Firm Emissions and Credit Allocation*

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January 2, 2026

Abstract

Do banks help or hamper green transition? To answer this question, we analyze the dynamics of bank lending to firms in the US, EU, and separately Denmark in relation to the borrowers' emissions of CO2. We evaluate the allocation of bank loans across industries and within industries across firms, allowing for heterogeneity of firm emissions and changes in these emissions. To facilitate green transition, bank lending needs to flow to greener and greening firms, but not out of high-emission industries that need funding to transition to cleaner production methods. Using syndicated loan data, we find that for US borrowers, bank lending was likely hampering green transition, while in the EU bank lending is more likely to facilitate it. Zooming in on Denmark, for which we have data on the full universe of firms and banks, we find more significant credit reallocation to greener firms, especially within industries. However, the reallocation of funds to green firms is, to a large extent, a byproduct of green firms becoming bigger. We do not find any evidence consistent with banks active stewardship of green transition.

Keywords: climate change, banks, loans, firm-level emission

JEL classification: G21, F21, Q54

*We thank Cesario Mateus, Xintong Li, and participants of the Conference on the Macroeconomic and Financial Aspects of Climate Change at the Bank of Mexico for helpful comments. All errors are ours.

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1 Introduction

Reduction of greenhouse gas emissions is an imperative to contain global warming, but the transition to cleaner economy is costly and will need support from the financial system. Several studies have shown that banks price climate policy risks in their lending contracts, especially following the Paris Agreement of 2015 (Degryse et al., 2023; Ehlers et al., 2022; Ho and Wong, 2023; Mueller and Sfrappini, 2022; Polo et al., 2023). However, much less is known about the quantities of loans allocated across industries and across firms.[1] Our paper fills this gap by providing a comprehensive analysis of loans extended to US and EU firms as a function of their emission intensities and improvements in their emission intensities.

There are three main ways in which banks can contribute to the green transition through reallocation of their credit.[2] First, they can move funds to firms that are greening their technologies (we call them greening firms thereafter) to facilitate this transition. Second, within a given industry, banks can reallocate funds to greener firms, thus providing incentives for other firms to also invest in greener technologies to attract loans. Third, they can direct more, not fewer, loans to high-emitting industries that are in most need of greening their technologies. As Hartzmark and Shue (2022) demonstrate, an increase in financing costs for high-emission firms leads to a large negative impact on firms' greening investment. Kacperczyk and Peydro (2022); Ye (2023) also find that high-emission firms reduce their investments and do not improve their environmental performance when their funding is reduced.

Thus, it is important to examine *how* credit is reallocated by banks in response to firms' emission intensities and changes in these intensities. Our analysis examines not only between-industry but also within-industry credit allocation in response to firm-level emission intensities and changes in these intensities over time. Moreover, we distinguish between the passive loan portfolio reallocation that follows changing market shares of firms, and active loan portfolio shifts.

First, we analyze syndicated bank lending to firms in the US and the EU, evaluating all aspects of lending: loan amounts, loan growth, new lender-borrower relations, and loan origination. The analysis is conducted at the loan level, using emissions reported by S&P Global TruCost (separately scope 1 and scope 2), and our sample period is 2010-2022. Then we zoom in on one of the "greenest" European countries, Denmark, for which we have data that covers the country's universe of firms and banks. For Danish data, we rely on firm-bank matched data sample, combined with firms' reported energy use (combined Scopes 1 and 2). We analyze loan amounts outstanding, their growth, loan origination, and the formation and dissolution of firm-bank relations. Because we observe the universe of Danish firms, we are also able to distinguish between active and passive reallocation of credit. The Danish sample covers 2003-2019. For both syndicated loan and Danish

[1] Ding et al. (2023) shows that Chinese firms with higher emissions receive fewer new bank loans. In our results, we only find limited evidence of this regularity for US and EU firms.

[2] We abstract from the impact banks' stewardship may have on firms' emissions. Hasan et al. (2023); Houston and Shan (2021); Morse and Sastry (Forthcoming, 2025) demonstrate that such activities can have an important impact.

data, we separate the sample to pre-2016 (pre Paris Climate accord) and 2016 onward. This is because most recent literature finds effects of credit reallocation only in Post-Paris years.[3]

For the US firms, we find that syndicated bank loans generally do not support the green transition. Pre-Paris, there does not seem to be any consistent correlation between firms emissions and syndicated loan allocation. Post-Paris, however, the evidence points more to credit allocation hampering green transition, with cleaner firms and firms that are greening their production having harder access to syndicated credit. For the EU firms, we find that in general bank lending has been more supportive of the green transition, especially Post-Paris. In particular, we find overall shift of funding towards cleaner firms (those with lower emission intensities), both across and within industries. However, we do not see better credit access for firms that are greening their technologies. Similar results hold for Danish sample, where we also fail to find any evidence of banks actively supporting green transition. When decomposing credit reallocation into active shifting to greener firms versus passive shifting due to composition effects, we find that most of the credit allocation to greener firms is passive credit reallocation in response to output shifts to greener firms. Active reallocation is very limited and is going in the opposite direction. We also find that loan growth rate is higher in cleaner industries, which is counterproductive to the investment needs for green transition in higher-emitting industries.

This paper makes two distinct contributions. First, it enriches our understanding of how bank credit allocation has changed, between and within industries, in response to firms' greenhouse gas emissions levels and dynamics. Our results reveal contrasting patterns for firms located in the US and in the EU. Our second main contribution lies in the use of data on the universe of firms and banks in Denmark to gain a more complete picture of firm emissions, bank credit reallocation, and bank-firm relations. We distinguish active bank credit reallocation in response to firms' emissions from passive credit reallocation in response to firms' output changes. We also study bank-firm relation formation and dissolution over time in relation to climate risk considerations.

Our paper contributes to the literature on climate risks and bank credit allocation, where the empirical findings are rather mixed. Bruno and Lombini (2023) find that banks in the global syndicated loan market do not adjust credit supply to account for higher climate transition risk after the Paris Agreement. Giannetti et al. (2023), using European banks' portfolio data, show that banks extend a higher volume of credit to browner borrowers, without charging higher interest rates or shortening debt maturity. In contrast, Kacperczyk and Peydro (2022) find that banks tend to reallocate credit away from high-emission firms using syndicated loan data and European bank lending data, respectively. Other papers have found mixed evidence depending on different factors. For instance, Mueller and Sfrappini (2022) show that banks reallocate credit to high-emission firms in the US but low-emission firms in Europe due to different regulatory environments. Miguel et al. (2024) find that after incorporating environmental risks in their capital assessments, large Brazilian

[3]Importantly, we do not attribute causality to Paris credit accord specifically, this is simply an indicator for discontinuity over time — the effects may be due to changes in emissions reporting, technological improvements, changes in the access to and cost of green energy generation, etc.

banks reallocate their lending away from high-emission sectors, while smaller banks expand their lending to those sectors. All of the above papers do not distinguish banks' possible strategies in shifting credit between industries versus across firms within industries.

Two recent papers are closely related to our analysis. Mésonnier (2021), using French lending data, finds evidence that higher levels of self-reported climate commitments by banks are associated with a slower growth of lending to large firms in the five most carbon-intensive industries but do not affect their lending to small and medium-sized enterprises. This paper, like ours, also distinguishes firms' characteristics within industries to examine banks' lending, but it focuses on firm size and lending in France only. Our paper focuses on firms' emission characteristics and has a much broader geographic coverage.

The second closely related paper is Hale et al. (2024). Also using syndicated loan data with global coverage, they find no substantial divestment of banks that made climate commitments from high-emission industries, and only find a limited decline in maturities of loans to firms in these industries. Our cross-industry results are consistent with their findings. We further contribute to the literature by examining credit allocation *across* firms *within* industries. Our use of Danish firm-bank-loan data also allows us to examine all the margins of credit adjustment more thoroughly.

Many banks have pledged to reduce their exposure to companies with high levels of greenhouse gas emissions. For instance, Citigroup became a signatory to the Principles for Responsible Banking (PRB) in 2020, Wells Fargo joined the Net-Zero Banking Alliance (NZBA) in 2021. Goldman Sachs, Bank of America, Morgan Stanley, and JP Morgan have all made similar commitments to a net-zero greenhouse gas (GHG) financing target in recent years.[4] The evidence on the effects of these commitments is, to date, mixed. Some recent studies find that banks that have made climate commitments reallocate their funding from high-emission firms and industries to low-emission ones (Kacperczyk and Peydro (2022); Newton et al. (2022); Reghezza et al. (2022)), others show opposite or mixed evidence (Mueller and Sfrappini (2022); Bruno and Lombini (2023); Giannetti et al. (2023); Miguel et al. (2024); Hale et al. (2024)). In our data we also fail to find the effects of climate commitments on loan allocation as a function of emissions.[5]

We begin our analysis with evidence from syndicated lending to the US and the EU firms, and then dive into an analysis of Denmark using its universal firm-bank data. For each section, we provide the corresponding data description, empirical strategies, and results. We conclude in Section 4.

[4]However, many of them backed out of the Net Zero Banking Alliance (NZBA) and other commitments in early 2025.

[5]In the interest of space we do not report these results, but they are available upon request.

2 Cross-Country Evidence

In this section we explore the response of syndicated loan origination to emission intensities and changes in such intensities and decompose any changes into those occurring within and industry and those between industries. We rely on the universe of global syndicated loans extended to firms in the US and the EU reported in Dealscan. We combine these data with S&P TruCost firm-level emissions data and Compustat balance-sheet data.

2.1 Data Description and Patterns

This section describes the datasets used in the cross-country analysis. Our sample period is 2010-2022.[6]

2.1.1 Syndicated Loan Data

Dealscan contains comprehensive information on the universe of loans from the global syndicated loan market. We obtain all observations available in the Dealscan data set from 2010 to 2022 and then apply several filters. First, we only include loans to firms in the non-financial sector. Second, we include only those borrowers for whom annual balance-sheet data are available in Compustat and emissions data in TruCost. Next, we only consider loans extended by banks.[7] Finally, we only consider borrowers in the US and the EU. We conduct our analysis at the loan level, and exclude loans within any facility that are administered by an institution that is distinct from the lead arranger.

To calculate the loan amounts for each lender within a facility, we take multiple steps. First, we use the reported lender shares and the total facility amount in Dealscan to calculate the loan amount by the lender. Then, in cases with unreported lender shares, or with lender shares adding up to more than 100 percent, we split the total deal amount in half, and then we further split one half by the number across lead arrangers and the other half equally across other participants. This allows us to get a loan amount that is reflective of the larger share of the deal usually assumed by lead arrangers.

Loan-level data are combined with firm-level emissions from TruCost in two steps. First, we match firms exactly using GVkey identifier and company name using the Chava and Roberts (2008) Dealscan–Compustat link. For firms without an exact match, we employ multi-variable fuzzy matching on borrower names, parent company names and country of headquarters. We use 2-digit SIC classification for the industrial classification of the borrower.

[6]To keep the paper concise, we do not present stylized facts in this section, since they are well documented in the existing literature on syndicated lending.

[7]Bank and non-bank lenders are classified following Aldasoro et al. (2023); Elliott et al. (2021).

The final sample includes 114,346 loan-level records, covering emission intensity for 3,452 firms and 1,652 banks across 74 countries.

2.1.2 Emission Intensity

Firm-level emission intensity data is from S&P TruCost, which provides standardized climate and environmental metrics for over 15,000 companies worldwide, including Scope 1, Scope 2, and Scope 3 emissions for each firm in our sample. TruCost compiles its data from multiple public disclosures, including company financial documents (e.g., annual reports, financial statements, 10-K/20-F filings, and regulatory submissions), as well as environmental reports such as Corporate Social Responsibility (CSR) or sustainability reports, Carbon Disclosure Project (CDP) disclosures, Environmental Protection Agency (EPA) records, and information posted on corporate websites or other public sources. In the absence of reported data, TruCost applies its environmentally extended input–output model, which integrates sector-specific environmental impact metrics with input–output data to estimate a firm's emissions.

We evaluate separately emission intensity with respect to Scope 1 and Scope 2 emissions, which are direct emissions and the emissions from electricity use, respectively. While TruCost provides information on firm-level emission intensity based on a company's annual consolidated revenues, we construct our own emission intensity metric as emissions per unit of *real* output, i.e., total revenue of the firm deflated by the country and year-specific GDP deflator.[8] Since a company's real revenue can be reasonably correlated with its scale of operations, at least within a sector, we believe it is a suitable normalizing factor.

We now describe the various emission intensity metrics we use for each part of our analyses.

General analysis. In our general analysis across firms, we use the following emission intensity measures:

$$EI_{it} = Firm\ emissions_{it}/Real\ revenues_{it}, \tag{1}$$

$$\Delta logEI_{it} = log(EI_{it}) - log(EI_{it-1}), \tag{2}$$

where EI stands for emission intensity of firm i in year t. $\Delta logEI$ measures the annual growth of EI in the year preceding t.

[8]Ideally, real value added would be a better measurement than real revenue, but we do not have data on firm value added.

Within-industry analysis. To capture a firm's emission intensity relative to other firms' within its industry, we construct a new metric called *Relative Emission Intensity (REI)* as follows:

$$REI_{ijt} = \frac{1}{\sigma_{jt}} \left[log(EI_{ijt}) - \sum_{i \in j} log(EI_{ijt})/N_{jt} \right], \tag{3}$$

$$\Delta REI_{ijt} = REI_{ijt} - REI_{ijt-1}, \tag{4}$$

where EI_{ijt} is the same as EI_{it} defined previously but now we keep track of industry of the firm, indicated by j. N_{jt} is the number of firms in industry j in year t. $\sum_{i \in j} log(EI_{ijt})/N_{jt}$ is the average emission intensity across all firms $i \in j$ in year t, while σ_{jt} is the corresponding standard deviation. Thus, REI_{ijt} is essentially a standardized score of a firm's emission benchmarked within its own industry. ΔREI_{ijt} measures the annual change of REI_{ijt} during the year preceding t.

Between-industry analysis. In our analysis across industries, we use the following metric for industry-level emission intensity, again distinguishing between Scope 1 and Scope 2 emissions:

$$\overline{EI}_{jt} = \sum_{i \in j} Firm\ emission_{it} \Big/ \sum_{i \in j} Real\ revenue_{it}, \tag{5}$$

$$\Delta \overline{EI}_{jt} = log(\overline{EI}_{jt}) - log(\overline{EI}_{jt-1}), \tag{6}$$

where EI_{jt} is industry overall emission intensity, built from our firm-level data, computed at the 2-digit SIC level.

Summary statistics for these measures and our control variables are provided in Supplement Tables A.1 and A.2.

2.2 Empirical Strategy and Results

We first describe a general analysis across all firm-bank pairs in our sample without distinguishing within- and between-industry effects. Then, we dig deeper into whether banks have been reallocating credit within an industry towards relatively cleaner firms and whether they have been shifting credit towards cleaner industries.

2.2.1 General Analysis

First, we conduct a general analysis to examine whether banks shift lending from dirtier firms to cleaner ones, similar to other papers in the literature (Kacperczyk and Peydro, 2022; Mueller and Sfrappini, 2022; Giannetti et al., 2023). This allows us to compare the results using our data with those in others' works. We use firm-level emission intensities in the US and EU, respectively, and the following specification:

$$
\begin{aligned}
Credit\ Outcome_{lijbt} = & (\beta_1 logEI1_{it-1} + \beta_2 logEI2_{it-1} + \beta_3 \Delta logEI1_{it-1} + \beta_4 \Delta logEI2_{it-1}) PreParis_t \\
& + (\beta_5 logEI1_{it-1} + \beta_6 logEI2_{it-1} + \beta_7 \Delta logEI1_{it-1} + \beta_8 \Delta logEI2_{it-1}) PostParis_t \\
& + \boldsymbol{X}'_{it-1}\gamma + \delta_i + \delta_{jt} + \delta_{bt} + \varepsilon_{lijbt}. \qquad (7)
\end{aligned}
$$

where l is a loan to firm i in industry j originated by b a bank in year t. The dependent variable is one of the following four credit outcomes of firms: 1) loan amount growth defined as amount relative to the previous loan issued by banks b to firm i, 2) log amount of loan l, 3) indicator if loan l is the first loan extended to firm i by any bank, and 4) indicator if loan l is the first loan extended to firm i by bank b. The first two measures capture the loan amount overall changing margins. The last two measures focus on the extensive margins: loan initiations and new relation establishment with a bank.

The key explanatory variables are $EI1_{it-1}$ and $EI2_{it-1}$ denoting Scope 1 and Scope 2 emission intensities, respectively. We include both scope measures in the same specification because they allow us to capture the effects of different types of emissions and they are not highly correlated (correlation is actually negative, -0.11). We also include the changes in these emission intensities to capture the (greening) progress and the changes are not highly correlated with the intensity levels either. The intensity variables are also lagged by one year in the regressions to capture any possible delayed impact on credit allocation. Overall, our focus is on examining how credit is allocated to green versus greening firms. Therefore, the coefficients for emission intensity should be interpreted in reverse, i.e., a lower (decreasing) emission intensity is evidence of green (greening).

In addition, we include Pre-Paris (equal to 1 for years prior to 2016, otherwise zero) and Post-Paris (equal to 1 for 2016 and onward, otherwise zero) indicators interacted with the emission intensity variables in the above specifications to highlight any regime differences before and after the Paris Agreement.[9] $\boldsymbol{X}$ is a matrix of firm characteristics over time, including log of total assets for the size of the firm, leverage ratio for indebtedness, capital expenditure ratio for long-term investment, and return on assets (EBITDA over total assets) for performance. δ_i is firm fixed effects, δ_{jt} is industry-year fixed effects, and δ_{bt} is bank-year fixed effects. Robust errors ε are clustered at the 2-digit level SIC industry code.

Table 1 reports the key results from the general analysis for the US and the EU. Pre-Paris, for the US firms, being relatively green (lower $Log(EI1)$) or greening the technology (lower $\Delta log(EI1)$) has no impact on firms' loan growth, amount, origination, or relation-building with banks. The effect of Scope 2 emissions is mixed. Firms with lower Scope 2 emissions (lower $Log(EI2)$) tend to get lower loan amounts and lower loan growth, but are more likely to obtain new loans. However, firms that are reducing their Scope 2 emissions (lower $\Delta log(EI2)$) are less likely to obtain new

[9]Main effects of these indicatros are absorbed by various fixed effects.

Table 1: General Analysis: Syndicated Loans - US and EU

	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)
	OLS	OLS	Logit	Logit
US firms				
Log $(EI1)_{t-1}$ × Pre-Paris	-2.714	-0.142	-0.183	0.014
Log $(EI2)_{t-1}$ × Pre-Paris	5.481**	0.329***	-0.285*	0.263
$\Delta\log(EI1)_{t-1}$ × Pre-Paris	-0.467	-0.131	0.155	-0.012
$\Delta\log(EI2)_{t-1}$ × Pre-Paris	-2.385*	0.020	0.337***	-0.215***
Log $(EI1)_{t-1}$ × Post-Paris	-0.984	-0.213	-0.381*	0.379
Log $(EI2)_{t-1}$ × Post-Paris	5.079*	0.533***	-0.092	0.131
$\Delta\log(EI1)_{t-1}$ × Post-Paris	1.557	0.313**	0.414***	-0.508***
$\Delta\log(EI2)_{t-1}$ × Post-Paris	-2.791*	-0.333***	-0.111	0.106
EU firms				
Log $(EI1)_{t-1}$ × Pre-Paris	-1.010	0.088	-0.240	-0.298
Log $(EI2)_{t-1}$ × Pre-Paris	-2.087	-0.140	0.037	0.019
$\Delta\log(EI1)_{t-1}$ × Pre-Paris	0.629	-0.005	0.110	-0.022
$\Delta\log(EI2)_{t-1}$ × Pre-Paris	0.802	0.077	-0.495	0.293
Log $(EI1)_{t-1}$ × Post-Paris	-0.447	0.026	-0.436	-0.320
Log $(EI2)_{t-1}$ × Post-Paris	-3.721	-0.159*	0.391	-0.082
$\Delta\log(EI1)_{t-1}$ × Post-Paris	0.617	0.119	0.513*	0.049
$\Delta\log(EI2)_{t-1}$ × Post-Paris	1.386	-0.069	-0.574**	0.380*

Notes: All US regressions have 26-29 thousand observations and include borrower, lender-year, and borrower industry-year fixed effects. EU regressions have 21-24 thousand observations and include in addition borrower-country fixed effects. All regressions include controls for total assets, leverage, CAPEX, EBITDA ratios. For full regression results, which include standard errors, see Table A.3. Significance levels: ***1%, **5%, *10%.

loans, but more likely to form new relationships, and have a higher loan growth. Overall, Pre-Paris, there seems only limited evidence of bank loans' support of greening activities. Post-Paris, the effects remain mixed. Loan growth is higher for firms with higher Scope 2 emissions but lower for those with increasing Scope 2 emissions. Larger loans are extended to firms with higher Scope 2 emissions, and firms that are increasing their Scope 1 emissions, but also to firms that are lowering their Scope 2 emissions. New loans are more likely to be extended to firms with lower Scope 1 emissions, but also to firms that are increasing their Scope 1 emissions. That said, firms that increase their Scope 1 emissions find it harder to form new bank relations.

For the EU firms, since multiple countries are in the EU sample, we have added country-year fixed effects to the specifications. Pre-Paris, we find no significant impact of emission levels or dynamics on any aspects of loan origination. However, after Paris, we observe that firms with lower Scope 2 emissions receive larger loans. New loans are more likely to be extended to firms with increasing

Scope 1 emissions and to firms that reduce Scope 2 emissions. A new banking relationship is more likely to form for firms with increasing Scope 2 emissions.

Overall, the general analysis presents a mixed picture for both the US and the EU, consistent with the findings of previous papers in the literature. Now we dig deeper into our main analysis for within- and between-industry credit reallocation to see if it yields a more informative picture.

2.2.2 Within-Industry Analysis

Do banks shift lending from browner firms to greener and greening firms within an industry? We address this question using all firms, as well as the subsamples of firms in dirty industries and non-dirty industries firms, for the US and EU, respectively.[10] Dirty industries are defined as those with emission intensities (based on Scope 1) above the 75th percentile of the entire sample, a fixed threshold over the years, the rest of industries are defined as non-dirty. We conduct regressions using bank-firm-year level data (reported here), as well as bank-industry-year level data (reported in the Appendix).

We use the following specification:

$$\begin{aligned} Credit\ Outcome_{lijbt} = {} & (\beta_1 REI1_{it-1} + \beta_2 REI2_{it-1} + \beta_3 \Delta REI1_{it-1} + \beta_4 \Delta REI2_{it-1})\, PreParis_t \\ & + (\beta_5 REI1_{it-1} + \beta_6 REI2_{it-1} + \beta_7 \Delta REI1_{it-1} + \beta_8 \Delta REI2_{it-1})\, PostParis_t \\ & + \boldsymbol{X}'_{it-1}\gamma + \delta_i + \delta_{jt} + \delta_{bt} + \varepsilon_{lijbt}. \end{aligned} \tag{8}$$

where as before loan l is issued to firm i in industry j by bank b in year t. The key variables are REI_{it-1} and its change from last year ΔREI_{it-1}, where REI stands for the relative emission intensity and is measured as in Equation (12). That is, a firm's REI is benchmarked against the firms in its own SIC 2-digit industry, instead of the entire universe of firms in a country's economy as in the general analysis. It captures a firm's emission intensity relative to its own industry. $\boldsymbol{X}$ is the same matrix of firm characteristic controls over time as in the general analysis. δ_i is firm fixed effects, δ_{jt} is industry-year fixed effects, and δ_{bt} is bank-year fixed effects. Robust errors ε are clustered at SIC 2-digit industry level.

Table 2 reports the combined within-industry analysis results. Each cluster of columns reports coefficients for the full sample, dirty sector firms, and non-dirty sector firms. Each cell within a cluster reports coefficients for loan growth (OLS) / loan amount (OLS) / new loans (logit) / first loan (logit).

For the US firms, we find that prior to Paris bank lending was not consistently related to firm emissions. Larger loan amounts and larger loan growth were observed for firms with higher emis-

[10] To maintain clarity, we refrain from referring to industries with lower emission intensities as "green", because these industries are not necessarily green, they just don't have a high weight on emission in their production function.

Table 2: Within Analysis: Syndicated Loans - US and EU - By industry type

	All Industries	Dirty Industries	Non-dirty Industries
	(1)	(2)	(3)
	Loan Growth (OLS) / Log(Loan Amount) (OLS) / New Loan (Logit) / First Loan (Logit)		
US firms			
$REI1_{t-1}$ × Pre-Paris	0.146 / -0.026 / -0.167 / 0.05	11.291 / 0.829* / -0.195 / -0.223	0.987 / -0.148 / -0.218 / 0.149
$REI2_{t-1}$ × Pre-Paris	8.126* / 0.092 / -0.254 / -0.119	12.957 / 0.24 / 1.089 / -0.615	7.414** / 0.115 / -0.451 / -0.085
$\Delta REI1_{t-1}$ × Pre-Paris	1.614 / -0.13 / 0.141 / 0.013	3.328 / -0.706*** / 0.084 / 0.199	-1.61 / -0.097 / 0.237 / -0.038
$\Delta REI2_{t-1}$ × Pre-Paris	-9.209** / -0.121 / 0.402 / -0.104	-26.868** / 0.254 / 0.138 / -0.32	-5.768 / -0.179 / 0.43 / -0.005
$REI1_{t-1}$ × Post-Paris	0.968 / -0.012 / -0.51 / 0.519**	16.155 / 0.706* / -0.438 / 0.488	-5.203 / -0.222 / -1.094*** / 0.737*
$REI2_{t-1}$ × Post-Paris	9.135 / 0.216 / 0.137 / -0.316	12.089 / 0.164 / 0.921 / -0.851***	14.580*** / 0.411 / 0.23 / -0.264
$\Delta REI1_{t-1}$ × Post-Paris	-0.128 / 0.136 / 0.688*** / -0.557**	-5.729 / -0.398 / 0.162 / -0.518	3.644 / 0.368* / 0.808*** / -0.441
$\Delta REI2_{t-1}$ × Post-Paris	-6.858 / -0.083 / -0.237 / 0.284	-11.391 / -0.058 / -0.317 / 0.858***	-8.163 / -0.095 / -0.051 / -0.115
EU firms			
$REI1_{t-1}$ × Pre-Paris	3.617 / 0.19 / 0.507 / -1.109***	17.869 / -0.007 / 6.903 / -0.569	2.397 / 0.164 / -0.351 / -1.004*
$REI2_{t-1}$ × Pre-Paris	3.867 / 0.144 / 0.251 / -0.132	-5.24 / -0.224** / -1.295 / 1.987***	4.876 / 0.36 / 0.237 / -0.946*
$\Delta REI1_{t-1}$ × Pre-Paris	-1.882 / 0.003 / -0.329 / 0.213	-7.176 / 0.052 / -0.43 / 0.082	-1.965 / -0.079 / -0.028 / 0.236
$\Delta REI2_{t-1}$ × Pre-Paris	-2.136 / -0.118 / -0.535 / 0.537	7.767** / 0.035 / 1.378 / -1.298***	-4.342 / -0.105 / -0.253 / 0.644
$REI1_{t-1}$ × Post-Paris	3.128 / -0.027 / -0.089 / -1.387**	16.642 / 0.077 / 5.59 / -0.353	0.651 / -0.055 / -0.885 / -1.366
$REI2_{t-1}$ × Post-Paris	-0.638 / 0.107 / 0.622 / 0.006	-1.768 / -0.358 / -0.225 / 0.605*	1.504 / 0.235 / 0.343 / 0.119
$\Delta REI1_{t-1}$ × Post-Paris	1.246 / -0.017 / 0.423 / 1.085	-3.864 / -0.088 / -0.856 / -0.997*	1.571 / 0.022 / 1.062 / 1.227
$\Delta REI2_{t-1}$ × Post-Paris	-0.586 / -0.234* / -0.487 / 0.35	5.511 / -0.339* / -1.05 / -1.28	-2.738 / -0.186 / -0.44 / 0.483

Notes: Reported are coefficients from within-industry regressions for full sample, high emission (dirty) industries, and the remaining (non-dirty) industries. All US regressions include borrower, lender-year, and borrower industry-year fixed effects. EU regressions include in addition borrower country-year fixed effects. All regressions include controls for total assets, leverage, CAPEX, EBITDA ratios. For full regression results, which include standard errors, see Tables A.4 and A.6. Significance levels: ***1%, **5%, *10%.

sions. Loan amounts in particular were higher for firms with higher Scope 1 emissions in the subsample of high-emission industries (column 2), while loan growth was higher for firms with higher Scope 2 emissions in all and non-dirty industries (columns 1 and 3). The picture, however, is the opposite for greening firms — they did experience a higher loan growth and amount, especially for dirty industries. This is an important segment, because these are exactly the firms that need financing for green transition. After Paris, the picture remained mixed with more evidence of firms with low emissions and greening firms finding it more difficult to access syndicated loans. In particular, there is no longer evidence of higher credit growth for greening firms in dirty industries.

For the EU firms, the evidence is more encouraging. For dirty industries, although firms with higher Scope 2 emissions were more likely to form new banking relationships both pre- and post-Paris and firms with increasing Scope 2 emissions had higher loan growth pre-Paris, the former also had lower loan amounts and the latter are less likely to form new banking relationships. The effects are less significant for non-dirty industries. Arguably, this is exactly what we want to see for the financial support of green transition—more green actions in the dirty industries.

While the picture remains still mixed, compared to overall results, there is a clear difference in lending to US vs. EU firms, especially when focusing on dirty industries, where this matters most.

In the US, there appears to be more lending to higher-emitting firms in dirty industries, while in the EU the effect tends to be the opposite.

2.2.3 Between-Industry Analysis

Now, we examine credit allocation across industries and answer the question: Do banks shift lending from dirty industries to non-dirty industries? We use the following specification:

$$\begin{aligned} Credit\ Outcome_{lijbt} = {} & (\beta_1 log\overline{EI1}_{jt-1} + \beta_2 log\overline{EI2}_{jt-1} + \beta_3 log\overline{EI1}_{jt-1} + \beta_4 log\overline{EI2}_{jt-1}) \times PreParis_t \\ & + (\beta_5 log\overline{EI1}_{jt-1} + \beta_6 log\overline{EI2}_{jt-1} + \beta_7 log\overline{EI1}_{jt-1} + \beta_8 log\overline{EI2}_{jt-1}) \times PostParis_t \\ & + \boldsymbol{X}'_{it-1}\boldsymbol{\gamma} + \delta_i + \delta_j + \delta_{bt} + \varepsilon_{lijbt} \end{aligned} \tag{9}$$

where as before loan l is issued to firm i in industry j by bank b in year t. The key variables are $\overline{EI}_{jt-1}$, industry emission intensity, measured as the ratio of industry emission over its real revenue and the ratio's log change from last year, $\Delta log\overline{EI}_{jt}$. Both variables are lagged by one year in the regressions to capture any possible delayed impact on credit allocation. $\boldsymbol{X}$ is again a matrix of firm characteristic controls over time. δ_i is firm fixed effects, δ_j is industry fixed effects, and δ_{bt} is bank-year fixed effects. Robust errors ε are clustered at the NACE-2-digit industry level.

The results are reported in Table 3. For the US, we find no evidence of reallocation of funds from or to high-emission industries. None of the coefficients are statistically significant, before or after Paris. For the EU firms, we observe higher loan growth for firms in industries with lower Scope 1 emissions before and after Paris.[11] While this reallocation leads to reduction of climate transition risks for these banks, it does not support green transition. Pre-Paris, there was also evidence that firms in increasingly dirty industries had a higher chance of getting new loans, i.e. greening industries less likely to get new loans, which is inconsistent with banks supporting green transition. There is no strong evidence one way or another in terms of other aspects of lending.

2.3 Summary of Empirical Results

To summarize all of our loan-level analysis, we have created a result summary table (Table 4). For the US firms, Pre-Paris, there is very little evidence of any relationship between firm emissions and syndicated loan origination. While some effects are statistically significant, they tend to not be robust across specifications, outcomes, and subsamples. One encouraging piece of evidence is in the dirty industries, where green transition matters the most: firms that were reducing their Scope 1 emissions were receiving larger loans and firms that were reducing their Scope 2 emissions experiences higher loan growth.

[11] This is consistent with banks decarbonizing their portfolios by increasing lending to firms in industries with low emissions (Miguel et al., 2024).

Table 3: Between Industry Analysis: Syndicated Loans - US and EU

	Loan Growth (1) OLS	Log(Loan Amount) (2) OLS	New Loan (3) Logit	First Loan (4) Logit
US firms				
Log (Ind. Intensity)$_{t-1}$($Scope1$) × Pre-Paris	-2.110	0.154	0.091	-0.062
Log (Ind. Intensity)$_{t-1}$($Scope2$) × Pre-Paris	2.394	0.164	0.187	-0.017
Δ(Ind. Intensity)$_{t-1}$($Scope1$) × Pre-Paris	1.131	-0.239	-0.291	0.149
Δ(Ind. Intensity)$_{t-1}$($Scope2$) × Pre-Paris	-3.002	0.093	0.202	-0.061
Log (Ind. Intensity)$_{t-1}$($Scope1$) × Post-Paris	-1.702	0.105	0.091	-0.012
Log (Ind. Intensity)$_{t-1}$($Scope2$) × Post-Paris	1.842	0.103	0.006	0.134
Δ(Ind. Intensity)$_{t-1}$($Scope1$) × Post-Paris	1.609	0.171	0.243	-0.262
Δ(Ind. Intensity)$_{t-1}$($Scope2$) × Post-Paris	0.941	0.010	-0.291	-0.180
EU firms				
Log (Ind. Intensity)$_{t-1}$($Scope1$) × Pre-Paris	-2.694*	-0.128	-0.071	0.135
Log (Ind. Intensity)$_{t-1}$($Scope2$) × Pre-Paris	-0.035	-0.054	0.312	-0.025
Δ(Ind. Intensity)$_{t-1}$($Scope1$) × Pre-Paris	-0.454	0.274	0.475*	-0.127
Δ(Ind. Intensity)$_{t-1}$($Scope2$) × Pre-Paris	-0.139	-0.181	-0.120	0.355
Log (Ind. Intensity)$_{t-1}$($Scope1$) × Post-Paris	-2.931*	-0.194	-0.046	0.171
Log (Ind. Intensity)$_{t-1}$($Scope2$) × Post-Paris	0.510	0.062	-0.065	-0.140
Δ(Ind. Intensity)$_{t-1}$($Scope1$) × Post-Paris	0.661	-0.081	-0.077	0.148
Δ(Ind. Intensity)$_{t-1}$($Scope2$) × Post-Paris	1.397	0.026	0.539	0.341

Notes: Analysis is conducted at loan level, but with industry intensity measures. All US regressions have 43-46 thousand observations and include borrower, lender-year, and borrower industry-year fixed effects. EU regressions have 32-34 thousand observations and include in addition borrower-country fixed effects. All regressions include controls for total assets, leverage, CAPEX, EBITDA ratios. For full regression results, which include standard errors, see Table A.7. Robust standard errors are clustered at the industry level. Significance levels: ***1%, **5%, *10%.

Post-Paris, the majority of the effects is actually going against green transition: the aforementioned effects are no longer present and we observe that firms with lower emissions (cleaner firms) tend to have harder access to credit, with just a couple exceptions. Consistent with recent evidence, we observe no reallocation of credit across industries.

For the EU firms, Pre-Paris, we observe predominantly the effects that support green transition, although the effects appear to be driven by cleaner industries here these effects are less important. That said, most significant effects are in terms of new lending relationships being more likely for cleaner firms, which has a potential for long-term impact and stewardship of green transition. We do observe higher loan growth for firms in greener industries (between industry analysis), which is potentially a cause for concern, especially when combined with observed decline in loan origination to industries that are reducing their emissions.

Table 4: Result Summary: US and EU

	All industries		Dirty industries		Non-dirty industries	
	Cleaner firms	Greening firms	Cleaner firms	Greening firms	Cleaner firms	Greening firms
US borrowers:						
Pre-Paris						
Overall (scope 1)	No effect	No effect				
Overall (scope 2)	↓ ▲ ■ ↑ ♦	↓ ♦ ↑ ▲ ●				
Within ind (scope 1)	No effect	No effect	↓ ■	↑ ■	No effect	No effect
Within ind (scope 2)	↓ ▲	↑ ▲	No effect	↑ ▲	↓ ▲	No effect
Between ind (scope 1)	No effect	No effect				
Between ind (scope 2)	No effect	No effect				
Post-Paris						
Overall (scope 1)	↑ ♦	↓ ■ ♦ ↑ ●				
Overall (scope 2)	↓ ▲ ■	↑ ▲ ■				
Within ind (scope 1)	↓ ●	↓ ♦ ↑ ●	↓ ■	No effect	↓ ● ↑ ♦	↓ ■ ♦
Within ind (scope 2)	No effect	No effect	↑ ●	↓ ●	↓ ▲	No effect
Between ind (scope 1)	No effect	No effect				
Between ind (scope 2)	No effect	No effect				
EU borrowers:						
Pre-Paris						
Overall (scope 1)	No effect	No effect				
Overall (scope 2)	No effect	No effect				
Within ind (scope 1)	↑ ●	No effect	No effect	No effect	↑ ●	No effect
Within ind (scope 2)	No effect	No effect	↓ ● ↑ ■	↓ ▲ ↑ ●	↑ ●	No effect
Between ind (scope 1)	↑ ▲	↓ ♦				
Between ind (scope 2)	No effect	No effect				
Post-Paris						
Overall (scope 1)	No effect	↓ ♦				
Overall (scope 2)	↑ ■	↓ ● ↑ ♦				
Within ind (scope 1)	↑ ●	No effect	No effect	↑ ●	No effect	No effect
Within ind (scope 2)	No effect	↑ ■	↓ ●	↑ ■	No effect	No effect
Between ind (scope 1)	↑ ▲	No effect				
Between ind (scope 2)	No effect	No effect				

Notes: ▲ indicates loan growth, ■ indicates loan amount, ♦ indicates new loan issuance, ● indicates new lending relationship. Green means encouraging evidence for green transition, red means discouraging evidence, organe means potentially counter-productive cross-industry loan reallocation, and gray means results are mixed or not robust. Industry-level analysis is not summarized here.

Post-Paris, the results are much more encouraging. Most importantly, greening firms in dirty industries, where the effects matter the most, are more likely to enter new lending relationships (Scope 1 greening), and receive larger loans (Scope 2). Larger loans also go to cleaner firms overall (Scope 2). We still observe higher loan growth in greener industries, but no longer observe reduction in lending to greening sectors.

We will gain further understanding of these dynamics by focusing on one of the greenest countries in Europe, Denmark.

3 The Danish Case

We now turn to the analysis of bank lending in Denmark and obtain the data on the universe of firms and bank credits to conduct analyses. Denmark has been actively pushing its climate initiatives and has ensured ambitious climate action by passing its 2020 Climate Act into law. It would be important to examine whether these actions translate into results in the banking sector. Moreover, the advantage of the Danish data is the universal coverage of firms and banks, which enables us to examine any changes to the entire distribution of firm emissions and bank credits.

3.1 Data Description and Patterns

This section describes the Danish data we are using. Our sample period runs from 2003 to 2019. While we obtain the data on the universe of banks and firms, we drop micro firms with fewer than 10 employees for data accuracy, as well as a small share of observations where the bank industry code is outside of NACE code 64, to ensure that only banks are included.

In order to account for the fact that some firms never entered into a firm–bank relationship, in the main analysis, we use a *full* sample that includes both firms that *never* entered into such relationships ("never firms" thereafter) and those that *ever* did ("ever firms" thereafter), and fill in missing loan outcome variables with zeros before running the regression. Our main results are robust when we use a sample that only includes those *ever* firms (see Appendix B.4).

3.1.1 Firm and Emission Data

We begin by collecting firm-level data from Statistics Denmark, specifically the general firm statistics (FIRM) and the firm-level accounting statistics (FIRE). The FIRM register covers all private-sector firms and provides detailed information on firm characteristics, including size, age, capital, revenue, geographic location, and industry classification. The FIRE register contains comprehensive accounting data at the firm level. Using these sources, we construct key firm-level control variables for our empirical analysis, such as log(assets), return on assets (ROA), and leverage ratio.[12] In the section below, we describe the specific energy/emission intensity measures we use for each part of our analyses.

General analysis: firm energy intensity. Due to the lack of firm-level direct emission data, we use firm-level energy consumption obtained from the FIRE register as a proxy. The data contains firms' energy purchase amounts for heating and production. This includes, among other things, expenses for electricity, oil, gas, and district heating. We consider such energy consumption a

[12] All monetary values are adjusted using the GDP deflator (pris112) from Statistics Denmark, with 2015 as the base year. The controls are all winsorized at the 99th percentile to account for outliers.

Scope 1+Scope 2 emission measurement.[13] We then calculate the energy intensity by normalizing the value by the real value added to account for the differences in firm output.

Specifically, for the general analysis, we calculate the following energy intensity measures:

$$EgI_{ijt} = Firm\ energy\ use_{ijt}/Real\ value\ added_{ijt}, \tag{10}$$

$$\Delta log EgI_{ijt} = log(EgI_{ijt}) - log(EgI_{ijt-1}), \tag{11}$$

where EgI_{ijt} stands for an energy-consumption-based emission intensity of firm i in industry j and year t.

Within-industry analysis: firm relative energy intensity. To capture a firm's energy intensity relative to other firms' within its industry, we construct *Relative Energy Intensity (REgI)* as follows:

$$REgI_{ijt} = \frac{1}{\sigma_{jt}} \left[log(EgI_{ijt}) - \sum_{i \in j} log(EgI_{ijt})/N_{jt} \right], \tag{12}$$

$$\Delta REgI_{ijt} = REgI_{ijt} - REgI_{ijt-1}, \tag{13}$$

where $REgI$ is essentially a standard score of a firm's energy intensity benchmarked within its own industry. $\Delta REgI$ measures the annual level change of $REgI$.

Between-industry analysis: industry emission (energy) intensity. Industry-level emission data is obtained from the air emission accounts from StatBank Denmark, administered by Statistics Denmark, which show emissions of greenhouse gases as well as other polluting substances caused by the industries' or households' use of energy. We focus on the greenhouse gas account (in CO2 equivalents) that captures the total emissions from direct emissions and the distribution of electricity and district heating.[14] We consider this as a Scope 1+Scope 2 emission measure.

Industry-level emission intensity $\overline{EI}$ is constructed as

$$\overline{EI}_{jt} = Industry\ emission_{jt}/Real\ value\ added_{jt}, \tag{14}$$

$$\Delta log \overline{EI}_{jt} = log(\overline{EI}_{jt}) - log(\overline{EI}_{jt-1}) \tag{15}$$

[13]Given firm energy consumption variable *KENE* is only available for the period 2000-2016; we therefore impute the missing emission intensity in years 2017-2019 based on the mean energy consumption at the firm level over a 3-year rolling window.

[14]For more information, see the link here: https://www.statistikbanken.dk/statbank5a/SelectVarVal/Define.asp?MainTable=DRIVHUS2&PLanguage=1&PXSId=0&wsid=cftree.

for industry j in year t.

We also calculate industry-level energy intensity $\overline{EgI}$ as the sum of the total energy consumption across all firms in an NACE 2-digit, weighted by real industry output:

$$\overline{EgI}_{jt} = Industry\ energy\ use_{jt}/Industry\ real\ value\ added_{jt}, \tag{16}$$

$$\Delta log\overline{EgI}_{jt} = log(\overline{EgI}_{jt}) - log(\overline{EgI}_{jt-1}). \tag{17}$$

3.1.2 Bank and Loan Data

To link firms with banks and their corresponding loan account information, we rely on a unique database from tax records, which provides account-level information for all bank loan relationships available in Statistics Denmark.[15] We focus on the part covering firms (URTEVIRK). Using unique identifiers for both banks and firms, we link each loan account to the relevant bank and borrowing firm. We then merge this information with the firm-level dataset described earlier via the unique firm identifiers (CVRNR), allowing us to assign firm and bank characteristics to each loan.

Finally, we aggregate the raw data from the firm–bank–account–year level to the firm–bank–year level by summing the loan account balances. This enables us to measure credit outcomes across different adjustment margins at the firm–bank–year level, including outstanding loan amounts, changes in outstanding loan amounts, new loan initiations, and bank–firm relationship formation or dissolution. The final sample consists 1,775,938 firm–bank–year observations, covering 274,896 firms and 342 banks over 17 years. Table B.9 in the Supplement presents the summary statistics for the key variables of interest, including firm-bank-level credit outstanding amount, firm energy intensity, industry emission intensity, and other firm controls.

3.1.3 Stylized Facts

Because the use of bank-firm data from Denmark is novel in the literature, we provide stylized facts on the Danish sample focusing on the distribution of firm energy intensity and credit allocation.

Figure 1 plots the distribution of all firms' average energy intensity for each of the five quantile bins, comparing the first three years of the sample (2003–2005) with the last three years (2017–2019). Firms with missing energy intensity are not included. One observation is that energy intensity is highly skewed. The top quantile bin exhibits significantly higher energy intensity compared with the other bins, indicating that a small group of firms is highly energy-intensive. Interestingly, over time, the most energy-intensive firms in the top quantile drastically increased their energy intensity.

[15] Each year, Danish entities that have extended credit over the past 12 months need to report to the Danish Tax Authority (SKAT), including account numbers, types, balances, ownership details, and total interest paid as of December 31. These reports are used for tax calculations, ensuring high data quality.

Figure 1: Average Firm Energy Intensity for Each Quantile Bin

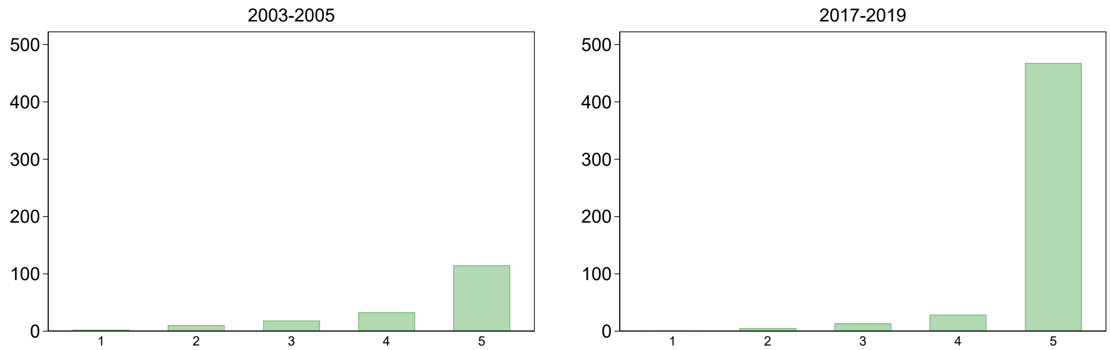
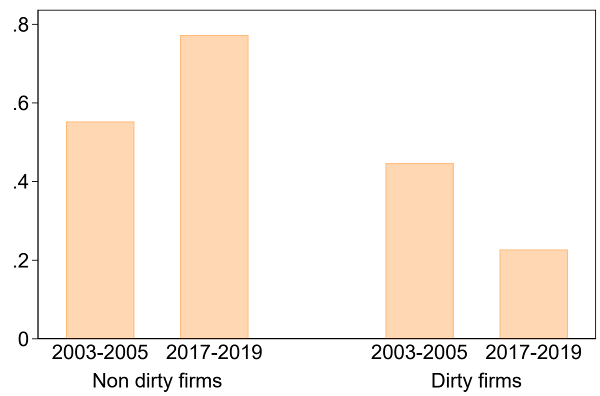


Figure 2: Credit Share to Dirty vs Non-dirty Firms in General



Do banks generally shift lending from dirty firms to greener (non-dirty) firms? In Figure 2, we split firms into the 0–75th percentile (non-dirty) and 75–100th percentile (dirty) based on their *firm energy intensity* over the entire sample period, and plot the total credit allocation (in percent) to each type of firm for the first three years combined and the last three years combined in the sample. In other words, for the first and last three years, we examine how much credit was allocated to dirty vs non-dirty firms as a share of total credit. Notice that the energy intensity threshold is based on the whole sample period and does not change over time. Firms with missing energy intensity are not included. Overall, there is some encouraging news that a higher credit share is reallocated from dirty to non-dirty firms.

Do banks shift lending from dirty firms to non-dirty firms within an industry? In Figure 3, we split firms into the 0–75th percentile (non-dirty) and 75–100th percentile (dirty) based on their *relative energy intensity* over the entire sample period, and plot the total credit allocation (in percent) to each type of firm for the first three years combined and the last three years combined in the sample. Again, the intensity threshold does not change over time, and firms with missing relative energy intensity are not included. There is also some encouraging news that

Figure 3: Credit Share to Dirty vs Non-dirty Firms Within-Industry For All Industry

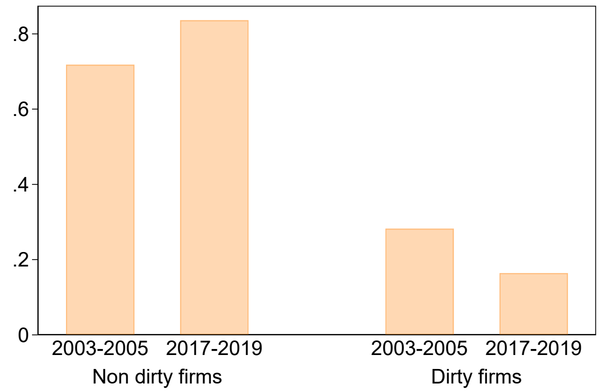
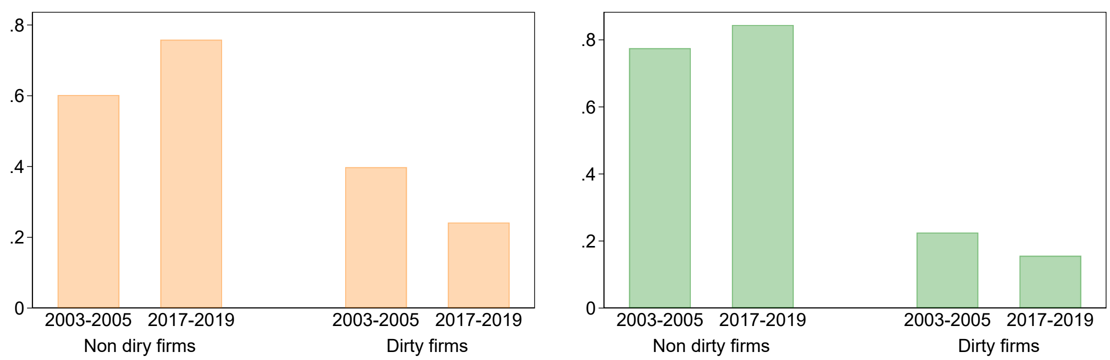


Figure 4: Credit Share Within Dirty (Left) vs Non-dirty (Right) Industry



a higher credit share is reallocated from dirty to non-dirty firms within industry over time, but the shift is less dramatic than in Figure 2.

Furthermore, we repeat the graphing exercise for dirty (top 25% dirty industries) and non-dirty industries, separately, in Figure 4. We see most shifts of credit from dirty firms to non-dirty firms in the dirty industries, which is an encouraging finding for the green transition.

Are industries getting cleaner in general? Figure 5 plots the distribution of average industry emission intensity for the first three years of the sample and the last three years, divided into five quantile bins. Emission intensity is again highly skewed, indicating that a few industries are very emission-intensive. Over time, the most polluting industries do not become cleaner.

Do banks shift lending from brown (dirty) industries to green (non-dirty) industries? Figure 6 splits 2-digit industries into the 0–75th percentile (non-dirty) and 75–100th percentile (dirty) based on their *industry emission intensity*, and plots the total credit allocation (in percent) to each type of industry for the first three years combined and the last three years combined in the sample. The industry emission intensity threshold is fixed over time. Only a very small share of

Figure 5: Average Industry Emission Intensity for Each Quantile Bin

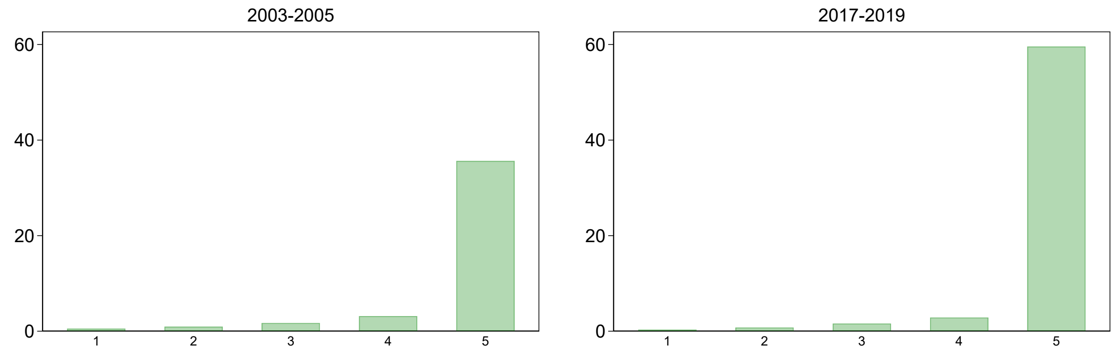
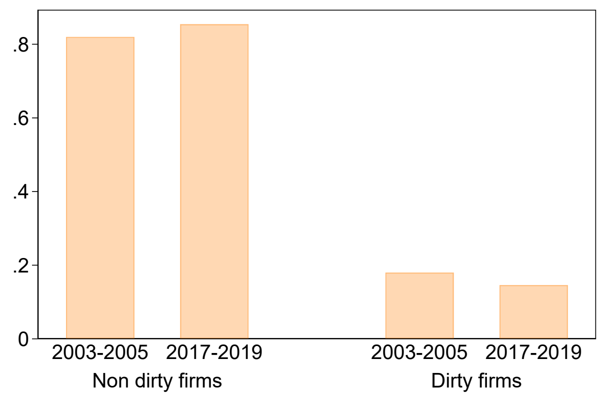


Figure 6: Credit Share to Dirty vs Non-Dirty Firms Between Industry



credit is reallocated to non-dirty industries over time.

Is observed credit reallocation passive or active? Next, we distinguish whether the credit allocation to cleaner firms is a response to output shifts (i.e., passive credit reallocation) or through active credit reallocation. The first step is to plot the distribution of credit and output. We split firms into five bins based on *firm energy intensity* in the first three years, and then plot credit density and output density, that is, the credit share of each bin out of total credit and the output share for each bin out of total output in the first and last three years, respectively, in Figure 7. The evidence suggests that, over time, the cleanest firms (bin 1) receive more credit and generate higher output, while the dirtiest firms (bin 5) appear to experience declining credit and output.

We further examine credit and output density both within and between industries in the Appendix. In Figure B.10, we split firms into five bins based on *relative energy intensity* in the first three years, and then plot bar charts of credit and output density for the first and last three years' total credit and total output for each bin. Similarly, Figure B.11 creates five bins based on *industry emission intensities* in the first three years, and then plots bar charts of credit and output density for the first and last three years. There is some encouraging news within the industry as bins 4 and

Figure 7: Passive vs Active Credit Reallocation: Credit and Output Density by Firm Energy Intensity

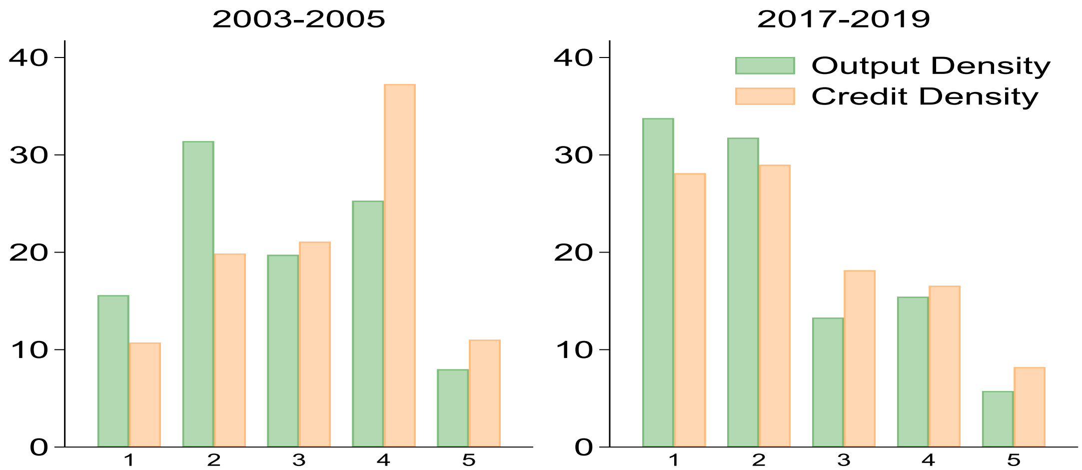
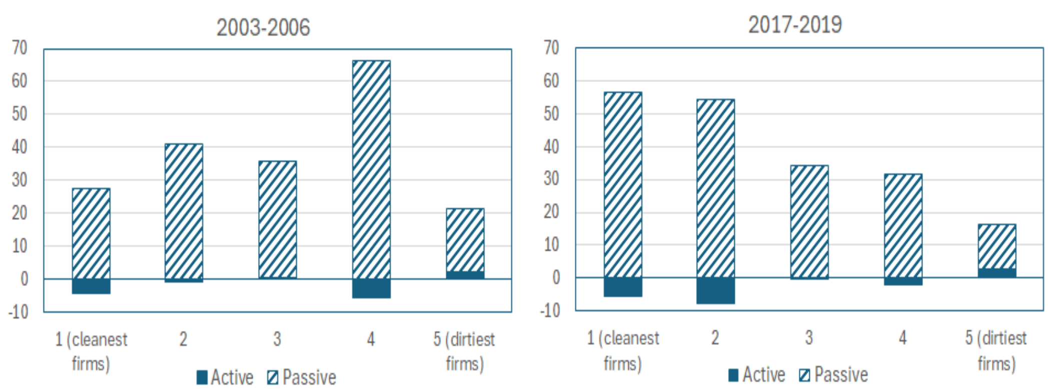


Figure 8: Active vs Passive Credit Allocation by Firm Energy Intensity



5 (relatively dirty firms within the industry) receive less credit and generate lower output relative to other bins over time. However, the trends between industries are less clear, although we do see that the majority of credit is allocated to the cleanest industries, which may have encouraged the growth of those industries over time.

What is more important is to examine whether banks shift credit allocation passively proportional to firm output or actively seek out firms with certain levels of energy intensity. To separate the passive credit allocation from the active credit allocation in response to firms' emissions, we construct the ratio of credit-density to output-density for each year in our sample, run an AR1 model, and use the estimates and the previous year's output density to generate predicted credit-density for each bin of firm energy intensity.[16] Then, we calculate passive credit allocation for each bin using the predicted credit density and the actual total credit of that year. The active allocation

[16]Wooldridge test for autocorrelation shows strong first-order autocorrelation in the ratio of credit-density to output-density.

is thus what is left in the actual credit in each bin after deducting the passive credit allocation.

Figure 8 plots the active and passive credit allocation for the median of the first three years in our sample and the last three years. When the active credit allocation is negative, it means that even passive allocation of credit is not enough to catch up with the output density changes in the bin, i.e., being underallocated in credit. We can see that bins 1 (the cleanest bin), 2, and 4 are usually underallocated in credit. Bin 3 has been quite adequate in catching up to the output. Bin 5 (the dirtiest bin) was overallocated in credit, i.e., more credit was actively allocated to them beyond its output density changes. Overall, we see that most of the credit allocation to cleaner firms is a response to output shifts (i.e., passive credit reallocation) and there exists a persistent active reallocation of credit to the dirtiest firms and a persistent *lack* of active reallocation of credit to the cleanest firms.

3.2 Regression analysis

We now turn to the formal regression analysis of credit allocation, where we control for firm size, other characteristics, and variety of fixed effects. Unless otherwise specified, the regression equations are the same as for syndicated loan analysis across countries.

3.2.1 General Analysis

Table 5 reports the empirical results for the general analysis, using a modified version of the specification in Equation (7) in the cross-country analysis. One key modification is that firm energy intensity (EgI_{ijt}) is used to proxy for firm emission intensity and corresponds to the sum of Scope 1 and Scope 2 emissions. We do not analyze the firm-bank relationships here but we do so in the within-industry analysis below.

We find that prior to the Paris Agreement, loan growth was higher for greener firms, those using less energy per unit of output. We do not find any other significant effects on loan allocation. Post-Paris, we observe that cleaner firms benefitted from larger loans, higher loan growth, and more loan origination. However, the opposite was true for greening firms, which had on average smaller loans and less loan origination.

3.2.2 Within-Industry Analysis

Now we examine whether banks shift lending from dirtier firms to greener firms within an industry, using the same empirical strategy (i.e., relative energy intensity to peer-firms in the same industry) as before in the cross-country evidence in Equation (8). We answer this question using all firms, the subsample of dirty firms, and the subsample of non-dirty firms. Here, the dirty industries are again defined as those whose industry emission intensity (based on Scope 1 + Scope 2) is above the 75th percentile of the entire sample, a fixed threshold over the years. In addition to the credit outcomes

Table 5: General Analysis: Full Sample

	Log (Loan Balance)	**Loan Growth**	**New Loan**
	(1)	(2)	(3)
Pre Paris × Log (EgI)$_{t-1}$	0.016	-0.366*	-0.001
	(0.012)	(0.208)	(0.001)
Pre Paris × Δ Log (EgI)$_{t-1}$	-0.005	-0.034	-0.000
	(0.008)	(0.152)	(0.001)
Post Paris × Log (EgI)$_{t-1}$	-0.073***	-1.144***	-0.005***
	(0.018)	(0.323)	(0.002)
Post Paris × Δ Log (EgI)$_{t-1}$	0.036***	0.254	0.002**
	(0.007)	(0.223)	(0.001)
Log (Assets)$_{t-1}$	0.122***	-0.280*	-0.001
Fixed Assets Ratio$_{t-1}$	0.002***	-0.027***	-0.000
Leverage Ratio$_{t-1}$	0.001***	-0.030***	-0.000***
ROA$_{t-1}$	0.000**	0.007***	0.000***
R-sq	0.726	0.195	0.389
N	1,328,445	1,328,445	1,328,445

Notes: This table presents the estimation results for the general analysis of the full sample of firms, including the Post Paris dummy. The dependent variables are Log (Loan Balance), Loan Growth, and New Loan Initiation. All regressions include firm, bank-time, industry-time fixed effects. All regressions have 1,484,604 observations. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels: ***1%, **5%, *10%.

of loan amount, loan growth, and loan origination, we also examine firm-bank relationship changes in this section.

Table 6 reports the results for the full sample as well as subsamples of dirty and non-dirty industries. In the full sample, prior to the Paris Agreement, the only significant effect is that firms with relatively higher energy intensity obtained larger loans on average. There is no other significant effects. Post-Paris, the results are similar to the general analysis. Firms with lower energy intensity relative to their own industries (cleaner firms) have received larger loans, had higher loan growth, and more new loans. However, greening firms received smaller loans and fewer new loans. These results support our stylized fact that most credit reallocation towards green firms observed in the data is passive.

The middle panel of Table 6 reports the results for dirty industries. Pre Paris, we see that lower relative energy intensity brings firms higher loan growth and more new loans. Greening firms, however, receive smaller loans. After the Paris Agreement, we observe less significant effects, except that firms with decreasing relative energy intensity (greening firms within the brown industry) experience lower loan growth. We observe a similar pattern if we restrict our firm sample to only traditionally dirty industries, as reported in Appendix Table B.12 (see traditionally dirty industry list in Table B.17 in the Appendix).

Table 6: Within-Industry Analysis: Different Samples

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	**(2)**	**(3)**
Full Sample			
Pre Paris × REgI_{t-1}	0.025**	-0.148	0.000
	(0.012)	(0.264)	(0.001)
Pre Paris × Δ $(\text{REgI})_{t-1}$	-0.013	-0.148	-0.001
	(0.009)	(0.154)	(0.001)
Post Paris × REgI_{t-1}	-0.070***	-1.201***	-0.005***
	(0.022)	(0.384)	(0.002)
Post Paris × Δ $(\text{REgI})_{t-1}$	0.035***	0.318	0.002**
	(0.008)	(0.224)	(0.001)
R-sq	0.726	0.195	0.389
N	1,328,438	1,328,438	1,328,438
Dirty Industries			
Pre Paris × REgI_{t-1}	-0.037	-1.391**	-0.005**
	(0.022)	(0.520)	(0.002)
Pre Paris × Δ $(\text{REgI})_{t-1}$	0.029**	-0.096	0.000
	(0.010)	(0.346)	(0.001)
Post Paris × REgI_{t-1}	-0.040	-1.335	-0.006
	(0.051)	(0.924)	(0.005)
Post Paris × Δ $(\text{REgI})_{t-1}$	-0.014	1.694*	0.004
	(0.030)	(0.942)	(0.004)
R-sq	0.737	0.205	0.390
N	86,310	86,310	86,310
Non-dirty Industries			
Pre Paris × REgI_{t-1}	0.032***	-0.025	0.001
	(0.011)	(0.262)	(0.001)
Pre Paris × Δ $(\text{REgI})_{t-1}$	-0.018**	-0.169	-0.001
	(0.008)	(0.160)	(0.001)
Post Paris × REgI_{t-1}	-0.072***	-1.208***	-0.005**
	(0.023)	(0.408)	(0.002)
Post Paris × Δ $(\text{REgI})_{t-1}$	0.036***	0.266	0.002**
	(0.008)	(0.231)	(0.001)
R-sq	0.726	0.200	0.393
N	1,235,788	1,235,788	1,235,788

Notes: This table presents the estimation results for within-industry analysis for the full sample of firms, dirty industries' firms, and non-dirty industries' firms. All regressions include firm, bank-time, and industry-time fixed effects as well as controls for log assets, fixed assets ratio, leverage ratio, and ROA. The full regression tables are in Table B.21, Table B.21, and Table B.23. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels: ***1%, **5%, *10%.

When focusing on the within-industry allocation in non-dirty industries (the bottom panel of Table 6), we see the results very similar to the full sample: there is mixed evidence before the Paris Agreement, but more encouraging evidence post-Paris, we observe that greener firms within industries receive larger loans, experience more loan growth, and are more likely to originate new loans, while greening firms have lower loan amount and fewer new loans.

Overall, we can see that bank lending in Denmark following Paris Agreement is largely supportive of the green transition — loans seem to be reallocated to firms that are greener relative to their industry peers. Importantly, this pattern is observed in brown industries where greening is most important. That said, consistent with our finding that most reallocation is passive, and active reallocation, however small, works in the opposite direction, we find that greening firms have less access to credit compared to their industry peers.

Extensive Margin: Firm-Bank Relationships. Now we turn to the question: Are cleaner firms within the industry more/less likely to form new relations with banks and exit old ones? To answer this question, we use our full sample, including firms both ever-entered and never-entered into a banking relation with missing account balances filled with zeros to capture non-existence of bank-firm relations.

Two outcome variables are measured: entry and exit into firm-bank relations. Specifically, "Entry" is defined as the establishment of a new firm-bank relationship. It is a dummy equal to 1 if a firm has a non-missing account balance in the current and subsequent year, but a missing value in the previous year. The base year (2003) is excluded and set as 0. Similarly, "Exit" is defined as the discontinuation of a firm-bank relationship. Specifically, it is a dummy equal to 1 if a firm has a non-missing account balance in the current and previous year, but a missing value in the subsequent year. The final year (2019) is excluded and set as 0.

The results with the entire balanced sample are reported in Table B.14 and those with the incumbent firms (defined as those that have been in the sample for at least the past 10 years 2009-2019) are reported in Table B.15 in the Appendix. For both samples, we find the effects are minimal. But when we use the sample of firm entrants (defined as firms that enter the sample during the period 2004–2019), the results became more sizeable and we include them here in Table 7. We find that there is no relationship between emissions and relationship exits, but we do find that Pre-Paris, cleaner firms were less likely to form new relationships, the effect that became less significant after the Paris Accord. Greening firms, however, were more likely to form new bank relationships throughout the sample.

Table 7: Within-Industry Analysis: Changes in bank-firm relationships (younger firms)

	New relationship	**Exit**
	(1)	**(2)**
Pre Paris × REgI_{t-1}	0.003*	-0.002
	(0.002)	(0.001)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	-0.002***	0.000
	(0.001)	(0.001)
Post Paris × REgI_{t-1}	0.002	0.000
	(0.001)	(0.001)
Post Paris × $\Delta(\text{REgI})_{t-1}$	-0.003**	-0.001
	(0.001)	(0.001)
Log(Assets)_t	0.000	-0.003***
Fixed Assets Ratio_t	0.001	-0.000
Leverage Ratio_t	0.000*	0.000***
ROA_t	0.000*	0.000***
R-sq	0.358	0.338
N	366,882	366,882

Notes: Estimated as linear probability model with firm, bank-time, and industry-time fixed effects are included in both regressions. Robust standard errors clustered at industry level in parentheses. Significance: ***1%, **5%, *10%.

3.2.3 Between-Industry Analysis

Now, we examine credit allocation across industries and answer the question: Do banks shift lending from dirty industries to non-dirty industries?

Table 8 presents the results using firm-bank-level data, using a similar specification in Equation (9). Before the Paris Agreement, we do not see much credit reallocation from firms in high-emission or high energy intensity industries to those in low-emission/energy intensity industries. However, after the Paris Agreement, firms in industries with decreasing emission intensity experienced lower loan growth and less loan origination.

Table 8: Between-Industry Analysis, Firm Level Regressions

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	**(2)**	**(3)**
Pre Paris × Log(EI)_{t-1}	-0.027	-0.320	-0.002
	(0.048)	(0.530)	(0.003)
Pre Paris × Log(EgI)_{t-1}	0.024	-0.409	-0.002
	(0.056)	(0.593)	(0.003)
Pre Paris × $\Delta\text{log(EI)}_{t-1}$	0.011	0.622	0.001
	(0.021)	(0.383)	(0.001)
Pre Paris × $\Delta\text{log(EgI)}_{t-1}$	0.010	0.174	0.001
	(0.010)	(0.268)	(0.001)
Post Paris × Log(EI)_{t-1}	-0.074	-0.504	-0.002
	(0.049)	(0.517)	(0.003)
Post Paris × Log(EgI)_{t-1}	0.052	-0.348	0.001
	(0.060)	(0.657)	(0.003)
Post Paris × $\Delta\text{log(EI)}_{t-1}$	0.024	2.341***	0.008**
	(0.048)	(0.779)	(0.003)
Post Paris × $\Delta\text{log(EgI)}_{t-1}$	0.002	0.296	0.000
	(0.023)	(0.597)	(0.002)
$\text{Log (Assets)}_{t-1}$	0.124***	0.097	0.000
$\text{Fixed Assets Ratio}_{t-1}$	0.001***	-0.024***	-0.000
$\text{Leverage Ratio}_{t-1}$	0.001***	-0.026***	-0.000***
ROA_{t-1}	0.000***	0.008***	0.000***
$\text{Industry Real Value Added Growth}_t$	-0.055*	-0.840	-0.001
R-sq	0.724	0.201	0.402
N	1,357,861	1,357,861	1,357,861

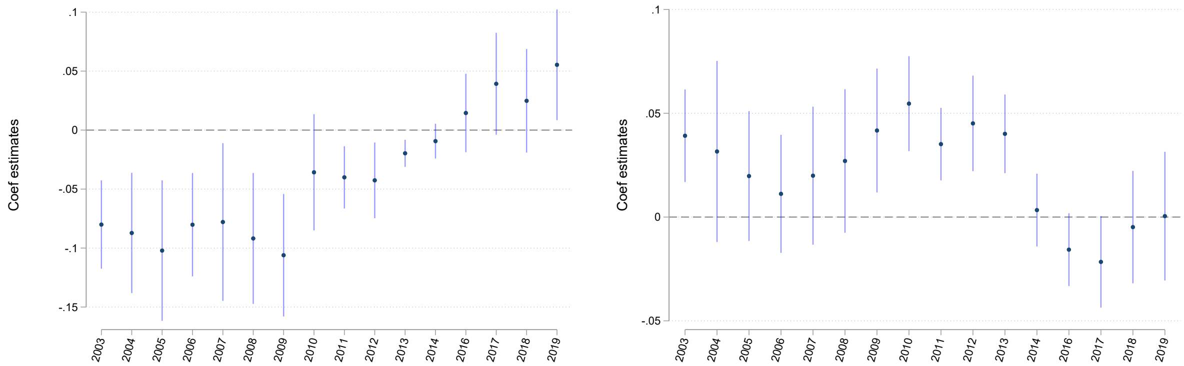
Notes: This table presents the estimation results for between industry analysis at the firm level regression. Firm, bank-year, and industry-year fixed effects are included in all regressions. Robust standard errors clustered at the industry level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

We use an alternative specification at the bank-year level to test credit reallocation across industries.

$$\frac{Bank\ Loans\ to\ Greenest\ (or\ Dirtiest)\ Industries_{bt}}{Bank\ Loans\ to\ All\ Industries_{bt}} = \beta_t + \beta_b + \varepsilon_{bt} \tag{18}$$

for bank b and year t. The left-hand side is a bank's share of loans in the greenest (or dirtiest) industries, which are defined as those at the bottom (or top) 25% of industry-level emission intensity. On the right-hand side, we have time fixed effects and bank fixed effects. The standard errors are clustered at the bank level.

Figure 9: Bank Loans in Green (Left) and Dirty (Right) Industries



Notes: Plotted are estimated fixed effects and their 95% confidence intervals for the regression estimated in equation 18. Left panel is for the share of loans to firms in the lowest 25% of industries by emission intensity, right panel is for the loans to firms in the highest 25%.

The estimated coefficients for the year fixed effects using 2015 as the base year are plotted in Figure 9. The plot on the left is bank loan share in the greenest industries, while the right plot is bank loan share in the dirtiest industries. There is a clear shift in credit after the Paris Agreement that increased bank loan shares in greenest industries while lowered shares in dirtiest industries. We do not see this result as a contradiction to the results in Table 8, because these plots show the loan shares to the extreme two ends of the industry emission intensity distribution, while Table 8 results show the loan reallocation across a continuum of industry emission intensity.

Overall, we find industry-level evidence that banks have been reallocating credit in recent years from the dirtiest industries to the cleanest ones, which is consistent with our syndicated loan results for the EU firms, and is not helpful for the green transition. However, the loan reallocation evidence is weaker when not limited to the extreme two ends of emission/energy intensity distribution using firm-bank level data.

3.3 Summary of Empirical Results

As with syndicated loan analysis, we summarize our results for Denmark in the summary table (Table 9). It shows that the evidence is quite mixed. Pre-Paris, overall and withing industries less lending appears to be going to cleaner firms. However, in a particular set of industries where this matters most, in dirty industries, the effect is the opposite — cleaner firms were able to benefit from higher loan growth and more loan origination. At the same time, firms in dirty industries that were lowering their energy use received lower loan amounts, which is not helpful for their green transition. Post-Paris, we see that cleaner firms overall had easier access to bank lending, which is consistent with the results of the analysis for syndicated loans for the EU (Table 4). In dirty industries, this effect is also observed, but is not statistically significant (larger standard errors).

At the same time, firms that reduce their energy consumption or emissions per unit of output, have worse access to bank loans, which we did not observe for the EU-wide syndicated lending Post-Paris.

As our analysis of stylized facts shows, the reallocation of credit to cleaner firm is actually the result of these firms taking up a larger share of their respective industries, and not active increase in their leverage. This result, combined with the fact that credit is reduced to firms that reduce their energy and emission intensities indicates passive support banks provide to the greening of technologies, not active stewardship as would be most desirable for rapid green transition.

Table 9: Result Summary: Denmark

Denmark:	**Cleaner firms/industries**	**Greening firms/industries**
Pre-Paris		
Overall (energy)	↑ ▲	No effect
Within ind (energy)	↓ ■ ●	↑ ●
Dirty ind only:	↑ ▲ ♦	↓ ■
Non-dirty ind only:	↓ ■	↑ ■
Between ind (energy)	No effect	No effect
Between ind (emission)	No effect	No effect
Post-Paris		
Overall (energy)	↑ ▲ ■ ♦	↓ ■ ♦
Within ind (energy)	↑ ▲ ■ ♦	↑ ● ↓ ▲ ♦
Dirty ind only:	No effect	↓ ▲
Non-dirty ind only:	↑ ▲ ■ ♦	↓ ■ ♦
Between ind (energy)	No effect	No effect
Between ind (emission)	No effect	↓ ▲ ♦

Notes: ▲ indicates loan growth, ■ indicates loan amount, ♦ indicates new loan issuance, ● indicates new lending relationship, ⊗ indicates termination of a relationship. "No Effect" indicates that the estimated coefficients are not statistically significant at 10% level. Green means encouraging evidence for green transition. Red means discouraging evidence. Industry-level analysis is not summarized here.

4 Conclusion

Over the past decades, banks have faced increasing climate transition risks, and many have pledged to reduce their lending to high-emission firms and industries across the globe. This led to some questioning the wisdom of this approach since high-emission industries are the ones that need funding for green transition.

In this paper, we examine whether banks reallocate their lending across firms within industries and across industries in relation to levels and changes of emission intensities of firms or industries. We segment our analysis by firms location, US vs. EU, and by time period, Pre- and Post- Paris

Climate Accord (i.e. prior to 2016 and from 2016 on).

We find that syndicated lending US firms is generally either unrelated to emissions and emission dynamics (Pre-Paris) or is counter to green transition, although not in a way that moves funds away from high-emission industries. In fact, Post-Paris, we observe that firms that have lower emissions and firms that are lowering their emissions have harder access to syndicated lending. For EU firms we find somewhat more encouraging results. Our overall results as well as detailed analysis of bank lending in the greenest country, Denmark, suggest that bank lending only passively supports green transition — increasing lending to cleaner firm as their share in the economy grows, but not actively reallocating credit shares and not supporting greening firms.

We only have limited evidence of the counterproductive reallocation of loans to firms in cleaner industries — this is in the case of syndicated lending to EU firms, both Pre- and Post-Paris, but not specifically in the Danish sample. While we do not have the data to analyze banks' stewardship activities in this paper, our results so far are not consistent with banks encouraging their borrowers to green their technologies: we actually observe harder access to credit for greening firms. Active stewardship would lead to firms that borrow more also greening more rapidly.

Green transition needs massive amounts of investment to scale up existing technologies, convert physical capital, and develop new solutions. This investment is likely impossible without participation of bank financing and bank stewardship. To date, however, we see very limited support from the banking system, even in Denmark, one of the greenest countries in the world.

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Appendix A Supporting Information for Cross-Country Evidence

A.1 US-EU summary statistics

Table A.1: Summary Statistics

	Mean	Median	SD	Min	Max
Loan Amount (USD million)	94.06	69.05	169.6	0.12	7300
Emission Intensity (Scope 1)	21547	2511	70954	6.13	2338718
Emission Intensity (Scope 2)	4187	2088	7590	0.28	126854
ΔEmission Intensity (Scope 1)	251.2	2.78	22834	-637201	158391
ΔEmission Intensity (Scope 2)	9.77	-26.76	3518	-46154	31883
Relative Emission Intensity (Scope 1)	0.02	0.07	1.23	-4.46	4.40
Δ Relative Emission Intensity (Scope 1)	-0.08	-0.00	1.00	-4.58	3.50
Relative Emission Intensity (Scope 2)	-0.00	0.15	1.00	-3.47	3.57
Δ Relative Emission Intensity (Scope 2)	0.10	0.02	0.82	-3.17	3.62
Industry Emission Intensity (Scope 1)	32198	6307	59778	162.6	270890
Industry Emission Intensity (Scope 2)	3361	2301	3517	371.9	25863
Total Assets	2533718	16969	23475491	94.73	351958000
Leverage Ratio	0.38	0.35	0.20	0.00	1.32
EBITDA/Total Assets	12.16	10.53	9.36	-70.01	94.89
CAPEX/Total Assets	0.39	0.30	0.31	0.01	1.19

Table A.2: Summary Statistics by sample

US sample	Mean	Median	SD	Min	Max
Loan Amount (USD million)	121.51	97.06	240.04	2.71	7300.00
Emission Intensity (Scope 1)	30076.85	2373.83	77281.93	7.33	499354.36
Emission Intensity (Scope 2)	3119.95	1682.46	3692.41	42.97	54166.56
ΔEmission Intensity (Scope 1)	-258.78	4.90	22874.54	-146802.16	70654.88
ΔEmission Intensity (Scope 2)	5.50	-21.01	1444.95	-21606.07	10328.43
Relative Emission Intensity (Scope 1)	0.28	0.35	1.30	-4.46	3.48
ΔRelative Emission Intensity (Scope 1)	-0.15	-0.04	1.16	-2.60	3.50
Relative Emission Intensity (Scope 2)	0.04	0.19	0.75	-3.47	2.27
ΔRelative Emission Intensity (Scope 2)	0.11	0.03	0.59	-2.15	3.62
Industry Emission Intensity (Scope 1)	21813.80	2910.99	49161.88	586.28	270889.64
Industry Emission Intensity (Scope 2)	2899.87	1860.93	3737.19	970.45	24693.36
Total Assets	18197.10	12094.97	25885.17	153.65	309129.00
Leverage Ratio	0.45	0.43	0.23	0.00	1.18
EBITDA/Total Assets	16.31	13.33	10.98	-70.01	94.89
CAPEX/Total Assets	0.47	0.36	0.35	0.02	1.19
EU sample	Mean	Median	SD	Min	Max
Loan Amount (USD million)	60.74	43.08	58.23	2.13	641.25
Emission Intensity (Scope 1)	12538.99	1413.53	28601.50	6.13	197373.30
Emission Intensity (Scope 2)	3425.52	1729.12	5953.06	62.23	84392.17
ΔEmission Intensity (Scope 1)	3250.53	1.89	24065.37	-82893.13	158390.59
ΔEmission Intensity (Scope 2)	46.95	-4.13	2724.04	-16792.74	18377.41
Relative Emission Intensity (Scope 1)	0.07	0.01	1.23	-2.90	2.78
ΔRelative Emission Intensity (Scope 1)	0.00	0.07	1.19	-4.58	2.73
Relative Emission Intensity (Scope 2)	0.05	0.17	1.15	-3.30	2.49
ΔRelative Emission Intensity (Scope 2)	0.14	0.10	0.90	-2.48	2.51
Industry Emission Intensity (Scope 1)	9824.27	3108.09	24064.34	162.57	270889.64
Industry Emission Intensity (Scope 2)	2823.76	2287.82	1855.20	371.85	10278.12
Total Assets	26279.93	5772.00	48390.43	94.73	202857.80
Leverage Ratio	0.29	0.28	0.15	0.00	1.32
EBITDA/Total Assets	11.06	9.37	7.69	-35.86	49.07
CAPEX/Total Assets	0.24	0.20	0.20	0.01	0.92

A.2 Full regression tables

Table A.3: General Analysis: Syndicated Loans - US and EU

	US				**EU**			
	Loan Growth	Log(Loan Amount)	New Loan	First Loan	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Log (Total Assets)$_{t-1}$	1.092	0.174	0.020	-0.068	0.456	0.323	0.604	0.252
	(2.652)	(0.116)	(0.150)	(0.135)	(1.476)	(0.167)	(0.331)	(0.259)
Leverage Ratio$_{t-1}$	3.786	-0.436	0.670	0.836	-12.515	-0.539	1.618	-2.370
	(7.057)	(0.546)	(0.758)	(0.591)	(7.881)	(0.500)	(1.930)	(1.874)
CAPEX/Total Assets$_{t-1}$	-27.737**	-0.973	3.750*	-3.123**	5.943	0.731*	-2.573	1.229
	(10.172)	(0.551)	(1.564)	(1.123)	(10.414)	(0.298)	(2.427)	(2.219)
EBITDA/Total Assets$_{t-1}$	-0.072	0.002	0.008	-0.010*	-0.319	-0.006	0.042	0.013
	(0.105)	(0.004)	(0.007)	(0.004)	(0.216)	(0.016)	(0.028)	(0.036)
Log (Intensity)$_{t-1}$($Scope1$) × Pre-Paris	-2.714	-0.142	-0.183	0.014	-1.010	0.088	-0.240	-0.298
	(2.924)	(0.149)	(0.120)	(0.193)	(2.344)	(0.143)	(0.316)	(0.204)
Log (Intensity)$_{t-1}$($Scope1$) × Post-Paris	-0.984	-0.213	-0.381*	0.379	-0.447	0.026	-0.436	-0.320
	(3.221)	(0.124)	(0.164)	(0.200)	(2.545)	(0.140)	(0.252)	(0.223)
Pre-Paris × Log (Intensity)$_{t-1}$($Scope2$)	5.481**	0.329***	-0.285*	0.263	-2.087	-0.140	0.037	0.019
	(1.866)	(0.090)	(0.124)	(0.166)	(2.334)	(0.108)	(0.442)	(0.317)
Post-Paris × Log (Intensity)$_{t-1}$($Scope2$)	5.079*	0.533***	-0.092	0.131	-3.721	-0.159*	0.391	-0.082
	(2.467)	(0.129)	(0.173)	(0.229)	(2.312)	(0.074)	(0.503)	(0.331)
Pre-Paris × ΔLog (Intensity)$_{t-1}$($Scope1$)	-0.467	-0.131	0.155	-0.012	0.629	-0.005	0.110	-0.022
	(1.841)	(0.083)	(0.102)	(0.139)	(1.192)	(0.091)	(0.113)	(0.120)
Post-Paris × ΔLog (Intensity)$_{t-1}$($Scope1$)	1.557	0.313**	0.414***	-0.508***	0.617	0.119	0.513*	0.049
	(2.228)	(0.111)	(0.123)	(0.129)	(1.666)	(0.089)	(0.252)	(0.253)
Pre-Paris × ΔLog (Intensity)$_{t-1}$($Scope2$)	-2.385*	0.020	0.337***	-0.215***	0.802	0.077	-0.495	0.293
	(1.092)	(0.043)	(0.094)	(0.058)	(1.381)	(0.082)	(0.342)	(0.323)
Post-Paris × ΔLog (Intensity)$_{t-1}$($Scope2$)	-2.791*	-0.333***	-0.111	0.106	1.386	-0.069	-0.574**	0.380*
	(1.133)	(0.047)	(0.066)	(0.097)	(1.656)	(0.053)	(0.205)	(0.154)
R^2	0.07724	0.68381			0.14838	0.82895		
Observations	28,596	29,267	26,579	28,075	23,547	24,018	21,240	22,365
Borrower fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects					✓	✓	✓	✓

Table A.4: Within-Industry Analysis - All Firms - US and EU

	US				EU			
	Loan Growth	Log(Loan Amount)	New Loan	First Loan	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Log (Total Assets)$_{t-1}$	-1.470	0.080	0.106	-0.095	-3.562	0.464	1.090	-0.102
	(3.188)	(0.113)	(0.250)	(0.176)	(2.474)	(0.290)	(0.568)	(0.495)
Leverage Ratio$_{t-1}$	-0.691	-1.020	0.935	0.470	-1.186	-1.082	-2.557	2.004
	(7.286)	(0.569)	(0.809)	(0.664)	(15.110)	(0.656)	(3.057)	(1.592)
CAPEX/Total Assets$_{t-1}$	-28.439	-1.249	1.722	-2.712	-5.093	0.884	-2.112	0.280
	(15.188)	(0.904)	(1.358)	(1.592)	(13.027)	(0.449)	(2.347)	(1.609)
EBITDA/Total Assets$_{t-1}$	-0.094	0.004	0.017**	-0.011*	-0.400	-0.027	-0.019	0.115**
	(0.098)	(0.005)	(0.006)	(0.005)	(0.213)	(0.018)	(0.033)	(0.041)
Relative Emission Intensity$_{t-1}$($Scope1$) × Pre-Paris	0.146	-0.026	-0.167	0.050	3.617	0.190	0.507	-1.109***
	(3.650)	(0.122)	(0.168)	(0.118)	(2.834)	(0.185)	(0.467)	(0.287)
Relative Intensity$_{t-1}$($Scope1$) × Post-Paris	0.968	-0.012	-0.510	0.519**	3.128	-0.027	-0.089	-1.387**
	(5.208)	(0.154)	(0.265)	(0.184)	(2.936)	(0.209)	(0.510)	(0.424)
Pre-Paris × Relative Emission Intensity$_{t-1}$($Scope2$)	8.126*	0.092	-0.254	-0.119	3.867	0.144	0.251	-0.132
	(3.385)	(0.197)	(0.326)	(0.278)	(2.908)	(0.201)	(0.416)	(0.590)
Post-Paris × Relative Emission Intensity$_{t-1}$($Scope2$)	9.135	0.216	0.137	-0.316	-0.638	0.107	0.622	0.006
	(4.737)	(0.184)	(0.376)	(0.363)	(1.895)	(0.172)	(0.627)	(0.736)
Pre-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	1.614	-0.130	0.141	0.013	-1.882	0.003	-0.329	0.213
	(2.340)	(0.110)	(0.082)	(0.133)	(1.035)	(0.100)	(0.358)	(0.208)
Post-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	-0.128	0.136	0.688***	-0.557**	1.246	-0.017	0.423	1.085
	(2.794)	(0.120)	(0.188)	(0.213)	(2.647)	(0.160)	(0.534)	(0.568)
Pre-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-9.209**	-0.121	0.402	-0.104	-2.136	-0.118	-0.535	0.537
	(3.205)	(0.151)	(0.246)	(0.232)	(2.694)	(0.115)	(0.343)	(0.459)
Post-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-6.858	-0.083	-0.237	0.284	-0.586	-0.234*	-0.487	0.350
	(3.743)	(0.144)	(0.164)	(0.229)	(1.244)	(0.095)	(0.419)	(0.599)
R^2	0.08878	0.69816			0.14969	0.84745		
Observations	24,830	25,416	22,839	24,228	20,267	20,677	18,019	19,009
Borrower fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects					✓	✓	✓	✓

Table A.5: Within-Industry Analysis: Dirty Industries - US and EU

	US				**EU**			
	Loan Growth	Log(Loan Amount)	New Loan	First Loan	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Log (Total Assets)$_{t-1}$	-5.860	0.023	-0.500*	-0.068	12.192	0.856*	1.541	0.301
	(4.794)	(0.067)	(0.197)	(0.124)	(6.480)	(0.328)	(1.131)	(0.466)
Leverage Ratio$_{t-1}$	-14.555	-0.130	0.788	0.079	-6.131	-1.422	1.464	5.587
	(8.001)	(0.343)	(1.252)	(1.072)	(47.006)	(1.942)	(8.352)	(7.525)
CAPEX/Total Assets$_{t-1}$	-97.329***	-0.179	3.295	0.072	-14.268	-0.563	8.574	4.567
	(20.085)	(1.033)	(1.719)	(1.141)	(35.831)	(0.971)	(8.850)	(2.584)
EBITDA/Total Assets$_{t-1}$	-0.099	-0.004	0.002	-0.018***	-0.205	0.005	-0.049	0.281
	(0.092)	(0.003)	(0.008)	(0.004)	(0.654)	(0.041)	(0.104)	(0.185)
Relative Emission Intensity$_{t-1}(Scope1)$ × Pre-Paris	11.291	0.829*	-0.195	-0.223	17.869	-0.007	6.903	-0.569
	(12.066)	(0.335)	(0.880)	(0.774)	(12.240)	(0.411)	(4.393)	(1.116)
Relative Intensity$_{t-1}(Scope1)$ × Post-Paris	16.155	0.706*	-0.438	0.488	16.642	0.077	5.590	-0.353
	(12.727)	(0.251)	(0.932)	(0.818)	(11.408)	(0.338)	(3.849)	(1.048)
Pre-Paris × Relative Emission Intensity$_{t-1}(Scope2)$	12.957	0.240	1.089	-0.615	-5.240	-0.224**	-1.295	1.987***
	(8.892)	(0.235)	(0.661)	(0.325)	(4.321)	(0.070)	(1.381)	(0.498)
Post-Paris × Relative Emission Intensity$_{t-1}(Scope2)$	12.089	0.164	0.921	-0.851***	-1.768	-0.358	-0.225	0.605*
	(8.311)	(0.258)	(0.591)	(0.249)	(2.877)	(0.256)	(0.592)	(0.283)
Pre-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	3.328	-0.706***	0.084	0.199	-7.176	0.052	-0.430	0.082
	(5.858)	(0.162)	(0.312)	(0.229)	(6.995)	(0.222)	(1.295)	(0.733)
Post-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	-5.729	-0.398	0.162	-0.518	-3.864	-0.088	-0.856	-0.997*
	(8.482)	(0.369)	(0.598)	(0.347)	(11.403)	(0.454)	(1.907)	(0.493)
Pre-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-26.868**	0.254	0.138	-0.320	7.767**	0.035	1.378	-1.298***
	(8.149)	(0.261)	(0.356)	(0.322)	(2.678)	(0.051)	(1.180)	(0.390)
Post-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-11.391	-0.058	-0.317	0.858***	5.511	-0.339*	-1.050	-1.280
	(7.468)	(0.188)	(0.379)	(0.247)	(4.283)	(0.134)	(0.750)	(2.023)
R^2	0.17889	0.73036			0.24573	0.89771		
Observations	6,852	7,013	5,885	6,418	5,714	5,819	4,730	4,743
Borrower fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects					✓	✓	✓	✓

Table A.6: Within-Industry Analysis: Non-dirty Industries - US and EU

	US				EU			
	Loan Growth	Log(Loan Amount)	New Loan	First Loan	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Log (Total Assets)$_{t-1}$	12.249*	0.649***	0.850*	-0.621	-1.912	0.447	1.144	0.094
	(6.015)	(0.165)	(0.432)	(0.318)	(4.870)	(0.367)	(1.142)	(0.696)
Leverage Ratio$_{t-1}$	-7.561	-2.600***	0.885	1.725	0.152	-1.431	-3.115	3.043
	(10.399)	(0.626)	(1.235)	(1.254)	(17.655)	(1.264)	(4.189)	(2.343)
CAPEX/Total Assets$_{t-1}$	-3.618	-0.747	2.263	-4.150	43.396	3.877*	-4.006	5.915
	(29.067)	(1.356)	(3.115)	(3.725)	(40.468)	(1.871)	(8.941)	(4.326)
EBITDA/Total Assets$_{t-1}$	0.504	0.062**	0.040	-0.004	-0.702**	-0.033	-0.015	0.050
	(0.363)	(0.019)	(0.040)	(0.033)	(0.237)	(0.017)	(0.068)	(0.050)
Relative Emission Intensity$_{t-1}(Scope1)$ × Pre-Paris	0.987	-0.148	-0.218	0.149	2.397	0.164	-0.351	-1.004*
	(2.398)	(0.106)	(0.242)	(0.132)	(3.917)	(0.258)	(0.694)	(0.409)
Relative Intensity$_{t-1}(Scope1)$ × Post-Paris	-5.203	-0.222	-1.094***	0.737*	0.651	-0.055	-0.885	-1.366
	(4.131)	(0.167)	(0.315)	(0.376)	(5.344)	(0.392)	(1.050)	(0.790)
Pre-Paris × Relative Emission Intensity$_{t-1}(Scope2)$	7.414**	0.115	-0.451	-0.085	4.876	0.360	0.237	-0.946*
	(2.512)	(0.229)	(0.375)	(0.385)	(3.569)	(0.271)	(0.545)	(0.422)
Post-Paris × Relative Emission Intensity$_{t-1}(Scope2)$	14.580***	0.411	0.230	-0.264	1.504	0.235	0.343	0.119
	(3.359)	(0.297)	(0.483)	(0.666)	(2.219)	(0.281)	(0.624)	(1.007)
Pre-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	-1.610	-0.097	0.237	-0.038	-1.965	-0.079	-0.028	0.236
	(2.471)	(0.102)	(0.150)	(0.181)	(2.041)	(0.165)	(0.515)	(0.215)
Post-Paris × Δ Relative Intensity (Scope1) $_{t-1}$	3.644	0.368*	0.808***	-0.441	1.571	0.022	1.062	1.227
	(2.224)	(0.137)	(0.229)	(0.304)	(3.248)	(0.191)	(1.083)	(0.627)
Pre-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-5.768	-0.179	0.430	-0.005	-4.342	-0.105	-0.253	0.644
	(3.157)	(0.150)	(0.308)	(0.305)	(3.104)	(0.176)	(0.541)	(0.373)
Post-Paris × Δ Relative Intensity (Scope2) $_{t-1}$	-8.163	-0.095	-0.051	-0.115	-2.738	-0.186	-0.440	0.483
	(4.658)	(0.267)	(0.281)	(0.404)	(1.853)	(0.216)	(0.548)	(0.866)
R^2	0.08433	0.70438			0.16608	0.85957		
Observations	17,960	18,385	16,536	17,315	12,470	12,747	10,796	11,469
Borrower fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects					✓	✓	✓	✓

Table A.7: Between Industry Analysis - US and EU

	US				EU			
	Loan Growth	Log(Loan Amount)	New Loan	First Loan	Loan Growth	Log(Loan Amount)	New Loan	First Loan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Log (Total Assets)$_{t-1}$	-0.341	0.138	-0.055	-0.150*	-1.022	0.198**	0.142	-0.007
	(0.717)	(0.099)	(0.130)	(0.070)	(1.265)	(0.066)	(0.224)	(0.181)
Leverage Ratio$_{t-1}$	-0.749	-0.381	-0.423	0.384	2.723	0.691	2.116**	-1.306*
	(2.790)	(0.235)	(0.345)	(0.346)	(3.461)	(0.514)	(0.650)	(0.631)
CAPEX/Total Assets$_{t-1}$	-12.389*	-1.149***	-1.060	0.977	-1.685	0.777	0.037	1.292
	(5.461)	(0.322)	(0.650)	(0.695)	(5.015)	(0.517)	(1.221)	(1.285)
EBITDA/Total Assets$_{t-1}$	0.062**	0.003	0.004	-0.006*	-0.061	0.005	-0.006	0.007
	(0.019)	(0.002)	(0.003)	(0.002)	(0.122)	(0.011)	(0.014)	(0.018)
Log (Industry Intensity)$_{t-1}$($Scope1$) × Pre-Paris	-2.110	0.154	0.091	-0.062	-2.694*	-0.128	-0.071	0.135
	(1.551)	(0.128)	(0.190)	(0.176)	(1.309)	(0.152)	(0.308)	(0.325)
Log (Industry Intensity)$_{t-1}$($Scope1$) × Post-Paris	-1.702	0.105	0.091	-0.012	-2.931*	-0.194	-0.046	0.171
	(1.530)	(0.124)	(0.187)	(0.183)	(1.366)	(0.152)	(0.316)	(0.331)
Pre-Paris × Log (Industry Intensity)$_{t-1}$($Scope2$)	2.394	0.164	0.187	-0.017	-0.035	-0.054	0.312	-0.025
	(2.271)	(0.201)	(0.247)	(0.311)	(1.912)	(0.158)	(0.363)	(0.375)
Post-Paris × Log (Industry Intensity)$_{t-1}$($Scope2$)	1.842	0.103	0.006	0.134	0.510	0.062	-0.065	-0.140
	(2.374)	(0.210)	(0.250)	(0.329)	(2.050)	(0.142)	(0.414)	(0.431)
Pre-Paris × ln_scope1_intensity_sic2digit_diff_lag	1.131	-0.239	-0.291	0.149	-0.454	0.274	0.475*	-0.127
	(1.727)	(0.138)	(0.209)	(0.161)	(1.620)	(0.146)	(0.242)	(0.187)
Post-Paris × ln_scope1_intensity_sic2digit_diff_lag	1.609	0.171	0.243	-0.262	0.661	-0.081	-0.077	0.148
	(2.097)	(0.117)	(0.284)	(0.236)	(0.962)	(0.114)	(0.187)	(0.245)
Pre-Paris × ln_scope2_intensity_sic2digit_diff_lag	-3.002	0.093	0.202	-0.061	-0.139	-0.181	-0.120	0.355
	(2.716)	(0.223)	(0.288)	(0.220)	(2.046)	(0.184)	(0.550)	(0.502)
Post-Paris × ln_scope2_intensity_sic2digit_diff_lag	0.941	0.010	-0.291	-0.180	1.397	0.026	0.539	0.341
	(2.660)	(0.221)	(0.257)	(0.348)	(2.400)	(0.144)	(0.357)	(0.391)
R^2	0.04862	0.56452			0.10902	0.76155		
Observations	39,436	40,505	37,222	39,383	27,148	27,764	25,372	26,168
Borrower fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Lender-Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
deal_year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country fixed effects					✓	✓	✓	✓

A.3 Bank-Industry Level Analysis

In addition to the bank-firm level analysis, we also conduct bank-industry analysis using the following specification to study within-industry credit reallocation:

$$\frac{Bank\ Loan\ to\ Cleanest\ Firms_{bjt}}{Bank\ Loan_{bjt}} = \beta_1 logEI1_{jt-1} \times PreParis_t + \beta_2 logEI1_{jt-1} \times PostParis_t + \beta_3 logEI1_{jt-1} \times NZBA_b + \alpha\, NZBA_b + \delta_t + \delta_j + \varepsilon_{bjt} \quad (19)$$

for bank b, industry j, and year t. $Bank\ Loan\ to\ Cleanest\ Firms_{bjt}$ is a bank's loan amount to the cleanest firms (in the bottom 25% of firm emission intensity) within an industry.

This specification has a different interpretation from the previous loan-level within-industry analysis. It examines how the loan share to the greenest firms within an industry varies with the dirtiness of the industry.

Table A.8: Within-Industry Analysis: Bank-Industry Level

	Ratio of loans to cleanest firms within industries		
	Full Sample	US	EU
NZBA	0.088	0.367*	-0.206
	(0.282)	(0.147)	(0.196)
Pre-Paris × Log (Industry Intensity)$_{t-1}$($Scope1$)	0.045	0.052	-0.001
	(0.066)	(0.033)	(0.033)
Post-Paris × Log (Industry Intensity)$_{t-1}$($Scope1$)	0.033	0.010	-0.018
	(0.062)	(0.031)	(0.031)
Log (Industry Intensity)$_{t-1}$($Scope1$) × NZBA	-0.012	-0.040*	0.020
	(0.027)	(0.018)	(0.021)
R^2	0.30436	0.10038	0.16256
Observations	4,099	8,232	9,036
deal_year fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓

Notes: NZBA is an indicator for the bank membership in the Net Zero Banking Alliance. Significance levels: ***1%, **5%, *10%.

The results are reported in Table A.8. The Net Zero Banking Alliance (NZBA) increases the bank loan share to greenest firms in general in the US, however, the effect is smaller for dirtier industries, where the credit reallocation matters more. In other words, for NZBA banks, credit reallocation towards cleanest firms happens more in already clean industries and less in dirty industries where it is needed most. For non-NZBA banks, there are no clear patterns as to in which type of industries banks reallocate their credit towards cleanest firms. There are no significant effects of industry emissions on loan allocation across EU firms and in the full sample.

Appendix B Supporting Information for the Danish Case

B.1 Full Sample Analysis

This subsection provides more details on the full sample analysis reported in the main text.

Table B.9: Summary Statistics, Danish Full Sample

Variable	Mean	Median	Sd
Loan outstanding (million DKK)	4.234	0.019	62.935
Firm energy intensity (EgI)	40.495	13.333	3,562.690
Change in firm energy intensity (ΔEgI)	-0.588	-0.452	3,632.311
Relative energy intensity ($REgI$)	-0.023	0.003	0.977
Change in relative energy intensity ($\Delta REgI$)	0.020	0.028	0.979
Industry emission intensity ($\overline{EI}$)	27.848	17.370	76.384
Change in industry emission intensity ($\Delta\overline{EI}$)	0.002	-0.203	27.278
Industry energy intensity ($\overline{EgI}$)	0.204	0.104	0.395
Change in industry energy intensity ($\Delta\overline{EgI}$)	-0.001	-0.001	0.102
Assets (million DKK)	84.320	1.462	2,168.785
Leverage ratio	0.793	0.532	42.860
Fixed assets ratio	0.433	0.406	0.304
ROA	0.556	0.136	102.217
Observations		1,774,704	

Figure B.10: Passive vs Active Credit Reallocation Within-Industry: Credit and Output Density by Relative Energy Intensity

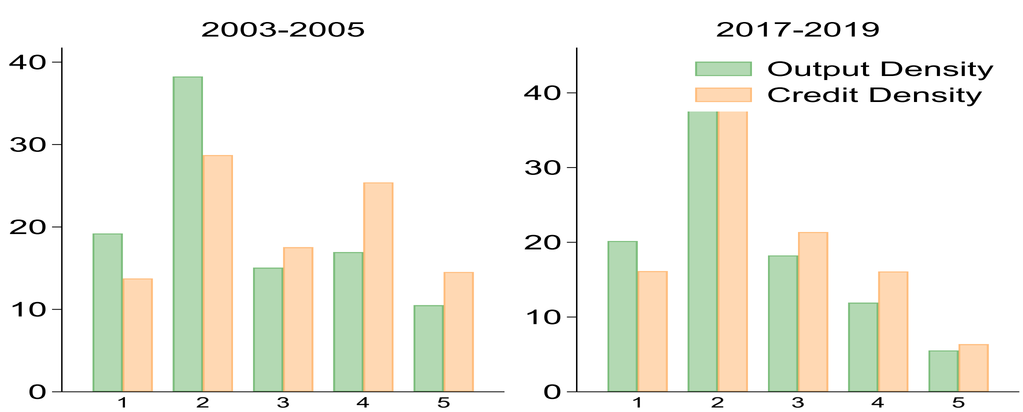

Figure B.11: Passive vs Active Credit Reallocation Between Industry: Credit and Output Density by Industry Emission Intensity

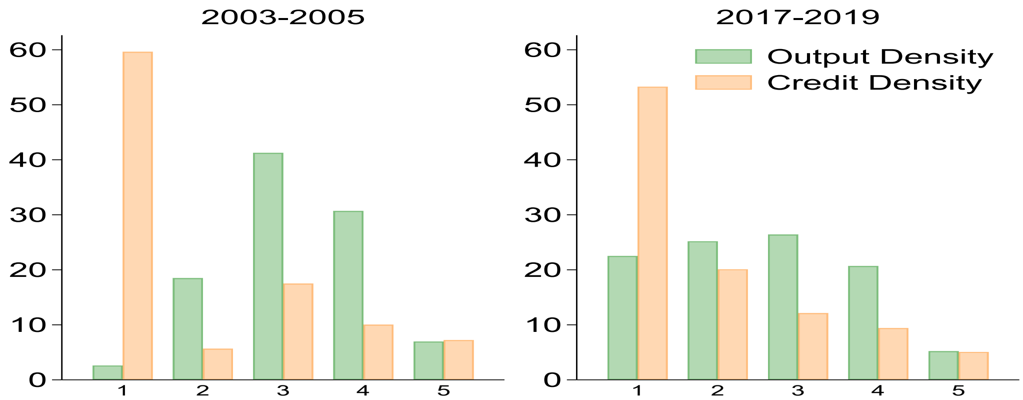

Table B.10: Within-Industry Analysis: Full Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	**(2)**	**(3)**
Pre Paris × REgI_{t-1}	0.025**	-0.148	0.000
	(0.012)	(0.264)	(0.001)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	-0.013	-0.148	-0.001
	(0.009)	(0.154)	(0.001)
Post Paris × REgI_{t-1}	-0.070***	-1.201***	-0.005***
	(0.022)	(0.384)	(0.002)
Post Paris × $\Delta(\text{REgI})_{t-1}$	0.035***	0.318	0.002**
	(0.008)	(0.224)	(0.001)
Log $(\text{Assets})_{t-1}$	0.125***	-0.239	-0.000
	(0.019)	(0.160)	(0.001)
Fixed Assets Ratio_{t-1}	0.002***	-0.027***	-0.000
	(0.000)	(0.006)	(0.000)
Leverage Ratio_{t-1}	0.001***	-0.030***	-0.000***
	(0.000)	(0.005)	(0.000)
ROA_{t-1}	0.000***	0.007***	0.000***
	(0.000)	(0.001)	(0.000)
Firm Fixed Effects	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes
R-sq	0.726	0.195	0.389
N	1,328,438	1,328,438	1,328,438

Notes: This table presents the estimation results for within-industry analysis for the full sample of firms. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.11: Within-Industry Analysis: Dirty Industries: Full Sample

	(1)	**(2)**	**(3)**
	Log (Balance)	**Loan Growth**	**New Loan**
Pre Paris × REgI_{t-1}	-0.037	-1.391**	-0.005**
	(0.022)	(0.520)	(0.002)
Pre Paris × Δ $(\text{REgI})_{t-1}$	0.029**	-0.096	0.000
	(0.010)	(0.346)	(0.001)
Post Paris × REgI_{t-1}	-0.040	-1.335	-0.006
	(0.051)	(0.924)	(0.005)
Post Paris × Δ $(\text{REgI})_{t-1}$	-0.014	1.694*	0.004
	(0.030)	(0.942)	(0.004)
Log(Assets)_{t-1}	0.225***	-0.095	-0.001
	(0.032)	(0.557)	(0.002)
Fixed Assets Ratio_{t-1}	0.003**	-0.026*	0.000
	(0.001)	(0.014)	(0.000)
Leverage Ratio_{t-1}	0.002***	-0.031**	-0.000*
	(0.001)	(0.012)	(0.000)
ROA_{t-1}	0.001***	0.007*	0.000
	(0.000)	(0.004)	(0.000)
R-sq	0.737	0.205	0.390
N	86,310	86,310	86,310

Notes: This table reports within-industry regression estimates for brown firms. Robust standard errors clustered at the industry level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.12: Within-Industry Analysis: Traditionally Dirty Industries: Full Sample

	(1) Log (Balance)	(2) Loan Growth	(3) New Loan
Pre Paris × REgI_{t-1}	-0.031	-1.290**	-0.005**
	(0.039)	(0.556)	(0.002)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	0.025	-0.027	0.001
	(0.017)	(0.426)	(0.002)
Post Paris × REgI_{t-1}	0.015	-0.774	-0.001
	(0.078)	(0.982)	(0.005)
Post Paris × $\Delta(\text{REgI})_{t-1}$	-0.065	0.130	0.001
	(0.068)	(1.015)	(0.005)
Log(Assets)_{t-1}	0.193***	0.350	0.001
	(0.038)	(0.435)	(0.002)
Fixed Assets Ratio_{t-1}	0.002**	-0.018	0.000***
	(0.001)	(0.011)	(0.000)
Leverage Ratio_{t-1}	0.001**	-0.022*	-0.000
	(0.000)	(0.010)	(0.000)
ROA_{t-1}	0.001***	0.005	0.000
	(0.000)	(0.003)	(0.000)
Firm FE	Yes	Yes	Yes
Bank-Time FE	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes
R-sq	0.749	0.230	0.425
N	56,471	56,471	56,471

Notes: Robust standard errors clustered at the industry level in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.13: Within-Industry Analysis: Non-dirty Industries: Full Sample

	(1) **Log (Balance)**	**(2)** **Loan Growth**	**(3)** **New Loan**
Pre Paris × REgI_{t-1}	0.032***	-0.025	0.001
	(0.011)	(0.262)	(0.001)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	-0.018**	-0.169	-0.001
	(0.008)	(0.160)	(0.001)
Post Paris × REgI_{t-1}	-0.072***	-1.208***	-0.005**
	(0.023)	(0.408)	(0.002)
Post Paris × $\Delta(\text{REgI})_{t-1}$	0.036***	0.266	0.002**
	(0.008)	(0.231)	(0.001)
Log $(\text{Assets})_{t-1}$	0.117***	-0.260	-0.001
	(0.020)	(0.170)	(0.001)
Fixed Assets Ratio_{t-1}	0.001***	-0.028***	-0.000
	(0.000)	(0.006)	(0.000)
Leverage Ratio_{t-1}	0.001***	-0.029***	-0.000***
	(0.000)	(0.005)	(0.000)
ROA_{t-1}	0.000**	0.007***	0.000***
	(0.000)	(0.001)	(0.000)
R-sq	0.726	0.200	0.393
N	1,235,788	1,235,788	1,235,788

Notes: This table reports within-industry regression estimates for non-brown firms before and after the Paris Agreement. Robust standard errors clustered at the industry level are in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.14: Within-Industry Analysis: Relation Change, Full Sample

	Entry	**Exit**
	(1)	**(2)**
Pre Paris × REgI_{t-1}	0.000	0.000
	(0.001)	(0.001)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	-0.001*	0.000
	(0.000)	(0.000)
Post Paris × REgI_{t-1}	0.000	-0.000
	(0.001)	(0.001)
Post Paris × $\Delta(\text{REgI})_{t-1}$	-0.002*	0.000
	(0.001)	(0.001)
Log(Assets)_t	0.001	-0.008***
	(0.000)	(0.001)
Fixed Assets Ratio_t	-0.001	0.006***
	(0.001)	(0.002)
Leverage Ratio_t	-0.000	-0.000
	(0.000)	(0.000)
ROA_t	-0.000	-0.000
	(0.000)	(0.000)
Firm FE	Yes	Yes
Bank-Time FE	Yes	Yes
Industry-Time FE	Yes	Yes
R-sq	0.336	0.318
N	1,388,315	1,388,315

Notes: The table presents the estimation results for within-industry analysis of relation changes for all firms. Dependent variables: Entry and Exit. Robust standard errors clustered at the industry level in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.15: Within-Industry Analysis: Relation Change, Incumbents

	Entry	**Exit**
	(1)	**(2)**
Pre Paris × REgI_{t-1}	-0.001	0.000
	(0.001)	(0.001)
Pre Paris × $\Delta(\text{REgI})_{t-1}$	-0.000	-0.001
	(0.001)	(0.000)
Post Paris × REgI_{t-1}	-0.000	-0.001
	(0.001)	(0.001)
Post Paris × $\Delta(\text{REgI})_{t-1}$	-0.001	0.001
	(0.001)	(0.001)
Log(Assets)_t	-0.001	-0.005***
	(0.001)	(0.001)
Fixed Assets Ratio_t	0.001	0.002
	(0.001)	(0.001)
Leverage Ratio_t	0.000	0.000
	(0.000)	(0.000)
ROA_t	-0.000	-0.000*
	(0.000)	(0.000)
Firm Fixed Effects	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes
R-sq	0.316	0.319
N	712,198	712,198

Notes: The table presents the estimation results for within-industry analysis of relation changes for incumbent firms. The dependent variables are Entry and Exit. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels: ***1%, **5%, *10%.

B.2 Bank-Industry Level Analysis

We now use an alternative specification at the bank-industry-year level to test credit reallocation within industries. Similar to the cross-country evidence section, the left-hand side is a bank's share of loans in the greenest firms within each industry. Greenest firms are defined as those at the bottom 25% of firm-level relative energy intensity. On the right-hand side, we have the industry emission intensity (EI_{jt-1}), change of industry emission intensity (ΔEI_{jt}), its interaction with the post-Paris period, industry level controls ($\boldsymbol{X}_{jt}$), year fixed effects, bank fixed effects, and industry fixed effects. Note that one difference is that we have two measures of emission intensity: industry emission or energy intensity. Furthermore, we do not have bank identities to include the NZBA dummy. The standard errors are clustered at NACE-2-digit industry level.

$$\frac{Bank\ Loans\ to\ Green\ Firm_{bjt}}{Bank\ Loans\ to\ All\ Firms_{bjt}} = \beta_1 EI_{jt-1} PreParis_t + \beta_2 \Delta EI_{jt} PreParis_t$$
$$+ \beta_3 EI_{jt-1} PostParis_t + \beta_4 \Delta EI_{jt} PostParis_t$$
$$+ \boldsymbol{X}'_{jt}\boldsymbol{\gamma} + \delta_t + \delta_j + \delta_b + \varepsilon_{bjt} \tag{20}$$

for bank b, industry j, and year t.

Table B.16: Within-Industry Analysis: Bank's Loan in Relatively Green Firms

	Green Firm Share	**Green Firm Share**	**Green Firm Share**
	(1)	**(2)**	**(3)**
Pre Paris × Log(EI)$_{t-1}$	-0.029**		-0.027**
	(0.011)		(0.011)
Pre Paris × Log(EgI)$_{t-1}$	0.004		0.003
	(0.003)		(0.003)
Pre Paris × Δlog(EI)$_{t-1}$		-0.003	-0.000
		(0.006)	(0.005)
Pre Paris × Δlog(EgI)$_{t-1}$		-0.001	-0.001
		(0.001)	(0.001)
Post Paris × Log(EI)$_{t-1}$	-0.028**		-0.027*
	(0.014)		(0.014)
Post Paris × Log(EgI)$_{t-1}$	0.006*		0.006*
	(0.003)		(0.003)
Post Paris × Δlog(EI)$_{t-1}$		-0.003	0.006
		(0.011)	(0.008)
Post Paris × Δlog(EgI)$_{t-1}$		0.001	-0.001
		(0.002)	(0.001)
Industry Real Value Added Growth$_t$	-0.013*	-0.024***	-0.014*
	(0.008)	(0.007)	(0.008)
Bank Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
2-digit Industry Fixed Effects	Yes	Yes	Yes
R-sq	0.429	0.434	0.435
N	1,511,950	1,263,502	1,263,502

Notes: This table presents the estimation results for bank industry analysis. Green firm share is the share of bank's loan in relatively green firms of an industry. Robust standard errors clustered at the industry level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table B.16 shows the results for bank's loan share in the greenest firms within an industry. For both the pre-Paris and post-Paris periods, bank loans tend to have a lower share of greenest firms in a dirtier industry with a higher emission intensity level. But during the post-Paris period, banks loans also tend to have a slightly higher share of greenest firms in a dirtier industry with a higher energy intensity level.

B.3 Lists of Traditional Dirty Industries

Table B.17: List of Traditionally Dirty Industries at the NACE 2-digit Industry Level

List of Traditional Brown Industries
05 – Mining of coal and lignite
06 – Extraction of crude petroleum and natural gas
07 – Mining of metal ores
08 – Other mining and quarrying
09 – Mining support service activities
19 – Manufacture of coke and refined petroleum products
35 – Electricity, gas, steam, and air conditioning supply (especially fossil fuel-based energy generation)
20 – Manufacture of chemicals and chemical products
23 – Manufacture of other non-metallic mineral products (includes cement production, which is highly carbon-intensive)
24 – Manufacture of basic metals (e.g., steel, aluminum production)
49 – Land transport and transport via pipelines (includes trucking, rail freight, and oil/gas pipelines)
50 – Water transport (maritime shipping, which has a high carbon footprint)
51 – Air transport (aviation is a major source of emissions)

B.4 Alternative Sample: Firms Ever Had a Bank Relation

We consider an alternative sample consisting only of firms that have ever entered a firm–bank relationship (at least have one bank account) recorded in the credit register.[17] We call this sample "Ever" sample. The summary statistics are reported below along with the regression results for the general, within-industry, and between-industry analyses. The results are similar to those obtained from the full sample.

[17] For data accuracy, we drop firms and banks with fewer than 10 employees.

Table B.18: Summary Statistics, Danish Ever Sample

Variable	Mean	Median	Sd
Loan outstanding (million DKK)	4.234	0.019	62.936
Firm energy intensity (EgI)	43.138	12.838	4,938.906
Change in firm energy intensity (ΔEgI)	0.252	-0.326	5,006.712
Relative energy intensity ($REgI$)	-0.042	-0.024	0.984
Change in relative energy intensity ($\Delta REgI$)	0.021	0.031	0.984
Industry emission intensity (EI)	28.794	17.027	88.019
Change in industry emission intensity (ΔEI)	-0.427	-0.255	32.889
Industry energy intensity (EgI)	0.255	0.146	0.549
Change in industry energy intensity (ΔEgI)	-0.002	-0.001	0.153
Assets (million DKK)	178.761	7.278	3,203.790
Leverage ratio	0.699	0.529	11.902
Fixed assets ratio	0.408	0.346	0.308
ROA	-0.158	0.050	150.589
Observations		808,238	

Table B.19: General Analysis: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	(2)	(3)
Pre Paris × Log (EgI)$_{t-1}$	0.009	-0.510	-0.002
	(0.017)	(0.326)	(0.002)
Pre Paris × Δ Log (EgI)$_{t-1}$	-0.007	-0.005	-0.000
	(0.011)	(0.251)	(0.001)
Post Paris × Log (EgI)$_{t-1}$	-0.127***	-1.878***	-0.009***
	(0.032)	(0.493)	(0.003)
Post Paris × Δ Log (EgI)$_{t-1}$	0.052***	0.518	0.003**
	(0.011)	(0.343)	(0.001)
Log (Assets)$_{t-1}$	0.231***	-0.820***	-0.002**
	(0.041)	(0.251)	(0.001)
Fixed Assets Ratio$_{t-1}$	0.004***	-0.078***	-0.000
	(0.001)	(0.015)	(0.000)
Leverage Ratio$_{t-1}$	0.004***	-0.099***	-0.000***
	(0.001)	(0.008)	(0.000)
ROA$_{t-1}$	-0.002***	0.104***	0.000***
	(0.001)	(0.014)	(0.000)
Firm Fixed Effects	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes
R-sq	0.574	0.182	0.274
N	627,852	627,852	627,852

Table B.20: Within-Industry Analysis: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	**(2)**	**(3)**
Pre Paris × Log(REgI)_{t-1}	0.027	-0.320	-0.000
	(0.020)	(0.485)	(0.002)
Pre Paris × Δ (REgI)_{t-1}	-0.021	-0.161	-0.001
	(0.013)	(0.298)	(0.001)
Post Paris × Log(REgI)_{t-1}	-0.137***	-2.163***	-0.010***
	(0.046)	(0.657)	(0.003)
Post Paris × Δ (REgI)_{t-1}	0.058***	0.667*	0.004***
	(0.015)	(0.385)	(0.002)
Log (Assets)_{t-1}	0.234***	-0.784***	-0.002*
	(0.040)	(0.250)	(0.001)
Fixed Assets Ratio_{t-1}	0.004***	-0.078***	-0.000
	(0.001)	(0.015)	(0.000)
Leverage Ratio_{t-1}	0.004***	-0.099***	-0.000***
	(0.001)	(0.008)	(0.000)
ROA_{t-1}	-0.002**	0.105***	0.000***
	(0.001)	(0.014)	(0.000)
Firm Fixed Effects	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes
R-sq	0.574	0.182	0.274
N	627,848	627,848	627,848

Notes: This table presents the estimation results for within-industry analysis for the full sample of firms. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.21: Within-Industry Analysis: Dirty Industries: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	(2)	(3)
Pre Paris × REgI$_{t-1}$	-0.084	-2.394*	-0.010**
	(0.053)	(1.303)	(0.005)
Pre Paris × Δ(REgI)$_{t-1}$	0.050**	-0.132	0.001
	(0.021)	(0.650)	(0.002)
Post Paris × REgI$_{t-1}$	-0.055	-2.174	-0.012
	(0.095)	(1.685)	(0.008)
Post Paris × Δ(REgI)$_{t-1}$	-0.016	2.999**	0.006
	(0.051)	(1.325)	(0.006)
Log(assets)$_{t-1}$	0.398***	-0.199	-0.004
	(0.057)	(1.008)	(0.004)
Fixed assets ratio$_{t-1}$	0.008**	-0.081**	0.000
	(0.003)	(0.030)	(0.000)
leverage ratio$_{t-1}$	0.008***	-0.157***	-0.001***
	(0.002)	(0.051)	(0.000)
ROA$_{t-1}$	-0.001	0.118	0.000
	(0.004)	(0.071)	(0.000)
R-sq	0.522	0.194	0.256
N	45,840	45,840	45,840

Table B.22: Within-Industry Analysis: Traditionally Dirty Industries: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan Initiation**
	(1)	**(2)**	**(3)**
Pre Paris × $REgI_{t-1}$	-0.084	-3.089	-0.011*
	(0.097)	(1.740)	(0.005)
Pre Paris × $\Delta(REgI)_{t-1}$	0.042	-0.182	0.000
	(0.043)	(0.951)	(0.003)
Post Paris × $REgI_{t-1}$	0.033	-1.163	-0.002
	(0.156)	(2.454)	(0.011)
Post Paris × $\Delta(REgI)_{t-1}$	-0.120	0.367	0.001
	(0.121)	(2.080)	(0.010)
Log(Assets)_{t-1}	0.422***	1.322	0.003
	(0.074)	(1.066)	(0.005)
$\text{Fixed Assets Ratio}_{t-1}$	0.007	-0.064*	0.000*
	(0.005)	(0.035)	(0.000)
$\text{Leverage Ratio}_{t-1}$	0.007**	-0.221***	-0.001***
	(0.002)	(0.035)	(0.000)
ROA_{t-1}	-0.006	-0.021	-0.000
	(0.004)	(0.034)	(0.000)
R-sq	0.555	0.216	0.288
N	23,303	23,303	23,303

Notes: Robust standard errors clustered at the industry level in parentheses. Significance levels: ***1%, **5%, *10%.

Table B.23: Within-Industry Analysis: Non-dirty Industries: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	**(2)**	**(3)**
Pre Paris × REgI_{t-1}	0.041**	-0.103	0.001
	(0.017)	(0.479)	(0.002)
Pre Paris × ΔREgI_{t-1}	-0.030**	-0.211	-0.002
	(0.011)	(0.311)	(0.001)
Post Paris × REgI_{t-1}	-0.143***	-2.213***	-0.010***
	(0.049)	(0.698)	(0.004)
Post Paris × ΔREgI_{t-1}	0.060***	0.569	0.004**
	(0.015)	(0.395)	(0.002)
Log(Assets)_{t-1}	0.221***	-0.856***	-0.002*
	(0.040)	(0.267)	(0.001)
Fixed Assets Ratio_{t-1}	0.004***	-0.079***	-0.000*
	(0.001)	(0.016)	(0.000)
Leverage Ratio_{t-1}	0.004***	-0.096***	-0.000***
	(0.001)	(0.009)	(0.000)
ROA_{t-1}	-0.002***	0.102***	0.000***
	(0.001)	(0.014)	(0.000)
R-sq	0.579	0.186	0.279
N	579,902	579,902	579,902

Table B.24: Between-Industry Analysis: Ever Sample

	Log (Balance)	**Loan Growth**	**New Loan**
	(1)	(2)	(3)
Pre Paris × Log(EI)_{t-1}	-0.042	-0.644	-0.002
	(0.113)	(1.410)	(0.007)
Pre Paris × Log(EgI)_{t-1}	0.056	-0.731	-0.004
	(0.109)	(1.346)	(0.006)
Pre Paris × $\Delta\text{log(EI)}_{t-1}$	0.025	1.569	0.002
	(0.060)	(1.497)	(0.005)
Pre Paris × $\Delta\text{log(EgI)}_{t-1}$	0.024	0.160	0.003
	(0.033)	(1.016)	(0.003)
Post Paris × Log(EI)_{t-1}	-0.155	-1.128	-0.003
	(0.119)	(1.308)	(0.007)
Post Paris × Log(EgI)_{t-1}	0.141	-0.626	0.001
	(0.114)	(1.384)	(0.007)
Post Paris × $\Delta\text{log(EI)}_{t-1}$	0.050	5.325***	0.019**
	(0.111)	(1.754)	(0.008)
Post Paris × $\Delta\text{log(EgI)}_{t-1}$	-0.017	-0.184	-0.002
	(0.048)	(1.346)	(0.005)
Log (Assets)_{t-1}	0.245***	-0.232	-0.001
	(0.031)	(0.298)	(0.001)
Fixed Assets Ratio_{t-1}	0.005***	-0.080***	-0.000**
	(0.001)	(0.015)	(0.000)
Leverage Ratio_{t-1}	0.003***	-0.082***	-0.000***
	(0.000)	(0.008)	(0.000)
ROA_{t-1}	-0.001**	0.074***	0.000***
	(0.000)	(0.010)	(0.000)
Industry Real Value Added Growth_t	-0.127**	-1.436	-0.001
	(0.061)	(1.312)	(0.005)
Firm Fixed Effects	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes
2-digit Industry Fixed Effects	Yes	Yes	Yes
R-sq	0.576	0.188	0.278
N	596,018	596,018	596,018

Notes: This table presents the estimation results for between industry analysis at the firm level regression. Robust standard errors clustered at the industry level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.