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**Climate Risk and Credit Allocation:
A Study of Domestic and Foreign Banks in Türkiye**

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Abstract

This study examines how banks in Türkiye adjust their lending in response to climate-related risks, with particular attention to ownership structures and home-country characteristics. Using firm-level credit data from the Turkish Credit Registry, we evaluate banks' exposures to high-carbon ("dirty") and low-carbon ("green") sectors across domestic private, state-owned, and foreign institutions. We find a general contraction in lending to dirty sectors, driven primarily by private and foreign banks in the post-Paris Agreement period, while state-owned banks continue to support high-carbon industries. Foreign banks headquartered in advanced economies also reduce dirty-sector lending over time, although the stringency of home-country climate policy does not have a statistically significant effect. These findings indicate that both ownership structures and home-country institutional environments shape banks' climate-related lending behavior in emerging markets. The paper offers the first systematic evidence from Türkiye on banks' transition strategies, underscoring sectoral credit reallocation and cross-border influences in climate-aligned banking.

JEL Codes: F23, G21, G28, Q54

Keywords: Climate change, bank lending, foreign banks, state banks, emerging country, Türkiye

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1. Introduction

Given the climate crisis, it is crucial for policy makers to assess whether the financial sector aligns its lending and investment activities with climate goals. Financial markets play a key role in the transition to a low-carbon economy, and climate-related risks are increasingly translating into traditional financial risks (Giglio et al., 2021; BIS, 2022). Given their central role in the economy wide allocation of finance, banks' financial decisions can significantly affect the outcomes of the decarbonization process. Consequently, the amount of credit allocated by banks to so-called green (low emission) vs brown (high emission) firms is a major concern for policy makers.

The economic factors motivating banks to voluntarily align their lending portfolios with a decarbonized economy are complex. Banks' lending behavior may be influenced by risk and profitability considerations (Kacperczyk & Peydró, 2024; Morse & Sastry, 2024). Banks may reduce credit to brown firms and increase lending to green firms as part of prudent risk management, since exposure to stranded assets, green regulations, and carbon-emitting sectors can increase risks. In particular, tightening environmental regulation can deteriorate the business prospects of high-polluting firms, affecting negatively their collateral and profits and increasing their default risk (Huang et al., 2021). At the same time, financing newer and unproven technologies within the decarbonization economy also entails higher risk, given uncertainties around their long-term viability. Profitability concerns also matter, as banks may seek to capture higher-margin loans and growth opportunities associated with the decarbonization transition (Morse & Sastry, 2024). Alternatively, banks' lending behavior may also reflect a preference for green assets over brown ones due to their own green commitments or external pressures from various stakeholders (Kacperczyk & Peydró, 2024). Research on corporate responses to environmental challenges identifies several sources of such pressures, including customers, shareholders, regulators, and community groups, as well as importance of financial resources and management capabilities for pursuing proactive environmental policies (Henriques & Sadosky, 1996; Clarkson et al., 2011).

Following the discussion above, this study aims to examine whether banks in Türkiye consider climate-related risks and adjust their lending across firms and sectors. Specifically, the study addresses the following research questions: (i) Is there a lending portfolio reallocation from high-carbon to low-carbon industries? (ii) Are there differences in strategies across ownership types (domestic private, domestic state-owned, and foreign owned) and is it changing in time? Additionally, given the heterogeneity of foreign banks based on their home country, which influences their business models, strategies and performance, we ask: (iii) Do foreign banks adopt different climate strategies based on the institutional and environmental policy strictness of their home countries?

The extent to which banks adjust their credit decisions in response to climate-related risks and actual or anticipated regulations has been explored in several studies. Kacperczyk and Peydró (2024), using a global sample of syndicated loans, find that firms with higher carbon footprints receive less bank credit when their lenders are committed to decarbonization targets, suggesting that such banks adjust credit supply based on preferences for green over brown assets. Miguel et al. (2024) show that, following a 2017 Brazilian policy requiring large banks to incorporate social and environmental risks into their capital assessments, these banks reallocated credit away from environmentally exposed sectors, particularly by reducing long-term loans to small firms, while smaller exempt banks expanded lending to these sectors. Takahashi and Shino (2025) find that Japanese banks significantly reduce lending to firms with higher greenhouse gas (GHG) emissions and emission intensity. The effect appears to be driven primarily by loan supply rather than credit demand, with highly leveraged and less profitable banks more likely to restrict credit to high-emission, low-profitability firms, highlighting the role of a credit risk channel.

In this context, several studies provide evidence on the effectiveness of the 2015 Paris Agreement in raising awareness of climate-related risks and strengthening the role of disclosing emissions-reducing strategies and climate change risk considerations in lending decisions. Aslan et al. (2022) examine the relationship between climate risk, proxied by province-level air pollution, and bank lending in Türkiye following the Paris Agreement, finding that banks curtailed credit to more polluted provinces in the post-agreement period. Similarly, Reghezza et al. (2022) show that European banks reduced lending to more polluting firms after the Paris Agreement, with the effect being more pronounced among well-capitalized banks with lower credit quality and profitability. Finally, Degryse et al. (2023) using a large international sample of syndicated loans from the period 2011–2019, find that environmentally conscious (“green”) banks offer cheaper loans to green firms, with this discount being statistically significant only after the ratification of the Paris Agreement.¹

However, while some studies acknowledge factors such as institutional ownership, systematic evidence on how ownership structures and governance characteristics shape banks’ climate strategies remains limited. There is extensive literature examining the distinct behaviours and performance outcomes of banks with different ownership types: state ownership, private domestic ownership, and foreign ownership. State-owned banks may prioritise social objectives over profit maximisation, and they may suffer from political interference in lending decisions as well as inefficient risk management capacity (La Porta et al., 2002;

¹ Related studies explore the link between banks’ environmental disclosures (ED) and lending behavior, yielding mixed results. Gambacorta et al. (2023) find that ED is negatively associated with brown lending in large European banks, though the effect depends on disclosure tone, with more positive language linked to greater lending to polluting firms. In contrast, Giannetti et al. (2023) report that higher ED corresponds to increased brown lending in European banks, while Mésonnier (2022) shows that greater ED is associated with slower credit growth to carbon-intensive sectors, particularly among large firms subject to mandatory emissions reporting in France.

Panizza, 2024). Foreign owned banks may have superior risk-management capabilities or access to advanced technologies compared with local banks, although they may also face costs associated with the liability of foreignness (Berger et al., 2000; Claessens & Van Horen, 2012).

In the context of climate risk management strategies across banks with different governance characteristics empirical evidence remains scarce. Compared with state-owned banks, privately owned banks, having stronger overall corporate governance structures, may be better equipped to assess and manage environmental risks. Indeed, Huang et al. (2021) report that in China Joint Equity Commercial Banks which face less government intervention and therefore exhibit stronger governance and profit orientation, were able to appropriately assess and manage environmental transition risks, while state-owned banks fell short.

Foreign-owned banks may also possess advanced technologies to assess environmental risks or may be more sensitive to these risks if they face stronger stakeholder pressures in their home countries to operate in a more environmentally responsible manner. However, it is also possible that they engage in regulatory arbitrage, potentially increasing their lending to high-carbon industries or firms in markets with weaker environmental regulations (Surroca et al., 2013). Laeven and Popov (2023), for example, use data on syndicated loans to show that multinational banks shift their fossil fuel lending in response to domestic carbon tax policies, decreasing domestic lending while increasing foreign lending, suggesting potential regulatory arbitrage. Similarly, Benincasa et al. (2025) examine the effect of home-country climate policy stringency on cross-border lending in the syndicated-loan market and find that banks respond to more stringent climate policies at home by increasing their cross-border lending, consistent with a “race to the bottom” behaviour.

In contrast, Demirgüç-Kunt et al. (2024) explore how global banks adjust their lending in response to host-country climate policies and find that banks with strong environmental performance scores increase credit and market presence in countries that strengthen climate actions. However, banks with low environmental scores, shift their growth to other jurisdictions rather than exiting countries implementing green policies. Accordingly, the findings suggest a selection mechanism through environmental preferences and supporting the findings of Kacperczyk and Peydró (2024). However, their study is unable to detect how subsidiaries of these banks allocate their lending across different industries and sectors in response to climate policies.

Türkiye provides an ideal context for our research due to its large, competitive, and diverse banking market, with significant participation from both state-owned and foreign banks - from advanced and emerging countries (Davutyan & Yildirim, 2017). The country also shares characteristics common to other emerging economies, such as macroeconomic volatility and institutional gaps, and, despite recent policy changes, lags behind developed countries in addressing climate change (Ediboğlu Sakowsky, 2023; Taymaz, 2025).

By way of preview, we have two main findings. First, our analysis of banks' credit exposure to high-carbon ("dirty") industries over time shows a general negative trend in lending to these sectors, although statistical significance emerges only in the final year. Second, both ownership and home-country characteristics influence banks' credit decisions. In particular, ownership matters: privately owned and foreign banks reduced their exposure to dirty industries relative to state-owned banks, with significant reductions in the post-Paris period. We also find that banks from advanced economies decreased exposure over time, with significance emerging after 2017 or 2018, depending on the alternative dirty-industry classifications. Finally, headquartered in countries with stricter climate policies also reduced their exposure, but the effect is not statistically significant.

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We contribute to the literature on climate change and finance in three main ways. First, our paper is related to the role of banks in the fight against climate crisis and transition to a low-carbon economy. We provide the first systematic evidence within an emerging country context on how governance shapes transition strategies. Specifically, we show how all three major ownership types, state-owned, private domestic, and foreign banks, adjust their lending portfolios in response to climate risks, revealing distinct behavioral patterns across sectors. Second, unlike prior studies relying on syndicated loan data and thus focus primarily on the largest corporations, our bank-firm-level dataset from the Turkish Credit Registry enables us to observe sectoral credit allocation behavior across a broader spectrum of firms. Third, our paper contributes to cross-border banking literature that examines the role of home- and host-country institutions in shaping banks' international activities. In particular, one stream of this literature highlights regulatory and tax arbitrage as drivers of bank international expansion (e.g., Karolyi & Taboada, 2015; Merz et al., 2017). Ongena et al. (2013), for example, show that home country regulation and supervision can have spill-over effects through the activities of international banks in that restrictive regulation at home may simply motivate multinational banks to reallocate risky behaviour abroad. Our analysis therefore complements this

literature by demonstrating that climate-related governance factors represent an additional source of cross-border spillover in banks' lending decisions.

The remainder of the paper is organized as follows. Section 2 presents an overview of Türkiye's climate policy and banking market landscape. Section 3 describes the data and outlines the empirical strategy and. Section 4 reports the empirical results. Section 5 concludes with a discussion of the study's main findings.

2. Türkiye's climate policy and banking market landscape

2.1 Climate policy and institutional framework

Türkiye's engagement with international climate policy began with its accession to the UNFCCC in 2004.² Climate change was first formally integrated into national development planning in the 9th Development Plan (2007-2013), which mandated a National Action Plan for reducing greenhouse gas (GHG) emissions. Although Türkiye signed the Paris Agreement in 2016, its ratification was delayed until 2021 due to concerns about its Annex I developed-country classification. Upon ratification, Türkiye declared that it would "implement the Paris Agreement as a developing country". In the same year, it also announced a net zero emissions target for 2053, later reaffirmed at COP28.

Significant institutional and policy reforms followed in 2021, including the establishment of the Ministry of Environment, Urbanization and Climate Change and the Directorate of Climate Change. However, domestic policies have continued to support carbon-intensive sectors, such as coal production and construction. Accordingly, Türkiye's policy landscape represents a blend of ambitious international commitments, such as the 2053 Net Zero target, and domestic measures promoting energy efficiency, counterbalanced by continued support for carbon-intensive industries (Taymaz, 2025). Some scholars suggest that Türkiye's climate initiatives are motivated more by the prospect of accessing climate finance than by a fundamental commitment to a low-carbon transition (Ediboğlu Sakowsky, 2023).

Taymaz (2025) examines manufacturing sector CO₂ emissions between 2007 and 2021 and finds that while Türkiye's overall CO₂ intensity has declined, the reduction is largely driven by a reallocation of value-added away from carbon-intensive industries, such as cement and iron and steel, rather than by significant efficiency improvements at the firm level. The study also shows that although the manufacturing sector's share in the economy has decreased, it continues to exhibit relatively high CO₂ intensity compared with other sectors.

Economic and political factors, including high inflation and external energy dependence, influence Türkiye's attitude toward climate action and contribute to deficient and inconsistent climate policies. A key

² This section's overview of Türkiye's climate policy developments is largely drawn from Taymaz (2025).

external driver shaping recent policy responses is the European Green Deal (EDG), introduced by the European Union on 11 December 2019 as a roadmap to make Europe the first climate-neutral continent by 2050 (Taymaz, 2025; Edibođlu Sakowsky, 2023). A central component of the EDG, the Carbon Border Adjustment Mechanism (CBAM), aims to prevent carbon leakage by imposing a carbon-related levy on imports from countries with less stringent climate policies. Given that the EU continues to be the country's main trading partner, CBAM is expected to have a substantial impact on Türkiye's emission-intensive export sectors (Taymaz, 2025; Acar et al., 2022).

Acar et al. (2022) analyze the economic implications of CBAM for the Turkish economy, estimating that in the absence of policy changes, Türkiye's Gross Domestic Product (GDP) could decline by 2.7% to 3.6% by 2030 due to the CBAM levy on carbon-intensive exports. Moreover, Acar et al. (2022) find that while key exporting sectors to the EU, such as machinery, automotive, iron and steel, and textiles, account for a large share of the total emissions embodied in Turkish exports, the relative burden, as measured by a shadow carbon tax rate, is highest for the cement and electricity sectors. Consequently, Turkish exporters face a strategic choice: reduce their carbon intensity by adopting green technologies or accept a loss of competitiveness and market share in the EU (Taymaz, 2025).

Türkiye has been responding to the climate crisis and the pressure exerted by CBAM through specific policies (Taymaz, 2025). The Green Deal Action Plan (2021) outlined steps toward a national carbon pricing mechanism aligned with the EU's CBAM. Similarly, Türkiye's updated Nationally Determined Contribution (NDC) 2023 set a target to reduce GHG emissions by 41% by 2030 relative to business as usual. The current Development Plan (2024-2028) emphasizes compliance with international climate frameworks, prioritizing renewable energy, electrification, energy efficiency, and nuclear power, and commits to finalizing a National Emissions Trading System (ETS).

According to Germanwatch (2025), Türkiye ranks 53rd out of 67 in the 2025 Climate Change Performance Index (CCPI), placing it in the lowest-performing countries. The country receives a medium rating for Renewable Energy, low for GHG Emissions and Energy Use, and very low for Climate Policy. This weak performance reflects inadequate and inconsistent climate measures, insufficient short-term targets, and a weak NDC that allows emissions to continue rising until 2030. It is also noted that the country continues to invest in coal, oil, gas, and nuclear power, with no clear fossil fuel phase-out policy.

2.2 Banking market structure

According to the Banking Regulation and Supervision Agency [Banking Regulation and Supervision Agency] (BDDK, 2024), the Turkish banking sector comprised a total of 64 banks as of December 2024. Of these, 35 are depository banks, accounting for 86% of the total assets; 20 are development and

investment banks, representing 6% of total assets; and 9 are participation banks, accounting for 8% of total assets. Among the 35 depository banks, 22 are foreign-owned. While foreign banks constitute the largest number of institutions (28 in total), state-owned banks hold the largest share of the sector's total assets and credits. At the end of 2024, state-owned banks held 46% of total assets, domestic private banks 30%, and foreign-owned banks 24%. As of end-2024, the Turkish banking market remained concentrated, with the top five banks holding 61.2% of total assets, 60.4% of credits, and 69.0% of deposits. Among these, three are state-owned banks (Türkiye Bankalar Birliği, 2025).

The Turkish banking market is notable for its heterogeneity concerning ownership structure, characterized by foreign participation from both advanced and emerging countries as well as significant state-ownership (Davutyan & Yildirim, 2017). Following economic stabilization and institutional reforms in the early 2000s, Türkiye attracted major foreign banks from advanced economies, mostly from Europe. However, after the 2008 Global Financial Crisis, several of these advanced-country banks divested due to home-market constraints. Their withdrawal created opportunities for banks from the Middle East, reflecting Turkey's growing regional economic ties, and from other emerging markets, including China, to enter and expand their presence in the sector. Although the state ownership has declined over time, the growing role of state-owned banks in Türkiye's economic activity in recent years is noteworthy. In particular, Akgündüz et al. (2024) find that state-owned banks have expanded their share of business loans, investment, and export financing, while increasingly providing financial access to credit-constrained firms, such as small and medium-sized enterprises (SMEs).

3. Data and methodology

3.1 Data sources

We utilize the Central Bank of the Republic of Türkiye's (CBRT) integrated database, which consolidates administrative records from various public institutions. Our primary dataset is the Credit Registry, which provides detailed monthly bank-firm level information on outstanding loans, including the type of credit (domestic currency vs. foreign currency), loan maturity, interest rates, collateral status, and other contractual characteristics. To complement this, we incorporate firm-level financial statements from the Revenue Administration, which cover all firms in Türkiye that report balance sheets and include more than 200 balance sheet and income statement variables. Finally, we use annual employee-employer matched data from the Social Security Institution, which contains rich information on workers such as age, gender, nationality and other employment characteristics and allows us to track individuals over time across jobs and employers. In addition to the CBRT datasets, we draw on other data sources. To classify industries as carbon-intensive, we use sector-level carbon emission data published by TURKSTAT.

We employ environmental policy stringency, the Climate Change Performance Index (CCPI), of the Germanwatch (Burck, et al. 2024), to capture variation in banks' home-country climate policy environments. The CCPI is an independent monitoring tool that tracks countries' climate protection performance. Climate performance is assessed across four categories: GHG emissions, renewable energy, energy use, and climate policy. Following Demirgüç-Kunt (2024), we use the climate policy component of the CCPI to proxy the stringency of climate policies in banks' home countries. This component is based on a questionnaire evaluating policies related to the promotion of renewable energy, energy efficiency, and other measures aimed at reducing emissions.

3.2 Classification of dirty industries

Our empirical strategy begins by identifying high-carbon industries (“dirty” or “brown” sectors”). Given that we have no data on firm-level carbon intensity, we follow the literature and employ TURKSTAT's sectoral carbon emission statistics to proxy firm level carbon risk exposure and classify borrowers into “green” and “brown” (see, e.g., Nguyen et al., 2025; Gianetti et al., 2023). We narrow our scope to manufacturing firms only due to data limitations. For NACE 2 sectors 10–12, 13–15, and 31–32, we allocate the aggregated carbon emissions data across sub-sectors by weighting emissions according to net sales. We then compute the sample-average carbon emissions for each sector and classify sectors into the top 10 and top 5 “dirty” sectors, following common practice in the literature. As shown in Table 1, the sectors classified as dirty are consistent with previous studies and include industries such as the manufacture of other non-metallic mineral products, manufacture of basic metals, and manufacture of coke and refined petroleum products (see, for example, Mésonnier, 2022; Taymaz, 2025).

Table 1 Average carbon emissions across economic activity

Economic Activity	Avg. Carbon Emission (1000 Tonnes)	Rank
Manufacture of other non-metallic mineral products	71.910	1
Manufacture of basic metals	25.248	2
Manufacture of coke and refined petroleum products	9.186	3
Manufacture of textiles	5.702	4
Manufacture of food products	4.909	5
Manufacture of wearing apparel	2.681	6
Manufacture of chemicals and chemical products	2.152	7
Manufacture of paper and paper products	1.203	8
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	824	9
Manufacture of fabricated metal products, except machinery and equipment	751	10
Manufacture of motor vehicles, trailers and semi-trailers	668	11
Manufacture of machinery and equipment n.e.c.	344	12
Manufacture of leather and related products	339	13
Manufacture of electrical equipment	287	14
Manufacture of beverages	265	15
Manufacture of rubber and plastic products	217	16
Repair and installation of machinery and equipment	203	17
Manufacture of furniture	157	18
Manufacture of other transport equipment	102	19
Other manufacturing	95	20
Manufacture of tobacco products	92	21
Manufacture of computer, electronic and optical products	28	22
Printing and reproduction of recorded media	26	23
Manufacture of basic pharmaceutical products and pharmaceutical preparations	24	24

Source: Own calculations

3.3 Bank-industry carbon exposures

Our bank sample includes only the depository banks and excludes both development and investment banks as well as participation banks. It consists of 35 unique banks, of which three are government-owned, 10 are domestic private, and 22 are foreign-owned banks. Three of the domestic private banks change their ownership status to foreign during the sample period. Among the 22 foreign banks, 16 originate from advanced countries.³ Over the analysis period, the ownership category of 2 banks changes from advanced to emerging, while 1 bank's ownership changes in the opposite direction. Figure 1 presents number of

³ We classify countries into advanced based on World Economic Outlook (April 2025).

unique firms in our sample according to their rank on carbon emission table while Figure 2 presents total loan volume of firms. Finally, Figure 3 presents the evolution of total loan volume across the three ownership categories and between dirty and non-dirty sectors (using the top-5 classification).

Figure 1 Number of unique firms in our sample according to their rank on carbon emission table

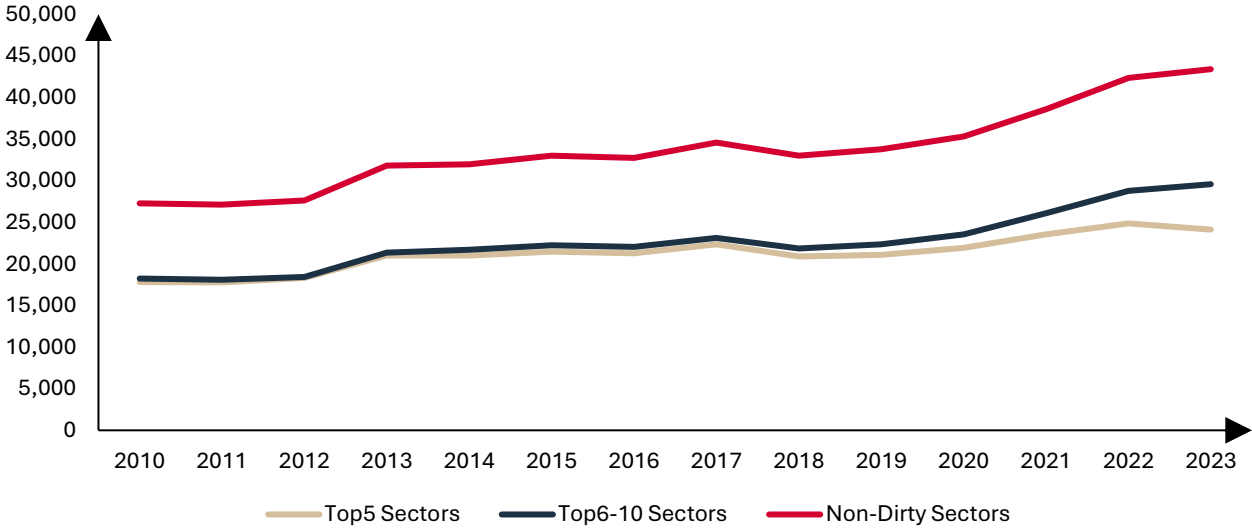


Figure 2 Total loan volume of firms in our sample according to their position in the carbon emissions ranking (2010 = 100).

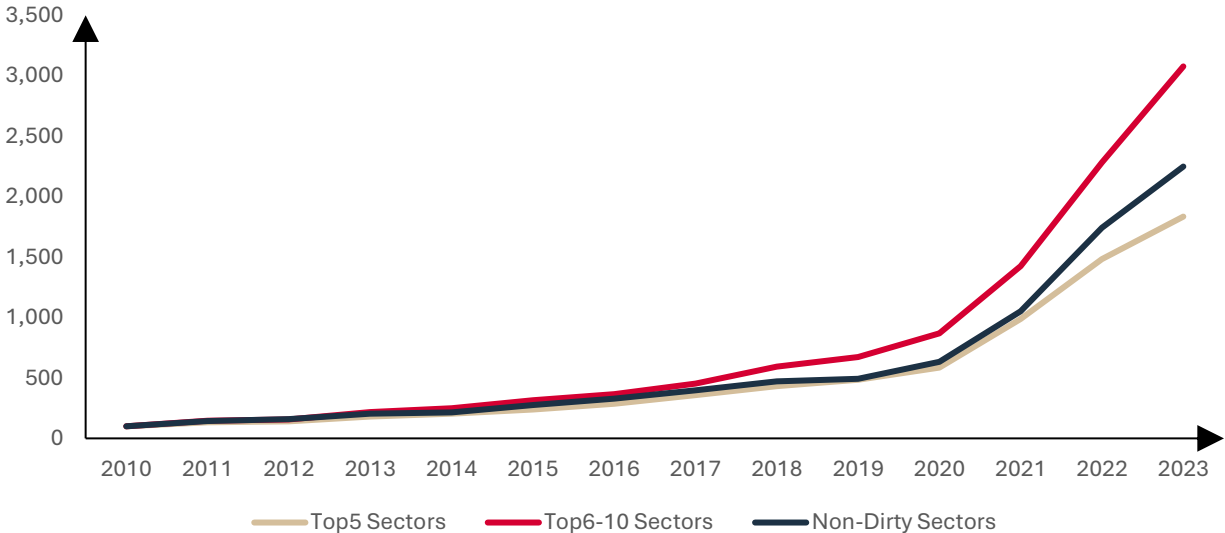
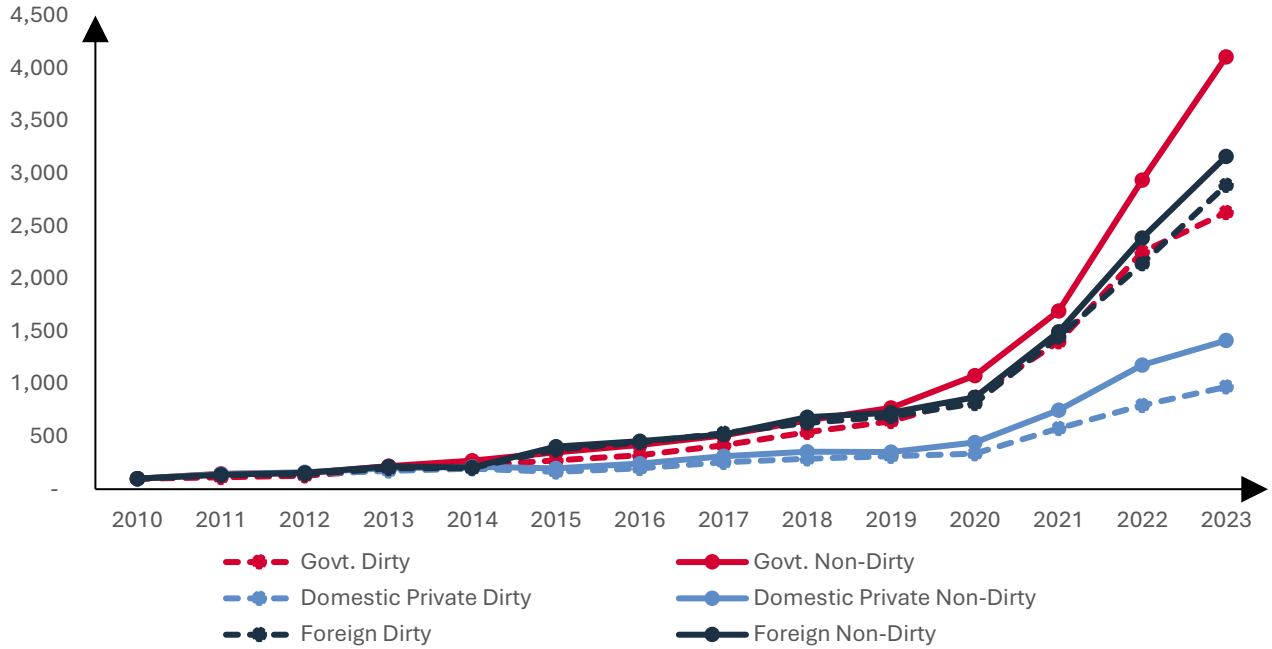


Figure 3 Total loan volume according to bank ownership types (2010 = 100) (Top 5 classification)



3.4 Models

Our regression analyses are conducted at the firm-bank-year level and cover the post-global financial crisis period. For our first research question, we adopt an event-study design to trace changes in bank credit allocation patterns and employ the following empirical specification (Model 1):

$$\log(Loans_{i,j,t}) = \beta_{dirty_j} \times year_t + \delta_{i,j} + \delta_{p,t} + \delta_{i,t} + u_{i,j,t} \quad (1)$$

Where $Loans_{i,j,t}$ is the logarithm of total loan amount of firm j from bank i in year t , $dirty_j$ is a dummy variable which takes the value of one if the firm is operating in an industry that is defined as “dirty” and 0 if it is operating in a clean industry. $year_t$ takes the value of one for the specific year. We control for firm x bank fixed effects ($\delta_{i,j}$) to absorb any time-invariant unobserved characteristics for firm-bank pairs. We also included bank x time ($\delta_{i,t}$) and province x time ($\delta_{p,t}$) fixed effects. Here, β coefficients, obtained for each year, will help us to see the change in the lending to the dirty sectors relative to clean sectors.

To examine our second research question, we use the following empirical specification (Model 2):

$$\log(Loans_{i,j,t}) = \gamma_{domestic_private_i} \times year_t \times dirty_j + \rho_{foreign_i} \times year_t \times dirty_j + \delta_{j,t} + \delta_{i,j} + u_{i,j,t} \quad (2)$$

where $domestic_private_i$ is a dummy variable that is equal to one for the domestic private banks and $foreign_i$ is a dummy variable that is equal to one for the foreign banks. The benchmark group is the domestic state-owned banks. To control for the loan demand, we include firm x year fixed effects ($\delta_{j,t}$) following (Khwaja and Mian, 2008). By including these fixed effects, we focus on firms that borrow from multiple banks and compare the changes in the loan supply by the type of the banks.

Finally, our third research question explores the role of institutional context in shaping bank behavior. For this, we extend the previous specification by incorporating information on the home countries of foreign banks. More specifically, we first distinguish between foreign banks originating from advanced countries and those from emerging countries and employ the following specification (Model 3.1):

$$\log(Loans_{i,j,t}) = \theta advanced_i x year_t x dirty_j + \delta_{j,t} + \delta_{i,j} + u_{i,j,t} \quad (3.1)$$

where $advanced$ is an indicator variable equal to one if the foreign bank's home country is classified as an advanced country. We expect that banks headquartered in advanced countries will exhibit greater sensitivity to climate risks, reflecting stronger societal and institutional pressures for sustainability in more developed institutional environments (Ioannou and Serafeim, 2012; Liang and Renneboog, 2017).

In a second specification, we replace ownership dummies with an index capturing the environmental policy stringency of each bank's country of origin and use the following empirical specification (Model 3.2):

$$\log(Loans_{i,j,t}) = \theta policy_strictness_i x year_t x dirty_j + \delta_{j,t} + \delta_{i,j} + u_{i,j,t} \quad (3.2)$$

where $policy_strictness_i$ is the environmental policy strictness of the home-countries of banks proxied by the climate policy component of the CCPI. While in the first specification we are able to include all the foreign banks in the analysis, in this specification only the banks which are covered in the Germanwatch are included.

4. Results

Figure 4a presents the regression results from estimating Model 1, with the full results reported in Appendix Table A1. We observe some evidence of a decline in 2017 in banks' credit exposure to firms in dirty industries. This exposure then increases over the following two years before starting to fall again. However, the decline is statistically significant only in the final year. Overall, there is a negative trend across the analysis period, especially after 2016 although it is not statistically significant. When using a more restrictive definition of dirty industries (top five industries), we observe a broadly similar pattern, with a significant drop only in the last year (see Figure 4b). We should note, however, that since we are not able to control for sector-specific time-varying shocks in our empirical setup, we cannot rule out the possibility that this shift is driven by changes in lending behaviour.

Figure 4a Bank credit exposure to dirty vs clean firms (using the top-10 classification)

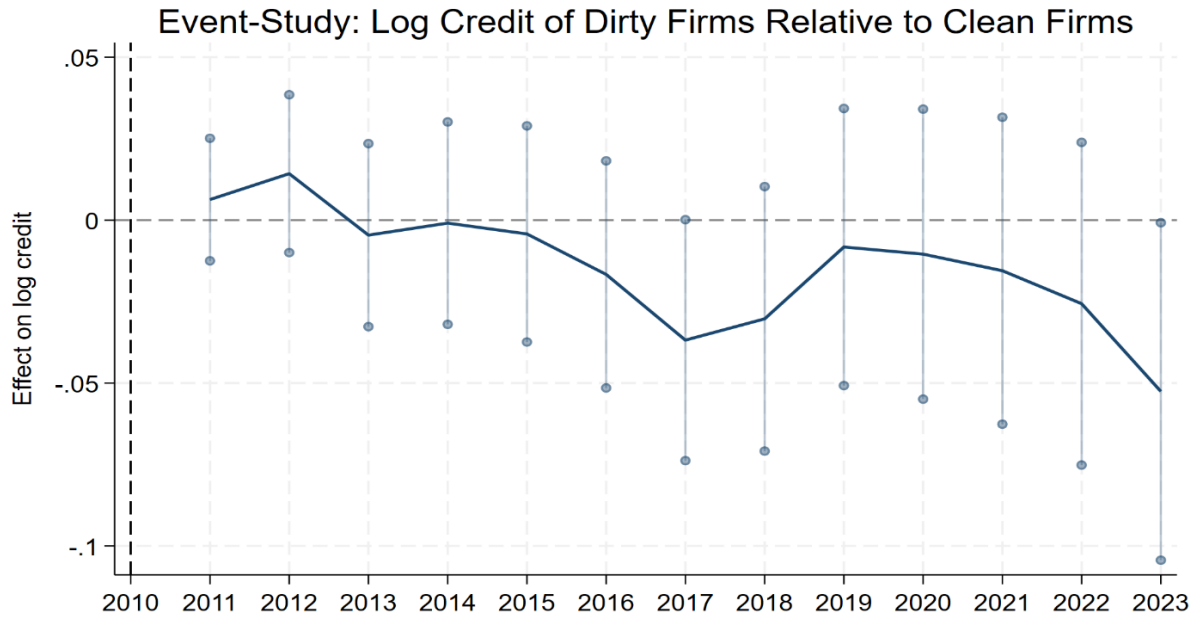
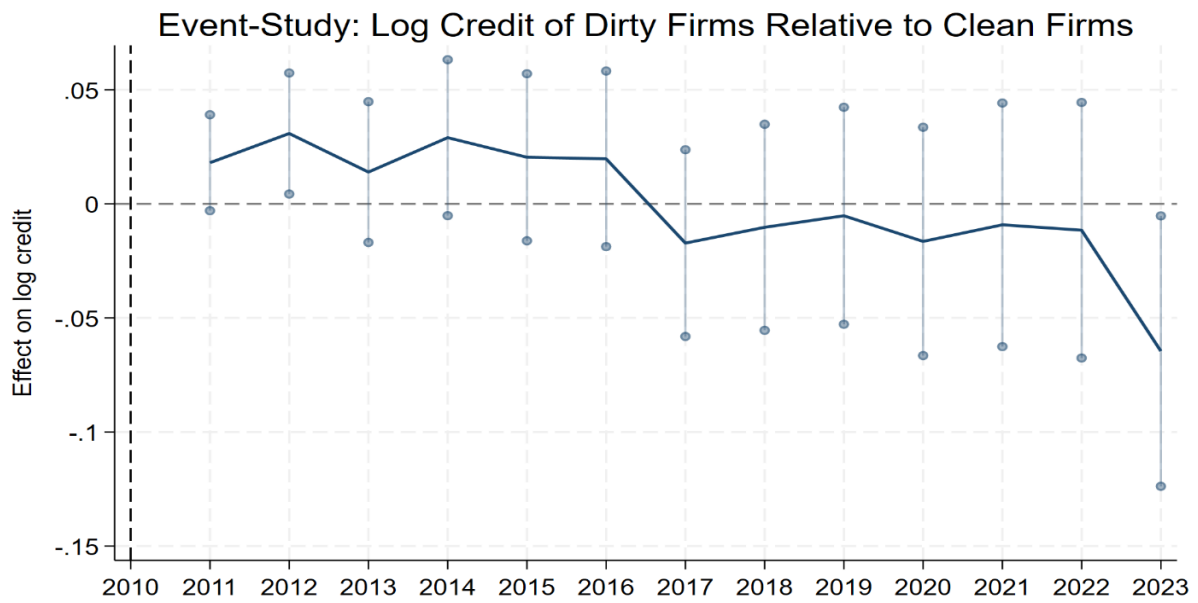
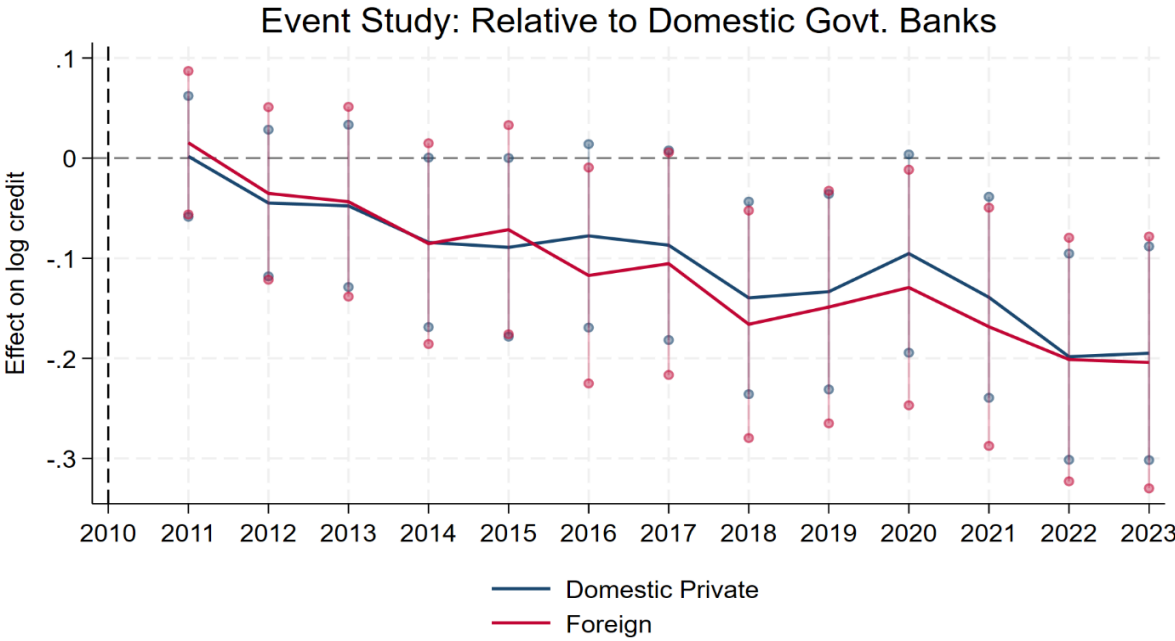


Figure 4b Bank credit exposure to dirty vs clean firms (using the top-5 classification)



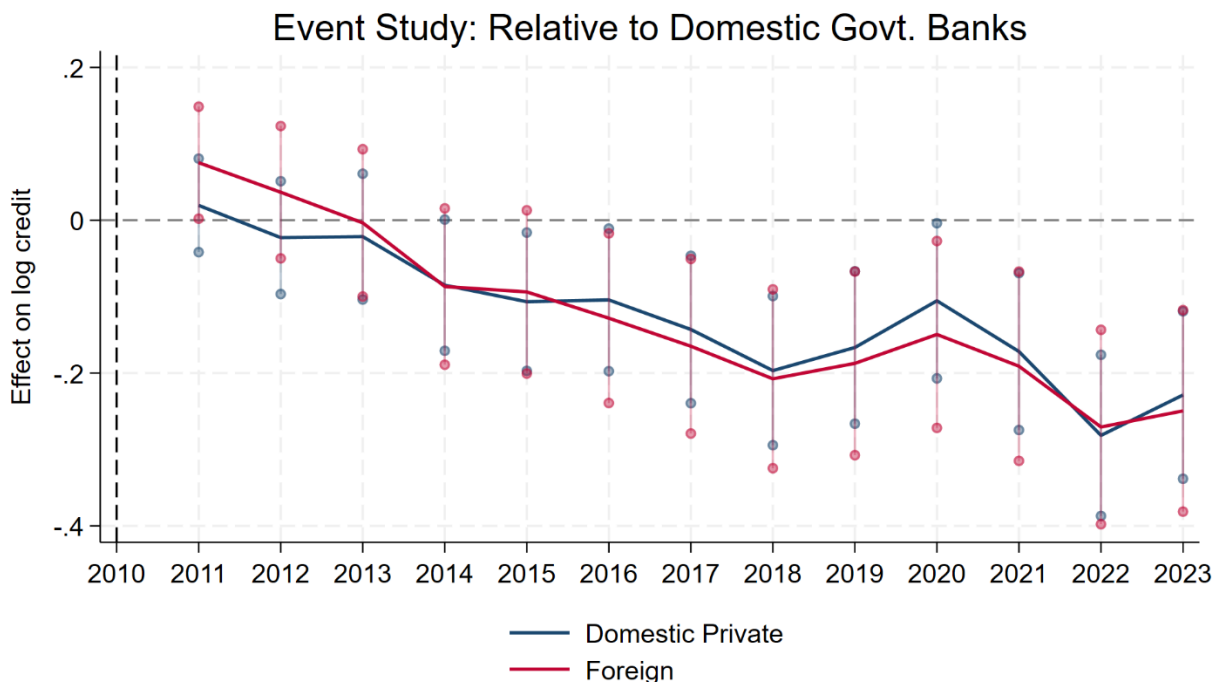
We next estimate Model 2 and present the regression results in Figures 5a and 5b.⁴ We find that, compared with state-owned banks, both privately owned and foreign-owned banks reduced their credit exposure to firms in dirty industries. This reduction is statistically significant in the post-Paris period. Although the effect appears to be more significant for foreign-owned banks, an additional specification excluding government-owned banks shows that private and foreign banks behave similarly (See Appendix Figure A1 and A2). Overall, the results suggest that, over the analysis period, state-owned banks continued to finance dirty industries, whereas privately owned Turkish banks and foreign banks increasingly avoided lending to these sectors.

Figure 5a Domestic private and foreign bank credit exposure to dirty vs clean firms (using the top-10 classification)



⁴ Regression results are reported in Appendix Tables A2.1 and A2.2.

Figure 5b Domestic private and foreign bank credit exposure to dirty vs clean firms (using the top-5 classification)



Finally, we estimate Models 3.1 and 3.2 to incorporate information on banks’ home countries’ climate policy contexts.⁵ First, Figure 6a shows that banks originating from advanced countries appear to reduce their exposure to the top 10 dirty industries over time, with the decline becoming statistically significant from 2018 onward. When using the top-5 classification, we again observe a similar negative trend, with statistical significance beginning in 2017 (see Figure 6b).

⁵ Regression results are reported in Appendix Tables A3.1 and A3.2.

Figure 6a Credit exposure to dirty versus clean firms across banks from advanced and emerging countries (top-10 classification)

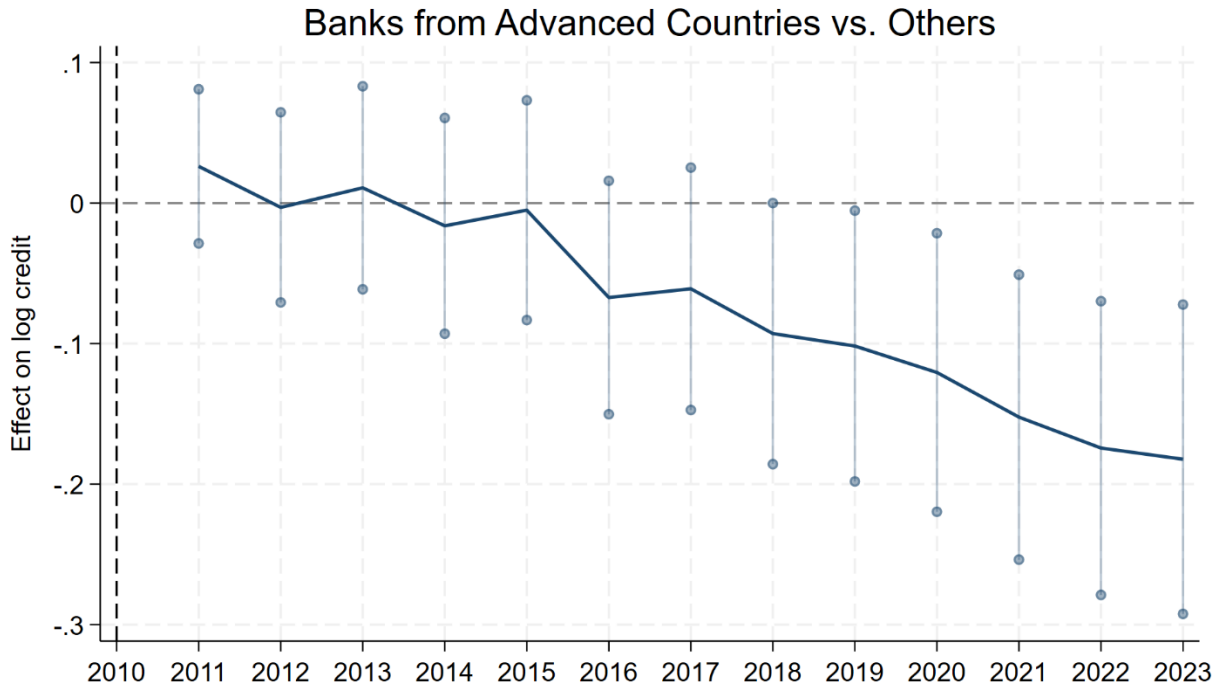
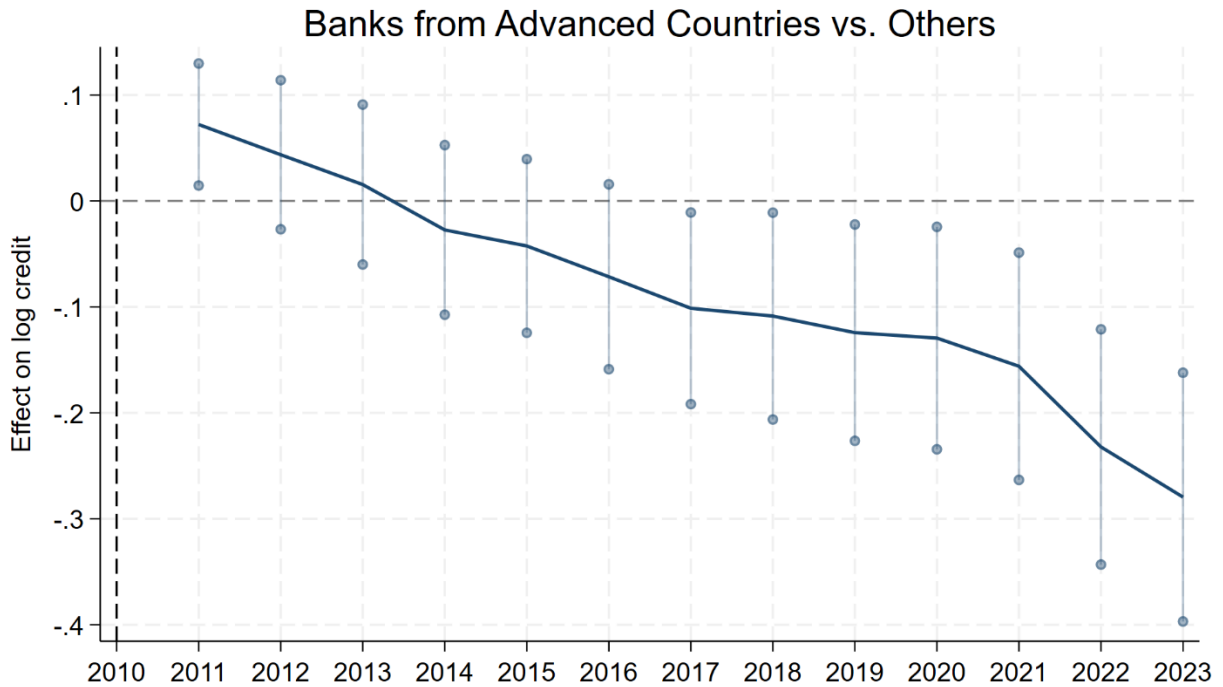


Figure 6b Credit exposure to dirty versus clean firms across banks from advanced and emerging countries (top-5 classification)



Next, we examine the climate policy strictness of banks' home countries as a proxy for their climate strategies or sensitivities. As shown in Figures 7a and 7b, although banks headquartered in stricter climate-policy countries appear to reduce their exposure to dirty industries, the effect is not statistically significant.

Figure 7a Climate policy strictness and credit exposure to dirty versus clean firms (top-10 classification)

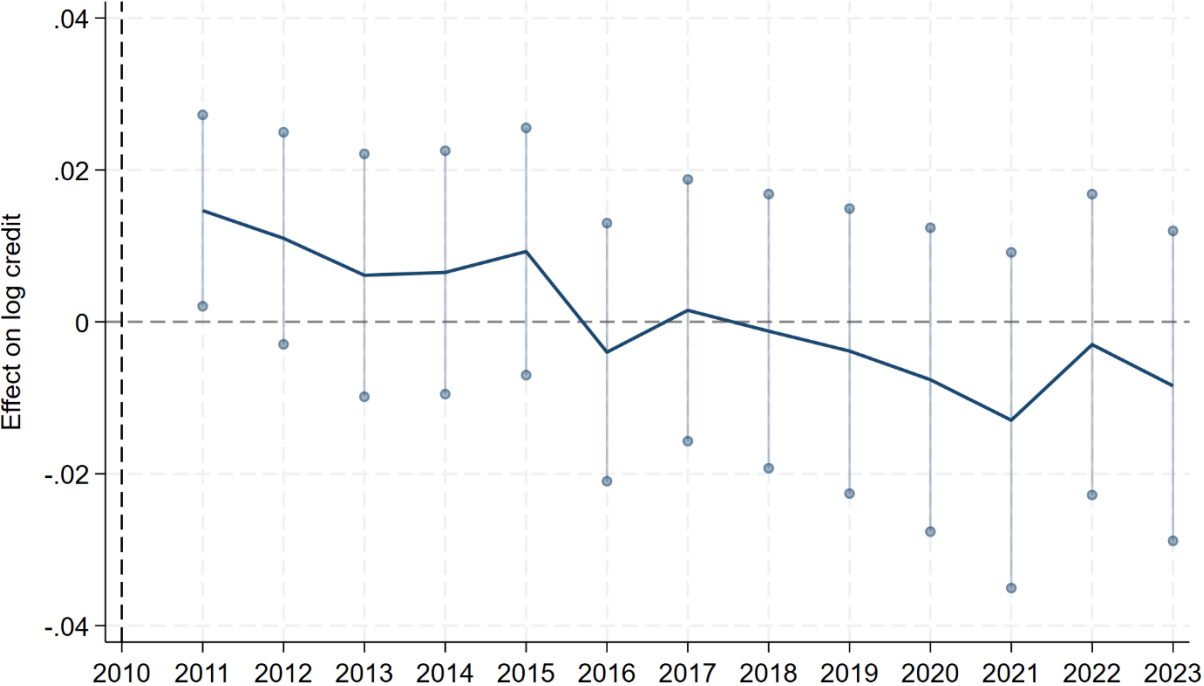
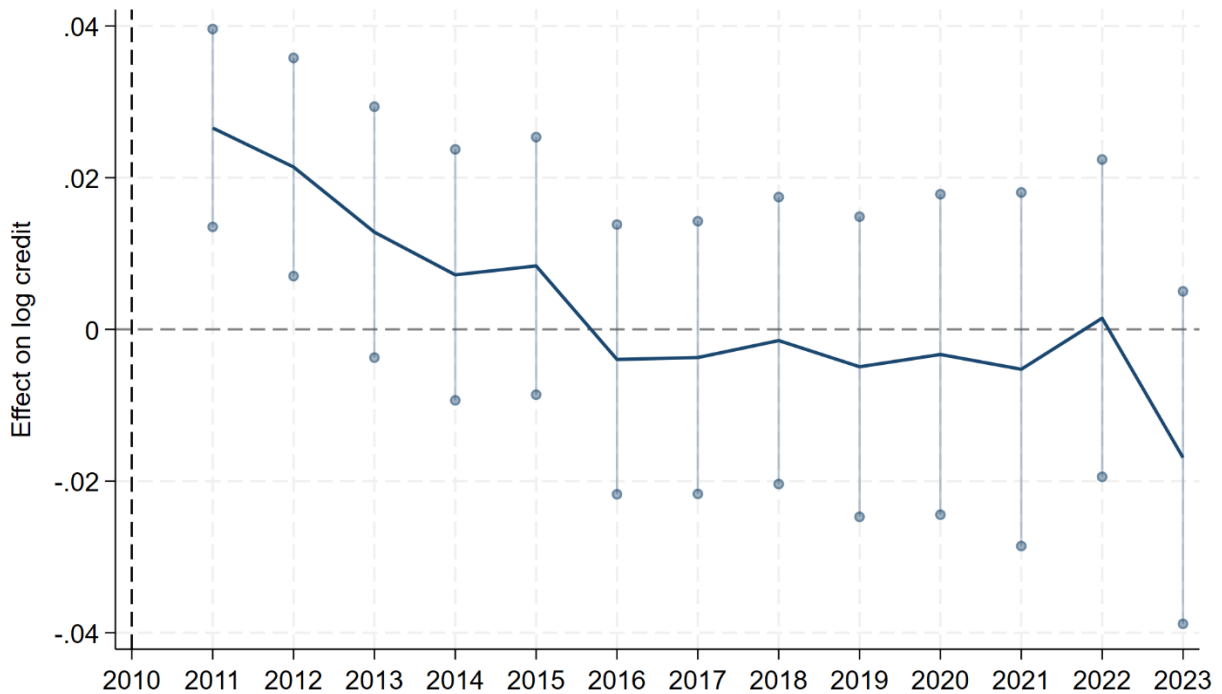


Figure 7b Climate policy strictness and credit exposure to dirty versus clean firms (top-5 classification)



5. Conclusion

Our analysis of banks’ credit exposure to dirty industries reveals several patterns. First, we observe a general decline in lending to dirty sectors, although statistical significance is limited to the final year. Second, ownership matters: privately owned and foreign banks reduced their exposure to dirty industries relative to state-owned banks, with significant reductions emerging in the post-Paris period. State-owned banks, however, continued financing high-carbon sectors. Finally, we show that banks from advanced economies decreased their exposure over time, with significance emerging in 2017–2018 depending on the dirty industry classification. Banks headquartered in countries with stricter climate policies also reduced exposure, but the effect is not statistically significant. Overall, both ownership and home-country characteristics influence banks’ credit decisions regarding dirty vs green industries.

Our research contributes to the expanding literature on climate risk and financial institutions by documenting how banks with differing ownership and governance structures adjust their lending behaviour in response to climate risks in emerging markets. Given the central role of risk preferences in shaping climate policy, our findings offer several policy-relevant insights. First, state-owned banks appear comparatively less responsive to climate considerations. This pattern may reflect inadequate incentives aimed at curbing financing to high-carbon sectors. It may also arise from political influence over credit

allocation or from institutional mandates that prioritize specific sectors or firm types, such as SMEs. Nevertheless, considering the substantial role that state-owned banks play in the domestic financial system, their limited responsiveness is concerning for the broader decarbonization needs of the economy and is indicative of the incentive structure confronting policymakers when designing and implementing robust climate policies.

The stronger response of private and foreign banks highlights the potential for international best practices and cross-border regulatory norms to promote climate-sensitive lending. Although the effect of home-country climate policy is not statistically significant, the observed negative trend indicates that stronger national climate policies could indirectly influence banks' lending behavior.

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Appendix

Figure A1 Foreign bank credit exposure to dirty vs clean firms excluding state-owned banks (using the top-10 classification)

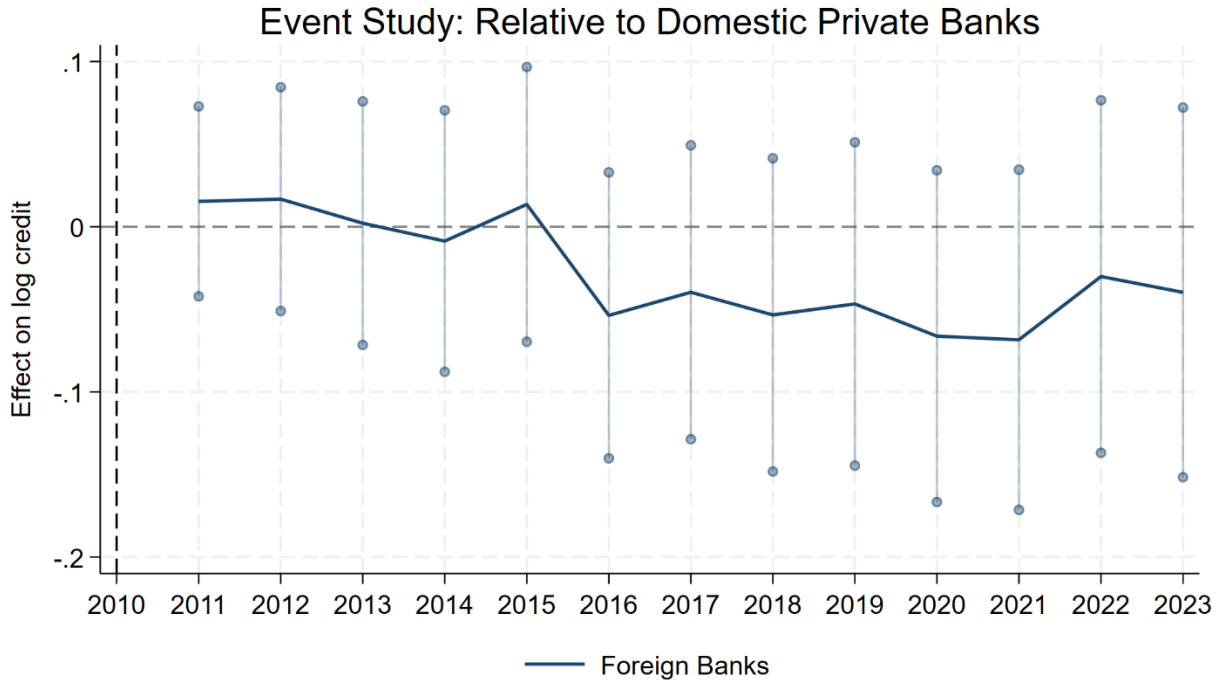


Figure A2 Foreign bank credit exposure to dirty vs clean firms excluding state-owned banks (using the top-10 classification)

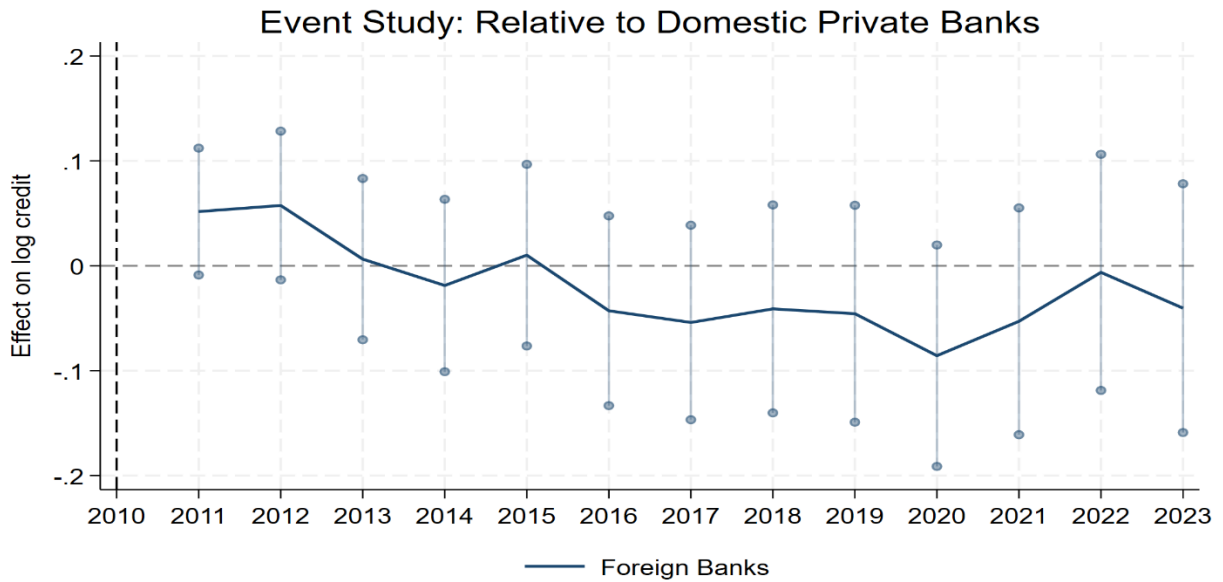


Table A1. Bank credit exposure to dirty vs clean firms

Dependent variable: Log credit, Model 1

	(1)	(2)	(3)	(4)	(5)	(6)
2010 x Dirty	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
2011 x Dirty	0.003 (0.009)	0.007 (0.009)	0.006 (0.010)	0.018* (0.010)	0.024** (0.010)	0.018* (0.011)
2012 x Dirty	0.015 (0.012)	0.020* (0.012)	0.014 (0.012)	0.043*** (0.013)	0.048*** (0.013)	0.031** (0.014)
2013 x Dirty	-0.002 (0.014)	0.006 (0.014)	-0.005 (0.014)	0.036** (0.015)	0.040*** (0.015)	0.014 (0.016)
2014 x Dirty	0.006 (0.016)	0.016 (0.016)	-0.001 (0.016)	0.057*** (0.017)	0.062*** (0.017)	0.029* (0.017)
2015 x Dirty	-0.002 (0.017)	0.013 (0.017)	-0.004 (0.017)	0.052*** (0.018)	0.058*** (0.018)	0.020 (0.019)
2016 x Dirty	-0.018 (0.018)	0.002 (0.018)	-0.017 (0.018)	0.050*** (0.019)	0.061*** (0.019)	0.020 (0.020)
2017 x Dirty	-0.042** (0.019)	-0.021 (0.019)	-0.037* (0.019)	0.011 (0.020)	0.020 (0.020)	-0.017 (0.021)
2018 x Dirty	-0.027 (0.021)	-0.012 (0.021)	-0.030 (0.021)	0.036 (0.022)	0.038* (0.022)	-0.010 (0.023)
2019 x Dirty	-0.004 (0.022)	0.011 (0.022)	-0.008 (0.022)	0.045* (0.023)	0.044* (0.023)	-0.005 (0.024)
2020 x Dirty	0.002 (0.023)	0.008 (0.023)	-0.010 (0.023)	0.050** (0.025)	0.034 (0.025)	-0.016 (0.026)
2021 x Dirty	-0.007 (0.024)	0.003 (0.024)	-0.016 (0.024)	0.056** (0.026)	0.043 (0.026)	-0.009 (0.027)
2022 x Dirty	-0.021 (0.025)	-0.004 (0.025)	-0.026 (0.025)	0.053* (0.028)	0.048* (0.028)	-0.012 (0.029)
2023 x Dirty	-0.043 (0.026)	-0.033 (0.026)	-0.053** (0.026)	0.008 (0.029)	-0.006 (0.029)	-0.065** (0.030)
Observations	2920865	2920848	2920848	2920865	2920848	2920848
R-squared	0.720	0.724	0.725	0.720	0.724	0.725
Firm x Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank x Year FE	No	Yes	Yes	No	Yes	Yes
Province x Year FE	No	No	Yes	No	No	Yes

Notes: Columns 1 to 3 employ the top-10 classification and Columns 4 to 6 employ the top-5 classification. Standard errors in parentheses. Clustered at firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2.1 Domestic private and foreign bank credit exposure to dirty vs clean firms (using the top-10 classification)

Dependent variable: Log credit, Model 2

	(1)	(2)	(3)	(4)
2010 x Dirty x Foreign	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
2011 x Dirty x Foreign	0.015 (0.037)	0.014 (0.037)	0.009 (0.029)	0.015 (0.029)
2012 x Dirty x Foreign	-0.035 (0.044)	-0.031 (0.044)	0.010 (0.034)	0.017 (0.035)
2013 x Dirty x Foreign	-0.044 (0.048)	-0.037 (0.048)	-0.001 (0.037)	0.002 (0.038)
2014 x Dirty x Foreign	-0.085* (0.051)	-0.085* (0.051)	-0.009 (0.040)	-0.009 (0.040)
2015 x Dirty x Foreign	-0.071 (0.053)	-0.079 (0.053)	0.018 (0.042)	0.014 (0.042)
2016 x Dirty x Foreign	-0.117** (0.055)	-0.134** (0.055)	-0.042 (0.044)	-0.054 (0.044)
2017 x Dirty x Foreign	-0.105* (0.057)	-0.128** (0.057)	-0.024 (0.045)	-0.040 (0.045)
2018 x Dirty x Foreign	-0.166*** (0.058)	-0.194*** (0.058)	-0.034 (0.048)	-0.053 (0.048)
2019 x Dirty x Foreign	-0.149** (0.059)	-0.182*** (0.059)	-0.023 (0.050)	-0.047 (0.050)
2021 x Dirty x Foreign	-0.129** (0.060)	-0.163*** (0.060)	-0.041 (0.051)	-0.066 (0.051)
2021 x Dirty x Foreign	-0.168*** (0.061)	-0.207*** (0.061)	-0.041 (0.052)	-0.068 (0.053)
2022 x Dirty x Foreign	-0.201*** (0.062)	-0.250*** (0.062)	0.004 (0.054)	-0.030 (0.054)
2023 x Dirty x Foreign	-0.204*** (0.064)	-0.254*** (0.064)	-0.004 (0.057)	-0.040 (0.057)
2010 x Dirty x Domestic private	0.000 (.)	0.000 (.)		
2011 x Dirty x Domestic private	0.002 (0.031)	-0.004 (0.031)		
2012 x Dirty x Domestic private	-0.045 (0.037)	-0.046 (0.038)		
2013 x Dirty x Domestic private	-0.048 (0.041)	-0.045 (0.042)		
2014 x Dirty x Domestic private	-0.084* (0.043)	-0.085* (0.043)		
2015 x Dirty x Domestic private	-0.089* (0.046)	-0.093** (0.046)		
2016 x Dirty x Domestic private	-0.078* (0.047)	-0.084* (0.047)		
2017 x Dirty x Domestic private	-0.087* (0.048)	-0.096** (0.049)		
2018 x Dirty x Domestic private	-0.140*** (0.049)	-0.148*** (0.049)		
2019 x Dirty x Domestic private	-0.133*** (0.050)	-0.143*** (0.050)		
2021 x Dirty x Domestic private	-0.095* (0.051)	-0.105** (0.051)		
2021 x Dirty x Domestic private	-0.139*** (0.051)	-0.152*** (0.051)		

	(0.051)	(0.052)		
2022 x Dirty x Domestic private	-0.198***	-0.215***		
	(0.053)	(0.053)		
2023 x Dirty x Domestic private	-0.195***	-0.211***		
	(0.054)	(0.055)		
Observations	2496486	2496503	1762817	1762837
R-squared	0.821	0.819	0.822	0.819
Firm x Bank FE	Yes	Yes	Yes	Yes
Bank x Year FE	Yes	No	Yes	No
Province x Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses, Clustered at firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2.2 Domestic private and foreign bank credit exposure to dirty vs clean firms (using the top-5 classification)

Dependent variable: Log credit, Model 2

	(1)	(2)	(3)	(4)
2010 x Dirty x Foreign	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
2011 x Dirty x Foreign	0.075** (0.037)	0.071* (0.038)	0.047 (0.031)	0.052* (0.031)
2012 x Dirty x Foreign	0.037 (0.044)	0.040 (0.044)	0.054 (0.036)	0.058 (0.036)
2013 x Dirty x Foreign	-0.003 (0.049)	-0.013 (0.049)	0.008 (0.039)	0.006 (0.039)
2014 x Dirty x Foreign	-0.087* (0.052)	-0.106** (0.052)	-0.012 (0.042)	-0.019 (0.042)
2015 x Dirty x Foreign	-0.094* (0.055)	-0.120** (0.055)	0.016 (0.044)	0.010 (0.044)
2016 x Dirty x Foreign	-0.128** (0.057)	-0.164*** (0.057)	-0.031 (0.046)	-0.043 (0.046)
2017 x Dirty x Foreign	-0.165*** (0.058)	-0.211*** (0.058)	-0.036 (0.047)	-0.054 (0.047)
2018 x Dirty x Foreign	-0.207*** (0.060)	-0.255*** (0.060)	-0.019 (0.050)	-0.041 (0.051)
2019 x Dirty x Foreign	-0.187*** (0.061)	-0.237*** (0.062)	-0.025 (0.053)	-0.046 (0.053)
2021 x Dirty x Foreign	-0.149** (0.062)	-0.199*** (0.063)	-0.062 (0.054)	-0.086 (0.054)
2021 x Dirty x Foreign	-0.191*** (0.063)	-0.244*** (0.063)	-0.032 (0.055)	-0.053 (0.055)
2022 x Dirty x Foreign	-0.271*** (0.065)	-0.333*** (0.065)	0.017 (0.057)	-0.006 (0.057)
2023 x Dirty x Foreign	-0.249*** (0.067)	-0.316*** (0.067)	-0.012 (0.061)	-0.040 (0.061)
2010 x Dirty x Domestic private	0.000 (.)	0.000 (.)		
2011 x Dirty x Domestic private	0.019 (0.031)	0.012 (0.031)		
2012 x Dirty x Domestic private	-0.023 (0.038)	-0.021 (0.038)		
2013 x Dirty x Domestic private	-0.021 (0.042)	-0.029 (0.042)		
2014 x Dirty x Domestic private	-0.085* (0.044)	-0.097** (0.044)		
2015 x Dirty x Domestic private	-0.107** (0.046)	-0.127*** (0.046)		
2016 x Dirty x Domestic private	-0.104** (0.048)	-0.128*** (0.048)		
2017 x Dirty x Domestic private	-0.143*** (0.049)	-0.173*** (0.050)		
2018 x Dirty x Domestic private	-0.197*** (0.050)	-0.222*** (0.050)		
2019 x Dirty x Domestic private	-0.167*** (0.051)	-0.195*** (0.051)		
2021 x Dirty x Domestic private	-0.105** (0.052)	-0.132** (0.052)		
2021 x Dirty x Domestic private	-0.172*** (0.052)	-0.206*** (0.052)		

	(0.052)	(0.053)		
2022 x Dirty x Domestic private	-0.282***	-0.321***		
	(0.054)	(0.054)		
2023 x Dirty x Domestic private	-0.229***	-0.267***		
	(0.056)	(0.056)		
Observations	2496486	2496503	1762817	1762837
R-squared	0.821	0.819	0.822	0.819
Firm x Bank FE	Yes	Yes	Yes	Yes
Bank x Year FE	Yes	No	Yes	No
Province x Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses, Clustered at firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3.1 Credit exposure to dirty versus clean firms across banks from advanced and emerging countries

Dependent variable: Log credit, Model 3.1

	(1)	(2)	(3)	(4)
2010 x Dirty x Advanced	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
2011 x Dirty x Advanced	0.026 (0.028)	0.016 (0.028)	0.072** (0.029)	0.066** (0.029)
2012 x Dirty x Advanced	-0.003 (0.035)	-0.015 (0.034)	0.044 (0.036)	0.037 (0.036)
2013 x Dirty x Advanced	0.011 (0.037)	-0.000 (0.037)	0.016 (0.039)	0.013 (0.038)
2014 x Dirty x Advanced	-0.016 (0.039)	-0.023 (0.039)	-0.027 (0.041)	-0.023 (0.041)
2015 x Dirty x Advanced	-0.005 (0.040)	-0.012 (0.040)	-0.042 (0.042)	-0.035 (0.042)
2016 x Dirty x Advanced	-0.067 (0.042)	-0.064 (0.042)	-0.072 (0.045)	-0.055 (0.045)
2017 x Dirty x Advanced	-0.061 (0.044)	-0.058 (0.044)	-0.101** (0.046)	-0.081* (0.046)
2018 x Dirty x Advanced	-0.093* (0.047)	-0.085* (0.047)	-0.109** (0.050)	-0.084* (0.050)
2019 x Dirty x Advanced	-0.102** (0.049)	-0.085* (0.049)	-0.124** (0.052)	-0.089* (0.052)
2021 x Dirty x Advanced	-0.121** (0.051)	-0.093* (0.051)	-0.129** (0.054)	-0.077 (0.054)
2021 x Dirty x Advanced	-0.152*** (0.052)	-0.125** (0.052)	-0.156*** (0.055)	-0.108** (0.055)
2022 x Dirty x Advanced	-0.174*** (0.053)	-0.138*** (0.053)	-0.232*** (0.057)	-0.178*** (0.057)
2023 x Dirty x Advanced	-0.182*** (0.056)	-0.142** (0.056)	-0.279*** (0.060)	-0.218*** (0.060)
Observations	2496503	2496486	2496503	2496486
R-squared	0.818	0.821	0.818	0.821
Firm x Bank FE	Yes	Yes	Yes	Yes
Bank x Year FE	No	Yes	No	Yes

Notes: Columns 1 and 2 employ the top-10 classification and Columns 3 and 4 employ the top 5 classification. Standard errors in parentheses. Clustered at firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3.2 Climate policy strictness and credit exposure to dirty versus clean firms

Dependent variable: Log credit, Model 3.2

	(1)	(2)	(3)	(4)
2010 x Dirty x Rank	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
2011 x Dirty x Rank	0.027*** (0.007)	0.025*** (0.007)	0.027*** (0.007)	0.025*** (0.007)
2012 x Dirty x Rank	0.021*** (0.007)	0.019*** (0.007)	0.021*** (0.007)	0.019*** (0.007)
2013 x Dirty x Rank	0.013 (0.008)	0.015* (0.008)	0.013 (0.008)	0.015* (0.008)
2014 x Dirty x Rank	0.007 (0.008)	0.010 (0.008)	0.007 (0.008)	0.010 (0.008)
2015 x Dirty x Rank	0.008 (0.009)	0.009 (0.009)	0.008 (0.009)	0.009 (0.009)
2016 x Dirty x Rank	-0.004 (0.009)	-0.002 (0.009)	-0.004 (0.009)	-0.002 (0.009)
2017 x Dirty x Rank	-0.004 (0.009)	-0.002 (0.009)	-0.004 (0.009)	-0.002 (0.009)
2018 x Dirty x Rank	-0.001 (0.010)	0.000 (0.010)	-0.001 (0.010)	0.000 (0.010)
2019 x Dirty x Rank	-0.005 (0.010)	-0.001 (0.010)	-0.005 (0.010)	-0.001 (0.010)
2021 x Dirty x Rank	-0.003 (0.011)	0.003 (0.011)	-0.003 (0.011)	0.003 (0.011)
2021 x Dirty x Rank	-0.005 (0.012)	0.003 (0.012)	-0.005 (0.012)	0.003 (0.012)
2022 x Dirty x Rank	0.001 (0.011)	0.006 (0.011)	0.001 (0.011)	0.006 (0.011)
2023 x Dirty x Rank	-0.017 (0.011)	-0.012 (0.011)	-0.017 (0.011)	-0.012 (0.011)
Observations	2254232	2254215	2254232	2254215
R-squared	0.825	0.828	0.825	0.828
Firm x Bank FE	Yes	Yes	Yes	Yes
Bank x Year FE	No	Yes	No	Yes

Notes: Columns 1 and 2 employ the top-10 classification and Columns 3 and 4 employ the top-5 classification. Standard errors in parentheses. Clustered at firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$