2º COLOCADO
CATEGORIA I – FINANCIAMENTO AO DESENVOLVIMENTO SUSTENTÁVEL, INCLUSIVO E INOVATIVO

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

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1. Introduction

Increasing agricultural productivity is crucial for ensuring growth in food production, promoting sustainability, and preserving the environment. However, the costs associated with the acquisition of machinery and equipment and the risks related to 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) municipality characteristics relative to production factor intensity, distinguishing between those with higher and those with lower labor intensity; 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 (BNDES), which contains detailed information on investment credit operations for agricultural machinery and equipment. We use data on municipal agricultural production and rural workers from the Brazilian Institute of Geography and Statistics (IBGE). Finally, land use and forest data come from the Brazilian Annual Land Use and Land Cover Mapping Project (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 comes from a modified Shift-Share Instrumental Variable (SSIV) adapted from Greenstone *et al.* (2020). It leverages exogenous variation from national-level yearly changes in credit amounts transferred to financial agents by BNDES combined with lagged market-shares of such banks in each municipality. To address concerns with SSIVs and provide correct inference, we implement Borusyak *et al.* (2022)' procedures and show the instrument to be valid under the shock exogeneity assumption.

Brazil is the second-largest food exporter, according to the Food and Agriculture Organization (FAO, 2021), and rural credit accounts for around 30% of the total production value.[1] Machinery, equipment and vehicles are key investments in the Brazilian agriculture. In the 2021/22 agricultural year, rural credit operations to finance such products 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. In theory, it is not entirely clear whether

1 Data from IBGE, 2020.

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

productivity gains yield positive or negative environmental impacts, as the Jevons Paradox and the Borlaug hypothesis generate conflicting predictions. The empirical evidence on this topic is quite mixed and context-specific (Jayachandran, 2022).[3] While our evidence aligns more with the Borlaug hypothesis, our main contribution is to show that credit-induced mechanization can have positive environmental externalities through more efficient land use. Credit for machinery investment increases agricultural productivity without pressure on forest areas, converting high-emissions activities (such as cattle) to lower-emission ones.

Besides that, the impacts of mechanization on productivity and land-use are largely dependent on the distribution of production factors. The seminal work of Hayami and Ruttan (1970) 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.[4] 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). However, more recent empirical research reveals that the effects of crop mechanization can be more complex and diverse.[5] 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 and structural transformation, leading to a migration from agricultural to manufacturing employment (Bustos *et al.*, 2016). Our paper contributes to this literature by showing that labor and land productivity gains associated with mechanization can be driven by increased credit availability.

The remainder of the paper is organized as follows. Section 2 presents the background on land use and agriculture in Brazil, along with an overview of

3 Byerlee *et al.* (2014), Hess *et al.* (2021) and Carreira *et al.* (2024) backs up the Jevons Paradox, while Emerick *et al.* (2016), Garcia (2020), Szerman *et al.* (2022) and Da Mata *et al.* (2023) support the Borlaug hypothesis.

4 Japan and the United States are paradigmatic examples. In Japan, where land was a relatively scarcer factor than labor, technological development in the 19th century prioritized chemical and biological inputs, expanding land productivity. In the United States, where labor was the scarcer factor, mechanical innovations (such as tractors and harvesters) predominated, which allowed the cultivation of larger areas with the same labor.

5 Daum & Birner (2020) find positive impacts on land productivity. In Côte d'Ivoire (Mano *et al.*, 2020) and Zambia (Belton *et al.*, 2021), 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.

the institutional context of BNDES and its role in rural credit for investment. Section 3 describes the data, and we lay out the empirical strategy in Section 4. Results are reported 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 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 accounts for, in 2020, 6.6% of the national GDP, approximately R$ 434 billion (IBGE, 2022). The IBGE 2017 Agricultural Census shows that 15.1 million people work in rural establishments.

The distribution of agricultural land in Brazil is quite unequal, with 4% of farms occupying 63% of the farmland.[6] Conversely, 65% of rural establishments with area lower than one fiscal module[7] occupy only 9% of land. Rural credit is also highly concentrated: 1% of the rural credit contracts were responsible for 33.7% of the total rural credit in 2022.

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. Between 1961 and 2016, 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%)

6 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.

7 The National Institute of Colonization and Land Reform (INCRA) 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.

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 crops, eliminating the need to clear new land. Between 2004 and 2012, Brazil reduced deforestation rates in the Amazon by 80%, while increasing its agricultural sector GDP (Gandour, 2019).

Brazil's agriculture has been modernizing and developing mainly 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). Productivity gains measured by the number of heads of cattle per hectare[9] and tons of harvested soybeans per hectare increased in all regions. However, pastureland in Brazil's Southeast region have decreased since 1975, and in all regions except the North since 1995. Soybean growth has remained steady, but crop areas are smaller compared to those of pastures. As of 2017, cattle productivity still 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 agricultural productivity without resorting to deforestation. By converting pasture to cropland and increasing yields, 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) increase the efficiency of their production. Efforts to eliminate inefficiencies will demand additional input and compel farmers to increase their operational costs and capital stocks to transition their produc-

8 CPI/PUC-Rio with data from MapBiomas (v.5.0).

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).

tion. The increase in the farm equipment value required to enable farmers to eliminate inefficiencies ranges from 48% to 52% of the current values. At the same time, substantial increases in operational costs (between 44% and 51% of the current figures) would also be required to maximize agricultural output (Assunção & Bragança, 2019).

The modernization and intensification of agriculture requires considerable resources. 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 pastures 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 institutional background of the analysis, with some descriptive statistics on BNDES' rural credit for equipment. In our period of study, the bank played a crucial role in financing rural activities in Brazil, accounting for a third of investment rural credit operations according to the Central Bank of Brazil (Souza *et al.*, 2022).

Credit provided by BNDES is mainly focused on crops, which historically use land more intensively than cattle. 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.[13]

Figure 1 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 such as the Investment Sustaining Program (PSI). This program considerably expanded all BNDES channeled financing resources during Dilma Rousseff's mandate, which also contributes to the exogeneity of this source of variation.

11 *MODERFROTA* was created in 2000 to finance the acquisition of tractors and agricultural equipment (Sant'Anna & Ferreira, 2006). 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 IBGE Agricultural Censuses.

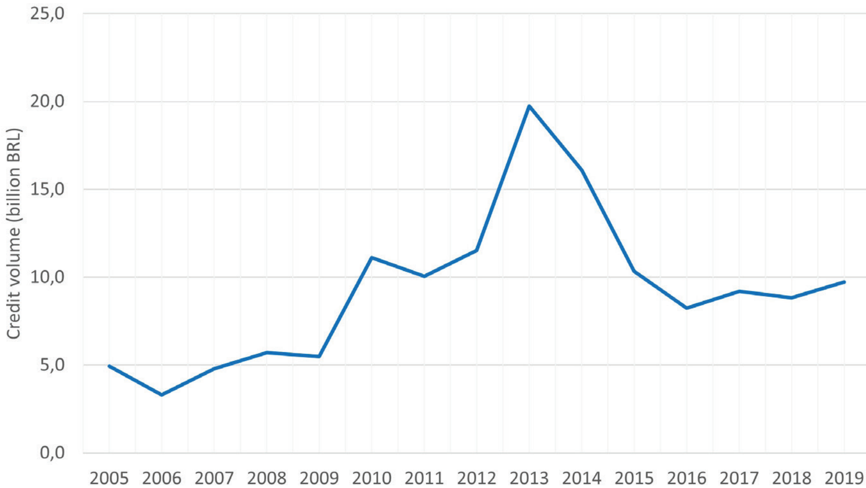
12 The different products provided by BNDES encompass those distinct lines. For example, *MODERFROTA* is a credit line that runs within *BNDES FINAME* product.

13 In 2020, 57% of the volume of BNDES's loans to the agricultural sector was granted through BNDES *FINAME*. 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 account for 56% of these funds between 2005 and 2019.

14 Real values of december 2019. Value deflated by the Extended National Consumer Price Index (IPCA).

FIGURE 1

EVOLUTION OF THE VOLUME OF RURAL CREDIT FOR EQUIPMENT, 2005-2019



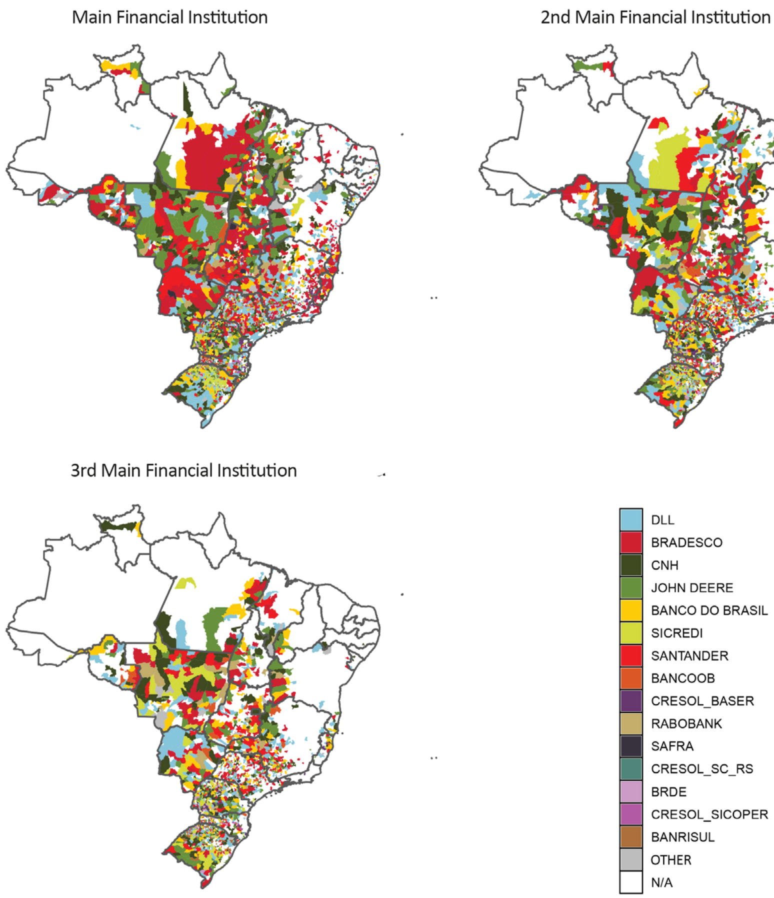
Notes: Values deflated by the IPCA, based on December 2019.
Source: CPI/PUC-Rio with data from BNDES, 2022.

The relevance of each financial institution acting as intermediary varies across regions. Figure 2 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 Midwest 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 associated 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 Midwest region.

15 Only municipalities that received some rural credit for equipment in 2019 were considered in this calculation.

FIGURE 2

MAIN PROVIDERS OF RURAL CREDIT FOR EQUIPMENT BY MUNICIPALITY, 2019



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

The map also reveals that many municipalities in the North and Northeast regions do not have access to BNDES rural credit for equipment (shown in white). Additionally, markets in these two regions are more concentrated than 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. 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 2. 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 supply. Section 4 will detail the strategy.

3. Data

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

Information on municipality characteristics and definitions of Brazilian biomes were obtained from IBGE, which also provides data on municipal GDP. We also use IBGE's Municipal Crop Production Survey (PAM) and Municipal Livestock Survey (PPM) for agricultural production variables. The number of rural workers is obtained through IBGE's Agricultural Census from 2006. Land use data comes 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 areas, forest and non-forest natural formation.[16]

16 Although PAM has information on crop area, PPM does not have information on pasture area. The pasture area variable 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' 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.

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 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

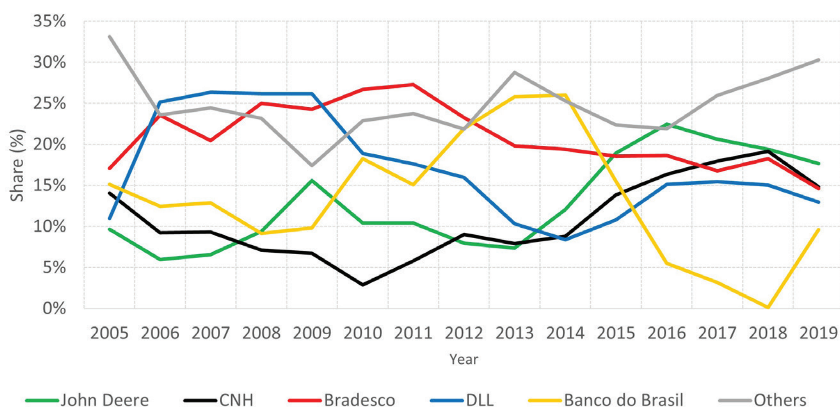
Our universe of analysis for building the instrument consists solely of BNDES rural credit for investment (henceforth referred simply as "BNDES credit") and the financial institutions that operate this credit (hereinafter simply "banks"). To illustrate the strategy, suppose Bank A has more access to 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 the participation of financial agents operating BNDES credit over time, and that market shares of these banks 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 3 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 the 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.

FIGURE 3

SHARE OF BANKS TRANSFERRING RURAL CREDIT FOR EQUIPMENT, 2005-2019



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

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. Consider the following estimating equation of interest:

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

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

In Equation (1), y_{it} is an outcome variable[18] (e.g., agricultural production) in municipality i and year t. The outcome is a function of 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 deal with unobserved determinants of the dependent variable that are correlated with BNDES rural credit for equipment lending such as reverse causality and omitted variable bias. The challenge is that municipal lending amounts are equilibrium outcomes, and estimation is susceptible to confounding supply and demand shocks.

To disentangle the common municipality (demand) effects from changes in lending supply, we isolate the component of changes in BNDES' credit lending attributed to supply factors by purging each bank's national change in BNDES' lending of its exposure to local markets (Greenstone *et al.*, 2020). To do that, we predict the change in BNDES' credit lending at the municipality level from 2006[19] 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):

$$\Delta Q_{ijt}^{B} = d_{it} + s_{jt} + e_{ijt}, \text{ for each t} = \{2006, \ldots, 2019\} \quad (2)$$

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

18 Typically, outcome variables are measured in log, but sometimes they are measured in inverse hyperbolic sine (ihs) or as shares of GDP. To simplify notation, we omit mathematical transformations from equations.

19 We have data for 2005, but we use from 2006 onward since we use lagged market-shares for the instrument.

pality. Accordingly, these municipality fixed effects provide the local demand for BNDES rural credit. The vector s_j is the financial agents fixed effects and provides the parameters of interest. They are estimates of changes in bank *j*'s supply of BNDES credit 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, financial agents fixed effects are re-centered within each year so their mean (weighted by 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 solution, defining an instrumental variable Z_{it} as a municipality-level measure of the expected rural credit supply shock:

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

Here is the estimated financial institution fixed effect from fitting equation 2 for changes in BNDES rural credit lending between consecutive years and 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, 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. d_i are municipality fixed effects and standard errors are clustered at the municipality level. The γ_t´s are the parameters of interest, the impact of the lending shocks on BNDES rural credit loans in the year of the shock.

The second stage is specified in equation 5, where y_{it} represents our dependent variables of agriculture, land use, and environmental outcomes, and 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.

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

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 tools for researchers 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 demands 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 3).

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:

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

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

In this system of equations, *j* indexes banks, so that is the shock part of the shift-share instrument, and $\bar{v}_{jt}^{\perp}$ 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 includes additional weights e_{it}, which are the lagged amount of lending provided by a bank, as explained in Section 4.1. Formally:

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

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 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 ran a robustness check in with we completed the sum of shares, creating a "missing" financial institution whose share is 1 minus the sum of all banks' shares in each municipality. The inclusion of this missing bank share does not generate 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 credit from their bank, 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 the dependent variable is BNDES rural credit for investment regressed on predicted shocks (the shift part of the shift-share instrument) interacted with year fixed effects. This is based on Borusyak *et al.* (2022)'s procedure to transform the municipal-level into a bank-level panel. 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. We use Borusyak *et al.* (2022)'s procedure to obtain 2SLS estimates, as explained in Section 4.2.

All coefficients are elasticities, the estimated impact of a 1% increase in the supply of municipal rural credit for equipment on the variables of interest.

TABLE 2

OLS AND 2SLS RESULTS

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

Notes: The table reports OLS and IV regressions of BNDES rural credit for investment on various outcomes. 2SLS estimates use Borusyak *et al.* (2022)'s procedure to transform the municipal-level into a bank-level panel and use directly the shocks as the instrument. OLS regression has 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.

Our main finding is that rural credit for equipment stimulates crop production via increasing crop productivity[20] without increasing deforestation within the same municipality. 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 and natural forests, is virtually zero.

20 Crop productivity is defined as the ratio between crop production and 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.

There is also suggestive evidence of conversion of pastures into cropland: the coefficient on pasture is negative, but not significant. Although not significant in 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 point to an increase in resource availability leading to growth in crop production, but with 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.

5.3. Heterogeneity

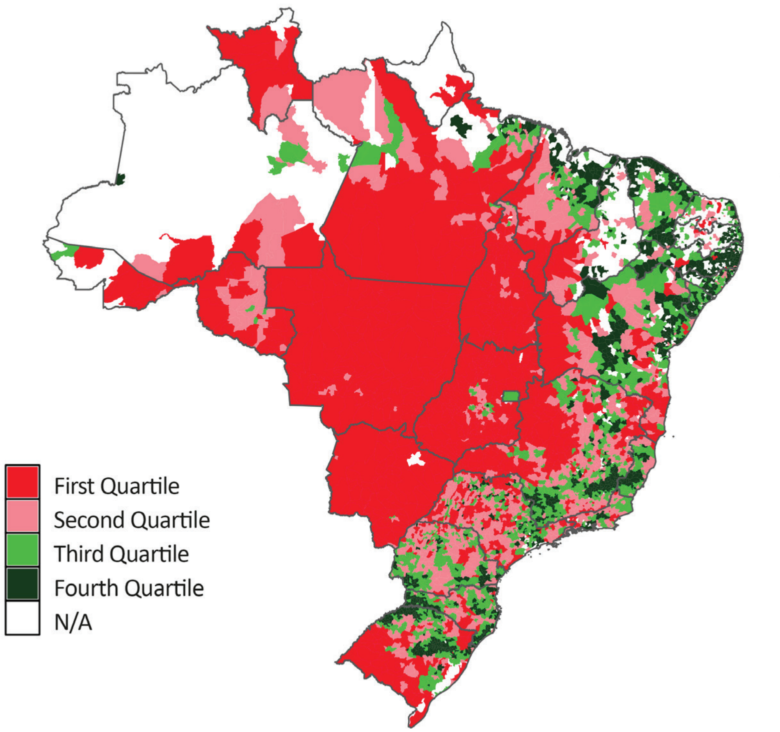
This section deepens the previous analysis in order to explore potential differences in the impact of credit for equipment in Brazil by dividing Brazilian municipalities into two types: more labor-intensive and less labor-intensive. We expect effects to be higher in magnitude in more labor-intensive 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.[21] Municipalities below the median, in turn, are deemed less labor-intensive.

21 Only municipalities with positive rural credit for equipment were considered when calculating the median.

Labor intensity is analyzed geographically in Figure 4.[22] It reveals that less labor-intensive municipalities are mainly in the North and Midwest regions. The Northeast, Southeast, and South regions show high availability of rural workers relative to the agricultural area.

FIGURE 4

DISTRIBUTION OF RURAL WORKERS OVER AGRICULTURAL 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.

Effects are indeed higher and more significant in more labor-intensive municipalities. Table 3 reports the impact 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 col-

22 The year 2006 was chosen for classification due to the availability of data from the Agricultural Census and for being the first year in the rural credit for equipment database used in this study.

umns, 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.

TABLE 3

2SLS RESULTS BY LABOR-INTENSITY MUNICIPALITY PROFILE (RURAL WORKERS PER AREA)

Dependent Variable	(1) Below median	(2) Above median	(3) First quartile	(4) Fourth quartile
Agricultural GDP (log)	0.081 (0.099)	0.151* (0.084)	0.119 (0.081)	0.287*** (0.076)
Share Agricultural GDP / Total GDP	0.012 (0.015)	0.020** (0.010)	0.014 (0.012)	0.031*** (0.008)
Crop Production (log)	0.126 (0.084)	0.074 (0.090)	0.330*** (0.071)	0.283*** (0.102)
Cattle Head (log)	0.094 (0.078)	0.048 (0.033)	0.050 (0.046)	-0.091 (0.064)
Farming area (ihs)	0.003 (0.011)	-0.002 (0.002)	-0.002 (0.014)	-0.006** (0.003)
Crop area (ihs)	0.011 (0.012)	-0.005** (0.002)	0.025** (0.012)	-0.007* (0.004)
Pasture area (ihs)	-0.003 (0.009)	0.002 (0.003)	-0.021 (0.013)	0.001 (0.004)
Forested area (ihs)	-0.003 (0.006)	0.002 (0.002)	-0.002 (0.006)	0.004** (0.002)
Crop production / Crop area (ihs)	-0.021 (0.124)	0.106 (0.125)	0.292*** (0.097)	0.356** (0.153)
Cattle head / Pasture area (ihs)	0.096 (0.069)	0.063** (0.030)	0.110** (0.053)	-0.080 (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 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 *et al.* (2022) to transform the dataset to the bank level and use directly the shift part of the shift-share as the instrument. Columns 3 and 4 repeat the same exercise with municipalities in the first and fourth quartiles of the distribution. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

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.

Most of the equipment used in agriculture is labor-saving. For example, 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. As a result, 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 restricted the analysis to credit for labor-saving equipment acquisition. Results are in Table 4.

At first, we observe that only specifications using observations above the median (column 2) or above the 75th percentile (column 4) have relatively strong first stages, making inference 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 the impact of credit for equipment varies according to municipality profiles. More labor-intensive municipalities have more significant responses in production compared to land-use variables, where 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.

TABLE 4

2SLS RESULTS FOR LABOR-SAVING EQUIPMENT BY MUNICIPALITY PROFILE ACCORDING TO THE DISTRIBUTION OF RURAL WORKERS PER AREA

Dependent Variable	(1)	(2)	(3)	(4)
	Below median	Above median	First quartile	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 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 *et al.* (2022) to transform the dataset to the bank level and use directly the shift part of the shift-share as the instrument. Columns 3 and 4 repeat the same exercise with municipalities in the first and fourth quartiles of the distribution. Standard errors are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

5.4. Robustness

As mentioned in Section 4.2, the 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 since 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 using the standard SSIV. As a result, while significant[23] 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 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. Causal identification relies on plausibly exogenous shocks on credit availability, employing recent developments of the Shift-Share literature (Borusyak *et al.*, 2022). Ad-

23 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).

ministrative 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.

TABLE 5

2SLS RESULTS - ROBUSTNESS

Dependent Variable	(1)	(2)	(3)	(4)
	SSIV	BHJ	BHJ	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 2SLS specifications in which the regressor is the BNDES rural credit for investment. Specification 1 uses the standard shift-share instrument (SSIV) with inference based on the Conditional Likelihood Ratio (CLR) Test. The instrument in the other specifications is the shock part of the shift-share (Borusyak *et al.*, 2022 – BHJ). Standard errors in specification 2 are heteroskedasticity-robust. We remove the "missing bank" used to make shares sum up to 1 in specification 4. *** p<0.01, ** p<0.05, * p<0.1.

Our main findings suggest that credit availability helps intensify crop production. 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 reveals 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.

The results indicate that credit for investment in the agricultural sector modifies producers' decisions. This credit is an effective instrument for both technological progress in agriculture and environmental conservation. Therefore, the impacts go beyond the explicit objectives of the financing lines, which are to promote the sector and expand 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 the credit policy towards greater production intensification, adoption of good practices, and sustainability can contribute to progress in economic, social, and environmental issues. From an economic standpoint, the conservation 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 removing 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.

References

ADÃO, R.;, KOLESÁR, M.; MORALES, E. Shift-share designs: theory and inference. **The Quarterly Journal of Economics**, vol.134, n.4, 1949-2010, 2019.

ANTONACCIO, L.; ASSUNÇÃO, J.; CELIDONIO, M.; CHIAVARI, J.; LOPES, C. L.; SCHUTZE, A. Ensuring Greener Economic Growth for Brazil. **Climate Policy Initiative**. 2018. Available at: https://climatepolicyinitiative.org/wp-content/uploads/2018/12/BID-Ensuring-Greener-Economic-Growth-for-Brazil.pdf. Access: 17 mar. 25.

ASSUNÇÃO, J.; BRAGANÇA, A. Pathways for Sustainable Agricultural Production in Brazil. **Climate Policy Initiative**, 2019. Available at: https://www.climatepolicyinitiative.org/publication/pathways-for-sustainable-agricultural-production-in-brazil/. Access: 17 mar. 25.

ASSUNÇÃO, J.; SOUZA, P.; FERNANDES, P.; MIKIO, S. Does credit boost agriculture? Impacts on Brazilian rural economy and deforestation. **Working Paper**, 2021. Available at: https://www.oicrf.org/-/does-credit-boost-agriculture-impacts-on-brazilian-rural-economy-and-deforestation. Access: 17 mar. 25.

BARTIK, T. J. **Who Benefits from State and Local Economic Development Policies?** W.E. Upjohn Institute, 1991. Available at: https://doi.org/10.17848/9780585223940. Access: 1 apr. 2022.

BELTON, B.; WIN, M. T.; ZHANG, X.; FILIPSKI, M. The rapid rise of agricultural mechanization in Myanmar. **Food Policy**, vol.101, n.102095, 2021. Available at: https://www.sciencedirect.com/science/article/pii/S0306919221000749. Access: 17 mar. 25.

BERGER, A. N.; MILLER, N. H.; PETERSEN, M. A.; RAJAN, R. G.; STEIN, J. C. Does function follow organizational form? Evidence from the lending practices of large and small banks. **Journal of Financial Economics**, vol.76, n.2, p.237-269, 2005. Available at: https://doi.org/10.1016/j.jfineco. Access: 1 apr. 2022.

BERNANKE, B. S.; GERTLER, M. Inside the Black Box: The Credit Channel of Monetary Policy Transmission. **Journal of Economic Perspectives**, vol.9, n.4, p.27-48, 1995. Available at: https://doi.org/10. 1257/jep.9.4.27. Acess: 1 apr. 2022.

BINSWANGER, H. Agricultural mechanization: a comparative historical perspective. **The World Bank Research Observer**, vol.1, n.1, p.27-56, 1986. Available at: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/642221468740199059/agricultural-mechanization-a-comparative-historical-perspective. Access: 17 mar. 25.

BORUSYAK, K.; HULL, P.; JARAVEL, X. Quasi-experimental shift-share research designs. **Review of Economic Studies**, vol.89, n.1, 2022.

BRAGANÇA, A.; NEWTON, P.; COHN, A.; ASSUNÇÃO, J.; CAMBOIM, C.; DE FAVERI, D.; FARINELLI, B.; PEREGO, V. M.; TAVARES, M.; RESENDE, J. *et al*. Extension services can promote pasture restoration: Evidence from brazil's low carbon agriculture plan. **Proceedings of the National Academy of Sciences**, vol.119, n.12, e2114913119, 2022.

BUSTOS, P.; CAPRETTINI, B.; PONTICELLI, J. Agricultural productivity and structural transformation: Evidence from brazil. **American Economic Review**, vol.106, n.6, p.1320-1365, 2016.

BYERLEE, D.; STEVENSON, J.; VILLORIA, N. Does intensification slow crop land expansion or encourage deforestation? **Global food security**, vol.3, n.2, p.92-98, 2014.

CARREIRA, I.; COSTA, F.; PESSOA, J. P. The deforestation effects of trade and agricultural productivity in brazil. **Journal of Development Economics**, vol.167, 103217 2024.

DA MATA, D.; DOTTA, M.; LOBO, T. Technological progress and climate change: Evidence from the agricultural sector. **SSRN**, 2023. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4358828. Access: 17 mar. 25.

DAUM, T., & BIRNER, R. Agricultural mechanization in Africa: Myths, realities and an emerging research agenda. **Global food security**, vol.26, n.100393, 2020. Available at: https://www.sciencedirect.com/science/article/pii/S221191242030047X. Access: 17 mar. 25.

DIAS, M.; ROCHA, R.; SOARES, R. R. Down the river: Glyphosate use in agriculture and birth outcomes of surrounding populations. **The Review of Economic Studies**, vol.90, n.6, p.2943-2981, 2023. Available at: https://doi.org/10.1093/restud/rdad011. Access: 17 mar. 25.

EMERICK, K.; DE JANVRY, A.; SADOULET, E.; DAR, M. H. Technological innovations, downside risk, and the modernization of agriculture. **American Economic Review**, vol.106, n.6, p.1537-1561, 2016.

GANDOUR, C. Why Is Protecting the Amazon Important? **Climate Policy Initiative**, 2019. Available at: https://www.climatepolicyinitiative.org/wp-content/

uploads/2020/07/Factsheet-Por-que-proteger-a-Amazonia-FINAL-EN.pdf. Access: 17 mar. 25.

GARCIA, A. **The environmental impacts of agricultural intensification.** Technical Note n.9. Rome: SPIA, 2020. Available at: https://iaes.cgiar.org//sites/default/files/pdf/Environmental%20Impacts%20of%20Ag%20Intensification%20TN9_July2020.pdf. Access: 17 mar. 25.

GOLDSMITH-PINKHAM, P.; SORKIN, I.; SWIFT, H. Bartik instruments: What, when, why, and how. **American Economic Review**, vol. 110, n.8, p.2586-2624, 2020.

GREENSTONE, M.; MAS, A.; NGUYEN, H.-L. Do credit market shocks affect the real economy? Quasi-experimental evidence from the great recession and "normal" economic times. **American Economic Journal: Economic Policy**, vol. 12, n.1, p. 200-225, 2020.

HAYAMI, Y.; RUTTAN, V. W. Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960. **Journal of Political Economy**, vol.78, n.5, p.1115–1141, 1970.

HESS, S.; JAIMOVICH, D.; SCHÜNDELN, M. Environmental effects of development programs: Experimental evidence from west african dryland forests. **Journal of Development Economics**, vol.153, 102737, 2021.

JAYACHANDRAN, S. How economic development influences the environment. **Annual Review of Economics**, vol. 14, n.1, p.229-252, 2022.

MANO, Y.; TAKAHASHI, K.; OTSUKA, K. Mechanization in land preparation and agricultural intensification: The case of rice farming in the Côte d'Ivoire. **Agricultural Economics**, vol.51, n.6, p.899-908, 2020.

MOREIRA, M. J. A conditional likelihood ratio test for structural models. **Econometrica**, vol.71, n.4, p.1027-1048, 2003.

NGUYEN, H.-L. Q. Do Bank Branches Still Matter? The Effect of Closings on Local Economic Outcomes. **Unpublished**, 2014.

PROJECT MAPBIOMAS. Collection 6.0 of Brazilian Land Cover and Transitions by Municipality, 2020. Available at: http://mapbiomas.org/. Access: 1 apr. 2022.

SANT'ANNA, A. A. Land inequality and deforestation in the Brazilian amazon. **Environment and Development Economics**, vol.22, n.1, p.1-25, 2017.

SANT'ANNA, A. A.; FERREIRA, F. M. R. Crédito Rural: da especulação à produção. **Visão do desenvolvimento**. Brasília: Secretaria de Assuntos Econômicos, vol.11, n.30, p.6.

SOUZA, P. SANT'ANNA, A.; MACHADO, L.; INTROPIDI, B.; VOGT, P. Credit for Investments in Brazilian Agriculture and the Role of the Brazilian

Development Bank. **Climate Policy Initiative**, 2022. Available at: https://www.climatepolicyinitiative.org/wp-content/uploads/2021/12/Credit-for-Investments-in-Brazilian-Agriculture-and-the-Role-of-the-Brazilian-Development-Bank.pdf. Access: 17 mar. 25.

STEVENSON, J. R.; VILLORIA, N.; BYERLEE, D.; KELLEY, T.; MAREDIA, M. Green revolution research saved an estimated 18 to 27 million hectares from being brought into agricultural production. **Proceedings of the National Academy of Sciences**, vol. 110, n.21, p.8363-8368, 2013.

SZERMAN, D.; ASSUNÇÃO, J. J.; LIPSCOMB, M.; MOBARAK, A. M. Agricultural productivity and deforestation: Evidence from Brazil. **Discussion Paper**, 2022. Available at: https://elischolar.library.yale.edu/egcenter-discussion-paper-series/1091/. Access: 17 mar. 25.