270)	(.275)			(.283)	(.284)
$Z_CTRE_{b,t-1}^{Quart=3}$			.123	.242			.143	.190
			(.178)	(.173)			(.143)	(.147)
$Z_CTRE_{b,t-1}^{Quart=4}$			.234***	.222***			.109**	.097**
			(.055)	(.059)			(.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	.556	.559	.560	.564
Obs.	499	499	499	499	501	501	501	501
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 exposure, 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 (lagged by one year, not reported). Summary statistics are provided in Table IA.A.3. 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			.193***	.174**		
	(.046)	(.050)			(.066)	(.074)		
$Z_CTRE_{b,t-1}^{Quart=1}$			1.323**	1.359**			.912	.942
			(.524)	(.531)			(.709)	(.730)
$Z_CTRE_{b,t-1}^{Quart=2}$			-.770**	-.808**			.180	.125
			(.346)	(.356)			(.358)	(.359)
$Z_CTRE_{b,t-1}^{Quart=3}$			.277	.313			.011	.027
			(.191)	(.199)			(.213)	(.221)
$Z_CTRE_{b,t-1}^{Quart=4}$			.058	.063			.221***	.194**
			(.060)	(.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	.468	.469	.475	.476	.623	.625	.624	.626
Obs.	501	501	501	501	501	501	501	501
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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent). $\Phi_{b,t}^{Loan\ Amount}$ measures the change in CTRE score of bank b between $t-1$ and t that is caused by loan book re-balancing, and $\Phi_{b,t}^{Scope\,1\ Emissions}$ measures the change in CTRE score that is caused by firm-level emission adjustments (both are scaled by the bank's CTRE score). Bank controls include $Log\,Total\ Assets$, $Debt\ Ratio$, and ROA (lagged by one year, not reported). Lobbying controls include $Political\ Stance$, $Total\ Lobbying\ Amount$, $Political\ Connections$, $Execs\ Political\ Preferences$ (lagged by one year, not reported). 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)	(9)	(10)
	$Climate\ Lobby\ Intensity_{b,t}^{Anti}$									
$\Delta CTRE_{b,t}$ (%)	.006***	.007***	.009	.100***	.068*					
	(.002)	(.003)	(.008)	(.036)	(.035)					
$\Phi_{b,t}^{LoanAmount}$(scaled by CTRE, %)						.023***	.028***	.065***	.252**	.096***
						(.008)	(.006)	(.019)	(.115)	(.020)
$\Phi_{b,t}^{Scope\,1\ Emissions}$(scaled by CTRE, %)						.037*	.054***	.161***	.481**	.215**
						(.020)	(.015)	(.045)	(.220)	(.104)
Bank controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Lobbying controls	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes	No	No	No	No	Yes	No
Bank fixed effects	No	No	No	No	Yes	No	No	No	No	Yes
Pseudo R^2	.010	.104	.709	.762	.719	.052	.152	.728	.767	.726
Obs.	238	238	176	50	66	238	238	176	50	66
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Nr years	19	19	19	5	19	19	19	19	5	19
Nr banks	21	21	20	18	5	21	21	20	18	5
Mean $\Delta CTRE_{b,t}$ (%)	6.210	6.210	5.411	10.860	-1.053					
Mean $\Phi_{b,t}^{LoanAmount}$(scaled by CTRE, %)						-4.037	-4.037	-6.351	-.394	-3.731
Mean $\Phi_{b,t}^{Scope\,1\ Emissions}$(scaled by CTRE, %)						-.218	-.218	.444	2.810	-.597

Internet Appendix

for

Climate Transition Risks of Banks

Internet Appendix A

Additional Figures and Tables Material

Figure IA.A1: **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 red bars represent industry loan shares in the unrestricted DealScan sample, whereas the blue bars represent industry loan shares if we restrict the sample to those borrowers with available Scope 1 emissions data.

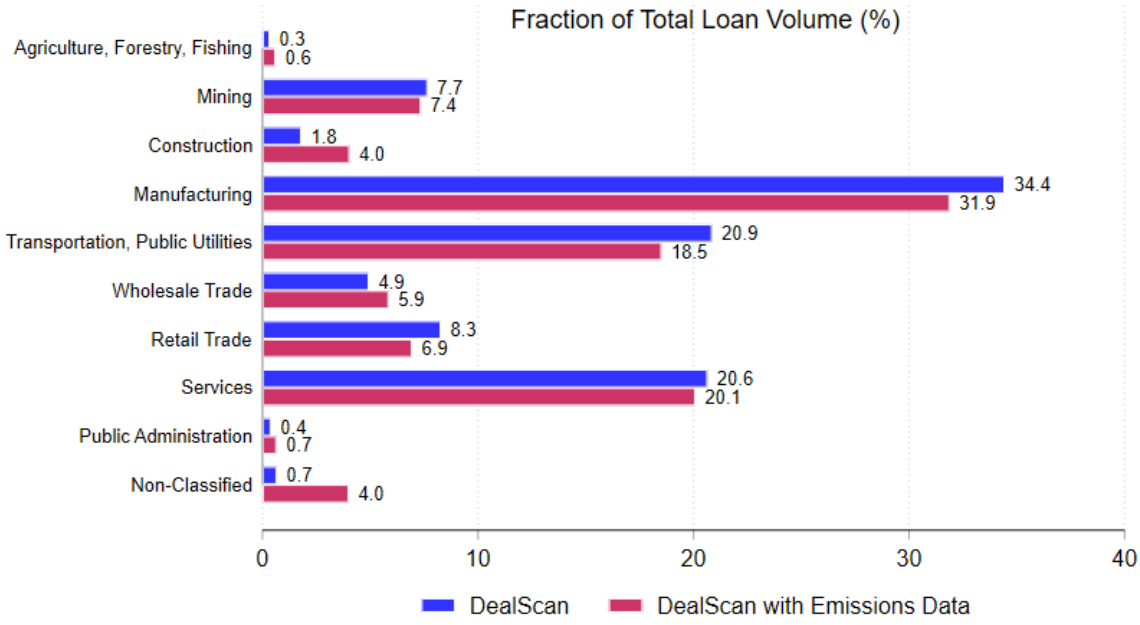


Figure IA.A2: **CTRE Contributions Over Time by Industry**

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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

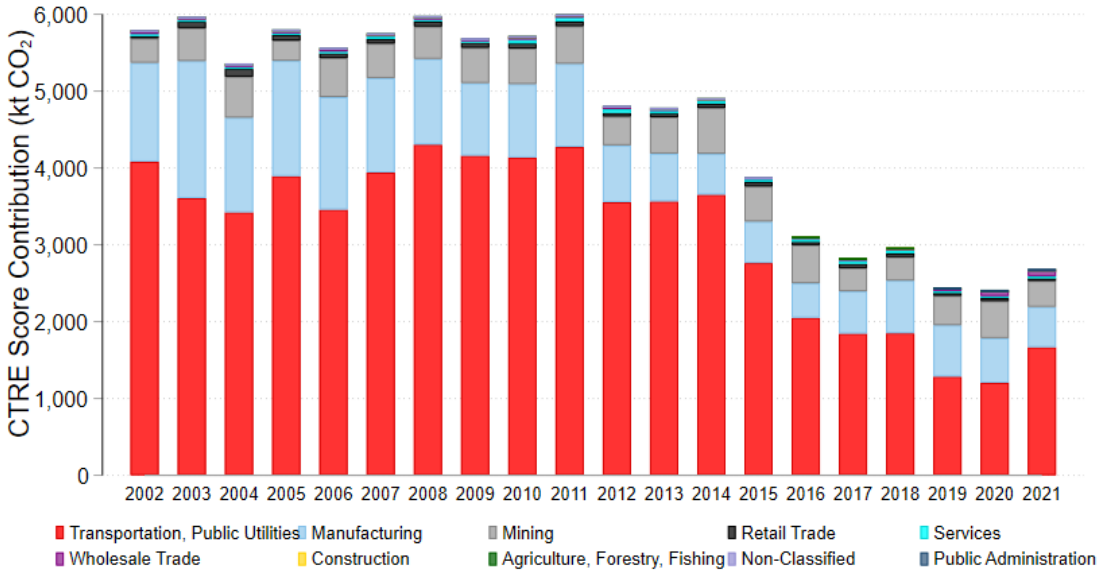


Figure IA.A3: **CTRE Contributions Over Time by Industry Share**

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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

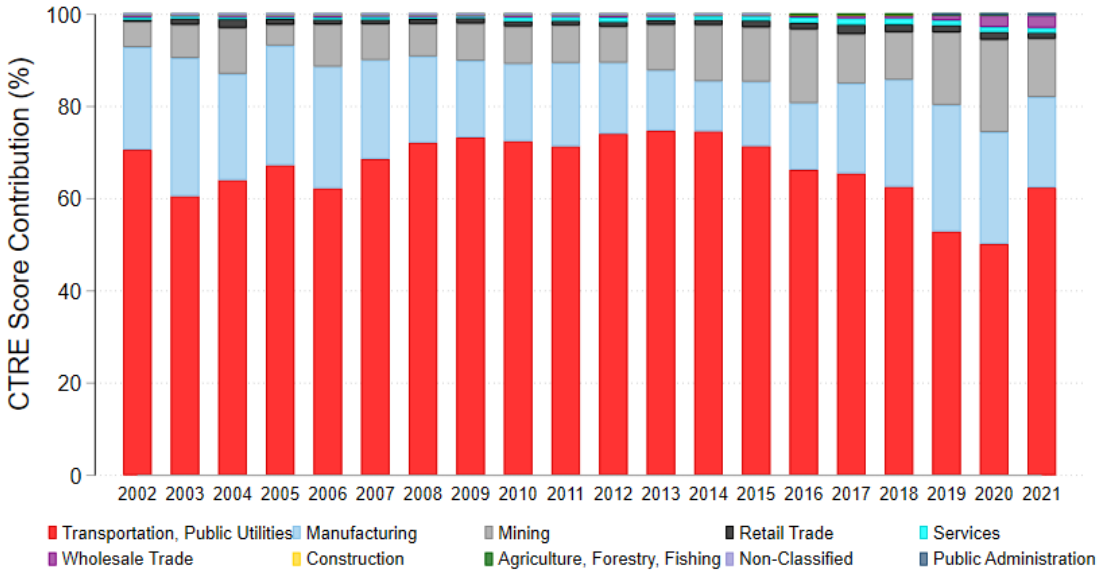


Figure IA.A4: **Decomposition using the 2015 Trucost Sample**

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 $\omega^{LoanAmount}$, 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).

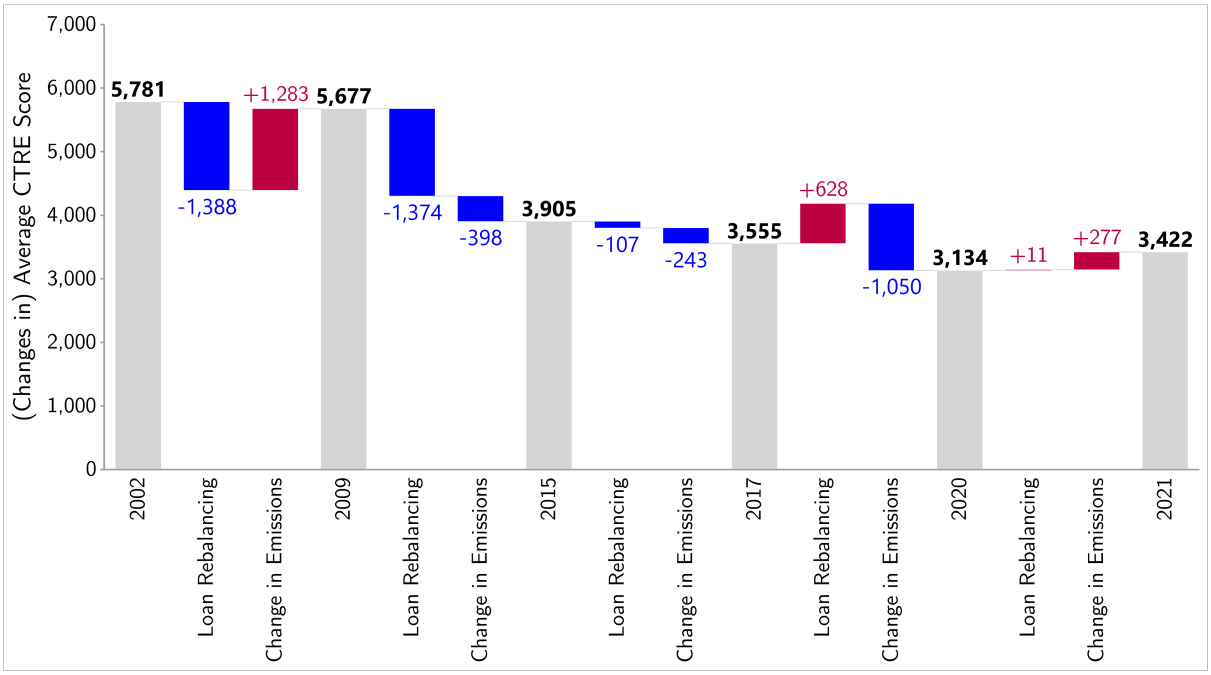


Table IA.A.1: **Decomposition of Changes in CTRE Scores: Summary Statistics**

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

	Sample Period	Mean	SD	Obs.
$\Phi_{i,b,t}^{LoanAmount}$	2002-2009	-0.5	153.7	39,040
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2002-2009	0.6	64.1	39,040
$Entry_{i,b,t}$	2002-2009	15.7%	0.4	39,040
$Exit_{i,b,t}$	2002-2009	7.7%	0.3	39,040
$\Phi_{i,b,t}^{LoanAmount}$	2010-2015	-0.7	127.1	42,194
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2010-2015	-0.2	29.8	42,194
$Entry_{i,b,t}$	2010-2015	12.2%	0.3	42,194
$Exit_{i,b,t}$	2010-2015	9.4%	0.3	42,194
$\Phi_{i,b,t}^{LoanAmount}$	2016-2017	-0.8	34.8	22,854
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2016-2017	-0.2	37.3	22,854
$Entry_{i,b,t}$	2016-2017	22.6%	0.4	22,854
$Exit_{i,b,t}$	2016-2017	8.5%	0.3	22,854
$\Phi_{i,b,t}^{LoanAmount}$	2018-2020	0.1	51.6	36,485
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2018-2020	-0.4	12.2	36,485
$Entry_{i,b,t}$	2018-2020	12.6%	0.3	36,485
$Exit_{i,b,t}$	2018-2020	11.0%	0.3	36,485
$\Phi_{i,b,t}^{LoanAmount}$	2021	0.4	56.8	12,543
$\Phi_{i,b,t}^{Scope\,1\,Emissions}$	2021	0.4	10.3	12,543
$Entry_{i,b,t}$	2021	13.0%	0.3	12,543
$Exit_{i,b,t}$	2021	15.5%	0.4	12,543

Table IA.A.2: **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 exposure, 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)
	$\Phi_{i,b,t}^{LoanAmount}$				
$Entry_{i,b,t}$	-2.945	-5.871**	-4.051*	-3.329	7.440
	(2.816)	(2.526)	(2.416)	(2.465)	(16.040)
$Exit_{i,b,t}$	9.695***	2.265	3.921**	-1.486	-.524
	(3.372)	(2.140)	(1.654)	(4.367)	(8.530)
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	.004	.024	.023	.057
Obs.	39,040	42,094	15,752	21,672	6,697
Model	OLS	OLS	OLS	OLS	OLS

Table IA.A.3: **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-K $Disclosure_{b,t}$	2.3	2.6	2.7	2.6	2.2	2.1	1.9	1.6	2.3	3.8
$CTRE_{b,t-1}$	4,724.7	4,309.1	684.9	453.4	2,674.3	531.8	4,917.9	858.5	10,669.3	4,174.2
$Z_CTRE_{b,t-1}$	-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	28.5	29.5	35.3	34.5	39.7	23.1	13.5	19.9	11.5
$Earnings\,Call\,Presentation_{b,t}$	24.3	26.7	26.7	32.6	33.1	36.3	18.4	12.0	18.8	14.0
$Earnings\,Call\,Q\&A_{b,t}$	24.5	34.4	27.2	42.2	31.4	47.2	22.7	21.9	16.5	11.4
$CTRE_{b,t-1}$	4,729.4	4,280.9	716.6	472.8	2,690.9	524.8	4,934.1	850.5	10,592.3	4,186.1
$Z_CTRE_{b,t-1}$	-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	0.9	11.8	1.2	12.6	1.3	12.6	1.4
$Debt\,Ratio_{b,t-1}$	89.6	2.7	88.4	3.5	89.1	2.4	89.9	1.8	90.9	2.3
$ROA_{b,t-1}$	0.9	1.1	1.0	0.9	0.8	1.7	1.0	0.5	0.7	0.9
Obs.	501		125		126		125		125	

Internet Appendix B

Climate Transition Risk Exposure and Bank Characteristics

In this internet appendix, 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:

$$Z_CTRE_{b,t} = \beta_1 X_{b,t-1} + \mu_b + \mu_t + \epsilon_{b,t}, \qquad \text{(Internet Appendix B1)}$$

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 IA.B.1, we provide different estimates of Eq. (Internet Appendix B1). 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 (4.7pp) is associated with a 0.49 standard-deviation increase in the CTRE score, equivalent to an increase of 2,031kt of CO_2.

In columns 2 and 4, when examining variation within banks, some differences emerge. Bank size becomes statistically insignificant, 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 47kt in a bank's CTRE score.

Table IA.B.1: **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 exposure, 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 IA.B.2. 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**	.084	.105**	-.116
	(.045)	(.149)	(.047)	(.161)
$ROA_{b,t-1}$	.027	.044	.038	.065
	(.065)	(.095)	(.066)	(.102)
$Loan\,Ratio_{b,t-1}$	-.010**	-.008	-.010**	-.002
	(.004)	(.008)	(.005)	(.009)
$Debt\,Ratio_{b,t-1}$	.100***	.052**	.103***	.057**
	(.023)	(.022)	(.023)	(.022)
$Market\text{-}to\text{-}Book_{b,t-1}$	-.159	-.083	-.185	-.054
	(.145)	(.164)	(.159)	(.176)
$Tier\,1\,Capital\,Ratio_{b,t-1}$	-.002	.007	.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	.521	.613	.522	.623
Obs.	465	465	450	450
Model	OLS	OLS	OLS	OLS

Table IA.B.2: **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 IA.B.1. Variables are defined in Appendix Table A1.

	Mean	SD	Min	Max	Obs.
$CTRE_{b,t}$	4,330.7	3,626.5	11.1	22,639.3	465
$Z_CTRE_{b,t}$	-0.0	1.0	-1.2	5.0	465
$Log\,Total\,Assets_{b,t-1}$	11.8	1.4	9.2	15.0	465
$ROA_{b,t-1}$	0.9	0.8	-6.0	3.1	465
$Loan\,Ratio_{b,t-1}$	53.1	17.8	4.3	78.7	465
$Debt\,Ratio_{b,t-1}$	89.6	2.4	76.0	94.8	465
$Market\text{-}to\text{-}Book_{b,t-1}$	1.5	0.8	0.3	5.0	465
$Tier\,1\,Capital\,Ratio_{b,t-1}$	11.4	2.6	6.8	29.5	465
$Board\,Gender\,Diversity_{b,t-1}$	20.5	8.9	0.0	55.6	450

Internet Appendix C

Average CTRE Scores over Time: Robustness

In this internet appendix, we mitigate potential concerns about the results in Figure 2 related to emission measurement, sample composition effects, and loan maturities.

C.1 CTRE Scores: Scope 2 and 3 Emissions

A potential concern is that the results in Figure 2 are driven by our focus on Scope 1 emissions to identify climate transition risk exposures. Figure IA.C.1 shows that this is not the case, illustrating similar aggregate trends in banks' transition risk exposures as in Figure 2 when factoring in Scope 2 and Scope 3 upstream emissions, or when considering Scope 1 intensities. Incorporating Scope 2 emissions elevates the trend line, but the downward CTRE trend persists. Adding Scope 3 emissions raises the trend line further, possibly reflecting some degree of double-counting, but we continue to observe a downward trend. Even when utilizing the Scope 1 intensity (Scope 1 emissions scaled by a revenues), the trend is downward-sloping.

C.2 CTRE Scores: Market-Cap Weighting and Sample Composition

In Figure IA.C.2, we document that the downward trend in CTRE scores in the later years remains robust when CTRE scores are calculated using bank market cap-weighted averages or a fixed sample of 21 banks consistently present throughout the entire sample period. These results mitigate potential concerns about emission sample composition effects.

C.3 CTRE Scores: Fixing the Trucost Sample

A potential concern is that the downward trend in CTRE scores results from changes in the set of firms covered by Trucost over time. As Trucost includes more firms each year, the addition of firms with lower emissions could mechanically lower average CTRE scores. To address this concern, we adopt a similar approach as Bolton and Kacperczyk (2023), maintaining a consistent set of Trucost firms to regenerate alternative versions of Figure 2. Through 17 iterations, we fix the sample to firms present in Trucost prior to each year from 2003 to 2019, and then recalculate 17 times 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 IA.C.3 shows that fixing the sample to Trucost firms present in the database from 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.

C.4 CTRE Scores: Maturity Adjustments

The CTRE measure in our baseline analyses reflects banks' outstanding lending volumes at a point in time, but it abstracts from the duration of banks' lending commitments. Some banks may manage their exposure to high-emission firms by strategically offering them loans with shorter maturities. Short maturities would grant banks flexibility to respond to future climate regulatory shocks (e.g., by terminating or choosing not to extend existing loans before legislation becomes binding), thereby mitigating transition risk exposures. To evaluate this possibility, we calculate maturity-adjusted CTRE scores. Specifically, we replicate Figure 2 using dynamically adjusted samples of loans that, in any given year, include only loans with a remaining time to maturity of at least one or at least two years. If banks actively shorten loan maturities for high-emission borrowers, we would expect the maturity-adjusted CTRE scores to be consistently lower than the unadjusted scores. However, as shown in Figure IA.C.4, this appears not to be the case.

Figure IA.C.1: **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 exposure, 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.

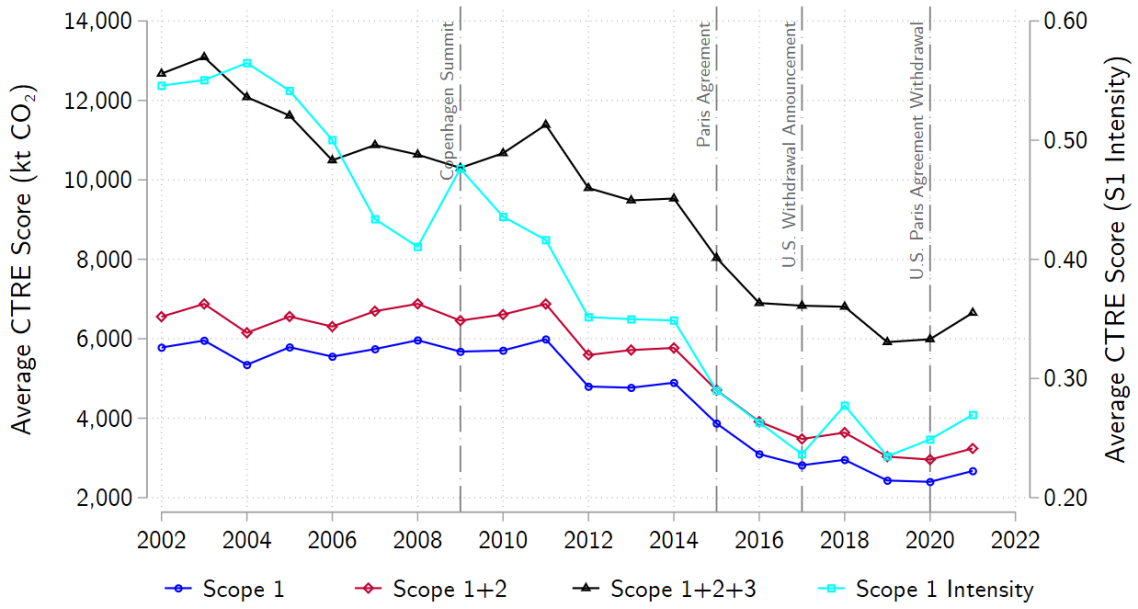


Figure IA.C.2: **Average CTRE Scores Over Time: Market Cap-Weighting and Fixed Lender Sample**

The figure displays the average CTRE scores of the U.S. banking system from 2002 to 2021 (solid blue line), corresponding to the baseline shown in Figure 2. In addition, the figure presents CTRE scores over time calculated based on (i) the bank market capitalization-weighted average (red line), and (ii) a fixed sample of 21 banks consistently present throughout the entire sample period (black line). The CTRE score is a bottom-up measure of a bank's climate transition risk exposure, constructed based on the bank's lending portfolio. The dashed 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 withdrawal from the Paris agreement by the U.S. in 2020.

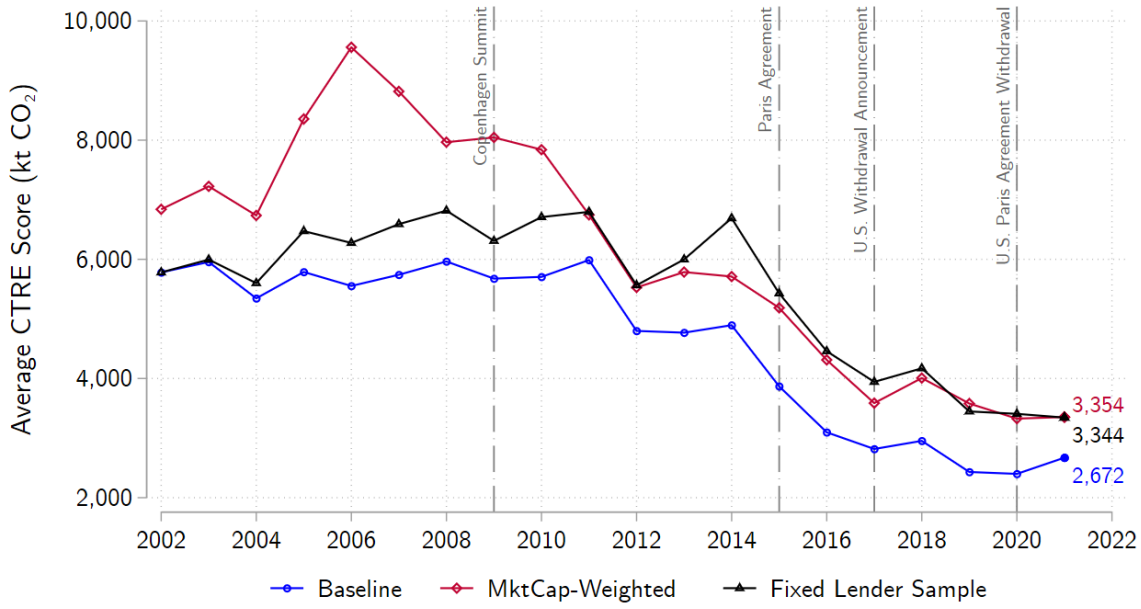


Figure IA.C.3: **Average CTRE Scores Over Time: Trucost Legacy Samples**

This figure displays the average CTRE score of the U.S. banking system from 2002 to 2021, depicted by the solid 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 exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).

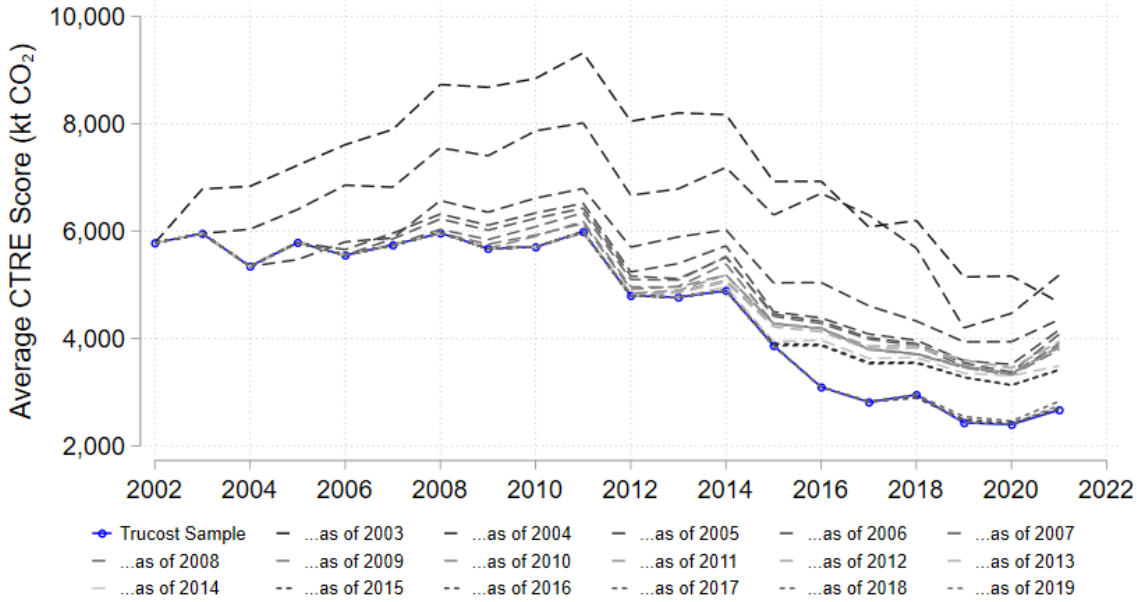
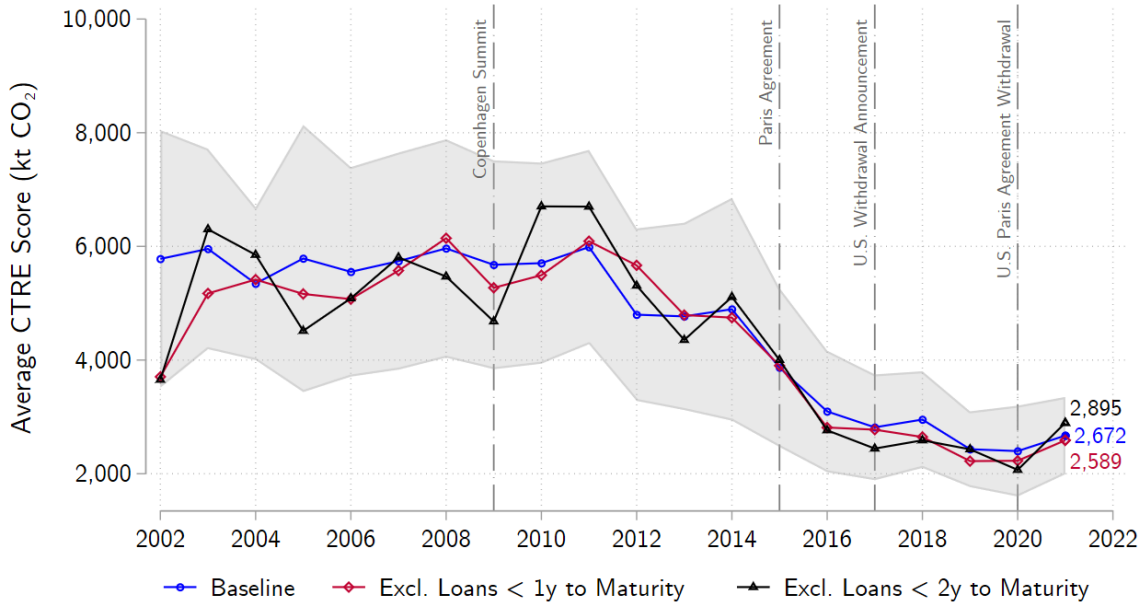


Figure IA.C.4: **Maturity-Adjusted CTRE Scores Over Time**

The figure displays the average CTRE scores of the U.S. banking system from 2002 to 2021, depicted by the solid blue line (replication of the CTRE trend illustrated in Figure 2). In addition, the figure presents the average CTRE scores computed using dynamically adjusted samples of loans that, in any given year, include only those loans with a remaining time to maturity of (i) at least one year (red line) and (ii) at least two years (black line). The CTRE score is a bottom-up measure of a bank's climate transition risk exposure, constructed based on the bank's lending portfolio (expressed in kt of CO_2-equivalent).



Internet Appendix D

Computation of the First-Order Derivatives in Eq. (5) and Eq. (6)

In this internet appendix, 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 $w_{i,b,t} \equiv w_{i,b,t}\left(LA_{i,b,t}, \{LA_{j,b,t}\}_{j\neq i}\right) = \frac{LA_{i,b,t}}{\sum_{i=1}^{N_{b,t}} LA_{i,b,t}} = \frac{LA_{i,b,t}}{LA_{1,b,t}+LA_{2,b,t}+\ldots+LA_{N,b,t}}$

D.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:

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

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

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

Internet Appendix E

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

In this internet appendix, we evaluate whether banks re-balance loan portfolios across borrower-industries or within borrower-industries. To this end, we re-estimate Eq. (11) 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 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). We estimate for bank b, firm i, and year t:

$$\Phi_{i,b,t}^{LoanAmount} = \beta_1 Entry_{i,b,t} + \beta_2 Exit_{i,b,t} + \mu_b \times \mu_i + \mu_i \times \mu_t + \epsilon_{i,b,t} \quad \text{(Internet Appendix E1)}$$

Estimates are reported in Table IA.E.1. Note that the sample decreases compared to Table 3 because singleton groups are dropped. This means that estimation is based on bank-industry groups with at least two borrower-observations within the group. We find no significant effects along the extensive margins adjustments, except for the years 2016 and 2017 (column 3), where the negative coefficient implies that banks actively decarbonize loan books by establishing new relationships with low-emitters operative within the same industry. 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 suggests that banks are gravitating towards new, lower-emitting clients within the same industry.

Table IA.E.1: **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 $\Phi_{i,b,t}^{LoanAmount}$ 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 exposure, 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 IA.A.1. Standard errors, reported in parentheses, are clustered at the bank-firm level. *, **, *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Within-Bank-and-Industry Estimates					
Sample Period	2002-2009	2010-2015	2016-2017	2018-2020	2021
	(1)	(2)	(3)	(4)	(5)
	$\Phi_{i,b,t}^{LoanAmount}$				
$Entry_{i,b,t}$	.329	-2.895	-3.507***	-.721	.466
	(3.397)	(2.933)	(.643)	(.896)	(2.111)
$Exit_{i,b,t}$	5.878	-.820	1.312	-2.196	-.391
	(4.131)	(2.743)	(1.106)	(2.299)	(2.909)
Bank x Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Industry x Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	.089	.089	.278	.184	.371
Obs.	38,675	41,752	22,507	35,854	9,862
Model	OLS	OLS	OLS	OLS	OLS

Internet Appendix F

CTRE Scores and Bank Screening and Monitoring

Are banks with higher CTRE scores more rigorous in screening and monitoring borrowers, particularly when lending to high-emission firms? To assess this question, we ideally need to observe banks' screening and monitoring efforts. As these efforts are unobservable, we follow prior literature and rely on indirect measures that capture how screening and monitoring incentives vary across loans arranged by the same bank. We consider price terms (spreads), non-price terms (maturity, collateral inclusion, covenant inclusion), and syndicate characteristics (lead arranger status and loan share). Spreads and collateral work as screening devices, while maturity and covenants help mitigate conflicts between creditors and equity holders, in turn creating monitoring incentives (Jensen and Meckling, 1976; Stiglitz and Weiss, 1981; Ivashina, 2009; Chava et al., 2019). Lead arranger status and the retained load share reflect "skin in the game" of and should enhance the lead bank's screening and monitoring incentives (Diamond, 1984; Sufi, 2007). Overall, we expect banks with higher CTRE scores to tighten screening and monitoring for loans to high-emission firms. Hence, loans to such borrowers should have stricter loan terms and more conservative syndicate structures.

To test these predictions, we estimate loan-level regressions for loan l, firm i, bank b, and year t to gauge the relationship between a borrower's Scope 1 intensitiy and screening- and monitoring-related measures. We estimate effects for banks grouped into quartiles based on their CTRE levels:

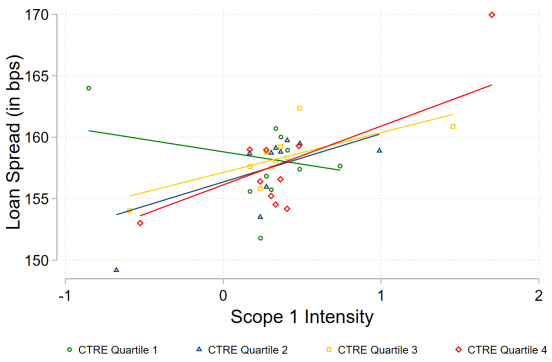
$$Y_{l,i,b,t} = \beta_1 Scope\,1\,Intensity_{i,t} + \mu_b + \mu_t + \beta_2 X_{b,t-1} + \beta_3 Z_{i,t-1} + \beta_4 W_{l,i,b,t} + \epsilon_{l,i,b,t}, \tag{Internet Appendix F1}$$

where $Y_{l,i,b,t}$ is a proxy for monitoring or screening incentives and $Scope\,1\,Intensity_{i,t}$ is a borrower's Scope 1 intensity. We isolate within-bank variation with bank fixed effects (μ_b) and account for year heterogeneity (μ_t). We control for bank, borrower, and loan features. $X_{b,t-1}$ includes banks' $Log\,Total\,Assets$, $Tier\,1\,Capital\,Ratio$, $Debt\,Ratio$, and ROA; $Z_{i,t-1}$ includes borrowers' $Log\,Total\,Assets$, $Leverage$, $Interest\,Coverage\,Ratio$, ROA, $Listing\,Status$, industry and country dummies; and $W_{l,i,b,t}$ includes the deal purpose, loan types, institutional loans, relationship loans, and—unless included as $Y_{l,i,b,t}$—lead arranger status, maturity, and collateral or covenants presence.

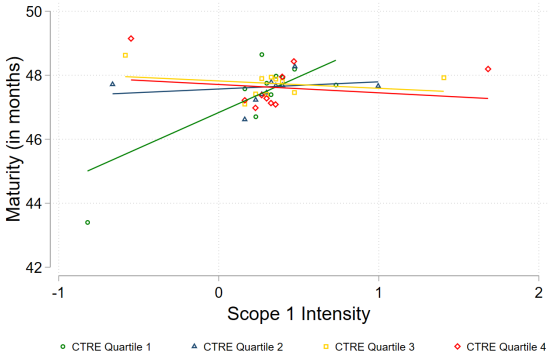
Estimates of Eq. (Internet Appendix F1) by bank CTRE quartile are reported in Figure IA.F.1. We plot for each bank group the average residualized outcome $Y_{l,i,b,t}$ by Scope

1 intensity decile (this allows us to summarize the estimates of 24 regressions; four bank CTRE groups times six outcomes). Panel A show that high-CTRE score banks demand higher spreads for loans to high-emission firms compared to low-CTRE score banks. In Panel C (D), the link between collateral (covenant) inclusion probabilities and borrowers emission intensities differs little across bank CTRE groups. In Panel B, however, maturity decreases modestly with higher emission intensities among high-CTRE group banks. Further, in Panel E, lead shares tend to increase with firms' emissions, but this relationship weakens for high-CTRE score banks. At the same time, these banks are more likely to act as lead arrangers for loans to high-emission firms. Together, these findings point to a (modest) overall increase in banks' screening and monitoring efforts for high-emission firms. Banks with higher transition risk exposure focus on some stricter contract terms to manage these risks, with little evidence that they retain a greater loan share.

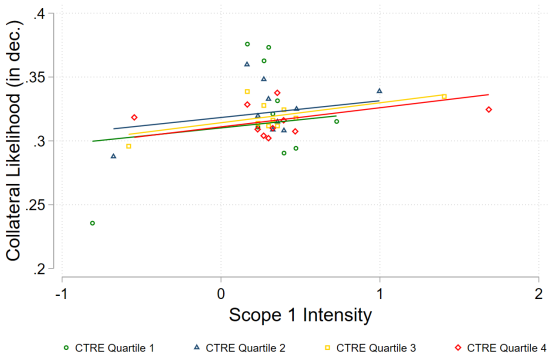
Figure IA.F.1: **Borrowers' Emission Intensity and Loan Terms by CTRE Quartiles**



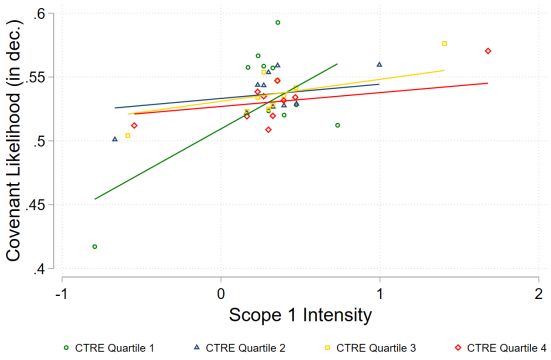
(a) Loan Spread



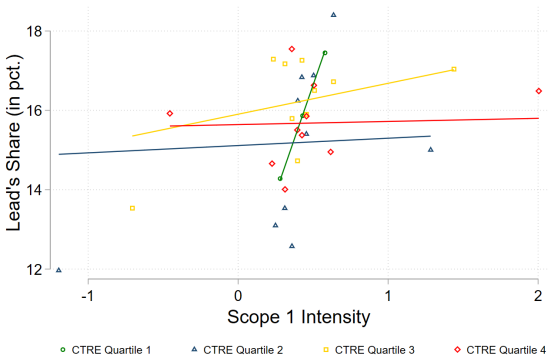
(b) Loan Maturity



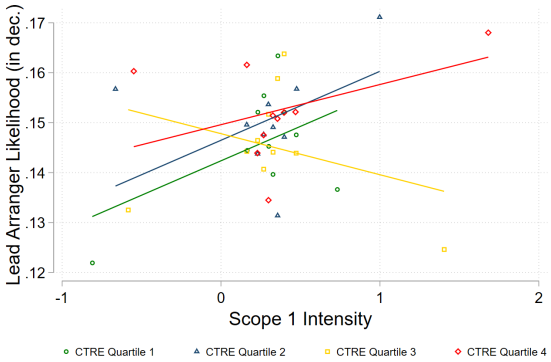
(c) Collateral Probabilities



(d) Covenant Probabilities



(e) Lead Arrangers' Loan Share



(f) Lead Arranger Status Probabilities