Who Bears the Transition Risk? Uneven Climate Risk Assessment of SMEs Across German Banking Groups*

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Abstract

In October 2018, the Network for Greening the Financial System (NGFS), founded by eight central banks and financial supervisors, declared that climate risks are financial risks. Using German loan-level data and a dynamic event-study difference-in-differences design, we show that this declaration marks the beginning of a shift in banks' treatment of transition risk: German banks subsequently increased risk weights for loans to carbon-intensive firms, measured as the ratio of risk-weighted assets to loan value. Three main results emerge. First, adjustments are uneven: large and private banks increase risk weights, whereas savings and cooperative banks expand lending to carbon-intensive firms without adjusting risk assessments. Second, private banks increase risk weights for carbon-intensive small and medium enterprises (SME), but not for large firms. Third, banks rely on sector-level rather than firm-level metrics, mispricing loans by over-penalising low-risk firms in high-emission sectors. Overall, German banks only partially integrate transition risks, creating systemic blind spots and tightening SME financing.

Keywords: Banks, banking groups, transition risks, SME credit exposure

JEL classification: G21, G32, G28, Q54, L25.

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1 Introduction

This paper examines how private, savings, and cooperative banks in Germany account for climate transition risks in their credit exposures. We focus particular on lending to small and medium-sized enterprises (SMEs), which make up more than 99% of German firms, generate over 47% of value added, and account for around 40% of business sector emissions (OECD (2024)). The transition to a low-emission economy creates both opportunities and costs (Acemoglu *et al.* (2012), Cline (2021)). Policies such as carbon pricing or technology bans can make existing business models unprofitable and pose risks to financial stability (NGFS (2019)). Firms with high transition exposure face higher credit risk, reflected in bond spreads and financing costs (Chava (2014), Delis *et al.* (2024)). However, evidence largely centres on large banks (significant institutions (SIs)) and large firms, mostly in the United States or in European Union (EU)-wide contexts. How smaller banks (less significant institutions (LSIs)) and SME borrowers manage transition risks remains unclear, despite their central role in Europe's bank-based system.

Using granular German credit-level data covering all banks and their firm borrowers[1], we employ an event-study difference-in-differences (DiD) design to examine banks' risk assessments. We show that following the 2018 Network of Greening the Financial System (NGFS) progress report, which emphasised that climate risks are financial risks, German banks increased risk weights for exposures to carbon-intensive firms. We define risk weights as the ratio of risk-weighted assets to exposure value and capture both changes in perceived credit risk and portfolio composition. Germany provides a particularly relevant setting: its banking sector faces substantial transition risks (D'Orazio, Hertel, and Kasbrink (2024); Gross *et al.* (2025)) and exhibits institutional diversity, comprising large private banks, cooperative banks, and municipally owned savings banks.

We find that firms in climate policy-relevant sectors (CPRS), as defined by Battiston, Mandel, *et al.* (2017), experienced a significant 2.77 percentage-point (pp) increase in risk weights relative to less-exposed firms. A 2.77 percentage-point increase in risk weights raises risk-weighted assets by €2.77 per €100 exposure. Under the Basel III total capital requirement, including buffers (10.5% of RWA) (BIS (2019b), BIS (2019c)), this implies an additional capital requirement of approximately €0.29 per €100 exposure. Compared with the average annual capital growth of about 5.2% observed for German banks in 2022 (Deutsche Bundesbank (2023)), the implied adjustment appears noticeable but moderate relative to typical annual capital accumulation. This adjustment is driven entirely by private banks, while cooperative and savings banks show no response. Within private banks, SMEs experience larger increases (4.5 pp) than large firms (1.3 pp, not statistically significant). In our interpretation, the surprising finding that risk weights rose for SME exposure might be due to a lack of appropriate, granular data (Koirala (2019)) and, hence, challenges in calibrating risk models. We further disentangle the risk weight channels by comparing movements in total credit and risk-weighted assets. All bank groups expand credit volumes to carbon-intensive firms. At the same time, private banks raise risk-weighted assets disproportionately, particularly for SME exposures. They therefore increase risk weights by assigning higher risk-weighted assets to their exposures rather than by contracting their portfolios. We also explore how bank characteristics, such as capital buffers, size, and exposure to transition risks, moderate these

[1] Although the MiO database that we use (see Section 2.2 reports exposures at the credit level, this notion corresponds to total borrower exposure under §14 KWG, covering on- and off-balance-sheet positions as well as trading-book securities (Deutsche Bundesbank (2021)). Accordingly, the term credit is used throughout the paper as shorthand for total borrower exposure.

adjustments. When replacing the CPRS-based measure of carbon intensity with firm-level transition risk metrics (Lepore *et al.* (2024)), we find no evidence that banks move beyond sector-level classifications to incorporate firm-specific information. Instead, they assign identical risk weights to all firms within a sector, despite substantial differences in emissions (EBA (2021)); for example, cattle and apple farms receive the same risk weight.

Our paper makes several contributions to the growing literature on how financial institutions incorporate transition risks into lending practices (e.g. Ehlers, Packer, and Greiff (2022); Carbone *et al.* (2022)).

First, to the best of our knowledge, we are the first to examine how banks manage transition risks in the German banking sector, distinguishing among banking groups, including LSIs such as cooperative and savings banks. Our results show that private banks, often SI and subject to greater regulatory and market scrutiny, are the primary drivers of transition risk assessment, whereas cooperative and savings banks show no measurable adjustment in risk weights. Although the LSI sector accounts for a smaller share of total banking assets, it is systemically relevant due to dense regional networks and institutional protection schemes (Deutsche Bundesbank (2015)). Undetected transition risks within these institutions may therefore pose broader financial stability concerns. These findings challenge approaches that treat the banking sector as homogeneous, despite supervisory guidance that sets uniform expectations for climate risk management across banks (BaFin (2019); ECB (2020); ECB (2022a); ECB (2022b); Deutsche Bundesbank (2022)). Our results complement existing evidence showing that bank type shapes credit supply responses to monetary policy shocks (Kakes and Sturm (2002)) and exposure profiles (D'Orazio, Hertel, and Kasbrink (2024)). By documenting systematic heterogeneity in transition risk management, the paper informs ongoing policy discussions on whether climate-related regulation should be differentiated by bank type rather than applied uniformly.

Second, we provide the first evidence on how banks' transition risk management differs between exposures to SMEs and to large firms. Existing studies on climate-related banking risks focus predominantly on large corporate borrowers, often using syndicated loan data (e.g. Ehlers, Packer, and Greiff (2022)), leaving the relevance of these findings for SMEs unclear. We find that private banks increase risk weights more strongly for carbon-intensive SMEs than for large carbon-intensive firms. This pattern is notable given that non-financial reporting has largely been confined to large listed firms, while disclosure by SMEs remains mostly voluntary (Cronin and Doyle-Kent (2022); Ozkan, Romagnoli, and Rossi (2023)). Consistent with this, banks may face greater data limitations when assessing transition risks for SMEs (Koirala (2019)). Building on evidence that higher regulatory capital requirements are passed through to SME borrowing costs (Bonaccorsi di Patti, Moscatelli, and Pietrosanti (2023)), our results suggest that banks actively incorporating transition risk may similarly transmit higher risk weights into higher financing costs for SMEs (Dafermos (2021)). This has implications for SME financing during the green transition, given their reliance on bank credit (ECB (2021)) and existing constraints in decarbonisation efforts (SME Climate Hub (2023)).

Third, we contribute to the debate on the granularity of transition risk metrics. Many banks still assess transition risk with insufficient granularity and methodological sophistication (Fernandez-Bollo (2024b)). Using *tilt* data, which distinguishes firms within the same sector by decarbonisation targets and product-level emission intensities, we find no evidence that banks incorporate this additional firm-level information into risk weights, suggesting that transition risk assessment remains largely sector-based.

Finally, our paper connects the climate-finance literature with broader research on bank risk management.

We examine whether bank-level characteristics, such as total assets, capital ratios, and overall transition risk exposure, moderate the incorporation of transition risks into lending. We find, for instance, that banks with larger total assets exhibit greater adjustments in risk weights, whereas banks with higher capital ratios do not necessarily manage transition risks more actively. Moreover, banks with higher overall exposure to transition risks adjust risk weights significantly more than less-exposed banks (3.2 pp vs. 1.4 pp; the latter not significant). These results (e.g.Cardot-Martin, Labondance, and Refait-Alexandre (2022), Laeven, Ratnovski, and Tong (2016)) complement studies showing that bank resilience and balance sheet structure shape banks' responses to financial stress and systemic risk outcomes, showing that similar mechanisms operate in the climate transition risk domain.

The rest of this paper is structured as follows. Section 2 gives an overview of the data sources. Section 3 states the empirical identification strategy. Section 4 reports our main results on the effect of carbon intensity on the risk weight management after October 2018. Section 5 examines additional bank characteristics that manage transition risks. Section 6 concludes.

2 Data

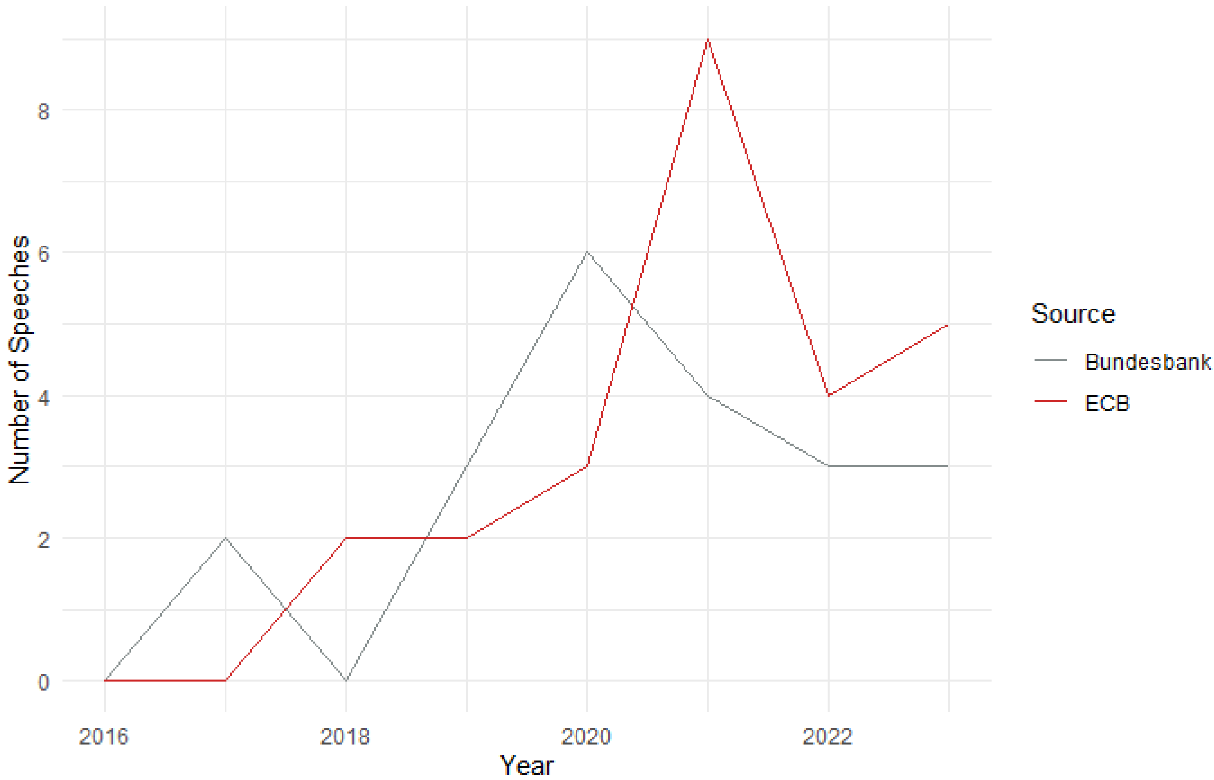
This section describes the selected event for our event study, the publication of the NGFS's first progress report in October 2018, and presents summary statistics.

We use five data sources: (i) credit exposure on debtor level from the Deutsche Bundesbank (credit register of credits over €1.0 million, so called Mio evidence) from 2016 until 2022 (Deutsche Bundesbank (n.d.)), (ii), the MamFi database categorising banks in different banking groups, such as private banks, cooperatives and savings banks, (Stahl and Schäfer (2025)) (iii), the JANIS company balance sheet database base (Becker *et al.* (2024)) and (iv), the BISTA bank balance sheet data base (Stahl (2024)) and, (v) climate-relevant information – following climate policy relevant sector (CPRS) by Battiston, Mandel, *et al.* (2017), a product-level transition risk metric by Lepore *et al.* (2024) and the transition risk vulnerability factors by Vermeulen *et al.* (2021). Table 15 in the Appendix shows definitions and sources of all variables used in our study.

2.1 The NGFS first progress report and its first expansion

In a dynamic DiD framework, selecting the event date is crucial, as it determines when treatment effects can plausibly emerge and be traced over time. While the Paris Agreement in 2015 placed climate transition risks on the global agenda, German financial authorities initially responded cautiously, with increasing attention from 2018 onwards, after the publication of the EU Sustainable Finance Action Plan (Kuhn (2022)). In line with this, the establishment of the NGFS in December 2017 by eight central banks, including the Deutsche Bundesbank, was an important institutional milestone, but its early activities focused on raising awareness. A more decisive signal came in October 2018, when the NGFS released its first progress report, which explicitly framed climate risks as financial risks and outlined supervisory implications (NGFS (2018)). In 2018, the NGFS further expanded its membership beyond its founding central banks. Fischer, Rapp, and Zahner (2024) show that such NGFS membership expansions are associated with abnormal stock market reactions, with clean energy stocks outperforming fossil fuel stocks, consistent with rising expectations of stricter climate-related financial supervision. Taken together with the launch of the EU Sustainable Finance Action Plan in 2018 and the sharp increase in climate-related communication by the Bundesbank and the ECB after 2018 (see Figure 1), this timing suggests a shift in banks' beliefs about supervisory expectations regarding transition risk management. October 2018, therefore, marks a plausible starting point for observed changes in banks' risk management practices.

Figure 1. Number of central bank speeches containing "climate" in the title



Note: We filter speeches by the Deutsche Bundesbank and the European Central Bank from the dataset compiled by Campiglio *et al.* (2025), retaining only speeches that include the term climate in the title. The dataset extends the Bank for International Settlements' Central Bankers' Speeches database through systematic web scraping of central bank websites and additional archival work and contains 35,487 unique speeches delivered by 131 central banks between January 1986 and December 2023.

Hence, we take October 2018 as the regulatory signal initiating the treatment period. A dynamic DiD design allows us not only to capture the immediate market response to this initial signal, but also to trace how the treatment effect evolves as follow-up measures, such as BaFin's 2019 guidance (BaFin (2019)) and supervisory climate stress-testing initiatives (ECB (2022a), reinforce or amplify the initial regulatory expectations over time.

2.2 Credit level data

Our main dataset is the Mio Evidence credit-level database ("Evidenzzentrale für Millionenkredite") maintained by the Deutsche Bundesbank (n.d.). Under Article 394 of the Capital Requirements Regulation (CRR) and Section 14 of the German Banking Act (KWG), banks in Germany must report quarterly all individual credit exposures exceeding €1 million. We use quarterly data from 2016 to 2022, excluding exposures to the financial sector, households, and credits fully secured by real estate.

Banks must report for each borrower–bank–time (i, b, t) observation the Risk Weighted Assets (RWA_{ibt}), which is the *sum of CRR risk-weighted position amounts* for all components included in the overall credit volume of a bank b towards firm i at time t:

$$\mathrm{RWA}_{ibt} = \sum_j \mathrm{RW}_{j,ibt}\,\mathrm{CreditSize}_{j,ibt}, \tag{1}$$

$$\mathrm{RW}_{j,ibt} = \begin{cases} \mathrm{RW}^{\mathrm{SA}}_{j,ibt}, & \text{(SA)}, \\ \phi\big(\mathrm{PD}_{j,ibt},\, \mathrm{LGD}_{j,ibt},\, \mathrm{EAD}_{j,ibt}\big), & \text{(IRB)}. \end{cases} \tag{2}$$

The variable $CreditSize_{ibt}$ captures the total credit volume from bank b to firm i at time t. Hence, each component j refers *only* to positions vis-à-vis firm i. The credit volume is the overall exposure of a bank b to firm i and aggregates all on- and off-balance-sheet positions toward firm i under §19 KWG, including credits, debt securities, guarantees/commitments (after credit-conversion), derivatives counterparty risk, and, where applicable, equity holdings and trading-book instruments issued by or referencing firm i. It does not include proprietary trading positions unrelated to firm i. Hence, our exposure and implied risk weight are specific to the i-b relationship and are not affected by the bank's other trading activities.

The Basel framework does not explicitly prescribe calculating RWA - covering credit risk, market risk and operational risks for individual firms; rather, it specifies how banks must assign it. The RWA can be calculated by using either the internal ratings-based (IRB) approach or the *standardised approach* (SA). Under the IRB approach (BIS (2020)), subject to supervisory approval, banks use internal models to estimate borrower-level risk parameters, including probability of default (PD), loss given default (LGD), and exposure at default (EAD), which enter equation 2. Developing, validating, and continuously supervising internal risk models is resource-intensive, making the IRB approach costly to implement and maintain. Consistent with these requirements, adoption of the IRB approach is concentrated among large, systemically important banks (SIs) (Mariathasan and Merrouche (2014), ECB (2025a)). Under the SA (BIS (2019a)), regulators prescribe baseline risk weights for exposure classes based on the borrower's credit rating. Banks, applying the SA, map external ratings to fixed regulatory risk-weight buckets, implying limited scope for bank-specific model adjustments. This approach entails lower implementation and compliance costs than internal model–based approaches. Consistent with this cost structure, the SA is predominantly used by smaller banks (LSIs) such as savings and cooperative banks. Regardless of the approach, banks, including those using the SA approach, can employ credit risk mitigation techniques, such as requiring collateral, to reduce risk and thereby the risk-weighted assets.

In both approaches, the final risk weight reflects the bank's own assessment within the Basel-prescribed framework. Because the minimum required regulatory capital is a fixed percentage of RWA (typically 10.5% plus conservative buffers under Basel III (BIS (2019b), BIS (2019c)), a higher RWA directly increases the amount of capital a bank must hold (BIS (2019b)). Holding more capital ties up resources and, by implication, restricts the amount of new credit a bank can grant, given an equity surplus, or triggers the need for new equity to meet regulatory requirements.

Banks can manage transition risks through two margins. First, they can adjust risk weights by reassessing borrowers as riskier, thereby increasing risk-weighted assets for a given credit volume. This can occur through updates to internal models under the IRB approach or through less favourable credit risk mitigation under the SA. Second, banks can adjust exposure by reducing credit volumes to borrowers perceived as riskier. To capture both channels, we transform equation 1 and calculate the *risk-weight* as our main dependent, defined as:

$$\text{risk weight}_{ibt} = \frac{\text{Risk-weighted assets (RWA)}_{ibt}}{\text{credit volume}_{ibt}} \tag{3}$$

Following Equation 3, banks can increase implied risk weights either by raising risk-weighted assets for a given exposure or by reducing credit volumes while keeping risk-weighted assets unchanged. The former reflects a reassessment of risk through higher assigned risk weights, whereas the latter reflects more cautious lending through portfolio contraction.

We first estimate our model using the risk weight as the dependent variable, as reported in Panels (a), to capture the net effect of both channels combined. We then estimate the model separately for credit volume, reported in Panels (b) and RWA, reported in Panels (c), to identify the relative contributions of the credit-supply channel (changes in exposure) and the risk-assessment channel (changes in the risk weight share that feed into RWA). To address skewness while preserving zero values, we apply the transformation $log(1 + x)$ to both variables. Since risk weight is mechanically the ratio of RWA to credit volume, the log specifications for these two variables make it transparent which component drives the result: a stronger response of log-RWA points to an adjustment in banks' risk assessment, whereas a stronger response of log-credit-volume indicates that the effect operates through the size of the exposure. Finally, we use the borrower's sector classification in Mio Evidence to determine the intensity of carbon emissions using a sector-specific metric (see subsection 2.6).

2.3 Banking group level data

The MamFi data (Stahl (2024)) consists of structural characteristics data from German banks, focusing on various banking groups, including (i) private banks, (ii) credit cooperatives, and (iii) savings banks (Sparkassen), and thus, covering the three main pillars of the German banking system. We use the groupings to filter different panels (see Table 1 for an overview) and examine whether the overall results for all banks (Panel 1) are primarily driven by private banks (Panel 2) or by credit cooperatives and savings banks (Panel 3).

2.4 Firm-level data

We integrate firm-level data from the JANIS database (Becker *et al.* (2024)) to complement debtors' balance sheet information. The JANIS database provides key covariates to meet the conditional parallel trend assumptions required by our DiD design. The data includes one observation date per firm and year. We select 20 variables, following Gross *et al.* (2025), to construct a range of financial ratios and indicators. These include profitability ratios (net profit margin and gross profit margin), liquidity measures (current ratio, quick ratio, and interest coverage ratio), leverage ratios (debt-to-equity ratio and debt-to-assets ratio), asset structure ratios (tangible asset ratio, intangible asset ratio, inventory ratio, and liquidity asset ratio), and risk ratios (provision-to-equity ratio, pension-to-equity ratio, deficit ratio, and return on equity). In addition, we incorporate size indicators such as sales, total assets, current assets, cash holdings, number of employees, and firm year.

Because audited financial statements are released with a delay, we lag all firm-level variables by one year to reflect the information available to lenders at credit origination and to avoid look-ahead bias, following, for example, Brown and Earle (2015). In addition, we apply logarithmic transformations to total assets, cash, current assets, and sales to normalise their distributions. We do this to scale outliers as in Gross *et al.* (2025).

We also construct an SME dummy. SMEs are defined as firms with less than 250 employees and sales less than 50 Mio EUR and total assets smaller than 43 Mio EUR, following the definition of SME EC (2026). We use this variable to filter our sample into banks' exposure to large firms (Panel 4) and those lending to SMEs (Panel 5) (see Table 1 for an overview of all panels) to assess whether the size of the client influences the risk management practices of the banks' transition.

2.5 Bank level data

Bank-specific characteristics may also shape lending decisions. To account for this, we add each bank's capital ratio, liquidity ratio, and log total assets to our dataset. These variables are used both as covariates in the DiD estimation and to explore heterogeneity in treatment effects, except for the liquidity ratio. Specifically, we filter the main sample (Panel 1) based on whether each bank's pre-treatment value is above or below the median of the respective variable. Banks below the median are coded as 0, and those above as 1. Using these binary indicators, we re-estimate the model within subpanels to test for heterogeneity by capitalisation and size. These dimensions are relevant for shock absorption: higher capital provides buffers during stress, while larger banks may benefit from scale and diversification that can support resilience, though size can also increase systemic risk (see e.g. Cardot-Martin, Labondance, and Refait-Alexandre (2022), Laeven, Ratnovski, and Tong (2016)). Details can be found in Table 2.

2.6 Climate data to measure transition risks

We identify firms exposed to climate transition risks using the CPRS classification of Battiston, Mandel, *et al.* (2017), which maps NACE sector codes to climate policy–sensitive sectors. CPRS include, for example, fossil fuels, utilities, and transport. Firms in CPRS are assigned a value of 1 for the sector-based transition risk indicator; all others are coded 0. The CPRS classification, widely used in academic (Battiston, Mandel, *et al.* (2017), Battiston, Monasterolo, *et al.* (2022), Monasterolo (2020), NGFS (2019), and ESRB (2016)) and policy (ESRB/ECB (2021), EIOPA (2019), EIOPA (2020), and EBA (2021)) contexts, incorporates criteria such as direct and indirect GHG emissions, climate policy sensitivity, and a sector's role in the energy value chain Bressan, Monasterolo, and Battiston (2021). These criteria are used solely to define sector membership; they are not included as separate variables in our regressions. While CPRS provides a structured framework for identifying climate-relevant sectors, several of these sectors remain heterogeneous in their exposure to transition risks (e.g., agriculture as discussed in the introduction) (EBA (2021)).

To capture the within-sector heterogeneity, we complement CPRS with a product-based transition risk measure derived from the *tilt* database by Lepore *et al.* (2024), which contains product-level activity and climate metrics for over 80,000 German firms, including SMEs. The database links firm-level activity codes to product-specific carbon intensities and sectoral decarbonisation targets, implying that transition risk may vary across products. Because the data source does not provide a breakdown of firms' revenue by product, we restrict the sample to firms producing a single product or a narrow set of closely related products with similar transition risk profiles. This still captures the variability across firms within a sector but reduces within-firm noise due to missing revenue shares.

We classify a firm as producing high transition-risk products if it operates in a sector with a high decarbonisation target and produces products whose transition risk ranks in the top third within the sector. Specifically, a product is classified as high transition risk if its carbon intensity exceeds that of two-thirds of other products in the same sector. For example, we assign a value of 1 to cattle rearing in agriculture, as its carbon intensity is higher than that of 2/3 of other products in the sector; otherwise, the value is 0 (e.g., apple farming).

We further construct a bank-level transition risk exposure measure based on the policy vulnerability factors of Vermeulen *et al.* (2021), which we match to firms at the two-digit NACE level. We aggregate these sector-level vulnerability measures to the bank level by weighting each firm's sector exposure by the bank's credit volume to that firm, so that sectors to which a bank lends more receive greater weight. Banks with above-median exposure are classified as high-transition-risk banks (dummy equals 1), and those below the median as low-transition-risk banks (dummy equals 0).

2.7 Descriptive Analysis and Summary Statistics

As a last step, we merge data from the JANIS, MamFi, BISTA, and Mio databases with our climate transition risk measures. To obtain a balanced panel for our estimations, we exclude firms with incomplete observations across the study period. This restriction means that our analysis covers only bank–firm relationships that were continuously observed from 2016 through the end of 2022.

Table 1 presents the six main panels used in the baseline analysis. Panel 1 includes the full sample of 759 banks, comprising 42 private banks and 717 cooperative and savings banks, and 7,071 firms, of which 4,053 are classified as carbon-intensive and 3,018 as low-carbon-intensive according to the CPRS. Each time period contains 6,888 bank–firm credits to carbon-intensive firms (treated group) and 4,854 credits to low-carbon-intensive firms (control group). Panel 2 restricts the sample to the 42 private banks, while Panel 3 includes 732 cooperative and savings banks. Panel 4 focuses on private banks lending to large firms, and Panel 5 on private banks lending to SMEs, to explore heterogeneity by client size. Panel 6 returns to the full bank–firm sample but replaces the sector-based CPRS measure with the product-level transition risk indicator introduced in the previous section. The panels may not sum to Panel 1 due to the estimation method employed. We apply a doubly robust estimator of the average treatment effect on the treated (ATT), which relies on a conditional DiD design conditioning on covariates that may vary across panels. To satisfy the common support assumption, observations with insufficient overlap between the treated and control groups are trimmed from the sample. As a result, some bank–firm pairs included in Panel 1 may be excluded from the subpanels due to a lack of common support under the panel-specific covariates.

Table 1. Panels 1–6: Number of Observations by Categories

	Panel 1 - All banks	Panel 2 - Private banks	Panel 3 - Coop. & saving banks	Panel 4 - Large firms	Panel 5 - SMEs	Panel 6 - Product metric
Observations per Treatment and Control Group						
Control (per quarter)	4,433	1,677	2,751	725	783	152
Control (2017–2022)	101,959	38,571	63,273	16,675	18,009	3,496
Treated (per quarter)	6,374	2,861	3,638	1,256	1,304	107
Treated (2017–2022)	146,602	65,803	83,674	28,888	29,992	2,461
Categories						
Banks (All)	741	39	712	34	31	121
Private Banks	40	39	0	34	31	10
Cooperative Banks	351	0	361	0	0	34
Saving Banks	350	0	351	0	0	77
Firms (All)	6,381	3,719	4,236	1,469	1,889	177
Carbon-Intensive Firms	3,680	2,341	2,417	918	1,193	69
Low-Carbon-Intensive Firms	2,701	1,378	1,819	551	696	108
SMEs	4,076	2,250	2,676	0	1,889	102
Large Firms	2,888	1,812	1,933	1,469	0	95

Notes: Observations are on the credit (bank–firm) level. Observations (2017–2022) are calculated over 23 quarters. Panel 1 covers all banks; Panel 2 covers all private banks; Panel 3 covers only saving and cooperative banks; Panel 4 covers only large firms; Panel 5 covers only SME clients from private banks. Panels 1–5 are measured with sector metrics. Panel 6 includes all banks, but the treatment and control groups are stratified by product metrics using the *tilt* database. Distinct entities show the number of unique banks and firms per panel. Treated group = credits to firms in climate-policy-relevant sectors (CPRS) or with transition-risk exposure following *tilt* (Panel 6). The panels may not sum to Panel 1 due to the estimation method employed. We apply a doubly robust estimator of the average treatment effect on the treated (ATT), which relies on a conditional DiD design conditioning on covariates that may vary across panels. To satisfy the common support assumption, observations with insufficient overlap between the treated and control groups are trimmed from the sample. As a result, some bank–firm pairs included in Panel 1 may be excluded from the subpanels due to a lack of common support under the panel-specific covariates. Source: Author's own calculations.

Table 2. Bank Specificities Testing – Observations and Distinct Entities

	Transition Risk		Capital Ratio		Log Total Assets	
	Low	**High**	**Low**	**High**	**Low**	**High**
Number of Observations by Categories						
Control (per quarter)	1,526	2,893	2,087	2,329	2,267	2,166
Control (2017–2022)	35,098	66,539	48,001	53,567	52,141	49,818
Treated (per quarter)	1,724	4,795	3,579	2,855	3,013	3,397
Treated (2017–2022)	39,652	110,285	82,317	65,665	69,299	78,131
Categories (Low vs High)						
Banks (All)	375	383	235	514	701	41
Private Banks	26	14	12	28	27	13
Cooperative Banks	235	132	92	266	346	6
Saving Banks	114	237	131	220	328	22
Firms (All)	2,510	5,088	4,158	3,726	3,559	4,227
Carbon-Intensive Firms	1,334	3,091	2,540	2,084	2,078	2,572
Low-Carbon-Intensive Firms	1,176	1,997	1,618	1,642	1,481	1,655
SMEs	1,446	3,235	2,569	2,244	2,306	2,538
Large Firms	1,283	2,320	1,982	1,824	1,569	2,075

Notes: Robustness panels split the sample into banks with high vs low transition risk exposure, capital ratios, and total assets. Observations are on the credit (bank–firm) level. Observations (2017–2022) are calculated over 23 quarters. Distinct entities and observations are displayed side-by-side for low vs high subgroups in each bank characteristic. The panels may not sum to Panel 1 due to the estimation method employed. We apply a doubly robust estimator of the average treatment effect on the treated (ATT), which relies on a conditional DiD design conditioning on covariates that may vary across panels. To satisfy the common support assumption, observations with insufficient overlap between the treated and control groups are trimmed from the sample. As a result, some bank–firm pairs included in Panel 1 may be excluded from the subpanels due to a lack of common support under the panel-specific covariates. Source: Author's own calculations.

Table 2 presents the panels used in the heterogeneity analysis of bank-specific characteristics. We compare banks with low versus high transition risk exposure, low versus high capital ratios, and smaller versus larger banks by total asset size.

3 Estimation Strategy

We estimate the Average Treatment Effect on the Treated (ATT) using the double-robust estimator proposed by Callaway and Sant'Anna (2021) and e.g. used by Fang and Vlaicu (2024), which allows for treatment-effect heterogeneity across groups and time. Our identification strategy exploits the timing of the October 2018 NGFS progress report as a quasi-exogenous shock, with carbon-intensive firms as the treated group.

The ATT for treated bank–firm pairs is defined as:

$$ATT = \mathbb{E}\left[Y_{ibt}(1) - Y_{ibt}(0) \,\middle|\, \text{CarbonIntensity}_{i,\text{pre}} = 1\right] \tag{4}$$

Where $Y_{ibt}(1)$ is the risk-weight ratio in percentage points *if treated* (i.e., bank lends to a carbon-intensive firm after the NGFS report);$Y_{ibt}(0)$ is the risk-weight ratio in percentage points *if untreated* so if the event would not have been happened (counterfactual outcome); $\text{CarbonIntensity}_{i,\text{pre}} = 1$ indicates the firm belongs to a carbon-intensive sector prior to treatment according to the CPRS-method by Battiston, Mandel, *et al.* (2017); $\text{CarbonIntensity}_{i,\text{pre}} = 0$ indicates the firm that does not belong to a carbon-intensive sector prior to treatment according to the CPRS-method by Battiston, Mandel, *et al.* (2017). We index firms by i, banks by b, and time by t (quarters).

The ATT can vary in time (dynamic treatment effects), which can be represented with a time average treatment effect ATT(t) :

The time-specific average treatment effect on the treated can be written as:

$$\begin{aligned} ATT(T) = {} & \mathbb{E}\big[Y_{ibt}(1) \;\big|\; \text{CarbonIntensity}_{i,\text{pre}} = 1,\ S_t(T) = 1\big] \\ & - \mathbb{E}\big[Y_{ibt}(0) \;\big|\; \text{CarbonIntensity}_{i,\text{pre}} = 0,\ S_t(T) = 1\big]\,. \end{aligned} \tag{5}$$

where Y_{ibt} denotes the outcome of bank–firm pair (b, i) at time t, $\text{CarbonIntensity}_{i,\text{pre}}$ indicates treatment status, and $S_t(T)$ is a binary indicator equal to one if period t corresponds to the T-th period relative to the common treatment start date, and zero otherwise. The treatment occurs after October 2018; due to the frequency of the data, December 2018 is the first post-treatment period observed in our sample. Because treatment occurs at a common calendar date for all units, $S_t(T)$ varies only over time and not across bank–firm pairs.

The first term is the *observed* average outcome for treated bank-firm pairs after October 2018. The second term captures the outcome for *never-treated bank–firm pairs* (those lending to non-carbon-intensive firms). It is the *best available proxy* for their unobserved counterfactual in **t**, constructed from untreated pairs (the non-carbon-intensive firms) and made credible through covariate balancing and doubly robust adjustments.

We report standard errors clustered at the firm level because treatment status-carbon-intensive versus non-carbon-intensive-is assigned at the firm level, and outcomes for the same firm may be correlated over time and across bank relationships. Results are robust to alternative clustering choices for standard errors (see Table 14 in Appendix 7.2). The doubly robust estimator accounts for common time shocks and time-invariant firm heterogeneity through its group–time comparison structure, rather than through an explicit unit–time fixed-effects regression specification (Callaway and Sant'Anna (2021)).

The DiD approach relies on some key assumptions: no anticipation and parallel trends (Roth *et al.* (2023)) as well as implicitly the Stable Unit Treatment Value Assumption (SUTVA) (Mealli and Viviens (2025)), which we argue are satisfied in this setting (see Appendix 7.1). The central identifying assumption is parallel trends, which require similar pre-treatment outcome dynamics for the treated and control groups. We assess this assumption using event-study specifications and DiD pre-tests and adopt a conditional parallel trends framework when necessary. To this end, we follow the suggested procedure of picking covariates by Cunningham (2024). We first identify pre-treatment covariates that jointly predict treatment assignment and potential outcomes. Starting from a set of 24 theoretically motivated variables, we apply LASSO regression (Chernozhukov, Hansen, and Spindler (2015)) to retain only covariates with predictive power. We then evaluate covariate balance using the normalised difference metric (Imbens and Rubin (2015)), where values below 0.25 indicate acceptable balance. Conditional on the selected covariates, we estimate treatment effects using the doubly robust DiD estimator of Callaway and Sant'Anna (2021), implemented via the DID R package.

As described in Section 2, we distinguish adjustment channels by sequentially estimating effects on risk weights (Panel A), log credit size (Panel B), and log risk-weighted assets (RWA) (Panel C). We further examine heterogeneity in transition risk management across bank types and firm sizes. We implement this analysis through sample splits, constructing mutually exclusive subpanels: private banks (Panel 2), savings and cooperative banks (Panel 3), private banks lending to large firms (Panel 4), private banks lending to SMEs (Panel 5), and all banks using product-level climate risk metrics (Panel 6). Further, we examine whether banks' transition risk exposure and shock-absorption capacity, proxied by capital ratios and total assets, moderate treatment effects. Because treatment is applied simultaneously across all treated banks, heterogeneity cannot be identified by variation in treatment timing. Instead, we study heterogeneous effects by estimating treatment effects separately for well-defined subgroups. The resulting subpanels yield causal subgroup-specific average treatment effects consistent with our identification strategy (Sant'Anna and Zhao (2020)).

For each subpanel, we repeat the LASSO-based covariate selection and assess balance before and after propensity-score weighting. Table 3 reports selected covariates and standardised mean differences. Across panels, firm size, tangible asset ratios, firm age, and total assets are most frequently selected, while pre-event bank liquidity and capital ratios are relevant in some subsamples. In all cases, post-weighting normalised differences indicate satisfactory balance between treated and control groups. Balance diagnostics for these robustness specifications are reported in Table 4 and are comparable to those of the baseline panels.

Finally, we conduct several robustness checks by estimating the Two-Way-Fixed-Effects (TWFE) estimator (see Appendix 7.6), restricting the outcome variable (see Appendix 7.5, and testing alternative outcome variables such as collateral and the probability of default (see Appendix 7.4).

Table 3. Treatment–Control Covariate Comparison (Before and After Matching) across all Panels

Panels	**Covariates Used**	**Control Mean**	**Treatment Mean**	**Norm. Diff (Before)**	**Norm. Diff (After)**
1a–c (All banks)	Employees	948.34	5183.76	0.2629	-0.0191
1a–c (All banks)	Tangible Asset Ratio	0.3013	0.4864	0.6082	0.0169
1a–c (All banks)	Lag Tangible Asset Ratio	0.3023	0.4872	0.6067	0.0167
2a-c (Private banks)	Liquidity Ratio (Banks)	0.0805	0.0707	0.2561	-0.0076
2a-c (Private banks)	Tangible Asset Ratio	0.2478	0.4744	0.7625	0.0168
2a-c (Private banks)	Lag Tangible Asset Ratio	0.2474	0.4756	0.7678	0.0161
3a–c (Coop. & Saving Banks)	Employees	1198.17	8085.97	0.3411	0.0905
3a–c (Coop. & Saving Banks)	Tangible Asset Ratio	0.3341	0.4955	0.5274	0.0089
3a–c (Coop. & Saving Banks)	Firm Age	47.24	58.98	0.2719	-0.0083
3a–c (Coop. & Saving Banks)	Log Total Assets	11.17	11.79	0.2627	0.0173
3a–c (Coop. & Saving Banks)	Lag Tangible Asset Ratio	0.3360	0.4960	0.5219	0.0093
3a,b (Coop. & Saving Banks)	Lag Firm Age	46.64	58.43	0.2724	-0.0082
3a–c (Coop. & Saving Banks)	Lag Log Total Assets	11.14	11.76	0.2616	0.0176
4a,c (Large Firms)	Tangible Asset Ratio	0.2565	0.3310	0.2884	-0.0012
4a–c (Large Firms)	Lag Tangible Asset Ratio	0.2559	0.3318	0.2928	-0.0024
5a-c (SMEs)	Liquidity Ratio (Banks)	0.0810	0.0618	0.5307	-0.0053
5a-c (SMEs)	Capital Ratio (Banks)	0.0522	0.0443	0.3316	-0.0224
5a-c (SMEs)	Tangible Asset Ratio	0.2377	0.5915	1.1759	0.0246
5a,b (SMEs)	Log Current Assets	9.49	8.95	0.4218	0.0100
5a-c (SMEs)	Lag Log Total Assets (Banks)	18.24	17.48	0.3280	-0.0107
5a-c (SMEs)	Lag Tangible Asset Ratio	0.2373	0.5931	1.1849	0.0235
5a-c (SMEs)	Lag Log Current Assets	9.46	8.92	0.4138	0.0115
5b,c (SMEs)	Lag Liquidity Ratio (Banks)	0.0485	0.0373	0.4035	-0.0056
6a-c (Product Metric)	Net Profit Margin	0.0755	0.0202	0.2904	-0.0621
6a-c (Product Metric)	Gross Profit Margin	0.4686	0.3598	0.4083	-0.0010
6a (Product Metric)	Tangible Asset Ratio	0.2762	0.3352	0.2781	-0.0393
6a,c (Product Metric)	Intangible Asset Ratio	0.0171	0.0076	0.2607	0.0146
6a,b (Product Metric)	Log Sales	10.95	11.41	0.3677	-0.0017
6a-c (Product Metric)	Lag Net Profit Margin	0.0733	0.0201	0.3012	-0.0415
6a,c (Product Metric)	Lag Gross Profit Margin	0.4633	0.3600	0.4125	-0.0033
6a-c (Product Metric)	Lag Tangible Asset Ratio	0.2774	0.3380	0.2837	-0.0331
6a-c (Product Metric)	Lag Intangible Asset Ratio	0.0175	0.0072	0.2679	0.0178
6a, b (Product Metric)	Lag Log Sales	10.90	11.37	0.3787	-0.0019

Notes: Each panel refers to a different outcome variable. Subpanel "a" refers to risk weight (%), "b" to log loan volume, and "c" to log risk-weighted assets (RWA). Panels are grouped when they use identical covariates. Small differences in normalised differences across panels reflect panel-specific propensity score weighting, and the resulting values are therefore due to grouping averaged for presentation; in all cases, post-weighting differences remain well below the 0.25 balance threshold. Balance statistics report standardised differences between treatment and control groups, both before and after weighting or matching. Covariates are selected in two steps: first, using Lasso regressions to identify predictors of the outcome variable; second, by including covariates with normalised differences greater than 0.25, following Imbens and Rubin (2015).

Table 4. Balance Statistics: Robustness Panels

Panels	**Covariates Used**	**Control Mean**	**Treatment Mean**	**Norm. Diff (Before)**	**Norm. Diff (After)**
Low Transition Risk Banks	Employees	1292.32	8775.44	0.3470	0.0202
	Tangible Asset Ratio	0.3153	0.4568	0.4549	0.0279
	Inventory Ratio	0.2658	0.3412	0.2950	0.0004
	Firm Age	46.24	58.69	0.2984	0.0209
	Log Total Assets	11.24	11.87	0.2689	0.0075
	Lag Tangible Asset Ratio	0.3163	0.4575	0.4527	0.0276
	Lag Inventory Ratio	0.2654	0.3420	0.2990	0.0007
	Lag Firm Age	45.61	58.13	0.2994	0.0210
	Lag Log Total Assets	11.21	11.84	0.2694	0.0076
High Transition Risk Banks	Tangible Asset Ratio	0.2940	0.4976	0.6768	0.0208
	Lag Tangible Asset Ratio	0.2950	0.4984	0.6757	0.0205
Low Capital Ratio Banks	Tangible Asset Ratio	0.3079	0.5354	0.7365	0.0236
	Lag Tangible Asset Ratio	0.3092	0.5362	0.7333	0.0234
High Capital Ratio Banks	Employees	1085.12	7791.51	0.3382	-0.0138
	Tangible Asset Ratio	0.2954	0.4284	0.4516	0.0122
	Log Total Assets	11.12	11.72	0.2598	0.0066
	Lag Tangible Asset Ratio	0.2962	0.4293	0.4516	0.0120
	Lag Log Total Assets	11.09	11.69	0.2585	0.0068
Low Log Total Assets Banks	Employees	1287.23	8939.67	0.3608	-0.0097
	Tangible Asset Ratio	0.3350	0.4889	0.5055	0.0137
	Log Total Assets	11.18	11.80	0.2545	0.0093
	Lag Tangible Asset Ratio	0.3369	0.4892	0.4997	0.0142
	Lag Log Total Assets	11.15	11.78	0.2542	0.0095
High Log Total Assets Banks	Tangible Asset Ratio	0.2660	0.4840	0.7217	0.0184
	Lag Tangible Asset Ratio	0.2661	0.4853	0.7248	0.0177

Notes: Balance statistics for robustness checks based on bank-level heterogeneity: transition risk, capital, and size (log total assets). Panels are grouped when covariate sets are identical. Small differences in normalised differences across panels reflect panel-specific propensity score weighting, and the resulting values are therefore due to grouping averaged for presentation; in all cases, post-weighting differences remain well below the 0.25 balance threshold. See main table notes for covariate selection methodology.

4 Results

4.1 Basic results: Does the German banking sector take transition risks into account in its lending practices?

We test whether the German banking sector incorporates transition risks into lending decisions (see Figure 2 and Table 5). The dynamic ATT shows a statistically significant increase of 2.77 pp in risk weights for carbon-intensive firms after October 2018, based on balanced covariates selected via LASSO, including employees, tangible assets, and lagged tangible assets (see Table 3). These results indicate that banks incorporate sector-level transition risk into lending decisions. After 2018, firms in CPRS were assigned higher risk weights than those in non-CPRS.

As an illustrative example, a 2.77 pp increase in risk weights raises risk-weighted assets by €2.77 per €100 exposure. Under the Basel III total capital requirement including buffers (10.5% of RWA (BIS (2019b), BIS (2019c)), this implies an additional capital requirement of approximately €0.29 per €100 exposure, corresponding to about 0.29% of the underlying loan amount. Compared with the average annual capital growth of about 5.2% observed for German banks in 2022 Deutsche Bundesbank (2023)), this calculation suggests that the implied adjustment is noticeable but moderate relative to typical annual capital accumulation.

Importantly, the estimated effect accumulates over the period from October 2018 to December 2022 rather than representing a one-year adjustment. Thus, while accounting for transition risks implies that banks need to hold somewhat higher capital levels, the magnitude does not indicate an extraordinary aggregate capital shortfall. Nevertheless, although manageable in aggregate, the additional capital requirement may still pose a meaningful burden for some individual institutions.

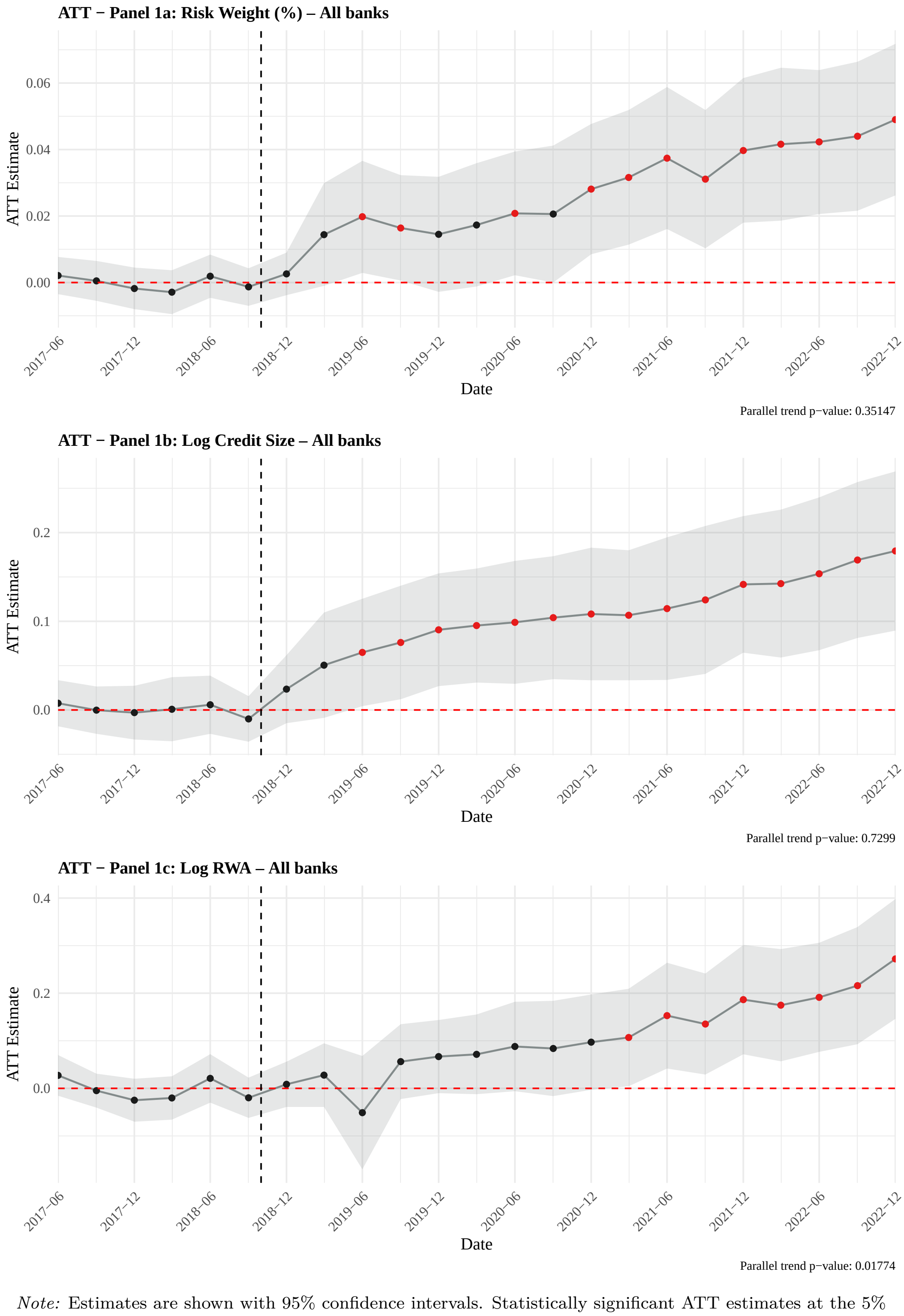
Panels 1b and 1c show that, for carbon-intensive firms, both credit sizes and risk-weighted assets increase after the event, with risk-weighted assets rising from 2019 onward. This pattern likely reflects the time required for banks to update risk models and lending policies. Risk-weighted assets increase more strongly than credit size, indicating that banks adjust risk weights more aggressively than credit supply. Importantly, credit volumes increase alongside risk-weighted assets. This indicates that, despite higher risk weights and associated capital costs, banks expand rather than contract credit to carbon-intensive firms. This pattern is notable, as rising risk would typically be expected to reduce exposure, in line with evidence that regulatory capital requirements significantly shape bank lending and credit allocation (e.g., see Bonaccorsi di Patti, Moscatelli, and Pietrosanti (2023)). One interpretation is that lending to these firms remains sufficiently profitable to offset higher capital requirements. Alternatively, banks may be extending credit to finance transformation and transition investments by large carbon-intensive firms. However, the available data do not allow us to empirically distinguish between these explanations. Overall, the larger increase in risk-weighted assets indicates heightened perceived transition risk.

We also find that the effects increase over time. This pattern is consistent with a growing set of regulatory and supervisory expectations to incorporate transition risks, including BaFin guidance (BaFin (2019)) issued in December 2019 and the 2020 announcement (EBA (2020)) and 2022 implementation (ECB (2022a)) of the ECB climate stress test. Anticipating such cumulative effects, we employ a dynamic specification to capture their evolving impact.

Identification relies on the parallel trends assumption. Event-study estimates for risk weights (Panel

1a), credit volumes (Panel 1b), and risk-weighted assets (Panel 1c) show coefficients close to zero in the pre-event period, indicating similar pre-treatment trends across carbon-intensive and non-carbon-intensive firms. Given this pre-treatment trend similarity, any divergence observed after the event can be attributed to the treatment rather than to pre-existing differences in trends.

Figure 2. Event Study ATT Estimates – Panel 1 - All Banks



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 5. Summary Results: Panels 1a, 1b, 1c – All Banks

Outcome Variable: Risk Weight (%)					
Panel 1a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0277	0.0055	0.0170	0.0385	*
Outcome Variable: Log credit size					
Panel 1b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1084	0.0222	0.0648	0.1520	*
Outcome Variable: Log RWA					
Panel 1c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1108	0.0277	0.0566	0.1650	*

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in pp, while credit size and RWA are measured in logs. Therefore, the magnitude of the coefficients is not directly comparable. Since risk weight is mechanically the ratio of RWA to credit size, the log specifications for these two variables make it transparent which component drives the result: a stronger response of log-RWA points to an adjustment in banks' risk assessment, whereas a stronger response of log-loan-volume indicates that the effect operates through the size of the exposure.

The results are robust also with the TWFE estimator, which lies even at around 6.3 pp difference (see Appendix 7.6). Because a definition change in June 2019 generates a visible break in Panel 1c, we re-estimate the results using a restricted outcome variable excluding firms with RWA changes exceeding 5% around this date. Definition changes may temporarily produce irregular movements that subsequently stabilise. Details are provided in Appendix 7.5. Choosing different outcome variables, such as log collateral, which also indicates risk perception, shows a positive and significant effect of 7.1 pp. However, estimates using probability of default as the outcome show no significant effects (see Appendix 7.4).

4.2 Does the transition risk management of banks differ between banking groups?

We next split the full sample into private banks and cooperative and savings banks. Panel 2a of Table 6 and Figure 3 show that for private banks, the average treatment effect on risk weights is positive and statistically significant. For carbon-intensive firms, risk weights increase by 3.5 pp after October 2018. In contrast, Panel 3a of Table 7 and Figure 4 show that for cooperative and savings banks, the average treatment effect on risk weights is negative and statistically significant, corresponding to a decline of 1.3 pp.

These results indicate that the overall effect reported in Panel 1 of Table 5 is driven by private banks. Their adjustment in risk weights exceeds that observed in the full sample. For both bank groups, lending to carbon-intensive firms increases after the event. However, only private banks simultaneously raise risk weights, while cooperative and savings banks do not.

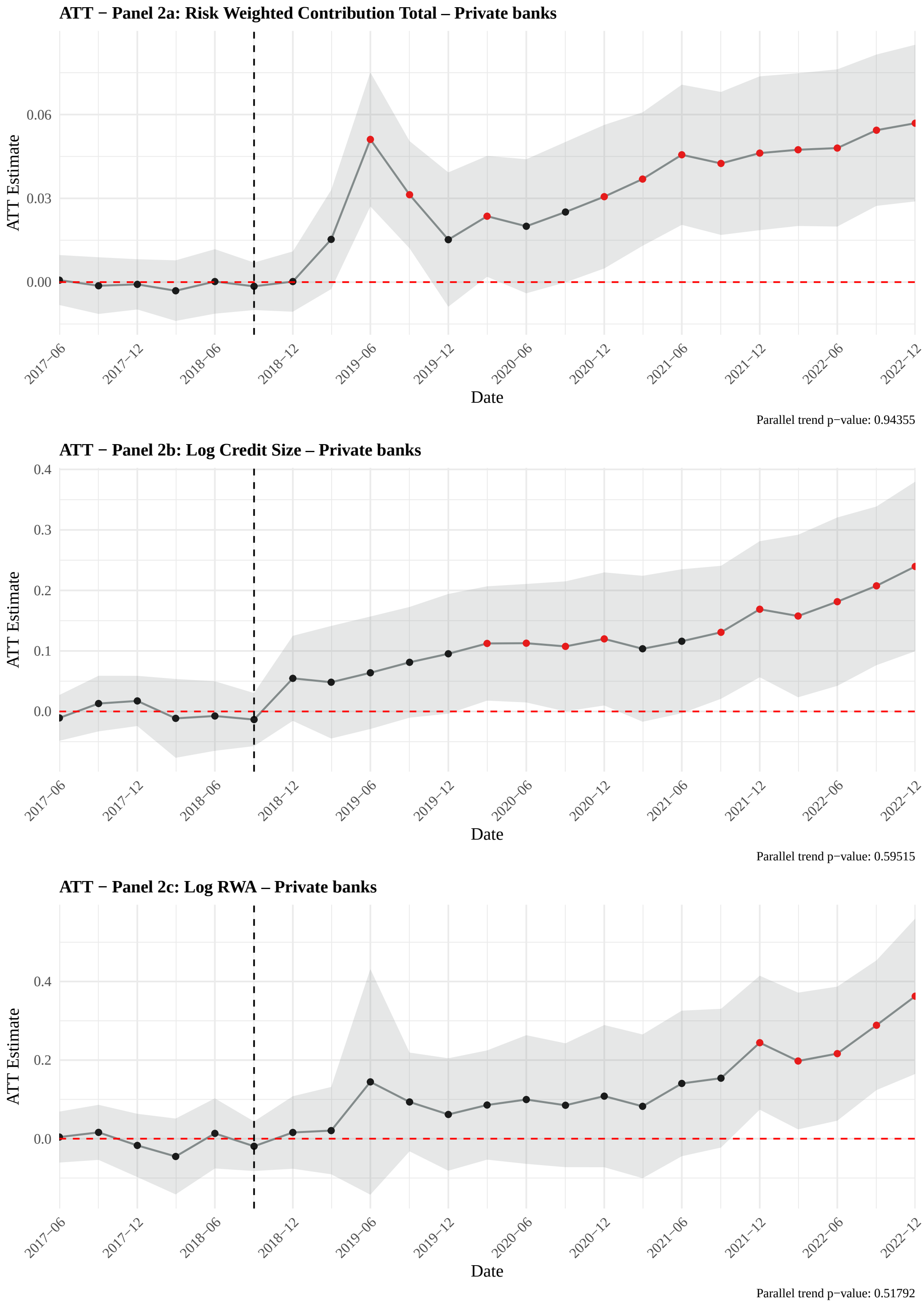
One explanation relates to differences in regulatory risk modelling frameworks. As discussed in Section

2, private banks are more likely to apply internal ratings-based approaches, which allow transition risk factors to enter credit risk parameters and thus RWAs more directly. Cooperative and savings banks predominantly rely on the standardised approach, which assigns risk weights to discrete rating buckets. Under this framework, transition risk affects risk weights only if it is strong enough to trigger a rating change or if the borrower is close to a threshold. This does not imply that banks that use a standardised approach lack control over RWAs. Even under the standardised approach, banks can influence RWAs through credit risk mitigation, such as collateral or guarantees. These adjustments, however, are typically slower or less flexible than those available under internal ratings-based frameworks.

A second explanation concerns incentives and supervisory intensity. Private banks are generally larger, more often listed, and more likely to be supervised as SIs by the ECB. As a result, they face stronger capital market discipline and more intensive supervisory expectations to integrate climate-related risks into risk management (see e.g. the climate EU-wide stress test ECB (2022a)). Cooperative and savings banks are predominantly LSIs with relationship-based lending models and hold more capital than larger banks (Deutsche Bundesbank (2015). For well-capitalised banks, increases in risk-weighted assets are, to some extent, irrelevant from a capital perspective.

Overall, the evidence supports our hypothesis that transition risk management differs across bank types. Private banks are the main contributors to the positive average treatment effect documented in subsection 4.1, while cooperative and savings banks exhibit an opposite adjustment pattern. This heterogeneity suggests that regulatory signals propagate unevenly across the banking sector, with implications for the allocation of credit to carbon-intensive firms.

Figure 3. Event Study ATT Estimates – Panel 2 – Private Banks



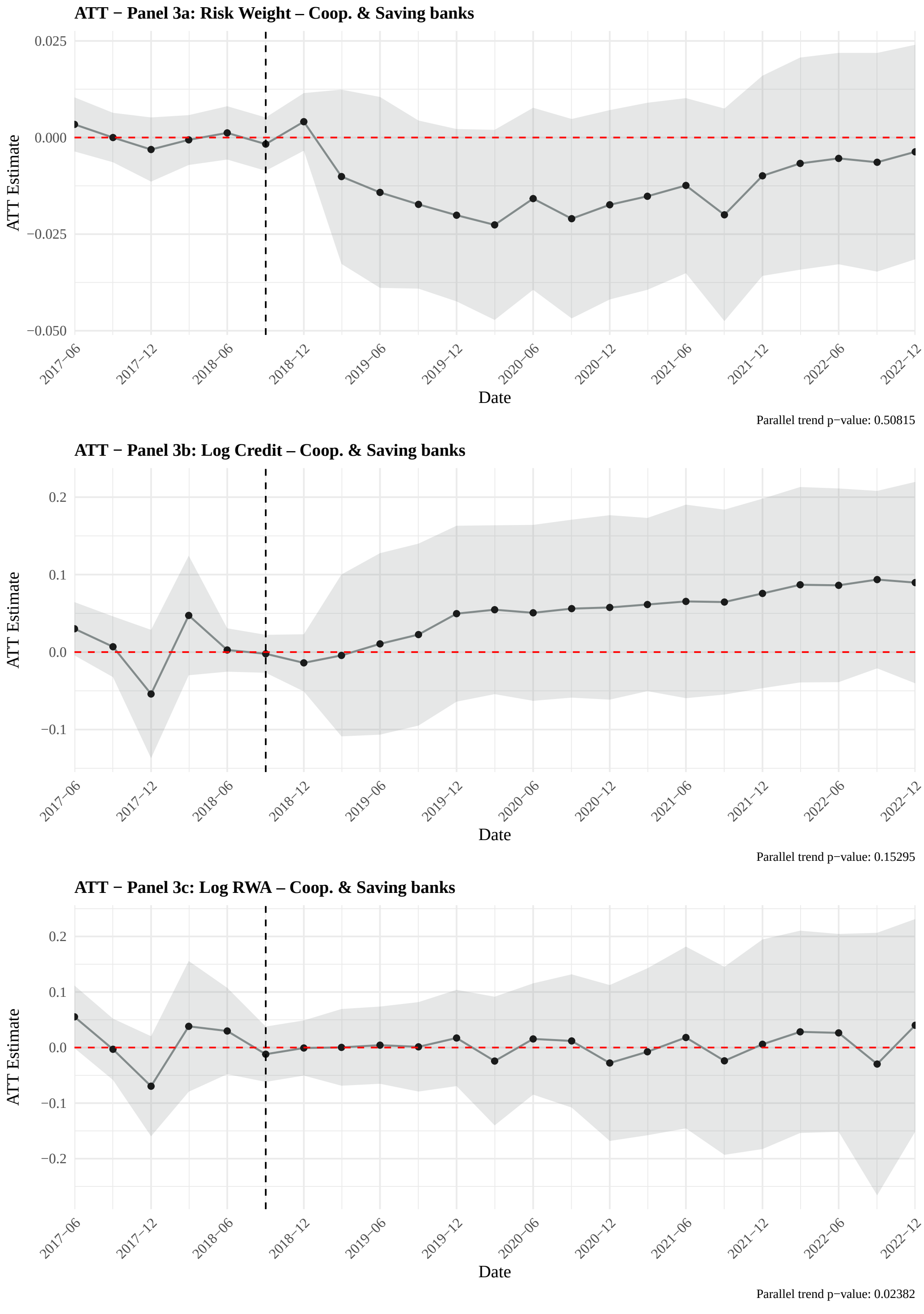
Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 6. Summary Results: Panels 2a, 2b, 2c – Private Banks

Outcome Variable: Risk Weight (%)					
Panel 2a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0347	0.0070	0.0210	0.0485	*
Outcome Variable: Log credit size					
Panel 2b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1236	0.0328	0.0594	0.1879	*
Outcome Variable: Log RWA					
Panel 2c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1413	0.0424	0.0581	0.2245	*

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in pp, while credit size and RWA are measured in logs. Therefore, the magnitude of the coefficients is not directly comparable. Since risk weight is mechanically the ratio of RWA to credit size, the log specifications for these two variables make it transparent which component drives the result: a stronger response of log-RWA points to an adjustment in banks' risk assessment, whereas a stronger response of log-loan-volume indicates that the effect operates through the size of the exposure.

Figure 4. Event Study ATT Estimates – Panel 3 – Cooperative and Savings Banks



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 7. Summary Results: Panels 3a, 3b, 3c – Cooperative and Savings Banks

Outcome Variable: Risk Weight (%)					
Panel 3a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	-0.0126	0.0077	-0.0277	0.0025	
Outcome Variable: Log credit size					
Panel 3b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0534	0.0420	-0.0289	0.1356	
Outcome Variable: Log RWA					
Panel 3c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0032	0.0396	-0.0743	0.0808	

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). The outcome variable, Risk Weight, is measured in pp, whereas credit size and RWA are in logs. Thus, the magnitude of the coefficients is not directly comparable. However, logs aid in interpreting the drivers of the effects.

4.3 Do Banks Treat Small and Large Firms Differently?

We next examine whether private banks' incorporation of transition risks differs by firm size. To this end, we split the sample into large firms and SMEs, as defined in Section 2. Panel 4a of Table 8 and Figure 5 show that for large firms, the ATT on the risk weight is positive but small at plus 1.3 pp relative to non-carbon-intensive firms and statistically insignificant. We only observe statistical significance for credit size and only from 2022 onward, as shown in Panel 4b.

Panel 5a of Table 9 and Figure 6 present the results for SMEs. In contrast to large firms, we find a positive and statistically significant ATT of 4.5 pp on the risk weight. Credit size in Panel 5b increases steadily after October 2018, indicating no material reduction in credit supply following the NGFS announcement, while the increase in RWA shown in Panel 5c is larger and statistically significant. Taken together, these findings suggest that carbon-intensive SMEs are perceived as riskier after the event, despite continued growth in lending volumes.

The asymmetric response of risk weights across firm size may reflect differences in credit relationships and information. Banks may be reluctant to tighten conditions for long-standing, profitable large clients with access to alternative financing sources such as capital markets, whereas SMEs depend more heavily on bank financing and typically have less bargaining power in lending relationships (Holton and Mccann (2017)).

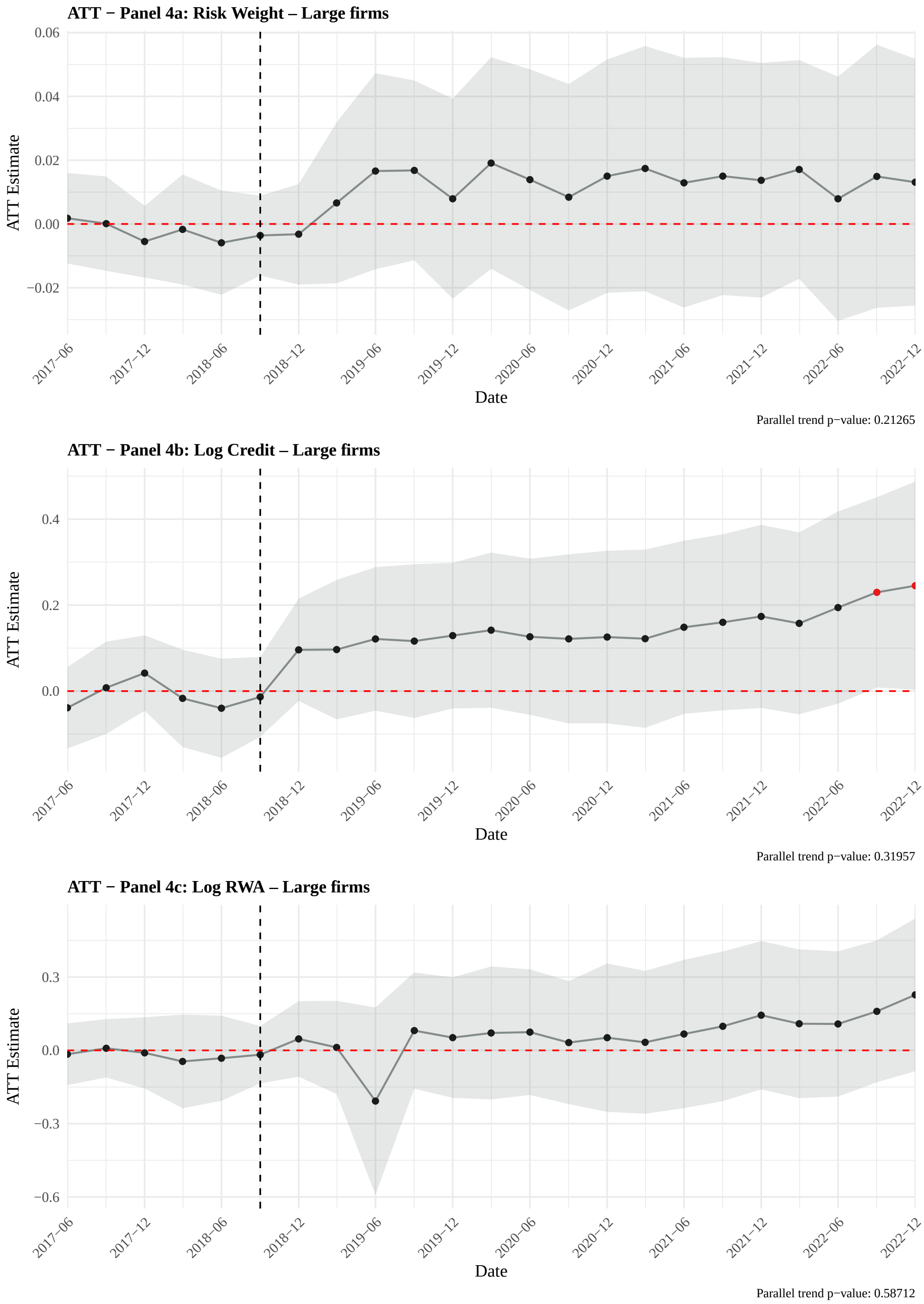
Further, differences in perceived resilience may play a role. If banks viewed large carbon-intensive firms as materially riskier due to transition exposure, a corresponding increase in RWA would be expected, as shown in Panel 4c. Since no such increase is observed, banks may assume that the substantial asset bases of large firms are sufficient to buffer transition shocks. However, SMEs generally have a more limited capacity to absorb shocks (Bakhtiari *et al.* (2020)), implying that any increase in perceived transition risk has more pronounced effects on their financing conditions. This is particularly relevant given that

SMEs already face less favourable financing conditions than large firms. Recent ECB survey evidence indicates that SMEs consistently report a greater deterioration in price terms and lending conditions than large enterprises (ECB (2025b)). If higher RWAs translate into higher loan pricing, incorporating transition risks into risk weights may therefore raise the cost of capital for SMEs (Dafermos (2021)).

Finally, the difference may also be attributable to our research design. The richer availability of ESG data for large firms relative to SMEs (Markopoulos, Al Katheeri, and Al Qayed (2023), Ozkan, Romagnoli, and Rossi (2023), and Koirala (2019)) may lead banks to rely more on firm-specific information for large borrowers and more on sector-level averages for SMEs. Under this interpretation, the sector-level transition risk signal captured by our metrics would more strongly affect SME portfolios, consistent with the observed pattern of results.

Overall, the evidence indicates that the private-bank effect documented earlier is driven primarily by SMEs rather than large firms. Both groups experience increases in lending, but only carbon-intensive SMEs, relative to green SMEs, are systematically perceived as riskier, resulting in higher risk weights and potentially higher borrowing costs.

Figure 5. Event Study ATT Estimates – Panel 4 - Large Firms



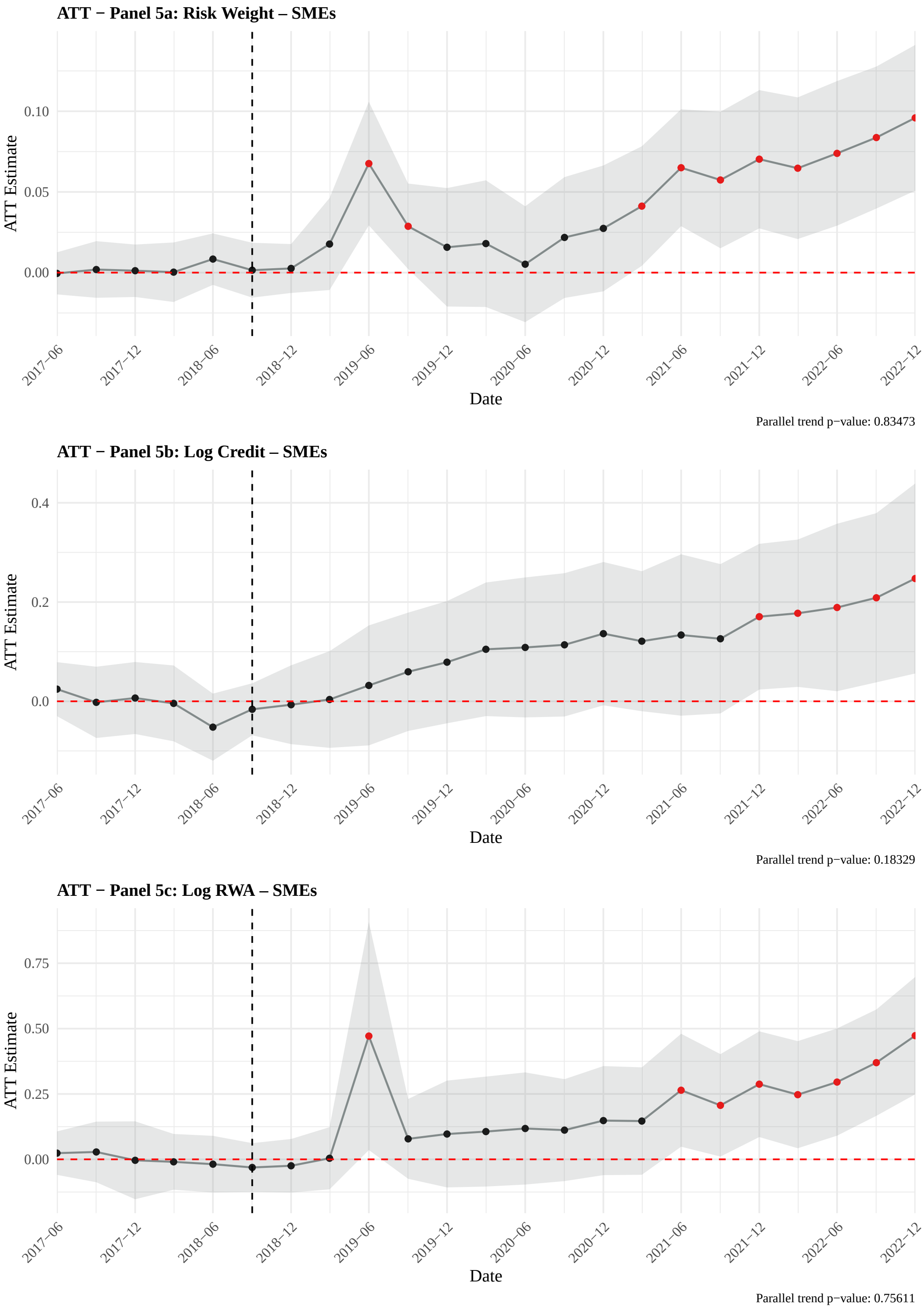
Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 8. Summary Results: Panels 4a–4c – Large Firms

Outcome Variable: Risk Weight (%)					
Panel 4a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0125	0.0100	-0.0070	0.0321	
Outcome Variable: Log credit size					
Panel 4b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1474	0.0634	0.0232	0.2716	*
Outcome Variable: Log RWA					
Panel 4c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0683	0.0809	-0.0903	0.2268	

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in pp, while credit size and RWA are measured in logs. Therefore, the magnitude of the coefficients is not directly comparable. Since risk weight is mechanically the ratio of RWA to credit size, the log specifications for these two variables make it transparent which component drives the result: a stronger response of log-RWA points to an adjustment in banks' risk assessment, whereas a stronger response of log-loan-volume indicates that the effect operates through the size of the exposure.

Figure 6. Event Study ATT Estimates – Panel 5 - SMEs



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 9. Summary Results: Panels 5a–5c – SMEs

Outcome Variable: Risk Weight (%)					
Panel 5a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.0445	0.0103	0.0244	0.0646	*
Outcome Variable: Log credit size					
Panel 5b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.1179	0.0451	0.0295	0.2063	*
Outcome Variable: Log RWA					
Panel 5c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	0.2000	0.0614	0.0798	0.3203	*

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in pp, while credit size and RWA are measured in logs. Therefore, the magnitude of the coefficients is not directly comparable. However, the log values of credit size and RWA help interpret the drivers of the effects.

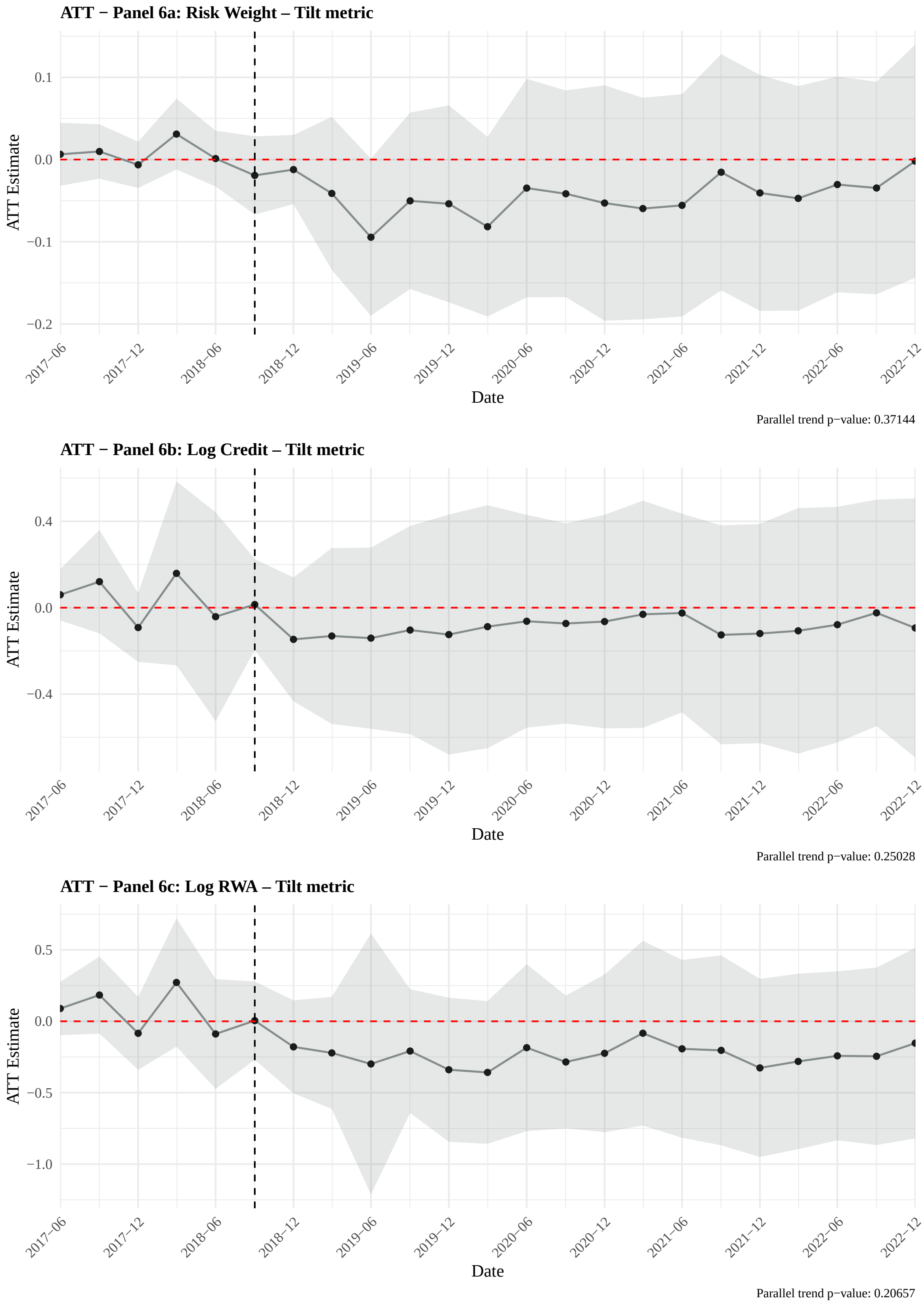
4.4 Do banks go beyond sector averages for perceiving transition risks?

Finally, we test whether banks go beyond sector-level metrics by employing a product-level transition-risk measure (see Table 10 and Figure 7). We find no significant effects on the overall risk weight, credit size, or RWA, although the sample size is small (332 observations per period). As the product metric differentiates higher-risk from lower-risk firms within the same sector, the absence of significant effects suggests no evidence that banks apply transition-risk assessments beyond sector averages.

These findings are not surprising. As shown in Section 2.6, the CPRS is widely used. Although the *tilt* database is a relatively new data source and therefore unlikely to be used by banks, our findings are consistent with the literature on emission data. Billio *et al.* (2021), Kalesnik, Wilkens, and Zink (2022) and Aswani, Raghunandan, and Rajgopal (2024) show in their research that most published emission data by data providers are driven only by the sector or the firm size, hiding heterogeneity within the sector. Only a few databases, such as GRESB (n.d.), capture asset-based emissions, and their sectoral coverage is limited. Other data providers, including MSCI (n.d.) and ISS (n.d.), report firm-level emission intensity, but these data primarily cover large firms. Furthermore, our findings align with the Fernandez-Bollo (2024a) call for banks to enhance climate- and environmental-risk management frameworks, including more sophisticated and granular models.

The findings imply that, due to the lack of emission data, we face an asymmetric information problem (Stiglitz and Weiss (1981)) whereby low-risk firms in high-risk sectors may be "penalised" if higher risk weights-driven by sector classification-are reflected in lending rates, creating potential mispricing.

Figure 7. Event Study ATT Estimates – Panel 6 - Carbon Intensity Measured with Product Metrics (*tilt*)



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 10. Summary Results: Panels 6a–6c – Carbon Intensity (Product-Based Metric)

Outcome Variable: Risk Weight (%)					
Panel 6a	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	-0.0440	0.0381	-0.1186	0.0306	
Outcome Variable: Log credit size					
Panel 6b	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	-0.0905	0.1696	-0.4229	0.2419	
Outcome Variable: Log RWA					
Panel 6c	**ATT**	**Std. Error**	**Lower 95% CI**	**Upper 95% CI**	**Sig.**
	-0.2368	0.1591	-0.5486	0.0750	

Notes: Estimation follows a doubly robust DiD approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in pp, while credit size and RWA are measured in logs. Therefore, the magnitude of the coefficients is not directly comparable. Since risk weight is mechanically the ratio of RWA to credit size, the log specifications for these two variables make it transparent which component drives the result: a stronger response of log-RWA points to an adjustment in banks' risk assessment, whereas a stronger response of log-loan-volume indicates that the effect operates through the size of the exposure.

5 Moderating Effects

We analyse whether bank-specific characteristics moderate the management of transition risks. Capital and bank size are natural candidates for moderating effects because they determine a bank's capacity to absorb shocks and therefore condition its risk-taking response. Well-capitalised banks can absorb losses more easily and face fewer balance-sheet constraints, improving resilience during stress episodes (see e.g., Cardot-Martin, Labondance, and Refait-Alexandre (2022)). Bank size captures additional dimensions of resilience. Larger institutions may benefit from diversification, scale economies in risk management, and better access to funding markets, which can enhance shock-absorption capacity (see e.g., Laeven, Ratnovski, and Tong (2016)). If transition risk interacts with these balance-sheet attributes, the same regulatory signal may trigger different adjustments across banks.

Furthermore, we investigate whether banks facing higher transition risks across their entire portfolios manage these risks more effectively than banks with lower exposure. The underlying assumption is that banks with limited exposure to climate transition risks face weaker incentives to adjust their risk management and lending behaviour, whereas more exposed banks are more likely to actively incorporate transition risks into their credit decisions.

Studying these moderating effects, therefore, helps identify whether the transmission of transition risk is shaped primarily by banks' financial strength or by their portfolio exposures.

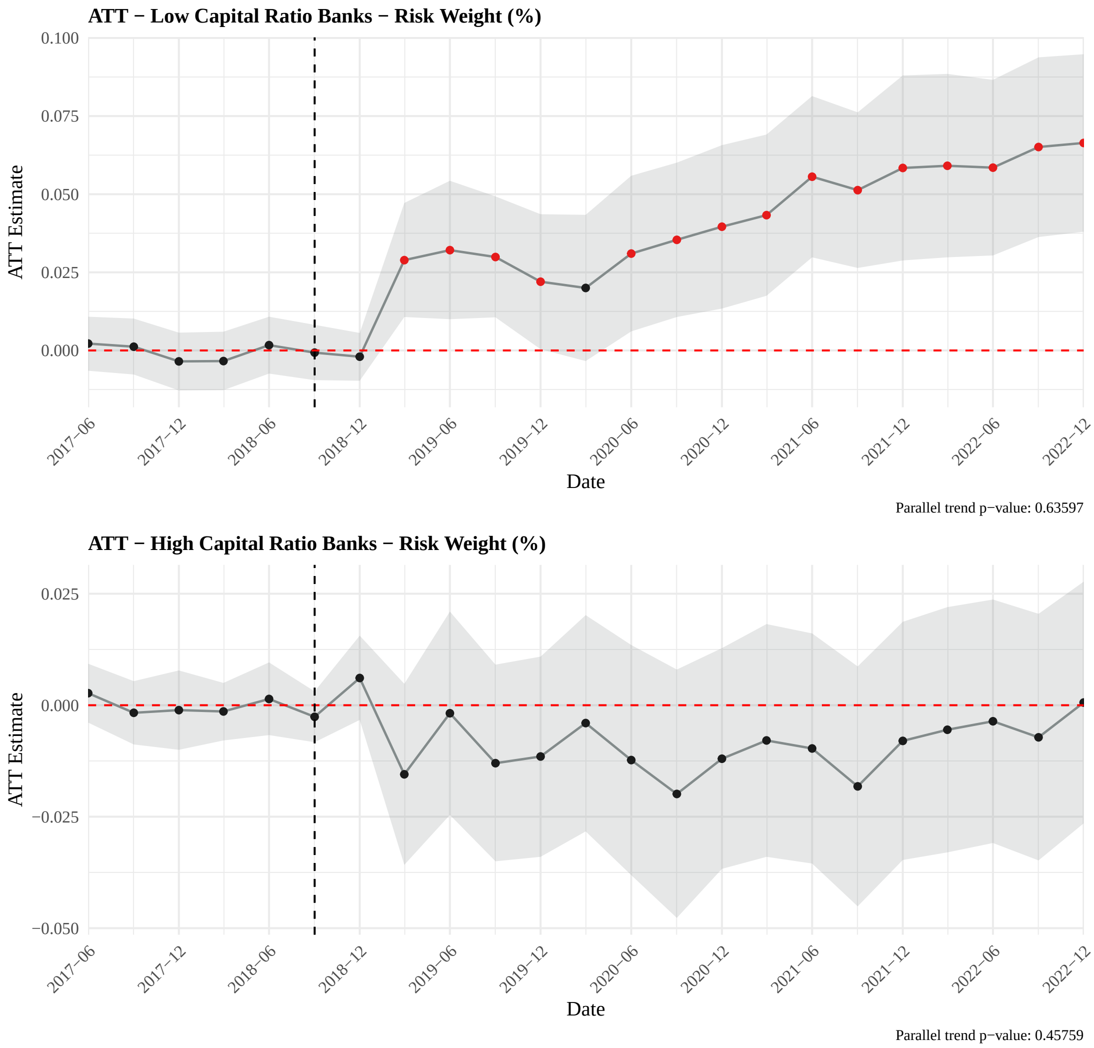
5.1 Does a bank's size or shock-absorbing capacity moderate its transition risk management response?

First, banks with low capital ratios exhibit the largest effect, with an ATT of 4.1 pp, exceeding the full-sample effect, whereas those with high capital ratios show a small negative effect (ATT = –0.8 pp) (see Table 11 and Figure 8). One possible interpretation is that low-capital banks increase risk weights for carbon-intensive borrowers to ensure adequate capitalisation for these exposures, without holding excess capital in the broader portfolio. This indicates that transition risk management is not necessarily tied to high overall buffers but may be targeted to carbon-intensive exposures.

Second, banks with higher total assets exhibit stronger management of transition risks, with an ATT of 3.1 pp, compared with –1.1 pp for smaller banks (see Table 12 and Figure 9). This aligns with the idea that larger institutions can diversify their exposures and invest in tailored risk-management tools, while also facing greater exposure.

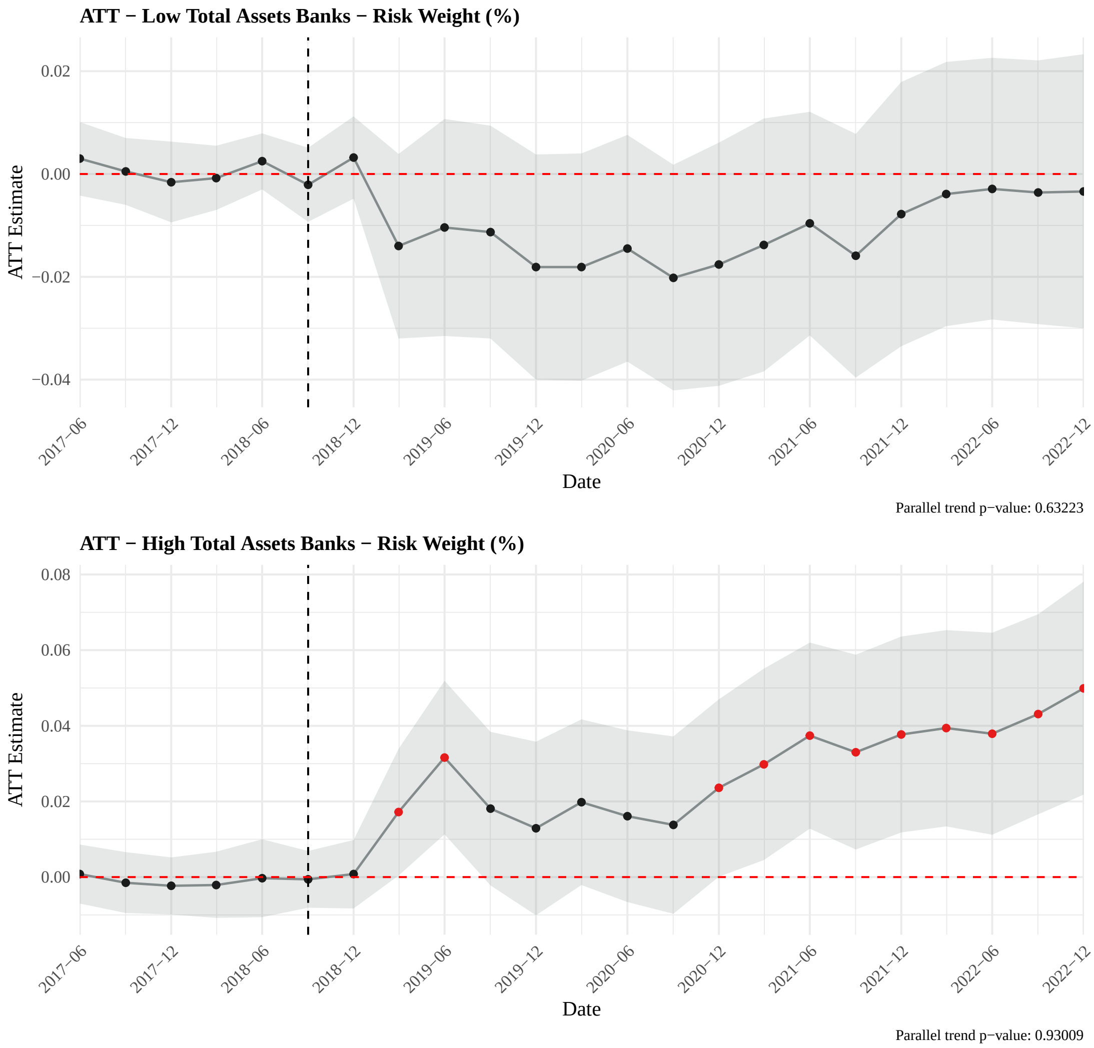
Both patterns are consistent with earlier results showing that private banks, which are generally larger and operate with higher leverage - implying lower capital buffers relative to assets (Deutsche Bundesbank (2015)) - drive the overall effect, whereas cooperative and savings banks do not. The bank-specific characteristics analysed here, therefore, help to explain part of the heterogeneity observed across bank types in their response to transition risks.

Figure 8. Event Study ATT Estimates – Comparing Banks with Low and High Capital Ratios



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Figure 9. Event Study ATT Estimates – Comparing Banks with Low and High Total Assets



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 11. Summary Results – Capital Ratio Heterogeneity

Outcome Variable: Risk Weight (%)					
Low Capital Ratio Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0409	0.0071	0.0269	0.0548	*
SE firm-level clustered					
High Capital Ratio Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	-0.0084	0.0075	-0.0231	0.0062	
SE firm-level clustered					

Notes: Estimation follows a doubly robust Difference-in-Differences approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Relative change and standardised change are calculated based on baseline means and ATT. Relative change is measured in percentage points. Standardised change is unitless. Results reflect heterogeneity based on banks' capital ratios.

Table 12. Summary Results: Total Assets Heterogeneity

Outcome Variable: Risk Weight (%)					
Low Total Assets Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	-0.0113	0.0074	-0.0258	0.0033	
SE firm-level clustered					
High Total Assets Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0319	0.0071	0.0179	0.0459	*
SE firm-level clustered					

Notes: Estimation follows a doubly robust Difference-in-Differences approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Relative change and standardised change are calculated based on baseline means and ATT. Relative change is measured in percentage points. Standardised change is unitless. Results reflect heterogeneity based on bank size, proxied by log total assets.

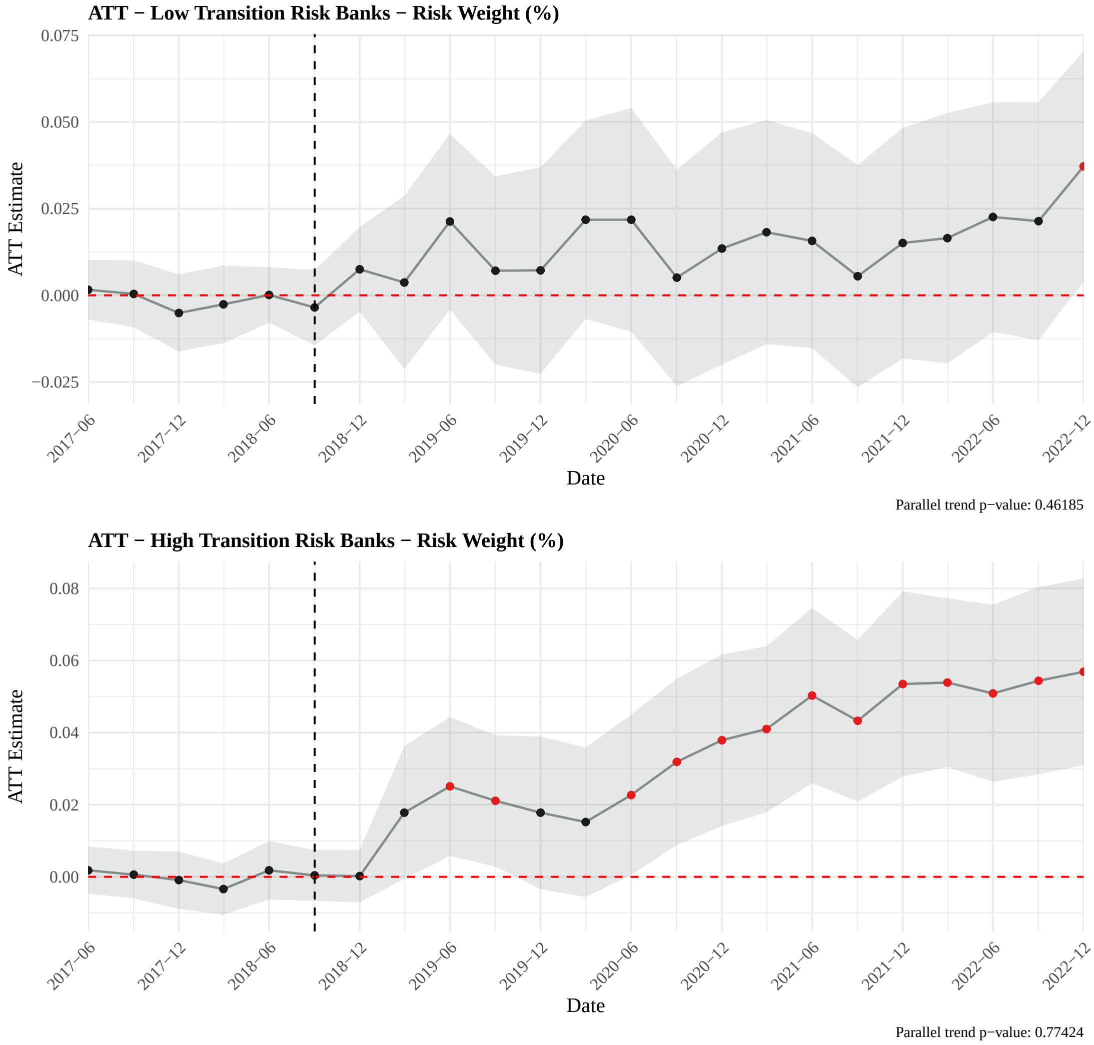
5.2 Does the transition risk exposure of banks moderate the results?

We next test whether banks with higher overall exposure to transition risks manage these risks more actively than banks with lower exposure.

High-transition-risk banks exhibit a statistically significant ATT of 3.5 pp, more than twice the 1.5 pp estimate for low-transition-risk banks, which is not statistically significant (see Table 13 and Figure 10). This suggests that banks facing greater portfolio vulnerability to the climate transition respond more decisively. These banks are raising risk weights for carbon-intensive borrowers, whereas banks with lower exposure to transition risks may perceive less urgency to adjust lending or risk-assessment practices. The stronger response among high-risk banks is consistent with both regulatory expectations and market incentives to proactively address concentrated transition-risk exposures (ECB (2020)).

This pattern is also consistent with former research by D'Orazio, Hertel, and Kasbrink (2024) showing that smaller banks may face relatively lower climate transition risks than larger private banks.

Figure 10. Event Study ATT Estimates – Comparing Banks with Low and High Transition Risk Exposure



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 13. Summary Results - Transition Risk Heterogeneity

Outcome Variable: Risk Weight (%)					
Low Transition Risk Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0154	0.0096	-0.0034	0.0341	
SE firm-level clustered					
High Transition Risk Banks	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0349	0.0065	0.0222	0.0476	*
SE firm-level clustered					

Notes: Estimation follows a doubly robust Difference-in-Differences approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package). Please note: The outcome variable Risk Weight is measured in percentage points. Results reflect heterogeneity based on banks' exposure to transition risk.

6 Conclusion

This paper shows that climate-related transition risks are not incorporated uniformly across the banking sector. Risk management practices differ systematically across banking groups and borrower types, implying that conclusions drawn from large banks or large firms do not necessarily generalise to the wider credit market. In particular, private banks adjust risk weights for carbon-intensive firms, while cooperative and savings banks expand lending to these firms without corresponding increases in risk weights. Within private banks, transition risk considerations are reflected more strongly in risk weights for carbon-intensive SMEs than for large firms. These patterns suggest that treating banks or borrowers as homogeneous may obscure important differences in how climate-related risks are currently assessed and priced.

This heterogeneity has several implications for policy and supervision. First, undetected or underpriced transition risk exposures in cooperative and savings banks may pose financial stability risks if risks materialise abruptly. Second, the incorporation of transition risks into risk weights by private banks may tighten financing conditions for SMEs, potentially amplifying existing credit constraints relative to large firms. Third, reliance on sector-level measures may lead to mispriced risks, with implications for capital allocation and the effectiveness of supervision. Taken together, the findings highlight the importance of accounting for institutional and borrower-level heterogeneity when designing and evaluating climate-related prudential policies.

We also discussed limitations in the data, including the exclusion of loans above €1 million, the coverage of only German banks, and reliance on the relatively recent *tilt* dataset, which we use to test a firm's product-specific risk management. Future work could extend the analysis to other jurisdictions and examine how bank practices evolve as climate policies, data availability, and supervisory expectations develop.

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7 Appendix

7.1 Assumptions Identification Strategy

We argued in Section 3 why the parallel trend assumptions hold. Here, we also argue for two other main assumptions of the DiD design: the no anticipation effect and the Stable Unit Treatment Value Assumption (SUTVA).

We argue that the *no anticipation effect* assumption holds. No anticipation effect means that banks do not adjust their behaviour before the treatment takes effect. Although the NGFS was established in December 2017, and public discourse on climate finance intensified in 2018, banks require considerable time to integrate new risk practices into decision-making processes. Given the complexity of credit risk models, regulatory adjustments, and internal implementation timelines, banks are unlikely to pre-emptively alter risk evaluations before October 2018.

We also argue that the *Stable Unit Treatment Value Assumption* (SUTVA) holds. SUTVA requires that the treatment status be well defined and stable, with no interference between units. This condition is met because each firm is assigned to a single sector category, ensuring that each firm is either in the treatment or control group without cross-contamination. Additionally, the CPRS uses uniform sector classifications, meaning that all firms within the same sector are treated identically, thereby eliminating the possibility of heterogeneous treatment effects arising from classification discrepancies. Importantly, there is no scaling process, meaning firms do not receive treatment to varying degrees. Treatment is binary rather than continuous, reinforcing the assumption of stable treatment assignment.

7.2 Standard Error robustness testing

Table 14 shows the main results with different standard error clustering. Results are robust across clusters. We use firm-level clustered standard errors because treatment occurs at the firm level.

Table 14. Summary Results Robustness Check Standard Error Clustering for Panels no SE, firm-SE, bank-SE, firm-bank SE – with Panel 1 (All Banks)

Outcome variable: Risk Weight (%)					
Panel no SE	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0277	0.0045	0.0188	0.0366	*
No SE clustering					
Panel firm-SE	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0277	0.0055	0.0170	0.0385	*
SE firm-level clustered					
Panel bank-SE	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0277	0.0108	0.0065	0.0489	*
SE bank-level clustered					
Panel firm-bank SE	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0277	0.0052	0.0176	0.0379	*
SE bank-firm-level clustered					

Notes: We test Panel 1 (all banks) using various clustering levels. Panel "no SE" uses no standard error (SE) clustering, panel "firm-SE" on the firm-level, panel "bank-SE" on bank-level and panel "bank-firm-SE" on bank-firm-level.

7.3 Variable used

Table 15. Definitions and Sources of the Main Variables

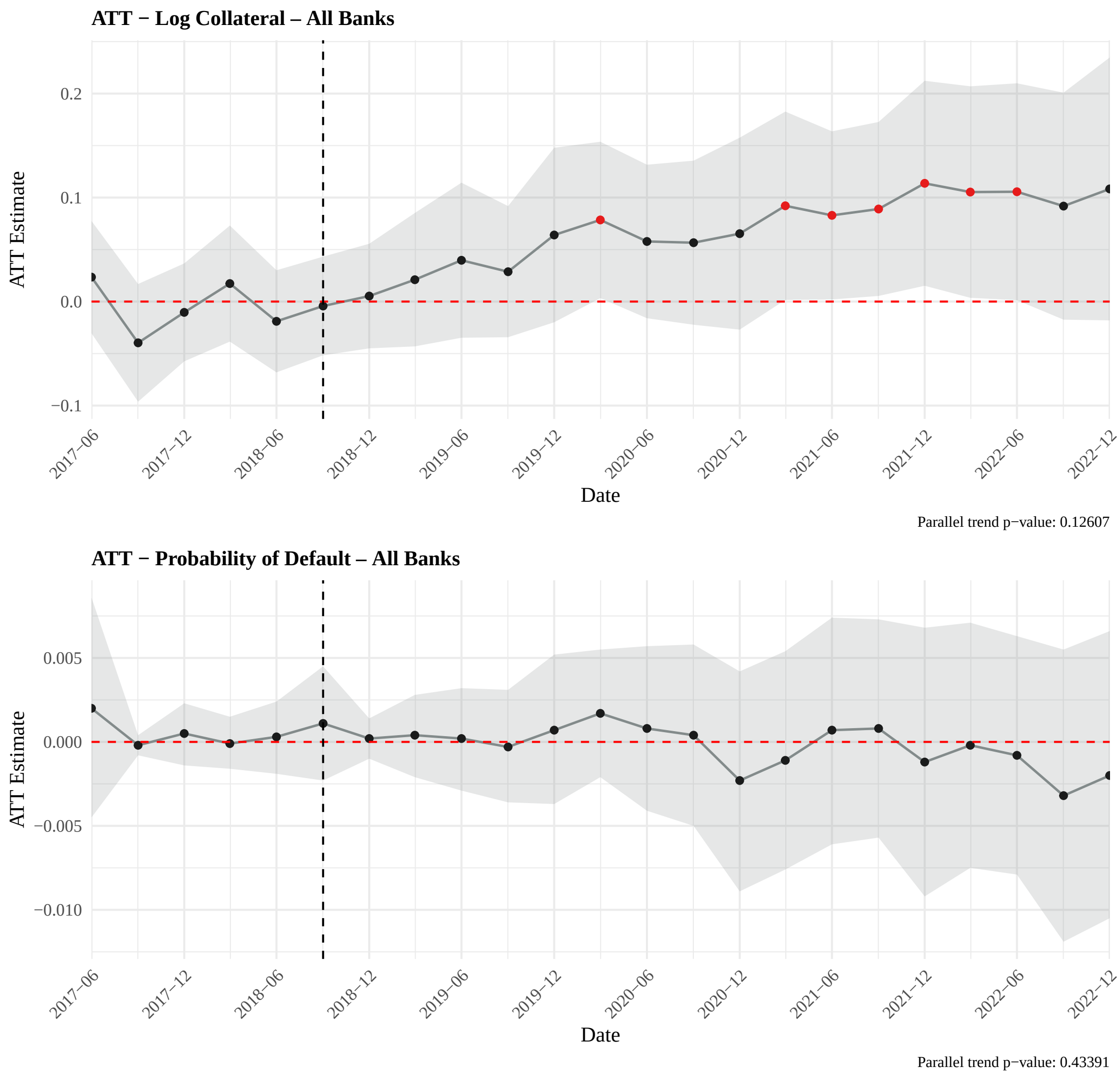
Variable	Definition	Unit	Source
Risk Weight	Loan-level risk-weighted assets over total loan volume	%	Loan data (Bundesbank (2023))
Log loan volume	Logarithm of the loan amount	log(Euro)	Loan data (Bundesbank (n.d.))
Log RWA	Logarithm of the risk-weighted assets	log(Euro)	Loan data (Bundesbank (n.d.))
WZ Code	German Economic sector classification (similiar to NACE codes)	-	Loan data (Bundesbank (2023))
BGRS	Banking group indicator (e.g. private, cooperative, savings bank)	-	MamFi (Stahl (2024))
Net Profit Margin	Net income (loss) over sales	%	JANIS (Becker et al. (2024))
Gross Profit Margin	Gross profit over sales	%	JANIS (Becker et al. (2024))
Current Ratio	Current assets over total liabilities	%	JANIS (Becker et al. (2024))
Quick Ratio	(Cash + Accounts Receivable) over total liabilities	%	JANIS (Becker et al. (2024))
Interest Coverage Ratio	Interest and other expenditures over total assets	%	JANIS (Becker et al. (2024))
Debt-to-Equity Ratio	Total liabilities over equity	%	JANIS (Becker et al. (2024))
Debt-to-Assets Ratio	Total liabilities over total assets	%	JANIS (Becker et al. (2024))
Tangible Asset Ratio	Tangible assets over total assets	%	JANIS (Becker et al. (2024))
Intangible Asset Ratio	Intangible assets over total assets	%	JANIS (Becker et al. (2024))
Inventory Ratio	Inventories over current assets	%	JANIS (Becker et al. (2024))
Liquidity Asset Ratio	Cash over total assets	%	JANIS (Becker et al. (2024))
Provision-to-Equity Ratio	Provisions over equity	%	JANIS (Becker et al. (2024))
Pensions-to-Equity Ratio	Pension provisions over equity	%	JANIS (Becker et al. (2024))
Deficit Ratio	Deficit not covered by equity over total assets	%	JANIS (Becker et al. (2024))
Return on Equity	Operating results over equity	%	JANIS (Becker et al. (2024))
Employees	Number of employees	Count	JANIS (Becker et al. (2024))
Firm Age	Current year minus founding year	Years	JANIS (Becker et al. (2024))
Log Total Assets	Logarithm of total assets	log(Euro)	JANIS (Becker et al. 2024)
Log Sales	Logarithm of total sales	log(Euro)	JANIS (Becker et al. (2024))
Log Current Assets	Logarithm of current assets	log(Euro)	JANIS (Becker et al. 2024)
Log Cash	Logarithm of cash holdings	log(Euro)	JANIS (Becker et al. (2024))
Log Total Assets (Banks)	Total assets of banks (base for balance sheet ratios)	log(Euro)	BISTA (Schäfer and Stahl (2025))
Capital Ratio (Banks)	Regulatory capital over total assets	%	BISTA (Schäfer and Stahl (2025))
Liquidity Ratio (Banks)	Sum of cash in hand, balances with central banks and treasury bills over total assets	%	BISTA (Schäfer and Stahl (2025))
Sector metric: Carbon Intensity	List of all climate-relevant policy sectors (CRPS)	0,1	Battiston et al. (2017)
Product metric: Carbon Intensity	High transition-risk products dummy within one sector	0,1	*tilt*(Lepore et al. 2024)
Transition Risk Exposure (Banks)	Transition risk exposure variable according to policy scenario	-	Vemeulen et al. (2021)

Notes: Loan data (MioEvidence) (variables are measured at the bank–firm level and observed quarterly. All JANIS variables are measured at the firm level and are annual, with lags applied to all firm-level variables. BISTA variables are measured at the bank level. The JANIS dataset contains balance sheet data for non-financial companies, while the BISTA dataset provides balance sheet information for financial institutions. We applied a logarithmic transformation to the level variable using log(variable + 1) to address skewness and account for zero values. The carbon-intensity sector and product metrics are firm-level dummy variables defined prior to the event. The transition risk exposure variable from Vermeulen *et al.* (2021) is measured at the bank level.

7.4 Robustness Test different outcome variables

We also examine alternative outcome variables that more directly capture banks' risk perceptions: collateral requirements and default probabilities. The ATT estimates for the outcome variable collateral are positive and significant with 7.1 pp, and the ATT with the probability of default outcome is slightly negative but non-significant (-0.03pp). In both cases, the parallel trends hold, as confirmed by the event-study plots and pre-trend tests (see Table 16 and Figure 11). The evidence based on the probability of default (PD) is less informative in our setting. First, the available PD sample is considerably smaller, limiting statistical power and making it harder to detect economically meaningful effects. Second, PD is only one component of banks' internal risk assessment and regulatory capital calculations. Risk weights also depend on factors such as loss given default (LGD), exposure at default (EAD), collateralisation, and other borrower and loan characteristics. Adjustments in collateral requirements, which we observe and which align with our main results, therefore reflect changes in perceived risk even if PD itself does not change significantly. Accordingly, the absence of significant PD effects does not contradict our findings, as banks may adjust lending conditions and capital requirements through channels other than changes in measured default probabilities.

Figure 11. Event Study ATT Estimates – Robustness Checks with Different Outcome Variables



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 16. Robustness Check – Alternative Outcome Variables: Log Collateral and Probability of Default (PD)

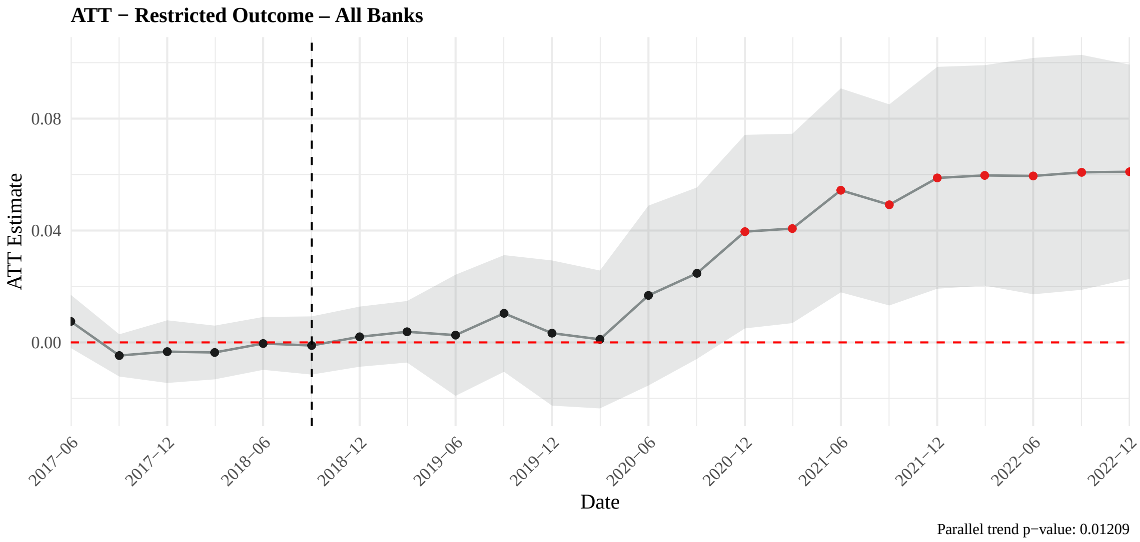
Outcome variable: Log Collateral					
Estimate	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0709	0.0238	0.0243	0.1176	*
SE firm-level clustered					
Outcome variable: Probability of Default (PD)					
Estimate	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	-0.0003	0.0015	-0.0033	0.0027	
SE firm-level clustered					

Notes: This table reports results from robustness checks using alternative outcome variables. Estimation follows a doubly robust Difference-in-Differences approach (Callaway and Sant'Anna (2021)). A * means the estimated effect is significant at the 5% level (the default in the did package).

7.5 Structural change in definition

In 2019-Q1, the definition of total exposure was expanded to include off-balance-sheet items and securities, thereby affecting both the definition of credit size and the definition of RWA and, consequently, the outcome variable. While definitions in panel data may pose challenges, this adjustment does not bias our results: first, it was applied uniformly across sectors and banks, and our difference-in-differences design captures only relative differences, making it robust to such common shocks. Second, Table 17 and Figure 12 confirm robustness – restricting the sample to firms with less than ±5% change in exposure or RWA yields similar effects. Third, although this was a one-time adjustment, our estimated effects persist well beyond 2019-Q1 and therefore cannot explain the sustained post-2018 trends.

Figure 12. Event Study ATT Estimates – Robustness Checks with Restricted Outcome Variable



Note: Estimates are shown with 95% confidence intervals. Statistically significant ATT estimates at the 5% level are highlighted in red. Reported p-values refer to pre-treatment parallel trends tests.

Table 17. Robustness Check – Restricted Outcome Variable (Definition Change)

Outcome variable: Risk Weight (%) – Restricted Sample					
Estimate	ATT	Std. Error	Lower 95% CI	Upper 95% CI	Sig.
	0.0323	0.0089	0.0149	0.0497	*
SE firm-level clustered					

Notes: This robustness check uses a restricted sample to ensure that the structural change in the outcome variable's definition in 2019 does not bias the results. We exclude all observations with changes greater than ±5 % in total credit and RWA between December 2018 and March 2019. This threshold is chosen because the average change over this period is approximately 2.5%, making larger changes unlikely to be attributable to the October 2018 event and more likely to reflect definitional adjustments. Estimation uses a doubly robust Difference-in-Differences approach (Callaway and Sant'Anna (2021)).

7.6 Robustness Test with TWFE estimator

Table 18 shows the positive and significant results with the two-way fixed effects (TWFE) estimator. The pre-period extends from January 2016 to September 2018. Post-periods are from December 2018 to December 2022. Similar to the results with the Callaway and Sant'Anna (2021) estimator, we conducted propensity score matching based on the imbalanced covariates selected through LASSO and Imbens and Rubin (2015). Additionally, we included the covariates in the equation.

Our baseline uses the Callaway and Sant'Anna (2021) DiD estimator, which identifies group-specific average treatment effects and aggregates them to summarise heterogeneity across groups and over time. We implement the doubly robust version, which is consistent if either the outcome regression or the (generalised) propensity score is correctly specified, as shown in Sant'Anna and Zhao (2020). This choice is motivated by evidence that the aggregate effect is driven by specific bank groups or borrower characteristics. In such settings, conventional TWFE regressions conflate comparisons across cohorts and can yield distorted event-study coefficients and problematic weights, particularly when effects are heterogeneous (for different banking groups) (Goodman-Bacon (2021), Sun and Abraham (2021)). Our Callaway and Sant'Anna (2021) estimates, therefore, directly report group-level effects and their dynamic evolution after 2018. Therefore, we retain TWFE solely as a robustness check.

$$\begin{aligned} \text{RiskWeight}_{ibt} = \alpha &+ \beta_1 \,\text{Employees}_{it} + \beta_2 \,\text{TangibleAssetRatio}_{it} \\ &+ \beta_3 \,\text{TangibleAssetRatio}_{i,t-1} + \theta \,(\text{CarbonInt}_i \times \text{Post}_t) \\ &+ \phi \,\text{CarbonInt}_i + \tau \,\text{Post}_t + \mu_i + \lambda_b + \delta_t + \varepsilon_{ibt}. \end{aligned} \tag{6}$$

where: RiskWeight_{ibt}: Total Risk-Weighted Contribution Share of firm i borrowing from bank b in period t (dependent variable); Employees_{it}: Number of employees of firm i in period t; $\text{TangibleAssetRatio}_{it}$: Ratio of tangible assets to total assets for firm i in period t; $\text{TangibleAssetRatio}_{i,t-1}$: One-period lag of the tangible-asset ratio; CarbonInt_i: Carbon-intensity dummy variable (1 if firm i is classified as carbon-intensive, 0 otherwise); Post_t: Post-event dummy variable (1 for periods after the NGFS first progress report in October 2018, 0 otherwise); $\text{CarbonInt}_i \times \text{Post}_t$: Interaction term capturing the differential effect for carbon-intensive firms in the post-event period; μ_i: Firm fixed effects; λ_b: Bank fixed effects; δ_t: Time fixed effects; ε_{ibt}: Error term. Standard errors are clustered at the firm level.

Table 18. Robustness Check – Alternative Estimation Method (TWFE)

Dependent Variable: Total Risk-Weighted Contribution Share				
Specification	Firm FE	Bank FE	Bank-Firm FE	OLS (No FE)
Observations	212,784	212,784	212,784	212,784
Fixed Effects	Firm, Time	Bank, Time	Firm–Bank	None
Clusters (Firm)	Yes	Yes	Yes	Yes
Employees	0.00000157	-0.00000167	0.00000073	0.00000641·
	(0.00002200)	(0.00000226)	(0.00001800)	(0.00000346)
Tangible Asset Ratio	0.0565·	-0.0069	0.1740***	0.0774*
	(0.0319)	(0.0322)	(0.0294)	(0.0378)
Lag Tangible Asset Ratio	0.1100***	-0.0448	0.0589*	-0.0248
	(0.0322)	(0.0327)	(0.0282)	(0.0416)
Carbon-intensity of firm (Dummy)	-	-0.0952***	-	-0.1331***
		(0.0109)		(0.0137)
Time (Dummy)	-	-	-0.1542***	-0.1563***
			(0.0055)	(0.0057)
Interaction term (CPRS $\times$ Time)	0.0631***	0.0630***	0.0630***	0.0638***
	(0.0066)	(0.0076)	(0.0068)	(0.0075)
(Intercept)	-	-	-	0.6487***
				(0.0136)
Adjusted R^2	0.5843	0.4041	0.7899	0.0454
Within R^2	0.0053	0.0178	0.1314	-
RMSE	0.2164	0.2619	0.1525	0.3320

Notes: This table reports OLS and TWFE regression results using different fixed-effects structures. Standard errors are clustered at the firm level. Asterisks denote significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$. Results reflect robustness checks for the treatment effect of the CPRS interaction term across models.