Short economic and financial analyses

The Impact of Credit Supply on Firms' Green Transition in the Euro Area

Author: Neža Ahčin

July 2025

BANKA SLOVENIJE

EVROSISTEM

Collection: Short economic and financial analyses

Title: The Impact of Credit Supply on Firms' Green Transition in the Euro Area

Author: Neža Ahčin, Banka Slovenije, email address: neza.ahcin@bsi.si

Issue: July 2025

Year: 2025

Place of publication: Ljubljana

Issued by:
Banka Slovenije
Slovenska 35, 1505 Ljubljana, Slovenija
www.bsi.si

Electronic edition:
Research publications | Banka Slovenije

Kataložni zapis o publikaciji (CIP) pripravili v Narodni in univerzitetni knjižnici v Ljubljani
COBISS.SI-ID **251139843**
ISBN 978-961-7230-23-9 (PDF)

Table of contents

Abstract

In this analysis, we combine loan-level credit register data for all euro area banks with granular firm-level carbon emission data to estimate the impact of credit supply on firms' green transition. To isolate bank-specific credit supply shocks from firm-specific demand shocks, we estimate a regression model including bank time and firm time fixed effects. Our findings indicate that greater credit supply leads to higher growth of firms' carbon intensity at least in the short term, which implies that credit supply expansion alone is unlikely to drive economy-wide decarbonization. Obtained estimates reveal substantial heterogeneity in firms' responses to changes in credit supply. We find that higher credit supply reduces the growth of carbon intensity among less polluting firms, indicating that already cleaner firms are (self)-incentivized to further green their operations. Importantly, the results show that additional credit can support the green transition even among more polluting firms, but only if they operate in sectors with recognized ability to adopt cleaner technologies and practices.

1 Introduction

In recent years, as the European Union has intensified its efforts to transition towards a net zero economy, this has also brought increased attention to the exposure of euro area banks to transition risks as a potential risk to financial stability. In the context of the adoption of climate-related policies and regulatory measures, evidence from existing literature indicates that these initiatives influence banks' lending behaviour. In particular, Reghezza et al. (2021) find that, following the Paris Agreement, European banks reallocated credit away from polluting firms. Similarly, Aiello (2024) shows that banks under direct supervision of the SSM shifted credit towards less polluting firms after the publication of the ECB's climate supervisory expectations in 2020. While reallocating credit away from polluting firms may reduce banks' exposure to transition risks, it can unintentionally also slow green transition amid the reduced availability of bank financing for carbon-intensive firms. Prior studies (EEA, 2024; SIAM, 2022) have shown that financially constrained brown firms often increase their carbon emissions to boost short-term cashflow while scaling back efforts towards long-term carbon reduction. Moreover, providing financing only to green firms may have limited potential to significantly lower overall carbon emissions (Liang et al., 2025).

Since investments in more sustainable processes and technologies require substantial funding, especially for firms operating in carbon-intensive sectors, credit can play an important role and can significantly affect firms' green transition. In this analysis, we combine loan-level credit register data and granular carbon emission data to estimate the impact of credit supply shocks on firms' growth in carbon intensity. Credit supply shocks are identified following the Khwaja and Mian (2008) approach. These shocks reflect bank-specific supply factors – both exogenous and endogenous – that influence lending activity, while controlling for firm credit demand shocks. The impact of credit supply shocks is estimated for firms in the euro area during the period 2020–2021.

In light of the growing awareness of the importance of providing funds to non-green sectors, we also study whether credit supply shocks affect firms' carbon intensity growth differently depending on the sector's transition potential. Given that NACE 4-digit classification does not provide information on sector greening potential, we propose the identification of sectors with greening potential leveraging on standardized and transparent coefficients that estimate transition risk exposure at the sector level, introduced by Alessi and Battiston.

The results show that an increase in credit supply increases the growth of firms' carbon intensity at least in the short term. However, the results support the idea that a positive credit supply reduces the growth of firms' carbon intensity if firms are (self)-incentivized to green their operations. In particular, this applies to firms that are already among the low emitters at the country sector level and to the higher-emitting firms operating in sectors with greening potential.

As regards applied methodology, this analysis relates to Alfaro et al. (2021) and Volk (2023), who study the impact of credit supply shocks on firm performance in Spain and Slovenia respectively, relying on credit register data. In the context of assessing the impact of credit supply on green transition, our analysis is closely related to Accetturo et al. (2024). Accetturo et al. (2024) construct an exogenous firm-specific time-varying measure of bank credit supply, following Berton et al. (2018), using the identification strategy proposed by Khwaja and Mian (2008) as a control for robustness of credit supply shocks.

The rest of the paper proceeds as follows. Section 2 describes the data and methodology, followed by Section 3 with the main results of the analysis. Section 4 concludes with a discussion of potential policy implications.

2 Data and Methodology

2.1 Data

For the purpose of this analysis, we combine several data sources. Information on bank loans is obtained from AnaCredit, the euro area credit register. AnaCredit is a dataset which provides detailed loan-by-loan information on all credit granted by credit institutions[1] resident in the euro area to legal entities.[2] A credit is reported to AnaCredit under the condition that the creditor's exposure to the individual borrower is equal or above €25,000, taking into consideration all eligible instruments at a given reference date. The collected loan data with associated information has been reported to AnaCredit monthly since September 2018.[3] The unique identification of counterparties in AnaCredit is obtained from the Register of Institution and Affiliates Database (RIAD), i.e. a business register, which contains specific counterparty reference and financial data.

As information on carbon emissions (or any kind of granular climate change-related information at the counterparty level) has not been part of the regular reporting framework in RIAD, the data on firms' carbon emissions is retrieved from a separate ECB climate change-related indicators dataset. Focusing only on carbon emission indicators linked to loans granted to euro area counterparties, these indicators are compiled annually at the single entity level using financial data inferred from AnaCredit and RIAD. Hence the first analytical indicators on carbon emissions are available for 2018. Indicators on carbon emissions cover only Scope 1 carbon emissions, reported in thousands of tons.[4] For companies participating in the EU European Emission Trading System (ETS), verified CO_2-equivalent emissions are used to derive the indicators, while for the remaining companies, emissions are estimated using a waterfall model based on aggregate data from Eurostat's Air Emissions Accounts (AEA). In particular, sector-level AEA Scope 1 emissions are attributed to a single entity in proportion to the entity's employment share in a given sector. The use of imputation methods is necessary as reporting of carbon emission remains largely voluntary.[5] Despite ongoing methodological improvements, indicators are still subject to limitations and caveats, so any analysis should be treated with caution.[6]

[1] Foreign branches not resident in the euro area of credit institutions that are resident in the euro area are also subject to the AnaCredit reporting requirements.

[2] Therefore excluding natural persons.

[3] Detailed descriptions on the general methodology, attributes and case studies are available in the AnaCredit reporting manuals (AnaCredit Reporting Manual Part I – General Methodology, AnaCredit Reporting Manual Part II – Datasets and Data Attributes, AnaCredit Reporting Manual Part III – Case Studies).

[4] Under the Greenhouse Gas (GHG) protocol, a firm's GHG emissions are classified in three categories: Scope 1, Scope 2 and Scope 3 emissions. Scope 1 emissions are those directly produced by sources owned or controlled by the firms.

[5] According to Towards climate-related statistical indicators – Technical annex, the average share of imputed emissions between 2018 and 2020 for the euro area was 49%. Some information on total assets and revenue is also imputed, but to a lesser degree.

[6] More detailed information on the imputation methods and remaining caveats can be found in Climate change-related statistical indicators and Towards climate-related statistical indicators – Technical annex.

2.2 Identifying Sectors with Potential for Greening

In the absence of information on the purpose of the loan in terms of green financing in AnaCredit, we introduce the concept of sectors with potential for greening. The idea of sectors with greening potential is based on the fact that the green transition is currently more feasible in some sectors than in others, often due to already existing cleaner technologies. For instance, for a firm involved in the extraction of coal, it could be more difficult to align its activity to climate targets compared to a firm involved in the manufacturing of light duty vehicles, which has the possibility to turn to electric vehicles (Alessi and Battiston, 2022). In order to identify the corresponding sectors, we leverage on the research work by Alessi and Battiston, who propose a methodology to estimate the exposure to transition risk of each economic sector with transition risk exposure coefficients (TECs), using publicly available information.[7] While the initial TECs proposed in Alessi and Battiston (2022) were estimated at the EU level, the authors developed country-specific TECs in their subsequent article (Alessi and Battiston, 2023) to account for differences across countries for each economic sector. The estimated coefficients are largely based on the definitions provided in the EU Taxonomy, while for economic activities not included in the Taxonomy, TECs are derived building on the framework of Climate Policy Relevant Sectors (CPRS, Battiston et al., 2017), which allows us to identify economic activities highly exposed to transition risk.[8,9]

As such, TEC serves as a proxy for estimating the share (in value terms) of activities included in a given economic sector (4-digit NACE code) that are exposed to high levels of transition risk. TEC values range from 0% – indicating sectors with no exposure to transition risk – to 100%, representing activities that are most likely to be negatively impacted by the shift to a low-carbon economy. By comparing TEC values for the same economic sector across different countries, we can identify the country with the smallest exposure of that particular sector to transition risk (i.e. the lowest TEC), theoretically reflecting the use of cleaner technologies and/or more sustainable materials. This cross-country variation indicates that, for a given economic sector in a given country, it is technically feasible to reduce its exposure to transition risk at least to the level observed in the best performing country. Hence we define the concept of potential for greening as the scope for reducing a sector's exposure to transition risk in a particular country by converging towards the lowest TEC value observed for that sector across euro area countries.

For example, TECs associated with electricity production are based on the shares of fossil energy (coal, oil and gas), which vary widely across countries. Hence countries with higher TEC for the electricity production sector have the potential to lower the use of fossil fuels, reaching the level of the country with the smallest exposure of its electricity production sector to transition risk, i.e. the highest share of energy production from renewable sources.

Using the NACE sector classification reported in AnaCredit, we are able to identify for each borrower whether it operates in an economic sector with greening potential. In the dataset used for this analysis, sectors identified as having greening potential account for approximately 4% of all reported sectors. As expected, given the current availability of more detailed climate-related information, most of these sectors fall within Manufac-

[7] Official statistics, reports of the relevant authorities and agencies, sectoral studies, and industry reports.

[8] By construction, TECs reflect a broader definition of transition risk, as the emphasis is not only on carbon emissions but also on energy inefficiency (for example when assessing buildings), and they are therefore more in line with the definition of transition risk underlying international and European climate-related and sustainability disclosure standards.

[9] The individual country-specific TECs for all relevant sectors and their rational are provided as an open source table: TAC TEC tool.

turing (C), Transporting and Storage (H), Electricity and Gas Supply (D), and Construction (F). Table 1 provides an insight into the relevance of these sectors across countries in terms of the number of firms and banks' credit exposure to those firms.

Table 1: **Selected summary statistics across countries**

	Percentage of all firms in sectors with potential for greening	**Percentage of total exposure to firms in sectors with greening potential**
AT	8%	8%
BE	2%	10%
CY	1%	0%
DE	1%	2%
EE	5%	25%
ES	8%	8%
FI	21%	21%
FR	4%	3%
GR	2%	11%
IE	4%	5%
IT	5%	7%
LT	6%	5%
LU	8%	66%
LV	16%	44%
MT	7%	37%
NL	3%	7%
PT	6%	9%
SI	3%	23%
SK	3%	33%

Sources: Banka Slovenije, AnaCredit, TAC & TEC tool (Alessi, L., & Battiston, S), own estimates.

2.3 Methodology

The methodology closely follows the approach applied in Alfaro et al. (2021) and Volk (2023), who estimated the effects of credit supply shocks on firm performance in Spain and Slovenia respectively. The analysis follows a two-step approach: first, credit supply shocks are identified, which are then used as the key explanatory variable for analysing the growth in firms' carbon intensity.

Bank lending is driven by both supply and demand factors, which often shift simultaneously and interact in complex ways. For example, if banks decide to prioritize lending to green firms – potentially offering them more favourable terms – this may reduce the supply of credit to high-emitting firms. At the same time, tighter credit standards for high-emitting firms can dampen their demand for loans and further reinforcing the overall decline in lending to these firms. Therefore changes in lending volumes cannot be considered as an exogenous variable.

The main concept of the first stage estimation is to decompose changes in observed loan amounts into supply and demand shocks. To achieve this, we applied the widely used method developed by Khwaja and Mian (2008), which isolates bank-specific credit supply shocks by exploiting firm–bank relationships using loan-level data. The idea behind the Khwaja and Mian approach is the following: if a firm borrows from more than one bank, and one bank reduces its lending to the firm while the others do not, this differential change can be attributed to a bank-specific shock, rather than a change in the firm's credit demand. Hence this approach requires firms to have relations with (at least) two banks.

Based on this framework, the following model was estimated:

$$\Delta L_{fbt} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{1}$$

where ΔL_{fbt} is loan growth of firm *f* obtained from bank *b* in year *t.*[10] Firm-time fixed effects, denoted by α_{ft}, capture all factors that simultaneously affect the firm's borrowing across all banks. Similarly, bank-time fixed effects, denoted by β_{bt}, depict supply-side effects, reflecting the bank-specific lending decisions.

In the second step, we estimate the effect of loan supply shock on growth in firms' carbon intensity

$$\Delta ci_{ft} = \gamma\bar{\beta}_{ft} + \theta * controls_{ft} + FE_{ILST} + \epsilon_{ft}, \tag{2}$$

where ci_{ft} denotes the carbon intensity of firm *f* in year *t*, defined as tons of Scope 1 carbon emissions per million EUR of revenue. Firm-time specific credit supply shock $\bar{\beta}_{ft}$ is calculated as the weighted average of the estimated bank-supply shocks in (1)

$$\bar{\beta}_{ft} = \sum_{b} w_{fbt-1}\,\hat{\beta}_{bt}, \tag{3}$$

where weight w_{fbt} is proportional to the loan amount l_{fbt}

$$w_{fbt} = \frac{l_{fbt}}{\sum_{\mathrm{b}} l_{fbt}}. \tag{4}$$

In the corresponding estimations, we include time-country-size-sector fixed effects,[11] together with time-varying firm-level controls: firm size measured by the logarithm of total assets, indebtedness measured by the total loan debt-to-asset ratio and the estimated demand effects α_{ft}.

For the purpose of this analysis, we limit our dataset to credit lines, revolving credit and other loans as the primary bank lending instrument. While the credit register contains data on a monthly frequency, we adjust the credit data to an annual frequency since firms' annual turnover and carbon emissions are available only annually. Moreover, in order to properly identify demand and supply shocks, only firms that obtain loans from at least two banks are included in the analysis. This limits our sample to around 18% of the total number of firms, which represents around 63% of the total loan amount. Additionally, we exclude all firms with loan repayments overdue by more than 90 days to avoid artificially inflated loan amounts due to accrued interest.

[10] Loan growth ΔL_{fbt} is defined as $\Delta L_{fbt} = \ln(L_{fbt}) - \ln(L_{fbt-1})$, where average loan amount in each year is considered.

[11] Fixed effects for each combination of year, 2-digit NACE industry, country, and firm size category (distinguishing between SMEs and large firms).

3 Results

This section summarizes the key findings from the estimation of the impact of credit supply shocks on firm-level decarbonization.

The results shown in Table 2 from the fixed effects regression indicate that a positive shock to loan supply is associated with an increase in firms' carbon intensity growth at least in the short term. Specifically, the estimated coefficient in column (1) on loan supply shock is 0.01 ($p < 0.05$), suggesting that a one percentage point higher loan supply leads to a 0.01 pp higher growth in firms' carbon intensity, holding firm characteristics and loan demand conditions constant. This, together with the results from the regression of annual turnover growth on loan supply shock, implies that firms tend to expand their production in ways that lead to disproportionate increase in carbon emissions (Table A.1).

Next, we extend the model by introducing an interaction term between the loan supply shock and a dummy variable that identifies country–sector pairs in the bottom quartile of carbon intensity. The main purpose of introducing the interaction term is to investigate whether the effect of loan supply shock on carbon intensity growth differs between relatively cleaner versus more polluting firms. The results show that the effect of a loan supply shock corresponds to a reduction of 0.07 pp in carbon intensity growth for cleaner firms, while more polluting firms increase their carbon intensity growth by 0.05 pp on average. This heterogeneous effect highlights the fact that additional credit is unlikely to drive low-carbon investments if a firm is not already on a less-polluting trajectory. The estimated coefficients thus suggest that cleaner firms are more (self-)incentivized to invest in cleaner technologies, in contrast to more polluting firms.

Table 2: **Impact of credit supply on growth in firms' carbon intensity**

	(1)	(2)	(3)	(4)
Supply shock	0.0114** (0.0053)	0.0479*** (0.0055)	0.0133** (0.0054)	0.0507*** (0.0057)
Supply shock × Low emitter		-0.123*** (0.0095)		-0.127*** (0.0097)
Supply shock × Greening potential			-0.0397** (0.0201)	-0.0534*** (0.0205)
Supply shock × Low emitter × Greening potential				0.0745 (0.0457)
Fixed effects				
ILS × Time	Yes	Yes	Yes	Yes
Number of observations	874,651	874,651	874,651	874,651
Adj. R2	0.332	0.359	0.332	0.359

Sources: Banka Slovenije, AnaCredit, ECB climate change-related indicators, TAC & TEC tool (Alessi, L., & Battiston, S), own estimates.
Notes: The table reports estimated coefficients of the impact of credit supply shock on the growth of carbon intensity. The coefficients are estimated for the sample period from 2020 to 2021, including only firms with multiple relations with banks. The supply shock is estimated with equation (1) and, for the purpose of estimating its impact on firms' carbon intensity, aggregated according to equation (3). "Cleaner firms" is defined as a dummy variable, which equals one for low-carbon intensive firms, while "Potential for greening" takes one if a sector is feasible to transition to green and zero other-wise. Fixed Effects ILS × Time stands for the interaction of the firm's industry (2-digit NACE code), country and size fixed effects with time. In addition to the variables shown in the table, all estimated regressions also include the following control: logarithm of total assets, loan debt-to-assets and firm's demand effects from equation (1). Standard errors clustered at the firm level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Further, we investigate whether credit supply shocks affect growth in firms' carbon intensity differently depending on the greening potential of the sector in which the firm operates. The estimated coefficients indicate that a one percentage point increase in the loan supply shock is associated with a 0.03 pp reduction in carbon intensity growth among firms in greenable sectors, while firms in non-greenable sectors experience, on average, a 0.01 pp increase in carbon intensity growth in response to the same shock. Thus the effect of loan supply shocks on carbon intensity growth is 0.04 pp lower for firms in greenable sectors relative to those in non-greenable sectors, with the interaction statistically significant at 5%.

We continue by analysing a triple interaction, which allows us to investigate whether the effect of credit supply shocks differs by both firms' carbon intensity levels and sectoral greening potential. The results reveal that a one unit positive loan supply shock marginally decreases carbon intensity growth for higher-emitting firms in sectors with greening potential. These findings indicate that additional credit can facilitate the green transition among more polluting firms, but only in sectors with the recognized ability to adopt cleaner technologies and practices.

4 Conclusion

This analysis studies the impact of credit supply on firms' green transition, measured by growth in carbon intensity. Credit supply shocks are decomposed from loan demand factors based on the Khwaja and Mian (2008) approach, using euro area credit register data between 2020 and 2021. The results obtained from the regression analysis suggest that higher credit supply can reduce the growth of firms' carbon intensity, especially if firms are (self)-incentivized to green their operations. In particular, this applies to firms that are already among the low emitters at the country-sector level and to the higher-emitting firms in sectors with greening potential. On the other hand, the results also support the view that more polluting firms in sectors with limited greening potential increase their growth of carbon intensity – at least in the short term – in response to a positive credit supply shock.

The findings of this analysis underscore the importance of providing bank financing also to high-emitting firms, as these are precisely the ones that currently contribute the largest share to overall carbon emissions. However, it is essential that banks undertake a comprehensive assessment of a firm's ability to decarbonize, along with the risks associated with the firm's transition.

5 References

1. Accetturo, A., Barboni, G., Cascarano, M., Garcia-Appendini, E. and Tomasi, M. (2024). *Credit supply and green investments* (Bank of Italy Working Paper No. 1456). SSRN.
2. Aiello, M. A. (2024, March 14). *Climate supervisory shocks and bank lending: Empirical evidence from microdata* (Bank of Italy Working Paper No. 1465). SSRN.
3. Alessi, L., & Battiston, S. (2022). *Two sides of the same coin: Green Taxonomy alignment versus transition risk in financial portfolios.* International Review of Financial Analysis, 84, 102319.
4. Alessi, L., & Battiston, S. (2023). *Taxonomy alignment and transition risk: A country-level approach* (JRC Technical Report No. JRC135889). European Commission.
5. Alfaro L., Garcia-Santana M. and Moral-Benito E. (2021). *On the direct and indirect real effects of credit supply shocks.* Journal of Financial Economics, 139(3), 895–921.
6. Altavilla, C., Boucinha, M., Pagano, M., & Polo, A. (2023). *Climate risk, bank lending and monetary policy* (ECGI Finance Working Paper No. 936/2023). European Corporate Governance Institute
7. Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). *A climate stress-test of the financial system.* Nature Climate Change, 7(4), 283–288.
8. European Environment Agency (EEA). (2024). *Modal shares (%) in EU-27 freight transport activity*. European Environment Agency.
9. Khwaja A.I. and Mian A. (2008). *Tracing the impact of bank liquidity shocks: Evidence from an emerging market.* The American Economic Review, 1413–1442.
10. Liang, H., Sun, Y., & Yao, T. (2025). *Greening brown sectors through transition finance*. Asian Management Insights*,* 7(1), 45–49. Singapore Management University.
11. Nerlich, C., Köhler-Ulbrich, P., Andersson, M., Pasqua, C., Abraham, L., Bańkowski, K., Emambakhsh, T., Ferrando, A., Grynberg, C., Groß, J., Hoendervangers, L., Kostakis, V., Momferatou, D., Rau-Goehring, M., Rariga, E.-J., Rusinova, D., Setzer, R., Spaggiari, M., Tamburrini, F., Vendrell Simon, J. M., & Vinci, F. (2025). *Investing in Europe's green future: Green investment needs, outlook and obstacles to funding the gap* (ECB Occasional Paper No. 367). European Central Bank.
12. Reghezza, A., Altunbas, Y., Marques-Ibanez, D., Rodriguez d'Acri, C., & Spaggiari, M. (2021). *Do banks fuel climate change?* ECB Working Paper Series No. 2550.
13. Society of Indian Automobile Manufacturers (SIAM). (2022). *Annual report 2021–22* (p. 6). Society of Indian Automobile Manufacturers.
14. Volk, M. (2023). *The impact of credit supply on firm performance: Micro-evidence from Slovenia* (Discussion Paper). Banka Slovenije.

6 Appendix

Table A.1: **Impact of credit supply on growth in annual turnover**

	(1)
Supply shock	0.0417*** (0.00404)
Fixed effects	
ILS × Time	Yes
Number of observations	874,651
Adj. R2	0.504

Sources: Banka Slovenije, AnaCredit, ECB climate change-related indicators, own estimates.
Notes: The table reports estimated coefficients of the impact of credit supply shock on the growth of annual turnover. The coefficients are estimated for the sample period from 2020 to 2021, including only firms with multiple relations with banks. The supply shock is estimated with equation (1) and, for the purpose of estimating its impact on firms' annual turnover, aggregated according to equation (3). Fixed Effects ILS × Time stands for the interaction of the firm's industry (2-digit NACE code), country and size fixed effects with time. In addition to the variables shown in the table, the estimated regression also includes the following control: logarithm of total assets, loan debt-to-assets and firm's demand effects from equation (1). Standard errors clustered at the firm level are shown in parentheses below the respective coefficient estimate. Significance: *** p<0.01, ** p<0.05, * p<0.1.