Cultivating Progress: The Impacts of Credit for Agricultural Investment in Brazil

immediate

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Abstract

This paper studies the impact of supply shocks in rural credit for investments on economic and land use outcomes in Brazil, focusing on agricultural productivity and deforestation. We use administrative data from the Brazilian National Development Bank (BNDES), the main provider of investment credit for agriculture in the country. The empirical strategy leverages as-good-as-random variation in aggregate lending supply shocks by a pool of financial institutions, employing novel developments in the Shift-Share Instrumental Variable (SSIV) literature and addressing the potential endogeneity that may arise from financial providers targeting farmers or regions with greater agricultural potential. The findings indicate that increased availability of rural credit for machinery acquisition is associated with growth in crop production and productivity, with suggestive evidence of a conversion of pastureland into cropland and zero effects on forest area. Therefore, these results suggest that credit for investment can foster productivity gains and enhance land use, without exerting pressure for deforestation. We find that the impact of rural credit for investment is more pronounced in more labor-intensive areas and when credit is directed towards the purchase of labor-saving equipment. This indicates that increases in labor productivity are the main driver of agricultural productivity gains.

Keywords: Rural Credit, Shift-Share Approach, Agriculture, Land Use.
JEL classification: G28, O13, Q14, Q15.

1 Introduction

Increasing agricultural productivity is crucial for ensuring food security, promoting sustainability, and preserving the environment. However, the costs associated with the acquisition of improved machinery and equipment and the implementation of technological innovations in agriculture can pose challenges. Access to credit for investment can play a critical role in enabling financially constrained farmers to modernize their operations and achieve productivity gains. This paper evaluates the impact of supply shocks on rural credit for machinery investment in Brazil, a country that holds a central role in global food production, environmental conservation, and climate change solutions. The results suggest that an increase in credit availability leads to higher crop production, improved productivity, and enhanced land use.

We find evidence that access to credit for investment encourages the replacement of low-productivity pasture areas with cropland, without exerting pressure on deforestation. In fact, the relationship between agricultural productivity gains and land use is theoretically ambiguous, as different theories provide contrasting predictions. The Jevons Paradox suggests that improvements in resource efficiency and innovations may prompt producers to expand in the extensive margin and advance on more land. On the other hand, the Borlaug hypothesis asserts that productivity gains induce farmers to adopt different agricultural practices and contribute to conservation. The evidence presented in this paper aligns with the Borlaug hypothesis by suggesting that credit for machinery investment increases agricultural productivity without pressure on forest areas.

These results are mostly explained by labor-saving equipment used in agriculture. Our heterogeneity analysis distinguishes two key dimensions: 1) the characteristics of the municipalities, distinguishing between those with higher labor intensity and those with lower labor intensity across Brazil, and 2) the type of equipment financed, with a focus on equipment identified as labor-saving, such as tractors and harvesters. Notably, increased productivity patterns, particularly in crop production, are predominantly found in the more labor-intensive municipalities and in loans directed towards equipment classified as labor-saving.

We build a panel of 4,790 municipalities for the period 2005-2019 using administrative data from the Brazilian National Development Bank (*Banco Nacional de Desenvolvimento Econômico e Social* - BNDES), which contains detailed information on operations of investment credit for agricultural machinery and equipment. We use data on municipal crop and livestock production and rural workers from the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* - IBGE). Finally, land use and forest data come from the Brazilian Annual Land Use and Land Cover Mapping Project (*Projeto de Mapeamento Anual do Uso e Cobertura da Terra no Brasil* - MapBiomas), which employs advanced remote sensing techniques and vegetation mapping to generate annual maps covering the entire country with a spatial resolution of 30 meters.

Identification of causal effects comes from a modified Shift-Share Instrumental Variable (SSIV) strategy adapted from Greenstone et al. (2020). It leverages exogenous variation coming from national-level year-to-year changes in the volume of credit transferred to financial agents by BNDES combined with lagged market-shares of financial agents in each municipality. We use novel developments in the literature to address concerns with SSIV strategies and provide corrected standard errors based on the shock exogeneity assumption (Borusyak et al., 2022). The instrument is shown to be valid under this hypothesis.

Brazil is the second-largest food exporter, according to FAO (2021), and rural credit accounts for around 30% of the total production value.[1] Machinery and equipment are key investments in Brazilian agriculture. In the 2021/22 agricultural year, rural credit operations to finance the purchase of machinery, equipment, and vehicles corresponded to more than half of the total credit for rural investment.[2] BNDES alone provided R$ 18 billion in credit for rural investment in Brazil in the 2020/21 agricultural year, playing a leading role in this segment. Of this amount, 71% was allocated to machinery, equipment, and vehicles. Between 1995 and 2020, BNDES disbursements to the rural sector almost quadrupled in real terms. This growth was associated with government initiatives to modernize and strengthen Brazil's agriculture. Understanding the impact of BNDES' credit for the acquisition of machinery and equipment in Brazil can thus provide useful evidence for the debate on rural credit, agricultural productivity, and land use.

There is an extensive debate in the economic literature about the impacts of mechanization on rural activity. The seminal work of Hayami and Ruttan (1970) on induced innovation explores how the pattern of technological development in crops depends on the local context of each country. From this perspective, the adoption of mechanical inputs, classified as labor-saving, is more intense in countries or regions with a greater shortage of labor.[3] Therefore, the mechanization process would be associated with a reduction in the cost of labor used in crops and, in general, would not significantly impact land productivity (Binswanger, 1986).

More recent empirical research reveals that the effects of crop mechanization can be more complex and diverse, including positive impacts on land productivity (Daum & Birner, 2020). In Côte d'Ivoire (Mano et al., 2020) and Zambia (Belton et al., 2021), for example,

[1] Data from IBGE, 2020

[2] Banco Central do Brasil. Matriz de Dados do Crédito Rural - MDCR - v2. bit.ly/3em1xNX

[3] Japan and the United States are paradigmatic examples. In Japan, where land was a relatively scarcer production factor than labor, technological development in crops throughout the 19^{th} century prioritized chemical and biological inputs (such as fertilizers and pesticides) that expanded land productivity. In the United States, where labor was the proportionally scarcer production factor, mechanical innovations (such as tractors and harvesters) predominated, which allowed the cultivation of larger areas with the same labor.

more intensive use of tractors is associated with greater use of complementary inputs, such as fertilizers and other non-mechanical components, as well as increased land productivity. In Myanmar, the rapid mechanization process was driven by several factors besides labor-saving, such as the management of climate risks and the reduction of production losses (Belton et al., 2021). Other studies point out that the results of mechanization also depend on the local institutional context and the design of public policies (Daum & Birner, 2017).

In Brazil, recent evidence of the introduction of genetically modified soybean - a proxy for a labor-saving technology - shows that it led to an increase in agricultural labor productivity, with reduction in the employment share of the agriculture. This release of agricultural labor was conducive to an increase to manufacturing employment, albeit with a decrease in wages (Bustos et al., 2016). Moreover, Bustos et al. (2019) show that this increase in manufacturing employment was led by unskilled labor, leading to an industrialization path without innovation.[4] It is important to highlight, however, that this process has generated negative externalities associated to the use of herbicides and its effects on infant mortality, as shown by Dias et al. (2023).

The remainder of the paper is organized as follows. Section 2 presents background information on land use and agriculture in Brazil, along with an overview of the institutional context of BNDES and its role in rural credit for investments. Section 3 describes our data sources and the construction of the dataset used for estimation. We lay out the empirical strategy in Section 4. We report the main results and the hererogeneity analysis in Section 5. Finally, we provide concluding remarks in Section 6.

2 Background

2.1 Land use and Agriculture in Brazil

Brazil's abundant natural resources, innovative agricultural policies, and private investments have made it a leading global food producer. According to the Food and Agriculture Organization (FAO), Brazil is the second-largest net food exporter in the world. The agricultural sector has always been an important component of Brazil's economy. It is a major exporter and accounts for, in 2020, 6.6% of the national GDP, approximately R$ 434 billion (IBGE, 2022). The 2017 Agricultural Census from the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* – IBGE) shows that 15.1 million people work in rural establishments.

The distribution of agricultural land in Brazil is significantly unequal, with about

[4] However, due to differences in productivity between sectors, it is plausible that the overall effect is to increase aggregate productivity (Gollin et al., 2014).

4% of farms occupying 63% of the farmland.[5] Conversely, 65% of rural establishments occupy only 9% of the land and have areas equivalent to less than one fiscal module.[6] Rural credit is also highly concentrated: as of 2022, 1% of the rural credit contracts were responsible for 33.7% of the total rural credit in that year.[7]

The global dominant trend in agriculture is given by production expanding faster than population growth, leading to productivity gains and a reduction in agricultural land. This is also the case of Brazil. Figure 1 shows the increase in agricultural productivity and area expansion in Brazil from 1961 to 2016. During this period, there was an increase in farmland along with productivity gains. However, area expansion has decelerated in recent years, while land productivity – measured by the gross production value per hectare – increased.

Brazil has an abundance of land and natural resources, including vast deforested areas available for agriculture, a remainder of its long history of land occupation focused on territorial expansion. Over half of Brazil's land (62%) remains covered in native forest or other vegetation, with pasture and grassland accounting for 27% of the area. Activities of higher economic value, such as cultivated land and planted forests, occupy less than 10% of the country's land.[8] Pasture lands are primarily degraded areas that offer plenty of space to increase production through pasture intensification or conversion to crop use, eliminating the need to clear new land. Between 2004 and 2012, Brazil reduced deforestation rates in the Amazon by 80%, while increasing the GDP of the agricultural sector of the region (Gandour, 2019).

Brazil's agriculture has been modernizing and developing tropical agriculture in the Cerrado (Savanna) region since the 1970s. This process of increasing productivity and replacing pastureland with cropland was part of the global "Green Revolution" that transformed agriculture (Stevenson et al., 2013). Figure 2 shows the changes in cattle and soybean production areas (horizontal axis) for each Brazilian region, with substantial productivity gains since 1970 (vertical axis). The productivity gains are measured by the number of heads

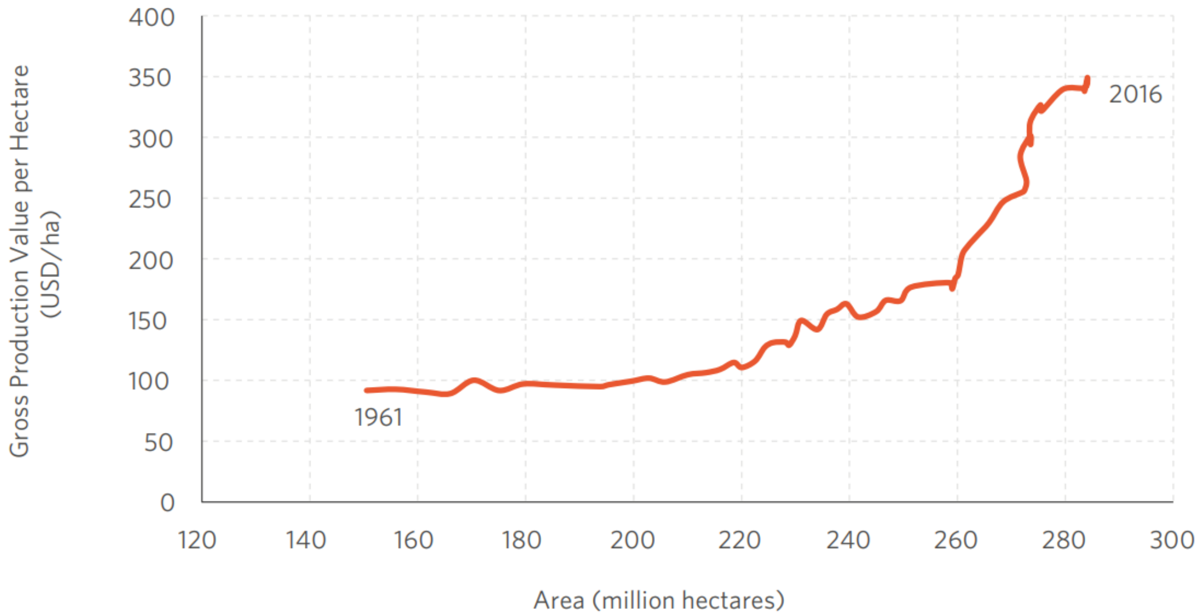
[5]As landowners act strategically to reduce access to land to create an olipsonic labor market, some individuals move to the agricultural frontier in order to clear land. Sant'Anna (2017) shows how land inequality in the municipalities of origin of migrants is conducive to more deforestation in the Brazilian Amazon.

[6]The National Institute of Colonization and Land Reform (*Instituto Nacional de Colonização e Reforma Agrária* - INCRA) holds the National Rural Registration System (Sistema Nacional de Cadastro Rural., which defines a fiscal module as the minimum area of agricultural activity in each municipality that can provide subsistence and contribute to the social and economic development of families who invest all their labor in it.

[7]Data from the *Matriz de Dados do Crédito Rural*, from the Brazilian Central Bank - https://olinda.bcb.gov.br/olinda/servico/SICOR/versao/v2/odata/Faixa?$top=10000&$format=text/csv&$select=AnoEmissao,Quantidade,Valor,ValorMedio.

[8]Climate Policy Initiative with data from MapBiomas (v.5.0)

Figure 1: Productivity and Area Expansion in Brazil, 1961-2016



Notes: 2004-2006 constant values (inflation adjusted by FAOSTAT).
Source: Climate Policy Initiative with data from Food and Agriculture Organization of the United Nations (FAOSTAT).

of cattle per hectare[9] (Figure 2a) and tons of harvested soybeans per hectare (Figure 2b).

Figure 2a shows that pastureland in Brazil's Southeast region have decreased since 1975, and in all regions except the North since 1995. Figure 2b shows that soybean growth has remained steady, but the areas associated with soybeans are smaller compared to those of pastures. In 2017, cattle productivity varied greatly among regions, indicating inefficiencies in land use. Addressing these gaps could make livestock production more similar across regions (Antonaccio et al., 2018).

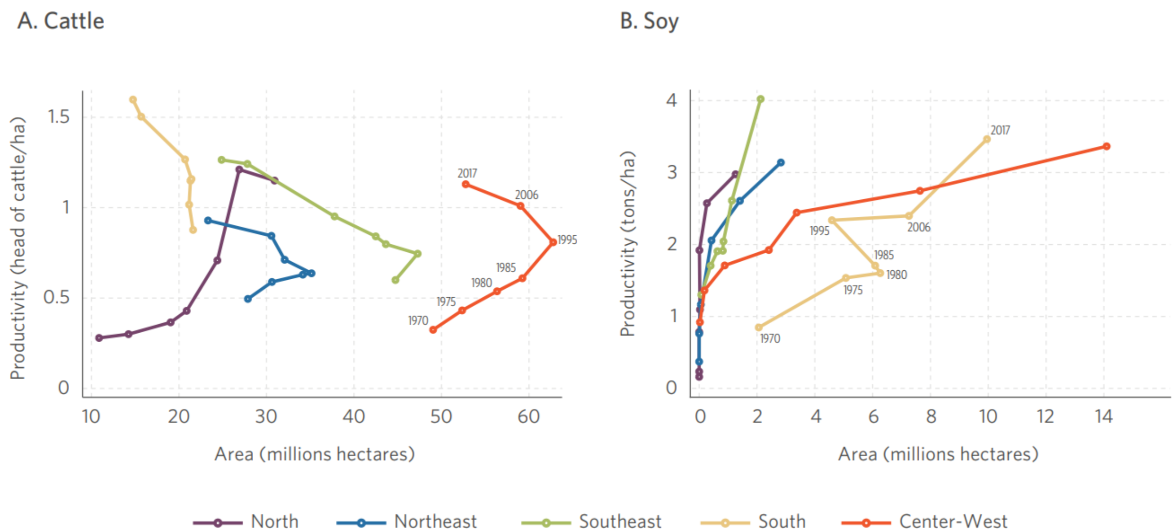
Brazil can significantly increase its agricultural productivity without resorting to deforestation. By converting pasture to cropland and increasing yield gains, particularly in pastureland, the country can achieve enormous agricultural gains (Antonaccio et al., 2018). These strategies alone can more than double crop production and increase cattle herds by 70%.

Nevertheless, significant investments will be required to drive the changes needed to maximize production in Brazil.[10] Farmers' inputs (labor, materials, and equipment)

[9]The number of heads per hectare is the only available measure from the Agricultural Census (IBGE) and serves as a proxy for livestock farming productivity, though it has its limitations.

[10]In addition to investments, there is also an important role for extension services in providing information and knowledge for rural producers (Bragança et al., 2022).

Figure 2: Patterns of Farming Growth (Livestock and Soybean) in Brazil, 1970-2017



Notes: The main financial institutions are defined as those that lend the largest volume of credit in each municipality.
Source: Climate Policy Initiative with data from the Brazilian Institute of Geography and Statistics Agriculture Census (IBGE).

increase the efficiency of their crop and beef production. That means that efforts to eliminate inefficiencies will demand additional input and compel farmers to increase their operational costs and capital stocks to transition their production. The increase in the farm equipment value (capital stock) required to enable farmers to eliminate inefficiencies range from 48% to 52% of the current farm equipment value. At the same time, substantial increases in operational costs would also be required to maximize agricultural output. These increases range from 44% to 51% of the current operational costs (Assunção & Bragança, 2019).

The modernization and intensification of agriculture requires considerable resources. Therefore, rural credit policies can play an important role in disentangling agricultural production and deforestation in Brazil. It is the most important agricultural policy in Brazil, accounting for 28% of the total agribusiness production in Brazil for 2022. Furthermore, there is evidence of its positive effects on farmers' production decisions and land use in Brazil, inducing the conversion of pastureland into cropland and increasing crop productivity without further deforestation (Assunção et al., 2021).

2.2 Rural credit for investment and the role of BNDES

This section provides an overview of the institutional background of the analysis, and presents descriptive statistics on rural credit for equipment provided by BNDES. In our period of study, the development bank played a crucial role in supporting rural activities in

Brazil, accounting for about a third of all rural credit operations for investments as reported by the Central Bank of Brazil (Souza et al., 2022).

Credit provided by BNDES is mainly focused on crop activities, which historically use land more intensively than cattle production. In the 2016/17 agricultural year, the bank accounted for more than 60% of all credit for investments in crop production. Soybeans are the main agricultural product in terms of financing for the purchase of machinery and equipment and its credit share has remarkably increased. In 2008, around 30% of the total volume of rural credit for equipment was borrowed by soybean producers. By 2018, this number had risen to 61%. Finally, rural credit for equipment was provided in 4,790 municipalities of Brazil over the period of study (2005-2019), indicating the comprehensiveness of BNDES credit coverage.

Another important aspect is that credit with BNDES funds can be borrowed either directly or indirectly. Direct operations are carried out directly between BNDES and the borrower and it usually entails higher amounts. On the other hand, indirect operations are those in which BNDES is the agent that transfers the funds to banks and other financial institutions, who then lend resources to borrowers, assuming the risk of non-payment. Indirect operations are by far the most important type of loan granted to the rural sector by BNDES, representing 99% of the credit volume in 2020. Financial agents that operate BNDES credit can be private entities (private commercial banks, credit cooperatives, and banks owned by machine manufacturers) or public entities (public commercial banks and other development banks).

Rural credit in BNDES can be granted by means of different products (such as *BNDES FINAME*, *BNDES Automático* and *BNDES FINEM*) and lines (such as *MODERFROTA*,[11] *MODERAGRO* and *INOVAGRO*).[12] This paper focuses on BNDES' credit indirect operations associated with the *FINAME* product, which aims to finance the production and acquisition of domestic machinery and equipment. In 2020, 57% of the volume of BNDES's loans to the agricultural sector was granted through *BNDES FINAME*.[13] These operations allow for the identification of the type and amount of financed equipment. Most of the credit for machinery and equipment is used to purchase harvesters and tractors, which

[11] A relevant milestone in the process of modernizing and invigorating Brazil's agriculture was the creation of the *MODERFROTA* program in 2000 to finance the acquisition of tractors and agricultural equipment (Sant'Anna & Ferreira, 2006). In that year, the low agriculture mechanization in Brazil was considered a problem that needed to be addressed, so the government sought to stimulate the productivity and competitiveness of the agricultural sector through a series of development measures grouped together in a program entitled *Programa Brasil Empreendedor Rural*. (Central Bank of Brazil. *Ata do Conselho Monetário Nacional de 24 de fevereiro de 2000*. bit.ly/3kgPgOb). For instance, there was a substantial growth in fleet numbers, with a 50% increase in the number of tractors in rural properties between the 2006 and 2017 Agricultural Censuses by the Brazilian Institute for Geography and Statistics (IBGE).

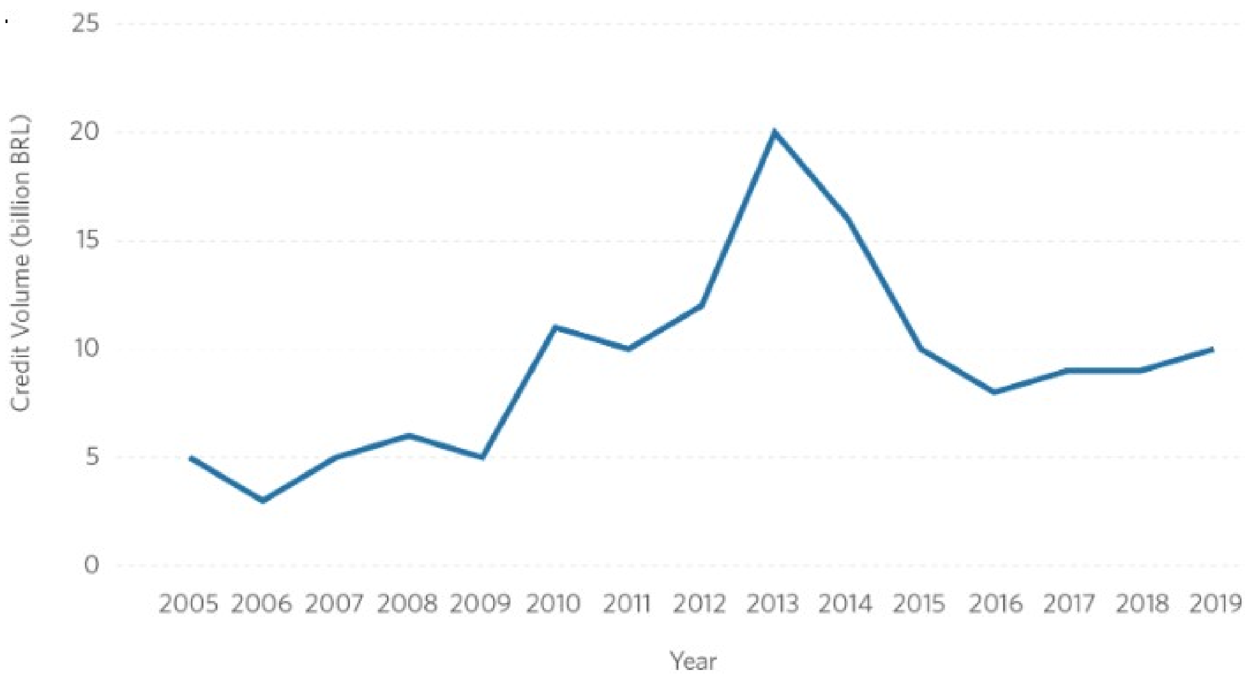
[12] The different products provided by BNDES (FINAME, FINEM and so on encompass those distinct lines. For example, MODERFROTA is a credit line that runs within BNDES FINAME product.

[13] BNDES. *Estatísticas Operacionais do Sistema BNDES*. bit.ly/3kjnkcA

account for 56% of these funds between 2005 and 2019.

Figure 3 shows the evolution of the amount of *BNDES FINAME* credit for the purchase of farming machinery and equipment, henceforth called "rural credit for equipment". Between 2005 and 2019, albeit with strong fluctuations, rural credit for equipment had a real increase of 97%, from R$ 4.9 billion in 2005 to R$ 9.7 billion in 2019.[14] The highest level of credit was observed in 2013, reaching R$ 19.7 billion, due to government initiatives following the 2008 global financial crisis.

Figure 3: Evolution of the Volume of Rural Credit for Equipment, 2005-2019



Notes: Values deflated by the IPCA, based on December 2019.
Source: CPI/PUC-Rio with data from BNDES, 2022.

The relevance of each financial institution acting as intermediary varies across regions. Figure 4 shows the three main financial agents responsible for transferring BNDES' rural credit resources for equipment in each Brazilian municipality in 2019. Main institutions are defined as those that lend the largest volumes of credit in each municipality. In the North, Northeast, and Central-West regions, *Bradesco*, one the largest Brazilian commercial banks, predominates as the largest intermediary in 38%, 31%, and 31% of the municipalities in these regions, respectively.[15] Meanwhile, in the Southeast region, *DLL*, a bank associ-

[14]Real values of december 2019. Value deflated by the Extended National Consumer Price Index (IPCA).
[15]Only the municipalities that received some rural credit for equipment in 2019 were considered in this calculation.

ated with a machinery manufacturer in Brazil, is the largest intermediary in 32% of the municipalities. In the South, the largest share is that of the *SICREDI* credit cooperative (main intermediary in 20% of the municipalities), which is also the largest in 15% of the municipalities in the Central-West region. The map also reveals that many municipalities in the North and Northeast regions do not have access to BNDES rural credit for equipment (municipalities shown in white). Additionally, markets in these two regions are more concentrated than those of the other regions. The maps for the second and third main financial institution also show more white municipalities in the North and Northeast, indicating that farmers often have no alternative to obtain loans, in the absence of the main or second main financial institution. For instance, in the Northeast, 65% of the municipalities had only one credit intermediary in 2019. In the North, this percentage was 38%.

The strategy for identifying the impacts of credit in this study leverages exactly those variations by interacting them with previous market-share distributions of bank branches in municipalities, as shown in Figure 4. This approach enables us to isolate credit variation in the municipality resulting from supply factors. For example, if *Bradesco* has more BNDES resources in a given year, the method considers that municipalities with a greater *Bradesco* presence are more likely to have more credit available. Section 4 discusses the strategy in more detail.

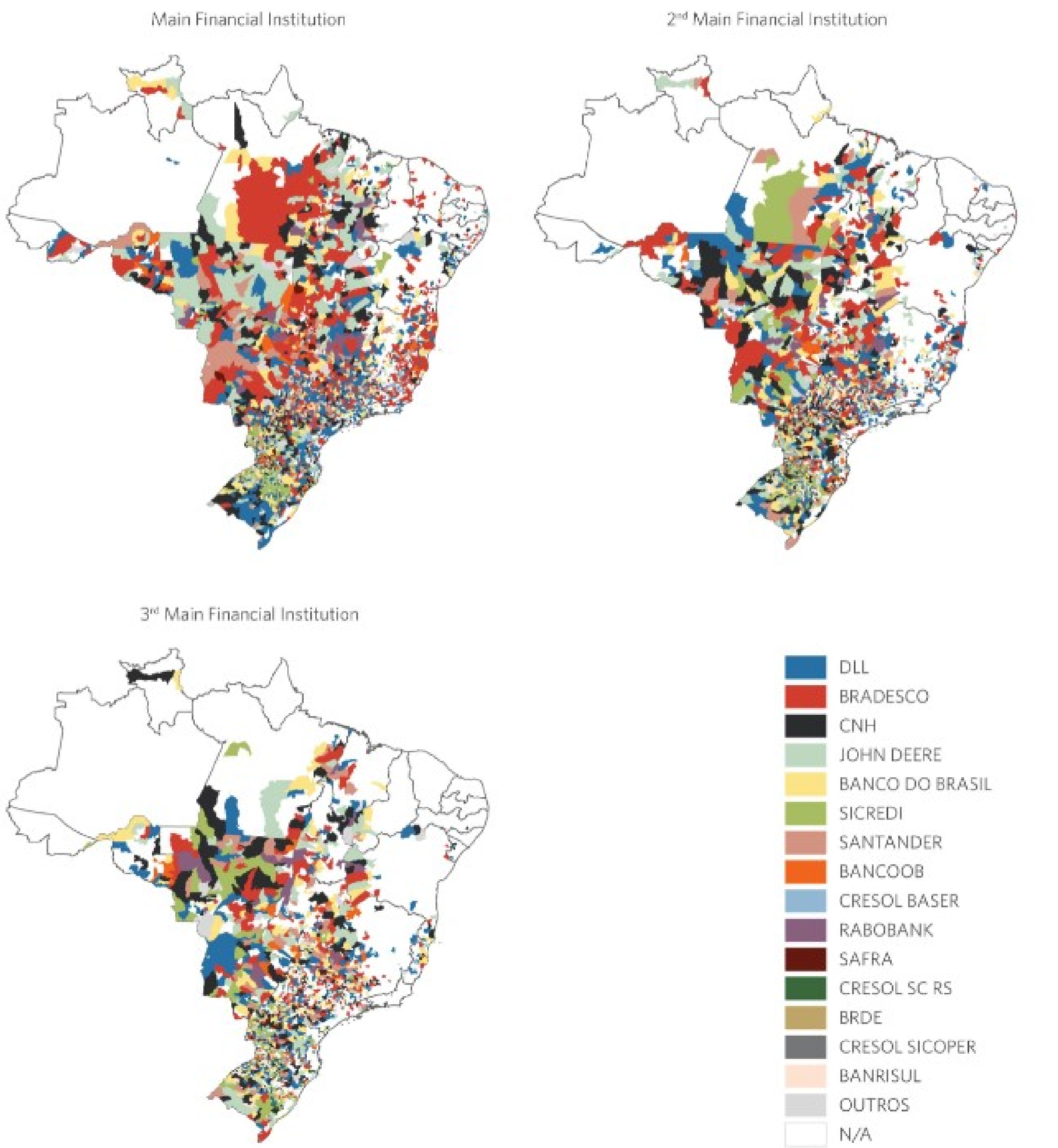
3 Data

We build a panel of 4,790 Brazilian municipalities during the period 2005-2019 from various data sources. Our primary data source was BNDES' administrative records containing detailed information on every BNDES rural credit for investment in machinery and equipment contract in the country. The data contained the date of release of resources, municipality, financial agent, equipment, total finance amount, investment amount, and type of financed equipment.

We aggregate this data by municipality and year to make it compatible with other datasets. Information on municipality characteristics and definitions of Brazilian biomes was obtained from IBGE. IBGE provides data on total municipal GDP and municipal agricultural GDP. It also produces the Municipal Crop Production Survey (*Produção Agrícola Municipal* - PAM), which has data on crop production. Data on cattle per municipality comes from the Municipal Livestock Survey (*Pesquisa da Pecuária Municipal* - PPM), and the number of rural workers is obtained throgh the IBGE Agricultural Census from 2006.

Land use data come from (Project MapBiomas, 2020), which uses remote sensing and vegetation mapping to produce annual maps for the entire country with a spatial resolution of 30m. MapBiomas provides data on farming area, forested formations and non-forest

Figure 4: Main Providers of Rural Credit for Equipment by Municipality, 2019



Notes: The main financial institutions are defined as those that lend the largest volume of credit in each municipality.
Source: CPI/PUC-Rio with data from BNDES, 2022.

natural formations.[16]

4 Empirical Strategy

The empirical strategy employed in this paper allows for causal identification of the effects of BNDES rural credit for investment in machinery and equipment on agricultural activity and land use in Brazil. The research design is based on a modified Shift-Share Instrumental Variable (SSIV) approach to predict lending shocks at the municipality level, using variation in pre-existing bank market shares and estimated bank supply shifts (Greenstone et al., 2020). Section 4.1 explains how we use the SSIV approach to leverage the substantial heterogeneity across banks in their year-to-year variation in rural credit lending, along with geographic variation in bank market shares. Section 4.2 explains how we employ recent developments in the SSIV literature to plausibly identify our source of variation based on the shock exogeneity hypothesis and to make correct inference about causal parameters.

4.1 Shift-Share Instrumental Variable (SSIV) strategy

Our universe of analysis for building the instrument consists solely of BNDES rural credit for investment (henceforth referred simply as "BNDES credit") and the financial institutions that operate this credit (hereinafter simply "banks"). To illustrate the strategy, suppose Bank A has more access to BNDES' resources and increases rural credit lending by 50% from one year to the next, whereas Bank B decreases it by 10%. In this scenario, we expect municipalities with a higher number of Bank A branches than Bank B branches in the starting period to witness an upsurge in bank lending with BNDES resources and consequently a boost in agricultural productivity. The underlying assumption is that farmers have limited ability to replace changes in credit supply from their banks. Therefore, any supply shock to banks within a specific municipality will impact the aggregate lending at the local level. Multiple studies provide evidence of such constraints (see Nguyen (2014), Berger et al. (2005) and Bernanke and Gertler (1995)).

The identification strategy relies on the fact that there is considerable variation in

[16] Although PAM has information on crop area, PPM does not have information on pasture area. The pasture area variable used in this paper is generated by combining the PAM dataset and MapBiomas. MapBiomas farming area is divided into three types of areas: crop, pasture and mosaic. The mosaic area is a type of farming area that could not be determined by the available images if it was destined for crop or pasture. To obtain the municipal pasture area, we first add both crop and mosaic areas from MapBiomas. From this value, we subtract the crop area from the PAM database. The result from this difference is an estimate of the pasture area contained in the MapBiomas´s mosaic area. Finally, we build our pasture area variable through the sum of MapBiomas' pasture area and this mosaic area identified as pasture from the information contained in the PAM database.

the participation of financial agents operating BNDES credit over time, and that market shares of these financial agents vary substantially across municipalities. Several factors explain the substantial variation in the volume loaned by the financial agents. The annual volume of funds operated by a given agent depends, among other factors, on the amount of funds allocated by BNDES for agricultural programs, on the agent's demand for this type of financing, on BNDES' risk exposure limit to the agent, and on government guidelines on the operation of public banks regarding this type of rural financing.

Figure 5 shows the evolution of the participation of the main financial agents in the total volume of BNDES' rural credit for equipment at the national level. There is substantial variation in the participation of agents over years. The figure reveals no specific general trend common to all intermediaries, we actually observe very different and sometimes erratic movements in the aggregate availability of credit for each intermediary at the national level. Banco do Brasil, for example, accounted for approximately 25% of the credit in 2013, but by 2018 its share had dropped to near zero.[17] In general, public banks oscillated between expanding (from 2009 to 2013) and contracting (from 2013 onwards) their share.

The "modified shift-share approach" is a variation of the "standard shift-share approach" introduced by Bartik (1991), but overcomes issues related to the validity of the instrument when analyzing the banking sector.[18] Consider the following estimating equation of interest:

$$y_{it} = \theta Q_{it}^{B} + d_i + \nu_t + \varepsilon_{it} \tag{1}$$

In Equation (1), y_{it} is an outcome variable[19] (e.g., agricultural production) in municipality i and year t. The outcome is a function of Q_{it}^{B}, the log of BNDES rural credit for equipment lending, municipality (d_i) and year (ν_t) fixed effects. Estimating this equation using OLS is likely to produce biased estimates of θ, since farmers in booming areas will both increase production and demand more credit. Therefore, we need to overcome the problem of reverse causality and omitted variable bias, that is, unobserved determinants of the dependent variable that are correlated with BNDES rural credit for equipment lending. The challenge is that municipal lending amounts are equilibrium outcomes of local supply and demand factors, and estimation is susceptible to confounding supply and demand shocks.

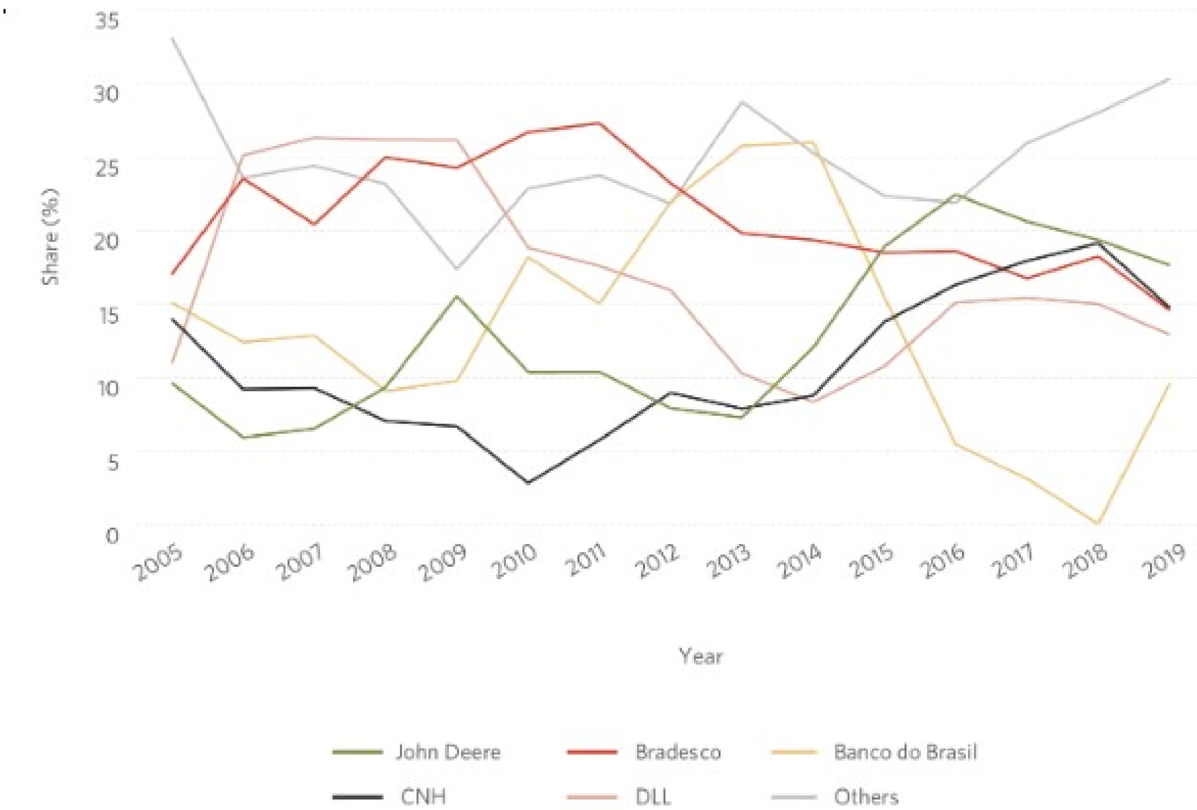
To disentangle the common municipality (demand) effects from changes in lending

[17] More details on the participation of each financial agent are addressed by Souza et al. (2022).

[18] It should be noted that the standard Bartik-style instrument may be affected by regional economies of scale in banking and by spatial correlation in demand shocks, which can undermine its validity. See Greenstone et al. (2020).

[19] Typically, outcome variables will be measured in log, but sometimes they will be measured in inverse hyperbolic sine (ihs) or as shares of GDP, for example. To simplify notation, we omit those mathematical transformations from equations.

Figure 5: Evolution of the Participation of Financial Agents Transferring Rural Credit for Equipment, 2005-2019



Source: CPI/PUC-Rio with data from BNDES, 2022.

supply, we build on Greenstone et al. (2020) to isolate the component of changes in BNDES' credit lending that can be attributed to supply factors by purging each bank's national change in BNDES' lending of its exposure to local markets. To do that, we predict the change in BNDES' credit lending at the municipality level from 2006[20] to 2019 by using interactions of banks' pre-period municipality market shares and their national change in lending. The first step is to estimate an equation that separates the impact of the change in equilibrium credit into two components: one for municipalities and another for banks, as shown in Equation (2):

$$\Delta Q^{B}_{ijt} = d_{it} + s_{jt} + e_{ijt} \text{ , for each t = \{2006, ..., 2019\}} \tag{2}$$

The outcome variable in Equation (2) is the log change in BNDES credit by finan-

[20]Although we have data for 2005, we use only from 2006 onward since we use lagged market-shares to build the instrument.

cial institution j in municipality i between two years. The equation is weighted by each bank's base period lending amount in municipality i so that an observation's influence is proportional to its BNDES rural credit lending in that year. The municipality fixed effects, d_i, measure the variation in banks' changes in BNDES' lending that is common across banks in the same municipality. Accordingly, these municipality fixed effects provide the local demand for BNDES rural credit. The vector s_j represents the fixed effects of financial agents and provides the parameters of interest. They are estimates of changes in bank j's supply of BNDES credit that are purged of their differential exposure to municipal-level variation in demand for BNDES rural credit. The s_{jt}'s are estimated for every year starting from 2006 to 2019. Furthermore, the financial institutions fixed effects are re-centered within each year so that their mean (weighted by their BNDES rural credit national asset size in the current period) becomes zero.

The second step is to interact predicted shocks with lagged bank market-shares in each municipality. Equation 3 presents a modified shift-share style solution, which defines an instrumental variable Z_{it} as a municipality-level measure of the expected rural credit supply shock:

$$Z_{it} := \sum_j ms_{ij,t-1} \times \hat{s}_{jt} \text{ , where } ms_{ijt} = \frac{Q^B_{ijt}}{\sum_j Q^B_{ijt}} \tag{3}$$

Here $\hat{s}_{jt}$ is the estimated financial institution fixed effect from fitting equation 2 for changes in BNDES rural credit lending between consecutive years and $ms_{ij,t-1}$ is financial institution j's BNDES credit market share in municipality i in the first of the consecutive years. The municipality-level predicted shock for lending is standardized using the mean and standard deviation from all years, and weighted by municipality-level BNDES' lending in the base year. Similar to the estimation of $\hat{s}_{jt}$, we compute the predicted lending shock for every year starting from 2006. Once the instrument is built, our first-stage regression with the SSIV approach is as follows:

$$Q^B_{it} = \gamma_t(Z_{it} \times \nu_t) + d_i + \nu_t + \epsilon_{it} \tag{4}$$

The dependent variable Q^B_{it} is the log of BNDES rural credit. The lending shocks Z_{it} for municipality i in year t are calculated in Equation 3. In the first-stage, the instrumental variable Z_{it} is interacted with year fixed effects ν_t. Municipality fixed effects are indicated by d_i and standard errors are clustered at the municipality level. The γ_t´s are the parameters of interest, which measure the impact of the lending shocks on BNDES rural credit loans in the year of the shock. The second-stage is then specified as follows:

$$y_{it} = \theta \hat{Q}^{B}_{it} + d_i + \nu_t + \varepsilon_{it} \tag{5}$$

y_{it} represents our dependent variables of agriculture, land use, and environmental outcomes, and $\hat{Q}^{B}_{it}$ was estimated in Equation (4). The coefficients of interest are represented by θ, which measure the causal impacts of BNDES rural credit for equipment on our dependent variables.

4.2 Identification and inference with as-good-as-random shocks

Shift-share instruments have been widely used in the literature due to their availability in many different contexts and relatively easy implementation. But identifying its source of exogenous variation may not be straightforward. A recent literature offered different frameworks to provide researchers with the tools to help identify and explicit the source of variation, test its validity with a series of robustness checks and implement valid inference procedures. While Goldsmith-Pinkham et al. (2020)'s framework demand a stronger share exogeneity hypothesis for SSIV identification, Borusyak et al. (2022) rely on conditions in which shock exogeneity is sufficient to guarantee identification even when the shares are endogenous. Besides that, Adão et al. (2019) argue that inference procedures need to be adjusted when using Bartik-like instruments to account for the correlation across regions with similar levels of exposure, independent of their geographic location.

We argue that identification in this paper is better classified as coming from shocks being exogenous, fitting into Borusyak et al. (2022)'s framework. This approach is adequate in settings where shocks are tailored to a specific question while the shares are "generic", in the sense they could conceivably measure an observation's exposure to multiple shocks. More specifically, our setting falls under the second category explored in their paper, when exogenous shocks are not directly observed, but are estimated. In our case, we estimate them using Equation (2). As noted before, our source of variation comes from differences in national credit shocks at the financial agent level provided by its access to resources from BNDES, which are distributed in municipalities according to each financial institution's lagged market shares in each municipality. We have demonstrated that those shocks can be regarded to be as-good-as-random (Figure 5).

Following Borusyak et al. (2022), using SSIVs is equivalent to use lending shocks directly as instruments in a bank-level regression. Their procedure averages out the outcome and the treatment variables using exposure shares as weights to obtain shock-level aggregates. Formally, we can adapt their framework to our setting and obtain our coefficient of interest θ by running the following bank-level IV system of equations:

$$\bar{Q}^{B\perp}_{jt} = \gamma_t(\hat{s}_{jt} \times \nu_t) + \nu_t + \epsilon_{jt} \tag{6}$$

$$\bar{y}^{\perp}_{jt} = \theta \bar{Q}^{B\perp}_{jt} + \nu_t + \varepsilon_{jt} \tag{7}$$

In this system of equations, j indexes financial institutions, so that $\hat{s}_{jt}$ is the shock part of the shift-share instrument, and $\bar{v}^{\perp}_{jt}$ denotes an exposure-weighted average at the bank-time level of a generic variable at the municipality-time level v_{it}, a process applied over treatment and outcome variables. This exposure-weighted average may include additional weights e_{it}, which are, in our case, the lagged total amount of lending provided by a bank, as explained in Section 4.1. Formally:

$$\bar{v}^{\perp}_{jt} = \frac{\sum_i e_{i,t-1} \cdot ms_{ijt} \cdot v_{it}}{\sum_i e_{i,t-1} \cdot ms_{ijt}} \tag{8}$$

The resulting regression at this level generates corrected F-statistics and standard errors, which are reported as our main estimates throughout the paper. We also report standard SSIV estimates for our main results as robustness. Our main specification under this framework will also cluster standard errors at the bank level, which is exactly the level of our variation. Finally, since some municipalities have shares that do not sum up to one only due to small imputation adjustments, we implemented the process without completing the sum of shares so they sum to one, which would create a "missing" financial institution whose share is 1 minus the sum of all banks' shares in each municipality. We also present robustness checks where we include this missing bank share without major changes in our results.

Notably, our empirical strategy uses the instrument interacted with year fixed effects in the first stage. In practice, this means we have several instruments. However, Borusyak et al. (2022)'s framework is more straightforwardly applied to settings with only one instrument, where just identification guarantees that point estimates using standard SSIVs are numerically equivalent to bank-level estimates. Under over-identification, our point estimates are slightly different using equation 7 compared to 5, but our results remain qualitatively the same under the two approaches. Our preferred specification uses the bank-level regression because it deals correctly with identification and inference issues under SSIV strategies in which the variation comes from shocks being exogenous. According to Borusyak et al. (2022), this is a more conservative approach compared to using SSIVs and inference is asymptotically equivalent to the procedure suggested by Adão et al. (2019). Indeed, confidence intervals using this approach are considerably larger compared to standard SSIVs, as reported in the following section.

5 Results

5.1 First Stage

This section provides evidence that our measure of BNDES' lending supply shocks is predictive of realized rural credit for investment lending. We interact the shocks with year indicators to allow each year's shock to affect its own year. The results in Table 1 confirm a robust and statistically significant relationship between the predicted lending shock and the realized rural credit loans at the bank level, which is the relevant level of variation of our analysis. Our first-stage F-statistic of 18.6 is reassuring in this regard. The table presents estimates from the main specification that controls for year fixed effects, clusters standard errors at the bank level and removes the missing bank generated by the Borusyak et al. (2022)'s procedure to deal with incomplete shares.

Overall, the results suggest that there are important frictions in the rural credit lending market for investment in machinery. The evidence indicates that when farmers lose access to this type of credit from their financial institution, there are meaningful costs that prevent them from immediately switching to other banks that intermediate resources from BNDES, thus leading to a decline in aggregate lending for investment in that area. This is particularly true considering the characteristics of our setting, in which many regions have only a few financial institutions operating, as shown in Section 2.2.

Table 1: First-stage Results

Independent Variable	Coefficients
BNDES shock * 2006	0.045
	(0.123)
BNDES shock * 2007	0.192***
	(0.047)
BNDES shock * 2008	0.011
	(0.064)
BNDES shock * 2009	0.045
	(0.035)
BNDES shock * 2010	-0.021
	(0.078)
BNDES shock * 2011	-0.191***
	(0.057)
BNDES shock * 2012	0.005
	(0.062)
BNDES shock * 2013	0.221*
	(0.114)
BNDES shock * 2014	-0.046
	(0.109)
BNDES shock * 2015	0.042
	(0.049)
BNDES shock * 2016	0.002
	(0.049)
BNDES shock * 2017	0.078
	(0.081)
BNDES shock * 2018	-0.044
	(0.044)
BNDES shock * 2019	0.120
	(0.156)
Observations	493
First Stage F-stat	18.60

Notes: The table reports first-stage results for the IV regression, in which we dependent variable is the BNDES rural credit for investment shock on the predicted shocks (the shift part of the shift-share instrument) interacted with year fixed effects. This is based on the procedure by Borusyak, Hull and Jaravel (2022) to transform the municipal-level panel into a bank-level panel. All regressions have year fixed effects. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Main Findings

Table 2 shows OLS and 2SLS estimates of the impact of rural credit for equipment on agricultural production and land use outcomes. 2SLS estimates are obtained using Borusyak et al. (2022)'s procedure, as explained in Section 4.2. All coefficients can be interpreted as elasticities, that is, the estimated impacts of a 1% increase in the supply of municipal rural credit for equipment on the variables of interest.

Our main finding is that rural credit for equipment stimulates crop production via increasing crop productivity[21] without increasing deforestation within the same municipality. There is also suggestive evidence of a conversion of pastures into cropland. Our 2SLS estimates indicate that a 1% increase in the availability of this type of credit is associated with a 0.13% growth in the value of crop production and a 0.16% growth in crop productivity. The coefficient on forested area, which includes both planted forests and natural forests, is virtually zero, while the coefficient on pasture is negative, but not significant. Although not entirely validated by our preferred 2SLS estimates, increasing rural credit for equipment is also associated with increases in agricultural GDP and cattle productivity.

Overall, 2SLS estimates are higher in magnitude than OLS, suggesting that endogeneity in BNDES' rural credit availability created a downward bias in OLS estimates. Additionally, standard errors are considerably noisier in 2SLS compared to OLS, a possible consequence of using Borusyak et al. (2022)'s approach rather than the standard shift-share strategy. Our inference procedure controls for the potential bias generated by municipalities with similar levels of credit exposure, which makes standard shift-share estimates more significant than they should be. In Section 5.4 we come back to this point and explore the differences between the two approaches.

Therefore, our findings indicate that an increase in resource availability leads to growth in crop production, but there are no significant results in cattle production. Even though cropland may substitute pasture areas, there is no significant increase in the total area allocated to agriculture and no evidence of deforestation increase. Consequently, land productivity increases for agriculture, especially for crops, which is expected given that BNDES rural credit for equipment plays a more substantial role in crop production than cattle.

[21] Crop productivity is defined as the ratio between the value of crop production and the area devoted to crops in a municipality. Cattle productivity is defined as the ratio between the number of heads of cattle and the pasture area.

Table 2: OLS and 2SLS Results

Dependent Variable	(1) OLS	(2) 2SLS
Agricultural GDP (log)	0.040***	0.078
	(0.002)	(0.080)
Share Agricultural GDP / Total GDP	0.005***	0.016
	(0.000)	(0.010)
Crop Production (log)	0.063***	0.126**
	(0.003)	(0.056)
Cattle Head (log)	0.000	0.010
	(0.001)	(0.064)
Farming area (ihs)	0.002***	0.003
	(0.000)	(0.005)
Crop area (ihs)	0.006***	0.011
	(0.001)	(0.008)
Pasture area (ihs)	-0.001***	-0.007
	(0.000)	(0.009)
Forested area (ihs)	-0.001***	0.001
	(0.000)	(0.002)
Crop production / Crop area (ihs)	0.031***	0.160*
	(0.004)	(0.095)
Cattle head / Pasture area (ihs)	-0.001	0.058
	(0.001)	(0.036)
Panel level	Municipal	Bank
Observations	43,762	493

Notes: The table reports OLS and IV regressions of the BNDES rural credit for investment shock on many outcomes related to agricultural production and land use. 2SLS estimates use the procedure based on Borusyak, Hull and Jaravel (2022) to transform the municipal-level panel into a bank-level panel and use directly the shocks as the instrument. All regressions have municipality and year fixed effects. The instrument is interacted with year fixed effects in the first stage. Standard errors are clustered at the municipality level for OLS and at the bank level for IV. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Heterogeneity

This section deepens the previous analysis in order to explore potential differences in the impact of credit for equipment in Brazil by dividing Brazilian municipalities into two types: more labor-intensive and less labor-intensive. We expect effects to be higher in magnitude in more labor-intensive areas since rural credit for investment should be allocated to purchase labor-saving equipment. More labor-intensive municipalities were defined as those with a ratio of the number of rural workers per area allocated to agriculture above the median.[22] Municipalities below the median, in turn, are deemed less labor-intensive. We also compared municipalities above the 75^{th} percentile with those below the 25^{th} percentile of the distribution of rural workers per area. Our goal was to capture the most distinguishing effects of these two types of municipalities.

Labor intensity is analyzed geographically in Figure 6 for 2006.[23] The figure reveals that less labor-intensive municipalities are located mainly in the North and Central-West regions. The Northeast, Southeast, and South regions show a high availability of rural workers relative to the area allocated to agriculture.

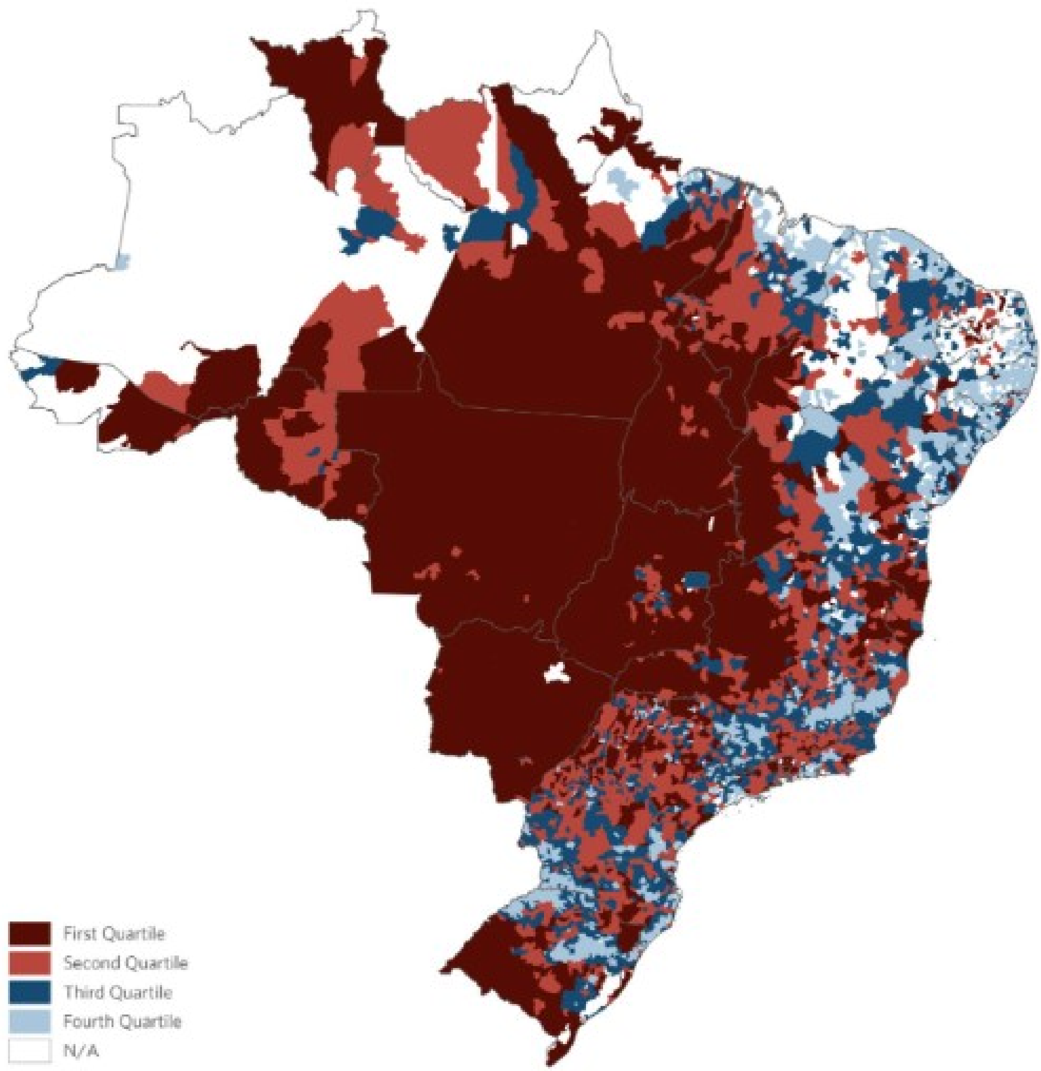
Effects are indeed higher and more significant in more labor-intensive municipalities. Table 3 reports the estimated impacts of rural credit for equipment on agricultural production, land use and productivity among municipalities with different labor intensities. We use our preferred 2SLS specification in all columns, but due to the reduced number of observations in the municipality-level data, the heterogeneity results should be interpreted with caution, considering that first stage F-statistics are generally lower.

Considering the regressions based on the median (columns 1 and 2), an increase in the availability of rural credit in municipalities with a high proportion of workers per area leads to growth in agricultural GDP, with no significant effects below the median. Those effects are even higher in the quartile comparison. Comparing the extremes of the distribution suggests that very high labor-intensity municipalities explain most of the general patterns we found. In those places, more access to credit for investment led to greater expansion of crop production, agricultural GDP and crop productivity associated with a slight decrease in crop area and even a slight increase in forested area. We note that although not significant, coefficients on forested area for low labor-intensity areas are negative, which is suggestive evidence of a small increase in deforestation when credit is expanded only to this subgroup of municipalities. Except for the fourth quartile of the distribution, we also observed increases in cattle productivity, but they are generally lower and less significant than gains observed in crop productivity.

[22] Only the municipalities that registered positive rural credit for equipment were considered when calculating the median.

[23] The year 2006 was chosen for classification due to the availability of data from the Agricultural Census

Figure 6: Distribution of Rural Workers over Agriculture Area, 2006



Notes: Less labor-intensive municipalities are shown in shades of red. In dark red are the 25% municipalities with the lowest intensity; in light red are the municipalities between the 25th and 50th percentile. More labor-intensive municipalities are shown in shades of blue. In light blue are the municipalities between the 50th and 75th percentile. In dark blue are the municipalities above the 75th percentile.
Source: CPI/PUC-Rio with data from the IBGE Agricultural Census (2006), 2022

Table 3: 2SLS Results by municipality profile according to the distribution of rural workers per area

Dependent Variable	(1) Below median	(2) Above median	(3) First quartile	(4) Fourth quartile
Agricultural GDP (log)	0.081	0.151*	0.119	0.287***
	(0.099)	(0.084)	(0.081)	(0.076)
Share Agricultural GDP / Total GDP	0.012	0.020**	0.014	0.031***
	(0.015)	(0.010)	(0.012)	(0.008)
Crop Production (log)	0.126	0.074	0.330***	0.283***
	(0.084)	(0.090)	(0.071)	(0.102)
Cattle Head (log)	0.094	0.048	0.050	-0.091
	(0.078)	(0.033)	(0.046)	(0.064)
Farming area (ihs)	0.003	-0.002	-0.002	-0.006**
	(0.011)	(0.002)	(0.014)	(0.003)
Crop area (ihs)	0.011	-0.005**	0.025**	-0.007*
	(0.012)	(0.002)	(0.012)	(0.004)
Pasture area (ihs)	-0.003	0.002	-0.021	0.001
	(0.009)	(0.003)	(0.013)	(0.004)
Forested area (ihs)	-0.003	0.002	-0.002	0.004**
	(0.006)	(0.002)	(0.006)	(0.002)
Crop production / Crop area (ihs)	-0.021	0.106	0.292***	0.356**
	(0.124)	(0.125)	(0.097)	(0.153)
Cattle head / Pasture area (ihs)	0.096	0.063**	0.110**	-0.080
	(0.069)	(0.030)	(0.053)	(0.060)
Number of observations	467	413	433	351
1st stage F-stat	2.94	7.95	8.71	5.85

Notes: The table reports heterogeneous 2SLS estimates on the effect of BNDES rural credit for investment shock on various outcomes. Columns 1 and 2 separate between municipalities below and above the median proportion of rural workers per area before implementing the procedure by Borusyak, Hull and Jaravel (2022) to transform the dataset to the shock (bank) level and use directly the shift part of the shift-share as the instrument. Columns 3 and 4 repeat the same exercise choosing only munipalities in the first and fourth quartiles of the distribution of the proportion of rural workers per area. The specification in all regressions is the preferred one where standard errors are clustered at the bank level and we remove the missing bank created by the procedure. *** p<0.01, ** p<0.05, * p<0.1.

Most of the equipment used in agriculture is labor-saving. For example, agricultural tractors, harvesters and soil preparation equipment (which accounted for 68% of the total BNDES rural credit for equipment between 2005 and 2019) reduce workers' efforts in planting and harvesting. In other words, using these machines should have a greater impact on labor productivity compared to land productivity. Therefore, in addition to considering the differences between municipalities, we also restricted the analysis to credit for the acquisition of labor-saving equipment. Results are reported in Table 4.

At first, we observe that only specifications using observations above the median (column 2) or above the 75^{th} percentile (column 4) have relatively strong first stages, making inference on coefficients more plausible. The pattern is more easily observed in column 4, which further reinforces evidence on growth of crop production (0.32%), crop productivity (0.48%) and agricultural GDP (0.35%) as a result of a 1% increase in rural credit to purchase labor-saving machinery. However, in such high labor-intensive municipalities, this specific type of credit led to a reverse pattern in land use, with an increase in pasture area and a decrease in crop area of similar magnitudes.

Therefore, the disaggregated analysis reveals that credit for equipment has different impacts on different profiles of municipalities. For example, more labor-intensive municipalities have more significant responses in production compared to land-use variables, which can be explained by the fact that land is a scarcer production factor due to more consolidated occupation in these locations. Furthermore, crop productivity in these municipalities exhibits a more significant growth than cattle productivity. Finally, the analysis shows that the effects on production and land use are greater when we focus on credit intended to finance labor-saving equipment, especially in more labor-intensive municipalities.

5.4 Robustness

As mentioned in Section 4.2, our over-identified first stage leads to slightly different point estimates in the second stage comparing standard SSIV with the bank-level regression based on Borusyak et al. (2022)'s framework. Besides that, choices regarding the standard errors clustering level and how to deal with incomplete shares can affect results. We document those differences in Table 5.

At first, we compare our main specification (column 4) to the standard SSIV approach (column 1). We observe that our main specification is more conservative in the sense that standard errors are higher, but also more reassuring, since the first stage F-statistic is above the usual threshold for evaluating weak instruments. This is not the case when

and for being the first year in the rural credit for equipment database used in this study.

Table 4: 2SLS Results for labor-saving equipment by municipality profile according to the distribution of rural workers per area

Dependent Variable	(1) Below median	(2) Above median	(3) First quartile	(4) Fourth quartile
Agricultural GDP (log)	0.202	0.077	0.193*	0.345***
	(0.125)	(0.072)	(0.104)	(0.062)
Share Agricultural GDP / Total GDP	0.014	0.013*	0.013	0.030***
	(0.016)	(0.007)	(0.013)	(0.008)
Crop Production (log)	0.234**	0.189	0.233*	0.315**
	(0.098)	(0.116)	(0.137)	(0.125)
Cattle Head (log)	0.002	-0.021	0.045	-0.028
	(0.078)	(0.026)	(0.048)	(0.064)
Farming area (ihs)	0.019	0.001	0.022*	-0.001
	(0.011)	(0.002)	(0.012)	(0.003)
Crop area (ihs)	0.036**	0.005	0.036**	-0.010**
	(0.017)	(0.004)	(0.014)	(0.004)
Pasture area (ihs)	-0.015	-0.004	-0.010	0.008**
	(0.018)	(0.005)	(0.009)	(0.004)
Forested area (ihs)	-0.001	-0.002	-0.008	0.001
	(0.007)	(0.001)	(0.007)	(0.002)
Crop production / Crop area (ihs)	0.293*	0.127	0.292	0.488***
	(0.153)	(0.093)	(0.236)	(0.139)
Cattle head / Pasture area (ihs)	0.087*	0.035	0.043	-0.032
	(0.051)	(0.025)	(0.038)	(0.051)
Number of observations	362	324	343	275
1st stage F-stat	4.76	20.14	3.72	19.92

Notes: The table reports heterogeneous 2SLS estimates on the effect of BNDES rural credit for investment in labor-saving equipment shock on various outcomes. Columns 1 and 2 separate between municipalities below and above the median proportion of rural workers per area before implementing the procedure by Borusyak, Hull and Jaravel (2022) to transform the dataset to the shock (bank) level and use directly the shift part of the shift-share as the instrument. Columns 3 and 4 repeat the same exercise choosing only munipalities in the first and fourth quartiles of the distribution of the proportion of rural workers per area. The specification in all regressions is the preferred one where standard errors are clustered at the bank level and we remove the missing bank created by the procedure. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: 2SLS Results - Robustness

Dependent Variable	(1) SSIV	(2) BHJ	(3) BHJ	(4) BHJ
Agricultural GDP (log)	0.071	0.079	0.079	0.078
	(0.036)	(0.086)	(0.090)	(0.080)
Share Agricultural GDP / Total GDP	0.015**	0.016*	0.016	0.016
	(0.006)	(0.009)	(0.012)	(0.010)
Crop Production (log)	0.127*	0.129	0.129*	0.126**
	(0.055)	(0.081)	(0.065)	(0.056)
Cattle Head (log)	0.012***	0.009	0.009	0.010
	(0.027)	(0.055)	(0.068)	(0.064)
Farming area (ihs)	0.003	0.003	0.003	0.003
	(0.003)	(0.005)	(0.005)	(0.005)
Crop area (ihs)	0.010***	0.012	0.012	0.011
	(0.004)	(0.011)	(0.009)	(0.008)
Pasture area (ihs)	-0.007	-0.008	-0.008	-0.007
	(0.004)	(0.010)	(0.010)	(0.009)
Forested area (ihs)	0.001	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Crop production / Crop area (ihs)	0.180***	0.193	0.193*	0.160*
	(0.064)	(0.131)	(0.105)	(0.095)
Cattle head / Pasture area (ihs)	0.075***	0.065	0.065	0.058
	(0.030)	(0.040)	(0.040)	(0.036)
Panel level	Municipal	Bank	Bank	Bank
Observations	41,788	507	507	493
1st stage F-stat	5.22	2.22	15.85	18.60
Municipality FE	X			
Year FE	X	X	X	X
Instrument interacted with year FE	X	X	X	X
Cluster at municipality level	X			
Cluster at bank level			X	X
Removing missing bank				X

Notes: The table reports different 2SLS specifications for robustness, in which the main regressor is the BNDES rural credit for investment shock. Specification 1 uses the standard shift-share instrument (SSIV) at the municipality level. In this case, inference on IV estimates is based on the Conditional Likelihood Ratio (CLR) Test. All the other specifications use the procedure based on Borusyak, Hull and Jaravel (2022) to transform the municipal-level panel into a bank-level panel and instrument directly the shock part of the shift-share (BHJ). Standard errors in specification 2 are heteroskedasticity-robust while in specifications 3 and 4 they are clustered at the bank level. Since the sum of the shares in the shift-share instrument does not add up to 1 in each municipality, BHJ's procedure creates an additional bank observation to store the difference between 1 and the sum of the shares in each year. We remove this missing bank in specification 4, which is our preferred specification. *** p<0.01, ** p<0.05, * p<0.1.

using the standard SSIV. As a result, while significant[24] increases in the share of agricultural GDP, crop area, cattle production, and cattle productivity are observed in column 1, these effects are not observed in column 4, meaning that coefficients on crop production and crop productivity are more reliably positive and significant. Nevertheless, the absence of effects on forested area is observed in both approaches, which provides additional reassurance for our main conclusions.

Comparing columns 2 and 3, we observe that clustering at the level of the relevant variation (financial agents) is crucial to generate a reasonable first stage, as noted by the increase in the first stage F-statistic. Finally, the comparison of columns 3 and 4 suggests that including or not the missing bank share to deal with incomplete shares does not make a substantial difference in our results.

6 Concluding remarks

This study evaluated the effects of providing rural credit for financing farming machinery and equipment on agricultural activity and land use. It draws on the Brazilian setting, a major player in global agricultural production, in which the national development bank (BNDES) plays a crucial role in financial technological improvements in agriculture. Causal identification relies on plausibly exogenous shocks on credit availability by financial agents that act as intermediaries of BNDES' resources, employing recent developments of the Shift-Share literature (Borusyak et al., 2022). Administrative data from BNDES enabled an in-depth analysis of loans for machinery and equipment purchases such as harvesting equipment and tractors, allowing for observations at the municipality-bank-time level, which was critical to implement the identification strategy.

Our main findings suggest that credit availability helps intensify crop production, confirming previous research (Assunção et al., 2021). In addition, results show that rural credit for equipment drives small changes in areas allocated to agriculture and does not lead to additional deforestation. In fact, estimates suggest a slight conversion of pasture areas, which are historically less productive, into cropland. The heterogeneity analysis reveal stronger crop production and productivity improvements in more labor-intensive municipalities and for credit intended to finance labor-saving machinery and equipment, suggesting increased labor productivity as the main driver of the results. This result is similar to the one found by Bustos et al. (2016), although we use credit as a source of intensification.

These results indicate that credit for equipment modifies producers' decisions. Credit made available by BNDES for investment in the agricultural sector is an effective

[24] For SSIV estimates, we employ an inference procedure that is robust to weak instruments, with p-values based on the Conditional Likelihood Ratio (CLR) test proposed by Moreira (2003).

instrument for public policies that combine technological improvements in agriculture and environmental conservation. Therefore, BNDES credit is shown to have impacts beyond the explicit objectives of the financing lines. Credit impacts the environment and the efficiency of agricultural production, complementing BNDES's objectives in promoting the sector and expanding the productivity of the Brazilian economy. Thus, it is important to consider environmental and agricultural productivity aspects when formulating the bank's credit policies.

Strengthening BNDES' credit policy towards greater production intensification, adoption of good practices, and sustainability is expected to contribute to the country's progress in economic, social, and environmental issues. From an economic standpoint, the conservation of rural properties' native vegetation is a public good that fail to reach a socially-desired level when provided by private agents. This is because private costs and benefits differ from public ones. Government support for rural credit aligned with environmental and deforestation reduction goals encourages the provision of these public goods.

This study highlights the potential benefits of providing rural credit for financing farming machinery and equipment on agricultural activity and land use in Brazil. With the abundance of deforested land in Brazil, modernization and intensification of production can more than double agricultural production without deforestation or removal of native vegetation. In addition, growing global concerns about forests and climate change have had an impact on trade agreement negotiations, with consequences for Brazil's exports. To meet the demands of consumers and large buyers for sustainable products based on zero deforestation, environmental protection is becoming a primary driver of Brazil's economic success. Credit policies not only should reflect this importance, but could play a critical role in promoting agricultural modernization and increasing productivity while considering the complexity and diversity of the effects of mechanization on rural activity.

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