Transparency and Real Effects of Climate Stress Tests for Banks

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Abstract: We examine whether microprudential climate stress tests affect banks' reporting choice, loan portfolios, and environmental performance. With heightened awareness and better data, we expect incentivized banks to expand transparency, adjust lending standards, and reduce their loan exposure to climate risks. Focusing on the 230 largest European banks from 2017 to 2022, we find that participants in supervisory climate stress tests increase their transparency, mainly if they have previously shown commitment to climate issues, incur lower data collection costs, have higher climate risk exposure, and face more climate-related market pressure. Corporate borrowers of such committed banks reduce their total and long-term loan financing and, in turn, display lower (fixed) assets and sales growth, but only if they are subject to high climate transition risks. On a portfolio level, we find a shift from long-term to short-term loan maturities and improvements in climate performance for committed banks, but the opposite for the remaining banks. Our results suggest that, while on average we find no effects, supervisory stress tests can expedite the internalization of climate risks for banks with strong climate-related incentives but also give rise to (unintended) substitution to less committed and less tightly regulated banks.

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"The [climate] stress test will make the heart of the financial system more responsive to changes in the climate and in government climate policies, creating the possibility of a virtuous circle in which the financial sector amplifies the positive impact of new climate policies […]."

Mark Carney, Governor of the Bank of England,
in the *Financial Times*, December 18, 2019.

1. Introduction

How do climate stress tests affect banks' climate-risk reporting and loan portfolios, and ultimately extend to their corporate clients' funding structure and investment policy? In this study, we examine the transparency, financing, and real effects of a series of recent supervisory climate stress tests for a large sample of banks and borrowers in Europe. Financial institutions, under the guidance of central banks, are often presumed to play a pivotal role in combating climate change. Through funding their clients' businesses, banks are exposed to borrowers' physical climate risks and transition risks. If borrowers get hit by negative climate events or suffer from market and regulatory pressure to decarbonize production processes and supply chains, the financial consequences affect lending institutions' loan exposure and credit risk (de Bandt et al., 2024; Martini et al., 2024; Altavilla et al. 2025). Many regulators therefore consider banks' resilience to climate risk an important factor for the stability of the global financial system and view regulatory measures on climate risk as potential change agents towards a 'greener' economy (e.g., Light and Skinner, 2021; ECB, 2024; IMF, 2024).

We focus on a recent series of climate stress tests conducted by bank regulators in the United Kingdom (U.K.), France, the Eurozone, and the European Union (EU) beginning in 2019. These climate stress tests share several common features (Baudino and Svoronos, 2021): They require the stress-tested banks to collect granular data and generate information about the risk of climate change in their loan portfolios; they largely focus on transition risk rather than physical risk; they use similar methodologies and prescribe similar climate scenarios to simulate impairments in banks' loan books; and they do not mandate individual participants to disclose their climate risks, but regulators eventually release aggregate climate-risk information for the banking sector as a whole.[1] Thus, climate stress tests provide an instructive setting to analyze the effects of climate-transparency regulation for financial institutions and their borrowers.

The European stress tests were among the first regulatory interventions worldwide that explicitly considered climate risks. For them to yield real effects implies the following conceptual chain. The requirement for banks to collect and estimate substantial data on their borrowers' climate risk exposures likely triggered a broader integration of such information into banks' risk management (e.g., Alix, 2021; Lehmann, 2020; Acharya et al., 2023; Fuchs et al., 2024). Once better climate-risk data is internally available, managers can signal their appreciation of the newly assessed risks in the loan portfolios to regulators and markets by expanding climate risk disclosures. Notably, such disclosures are voluntary but once initiated may prove costly to unwind and can serve as credible commitment device (Leuz and Verrecchia, 2000; Bischof and Daske, 2013; Daske et al. 2013). When banks start to systematically collect and disclose climate risk data, they also consider this information in the credit assessment process which, in turn, can affect borrowers' financing (Kacperczyk and Peydró, 2022; Wang, 2023). For borrowers exposed to substantive climate risks, the ensuing financing constraints likely extend to their operating activities (e.g., Winker, 1999; Campello et al., 2010; Ferrando and Mulier, 2022). These real effects are in line with what has been shown for traditional bank stress tests (e.g., Acharya et al., 2018; Cortés et al., 2020). As the terms and structure of the individual loans change, banks' aggregate loan portfolio and their exposure to climate risk should change as well. Consequently, we expect

[1] The Basel Committee on Banking Supervision (BCBS) describes transition risks as those risks that are "[…] related to the process of adjustment towards a low-carbon economy" (BCBS, 2021).

banks' environmental performance to improve, in line with the ESG feedback effects shown to realize through firms' disclosures (e.g., Christensen et al., 2017; Chen et al., 2018).

The above chain of thought derives its tension from at least three counterarguments. First, climate stress tests represent a soft form of transparency regulation (Baudino and Svoronos, 2021). Their impact stems from the necessity for banks to invest in collecting new risk data, rather than from imposing additional capital requirements or the public disclosure of individual bank results. Even if individual results became available, it is unclear if investors would use the climate-risk information in the assessment of a bank's risk premium. Instead, they could perceive substantial overlap with other commonly used risk factors, discount climate risks because of their extremely long horizon, or expect future governments to bail out banks from these risks. Thus, climate stress tests could have little if any impact on market discipline, which has been shown to be a key driver of real effects in traditional bank stress tests (Flannery et al., 2017; Acharya et al., 2018).

Second, it is unclear whether any voluntary disclosure of climate risks constitutes a credible commitment for participating banks and contains relevant information about their actual and planned climate actions for interested stakeholders. Doing so is a necessary condition to trigger feedback effects (Roychowdhury et al. 2019; Christensen et al., 2021). Because loan exposures are costly to adjust and difficult to observe, stress-tested banks could prioritize signaling compliance over making substantive changes to their lending practices (Gambacorta, 2023; Giannetti et al., 2023; Bolton and Kacperczyk, 2025). Moreover, as the perceived costs and benefits of the new data requirements likely vary across banks (e.g., Daske et al., 2013), their heterogeneous response to the climate stress tests could render the detection of average treatment effects difficult.

Third, any changes in the lending policies of stress-tested banks could plausibly be offset by substitution from non-stress-tested banks or unregulated lending markets (e.g., private credit). For instance, if some banks restrict lending to high-risk borrowers amidst the climate stress tests, these borrowers can turn to less transparent and less tightly regulated banks or private lenders whose climate risk exposure remains opaque and, hence, they would not have to bear the costs of climate externalities (Houston et al., 2012; Rauter, 2020; Cascino and Correia, 2025). As a result, even if we were to observe a shift in the composition of stress-tested banks' loan portfolios, borrowers' real activities could be left little affected.

Against this backdrop, we examine the reporting and real effects of climate stress tests for the 230 largest listed European banks with disclosure data available over the 2017 to 2022 period. Of those banks, 55 institutions were subject to the national climate stress tests by the Bank of England and the Banque de France or the supranational climate stress tests by the European Central Bank (ECB) and the European Banking Authority (EBA). The remaining 175 banks serve as control group. In additional tests, we extend our sample to the borrowers of these banks. We identify a borrower's lending relationships from the list of lenders as indicated in Orbis Bankers and manually match them with our list of banks. Doing so yields a sample of more than 66,000 unique nonfinancial and predominantly private firms, for which we can examine their lending and investment behavior.[2] Private firms are of particular interest to regulators, as they are highly dependent on bank financing and are typically not covered by alternative climate policies such as the EU Emissions Trading System (Alogoskoufis et al., 2021).

Our analysis proceeds in three steps: (1) we examine whether affected banks change their climate disclosure practices, (2) we examine whether these changes in banks' climate risk reporting extend to borrowers' financing policies and real investments, and (3) we examine, on an aggregate

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[2] Because we cannot observe the actual lending agreements nor terms in Orbis Bankers, we infer borrowers' loan exposure and maturity structure from financial statement disclosures. See Section 4 for details and sensitivity analyses.

level, whether the changes induced by the climate stress tests are reflected in banks' loan portfolios and their environmental performance. To test the first link, we construct a *Climate Disclosure Score*. For each bank and year, we use financial statements and other formal publications (e.g., Pillar 3 reports and ESG reports) to manually code 35 items that we directly derive from the ECB's expectations on banks' climate risk disclosures (ECB, 2020; see also Section 2.1 and Appendix B). The ECB is the primary supervisory institution in the EU, and its expectations form the basis for climate stress test assessments for many national and supranational regulators. Since these were the first bottom-up climate stress tests for most banks, they had to first develop a measurement system and methodically collect the necessary data.[3]

When we trace the *Climate Disclosure Score* over time, we observe a positive trend, but a notable uptick for stress-tested banks from 2019 onwards. We formally test these patterns with a staggered and stacked difference-in-differences design (Cengiz et al., 2019) around the announcement of the climate stress tests. Our regression estimates suggest that the average treated bank expands its reporting by about 12 disclosure items relative to the pre-period mean (equaling an increase by 160 percent), which is double the new disclosure items observed among non-treated banks. These relations hold after controlling for time-varying bank attributes as well as bank, year, or bank country-by-year fixed effects. The latter account for common macroeconomic conditions and regulatory changes in a country and year such as the 2018 adoption of the EU Non-Financial Reporting Directive (Fiechter et al., 2022) or the 2020 outbreak of the COVID-19 pandemic.

Closer inspection reveals that the effects are not uniform but are driven by about half of the stress-tested banks. The disclosure change for the other half is no different from the benchmark

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[3] Bottom-up stress tests ask participating banks to collect and share data that the regulator then aggregates. In contrast, in a top-down approach (as conducted by the Dutch central bank in 2018), the regulator itself makes assumptions about banks' climate risk exposure based on internal models and data it already possesses.

group. Cross-sectional tests show that banks expanding their transparency already have a proven track record of committing to climate issues, expect lower costs to collect the emissions data, bear higher climate risks, and face more climate-related pressures from investors and product markets. Our results support the notion that climate stress tests improve data availability and enable banks to increase their climate risk transparency, but only if the proper reporting incentives are in place. Thus, market discipline seems to play a critical role in enhancing the effectiveness of the regulatory intervention (Krueger et al., 2020; Bolton and Kacperczyk, 2021; Ilhan et al., 2023).

In the second step, we examine borrowers' debt financing and investment activities. We construct a panel of up to 399,000 borrower-years and then compare various borrower attributes around the climate stress tests in difference-in-differences analyses. The models include borrower-level controls, borrower fixed effects, and country-by-year fixed effects. Our primary dependent variables are the absolute loan amounts as well as the term structure of these loans (short-term versus long-term). In the full sample, we do not find differential relations between borrowers from stress-tested and non-stress-tested banks, neither pre- nor post-stress tests. If anything, borrowers from exempted banks expand their long-term loan financing after the climate stress tests.

We next focus on the treated banks only to exploit the observed variation in their commitment to climate risk transparency. One source of variation is borrowers' exposure to transition risks. Using estimates of Scope 1 and 2 emission intensity provided by S&P Trucost, we find that the distribution of climate risk is highly skewed. A relatively small set of firms bears most of the transition risks. When we compare the firms in the top tercile of the risk distribution to the rest, we find that these borrowers reduce their long-term loans after the climate stress tests. This finding holds for absolute loan amounts, the share of long-term loans over total loans, and yearly changes in long-term loans. Notably, low-risk borrowers increase their long-term loan exposure in the same period, suggesting that a substitution from high-risk to low-risk borrowers takes place.

Another source of variation is whether the lending bank conveys a credible commitment to climate risk transparency. We therefore run the analysis separately for treated banks with above and below median changes in the *Climate Disclosure Score* around the stress tests. We find that the reduction in long-term and total loans is largely confined to high-risk borrowers from lenders committed to climate risk transparency. Low-risk borrowers and borrowers from banks without commitment show less, if any, reduction in their loan exposure. Our evidence points to substitution within high-transparency banks (from long-term to short-term loans for high-risk borrowers and from high-risk to low-risk borrowers) as well as from more to less transparent lenders.

To examine the real effects at the borrower level, we run the same analysis with various investment proxies as the dependent variables. We find that high-transition risk firms have higher asset and sales growth. Yet, borrowers linked to committed banks post significantly lower growth numbers than their peers. The lower growth figures seem to be driven by reduced investments in tangible fixed assets, pointing to finance-induced capacity constraints. Overall, our findings are consistent with high-risk borrowers being limited in their (long-term) funding, but only if they are connected to banks that have substantially changed their approach to climate risk. The finance restrictions, in turn, inhibit firms' growth potential.

In our third and final step, we study feedback effects for stress-tested banks. We construct a panel by aggregating borrowers' loan amounts and term structure at the portfolio level of each bank. This procedure yields a sample of 480 bank-years, which we use to estimate similar difference-in-differences regressions as before. The model includes bank-level controls as well as bank and year fixed effects. For the full sample, we do not find changes in banks' short-term or long-term loan exposure. However, when we limit the analysis to the treated banks and distinguish between more and less transparent institutions, we find that banks with a proven commitment to climate risk transparency reduce their long-term loan exposure and increase short-term loans. Banks with little changes to their climate risk reporting display the opposite pattern. That is, they hold more long-term loans and fewer short-term loans. Lastly, we examine whether the observed changes in the loan portfolios have real effects on banks' climate performance, as intended by the regulators.[4] We use general ESG ratings, environmental impact scores, environmental cost estimates, and downstream Scope 3 emission intensity as proxies for banks' climate performance related to their loan portfolio. Our analysis shows that banks committed to transparency improve along all these metrics relative to the other stress-tested banks post regulatory intervention.

Our paper contributes to multiple strands of literature. First, several studies examine the role of banks and lending standards for the implementation of climate-related goals and policies. For instance, Houston and Shan (2022), Huang et al. (2022), or Nguyen et al. (2023) show the relation between lending terms and borrowers' ESG profiles, particularly their climate risk exposure. Basu et al. (2022) and Wang (2023) study how ESG regulation for banks transmits to borrowers' real activities. Altavilla et al. (2025) study the effects of monetary policy on banks' climate risks. We contribute to this research by focusing on microprudential climate stress tests, a relatively novel tool for central banks. By requiring participating banks to provide data on climate risk, regulators can foster awareness and, as we show, initiate a push towards more climate risk transparency. This is a distinctly different mechanism than, for instance, mandating ongoing regular ESG disclosures, imposing climate-related capital requirements, or forcing banks to reduce or offset their emissions footprint. Our findings show that climate stress tests can lead to changes in the loan exposures,

[4] The opening quote provides an example of such climate-related goals of bank regulators.

affect the operations of high-risk borrowers, and—through feedback effects—improve banks' environmental performance, but only for banks committed to serious climate risk management.

Second, our study contributes to the emerging literature on the effects of climate stress testing. For instance, Fuchs et al. (2024) demonstrate that French banks increase lending to borrowers with high climate risk but also adjust the loan terms to reflect the higher risk. Similar to our findings, Aiello (2024) and De Cicco et al. (2025) show a shift in Eurozone banks' credit allocation to less polluting firms following the ECB climate stress test.[5] We extend this work by focusing on the role of transparency in understanding the heterogeneity of banks' responses to the climate stress tests and in the transmission of the effects to borrowers. Our findings suggest that some (but not all) banks significantly increase their transparency around climate stress tests as a means of committing to improved climate risk management. We then show that these committed banks change the maturity structure of their loan portfolios and, in turn, induce funding and capacity constraints on high-risk borrowers. This effect is particularly pronounced among smaller clients, indicating that banks wield more market power in this economically critical but often understudied market. Our results also complement studies on the disclosure (Bischof and Daske, 2013; Petrella and Resti, 2013) and real effects (Acharya et al., 2018; Cornett et al., 2020) of traditional stress tests.

Finally, we add to the literature on the general role of transparency regulation in the policy mix (Weil et al., 2013; Christensen, 2022). Such regulation is often used as a last resort when there is no political consensus on more stringent measures to internalize externalities. Climate stress tests represent a softer approach of transparency regulation and focus primarily on the internal use

[5] Aiello (2024) and De Cicco et al. (2025) rely on proprietary ECB data and focus on changes in banks' loan portfolios. In comparison, we use publicly available data, which lets us extend our sample to a broad cross-section of smaller private firms. Conceptually, we focus on the channels through which the documented effects realize (i.e., market discipline and better data) and include the real effects on the borrower and lender level in the analysis.

of the information they generate. Despite concerns about limited enforceability and the difficulty of observing banks' lending decisions, our findings suggest that climate stress tests are associated with meaningful transparency, financing, and real effects. However, these effects are confined to banks facing plausible ESG incentives, suggesting a complementary role of market discipline in enhancing the effectiveness of soft transparency interventions. We also point out the substitution that can occur as both participating and non-participating banks are affected. Depending on their commitment to climate-risk transparency, stress-tested banks reshuffle their loan portfolios towards shorter or longer maturities and more risky or less risky firms. Similarly, high risk borrowers may move to less transparent, less tightly regulated lenders. These findings emphasize some unintended consequences of regulations (e.g., Christensen et al., 2016, Leuz and Wysocki, 2016) that might counteract overruling welfare objectives (Ball 2024).

2. Institutional Details and Data

2.1 Institutional Background

We build our empirical approach on three institutional features: (1) the initiation of bottom-up climate stress tests in Europe, (2) the ability to measure and benchmark banks' climate risk transparency, and (3) the availability of lending data for a large sample of private corporate borrowers. European regulators and central banks were at the forefront of conducting climate stress tests of the banking system. Table 1, Panel C, summarizes the timing and coverage of the four stress test exercises we examine. The climate stress tests share similar scopes, degrees of participation, and design characteristics (Baudino and Svoronos, 2021), allowing us to group them together for the tests. First, they all serve as learning exercises for participating banks to collect granular (bottom-up) data and generate information about the risks of climate change in their loan portfolios. Second, they all focus on climate change transition risk rather than physical climate risk. Third, they apply similar methodologies and rely on comparable climate scenarios drawn from the Network for Greening the Financial System, a cooperation of banking supervisors striving to accelerate the green transition in capital markets (NGFS, 2019), to simulate the capital effects of impairments in banks' loan books. These scenarios incorporate long-term changes in carbon prices and energy standards with time horizons of up to 30 years (Baudino and Svoronos, 2021). Lastly, the regulators do not require individual banks to disclose the results of the climate risk assessments; instead, they publish aggregate climate risk information for the entire banking sector.

The second institutional feature is the opportunity to observe the climate risk transparency expectations of the ECB, the primary banking regulator in Europe, and use them to evaluate the concurrent reporting efforts undertaken by the banks. The ECB issued disclosure expectations on climate risk in its "Guide on climate-related and environmental risks" (ECB, 2020) around the launch of the stress test exercises. This guide outlines supervisory expectations for how financial institutions should approach and disclose their climate risks. It also emphasizes the importance of transparency, enabling market participants to assess the financial implications of such risks. We use this guide to construct a *Climate Disclosure Score,* consisting of 35 disclosure items that measure a bank's compliance with the disclosure expectations of the ECB. The items include disclosure policies and procedures (e.g., whether a bank considers climate issues for the computation of its credit risk) as well as the content of the disclosures (e.g., whether a bank publishes its carbon emissions under Scope 1, 2, and 3). We then search the websites of our sample banks for an English version of the consolidated financial statements, Pillar 3 reports, separate ESG reports, and other disclosures, and use these documents to manually code yearly disclosure scores.[6] See Appendix B for details on the composition and computation of the *Climate Disclosure Score*, together with descriptive statistics on the mean compliance among stress-tested and non-stress-tested banks at the beginning and end of our sample period.

The third institutional feature is the ability to collect data on short-term and long-term loans outstanding for a large sample of primarily privately held corporate borrowers in Orbis and Orbis Bankers. Private firms are particularly reliant on relationship lending, make up a significant share of banks' loan portfolios, and are typically not subject to other climate policies such as the EU Emissions Trading System (Alogoskoufis et al., 2021). As a result, they represent a key area of interest to regulators in climate stress tests. In addition, private firms offer the advantage of eliminating many of the confounding factors associated with the increased scrutiny from public oversight and market pressure and, hence, allow us to better zoom in on the effects of lending-induced changes to their financing and operating activities.

2.2 Sample Selection and Description

In Panel A of Table 1, we outline the sample selection process for the disclosure analyses. The sample starts in 2017, two years before the announcement of the first set of climate stress tests, and runs through 2022, two years after the second group of climate stress tests were announced. We start our sample collection with the 250 largest European publicly listed banks based on market capitalization in 2022 as indicated in Datastream. We could collect data for the *Climate Disclosure Score* for 230 of these banks (of which 55 are treatment banks). We next drop years with missing

[6] To ensure consistency of the coding, we first provided detailed guidelines and trained the research assistants for the data collection. In a second step, the author team independently verified the coding for a random selection of firm-years. The consistency checks yield an average correlation of more than 90% between our own coding and that of the research assistants, lending support to the internal validity of our measure.

bank-level control variables as well as singleton observations. This process yields a final bank-level disclosure sample of 185 unique banks and 970 bank-years.

Panel B of Table 1 summarizes the sample selection process for the lending analyses. Because these analyses are conducted on the borrower level, we first identify all firms that have a lending relationship with one of our sample banks. To do so, we start with the universe covered in Orbis Bankers and retrieve the list of lenders of each firm as indicated in the field "bnkfullname." We then manually match the bank names to our list of 230 sample banks with disclosure data available and only retain borrower firms for which we could identify at least one bank relationship.[7] As a second filter, we require data on Scope 1 and Scope 2 carbon emission intensity for each borrower as estimated by S&P Trucost. We need this data to classify borrowers according to their climate change transition risk, which is largely driven by emissions (Bolton and Kacperczyk, 2023). This process yields an initial sample of 1,599,684 borrower-year observations, consisting of 266,614 unique borrowers. In the next step, we remove observations with missing data in Orbis on loans outstanding and borrower-level controls (e.g., total assets).[8] Finally, we retain only borrowers with a fiscal year-end of December 31 to ensure loan exposures are assessed at the same point in time and exclude borrowers with incomplete time-series data as well as from the financial industry. This process yields a sample of 66,669 borrowers with known lending relationships to 75 sample banks, resulting in 399,175 yearly observations.[9]

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[7] We obtain annual flat files for the years 2018 to 2022. Due to the difficulty to determine start and end dates of bank relationships in Orbis Bankers (e.g., due to varying annual coverage), we include and retain all relationships we could identify for a given borrower over the entire sample period. We believe this assumption is plausible, as many firms maintain their bank relationships over long periods (Even-Tov et al., 2023).

[8] We also drop observations with zeros for key variables (i.e., total assets, total equity, and total debt) from the sample because in these cases, Orbis does not let us distinguish a "true" zero from a missing entry.

[9] We construct the sample for our third set of analyses on the bank portfolio level by aggregating the borrower-years to bank-years (see details in Section 5.1).

In Panel D of Table 1, we provide a breakdown of the sample composition by country. For the disclosure analyses, no country dominates the sample. The three countries with the largest number of banks (U.K., Switzerland, and Italy) each makes up no more than 12 percent of the sample. The composition of the lending sample is more uneven, reflecting the well-known data constraints in Orbis and Orbis Bankers (Peek et al., 2010; Beuselinck et al., 2023; Chen et al., 2024). Four countries (Spain, France, Portugal, and the U.K.) account for more than 85 percent of the sample observations. Similarly, the variation between stress test banks and benchmark banks is limited as more than 62,000 borrowers are identified as having a lending relationship with a (larger) treatment bank. Nonetheless, our approach provides significant advantages despite these data constraints. First, Orbis Bankers enables us to examine loan exposures from relationship lending rather than transactional lending. Relationship lending is the dominant form of corporate financing for private European firms (Kysucky and Norden, 2016).[10] Second, our data source encompasses borrowers of all sizes, including a significant number of unlisted firms. Notably, 98.9 percent of sample borrowers lack any financial instruments listed on regulated stock exchanges. This comprehensive coverage is especially important given the economic and climate significance of SMEs (OECD, 2022). Finally, to address the limited variation of stress test participation, we conduct several of the analyses that follow within treatment sample and focus on cross-sectional differences among equally treated banks and borrowers.

In Table 2, we present descriptive statistics for the variables used in the bank-level disclosure analyses (Panel A), borrower-level lending analyses (Panel B), and the bank portfolio-level lending

[10] When we compare our data to the main data source for transactional lending (DealScan) and use the overall loan exposures according to banks' Pillar 3 reports as benchmarks, we find that with our approach we can explain up to one-third of banks' corporate loan portfolios relative to only ten percent based on DealScan data. For a replication of the borrower-level analyses using DealScan syndicated loan data, see Appendix C.

tests (Panel C). We provide details on the variable definitions in Appendix A and discuss the dependent and independent variables together with the controls in the respective sections below.

3. Bank-level Disclosure Analyses

3.1 Research Design

Our first set of analyses focuses on changes in bank-level climate risk transparency around climate stress tests. The argument is that participating banks were required to collect granular data on their borrowers' climate risk exposure and integrate this information in their risk models and scenario analyses. We therefore expect banks committed to climate risk objectives to make the newly gained information publicly available, which allows them to cater to the information needs of regulators, investors, and other stakeholders. To test these predictions, we construct a bank-year panel and estimate the following generalized difference-in-differences (DiD) model for bank *i* in year *t* using ordinary least squares (OLS) regressions:

$$\textit{Climate Disclosure Score}_{i,t} = \beta_0 + \boldsymbol{\beta_1}\, \textit{Post}_{i,t} \text{ x } \textit{Stress-Test Bank}_i + \beta_2\, \textit{Post}_{i,t}$$

$$+ \beta_3\, \textit{Stress-Test Bank}_i + \sum \beta_j\, \textit{Controls}_{j,i,t} + \sum \beta_{k,i,t}\, \textit{Fixed Effects}_{k,i,t} + \varepsilon. \qquad (1)$$

The dependent variable is the *Climate Disclosure Score*, representing the percentage of climate disclosure items reported in a year (see Section 2.1 and Appendix B for details). *Post* is an indicator variable marking the years of and after the first announcement of a climate stress test in a country. That is, in France and the U.K., we set *Post* = '1' beginning in 2019 (i.e., the year of the national stress tests). In all the other countries, we set *Post* = '1' beginning in 2020 (i.e., the year of the supranational stress tests).[11] Because sample banks participated in more than one climate

[11] The announcements usually mark the beginning of private interactions between banks and regulators and are promptly followed by the release of the stress test methodologies and scenarios. Thus, they give participating banks

stress test, the indicator marks the first occurrence of the regulatory intervention per bank. *Stress-Test Bank* is an indicator for the participating banks in these stress tests and allows us to capture innate differences between treatment and benchmark banks. The interaction term *Post x Stress-Test Bank* is our main variable of interest and estimates the disclosure change for the participating banks incremental to the pre-period and the benchmark banks.

The model includes a set of time-varying bank-level controls to account for systematic differences between treatment and benchmark banks, as well as for well-known determinants of firm transparency (e.g., Lang and Lundholm, 1993; Burks et al., 2018; Bischof et al., 2022). Specifically, we control for size ($\textit{Total Assets}_{BK}$), profitability ($\textit{ROE}_{BK}$), the proportion of income generated from interest ($\textit{Interest Income}_{BK}$), and a measure of bank efficiency ($\textit{Cost/Income Ratio}_{BK}$). See Appendix A for variable details and measurement.

Finally, we include bank and year fixed effects, which account for unobservable, time-invariant bank attributes and general time trends or market-wide changes such as the 2018 adoption of the Non-Financial Reporting Directive in the EU (Fiechter et al., 2022), the introduction of the expected credit loss model under IFRS 9 (Ertan, 2025), or the 2020 outbreak of the COVID-19 pandemic that affected most banks in our sample. The time-fixed effects are especially relevant given that the regulatory focus on climate topics is likely intensifying the public pressure on all European banks to increase climate-risk transparency. In our most stringent specification, we replace the year fixed effects with bank country-by-year fixed effects, essentially estimating the coefficients of interest from within-country and year variation in stress-test participation. This structure alleviates concerns about concurrent regulatory shocks and economic conditions in a

and their stakeholders a first impression of the regulatory priorities and expectations and can plausibly be regarded as the impetus for behavioral changes.

country and year and comes on top of the DiD design we employ. In all our disclosure tests, we draw statistical inferences based on standard errors clustered by bank headquarter country.

3.2 Climate Risk Disclosures following Climate Stress Tests

We begin our analysis by graphically examining the trends in climate risk transparency over time. Figure 1, Panel A, plots the mean *Climate Disclosure Score* separately for stress test banks and non-stress test banks. Both groups exhibit relatively low levels of climate risk disclosures in 2017, indicating a widespread lack of market interest in and awareness of this type of risk among banks which, in turn, had little incentives to collect the respective data. Climate risk transparency generally improves in the following years. However, there is a notable divergence in the upward trends between treatment and control banks, starting right around the early climate stress test exercises. By 2022, the disclosure gap between the two groups has risen from a mean difference of about 0.05 in 2017 to 0.39. These patterns are in line with a transparency effect.

To formally test the differential disclosure behavior between stress-tested and non-stress-tested banks, we estimate equation (1) in a staggered DiD design and report results in Table 3, Panel A. Column 1 reports coefficient estimates for the main variables of interest, *Post*, *Stress-Test Bank*, and the interaction between the two. The results support the observations from Figure 1. They show that stress-test banks were already more transparent to begin with, all banks improved their transparency in the post-period, and participating banks increased their climate risk transparency by a significant margin after the regulatory intervention. The magnitude of the coefficient on *Post x Stress-Test Bank* of 0.175 suggests that the average treated bank expands its reporting by about 12 disclosure items relative to the pre-period mean. This translates into an increase of 160 percent, which is double the new disclosure items observed among non-treated banks.[12] In column 2, we add the bank-level controls. Large, profitable banks tend to be more transparent, as one would expect. In columns 3 and 4, we include various fixed effects. Across all specifications, the coefficient on *Post x Stress-Test Bank* remains positive and highly significant, and its magnitude is only slightly attenuated when we include bank country-by-year fixed effects.

A potential concern with these results is related to the staggered nature of the stress tests. Prior literature suggests that staggered treatment can introduce bias, particularly in case of dynamic treatment effects (e.g., Cengiz et al. 2019, Baker et al., 2022; Barrios, 2022). To address this issue, we re-estimate equation (1) using a stacked DiD design and report results in Panel B of Table 3. For each treatment cohort (i.e., the two national or the two supranational stress tests), we create a separate dataset including the banks treated in the respective year as well as either all control banks (columns 1 to 4) or only those domiciled in the same countries as the treatment banks (column 5). We then combine these cohort-specific datasets to run the analyses. The results are very similar both in terms of magnitude and statistical significance to those reported in Panel A. Notably, in column 5, when we only include the benchmark banks located in the same countries as the stress test banks and control for general trends and common shocks in a country and year, the *Post x Stress-Test Bank* coefficient is 0.157 and highly significant.

To graphically assess the sharpness of the treatment effect and evaluate the parallel trends assumption, we plot yearly coefficients for the interaction with *Stress-Test Bank* in Figure 2. The model in column 4 of Panel B serves as baseline for this specification and year *t*–1 (i.e., the year before the announcement of the stress tests) is dropped from the analysis. As the figure shows, the pre-stress test coefficients are small and statistically indistinguishable from zero. The absence of

[12] We calculate the economic magnitudes like follows: Relative to the pre-period mean (i.e., intercept of 0.114 + 0.104, or 7.63 disclosure items), stress test banks improve their disclosures by (0.173 + 0.175) or, multiplied by the maximum of 35 disclosure items, 12.18 disclosure items. In percentage terms, the increase is equal to (12.18/7.63) = 159.6%.

any discernible effects lends support to the parallel trends assumption. Starting from the year of the announcement of the climate stress tests, the coefficients on the interaction term are positive and significant, suggesting a sharp and immediate reaction to the regulatory intervention.

Next, we examine the heterogeneity among treatment banks and distinguish between those that experience a change in the *Climate Disclosure Score* around the stress test at or above the sample median and the rest. We then plot the yearly means for these two groups together with the benchmark banks in Panel B of Figure 1.[13] The graph shows that only a subset of stress-tested banks—about half—displays a substantive increase in climate risk transparency over the sample period. The other half of the treatment banks behave no different than the benchmark group. This pattern points to the existence of selection effects. While some institutions are responsive to the heightened attention by regulators and other stakeholders to the topic and react by expanding their climate risk transparency, others simply follow the general trend without substantively changing their reporting and, arguably, the underlying data basis.

To shed light on the underlying incentives driving the differential reporting behavior, we estimate a variation of equation (1) in which we interact the *Post* indicator with a (binary) partitioning variable that captures potential explanations for more climate risk transparency. We measure the partitioning variables *prior* to the climate stress tests to get at the notion of pre-commitment unaffected by the announcement of the regulatory intervention. Table 4 reports the results of the cross-sectional tests.

In Panel A, we proxy for management's ex ante commitment to ESG issues and the ease of collecting borrower-level emissions data. Specifically, we create binary indicators for banks that

[13] We compute the change in the *Climate Disclosure Scores* for each bank by comparing post-stress test means to pre-stress test means. Note that we limit the sample for Panel B of Figure 1 to the banks for which we have individual lending data as we will use this partition in the later borrower-level analyses (see Section 4).

have (1) published a comprehensive *ESG Report* (measured by at or above median page count), (2) a designated *ESG Committee* on their board, (3) issued an *SDG 13 Pledge* to commit to urgent climate action, (4) at or above median MSCI *ESG Ratings*, and (5) a bigger share of borrower-level Scope 1 and 2 *Emissions Data* readily available in commercial databases (S&P Trucost). We find that across all these partitions the coefficient on *Post x PART* is positive and, with one exception, significant.

In Panel B, we proxy for banks' exposure to climate risks as well as market pressures from ESG investors and customers interested in climate related products. Specifically, we create binary indicators for banks that (1) have at or above median *Downstream Scope 3 Intensity* which captures greenhouse gas (GHG) emissions from banks' loan portfolios, (2) received at or above median attention to climate topics during earnings conference calls as measured by Sautner et al. (2023), (3) have at or above median ownership stakes by ESG-focused institutional investors, and (4) launched an at or above median number of ESG funds over the last five years. In column 5, we set the partitioning variable equal to the natural logarithm of banks' *Green Bond Volume* issued over the last five years. As the panel shows, the interaction term is positive throughout and significant in columns 1, 2, and 3 of the five models.

Overall, the cross-sectional findings suggest that only—what we call—committed banks with the right incentives in place as shown by their prior dedication to climate issues, lower expected integration cost, higher exposure to climate risks and greater climate-related market opportunities expand their climate risk disclosures following the regulatory intervention. This insight highlights the key role of incentives and market discipline in strengthening the impact of climate stress tests (Krueger et al., 2020; Bolton and Kacperczyk, 2021; Ilhan et al., 2023).

4. Borrower-level Lending Analyses

4.1 Research Design

Our second set of analyses focuses on changes in borrowers' financing and operating activities around climate stress tests. The argument is that due to the higher weight put on climate risks in the lending standards, borrowers with a relationship to a stress test-participating bank experience more scrutiny regarding the availability and terms of their loan financing. This newfound financial scrutiny should primarily stem from lenders which made substantive changes to the risk management processes amidst the climate stress tests and apply to those borrowers with a high exposure to climate (transition) risks. The resulting financial constraints could eventually affect borrowers' investment behavior. To test these predictions, we construct a borrower-year panel and estimate the following generalized DiD model for borrower *i* in year *t* using OLS regressions:

$$\textit{Debt Financing / Asset Growth Variables}_{i,t} = \beta_0 + \boldsymbol{\beta_1}\, \textit{Post}_{i,t} \text{ x } \textit{Stress-Test Bank}_i + \beta_2\, \textit{Post}_{i,t} + \beta_3\, \textit{Stress-Test Bank}_i + \sum \beta_j\, \textit{Controls}_{j,i,t} + \sum \beta_{k,i,t}\, \textit{Fixed Effects}_{k,i,t} + \varepsilon. \quad (2)$$

In the debt financing tests, we use log transformed absolute amounts (*Short-term Loans, Long-term Loans, Total Loans*), the proportion of *Long-term Loans / Total Loans* and the percentage change (Δ) in *Long-term Loans* as the dependent variables. Because we do not have individual loan data (including interest rates) available for our large sample of mainly private firms, we derive these variables from annual financial statements. In the investment tests, we use yearly percentage changes (Δ) in *Total Assets*, *Fixed Assets*, *Fixed Tangible Assets*, net working capital (*NWC*), and *Sales* as the dependent variables. See Appendix A for variable details.

Stress-Test Bank is a time-invariant indicator for whether borrower *i* has at least one lending relationship with a bank that participated in a national or supranational climate stress test. This variable allows us to capture systematic differences between having a stress-tested and non-stress-tested lender. For each borrower, we identify the lending relationships in place over the sample period from the list of lenders as indicated in Orbis Bankers and manually match them with the list of banks in our sample. *Post* is an indicator variable marking the years of and after the first announcement of a climate stress test in a country. That is, for borrowers with lenders domiciled in France or the U.K. the variable takes on the value of '1' beginning in 2019, for all other borrowers it starts in 2020. The interaction term *Post x Stress-Test Bank* is our main variable of interest and estimates the loan financing (or investment) effects of having a lending relationship with a stress test bank relative to the pre-period and borrowers without such loan exposure. The model includes time-varying controls for borrower size ($Total\ Assets_{BOR}$), profitability (ROA_{BOR}), and financial leverage ($Leverage_{BOR}$). We also include borrower and borrower country-by-year fixed effects to account for constant firm attributes and country-specific time trends or market-wide changes.[14] Thus, we estimate the coefficients of interest from within-country and year variation between borrowers with and without a lending relationship with a stress test bank. We draw statistical inferences based on standard errors clustered by the headquarter country of a borrower's relationship bank. In cross-sectional tests, we adjust the model in equation (2) to examine whether changes in borrowers' financing policies depend on their exposure to transitional climate risks as well as their lending banks' commitment to climate risk transparency. We discuss the design of these additional tests in the results section.[15]

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[14] The borrower fixed effects subsume the main effect of *Stress-Test Bank* in equation (2), whereas the main effect of *Post* is identified by the (relatively few) observations (i.e., about 2.5 percent of sample firms) for which the country of incorporation of the borrower is different from the headquarter country of the lending bank and the treatment timing differs across the two jurisdictions.
[15] As Table 2, Panel B, shows some of the variables used in the model estimation have extreme values (e.g., Δ *Long-term Loans*). Thus, in sensitivity analyses (not tabulated), we repeat the borrower-level tests after winsorizing at the 5 (instead of 1) percent level and find results very similar to those reported. None of the inferences change.

4.2 Debt Financing Effects following Climate Stress Tests

We start the borrower-level analyses by estimating equation (2) and report the results for the five debt financing variables in Table 5. The table shows that larger, highly levered firms rely more on loan financing whereas more profitable firms do less so. When it comes to our main variables of interest, we do not find significant differences between borrowers with and without relationships to a stress-tested bank before or after the regulatory intervention. None of the interaction terms *Post x Stress-Test Bank* are significant and their magnitudes are small. If anything, the significantly positive coefficients on *Post* in columns 2 and 5 suggest that borrowers with a lender exempted from the stress tests appear to increase their long-term loan financing, consistent with substitution from regulated to unregulated banks. Overall, we find no evidence that a lending relationship with a stress-tested bank, on average, affects borrowers' debt financing. This finding is inconsistent with economy-wide changes in bank lending and firm financing due to the climate stress tests.[16]

However, the stricter scrutiny of climate risk assessments should not apply uniformly but primarily be found among lenders that made substantive changes to their risk management processes, and then extend to their borrowers with high exposure to climate (transition) risks. Thus, we further examine the role of borrowers' climate change transition risk for the results. We proxy for a borrower firm's transition risk in a year by its Scope 1 and 2 carbon *Emission Intensity* as estimated by S&P Trucost. Scope 1 and 2 emissions capture a firm's direct GHG emissions from its own sources and the indirect GHG emissions from purchased energy. In Figure 3, we plot the distribution of the mean *Emission Intensity* variable, normalized to fall between [0,1], for the borrower firms in our sample. The graph shows that only a relatively small portion of firms bear

[16] When we repeat the analyses in Table 5 with the five investment proxies as dependent variables (not tabulated), we also find insignificant results for the *Post x Stress-Test Bank* interaction terms, suggesting that the climate stress tests, on average, had no real effects in the economy.

most climate change transition risks. The variable cutoff for the upper tercile of firms is 0.042. We make use of this highly skewed risk distribution for our regression analysis. Specifically, we set a binary indicator *High Transition Risk* equal to '1' if a borrower's mean *Emission Intensity* falls into the top tercile of the sample distribution. We re-estimate equation (2) for the subset of borrowers with at least one lending relationship with a treatment bank and replace the *Stress-Test Bank* variable with the *High Transition Risk* indicator. This modification essentially compares the debt financing effects among high-risk and low-risk borrowers, conditional on having a lending relationship with a stress test bank. Panel A of Table 6 reports the results.[17]

The table shows that borrowers with high climate risk experience a reduction in long-term loan financing after the climate stress tests were announced. The relation holds for the absolute loan amounts (column 2), the relative loan amounts (column 4), and the changes in long-term loans (column 5). In each of these models, the coefficient on *Post x High Transition Risk* is negative and significant. In terms of economic magnitude, the reduction is on the order of 10 percent. Interestingly, we observe positive and significant coefficients on the main effect of *Post* for the same three specifications. This finding indicates that low-climate-risk borrowers could extend their long-term loan financing and suggests a substitution between the different types of borrowers. That is, stress-tested banks seemingly reduced their long-term loan exposure to borrowers with high climate risks but increased their exposure to low-risk borrowers. These changes are on top of the increases in the long-term loan volume for unregulated banks shown in Table 5.

We also consider the insights from the disclosure analysis (see Section 3.2) that incentives and better underlying data are prerequisites for banks to effectively integrate climate risk issues into the internal risk management systems. Specifically, we rerun the analysis of borrowers' climate

[17] Because the variable *High Transition Risk* is constant over time, it is subsumed by the borrower fixed effects.

risk exposure (see Table 6, Panel A), but now separately for borrowers with committed or less committed lenders. We proxy for banks' commitment to effective climate-risk management with their revealed preferences as indicated by the change in the reported *Climate Disclosure Score* around the stress test. We classify those with at or above (below) median changes in the score as *High* (*Low*) transparency banks, in line with their commitment to climate issues. Table 6, Panel B, reports the results for the separate regressions together with *p*-values from *F*-tests comparing coefficients across subsamples.

The table allows several insights. First, only the high-climate risk borrowers with a committed lender experience a reduction of their total loans (column 5), accompanied by a shift from long-term loans (columns 3, 7, and 9) to short-term loans (column 1). This pattern is consistent with banks that seriously integrated climate issues into their risk management imposing financing constraints on their at-risk clients. Second, the high-risk borrowers with less committed lenders show a substantially smaller reaction to the climate stress tests and no evidence of substitution from long-term to short-term maturities. The only significantly negative coefficient on *Post x High Transition Risk* is in column 8, and for each dependent variable the interaction term is significantly smaller in magnitude than the one for highly committed lenders. Thus, if a bank lacks incentives for a serious climate-risk management (beyond merely participating in the regulatory exercise), the stress tests seemingly have little effect—even for those borrowers most susceptible to climate risks. Third, we find further evidence of substitution from high-risk to low-risk borrowers across both committed and less committed banks. Using long-term loans as the dependent variable, the

Post coefficient in columns 3 and 4 is positive and significant, suggesting that the long-term loan market is generally growing and/or banks are actively courting these low-risk borrowers.[18]

4.3 Real Effects following Climate Stress Tests

Having found that high-climate-risk borrowers with committed lenders are potentially subject to financial constraints, we now turn to the operating implications of the reduced loan financing. To do so, we repeat the analysis of borrowers' climate risk exposure for the five investment outcome variables. We estimate the regressions separately for borrowers with a lender that is classified as more (*High*) or less (*Low*) transparent about its climate risks and, hence, more or less committed to serious climate-risk management. Table 7 (which is similar in structure and format to Panel B of Table 6) reports the results.

The table yields two main insights. First, firms that are exposed to higher climate transition risks tend to grow faster than their low-risk counterparts, which can be seen from the positive and significant coefficients on *Post x High Transition Risk* for growth in total assets (columns 1 and 2) and sales (columns 9 and 10). Yet, high-climate-risk borrowers with a committed lender experience lower growth than firms with a comparably high climate risk but with a lender less committed to climate risk transparency, consistent with the former suffering from financial constraints. The coefficients in columns 1 and 9 are significantly smaller than the coefficients in columns 2 and 10.

[18] We conduct two additional sensitivity analyses for the borrower-level lending tests. First, we assess the impact of using Orbis data and the ensuing assumptions to identify loan volumes on the results. To do so, we repeat the analyses from Tables 5 and 6 using a substantially smaller sample of syndicated loans from European borrowers (source: DealScan). The results are generally similar to those reported albeit weaker (see Appendix C for details). Notably, high-risk borrowers of committed banks tend to increase their short-term syndicated loans and reduce their long-term syndicated loans. Second, we examine the role of client size for the results. To do so, we split the sample into large corporate clients (upper tercile of *Total Assets$_{BOR}$* distribution in pre-period) and the remaining medium-sized and small corporate clients and separately repeat the analyses for the two subsets (not tabulated). We find that the results in Tables 5 and 6 are primarily driven by the medium-sized/smaller borrowers, suggesting that for these clients banks wield more market power to incorporate climate risks in their lending terms. For large clients, the results are directionally consistent but largely insignificant.

The 0.008 coefficient difference for Δ *Total Assets* between the two groups translates into lower growth by about 10 percent for the average firm, which is economically meaningful. Second, one potential explanation for the lower growth numbers by the high-risk borrowers with committed lenders is the reduced ability to invest in (tangible) fixed assets. The coefficients on *Post x High Transition Risk* for changes in fixed assets (column 3) and changes in tangible fixed assets (column 5) are negative and significant. Notably, none of the other borrower groups report reductions in (tangible) fixed asset growth, suggesting that the observed lack of investment is unique to the specific subset of firms. The pattern on the investment side mimics the pattern we observe for the financing side, thereby increasing our confidence that we can attribute the findings to the changes around the climate stress tests. Finally, these borrowers tend to offset portions of the lower investments in fixed assets by higher growth in net working capital as shown by the positive and significant coefficient in column 7.

Collectively, our analyses on the borrower-level find no effect of climate stress tests on firms' debt financing and investment behavior, on average. However, when combined with the right incentives, the climate stress tests can act as change agents (Xue, 2023; Friedman and Ormazabal, 2024; Bonham and Riggs-Cragun, 2025). They trigger incentivized banks to impose financial restrictions and, in turn, capacity constraints on borrowers exposed to high climate risks, as intended by the regulators. At the same time, we also find evidence of substitution from high-risk to low-risk borrowers among committed banks, and from more committed to less committed and less tightly regulated banks among high-risk borrowers. This pattern is consistent with the general drawbacks of uneven implementation of the same regulation among firms in the same industry (Houston et al., 2012; Acharya et al., 2018; Breuer and Breuer, 2022).

5. Bank Portfolio-level Analyses

5.1 Research Design

Our third and final set of analyses focuses on changes in banks' overall loan portfolios and the consequences for their environmental performance. The argument is that by putting special emphasis on climate-risk issues, banks start to actively manage (and reduce) their loan exposure to firms subject to high climate transition risks, such that these affected borrowers implement operational adjustments. The ensuing changes to the composition of the loan portfolios—due to both, their own lending decisions and borrowers' operational adjustments—improve banks' environmental footprint.

To test these predictions, we go back to our bank-year panel from Section 3 and estimate the generalized DiD model in equation (1), but with a different set of dependent variables. Specifically, we consider the same debt financing variables used in the borrower tests (i.e., *Short-term Loans, Long-term Loans, Total Loans*, *Long-term Loans / Total Loans*, and Δ *Long-term Loans*) computed on the aggregate bank level (as indicated by the subscript *BK*). Because we do not observe portfolio-level amounts for individual banks, we proxy for them by aggregating the granular borrower-level data we have. For instance, to compute *Short-term Loans*$_{BK}$, we sum up the short-term loan amounts of all borrowers with a known lending relationship with bank *i* in year *t* (and then take the natural logarithm for the analyses). We derive the lending relationships from the list of lenders in Orbis Bankers and manually match them with our sample banks. If a borrower's disclosures indicate multiple lending relationships, we allocate the loan amounts in equal parts to the respective banks to avoid double counting.[19] See Appendix A for variable details.

The model includes the same bank-level controls as before (*Total Assets*$_{BK}$, *ROE*$_{BK}$, *Interest Income*$_{BK}$, and *Cost/Income Ratio*$_{BK}$). Because the number of bank-years with granular loan data available is small (≤ 480), we can only include bank and year fixed effects in the specification and draw statistical inferences based on robust standard errors. In cross-sectional tests, we adjust the model in equation (1) to examine whether changes in loan portfolios align with a bank's commitment to climate risk transparency. We also use aggregate environmental performance metrics as additional dependent variables (see Section 5.3).

5.2 Loan Exposure Effects following Climate Stress Tests

We start the bank portfolio-level analyses by estimating equation (1) for the full sample and report results in Table 8. For each of the five debt financing variables, we tabulate two models, one without bank-level controls and only including bank fixed effects, and one with bank-level controls as well as bank and year fixed effects. The table shows little evidence of changes in banks' loan portfolio structure after the climate stress tests. The only dependent variable that indicates a differential behavior between stress test and non-stress test banks is *Total Loans*$_{BK}$. Participating banks expand their total loan volume more than benchmark banks after the regulatory intervention, as the positive and significant coefficient on *Post x Stress-Test Bank* in columns 5 and 6 show. This accelerated growth could merely be a function of the treatment banks being larger institutions that

[19] About half of our sample borrowers have more than one bank relationship (with a mean of 2.8 and a median of 3 different lenders). The multi-relationship borrowers account for approximately 60 percent of the total loan exposure in our sample. If we drop these borrowers and rerun the bank portfolio-level analyses with the strongly reduced sample (not tabulated), the results remain directionally consistent, but in most cases are not statistically significant anymore.

benefited more from changes in the general economic environment at the time. However, we do not find systematic evidence of banks shifting to shorter maturities after the climate stress tests.

We next zoom into our sample to examine cross-sectional variation aligned with banks' climate risk transparency as a signal of their underlying commitment to serious climate-risk management. Thus, we limit the sample to the treatment banks and modify equation (1) by interacting the *Post* indicator with a binary indicator *High Disclosure Change*, marking banks with at or above sample median changes in the *Climate Disclosure Score* around the stress tests (following the same definition used in Table 6, Panel B). This modification allows us to compare loan portfolio changes among more transparent and less transparent banks.

Table 9 reports the results. The table shows that more transparent banks which are plausibly committed to serious climate-risk management shorten the maturity of their aggregate loan portfolios. The coefficients on *Post x High Disclosure Change* are significantly negative for long-term loans (columns 3 and 4) and significantly positive for short-term loans (columns 1 and 2). As a result, the loan maturity ratio decreases (columns 7 and 8), whereas the total loan volume remains unaffected (columns 5 and 6). Banks less committed to climate-related issues display the opposite behavior as can be seen from the *Post* coefficients in the table. They increase the long-term loans, reduce the short-term loans, and lengthen the maturity of the loan portfolio. They also appear to be expanding their overall loan volume. Figure 4 plots the average long-term maturity ratios in event time to illustrate the differential changes in loan portfolios across banks. The graph distinguishes between more and less transparent stress test banks and benchmark banks. Consistent with the OLS regression results, the figure shows that committed banks significantly reduce the relative proportion of their long-term lending around the regulatory intervention, more so than less committed banks or non-stress-tested institutions. The drop in the maturity ratio seems to start in year t–1 suggesting some anticipation. Overall, the above results mirror the patterns observed at the individual borrower level and suggest that banks that seriously manage their climate transition risks adjust their loan portfolios to limit their exposure to such risks.

5.3 Real Effects following Climate Stress Tests

We next turn to the real effects on the bank level. Specifically, we are interested in whether banks that rebalance their loan portfolios to manage climate risks improve environmental performance, as intended by the regulators. We examine the following yearly nonfinancial performance metrics: (1) *ESG Ratings* are aggregate ESG scores as published by MSCI [0,10]. Higher values represent better ESG performance and lower risk exposure. (2) *Environmental Impact Scores* are measures for a bank's exposure to adverse environmental impacts through its lending portfolio as published by MSCI [0,10]. Lower values represent less environmental risk exposure. (3) *Environmental Costs* measure a bank's overall environmental costs incurred through its business activities (in percent of revenue; source: S&P Trucost). Lower values represent lower cost. (4) *Downstream Scope 3 Intensity* is as proxy for the GHG emissions from a bank's loan portfolio as measured by S&P Trucost. Lower ranks indicate lower downstream Scope 3 emission intensity.[20] We use these environmental performance metrics as dependent variables in a regression framework akin to the one in Table 9. That is, we compare environmental performance across more transparent and less transparent treatment banks around the climate stress tests.

Table 10 presents the results. The table shows improvements across all four dimensions, but only for banks committed to serious climate-risk management and, hence, with higher levels of

[20] Because S&P Trucost changed its methodology for this variable several times over our sample period, we transform the annual observations into percentile ranks [0,1]. To increase sample size, we linearly extrapolate or interpolate missing ranks based on its adjacent observations.

climate risk transparency. The coefficients on *Post x High Disclosure Change* indicate higher ESG ratings, reduced environmental impact and costs, and—most to the point—lower downstream Scope 3 GHG emissions for committed banks. This finding suggests that for banks that incorporate climate-risk concerns into their risk management and lending standards, the subsequent changes to their loan portfolios and, indirectly, the changes to their borrowers' operating activities feed back into an improved environmental footprint. At the same time, the less committed banks display opposite patterns as can be seen from the *Post* coefficients in the table. Their ESG ratings go down, and—if anything—the environmental impact scores and the downstream Scope 3 intensity worsen. It follows that the net impact of the regulatory intervention remains ambiguous.

In Figure 5, we graphically confirm the results for two of the four environmental metrics, *ESG Ratings* (Panel A) and *Downstream Scope 3 Intensity* (Panel B). For each measure, we plot the group means in event time. The differential patterns for more transparent and less transparent banks are easy to spot, and the two groups start drifting apart around t=0, the announcement of the climate stress tests. In Panel A, ESG ratings for committed banks improve, whereas they drop for less committed banks. In Panel B, downstream Scope 3 emissions for committed banks drop or remain stable, whereas they increase for less committed banks. In sum, our findings show that banks committed to transparency improve their environmental performance relative to the other stress-tested banks. This evidence is consistent with supervisory climate stress tests eliciting feedback effects, but only if the participating banks face strong climate-related incentives to begin with.

6. Conclusion

The recent series of climate stress tests of European banks constituted a new approach to foster banks' internal information production about climate risks in their credit portfolios. We examine whether this regulatory intervention affects banks' reporting decisions, loan portfolios, and ultimately environmental performance. We document that participating banks significantly expand their climate risk disclosures around the stress tests, especially if they have previously shown a commitment to climate-risk issues, expect to incur lower integration costs, bear more climate-related transition risks, and are subject to intense ESG market pressure. When it comes to real effects, we find—on average—no evidence of changes to borrowers' debt financing and investment activities or banks' loan portfolios following the climate stress tests. However, when we focus on the subset of banks that have incentives to seriously address climate transition risks and now have the necessary internal risk data available, we find that the high-climate-risk borrowers of these banks reduce their total and long-term loan financing and experience lower (tangible) fixed asset and sales growth. This finding is consistent with finance-induced investment constraints. In turn, these committed banks shorten the maturity structure of their high-risk loan portfolios and improve their overall environmental performance as reflected in higher ESG ratings and lower Scope 3 emission intensity.

These findings suggest that climate stress tests can serve as change agents and prompt banks to integrate climate risks into their financial risk management, while also influencing borrowers' operational activities, as intended by the regulators. Yet, the effects are limited to banks with the right incentives in place, highlighting the role of market discipline in enhancing the effectiveness of soft transparency interventions such as climate stress tests. At the same time, we also provide evidence of substitution from riskier to less risky clients as well as from more committed to less committed and less tightly regulated banks. It follows that the net benefits of the regulatory intervention remain ambiguous, as any intended environmental effects among the committed banks and their clients could be undone by unintended consequences among the remaining banks.

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Appendix A: Description of Variables

Panel A: Bank-level Disclosure Analyses

Variable	Description
Dependent variable:	
Climate Disclosure Score	Self-constructed score for each bank *i* and year *t* computed as the percentage of climate risk disclosure items (out of 35) that are reported in various bank disclosures (i.e., annual reports, nonfinancial reports such as ESG reports, and Pillar 3 reports). We derive the list of disclosure items from the ECB Supervisory Expectations on Climate Risk Management (ECB, 2020). In this guide, the ECB outlines supervisory expectations for how banks should manage and disclose climate risks and emphasizes the importance of transparency for market participants to assess (the financial implications of) climate risks. The score ranges between [0,1]. For more details, see Appendix B.
Independent variables:	
Stress-Test Bank	An indicator variable that takes on the value of '1' if bank *i* participated in any of the national (France and U.K.) or supranational (EBA and ECB) bottom-up climate stress tests over the sample period, and '0' otherwise. We collect the participating banks from the regulators' websites. In a second step, we manually match them with the list of banks from Orbis Bankers and limit the sample to the 250 largest European public banks by market capitalization in 2022. The matching occurs on the level of the listed parent and excludes all banks that underwent a merger over the sample period.
Post	An indicator variable that takes on the value of '1' for years *t* of and following the first announcement of a bottom-up climate stress test in a country, and '0' otherwise. That is, if bank *i* is domiciled in France or the U.K., we set the variable to '1' beginning in 2019. For all other banks, we set the variable to '1' beginning in 2020.
Bank-level control variables:	
Total Assets$_{BK}$*	The natural logarithm of total assets (field: 191100) of bank *i* in year *t* in EUR million. Source: Orbis Bank Focus.
ROE$_{BK}$*	Return on equity, defined as net income divided by shareholders' equity (field: roe) of bank *i* in year *t*. Source: Orbis Bank Focus.
Interest Income$_{BK}$*	Interest income (field: 193200) divided by operating income generated from core operating activities (field: 194400) of bank *i* in year *t*. Source: Orbis Bank Focus.
Cost/Income Ratio$_{BK}$*	Total operating expenses divided by operating income (field: 195300) generated from core operating activities of bank *i* in year *t*. Total operating expenses include staff expenses, administrative expenses and other operating expenses. Source: Orbis Bank Focus.
Cross-sectional variables:	
ESG Report	An indicator variable that takes on the value of '1' if bank *i*'s 2017 ESG report has an at or above sample median page count, and '0' otherwise. We set the variable to '0' if the bank does not release a separate ESG report in 2017. We collect the ESG reports from banks' websites.
ESG Committee	An indicator variable that takes on the value of '1' if bank *i* has a designated ESG committee in 2017 (based on the BoardEx field: CommitteeName), and '0' otherwise.
SDG13 Pledge	An indicator variable that takes on the value of '1' if bank *i* has issued an SDG 13 Pledge by 2017 to commit to urgent climate action (based on the Refinitiv field *CGVSDP054*), and '0' otherwise.
ESG Ratings	An indicator variable that takes on the value of '1' if bank *i*'s mean pre-stress test period ESG rating is at or above the sample median, and '0' otherwise. We use the MSCI aggregate ESG rating (field: weighted_average_score) in years *t* for the computation of this variable.

Variable	Description
Emissions Data	An indicator variable that takes on the value of '1' if bank *i*'s 2017 share of loans with borrower-level Scope 1 and 2 GHG emissions data available is at or above the sample median, and '0' otherwise. We compute the share of loans with emissions data by aggregating the *Total Loans* (Orbis: LOAN + LTDB) of all borrowers with *Emission Intensity* data in S&P Trucost (field: 319404) and divide it by the *Total Loans* of all the bank's borrowers.
Downstream Scope 3 Intensity	An indicator variable that takes on the value of '1' if bank *i*'s 2017 downstream Scope 3 intensity is at or above the sample median, and '0' otherwise. Downstream Scope 3 intensity measures the amount of GHG emissions (in metric tons scaled by total sales) of the borrowers in bank *i*'s portfolio as estimated by S&P Trucost (field: 326738).
Earnings Call Attention	An indicator variable that takes on the value of '1' if bank *i*'s mean pre-stress test period attention to climate-change related issues during earnings conference calls is at or above the sample median, and '0' otherwise. We use the firm-level climate change exposure measure in years *t* (field: cc_expo_ew) from Sautner et al. (2023) for the computation of this variable.
ESG Investors	An indicator variable that takes on the value of '1' if bank *i*'s 2017 stock ownership by ESG-focused institutional investors is at or above the sample median, and '0' otherwise. We use the percentage of shares held by ESG-focused investors based on S&P's classification of institutional investors for the computation of this variable.
ESG Fund Launches	An indicator variable that takes on the value of '1' if the number of investment funds with an ESG label launched by bank *i* over the five years up to 2017 is at or above the sample median, and '0' otherwise. We identify the launch of ESG funds in year *t* based on the mutual fund universe in Refinitiv (if classified as *ESG-Environmental*, *Impact Investing*, *Responsible Investments* or *SRI*), and then manually match the promoters of the respective funds to the sample banks.
Green Bond Volume	The natural logarithm of the aggregate principal amount (in USD) of bond securities with a green label issued by bank *i* over the five years up to 2017. We identify green bond issues in year *t* based on the Green Bond Guide in Refinitiv, and then manually match them to the sample banks.

Panel B: Borrower-level Lending Analyses

Variable	Description
Dependent variables:	
Short-term Loans[*]	The natural logarithm of short-term loans outstanding (field: LOAN) of borrower *i* in year *t* in EUR million. Source: Orbis.
Long-term Loans[*]	The natural logarithm of long-term loans outstanding (LTDB) of borrower *i* in year *t* in EUR million. Source: Orbis.
Total Loans[*]	The natural logarithm of short-term and long-term loans outstanding (LOAN + LTDB) of borrower *i* in year *t* in EUR million. Source: Orbis.
Long-term Loans / Total Loans[*]	Borrower *i*'s long-term loans outstanding divided by total loans outstanding in year *t,* computed as LTDB / (LOAN + LTDB). Source: Orbis.
Δ Long-term Loans[*]	Percentage change in borrower *i*'s long-term loans outstanding in year *t* computed as ($LTDB_t$ – $LTDB_{t-1}$) / $LTDB_{t-1}$. Source: Orbis.
Δ Total Assets[*]	Percentage change in borrower *i*'s total assets in year *t* computed as ($TOAS_t$ – $TOAS_{t-1}$) / $TOAS_{t-1}$. Source: Orbis.
Δ Fixed Assets[*]	Percentage change in borrower *i*'s fixed assets in year *t* computed as ($FIAS_t$ – $FIAS_{t-1}$) / $FIAS_{t-1}$. Source: Orbis.
Δ Fixed Tangible Assets[*]	Percentage change in borrower *i*'s fixed tangible assets in year *t* computed as ($TFAS_t$ – $TFAS_{t-1}$) / $TFAS_{t-1}$. Source: Orbis.

Variable	Description
*Δ NWC**	Percentage change in borrower *i*'s working capital (i.e., net working capital equal to inventories plus accounts receivable minus accounts payable) in year *t* computed as ($WKCA_t$ – $WKCA_{t-1}$) / $WKCA_{t-1}$. Source: Orbis.
*Δ Sales**	Percentage change in borrower *i*'s sales in year *t* computed as ($TURN_t$ – $TURN_{t-1}$) / $TURN_{t-1}$. Source: Orbis.
Independent variables:	
Stress-Test Bank	An indicator variable that takes on the value of '1' if borrower *i* has at least one lending relationship with a bank that participated in any of the national (France and U.K.) or supranational (EBA and ECB) bottom-up climate stress tests over the sample period, and '0' otherwise. We identify a borrower's lending relationships from the list of lenders (field: bnkfullname) as indicated in Orbis Bankers and manually match them with the list of the 250 largest European public banks by market capitalization in 2022.
Post	An indicator variable that takes on the value of '1' for years *t* of and following the first announcement of a bottom-up climate stress test applicable to the relationship banks of borrower *i*, and '0' otherwise. That is, if borrower *i* has a relationship with a bank domiciled in France or the U.K., we set the variable to '1' beginning in 2019. For all other borrowers, we set the variable to '1' beginning in 2020.
Emission Intensity	Carbon emission intensity of borrower *i* in year *t*, measured by the amount of Scope 1 and 2 GHG emissions (in metric tons scaled by total sales) as estimated by S&P Trucost (field: 319404). We normalize the variable to fall in a range between [0,1]. Higher values indicate higher Scope 1 and 2 emission intensity. Source: S&P Trucost.
High Transition Risk	An indicator variable that takes on the value of '1' if borrower *i*'s mean *Emission Intensity* over the sample period falls into the top tercile of the overall sample distribution, and '0' otherwise.
Borrower-level control variables:	
*$Leverage_{BOR}$**	One minus the ratio of share capital (field: CAPI) divided by total assets (TOAS) of borrower *i* in year *t*. Source: Orbis.
*ROA_{BOR}**	Profit before taxes (PLBT) divided by total assets (TOAS) of borrower *i* in year *t*. Source: Orbis.
*Total $Assets_{BOR}$**	The natural logarithm of total assets (TOAS) of borrower *i* in year *t* in EUR million. Source: Orbis.

Panel C: Bank Portfolio-level Lending Analyses

Variable	Description
Dependent variables:	
*Short-term $Loans_{BK}$**	The natural logarithm of the sum of short-term loans outstanding in year *t* (in EUR million) aggregated over all individual borrowers (field: LOAN) with a known lending relationship with bank *i*. We identify a borrower's lending relationships from the list of lenders (field: bnkfullname) as indicated in Orbis Bankers and match them to the banks in our sample. If a borrower's disclosures indicate multiple bank lending relationships, we allocate the loan amounts in equal parts to the respective banks. For instance, if a borrower has EUR 100 million loans outstanding and reports two bank relationships, each bank gets a loan allocation of EUR 50 million. Source: Orbis.
*Long-term $Loans_{BK}$**	Same as above but for long-term loans outstanding in year *t* (in EUR million; field: LTDB). Source: Orbis.
*Total $Loans_{BK}$**	Same as above but for short-term plus long-term loans outstanding in year *t* (in EUR million; fields: LOAN + LTDB). Source: Orbis.
*Long-term $Loans_{BK}$ / Total $Loans_{BK}$**	Bank *i*'s long-term loans outstanding divided by total loans outstanding in year *t,* computed as *Long-term $Loans_{BK}$* divided by *Total $Loans_{BK}$.*
Δ *Long-term $Loans_{BK}$**	Percentage change in bank *i*'s long-term loans in year *t* computed as (*Long-term $Loans_{BK,t}$* – *Long-term $Loans_{BK,t-1}$*) / *Long-term $Loans_{BK,t-1}$*.

Variable	Description
ESG Ratings	Aggregate ESG rating (field: weighted_average_score) of bank *i* in year *t*. The score ranges between [0,10]. Higher values represent better ESG performance and lower risk exposure. Source: MSCI.
Environmental Impact Scores	Rating of bank *i*'s exposure to adverse environmental impacts through its lending portfolio (field: financing_env_imp) in year *t*. The score ranges between [0,10]. Lower values represent less environmental risk exposure. Source: MSCI.
Environmental Costs (% of revenue)	Estimate of bank *i*'s overall environmental costs incurred through its business activities (in percent of revenue; field: 319535) in year *t*. Lower values represent lower cost. Source: S&P Trucost.
Downstream Scope 3 Intensity	Bank *i*'s carbon emission intensity from its loan portfolio in year *t*, measured by the amount of Scope 3 GHG emissions (in metric tons scaled by total sales) as estimated by S&P Trucost (field: 326738). Because Trucost changed its methodology for this variable several times over our sample period, we transform the observations into annual percentile ranks (ranging between [0,1]), using the maximum value within each methodology window as scalar. To increase sample size, we then linearly extrapolate or interpolate bank *i*'s missing ranks based on its adjacent observations (and requiring at least two observations per bank). For instance, if a bank is ranked 0.8 in 2018 and 0.6 in 2020, we fill in the value for 2019 with 0.7. Lower ranks indicate lower downstream Scope 3 emission intensity. Source: S&P Trucost.
Independent variables:	
Stress-Test Bank	See Panel A.
Post	See Panel A.
High Disclosure Change	An indicator variable that takes on the value of '1' if bank *i*'s change in the *Climate Disclosure Score* around the climate stress tests is at or above the sample median, and '0' otherwise. We compute the change as bank *i*'s mean *Climate Disclosure Score* in the post-stress test period minus the mean in the pre-stress test period. For banks domiciled in France or the U.K. (all other countries), the pre period spans the years 2017 and 2018 (2017 to 2019) and the post period the years 2019 to 2022 (2020 to 2022).
Bank-level control variables:	
*Total Assets$_{BK}$**	See Panel A.
*ROE$_{BK}$**	See Panel A.
*Interest Income$_{BK}$**	See Panel A.
*Cost/Income Ratio$_{BK}$**	See Panel A.

* We winsorize these variables at the 1% and 99%.

Appendix B: Climate Disclosure Score

The table reports the detailed composition of the variable *Climate Disclosure Score*. We construct the score as the sum of 35 disclosure items measuring a bank's compliance with the disclosure expectations on climate risk of the ECB. These expectations form the basis for banks' climate stress test assessments by the national or supranational supervisory institutions. Specifically, we derive our list of climate risk disclosure items from the "Guide on climate-related and environmental risks" of the ECB (ECB, 2020; referenced below as ECB with the respective expectation numbers). In this guide, the ECB outlines supervisory expectations for how banks should disclose their approach to climate risks and emphasizes the importance of transparency for market participants to assess (the financial implications of) climate risks. For its disclosure expectations, the ECB heavily draws from the non-binding "Guidelines on non-financial reporting: supplement on reporting climate-related information" issued by the European Commission (EC, 2019/C 209). The EC guidelines (referenced below as EC 209 with the respective page numbers) include both general and, in Annex I, bank-specific disclosure guidelines that closely follow the risk disclosure framework of the Task Force on Climate-related Financial Disclosures (TCFD). In the table, we indicate the ECB disclosure expectations together with the EC 209 cross-references (where applicable) that we used to define the 35 disclosure items. To construct the score, we assign a value of '1' to each disclosure item if included in bank *i*'s disclosures (i.e., annual reports, non-financial reports such as ESG reports, and Pillar 3 reports) and scale the sum by 35. The total score ranges from zero (non-disclosure) to one (full disclosure). The table also reports the average compliance with the individual disclosure items at the beginning and end of our sample period, separately for stress-test and non-stress-test banks.

			Mean Disclosure in 2017		Mean Disclosure in 2022	
Individual Disclosure Items	Disclosure Type	Main Reference (Cross Reference)	Stress-test Banks	Non-stress-test Banks	Stress-test Banks	Non-stress-test Banks
I. Disclosure Policies and Procedures						
1. Does the institution disclose any information with respect to the (im)materiality of climate risk for its credit risk?	Risk profile	ECB 1.1, 1.2, 13.1, 13.2 (EC 209/23)	11%	6%	89%	45%
2. Does the institution disclose any information with respect to the (im)materiality of climate risk for its market risk?	Risk profile	ECB 1.1, 1.2, 13.1, 13.2 (EC 209/23; ECB 1)	0%	3%	78%	31%
3. Does the institution disclose any information with respect to the (im)materiality of climate risk for its liquidity risk?	Risk profile	ECB 1.1, 1.2, 13.1, 13.2 (EC 209/23)	0%	0%	73%	25%
4. Does the institution disclose any information with respect to the (im)materiality of climate risk for operational risk like its reputation or liability risk?	Risk profile	ECB 1.1, 1.2, 13.1, 13.2 (EC 209/23)	15%	3%	85%	43%
5. Does the institution disclose any methodologies, definitions and criteria associated with any climate-related figure(s), metric(s) or target(s) reported?	Substantiation of disclosures	ECB 13.3	60%	37%	95%	66%
6. Does the institution explicitly disclose that the section on climate risk has been externally audited?	Substantiation of disclosures	ECB 13.3 (EC 209/13)	25%	6%	47%	18%
II. Content of Disclosures						
7. Does the institution describe the potential strategic impact of transition risks? (For their specific business model, not generic.)	Business model and strategy	ECB 2.1, 13.4 (EC 209/9+21)	5%	3%	91%	50%
8. Does the institution describe the potential strategic impact of transition risks in the short term? (For their specific business model, not generic.)	Business model and strategy	ECB 2.1, 13.4 (EC 209/9+21)	2%	2%	60%	21%
9. Does the institution describe the potential strategic impact of physical risks? (For their specific business model, not generic.)	Business model and strategy	ECB 2.1, 13.4 (EC 209/9+21)	9%	4%	93%	51%

Individual Disclosure Items	Disclosure Type	Main Reference (Cross Reference)	Mean Disclosure in 2017		Mean Disclosure in 2022	
			Stress-test Banks	Non-stress-test Banks	Stress-test Banks	Non-stress-test Banks
10. Does the institution describe the potential strategic impact of physical risks in the short term? (For their specific business model, not generic.)	Business model and strategy	ECB 2.1, 13.4 (EC 209/9+21)	2%	1%	51%	21%
11. Does the institution disclose its key performance indicators (KPI) related to climate risks?	Business model and strategy	ECB 2.2, 13.4+6 (EC 209/12)	24%	19%	91%	53%
12. Does the institution describe the individual(s) on the board with responsibility for climate-related issues?	Governance	ECB 3.1, 3.2, 13.4 (EC 209/10)	24%	9%	89%	53%
13. Does the institution describe the board's oversight of climate-related risks?	Governance	ECB 3.3, 13.4 (EC 209/10)	40%	19%	93%	61%
14. Does the institution describe the incentives for the management of climate-related issues, including the attainment of targets/KPIs?	Governance	ECB 3.4, 13.4 (EC 209/10)	9%	2%	60%	21%
15. Does the institution describe the organization's policies and processes for identifying, assessing and managing climate-related risks (e.g., risk management framework or as part of periodic internal reviews)?	Risk management	ECB 7.4, 7.7, 13.4 (EC 209/11+22)	44%	15%	95%	55%
16 Does the institution disclose that it uses climate-related classification lists (e.g., exclusion lists) (pre-contracting)?	Risk management	ECB 8.2, 13.4 (EC 209/22)	29%	9%	82%	43%
17. Does the institution disclose that it considers climate-related risks in the credit-processing (e.g., collateral valuations or loan pricing) (pre-contracting)?	Risk management	ECB 8.3, 8.5, 8.6, 13.4 (EC 209/22)	40%	20%	87%	51%
18. Does the institution disclose that it uses monitoring measures to consider climate-related risks in their portfolios (post contracting)?	Risk management	ECB 8.4, 13.4 (EC 209/22)	11%	7%	80%	33%
19. Does the institution disclose that it uses climate-related internal scenario analysis?	Risk management	ECB 11, 13.4 (EC 209/23)	7%	2%	89%	30%
20. Does the institution disclose that it uses climate-related internal stress testing?	Risk management	ECB 11, 13.4 (EC 209/22)	2%	0%	76%	16%
21. Does the institution disclose any metrics it uses with respect to climate risk?	Metrics and targets	ECB 13.4, 13.5 (EC 209/23)	65%	41%	95%	70%
22. Does the institution disclose any targets it sets related to climate risks?	Metrics and targets	ECB 13.4, 13.6 (EC 209/10+15)	67%	26%	93%	69%
23. Does the institution disclose portfolio alignment metrics (e.g., portfolio alignment with the Paris Agreement)?	Metrics and targets	ECB 13.4, 13.6 (EC 209/11+22)	0%	0%	45%	10%
24. Does the institution disclose industry-specific portfolio alignment metrics (e.g., industry-specific portfolio alignment with the Paris Agreement)?	Metrics and targets	ECB 13.4, 13.6 (EC 209/11+22)	0%	0%	42%	5%
25. Does the institution mention the EU taxonomy for sustainable activities?	Metrics and targets	ECB 13.4, 13.6 (EC 209/11+25)	2%	0%	91%	50%
26. Does the institution provide metrics on the alignments with the EU taxonomy for sustainable activities?	Metrics and targets	ECB 13.4, 13.6 (EC 209/11+25)	0%	0%	84%	31%

Individual Disclosure Items	Disclosure Type	Main Reference (Cross Reference)	Mean Disclosure in 2017		Mean Disclosure in 2022	
			Stress-test Banks	Non-stress-test Banks	Stress-test Banks	Non-stress-test Banks
27. Does the institution disclose the results of the climate-related scenario analysis?	Metrics and targets	ECB 13.4 (EC 209/23)	0%	0%	55%	17%
28. Does the institution disclose the results of the climate-related internal stress testing?	Metrics and targets	ECB 13.4 (EC 209/23)	0%	0%	25%	5%
29. Does the institution provide metrics on collateral and energy performance certificates (households)?	Metrics and targets	ECB 13.4, 13.5 (EC 209/23)	0%	0%	53%	10%
30. Does the institution provide metrics on collateral and energy performance certificates (corporate)?	Metrics and targets	ECB 13.4, 13.5 (EC 209/23)	0%	0%	40%	3%
31. Does the institution disclose information on the carbon intensity of their portfolios?	Metrics and targets	ECB 13.4, 13.5 (EC 209/22)	13%	6%	71%	31%
32. Does the institution disclose their Scope 1 and 2 GHG emissions?	Metrics and targets	ECB 13.4 (EC 209/13+14)	60%	36%	93%	69%
33. Does the institution disclose the methodology used to disclose GHG emissions?	Metrics and targets	ECB 13.4, 13.5 (EC 209/24)	55%	30%	93%	67%
34. Does the institution disclose any Scope 3 financed GHG emissions?	Metrics and targets	ECB 13.4, 13.5 (EC 209/14+24)	0%	1%	71%	32%
35. Does the institution disclose Scope 3 financed GHG emissions separately for different portfolio components?	Metrics and targets	ECB 13.4, 13.5 (EC 209/14+24)	0%	1%	65%	22%

Appendix C: Borrower-level Debt Financing Effects following Climate Stress Tests Using a Sample of Syndicated Loans

In this appendix, we repeat the main borrower-level debt financing analyses using a sample of syndicated loans instead of individual borrowers' loan characteristics derived from financial statement data. Following Martini et al. (2023), we begin the sample selection with all syndicated loan facilities from DealScan between 2010 and 2022. We then restrict the sample to borrowers located in Europe and exclude facilities from banks, non-bank financial institutions, and government-related entities. In line with Berg et al. (2016), we retain only revolving credit lines, term loans, and 364-day facilities. We use the updated linking table from Chava and Roberts (2008) to identify the borrowers, check for the availability of the borrower-level control variables, and match them with S&P Trucost for the emissions data. For each loan facility, we identify the lead arranger following De Haas and Van Horen (2013) and manually match them to our sample banks. For consistency with the main analyses, we assume each loan remains on the bank's balance sheet until the reported maturity date in DealScan (Gropp et al., 2019; Doerr and Schaz, 2021). This sample selection process yields a set of 7,146 borrower-year observations over the 2017 to 2022 period, representing 1,158 corporate borrowers from 68 banks domiciled in 22 countries. The average short-term and long-term syndicated loan amounts outstanding (each in EUR million and transformed using the natural logarithm plus one) are 2.05 and 3.52, respectively. The average borrower with a syndicated loan outstanding is publicly listed and has *Total Assets$_{BOR}$* of 20.47 (ln, in EUR mil.), suggesting that these are the largest corporate clients in a bank's portfolio.

With this data, we repeat the main analyses from Tables 5 and 6 and report results below. In the table, *Stress-Test Bank* is an indicator for borrowers with at least one syndicated loan from a bank participating in the climate stress tests. *Post* is an indicator variable marking bank relationships in the years of and following the first announcement of a bottom-up climate stress test in a country. The dependent variables are *Short-term Loans* and *Long-term Loans*, but now constructed using the syndicated loan data. We assess statistical significance based on robust standard errors and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *. For details on the model specifications and variable definitions, see the respective table notes as indicated in the header.

We start with the full sample analyses and examine the general debt financing effects following climate stress tests (columns 1 and 2). The interaction of *Post x Stress-Test Bank* is insignificant for both short-term and long-term loans, indicating no effect, on average, of climate stress tests on syndicated loan financing. This result is similar to what we found in Table 5. Notably, the variation of interest is minimal in this analysis, as 99.9 percent of borrowers with syndicated loans have lending relationships with a stress test bank.

Next, we limit the sample to borrowers with at least one syndicated lending relationship with a stress test bank and compare firms with high versus low climate change transition risk (i.e., borrowers in the upper tercile of the *Emission Intensity* distribution versus the rest). As columns 3 and 4 show, these large syndicated-loan borrowers with high transition risk tend to extend their long-term positions and reduce their short-term positions after the climate stress tests. This finding is opposite to the results in Table 6, Panel A, but in line with Fuchs et al. (2024), who also show that banks increase their lending to high-carbon emitters using syndicated loan data. One explanation for these differential results is that banks have relatively little bargaining power towards their largest, most important corporate clients to adequately incorporate climate risks in the highly competitive syndicated loan market. When it comes to the smaller, private corporate clients, banks have more leeway to impose adjusted credit terms given the new climate risk data at their disposal.

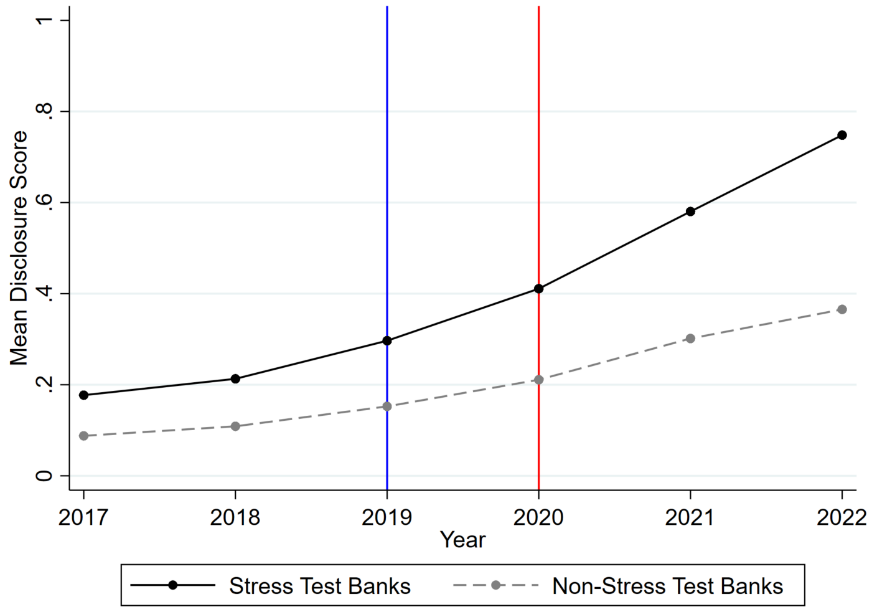
Finally, we distinguish between more and less committed banks based on above (*High*) and below (*Low*) median changes in the *Climate Disclosure Score* around the climate stress tests. The results in columns 5 to 8 indicate that borrowers of committed banks tend to increase their short-term syndicated loans and reduce their long-term syndicated loans. Borrowers of less committed banks display the opposite pattern. Even though most of the individual coefficients are not statistically different from zero, when comparing the two groups, the coefficients on *Short-term Loans* and *Long-term Loans* are significantly different from each other as can be seen from the F-tests. These results are consistent with our findings in Table 6, Panel B. They suggest that soft transparency interventions such as climate stress tests can even play a role for the largest corporate borrowers in a competitive environment such as the market for syndicated loans, but only when the right incentives are in place to shape bank behavior.

Reference to analyses in main document:	*Full sample, debt financing following climate stress tests* (Table 5, columns 1 & 2)		*Treatment sample, high versus low transition risk* (Table 6, Panel A, columns 1 & 2)		*Treatment sample, high versus low transition risk conditional on bank-level disclosure changes (high versus low)* (Table 6, Panel B, columns 1 – 4)			
					High	*Low*	*High*	*Low*
Dependent variables:	*Short-term Loans* (1)	*Long-term Loans* (2)	*Short-term Loans* (3)	*Long-term Loans* (4)	*Short-term Loans* (5)	*Short-term Loans* (6)	*Long-term Loans* (7)	*Long-term Loans* (8)
(1a) *Post* × *Stress-Test Bank*	**0.982**	**1.556**	–	–	–	–	–	–
	(0.95)	**(1.09)**						
(1b) *Post* × *High Transition Risk*	–	–	**-0.062**	**0.257****	**0.138**	**-0.256**	**-0.127**	**0.665*****
			(-0.58)	**(2.31)**	**(1.00)**	**(-1.38)**	**(-0.91)**	**(3.77)**
(2) *Post*	-0.526	-1.353	0.500***	0.094	0.405*	0.761**	0.401**	-0.084
	(-0.50)	(-0.95)	(2.98)	(0.66)	(1.70)	(2.62)	(2.05)	(-0.28)
F-Tests (p-values):								
(1a) + (2) = 0	0.340	0.274						
(1b) + (2) = 0			0.564	0.021	0.317	0.169	0.364	0.000
$(1b)^{High} = (1b)^{Low}$					0.072		0.000	
Borrower-level controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Borrower	YES	YES	YES	YES	YES	YES	YES	YES
Borrower-Country x Year	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,146	7,146	7,122	7,122	3,642	3,480	3,642	3,480
thereof: *Stress-Test Bank* = 1	7,128	7,128	7,122	7,122	3,642	3,480	3,642	3,480
thereof: *High Transition Risk* = 1	n.a.	n.a.	2,358	2,358	1,206	1,152	1,206	1,152
adj. R-sq.	0.358	0.496	0.359	0.498	0.372	0.325	0.510	0.481

Figure 1: Climate Risk Disclosures over Time

The figure plots banks' mean *Climate Disclosure Score* by group and calendar year. We measure the *Climate Disclosure Score* for each bank and year as the percentage of items reported in various bank disclosures (i.e., annual reports, nonfinancial reports such as ESG reports, and Pillar 3 reports) out of the total number of disclosure items recommended by the ECB Supervisory Expectations on Climate Risk Management (ECB, 2020; see also Appendix B for details). The blue line indicates the announcement year of the climate stress tests in the United Kingdom and France (2019), the red line the respective announcement year by the European Central Bank and the European Banking Authority (2020). In Panel A, the sample comprises disclosure data for 230 banks from 40 countries, of which 55 participate in bottom-up climate stress tests. In Panel B, the sample comprises 80 banks from 20 countries with detailed borrower-level lending data, of which 45 are treatment banks. Among the stress test banks, 27 exhibit changes in the *Climate Disclosure Score* around the climate stress tests at or above the sample median.

Panel A: Disclosure Sample



Panel B: Lending Sample

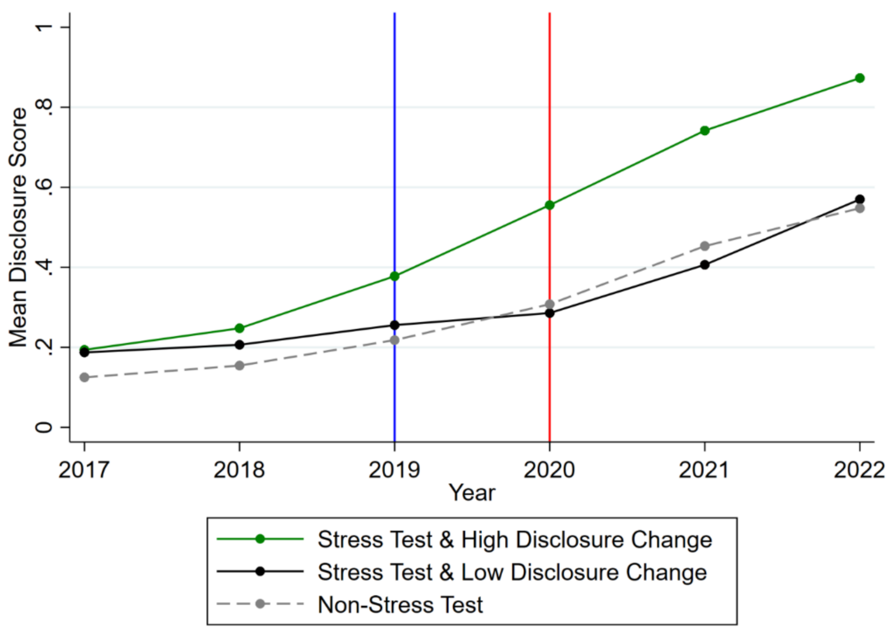


Figure 2: Climate Risk Disclosures around Climate Stress Tests

The figure plots the coefficients (together with the 95% confidence intervals) for *Year x Stress-Test Bank* in event time. Year $t = 0$ represents the announcement year of the first bottom-up climate stress test in which a bank participates. We derive the estimates from our main specification using a stacked linear regression design (i.e., column 4 in Table 3, Panel B), but replace the *Post* indicator variable with separate indicators for each year relative to year $t = 0$. We omit the indicator for period $t - 1$ in the model and do not include year $t + 3$ in the graph as we only have 12 treatment observations for that period. The dependent variable is the *Climate Disclosure Score*.

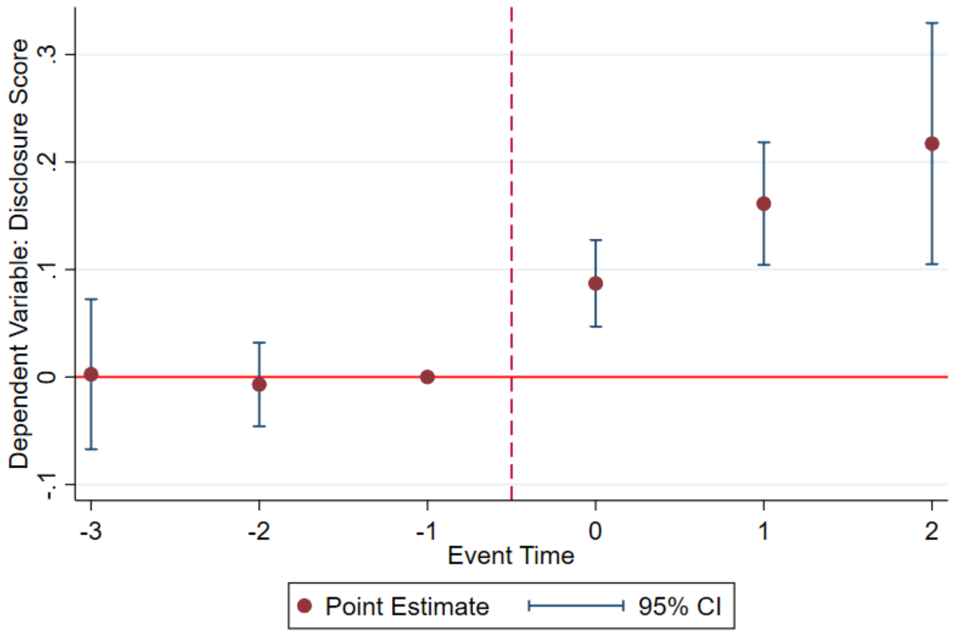


Figure 3: Distribution of Climate Change Transition Risk at the Borrower Level

The figure plots the frequency distribution of the average climate change transition risk for the borrower firms in our sample. We measure a borrower's transition risk in a year as its Scope 1 and 2 carbon *Emission Intensity* (i.e., GHG emissions in metric tons scaled by total sales; source: S&P Trucost), normalized within sample to fall between [0,1] (horizontal axis). We plot the borrower-level means over the sample period in the figure. The blue (red) line indicates the second (third) tercile cutoffs of the distribution.

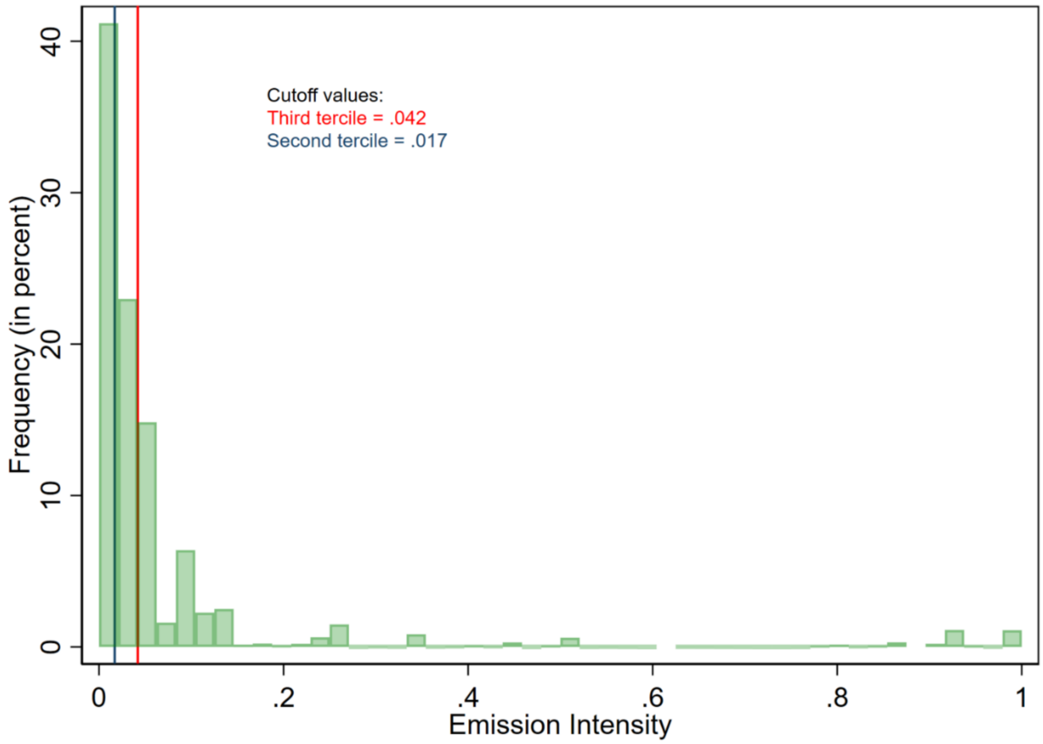


Figure 4: Long-term Loan Maturity Ratio around Climate Stress Tests

The figure plots banks' mean long-term loan maturity ratio by group and event year. We measure the *Long-term Loans$_{BK}$ / Total Loans$_{BK}$* variable for each bank and year at the bank portfolio level by aggregating individual borrowers' lending data. If a borrower's disclosures indicate multiple bank lending relationships, we allocate the loan amounts in equal parts to the respective banks. Year t = 0 represents the announcement year of the first bottom-up climate stress test in which a bank participates (i.e., 2019 for France and the U.K. and 2020 for all the other countries). We do not include year t + 3 in the graph as we only have 9 treatment observations for that period. The sample comprises 80 banks from 20 countries with detailed borrower-level lending data, of which 45 are treatment banks. Among the stress test banks, 27 exhibit changes in the *Climate Disclosure Score* around the climate stress tests at or above the sample median.

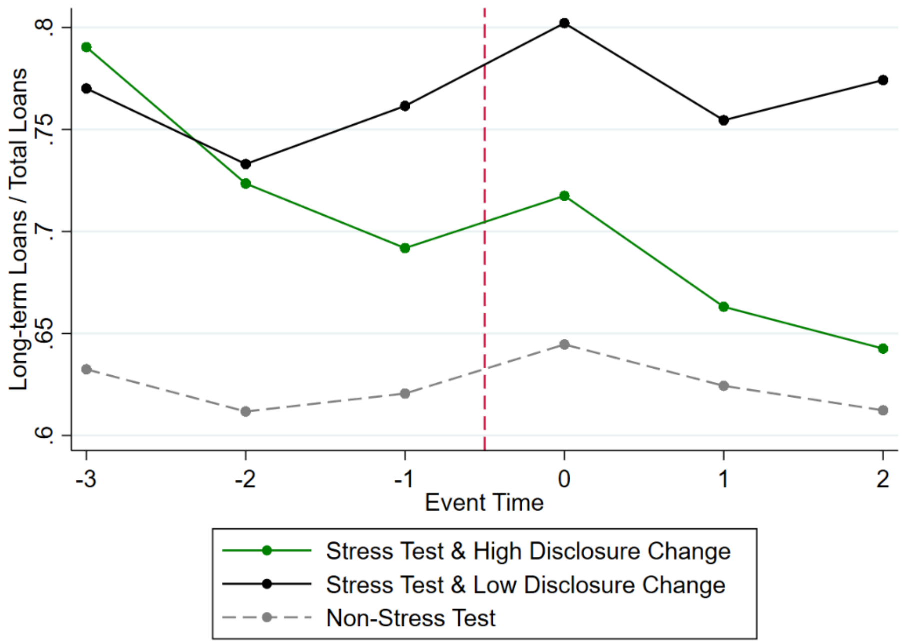
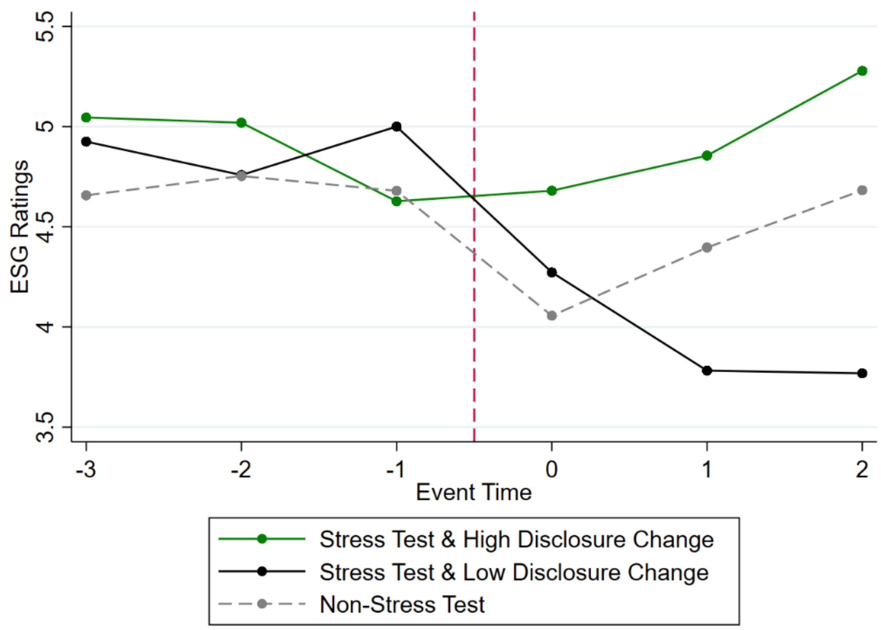


Figure 5: Nonfinancial Performance Measures around Climate Stress Tests

The figure plots banks' mean *ESG Ratings* (Panel A) and mean *Downstream Scope 3 Intensity* (Panel B) by group and event year. We measure *ESG Ratings* as the yearly MSCI aggregate ESG score [0,10], for which higher values represent better ESG performance and lower risk exposure. *Downstream Scope 3 Intensity* is as proxy for GHG emissions from banks' loan portfolio as measured by S&P Trucost. Because Trucost changed its methodology for this variable several times over our sample period, we transform the annual observations into yearly ranks [0,1] before computing means. To increase sample size, we linearly extrapolate or interpolate bank *i*'s missing annual ranks based on its adjacent observations. Lower ranks indicate lower downstream Scope 3 emission intensity. Year $t = 0$ represents the announcement year of the first bottom-up climate stress test in which a bank participates (i.e., 2019 for France and the U.K. and 2020 for all the other countries). We do not include year $t + 3$ in the graph as we only have a maximum of 9 treatment observations for that period. The sample comprises MSCI (S&P Trucost) data for 150 (109) banks from 20 (16) countries, of which 47 (36) are treatment banks. Among the stress test banks, 33 (27) exhibit changes in the *Climate Disclosure Score* around the climate stress tests at or above the sample median.

Panel A: Aggregate ESG Ratings



Panel B: Relative Downstream Scope 3 Intensity (in ranks)

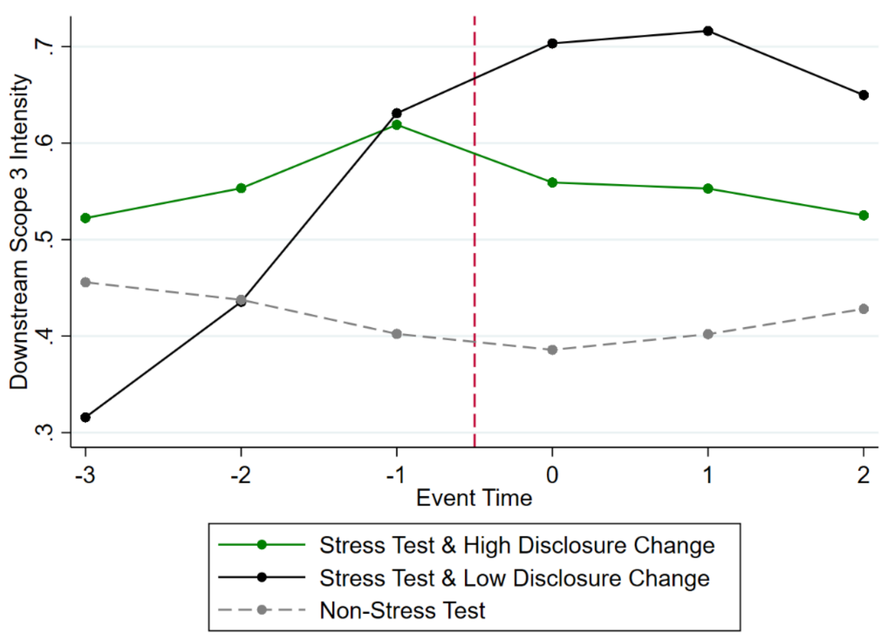


Table 1: Sample Selection and Description

The table provides descriptive information on the various samples used in the analyses. In Panel A, we summarize the sample selection process for the banks and years used in the disclosure analyses. In Panel B, we summarize the sample selection process for the borrowers and years used in the lending analyses. In Panel C, we list the announcement years of the bottom-up climate stress tests in Europe. We also indicate the number of banks that participated in each climate stress test as well as those that were treated for the first time. In Panel D, we list the number and percentages of banks (borrowers) used in the disclosure (lending) analyses by country. Countries with fewer than three banks (and no lending data) are subsumed under *Other Countries*. We mark borrowers as treated if they maintain a lending relationship with at least one stress test bank.

Panel A: Bank-level Disclosure Sample

	# Banks	# Bank-Years
Initial sample of 250 largest European listed banks (2017-2022)	250	1,500
Less: banks with no disclosure data	20	120
Regression sample (no bank controls and fixed effects)	230	1,380
Less: bank-years with missing control variables and singletons	45	410
Final bank-level regression sample (for the disclosure analysis)	185	970
Thereof: bank-years with lending data available	75	407

Panel B: Borrower-level Lending Sample

	# Borrowers	# Borrower-Years
Initial sample with borrower-level emissions data (2017-2022)	266,614	1,599,684
Less: borrowers with missing loan variables	175,903	1,055,418
Less: borrowers with missing control variables	8,978	53,868
Less: borrowers with fiscal year end other than December 31 or from the banking and insurance industry (NACE code section K)	14,394	86,364
Less: singletons	670	5,099
Final borrower-level regression sample (for the lending analysis)	66,669	399,175

Panel C: Announcement Years of Climate Stress Tests

Authority	Announcement Year	# Stress-Test Banks in Disclosure (Lending) Sample	# Stress-Test Banks Treated for First Time in Disclosure (Lending) Sample
Bank of England (U.K. Climate Stress Test)	2019	6 (4)	6 (4)
Banque de France (French Climate Stress Test)	2019	6 (6)	6 (6)
European Banking Authority (EBA Climate Pilot Exercise)	2020	16 (15)	11 (10)
European Central Bank (ECB Climate Stress Test)	2020	48 (33)	32 (18)

(*continued on next page*)

Panel D: Sample Composition by Country

	Disclosure Sample (Bank-level)		Lending Sample (Borrower-level)	
	# Sample Banks (thereof: Treated)	%	# Sample Borrowers (thereof: Treated)	%
Austria	8 (4)	3.48%	714 (597)	1.04%
Croatia	2 (0)	0.87%	18 (17)	0.03%
Cyprus	3 (2)	1.30%	-	-
Denmark	10 (0)	4.35%	1,166 (348)	1.75%
Estonia	2 (0)	0.87%	2 (1)	0.00%
Finland	5 (1)	2.17%	-	-
France	10 (6)	4.35%	8,968 (8,825)	13.45%
Germany	13 (4)	5.65%	3,099 (3,078)	4.65%
Greece	5 (4)	2.17%	29 (29)	0.04%
Hungary	1 (0)	0.43%	1,335 (1,226)	2.00%
Iceland	3 (0)	1.30%	-	-
Ireland	3 (2)	1.30%	226 (216)	0.34%
Italy	22 (10)	9.57%	-	-
Lithuania	1 (1)	0.43%	2 (1)	0.00%
Luxembourg	1 (0)	0.43%	55 (55)	0.08%
Netherlands	2 (2)	0.87%	25 (25)	0.04%
North Macedonia	3 (0)	1.30%	-	-
Norway	17 (0)	7.39%	-	-
Poland	11 (1)	4.78%	2,665 (862)	4.00%
Portugal	1 (1)	0.43%	7,282 (7,282)	10.92%
Romania	3 (0)	1.30%	-	-
Russia	4 (0)	1.74%	-	-
Serbia	1 (0)	0.43%	360 (314)	0.54%
Slovenia	2 (1)	0.87%	169 (128)	0.25%
Spain	7 (6)	3.04%	35,679 (35,679)	53.52%
Sweden	12 (1)	5.22%	-	-
Switzerland	21 (0)	9.13%	-	-
Turkey	12 (0)	5.22%	-	-
United Kingdom	27 (6)	11.74%	4,989 (3,830)	7.35%
Other Countries	18 (3)	7.82%	-	-
Total	230 (55)	100.00%	66,669 (62,490)	100.00%

Table 2: Descriptive Statistics

The table reports the descriptive statistics for the main variables used in the regression analyses. In Panel A, the sample comprises up to 230 banks from 40 countries for which we have disclosure data. In Panel B, the sample comprises up to 66,669 borrowers from 18 countries for which we have detailed borrower-level lending data. In Panel C, the sample comprises up to 80 banks from 20 countries for which we have borrower-level lending data to compute exposure measures on the bank portfolio level. We winsorize all continuous variables at the 1st and 99th percentile to mitigate the influence of outliers. For variable definitions and details see Appendix A.

Panel A: Bank-level Disclosure Sample

	N	Mean	SD	P25	P50	P75
Dependent variable:						
Climate Disclosure Score [0,1]	1380	0.25	0.26	0.00	0.20	0.41
Independent variables:						
Stress-Test Bank (indicator)	1380	0.24	0.43	0.00	0.00	0.00
Post (indicator)	1380	0.53	0.50	0.00	1.00	1.00
Bank-level controls:						
Total Assets$_{BK}$ (ln, EUR mil.)	970	23.87	2.13	22.43	23.86	25.08
ROE$_{BK}$ (%)	970	0.09	0.09	0.05	0.08	0.13
Interest Income$_{BK}$ (%)	970	0.56	0.24	0.45	0.60	0.72
Cost/Income Ratio$_{BK}$ (%)	970	0.59	0.17	0.49	0.60	0.70

Panel B: Borrower-level Lending Sample

	N	Mean	SD	P25	P50	P75
Dependent variables:						
Short-term Loans (ln, EUR mil.)	337,670	12.87	2.43	11.54	13.01	14.41
Long-term Loans (ln, EUR mil.)	358,901	13.40	2.20	12.10	13.35	14.67
Total Loans (ln, EUR mil.)	399,175	13.88	2.33	12.63	13.93	15.27
Long-term Loans / Total Loans (%)	399,175	0.60	0.35	0.32	0.68	0.92
Δ Long-term Loans (%)	355,037	0.73	3.92	-0.28	-0.07	0.21
Δ Total Assets (%)	397,872	0.08	0.21	-0.04	0.04	0.15
Δ Fixed Assets (%)	395,746	0.02	0.10	-0.02	0.00	0.03
Δ Fixed Tangible Assets (%)	388,344	0.01	0.07	-0.01	0.00	0.02
Δ NWC (%)	388,396	0.02	0.12	-0.03	0.01	0.06
Δ Sales (%)	386,912	0.10	0.34	-0.05	0.06	0.19
Independent variables:						
Stress-Test Bank (indicator)	399,175	0.94	0.24	1.00	1.00	1.00
Post (indicator)	399,175	0.54	0.50	0.00	1.00	1.00
Emission Intensity [0,1]	399,175	0.08	0.17	0.02	0.03	0.06
High Transition Risk (indicator)	399,175	0.33	0.47	0.00	0.00	1.00
Borrower-level controls:						
Leverage$_{BOR}$ (%)	399,175	0.91	0.13	0.90	0.97	0.99
ROA$_{BOR}$ (%)	399,175	0.05	0.10	0.01	0.04	0.09
Total Assets$_{BOR}$ (ln, EUR mil.)	399,175	15.90	1.66	14.70	15.68	16.84

(*continued on next page*)

Panel C: Bank Portfolio-level Lending Sample

	N	Mean	SD	P25	P50	P75
Dependent variables:						
Short-term Loans$_{BK}$ (ln, EUR mil.)	480	19.80	3.16	18.12	19.98	21.94
Long-term Loans$_{BK}$ (ln, EUR mil.)	473	20.78	3.29	19.09	21.30	23.18
Total Loans$_{BK}$ (ln, EUR mil.)	480	21.16	3.20	19.38	21.62	23.41
Long-term Loans$_{BK}$ / Total Loans$_{BK}$ (%)	480	0.68	0.21	0.58	0.71	0.84
Δ *Long-term Loans$_{BK}$* (%)	473	-0.18	0.33	-0.42	-0.17	-0.01
ESG Ratings [0,10]	342	4.83	1.37	4.50	5.00	5.50
Environmental Impact Scores [0,10]	342	4.75	1.81	3.90	5.10	6.20
Environmental Costs (% of revenue)	310	0.29	0.05	0.26	0.28	0.30
Downstream Scope 3 Intensity [0,1]	276	0.47	0.29	0.24	0.37	0.76
Independent variables:						
Stress-Test Bank (indicator)	480	0.56	0.50	0.00	1.00	1.00
Post (indicator)	480	0.54	0.50	0.00	1.00	1.00
High Disclosure Change (indicator)	480	0.50	0.50	0.00	0.50	1.00
Bank-level controls:						
Total Assets$_{BK}$ (ln, EUR mil.)	409	25.24	1.90	23.96	25.09	26.86
ROE$_{BK}$ (%)	409	0.06	0.07	0.04	0.07	0.11
Interest Income$_{BK}$ (%)	408	0.56	0.14	0.48	0.57	0.66
Cost/Income Ratio$_{BK}$ (%)	408	0.63	0.15	0.54	0.62	0.70

Table 3: Bank-level Climate Risk Disclosures following Climate Stress Tests (Full Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from regressions of the *Climate Disclosure Score* on the interaction term *Post* x *Stress-Test Bank*, the main effects, and various controls. We construct the *Climate Disclosure Score* for each bank and year as the percentage of items reported in various bank disclosures (i.e., annual reports, nonfinancial reports such as ESG reports, and Pillar 3 reports) out of the total number of disclosure items recommended by the ECB Supervisory Expectations on Climate Risk Management (ECB, 2020; see also Appendix B). *Post* is an indicator variable marking the years of and following the first announcement of a bottom-up climate stress test in a country. That is, in France and the U.K., we set *Post* = 1 beginning in 2019 (i.e., the year of the national stress tests). In all the other countries, we set *Post* = 1 beginning in 2020 (i.e., the year of the supranational stress tests). *Stress-Test Bank* is an indicator for banks participating in these stress tests. The sample comprises up to 1,380 bank-year observations from 40 countries over the 2017 to 2022 period. The bank-level controls are $Total\ Assets_{BK}$, ROE_{BK}, $Interest\ Income_{BK}$, and $Cost/Income\ Ratio_{BK}$. For variable definitions, see Appendix A. In Panel A, we use a staggered difference-in-differences design in calendar time. In Panel B, we use a stacked difference-in-differences design as described in Barrios (2021) and Cengiz et al. (2019). For each of the two treatment cohorts (U.K./France and EBA/ECB), we create a separate dataset including the banks treated in the respective year as well as either all control banks (columns 1 to 4) or only those domiciled in the same countries as the treatment banks that never participated in a stress test (column 5). We then combine these cohort-specific datasets to run our analysis. In these tests, we set *Post* = 1 beginning in 2019 or 2020 depending on whether the national or supranational stress tests define the treatment cohort. We include an intercept and fixed effects (as indicated) in the models, but do not report the coefficients. We assess statistical significance based on robust standard errors clustered by country of banks' headquarters and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Panel A: Staggered Difference-in-Differences Tests

	Dependent variable: *Climate Disclosure Score*			
	(1)	(2)	(3)	(4)
Post x Stress-Test Bank	**0.175*****	**0.165*****	**0.185*****	**0.151*****
	(5.23)	**(4.20)**	**(6.00)**	**(4.63)**
Post	0.173***	0.160***	-0.071*	–
	(9.30)	(7.12)	(-1.91)	
Stress-Test Bank	0.104***	-0.074	–	–
	(3.82)	(-1.68)		
Bank-level controls:				
$Total\ Assets_{BK}$	–	0.060***	0.010	-0.040
		(7.95)	(0.29)	(-0.94)
ROE_{BK}	–	0.325**	-0.001	0.081
		(2.70)	(-0.01)	(1.59)
$Interest\ Income_{BK}$	–	0.099**	0.123	-0.000
		(2.09)	(1.20)	(-0.00)
$Cost/Income\ Ratio_{BK}$	–	0.038	-0.042	-0.034
		(0.56)	(-0.48)	(-0.55)
Fixed effects:				
Bank	NO	NO	YES	YES
Year	NO	NO	YES	NO
Bank-Country x Year	NO	NO	NO	YES
Observations	1,380	970	970	970
thereof treated	330	280	280	280
adj. R-sq.	0.307	0.462	0.803	0.837

(*continued on next page*)

Panel B: Stacked Difference-in-Differences Tests

	Dependent variable: *Climate Disclosure Score*				
	(1)	(2)	(3)	(4)	(5)
Post x Stress-Test Bank	**0.184*****	**0.173*****	**0.178*****	**0.152*****	**0.157*****
	(5.34)	**(4.47)**	**(5.72)**	**(4.80)**	**(4.79)**
Post	0.163***	0.152***	–	–	–
	(12.03)	(9.00)			
Stress-Test Bank	0.109***	-0.071**	–	–	–
	(4.62)	(-2.01)			
Benchmark Banks	All	All	All	All	Same Country
Bank-level controls	NO	YES	YES	YES	YES
Fixed effects:					
Cohort x Bank	NO	NO	YES	YES	YES
Cohort x Year	NO	NO	YES	NO	NO
Cohort x Bank-Country x Year	NO	NO	NO	YES	YES
Observations	2,430	1,641	1,641	1,641	577
thereof treated	330	280	280	280	280
adj. R-sq.	0.241	0.427	0.793	0.827	0.862

Table 4: Cross-sectional Analyses of Climate Risk Disclosures (Treatment Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from estimating variations of our base specification (see Table 3, Panel A, column 3) for the subset of stress test banks in our sample. Specifically, we interact the *Post* variable with various bank characteristics (*PART*) to examine how the *Climate Disclosure Score* varies across treatment banks. In Panel A, we use proxies for management's commitment to ESG issues and the ease of data collection of borrowers' climate risk. That is, we code *PART* equal to '1' (and '0' otherwise) if bank *i* has (1) published a comprehensive *ESG Report* (measured by page count at or above the treatment sample median), (2) a designated *ESG Committee* on its board, (3) issued an *SDG 13 Pledge* to commit to urgent climate action, (4) superior *ESG Ratings* (measured by MSCI ESG scores at or above the treatment sample median), or (5) more *Emissions Data* readily available (measured by an at or above treatment sample median share of loans with borrower-level data on Scope 1 and 2 GHG emissions in S&P Trucost). In Panel B, we use proxies for a bank's exposure to climate risk and the market pressure to offer ESG products. That is, we code *PART* equal to '1' (and '0' otherwise) if bank *i*'s (1) *Downstream Scope 3 Intensity* as proxy for GHG emissions from its loan portfolio (source: S&P Trucost), (2) overall attention to climate change topics as extracted from earnings calls (*Earnings Call Attention*; source: Sautner et al., 2023), (3) ownership shares held by *ESG Investors* (based on the S&P classification of institutional investors), or (4) the number of *ESG Fund Launches* over the last five years (source: Refinitiv) rank at or above the treatment sample median. In column 5, we set *PART* equal to the natural logarithm of the *Green Bond Volume* issued by bank *i* over the last five years (source: Refinitiv). We code these partitioning variables as of 2017 (our first sample year) or as the average over the pre-stress test period (i.e., in Panel A, column 4, and Panel B, column 2) to identify banks with an early (voluntary) focus on ESG issues. For detailed variable definitions see Appendix A. We include an intercept, the full set of controls, and fixed effects (as indicated) in the models, but do not report the coefficients. We assess statistical significance based on robust standard errors clustered by country of banks' headquarters and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Panel A: Management Commitment to ESG Issues and Availability of Borrower-level Emissions Data

Partitioning Variables (*PART*):	*ESG Report*	*ESG Committee*	*SDG13 Pledge*	*ESG Ratings*	*Emissions Data*
	(1)	(2)	(3)	(4)	(5)
(1) *Post*	0.099*	0.108**	0.041	0.036	0.080
	(1.80)	(2.65)	(1.25)	(1.54)	(1.92)
(2) *Post x PART*	**0.074***	**0.066***	**0.099**	**0.099****	**0.046***
	(2.01)	**(1.75)**	**(1.45)**	**(2.16)**	**(1.85)**
F-Test (p-value): (1) + (2) = 0	.000	.000	.060	.006	.005
Bank-level controls	YES	YES	YES	YES	YES
Fixed effects:					
Bank	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Year x PART	YES	YES	YES	YES	YES
Observations	291	291	238	234	261
thereof *PART* = 1	110	50	148	126	121
adj. R-sq.	0.837	0.839	0.858	0.849	0.835

(*continued on next page*)

Panel B: Bank Exposure to Climate Risk and Market Pressure for ESG Products

Partitioning Variables (*PART*):	*Downstream Scope 3 Intensity*	*Earnings Call Attention*	*ESG Investors*	*ESG Fund Launches*	*Green Bond Volume*
	(1)	(2)	(3)	(4)	(5)
(1) *Post*	-0.065	0.015	0.079***	-0.060	0.083
	(-1.72)	(0.81)	(5.00)	(-1.92)	(1.41)
(2) *Post x PART*	**0.175****	**0.150*****	**0.001**	**0.178*****	**0.003**
	(2.97)	**(4.23)**	**(0.02)**	**(3.22)**	**(0.99)**
F-Test (p-value): (1) + (2) = 0	.043	.000	.265	.030	.146
Bank-level controls	YES	YES	YES	YES	YES
Fixed effects:					
Bank	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Year x PART	YES	YES	YES	YES	YES
Observations	216	230	231	178	291
thereof *PART* = 1	154	118	137	89	n.a.
adj. R-sq.	0.861	0.848	0.859	0.864	0.854

Table 5: Borrower-level Debt Financing Effects following Climate Stress Tests (Full Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from regressions of individual borrowers' loan characteristics on the interaction term *Post* x *Stress-Test Bank,* the main effects, and various controls. The dependent variables are the amounts of *Short-term Loans*, *Long-term Loans*, and *Total Loans* outstanding (each transformed using the natural logarithm). In column 4, we use the long-term loans scaled by total loans and, in column 5, the percentage change (Δ) in long-term loans as dependent variables. *Post* is an indicator variable marking bank relationships in the years of and following the first announcement of a bottom-up climate stress test in a country. *Stress-Test Bank* is an indicator for borrowers with at least one lending relationship with a bank participating in these stress tests. The sample comprises up to 399,175 borrower-year observations from 18 countries over the 2017 to 2022 period. The borrower-level controls are $Leverage_{Bor}$, ROA_{Bor}, and $Total\ Assets_{Bor}$. For variable definitions, see Appendix A. We include an intercept and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *Stress Test Bank* is subsumed by the *Borrower* fixed effects. We assess statistical significance based on robust standard errors clustered by country of banks' headquarters and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Dependent variables:	*Short-term Loans*	*Long-term Loans*	*Total Loans*	*Long-term Loans / Total Loans*	*Δ Long-term Loans*
	(1)	(2)	(3)	(4)	(5)
(1) *Post x Stress-Test Bank*	**-0.022**	**-0.017**	**-0.017**	**0.004**	**-0.044**
	(-1.21)	**(-0.83)**	**(-0.55)**	**(0.75)**	**(-0.81)**
(2) *Post*	-0.022	0.059*	0.023	0.011	0.134*
	(-0.93)	(2.10)	(1.04)	(1.35)	(2.07)
Borrower-level controls:					
$Leverage_{BOR}$	0.755***	0.966***	1.112***	0.045***	1.554***
	(5.23)	(15.44)	(14.08)	(5.67)	(12.14)
ROA_{BOR}	-1.775***	-1.629***	-1.961***	-0.004	-2.659***
	(-26.55)	(-18.67)	(-69.85)	(-0.20)	(-7.88)
$Total\ Assets_{BOR}$	1.113***	1.203***	1.227***	0.016	0.797***
	(21.19)	(36.87)	(32.36)	(1.23)	(18.42)
F-Test (p-value): (1) + (2) = 0	.014	.092	.705	.118	.122
Fixed effects:					
Borrower	YES	YES	YES	YES	YES
Borrower-Country x Year	YES	YES	YES	YES	YES
Observations	336,067	357,847	399,175	399,175	353,979
thereof: treated	311,870	339,209	374,140	374,140	335,791
adj. R-sq.	0.823	0.849	0.867	0.677	0.011

Table 6: Cross-sectional Analyses of Borrower-level Debt Financing Effects (Treatment Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from estimating variations of the models in Table 5 for the subset of borrowers with at least one lending relationship with a stress-test bank in our sample (i.e., up to 374,128 borrower-year observations from 16 countries). In Panel A, we interact the *Post* variable with a binary indicator (*High Transition Risk*) to examine how the debt financing effects vary across borrowers with high and low climate change transition risk. Specifically, we code *High Transition Risk* equal to "1" (and "0" otherwise) if borrower *i*'s Scope 1 and 2 carbon *Emission Intensity* score in year *t* falls into the top tercile of the overall sample distribution (see also Figure 3). In Panel B, we run this analysis separately for borrowers with lending relationships to stress-test banks that report at or above (*High*) or below (*Low*) median changes in the *Climate Disclosure Score* around the climate stress tests. We also indicate *p*-values from F-tests comparing coefficients across subsamples. For detailed variable definitions see Appendix A. We include an intercept, the full set of controls, and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *High Transition Risk* is subsumed by the *Borrower* fixed effects. We assess statistical significance based on robust standard errors clustered by country of banks' headquarters and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Panel A: Partitioning by (Borrower-level) Climate Change Transition Risk

Dependent variables:	*Short-term Loans*	*Long-term Loans*	*Total Loans*	*Long-term Loans / Total Loans*	*Δ Long-term Loans*
	(1)	(2)	(3)	(4)	(5)
(1) *Post x High Transition Risk*	**0.014**	**-0.078****	**-0.026**	**-0.014*****	**-0.101****
	(1.75)	**(-2.36)**	**(-1.26)**	**(-3.33)**	**(-2.16)**
(2) *Post*	-0.036	0.077**	0.027	0.020*	0.102**
	(-1.39)	(2.37)	(1.54)	(1.89)	(2.89)
F-Test (p-value): (1) + (2) = 0	.351	.910	.960	.417	.992
Borrower-level Controls	YES	YES	YES	YES	YES
Fixed effects:					
Borrower	YES	YES	YES	YES	YES
Borrower-Country x Year	YES	YES	YES	YES	YES
Observations	311,858	339,197	374,128	374,128	335,779
thereof: *High Transition Risk* = 1	102,485	111,704	121,143	121,143	110,751
adj. R-sq.	0.820	0.849	0.866	0.669	0.011

(*continued on next page*)

Panel B: Partitioning by (Borrower-level) Climate Change Transition Risk and (Bank-level) Disclosure Change around Climate Stress Tests

Dependent variables:	*Short-term Loans*		*Long-term Loans*		*Total Loans*		*Long-term Loans / Total Loans*		*Δ Long-term Loans*	
Bank-level disclosure change:	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Post x High Transition Risk*	**0.028****	**-0.000**	**-0.100*****	**-0.053**	**-0.039****	**-0.011**	**-0.019*****	**-0.009***	**-0.169*****	**-0.025**
	(3.11)	**(-0.02)**	**(-3.49)**	**(-1.55)**	**(-2.51)**	**(-0.45)**	**(-6.36)**	**(-1.98)**	**(-5.86)**	**(-0.51)**
(2) *Post*	-0.094	-0.010	0.059*	0.073*	-0.021	0.037	0.026	0.015	0.219	0.066
	(-1.04)	(-0.33)	(2.17)	(1.91)	(-0.97)	(1.71)	(1.18)	(1.38)	(0.72)	(1.03)
F-Tests (p-values):										
(1) + (2) = 0	.473	.679	.221	.322	.049	.293	.740	.473	.876	.523
$(1)^{High} = (1)^{Low}$	.010		.000		.000		.000		.000	
Borrower-level controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:										
Borrower	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower-Country x Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	156,823	155,021	180,984	158,211	192,725	181,399	192,725	181,399	179,364	156,415
thereof: *High Transition Risk* = 1	50,897	51,588	58,190	53,514	61,441	59,702	61,441	59,702	57,764	52,987
adj. R-sq.	0.807	0.826	0.834	0.859	0.858	0.870	0.655	0.676	0.015	0.007

Table 7: Cross-sectional Analyses of Borrower-level Real Effects following Climate Stress Tests (Treatment Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from regressions of individual borrowers' operating and investment characteristics on the interaction term *Post* x *High Transition Risk* for the subset of borrowers with at least one lending relationship with a stress-test bank in our sample (analogous to Table 6, Panel B). The dependent variables are the percentage changes (Δ) in *Total Assets*, *Fixed Assets*, *Fixed Tangible Assets*, *NWC* (i.e., net working capital equal to inventories plus accounts receivable minus accounts payable), and *Sales*. *Post* is an indicator variable marking bank relationships in the years of and following the first announcement of a bottom-up climate stress test in a country. We code *High Transition Risk* equal to "1" (and "0" otherwise) if borrower *i*'s Scope 1 and 2 carbon *Emission Intensity* score in year *t* falls into the top tercile of the overall sample distribution (see also Figure 3). We run this analysis separately for borrowers with lending relationships to stress-test banks that report at or above (*High*) or below (*Low*) median changes in the *Climate Disclosure Score* around the climate stress tests. We also indicate *p*-values from F-tests comparing coefficients across subsamples. For detailed variable definitions see Appendix A. We include an intercept, the full set of controls, and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *High Transition Risk* is subsumed by the *Borrower* fixed effects. We assess statistical significance based on robust standard errors clustered by country of banks' headquarters and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Dependent variables:	*Δ Total Assets*		*Δ Fixed Assets*		*Δ Tangible Fixed Assets*		*Δ NWC*		*Δ Sales*	
Bank-level disclosure change:	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Post x High Transition Risk*	**0.005*** **	**0.013*** **	**-0.004*** **	**0.000**	**-0.005*** **	**-0.001**	**0.007*** **	**0.004** **	**0.015*** **	**0.025*** **
	(8.56)	**(5.17)**	**(-8.85)**	**(0.04)**	**(-24.88)**	**(-0.75)**	**(12.64)**	**(2.64)**	**(6.43)**	**(4.80)**
(2) *Post*	0.005	-0.014**	0.005	-0.002	0.007	-0.002	0.005	0.003	0.029*	-0.017
	(0.48)	(-2.67)	(0.37)	(-0.51)	(0.68)	(-0.81)	(0.73)	(0.93)	(2.00)	(-1.12)
F-Tests (p-values):										
(1) + (2) = 0	.345	.767	.983	.644	.827	.339	.130	.066	.006	.534
$(1)^{High} = (1)^{Low}$	.000		.000		.000		.002		.000	
Borrower-level controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:										
Borrower	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower-Country x Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	192,106	180,805	191,453	179,545	187,907	176,112	191,393	177,227	189,973	173,826
thereof: *High Transition Risk* = 1	61,245	59,502	61,117	59,248	60,308	58,506	61,051	58,328	60,648	57,369
adj. R-sq.	0.209	0.216	0.114	0.132	0.122	0.144	0.015	0.009	0.094	0.099

Table 8: Bank Portfolio-level Loan Exposure Effects following Climate Stress Tests (Full Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from regressions of banks' loan exposure on the interaction term *Post* x *Stress-Test Bank,* the main effects, and various controls. We use the same dependent variables as in Table 5 but compute them for each bank and year at the bank portfolio level by aggregating individual borrowers' lending data. For instance, in columns 1 and 2, we sum the *Short-term Loans* of bank *i*'s individual borrowers in a year and take the natural logarithm. If a borrower's disclosures indicate multiple bank lending relationships, we allocate the loan amounts in equal parts to the respective banks. *Post* is an indicator variable marking the years of and following the first announcement of a bottom-up climate stress test in a country. *Stress-Test Bank* is an indicator for banks participating in these stress tests. The sample comprises up to 480 bank-year observations from 20 countries over the 2017 to 2022 period. The bank-level controls are *Total Assets$_{BK}$*, *ROE$_{BK}$*, *Interest Income$_{BK}$*, and *Cost/Income Ratio$_{BK}$*. For variable definitions, see Appendix A. We include an intercept and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *Stress Test Bank* is subsumed by the *Bank* fixed effects. We assess statistical significance based on robust standard errors and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Dependent variables:	*Short-term Loans$_{BK}$*		*Long-term Loans$_{BK}$*		*Total Loans$_{BK}$*		*Long-term Loans$_{BK}$ / Total Loans$_{BK}$*		*Δ Long-term Loans$_{BK}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Post x Stress-Test Bank*	**0.120**	**0.059**	**0.053**	**0.042**	**0.109****	**0.084***	**-0.024**	**-0.018**	**0.072**	**0.069**
	(1.35)	**(0.74)**	**(0.84)**	**(0.86)**	**(2.19)**	**(1.90)**	**(-1.22)**	**(-1.08)**	**(1.43)**	**(1.14)**
(2) *Post*	-0.005	-0.113	0.013	0.013	0.018	-0.041	0.011	0.041	-0.062	0.053
	(-0.08)	(-0.95)	(0.29)	(0.17)	(0.44)	(-0.76)	(0.74)	(1.42)	(-1.53)	(0.43)
Bank-level controls:										
Total Assets$_{BK}$	–	-0.255*	–	0.199	–	-0.166**	–	0.044	–	-0.012
		(-1.76)		(0.77)		(-2.35)		(1.12)		(-0.09)
ROE$_{BK}$	–	0.624*	–	-0.546*	–	-0.096	–	-0.198**	–	-0.114
		(1.70)		(-1.75)		(-0.57)		(-2.13)		(-0.34)
Interest Income$_{BK}$	–	1.148***	–	0.045	–	0.354**	–	-0.154**	–	-0.853
		(3.03)		(0.28)		(2.49)		(-2.11)		(-1.44)
Cost/Income Ratio$_{BK}$	–	-0.042	–	-0.414	–	0.065	–	-0.073	–	0.120
		(-0.14)		(-1.14)		(0.39)		(-1.03)		(0.46)
F-Test (p-value): (1) + (2) = 0	.049	.644	.127	.366	.000	.423	.315	.413	.739	.314
Fixed effects:										
Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	480	407	473	400	480	407	480	407	472	399
thereof treated	270	238	270	238	270	238	270	238	269	237
adj. R-sq.	0.978	0.983	0.990	0.995	0.994	0.995	0.739	0.834	0.355	0.388

Table 9: Cross-sectional Analyses of Bank Portfolio-level Loan Exposure Effects (Treatment Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from estimating variations of the models in Table 8 for the subset of stress test banks in our sample (i.e., up to 270 bank-year observations from 15 countries). We interact the *Post* variable with a binary indicator (*High Disclosure Change*) to examine how the loan exposure effects vary across banks that report at or above (equal to "1") or below ("0") median changes in the *Climate Disclosure Score* around the climate stress tests. For detailed variable definitions see Appendix A. We include an intercept, the full set of controls, and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *High Disclosure Change* is subsumed by the *Bank* fixed effects. We assess statistical significance based on robust standard errors and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Dependent variables:	*Short-term Loans$_{BK}$*		*Long-term Loans$_{BK}$*		*Total Loans$_{BK}$*		*Long-term Loans$_{BK}$ / Total Loans$_{BK}$*		*Δ Long-term Loans$_{BK}$*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Post x High Disclosure Change*	**0.344*** **	**0.202***	**-0.162****	**-0.128****	**0.031**	**-0.044**	**-0.078*****	**-0.046***	**-0.003**	**0.043**
	(3.17)	**(1.68)**	**(-2.09)**	**(-2.39)**	**(0.57)**	**(-0.76)**	**(-3.23)**	**(-1.94)**	**(-0.05)**	**(0.53)**
(2) *Post*	-0.092	-0.300*	0.164***	0.183**	0.108***	0.054	0.034**	0.076*	0.012	0.083
	(-1.30)	(-1.79)	(4.09)	(2.20)	(3.40)	(0.76)	(2.20)	(1.77)	(0.25)	(0.44)
F-Test (p-value): (1) + (2) = 0	.002	.539	.985	.411	.002	.900	.018	.440	.822	.421
Bank-level controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Fixed effects:										
Bank	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	270	238	270	238	270	238	270	238	269	237
thereof: *High Discl. Change* = 1	162	149	162	149	162	149	162	149	161	148
adj. R-sq.	0.979	0.981	0.989	0.997	0.995	0.994	0.675	0.744	0.367	0.412

Table 10: Cross-sectional Analyses of Bank-level Nonfinancial Performance Measures following Climate Stress Tests (Treatment Sample)

The table reports OLS coefficient estimates and (in parentheses) *t*-statistics from regressions of individual banks' nonfinancial performance metrics on the interaction term *Post* x *High Disclosure Change* for the subset of stress test banks in our sample (i.e., up to 194 bank-year observations from 14 countries), analogous to Table 9. We use the following dependent variables: (1) *ESG Ratings* are bank *i*'s yearly aggregate ESG scores as published by MSCI [0,10]. Higher values represent better ESG performance and lower risk exposure. (2) *Environmental Impact Scores* are yearly measures for bank *i*'s exposure to adverse environmental impacts through its lending portfolio as published by MSCI [0,10]. Lower values represent less environmental risk exposure. (3) *Environmental Costs* measure bank *i*'s overall environmental costs incurred through its business activities in a year (in percent of revenue; source: S&P Trucost). Lower values represent lower cost. (4) *Downstream Scope 3 Intensity* is as proxy for bank *i*'s GHG emissions from its loan portfolio as measured by S&P Trucost. Because Trucost changed its methodology for this variable several times over our sample period, we transform the annual observations into percentile ranks [0,1]. To increase sample size, we linearly extrapolate or interpolate bank *i*'s missing ranks based on its adjacent observations. Lower ranks indicate lower downstream Scope 3 emission intensity. For detailed variable definitions see Appendix A. We include an intercept, the full set of controls, and fixed effects (as indicated) in the models, but do not report the coefficients. The main effect of *High Disclosure Change* is subsumed by the *Bank* fixed effects. We assess statistical significance based on robust standard errors and indicate significance at the 1%, 5%, and 10% levels (two-tailed) with ***, **, and *.

Dependent variables:	*ESG Ratings*		*Environmental Impact Scores*		*Environmental Costs*		*Downstream Scope 3 Intensity*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) *Post x High Disclosure Change*	**0.943****	**0.955****	**-0.959****	**-0.913***	**-0.024**	**-0.024***	**-0.215*****	**-0.228*****
	(2.51)	**(2.31)**	**(-2.03)**	**(-1.72)**	**(-1.56)**	**(-1.69)**	**(-3.33)**	**(-3.37)**
(2) *Post*	-0.800**	-0.995	-0.781**	2.159***	0.006	0.013	0.196***	0.038
	(-2.48)	(-1.43)	(-2.14)	(3.03)	(0.41)	(0.64)	(4.51)	(0.37)
F-Test (p-value): (1) + (2) = 0	.460	.948	.000	.064	.000	.445	.692	.045
Bank-level controls	NO	YES	NO	YES	NO	YES	NO	YES
Fixed effects:								
Bank	YES	YES	YES	YES	YES	YES	YES	YES
Year	NO	YES	NO	YES	NO	YES	NO	YES
Observations	194	194	194	194	172	172	151	151
thereof: *High Discl. Change* = 1	131	131	131	131	119	119	109	109
adj. R-sq.	0.205	0.202	0.265	0.372	0.399	0.546	0.414	0.432