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A computational model of the effects of borrower default on the stability of P2P lending platforms

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Abstract

Peer-to-peer (P2P) lending has attracted scholarly attention because of its economic significance and potential to democratize access to finance. However, P2P lending platforms face many challenges and failures that we need to understand more clearly. We build a computational model to study how borrower default affects P2P platform lending. We show that borrower default disrupts the P2P network formation process and undermines platform stability. Moreover, we find that defaults increase the inequality in accessing funding and provide a rationale for using curation rules, widely used in P2P platforms, in contrast to P2P insurance, which fosters cascading defaults. We also address a new trend in P2P lending platforms in which large companies (institutional investors) play an increasingly important role. We find that the presence of large companies creates a denser network (more loans) but generates a trade-off between making the platform more resilient to cascading defaults and more dependent on specific players. Overall, we explain how borrower defaults affect platform stability and what makes a platform vulnerable, threatening its survival. We discuss research and managerial insights into platform stability and the economic effect of P2P lending platforms.

Keywords Fintech · Digital platform · Platform stability · Peer-to-peer lending · Digital financial service · Network structure · Network effect · Network collapse

JEL Codes: D39, G20, G23, M10

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1 Introduction

A peer-to-peer (P2P) lending platform is a new digital platform business model (Parker et al., 2016; Cusumano et al., 2020; Cumming & Hornuf, 2021a) that challenges bank incumbents because it provides an alternative to traditional bank loans. Instead of borrowing from a single bank, SMEs and entrepreneurs borrow from several sources through the platform. Lending platforms create two-sided platform markets that facilitate matching borrowers and lenders. These platforms have bloomed in countries like India and China, promising to democratize access to finance and reduce inequality and poverty (OECD, 2020).

Despite their rapid growth and potential benefits, these platforms have been controversial, especially in China, where almost one-third of P2P lending platforms face operational difficulties (Yan et al., 2018). P2P platform lending failures have been widely reported in the business press[1] (Chorzempa, 2018). In March 2022, for instance, Funding Circle permanently closed its retail platform to new investments, joining other platforms such as Zopa and Landbay in the UK (Venkataramakrishnan, 2022).

Understanding why these platforms face such challenges is of utmost relevance because of their ability to boost financial inclusion and foster the economic participation of underrepresented groups. As P2P platforms continue to face significant distress, interest in what factors affect their performance and viability concerns policy markets and managers alike.[2]

The mechanisms that may disrupt P2P lending platform growth, create platform instability, and potentially lead to platform failure are currently unclear. The P2P lending literature has studied many issues, such as what characteristics make borrower default more likely (Zhao et al., 2017; Basha et al., 2021) or the reasons behind P2P lending failures in China (Chen et al., 2021). However, there is little work that integrates those two themes. This paper fills this research gap by addressing how borrower default can affect the P2P lending networks and how different platform characteristics influence the severity of those effects.

We build and simulate a computational model of endogenous network formation that represents the SME interactions on a P2P lending platform. Borrower firms have investment opportunities but may lack funds (liquidity), while lenders have the liquidity to invest. Loans on the platform create a network in which the nodes are SMEs (agents), and the links are loans. We consider one platform characterized by its size (number of SMEs on the platform), the matching technology (reach), and a set of curation rules (risk thresholds used to screen SMEs or the availability of insurance).

The main objective of this research is to understand the effects of borrower default on the endogenous loan network formation on the platform and its implications for platform stability. Therefore, given specific platform characteristics, we explain the

[1] https://techcrunch.com/2018/08/01/the-dramatic-rise-and-fall-of-online-p2p-lending-in-china/and https://www.icaew.com/insights/viewpoints-on-the-news/2020/aug-2020/what-happened-to-peertopeer-lending.

[2] https://www2.deloitte.com/uk/en/blog/auditandassurance/2020/changes-and-concerns-in-the-peer-to-peer-p2p-lending-market.html.

mechanism that links borrower default and platform stability. The paper adds to previous literature on P2P lending platform failures by providing context on how the platform will be affected by defaults. Moreover, we seek to provide insights into what a platform could do to prevent or mitigate this problem.

We show that curation rules, widely used in this sector, have a rationale over other measures, such as P2P insurance. P2P insurance weakens platform stability, while curation rules strengthen it. Intuitively, P2P insurance spreads risk across the network, increasing the exposure of all players and magnifying the shocks. However, the curation rules limit the access of high-risk players, mitigating their direct and indirect impact on the network. In addition, we document novel effects on how network topology changes after a default crisis or how defaults can influence corporate inequality. We show that even if the platform survives, the resulting network topology is weaker, showing that second shocks can be damaging in many cases. The after-shock network topology depends more on specific nodes. Characterized by fewer communities, there is less redundancy, and the loss of a node is more critical. We also document that it is likely that corporate inequality, understood as access to investment, may increase after a default crisis. This is because those who remain on the platform are the ones who need fewer resources but concentrate more loans. Finally, we also address a trend in this business model that aims to include large firms (institutional investors) in the platforms. We show that this trend faces a new trade-off between making the platform more vulnerable or dependent on these large firms and reducing cascading defaults.

The following section reviews related literature. The model is presented in Sect. 3, followed by simulation results and discussion.

2 Related literature

We discuss P2P lending definitions and benefits, challenges, and P2P lending for SMEs.

2.1 P2P lending definitions and challenges

P2P lending platforms, also called debt crowdfunding or crowdlending (Ribeiro-Navarrete et al., 2022; Darmon et al., 2022), provide fast and convenient access to loans for borrowers and a new investment opportunity for lenders. Platforms use technology to offer financial products that improve the customer experience or the lenders' screening and monitoring of borrowers (Berg et al., 2021), offering a new fintech product (Jagtiani & Lemieux, 2017) that helps internalize several externalities across and within groups (Belleflamme et al., 2016).

There exists a vibrant body of research on P2P lending. An early comprehensive survey on P2P lending (Zhao et al., 2017) attempts a classification of platforms (e.g., general vs. niche, for-profit vs. not-for-profit, personal vs. business loans, trading mechanisms), open research issues (pricing of loans, risk management, privacy, and personalization), and research approaches (economics vs. data-driven). Part of the literature focuses on credit scoring (Wang et al., 2019) and the prediction of borrower's default risk (Serrano-Cinca et al., 2015; Zeng et al., 2017; Ma et al., 2018; Croux et al., 2020; Chen et al., 2021b). It is skewed toward the US and China (Basha et al., 2021), where there is an intense debate about platform regulation and a need to understand the interaction between platform lending (alternative finance) and traditional finance. In this regard, (Milne & Parboteeah, 2016) argue that P2P lending is fundamentally complementary to, and not competitive with, conventional banking.

Despite the promised benefits (OECD, 2020), P2P lending platforms face several challenges. Several studies find bias in lending (Burtch et al., 2014; Lin & Viswanathan, 2015) or unequal economic opportunities, which rejects a flat-world hypothesis (Singh et al., 2018). Similarly, over-indebtedness aggravates poverty and is a potential unintended consequence of a push to increase financial inclusion (Fanta & Makina, 2019). Furthermore, the ease of receiving a loan causes some borrowers to overextend themselves financially, leading to default (Wang & Overby, 2021). Moreover, (Igra et al., 2021) shows that crowdfunding provides higher benefits in wealthier counties with higher levels of education, thus exacerbating inequalities. This has led some authors to argue that lending platforms should function as gatekeepers of social impact and cannot outsource social impact evaluation to retail investors (Kollenda, 2021).

Other challenges that face P2P lending platforms are related to platform risk (Wang et al., 2021) and platform failures, especially in China (Chen et al., 2021a; Gao et al., 2021). (Deng, 2022) finds that formal finance exerts a crowding-out effect on the P2P lending market, explaining failures in China's P2P lending industry, which are also related to political factors (He & Li, 2021). On the other hand, platform default risk may increase due to intense competition (Yoon et al., 2019) or a gap between lender preferences and platform offerings (Klein et al., 2023). Reputation and the broader fintech ecosystem also affect the platform's cash flow (Chen et al., 2021), and recent evidence shows that bad news about a P2P lending platform makes everyone on a second platform worse off (Cheng et al., 2022). This was especially relevant in China, where problematic business models plagued the P2P lending industry before its regulation (Chen et al., 2021). However, introducing a strict new regulatory regime reduces the volume of P2P lending substantially.

In general, the focus has been on risk, preferences, and regulation, all of which are pre-shock factors. Our paper builds on this evidence to show how SME defaults weaken P2P platforms and the subsequent consequences.

2.2 SMEs and P2P lending

We should emphasize that there is little literature on platform lending for SMEs (Ariza-Garzón et al., 2021; Cumming & Hornuf, 2021a). Most P2P lending papers focus on platforms for personal loans (and personal defaults), e.g., Lending Club in the US, while we focus on SME loans (and SME defaults). The distinction is important because the two contexts (loans for personal consumption vs. business loans) have different features and economic implications.

SMEs and entrepreneurs can use platform lending to start and grow ventures (Bruton et al., 2015). Abbasi et al., (2021) uses an OECD dataset to show that P2P lending platforms increase SMEs' access to finance. It recommends that SME managers should make more use of P2P lending platforms. However, P2P lending brings new regulation challenges (Nemoto et al., 2019). (Cumming & Hornuf, 2021b) studies marketplace lending for SMEs and finds that platforms should offer simple ratings to influence investor behavior. (Au & Sun, 2019; Au et al., 2020) conducted a case study of Tuodao, one of China's leading P2P lending platforms, to understand how to develop a digital platform. They propose a three-stage sequential qualitative process: leverage partnerships, subsidize lenders, and facilitate borrowers.

Overall, there is extensive literature on P2P lending but limited literature looking at business loans, and even less work on explaining how borrower defaults can affect the P2P platform and how to mitigate those effects (Kumar et al., 2020; Rao et al., 2021). Given that gap in the literature, there is a need for computational modeling research to clarify the mechanisms behind how borrower default affects the stability of lending platforms, potentially leading to platform failure.

3 Computational model

Our model extends the computational model of (Katsamakas & Sánchez-Cartas, 2022), which considers the behavior of N agents representing SMEs on a P2P lending platform.

The flow of the model is as follows. SMEs have investment opportunities and liquid assets. SMEs want to maximize returns on their liquid assets and can choose to invest in their opportunities, lend to others who may have better opportunities and need resources, or exit the market. The key constraint is that they need a minimum amount to invest in their opportunities. If their liquid assets are insufficient, they have to ask for more resources from their surrounding peers, who will only lend money if the expected return is greater than (or equal to) the market return and their own opportunities. Each SME calculates its total assets as the sum of its initial assets plus the income it earns as a lender and its liabilities (the sum of its debts as a borrower). The platform calculates each SME's risk metric (liabilities/assets). Note that this is an iterative process where the decisions of SMEs are interrelated.

In some scenarios, we allow the platform to offer an insurance product (P2P insurance). When insurance is available, if a borrower becomes riskier than when the loan contract was signed, the lender may contract insurance with another peer on the platform (Wu et al., 2020). Our analysis compares insurance and no-insurance cases to explore their impact on platform stability.

Borrower failure can take many forms and have many origins. To simplify the model, SMEs whose liabilities exceed their total assets will face default. This way of modeling borrower default allows us to address two key aspects. First, many crises (or their effects) are unexpected for SMEs; thus, they could find themselves in a weak position (more debts than assets), forcing them out of business. Second, this specification gives us a clear picture of the cascade effects because it establishes a single criterion for default. Other specifications might consider debt renegotiation, bailouts, or partial repayment. However, these cases may distort or lessen the cascading effects that follow default. Therefore, our experiment can be considered an extreme case to highlight where the greatest threats to the platform lie.

3.1 SMEs and platform characteristics

To make the model as simple as possible, our SMEs are characterized by three variables: liquid assets, investment opportunities, and risk. Furthermore, the platform is defined by three variables: curation rules, matching technology, and size (number of SMEs on the platform).

To represent prior inequalities that may exist before participating in the lending platform, we assume that SME assets are log-normally distributed (with $\mu = 1$, $\sigma = 0.5$). Intuitively, a few SMEs are well-funded, while others lack resources. Similarly, investment opportunities are log-normally distributed (with. $\mu = 0$, $\sigma = 1$). In comparison, investment opportunities are more skewed than assets, representing that there may be exceptional cases of investments with great returns.

We also assume each agent has a different risk threshold that reflects the level of risk the agent is willing to accept and limits the agent's exposure to other agents (SMEs). This threshold is based on the ratio of liabilities over assets, which we assume is common knowledge on the platform. In particular, an SME will only consider giving loans to SMEs with a lower risk than the SME's risk threshold. The SME's risk threshold is randomly distributed between 0 and X, where $X \in [0.5; 0.7; 1]$ is the maximum risk threshold set by the platform. This maximum risk threshold represents a kind of curation imposed by the platform. The lower this threshold, the more curated the platforms' selection. For example, if the maximum risk threshold is 50%, only lower than 50% risk threshold agents will be active on the platform. In other words, the platform will not allow firms to expose themselves to risky agents above the maximum risk threshold. To rule out cases of asymmetric information and make the model as simple as possible, we assume that the platform calculates and publishes each SME's risk, defined as the SME's total assets over its liabilities. Additionally, each SME can reach only a subset of all the agents on the platform. This assumption allows us to limit the set of peers with whom an agent can transact (lend or borrow), reflecting the quality of the platforms' matching technology. As the quality of platform technology improves over time, the SME reach increases. The reach is defined as a percent of platform size N, which ranges from 10 to 100% in our experiments. If we assume 100% reach, it is possible to find the best match between lenders and borrowers, but any reach below 100% implies that matches are likely to be suboptimal. Finally, we consider three different platform sizes (N) where we assume 50, 100, and 150 representative firms (SMEs) and assume that the interest rate of the external market is exogenously determined, ranging from 0.5% up to 8.5% in steps of 0.5% points. Therefore, we assume the lending platform is small with respect to the financial market. In other words, it cannot unilaterally affect interest rates.

4 Computational experiments and results

To provide a multidimensional view of the effects of borrower default on the P2P platform, we explore multiple scenarios with varying platform characteristics. All the possible combinations of platform sizes, matching technologies, and external interest rates are simulated. In all cases, we run the simulations until a stationary state is reached in which no SME modifies its behavior. For each combination of parameters, we run 100 simulations to mitigate any stochastic noise. The results presented hold for other parameter combinations that we tested.

Once the model has converged, all SMEs whose liabilities exceed their total assets default on their loans. This implies that all their loans are unpaid, and their creditors lose that money. If the creditors have signed insurance before the default, they can recover their money, but the insurer has to cover that loan with its assets. This process is repeated 50 times to address the cascading (or contagion) effects that can occur after one company fails and creates losses in other companies that also fail, and so on. We consider 50 periods only because no further changes are observed after that.

4.1 Borrower default effects on SMEs and loans

The larger the number of SMEs participating on the platform or the better its matching technology, the more loans are generated. This reflects the power of network effects that are fueled by the total number of SMEs or by increasing their exposure to other peers.

However, when a crisis emerges, the damage is greater on larger platforms than on smaller ones. Their primary source of power (network effects) can also be their source of distress. In large networks, almost a quarter of all SMEs might be lost. As expected, this effect is mitigated if the platform follows some curation rules that limit the risk of participating firms (e.g., reducing the risk threshold of accepted SMEs on the platform). However, these effects are more noticeable in large networks ("Big" in Fig. 1).

One reason why larger platforms are more affected is cascading or contagion effects. In larger networks, the interconnectedness may help spread the crisis. If we compare the platform structures of our experiments, the losses in larger platforms can be almost two times those of the smallest one on average (red bars in Fig. 1). However, platform curation plays a key role, too. Comparing cases with the smallest and largest levels of risk allowed ("low" and "high"), the number of defaults in the latter is significantly higher than in the former. Therefore, our first result highlights the double-edged feature that network effects can have, even without competition. The interconnection of larger networks helps to spread the effects of the crisis further.

Proposition 1 Large P2P platforms are expected to generate proportionally more defaults than smaller ones. However, using self-regulation (e.g., curation rules) mitigates that problem.

Wang et al., (2021) show that information disclosure reduces default probability while network size does not. Our work provides an alternative explanation for their result, as soft factors such as self-regulation may influence this outcome.

Intuitively, a way to limit the effect of defaults could be the use of insurance. Our simulation shows that SMEs are more inclined to insurance when risk thresholds are low (Fig. 2). In other words, when SMEs are risk-averse, they tend to rely more on insurance. A priori, we would expect a lower default ratio if SMEs are insured. However, we did not find such a result.

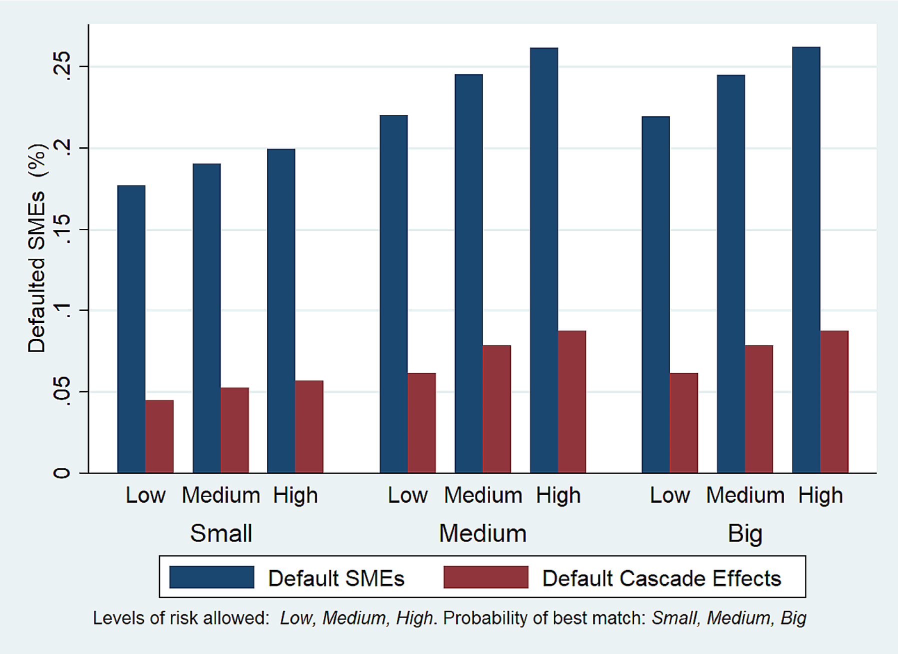

Fig. 1 Average percentage of defaulted SMEs and cascade effects

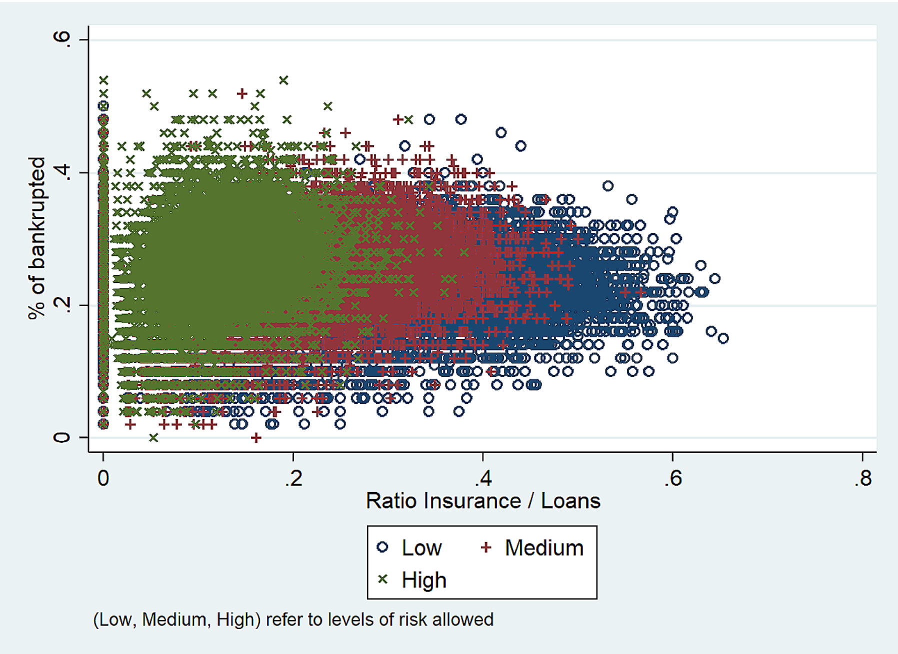

Fig. 2 Use of insurance among SMEs

Surprisingly, P2P insurance leads to a higher rate of business defaults (Fig. 3). This counterintuitive result occurs because SMEs insure each other, exposing themselves and transferring risk to other players in the network. Typically, SMEs that act as insurers have higher risk thresholds and are more likely to be exposed. When there is no possibility of insurance, these SMEs do not assume these additional risks, and the effects of default are limited. This result highlights that insurance could backfire if the platform allows such services to be in the hands of other SMEs. In other words, although P2P insurance is becoming trendy among microbusinesses[3], our simulation shows that it may weaken the whole network structure. Therefore, platforms must balance the potential profits that introducing this new product may have with the risk of weakening the stability of the entire platform. This result explains the broader use of curation rules among P2P platforms[4] in contrast to the use of insurance, which is either absent or carried out by the platform directly[5]. In terms of stability, it is optimal for the platform to rely on curation rules rather than P2P insurance. To our knowledge, the use of P2P insurance is relatively novel, and our results could explain why it is not widely adopted.

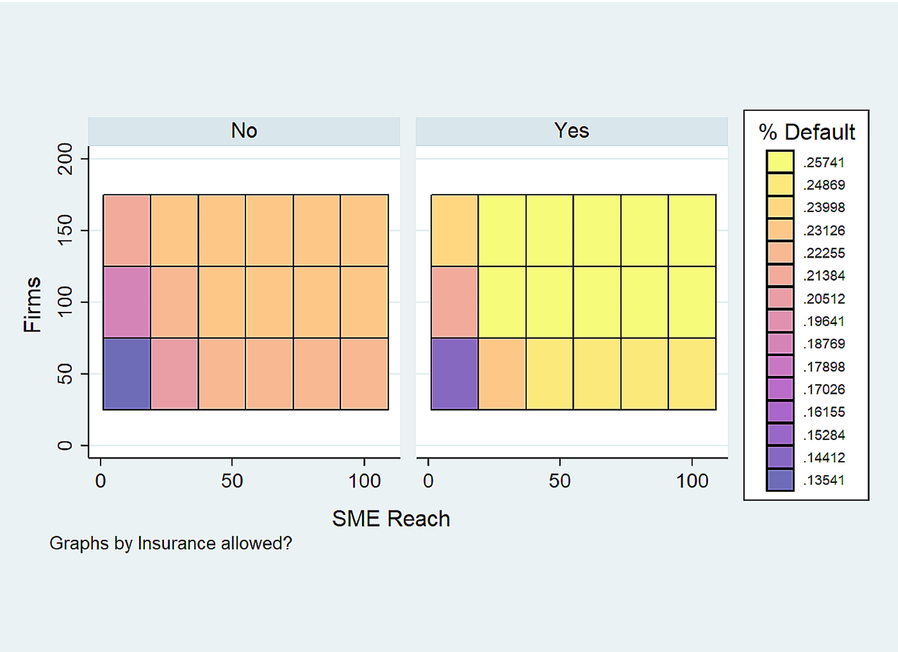

Fig. 3 Percentage of SME defaults

[3] https://www.businessnewsdaily.com/10362-peer-to-peer-insurance.html.

[4] https://economictimes.indiatimes.com/wealth/p2p/how-do-p2p-companies-handle-defaults/articleshow/66440834.cms.

[5] https://monexo.co/what-if-a-borrower-defaults-on-your-p2p-loans/.

Proposition 2 Curation rules (i.e., self-regulation) improve the robustness of P2P lending platforms.

This result is in line with recent evidence highlighting that self-regulation may be a better way to improve market resilience than other forms of regulation (Basha et al., 2021). However, platforms may prefer to introduce new products (e.g., P2P insurance) that may be profitable in the short term but weaken the platform in the long term.

The main force driving these results is cascading effects. Although insurance protects against external risk, this protection is limited and only partially protects against cascading effects. After one firm defaults, the contagion may spread through the network, and insurance may not be enough to block that effect. Figure 4 shows the percentage of defaults and their increase due to cascading effects. We compare cases with and without insurance and observe that although insurance blocks at most 10% of the cascading effects, in some cases, cascading effects can increase the number of defaults up to 30%.

If we now pay attention to the reduction in lending, we observe that post-default lending follows the same pattern as the reduction in SMEs. However, the effects are more dramatic when loans are considered. In comparison, the reduction in loans can be twice that of SMEs. In some cases, nearly two-thirds of loans might disappear (Fig. 5). This result highlights the extent to which the platform landscape can change after a borrower default shock. Firms and their loans and connections with other firms

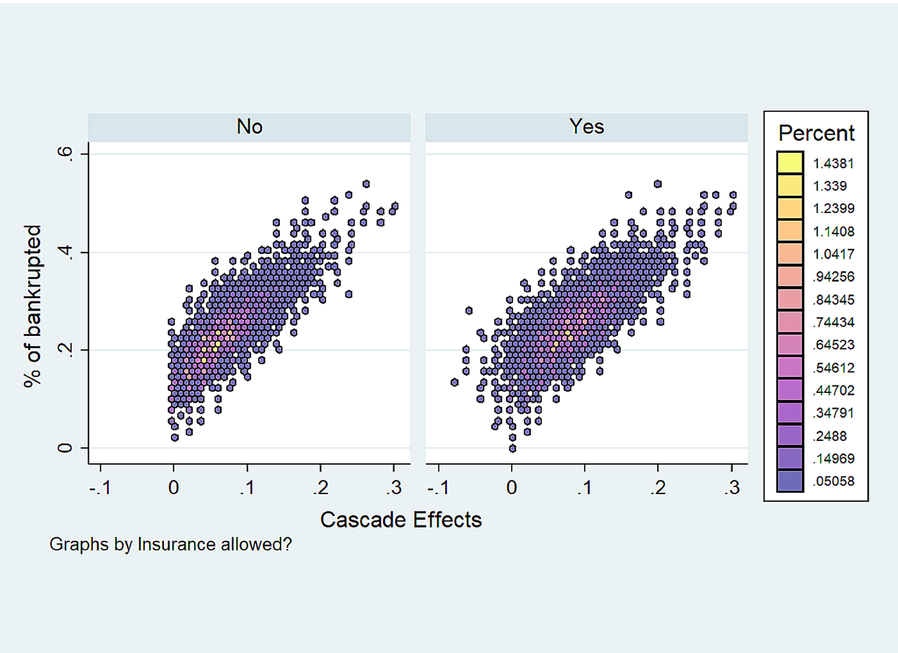

Fig. 4 Defaults and cascade effects (increase of defaults attributable to other SMEs)

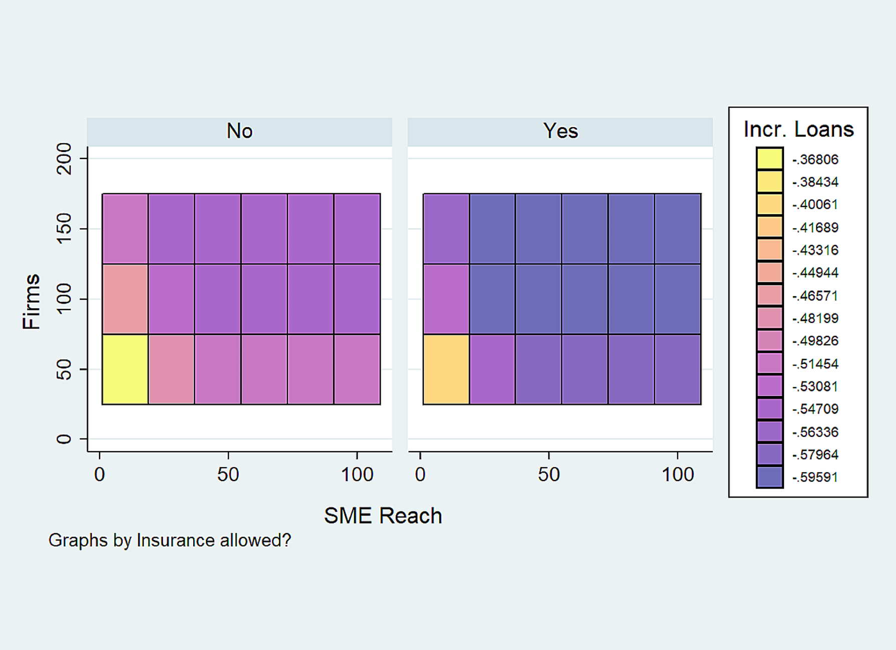

Fig. 5 Change in the number of loans (%)

disappear, which alters the network topology and its characteristics, as shown in the following sections.

4.2 Borrower default effects on the distribution of debts and investments

So far, borrower default seems to cause more harm to big platforms with better matching technology and lax curation rules. However, the effects of SME defaults are not limited to the number of active firms and loans on the platform. It also affects the distribution of investments and debts among the surviving players. In Fig. 6, we observe that defaults increase the inequality in the distribution of debts among players in all cases but are more pronounced in cases with better matching technology and insurance. This last effect is perhaps the most surprising but highlights the pernicious effects that P2P insurance might have once a crisis kicks in. We will find a similar conclusion if we look at debts instead of investments. In this regard, platforms may experience different consequences after defaults due to their curation, size, and P2P policies.

Overall, these results highlight that defaults can generate inequality as a by-product. Regarding recent failures in China, our theoretical results suggest that corporate inequality, understood as access to financial resources, is likely to increase after default events. Moreover, these effects should be greater the larger the platform involved. From a policymaking point of view, our results encourage the supervision of large platforms and their offerings. Since introducing insurance can have perverse consequences, stricter supervision is advisable.

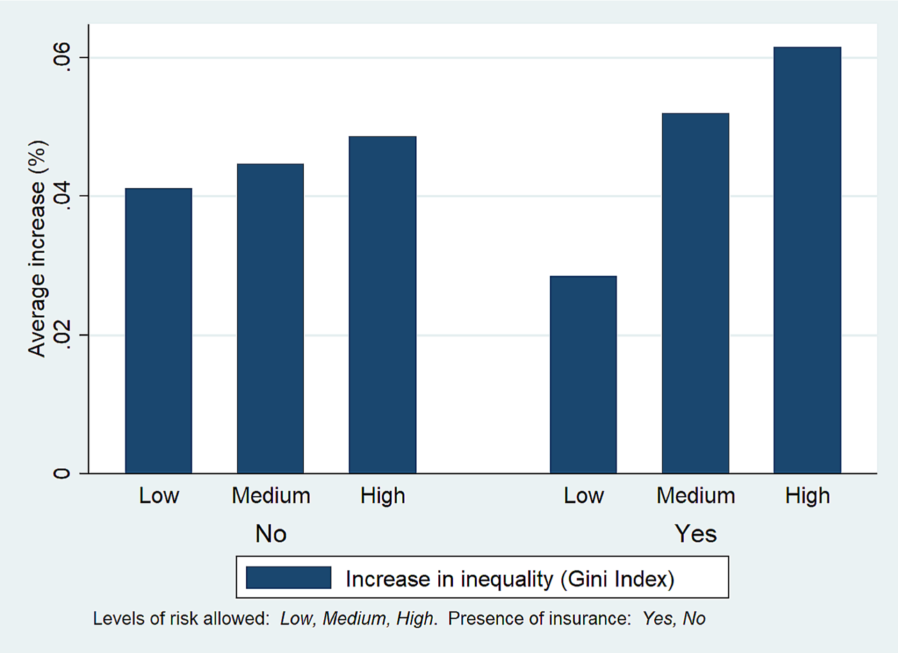

Fig. 6 Effects on the distribution of debts measured as an increase in the Gini index

Proposition 3 SME defaults generate inequality in loan access.

Recent evidence has highlighted that the failures of P2P lending platforms generate unequal opportunities and foster biases (Burtch et al., 2014; Lin & Viswanathan, 2015) (Singh et al., 2018). Our results theoretically support this evidence by showing that this effect can be enhanced even if the platforms survive an SME default shock. Therefore, current discrepancies regarding the impact of P2P lending can also be attributed to the formation of endogenous networks that persist after crises.

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4.3 Borrower default effects on network characteristics

An overlooked aspect of defaults is what happens in terms of power and influence. The network topology can give us a rough idea of how power and influence change once the weakest or most vulnerable SMEs are pushed out of the market. Two metrics that help us to represent the power and influence of firms are the distribution of betweenness and average clustering. Betweenness is a measure of centrality that accounts for the degree to which nodes stand between each other. A node with a large betweenness implies that many connections between nodes pass through it. On the other hand, clustering measures the degree to which graph nodes tend to group together. A large clustering coefficient implies that nodes tend to create tightly knit groups. In the case of a debt network, a more egalitarian distribution of betweenness means that the network is less dependent on central nodes. Similarly, if we observe a reduction in clustering, it implies that sub-communities among groups of nodes are less common, which is related to greater instability (Onnela et al., 2003, 2005; Saramäki et al., 2007; Kauê Dal'Maso Peron, da Fontoura Costa and Rodrigues, 2012). The crucial issue is understanding how defaults disrupt the network structure.

We find an increase in the inequality of centrality measured by the Gini index, which ranges from 4 to 16% (Fig. 7). Interestingly, the increase is greater on larger platforms and when P2P insurance is available. This result reinforces the previous ones, highlighting the double-edged nature of network effects and the threats that P2P insurance imposes on platform stability. Moreover, the increase in the betweenness of some nodes implies that the resulting network structure is more dependent on specific nodes, increasing the network's vulnerability to secondary shocks.

Defaults also influence how tightly knit SMEs are on the network. In particular, defaults destroy communities in a pattern similar to the above. The bigger the platform, the more likely this effect. Similarly, the possibility of P2P insurance also increases this effect. We generally observe that the average clustering reduction ranges from 48 to 70%. This means that virtually every SME in the network loses some peer, and the final structure of the network is much looser. As mentioned, clustering is related to network resilience; thus, crises in which the clustering coefficient is significantly reduced might lead to a weaker network structure (Fig. 8).

Proposition 4 Default shocks make the platform structure more dependent on specific nodes, increasing the network's vulnerability to secondary shocks.

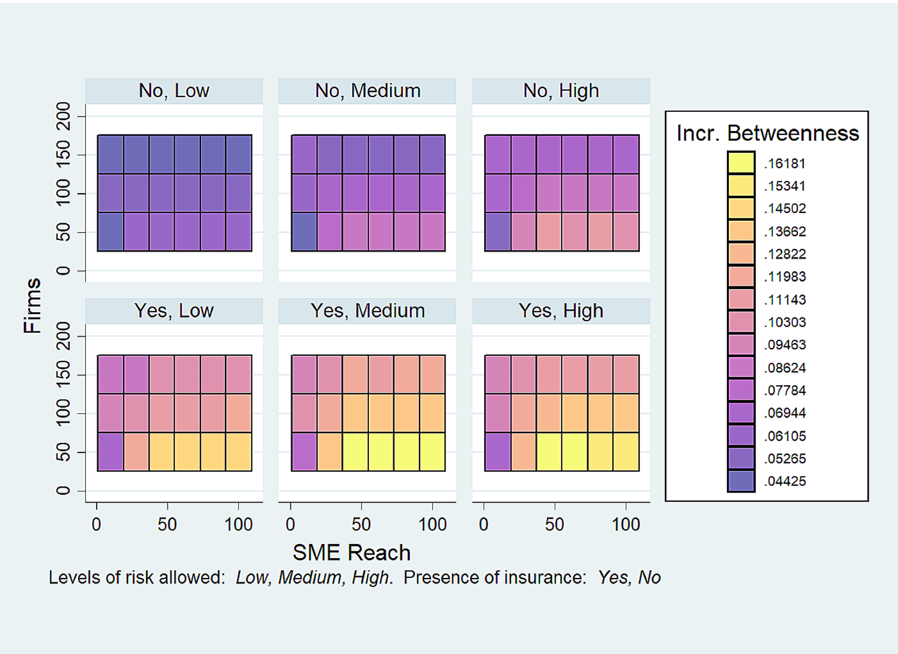

Fig. 7 Change in the distribution of betweenness measured as percentual increments over the Gini Index

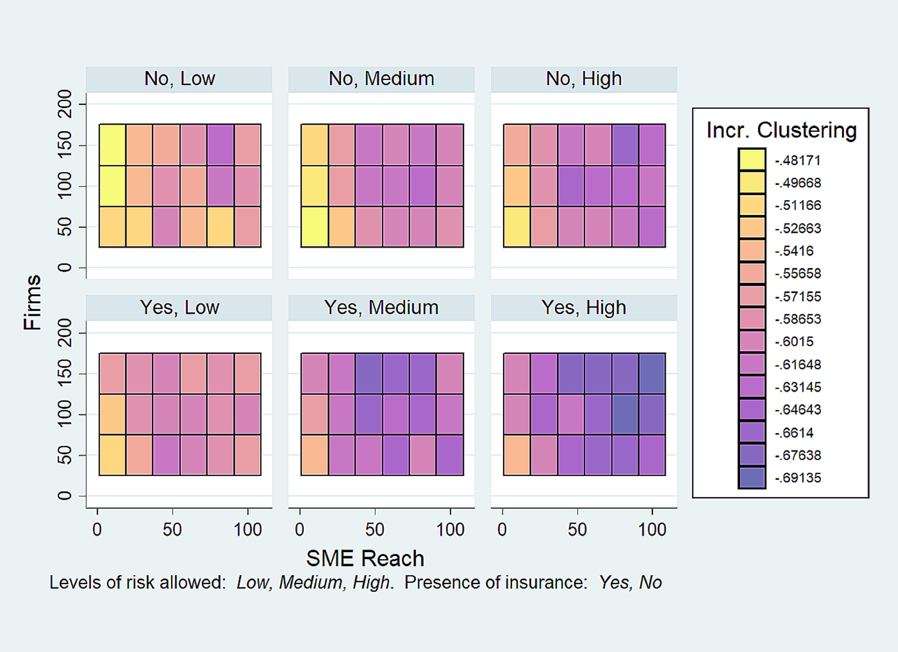

Fig. 8 Change in the average clustering measured as percentual increments

These results provide an alternative hypothesis to recent failures of P2P platforms in China and are in line with previous evidence that highlights the relevance of network topology in finance (Li et al., 2018). Platforms can withstand direct impacts such as defaults, but their structure may be vulnerable to contagion. (Cheng et al., 2022) finds evidence that bad news about a P2P lending platform makes everyone on a second platform worse off, and as our results suggest, this can be the catalyst for platform failure. In addition, we also find that P2P communities will be less tightly knit after defaults. Therefore, trust is also expected to decline because communities on the platform lose members. At the same time, those who remain may gain more internal relevance and gain power vis-à-vis the platform.

5 Extension: platform lending with large firms

Numerous failures of P2P platforms have caused significant damage to the industry, which is now evolving towards a more centralized scheme in which a few players with deeper pockets are taking an increasingly important role. The concentration level varies by platform, from abandoning P2P lending altogether to allowing a few major players to be on the platform[6]. We focus on the latter case because it allows us to address the new challenges or trade-offs platforms face as they move from a decen-

[6] https://www.fintechfutures.com/2020/10/lendingclub-shuts-retail-p2p-offering-as-it-focuses-on-institutional-investors/.

tralized to a more centralized scheme. This scenario is more prospective than the previous one, but it gives us an idea of what the future of these platforms may look like.

Previously, we assumed a log-normal distribution ($\mu = 1, \sigma = 0.5$) of assets among the SMEs that ensured that asset differences were not extreme. However, some of the participants in lending marketplaces may be institutional investors or large firms (LFs) with many assets (Perkins, 2018). Does the presence of LFs increase or reduce the previous borrower default effects? To answer this question, we now examine two new cases with $\mu = 1$, $\sigma = 2$, which we call Large and Extreme, respectively, and compare them with the Original case. In the Large case, the top 10% of firms have twice as many resources as in the Original case. In the Extreme case, the top 10% have seven times the resources of the 10% in the Original case.

The presence of LFs facilitates the investment required by other companies, leading to the creation of more loans. However, the presence of LFs also leads to higher levels of defaults, as Fig. 9 shows.

Surprisingly, the default dynamics are different with LFs. Cascading effects play a minor role compared to previous results. The presence of LFs mitigates cascading effects but makes the network more vulnerable to direct threats. If we compare the original and extreme cases, cascading effects are always smaller in the extreme case. Thus, defaults hit the network more powerfully and directly when LFs are present, while they hit weakly and indirectly when firms are more homogeneous.

Proposition 5 Large firms with deep pockets mitigate cascading effects but make the platform network more dependent on them to guarantee stability.

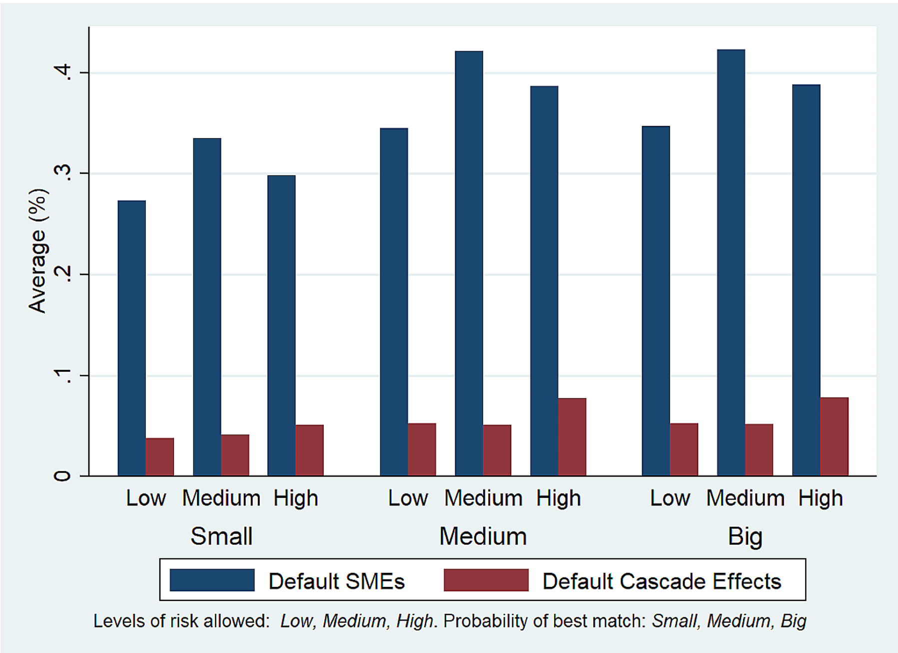

Fig. 9 Defaults and cascade effects with large firms

The endogenous nature of the network is responsible for this result. Large firms with deep pockets act as a catalyst for investment. Instead of interacting with other SMEs in the P2P network, SMEs prefer to deal directly with a big investor because managing one loan is easier than waiting for N small creditors to provide enough funding. In this way, the effects of default tend to be concentrated on LFs and their direct contacts instead of propagating in the network. This result gives a reassuring message to some platforms that have decided to allow entry to these players. In this situation, platforms can focus their curation efforts on the big players because they are crucial to the network. This allows platforms to focus resources on a few players rather than the overall network. However, it has one major drawback. It creates a dependency on these LFs. Once LFs default, the distribution of debts and investment in the network is also affected. The presence of LFs leads to greater increases in inequality as measured by the Gini index, Fig. 10.

The role of insurance seems to be limited when LFs coexist with small SMEs. However, the network characteristics are strongly influenced by insurance. We find that the largest betweenness increases occur in cases with P2P insurance (Fig. 11). In contrast, when we consider clustering, the effects of insurance and LFs are reduced. These results highlight that, when LFs are present, the impact is on the centrality of the network, i.e., the power of some players, but not on the community relationship between them (clustering).

Overall, this scenario highlights that the current evolution of P2P lending platforms faces significant trade-offs. Platforms must decide what kind of risk they want to deal with and how to invest their resources. Allowing a fully decentralized scheme

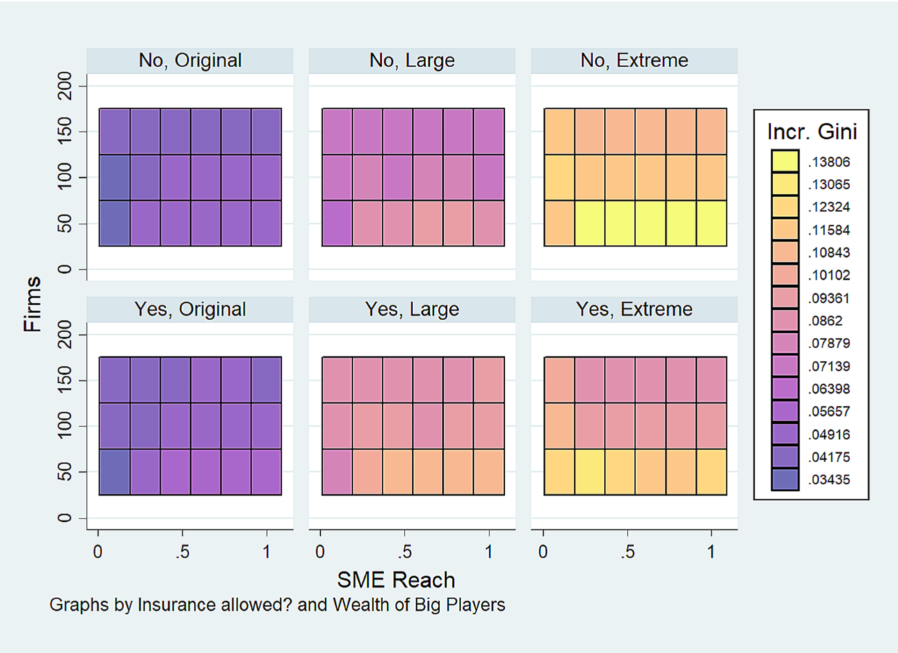

Fig. 10 Effects of defaults on the distribution of debts measured by the increase in the Gini index

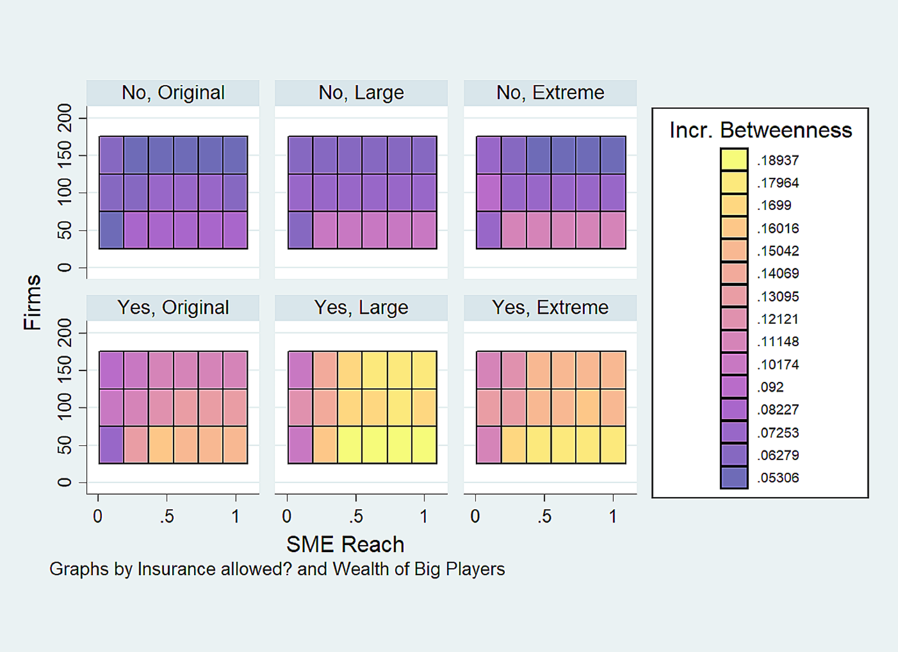

Fig. 11 Effects of firms' size on betweenness

can create networks vulnerable to secondary impacts or cascading effects. On the other hand, a more centralized scheme creates a dependency on key players that may become 'too big to fail.' Therefore, the future of P2P lending appears to be uncertain, and in terms of network structure, there is no superior business model. It will be interesting to track how these two approaches compete or cooperate in the coming years (Fig. 12).

6 Conclusions

SMEs are a crucial source of employment, but access to financing is a significant challenge for them (Rao et al., 2021). Platform lending is a fintech innovation that promises the democratization of access to funding, but many platforms have been challenged. Moreover, it is unclear how borrower default affects platform stability, which could lead to platform default.

This research uses a computational modeling approach to study the platform stability effects of borrower default. Therefore, it makes a theoretical contribution to the platform lending literature. In addition, from a practical standpoint, we contribute to a better understanding of fintech lending for SMEs and entrepreneurs.

Computational experiments allow us to evaluate platform stability and risk by running multiple scenarios in controlled environments where the effects of different variables are tested in isolation. Our results show how borrower default can threaten platform stability and what a platform could do to prevent or mitigate that. P2P lend-

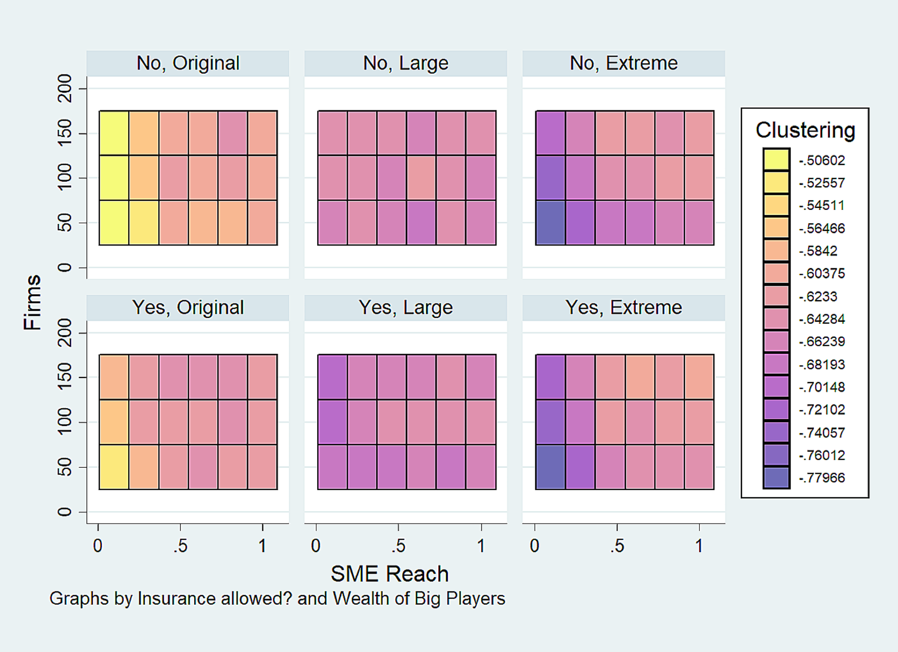

Fig. 12 Effects of firms' size on clustering

ing platforms rely on network effects to maintain their operations. However, given the interconnected nature of lending platforms, large platforms are more exposed to the impact of defaults. Although some curation rules may help contain the cascading effects of defaults, they might not be enough. In this regard, introducing P2P insurance may seem a good idea for damage control. However, our results show that P2P insurance could help spread contagion, as those who become insurers are often risk-lovers (they have a higher risk threshold). This result justifies the current adoption of curation rules instead of the introduction of P2P insurance products on these platforms. In fact, the use of P2P insurance seems to be residual, while the use of curation rules is widespread. From our results, this decision makes sense and highlights the interest of current P2P platforms in maintaining their stability. This is especially relevant for big platforms, which are more vulnerable to network effects. Even if expectations favor them, an exogenous shock, such as an economic crisis, may affect them more than smaller competitors. In this sense, curation rules partially mitigate the damage, but they are not enough.

In addition, defaults influence the network topology and the distribution of debts and investments. On the one hand, the network becomes more unevenly distributed after a shock in both debt and investment. As a by-product of the first shocks, a wave of defaults leads to a platform where firm inequality increases. In other words, access to financial resources tends to be more concentrated, which goes against the platform's objective to democratize financial access. This happens because those who remain in the network after a shock are the ones who need the least resources. On the other hand, the network that survives the shock tends to be more concentrated and less clustered, which is a sign of vulnerability. Thus, second shocks might be real platform killers after some initial crisis damages the network sufficiently.

Lastly, we carry out additional experiments that allow for the presence of large firms (institutional investors), which reflects a recent evolution of the lending business model. We show that introducing large firms helps create more investment opportunities on the platform, but once a crisis kicks in, the effects are more direct and stronger. Large firms with deep pockets act as a catalyst for investment. Instead of interacting with other SMEs in the P2P network, SMEs prefer to deal directly with a big investor because managing one loan is easier than waiting for N small creditors to provide enough funding. In this way, the effects of default tend to be concentrated on large firms and their direct contacts instead of propagating in the network. This also means that adverse cascading effects are limited due to the unique network topology that large firms create around them. This situation highlights a current dilemma in the industry between reducing cascading defaults or becoming more dependent on large investors. Each case has pros and cons, and it will be interesting to see how the sector will shape in the coming years. Platform designers need to understand how borrower default affects their platform stability and what measures they can take to prevent or mitigate a crisis.

Future research can extend the model in several directions. One direction is the study of platform competition. So far, we studied the platform in isolation in a market with a fixed number of SMEs. Endogenizing the number of SMEs accessing the platform and the competition to attract them from several platforms can also generate interesting new effects and insights. For example, the size of the platform may act as a catalyst to attract new borrowers and lenders that strengthen the platform network. In addition, our research assumes exogenous interest rates to simplify the model but misses significant financial effects that may impact platform stability. Another research issue is the role of regulation, which has proven to be essential in some markets, such as China. For example, we assumed that risk scores are known, but privacy laws may hinder the display of this information. Another potential extension is the inclusion of more formal financial regulations. We did not include the possibility of mandatory reserves, a common requirement for traditional banks. Our framework is flexible enough to consider these and other regulation changes, but implementing different policies to see their effects is a topic for future research.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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