

CARBON RISK AND SYNDICATED LOANS: A NETWORK ANALYSIS APPROACH. *

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Abstract

The indirect emissions that are financed by financial institutions represent a source of risk. Transition risk, albeit not being directly borne by banks, may indirectly affect financial intermediaries via their financing activities. This study contributes to this literature by giving a novel insight on the structure of this risk: by means of syndicated loans, a network empirical model is built to relate the lenders with their financed emissions while also considering their respective position within the loan market. The results show that the most central financial intermediaries are associated with higher shares of emissions. Several robustness checks as well as different ways to account for emissions are considered, confirming the main results. The conclusions drawn from this paper may be relevant for practitioners and regulators alike.

Keywords: Climate change; Financial stability; Financial instruments; Network models.

JEL Classification: G21; G10; E44.

1 Introduction

The role of carbon emissions and the attention paid to their respect has been rising since at least 2015 with the Paris agreement and regulations trying to curb CO₂ emissions and other greenhouse gases raised in the past decade. The risk represented by the CO₂ has been labeled by the literature as transition risk: namely, the risk that transitioning to lower or zero emissions poses to high emitting firms (Owolabi et al., 2024). A long-standing literature has been focusing on CO₂ representing a risk factor in the cross section of stock market returns. Bolton and Kacperczyk (2021) analyze the US market and show how the carbon risk is priced in stocks especially by institutional investors. Moreover, Monasterolo and De Angelis (2020) show even a stock market reaction to the Paris agreement. This is in line with the uncertainty related to policies intended to curb emissions as Ilhan et al. (2021) show for the option market and the effect is present despite dramatic changes like the election of President Trump and his abrupt policy change. Indeed, policies in advanced economies have been undertaken to fight climate change targeting carbon emissions: for example, the European Union has introduced a policy of emissions trading systems setting

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quotas to firms and taxing the extra emissions. So, with emissions representing a risk factor for firms and stock markets the question arises: how do financial intermediaries behave with respect to carbon emissions? Indeed, the role of financial intermediaries has often been called upon to tackle and help economies meet these targets. Indeed, via their intermediating processes banks can provide funds to non-financial firms and may influence their access to credit by changing the costs, terms and collateral requirements of credit. Moreover, the literature has pointed out that despite the lack of direct emissions for financial institutions, like other services, the financial activity is related to the emissions that such institutions indirectly finance. Moreover, the financial relationships through lending are more fixed than equity or other financial positions that can be easily hedged or traded away, hence banks may find themselves stuck with an exposure previously unidentified or undervalued. Financial intermediaries and policymakers are increasingly concerned about the potential risks that climate change poses to economic activity, corporate performance, and asset valuations (Hong et al., 2020; Krueger et al., 2020; Giglio et al., 2021; Litterman et al., 2021; Stroebel and Wurgler, 2021). In response, regulatory authorities around the world have begun assessing whether climate-related risks could threaten financial stability and adversely affect the broader economy (Carney, 2015; Bailey, 2020; FSOC, 2021). These efforts include initiatives such as stress testing financial institutions for climate-related vulnerabilities (Acharya, Annual Review) and introducing climate-related disclosure requirements to supplement traditional financial reporting (XXX). In this paper the main analysis tries to look at the CO₂ emissions associated with banks lending portfolios by looking at the network structure of the credit market. By means of a sample of syndicated loans, a network of lenders and borrowers is constructed for the year 2018, and the topological characteristics of the networks are used to account for the emissions financed by banks. The centrality measure is correlated to the total emissions and relative share of emissions given the loan amounts lent by each bank. The study contributes the literature of transition risk for banks and financial stability as it points out the structure of financed emissions across the lending market and the literature of syndicated loans by associating the lending to the carbon emissions of firms.

2 Literature Review

The literature examining the impact of climate change on banking remains relatively limited. Only a handful of studies investigate how loan pricing reflects firms' exposure to carbon risk via their emissions (Delis, de Greiff, and Ongena, 2019; Degryse et al., 2021; Ehlers, Packer, and de Greiff, 2021). Ginginler and Moreau (2019) and Nguyen and Phan (2020) find that heightened climate risk exposure is linked to reduced corporate financial leverage. Using loan-level data, Reghezza et al. (2021) demonstrate a decline in bank lending following the Paris Agreement and an increase in lending prices.

More related to the wider field of financial stability. Roncoroni et al. (2021) examine how the interaction between climate transition risk and market conditions—specifically asset

price volatility and recovery rates—affects financial stability. They model the dynamics of indirect contagion between banks and investment funds—two critical actors in the low-carbon transition—arising from their shared exposures to common asset classes. Hence, they derive a set of analytical results and apply the model to a unique supervisory dataset across a range of climate policy scenarios and market environments. Their findings suggest that, in the case of a disorderly transition to a low-carbon economy, stronger market conditions—such as higher asset recoveries and lower volatility—can enable the implementation of more ambitious climate policies without increasing systemic financial risk. Use of network theory to analyze financial network topology and systemic risk

Analysis of the Argentinian interbank market reveals a 'robust-yet-fragile' structure meaning that a random shock would be easily contained whereas a targeted shock to one of the more connected nodes might destabilize the network.

Champagne's analysis of the syndicated loan market network discovers it exhibits Champagne (2014)

relevant topological structure in the system connected via syndicated loans.

As transition risk represents a general factor of risk in the financial system, the financing of emission, may be expected to be positively associated with the centrality of the banks in the syndicated loans market.

In brief our main hypothesis is that carbon emissions are associated with banks more central to the syndicated lending market.

3 Methodology

3.1 Data

3.1.1 Loan Data - DealScan

The global loan data analyzed in this project comes from the LPC DealScan database. The loans analyzed are syndicated loans that are open during the year 2018 which amounts to a total of

- 8753 syndicated loans, broken down into 71 570 individual loans,
- 2201 lenders,
- and 2389 borrowers.

General information on the loans and the lenders and borrowers is available, such as the initial and end dates of the loan, the total loan amount and id, the geographical information of the lender, the loan maturity, the loan type, the loan's primary purpose, the lender's role and the lender's allocation. All loan types and purposes were kept in the analysis, as the goal of this project is to relate emissions responsibility to the topology of the financial network.

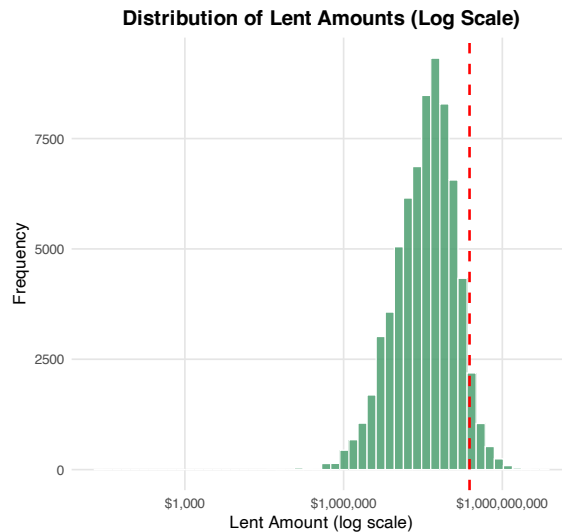


Figure 1: Distribution of lent amounts with 99th percentile marked in red

Because the lender’s allocation was not always fully disclosed or the sum of the allocations did not always add up to a 100 for a same syndicated loan, the assumption was made that in the case none of the allocations are disclosed (74% of all syndicated loans) that all lenders have an equal share of the loan, and in the second case (10% of all syndicated loans) that the allocations were normalized to sum to a 100. When only a portion of the allocations is disclosed (3% of all syndicated loans), the missing allocations are all taken as equal to the average of the disclosed values within the same loan. The exact loan amount lent by the financial institution is then simply obtained by multiplying the allocation by the total loan amount.

The distribution of amount lent by financial institutions is shown in Figure 1. The red dashed line marks the 99th percentile of the lent amounts, 1% of the loans of this database are responsible for moving a total of 1.6e+12 USD combined which represents around third (31%) of the total amount compiled in this data (5.17e+12 USD). The country of the lenders is compiled in the Table 2 with a great majority of lenders being located

3.1.2 Carbon equivalent emissions data - Eikon

The Eikon database, offers financial data on companies across the globe private and public as well as CO₂ equivalent emissions data. The data used in this project is the emission data of 2018 of companies from the loan database (see Table 1). The sector classification also comes from this database and follows the The Refinitiv Business Classification (TRBC).

3.1.3 Debt data - Orbis

The Orbis database compiles information on private companies financials and ownerships. The equity, debt and total assets of a company were used in the research.

Variable	Unit	Min	Standard deviation	Mean	Max
Syndicated loan amount	USD	5.43e+01	1.68e+09	1.01e+09	3.57e+10
Loan maturity	Months	3	44.42	64.79	1200
CO ₂ emissions	tCO ₂ e	0	1.31e+07	4.59e+06	2.32e+08

Table 1: Description of data used in the metrics

3.2 Financed emissions metrics

The main method to assess financed emissions of a financial institution, referred to here as weighted metric, is to weight the outstanding loan amount by the total assets of the borrowing company, allocating emissions in proportion to the financial share of the loan.

$$Financed\ emissions^{weighted} = \sum_c \frac{Outstanding\ loan\ amount_c}{Total\ debt + equity_c} * Company\ emissions_c \quad (1)$$

A second metric allocates emissions as a function of binary choice, either an institution chooses to lend to a company, or it does not. In the case where it does, the institution is attributed the entirety of the borrower’s emissions, regardless of loan amount or total assets. This metric is here referred to as absolute metric.

$$Financed\ emissions^{absolute} = \sum_c Company\ emissions_c \quad (2)$$

This metric will result in greater financed emissions for every bank, but the relative differences should inform about the ties of banks with highly or less emitting companies.

The last method to assess financed emissions is called the benchmark metric. This metric is based on the benchmarking of the emissions of a company related to its total revenues, both variables on logarithmic scales. There is a significant relationship between the two variables, even stronger when desaggregating between sectors. This benchmarking allows the responsibility metric to take into account the average of the sector’s practice and how far from it the company is operating. It could be intuitively stated that a strongly ‘worse-than-average’ practicing company has more margin to improve and can be more presently expected to do so.

The value of the metric represents how far a company finds itself from the average practice. A benchmark greater than 1 signifies that the company has margin to improve their emissions when comparing to the average practice. On the contrary, a benchmark between 0 and 1 signifies a better-than-average practice. This metric assigns financed emissions to a bank through the relative practice quality of their portfolio. It takes into account the total revenues of a firm, therefore avoiding the size bias that can happen with the absolute metric.

$$Financed\ emissions^{benchmark} = \sum_c \frac{Company\ emissions_c}{Sectoral\ emissions\ benchmark} \quad (3)$$

Table 2: Number of lenders per country

Country	Lenders	Country	Lenders
United States	518	Japan	285
Taiwan	122	Hong Kong	108
France	98	China	96
United Kingdom	95	India	79
Germany	68	Singapore	62
Italy	51	Canada	47
Indonesia	40	Australia	36
Spain	35	South Korea	32
Netherlands	31	Switzerland	30
United Arab Emirates	23	South Africa	19
Poland	17	Sweden	15
Macao	14	Luxembourg	13
Norway	13	Philippines	13
Belgium	12	Chile	11
Malaysia	11	Saudi Arabia	11
Thailand	11	Austria	10
Kuwait	9	Brazil	8
Ireland	8	Denmark	7
Mauritius	7	Turkey	7
Bahrain	6	Colombia	6
Mexico	6	Panama	6
Portugal	6	Czech Republic	5
Finland	5	Greece	5
Hungary	5	New Zealand	5
Egypt	4	Israel	3
Jordan	3	Morocco	3
Pakistan	3	Qatar	3
Russia	3	Slovakia	3
Brunei	2	Dominican Republic	2
Ghana	2	Oman	2
Trinidad and Tobago	2	Argentina	1
Bangladesh	1	Bulgaria	1
Bermuda	1	Democratic Republic of the Congo	1
Cayman Islands	1	Cyprus	1
Fiji	1	Jamaica	1
Lebanon	1	Namibia	1
Peru	1	Romania	1
Togo	1	Tanzania	1
British Virgin Islands	1	Zimbabwe	1

3.3 Network analysis

For each metric, a network is built where the nodes are the companies and financial institutions, and the links are the responsibility associated with the loans. The networks are directed and weighted that can be considered as almost bipartite, as entities either lend or borrow, and only a very few do both (42 entities). The direction of the links "follows the money": the source is the lender, and the target is the borrower.

A network can be described by what is called an adjacency matrix. This matrix is a squared matrix having as row and column names the entire list of nodes at play in the network; in this case, all the entities present in the lending data. With an adjacency matrix of the binary network named A , the element indexed in $[i,j]$, a_{ij} is either equal to 1 if there exists a link originating from node i and directed to node j , or it is equal to zero if there is no link between i and j . When it comes to the weight of a link, it is referred to as s_{ij} .

Several networks are at play in this thesis, first of all the loan network, strictly based on the loan data, where links have the amount of the loan as weight, and the three metrics networks, where the weights represent the responsibility associated to each loan. A more visual representation of the networks is given in Section 3.4.

3.3.1 Strength – Total CO₂ responsibility

The strength of a link is the sum of the weights of all the links originating from the node (for the out-strength) or going towards the node (for the in-strength).

$$S_i^{out} = \sum_j s_{ij} \quad (4)$$

$$S_j^{in} = \sum_i s_{ij} \quad (5)$$

The metrics described compute the emissions tied to one loan. For financial institutions, summing the financed emissions over their whole portfolio will give the total value, with the entities scoring higher being the ones financing the highest amounts of emissions.

For borrowing companies, the responsibility adopts different interpretations depending on the metric. Summing all incoming responsibilities with the weighted metric represents the amount of emissions of the company that are financed through debt. The same operation with the other metrics loses this interpretation as they are not proportional to the loan amount anymore and only to the information of the borrowing company. For the absolute metric and the benchmark metric, there is a direct correlation between the emissions considered for that company and the companies in-degree, as it will amount to the multiplication of the number of loans the company is taking to its total emissions or its difference to the average practice emissions. The borrowing CO₂ responsibility and the actual emissions of a company are therefore proportional.

3.3.2 Second order measures - Average Nearest Neighbors

The Average Nearest Neighbor Degree (ANND) and Strength (ANNS) are second order network measures that attribute a score to a node depending on the behavior of its closest neighbors. In this network the directionality is relevant to the interpretation.

ANN out-out

The 'out-out' case takes the neighbors who are borrowing from the considered node, and looks at the average degree/strength of these neighbors outgoing loans. It involves entities that both lend and borrow at the same time; a high value would indicate that the borrowers of the node are also highly active in lending activities. This would mean that the considered node engages in indirect loans (lending to a company through another financial institution).

$$ANNS_i^{out-out} = \frac{\sum_t a_{ij}^{out} S_t^{out}}{K_s^{out}} \quad (6)$$

For $ANND_i^{out-out}$, instead of taking the total in-strength of the out-neighbors S_t^{out} , the total in-degree of the out-neighbors is used K_t^{out} .

ANN out-in

The 'out-in' case takes the neighbors who are borrowing from the considered node and looks at the average degree/strength of these neighbors' incoming loans. This measure informs on the portfolio choice of financial institutions as it quantifies the borrowing behavior of the companies it is financing. A high value would indicate that the financial institution tends to lend to companies that are very interconnected in the financial system (degree) or that rely on important amounts of debt financing (strength for the weighted metric) from other banks, or that are responsible themselves for high levels of emissions (strength for the absolute and benchmark metric).

$$ANNS_i^{out-in} = \frac{\sum_t a_{ij}^{out} S_t^{in}}{K_s^{out}} \quad (7)$$

For $ANND_i^{out-in}$, instead of taking the total in-strength of the out-neighbors S_t^{in} , the total in-degree of the out-neighbors is used K_t^{in} .

3.3.3 Clustering coefficients

In a network, a cluster is a group of nodes that is interconnected. In this paper, it will more precisely designate a group of three nodes that are connected to each other. There are different cases of clustering coefficients, depending on the role of the studied node in the clusters. For one node, it is defined as the ratio between the number of clusters that node participates in over the total number of clusters it could participate in. It is considered that a cluster has the possibility to participate in a cluster the moment it is connected to a pair

of two different nodes, therefore all pair combinations of all the nodes it is connected to. Because the sample has a substantial amount of nodes, values can be expected to be very low.

Because some indirect loans and interbank loans are present in the sample, the analysis will be on the out-clustering coefficient and the middleman clustering coefficient. The first one gives the frequency of clusters where the studied node adopts the role of the source of the cluster, or in this case the source of the indirect loan. For the second method, the studied node acts as a middleman in the indirect loan, or is the recipient of an interbank loan.

$$\text{clustering coefficient}_i^{\text{out}/\text{mid}} = \frac{\text{number of clusters where } i \text{ is the source / middleman}}{\text{total number of clusters possible}} \quad (8)$$

$$cc_i^{\text{out}} = \frac{\text{diag}(A.A.A^T)_i}{K_i^{\text{out}}(K_i^{\text{out}} - 1)} \quad (9)$$

$$cc_i^{\text{mid}} = \frac{\text{diag}(A.A^T.A)_i}{K_i^{\text{in}}K_i^{\text{out}} - K_i^{\text{rec}}} \quad (10)$$

Where K^{rec} refers to the reciprocated degree, so the numbers of links coming out of the node that have a corresponding link coming back.

3.3.4 Centrality

Degree centrality

The first and most intuitive one is the degree centrality, which relates how central a node is in the network to how many connections it has. In the financial network, having a high out-degree would mean that the entity is lending to a high number of other entities, which can also represent how diversified their portfolio is. A high in-degree for a borrowing company means their debt is financed by a great number of different financial institutions. The degree centrality of a node is the same as its degree.

$$\text{degree centrality}_i^{\text{out}/\text{in}} = k_i^{\text{out}/\text{in}} \quad (11)$$

Betweenness centrality

The second method to assess the centrality of a node is betweenness centrality. As the name indicates, this local measure assesses the rate of participation of a node in the shortest paths between pairs of other nodes. A node will be highly central through this method if, over all the shortest paths between all other nodes paired up, it has the highest amount of paths passing through it.

This measure is undirected, therefore an entity having a high betweenness centrality is an indication of its presence in a long financial interaction chain, but does not require the chain to be in one direction. For a node i , its betweenness centrality looks at the short-

est paths between any two other nodes of the network, and is defined as the ratio of the amount of the shortest paths that go through i over the total amount.

$$\text{betweenness centrality}_i = \sum_{(s,t)i} \frac{\text{amount of shortest paths between } s \text{ and } t \text{ that go through } i}{\text{total amount of shortest paths between } s \text{ and } t} \quad (12)$$

To calculate this measure, the RStudio *igraph* package is used, where an algorithm called Breadth-first search analyzes layer by layer the possible paths to return the shortest ones ?.

Eigenvector centrality

The last centrality method and maybe the most efficient one is the eigenvalue centrality. The eigenvector or eigenvalue centrality is a measure of the influence of a node through the importance of the nodes it is connected to. Each node is given a score dependent on the number of connections it has and the operation iterates itself until the vector converges towards the eigenvalues. The maximum resulting vector is normalized so as to have a score out of 1.

$$\text{eigenvector centrality}_i = \frac{1}{\lambda} A * \text{eigenvector centrality}_i \quad (13)$$

To calculate this measure, the RStudio *igraph* package is used ?.

3.4 Overview of networks

The DealScan database procures the elements to build a weighted financial network, where the links weights are the loan amounts, and the link direction "follows the money" (see Figure 2). From that weighted network, the undirected version of the network can be computed. This version of the financial network, shown in Figure 3, is used to calculate metrics that depend on how nodes are connected without looking into the weights. Combining the loan data, the emission data and the companies financial data, the third class of network is computed for each responsibility metric. This version of the network has the same topological connections as the financial network, but the links now represent the responsibility associated to a loan as can be seen in Figure 4. The direction makes it a lending responsibility for the sources and a borrowing responsibility for the borrowers.

ANNS measures are calculated internally to the responsibility network, the goal being how the responsibility of the surroundings of a node correlates with its own responsibility.

Centrality measures are calculated on the undirected network to focus on its topology.

ANND measures are by definition binary and thus ignore weights.

An overview of the network characteristics is given in the table 3.

Size	4557
Number of borrowers	2389
Number of lenders	2201
Average out degree	13.87
Maximum out degree	679
Average in degree	12.78
Maximum in degree	121
Density	3.24 e-05
Diameter (directed)	4
Diameter (undirected)	10
Average geodisic distance (undirected)	3.66
Average geodistic distance (directed)	1.19
Reciprocity	0
Clustering coefficient	7.00 e-04

Table 3: Characteristics of the network

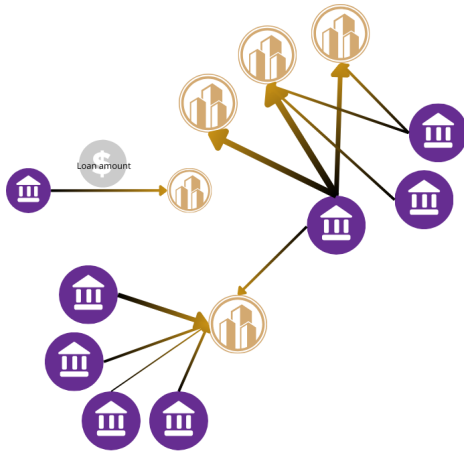


Figure 2: Representation of directed network where weights are defined by the lent amount from lender to borrower.

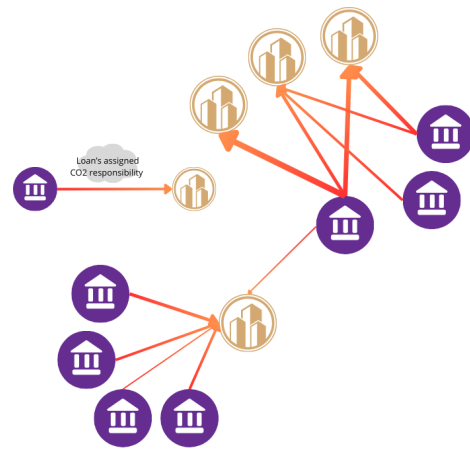


Figure 3: Representation of directed network where weights are defined by the CO₂ responsibility associated to the loan.

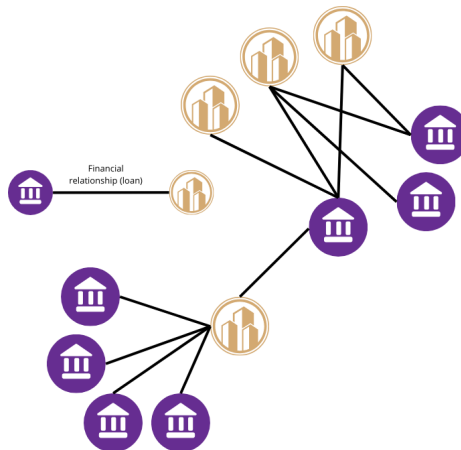


Figure 4: Representation of undirected binary network.

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4 Results

4.1 Comparison between metrics

The correlation table (Table 4) shows how similar the results of each metrics are. No metric gives results that are drastically different, an entity scoring high with one metric will also score high with another metric. In the table, the comparison with the out-strength from the loan network is also computed, so as to have a first idea of the correlation between financed emissions and amount lent.

A bigger difference could have been expected between the loan-weighted and loan-absolute correlations, as the weighted metric is directly proportional to the loan amount and the absolute and benchmark metrics ignore it. All three metrics are highly correlated with the loan amounts, indicating that lending behavior in quantity is hardly dissociable of emissions on the side of the borrower, regardless of the way the financed emissions are

computed.

	Weighted	Absolute	Benchmark	Loans
Weighted	1.00	0.92	0.84	0.93
Absolute	0.92	1.00	0.89	0.93
Benchmark	0.84	0.89	1.00	0.90
Loans	0.93	0.93	0.90	1.00

Table 4: Correlation table between the different financed emissions metrics and the out strength

The benchmark metric classifies financial institutions in a very close order to the absolute metric (89% correlated). The goal of the benchmark metric is to focus on the emission practice of a company relative to its sector, while taking into account its size, so as not to blindly assign responsibility to high emitters when it could be attributed to higher financial weight. Seeing the similarity between the classification in lending responsibility with these two metrics indicates that taking into account the size of the borrower and its distance to sectoral practice does not influence the classification. High level emitters in absolute values are also responsible for worse-than-average emission practice, regardless of size.

4.2 Correlation between weighted financed emissions metric and network measures

4.2.1 Centrality measures

The centrality measures are computed on the binary undirected network (as represented in Figure 4), taking into account only the topology of the financial network, without the weight of the loan interactions.

Eigenvalue centrality

There is a statistically significant relationship between the total financed emissions of a financial institution and its binary eigenvector centrality. With a positive correlation, the relationship indicates that banks that finance a high level of emissions tend to occupy a prominent place in the financial network. Influence in the network here is determined as an iterative loop of the importance of a node’s neighbors. A heteroskedastic behavior is visible: variance decreases along both variables and the relationship becomes more precise at high values. The log-log linear relationship slope picks up in those high values, indicating it gets closer to a linear relationship between the variables and further from a power law with a power between 0 and 1. Where the power law would indicate that the centrality increases at a slower pace for the same increase in financed emissions, a purely linear relationship keeps the increase consistent between both variables. For low levels, the variance of centrality changes less and makes the contrast less obvious between a slightly

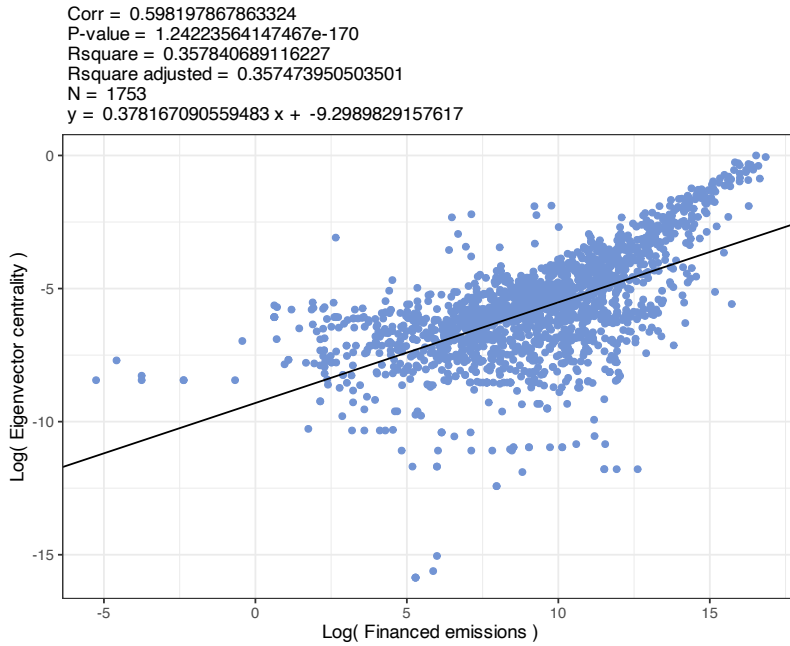


Figure 5: Log-log linear model for the eigenvalue centrality of lenders vs their financed emissions

more and a slightly less central node. This reduction of the points variance could be explained by the number of actors operating at such levels. As can be seen in Figure 1, 1% of actors move more than half of the total amount of loans from the dataset, and it has been shown through the correlations between metrics and loan amounts in Table 4 that all three metrics correlate positively responsibility with total amount lent. Therefore, a small portion of lenders can be expected to be responsible for a great amount of financed emissions, relatively to the rest of the data, leading to a less dispersed relationship.

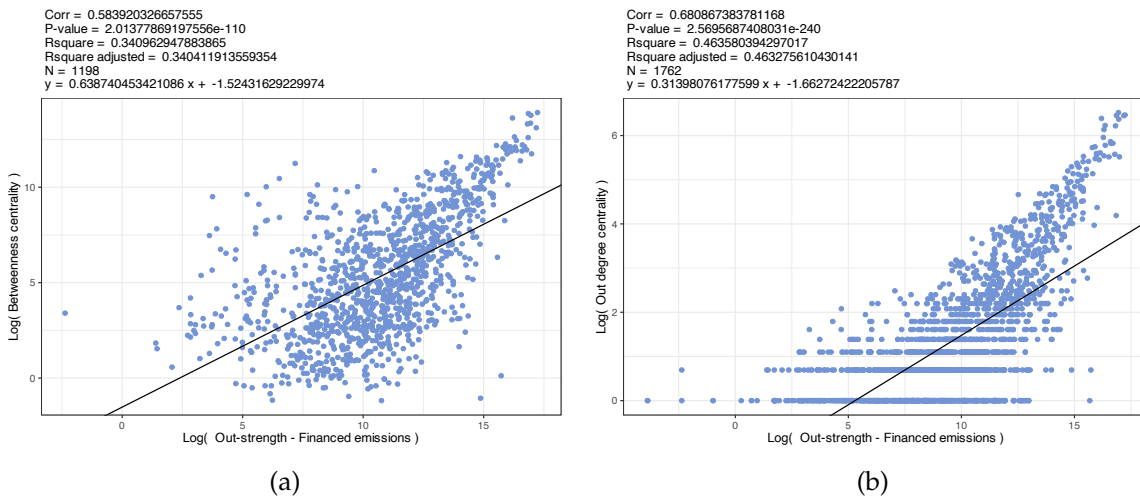


Figure 6: Log-log linear model for betweenness (a) and out-degree centrality of lenders (b) vs their financed emissions

Betweenness centrality

The betweenness centrality informs on the rate of participation of a node in the shortest paths between other nodes. The statistical values of the relationship between the betweenness centrality and financed emissions indicate a significant and strong relationship between the variables (see Figure 6a). The higher a bank ranks in financed emissions, the more it can be expected to be found in numerous chains of financial interactions, facilitating financial flows. A node that is highly central through the betweenness centrality presents influence and extended indirect reach over the network.

As can be seen in Figure 6b, the relationship between the out-degree centrality and the out-strength is statistically significant. Financial institutions with high levels of financed emissions also have a higher number of different borrowers in their portfolios, extending their reach towards more agents in the financial network. The results present a cone shaped graph with a large base. This indicates there is a high quantity of financial institutions for which the out degree is very low (the first steps are clearly visible for out-degrees equal to 1, 2, 3 and 4), independently of their financed emissions levels. This group of entities represented at the base are entities whose entire lending responsibility is tied to a small number of loans. For the institutions in this case that have higher responsibility, this means a more concentrated loan exposure.

The linear regression presents a clear heteroskedasticity, with the variance decreasing along the variables.

4.2.2 Average Nearest Neighbors

Case out-in

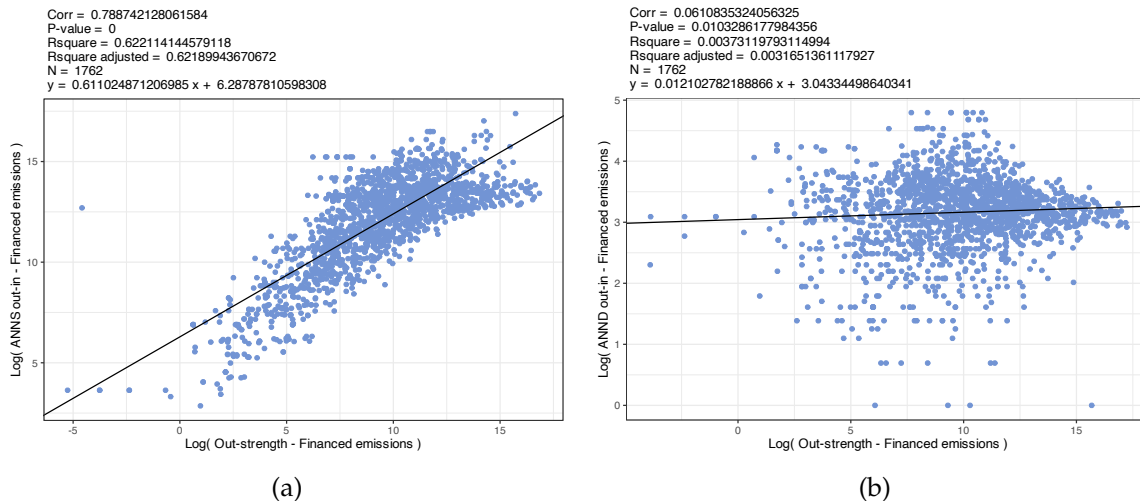


Figure 7: Log-log linear model for the average nearest neighbor out-strength (left) and out-degree (right) of lenders vs their financed emissions

There is a statistically significant relationship ($p < 0.01$) between the financed emissions of the lender and the average emitting practices of its borrowers as shown in Figure

7a. The high correlation coefficient of 79% indicates a strong relationship between how much a financial institution finances emissions through loans and the average borrowing responsibility over all its borrowers.

This means financial institutions with highly carbonated portfolios lend to entities that are more highly active in borrowing activities, and have more emissions financed through debt; bigger banks lend to bigger 'debt emitters'.

The ANND out-in informs on the borrowing activity of the entities a bank lends to, similar to ANNS out in, but focusing on the number of loans rather than their associated financed emissions. This measures quantifies how diverse the debt financing of the borrowers of a bank is.

A statistically significant relationship is found (p -value < 0.01), but the correlation is low (see Figure 7b). A positive correlation indicates that the more responsible a bank is, the more diversified the debt financing of its borrowers is. The in-degree of the borrowers also gives an indication of degree centrality within the network, resulting in banks responsible for more financed emissions lending to borrowers that are more widely connected. However, with low correlation, it cannot be stated that the in-degree, or portfolio diversification of the borrowers is systematically looked for by highly responsible banks.

Case out-out

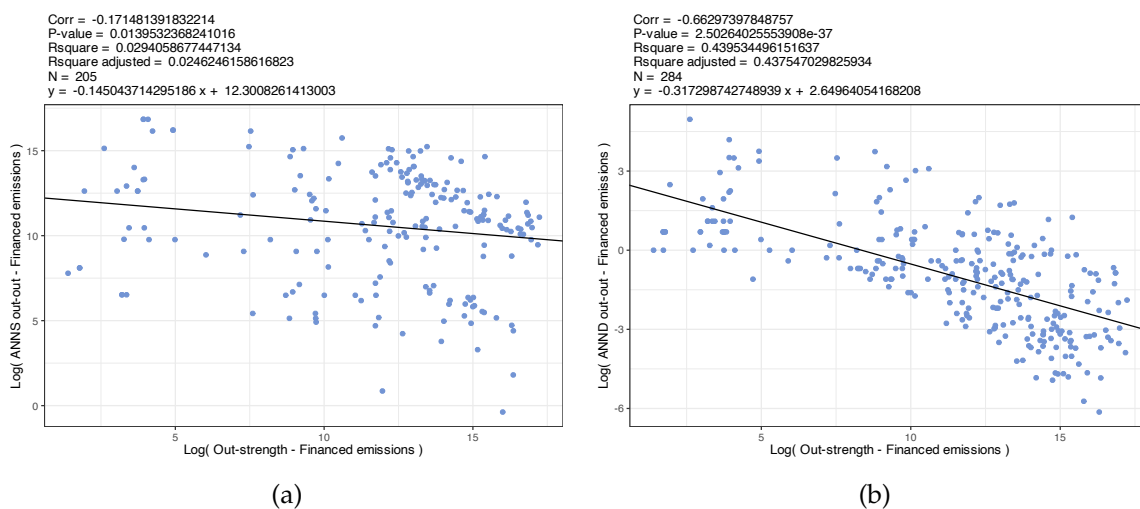


Figure 8: Log-log linear model for the average nearest neighbor out-strength (a) and out-degree (b) of lenders vs their financed emissions

The ANNS out-out has drastically less data points to work with because this case looks into network agents acting as lender and borrower simultaneously. These actors can be businesses issuing credits to customers or other banks taking part in interbank loans. A negative correlation implies that the more a financial institution finances emissions, the less the banks it lends to within the interbank sub-network tend to be active in lending activity.

The log-log linear regression has weak but significant statistical values (see Figure 8a). In

this sample, it appears that financial institutions with low levels of financed emissions will tend to lend to institutions with high levels of financed emissions.

The ANND out-out is relevant in the situation of interbank loans because it quantifies the diversification of lending portfolio of the entities a bank lends to. A negative statistically significant relationship is found through all metrics (see Figure 8b). The negative correlation can be interpreted as highly responsible banks using banks with less diverse lending portfolios as middlemen for indirect loans.

4.2.3 Clustering coefficients

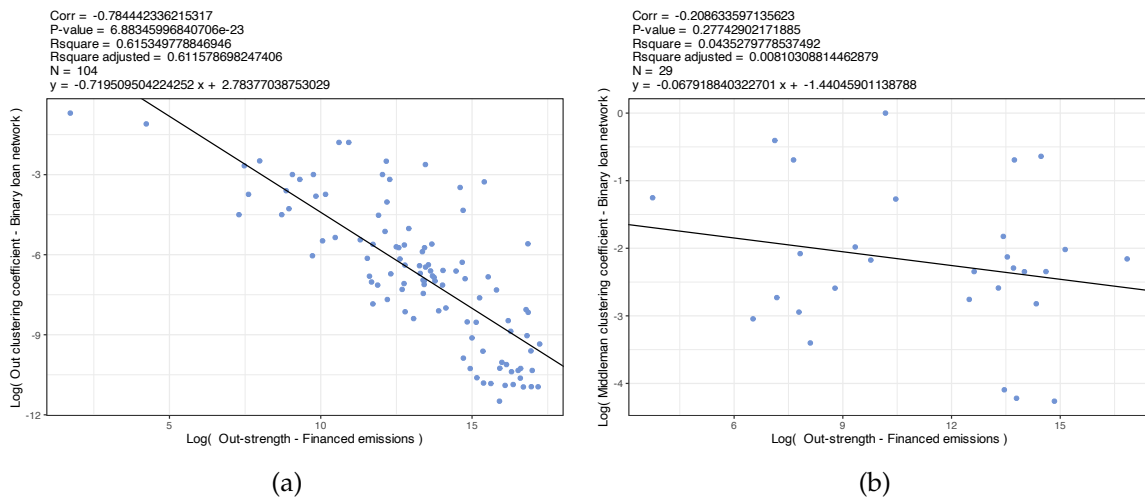


Figure 9: Log-log linear model for the out (a) and middleman (b) clustering coefficients of lenders vs their financed emissions

Out clustering coefficient

The log-log linear regression models show a significant ($p\text{-value} < 0.01$) and strong relationship between the financed emissions levels and the out-clustering coefficient of a node. The negative correlation expresses that financial institutions that finance more emissions will have a lower density of nodes to which they lend to that also interact with each other. This type of internal interaction could represent indirect loans or interbank loans where the flow of capital takes two different paths to the same destination. This poses the question of how to account for financed emissions in these cases. In this project, the financed emissions was defined as a first order operation, with its calculation involving the immediate source and target of a link. However in a case where a financial bank goes through another financial institution, it could be argued that this constitutes an indirect financing of emissions. The question of how the exposure trickles down the financial chain and integrate it in the responsibility network would be interesting to explore for future research.

Middleman coefficient

The linear regression model shown in Figure 9b present relationships that are, for all three metrics, not statistically significant (p -value > 0.05). The responsibility of a financial institution has no correlation with the how much it acts as middleman in indirect or interbank loans. The number of data points available for this measure are around a fifth of the amount available for the out-clustering coefficient. The number of clusters in the network is fixed but the role of the node that is being measured changed. From the number of data points it can be deduced that some of the entities that initiate the indirect loans go through the same middlemen. These middlemen, besides their role in these indirect loans, present a concentration of incoming loans from banks, therefore play a more central role (degree centrality) in the interbank sub-network.

5 Discussion and Conclusions

In this paper we try to explore the relationship between carbon emissions financed and the network structure of the market for syndicated loans. By means of different measures of network centrality as well as various definitions of the carbon emissions financed by banks, we show how there exists a positive and consistent relationship between how central a bank is in the lending market and the amount of carbon emissions financed by the bank. These results are in line with the existing literature on financial stability, sustainable finance, networks and syndicated loans. Our results give some insights into the structure of the financing of CO₂ and may be useful as they uncover potential climate threat to financial stability previously only considered in terms of price and other empirical corporate finance results (Reghezza et al., 2021; Degryse et al., 2021). Banks while considering the emissions in the lending process fail to do so from a network perspective, calling on considering this aspect as a potential risk to the financial system. These results represent, in fact, a call for both practitioners and supervisors and regulators to consider more widely the network and potential spillovers of climate risk also from a systemic point of view.

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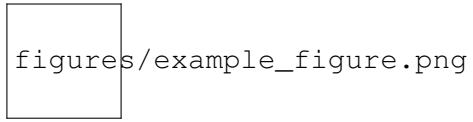


Figure 10: Example figure.