Replication Project:

"A Matter of Time: An Impact Evaluation of the Brazilian National Land Credit Program" by Helfand, Sielawa, & Singhania (2019)

Virginia Callison (vwc28), Gemma Del Rossi (gld42), Juan Vergara (jmv235), and Pradhyumna Wagle (pw382)

Dyson School of Applied Economics and Management

AEM 6120: Applied Econometrics

Professor Brian Dillon

December 18, 2021

Contributions by Group Member:

Virginia Callison

Organized initial group responsibilities. Wrote the coding for descriptive statistics tables (Table 1) and formatted the table for easier visuals. Contributed to consolidating coding into a single file. Together with Gemma, wrote Section 1 below, and contributed to other sections as needed. Reviewed final document for consistency, grammar, and formatting before submission.

Gemma Del Rossi

Wrote the code for the probit models (Table 2). Wrote Section 1 with Virginia, portions of the summary of the replication results with Juan, and wrote the analysis of project challenges. Helped with table formatting. Reviewed final document for consistency, grammar, and formatting before submission.

Juan Vergara

Contributed to summarizing the method, the data, and the findings of the study. Wrote Section 2 of the replication results regarding the interpretation of treatment effects, and a portion of analysis of project challenges with Gemma. Reviewed final document for consistency, grammar, and formatting before submission.

Pradhyumna Wagle

Cleaned the data: converted raw data to panel data, created new and dummy variables, and removed outliers for analysis and executing the models. Wrote the codes for Difference in Difference model (Table 3). Helped Virginia with debugging for Table 1. Compiled all codes to a single annotated .do file.

Section 1: Study overview

Research Question

What is the impact of Programa Nacional de Credito Fundiario (the market-assisted land reform program in Brazil) on agricultural production and earned income, taking into account the effects of additional years of land ownership?

Relevance of the Topic

The program is worth researching because of the possible impacts on agricultural yields and rural development, areas of interest for policymakers concerned with rural poverty rates, and how to improve the livelihoods of the poor. In addition, few rigorous evaluations of land reform programs have been conducted. The paper contributes to the overall literature on land reform programs by conducting an in-depth analysis on the effectiveness of the CPR program on rural poverty alleviation through Programa Nacional de Credito Fundiario (PNCF) through a difference-in-differences (DID) econometric approach.

Sample Data

The study uses panel data from 2006 and 2010, from an interview-based survey that was designed and implemented by the authors. All data was focused on the rural poverty alleviation credit (CPR) portion of the PNCF. The authors focused on farmers in the northeast of Brazil, where poverty is more prevalent. Participants were selected randomly from members of different beneficiary associations; groups which formed in order to apply for the PNCF. Six members were selected from each association. The panel was broken into two groups: beneficiaries who received land and pipeline non-beneficiaries who had been deemed eligible for the program but had not yet made a land purchase. The individuals in the pipeline non-beneficiary group represent the control group in the analysis, whereas those who received land and credit (beneficiaries) are the treated individuals.

Econometric Specification

The study suffered from significant attrition (people dropping out of the program). Though there were 1,335 individuals in the original sample, the balanced panel only had 763 members. Further, selection bias was a high risk in this study, as participants were highly motivated to receive funding through the PNCF. To account for this issue the authors employ the following strategies: 1.) the selection of participants was randomized in both the treatment (beneficiary) and control (pipeline) groups, 2.) a DID model was run with fixed effects at the municipal and individual level, accounting for endogeneity between municipal/individual characteristics and the treatment, 3.) To address potential heteroskedasticity across projects, all models in the paper were run with standard errors clustered at the project code or municipality level (276 clusters), depending on data availability. Further robustness checks included creating a proxy for eagerness and running a beneficiary to beneficiary comparison.

Findings

We will now discuss the main models and findings of the papers. First, the authors ran a basic DID model with the treatment effect being if the participant acquired land. They then ran a DID with time period dummies (less than 3 years, 4 years, and 5-6 years) and fixed effects (FE) at the municipal and individual level to determine in what year following the program the participants started to see the benefits of enrolling. Further, Helfand et al. (2019) ran a probit model to see the rates of spillover between treatment and control - that is, pipeline non-beneficiaries receiving land over the course of the study.

The DID models with municipal and individual FE’s confirm the results of previous studies that there are significant and positive effects to receiving land, but only after a period of time (4 years). The results follow the same trend regardless of whether it's municipal or individual FE. For the preferred individual FE model, the authors find that "coefficients on being a landowner for three years or less are all positive, but none are statistically significant. The coefficients on being a landowner for four years are all positive and significant at ten percent" (p.7). Holding all else constant, the authors find that there is a return of R$373.83 in years 4-5 and R$710.67 to agricultural production (significant at the 10% and 1%, respectively). The probit model was run to investigate spillover effects between the treated and control groups. Helfand et al. (2019) fail to find any significant impact of earned income and agricultural production (and addition to control variables) in determining whether control participants moved into the treatment group.

Finally, the authors run a series of robustness checks to ensure the validity of their findings. We do not address any robustness checks in our replication portion of the paper as they are beyond the scope of this econometrics class. When looking at heterogeneity, the authors find that agricultural production does not vary by farm size or sex. Robustness checks include estimating attrition weights and a proxy for eagerness of enrollment, calculating Lee bounds, and estimating the program effects using repeated cross-sections of data instead of the panel data. A key takeaway is that while the findings are robust, "beneficiaries face a trade-off between current welfare and asset accumulation" (pg. 16). So while there are significant improvements in earned income and agricultural production, much of the income gains farmers may experience appears to be put back into loan repayments for the program. The authors conclude that the loan payment grace periods should be made longer so the participants can have time for projects to mature and experience greater financial returns before repaying the loans. They also recommend greater TA to assist in the development of these projects. Overall, Helfand et al. (2019) conclude that PNCF does indeed provide a pathway out of poverty, and provide several policy suggestions to further strengthen the program.

Section 2: Replication of Tables 1, 2, and 3

Many of the replication results below differ slightly from the results reported in the paper. We attribute the majority of these differences to undisclosed data manipulation/data cleaning on the part of the authors. For example, the authors indicate that they removed outliers for agricultural production above $28,000 and earned income above $15,000. They also removed two individuals which had missing data, but we were unable to locate and replicate this last portion of the analysis. Also, some variables were hard to interpret given limited description and inconsistent naming. The table states Daily Agricultural Wage but the variables similar were aggregate daily wage and daily wage in a micro-regional level. Thus, our observations used differ slightly from those reported in the paper, which translates through to our results.

Table 1: Descriptive Statistics

Table 1
Descriptive statistics by beneficiary status

	N	Pipeline NB		Beneficiary		p-value
		Mean	SE	Mean	SE	
Agricultural Production	562, 202	952.28	110.86	789.38	60.78	0.18
LO 0-3 Years	100			792.27	88.86	0.69
LO 4 Years	315			979.02	88.01	0.00
LO 5-6 Years	147			1055.15	176.48	0.00
Earned Income	562, 202	1558.86	117.12	1474.24	66.18	0.52
LO 0-3 Years	100			1241.46	116.75	0.52
LO 4 Years	315			1406.08	107.55	0.00
LO 5-6 Years	147			1793.16	196.31	0.00
Individual Characteristics						
Age		37.64	0.87	36.46	0.50	0.23
Sex		0.71	0.03	0.86	0.01	0.00
White		0.19	0.03	0.18	0.02	0.59
Married		0.82	0.03	0.79	0.02	0.29
Urban		0.28	0.03	0.21	0.02	0.04
Years of Schooling		4.03	0.22	4.36	0.16	0.28
Years of Experience		23.37	0.93	22.56	0.54	0.45
Social Capital Variables						
Position Held		0.42	0.03	0.56	0.02	0.00
Frequency of Meeting		2.29	0.06	2.16	0.04	0.06
Trust		2.80	0.03	2.70	0.02	0.01
Individual Agricultural Variables						
Technical Assistance		0.04	0.01	0.07	0.01	0.16
PRONAF		0.32	0.03	0.25	0.02	0.09
Local Agricultural Variables						
Yield of Corn		1.18	0.03	0.89	0.02	0.00
Daily Agricultural Wage		12.34	0.91	12.42	0.04	0.05

Note, due to the limitations of Stata code and the complexity of this table, we generated each group of results independently, then manually formatted the table above in excel (see appended code for details). This was far simpler and saved a significant amount of time in comparison to coding Stata to return the table as formatted in the paper.

The table compares the mean values of the variables listed in the right-most column between the pipeline non-beneficiaries and the beneficiaries of the program. The first two variables, agricultural production and earned income, were described with respect to the entire sample at the baseline and with respect to the length of land ownership identified in the follow-up period. The p-values for the total sample generally represent a t-test of the differences in means of the pipeline and beneficiary groups. However, for the length of land ownership, the p-values compare the land ownership means against the mean of the beneficiary group as a whole. Like the authors, our results find that the agricultural production and earned income are significant when the beneficiary has owned land between 5-6 years.

With the exception of the results in yellow, our results generally follow the descriptive statistics the authors present under Table 1. We were unable to exactly match the descriptive statistics results in magnitude from Helfand et al. (2019), an issue likely related to the data cleaning concerns discussed above. Most notably, we also found that land ownership between 4-5 years was statistically significant in both agricultural production and earned income. This deviates from the paper, which only finds significance at 5-6 years of land ownership.

Table 2. Probit model results

Table 2

Probits for the probability of acquiring land between the baseline and follow-up periods

	(1)	(2)	(3)	(4)
Agricultural Production	-0.000017		-0.000061	
	(0.00005)		(0.00008)	
Earned Income		-0.000073		-0.000044
		(0.00004)		(0.00009)
N	324	324	324	324
State FE	N	N	Y	Y
Individual Capital Controls	N	N	Y	Y
Social Capital Controls	N	N	Y	Y
Individual Agricultural Controls	N	N	Y	Y
Local Agricultural Controls	N	N	Y	Y

In order to test the possibility that unobservable factors within earned income and agricultural production may have influenced enrollment in the program, the research team ran a probit regression aiming to predict the probability that a pipeline non-beneficiary individual acquired land between the baseline and the follow-up period. Our probit regression is aligned with the outcome from the study, showing that earned income and agricultural production are not statistically significant predictors of movement into the treatment group. Results are shown in Table 2.

Although our replication results matched in magnitude, the signs differed and we were unable to exactly match the probit results from Helfand et al. (2019). Potential causes of this discrepancy are the data cleaning issues as previously mentioned, and the difference in sample size between our probit model and the study's probit model. Our sample included only those who the authors identified as "late beneficiaries," or those who switched from a pipeline non-beneficiary to a beneficiary over the course of the study period. There were 162 individuals who did switch, which mirror's Helfand et al. (2019) results, but fewer individuals in our overall sample (n = 324 compared to n = 352). It was unclear in the paper exactly who the authors included in the probit model but this was our best guess. Further, we clustered the results by project code as suggested by Helfand et al. (2019) except in model 3 because clustering by municipality produced smaller standard errors.

Table 3. The DID model results for program effect on agricultural production with municipal FE and individual FE.

Table 3
Program effects on agricultural production

	DD-Mun. FE				DD-Indiv. FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Binary						
Time*Status	440.55*	441.18*	478.17*	472.29*	431.46*	430.45*
	(200.02)	(204.97)	(220.84)	(225.55)	(178.39)	(180.02)
Panel B: Duration of Treatment						
LO 0-3 Years	297.86	290.34	334.59	332.79	332.79	229.94
	(247.47)	(247.41)	(265.97)	(267.51)	(267.51)	(236.84)
LO 4 Years	364.19	360.13	392.96	388.52	338.52	300.16
	(211.41)	(217.76)	(228.52)	(230.35)	(230.35)	(163.80)
LO 5-6 Years	698.136**	718.708**	765.446**	765.446**	758.405**	638.505**
	(234.59)	(239.73)	(254.25)	(254.25)	(260.83)	(212.04)
N	1528.00	1526.00	1522.00	1522.00	1528.00	1528.00
Mean of control group	952.28	952.28	952.28	952.28	952.28	952.28
Individual controls	N	Y	Y	Y	N	N
Social Capital Controls	N	N	Y	Y	N	N
Individual Agricultural Controls	N	N	N	Y	N	N
Local Agricultural Controls	N	N	N	Y	N	Y

For interpretation reasons, we will mostly focus on the model with individual fixed effects because it is the one considered superior by Helfand et al. (2019). The results for the DID models with municipal fixed effects are shown in the first four columns of Table 3, meanwhile, columns five and six show the result for the model with individual fixed effects. The dummy variables time, status, and municipal fixed effects were included in all the specifications. Time*Status is the Difference in Difference variable calculated using (t*Ben), where the value is

1 if time period = 1 and beneficiary status is = 1. This implies that the individual has acquired land in the follow-up period. Helfand et al. (2019) have mentioned that errors were clustered at the project level of majority of pipeline non-beneficiaries and beneficiaries and at the municipality level. There are roughly 276 clusters, increasing the standard error but preserving significance. It is not clear why the number of clusters is large which translates to fewer observations within each cluster. That could result in poor performance of the model.

The difference between the first four columns is the addition of control variables for: individual demographic data in (2), baseline social capital in (3), and both individual and local agriculture in (4); column one is the raw model without any additional control variables. On the other side, the difference between specifications five and six is the addition of individual agricultural control variables in (6). Individual agricultural control refers to the technical assistance and PRONAF loans assigned to the farmer during the period monitored; daily agricultural wage and corn yield are the variables included in agricultural control.

Regarding the results, we can observe that the treatment effect on agricultural production is not statistically significantly different from zero for all specifications, up to the fifth year of the program. After the fourth year, the difference-in-differences models suggest a meaningful difference in earnings between beneficiaries and non-beneficiaries within the range of R$638 to R$765, depending on the control variables included. This translates as a positive impact of the program on agricultural production as a result of being a beneficiary. Overall, our replication results are very similar to those of Helfand et al. (2019). There are some differences in magnitude where our regression results slightly over or underestimate the value of the explanatory variable and time dummies. However, we attribute these differences to the changes in sample size in the 6 models due to potential data cleaning errors on our end. Despite these differences, our replication model shows the same trend as the study's model: that there is no significant impact on agricultural production until the participant has been enrolled in the program for at least 5 years, controlling for individual effects, social capital, and agricultural variables.

Section 3: Analysis of Project Challenges

Overall, our results aligned strongly with the findings from Helfand et al. (2019), although they were not a complete match. Given our in-depth exploration of the author's data, we do believe that their methods match with their results, but there are certain small inconsistencies/lack of clarity around certain issues which make it challenging to replicate their results exactly. For example, the data cleaning presented some difficulties. Using the methods specified in the paper, outliers have been removed. But the paper vaguely states that some individuals were dropped due to missing values that are not specified, so we could not exactly replicate the data cleaning process. This is also the reason for inconsistency in the total number of observations for some models. Additionally, it is stated that the first three years were grouped together and a model was estimated that suggested no statistical significance difference across the first three years but it was difficult to check this significance as the model is not explained well. Furthermore, as the authors mentioned there was significant attrition (and potential spillover) over the course of the study. While they addressed these concerns in the robustness checks of the paper, understanding the full effect of attrition in the data did prove challenging for us in cleaning the data and generating the correct variables due to the presence of multiple variables relating to the participants' status. It is possible that there were subtleties Helfand et al. (2019) used in their data cleaning process to address attrition and spillover that were not clearly laid out in the paper, which could have contributed to our replication results not being identical. Despite these challenges, we were still able to replicate the paper's results to achieve similar findings, which speaks to the strength, robustness, and validity of Helfand et al.'s (2019) paper structure and clear methodology.

While the overall structure and methodology of the paper were clear, there are several suggestions we have to improve the clarity of the data and make replication of this study easier. First, we suggest that the authors include a detailed variable key in addition to the dataset, as there were challenges in understanding what each variable meant as coded. For example, the authors use daily agricultural wages in much of their analysis. However, they do not specify if the variable used was w_agd (daily agricultural wages by individual) or dayw_mr (the daily agricultural wages at the micro-region level). Further, the authors could reduce redundant variables; there were several variables regarding participation status, and it was difficult to know which one to use to generate the most accurate results. Finally, we suggest that the authors use an open access data or code repository such as GitHub, which is starting to become a "best practice" in the field of econometrics. By putting code and data in a repository can ensure the papers' results are exactly replicable; people can check to make sure the methodology, data cleaning, and coding stands up to academic rigor and matches the results presented in the study.

References

Helfand, S. M., Sielawa, V. H., & Singhania, D. (2019). A matter of time: An impact evaluation of the Brazilian National Land Credit Program. *Journal of Development Economics*, *141*. https://doi-org.proxy.library.cornell.edu/10.1016/j.jdeveco.2019.06.004