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Local Financial Institutions and Income Inequality: Evidence from Brazil's Credit Cooperative Movement

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ABSTRACT

Local financial institutions can play a crucial role in reducing income inequalities at the within-country level by promoting inclusive economic growth and development across time and space. This is against a backdrop of increasing financial and economic fragility, to which emerging economies have also been exposed over more recent decades and years. This article adds emerging economy evidence from Brazil to an empirical literature on the income inequality implications of cooperative financial institutions. Panel-data estimations for 2004–19 reveal that Brazilian credit cooperatives have gone beyond commercial banks in supporting communities that have traditionally been underserved financially. Additionally, the article provides new evidence and insights on credit cooperatives' resilience in the context of a relatively recent but severe economic crisis in Brazil. The results indicate that credit cooperatives have helped fill gaps in finance and economic opportunity that tend to arise in an emerging economy setting. Furthermore, the contribution of credit cooperatives in filling these gaps is found to be more significant at lower levels of development. These findings add theoretical and, importantly, empirical support to the relationship channel of financial inclusion, which is in line with the optimistic perspective in this debate.

INTRODUCTION

Despite improvements in our understanding of the income inequality–finance nexus for advanced economies, relatively little is known about how local financial institutions, including cooperative financial institutions, affect income inequality in emerging economies. This relationship remains an under-explored issue particularly for emerging market economies, which are more exposed to exchange rate volatility, capital reversals, financial exclusion and uneven development. This article adds to the literature by providing an empirical analysis of income inequality in one of the world's most prominent emerging economies, Brazil. In this contribution, we pay

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particular attention to Brazil's thriving credit cooperative movement, drawing on a relatively recent but severe economic crisis and prolonged recession, also known as the great Brazilian recession, as a setting within which to explore the inequality implications of financial cooperatives and their consequences for regional resilience.[1] Specifically, we aim to test the following: 1) whether Brazilian credit cooperatives have affected income inequality over the sample period, including around the Brazilian crisis; 2) whether credit cooperatives' impact on inequality has differed from that of traditional banks; and 3) how, in relation to relevant channels of financial inclusion, income inequality has been affected in Brazil.

Cooperative financial institutions are member-owned financial intermediaries, which are variously referred to as credit unions, cooperative banks and credit cooperatives (McKillop et al., 2020: 1). Although there are some differences in terms of how they operate under specific national legal frameworks, cooperative financial institutions essentially enable their members to meet shared objectives by pooling financial resources (ICA, 2015). Unlike traditional banks, financial cooperatives are not-for-profit institutions, and have a commitment to enhance local economic development and foster social capital formation (Minetti et al., 2021). Due to their local orientation, financial cooperatives have an advantage in financing communities that would usually be underserved by the traditional financial system, with many banks increasingly concentrating their activities in more economically developed areas and in larger urban centres (Alessandrini et al., 2009). Local financial institutions can also provide a more stable source of credit during crises due to their access to soft information and their focus on relationship lending (Berger and Udell, 2006; Ferri et al., 2019; Sette and Gobbi, 2015).[2] Consequently, a stronger presence of financial cooperatives in the local economy can better mitigate the fallout from severe crises in terms of under-provision of credit, job destruction and rising income inequality (Ferri et al., 2014; Minetti et al., 2021; Schneiberg and Parmentier, 2022). However, others argue that financial cooperatives are more constrained in their capacity to raise additional finance at short notice due to their smaller size, lower capital levels and operational focus on longer-term lending (Fonteyne, 2007).[3] Given these different arguments, it is unclear whether cooperative

1. The crisis pushed Brazil into a technical recession at the end of the second quarter of 2014.
2. Liberti and Petersen define soft information as: 'Information that is difficult to completely summarize in a numeric score, that requires a knowledge of its context to fully understand, and that becomes less useful when separated from the environment in which it was collected' (Liberti and Petersen, 2019: 2).
3. For example, if financial cooperatives' members redeem their shares during a crisis, this can constrain the supply of credit to other members; alternatively, or at the same time, if emergency funding is requested by firms during a crisis, financial cooperatives might not be able to raise the necessary finance at short notice. Therefore, larger commercial banks may be better positioned to absorb unfavourable shocks because of their larger size, higher capital levels and operational focus on shorter-term lending. Furthermore, larger

financial institutions have contributed to alleviating or exacerbating income inequality in emerging economies in a crisis context.

Brazil is a useful case for an analysis of the income inequality–finance nexus because the gap between rich and poor remains large compared to most other countries, while inequality has been on the rise again since 2015, and during the COVID-19 pandemic (OECD, 2020a). Although the initial slowdown of growth in 2014, which tipped the Brazilian economy into a technical recession, was largely attributed to a decline in global commodity prices (e.g. Ciaschi et al., 2020: 3), this can be viewed as distinct from the more fundamental economic weaknesses and internal political issues that worsened the country's prolonged recession between 2014 and 2016, with its slowest economic recovery on record (Carvalho, 2018). However, the fall in global commodity prices contributed to a balance of payments problem in 2014, significant capital outflows and a recognized currency crisis in mid-2015 (e.g. Laeven and Valencia, 2020; Nguyen et al., 2022). Currency depreciation was relatively severe during 2014 and 2015, fuelling higher inflation (Ciaschi et al., 2020). This encouraged further interest rate hikes (from 7.25 per cent in March 2013 to 14.25 per cent in September 2016), as the Central Bank of Brazil tried to tame inflation and restore confidence in financial markets (OECD, 2020b: 2). Indeed, increased funding costs and decreased investment have been cited as significant sources undermining Brazil's economic recovery since 2014 (Krznar and Matheson, 2018). However, smaller enterprises, which provide a major source of employment in Brazil's local economies, experienced more significant vulnerability during the great Brazilian recession, with a lower capacity to raise external finance and weaker demand conditions.[4,5] Therefore, the Brazilian crisis, whilst rather extreme, highlights the urgent need for emerging countries to develop more inclusive and resilient local financial systems.

Despite the economic and financial problems highlighted above, a more positive development in Brazil has been the remarkable growth of cooperative financial institutions — or *cooperativas de crédito* (credit cooperatives) as they are known locally — over the last decade or so. While credit cooperatives do not predominate in terms of market share over traditional

commercial banks have more capacity to source external finance from global banking networks and international financial markets (BIS, 2019).

4. For example, the Organisation for Economic Co-operation and Development (OECD) notes that smaller enterprises were disproportionately exposed to changes in the cost of funding during (and for several years after) the 2014 crisis, with interest rates on loans to small and medium sized enterprises (SMEs) peaking at around 35 per cent in 2015, along with increased lending spreads relative to larger firms, while interest rates were also slower to fall for SMEs in subsequent years (OECD, 2020b: 5).
5. Around the same time, and to shore-up public finances, the Brazilian government also implemented a programme of welfare state retrenchment (Góes and Karpowicz, 2017). The National Bank for Economic and Social Development (BNDES), for example, has obtained no new funding from the state since 2015, and credit granted from the BNDES has fallen each year since the onset of the crisis (BNDES, 2018).

banks and other financial institutions, their consolidated assets have increased more than fivefold between 2008 and 2017 (from BRL 34 billion to BRL 178 billion), whilst their relative importance in Brazil's financial system has more than doubled over the same period (BIS, 2019: 36). Brazil's credit cooperative movement is also now recognized from an international perspective. For example, not only is Brazil the dominant country in Latin America within this movement, but Brazilian credit cooperatives grant more credit than almost all other emerging countries, except for China and India (BIS, 2019; WOCCU, 2021).[6] Yet, despite the relevance of this development to academics and policy makers, the income inequality implications of cooperative financial institutions still need to be investigated further beyond advanced economies, and across a wider range of developing and emerging countries — including in prominent emerging economies like Brazil.

In this contribution, we exploit the increased data availability on local financial institutions and more contemporary microdata on personal incomes to conduct a panel data analysis of the income inequality–credit cooperatives nexus from 2004 to 2019 across Brazil's 27 federative units.[7] Inequality data are sourced from the Brazilian Institute of Geography and Statistics (IBGE), based on the Annual National Survey by Household Sample (PNAD), its continuous counterpart (PNADCA), and the 2010 Population Census; we construct measures of local institutional presence using the Central Bank of Brazil's UNICAD and IF.Data databases (more details are given in a later section). Our estimation strategy is based on a suite of static and dynamic panel data models, which are combined with instrumental variables (IV) techniques to mitigate endogeneity problems. For robustness, we consider an alternative set of external instruments, which reflect the historical origins of Brazil's credit cooperative movement. Our model is extended to account for time- and development-specific interactions with the local financial institutional presence, thereby enabling us to identify the dynamic effects of credit cooperatives on income inequality before, during and after the Brazilian crisis, as well as across different parts of the country.

6. The emergence of credit cooperatives in Brazil has coincided with a growing penetration of financial cooperatives in other developing and emerging economies. For example, between 2005 and 2021 the penetration of financial cooperatives increased from 4.2 per cent to 16.5 per cent in Latin America, from 2.4 per cent to 5.9 per cent in Asia, and from 5.7 per cent to 15.7 per cent in Africa (WOCCU, 2005, 2021).
7. Brazil's first-level territorial classification consists of five macro regions: North, Northeast, Mid-west, South-east and South. The country's second-level territorial classification consists of 27 federates: North: Acre, Amapá, Amazonas, Pará, Rondônia, Roraima and Tocantins; North-east: Alagoas, Bahia, Ceará, Maranhão, Paraíba, Pernambuco, Piauí, Rio Grande do Norte and Sergipe; Mid-west: Goiás, Mato Grosso, Mato Grosso do Sul and Distrito Federal; South-east: Espírito Santo, Minas Gerais, Rio de Janeiro and São Paulo; and South: Paraná, Rio Grande do Sul and Santa Catarina. In this article, we use the terms federative units and federates interchangeably.

This article's contributions are as follows. First, we investigate the income inequality implications of cooperative financial institutions in an emerging economy context, adding Brazil to an empirical literature which has focused first and foremost on advanced economies. Although financial cooperatives have been studied elsewhere, including in other developing and emerging countries such as Africa, China and India, most studies have adopted a case study approach, relying primarily on informal accounts and anecdotal evidence. This reflects in part the relative scarcity of microdata and regional time-series data needed to compute measures of income inequality and local financial institutions. Second, we produce some novel evidence from a recent but severe crisis in Brazilian history to shed further light on the inequality implications from a regional resilience perspective. In doing so, we take Brazil as a relatively extreme case, but one which is also quite characteristic of other emerging market economies.[8] Third, we provide some new evidence for the relationship channel of financial inclusion by linking our results to credit cooperatives' comparatively strong relationships with smaller enterprises. By adding this explanation, our analysis provides some further theoretical insights from Brazil.[9]

Our empirical analysis reveals several findings. First, Brazilian credit cooperatives have had a favourable effect on income inequality overall, especially compared to commercial banks, thereby corroborating in an emerging economy context the findings reported for advanced economies. Second, our results highlight the inequality-alleviating impact of credit cooperatives, which is especially significant around the onset of the Brazilian crisis. Therefore, our results suggest that Brazilian credit cooperatives have helped smooth out unfavourable shocks during the crisis. Third, we find that credit cooperatives' capacity to alleviate inequality is stronger in Brazil's economically less developed regions, where financial inclusion is also lower. Consistent with the relationship channel of financial inclusion we find that smaller enterprises, which are more prominent in Brazil's less developed regions, have been better protected from the crisis. Our findings are relevant to other developing and emerging countries, where local credit markets are usually underdeveloped, and where the state is more limited in its capacity to fill gaps in finance.

This article is organized as follows. The next section provides a brief review of the relevant literature. The remaining sections provide some background on Brazil's credit cooperative movement and discuss its connections to income inequality. The article sets out its empirical methodology and

8. Overall, Brazil's problems reflect complex confounding factors. However, we would argue that the resource curse, currency crises, balance of payments problems and associated policy constraints are problems faced in other emerging market economies.
9. Though the theoretical channels through which financial cooperatives affect income inequality have recently been investigated empirically for developed economies (see, for example, Minetti et al., 2021, for Italy), there is a gap in the literature for emerging economies.

discusses the testable hypotheses, before describing the data and discussing variable selection. It then discusses the estimation results and outcomes from various robustness checks. Finally, it provides a summary and concluding remarks.

LITERATURE REVIEW

The relationship between income inequality and finance has received considerable attention in the literature (Beck et al., 2007). For example, one prominent viewpoint states that by reducing transactions costs and informational asymmetries, the development of banking systems boosts credit availability amongst the poor (Aghion and Bolton, 1997). Others argue that financial development and the establishment of traditional financial institutions can exacerbate income inequality below a certain threshold in economic development; but that over time, financial development tends to alleviate inequality (Greenwood and Jovanovic, 1990). An important implication of the latter is that traditional financial institutions can have less favourable effects on inequality in less developed countries and regions.

Over time, however, there has been a shift in the debate to better understand how different aspects of financial development and types of financial institutions can affect income inequality, including cooperative financial institutions (see McKillop et al., 2020, for an overview).[10] From a theoretical perspective, local financial institutions have an advantage in financing informationally opaque customers due to their local orientation and access to soft information (Berger and Udell, 2006). This enables them to bring finance to communities which would otherwise be underserved by the traditional financial system. Moreover, because traditional banks and major financial institutions tend to cluster in larger cities and urban centres, this has created gaps in finance for those located in more remote and typically less developed areas (e.g. Alessandrini et al., 2009). Therefore, more localized financial institutions could play an important role in financing more inclusive growth in relatively underdeveloped areas.

Financial cooperatives have received particular attention in the literature due to their strong commitment to fostering social capital and to actively promoting developments in the local economy (Minetti et al., 2021). They are not-for-profit institutions which have established a reputation for

10. We note that other local financial institutions can play a role in promoting more inclusive growth. For example, microfinance institutions (MFIs) have received considerable attention in the literature (see Lensink and Bulte, 2019, for a review). Whilst not discounting their role in the development process, only certain types of MFIs play a similar role to Brazilian credit cooperatives in financing local economic developments, with a not-for-profit status. However, there is considerable variation in the objective functions of MFIs, whereas Brazilian credit cooperatives are arguably more homogeneous in this respect.

relationship lending and extending credit during periods of economic and financial turmoil (Ferri et al., 2014; Ferri et al., 2019; Sette and Gobbi, 2015). Financial cooperatives can also draw on more stable financial surpluses and larger cooperative networks of affiliated banks to alleviate credit constraints and job destruction during crises (Ashcraft, 2006). However, others argue that financial cooperatives do not alleviate inequalities, or at least not to the same extent as more traditional financial institutions. As noted above, for example, Fonteyne (2007) contends that financial cooperatives are smaller in size, have less capital, and are more reliant on members' deposits than commercial banks; therefore, they have less capacity to raise additional finance when faced with unfavourable supply and demand shocks during crises.

A growing number of studies have empirically investigated the economic consequences of financial cooperatives. Hakenes et al. (2015) analysed small banks in Germany using a dynamic panel estimator, including savings banks and credit cooperatives, and found a positive link with economic growth. Coccorese and Shaffer (2021) analysed Italian municipalities using cross-sectional regression techniques between 2001 and 2011; they found that cooperative bank presence was correlated more strongly with growth in incomes, number of firms and employment than traditional banks. Schneiberg and Parmentier (2022) estimated a series of structural equation models to explore the impact of the US banking structure on economic indicators during the US Great Recession. Credit unions and localized banks were found to moderate unemployment spikes and contractions to a much greater extent than larger, more geographically diversified banks. Empirical income inequality studies are relatively rare. One exception is Minetti et al.'s (2021) study, which exploited exogenous spatial variation in local bank presence across Italian provinces to investigate the inequality implications of cooperative banks. Cooperative banks were found to have reduced income inequality mainly by slowing the turnover of firms and communities.

The role of financial cooperatives has also received attention in developing and emerging economy settings, but significant gaps remain. For example, studies highlight the difficulties that traditional financial institutions face when trying to channel credit to effectively alleviate poverty and income inequality in developing countries and examine the potential for credit cooperatives, savings cooperatives and credit unions to fill these gaps (see Braverman and Guasch, 1986, for a review of case-study evidence on rural credit markets in Africa, Asia and Latin America). African countries, as well as countries from Asia (particularly China and India), have received most attention in this literature because of cooperatives' historical importance in rural financial systems (see, for example, Develtere et al., 2008, for African countries; Huang and Zhang, 2020, for China; Misra, 2010, for India).[11] Over time, the literature has evolved to consider a wider range of country contexts, while recognizing also the broader growth of cooperative financial institutions in developing and emerging economies. However, in emerging economies especially, there is a lack of proper investigation of financial cooperatives' impact on (and relationship with) income inequality in a crisis context. This is despite the more volatile macroeconomic and financial environments that emerging countries tend to face, as well as their higher levels of economic inequality, poverty and financial exclusion compared to developed countries.

BACKGROUND ON BRAZIL'S CREDIT COOPERATIVE MOVEMENT

Brazilian credit cooperatives have their origins in 19th-century Germany and operate as autonomous not-for-profit associations, which enable individuals — often those with low and irregular incomes — to pool financial resources or savings for common purposes. The cooperative pioneer, Friedrich Wilhelm Raiffeisen, established the first rural credit union in Germany in 1864; cooperative banking subsequently spread across Europe, into North America and beyond (e.g. McKillop et al., 2020: 2). In Latin America, the first credit cooperative, Armstad Savings and Loans Bank, was established in 1902 in Nova Petropolis in Brazil's far south. Based on the German cooperative banking model, the Armstad Savings and Loans Bank provided poor rural communities with a basic financial institution, through which members could deposit and lend to each other on a not-for-profit basis. Due to Brazil's large geographic size and the dispersion of its population across the country, credit cooperatives have grown to fill gaps in finance beyond the country's major urban centres and modern financial districts, where larger commercial banks and other financial firms have tended to cluster. According to data collected from the Central Bank of Brazil's database, IF.Data, there were 909 credit cooperatives active in 25 Brazilian states and in the Federal District as of December 2019, supporting customers with over 6,000 service outposts and US$ 37 billion in credit operations (see Table 1).

Brazilian credit cooperatives' relative importance has more than doubled at the within-country level between 2008 and 2017, while their consolidated assets have increased more than fivefold over the same time (BIS, 2019: 36). As evidenced in Table 1, credit cooperatives do not dominate Brazil's

11. For example, Huang and Zhang (2020) apply panel cointegration techniques to estimate the impact of regional financial inclusion on rural–urban income inequality in Chinese provinces between 1985 and 2013. Financial institutions were found to have reduced income inequality over longer horizons, but their short-run effect has been weaker. Critically, however, Huang and Zhang's analysis (ibid.) does not distinguish between different types of financial institutions (for example, traditional banks, savings banks and rural credit cooperatives), which are assumed to have an equal impact on income inequality, even though the relationships may differ.

Table 1. General Characterization of Credit Cooperatives in the Brazilian Financial System

Location	Credit Cooperatives	Service Outposts	Total Loans (US $ 1,000s)	Total Assets (US $ 1,000s)	Regional Distribution of Assets (%)	Market Share (%)	Change 2004–19 (%)
North	37	220	1,307,226	1,962,020	2.449	0.586	0.549
Acre	4	4	53,302	68,141	0.085	0.167	0.167
Amapá	0	0	0	0	0.000	0.000	0.000
Amazonas	4	4	32,062	39,351	0.049	0.101	0.055
Pará	9	26	91,136	138,889	0.173	0.286	0.246
Rondônia	18	175	1,099,997	1,664,896	2.078	3.450	3.302
Roraima	1	0	3,807	6,169	0.008	0.012	0.012
Tocantins	1	11	26,922	44,574	0.056	0.084	0.063
North-east	67	282	1,349,732	3,180,279	3.968	0.470	0.314
Alagoas	7	11	132,565	245,307	0.306	0.416	0.228
Bahia	24	123	244,272	606,431	0.757	0.766	0.277
Ceará	4	19	97,370	243,796	0.304	0.305	0.079
Maranhão	6	25	43,633	73,912	0.092	0.137	0.127
Paraíba	12	36	431,206	1,345,180	1.679	1.352	1.110
Pernambuco	7	51	241,617	363,298	0.453	0.758	0.645
Piauí	2	6	11,325	25,197	0.031	0.036	0.022
Rio Grande do Norte	3	9	98,919	200,878	0.251	0.310	0.184
Sergipe	2	2	48,825	76,280	0.095	0.153	0.153
Mid-west	78	591	6,701,099	11,528,277	14.387	5.255	4.059
Goiás	36	192	1,791,957	4,091,896	5.107	5.620	5.048
Mato Grosso	18	239	2,933,214	4,500,692	5.617	9.200	7.107
Mato Grosso do Sul	10	110	1,281,906	1,831,201	2.285	4.021	3.541
Distrito Federal	14	50	694,022	1,104,488	1.378	2.177	0.541
South-east	450	1,751	9,555,897	23,368,202	29.166	7.493	4.467
Espírito Santo	29	158	1,243,477	2,767,917	3.455	3.900	2.936
Minas Gerais	181	975	4,524,974	11,425,995	14.261	14.192	9.443
Rio de Janeiro	45	83	230,950	884,899	1.104	0.724	0.058

(*Continued*)

Table 1. (Continued)

Location	Credit Cooperatives	Service Outposts	Total Loans (US $ 1,000s)	Total Assets (US $ 1,000s)	Regional Distribution of Assets (%)	Market Share (%)	Change 2004–19 (%)
São Paulo	195	535	3,556,496	8,289,391	10.346	11.155	5.431
South	277	3,214	18,364,373	40,084,003	50.028	19.200	13.599
Paraná	75	1,315	6,562,558	14,193,861	17.715	20.583	15.088
Rio Grande do Sul	103	928	6,997,544	13,085,367	16.332	21.948	13.817
Santa Catarina	99	971	4,804,271	12,804,775	15.981	15.068	11.893
Brazil	909	6,058	37,278,327	80,122,781	100.000	4.330	3.021

Notes: Regional Distribution of Assets (%) corresponds to the share of credit cooperatives' assets in each federate or macro region relative to the total assets of all Brazilian credit cooperatives in 2019. Market Share (%) corresponds to the share of credit cooperatives' assets in each federate or macro region relative to the total assets held by all financial institutions in 2019. Change 2004–19 (%) corresponds to the change in credit cooperatives' market share from 2004 to 2019. The values for North, North-east, Mid-west, South-east and South macro regions and for Brazil are summations across all the relevant federates, except for Market Share (%) and Change 2004–19 (%), which are averages across the relevant federates.
Source: authors' own computations based on the database IF.Data (www3.bcb.gov.br/ifdata).

financial system, having an overall market share of approximately 4 to 5 per cent; however, this masks considerable spatial heterogeneity across the country, with a market share of about 15 to 22 per cent in Brazil's southern macro region.[12] The market share of credit cooperatives (in terms of their asset share across all Brazilian financial institutions) has increased in almost all federates between 2004 and 2019. Therefore, credit cooperatives have become more important intra-nationally, while increasing Brazil's prominence from a comparative international perspective. For example, not only is Brazil the predominant country in Latin America in this movement, but credit cooperatives in Brazil grant more credit than in almost all emerging economies, except for China and India (BIS, 2019; WOCCU, 2021).

A key difference between financial cooperatives and commercial banks relates to the egalitarian structure of ownership, whereby each member of the cooperative has only one vote. By contrast, voting power in commercial banks can be increased through the purchase or transfer of shares. Since 1969, the Organization of Brazilian Cooperatives (OCB) has overseen the cooperatives sector, with a legal framework introduced in 1971. From a regulatory standpoint, credit cooperatives are audited by licensees of the Central Bank of Brazil, which also has sole supervisory authority and the power to remove senior management and board members due to misconduct, fraud or regulatory breaches. Like other financial institutions, credit cooperatives are subject to regulatory requirements and macro-prudential policy, including capital adequacy requirements, which reflect their size, operations and risk profile (BIS, 2019: 37). Members' deposits are protected by the Cooperative Credit Guarantee Fund, which was established in 2013 to offer the same level of protection as commercial banks (ibid.: 38). Therefore, Brazil's credit cooperatives act to support their members' interests, while operating under a developing regulatory and macro-prudential architecture.

Brazilian Credit Cooperatives and Income Inequality

Credit cooperatives are known for their support of initiatives to address pressing economic and social issues, such as poverty, inequality and socio-economic exclusion. Their values are deeply interlinked with the UN's Sustainable Development Goals (SDGs) (Moxon et al., 2022).[13]

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12. This is consistent with findings reported elsewhere, with credit cooperatives' estimated market share at approximately 17 per cent in the southern macro region (see, for example, BIS, 2019: 36).
13. The International Cooperative Alliance (ICA), which issues guidelines for cooperatives worldwide, has set out the following principles of operation: 'self-help, self-responsibility, democracy, equality, equity and solidarity. In the tradition of cooperative founders, cooperative members believe in the ethical values of honesty, openness, social responsibility and caring for others' (ICA, 2015: 1).

Although Brazilian credit cooperatives support inclusive growth and social capital accumulation quite broadly, they have a particular reputation for supporting financial inclusion in the local economy, which reflects their historical roots in supporting Brazil's more remote and rural communities. For example, Cooperativa Alios, which is a network of 13 credit cooperatives, supports entrepreneurship through an educational programme called Progrid in collaboration with non-profit organizations, and aims to promote the competitive development of small enterprises (CREA-SC, 2018). The cooperative bank Sicredi, which is a parent cooperative within a network of 116 affiliated cooperatives, has established partnerships with international organizations such as the World Bank's International Finance Corporation (IFC) to support development and enterprise in underserved rural areas and smaller cities (IFC, 2011). Additionally, as part of the 'Women, Micro and Small Enterprises' (MMPE) initiative, Sicredi has granted more than BRL 5 billion in financing for female enterprises and claims that more than 50,000 Brazilian women have been positively impacted (Sicredi, 2022a). Sicredi's participation in '2X Challenge — Finance for Women', which was launched by the G7 development financial institutions, aims to allocate finance to support female entrepreneurship in emerging countries. Although global in outlook, its initiatives are implemented primarily at local and regional levels, with Sicredi having recently raised US$ 100 million to support female-owned micro, small and medium sized enterprises (Sicredi, 2022b).

Brazilian credit cooperatives also have a reputation for extending credit to support businesses and employment during crises. After the onset of Brazil's 2014 crisis, many credit cooperatives and their networks continued to expand their operations (see Unicred, 2016 for evidence from the Unicred cooperative network). Sicoob Credicom, a cooperative within Sicoob, which is the largest network of credit cooperatives in Brazil, increased total lending from 2015 to 2016, while it distributed millions in financial surplus to its members during the Brazilian crisis (Sicoob Credicom, 2017). Such actions helped mitigate the reduction in bank lending to small enterprises during the crisis, as highlighted by the OECD (2020b), amongst others. More recently, during the global COVID-19 pandemic, Sicoob was recognized for providing more credit to small businesses than any other financial institution, while holding interest rates below their pre-pandemic levels (Sicoob, 2021). Sicredi was also acknowledged during the pandemic as the best performer in terms of allocating emergency credit (Sicredi, 2020). Thus, credit cooperatives have, via their local presence and broader networks, brought finance to parts of the country which would otherwise be underserved, thereby cushioning the impact of recent crises.

In summary, some recent evidence and accounts suggest that Brazil's credit cooperatives have helped foster more inclusive growth and resilience in Brazil's federates. This is in line with the optimistic perspective in the literature, which emphasizes the role of financial cooperatives in supporting local economic developments because of their commitment to the communities they serve and their engagement in relationship lending during crises (e.g. Ferri et al., 2014; Ferri et al., 2019; Sette and Gobbi, 2015). However, because of the theoretical ambiguities and lack of formal empirical investigation in the emerging economy context, further research is now needed to build up a clearer picture in support of either the more optimistic or the more pessimistic perspective on this issue.

METHODOLOGY AND DATA

Empirical Model

This article's main objective is to estimate the relationship between income inequality and local credit cooperative presence in Brazilian federates to determine the magnitude and significance of this relationship. We start from the panel-data regression model in equation 1, in which the dependent variable, $GINI_{it}$, corresponds to the Gini coefficient of income inequality for federate i and year t:

$$GINI_{it} = \alpha + \beta X_{it} + \gamma' Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

In equation 1, income inequality responds to changes in a measure of local credit cooperative presence, X_{it}, according to the coefficient, β. Also included is a column vector Z_{it} of conditioning variables, which are reputed to be important in the determination of income inequality. This includes measures of financial and economic development, the structure of production, labour-market conditions, international trade openness and skill-biased change, amongst other influences. All variables in the model are defined and discussed below. The model also includes a collection of federate and year fixed effects, μ_i, and θ_t, respectively, which help control for unobserved or hard-to-measure spatial and dynamic heterogeneity. Finally, a normally distributed error term is included to capture residual variation, ε_{it}.

$$GINI_{it} = \alpha + \beta \hat{X}_{it} + \gamma' Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

Equation 1 only partially addresses endogeneity problems; hence IV estimation is used as a more general solution. We start with an application of two-stage least squares (TSLS), whereby X_{it} is replaced by $\hat{X}_{it}$, as in equation 2, and varies exogenously through its association with a set of instruments. Therefore, financial institutional presence, X_{it}, is treated as endogenous under TSLS. However, a limitation of equations 1 and 2 is that these model specifications do not account for the potential for income inequality to persist over time. Therefore, additionally, we employ the dynamic model in equation 3, which includes a one period lag of the dependent variable on the right-hand side to capture the temporal persistence in income inequality. In estimating equation 3, we employ Blundell and Bond's (1998) two-step GMM system estimator (GMM-SYS). Essentially, GMM-SYS employs variables in levels, which are instrumented using lagged values of their differences to exploit efficiency gains created by additional moment conditions. Therefore, the GMM-SYS is a more efficient alternative than the traditional (first difference) GMM dynamic panel estimator. Another advantage of GMM-SYS over TSLS is that other explanatory variables can easily be treated as endogenous. Moreover, because our endogeneity concerns are not limited to local credit cooperative presence, we take a cautious approach and consider that the penetration of commercial banks, GDP per capita, unemployment, trade openness and the share of high-tech exports are also potentially endogenous. Therefore, under GMM-SYS, we control for endogeneity more broadly by considering a wider set of endogenous regressors.

$$GINI_{it} = \alpha + \rho GINI_{it-1} + \beta \widehat{X}_{it} + \gamma' Z_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

Following many others in the relevant literature, our baseline IV identification strategy under TSLS and GMM-SYS involves using internal instruments in the form of two lags of the endogenous regressor(s) (e.g. D'Onofrio et al., 2019). Because this introduces many instruments under GMM-SYS, we impose constraints on the instrument matrix as suggested by Roodman (2009) to reduce problems arising from excessive instruments.[14] For robustness, we also consider an alternative identification strategy by introducing external instruments, which reflect the historical origins of the Brazilian credit cooperative movement. Here we exploit the fact that financial cooperatives were first established in Germany and spread quickly to other European countries, such as France, Italy and Switzerland, before their establishment in Brazil (McKillop et al., 2020). We contend that the early establishment of credit cooperatives in the rural south of Brazil was associated with significant early German immigration in the same parts of the country.[15] To be clear, there were significant waves of immigration in the 19th and early 20th centuries from other European countries too, notably from Italy, Portugal and Spain as detailed in Levy's (1974) historiography. However, the early German rural migrant communities were geographically isolated, had a different culture and were not well integrated in Brazilian society (Jordan, 1962: 350). European migrants from Italy, Portugal and Spain were more rapidly integrated partly due to their linguistic similarities with Brazilians.[16] Therefore, we argue that German migrants were relatively poorly positioned to access finance from Brazil's traditional banking system;

14. We apply the 'collapse' option when using the STATA command 'xtabond2' for GMM-SYS, which reduces problems arising from excessive instruments.
15. The channelling of significant inward migration of Europeans towards Brazil's southern region reflects in part the motives of Emperor Dom Pedro I to deter Spanish encroachment via Argentina, following Brazil's independence (Jordan, 1962).
16. Mortara's (1950) analysis of Brazilian census records identifies a relatively weak linguistic assimilation of Germany migrants compared to their Spanish and Italian counterparts.

instead, they were more likely to depend on and encourage more localized and communal forms of finance.

As a first external instrument, we use the distance (in 1,000s of kilometres) from a federate's geographic centre to the municipality of Nova Petropolis, which contained a sizeable community of early German settlers, and is where Brazil's first credit cooperative was established in 1902. As a second instrument, we use a dummy variable, which indicates whether a federate housed the first wave of Germany settlers.[17] As an alternative, time-varying instrument, we also construct a third instrumental variable, which is equal to the number of years since the establishment of a federate's first German colony. In effect, we contend that patterns of early German migration to Brazil and subsequent development of credit cooperatives were significantly shaped by historical-political considerations; but this did not have any obvious direct effect on income inequality in the sample of the current study.[18] We employ these external instruments as follows. First, we conduct TSLS using all three external instruments and include both year and macro region fixed effects.[19] Second, we conduct TSLS using only the time-variant external instrument and include both year and federate fixed effects. Third, we add the external instruments as additional instruments under GMM-SYS, including fixed effects for individual years and fixed effects either for individual macro regions or federates, depending on the time-variance of the instrument set.[20] The outcomes are discussed further as part of our robustness checks in the results section.

The empirical methodology provides a basis for testing our central hypothesis. This involves establishing the sign and significance of the estimated coefficient for β to determine whether the Brazilian credit cooperative movement lends empirical support for arguments linking financial

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17. To identify the federates which contained the early Germany settlers and the number of colonies established since 1808 we rely on Brazilian historian Toni Jochem's chronology of historical German migration (see: www.tonijochem.com.br/colonias_alemas.htm). Jochem's chronology reveals that the earliest German settlements were in the states of Bahia, Espírito Santo, Paraná, Rio de Janeiro, Rio Grande do Sul, Santa Catarina and São Paulo.
18. This choice of external instruments is supported by visual inspection of our dataset, which does not reveal any obvious relationship between contemporary income inequality and historical German settlement. For example, the state of Bahia contained several German colonies, yet it has an extremely high degree of income inequality in modern-day Brazil. Contrarily, contemporary inequality is much lower in other states where German colonies were established like Santa Catarina. The state of Rio Grande do Sul also housed many early German settlers, yet it has a very average degree of income inequality.
19. It is reassuring to note that in Columns 3–5 of Table AII.2 (in Appendix II), the external instruments are related to credit cooperative presence in the first stage of TSLS estimation with the expected signs: distance from Nova Petropolis (-); whether a federate housed the first wave of German settlers (+); the number of years since the establishment of the first German colony (+).
20. Our approach is consistent with other studies in the literature, which have combined time-invariant instruments with time-varying instruments under GMM-IV estimation (see, for example, D'Onofrio et al., 2019: 439).

cooperatives' establishment to lower or higher levels of income inequality. Taking this a step further, we also consider adding a dummy variable interaction term, $X_{it}.CRISIS_{it}$, to equations 1–3, where the variable $CRISIS_{it}$ indicates the presence of the 2014 Brazilian crisis and subsequent recession in our sample. This enables us to investigate whether the main relationship has shifted around the crisis, so that we can validate different perspectives in the literature on financial cooperatives' role in alleviating or exacerbating income inequality in a Brazilian crisis context (see, for example, Ferri et al., 2019 versus Fonteyne, 2007). In terms of implementation, we first estimate equation 1 using least squares dummy variables estimation (LSDV), which includes federate, year fixed effects. Second, we estimate equation 2 using TSLS with federate, year fixed effects. Third, we estimate equation 3 using the dynamic panel estimator, GMM-SYS, with two-way fixed effects, and employ Windmeijer's (2005) robust standard errors.

Data Description

We employ regional panel data for Brazil's 27 federative units, which correspond to the country's second-level territorial units, including 26 states and the Federal District.[21] Time-series data on local financial institutional presence for the federative units is much more limited in the early 2000s, but we have sourced annual data over the period 2004–19 for all 27 federates, giving us a balanced panel.

We employ the Gini coefficient ($GINI_{it}$) as the principal measure of income inequality in federate *i*, year *t*. Scaled from 0 to1, larger values correspond to higher levels of inequality. Given the relative merits of different inequality indicators (see McGregor et al., 2019, for a useful discussion), we consider also the S80/S20 ratio ($S80/S20_{it}$), which is the ratio of average income earned by the richest 20 per cent of the population to the poorest 20 per cent, as an alternative for robustness.[22] Inequality data are published by the IBGE based on the Annual National Survey by Household Sample (PNAD), its continuous counterpart (PNADCA) and the 2010 Population Census.

21. It would be interesting to conduct our analysis for different regional spatial scales, including for Brazil's municipalities, which correspond to the country's third-level territorial units. However, data for municipalities are less consistent due to the many boundary changes that have arisen at this level. For example, according to the IBGE (2022), there were boundary changes in 342 municipalities between May 2020 and April 2021 alone. Also, Brazil's Annual National Survey by Household Sample contains over 100,000 households. However, there are currently more than 5,500 municipalities in Brazil, so focusing instead on more local regions would drastically reduce the sample size from which income inequality could be computed.
22. Other inequality measures are often used in the literature such as the Theil index or income shares of the top 10 and 25 per cent of the population relative to the bottom 10 and 25 per cent, i.e., P90/P10 and P75/P25 (see, for example, Beck et al., 2010). We note that the results obtained using these other measures were qualitatively similar, but for brevity we do not present these results.

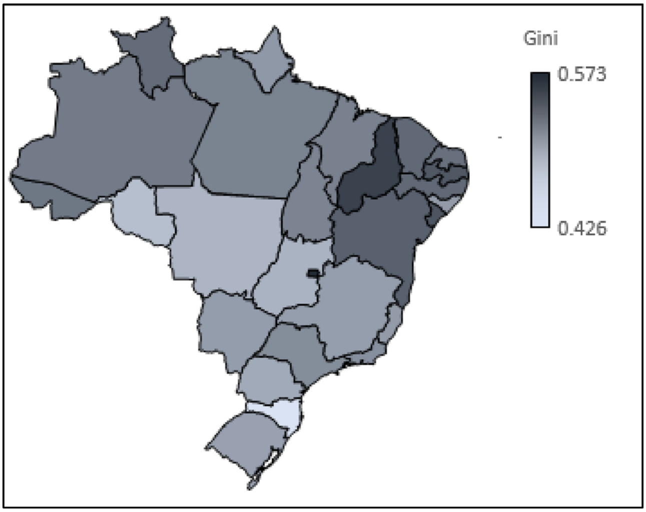
To measure financial institutional presence, we take the number of branches and service outposts in each federate and normalize by its population (1,000s). This measure has been widely used elsewhere and is suitable because it captures well the demographic penetration of financial-banking services (e.g. Beck et al., 2007). To compare different financial institutions, we construct two separate measures based on Brazil's main financial institutions, namely commercial banks ($COMM_{it}$) and credit cooperatives ($COOP_{it}$). In the former, we include also universal banks because both types of banks follow an objective function based on profit maximization. Data on branches and service outposts are obtained from the Central Bank of Brazil's UNICAD and IF.Data databases.[23] Population data are sourced from the IBGE.

Several variables are added as controls drawing on the empirical literature into the determinants of income inequality in a banking development context (e.g. Arestis and Phelps, 2019; D'Onofrio et al., 2019; Minetti et al., 2021). The natural logarithm of the unemployment rate ($UNRATE_{it}$) is included as a general control for labour-market conditions. The natural logarithm of real GDP per capita ($GDPCAP_{it}$) as well as its square ($GDPCAP^2{}_{it}$) are included to control for (potentially non-linear) economic development effect(s) on inequality as hypothesized by Kuznets (1955).[24] The shares of agriculture (AGR_{it}), extractive industries (IND_{it}) and construction output (CST_{it}) are included to control for production structure. Data on unemployment, GDP per capita and production structure are sourced from the IBGE. A measure of technological diffusion ($TECH_{it}$) is included to control for skill-biased change, using the share of high-tech exports in international exports.[25] Global trade integration ($TRADE_{it}$) is controlled for by normalizing international trade (exports and imports) by nominal GDP using data from Brazil's Ministry of Development, Industry and Foreign Trade (MDIC). All variables are computed at the level of Brazil's federates and those expressed as shares are scaled in percentage points.

Finally, to control for the effects of the 2014 Brazilian crisis on income inequality, a dummy variable is also included ($CRISIS_{it}$), which takes a value of unity for the years 2014 to 2016, and zero otherwise.[26] Additionally, the

23. From UNICAD, we obtained detailed information about all registered commercial and universal banks across Brazilian federates. From the database IF.Data, we obtained information about individual credit cooperatives according to the federate in which their headquarter is based.
24. Kuznets's (1955) hypothesis relates to uneven capital accumulation, demographics and migration, amongst other factors, which can shift according to the level of economic development.
25. We consider Mercosur Common Nomenclature codes 84–85, which correspond to high-technology exports.
26. Due to the complexity of the Brazilian crisis and the difficulty of precisely identifying its onset, we also considered treating only 2015 and 2016 as crisis years. However, the estimation results were very similar, and the outcomes are consistent with our main conclusions.

Figure 1. Gini Coefficient in Brazil's Federates, 2004–19



Source: authors' own computations based on IBGE data (see: www.ibge.gov.br/estatisticas/sociais/rendimento-despesa-e-consumo).

inclusion of time-specific, year fixed effects helps to control for temporal shocks that affect income inequality across the sample period.

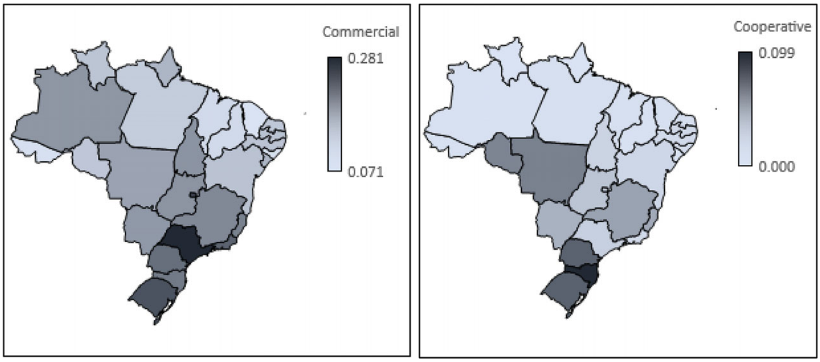
Statistical Summary

There are long-standing and deep spatial divides in income inequality in Brazil's federates (see Azzoni, 1999 for a historical overview). The country's northernmost parts generally suffer from higher levels of income inequality (see Figure 1), while having relatively low access to the financial system via commercial bank branches and credit cooperative outposts (see Figure 2). This partly reflects the clustering of many commercial banks in the country's major urban centres and financial districts like São Paulo and the Distrito Federal (see Figure 2a). Although credit cooperatives have expanded across Brazil, their service outposts are more concentrated in southern states like Santa Catarina and Rio Grande do Sul, which is where the first credit cooperatives were established (see Figure 2b).

The high variation in income inequality and local financial institutional presence reflects both spatial and temporal dimensions. Table AII.1 in Appendix II contains summary statistics for the different variables used in our estimations. The Gini coefficient decreased initially until around 2014 or 2015, after which there has been a reversal in all the macro regions, especially in the north and north-east (see Figure AI.1 in Appendix I). Figure AI.2 in Appendix I highlights the different evolutions in demographic penetration of commercial and cooperative financial institutions. Over time,

Figure 2. Commercial Bank (left) and Credit Cooperative (right) Presence in Brazil's Federates, 2004–19

a. Commercial Banks *b. Credit Cooperatives*



Notes: Commercial and universal plus bank branches (per 1,000 inhabitants) (see Figure 2a, left). Credit cooperative service outposts (per 1,000 inhabitants) (see Figure 2b, right).
Source: authors' own computations.

credit cooperatives have substantially expanded their services across different parts of Brazil. Growth of local credit cooperative presence in the north (506 per cent) and north-east (154 per cent) macro regions has outstripped growth in both the south-east (129 per cent) and mid-west (72 per cent), whilst growth in the south (165 per cent) macro region has remained strong. In contrast to the robust growth of credit cooperative service points, many commercial banks cut back the number of service points following the onset of the Brazilian crisis in 2014.

ESTIMATION RESULTS

Baseline Results

This section presents the estimation results when the income inequality measures are regressed on our indicator for local credit cooperative presence. LSDV, TSLS and GMM-SYS results are presented in Table 2 using different sets of covariates and measures of income inequality. The Gini coefficient is used as the dependent variable in Columns 1–3, 5–7 and 9–11, whereas the S80/S20 ratio is used instead in Columns 4, 8 and 12.

Table 2 reveals a negative and statistically significant relationship between credit cooperative presence and income inequality in Brazil's federates. Under different estimation approaches (LSDV, TSLS and GMM-SYS), the point estimates are quite similar. The outcome is also robust to the inclusion of commercial banks, which suggests that credit cooperatives' effect on inequality goes beyond that of commercial banks. Specifically, the

Table 2. Income Inequality and Credit Cooperative Presence: Baseline Estimation Results

	Least Squares Dummy Variables (LSDV)				Two-Stage Least Squares (TSLS)				GMM Dynamic Panel (GMM-SYS)			
	LSDV	**LSDV**	**LSDV**	**LSDV**	**TSLS**	**TSLS**	**TSLS**	**TSLS**	**GMM-SYS**	**GMM-SYS**	**GMM-SYS**	**GMM-SYS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Gini	*Gini*	*Gini*	*S80/S20*	*Gini*	*Gini*	*Gini*	*S80/S20*	*Gini*	*Gini*	*Gini*	*S80/S20*
Lag Gini / Lag S80/S20	—	—	—	—	—	—	—	—	0.334***	0.332***	0.337***	0.422***
									(3.784)	(3.643)	(3.876)	(5.894)
Credit Cooperatives	−1.399***	−0.645***	−0.662***	−36.257**	−1.289***	−0.520***	−0.542***	−46.241**	−0.660***	−0.394**	−0.438**	−49.673**
	(6.951)	(4.110)	(4.165)	(2.350)	(6.768)	(3.212)	(3.218)	(2.380)	(2.865)	(2.074)	(2.139)	(2.219)
Commercial Banks	—	—	−0.135	−16.707	—	—	−0.158	−4.721	—	—	−0.274	−14.109
			(0.880)	(1.260)			(0.786)	(0.183)			(1.475)	(0.832)
Crisis Dummy	—	0.006	0.005	0.084	—	0.006*	0.005	0.131	—	0.002	0.001	0.999**
		(1.639)	(1.378)	(0.185)		(1.743)	(1.313)	(0.251)		(0.541)	(0.185)	(2.026)
Dummy2017	—	0.018***	0.016**	2.298***	—	0.018**	0.016*	2.570***	—	0.009	0.006	−0.334
		(3.122)	(2.292)	(2.945)		(2.351)	(1.866)	(2.941)		(1.437)	(0.922)	(0.390)
Dummy2018	—	0.034***	0.032***	4.078***	—	0.034***	0.031***	4.382***	—	0.024***	0.019***	1.087
		(6.143)	(4.616)	(4.947)		(4.832)	(3.834)	(4.471)		(3.227)	(2.827)	(1.111)

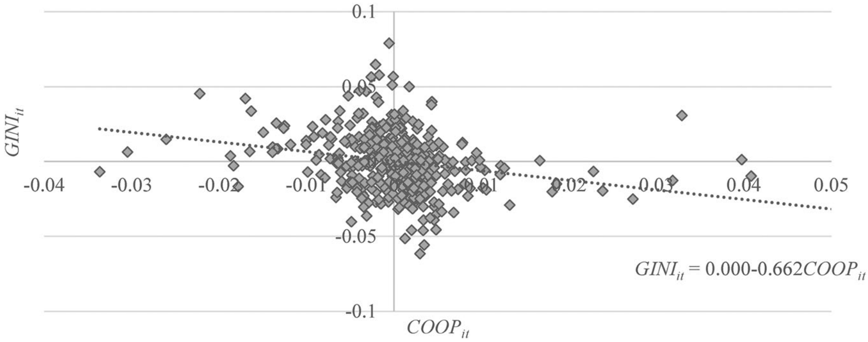
(*Continued*)

Table 2. (Continued)

	Least Squares Dummy Variables (LSDV)				Two-Stage Least Squares (TSLS)				GMM Dynamic Panel (GMM-SYS)			
	LSDV	LSDV	LSDV	LSDV	TSLS	TSLS	TSLS	TSLS	GMM-SYS	GMM-SYS	GMM-SYS	GMM-SYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dummy2019	—	0.036***	0.033***	4.162***	—	0.035***	0.031***	4.541***	—	0.022***	0.016**	0.547
		(7.237)	(4.963)	(5.024)		(5.061)	(3.890)	(4.518)		(3.417)	(2.296)	(0.534)
Additional Controls	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Federate FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-Statistic IV 1st Stage	—	—	—	—	17.250***	20.776***	21.060***	21.060***	—	—	—	—
JP	—	—	—	—	[0.956]	[0.592]	[0.891]	[0.506]	[0.182]	[0.217]	[0.199]	[0.972]
AR1P	—	—	—	—	—	—	—	—	[0.000]***	[0.000]***	[0.000]***	[0.002]***
AR2P	—	—	—	—	—	—	—	—	[0.156]	[0.196]	[0.304]	[0.339]
R^2 / Pseudo R^2	0.648	0.776	0.777	0.761	0.683	0.778	0.779	0.776	0.628	0.671	0.740	0.764
Observations	432	432	432	432	378	378	378	378	405	405	405	405

Notes: Credit Cooperatives and Commercial Banks indicate the presence of credit cooperative outposts and commercial bank branches per 1,000 inhabitants. In Columns 4, 8 and 12 the dependent variable is the S80/S20 ratio, otherwise the Gini coefficient is employed. The constant terms are not reported for brevity but are included in all estimations. Two lags of endogenous regressors are used as instruments for TSLS and GMM-SYS. The estimated coefficients for year fixed effects in 2017, 2018 and 2019 are indicated in the table by Dummy2017, Dummy2018 and Dummy2019, respectively. Additional Controls indicates whether the regression model includes the additional controls ($UNRATE_{it}$, $GDPCAP_{it}$, $GDPCAP^2{}_{it}$, AGR_{it}, IND_{it}, CST_{it}, $TECH_{it}$, $TRADE_{it}$) as defined previously. F-Statistic IV 1st Stage corresponds to Kleibergen and Paap's (2006) F-test for weak instruments. JP is the p-value for Hansen's (1982) over-identification test. AR1P and AR2P correspond to the p-values for first- and second-order tests for autocorrelation under GMM-SYS. The R-squared statistic, and its pseudo counterpart, indicate model fit. Absolute t-statistics are reported (in parentheses), which are robust to heteroscedasticity and autocorrelation. Under GMM-SYS, Windmeijer's (2005) corrected standard errors are employed. Significance is indicated by * (10%), ** (5%), *** (1%).
Source: authors' own computations.

Figure 3. Partial Correlation Plot of the Gini Coefficient and Credit Cooperative Presence



Notes: Plot of the residuals from LSDV estimation of the inequality indicator, $GINI_{it}$, and credit cooperative presence, $COOP_{it}$, on all other control variables.
Source: authors' own computations.

TSLS estimates in Column 7 imply that an increase in the presence of credit cooperatives by one standard deviation reduces the Gini coefficient by 0.014 (0.026 x -0.542), or by about one third of a standard deviation (0.341 = 0.014/0.041). Furthermore, the partial correlation plot in Figure 3 indicates a strong correlation between these two variables after partialling out all other influences. On the other hand, an increase in the presence of commercial banks by one standard deviation reduces the Gini coefficient by only 0.008 (0.049 x -0.158), or by about one fifth of a standard deviation (0.195 = 0.008/0.041), but the effect is not statistically significant. Therefore, the impact of credit cooperatives on inequality seems large both in absolute terms, and relative to the impact of commercial banks. This outcome is also robust to the use of the alternative inequality measure, the S80/S20 ratio in Columns 4, 8 and 12. By comparison, Minetti et al. (2021) found that a 10 per cent increase in the financial cooperative branches per 1,000 inhabitants reduced the Gini coefficient in Italian provinces by 0.4 per cent. If we impose the same change in credit cooperative presence for Brazilian federates using Column 7, this also reduces the Gini by approximately 0.4 per cent.[27] Overall, our results corroborate the more optimistic view in the literature, which asserts that financial cooperatives can help finance more inclusive growth (e.g. Ferri et al., 2014; Ferri et al., 2019; Minetti et al., 2021; Sette and Gobbi, 2015).

The LSDV results are quite similar qualitatively and quantitatively to those obtained under TSLS and GMM-SYS. Overall, we slightly prefer our

27. From Minetti et al. (2021: 426) we multiply 0.0074 (0.1 x 0.074) in their Table 1 by -0.542 (Column 7 in our Table 2), which gives 0.004 or 0.4 per cent of the Gini coefficient in its 0 to 1 scale.

IV results (TSLS and GMM-SYS) because they provide a more general robustness to endogeneity problems. IV estimations are also supported by relevant diagnostics including Hansen's (1982) over-identification test, which indicates that the instruments are valid. Under TSLS, the F-statistic from the 1st stage suggests that the instruments are useful, since in each case the F-statistic exceeds the critical value at the 1 per cent level from Kleibergen and Paap's (2006) F-test for weak instruments. Additionally, the null hypothesis of no second-order autocorrelation of the error terms is not rejected as is required for consistent GMM-SYS estimation. In terms of the crisis's implications for inequality, the results in Table 2 indicate that the Brazilian crisis correlated positively with inequality, but not significantly so; however, we find that inequality increased more significantly in the following years, from 2016 to 2019. This is consistent with observations — both in Brazil and elsewhere — that severe crises can have long-lasting effects on income inequality, for example, because of job destruction or subsequent public expenditure cutbacks (e.g. Góes and Karpowicz, 2017).

Dynamics around the Brazilian Crisis

To provide further exploration of the dynamics of the main nexus around the great Brazilian recession, Panel A of Table 3 reports the estimation output when equations 1–3 include also dummy variable interactions of local financial institutional presence with the crisis indicator. The interaction estimates for credit cooperatives in Columns 1–7 are statistically significant at conventional levels. Not only did credit cooperatives alleviate inequality during the crisis, but their effect was relatively large in this period. By comparison, when we explore the interaction-term effect for commercial banks, the estimates are quantitatively smaller and statistically insignificant. Panel B of Table 3 contains the estimates for the year-interactions of local financial institutional presence across the post-crisis years, from 2014 to 2019.[28] For illustration, we also present the time-varying estimates (i.e. $\hat{\beta}_t$) for credit cooperatives and for commercial banks (see Figures 4a and 4b) when year-interactions are included for all years in the sample, from 2004 to 2019. Evidently, credit cooperatives had the largest effects during 2014 and 2015, before gradually reverting to their pre-crisis strength. The LSDV and GMM-SYS estimates for the interaction terms are much larger (in absolute terms) around the onset of the crisis in 2014 for credit cooperatives (until around 2016 or 2017), revealing their greater role in mitigating the rise in inequality during the period of crisis and recession than commercial banks (as shown in Figure 4). These outcomes are robust when we employ the S80/S20 ratio instead of the Gini coefficient.

28. When estimating, we include year-interaction terms for both credit cooperatives and commercial banks.

Table 3. Income Inequality and Credit Cooperative Presence: Dynamics around the Brazilian Crisis

	Panel A: Institutional Presence-Crisis Dummy Interactions							Panel B: Institutional Presence-Year Interactions			
	Least Squares Dummy Variables (LSDV)		Two-Stage Least Squares (TSLS)		GMM Dynamic Panel (GMM-SYS)			Various Fixed Effects / IV Estimations (LSDV, TSLS, GMM-SYS)			
	LSDV	LSDV	TSLS	TSLS	GMM-SYS	GMM-SYS	GMM-SYS	LSDV	TSLS	GMM-SYS	GMM-SYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Gini	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*S80/S20*	*Gini*	*Gini*	*Gini*	*S80/S20*
Lag Gini / Lag S80/S20	—	—	—	—	0.317***	0.324***	0.419***	—	—	0.324***	0.486***
					(3.529)	(3.723)	(5.722)			(4.023)	(4.971)
Credit Cooperatives (CC)	−0.584***	−0.601***	−0.455***	−0.406**	−0.390**	−0.425*	−40.210**	—	—	—	—
	(3.878)	(3.814)	(2.737)	(2.281)	(1.983)	(1.877)	(2.236)				
CC x Crisis Dummy	−0.215***	−0.212**	−0.264**	−0.506**	−0.201**	−0.204*	−2.620**	—	—	—	—
	(2.786)	(2.164)	(2.036)	(2.179)	(2.110)	(1.918)	(2.311)				
Commercial Banks (CB)	—	−0.129	—	−0.287	—	−0.274	—	—	—	—	—
		(0.845)		(1.240)		(1.535)					
CB x Crisis Dummy	—	−0.001	—	0.306	—	0.018	—	—	—	—	—
		(0.015)		(1.246)		(0.265)					
CC x Dummy2004–13								−0.508**	−0.565***	−0.516***	−38.361***
								(2.266)	(2.715)	(2.762)	(2.665)
CC x Dummy2014	—	—	—	—	—	—	—	−0.665***	−0.812***	−1.041***	−192.691***
								(2.785)	(4.492)	(2.983)	(2.962)

(*Continued*)

Table 3. (Continued)

	Panel A: Institutional Presence-Crisis Dummy Interactions							Panel B: Institutional Presence-Year Interactions			
	Least Squares Dummy Variables (LSDV)		Two-Stage Least Squares (TSLS)		GMM Dynamic Panel (GMM-SYS)			Various Fixed Effects / IV Estimations (LSDV, TSLS, GMM-SYS)			
	LSDV	LSDV	TSLS	TSLS	GMM-SYS	GMM-SYS	GMM-SYS	LSDV	TSLS	GMM-SYS	GMM-SYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CC x Dummy2015	—	—	—	—	—	—	—	−0.817***	−0.784***	−0.749***	−58.623***
								(3.618)	(4.650)	(2.577)	(3.306)
CC x Dummy2016	—	—	—	—	—	—	—	−0.802***	−0.676***	−0.695**	−40.461***
								(3.804)	(4.164)	(2.531)	(2.956)
CC x Dummy2017	—	—	—	—	—	—	—	−0.705***	−0.736***	−0.633**	−51.816**
								(3.575)	(4.781)	(2.522)	(2.143)
CC x Dummy2018	—	—	—	—	—	—	—	−0.485***	−0.535***	−0.398*	−47.205**
								(2.644)	(3.759)	(1.670)	(2.280)
CC x Dummy2019	—	—	—	—	—	—	—	−0.513***	−0.529***	−0.476**	−46.166**
								(3.141)	(4.170)	(2.258)	(2.340)
Crisis Dummy	0.010**	0.009	0.011***	−0.028	0.006	0.002	1.028*	0.018*	0.011***	0.013	1.312
	(2.518)	(0.985)	(2.653)	(0.904)	(1.426)	(0.220)	(1.851)	(1.712)	(3.292)	(1.137)	(1.248)
Additional Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Federate FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-Statistic IV 1st Stage	—	—	116.480**	24.053***	—	—	—	—	79.831***	—	—
JP	—	—	[0.328]	[0.475]	[0.827]	[0.958]	[0.325]	—	[0.217]	[0.146]	[0.199]

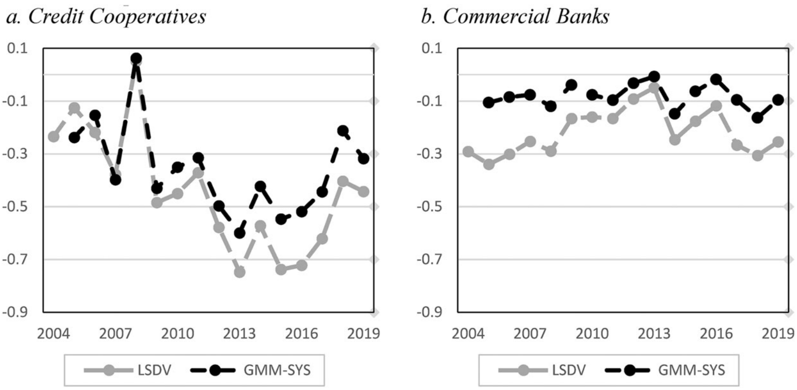
(Continued)

Table 3. (Continued)

	Panel A: Institutional Presence-Crisis Dummy Interactions							Panel B: Institutional Presence-Year Interactions			
	Least Squares Dummy Variables (LSDV)		Two-Stage Least Squares (TSLS)		GMM Dynamic Panel (GMM-SYS)			Various Fixed Effects / IV Estimations (LSDV, TSLS, GMM-SYS)			
	LSDV	**LSDV**	**TSLS**	**TSLS**	**GMM-SYS**	**GMM-SYS**	**GMM-SYS**	**LSDV**	**TSLS**	**GMM-SYS**	**GMM-SYS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
AR1P	—	—	—	—	[0.000]***	[0.000]***	[0.003]***	—	[0.000]****	[0.000]***	[0.000]***
AR2P	—	—	—	—	[0.203]	[0.278]	[0.386]	—	[0.196]	[0.291]	[0.304]
R^2 / Pseudo R^2	0.502	0.502	0.369	0.335	0.919	0.817	0.474	0.785	0.775	0.813	0.699
Observations	432	432	378	378	405	405	405	432	378	405	405

Notes: Credit Cooperatives and Commercial Banks indicate the presence of credit cooperative outposts and commercial bank branches per 1,000 inhabitants. In Columns 7 and 11 the dependent variable is the S80/S20 ratio, otherwise the Gini coefficient is employed. The constant terms, fixed effects and the full set of control variables are included in all estimations but are omitted from the table for brevity. Two lags of endogenous regressors are used as instruments for TSLS and GMM-SYS. Dummy2004-2013 is a dummy variable equal to one for the period before the crisis, i.e., 2004–13, and zero otherwise. Additional Controls indicates whether the regression model includes the additional controls ($UNRATE_{it}$, $GDPCAP_{it}$, $GDPCAP^2{}_{it}$, AGR_{it}, IND_{it}, CST_{it}, $TECH_{it}$, $TRADE_{it}$) as defined previously. F-Statistic IV 1st Stage corresponds to Kleibergen and Paap's (2006) F-test for weak instruments. JP is the p-value for Hansen's (1982) over-identification test. AR1P and AR2P correspond to the p-values for first- and second-order tests for autocorrelation under GMM-SYS. The R-squared statistic, R^2, or its pseudo counterpart, indicate model fit. Absolute t-statistics are reported (in parentheses), which are robust to heteroscedasticity and autocorrelation. Under GMM-SYS, Windmeijer's (2005) corrected standard errors are employed. Significance is indicated by * (10%), ** (5%), *** (1%).
Source: authors' own computations.

Figure 4. Time-varying Impact of Local Financial Institutional Presence on the Gini Coefficient ($\hat{\beta}_t$) for Credit Cooperatives (left) and Commercial Banks (right)



Notes: Plot of the estimated annualized impact of credit cooperative presence (see Figure 4a, left) versus commercial bank presence (see Figure 4b, right) on the Gini coefficient based on LSDV and GMM-SYS estimations with local institutional presence-year interactions for all years.
Source: authors' own computations.

The dynamic patterns revealed in Figure 4 are consistent with the growing financial constraints that have emerged in Brazil across our sample. This includes a series of contractionary monetary policy shocks from around 2013 until 2016, as the Central Bank of Brazil tried to tame high inflation and growing capital outflows, which contributed to a recognized currency crisis in mid-2015 (Laeven and Valencia, 2020; Nguyen et al., 2022). Interest rates remained high until 2016, before falling consistently in 2017, although funding costs for SMEs decreased more slowly (OECD, 2020b). Therefore, the Brazilian evidence is consistent with financial cooperatives' reputation for smoothing out unfavourable shocks to income and the cost of funding, which can arise during crises (Ferri et al., 2014). The results may also reflect financialization processes, which have emerged over recent decades in Brazil. For example, Crocco et al. (2014) argue that commercial banks have gradually shifted their operations away from traditional bank lending, while increasing their holdings of more liquid financial assets and fixed-income securities, which offer more favourable risk–return ratios (see also, Arestis and Phelps, 2019). The results underline the increased potential for Brazilian credit cooperatives to fill funding gaps arising also from economic policy changes (Góes and Karpowicz, 2017), with no new state funding allocated to the Brazilian development bank since 2015 (BNDES, 2018).

Additional Estimations

Several additional estimations are conducted for robustness. First, the S80/S20 inequality measure is used instead of the Gini coefficient, and we obtain very similar results across different model specifications, as shown in Tables 2 and 3. Second, in Columns 1–2 of Table AII.2 (in Appendix II) we employed a bias-corrected dynamic least squares dummy variables estimator (LSDVC) in the spirit of Kiviet (1995) and Bruno (2005). LSDVC is an unbiased dynamic counterpart to LSDV, which provides an alternative estimator of equation 3. Third, in Columns 3–5 of Table B.1, we repeat the analysis by dropping the internal instruments (lagged variables) originally used under TSLS and employ instead the external instruments. In Columns 6–9 we add the external instruments to the internal instruments under GMM-SYS.[29] In all cases, credit cooperatives have a significant and relatively favourable effect on income inequality, which exceeds that of commercial banks, and is more sustained following the crisis's onset.

Fourth, we explore robustness to development differences across the sample, since prominent theories in economics and finance indicate that the inequality–finance nexus is contingent on the level of development (e.g. Greenwood and Jovanovic, 1990). This is interesting to note here also because the importance of smaller enterprises in the local economy is not evenly distributed across Brazil, with a greater share of small businesses operating in less developed regions (see, for example, DIEESE, 2018: 59). Therefore, we add a dummy variable interaction term to capture any differences in local financial institutional presence on inequality for the less developed federates during the crisis. We add an interaction term indicating the marginal effect of local financial institutional presence during the crisis for federates with below-average levels of GDP per capita and bank branch density. We repeat this exercise by introducing an interaction term indicating the marginal effect of local financial institutional presence on inequality during the crisis for federates with an above-average share of microentrepreneurs as employers, as well as above-average shares of sole proprietors and business owners in total employment, using data from the Inter-union Department of Statistics and Socio-economic Studies (DIEESE).[30] The results are summarized in Table 4.

The results in Table 4 confirm that credit cooperatives' impact on income inequality is robust to the inclusion of different development indicators. The interaction-term estimates highlighted in bold clearly reveal that credit

29. Under TSLS and GMM-SYS, federate fixed effects are initially excluded to avoid collinearity with the (time-invariant) external instruments, but we include instead macro region fixed effects. This approach is consistent with other studies in the literature, albeit in a different country context (see, for example, D'Onofrio et al., 2019, for Italy). However, in Columns 5 and 9 of Appendix Table AII.2, we also include just the time-variant external instrument, while including both year and federate fixed effects.
30. Specifically, we rely on 2018 data to establish whether a federate is above average (see Table 18 in DIEESE, 2018: 59, for microenterprises; see Map 2 in DIEESE, 2018: 55, for sole proprietors; and see Map 3 in DIEESE, 2018: 56, for business owners). The data clearly indicate a negative correlation between the level of development and the importance of smaller enterprises in the local economy.

Table 4. *Credit Cooperatives, Income Inequality, and the Brazilian Crisis: Robustness to Development Differences*

	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Gini	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*
Credit Cooperatives	−0.851***	−0.857***	−0.790***	−0.890***	−0.892***	−0.712***	−0.692***	−0.682***	−0.750***	−0.706***
	(5.636)	(5.589)	(5.396)	(5.613)	(5.663)	(4.922)	(4.799)	(4.745)	(5.103)	(4.795)
Commercial Banks	−0.170	−0.165	−0.144	−0.196	−0.201	−0.493***	−0.158	−0.226	−0.459***	−0.622***
	(1.342)	(1.296)	(1.154)	(1.525)	(1.581)	(3.574)	(1.350)	(1.786)	(3.335)	(4.502)
Credit Cooperatives (CC) x Crisis Dummy (CD)	0.042	−0.058	−0.070	−0.092	−0.002					
	(0.495)	(0.761)	(1.022)	(1.190)	(0.025)					
CC x CD x Below Average GDP-per-Capita Dummy	**−0.554*** **	—	—	—	—	—	—	—	—	—
	(3.051)									
CC x CD x Below Average Bank Presence Dummy	—	**−0.463** **	—	—	—	—	—	—	—	—
		(2.275)								
CC x CD x Above Average Employers Share Dummy	—	—	**−0.439*** **	—	—	—	—	—	—	—
			(2.733)							
CC x CD x Above Average Microenterprises Share Dummy	—	—	—	**−0.456** **	—	—	—	—	—	—
				(2.239)						
CC x CD x Above Average Sole Proprietors Share Dummy	—	—	—	—	**−0.586*** **	—	—	—	—	—
					(2.913)					
Commercial Banks (CB) x Crisis Dummy (CD)	—	—	—	—	—	0.206**	0.060	0.004	−0.073	0.013
						(2.336)	(0.684)	(0.059)	(0.966)	(0.202)
CB x CD x Below Average GDP-per-Capita Dummy	—	—	—	—	—	**−0.284** **	—	—	—	—
						(2.141)				
CB x CD x Below Average Bank Presence Dummy	—	—	—	—	—	—	0.018	—	—	—
							(0.073)			
CB x CD x Above Average Employers Share Dummy	—	—	—	—	—	—	—	**−0.264** **	—	—
								(1.996)		

(*Continued*)

Table 4. *(Continued)*

	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
CB x CD x Above Average Microenterprises Share Dummy	—	—	—	—	—	—	—	—	0.020	—
									(0.127)	
CB x CD x Above Average Sole Proprietors Share Dummy	—	—	—	—	—	—	—	—	—	−0.241
										(1.794)
Crisis Dummy	−0.006	0.001	0.004	0.004	−0.002	−0.040**	−0.011	0.004	0.017	0.001
	(1.024)	(0.202)	(0.820)	(0.714)	(0.415)	(2.449)	(0.661)	(0.303)	(1.222)	(0.116)
Additional Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Federate FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.786	0.784	0.783	0.785	0.787	0.789	0.780	0.781	0.792	0.803
Observations	432	432	432	432	432	432	432	432	432	432

Notes: Credit Cooperatives and Commercial Banks indicate the presence of credit cooperative outposts and commercial bank branches per 1,000 inhabitants Columns 1–5 contain development-interactions for credit cooperatives, whereas Columns 6–10 contain development-interactions for commercial banks. Additional Controls indicates whether the regression model includes the additional controls ($UNRATE_{it}$, $GDPCAP_{it}$, $GDPCAP^2{}_{it}$, AGR_{it}, IND_{it}, CST_{it}, $TECH_{it}$, $TRADE_{it}$) as defined previously. Constant terms, fixed effects, and other interaction terms (i.e., local financial institutions x development dummy; local financial institutions x crisis dummy; development dummy x crisis dummy) are included in all estimations but not reported in the table to conserve space. The R-squared statistic, R^2, indicates model fit. Absolute t-statistics are reported (in parentheses), which are robust to heteroscedasticity and autocorrelation. Significance is indicated by ** (5%), *** (1%).
Source: authors' own computations.

cooperatives have had a much stronger and more significant effect on mitigating the rise in inequality in less developed regions during the crisis (Columns 1–5). By contrast the corresponding interaction-term estimates for commercial banks are smaller and less significant (Columns 6–10). Drawing on literatures showing that SMEs get the greatest benefit from relationship lending, this finding is consistent with the theoretical channel of financial inclusion and credit cooperatives' stronger relationship with smaller enterprises (Berger and Udell, 2006; Ferri et al., 2019). In the Brazilian context, the outcome is also consistent with Brazil's economic geography, where sole proprietors and microenterprises are relatively prominent in its less developed regions (e.g. DIEESE, 2018).

SUMMARY AND CONCLUSIONS

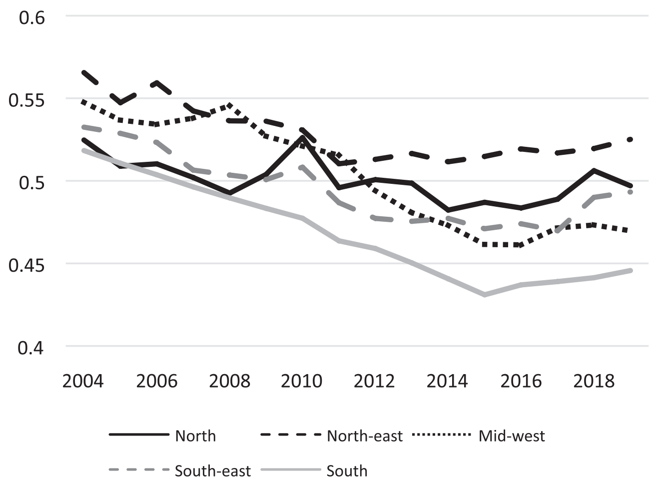
This contribution investigates the role of cooperative financial institutions in the inequality–finance nexus, focusing on Brazil's credit cooperative movement. We explore the relationship around a relatively recent but severe crisis in Brazilian history, thereby providing some novel evidence and insights into the inequality implications of credit cooperatives from a regional resilience perspective.

Our empirical analysis reveals that Brazil's credit cooperatives played a significant part in alleviating income inequality from 2004 to 2019, thereby adding some novel emerging economy evidence to the extant literature. Economically, we find that an increase in their local presence by one standard deviation reduces the Gini coefficient by approximately 0.014, whereas the outcome for commercial banks is smaller and less significant. Our results corroborate the more optimistic perspective in this debate that credit cooperatives have had favourable effects on inequality by bringing finance to parts of the country that are not well served by traditional banks. This is despite the existence of prominent theories in economics and finance, which assert that financial institutions reduce income inequality first and foremost in more developed areas. Therefore, Brazil's credit cooperatives have helped mitigate the upturn in inequality experienced around the onset of crisis, especially in less developed parts of Brazil. Drawing on literatures showing that SMEs receive most benefit from relationship lending, our findings are consistent with the theoretical channel of financial inclusion and credit cooperatives' stronger relationship with smaller enterprises relative to commercial banks. The outcome is also consistent with Brazil's economic geography, where sole proprietors and microenterprises are relatively prominent in its less developed regions.

In conclusion, local financial institutions can contribute to more inclusive and sustained growth, not only in advanced economies, but also in emerging countries, as evidenced for Brazil's credit cooperatives. Our findings show that over the last decade or so, the cooperative model of banking has clearly outperformed commercial banks from a regional resilience perspective. Our analysis points to the potential for financial cooperatives to boost resilience further in the local economies of other developing and emerging countries, which are heavily reliant on exports of commodities and other natural resources, more exposed to currency crises, and where the state is more constrained in its capacity to support development. Our results underline the need for policy makers to protect financial cooperatives from the pressures of adopting a more commercial business model. Going forward, further work should be undertaken to check whether our findings extend also to other emerging economies and countries at the lowest levels of development.

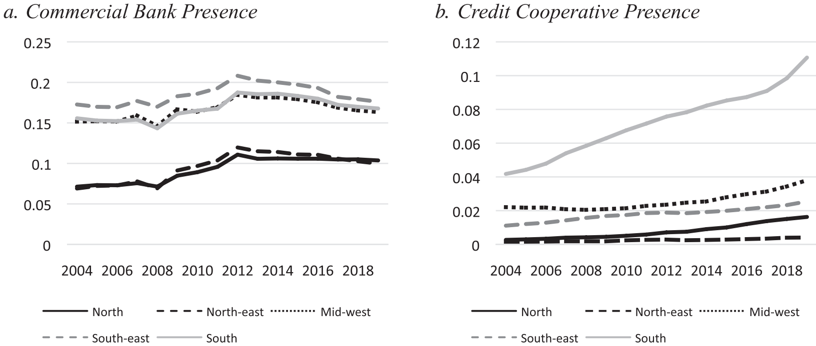
APPENDIX I

Figure AI.1. Evolution of the Gini Coefficient in Brazil's Macro Regions, 2004–19



Source: see Figure 1 in the main text.

Figure AI.2. Evolution of Commercial Bank (left) and Credit Cooperative (right) Presence in Brazil's Macro Regions, 2004–19



Notes: Commercial and universal plus bank branches (per 1,000 inhabitants) (see AI.2a, left). Credit cooperative service outposts (per 1,000 inhabitants) (see AI.2b, right).
Source: see Figure 2 in the main text.

APPENDIX II

Table AII.1. Summary Statistics

	Gini Coefficient		S80/S20 Ratio		Commercial Banks		Credit Cooperatives		GDP-per-Capita (R$)		Agriculture Share (%)		Extractive Share (%)		Construction Share (%)		Unemployment Rate (%)		Trade Openness		High-Tech Exports Share	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
North	0.501	0.026	17.322	3.102	0.102	0.019	0.008	0.005	14948	5276	8.332	1.273	2.453	1.232	6.442	1.806	9.938	2.315	13.953	2.856	2.736	3.190
AC	0.520	0.030	22.698	4.224	0.094	0.017	0.001	0.002	12657	4344	9.802	1.286	0.130	0.139	6.244	1.982	9.356	2.833	0.579	0.245	0.935	1.455
AP	0.485	0.027	16.320	3.414	0.104	0.021	0.000	0.001	14366	4641	2.349	0.436	0.788	0.705	5.489	1.232	13.975	3.266	8.120	1.913	0.000	0.010
AM	0.501	0.027	18.272	3.212	0.099	0.013	0.001	0.000	18331	5060	5.718	1.808	2.991	1.508	5.163	1.062	11.397	2.278	38.444	6.742	17.888	19.560
PA	0.503	0.016	15.233	2.047	0.078	0.014	0.001	0.001	12434	4917	11.470	1.238	12.205	5.664	6.047	1.378	9.281	1.549	31.931	3.047	0.000	0.030
RO	0.469	0.041	14.113	2.158	0.097	0.018	0.044	0.028	16585	6292	12.634	1.349	0.334	0.175	8.748	3.826	7.028	1.607	9.649	4.563	0.005	0.282
RR	0.521	0.018	18.543	5.148	0.104	0.022	0.000	0.000	16068	5510	3.909	1.212	0.299	0.299	6.647	1.654	10.309	2.784	0.710	0.213	0.322	0.950
TO	0.506	0.025	16.076	1.512	0.136	0.031	0.007	0.002	14194	6169	12.445	1.582	0.423	0.133	6.759	1.509	8.219	1.886	8.243	3.271	0.000	0.043
North-east	0.529	0.025	19.493	2.974	0.089	0.016	0.003	0.001	11265	4363	7.483	1.505	2.218	1.154	6.455	1.549	10.508	2.343	9.904	2.158	1.056	2.589
AL	0.495	0.048	20.239	3.749	0.083	0.017	0.003	0.001	10452	4107	13.909	2.727	1.764	1.243	5.427	1.344	11.641	2.692	8.502	1.312	0.173	11.777
BA	0.528	0.014	19.624	2.465	0.094	0.015	0.006	0.002	12365	4652	8.691	1.636	2.353	1.065	6.720	1.249	12.338	2.710	21.019	2.985	0.714	0.277
CE	0.528	0.017	18.774	1.941	0.075	0.011	0.002	0.000	10956	4517	5.917	1.153	0.562	0.249	6.076	1.235	8.781	1.918	9.361	1.572	2.202	2.015
MA	0.514	0.032	21.315	3.827	0.068	0.013	0.001	0.001	8718	3565	11.022	1.989	1.352	0.736	7.316	2.011	9.366	2.708	26.190	4.952	0.000	0.015
PB	0.542	0.025	18.589	2.512	0.093	0.022	0.004	0.002	10517	4157	4.923	1.103	0.391	0.120	5.390	1.176	9.744	1.167	4.104	0.834	0.098	0.219
PE	0.530	0.024	19.981	2.949	0.092	0.013	0.004	0.001	12827	5219	4.806	1.152	0.075	0.053	6.950	1.930	12.175	2.843	10.906	3.271	5.166	5.356
PI	0.561	0.026	19.158	3.594	0.082	0.021	0.001	0.000	8940	4281	8.285	1.801	0.316	0.184	7.247	2.084	7.588	2.874	3.054	1.552	0.000	0.272
RN	0.525	0.028	18.711	2.291	0.090	0.021	0.002	0.001	13017	4608	4.004	0.776	7.463	3.819	6.519	1.467	11.481	1.700	3.649	2.529	0.111	1.442
SE	0.538	0.013	19.046	3.440	0.121	0.010	0.000	0.000	13597	4157	5.789	1.207	5.683	2.917	6.447	1.447	11.456	2.474	2.355	0.416	1.044	1.929
Mid-west	0.504	0.035	16.746	2.564	0.161	0.015	0.026	0.006	31834	11850	12.893	1.802	0.483	0.202	5.082	1.004	8.280	1.768	20.287	3.496	0.209	0.455
GO	0.476	0.039	12.961	1.828	0.146	0.016	0.014	0.006	19959	7144	11.049	1.434	0.959	0.354	6.545	1.209	7.806	1.960	15.576	2.980	0.187	0.464

(*Continued*)

Table AII.1. (Continued)

	Gini Coefficient		S80/S20 Ratio		Commercial Banks		Credit Cooperatives		GDP-per-Capita (R$)		Agriculture Share (%)		Extractive Share (%)		Construction Share (%)		Unemployment Rate (%)		Trade Openness		High-Tech Exports Share	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
MT	0.471	0.036	13.244	2.247	0.130	0.020	0.053	0.008	24808	10711	21.943	3.835	0.338	0.072	5.190	1.075	7.172	1.648	37.114	6.170	0.000	0.019
MS	0.490	0.039	13.705	2.118	0.139	0.012	0.024	0.006	23766	10220	18.207	1.869	0.609	0.347	5.117	0.774	6.909	1.484	26.392	4.508	0.204	0.145
DF	0.577	0.024	27.074	4.061	0.227	0.010	0.011	0.003	58803	19324	0.375	0.068	0.027	0.035	3.476	0.959	11.231	1.979	2.068	0.327	0.444	1.192
South-east	0.495	0.024	15.261	1.525	0.166	0.013	0.018	0.004	27726	9011	3.113	0.392	8.308	3.431	5.072	0.991	9.486	2.296	24.095	3.493	4.735	2.501
ES	0.492	0.027	15.566	1.741	0.141	0.010	0.027	0.007	25360	7693	3.771	0.444	15.453	6.792	5.163	1.003	8.972	2.186	39.873	5.852	0.135	0.081
MG	0.489	0.025	14.186	1.298	0.146	0.015	0.032	0.006	19767	7118	6.053	0.660	4.338	1.959	5.467	1.386	8.584	1.810	20.300	1.601	2.506	1.060
RJ	0.500	0.029	16.855	1.487	0.159	0.013	0.004	0.001	31463	9950	0.494	0.058	13.103	4.733	5.015	0.856	10.447	2.905	17.207	3.641	3.164	4.137
SP	0.498	0.015	14.436	1.573	0.219	0.012	0.009	0.002	34312	11281	2.134	0.406	0.337	0.240	4.643	0.719	9.941	2.285	19.001	2.879	13.134	4.725
South	0.468	0.030	12.356	1.659	0.200	0.015	0.072	0.020	26504	10075	8.451	1.006	0.225	0.053	4.976	0.892	5.991	1.370	24.644	2.957	10.831	3.043
PR	0.483	0.035	13.400	2.186	0.190	0.019	0.062	0.023	25557	9803	9.497	0.731	0.172	0.039	4.815	1.042	6.519	1.614	25.063	2.882	6.459	2.933
RS	0.485	0.020	13.648	1.712	0.209	0.014	0.065	0.011	25895	10091	9.011	1.145	0.161	0.046	4.471	0.779	6.584	1.253	24.320	3.353	6.078	1.814
SC	0.436	0.035	10.021	1.078	0.201	0.013	0.090	0.027	28060	10332	6.844	1.143	0.342	0.073	5.643	0.856	4.869	1.242	24.548	2.636	19.957	4.381
Brazil	0.506	0.027	17.103	2.586	0.127	0.016	0.017	0.005	19399	7032	7.965	1.268	2.703	1.248	5.879	1.379	9.377	2.135	16.232	2.824	2.997	2.466

Notes: The sample mean (μ) and standard deviation (σ) are computed for individual federates over the sample period, 2004–2019. The values for North, North-east, Mid-west, South-east and South macro regions and for Brazil are averages across all the relevant federates. Federate abbreviations are used as follows: (1) North: Acre (AC), Amapá (AP), Amazonas (AM), Pará (PA), Rondônia (RO), Roraima (RR) and Tocantins (TO); (2) North-east: Alagoas (AL), Bahia (BA), Ceará (CE), Maranhão (MA), Paraíba (PB), Pernambuco (PE), Piauí (PI), Rio Grande do Norte (RN) and Sergipe (SE); (3) Mid-west: Goiás (GO), Mato Grosso (MT), Mato Grosso do Sul (MS) and Distrito Federal (DF); (4) South-east: Espírito Santo (ES), Minas Gerais (MG), Rio de Janeiro (RJ) and São Paulo (SP); and (5) South: Paraná (PR), Rio Grande do Sul (RS) and Santa Catarina (SC).

Source: authors' own computations.

Table AII.2. Additional Estimations and Robustness Checks

	Bias-Corrected LSDV (LSDVC)		Two-Stage Least Squares (TSLS)			GMM Dynamic Panel (GMM-SYS)			
	LSDVC	LSDVC	TSLS	TSLS	TSLS	GMM-SYS	GMM-SYS	GMM-SYS	GMM-SYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Gini	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*	*Gini*
Lag Gini	0.719***	0.579***	—	—	—	0.462***	0.455***	0.440***	0.324***
	(17.081)	(10.104)				(4.640)	(4.257)	(4.609)	(3.748)
Credit Cooperatives (CC)	−0.328**	−0.241*	−1.464***	−1.449***	−1.024**	−0.429***	−0.415***	−0.409**	−0.462**
	(2.310)	(1.655)	(5.054)	(3.278)	(2.046)	(3.289)	(3.072)	(2.183)	(1.965)
Commercial Banks (CB)	—	−0.160	—	0.058	−0.169	—	0.123	−0.006	−0.266
		(1.246)		(0.429)	(1.326)		(0.865)	(0.035)	(1.445)
CC x Crisis Dummy	—	—	—	—	—	—	—	−0.224**	−0.209**
								(2.384)	(2.198)
CB x Crisis Dummy	—	—	—	—	—	—	—	0.027	0.010
								(0.481)	(0.149)
Crisis Dummy	−0.004	0.002	−0.021***	−0.013**	0.004	−0.008	−0.007	−0.001	0.003
	(1.253)	(0.633)	(5.748)	(2.370)	(1.212)	(1.593)	(1.302)	(0.182)	(0.354)
Instruments (First Stage of TSLS)									
Distance to Nova Petropolis	—	—	−0.006***	−0.006***	—	—	—	—	—
			(3.690)	(2.885)					
First German Communities Dummy	—	—	0.006**	0.006**	—	—	—	—	—
			(2.177)	(2.170)					
Years Since First German Colony Established	—	—	0.000**	0.000**	0.000***	—	—	—	—
			(2.224)	(2.183)	(8.856)				

(*Continued*)

Table AII.2. (Continued)

	Bias-Corrected LSDV (LSDVC)		Two-Stage Least Squares (TSLS)			GMM Dynamic Panel (GMM-SYS)			
	LSDVC	LSDVC	TSLS	TSLS	TSLS	GMM-SYS	GMM-SYS	GMM-SYS	GMM-SYS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Additional Controls	NO	YES	NO	YES	YES	NO	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro Region FE	—	—	YES	YES	NO	YES	YES	YES	NO
Federate FE	—	—	NO	NO	YES	NO	NO	NO	YES
F-Statistic IV 1st stage	—	—	13.967***	13.339***	10.948***	—	—	—	—
JP	—	—	[0.104]	[0.101]	—	[0.920]	[0.911]	[0.826]	[0.820]
AR1P	—	—	—	—	—	[0.000]***	[0.000]***	[0.000]***	[0.000]***
AR2P	—	—	—	—	—	[0.146]	[0.177]	[0.160]	[0.280]
Observations	405	405	432	432	432	405	405	405	405

Notes: The constant terms are included in all estimations but are omitted from the table for brevity. Similarly, we do not present the estimated fixed effects, including the year fixed effects for 2017, 2018 and 2019, to conserve space in the table. Columns 1 and 2 contain the estimates from bias-corrected least squares dummy variables estimation (LSDVC). Columns 3–5 contain the TSLS estimates using the external instruments — distance to Nova Petropolis, a dummy variable indicating whether a federate contained the first German communities, and the number of years since establishment of a federate's first German colony. The output from the first stage of TSLS estimation is reported in the table under Instruments. Columns 6–9 contain the estimates using Blundell and Bond's (1998) GMM systems estimator (GMM-SYS), when the two lags of endogenous regressors are used as internal instruments as well as the external instruments used under TSLS. Due to the time-invariance of some of the external instruments, both time fixed effects and macro region fixed effects are included. Columns 5 and 9 are exceptions, whereby we include under TSLS and GMM-SYS only the time-variant instrument(s) and federate fixed effects. For GMM-SYS in Column 9, this involves the number of years since establishment of a federate's first German colony as well as the internal instruments. Crisis Dummy is a dummy variable equal to one during the crisis years of 2014–16, and zero otherwise. Additional Controls indicates whether the regression model includes additional controls ($UNRATE_{it}$, $GDPCAP_{it}$, $GDPCAP^2{}_{it}$, AGR_{it}, IND_{it}, CST_{it}, $TECH_{it}$, $TRADE_{it}$) as defined previously. F-Statistic IV 1st Stage corresponds to Kleibergen and Paap's (2006) F-test for weak instruments. JP is the p-value for Hansen's (1982) over-identification test. AR1P and AR2P correspond to the p-values for first- and second-order tests for autocorrelation under GMM-SYS. Absolute t-statistics are reported (in parentheses), which are robust to heteroscedasticity and autocorrelation. Under GMM-SYS, Windmeijer's (2005) corrected standard errors are employed. Significance is indicated by * (10%), ** (5%), *** (1%).

Source: authors' own computations.

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