Industrial and Corporate Change, Volume 00, Number 00, pp. 1–26
doi:10.1093/icc/dtag032
Published: 23 June 2026
Original Article

OXFORD

The worth of connections. An assessment of the impact of interlocking directorates on resources allocation

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To what extent do connections between bankers and firms distort lending decisions, acting as a misallocative financial friction? This paper examines credit misallocation arising from the network of interlocking directorates in Portugal. We show empirically that ties between firms and lenders generate preferential lending, in contrast to the relationship-lending view that such ties primarily alleviate asymmetric information. Yet in a counterfactual where interlocks are removed and credit is reallocated to equalize marginal returns across firms, aggregate output barely moves. This muted macroeconomic response implies that the distortions induced by favoritism are surprisingly limited. We argue that this result stems from the fact that less efficient firms are located farther from banks in the network—greater geodesic distance restricts their access to preferential credit—thereby attenuating the misallocative impact of interlock-driven favoritism.

JEL Classification: G21, G34, L14

1. Introduction

In recent years, a growing body of research has examined the role of both formal (e.g. interlocking directorships, where two or more legal entities share at least one board member) and informal (e.g. personal acquaintance relationships among executives across organizations) firm-bank ties in shaping credit availability for borrowing firms. Ongena and Smith (2000) provide a review of the theoretical underpinnings, while Kysucky and Norden (2016) offer a meta-analysis discussing the cross-country evidence. While this literature consistently documents a positive association between firm-bank ties and both credit access and credit volume, their effects on credit allocation efficiency and macroeconomic performance remain insufficiently explored.

This gap is critical, given the well-known role of financial distortions in driving resource misallocation. Distortions in the allocation of financial resources across sectors (Bleck and Liu, 2018) and across firms and plants (Midrigan and Xu, 2014) have been identified as possible sources of inefficiency, with significant consequences for economic growth (Jones, 2013; Jovanovic, 2014) and cross-country

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differences in total factor productivity (TFP) (Restuccia and Rogerson, 2013).[1] Financial frictions can impede the growth of productive firms through two primary channels. First, they may restrict credit to more efficient firms while allowing less efficient firms to survive, distorting competitive dynamics and resource allocation (Banerjee and Moll, 2010; Schivardi *et al.*, 2022). Second, they can raise entry barriers, discouraging the market entry of firms with superior technologies despite their potential efficiency advantages (Caballero *et al.*, 2008; Casares and Poutineau, 2013; Bergin *et al.*, 2018). Thus, financial frictions contribute to misallocation both by constraining the growth trajectories of high-productivity firms and by distorting the entry and exit dynamics that are central to industrial organization and aggregate productivity.

A growing body of work in corporate finance and organizational sociology suggests that interlocking directorates may operate as a nontrivial financial friction, with ambiguous implications for the allocation of credit. Theoretically, two opposing mechanisms emerge. The first is rooted in the traditional view that stable, repeated interactions enhance the production and transmission of information. A long-established literature argues that enduring relationships reduce the cost of generating soft information on borrowers (Petersen and Rajan, 1994; Berger and Udell, 1995; Boot, 2000). Interlocking directorates, by creating channels for sustained interaction among board members, extend this logic: directors exchange assessments of managerial practices, corporate culture, and individual reputation (Davis, 1991; Davis and Greve, 1997; Haunschild and Beckman, 1998). These exchanges render informational flows more efficient, lowering the transaction costs of screening and monitoring (Liberti and Petersen, 2019). From this perspective, proximity within the interlocking network parallels the role of physical proximity in relationship lending (Petersen and Rajan, 2002; Berger *et al.*, 2005; Degryse and Ongena, 2005; Degryse *et al.*, 2009). Firms that lie closer in the director network can be assessed at lower cost, thus reducing informational asymmetries (Engelberg *et al.*, 2012; Ferreira and Matos, 2012; Karolyi, 2018). If banks leverage these informational advantages correctly, interlocks should, in principle, improve the efficiency with which credit is allocated across heterogeneous firms.

A second mechanism, however, points toward a potentially distortionary role of interlocks. Social proximity may alter subjective evaluations of firms in ways that depart from fundamentals. Psychological and sociological theories suggest that organizations may "bask in reflected glory" (Kilduff and Krackhardt, 1994), interpreting a firm's association with high-status directors as an implicit quality signal. Likewise, relational closeness within the network may engender perceptions of firms as "friends" or "friends of friends," increasing the scope for favoritism independent of underlying creditworthiness (Barone *et al.*, 2021). In this view, interlocks shape not only the quantity of information available but also the manner in which this information is interpreted, thereby affecting the allocation of credit even in settings where information is abundant. These concerns extend to corporate governance more broadly. Shared directors may align corporate decisions with the interests of lenders in ways that need not enhance shareholder value. Güner *et al.* (2008) show that firms with commercial bankers on their boards exhibit reduced investment–cash flow sensitivity and higher leverage, including among firms that appear financially unconstrained and face relatively weak investment opportunities. Dittmann *et al.* (2010) document similar patterns in German data. Together, these findings underscore that interlocking boards may simultaneously mitigate informational frictions and introduce behavioral or incentive-based distortions, leaving the net effect on credit allocation an empirical question.

Whether firm-bank interlocking directories are in the end good or bad for the economy as a whole is an empirical issue, therefore. When the distortions due to favoritism caused by interlocks outweigh the benefits associated with improved screening and information gathering, such ties may contribute to credit misallocation, with adverse consequences for aggregate productivity and growth. Such an assessment is key for the evaluation of the (mainly sector-specific) regulatory bans on interlocks present in several jurisdictions, in addition to and beyond traditional criticisms related to anti-competitive behaviors and collusive practices (Baccini and Marroni, 2016; Battaggion and Cerasi, 2020).

The aim to shed light on this conundrum provides the main motivation for this paper. We start by acknowledging that any empirical assessment of the extent of misallocation associated with distortions in the allocation of credit due to interlocking revolves around four key ingredients, that must be

[1] Surveys on the topic of misallocation are provided by Hopenhayn (2014) and Restuccia and Rogerson (2017).

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appropriately combined. First, measuring misallocation requires quantitative methods to measure firm-specific marginal capital productivity, a variable which is unfortunately not directly observable. Second, we need fine-grained data on firms' balance-sheets, board exponents and individual loans in order to assess how the complex network of social relationships among interlocked board members impacts on the allocation of loans to firms characterized by heterogenous productivities. Third, three primary sources of endogeneity—respectively due to demand effects, supply effects, and what we shall call the fixed effect of firm-bank relationships—have to be carefully addressed. Finally, given that our focus is on the macroeconomic consequences of misallocation, we need a model for aggregating the results obtained at the microeconomic level.

In order to cope with all these issues, we exploit the richness of data available in the Bank of Portugal's *Central Credit do Balancos*, a central credit register reporting detailed balance-sheet and individual loans data for a very large sample of firms, and we integrate it with information on the personal identity of board members coming from the commercial database ORBIS by Bureau Van Dijk. Building on the detailed analysis by Reis (2013, 2015), Portugal has emerged as a compelling case study for examining how episodes of large capital inflows can give rise to boom-and-bust cycles, productivity slowdowns, and resource misallocation, while also shedding light on the effectiveness of crisis management and structural adjustment policies within a monetary union (Dias *et al.*, 2016, 2020; Terzi, 2020; Dias and Robelo Marques, 2021). Investigating the misallocative effects of a specific type of financial friction—one that becomes particularly relevant during periods of credit expansion—within this same framework provides a valuable extension to the existing literature.

While most of the literature on interlocking directorates focuses exclusively on direct ties between firms and banks, we adopt a broader perspective by considering the entire network formed through shared board members (Battiston *et al.*, 2003; Davis *et al.*, 2003; Vitali *et al.*, 2011; Heemskerk *et al.*, 2013). In particular, in this paper we examine a firm's proximity to a bank within the network of interlocking directorates, where proximity is formally defined in terms of geodesic distances between firms and banks. Our choice is motivated by the premise that information propagates across the whole network rather than being confined to dyadic relationships, so that the full extent of the impact of interlocking directorates can only be understood by extending the analysis beyond simple firm-bank linkages. Our empirical findings, based on panel data estimation techniques, are consistent with prior literature highlighting interlocking directorates as a source of favoritism: firms connected to banks are more likely to receive credit, irrespective of their efficiency. Furthermore, an extensive set of interaction terms reveals that efficient and inefficient firms benefit differently from these ties.

This result motivates an additional analysis aimed at quantifying the total impact of this financial friction on aggregate misallocation. To evaluate whether firm-bank interlocking directorates introduce biases in credit allocation, we apply the three-factor quantitative model developed by Dias *et al.* (2016) to estimate the revenue marginal productivity of capital (MP_KR). This methodology allows us to empirically assess the relationship between individual loan allocations and the relative efficiency of borrowers at the micro level, thereby identifying potential credit misallocation.[2] In the presence of misallocation, the most efficient firms receive less funds relative to an optimal allocation, whereas inefficient firms obtain disproportionately large loans. In order to measure the aggregate (macro level) implication of the financial friction associated to favoritism in lending, the Dias *et al.* (2016) framework is employed to aggregate the micro level evidence and compare actual gross domestic product (GDP) with a counterfactual scenario in which all interlocking ties are severed and credit is synthetically reallocated to equalize marginal revenues across firms.[3] Somehow surprisingly, results indicate that removing links and reallocating credit generates negligible changes.

Our central insight to rationalize this puzzle is that favoritism in lending, while a deviation from frictionless capital allocation, need not be highly distortionary if it benefits firms that are already

[2] In the paper, we consider MP_KR as a continuous measure of efficiency. Firms are more efficient than others when they exhibit higher MP_KR. However, we often refer to efficient and inefficient firms for ease of explanation.

[3] The underlying intuition is straightforward. A firm with a higher marginal product of capital—one that would generate greater returns from additional investment—should also be willing to pay more for capital. Under profit maximization, the firm's marginal product of capital equates to one plus the interest rate. Consequently, in a frictionless market, investors would allocate capital to firms with the highest marginal product, continuing to do so until returns are equalized across all firms, ensuring an efficient allocation of resources.

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more productive, so that the differential probability of bank connections between efficient and inefficient firms counterbalances the potential misallocation effects induced by favoritism in interlocking directorates. When banks systematically direct preferential credit toward efficient firms—firms that would likely attract substantial financing even in the absence of distortions—the resulting misallocation can be limited. To illustrate, consider a counterexample in which favoritism instead channels credit primarily to inefficient firms. In that scenario, misallocation is severe: capital is diverted from high-productivity firms, directly reducing aggregate output and slowing productivity growth. By contrast, if interlocking directorates generate a network in which more productive firms are more likely to receive preferential lending, the distortionary effects of favoritism are mitigated. Financial frictions persist, but their aggregate impact is attenuated because capital remains disproportionately allocated to firms with higher marginal productivity. This pattern corresponds to a negative elasticity of distortions with respect to productivity, as described in Restuccia (2019): reallocating resources across productivity types in this manner alters firms' scale but produces only modest aggregate misallocation relative to a scenario with a positive elasticity. Indeed, regression analysis confirms that in our sample efficient firms have a higher likelihood of establishing bank connections. In other words, credit misallocation due to preferential access to credit does not affect all firms equally, since it disproportionately disadvantages less efficient firms relative to their more efficient counterparts. Our analysis provides a concrete instance of this mechanism and suggests caution in the conventional policy response of banning interlocks irrespective of their actual economic content.

Our work contributes to the broader literature on the impact of financial frictions on resource misallocation, both across sectors and among firms within sectors (Barlevy, 2003; Gopinath *et al.*, 2017; Müller and Verner, 2024). We argue that if favoritism—a distortive mechanism in credit allocation by itself—is systematically biased toward more efficient firms, aggregate misallocative effects are attenuated as the firms benefiting from preferential lending are those that would have received substantial credit even in a frictionless environment. This mechanism offers a plausible explanation for a well-documented result, that is that financial frictions—despite their strong theoretical relevance—in several empirical instances account for only a small fraction of observed aggregate misallocation (Gilchrist *et al.*, 2013; Midrigan and Xu, 2014). By identifying a channel through which distortions in credit markets fail to translate into sizable macroeconomic inefficiencies, our findings help reconcile empirical evidence with prevailing models of imperfections in financial markets and misallocation by offering a nuanced view of the relationship between financial distortions and economic performance. As a result, policies aimed at reducing preferential lending in an environment where firms' productivity and proximity to banks are key factors may not necessarily lead to significant improvements in macroeconomic outcomes, as soon as the misallocation is predominantly concentrated in more efficient firms that are already closer to banks.

This paper also contributes to the literature on interlocking directorates and preferential lending (Engelberg *et al.*, 2012; Ferreira and Matos, 2012; Sisli-Ciamarra, 2012; Karolyi, 2018; Braun *et al.*, 2019; Barone *et al.*, 2021; Fracasso *et al.*, 2024) by extending the analysis beyond firm-level credit allocation to assess its macroeconomic implications. While existing research has extensively documented the role of interlocks in shaping lending decisions, primarily through the lens of informational advantages and favoritism, the broader impact on aggregate efficiency and resource allocation remains largely unexplored. Our study fills this gap by quantifying the extent to which interlocking directorates influence credit misallocation and, consequently, macroeconomic performance. By integrating firm-level credit dynamics with a general equilibrium perspective, we provide novel insights into whether and how interlocks translate into aggregate distortions, offering a more comprehensive understanding of the economic relevance of preferential lending.

A key limitation of our analysis is its static nature. While our framework allows us to assess the contemporaneous effects of interlocking directorates on credit allocation and macroeconomic efficiency, it does not capture the dynamic interactions between preferential lending and firm-level productivity growth. In reality, distortions in credit allocation may have long-term implications by affecting firms' investment decisions, innovation incentives, and the evolution of total factor productivity (Meza *et al.*, 2019). Extending our analysis to a dynamic setting would enable a more comprehensive evaluation of how inter-firm credit misallocation propagates over time and whether preferential lending to distorted

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firms reinforces or mitigates long-run inefficiencies. Future research incorporating firm dynamics and credit market frictions into a general equilibrium framework could shed light on the persistence and cumulative effects of interlocking directorates between borrowers and lenders on macroeconomic performance.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical framework employed in the calculation of MP_KR at the firm, sectoral, and aggregate levels. Section 3 provides a description of the data. Section 4 presents empirical results, while Section 5 details the counterfactual analysis. Section 6 discusses the attenuating effect of the probability of interlocking connections. Finally, Section 7 concludes.

2. Explaining and measuring misallocation

An efficient allocation of credit requires directing funds toward firms with the highest revenue marginal return of capital, a variable that cannot be directly observed from balance sheet data. To estimate this measure at the firm level, we adopt the framework developed by Dias *et al.* (2016). Given that both our empirical analysis and the construction of the counterfactual scenario—where interlocking connections are removed—build upon their approach, this section provides a concise overview of the model. We refer to the original source for proofs and motivation.

A key feature of this framework is its focus on within-industry misallocation, abstracting from distortions in the inter-industry allocation of resources. The economy consists of S industries, each contributing to the production of a single final good, Y, which is supplied in a competitive market. The aggregate production function follows a Cobb–Douglas specification with constant returns to scale:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}; \sum_{s=1}^{S} \theta_s = 1 \tag{1}$$

where Y_s the gross output in industry $s \in S$. Cost minimization and the assumption of competitive markets implies that Cobb–Douglas exponents are equal to the factor shares:

$$\theta_s = \frac{P_s Y_s}{PY}. \tag{2}$$

The final good is assumed to be the numeraire and we set $P = 1$. At the industry level, the gross output is produced by the following constant-elasticity-of-substitution (CES) production function:

$$Y_s = \left(\sum_{i=1}^{M_s} (Y_{si})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where Y_{si} is the gross output of firm i in sector s, M_s the total number of firms in the industry, and σ is the elasticity of substitution. The assumption of free entry and monopolistic competition determine the following inverse demand function for firm i in the in industry s:

$$P_{si} = Y_s^{\frac{1}{\sigma}} P_s (Y_{si})^{-1/\sigma}. \tag{4}$$

We assume that the number of firms in a sector is so large that $\frac{\partial Y_s}{\partial Y_{si}} \cong 0$. As a consequence, $Y_s^{\frac{1}{\sigma}} P_s = \gamma_s$ appears in the maximization simply as a scale factor that is common for each firm in any given sector. Each single firm produces using a Cobb–Douglas technology with constant return to scale:

$$Y_{si} = A_{si} K_{si}^{a_s} H_{si}^{b_s} Q_{si}^{1-a_s-b_s}, \tag{5}$$

where K_{si}, H_{si}, Q_{si} are respectively capital, labor, and intermediate products of firm i in sector s. As customary in the literature on misallocation (Hsieh and Klenow, 2009), the profit function is defined as:

$$\pi_{si} = \left(1 - \tau_{Y_{si}}\right) P_{si} Y_{si} - \left(1 + \tau_{K_{si}}\right) R_s K_{si} - \left(1 + \tau_{H_{si}}\right) W_s H_{si} - Z_s Q_{si}, \tag{6}$$

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where K, W, and Z denote the user cost of capital, labor wage and intermediate inputs price, respectively. Resource misallocation arises due to firm-specific distortions, captured by a set of wedges (τ) that affect different production inputs: $\tau_{Y_{si}}$ reflects distortions on output, $\tau_{K_{si}}$ captures distortions on capital, and $\tau_{H_{si}}$ accounts for distortions in labor. For instance, $\tau_{Y_{si}}$ may stem from heterogeneous taxation on revenues, while $\tau_{H_{si}}$ could represent labor cost taxation. Interlocking directorates influence misallocation primarily through the capital wedge $\tau_{K_{si}}$, affecting firms' cost of capital. More opaque firms tend to face higher capital wedges, reflecting elevated borrowing costs. However, firms with direct ties to banks can experience a reduction in $\tau_{K_{si}}$, as common board members facilitate access to soft information, thereby lowering perceived risk. Similarly, firms in close proximity to banks may benefit from reduced capital costs, as they are perceived as "preferred" borrowers. This mechanism generates distortions in credit allocation, with ties systematically influencing the cost of capital across firms.

Profit maximization leads to the conditions:

$$\left(1+\tau_{K_{si}}\right) = \frac{a_s}{1-a_s-b_s}\frac{Z_s Q_{si}}{R_s K_{si}} \tag{7}$$

$$\left(1-\tau_{H_{si}}\right) = \frac{b_s}{1-a_s-b_s}\frac{Z_s Q_{si}}{W_s H_{si}} \tag{8}$$

$$\left(1-\tau_{Y_{si}}\right) = \frac{\sigma}{\sigma-1}\frac{1}{(1-a_s-b_s)}\frac{Z_s Q_{si}}{P_{si}Y_{si}}. \tag{9}$$

Building on this framework, we introduce a slight modification to the approach of Dias *et al.* (2016) in computing the revenue marginal return of capital ($\mathrm{MP_K R}$) at the firm level. Let firm revenue be denoted as $P_{si}Y_{si}$. Then, using Equation (4) and the assumed functional form of the firm's production function, we derive:

$$P_{si}Y_{si} = \gamma_s (Y_{si})^{-\frac{1}{\sigma}} Y_{si} = \gamma_s (Y_{si})^{1-\frac{1}{\sigma}} = \gamma_s (Y_{si})^{\frac{\sigma-1}{\sigma}} = \gamma_s \left(A_{si} K_{si}^{\alpha_s} H_{si}^{\beta_s} Q_{si}^{1-\alpha_s-\beta_s}\right)^{\frac{\sigma-1}{\sigma}}. \tag{10}$$

If we take the derivatives with respect to capital:

$$\frac{\partial P_{si}Y_{si}}{\partial K_{si}} = \gamma_s \frac{\sigma-1}{\sigma}\left(A_{si} K_{si}^{\alpha_s} H_{si}^{\beta_s} Q_{si}^{1-\alpha_s-\beta_s}\right)^{\frac{-1}{\sigma}} \alpha_s K_{si}^{\alpha_s-1} A_{si} H_{si}^{\beta_s} Q_{si}^{1-\alpha_s-\beta_s}. \tag{11}$$

Unfortunately, since we do not observe the firm's gross output, we cannot directly use this formula. To overcome this limitation, recall that by (4), $Y_{si} = \left(\frac{P_{si}Y_{si}}{\gamma_s}\right)^{\frac{\sigma}{\sigma-1}}$, and that by defining the total factor productivity quantity as $TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} H_{si}^{\beta_s} Q_{si}^{1-\alpha_s-\beta_s}}$, Equation (11) becomes:

$$\frac{\partial P_{si}Y_{si}}{\partial K_{si}} = \frac{\alpha_s\,(\sigma-1)\,P_{si}Y_{si}}{\sigma\,\gamma_s K_{si}}. \tag{12}$$

This expression is observable, as firm revenue $P_{si}Y_{si}$ is reported in balance sheet data. However, the parameter γ_s remains unobserved, which limits our analysis to within-sector misallocation. To address this, we normalize the $\mathrm{MP_K R}$ by the minimum value within each two-digit sector.[4] This normalization does not affect our results, as our primary focus is on misallocation within industries rather than across them. We denote the normalized $\mathrm{MP_K R}$ of a given firm i as EFF_i.

3. Data

A comprehensive analysis of the effects of formal interlocking directorates on credit allocation requires granular loan-level data that explicitly identifies lending relationships. While some studies

[4] We employ the NACE-rev2 classification.

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Table 1 Descriptive statistics—Agriculture

	Mean	SD	Count
Total credit in 2017	749.381	30188.69	769,454
Log(Total credit in 2017)	9.666052	2.590251	5,227
DicoCredit2017[a]	0.0067931	0.0821401	769,454
Dis	0.939179	1.812572	769,454
EFF_i	10324.37	48858.11	769,454
Equity/Total assets	0.2663464	0.9116309	769,454
$RelDummy_{ij}$	0.0133393	0.1147232	769,454
$RelAmount_{ij}$	0.0064305	0.0721595	769,454
Distancereachable[b]	4.199456	0.9995265	172,083
Notevenreachable[c]	0.223643	0.4166858	769,454
N	769,454		

[a] A dummy equal to one if the firm borrows from the bank in the couple. [b] This is the mean distance calculated only on those observations that have a path. [c] This is a dummy equal to one if the bank in the couple is reachable and 0 otherwise.

rely exclusively on balance sheet data (Stearns and Mizruchi, 1993), national credit bureau data remains essential for capturing the full extent of preferential lending. To this end, we leverage data from the Bank of Portugal's central credit register, which records the credit exposures of all financial institutions operating in Portugal. Despite a decade-long deleveraging process in Portugal, the country remains an appropriate setting for our study due to the pivotal role of the banking system in credit allocation (Bonfim *et al.*, 2009; Ferreira *et al.*, 2011). Moreover, Portugal's economic structure closely resembles that of larger economies in Southern Europe. The service sector contributes the largest share of value-added, while the manufacturing sector's relative weight is comparable to that of Italy, France, and Spain. Similarly, the share of agriculture, forestry, and fishing in value-added, as well as the distribution of firm sizes, is also similar to that of other Southern European countries, with a relatively high prevalence of small firms (0–9 employees), exceeding the EU-28 average.

Balance sheet information is sourced from the *Central de Balanços* database (Sforza, 2020), constructed by the Bank of Portugal, which covers the universe of Portuguese non-financial firms on an annual basis and primarily relies on financial statements submitted through the *Informação Empresarial Simplificada* procedure. This dataset is highly detailed, encompassing every credit exposure above 50 euros and providing monthly updates. For our analysis, we aggregate loan-level data at the firm-bank level to facilitate empirical estimation. Following Dias *et al.* (2016), we focus on firms operating in the Agriculture, Manufacturing, and Services macro-sectors.[5] The final sample comprises 89,328 firms and 119 banks. By double checking with the ORBIS (Bureau Van Dick) database, we verify that firms and banks in the dataset account for 85% of total lending in 2017. Our final dataset consists of 10,630,032 bank-firm pairs, obtained by constructing the Cartesian product of all firms and banks in the sample.[6]

Tables 1–3 provide descriptive statistics segmented by macro-sectors. In particular, the variables related to the structural properties of the interlocking directorates network correspond to the data that we present below. To construct the interlocking network, we utilize board membership data extracted from ORBIS, a widely recognized source for research on corporate interconnections (Heemskerk *et al.*, 2016; Garcia-Bernardo and Takes, 2018). However, ORBIS does not provide reliable historical data on board composition, as its records are continuously updated rather than maintaining past membership records. Since ORBIS primarily collects its information from annual reports, we assume that board data retrieved in January 2019 accurately reflects firm structures for the years 2017–2018.

[5] Agriculture includes NACE-rev2 two digits sectors: 01–09; Manufacturing includes NACE-rev2 two digits sector: 10–33; Services includes NACE-rev2 two digits sector: 35–43, 49–63, 68–82, 90–96.

[6] It is well known that in ORBIS larger firms are overrepresented (Garcia-Bernardo and Takes, 2018). Since these are also more likely to be interlocked with banks, omission biases in our estimation are likely to be limited.

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Table 2 Descriptive statistics—Manufacturing

	Mean	SD	Count
Total credit in 2017	1982.405	120597.1	3,058,419
Log(Total credit in 2017)	9.720319	2.837247	29,246
DicoCredit2017[a]	0.0095625	0.0973192	3,058,419
Dis	0.5620767	1.444007	3,058,419
EFF_i	2027.14	3812.08	3,058,419
Equity/Total assets	0.1418812	1.547398	3,058,419
$RelDummy_{ij}$	0.0177844	0.1321668	3,058,419
$RelAmount_{ij}$	0.0068594	0.071333	3,058,419
Distancereachable[b]	4.033946	0.9795658	426,150
Notevenreachable[c]	0.1393367	0.3462976	3,058,419
N	3,058,419		

[a] A dummy equal to one if the firm borrows from the bank in the couple. [b] This is the mean distance calculated only on those observations that has a path. [c] This is a dummy equal to one if the bank in the couple is reachable and 0 otherwise.

Table 3 Descriptive statistics—Services

	Mean	SD	Count
Total credit in 2017	631.9713	98812.06	6,802,159
Log (Total credit in 2017)	8.559341	2.778356	38,228
DicoCredit2017[a]	0.00562	0.0747556	6,802,159
Dis	0.3994516	1.278239	6,802,159
EFF_i	11593.53	39295.84	6,802,159
Equity/Total assets	−0.5125745	3.761023	6,802,159
$RelDummy_{ij}$	0.01123	0.1053748	6,802,159
$RelAmount_{ij}$	0.0059757	0.0709689	6,802,159
Distancereachable[b]	4.237496	1.033987	641,212
Notevenreachable[c]	0.094266	0.2921984	6,802,159
N	6,802,159		

[a] A dummy equal to one if the firm borrows from the bank in the couple. [b] This is the mean distance calculated only on those observations that has a path. [c] This is a dummy equal to one if the bank in the couple is reachable and 0 otherwise.

Our sample includes all individuals identified as holding significant roles in firms and banks, rather than being limited to official board members. This approach assumes that any individual listed in ORBIS as affiliated with a firm likely holds a position of influence, capable of shaping decision-making processes within firms or banks. Using this data, we construct an interlocking network in which firms and banks are represented as nodes, while edges capture shared directorships and key affiliations. Firms and banks are considered connected if they share at least one key individual. Based on this dataset, we compute the geodesic distance—the shortest path length—for each firm to every bank.[7] Due to ORBIS data limitations, we restrict our sample to firms that were active in both 2016 and 2017. Additionally, we impose an upper bound on geodesic distances, setting values greater than six to infinite. This choice is motivated by two factors: first, effects beyond this threshold are unlikely to be economically significant, making their inclusion unnecessary; second, measurement error tends to increase with distance, potentially introducing noise into the analysis.

[7] Calculations have been executed with the *R* package *igraph* (Csardi and Nepusz, 2006).

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Table 4 Geodesic distance by macro-sector

Distance	Agriculture Freq (%)	Manufacturing Freq (%)	Services Freq (%)
∞	597,371	2.632.000	6.161.000
	(77.64)	(86.07)	(90.57)
1	395	947	1,483
	(0.0513)	(0.0310)	(0.0218)
2	6,308	17,655	22,267
	(0.820)	(0.577)	(0.327)
3	33,804	107,773	131,418
	(4.393)	(3.524)	(1.932)
4	66,771	170,433	230,951
	(8.678)	(5.573)	(3.395)
5	47,682	98,294	177,500
	(6.197)	(3.214)	(2.609)
6	17,123	31,048	77,593
	(2.225)	(1.015)	(1.141)
Total	769,454	3.058e+06	6.802e+06

Table 5 Mean credit by geodesic distance

	Dis^1 Mean (Freq)	Dis^2 Mean (Freq)	Dis^3 Mean (Freq)	Dis^4 Mean (Freq)	Dis^5 Mean (Freq)	Dis^6 Mean (Freq)	Dis^∞ Mean (Freq)
Credit	79,003	33,157	11,503	4,660	1,956	1,093	329.1
	(2,825)	(46,230)	(272,995)	(468,155)	(323,476)	(125,764)	(9.391e+06)

As expected, most firm-bank pairs exhibit an infinite geodesic distance, which we record as zero (Table 4). Among macro-sectors, the service sector appears to maintain the closest ties to banks. However, in relative terms, viable connections are more frequently observed in Agriculture. This pattern is likely driven by the extensive regional presence of the Crédito Agrícola Group, a financial institution historically specialized in agricultural lending (Stefanelli, 2010).

Examining credit allocations[8] in 2017 (see Tables 1–3), we observe that the manufacturing sector displays the highest mean credit received, whereas Agriculture and Services exhibit similar patterns. The mean loan amount decreases markedly with distance: firms directly connected to banks (distance of one) receive an average of 79,003 Euros, whereas firms with no connections (infinite distance) receive only 329.1 euros (Table 5).

To estimate MP_KRs, we adhere closely to the methodology proposed by Dias *et al.* (2016). We define capital K_{si} as the book value of total capital stock net of depreciation. The elasticity of substitution σ is set to 3. Labor (H_{si}) is measured as the firm's total labor cost, implicitly assuming that wages per worker adjust for individual skill levels and hours worked ($W_s = 1$). Similarly, intermediate product usage Q_{si}

[8] We consider the total amount of credit a firm can access. This includes both regular credit (such as loans used for acquiring financial instruments) and potential credit (such as lines of credit).

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is proxied by total expenditures on intermediate goods. For robustness, we also measure labor as the firm's total number of employees. These data are sourced from the *Central de Balanços*.

Sector-specific Cobb–Douglas parameters could be estimated through constrained regression on the logarithm of the production function, following the methodology outlined in Coelli *et al.* (2005):

$$\ln\left(P_{si}Y_{si}\right) = \ln\left(P_{si}A_{si}\,K_{si}^{a_s}\;\;H_{si}^{b_s}\;\;Q_{si}^{1-a_s-b_s}\right). \tag{13}$$

However, this approach would fail to account for the endogeneity of observed factor inputs, which are themselves influenced by misallocation within the system. To address this issue, we follow the methodology popularized by Hsieh and Klenow (2009), and we estimate industry-level factor shares using data from the United States—a benchmark economy typically regarded as relatively undistorted.

We obtain data from the Bureau of Economic Analysis and construct a concordance between the North American Industry Classification System (NAICS) 2017 and the classification of economic activities in the European Union (NACE) Rev. 2. The mapping follows the conversion file provided by Eurostat. Since the correspondence between these classifications is not always one-to-one, we adopt an averaging approach: for each NACE Rev. 2 industry with multiple NAICS matches, we compute factor shares as the mean of the corresponding NAICS industries. Finally, to ensure robustness, we recover the Cobb–Douglas parameters for each sector by averaging factor shares over the period 2008–2016.

4. Results

The first part of our empirical analysis examines whether efficient and non-efficient firms derive differential advantages from their proximity to banks. To investigate this, we estimate the intensive margin of credit extension using the following model:

$$\ln\left(Borrow_{ij}^{2017}\right) = \alpha + \sum_{l=1}^{\max dist}\beta_{1l}Dis_{ij}^{l} + \beta_2 EFF_i + \sum_{l=1}^{\max dist}\beta_{3l}\left(Dis_{ij}^{l} * EFF_i\right) + \beta_4 ILS_i + \beta_5 BA_j + \beta_6 RelDummy_{ij} + \beta_7 RelAmount_{ij} + \beta_8\frac{Equity}{TotalAsset} + \varepsilon_{ij}. \tag{14}$$

In this model, $Borrow_{ij}^{2017}$ represents the new credit extended to firm i by bank j in 2017.[9] The variable Dis_{ij}^{l} is a binary indicator that takes the value of 1 if the geodesic distance between firm i and bank j is equal to l, and 0 otherwise. The geodesic distance is computed based on the network formed by interconnections between banks and firms that share at least one common exponent. Specifically, a firm or a bank is considered linked if they share a board member. In this specification, the reference category corresponds to an infinite distance, which has been recorded as 0. To avoid imposing any ex-ante functional form on the relationship between distance and the intensive margin of credit, we opt for a dichotomous representation of distances.

The term EFF_i represents the normalized marginal revenue return of capital for firm i. To examine whether the effect of bank-firm connections differs between efficient and non-efficient firms, we include a full set of interaction terms between EFF_i and the distance dummies. Misallocation may occur if both types of firms benefit similarly from proximity to banks. In this case, we expect the coefficients of the distance dummies to be positive and significant, while the interaction terms remain insignificant. Conversely, if connections primarily help mitigate informational asymmetries, we should observe positive and significant coefficients for the interaction terms between firm efficiency and proximity to banks.

[9] The variable $Borrow_{ij}^{2017}$ is calculated by exploiting the monthly frequency of the Central Credit Register as follows: $Borrow_{ij}^{2017} = \sum_{t=1}^{12} Borrow_{ijt}^{2017} - Borrow_{ij(t-1)}^{2017}$, where t represents months and $Borrow_{ij0}^{2017} \equiv Borrow_{ij12}^{2016}$.

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This estimate, however, may be biased due to three factors: supply effects, demand effects, and bank-firm relationship fixed effects. To control for supply effects, we incorporate bank fixed effects BA_j (Schivardi *et al.*, 2022), implemented as a set of dummy variables (one for each bank). To address demand effects, we follow Degryse *et al.* (2019), who finds that firm demand is homogeneous within clusters based on the triple: industry (firm's two-digit NACE code), location (firm's two-digit postal code), and size (firm's total asset decile). Consequently, we include a set of "cluster" dummies in our model. The cluster to which the firm belongs is indicated by ILS_i in Equation (14). One limitation of using ILS_i to proxy demand effects instead of firm fixed effects is that it does not fully resolve endogeneity arising from firm leverage. Leverage may be correlated with bank-firm connections because banks' lending to highly leveraged firms might exert greater control over borrowers, potentially through the appointment of trusted individuals. To mitigate this issue, we control for the equity-to-total-assets ratio.

Given that a lending relationship could increase the likelihood of interlocking, we also control for key dimensions of relationship lending (Degryse *et al.*, 2009; Sette and Gobbi, 2015), including the duration of the relationship and the share of credit granted by the bank. Specifically, we adopt indicators suggested by Sette and Gobbi (2015) and Bharath *et al.* (2009): RelDummy_{ij}, a dummy variable equal to 1 if the total loan amount from bank *j* to firm *i* over the past 5 years exceeds zero, and RelAmount_{ij}, the fraction of firm i's total lending obtained from bank *j* over the past 5 years. Controls and the efficiency measure refer to the year 2016.

To detect multivariate outliers, we apply the BACON algorithm (Billor *et al.*, 2000; Weber, 2010) to both covariates and outcomes. The algorithm follows five steps: (i) it selects an initial subset of observations; (ii) using this subset, it estimates the mean and covariance matrix of the model variables; (iii) it computes the Mahalanobis distance for the entire sample; (iv) it expands the initial subset by adding observations with distances below a given threshold; and (v) it iterates until the subset stabilizes. Any observation remaining outside the subset is classified as an outlier. We set the threshold at 15% and did not identify any outliers.

Following the approach suggested in the existing literature (Accetturo *et al.*, 2023; Schivardi *et al.*, 2022), confidence intervals are double-clustered at both the bank and firm levels. To account for potential macro-sector-specific effects, we estimate separate models for each macro-sector. The regression results are reported in Tables 6–8.

Closeness exhibits varying effects across the macro-sectors analyzed.[10] For the Agriculture sector, none of the models indicate significant effects of bank-firm connections for low-efficiency firms. In contrast, the effects appear to be directly proportional to the firm's marginal revenue return of capital. Specifically, in our preferred specification (model 6), borrowings increase with efficiency when the firm is at a geodesic distance of 3, 4, or 5. Although controls for relationship lending and leverage are consistently significant, their introduction does not substantially alter the magnitude of the coefficients, suggesting a limited impact on the overall estimation.

For the Manufacturing sector, estimates return a different pattern. Here, distance influences both efficient and non-efficient firms. The distance dummies exhibit positive and statistically significant coefficients from a distance of 2 to 5 across all models. Additionally, only the interaction term for a distance of 1 is positive and significant, suggesting that direct connections enhance bank screening. Unlike in Agriculture, firm efficiency remains consistently positive and significant, indicating that more efficient firms secure larger loans compared to their less efficient counterparts.

The results for the Service sector align closely with those observed in Manufacturing. However, in this case, the coefficient for direct connections (distance equal to 1) is positive for all firms, with no significant interaction with efficiency. Instead, the interaction between the dummy for a five-step path and efficiency is positive. This suggests that, overall, the effect of connections does not substantially differ between efficient and non-efficient firms.

[10] The number of observations differs from the one reported in the descriptive statistics because the *R* package *reghdfe* iteratively removes singletons (Correia, 2015, 2016).

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Table 6 Regression for the intensive margin of credit—Agriculture

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
1. Dis^1	0.771	0.804	0.771	0.771	0.758	0.761
	(0.955)	(0.994)	(0.955)	(0.988)	(0.966)	(0.997)
2. Dis^2	0.347	0.341	0.347	0.306	0.336	0.297
	(0.369)	(0.376)	(0.369)	(0.373)	(0.369)	(0.374)
3. Dis^3	−0.253	−0.240	−0.253	−0.252	−0.261	−0.258
	(0.259)	(0.248)	(0.259)	(0.241)	(0.257)	(0.240)
4. Dis^4	−0.191	−0.160	−0.191	−0.194	−0.199	−0.200
	(0.159)	(0.156)	(0.157)	(0.153)	(0.156)	(0.151)
5. Dis^5	−0.343	−0.400	−0.343	−0.418	−0.338	−0.413
	(0.320)	(0.330)	(0.320)	(0.339)	(0.323)	(0.341)
6. Dis^6	−0.145	−0.280	−0.145	−0.316	−0.120	−0.293
	(0.366)	(0.374)	(0.366)	(0.368)	(0.367)	(0.368)
EFF_i	−1.06e-07	4.78e-08	−1.05e-07	3.39e-08	2.62e-08	1.43e-07
	(4.58e-07)	(4.66e-07)	(4.58e-07)	(4.77e-07)	(6.78e-07)	(6.58e-07)
1. Dis^{1*} EFF_i	−7.26e-05	−6.59e-05	−7.24e-05	−7.16e-05	−7.14e-05	−7.07e-05
	(0.000158)	(0.000159)	(0.000158)	(0.000161)	(0.000159)	(0.000162)
2. Dis^{2*} EFF_i	1.94e-05	1.67e-05	1.94e-05	1.69e-05	1.94e-05	1.70e-05
	(1.24e-05)	(1.18e-05)	(1.23e-05)	(1.27e-05)	(1.25e-05)	(1.29e-05)
3. Dis^{3*} EFF_i	6.77e-05***	6.90e-05***	6.77e-05***	7.18e-05***	6.88e-05***	7.26e-05***
	(1.76e-05)	(1.79e-05)	(1.78e-05)	(1.84e-05)	(1.74e-05)	(1.82e-05)
4. Dis^{4*} EFF_i	3.72e-05***	3.54e-05**	3.71e-05***	3.82e-05***	3.81e-05***	3.91e-05***
	(1.40e-05)	(1.40e-05)	(1.40e-05)	(1.40e-05)	(1.39e-05)	(1.39e-05)
5. Dis^{5*} EFF_i	4.19e-05**	4.54e-05**	4.19e-05**	4.93e-05**	4.21e-05**	4.93e-05**
	(2.07e-05)	(2.06e-05)	(2.07e-05)	(2.07e-05)	(2.07e-05)	(2.08e-05)
6. Dis^{6*} EFF_i	7.08e-06	1.42e-05	7.13e-06	1.29e-05	6.37e-06	1.23e-05
	(2.20e-05)	(2.32e-05)	(2.20e-05)	(2.47e-05)	(2.22e-05)	(2.48e-05)
$RelDummy_{ij}$		−1.011***		−1.354***		−1.337***
		(0.0925)		(0.120)		(0.118)
$RelAmount_{ij}$			−0.00839	0.620***		0.613***
			(0.120)	(0.149)		(0.149)
Equity/Total assets					0.211**	0.177**
					(0.0857)	(0.0673)
Constant	9.659***	10.52***	9.662***	10.55***	9.594***	10.48***
	(0.0344)	(0.0812)	(0.0614)	(0.0801)	(0.0522)	(0.0778)
Observations	5,137	5,137	5,137	5,137	5,137	5,137
R-squared	0.232	0.247	0.232	0.252	0.234	0.253
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$

Except for the Agriculture sector and direct links in Manufacturing, our findings are in line with the literature portraying shared exponents as a channel for favoritism (Barone *et al.*, 2021) rather than as a mechanism for reducing informational asymmetry (Ferreira and Matos, 2012). If interlocking

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Table 7 Regression for the intensive margin of credit—Manufacturing

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
1. Dis^1	−0.0669	−0.0717	−0.0657	−0.0642	−0.0588	−0.0579
	(0.424)	(0.441)	(0.423)	(0.446)	(0.422)	(0.444)
2. Dis^2	0.379***	0.384***	0.380***	0.394***	0.383***	0.397***
	(0.127)	(0.128)	(0.128)	(0.131)	(0.127)	(0.132)
3. Dis^3	0.361***	0.346***	0.363***	0.356***	0.366***	0.360***
	(0.0796)	(0.0813)	(0.0804)	(0.0827)	(0.0798)	(0.0829)
4. Dis^4	0.299***	0.295***	0.301***	0.307***	0.302***	0.310***
	(0.0873)	(0.0869)	(0.0879)	(0.0879)	(0.0877)	(0.0884)
5. Dis^5	0.190**	0.168**	0.192**	0.177**	0.196***	0.181**
	(0.0731)	(0.0725)	(0.0749)	(0.0742)	(0.0738)	(0.0751)
6. Dis^6	−0.0448	−0.0758	−0.0440	−0.0777	−0.0400	−0.0737
	(0.134)	(0.134)	(0.135)	(0.139)	(0.134)	(0.139)
EFF_i	8.19e-05***	7.99e-05***	8.20e-05***	8.03e-05***	8.57e-05***	8.33e-05***
	(1.57e-05)	(1.62e-05)	(1.58e-05)	(1.61e-05)	(1.62e-05)	(1.65e-05)
1. Dis^{1*} EFF_i	4.12e-04***	3.90e-04**	4.13e-04***	3.95 e-04**	4.11e-04***	3.95e-04**
	(0.000145)	(0.000153)	(0.000147)	(0.000154)	(0.000144)	(0.000154)
2. Dis^{2*} EFF_i	−3.16e-05	−2.96e-05	−3.20e-05	−3.20e-05	−3.37e-05	−3.37e-05
	(3.50e-05)	(3.49e-05)	(3.51e-05)	(3.47e-05)	(3.51e-05)	(3.49e-05)
3. Dis^{3*} EFF_i	−2.20e-05	−2.06e-05	−2.23e-05	−2.25e-05	−2.46e-05	−2.45e-05
	(1.57e-05)	(1.57e-05)	(1.57e-05)	(1.62e-05)	(1.55e-05)	(1.59e-05)
4. Dis^{4*} EFF_i	3.03e-07	−1.19e-06	1.72e-07	−2.55e-06	−1.52e-06	−3.97e-06
	(2.36e-05)	(2.37e-05)	(2.36e-05)	(2.38e-05)	(2.34e-05)	(2.36e-05)
5. Dis^{5*} EFF_i	−1.06e-05	−9.36e-06	−1.06e-05	−9.12e-06	−1.27e-05	−1.08e-05
	(1.86e-05)	(1.79e-05)	(1.88e-05)	(1.87e-05)	(1.88e-05)	(1.87e-05)
6. Dis^{6*} EFF_i	−1.38e-05	−8.05e-06	−1.37e-05	−5.76e-06	−1.53e-05	−7.00e-06
	(3.37e-05)	(3.37e-05)	(3.36e-05)	(3.34e-05)	(3.36e-05)	(3.33e-05)
$RelDummy_{ij}$		−0.867***		−1.088***		−1.081***
		(0.104)		(0.118)		(0.118)
$RelAmount_{ij}$			0.0614	0.460***		0.455***
			(0.0916)	(0.104)		(0.103)
Equity/Total assets					0.102**	0.0807*
					(0.0415)	(0.0429)
Constant	9.512***	10.29***	9.489***	10.32***	9.476***	10.29***
	(0.0303)	(0.109)	(0.0561)	(0.111)	(0.0414)	(0.119)
Observations	28,762	28,762	28,762	28,762	28,762	28,762
R-squared	0.295	0.302	0.295	0.304	0.295	0.304
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

directorates primarily mitigated informational asymmetry, we would expect positive and significant interactions between distance measures and firm efficiency. However, this is only the case for firms in Agriculture and those in Manufacturing that are directly connected to banks.

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Table 8 Regression for the intensive margin of credit—Services

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
1. Dis^1	1.348***	1.274***	1.348***	1.249***	1.349***	1.250***
	(0.417)	(0.407)	(0.413)	(0.426)	(0.416)	(0.425)
2. Dis^2	0.457***	0.471***	0.451***	0.504***	0.462***	0.508***
	(0.134)	(0.130)	(0.135)	(0.130)	(0.135)	(0.130)
3. Dis^3	0.654***	0.643***	0.649***	0.668***	0.656***	0.670***
	(0.133)	(0.131)	(0.134)	(0.131)	(0.133)	(0.131)
4. Dis^4	0.377***	0.370***	0.373***	0.388***	0.379***	0.390***
	(0.0813)	(0.0768)	(0.0819)	(0.0751)	(0.0810)	(0.0750)
5. Dis^5	0.0333	−0.00243	0.0302	0.00260	0.0171	−0.0108
	(0.101)	(0.103)	(0.102)	(0.101)	(0.107)	(0.104)
6. Dis^6	0.183	0.119	0.180	0.116	0.186	0.119
	(0.146)	(0.150)	(0.147)	(0.149)	(0.146)	(0.149)
EFF_i	5.22e-06**	5.01e-06**	5.18e-06**	5.10e-06**	5.56e-06**	5.40e-06**
	(2.37e-06)	(2.41e-06)	(2.39e-06)	(2.45e-06)	(2.67e-06)	(2.72e-06)
1. Dis^{1*} EFF_i	−9.75e-05	−9.18e-05	−9.74e-05	−9.02e-05	−9.73e-05	−9.02e-05
	(6.90e-05)	(7.29e-05)	(6.97e-05)	(7.07e-05)	(6.92e-05)	(7.08e-05)
2. Dis^{2*} EFF_i	1.67e-05	1.19e-05	1.64e-05	1.19e-05	1.65e-05	1.18e-05
	(1.40e-05)	(1.43e-05)	(1.40e-05)	(1.37e-05)	(1.40e-05)	(1.37e-05)
3. Dis^{3*} EFF_i	1.09e-05*	9.68e-06	1.07e-05*	1.01e-05	1.10e-05*	1.02e-05
	(5.88e-06)	(6.02e-06)	(5.82e-06)	(6.19e-06)	(5.83e-06)	(6.18e-06)
4. Dis^{4*} EFF_i	5.66e-06	5.21e-06	5.72e-06	4.76e-06	5.37e-06	4.53e-06
	(4.28e-06)	(3.68e-06)	(4.25e-06)	(3.71e-06)	(4.37e-06)	(3.81e-06)
5. Dis^{5*} EFF_i	1.33e-05**	1.42e-05**	1.33e-05**	1.45e-05**	1.67e-05***	1.74e-05***
	(6.01e-06)	(5.99e-06)	(5.97e-06)	(6.19e-06)	(5.23e-06)	(5.48e-06)
6. Dis^{6*} EFF_i	−1.26e-06	−8.89e-09	−1.28e-06	4.63e-07	−9.76e-07	6.89e-07
	(1.58e-05)	(1.62e-05)	(1.59e-05)	(1.57e-05)	(1.58e-05)	(1.57e-05)
$RelDummy_{ij}$		−1.051***		−1.376***		−1.363***
		(0.136)		(0.136)		(0.137)
$RelAmount_{ij}$			−0.104	0.527***		0.525***
			(0.1000)	(0.0661)		(0.0649)
Equity/Total assets					0.0559***	0.0474***
					(0.0103)	(0.0108)
Constant	8.443***	9.338***	8.495***	9.352***	8.442***	9.340***
	(0.0219)	(0.136)	(0.0667)	(0.137)	(0.0243)	(0.140)
Observations	37,245	37,245	37,245	37,245	37,245	37,245
R-squared	0.291	0.305	0.292	0.309	0.293	0.310
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

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5. A counterfactual scenario with removed interlocks

Our empirical findings suggest that firm-bank interlocking directorates contribute to resource misallocation in the Portuguese economy. In particular, close ties between firms and banks appear to facilitate lending independently of the fundamental productivity of the connected firm. This section quantifies the aggregate implications of these linkages by comparing observed GDP with a counterfactual scenario in which all interlocks are eliminated. To construct this counterfactual, we employ the structural framework introduced in Section 3.

Prior to assessing the macroeconomic consequences, we first estimate the effects of removing interlocks on firm-level credit allocation and capital misallocation. Specifically, we define counterfactual borrowing in the absence of interlocking directorates as follows:[11]

$$Borrow_{ij(C)} = \exp\left(X_i'\beta_{(C)} + \varepsilon_{ij}\right), \tag{15}$$

where X_i' denotes the vector of covariates in the econometric specification outlined above, and $\beta_{(C)}$ represents the vector of coefficients with all distance-related terms set to zero. Given that observed borrowing is defined as $Borrow_{ij} = \exp\left(X_i'\beta + \varepsilon_{ij}\right)$, we construct counterfactual borrowing as follows:

$$Borrow_{ij(C)} = \frac{Borrow_{ij}}{\exp\left(B_{1l}Dis_{ij}^{l} + B_{3l}\left(Dis_{ij}^{l} * EFF_i\right)\right.}. \tag{16}$$

Since the removal of interlocking ties affects misallocation exclusively through capital—specifically, by altering the wedges $\tau_{K_{si}}$—profit maximization implies:

$$\left(1 + \tau_{K_{si}}^{*}\right) = \frac{a_s}{1 - a_s - b_s}\frac{Z_s Q_{si}^{*}}{R_s K_{si}^{*}}$$

$$\left(1 + \tau_{H_{si}}\right) = \frac{b_s}{1 - a_s - b_s}\frac{Z_s Q_{si}^{*}}{W_s H_{si}^{*}}$$

$$\left(1 - \tau_{Y_{si}}\right) = \frac{\sigma}{\sigma - 1}\frac{1}{(1 - a_s - b_s)}\frac{Z_s Q_{si}^{*}}{P_{si}^{*} Y_{si}^{*}}.$$

Therefore, it must hold that:

$$\frac{Z_s Q_{si}^{*}}{W_s H_{si}^{*}} = \frac{Z_s Q_{si}}{W_s H_{si}}$$

$$\frac{Z_s Q_{si}^{*}}{P_{si}^{*} Y_{si}^{*}} = \frac{Z_s Q_{si}}{P_{si} Y_{si}}$$

$$Y_{si}^{*} = A_{si}\left(K_{si}^{*}\right)^{a_s}\left(H_{si}^{*}\right)^{b_s}\left(Q_{si}^{*}\right)^{1-a_s-b_s}$$

$$P_{si}^{*} = \gamma_s\left(Y_{si}^{*}\right)^{-\frac{1}{\sigma}}.$$

Under the assumption that $Z_s = W_s = 1$ as before, this simplifies to:

$$\frac{Q_{si}^{*}}{H_{si}^{*}} = \frac{Q_{si}}{H_{si}}$$

$$\frac{Q_{si}^{*}}{P_{si}^{*} Y_{si}^{*}} = \frac{Q_{si}}{P_{si} Y_{si}}$$

[11] Since clustering is implemented at both the firm and bank levels, the assumption of homoscedasticity across observations is unlikely to hold. As a result, using the estimated expectation of the untransformed scale to construct the counterfactual would be inappropriate, as it would neglect the role of residual variance (Duan, 1983). To address this concern, we assume that heteroscedasticity is not systematically driven by the presence of interlocking directorates.

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$$Y_{si}^{*} = A_{si}\left(K_{si}^{*}\right)^{a_s}\left(H_{si}^{*}\right)^{b_s}\left(Q_{si}^{*}\right)^{1-a_s-b_s}$$

$$P_{si}^{*} = \gamma_s\left(Y_{si}^{*}\right)^{-\frac{1}{\sigma}}.$$

For computational tractability, we further assume that the prices of labor and intermediate inputs remain unchanged and that $Y_s^{\frac{1}{\sigma}}P_s = Y_s^{*\frac{1}{\sigma}}P_s^{*} = \gamma_s$. Solving the system yields the counterfactual output quantity:

$$Y_{si}^{*} = \left[A_{si}\left(K_{si}^{*}\right)^{a_s}\left(\gamma_s\frac{H_{si}}{P_{si}Y_{si}}\right)^{b_s}\left(\gamma_s\frac{Q_{si}}{P_{si}Y_{si}}\right)^{1-a_s-b_s}\right]^{\frac{\sigma}{1+(\sigma-1)a_s}}. \tag{17}$$

K_{si}^{*} comprises two components: (*i*) the capital allocated independently of interlocks, which remains unaffected by their removal; and (*ii*) the capital that is allocated through interlocks. We denote these quantities by K_{si}^{R} and K_{si}^{RM}, respectively, such that $K_{si}^{*} = K_{si}^{R} + K_{si}^{RM}$. Given J as the number of banks, the capital allocation component K_{si}^{R} is given by:

$$K_{si}^{R} = K_{si} - \sum_{j=1}^{J} Borrow_{sij} + \sum_{j=1}^{J} Borrow_{sij(C)}. \tag{18}$$

For a given sector, the amount of financing allocated through interlocks is given by:

$$\sum_{i=1}^{|s|}\left(\sum_{j=1}^{J} Borrow_{sij} - \sum_{j=1}^{J} Borrow_{sij(C)}\right) = K_{s}^{RM}. \tag{19}$$

In line with the existing literature on misallocation, we evaluate the impact of interlocking directorates by considering a counterfactual scenario in which the capital allocated through these links is reallocated efficiently. The main innovation of our framework is its ability to isolate a specific source of misallocation while holding all other distortions constant, allowing for a precise quantification of its effects. In this counterfactual setting, firms solve the following maximization problem:

$$\max_{K_{si}^{RM}}\left(1-\tau_{Y_{si}}\right)P_{si}^{*}Y_{si}^{*} - R_s K_{si}^{RM} \tag{20}$$

for an interest rate R_s such that the final allocation satisfies $\sum_{i=1}^{|s|} K_{si}^{RM} = K_{s}^{RM}$. Finally, the problem turns out to be more manageable as we rewrite it in the following equivalent form:[12]

$$\begin{aligned} \max_{K_{s1}^{RM},\ldots,K_{s|s|}^{RM}} & \sum_{i=1}^{|s|} \frac{\sigma}{\sigma-1}\frac{1}{(1-a_s-b_s)}\frac{Z_s Q_{si}}{P_{si}Y_{si}}\gamma_s\left(Y_{si}^{*}\right)^{\frac{\sigma-1}{\sigma}} \\ s.t. \quad & \sum_{i=1}^{|s|} K_{si}^{RM} = K_{s}^{RM} \\ & K_{si}^{RM} \geq 0. \end{aligned} \tag{21}$$

We solve this problem for the Manufacturing and Service sectors, while excluding Agriculture from the counterfactual redistribution. Our empirical estimates suggest that interlocks do not contribute to misallocation in the Agriculture sector, and redistributing credit in it would introduce some degree of

[12] The problem is equivalent to assuming that each firm maximizes profit, $\pi_{si} = \left(1-\tau_{Y_{si}}\right)P_{si}^{*}Y_{si}^{*} - R_s K_{si}^{RM}$, with R_s chosen such that, in equilibrium, the total quantity of financing is K_{s}^{RM}.

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Table 9 Counterfactual gain by macro-sector

	Manufacturing	Services
VGO_tlc	1.000859	1.001663
VGO_emp	1.00079	1.001585
VVA	1.000543	0.9988073

spurious misallocation. To replicate a scenario in which interlocks function by reducing informational asymmetries, we restrict the redistribution to firms with a geodesic distance of six or fewer from a bank.

After recovering the counterfactual borrowings, we apply the methodology of Dias *et al.* (2016) to aggregate the results at the macroeconomic level. The aggregate variation in gross output (VGO_*x*) is then calculated as:[13]

$$\frac{Y^*}{Y} = \prod_{s=1}^{S}\left(\frac{Y_s^*}{Y_s}\right)^{\theta_s} = \prod_{s=1}^{S}\left(\frac{\left(\sum_{i=1}^{M_s}\left(Y_{si}^*\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_{i=1}^{M_s}\left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}\right)^{\theta_s} = \prod_{s=1}^{S}\left(\left(\frac{\sum_{i=1}^{M_s}\left(Y_{si}^*\right)^{\frac{\sigma-1}{\sigma}}}{\sum_{i=1}^{M_s}\left(Y_{si}\right)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\sigma}{\sigma-1}}\right)^{\theta_s}. \quad (22)$$

In performing this calculation, we also include the output of firms that have not received any lending by using the relationship $Y_{si} = \left(\frac{P_{si}Y_{si}}{\gamma_s}\right)^{\frac{\sigma}{\sigma-1}}$. To ensure robustness, counterfactuals for gross output are calculated by measuring labor both as total labor cost (x = tlc) and as the number of employees (x = emp). Similar calculations allow us to estimate also the gain from fixing distortions in credit allocation in the value added.

Table 9 presents the results disaggregated by macro sectors. We observe that the proportional distances are too small to reasonably suggest any significant difference between the real data and the counterfactual for either variation metric. This result is somewhat puzzling, given that the econometric evidence indicates a distortion in the allocation of credit due to favoritism lending practices associated with interlockings. The issue of shedding light on this puzzle is explored in the next section.

6. Favoritism in credit allocation: friend or foe?

We argue that the negligible aggregate effects of lending favoritism—typically viewed as a financial friction that should generate meaningful distortions—might stem from the fact that interlock-induced distortions might apply asymmetrically across firms: they tend to penalize relatively efficient firms while directing additional credit toward firms that are already productive. Preferential lending to efficient firms is far less distortionary than extending credit to inefficient firms, as efficient firms would have attracted substantial credit even in the absence of interlocks. This mechanism parallels Restuccia's (2019) notion of a negative elasticity of distortions with respect to productivity: when subsidies or similar advantages shift resources toward more productive establishments—even while distorting their optimal scale—aggregate productivity losses remain limited.[14] In our setting, this logic implies that although interlocks do generate capital misallocation, their macroeconomic footprint stays small when

[13] In practice, the data allows us to recover only $Y_{si}^{*\,not\gamma} = \left[A_{si}\left(K_{si}^*\right)^{a_s}\left(\frac{H_{si}}{P_{si}Y_{si}}\right)^{b_s}\left(\frac{Q_{si}}{P_{si}Y_{si}}\right)^{1-a_s-b_s}\right]^{\frac{\sigma}{1+(\sigma-1)a_s}}$, as γ_s is unobserved. This is not problematic, however, since we can calculate the ratio between Y_{si}^* and Y_{si}, and use formula (17) to recover $Y_{si}^{not\gamma}$ by using actual capital. Similarly, for the intermediate products, we observe only $Q_{si}^{*\,not\gamma} = \frac{Q_{si}}{P_{si}Y_{si}}\left(\left[A_{si}\left(K_{si}^*\right)^{a_s}\left(\frac{H_{si}}{P_{si}Y_{si}}\right)^{b_s}\left(\frac{Q_{si}}{P_{si}Y_{si}}\right)^{1-a_s-b_s}\right]^{\frac{\sigma}{1+(\sigma-1)a_s}}\right)^{\frac{\sigma-1}{\sigma}}$, so we must recalculate Q_{si} and ${Q_{si}}^{not\gamma}$.

[14] This point has been initially raised in Restuccia and Rogerson (2008).

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board ties disproportionately link banks to high-efficiency firms. Favoritism thus reshapes the firm-level distribution of credit without producing large aggregate distortions.

To formally illustrate the intuition, we sketch a simple model that provides the theoretical underpinning of the empirical analysis to follow, aimed at testing whether this assumption of preferentiality toward efficient firms is borne out in the data. Consider an economy with two firms producing a homogeneous final good using a Cobb–Douglas production function with capital K as the sole input. Both firms operate as price-takers, but they differ in their total factor productivity by a factor c, where $c > 0$ indicates a relative advantage and $c < 0$ a relative disadvantage. The difference in total factor productivity determines which firm is the most efficient. Formally, output for each firm is given by:

$$Y_1 = AK_1^{\alpha}$$

$$Y_2 = (A + c)\,(K_2)^{\alpha},$$

where Y_i is the output and $0 < \alpha < 1$ is a measure of the degree of marginal returns.

As we let $\theta > 1$ being a wedge determining capital distortion due to an unspecified financial friction and R the user cost of capital, for a competitive market price P profits are given by:

$$\pi_1 = PY_1 - RK_1$$

$$\pi_2 = PY_2 - \frac{1}{\theta}RK_2.$$

Solving for K_1 and K_2 returns $K_1^* = \left(\frac{R}{PA\alpha}\right)^{\frac{1}{\alpha-1}}$ and $K_2^* = \left(\frac{R}{P\theta(A+c)\alpha}\right)^{\frac{1}{\alpha-1}}$, and in equilibrium total capital is $M = K_1^* + K_2^*$. Aggregate outcome then becomes:

$$Y_\theta = Y_1\left(K_1^*\right) + Y_2\left(K_2^*\right) = A\left(\frac{M}{1 + \left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + (A + c)\left(M - \frac{M}{1 + \left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}. \tag{23}$$

Without misallocation and maintaining M constant, the aggregate outcome would be:

$$Y = A\left(\frac{M}{1 + \left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + (A + c)\left(M - \frac{M}{1 + \left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}. \tag{24}$$

In line with the theoretical approach followed so far, we are interested in the ratio between the aggregate output with and without misallocation, that is:

$$\begin{aligned}\frac{Y}{Y_\theta} &= \frac{A\left(\frac{M}{1+\left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + (A+c)\left(M - \frac{M}{1+\left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}}{A\left(\frac{M}{1+\left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + (A+c)\left(M - \frac{M}{1+\left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}} \\ &= \frac{AM^{\alpha}\left[\left(\frac{1}{1+\left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + \frac{(A+c)}{A}\left(1 - \frac{1}{1+\left(\frac{A}{(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}\right]}{AM^{\alpha}\left[\left(\frac{1}{1+\left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha} + \frac{(A+c)}{A}\left(1 - \frac{1}{1+\left(\frac{A}{\theta(A+c)}\right)^{\frac{1}{\alpha-1}}}\right)^{\alpha}\right]}.\end{aligned} \tag{25}$$

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The ratio of the two quantities remains independent of M and is determined by $\frac{A}{(A+c)}$ rather than the absolute level of A. To explore the implications, we conduct a series of simulations examining the behavior of $\frac{Y}{Y_\theta}$ as this ratio and other parameters vary. Our primary focus is on assessing whether a distortion on the allocational choice of capital toward more productive firms might operate as a mitigating mechanism in the overall impact of misallocation derived from θ. Therefore, we concentrate on $\frac{Y}{Y_\theta}$ as a function of c, which is the quantity determining the relative efficiency of the two firms.

Panels (*a*)-(*c*) of Figure 1 present simulation results for $\frac{Y}{Y_\theta}$ across different values of c, holding $A = 50$ and $\theta = 1.8$, and considering values of α set at 0.10, 0.20, and 0.60. We evaluate c over the range $\{-15, \ldots, 15\}$, which implies that the ratio $\frac{A}{(A+c)}$ varies between 0.7 and 1.3. Across all simulations, the qualitative pattern remains consistent, though the magnitude of the effect varies with changes in parameter values. As expected, any degree of misallocation reduces aggregate efficiency ($Y/Y_\theta > 1$ for all values of c), but the results indicate that reallocating capital toward the more productive firm entails a smaller efficiency loss than directing it toward the less productive one. On the right side of each panel (*a*)-(*c*) of Figure 1 are the cases in which c is higher than 0 and Firm 2, which is the firm benefiting from the distortion, is the most efficient firm. Conversely, the left side presents the cases in which Firm 2 is the least efficient. In each panel, the ratio between the aggregate output without misallocation and with misallocation is higher in the scenarios in which the firm benefiting from the distortion is the least productive, indicating that misallocation toward more efficient firms is comparatively less harmful than misallocation toward inefficient firms.[15]

To corroborate this mechanism, we assess whether more efficient firms are indeed more likely to form ties with banks.[16] Specifically, we estimate the effect of firm efficiency on the probability of establishing a link within the interlocking-directorates network, a necessary condition for the negative elasticity of distortions to operate. The econometric model takes the following form:

$$Len_{ij} = \alpha + \beta_1 EFF_i + \beta_3 ILS_i + \beta_4 BA_j + \beta_5 RelDummy_{ij} + \beta_6 RelAmount_{ij} + \beta_7 \frac{Equity}{TotalAsset} + \varepsilon_{ij}. \quad (26)$$

Len_{ij} represents the length of the shortest path between a bank and a firm, ranging from 1 to 7, with the latter category encompassing firm-bank pairs that are not connected through any path (i.e. infinite distance). The remaining covariates mirror those included in the model estimating the intensive margin of credit, the results of which are reported in Tables 10–12. As in the previous specifications, we cluster standard errors at the bank and firm level and estimate separate models for each macro-sector. We interpret a negative coefficient β_1 as evidence that the proposed mechanism is at work in Portugal.

With the exception of the Agriculture sector, the marginal revenue of capital consistently predicts a firm's proximity to a bank. In other words, more efficient firms are more likely to be linked to banks through personal connections among board members or interlocking directorates. In both the Manufacturing and Service sectors, the coefficient on firm efficiency remains negative across specifications, with its magnitude largely unaffected by the inclusion of additional controls.[17] Similar results (omitted for brevity) emerge when estimating a model in which the dependent variable is a binary indicator equal to one if a firm is connected to a bank by any path and zero otherwise. This suggests that banks may be motivated less by concerns over financial stability and more by a preference for firms with a demonstrated capacity for higher returns on investment. Consequently, the presence of interlocks may not only serve as a mechanism for mitigating risk but could also reflect banks' desire to align with firms that are positioned for superior performance.

[15] Notably, higher values of α magnify the aggregate impact of misallocation. Additionally, we observe concavity in the function for negative values of c, driven by the fact that as c approaches -50, $(A + c)$ converges to zero, effectively eliminating firm 2's contribution to aggregate output despite the additional capital it receives. However, this represents an extreme case: in our empirical analysis, we assume that productivity differentials among active firms remain within a more reasonable range.

[16] Notably, this would imply that closeness to banks mediates the effect of being relatively more efficient on the amount of credit.

[17] Reported R^2 do not vary due to rounding.

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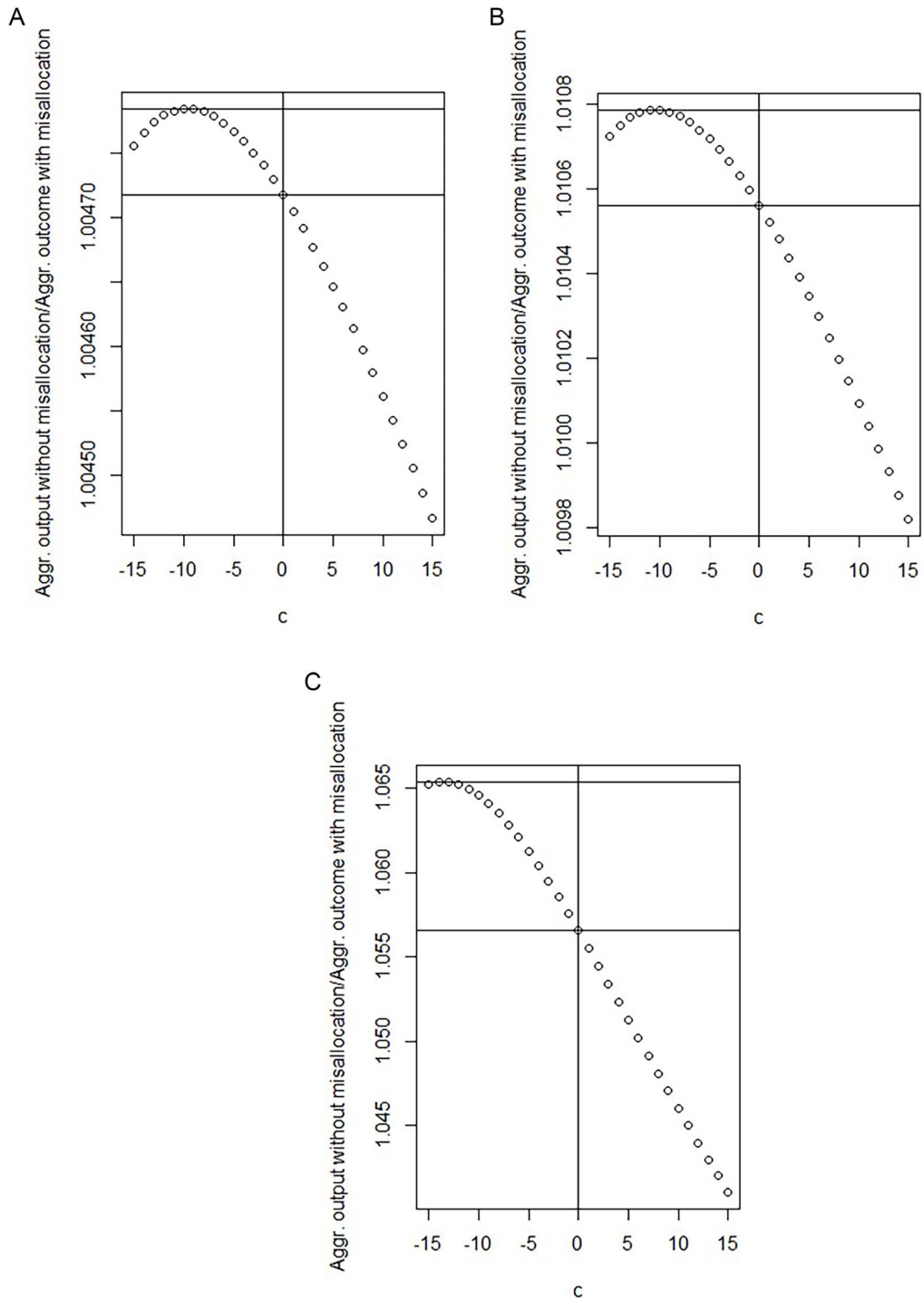


Figure 1 The figure shows three panels presenting the simulation results for $Y/Y\theta$. The settings corresponding to panels (A), (B), and (C) are: (A) $a = 50$, $\theta = 1.8$, $\alpha = 0.10$. (B) $a = 50$, $\theta = 1.8$, $\alpha = 0.20$. (C) $a = 50$, $\theta = 1.8$, $\alpha = 0.60$.

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Table 10 Regression for distance—Agriculture

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
EFF_i	3.20e-07	3.20e-07	3.20e-07	3.20e-07	3.38e-07	3.38e-07
	(2.64e-07)	(2.64e-07)	(2.64e-07)	(2.64e-07)	(2.88e-07)	(2.88e-07)
$RelDummy_{ij}$		−0.0153		0.00342		0.00449
		(0.0302)		(0.0424)		(0.0423)
$RelAmount_{ij}$			−0.0345	−0.0385		−0.0391
			(0.0348)	(0.0460)		(0.0460)
Equity/Total assets					0.0199*	0.0199*
					(0.0119)	(0.0119)
Observations	769,454	769,454	769,454	769,454	769,454	769,454
R-squared	0.273	0.273	0.273	0.273	0.273	0.273
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

Table 11 Regression for distance—Manufacturing

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
EFF_i	−5.21e-06***	−5.21e-06***	−5.21e-06***	−5.21e-06***	−4.84e-06***	−4.83e-06***
	(1.63e-06)	(1.63e-06)	(1.63e-06)	(1.63e-06)	(1.67e-06)	(1.67e-06)
$RelDummy_{ij}$		−0.0468**		−0.0779**		−0.0776**
		(0.0207)		(0.0313)		(0.0313)
$RelAmount_{ij}$			−0.0121	0.0813**		0.0811**
			(0.0199)	(0.0336)		(0.0335)
Equity/Total assets					0.00366	0.00363
					(0.00235)	(0.00235)
Observations	3,058,419	3,058,419	3,058,419	3,058,419	3,058,419	3,058,419
R-squared	0.449	0.449	0.449	0.449	0.449	0.449
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

7. Conclusion

This paper employes micro-level data from Portugal to examine the role of interlocking directorates in firms' borrowing behavior. Unlike previous studies, we assess the implications of interlocks at both the micro and macro levels. Our empirical analysis consists of two main components: first, we investigate the impact of interlocks on the intensive margin of credit allocation; second, we evaluate their broader effects on Portugal's GDP.

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Table 12 Regression for distance—Services

VARIABLES	(1) MODEL 1	(2) MODEL 2	(3) MODEL 3	(4) MODEL 4	(5) MODEL 5	(6) MODEL 6
EFF_i	−1.57e-07**	−1.57e-07**	−1.57e-07**	−1.57e-07**	−1.34e-07*	−1.34e-07*
	(7.56e-08)	(7.55e-08)	(7.56e-08)	(7.55e-08)	(7.02e-08)	(7.01e-08)
$RelDummy_{ij}$		−0.0494***		−0.110***		−0.110***
		(0.0146)		(0.0288)		(0.0288)
$RelAmount_{ij}$			−0.00915	0.114***		0.114***
			(0.0103)	(0.0272)		(0.0271)
Equity/Total assets					0.00192***	0.00192***
					(0.000448)	(0.000448)
Observations	6,802,159	6,802,159	6,802,159	6,802,159	6,802,159	6,802,159
R-squared	0.389	0.389	0.389	0.389	0.389	0.389
ILS	YES	YES	YES	YES	YES	YES
bank FE	YES	YES	YES	YES	YES	YES
Clustered errors	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank	Firm bank

Robust standard errors in parentheses. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

Examining the impact of ties on the intensive margin, we find evidence that interlocks can contribute to resource misallocation. Our findings align with the existing literature that identifies interlocking directorates as a source of favoritism, as ties generally increase the amount of credit received regardless of firm efficiency. To assess the macroeconomic implications, we conduct a counterfactual exercise estimating the GDP effects of removing interlocks. Simulations indicate that eliminating interlocking ties would lead to minimal changes in aggregate output. This calls for an additional analysis aimed at exploring whether firm efficiency influences the likelihood of establishing bank connections. In fact, we find that efficiency negatively correlates with the firm's distance from banks, suggesting that more efficient firms tend to be closer to banks. We argue that this mechanism tends to attenuate the misallocation potential of interlocks, as the firms most likely to benefit from these relationships are also those that would be favored in a frictionless credit environment.

In terms of policy implications, our results suggest that regulations aimed at preventing interlocking directorates and the consequent favoritism in credit allocation may not necessarily lead to significant improvements in macroeconomic outcomes if the misallocation is predominantly concentrated in more efficient firms that are closer to banks. This finding offers a nuanced view of the relationship between financial distortions and economic performance, suggesting that reducing preferential lending in an environment where firms' productivity and proximity to banks are key factors may not always be a straightforward solution.

Acknowledgments

We are grateful to Domenico Delli Gatti, Sujiao Zhao and all members of the Banco de Portugal's *Microdata Research Laboratory* (BPLIM) for their help with data availability and valuable suggestions throughout the development of this research project, as well as to an anonymous referee and seminar participants at the Third DISEI workshop (Florence) and the 66th Annual Conference of the Italian Economic Association (Naples) for their comments and advice. We thank Roberto Gabriele, Davide Bernardini, and Giulio Galdi for their comments on a previous version of the manuscript. The usual disclaimers apply.

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Conflict of interest

None declared.

Funding

None declared.

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Industrial and Corporate Change, 2026, 00, 1–26
https://doi.org/10.1093/icc/dtag032
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