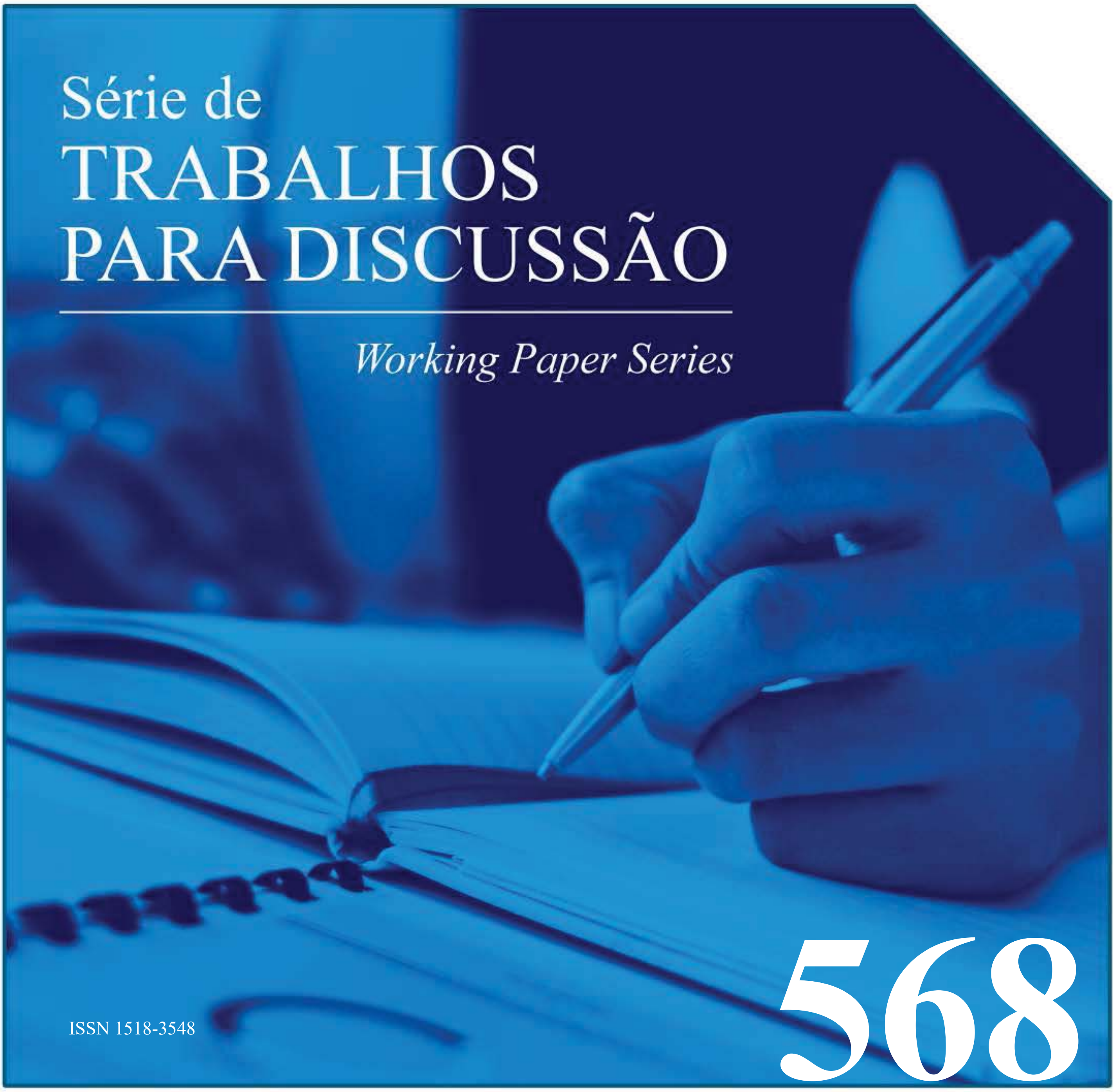

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Efficiency-stability Trade-off in Financial Systems: a multi-objective optimization approach

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Non-Technical Summary

Financial regulators often face conflicting objectives. A clear example concerns capital requirements – i.e. when banks are required to meet a minimum capital level, set according to the amount and risk of their assets. A tight capital requirement boosts financial stability. However, it may be harmful to the efficiency of financial intermediation. The reason is that banks may try to meet a higher capital requirement by either reducing assets – i.e., decreasing the loan supply – or increasing the loan interest rate, which leads to a reduction in the demand for loans.

In this paper, we tackle this efficiency-stability trade-off in the financial system. Specifically, we address this dilemma in the interbank (IB) market. The decision variable to be chosen by the financial regulator is the net worth-to-IB assets ratio, the capital requirement (CR). Besides this variable, financial regulators are also concerned with the fraction of IB assets lost as a consequence of an exogenous initial shock. We assess two different capital requirement (CR) regimes: the homogeneous (same CR for all banks) and the heterogeneous (different CRs for each bank) regime. For the heterogeneous regime, we design a multi-objective optimization problem (MOP) to minimize the two above-mentioned variables. The algorithm used to solve this MOP is the multi-objective evolutionary algorithm based on decomposition (MOEA/D).

Applying this framework to a Brazilian data set, we have found that the heterogeneous capital requirement regime brings a Pareto gain over the homogeneous capital requirement regime. That is, it is possible to obtain a smaller level of losses for the same aggregate capital requirement level under the heterogeneous capital requirement regime. In the heterogeneous regime, for each level of the initial shock, there is a critical value of CR below which financial crises become more frequent and more severe. Moreover, the CR assigned to the same bank in different critical Pareto optimal points – i.e., those which generate values of CR close to its critical value – varies significantly. Moreover, this variable is smaller and less volatile for banks with a higher degree (i.e., those with more connections in the IB market, as well as a higher volume of IB assets and liabilities).

Sumário Não Técnico

Muitas vezes, os reguladores financeiros enfrentam objetivos conflitantes. Um exemplo claro diz respeito ao requerimento mínimo de capital — ou seja, quando os bancos são obrigados a cumprir um nível mínimo de capital, estabelecido de acordo com o valor e o risco de seus ativos. Um requerimento de capital mais apertado favorece a estabilidade financeira. No entanto, isto também pode ser prejudicial à eficiência da intermediação financeira. A razão é que os bancos podem atender a um maior requerimento de capital reduzindo ativos -— ou seja, diminuindo a oferta de empréstimos — ou aumentando a taxa de juros, o que leva à redução da demanda por empréstimos.

Neste artigo, abordamos esse trade-off eficiência-estabilidade no sistema financeiro. Mais especificamente, abordamos esse dilema em um mercado interbancário. A variável de decisão a ser escolhida pelo regulador financeiro é a relação patrimônio líquido/ativos interbancários atribuída a cada banco, o requerimento de capital (RC). Além desta variável, o regulador financeiro avalia também a proporção de ativos interbancários perdidos em consequência de um choque inicial exógeno. Avaliamos dois regimes de RC: o regime homogêneo (mesmo RC para todos os bancos) e o heterogêneo (diferentes RCs para cada banco). No caso do regime heterogêneo, elaboramos um problema de otimização multi-objetivo (MOP, na sigla em inglês) com o propósito de minimizar as duas variáveis citadas acima. O algoritmo usado para resolver este MOP é o algoritmo evolutivo multi-objetivo baseado em decomposição (MOEA/D, sigla em inglês).

Aplicando esse modelo a um conjunto de dados brasileiros, descobrimos que o regime heterogêneo traz um ganho de Pareto em relação ao regime homogêneo. Em outras palavras, é possível obter um nível menor de perdas para o mesmo valor agregado de RC. No caso do regime heterogêneo, para cada nível do choque inicial, há um valor crítico de RC abaixo do qual crises financeiras tornam-se mais frequentes e mais graves. Além disso, a relação patrimônio líquido/ativos interbancários atribuídos ao mesmo banco em diferentes pontos ótimos de Pareto críticos -— ou seja, aqueles que geram valores de RC próximos ao seu valor crítico -— varia significativamente. Além disso, esta variável é menor e menos volátil para bancos com maior grau (ou seja, aqueles com mais conexões no mercado interbancário, bem como com um maior volume de ativos e passivos interbancários).

Efficiency-Stability Trade-off in Financial Systems: a multi-objective optimization approach

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Abstract

In this paper, we address the efficiency-stability trade-off in the interbank (IB) market. The decision variable to be chosen by the financial regulator is the net worth-to-IB assets ratio assigned to each bank – the capital requirement (CR) – , aiming at minimizing both the fraction of IB assets lost as a consequence of an exogenous initial shock and the total net worth as a fraction of total IB assets. This framework is applied to a Brazilian data set considering two CR regimes: the homogeneous (same CR for all banks) and the heterogeneous regime (different CRs for each bank). The optimization in the heterogeneous regime is performed through a multi-objective optimization problem (MOP), solved through a multi-objective evolutionary algorithm based on decomposition (MOEA/D). We have found that the heterogeneous regime brings a Pareto gain over the homogeneous one: a smaller level of losses is achieved for the same aggregate CR. In the heterogeneous case, for each level of the initial shock, there is a critical value of aggregate CR below which financial crises become more frequent and more severe. Moreover, the decision variable assigned by different critical Pareto optimal points – i.e., those which generate values of CR close to its critical value – varies significantly. Finally, this variable is smaller and less dispersed for banks with a higher degree (i.e., those with more connections in the IB market, as well as a higher volume of IB assets and liabilities).

Keywords: financial stability, financial intermediation, systemic risk, interbank networks, multi-objective optimization

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1 Introduction

This paper addresses the trade-off between efficiency and stability in the financial system. Financial stability is a serious concern for financial regulators. Capital requirements are at the core of the tools used to achieve this goal. Banks are required to have a capital level set according to the amount and risk of their assets. The Basel III accord proposes the common equity, Tier 1 (common equity plus additional Tier 1), and total capital (Tier 1 plus Tier 2) to be at least 4.5%, 6%, and 8%, respectively, of risk-weighted assets (Basel Committee on Banking Supervision, 2011). Complementing this framework, the Basel III accord introduced the leverage ratio requirement (LRR). According to the current LRR calibration, the minimum capital-to-non-risk-weighted total assets, including off-balance sheet items, should be 3% (Basel Committee on Banking Supervision, 2011).

A tight capital requirement promotes financial stability by reducing the probability of banks' financial distress and minimizing their loss given default (Martynova, 2015). Although the adoption of capital requirements enhances financial stability, it is not possible to say that this comes at no cost. Banks may try to meet a higher capital requirement by either reducing assets – causing a reduction in loan supply – or increasing the loan interest rate, decreasing the loan demand (Thakor, 2014). The main reason is that rising equity to comply with a higher capital requirement is costly due to the presence of frictions, such as agency costs (Diamond and Rajan, 2000) and asymmetric information (Myers and Majluf, 1984). Some studies offer empirical support to these theoretical arguments. Fraisse et al. (2020) found a one-percentage-point increase in the minimum capital requirement (MCR) reduces lending by 10%. Furfine (2000) estimated a one percentage point increase in MCR leads to a 5.5% reduction in loan growth. Other empirical studies (Baker and Wurgler, 2015; Slovik and Cournède, 2011) also report an increase in the lending rates as a result of an increase in the MCR.[1] There are similar concerns regarding the LRR. For instance, Kiema and Jokivuolle (2014) show the LRR might induce banks with low-risk lending strategies to diversify their portfolios into high-risk loans until the LRR is no longer the binding capital constraint on them. Therefore, capital requirements engender a trade-off between financial stability and the efficiency of financial intermediation. In other words, higher financial stability comes at a cost in terms of supply and cost of loans.

The dilemma faced by financial regulators can be well represented by an optimization problem. Their aim is optimizing $F(x) = (f_1(x), ..., f_m(x))$ subject to $x \in \Omega$, where F are m real-valued objective functions and Ω is the decision variable space. Some functions $f_i(x)$ contradict each other, in the sense that no point in Ω can optimize all functions at the same time. A change in x causing an improvement in one objective leads to a deterioration in at least one other objective. In the specific case of the financial regulators, the decision variable can be one of their policy instruments (e.g., capital requirement) and the objective functions are related to their targets (e.g., measures of financial stability, loan supply, etc.).

[1]A nice review of the potential negative impacts of capital requirements can be found in Martynova (2015), Sec. 3.

A vector $F(u)$ is said to *dominate* $F(v)$ if $f_i(u) \leq f_i(v)$ for every $i \in \{1,...,m\}$ and $f_j(u) < f_j(v)$ for at least one $i \in \{1,...,m\}$.[2] A point $x^* \in \Omega$ is *Pareto optimal* (PO) if there is no point $x \in \Omega$ such that $F(x)$ dominates $F(x^*)$. The vector $F(x^*)$ is called a *Pareto optimal objective vector*. The set of all PO points is called the *Pareto set* (PS), and the set of all $F(x^*)$ is called the *Pareto front* (PF).

The PF contains all the efficient combinations (i.e., non-dominated) of the objective functions. Figure 1 depicts a simple example of a PF. There are only two functions to be optimized ($m = 2$) and the goal is to minimize both f_1 and f_2. All the solutions above the curve are not efficient. For instance, solution C is dominated by solution A, as in the latter the same value for f_1 is obtained with a smaller value for f_2. Similarly, C is also dominated by B, as in B the same value for f_2 can be obtained with a smaller value for f_1.

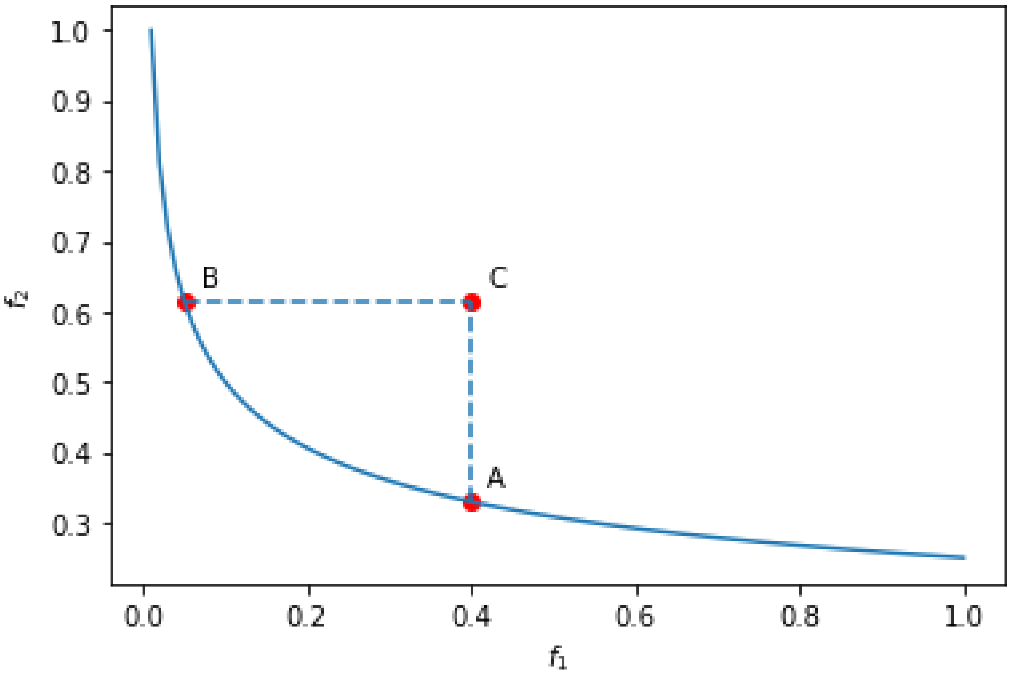

Figure 1: *A simple example of a Pareto front.*

The purpose of this paper is to assess the efficiency-stability trade-off in the interbank (IB) market. The decision variable to be chosen by the financial regulator is the net worth-to-IB assets ratio assigned to the banks – the capital requirement (CR). Two variables are computed: i) the fraction of IB assets lost as a consequence of an exogenous initial shock, represented by the failure of a given fraction of banks (f_2); and ii) the total net worth as a fraction of total IB assets (f_1), the aggregate CR. We consider two CR regimes. In the homogeneous CR regime, the CR is the same for all banks. In the heterogeneous CR regime, the capital requirement is assumed to be heterogeneous across banks, as suggested in Jamilov (2021). This framework is applied to a Brazilian data set, considering different

[2]Clearly, it refers to a minimization problem. If it was a maximization problem, the dominance conditions would be $f_i(u) \geq f_i(v)$ and $f_j(u) > f_j(v)$.

levels of the initial shock. The resulting Pareto front is a valuable tool in the decision process of choosing the most suitable CR.

In the homogeneous CR regime, the PF is approximated by varying f_1 and computing the corresponding f_2 value. For the heterogeneous regime, we formulate a multi-objective optimization problem (MOP) to minimize both f_1 and f_2. A MOP is an optimization problem characterized by the presence of conflicting objectives (Deb, 2001). In this paper, the MOP will be solved through the multi-objective evolutionary algorithm based on decomposition (MOEA/D). A plethora of optimization methods has been employed to solve MOPs in economics and finance. Gaffeo and Gobbi (2021) relied on the MOORA (multi-objective optimization on the basis of ratio analysis) method to determine the best policy options in a model of liquidity cascades applied to credit networks. Gaspar-Cunha et al. (2014) used the reduced Pareto set genetic algorithm (RPSGA) for feature selection in the classification of bankruptcy data sets, simultaneously minimizing the number of features and maximizing the classifier quality measure. Shaghagi and Markose (2013) designed a genetic algorithm to reconstruct the structure of financial derivatives networks, satisfying multi-objectives such as minimizing the weighted sum of squared deviations from the row and column sum constraints. Soui et al. (2019) tested four multi-objective evolutionary algorithms (NSAG-II, MOEA/D, SPEA 2, and SMOPSO) in a credit risk evaluation model, whose goal is to minimize the complexity of the generated solution and to maximize the accuracy and the weight which represents rules' importance.

We have found the heterogeneous capital requirement regime brings a Pareto gain over the homogeneous capital requirement regime. That is, it is possible to obtain a smaller level of losses (f_2) for the same aggregate CR level (f_1) under the heterogeneous CR regime. In the heterogeneous case, for each level of the initial shock, there is a critical value of f_1 below which financial crises (represented by f_2) become more frequent and more severe. Moreover, there is great variability in the decision variable assigned by different critical PO points – i.e., those which generate values of f_1 close to its critical value – assigned to the same bank. In general, the decision variable assigned by critical PO points decreases with the bank's degree, both in terms of in-/out-degree, and weighted/unweighted degree. Finally, the variability of this variable is smaller for banks with a higher degree.

This paper proceeds as follows. The data set and methodological issues are discussed in Section 2. The results are presented in Section 3. Finally, Section 4 brings some final considerations.

2 Data set and methodological issues

2.1 The data set

Our data set considers net financial exposures in the Brazilian IB market among different financial conglomerates or individual financial institutions that do not belong to conglomerates – i.e., intra-conglomerate exposures are removed – as of December 2015. The financial institutions can be banks (classified as "b1", "b2", or "b4" in the Central Bank of Brazil's classification system) or credit unions (classified as "bC3" or "bS3").[3] As we compute the optimal net worth as a fraction of IB loans (more details in Section 2.2), we exclude financial institutions without assets in the IB market.

The IB exposures encompass all types of unsecured financial instruments registered in the Central Bank of Brazil (BCB). The main types of financial instruments are credit, capital, foreign exchange operations, and money markets. These operations are registered and controlled by different custodian institutions: Cetip[4] (private securities), the BCB's Credit Risk Bureau System (SCR)[5] (credit-based operations), and the BM&FBOVESPA[6] (swaps and options operations).

Our network is sparse – i.e., its density is low. Moreover, it is disassortative, meaning that highly-connected nodes are more likely to connect with nodes that have few connections. Evidence of negative assortativity in financial networks has been reported in other empirical studies (Bottazzi et al., 2020). These statistics are presented in Table 1.

Table 1: *Some statistics of the data set*

Variable	Value
Number of banks	230
Number of nodes	1,557
Density	0.0296
Average degree	6.7696
Assortativity	-0.3872

2.2 Financial efficiency and financial stability

From our data set, we compute two variables: the total net worth-to-IB assets ratio (f_1) and the fraction of IB assets lost as a consequence of an initial shock (f_2). While the former is regarded as a proxy for financial efficiency, the latter is assumed to measure the stability of the financial network. In the following, we explain how these variables will be computed.

[3]For the sake of simplicity, the two types of financial institutions will be called "bank".

[4]Cetip is a depositary of mainly private fixed income, state and city public securities, and other securities. As a central securities depositary, Cetip processes the issue, redemption, and custody of securities, as well as, when applicable, the payment of interest and other events related to them. The institutions eligible to participate in Cetip include commercial banks, multiple banks, savings banks, investment banks, development banks, brokerage companies, securities distribution companies, goods and future contracts brokerage companies, leasing companies, institutional investors, non-financial companies (including investment funds and private pension companies) and foreign investors.

[5]SCR is a very thorough data set that records every single credit operation within the Brazilian financial system worth 200BRL or above. Up to June 30th, 2016, this lower limit was 1,000BRL. Therefore, all the data we are assessing have been retrieved under this rule. SCR details, among other things, the identification of the bank, the client, the loan's time to maturity and the parcel that is overdue, modality of loan, credit origin (earmarked or non-earmarked), interest rate, and risk classification of the operation and the client.

[6]BM&FBOVESPA is a privately-owned company that was created in 2008 through the integration of the Sao Paulo Stock Exchange (Bolsa de Valores de Sao Paulo) and the Brazilian Mercantile & Futures Exchange (Bolsa de Mercadorias e Futuros). As Brazil's main intermediary for capital market transactions the company develops, implements and provides systems for trading equities, equity derivatives, fixed income securities, federal government bonds, financial derivatives, spot FX, and agricultural commodities. On March 30th, 2017, BM&FBOVESPA and Cetip merged into a new company named B3.

The loan extended by bank i to bank j is L_{ij}, and the total loans extended by i is L_i. At time step $t = 0$, a vector $x = \{x_1,...,x_B\}$ is generated, where B is the number of banks and x_i is the net worth-to-IB assets ratio assigned to the bank i by the financial regulator – the bank i's CR. The optimal net worth of bank i is equal to $NW_i^* = x_i L_i$. The variable f_1 is equal to $\sum_i NW_i^* / \sum_i L_i$.

At time step 1, a fraction ζ of the banks is eliminated. Be $\lambda(1) = \{\lambda_1(1),...,\lambda_L(1)\}$, where $L \leq B$, the index of the banks eliminated at time step 1. At time step $t = 2$, all creditors of these banks, indexed by j, will suffer a loss equal to the loan they extended to them, $L_{j\lambda(1)}$. The idea is that, when a given bank goes bankrupt, all its creditors will not receive the loans they extended to this bank. If $L_{j\lambda(1)} \geq NW_j^*$, j will be eliminated as well. At time step $t = 3$, the banks eliminated at the previous time step will propagate losses to their creditors in a similar fashion, and so on. The process goes on until a sufficiently large number of time steps $T \gg 1$ when no more banks are eliminated. The total loss accumulated during this process is given by

$$R_T = \sum_{t=1}^{T} L_{\lambda(t)}, \tag{1}$$

where $L_{\lambda(t)}$ is the total loan extended by the banks eliminated at time step t. The variable f_2 is equal to the accumulated losses over the total IB loans, $R_T / \sum_i L_i$.

2.3 The MOEA/D [7]

If the CR assigned by the financial regulator is uniform across banks (say, x^*), the approximation of the PF for f_1 and f_2 is straightforward: we vary the value of x^*, f_1 is equal to x^*, and f_2 is computed following the steps described in Section 2.2. However, for the case in which the CR is heterogeneous across banks, we formulate a multi-objective optimization problem (MOP) to minimize both f_1 and f_2. In this paper, the algorithm used to solve the MOP is the MOEA/D.

The MOEA/D (Zhang and Li, 2007) is an algorithm employed to solve MOPs characterized by its low computational complexity. The MOP consists in minimizing $F(x) = (f_1(x), f_2(x))$. The decision variable to be chosen by the financial regulator is $x^* = \{x_1^*,...,x_B^*\}$, where x_i^* is the CR assigned to bank i. The MOEA/D algorithm decomposes the MOP into N scalar optimization sub-problems. Usually, the decomposition is done through the Tchebycheff approach. The objective function of the jth sub-problem is represented by

$$g(x|\lambda^j, z^*) = min_{1 \leq i \leq m}\{\lambda_i^j |f_i(x) - z_i^*|\}, \tag{2}$$

where x is the decision variable, $\lambda^j = (\lambda_1^j,...,\lambda_m^j)$ is a weight vector, and z^* is the minimal point, i.e., $z_i^* = min\{f_i(x)|x \in \Omega\}$.

[7] See Zhang and Li (2007), Sec. III for more details.

All these N sub-problems are minimized simultaneously by the MOEA/D in a single run. The neighborhood of weight vector λ^i is defined as a set of its T closest weight vectors. At each time step t, the MOEA/D maintains the following elements: i) a population $x^1,...,x^N$, where x^i is the current solution to the ith sub-problem; ii) a vector $FV^1,...FV^N$, where FV^i is the F-value of x^i; iii) $z = (z^1,...,z^m)$, where z^i is the best solution so far for objective f_i; and iv) an external population EP, which corresponds to the set of non-dominated solutions.

Besides the MOP, the MOEA/D needs a stop criterion. The output is the EP with the non-dominated solutions for the objective functions $f_1,...,f_m$. The MOEA/D has three main steps:

(i) Initialization of $x^1,...,x^N$ and $z = (z^1,...,z^m)$ and the computation of the Euclidean distances between any two weight vectors. For each $i = (1,...,N)$, a vector $B(i) = \{i_1,...,i_T\}$ is generated, where $\lambda^{i1},...,\lambda^{iT}$ are the T closest weight vectors to λ^i. The Euclidean distance is used as a measure of distance between weight vectors and $B(i)$ contains the indexes of the T closest vectors to λ^i.

(ii) By choosing randomly two indexes k,l from $B(i)$, for each sub-problem $1,...,N$ a new solution y is generated through genetic operators from x^k and x^l. A problem-specific heuristic is used to repair y and produce y', a hopefully good solution to the ith problem. Solution x^j is replaced with y' if the latter performs better than the former with regard to the jth sub-problem. The EP is updated by removing all the vectors dominated by $F(y')$ and adding $F(y')$ if no vectors in EP dominate $F(y')$.

(iii) If the stopping criterion is satisfied, the algorithm stops and generates EP. Otherwise, it comes back to step (ii).

After the computation of f_1 and f_2, the algorithm will generate a new solution x and the whole process is repeated. The running time is used as the stopping criterion, with a time limit of 6 hours.

3 Results

3.1 General results

We consider four values of the initial shock size ζ: 0.01, 0.05, 0.1, and 0.2. For each level of ζ, we run 100 iterations. In the homogeneous CR regime, we vary the level of f_1 within the interval (0.01,1] with step 0.01. The corresponding f_2 value is computed as described in Section 2.2. In the heterogeneous CR regime, the value of the functions is computed through the MOP (Section 2.3). The parameters of the MOEA/D, used to solve the MOP, are presented in Table 2.

Table 2: Parameters of the MOEA/D

Parameter name	Value
Population size	1000
Neighborhood size	21
Number of solutions replaced	2
Prob. parents from neighborhood	0.9
Crossover probability	1.0
Mutation rate	0.1

The efficiency-stability trade-off can be observed in Figure 2. A smaller level of losses (f_2) is obtained at the cost of a higher aggregate CR (f_1). In the homogeneous CR regime, the relationship between f_1 and f_2 is well represented by a convex curve for smaller levels of the initial shock (ζ=0.01 and ζ=0.05). As far as the level of the initial shock increases (ζ=0.10 and ζ=0.20), a more linear relationship between the variables appears. It is possible to observe that the heterogeneous capital requirement regime brings a Pareto gain over the homogeneous capital requirement regime. That is, it is possible to obtain a smaller level of losses for the same aggregate CR level under the heterogeneous capital requirement regime.

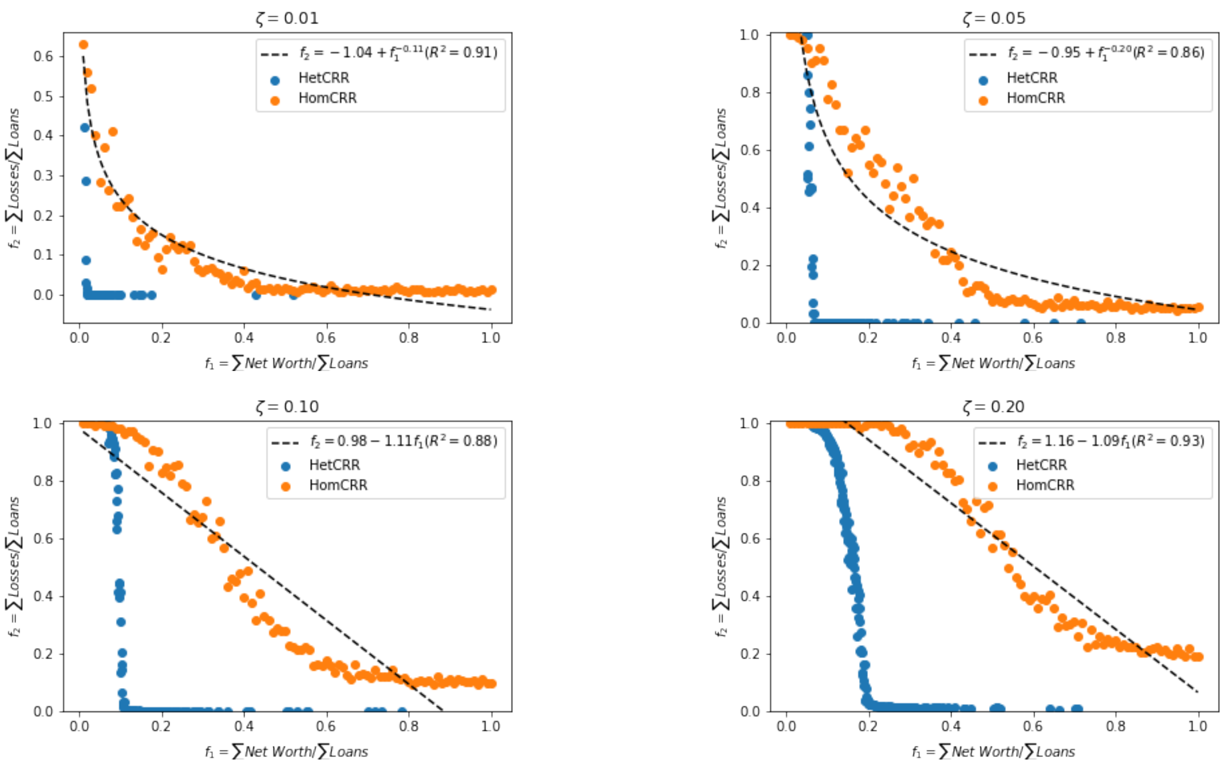

Figure 2: *Pareto front for f_1 and f_2 considering the heterogeneous (HetCRR) and homogeneous (HomCRR) regimes of capital requirement for each value of ζ.*

In the heterogeneous CR regime, for each value of ζ, there is a critical point f_1^C below which financial crises become more frequent and more severe (i.e., higher values of f_2). For example, when

$\zeta = 0.1$, losses are negligible for f_1 higher than $f_1^C \approx 0.11$. However, if $f_1 < f_1^C$, the elimination of 10% of the banks can cause severe losses, up to 100% of the system's assets.

These considerations are clearer in Figure 3. For each value of the initial shock ζ under the heterogeneous regime, we set a critical value f_1^C. Then, we assessed the distribution of f_2 when f_1 is below this critical value. For instance, for $\zeta = 0.01$ ($f_1^C = 0.018$), harsh crises when the net worth-to-IB loans ratio is below its critical value are quite rare. In only 9% of the cases, the losses of IB loans will be above 90%. On the other hand, when $\zeta = 0.1$ ($f_1^C = 0.11$), the probability of losses being above 90% when f_1 is below its critical level is higher than 50%.

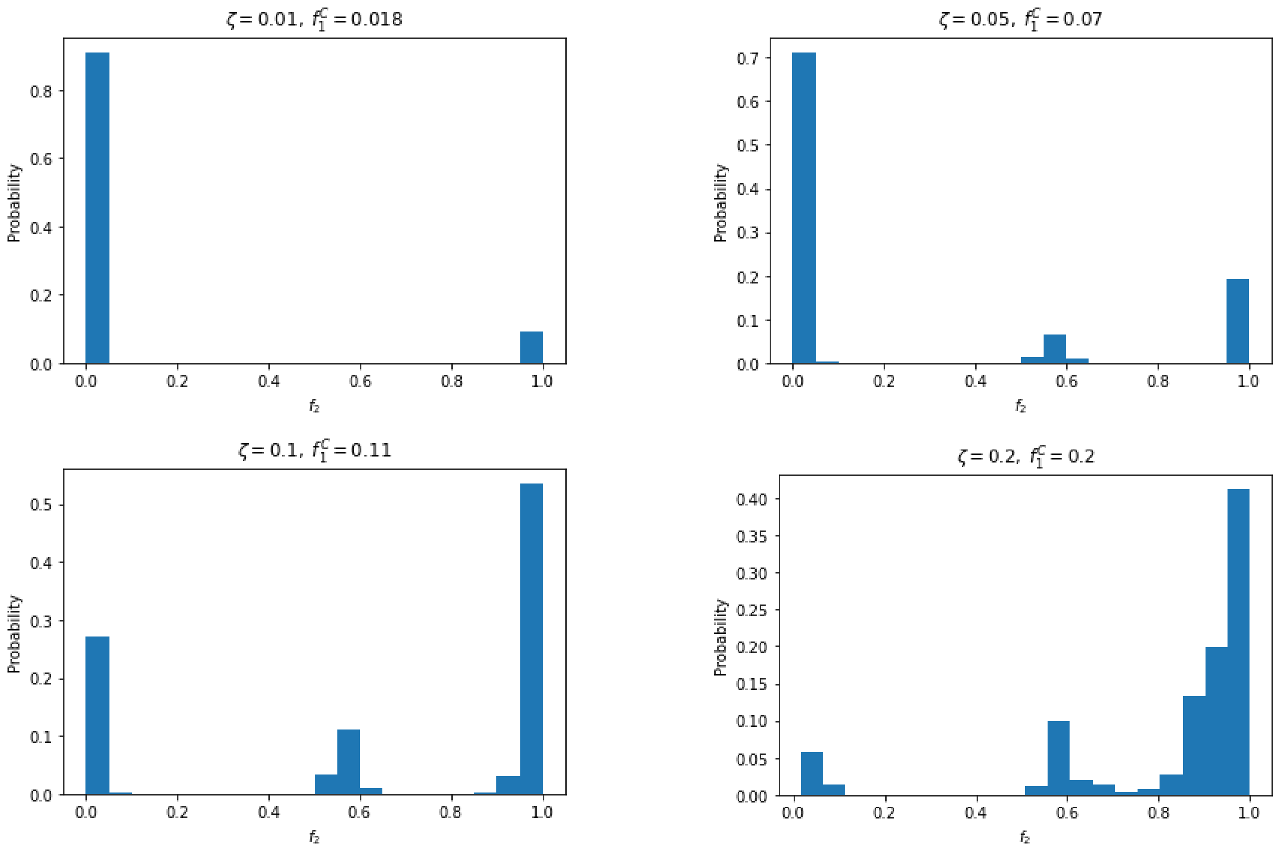

Figure 3: *Distribution of f_2 for values of f_1 below f_1^C for each value of ζ under the heterogeneous CR regime.*

3.2 Choosing the PO point

According to the results presented in the previous section, it is reasonable to assume the financial regulator is willing to adopt the heterogeneous CR regime and set the decision variable x so that f_1 is as close as possible to its critical value. This would guarantee maximum leverage without allowing for harsh crises in case of exogenous shocks. A natural question that arises is the following: which PO point in the PS should be chosen? Thus, in this section, we explore the PS in a narrow range of values of f_1 around its critical value. We have chosen $\zeta = 0.05$ because, in this case, the critical net worth-to-IB assets ratio (7%) is close to the total capital-to-risk-weighted assets suggested in the Basel III agreement (8%).

Within the interval $0.0695 \leq f_1 \leq 0.0705$, there are 35 points. Let us call $x_i^* = \{x_{i1}^*, ..., x_{i35}^*\}$ the set of decision variables assigned to bank i, $i = 1, ..., N$, where x_{ij}^* is the net worth-to-IB assets ratio assigned to bank i in PO point j. The maximum $f_2(x_i^*)$ is negligible (0.0029).

In most cases, the net worth-to-IB assets ratio assigned to the same bank by different PO points varies considerably (Figure 4). In a few cases, this volatility is relatively low. For instance, the decision variable assigned to bank number 2 (top-left panel, second bar) varies between 0.0296 and 0.1856. On the other hand, the decision variable assigned to bank number 160 (center-right panel, last bar) varies between 0.0153 and 0.9881.

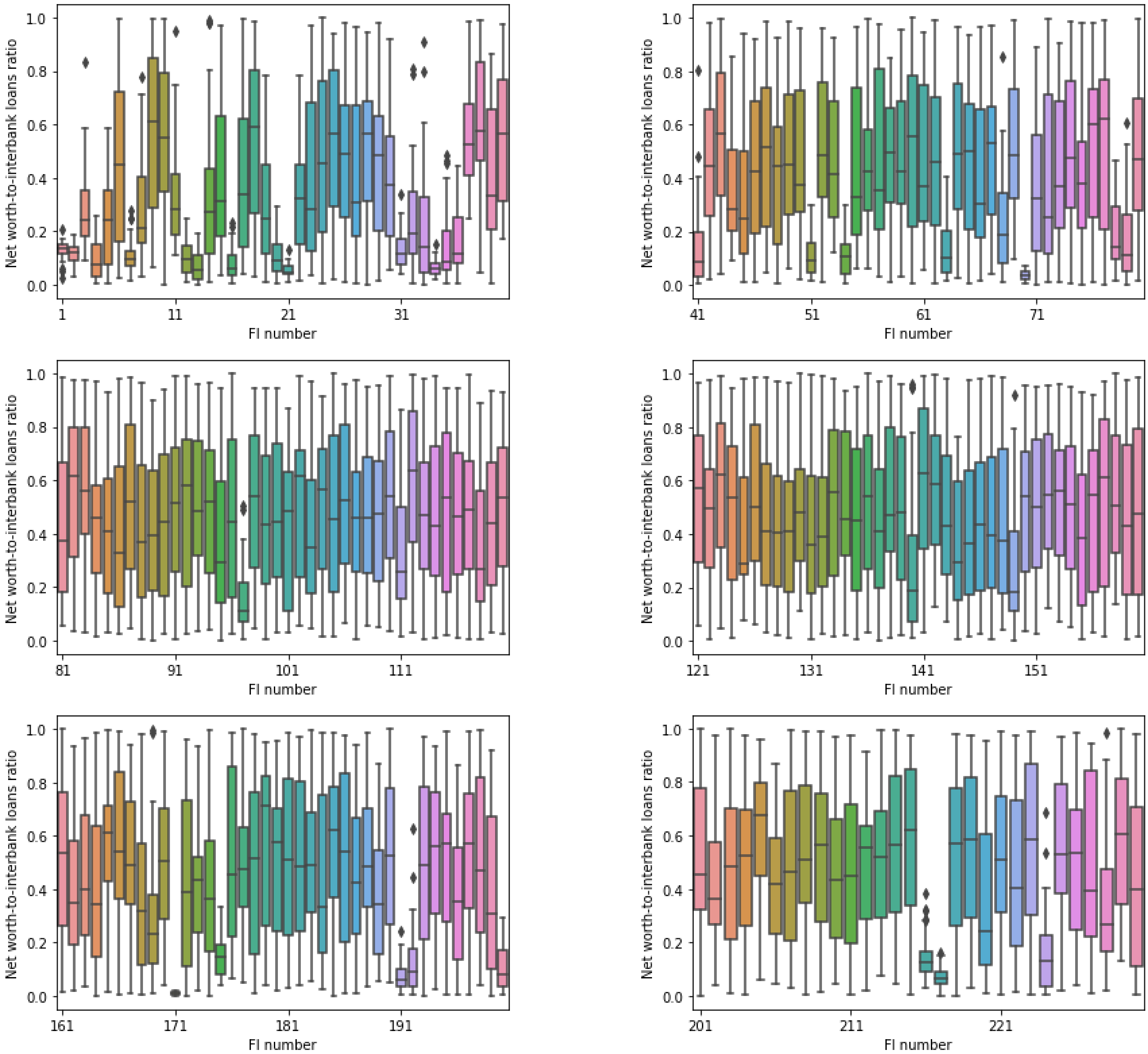

Figure 4: *Decision variable assigned to each bank under the heterogeneous CR regime.*

There is a negative correlation between x_i^* and the bank's degree. This can be observed both in terms of weighted and unweighted degree, and in- and out-degree. Note the weighted in- and out-degree correspond to IB liabilities and assets, respectively. The dispersion of x_i^*, as measured by its standard deviation $\sigma(x_i^*)$, is smaller for banks with a higher degree. Therefore, the decision variable assigned to higher degree banks is smaller and less dispersed according to different PO points. These considerations can be observed in Figure 5 and Table 3.

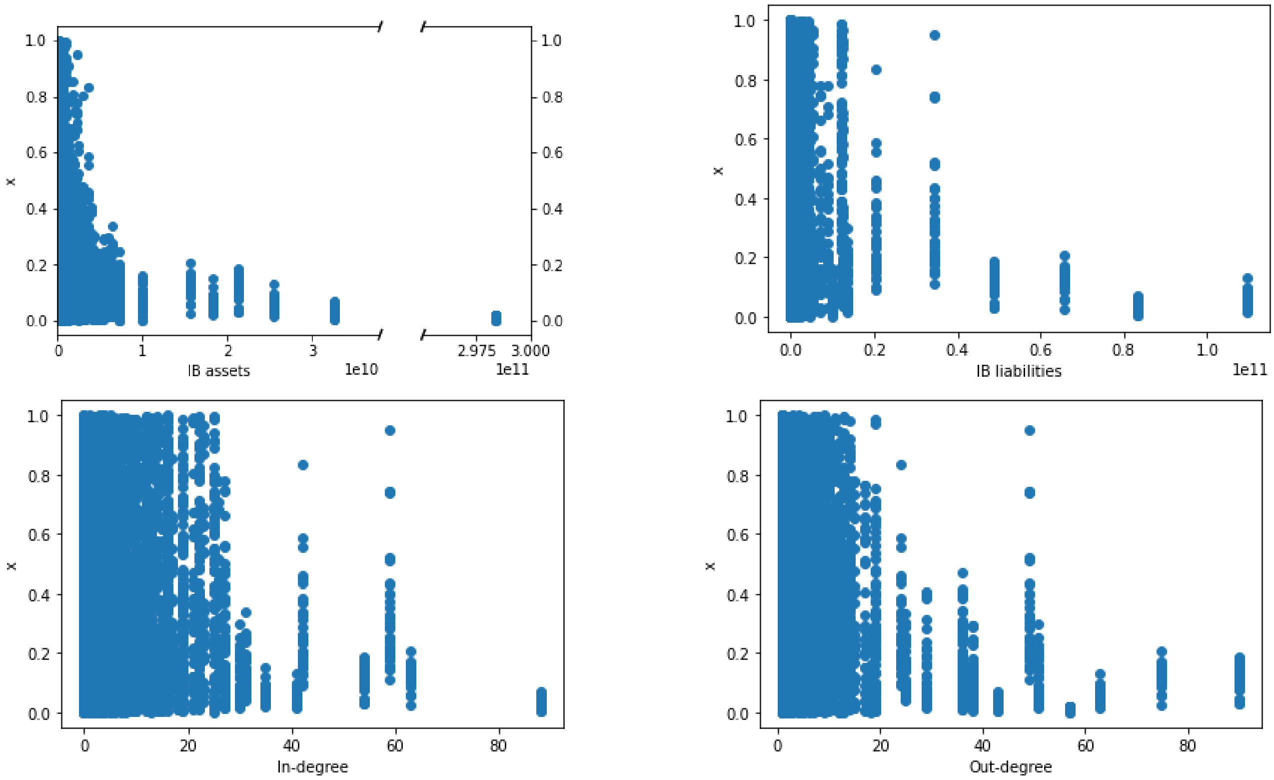

Figure 5: *Scatter plot between x and bank's IB assets, IB liabilities, in-degree, and out-degree under the heterogeneous CR regime.*

Table 3: *Correlations between x_i^* and $\sigma(x_i^*)$ and bank's features under the heterogeneous CR regime.*

Variable	x_i^*	$\sigma(x_i^*)$
IB assets	-0.15	-0.35
IB liabilities	-0.17	-0.46
In-degree	-0.21	-0.52
Out-degree	-0.29	-0.69

4 Concluding remarks

In this paper, we addressed the stability-efficiency trade-off in financial systems. Although capital requirements boost financial stability, there may be some costs associated with them. The reason is that banks may respond to stricter capital requirements ratio by decreasing assets – reducing loan supply – and/or increasing loan cost, which leads to a reduction in loan demand. Therefore, higher financial stability may be obtained at the cost of a higher inefficiency in the financial system.

We tackled this issue for the IB market. In our framework, the financial regulator is willing to minimize two objective functions: the total net worth-to-IB assets ratio (f_1) and the fraction of IB assets lost as a consequence of an exogenous initial shock (f_2). The decision variable to be set by the financial regulator is the net-worth-to-IB assets ratio. There are two CR regimes. In the first one, the CR is uniform across banks, and in the second one, it is assumed to be heterogeneous across banks. For the heterogeneous case, we formulate a MOP to minimize both f_1 and f_2. The MOP was solved through the MOEA/D algorithm.

We applied this framework to a Brazilian data set considering different levels of the initial shock, represented by a fraction ζ of banks that are eliminated. In the homogeneous CR regime, the relationship between f_1 and f_2 is well represented by a convex curve for smaller levels of the initial shock (ζ=0.01 and ζ=0.05). As far as the level of the initial shock increases (ζ=0.10 and ζ=0.20), a more linear relationship between the variables appears. We have found the heterogeneous CR regime brings a Pareto gain over the homogeneous CR regime. It is possible to achieve a smaller level of losses (f_2) for the same aggregate CR (f_1) under the heterogeneous regime.

In the heterogeneous CR case, for each level of the initial shock, there is a critical value of f_1 below which financial crises (represented by f_2) become more frequent and more severe. Assessing the critical PO points – i.e., those that generate values of f_1 close to its critical value –, we have found that there is great volatility in the net worth-to-IB loans ratio assigned to the same bank by different PO points. In general, the decision variable assigned by critical PO points decreases with the bank's degree, both in terms of in-/out-degree, and weighted/unweighted degree. Moreover, its variability is smaller for banks with a higher degree.

Note the decision variable assigned by critical PO points to some banks is unrealistic (close to 1). To generate more realistic decision variables, we would need to include more data (e.g., banks' net worth and other assets/liabilities) in our model. In this paper, we only present a simple example of how this tool – the MOP – can be used by financial regulators.

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