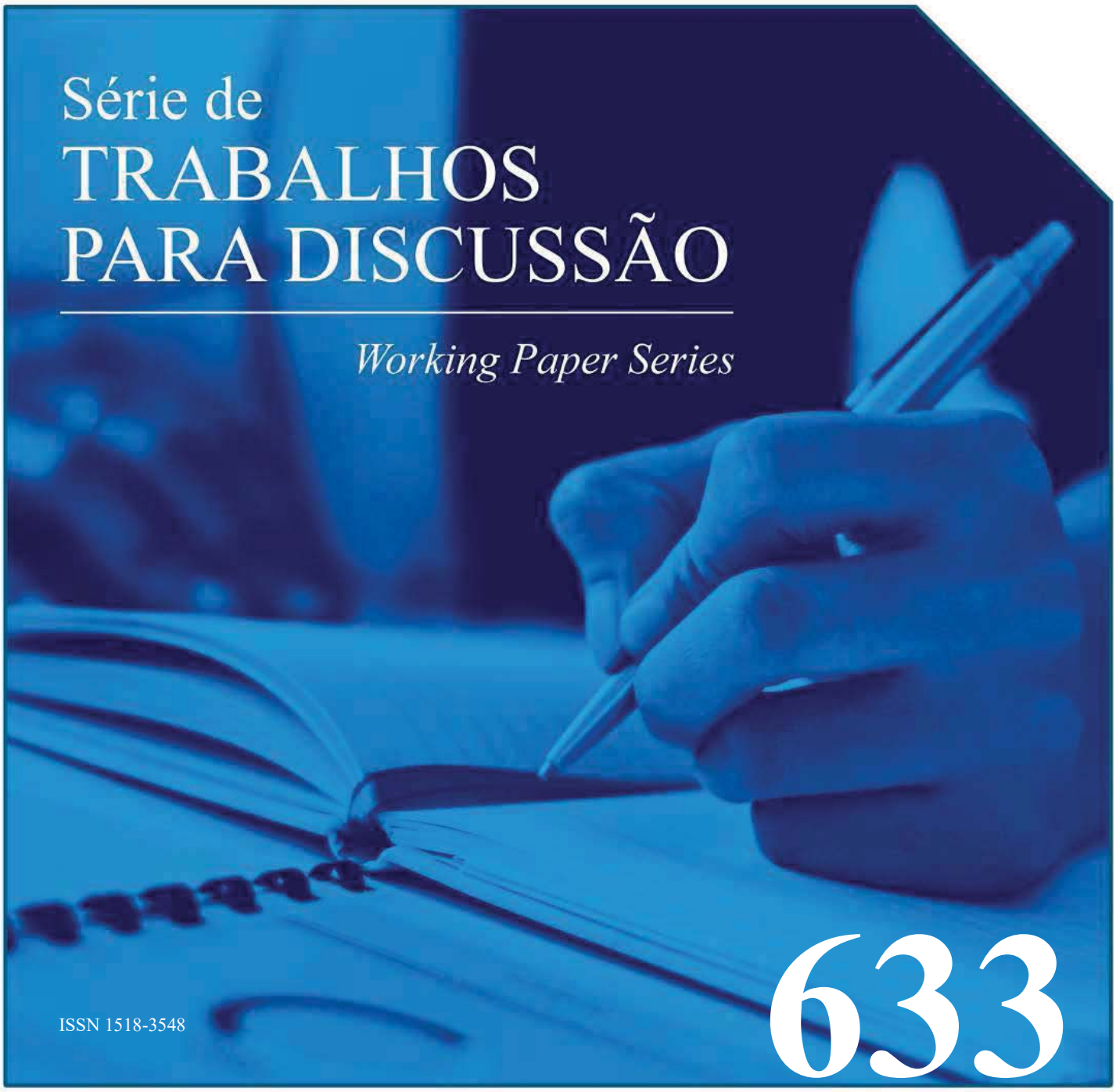


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The Impact of Climate Transition Risks on the Brazilian Financial Sector

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Non-Technical Summary

Climate risks are divided into two types: physical and transition risks. Climate physical risks refer to extreme climate events, such as floods and droughts. Climate transition risks are related to the strategies adopted by society in general (governments, corporations, etc.) to overcome the impacts of these climate events. An example of climate physical risk is the destruction of crops caused by floods or droughts. Regarding climate transition risks, some examples are (*i*) a sharp decline in asset prices in carbon-intensive sectors brought by climate change mitigation policies (e.g., carbon taxes) and (*ii*) additional operational and managerial costs to corporations due to the adoption of climate-neutral technologies.

Both physical and transition climate risks threaten financial stability, in the sense that the financial sector is exposed to agents that can suffer physical and financial losses related to climate risks. For instance, farmers whose crops were destroyed by extreme climate events will very likely not be able to honor their debt obligations against financial institutions fully. For this reason, with the recent upsurge of climate change, it is crucial for financial regulators to have a tool to measure the impacts of the risks associated with climate change on the financial sector.

In this article, we propose a methodology for calculating the impact of climate transition risks on the financial system. We assume that a carbon-intensive sector, the fossil mining sector (MINfos), will suffer an exogenous reduction in its production level due to the adjustment to a low-carbon economy. In the first round, this will cause a fraction of the physical capital stock of the other economic sectors to become stranded (i.e., unused). This effect will occur through two different channels: a reduction in both the MINfos sector's supply of inputs and the MINfos sector's demand for inputs. Next, the direct potential loss of the financial sector is calculated on the basis of the loans granted to the real sector as a whole. Finally, the financial sector's indirect potential loss is calculated by considering exposures in the interbank market.

Applying this methodology to a rich Brazilian financial dataset alongside with reputable international input-output databases, we observed that (*i*) the ranking of the sectors with the highest fraction of physical capital stranding varies with the model adopted to compute such stranding, (*ii*) there are many financial institutions (FIs) with a small potential (direct and indirect) loss and few FIs with a large potential loss, and (*iii*) the aggregate potential loss, both direct and indirect, declined during the period assessed in this study (2015-2022).

Sumário Não Técnico

Os riscos climáticos são divididos em dois tipos: riscos físicos e de transição. Os riscos físicos climáticos referem-se a eventos climáticos extremos, como enchentes e secas. Os riscos de transição climáticos estão relacionados às estratégias adotadas pela sociedade em geral (governos, empresas etc.) para superar os impactos desses eventos climáticos. Um exemplo de risco físico climático é a destruição de plantações causada por enchentes ou secas. Com relação aos riscos de transição climáticos, alguns exemplos são i) um declínio acentuado nos preços dos ativos em setores com uso intensivo de carbono causado por políticas de mitigação das mudanças climáticas (por exemplo, impostos sobre o carbono) e ii) custos operacionais e gerenciais adicionais para as empresas devido à adoção de tecnologias neutras do ponto de vista climático.

Tanto os riscos climáticos físicos quanto os de transição representam uma ameaça à estabilidade financeira, no sentido de que o setor financeiro está exposto a agentes que podem sofrer perdas físicas e financeiras relacionadas aos riscos climáticos. Por exemplo, os agricultores cujas colheitas foram destruídas por eventos climáticos extremos muito provavelmente não conseguirão pagar totalmente suas dívidas junto a instituições financeiras. Por esse motivo, com o recrudescimento das mudanças climáticas, é muito importante que os reguladores financeiros tenham uma ferramenta para medir os impactos dos riscos associados à mudança climática no setor financeiro.

Neste artigo, propomos uma metodologia para calcular o impacto dos riscos da transição climáticos no sistema financeiro. Supomos que um setor com uso intensivo de carbono, o setor de mineração fóssil (MINfos), sofrerá uma redução exógena em seu nível de produção devido ao ajuste para uma economia de baixo carbono. Na primeira rodada, isso fará com que uma fração do estoque de capital físico dos outros setores econômicos fique encalhada (ou seja, não utilizada). Esse efeito ocorrerá por meio de dois canais diferentes: uma redução tanto na oferta de insumos do setor MINfos quanto na demanda de insumos pelo setor MINfos. Em seguida, a perda potencial direta do setor financeiro é calculada com base nos empréstimos concedidos ao conjunto do setor real. Finalmente, a perda potencial indireta do setor financeiro é calculada considerando-se as exposições no mercado interbancário.

Aplicando essa metodologia a uma rica base de dados financeiros brasileira e respeitadas bases internacionais de insumo-produto, observamos que (*i*) o ranqueamento dos setores com a maior fração de perda de capital físico varia de acordo com a abordagem adotada para calcular tal perda, (*ii*) há muitas instituições financeiras (IFs) com pequena perda potencial (direta e indireta) e poucas IFs com grande perda potencial e (*iii*) a perda potencial agregada, tanto direta quanto indiretamente, diminuiu durante o período analisado neste estudo (2015-2022).

The Impact of Climate Transition Risks on the Brazilian Financial Sector

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Abstract

In this paper, we propose a methodology for computing the impact of climate transition risks on the financial system. The novelty of our analytical approach is that it accounts for indirect impacts stemming from inter-sectoral linkages (on the real sector side) and interbank loans (on the financial sector side). Our proposed methodology is carried out in three sequential steps: physical capital stranding due to a shock on a carbon-intensive economic sector (the mining fossil sector), potential direct losses experienced by the financial sector caused by its loan exposures to the real sector, and indirect potential losses due to interbank exposures. Applying this methodology to a rich Brazilian financial dataset alongside with reputable international input-output databases, we show that (*i*) the sectors with the highest rates of stranding physical capital vary with the model used to compute such stranding, (*ii*) the distribution of the individual direct and indirect losses are well-fitted by a power law, and (*iii*) the aggregate potential loss, both direct and indirect, declined during the period assessed in this study (2015-2022).

JEL classification codes: G21, G23, Q54, Q58.

Keywords: climate transition risk, financial stability, climate change.

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1 Introduction

The recent upsurge in climate change has become a major concern for central banks around the world. One of the well-founded reasons for this is the potentially detrimental effect of climate change on financial stability. Both climate change itself, as a consequence of the physical risks associated with extreme weather events (Botzen et al., 2019; Wallemacq and House, 2017) and chronic long-term shifts in climate patterns (Burke et al., 2015; Dietz and Stern, 2015; Kotz et al., 2024), and the costly actions adopted to combat and/or prevent its effects reflecting transition risks (NGFS, 2020; Semieniuk et al., 2021) can impair the ability of economic agents (e.g., firms and households) to honor some of or all their debt obligations against financial institutions (FIs onward). This can take place through many different channels. Extreme climate events, such as floods and droughts, can cause a reduction in production capacity, supply chain disruptions (Di Noia et al., 2025; Galbusera and Giannopoulos, 2018), and devaluation of assets through the impact on key sectors such as agriculture and energy. Unanticipated climate change mitigation policies, such as carbon taxes, may cause a sharp decline in asset prices in carbon-intensive sectors (Battiston et al., 2017; Campiglio et al., 2022; Gan et al., 2024). Corporate bonds issued by firms affected by climate change may offer yield spreads (Ye et al., 2024), bringing financial stress to these firms (FSB, 2020). Finally, the transition to more sustainable business models (e.g., by adopting climate-neutral technologies) can imply additional operational and managerial costs (Diluiso et al., 2021; Dunz et al., 2021; Gourdel et al., 2024).

This paper aims to propose a methodology for computing the impact of climate transition risks on the financial system. The key contribution of our research is that it advances the existing literature on climate transition risks faced by the financial sector (Battiston et al., 2017; Broccardo et al., 2024; Roncoroni et al., 2021; Semieniuk et al., 2021; Stolbova et al., 2018), which has primarily focused on potential losses arising from *direct* exposure to real-economy activities affected by the low-carbon transition. Our proposed framework also considers *indirect* losses experienced by both the real sector and financial institutions, stemming from inter-sectoral linkages among firms. The costs and losses experienced by a given economic sector due to the materialization of climate transition risks may, in fact, spill over into other sectors. This can occur because the affected sector will both reduce its demand for inputs from other sectors and decrease its supply of inputs to them. Meanwhile, losses experienced by FIs due to direct exposures to affected activities may propagate through interbank connections, engendering indirect losses. By properly accounting for indirect losses in both the real and financial sectors, we aim at providing a more comprehensive and robust estimate of aggregate potential losses stemming from climate transition risks.

Our proposed methodology is carried out in three sequential steps, as we detail in Section 3. First, we compute the stranding of physical capital caused by an exogenous shock to a carbon-intensive sector, as discussed in Van der Ploeg and Rezai (2020). More precisely, we consider an exogenous shock to the production of the mining of fossil fuels (MINfos) sector, reflecting the adjustment required to transition to a low-carbon economy. This reduction in the output of the MINfos sector, leads to a fraction of physical capital for each economic sector becoming stranded (i.e., unutilized) through two different channels: the shrinking production, on the one hand, leads to a reduced

supply of inputs to downstream sectors (captured using the Ghosh model); on the other hand, it induces a reduction in demand for inputs from upstream sectors (captured using the Leontief model).

In the second stage, we compute the direct potential loss of the financial system in light of the loans it extended to the (directly and indirectly) affected real economic sectors. In accordance with the original formulation of the DebtRank methodology, one of the most common frameworks used to analyze shock propagation across financial networks (Battiston et al., 2012a,b), we pose that losses on credit extended to a given debtor are proportional to the fraction of equity lost by that debtor (i.e., the debtor's *distress*). This equity loss, in turn, is proxied by the percentage of the debtor's stock of physical capital that becomes stranded. Therefore, a debtor i facing a capital stranding of $x_i\%$ will lose $x_i\%$ of her equity, and creditor j will suffer a loss equal to $A_{ji}x_i$, where A_{ji} is the exposure of j towards i.[1] The potential loss for a given financial institution FI is hence computed as the outstanding loans extended to different economic sectors multiplied by the corresponding fraction of stranded capital, divided by the FI's equity.

Finally, we compute the indirect potential loss experienced by the FIs by applying the *differential DebtRank* (DDR) methodology (Bardoscia et al., 2015) to the interbank exposures. The underlying rationale remains the same as in the previous stage: a FI i experiencing an equity loss equal to $x_i\%$ of its equity will default on the same percentage on its outstanding debt obligations to creditors in the interbank market. However, in this final stage, the distress to the equity of the FI corresponds to the direct loss it suffered, as calculated in the previous step. This implies that the direct financial losses caused by the initial shock will propagate following a cascade dynamics through the interbank network. This indirect loss is also expressed in terms of loss-to-equity ratio.

This extended methodology is applied to a rich Brazilian data set. We use input-output matrix data for the Brazilian economic sectors to compute the fraction of stranding physical capital after an exogenous shock on the MINfos sector. Additionally, we employ quarterly data on the loans extended by Brazilian FIs to firms, as well as data on the corresponding interbank exposures, between 2015-03 and 2022-12 to compute the direct and indirect impact on the Brazilian financial system.

We considered three levels of exogenous shock (represented by the percentage of output loss) in the MINfos sector: 5%, 10%, and 15%.[2] Our results show that (*i*) the ranking of most vulnerable

[1] See also Alexandre et al. (2023), who propose a slightly modified version of the DebtRank approach where debtors tend to default first on loans extended by weaker creditors.

[2] Although the magnitude of these shocks is primarily motivated by illustrative purposes—to demonstrate the transmission mechanisms and potential losses under three distinct transition scenarios differentiated by their stringency—they are not devoid of empirical grounding. The International Energy Agency (IEA) (IEA, 2021) outlines a pathway for phasing out fossil fuels to achieve net-zero emissions by 2050. According to this scenario, between 2020 and 2025, oil supply is expected to decline by 4% globally, coal by 21%, while natural gas is still projected to grow by 9%. Over a slightly longer horizon (2020–2030), oil supply should shrink by 21%, coal by 53%, and natural gas by 6%. It does not seem unreasonable to posit that a reduction in fossil fuel demand would lead to an almost proportional decline in the output of the MINfos sector. In the case of Brazil, IEA data (iea.li/nzedata) indicate that domestic oil production accounts for 89% of total fossil fuel output, while natural gas represents approximately 10%, and coal the remaining 1%. Taking these shares into account, and applying the IEA's projected supply reductions for each fossil fuel type, the weighted average reduction in fossil fuel production for Brazil would be approximately 3% between 2020 and 2025, and 20% between 2020 and 2030. These values suggest that the three shock magnitudes tested in our scenarios provide a plausible range for analyzing the potential impact of transition risks on the MINfos sector over the coming years.

sectors (i.e., those with a higher percentage of physical capital stranding after an exogenous shock on the MINfos sector) varies according to the model adopted to compute such stranding. Under the Ghosh model, the most vulnerable sectors are *Coal coke and refined petroleum products*, *Air transport*, and *Electricity and gas*. If the Leontief model is employed instead, the most vulnerable sectors are *Water transport*, *Mining support services*, and *Warehousing*. Furthermore, (*ii*) the distribution of the individual direct and indirect losses experienced by FIs are well-fitted by a power law (also called a scaling law). The economic substance of this statistical finding is that, while the majority of financial institutions are exposed to relatively small potential losses, a non-negligible number of institutions face disproportionately large potential losses with the potential to trigger systemic disruptions. Finally, (*iii*) both the aggregate direct and indirect potential loss declined during the period assessed in this study (2015-2022). For instance, the direct potential loss under the Ghosh model (considering a 5% shock on the MINfos sector) declined from 30% of the aggregate equity of the financial sector in 2015-03 to less than 15% in 2022-12. This decline reflects a reduction in the exposure of financial institutions to the fossil fuel mining sector (MINfoss) and to sectors closely linked to it. This shift is likely at least partly attributable to regulatory and supervisory developments that have taken place in recent years, particularly following the signing of the Paris Agreement in 2015, as we argue more extensively in section 4.

The remainder of this paper is structured as follows. The data set and related methodological aspects are described in Sections 2 and 3, respectively. Section 4 presents and discusses the results. Lastly, Section 5 provides final considerations.

2 The dataset

2.1 Inter-sectoral linkages

We obtained the inter-sectoral linkages among Brazilian economic sectors from two sources: the World Input-Output Database (WIOD) and the OECD Inter-Country Input-Output (ICIO) database. The analysis primarily relies on data from WIOD, a Multi-Regional Input-Output (MRIO) dataset that encompasses 43 countries alongside with a Rest of the World (ROW) region, and provides information for 56 economic sectors, categorized according to *Nomenclature statistique des activités économiques dans la Communauté européenne* (NACE) level 2 classifications. WIOD is particularly valuable for the main purposes of this novel empirical study as it uniquely offers sector-level estimates of physical capital stock.

However, a limitation of the WIOD database is that it aggregates all mining activities – both fossil fuel extraction and non-fossil mineral extraction – into a single sector. This poses a challenge for our analysis, which aims to investigate the risk of capital stranding resulting specifically from a transition shock affecting fossil fuel extraction. To properly address this limitation, we disaggregate the mining sector in WIOD using data from the OECD Inter-Country Input-Output (ICIO) database, which provides a more detailed breakdown, distinguishing between *Mining and extraction of energy-producing products* (NACE B05 & B06), *Mining and quarrying of non-energy producing products*

(NACE B07 & B08), and *Mining support service activities* (NACE B09).[3] After combining the two databases, we obtain an input-output (IO) matrix considering 58 different economic sectors in Brazil.[4] Each sector corresponds either to a single NACE code (considering the two-digit classification) or to a set of NACE codes.

A stylized representation of an IO matrix is depicted in Table 1. In this simple example, the economy is composed of two sectors, A and B. The area of the table depicted in yellow is the intermediate consumption matrix Z. If read vertically, the IO table displays the values of the inputs employed by each sector. Thus, Sector A bought \$100 in intermediate inputs from Sector A and \$250 from Sector B. The value of intermediate inputs plus the value added by the sector is equal to total output. The value added corresponds to the primary inputs (plus indirect business taxes and imports), whose main components are labor and capital inputs (Miller and Blair, 2009). If read horizontally, the IO table shows the destination of the production of each sector. For instance, Sector B sold \$250 in intermediate inputs to Sector A, \$50 to Sector B and \$100 to satisfy final demand (commonly further disaggregated into households and government consumption, investment, and net exports). The sum of intermediate inputs and the final demand is equal to the total output.

Table 1: *A stylized input-output table*

Inter-industry matrix	Sector A	Sector B	Final demand (f)	Total use (x)
Sector A (intermediate inputs)	\$100	\$150	\$200	\$450
Sector B (intermediate inputs)	\$250	\$50	\$100	\$400
Value added (v) (primary inputs)	\$100	\$200		
Total supply (x^T)	\$450	\$400		

As noted earlier, the WIOD database offers the valuable advantage of providing data on the physical capital stock of each sector. Table 2 provides a snapshot of the economic sectors with the highest levels of physical capital stock: real estate (RES+), public administration and defense (PUB+), and mining and extraction of energy-producing products (MINfos).

[3] In this paper, we use the most updated version of ICIO, dating from 2020 (https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm).

[4] For more details on how the databases were combined to disaggregate the mining sector in WIOD, see Modica Scala et al. (2024).

Table 2: *Most relevant economic sectors by physical capital stock*

Sector	NACE code(s)	Physical capital stock (US$ bi)
RES+	L	3,005.1
PUB+	O	892.5
MINfos	B05-06	333.9
MINoth	B07-08	291.6
AGRagr	A01	273.7
Other sectors		2,658.0

Legend:
RES+: *Real estate activities*.
PUB+: *Public administration and defense; compulsory social security*.
MINfos: *Mining and extraction of energy-producing products*.
MINoth: *Mining and quarrying of non-energy producing products*.
AGRagr: *Crop and animal production, hunting and related service activities*.

2.2 Financial dataset

Our rich financial dataset comprises the exposures of Brazilian FIs in two different networks: (*i*) the bank-firm corporate loans network, and (*ii*) the interbank market. The data is quarterly and spams from March 2015 (2015-01) through December 2022 (2022-04), totaling 32 periods. We included in our dataset FIs that are financial conglomerates or individual FIs and that have positive equity.[5]

The main source of information on the bank-firm credit network is the Central Bank of Brazil (BCB)'s Credit Risk Bureau System (SCR). The database comprises information on the ID of the lending FI, the ID of the firm, the amount of the loan, and the sector of the firm (represented by the two-digit NACE classification). We consider only firms listed in the *Alexandria* database (Docha and Rodrigues, 2023), as their sector classification is sourced from this database.

The interbank network considers all types of unsecured financial instruments, such as capital, credit, money markets, and foreign exchange operations. Different custodian institutions – Cetip, Central Bank of Brazil, and B3 – are responsible for the registration of these financial instruments. Exposures between FIs belonging to the same financial conglomerate are excluded. Also in this case, the dataset includes the ID of the lending FI, the ID of the borrowing FI, and the loan amount. As shown in Figure 1, the volume of interbank loans fluctuates between 75% and 97% of the volume of corporate loans during the period analyzed in this empirical study. *Electricity, gas, steam and air conditioning* (PWR+), *Wholesale trade, except of motor vehicles and motorcycles* (TRDwho), and *Food, beverages and tobacco products* (MANfoo) are the sectors that received most of the corporate loans (Figure 2).

[5]FIs' equity was retrieved from `https://www3.bcb.gov.br/ifdata`.

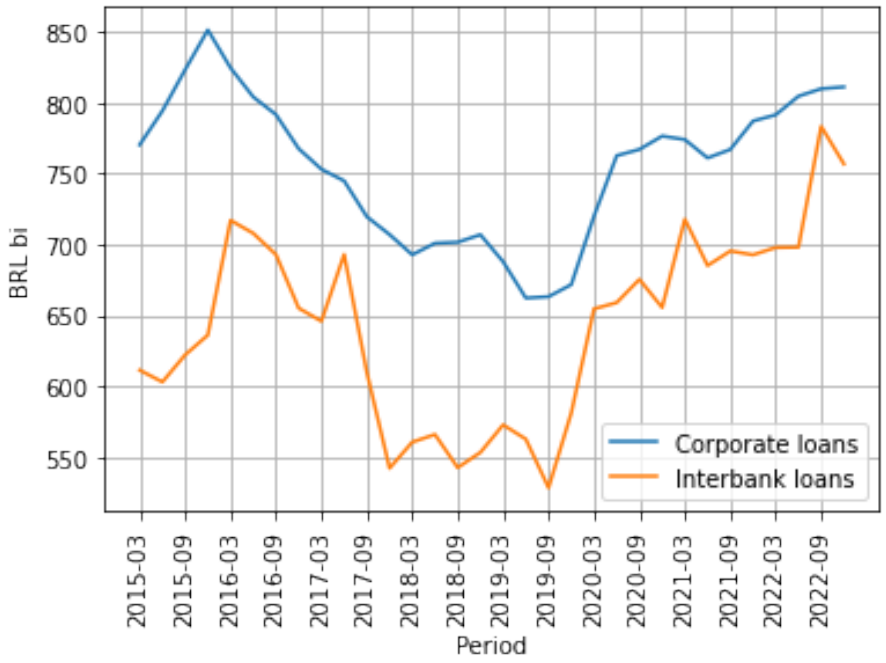


Figure 1: *Value of corporate and interbank loans (in BRL bi)*

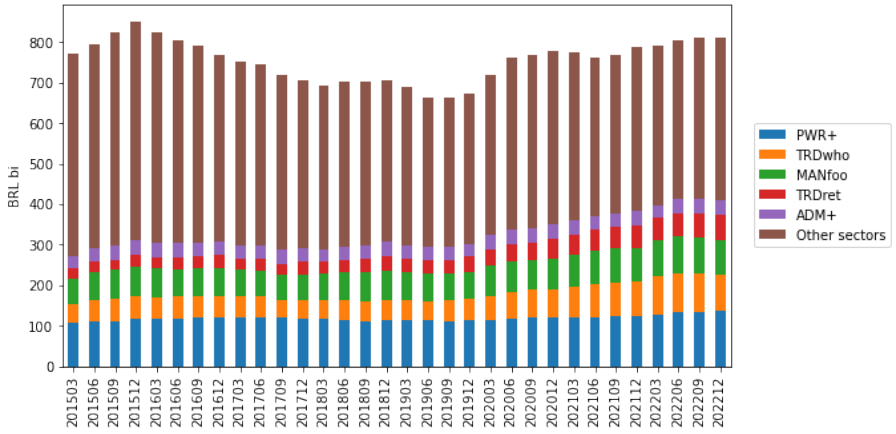


Figure 2: *Corporate loans by sector (in BRL bi). Legend: PWR+: Electricity, gas, steam and air conditioning; TRDwho: Wholesale trade, except of motor vehicles and motorcycles; MANfoo: Food, beverages and tobacco products; TRDret: Retail trade services, except of motor vehicles and motorcycles; ADM+: Administrative and support service activities.*

3 Methodology

3.1 Physical capital stranding

We rely on the two most diffused input-output models to compute the physical capital stranding across different economic sectors: the Leontief (Leontief, 1986, 1991) and Ghosh (Ghosh, 1958) models. These valuable analytical frameworks provide two complementary perspectives on economic production. The Leontief model looks at the *upstream* propagation of a given exogenous shock, moving from final demand back through the supply chain, from customers to suppliers. It is demand-driven, focusing on the inputs each sector requires to meet a given level of demand for its output. Conversely, the Ghosh model looks at the *downstream* propagation, from suppliers to their customers,

focusing on how a sector's output is distributed to other sectors, which reflects how resources are allocated moving forward through the supply chain.

Technically, the Leontief model involves calculating the *technical coefficients* of production a_{ij}, the direct inputs from sector i that sector j requires to produce one unit of its own output. The matrix A containing all the technical coefficients is derived dividing each column of the intermediate consumption matrix Z for the total output x of the corresponding sector. In the example depicted in Table 1, the input coefficients for sector A are $a_{AA} = 100/450 = 0.22$ and $a_{BA} = 250/450 = 0.56$.

The total intermediate inputs required to produce x, the vector of sectoral outputs, is then given by the matrix Ax. Reading the rows of the IO table, we can then write the accounting identity $x = Ax + f$, where f is the column vector of final demand. From this equation, the typical Leontief application assesses the output variation Δx due to a change in final demand Δf as follows:

$$\Delta x = (I - A)^{-1} \Delta f, \tag{1}$$

where $(I-A)^{-1}$ is the "Leontief inverse" L which captures the total impact on output emerging directly from the initial change in final demand, and indirectly from the recursive changes in input requirements and output levels triggered by that original variation.

On the other hand, the Ghosh model takes a downstream perspective by focusing on how a sector's output is allocated to other sectors. It calculates the *allocation coefficients* by dividing each row of the intermediate consumption matrix Z by the gross output of each industry. The matrix B represents these allocation coefficients, showing the share of sector i's output used by other sectors. For instance, considering Table 1, b_{AB}, the share of sector A's output that is used by sector B, is 0.33 (150 divided by 450). The Ghosh inverse matrix G is derived in a similar way to the Leontief inverse, starting from the accounting identity obtained by reading the IO table vertically. The model then defines the change in output due to a change in primary inputs v as:

$$\Delta x' = \Delta v' (I - B)^{-1}, \tag{2}$$

where $(I-B)^{-1}$ is the "Ghosh inverse" G, which shows the total (direct and indirect-recursive) effects of a change in supply on the output levels of the sectors of the economy.

The Leontief and Ghosh models can also be used to assess capital stranding, which measures how the capital stock of sectors may become idle due to changes in output levels caused by an exogenous shock to either final demand or the supply of primary inputs. We define $\hat{K}$ as a diagonal matrix containing the capital intensities of each sector i defined as:

$$K_i = k_i / x_i, \tag{3}$$

where k is the sector's stock of physical capital and x is the total output of the sector.

We define the matrix of *capital stranding multipliers* as:

$$S_L = \hat{K}L, \tag{4}$$

under the Leontief model, and

$$S_G = \hat{K}G^T, \tag{5}$$

under the Ghosh model. [6] The matrices S_L and S_G thus allow to capture the effect on the utilization of capital as a consequence of the direct and indirect impacts on output of a shock under the Leontief and Gosh models, respectively.

We label transition shocks, that is the exogenous change imposed to final demand or primary inputs of the focus sector j, by the symbol Θ_j. More precisely, Θ_j is a column vector with all 0 elements apart from its j^{th} element, which is equal to the exogenous shock on sector j. Subsequently, the vector representing the capital exposed to the shock (capital stranding) in each sector can be computed according to the Leontief model as follows:

$$K_L = S_L \cdot \Theta_j, \tag{6}$$

and, according to the Ghosh model, as:

$$K_G = S_G \cdot \Theta_j. \tag{7}$$

Each element of the vectors K_L and K_G measures the total change in capital stock of a given sector resulting from the considered exogenous shock, including direct and indirect effects. While the former measures sectors' capital stranding triggered by the decrease in the inputs demanded from the sector impacted by the shock, the latter measures the value of stranded physical capital triggered by the reduction in the supply of inputs from that affected sector. We then obtain the fraction of stranded capital in each sector by dividing this values by the sectors' stock of physical capital.

In our investigation, a decline in the output of the MINfos sector will lead to either a reduction in input demand from other sectors (under the Leontief framework) or a reduced supply of inputs to other sectors (under the Ghosh framework), thereby impacting the output of those sectors. These latter changes in output, in turn, will affect other sectors' demand or supply of inputs across the economy, creating further ripple effects, whose cumulative impacts are captured by the L and G inverse matrices. Each step of this recursive adaptation process of ouput – from the direct effects to higher-order indirect impacts – is associated with incremental increases in physical capital stranding, whose final scope is captured by the stranding multipliers.

[6] This definition of stranding multipliers assumes a linear relationship between production and capital utilisation, that is, constant returns to scale (Cahen-Fourot et al., 2021).

3.2 Direct potential loss

After computing the fraction of stranded physical capital, we compute the potential direct loss of FI i at period t according to:

$$DL_{it} = \frac{\sum_j A_{ijt}\beta_j}{E_{it}}, \tag{8}$$

where A_{ijt} is the loan extended by FI i to firm j at period t, β_j is the fraction of stranded capital of the economic sector to which firm j belongs, and E_{it} is the equity of FI i at period t. It is assumed that β is uniform across all firms belonging to a given economic sector.

Thus, the potential direct loss for a given financial institution equals the sum of its exposures to various economic sectors, each weighted by the proportion of stranded physical capital in that sector, expressed as a share of the institution's equity. The underlying hypothesis is borrowed from the *differential DebtRank* approach (Bardoscia et al., 2015), which posits that a debtor's potential default is proportional to its equity loss – in our case, arising from the stranding of a portion of its physical capital stock. The aggregate direct potential loss at period t is then computed as the sum of potential losses across all financial institutions:

$$DL_t = \sum_i DL_{it} w_{it}, \tag{9}$$

where $w_{it} = E_{it} / \sum_i E_{it}$.

3.3 Indirect potential loss

The final step of our analysis involves evaluating the indirect potential losses of financial institutions resulting from their mutual exposures in the interbank market. This is computed using the differential DebtRank (DDR) approach (Bardoscia et al., 2015). At period $s = 0$,[7] it is assumed that financial institutions with exposures to the real sector will incur a direct loss, as calculated in the previous step. At $s = 1$, these FIs will transmit part of this loss to their creditors in the interbank market, by partially defaulting on their outstanding debt, in proportion to the equity losses they have incurred. In the next iteration, financial institutions that incurred losses in the interbank market pass on part of these losses to their own creditors. This process of loss propagation continues over subsequent periods.

Let A_{ij} denote the exposure of FI i towards FI j in the interbank market. The cumulated loss transmitted by FI j to its creditor FI i at a given period s is denoted by $L_{ij}(s)$. Considering all the debtor's of FI i, the aggregate loss experienced by FI i up to period s is $L_i(s)$. The dynamics of these two variables are governed by the following equations:

[7] In this paper, there are two different period notations. The subscript notation t used in the previous section and omitted in this subsection for simplicity refers to the date (month-year). The notation s refers to the number of iterations after the shock, where $s = 0$ refers to the period in which the shock is imposed.

$$\Delta L_{ij}(s) = min\left(A_{ij} - L_{ij}(s-1), A_{ij}\frac{[L_j(s-1) - L_j(s-2)]}{E_j}\right), \tag{10}$$

$$\Delta L_i(s) = min\left(E_i - L_i(s-1), \sum_j \Delta L_{ij}(s)\right). \tag{11}$$

Equation 10 states that the the new flow of loss transmitted from debtor FI j to creditor FI i at period s, i.e., $\Delta L_{ij}(s) = L_{ij}(s) - L_{ij}(s-1)$, is equal to the exposure of creditor i to debtor j multiplied by the equity loss suffered by debtor j in the previous step. Equation 10 also implies that the loss imposed by FI j to FI i cannot exceed the exposure of FI i towards FI j. Moreover, the variation in the total loss transmitted to FI i by their debtors at period s, given by $\Delta L_i(s) = L_i(s) - L_i(s-1)$, cannot exceed the equity of i minus the previous stock of loss, which means that a creditor FI cannot suffer a loss greater than its equity, as per equation 11.

The process converges after a sufficiently large number of periods $S \gg 1$, when no further loss transmission occurs. Upon convergence, the total indirect potential loss incurred by FI i is calculated as follows:

$$IL_{it} = \frac{L_i(S)}{E_{it}}, \tag{12}$$

while the aggregate indirect potential loss is computed according to:

$$IL_t = \sum_i IL_{it} w_{it}, \tag{13}$$

where $w_{it} = E_{it} / \sum_i E_{it}$.

4 Results

Tables 3 and 4 show the five sectors with the highest rates of stranded physical capital after an exogenous shock on the MINfos sector according to the Ghosh and Leontief models, respectively. The ranking of the most affected sectors varies according to the model perspective employed. Note that only the *Air transport* (TRAair) sector figures among the five most affected sectors according to both methodologies.

According to the Ghosh model, which looks at the *downstream* propagation – i.e., how a reduction in the production allocated from suppliers to customers affects sectors' output levels –, the most impacted sector is the *Coke and refined petroleum products* (MANref) sector, which has a potential loss of 1.88% of its physical capital stock for a 5% negative shock on the MINfos sector. In addition to the *Air Transport*, sectors related to land transport, power generation, and the manufacture of chemical products are also highly affected, due to their strong reliance on inputs sourced from the

MINfos sector.

The physical capital stranding computed according to the Leontief model adopts instead an *upstream* perspective, focusing on the impact on output resulting from the cumulative reduction in inputs demand triggered by the shock. The most impacted sectors, in this case, are those that rely more heavily on (direct and indirect) sales to the MINfos sector – that is, sectors for which a larger share of their output is purchased as input by MINfos, either directly or through its other suppliers. The most affected sector in this case is *Water transport* (TRAwat), followed by *Mining Support Service Activities*, services related to transport, legal and accounting services and, again, *Air Transport*.

A comparison of tables 3 and 4 allows to appreciate that the Ghosh model is generally associated with higher rates of physical capital stranding. It is worth noting, however, that the plausibility of the supply-driven Ghosh model as a quantity model has been questioned (Dietzenbacher, 1997; Giarratani, 1980). This partly motivates our extension of Cahen-Fourot et al. (2021) through the inclusion of the more reliable demand-driven Leontief quantity model. While these considerations advise caution when interpreting results from the Ghosh model, the significance of these findings should not be entirely dismissed. In fact, it has been shown that the Ghosh supply-driven model becomes more plausible if it is interpreted as a price model (Dietzenbacher, 1997), where sectoral output values change due to price changes triggered by an exogenous shock to primary inputs. This offers an alternative perspective for interpreting the results of our scenario based on the Ghosh model, where the shock can be seen as a devaluation (rather than a quantity reduction) of the MINfos sector's output. Such a devaluation is also a plausible consequence of reduced demand during the fossil fuel phase-out. This shock then propagates downstream, triggering devaluations in other sectors' outputs, which ultimately translate into a devaluation of the physical assets used to produce those outputs – i.e., capital stranding as a negative capital gain – and, eventually, a reduction in the value of their equity, with similar effects on their financial solvency.

Table 3: Most affected sectors according to the Ghosh model

Sectors with the highest rates of physical capital stranding after a shock of magnitude ζ in the MINfos sector.

Sector	$\zeta = 5\%$	$\zeta = 10\%$	$\zeta = 15\%$
MANref	1.88	3.76	5.64
TRAair	0.42	0.85	1.27
PWR+	0.41	0.81	1.22
TRAinl	0.29	0.58	0.86
MANche	0.17	0.33	0.50
Other sectors	0.02	0.05	0.07

Legend:
MANref: *Coke and refined petroleum products*.
TRAair: *Air transport*.
PWR+: *Electricity, gas, steam and air conditioning*.
TRAinl: *Land transport and transport via pipelines*.
MANche: *Chemicals and chemical products*.

Table 4: Most affected sectors according to the Leontief model

Sectors with the highest rates of physical capital stranding after a shock of magnitude ζ in the MINfos sector.

Sector	$\zeta = 5\%$	$\zeta = 10\%$	$\zeta = 15\%$
TRAwat	1.05	2.11	3.16
MINsup	0.33	0.66	0.99
TRAwar	0.19	0.38	0.56
PROleg	0.19	0.37	0.56
TRAair	0.15	0.30	0.45
Other sectors	0.02	0.03	0.05

Legend:

TRAwat: *Water transport*.

MINsup: *Mining support service activities*.

TRAwar: *Warehousing and support activities for transportation*.

PROleg: *Legal and accounting services; activities of head offices; management consultancy activities*.

TRAair: *Air transport*.

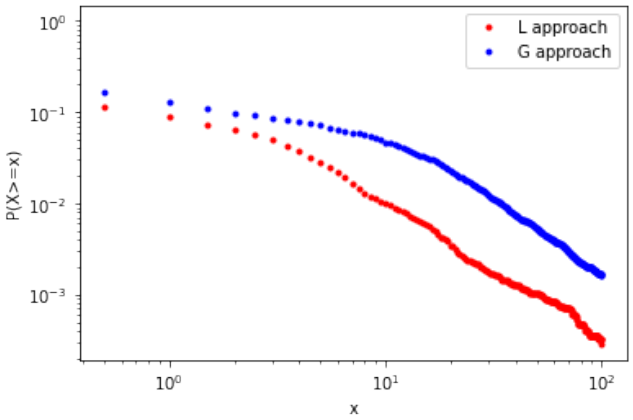
The distribution of individual direct potential losses of the Brazilian FIs is depicted in Figure 3. This distribution appears to be well-fitted by a power law. Notably, once again the Ghosh model tends to predict higher potential direct losses compared to the Leontief model. Similar patterns are observed in the distribution of individual indirect financial losses in light of the mutual exposure of banks on the interbank market, as shown in Figure 4.

The power law distribution of potential (direct and indirect) losses to which financial institutions are exposed has important implications for macro-financial stability, as it suggests that while most financial institutions are likely to experience moderate losses, a non-negligible share faces the risk of disproportionately high potential losses, with possible system-wide repercussions.[8]

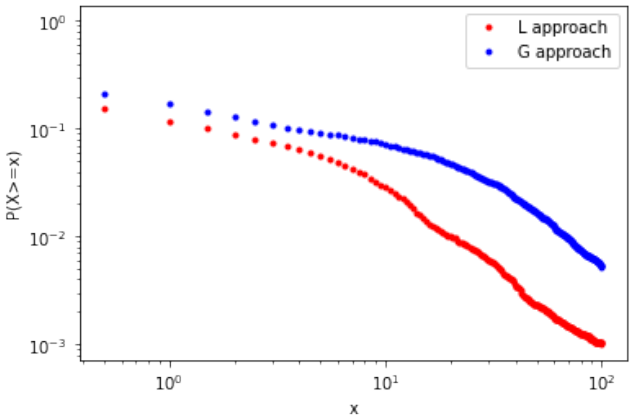
[8]Financial markets exhibit a range of pervasive empirical regularities that follow power-law distributions, as aptly reviewed and discussed, *inter alia*, in Gabaix (2009, 2016) and Lux and Alfarano (2016). For example, stock market returns are characterized by an approximately cubic power law, and volatility displays long-range dependence, evidenced by a hyperbolic decline in its autocorrelation function. However, to the best of our knowledge, our finding that individual direct and indirect losses incurred by FIs in response to climate transition risk follow a power-law distribution has not yet been documented in existing studies.

Figure 3: Individual direct impact

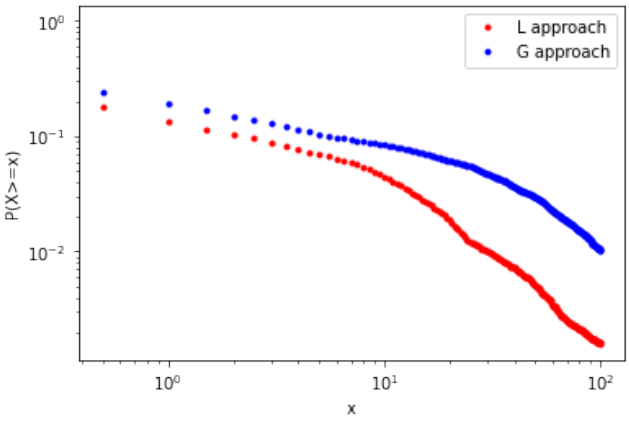
Distribution of individual direct potential losses



$\zeta = 5\%$

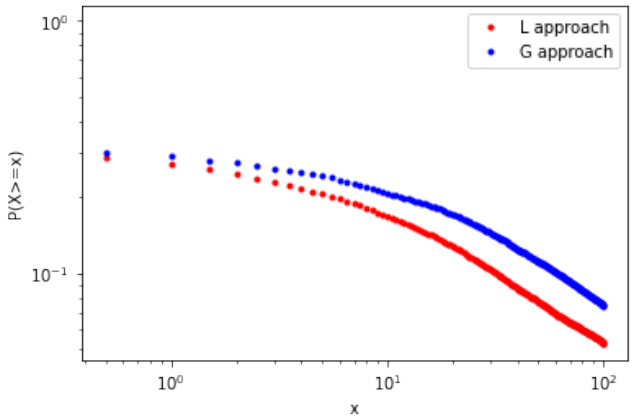


$\zeta = 10\%$

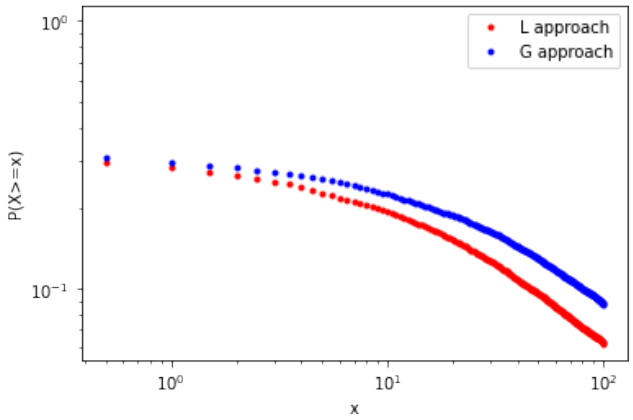


$\zeta = 15\%$

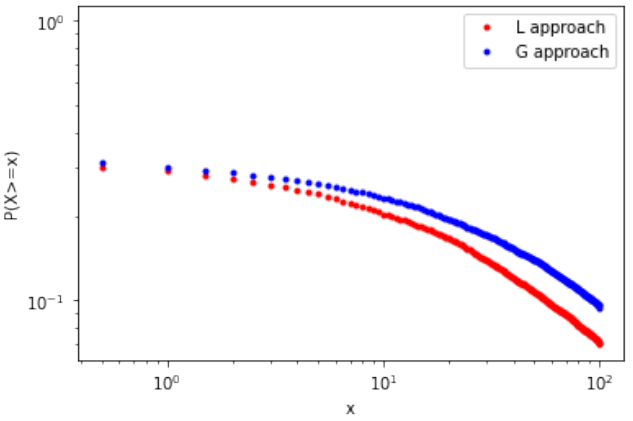
Figure 4: Individual indirect impact
Distribution of individual indirect potential losses



$\zeta = 5\%$



$\zeta = 10\%$

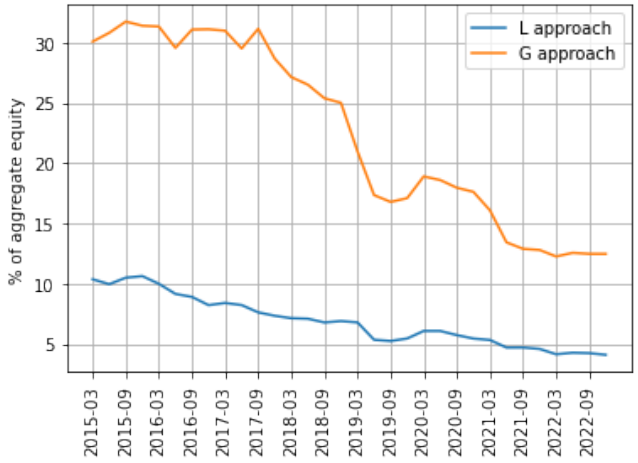


$\zeta = 15\%$

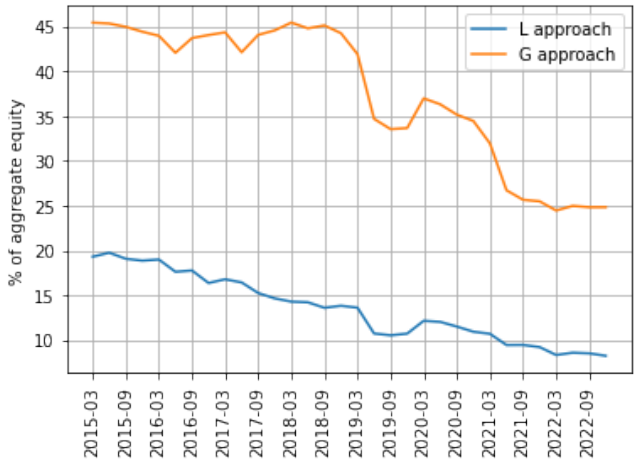
The aggregate – i.e., related to the whole financial system – direct (Figure 5) and indirect (Figure 6) potential losses have both decreased over the period analyzed in this empirical study (2015–2022). For example, under the Ghosh model, a 5% negative shock to the MINfos sector led to a decline in direct potential losses from 30% of the financial sector's total equity in 2015-3 to under 15% by 2022-12.[9]

[9]The magnitude of potential losses for the Brazilian financial sector due to the propagation of shocks in financial networks presented here is consistent with the findings of other studies, such as Alexandre et al. (2024).

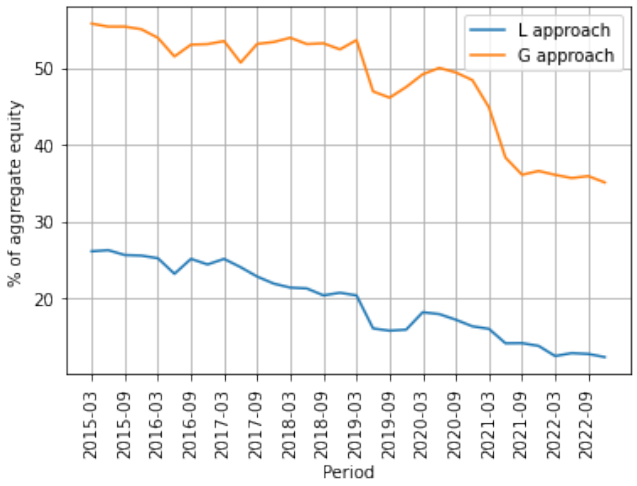
Figure 5: Aggregate direct impact
Direct potential loss of the whole financial system as a % of equity



$\zeta = 5\%$



$\zeta = 10\%$



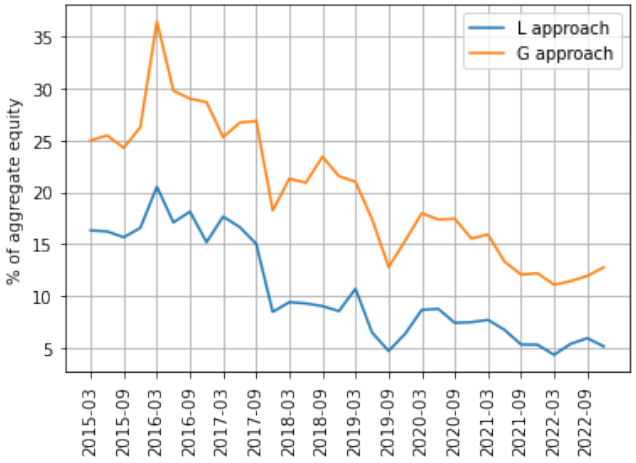
$\zeta = 15\%$

This shift may partly reflect an increased awareness of transition risks among financial institutions and partly result from regulatory and supervisory developments implemented in recent years. Since the Paris Agreement, many central banks have started to incorporate climate risk into the scope of macroprudential supervision. These efforts have aimed to enhance transparency in climate-related disclosures and have included the implementation of climate stress tests on the portfolios of financial

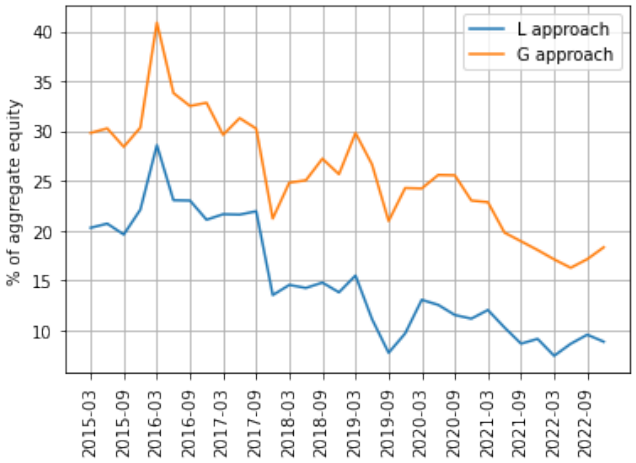
institutions. Similar initiatives have also been underway in Brazil. While many of these initiatives have been implemented only in the later part of our time sample, the commitment of Brazilian Financial Supervisory Authorities – and the inclusion of climate-related aspects in their mandate – began earlier, shortly after the signing of the Paris Agreement. This evolving regulatory environment may have contributed to shaping financial investor expectations and encouraging the reallocation of capital away from portfolios heavily exposed to carbon-intensive sectors.[10]

[10]Since 2020, the Brazilian Central Bank has begun including environmental, social, and climate-related risks in its prudential supervision framework, launching a new agenda (called Agenda BC) to integrate climate risks into financial regulation. Resolutions 4.943/21 and 4.944/21 of the Conselho Monetário Nacional (CMN, National Monetary Council) mandate that financial institutions implement governance structures and risk management frameworks to identify, assess, and manage environmental, social, and climate-related risks in their operations and credit allocation processes. After joining the Network for Greening the Financial System (NGFS) in 2020, the Brazilian Central Bank started requiring all banks operating in the country to conduct climate-related stress tests starting in 2022.

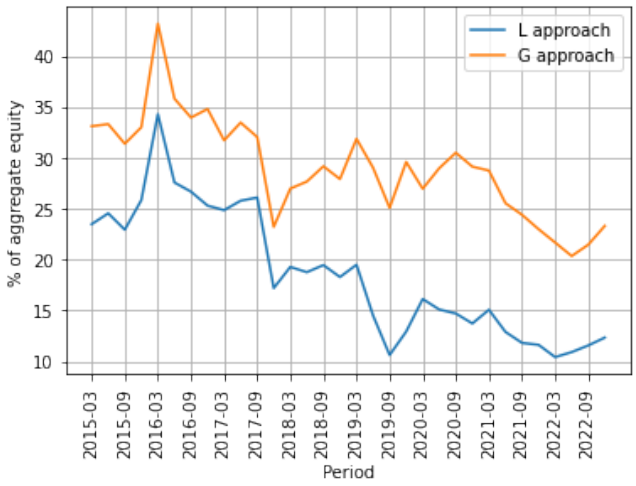
Figure 6: Aggregate indirect impact
Indirect potential loss of the whole financial system as a % of equity



$\zeta = 5\%$



$\zeta = 10\%$



$\zeta = 15\%$

5 Concluding remarks

Climate-related risks are increasingly recognized as significant potential sources of financial instability, necessitating proactive management and coordinated action from both private economic

agents and governments, including financial regulatory and supervisory authorities. Both physical risks – such as extreme weather events and rising sea levels – and transition risks – stemming from shifts towards a low-carbon economy – can impair the ability of economic agents to meet their debt obligations, thereby posing threats to the financial system.

This paper presents a methodology to assess potential losses to the financial system through financial institutions' (FIs') exposure to an exogenous climate transition shock associated with the phase-out of fossil fuels. More specifically, we model an exogenous decline in the output of a carbon-intensive sector, namely the mining and extraction of fossil fuels (MINfos). This initial shock propagates through inter-sectoral linkages, causing capital stranding across the economy, and subsequently affecting the financial sector via financial institutions' exposures to the real economy, as well as their mutual exposures through interbank lending. The model is empirically implemented using comprehensive financial data from the Central Bank of Brazil, alongside input-output data for Brazil sourced from the World Input-Output Database (WIOD) and the OECD Inter-Country Input-Output (ICIO) tables.

The proposed analytical methodology is carried out in three sequential steps: (*i*) computation of sectors' physical capital stranding resulting from a reduction in the output of the MINfos sector, using two complementary perspectives – a supply-driven (Ghosh) and a demand-driven (Leontief) model; (*ii*) calculation of the financial system's direct potential losses, measured as the outstanding value of corporate loans to different economic sectors multiplied by their fraction of stranded capital, and expressed as a share of each FI's equity; and (*iii*) computation of the indirect potential loss experienced by the financial institutions through the differential DebtRank methodology, accounting for their reciprocal interbank exposures.

We apply three plausible levels of exogenous shock, featuring reductions of 5%, 10%, and 15% in the output of the MINfos sector. Our key results are the following. First, the ranking of most vulnerable sectors (i.e., those displaying higher capital stranding) depends on the model adopted. According to the Ghosh model, focusing on how a sector's output is distributed to other sectors, the most vulnerable sectors are *Coal coke and refined petroleum products*, *Air transport*, and *Electricity and gas*; according to the Leontief model, focusing on the demand for inputs needed by a sector to produce so to meet its demand, the most vulnerable sectors are *Water transport*, *Mining support services*, and *Warehousing*. Second, the distribution of the individual direct and indirect losses experienced by FIs is well-fitted by a power law. The economic significance of this novel statistical finding is that, although losses are generally low for most institutions, the possibility of exceptionally high losses with systemic repercussions is non-negligible. Third, both the aggregate direct and indirect potential losses has declined during time span analyzed in this empirical study (2015-2022). Given the static character of the input-output analysis of capital stranding over this period, this result highlights that financial institutions have partly reallocated their portfolios away from sectors more exposed to mining and extraction of fossil fuels. This shift seems to reflect both increased awareness of transition risks, and the effective enforcement of recent supervisory and regulatory policies aimed at promoting the reallocation of capital from portfolios heavily exposed to carbon-intensive sectors.

The proposed methodological framework is not without inevitable limitations, many of which stem from the inherent constraints imposed by the modeling approaches used in the empirical study. For instance, while we have discussed potential criticisms of the Ghosh model as a quantity model, the widely used Leontief model is also often criticized for its rigidity due to the assumption of perfect complementarity. Additionally, the assumption of constant technological coefficients implies no technological progress, which reduces the model's plausibility over longer time horizons (but recall that we use data from 2015 to 2022 only). Similarly, the assumed relationship between physical capital stranding, equity losses, and debt defaults – common in financial network analyses such as the DebtRank approach used here – may be plausible on average and over medium to long-term horizons, but may be overly simplistic when analyzing short-term situations for individual entities. Finally, this article does not address the interaction between physical and transition climate risk.[11] While we acknowledge these inevitable limitations, we believe that these very features of our proposed approach offer offsetting benefits in terms of simplicity, intuitiveness, and clarity of results, contributing also to enhance its proper replicability in other geographical contexts or time spans. In this regard, the proposed methodology serves as a fast and flexible tool for financial regulators and supervisory authorities. When effectively used alongside other complementary climate stress-testing tools, it can certainly provide a rapid yet reasonably accurate snapshot of the exposure of real and financial sectors to various types of transition shocks.

[11] On this topic, see, for instance, Rebonato et al. (2025).

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