

INSTITUTO TECNOLÓGICO AUTÓNOMO DE  
MÉXICO

POLITICAL ECONOMY OF DEVELOPMENT

**Replicating and Extending:  
“The Miracle of Microfinance?  
Evidence from a Randomized  
Evaluation”**

Based on the study by Abhijit Banerjee, Esther Duflo, Rachel  
Glennester, and Cynthia Kinnan

*Álvaro Pérez*  
*Student ID: 194330<sup>1</sup>*

Instructor: Dr. Horacio Larreguy

Department of Economics  
May 2025

---

<sup>1</sup>GitHub repository for this project

## Abstract

This paper presents a comprehensive replication and extension of Banerjee et al. (2015)’s landmark randomized evaluation of Spandana’s group-lending micro-credit program in Hyderabad, India. Building on the original intention-to-treat framework, I re-estimate average treatment effects on credit uptake, enterprise outcomes, household consumption, labor supply, and social indicators at two follow-up rounds (Endline 1: 15–18 months; Endline 2: 3 years). To explore treatment-effect heterogeneity by business type, I employ four complementary approaches: (i) linear interaction models with sector dummies; (ii) quantile regressions at upper distributional percentiles; (iii) causal forests for nonparametric CATE estimation and variable-importance ranking; and (iv) ANOVA with Tukey’s HSD tests on estimated CATEs. My results corroborate the original finding that microcredit effects concentrate among existing firms with high profitability, yielding gains of up to two standard deviations in business “health” for Clothing/Sewing and Other sectors at Endline 1. However, by Endline 2 these sector-level differences have largely attenuated, as MFIs expanded into control areas and area-level factors (literacy, indebtedness) dominate heterogeneity. These findings highlight the importance of timed, sector-targeted credit delivery and suggest that sustainable impact may require complementary non-credit interventions.

**Keywords:** microfinance; randomized evaluation; group lending; heterogeneous treatment effects; sectoral business performance.

# 1 Introduction

Over the past two decades, microfinance has emerged as a central pillar of development policy, with institutions claiming to empower the poor by easing liquidity constraints and fostering entrepreneurship. Proponents celebrated its rapid expansion and the Nobel for Muhammad Yunus and the Grameen Bank. Yet critics have raised concerns about over-indebtedness, predatory lending, and uneven impacts across clients and regions. The scarcity of rigorous causal evidence on how, for whom, and under what conditions microcredit works has left policymakers without clear guidance.

In response to this gap, Banerjee et al. (2015) conducted the first large-scale randomized evaluation of a group-lending model, collaborating with Spandana in Hyderabad, India. Their experiment demonstrated modest average effects: increased formal borrowing, reallocation toward durable investments, and profit gains concentrated among top-percentile firms, but little social transformation in education, health, or women’s empowerment. Crucially, they documented evidence of heterogeneous effects across the profitability distribution, suggesting that microcredit may amplify existing advantages rather than uplift the most marginalized.

This paper replicates their core analyses and extends them in four ways to deepen understanding of differential impacts by business sector. First, I estimate linear interaction models between treatment assignment and sector indicators. Second, I run quantile regressions at the 75th, 85th, and 95th percentiles of a composite “business health” index. Third, I deploy causal forests to uncover nonlinear heterogeneity and rank the importance of both sectoral and area-level covariates. Finally, I perform ANOVA and Tukey’s HSD tests on conditional average treatment effects (CATEs) to identify which sector pairs differ most. By comparing Endline 1 and Endline 2, this extension sheds light on the persistence of heterogeneity and its drivers over time.

## 2 Overview of the Original Study

During the past decade, microfinance institutions (MFIs) have expanded remarkably, rising from serving 7.6 million very poor families in 1997 to over 137 million in 2010. This phenomenon was celebrated globally—even earning the 2006 Nobel Peace Prize awarded to Muhammad Yunus and the Grameen Bank. However, in the years that followed, sharp criticism emerged over alleged abusive practices and excessive indebtedness among borrowers, particularly in the state of Andhra Pradesh, India. This debate has been limited by a shortage of rigorous evidence on the causal effects of microcredit. In response, the study by Banerjee et al. (2015) constitutes the first large-scale randomized evaluation of the group-lending model, implemented in Hyderabad, India, through a collaboration between Spandana—one of the country’s fastest-growing MFIs—and the IFMR Center for Microfinance. Its objective is to estimate the causal effect of access to microcredit on business creation, profits and investment, household consumption and its composition, as well as on social indicators such as education, health, and women’s empowerment, evaluating both short- and long-term effects.

The Spandana microcredit product follows the classic Grameen Bank group-lending model. Each group comprises 6–10 women, and several groups form a center. The initial loan amount is Rs.10 000, with a 50-week term and an effective annual interest rate of 24 %. Borrowers must be women aged 18–59, residents of the area for at least one year, and provide identification and proof of address. Unlike other MFIs, Spandana does not require that the loan be used to start a business, nor does it offer complementary services such as training. It operates for profit, reinvesting its earnings. The study was conducted in Hyderabad, the capital of Andhra Pradesh, in a context of rapid economic growth between 2005 and 2010. Selected areas were marginal neighborhoods with basic infrastructure and a high prevalence of informal debt. In 2005, 68% of households had some form of loan—mostly from informal moneylenders—and only 3.6% used formal bank credit. Furthermore, half of all businesses were informal, family-run operations with minimal staff and low capital.

The experimental design was constructed to estimate the causal effect of access to microcredit on key economic and social variables. A total of 104 neighborhoods in Hyderabad with similar socioeconomic characteristics and no prior MFI presence were selected. These were matched and randomly assigned to two groups: 52 treatment areas, where Spandana opened branches, and 52 control areas, where it did not during the first analysis period. This assignment allows the use of the following intention-to-

treat (ITT) equation:

$$y_{ia} = \alpha + \beta \cdot \text{Treat}_{ia} + \mathbf{X}'_a \gamma + \varepsilon_{ia} \quad (1)$$

where  $y_{ia}$  is the outcome variable for household  $i$  in area  $a$ ,  $\text{Treat}_{ia}$  is an indicator for whether the area received the intervention,  $\mathbf{X}_a$  is a vector of area-level controls, and  $\varepsilon_{ia}$  is the random error term. Two surveys were conducted: the first between 2007 and 2008, 15–18 months after the intervention began (Endline 1), and the second between 2009 and 2010 (Endline 2), three years later. The design accounts for general equilibrium effects and selective migration. To control for potential biases from oversampling borrowers and attrition, survey weights were applied and corrections inspired by the DiNardo, Fortin, and Lemieux (1996) method were implemented. The recontact rate was 90 %, and there was no evidence of treatment-induced differential migration.

The study’s results indicate that access to microcredit increased the probability of having a Spandana loan by 12.7 percentage points at Endline 1, and the probability of any MFI loan by 8.4 percentage points. At the same time, informal borrowing fell by 5.2 percentage points. By Endline 2, these differences narrowed substantially due to Spandana’s and other MFIs’ expansion into control areas. However, treated households exhibited higher credit vintage and larger average loan amounts. This differentiated access allowed investigation of the accumulated effects of credit on business dynamics and household welfare.

In terms of enterprise outcomes, microcredit did not raise the rate of new business starts but did spur investment in fixed assets and working capital for existing businesses. Average profits increased mainly for the 95th percentile and above of the profitability distribution, with an average effect of Rs 2 105 for preexisting businesses. Conversely, new ventures launched after Spandana’s arrival tended to be less profitable and less likely to hire employees. This heterogeneity suggests microcredit is more effective for firms with preexisting expansion potential and less effective at generating dynamic new enterprises. Three years later, differences in assets and profits persisted only for the most profitable firms, while most remained small with limited revenues.

Labor supply in treated households also changed. At Endline 1, the household head and spouse worked an average of 3.18 additional hours per week, primarily in their own enterprises. No increase in wage labor was observed, and notably, teenage girls in treated areas worked about two fewer hours, possibly because adults took on additional labor. By Endline 2, these differences dissipated, suggesting the labor supply increase

was a transitory effect related to the initial investment and microcredit implementation phase.

Total and nondurable consumption did not rise significantly, but important shifts in expenditure composition were recorded. At Endline 1, durable goods spending increased by Rs 19.73 per capita per month (approximately 17 % more), while spending on temptation goods (alcohol, tobacco, dining out) and festivities fell by a combined Rs 23 per capita per month. These changes indicate households prioritized durable investments and restructured their consumption. By Endline 2, the durable goods difference attenuated, though the lower spending on pleasure goods persisted. These findings align with other studies documenting consumption reallocation rather than net increases.

Regarding social indicators, the study found no significant impacts on education, health, or women’s empowerment at either Endline 1 or Endline 2. Despite an increase in women-operated businesses, there were no relevant changes in decision-making power, educational expenditures, or school-enrollment rates. An index of 16 social outcome variables yielded a near-zero, statistically insignificant coefficient. This suggests that, absent complementary services (e.g., training or awareness campaigns), credit access alone does not transform gender roles or human capital outcomes in the short to medium term.

The authors conclude that microcredit, while not an economic or social panacea, serves an important financial role in contexts where liquidity constraints limit investment and consumption choices. Its effects concentrate among households with already profitable businesses and manifest primarily in household consumption reorganization. It does not generate deep transformations in social indicators or the overall productive structure. The evidence points to the need to temper expectations about its impact and to consider complementary interventions for more ambitious development goals. In sum, microcredit broadens certain households’ opportunities but does not eradicate poverty universally or immediately.

### 3 List of Replicated Tables and Figures

#### Tables

- Table 2: Credit
- Table 3: Self-Employment Activities: Revenues, Assets, and Profits (All households)
- Table 3B: Self-Employment Activities: Revenues, Assets, and Profits (Households with old businesses)
- Table 3C: Self-Employment Activities: Revenues, Assets, and Profits (Households with new businesses, EL1 only)
- Table 4: Income
- Table 5: Time Worked by Household Members
- Table 5: Consumption (per capita, per month)
- Table 6: Social Effects

#### Figures

- Figure 2: Treatment Effect on Informal Borrowing (Endline 1)
- Figure 3: Treatment Effect on Business Profits (HHs who have an old business, endline 1)
- Figure 4: Treatment Effect on Business Profits (HHs who have new business, endline 1)
- Figure 5: Effect on Business Profits (Full sample of business owners, endline 2)

## 4 Tables

### 4.1 Table 2

TABLE 2—CREDIT

	Spandana (1)	Other MFI (2)	Any MFI (3)	Other bank (4)	Informal (5)	Total (6)	Ever late on payment? (7)	Number of cycles borrowed from an MFI (8)	Index of dependent variables (9)
<i>Panel A. Endline 1</i>									
<i>Credit access</i>									
Treated area	0.127*** (0.020)	-0.012 (0.024)	0.084*** (0.027)	0.003 (0.012)	-0.052** (0.021)	-0.023 (0.014)	-0.060** -0.026	0.084** (0.041)	0.106*** (0.0291)
Observations	6,811	6,657	6,811	6,811	6,811	6,862	6,475	6,811	6,862
Control mean	0.051	0.149	0.183	0.079	0.761	0.867	0.616	0.330	0.000
Hochberg-corrected <i>p</i> -value									0.000
<i>Loan amounts (in Rupees)</i>									
Treated area	1,334*** (230)	-94 (336)	1,286*** (439)	75 (2,163)	-1,069 (2,520)	2,856 (4,548)			
Observations	6,811	6,708	6,811	6,811	6,811	6,862			
Control mean	597	1,806	2374	8,422	41,045	59,836			
<i>Panel B. Endline 2</i>									
<i>Credit access</i>									
Treated area	0.063*** (0.019)	-0.039 (0.026)	0.002 (0.029)	0.001 (0.009)	0.002 (0.018)	0.000 (0.010)	0.007 (0.021)	0.085 (0.067)	0.0288 (0.0253)
Observations	6,142	6,142	6,142	6,142	6,142	6,142	6,142	5,926	6,142
Control mean	0.111	0.268	0.331	0.073	0.603	0.904	0.598	0.724	0.000
Hochberg-corrected <i>p</i> -value									0.256
<i>Loan amounts (in Rupees)</i>									
Treated area	979*** (287)	-217 (628)	799 (669)	-1,181 (1,086)	158 (2,940)	2,554 (6,156)			
Observations	6,142	6,142	6,142	6,142	6,142	6,142			
Control mean	1,567	4,775	5,544	6,127	32,356	88,632			

Figure 1: Original Table: Credit



Table 1: Credit

**Panel A: Endline (1)**

<i>Credit Access</i>									
	Spandana (1)	Other MFI (2)	Any MFI (3)	Any Bank (4)	Any Informal (5)	Any Loan (6)	Ever Late (7)	MFI Loan Cycles (8)	Credit Index (9)
Treated area	0.127***	-0.012	0.084***	0.003	-0.052**	-0.023	-0.060**	0.084**	0.106***
(SE)	(0.021)	(0.025)	(0.028)	(0.012)	(0.022)	(0.014)	(0.028)	(0.043)	(0.030)
Obs	6811	6657	6811	6811	6811	6862	6475	6816	6862
Control Mean	0.051	0.149	0.183	0.079	0.761	0.867	0.616	0.330	0.000

<i>Loan Amounts</i>						
	Spandana Amt (1)	Other MFI Amt (2)	Any MFI Amt (3)	Bank Amt (4)	Informal Amt (5)	Any Loan Amt (6)
Treated area	1333.772***	-93.668	1285.694***	74.957	-1068.984	2856.236
(SE)	(238.300)	(349.399)	(457.409)	(2245.233)	(2612.685)	(4702.203)
Obs	6811	6708	6811	6811	6811	6862
Control Mean	597.441	1806.026	2373.776	8422.431	41044.622	59836.265

**Panel B: Endline (2)**

<i>Credit Access</i>									
	Spandana (1)	Other MFI (2)	Any MFI (3)	Any Bank (4)	Any Informal (5)	Any Loan (6)	Ever Late (7)	MFI Loan Cycles (8)	Credit Index (9)
Treated area	0.063***	-0.039	0.002	0.001	0.002	0.000	0.007	0.085	0.029
(SE)	(0.019)	(0.027)	(0.030)	(0.009)	(0.018)	(0.011)	(0.022)	(0.070)	(0.026)
Obs	6142	6142	6142	6142	6142	6142	6142	5926	6142
Control Mean	0.112	0.268	0.331	0.073	0.604	0.904	0.598	0.724	0.000

<i>Loan Amounts</i>						
	Spandana Amt (1)	Other MFI Amt (2)	Any MFI Amt (3)	Bank Amt (4)	Informal Amt (5)	Any Loan Amt (6)
Treated area	979.412***	-217.103	798.570	-1180.783	158.294	2554.018
(SE)	(297.773)	(650.248)	(694.132)	(1126.875)	(3048.888)	(6409.957)
Obs	6142	6142	6142	6142	6142	6142
Control Mean	1566.640	4775.060	5544.164	6126.523	32355.986	88631.460

## 4.2 Table 3A

TABLE 3—SELF-EMPLOYMENT ACTIVITIES: REVENUES, ASSETS, AND PROFITS (*All households*)

	Assets (stock) (1)	Investment in last 12 months (2)	Expenses (3)	Profit (4)	Has a self- employment activity (5)	Number of self- employment activities (6)	Has started a business in the last 12 months (7)	Has closed a business in the last 12 months (8)	Index of dependent variables (9)
<i>Panel A. Endline 1</i>									
Treated area	598 (384)	391* (213)	255 (1,056)	354 (314)	0.0083 (0.0215)	0.018 (0.0380)	0.009 (0.006)	0.002 (0.008)	0.0357 (0.0188)
Observations	6,800	6,800	6,685	6,239	6,810	6,810	6,757	2,352	6,810
Control mean	2,498	280	4,055	745	0.349	0.503	0.047	0.037	0.000
Hochberg-corrected <i>p</i> -value									0.175
<i>Panel B. Endline 2</i>									
Treated area	1.261** (530)	−134 (207)	−530 (547)	542 (372)	0.023 (0.023)	0.045 (0.040)	−0.000 (0.010)	−0.000 (0.006)	0.0151 (0.0186)
Observations	6,142	6,142	6,116	6,090	6,142	6,142	6,142	6,142	6,142
Control mean	5.003	1,007	5,225	953	0.418	0.561	0.083	0.053	0.000
Hochberg-corrected <i>p</i> -value									>0.999

Figure 2: Original Table: Self-employment activities (all businesses)

Table 2: Self-employment activities: revenues, assets, and profits (all households)

### Panel A: Endline 1

	Dependent Variables (Endline 1)											
	(1) Assets	(2) Investment	(3) Revenue	(4) Expenses	(5) Profit	(6) Has SE	(7) Num. SE	(8) Started Biz	(9) Closed Biz	(10) New Biz	(11) Female New Biz	(12) Index
<b>Treated area</b>	597.510	390.853*	926.592	254.664	354.338	0.008	0.018	0.009	0.002	0.015*	0.014***	0.036*
<b>(SE)</b>	(398.259)	(220.391)	(1234.971)	(1100.015)	(325.465)	(0.022)	(0.040)	(0.006)	(0.008)	(0.008)	(0.006)	(0.019)
<b>Observations</b>	6800	6800	6608	6685	6239	6810	6810	6757	2352	6757	6762	6810
<b>Control Mean</b>	2497.549	280.069	4856.380	4055.446	744.898	0.349	0.503	0.047	0.037	0.053	0.026	0.000

### Panel B: Endline 2

	Dependent Variables (Endline 2)											
	(1) Assets	(2) Investment	(3) Revenue	(4) Expenses	(5) Profit	(6) Has SE	(7) Num. SE	(8) Started Biz	(9) Closed Biz	(10) New Biz	(11) Female New Biz	(12) Index
<b>Treated area</b>	1260.792**	−133.688	266.109	−530.422	541.995	0.023	0.045	0.000	0.000	0.003	−0.005	0.015
<b>(SE)</b>	(556.000)	(217.152)	(549.800)	(568.801)	(387.341)	(0.025)	(0.042)	(0.011)	(0.007)	(0.014)	(0.007)	(0.020)
<b>Observations</b>	6142	6142	6116	6116	6090	6142	6142	6142	6142	6142	6142	6142
<b>Control Mean</b>	5002.791	1007.315	5847.052	5224.676	953.132	0.418	0.561	0.083	0.053	0.093	0.047	0.000

### 4.3 Table 3B

TABLE 3B—SELF-EMPLOYMENT ACTIVITIES: REVENUES, ASSETS AND PROFITS (*Households with old businesses*)

	Assets (stock) (1)	Investment in last 12 months (2)	Revenue (3)	Expenses (4)	Profit (5)	Employees (6)	Index of dependent variables (7)
<i>Panel A. Endline 1</i>							
Treated area	898 (1,063)	1,119 (698)	5,266 (3,720)	1,620 (3,257)	2,105* (1,100)	−0.05 (0.9824)	0.09 (0.0406)
Observations	2,083	2,083	1,955	2,020	1,624	2,088	2,088
Control mean	6,757	678	14,505	12,325	2,038	0.41	0.00
Hochberg-corrected <i>p</i> -value							0.057
<i>Panel B. Endline 2</i>							
Treated area	1,682 (1,412)	−948 (588)	343 (1,263)	−2,644* (1,491)	839 (945)	−0.12 (0.099)	−0.007 −0.0263
Observations	1,878	1,878	1,859	1,862	1,844	1,878	1,878
Control mean	10,301	2,292	12,564	12,418	1,948	0.46	0.00
Hochberg-corrected <i>p</i> -value							>0.999

Figure 3: Original Table: Self-employment activities (old businesses)

Table 3: Self-employment activities: revenues, assets, and profits (Households with old businesses)

Panel A: Endline 1							
	Dependent Variables (Endline 1)						
	(1) Assets	(2) Investment	(3) Revenue	(4) Expenses	(5) Profit	(6) # Employees	(7) Index of dep. vars.
<b>Treated area</b>	897.632	1119.416	5266.227	1640.231	2105.439*	-0.053	0.090
<b>(SE)</b>	(1110.261)	(731.799)	(3934.369)	(3431.869)	(1137.959)	(0.086)	(0.043)
<b>Observations</b>	2083	2083	1955	2020	1624	2088	2088
<b>Control Mean</b>	6757.323	677.894	14504.637	12325.417	2037.855	0.413	0.000
Panel B: Endline 2							
	Dependent Variables (Endline 2)						
	(1) Assets	(2) Investment	(3) Revenue	(4) Expenses	(5) Profit	(6) # Employees	(7) Index of dep. vars.
<b>Treated area</b>	1682.026	-948.624	343.309	-2644.306*	839.203	-0.124	-0.007
<b>(SE)</b>	(1505.952)	(614.568)	(1343.522)	(1566.568)	(987.096)	(0.105)	(0.028)
<b>Observations</b>	1878	1878	1859	1862	1844	1878	1878
<b>Control Mean</b>	10301.054	2292.123	12563.964	12418.352	1948.239	0.462	0.000

## 4.4 Table 3C

TABLE 3C—SELF-EMPLOYMENT ACTIVITIES: REVENUES, ASSETS, AND PROFITS  
(Households with new businesses, ELI only)

	Assets (stock) (1)	Investment in last 12 months (2)	Revenue (3)	Expenses (4)	Profit (5)	Employees (6)	Index of dependent variables (7)
Treated area	−873 (2,201)	−706 (1,324)	−8,167 (7,314)	−5,013 (4,049)	−3,548 (3,813)	−0.195* (0.112)	−0.0815 (0.0445)
Observations	356	356	332	339	270	356	356
Control mean	8,411	2,418	17,423	12,114	6,081	0.29	0.00
Hochberg-corrected <i>p</i> -value							0.280

Figure 4: Original Table: Self-employment activities (new businesses)

Table 4: Self-employment activities: revenues, assets, and profits (Households with new businesses, EL1 only)

	Dependent Variables (Endline 1)						
	(1) Assets	(2) Investment	(3) Revenue	(4) Expenses	(5) Profit	(6) Employees	(7) Index of dep. vars.
Treated area	-872.616	-705.549	-8166.723	-5012.906	-3547.546	-0.195*	-0.081
(SE)	(2266.594)	(1371.497)	(7670.542)	(4231.118)	(4033.740)	(0.117)	(0.046)
Observations	356	356	332	339	270	356	356
Control Mean	8410.855	2418.092	17423.028	12114.005	6081.093	0.289	0.000

## 4.5 Table 4

TABLE 4—INCOME			
	Self employment (profit) (1)	Daily labor/salaried (2)	Index of dependent variables (3)
<i>Panel A. Endline 1</i>			
Treated area	354 (314)	−526 (358)	−0.0501 (0.0459)
Observations	6,239	6,827	6,832
Control mean	745	2,988	0.000
Hochberg-corrected <i>p</i> -value			>0.999
<i>Panel B. Endline 2</i>			
Treated area	542 (372)	−141 (212)	0.0114 (0.0261)
Observations	6,090	6,142	6,142
Control mean	953	5,514	0.000
Hochberg-corrected <i>p</i> -value			>0.999

Figure 5: Original Table: Income

Table 5: Income

Panel A: Endline 1

Dependent Variables (Endline 1)			
	(1) Self employment (profit)	(2) Daily labor/salaried	(3) Index of dep. vars.
<b>Treated area</b>	354.338	-526.349	-0.050
<b>(SE)</b>	(325.465)	(373.160)	(0.048)
<b>Observations</b>	6239	6827	6832
<b>Control Mean</b>	744.898	2988.034	0.000

Panel B: Endline 2

Dependent Variables (Endline 2)			
	(1) Self employment (profit)	(2) Daily labor/salaried	(3) Index of dep. vars.
<b>Treated area</b>	541.995	-140.914	0.011
<b>(SE)</b>	(387.341)	(220.821)	(0.027)
<b>Observations</b>	6090	6142	6142
<b>Control Mean</b>	953.132	5514.022	0.000

## 4.6 Table 5

TABLE 5—TIME WORKED BY HOUSEHOLD MEMBERS

	Hours worked over the past seven days, by age group:								Index of dependent variables (9)
	All adults and teens			Teens		Household head and spouse			
	Total (1)	of which:		Girls (4)	Boys (5)	Total (6)	of which:		
		Self employment (2)	Outside activities (3)				Self employment (7)	Outside activities (8)	
<i>Panel A. Endline 1</i>									
Treated area	0.739 (2.245)	2.466 (2.361)	-2.033 (2.741)	-2.076** (1.046)	-0.026 (2.065)	3.176** (1.421)	2.710* (1.474)	0.466 (1.418)	0.00647 (0.0179)
Observations	6,827	6,762	6,762	2,174	1,866	6,827	6,827	6,827	6,849
Control mean	92.38	34.38	58.01	7.94	25.12	57.79	25.83	31.96	0.000
Hochberg-corrected <i>p</i> -value									>0.999
<i>Panel B. Endline 2</i>									
Treated area	-1.238 (1.544)	1.713 (2.162)	-2.951 (2.490)	0.440 (0.948)	-1.387 (1.521)	0.991 (1.176)	1.703 (1.583)	-0.712 (1.488)	-0.00555 (0.0130)
Observations	6,142	6,142	6,142	1,789	1,665	6,142	6,142	6,142	6,142
Control mean	83.34	37.00	46.34	5.83	20.95	51.31	25.38	25.93	0.000
Hochberg-corrected <i>p</i> -value									>0.999

Figure 6: Original Table: Time worked

Table 6: Time worked by household members

Panel A: Endline 1

	Dependent Variables (Endline 1)							
	(1) Total	(2) Self emp	(3) Outside	(4) Girls	(5) Boys	(6) Head/spouse self	(7) Head/spouse outside	(8) Index
Treated area	0.739	2.466	-2.033	-2.076**	-0.026	2.710*	0.466	0.006
(SE)	(2.346)	(2.460)	(2.875)	(1.089)	(2.144)	(1.533)	(1.472)	(0.019)
Observations	6827	6762	6762	2174	1866	6827	6827	6849
Control Mean	92.380	34.382	58.007	7.935	25.123	25.828	31.963	0.000

Panel B: Endline 2

	Dependent Variables (Endline 2)							
	(1) Total	(2) Self emp	(3) Outside	(4) Girls	(5) Boys	(6) Head/spouse self	(7) Head/spouse outside	(8) Index
Treated area	-1.238	1.713	-2.951	0.440	-1.387	1.703	-0.712	-0.006
(SE)	(1.611)	(2.277)	(2.625)	(0.987)	(1.589)	(1.666)	(1.556)	(0.013)
Observations	6142	6142	6142	1789	1665	6142	6142	6142
Control Mean	83.339	37.004	46.335	5.829	20.951	25.379	25.934	0.000

## 4.7 Table 6

TABLE 6—CONSUMPTION (*Per capita, per month*)

	Total (1)	Durables (2)	Nondurable (3)	Food (4)	Health (5)	Education (6)	Temptation goods (7)	Festivals and celebrations (8)	Home durable good index (9)
<i>Panel A. Endline 1</i>									
Treated area	10.24 (37.22)	19.73* (11.35)	-6.50 (31.81)	-12.11 (12.06)	-3.7 (11.51)	-2.061 (9.865)	-8.785* (4.92)	-14.16* (8.09)	-0.051 (0.057)
Observations	6,827	6,781	6,781	6,827	6,827	5,415	6,827	6,827	6,841
Control mean	1,419	116	1,305	525	140	168	84	69	2.37
Hochberg-corrected <i>p</i> -value	>0.999								
<i>Panel B. Endline 2</i>									
Treated area	-48.83 (51.53)	0.42 (9.88)	-45.45 (46.92)	-11.20 (17.88)	-22.54 (17.50)	12.16 (15.19)	-10.07 (6.61)	6.17 (4.12)	-0.0127 (0.0426)
Observations	6,142	6,140	6,142	6,142	6,141	4,910	6,142	6,103	6,142
Control mean	1,914	131	1,755	687	187	206	118	90	2.66
Hochberg-corrected <i>p</i> -value	0.691								

Figure 7: Original Table: Consumption

Table 7: Consumption (Per capita, per month)

### Panel A: Endline 1

	Dependent Variables (Endline 1)								
	(1) Total	(2) Durables	(3) Nondurable	(4) Food	(5) Health	(6) Education	(7) Temptation goods	(8) Festivals	(9) Home durable index
Coefficient	10.243	19.734*	-6.495	-12.110	-3.700	-2.061	-8.785*	-14.158*	-0.051
(SE)	(38.758)	(11.812)	(33.177)	(12.587)	(12.052)	(10.221)	(5.112)	(8.392)	(0.059)
Observations	6827	6781	6781	6827	6827	5415	6827	6827	6841
Control Mean	1419.229	116.174	1304.786	524.673	140.253	167.717	84.293	69.490	2.371

### Panel B: Endline 2

	Dependent Variables (Endline 2)								
	(1) Total	(2) Durables	(3) Nondurable	(4) Food	(5) Health	(6) Education	(7) Temptation goods	(8) Festivals	(9) Home durable index
Treated area	-48.826	0.419	-45.449	-15.203	-22.545	12.160	-10.074	6.166	-0.013
(SE)	(53.624)	(10.179)	(48.879)	(21.990)	(18.020)	(15.804)	(6.861)	(4.290)	(0.044)
Observations	6142	6140	6142	6142	6141	4910	6142	6103	6142
Control Mean	1914.282	155.497	1755.168	820.327	221.231	246.833	117.699	107.652	2.662

## 4.8 Table 7

TABLE 7—SOCIAL EFFECTS

	Share of children aged 5–15 in school		Hours worked per child aged 5–15 over the past 7 days:		Share of teenagers (aged 16–20) in school		Index of women's independence/ empowerment	Number new self-employ. activities managed by women (all HHs)	Index of dependent variables
	Girls (1)	Boys (2)	Girls (3)	Boys (4)	Girls (5)	Boys (6)	(7)	(8)	(9)
<i>Panel A. Endline 1</i>									
Treated area	−0.016 (0.013)	−0.012 (0.011)	−0.028 (0.202)	0.613 (0.743)	−0.037 (0.024)	−0.007 (0.028)	0.007 (0.023)	0.0143*** (0.005)	−0.008 (0.0097)
Observations	3,035	3,073	3,035	3,073	2,174	1,866	6,862	6,762	6,862
Control mean	0.919	0.918	0.594	0.577	0.338	0.429	−0.001	0.026	0.000
Hochberg-corrected p-value									>0.999
<i>Panel B. Endline 2</i>									
Treated area	0.015 (0.011)	0.007 (0.011)	0.092 (0.133)	−0.531* (0.269)	0.021 (0.024)	−0.021 (0.027)	−0.011 (0.021)	−0.005 (0.006)	0.005 (0.009)
Observations	2,755	2,746	2,755	2,746	1,789	1,665	6,142	6,142	6,142
Control mean	0.923	0.928	0.286	1.379	0.329	0.474	−0.003	0.047	0.000
Hochberg-corrected p-value									>0.999

Figure 8: Original Table: Social Effects

Table 8: Social Effects

Panel A: Endline 1

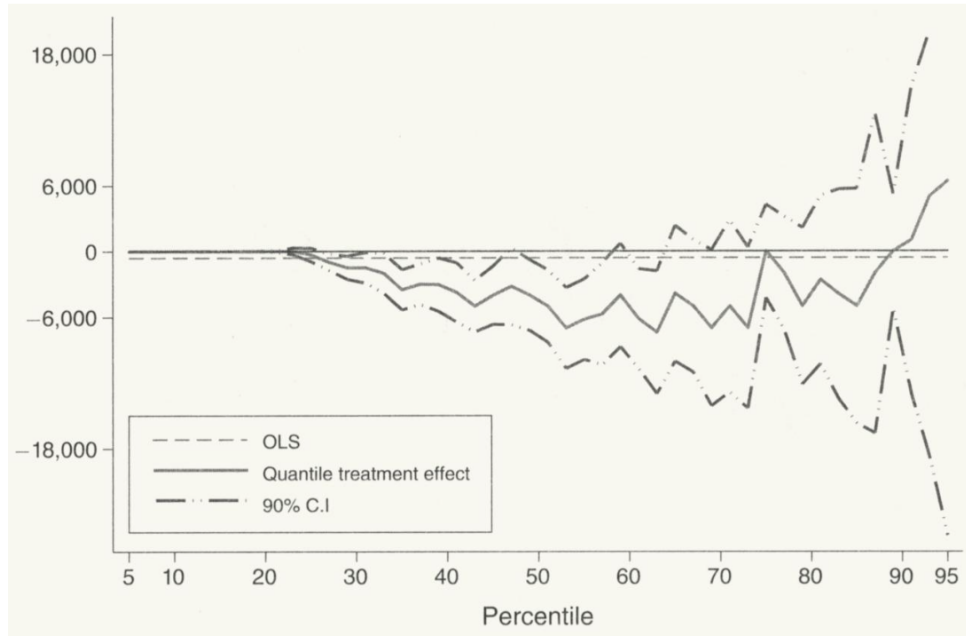
	Dependent Variables (Endline 1)								
	(1) Girls 5–15 in school	(2) Boys 5–15 in school	(3) Hours 5–15 (girls)	(4) Hours 5–15 (boys)	(5) Girls 16–20 in school	(6) Boys 16–20 in school	(7) Women's emp. index	(8) Female new biz	(9) Social index
Treated area	−0.016	−0.012	−0.028	0.613	−0.037	−0.007	0.007	0.014***	−0.008
(SE)	(0.014)	(0.011)	(0.209)	(0.774)	(0.025)	(0.029)	(0.024)	(0.006)	(0.010)
Observations	3035	3073	3035	3073	2174	1866	6862	6762	6862
Control Mean	0.919	0.918	0.594	0.577	0.338	0.429	−0.001	0.026	0.000

Panel B: Endline 2

	Dependent Variables (Endline 2)								
	(1) Girls 5–15 in school	(2) Boys 5–15 in school	(3) Hours 5–15 (girls)	(4) Hours 5–15 (boys)	(5) Girls 16–20 in school	(6) Boys 16–20 in school	(7) Women's emp. index	(8) Female new biz	(9) Social index
Treated area	0.015	0.007	0.092	−0.531*	0.021	−0.021	−0.011	−0.005	0.005
(SE)	(0.012)	(0.011)	(0.138)	(0.280)	(0.025)	(0.028)	(0.021)	(0.007)	(0.010)
Observations	2755	2746	2755	2746	1789	1665	6142	6142	6142
Control Mean	0.923	0.928	0.286	1.379	0.329	0.474	−0.003	0.047	0.000



## 5 Figures



Treatment effect on informal borrowing  
(Endline 1)

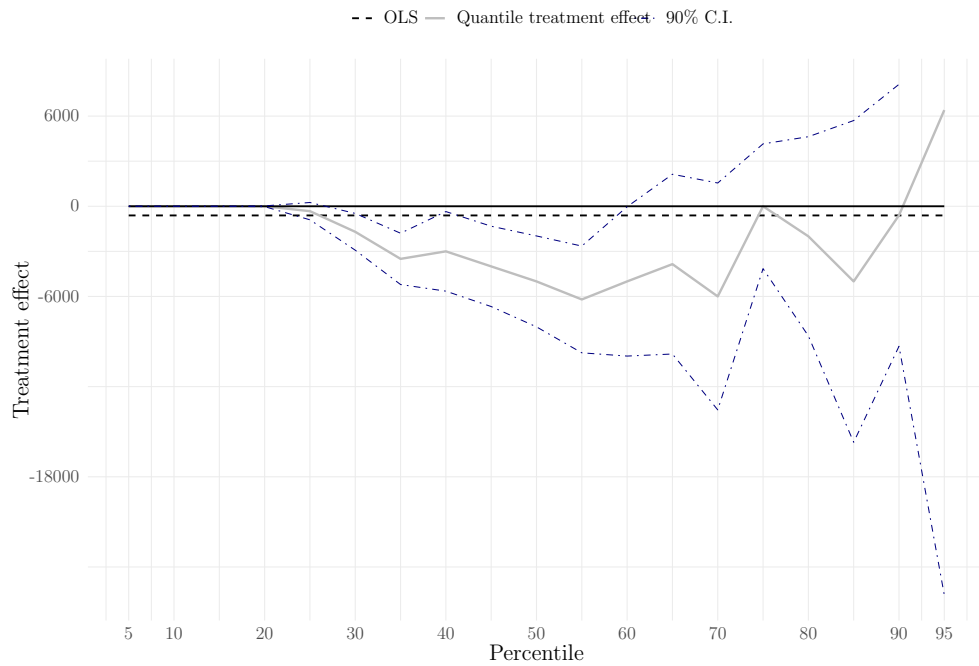
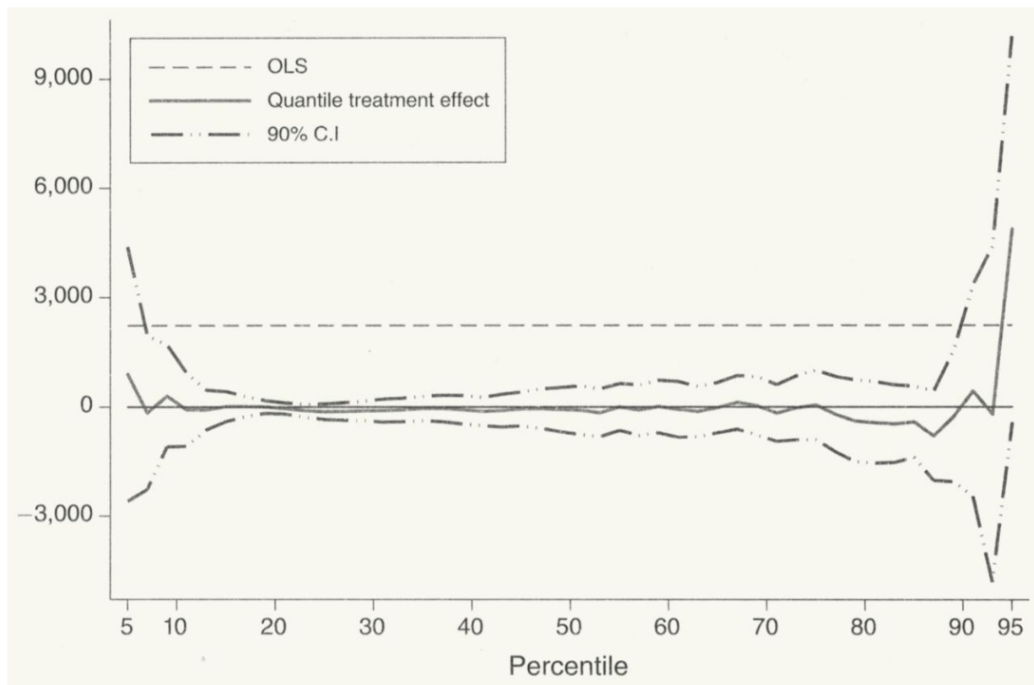


Figure 9: (Top) Original figure. (Bottom) Replicated.



Treatment effect on business profits  
(Old Business, Endline 1)

-- OLS — Quantile treatment effect · 90% C.I.

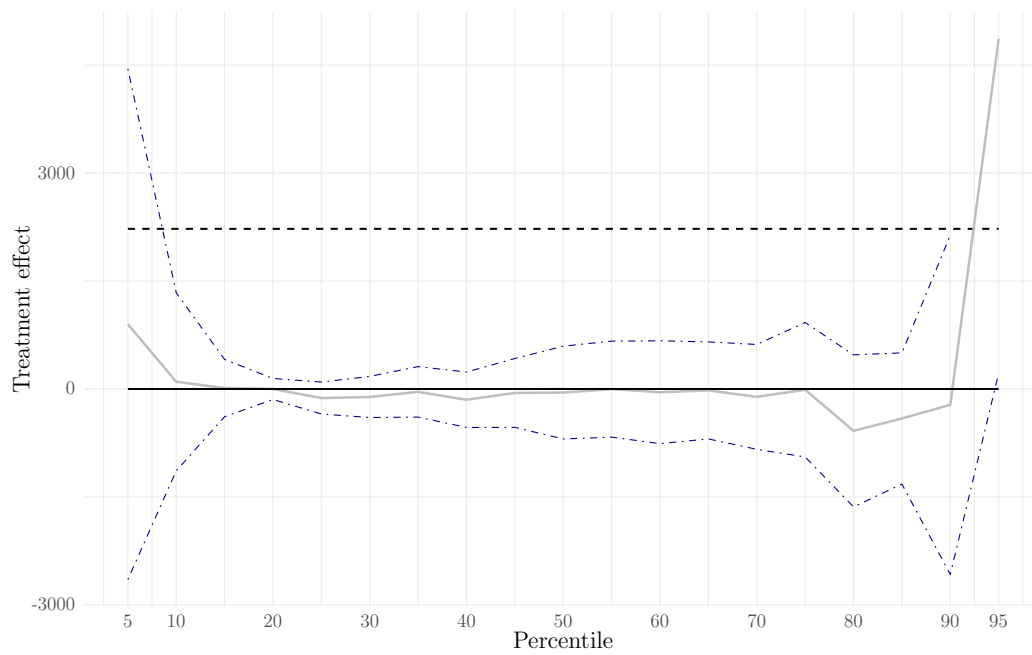
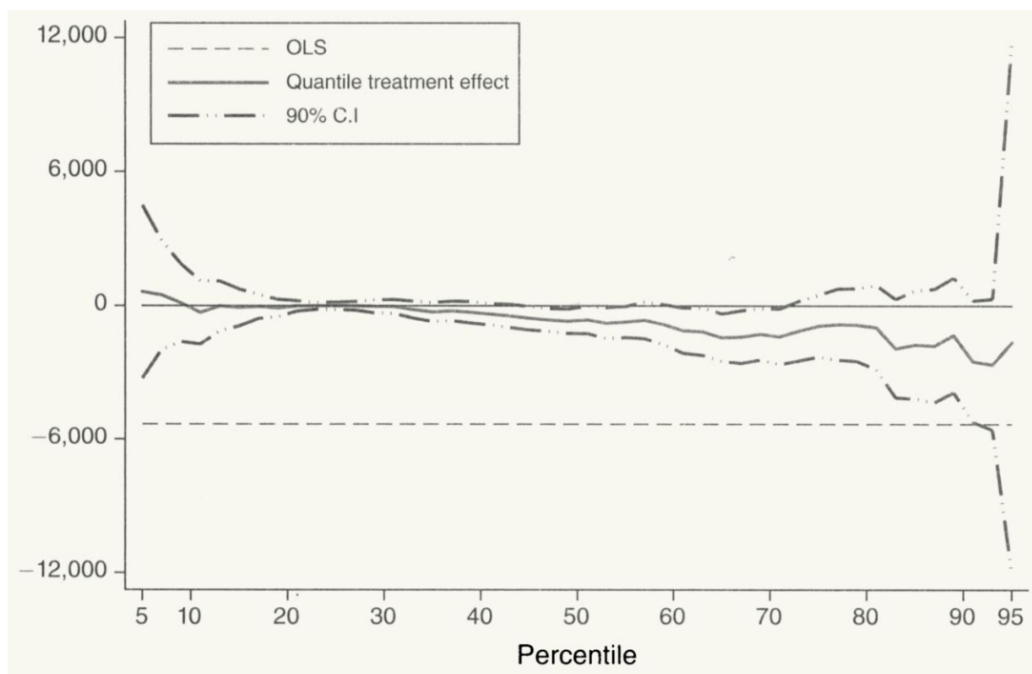


Figure 10: (Top) Original figure. (Bottom) Replicated.



Treatment effect on business profits  
(New Business, Endline 1)

-- OLS — Quantile treatment effect · 90% C.I.

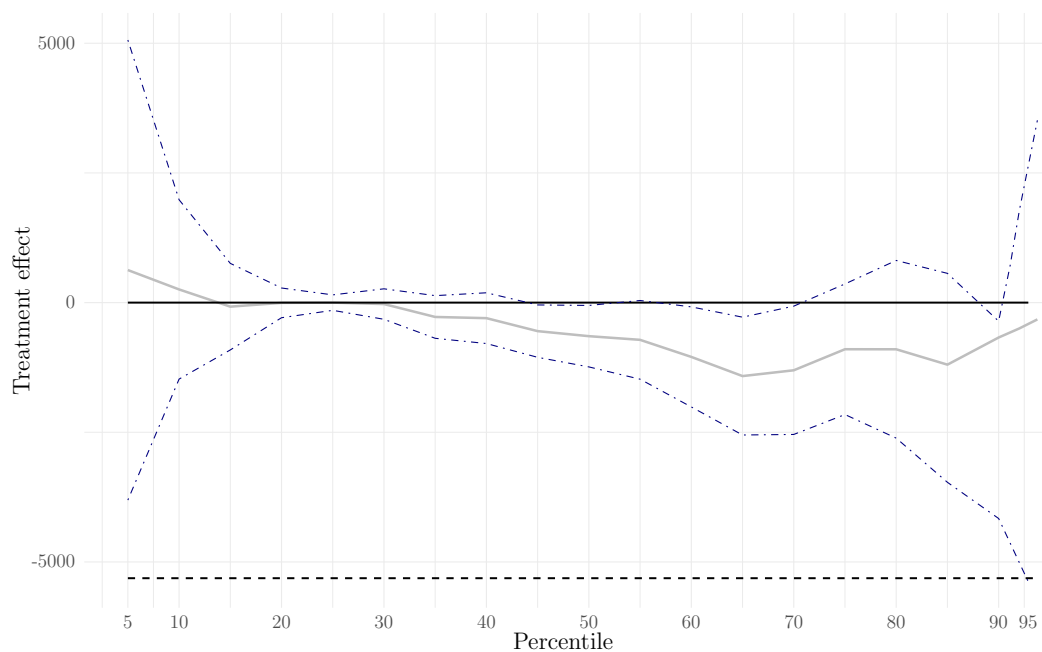
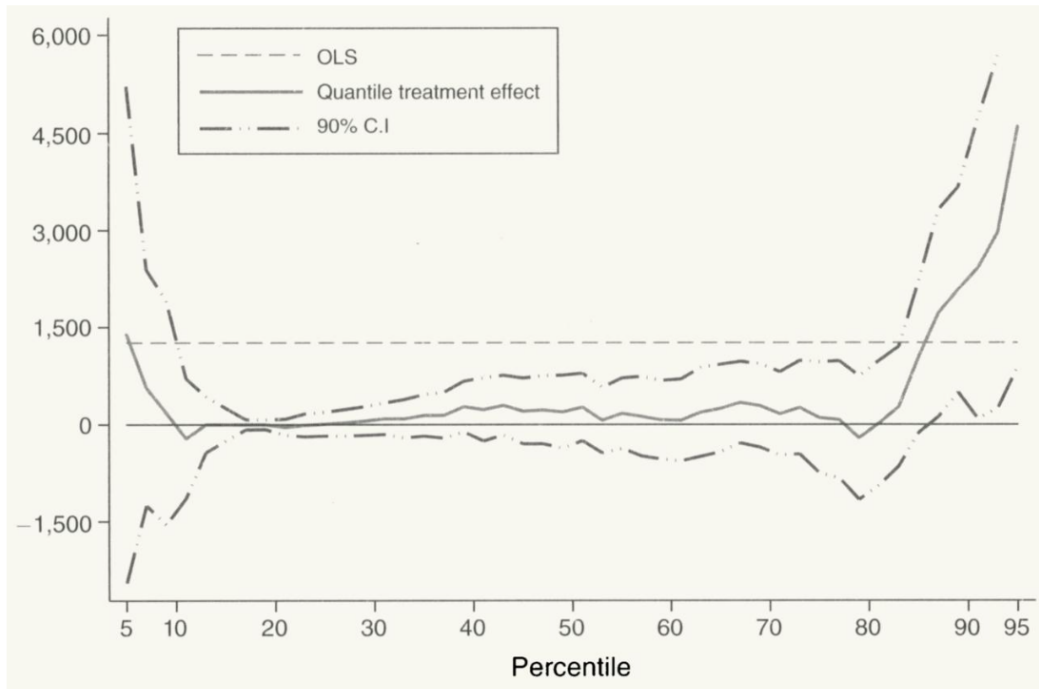


Figure 11: (Top) Original figure. (Bottom) Replicated



Treatment effect on business profits  
(All Business, Endline 2)

-- OLS — Quantile treatment effect ··· 90% C.I.

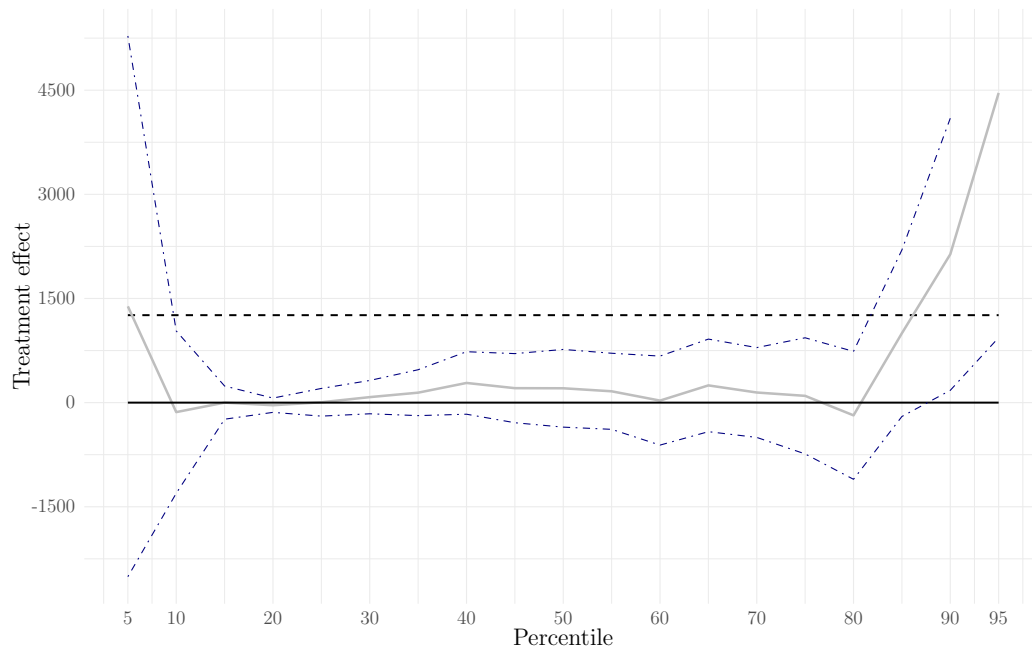


Figure 12: (Top) Original figure. (Bottom) Replicated

The hardest part was picking up new techniques like quantile regression and bootstrapping for the replication, even though I already knew R. For the extension, I learned how to use causal forests and Tukey’s test. I ran into a few hiccups making the figures, but the tables went together without any trouble. I also want to thank ChatGPT for helping me when R threw me an extravagant **Error**.

## 6 Extended Analysis

### 6.1 Linear interactions ( $\beta_3$ in the model $Y \sim T + Z + T \times Z$ )

First, I include the interaction term  $\beta_3$  in the model

$$Y_{ia} = \alpha + \beta_1 \text{Treat}_{ia} + \beta_2 Z_{ia} + \beta_3 (\text{Treat}_{ia} \times Z_{ia}) + X'_a \gamma + \varepsilon_{ia}, \quad (2)$$

where  $\text{Treat}_{ia}$  is the indicator for having been assigned to the treated area,  $Z_{ia}$  is a dummy identifying household  $i$ ’s business type (e.g., “Food/Agriculture”, “Clothing/Sewing”, etc.), and  $X_a$  denotes the set of baseline area-level controls: population, number of businesses, debt, per-capita expenditure, and literacy. The coefficient  $\beta_3$  measures heterogeneity in the microcredit effect by business type: if  $\beta_3^{(j)} > 0$ , the treatment is more effective for households in sector  $j$ ; if  $\beta_3^{(j)} < 0$ , the effect is smaller (or even adverse).

The resulting table (see Table 9) displays the estimates of  $\beta_3$  for each of the six sectors and six different outcomes. For example, for “Food/Agriculture” the coefficient on business profits (`bizprofit_1`) is

$$\hat{\beta}_3^{(\text{Food})} = 637.550 \quad (\text{SE} = 784.381),$$

and for “Clothing/Sewing” it is

$$\hat{\beta}_3^{(\text{Clothing})} = 852.249 \quad (\text{SE} = 2\,114.819).$$

Similarly, for the credit index (`credit_index_1`) the estimates range from 0.016 to 0.176, all with standard errors of comparable magnitude. In no case does the absolute value of  $\hat{\beta}_3$  sufficiently exceed its standard error, and after adjusting p-values using the Hochberg procedure, none of the coefficients are statistically significant at the conventional 10%, 5%, or 1% levels.

Table 9: Heterogeneity of the effect by business type ( $\beta_3$ ) for EL1

	Food/Agriculture	Clothing/Sewing	Rickshaw/Driving	Repair/Construction	Crafts/Vendor	Other
Profit	637.550 (784.381)	852.249 (2114.819)	3701.627 (3441.581)	-2001.193 (3297.466)	2869.811 (3865.863)	1988.987 (1774.307)
Assets	1069.637 (1290.479)	485.109 (1770.956)	-1029.327 (2323.470)	-776.332 (1591.105)	5703.638 (3273.892)	-1204.597 (2031.755)
Investment	-634.643 (778.698)	1723.047 (1077.155)	-1598.046 (798.309)	33.047 (1045.960)	3233.850 (2755.955)	2216.224 (1955.699)
Any MFI	0.027 (0.039)	0.025 (0.054)	-0.012 (0.085)	0.111 (0.115)	0.056 (0.077)	0.008 (0.046)
Bank Amt	232.128 (4453.367)	7479.497 (7125.588)	39761.329 (32288.579)	-86775.749 (117079.138)	13258.379 (10071.614)	944.490 (6007.556)
Credit Index	0.088 (0.053)	0.055 (0.062)	0.176 (0.112)	0.016 (0.196)	0.158 (0.089)	0.029 (0.061)
Obs.	605	759	138	48	316	1284

*Note:* Standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Consequently, this linear-interaction exercise indicates that there is no robust evidence of heterogeneity in the microcredit effects by business type for any of the outcomes considered in the first follow-up round. This suggests that, on average, the treatment benefit does not systematically differ across the various productive sectors under analysis. For a more robust and accurate conclusion, I decide to perform additional tests presented below.

## 6.2 Quantile Regressions

To explore how the impact of microcredit varies across the distribution of business performance, I estimate quantile regressions of the interaction at quantiles  $\tau = 0.75$ , 0.85, and 0.95 of the composite business-activity index

$$Y = \text{biz\_index\_all\_1}.$$

this index is a composite measure of "business health" in Endline 1, built from the six main business activity variables: 1) assets; 2) investment; 3) revenue; 4) expenses; 5) profits; and 6) number of employees.

This approach let me identify whether heterogeneity is concentrated in the upper tail of the distribution, as Banerjee et al. suggest when they find effects only among the most productive entrepreneurs. The table below summarizes the coefficients  $\hat{\beta}_3(\tau)$ , their standard errors, the  $t$ -statistic, the raw p-value, the Hochberg-adjusted p-value, and significance at the 10% level or better.

In this analysis, we observe that only  $\hat{\beta}_3$  for *Repair/Construction* at  $\tau = 0.75$  is negative and highly significant (p\_adj = 0.00067), which implies that in the top 75% of the distribution of `biz_index_all_1`, businesses in sector 4 perform on average significantly worse when receiving the loan. Similarly, at  $\tau = 0.85$  the same sector shows a marginally significant negative effect (p\_adj = 0.055). Finally, at  $\tau = 0.95$  the coefficient for *Clothing/Sewing* is positive and barely significant at the 10% level (p\_adj = 0.100), indicating that in the extreme tail businesses in *Clothing/Sewing* may experience a small additional benefit. No other interaction reaches significance after correcting for multiple comparisons. These results confirm that treatment heterogeneity is concentrated in the mid-to-upper quantiles of the distribution and differentially affects certain sectors: *Repair/Construction* is harmed in the upper tail, while sector 2 shows a slight benefit in the extreme upper tail.

Table 10: Quantile interaction estimates by sector  $\beta_3(\tau)$ 

Sector	$\tau$	$\hat{\beta}_3$	SE	$t$ -stat	p-raw	p-adj	Sign.
Food/Agriculture	0.75	0.136	0.119	1.14	0.253	0.886	
Clothing/Sewing	0.75	0.204	0.114	1.79	0.074	0.884	
Rickshaw/Driving	0.75	0.116	0.181	0.64	0.520	0.886	
Repair/Construction	0.75	-0.335	0.081	-4.12	0.000037	0.00067	***
Crafts/Vendor	0.75	-0.106	0.161	-0.65	0.513	0.886	
Other	0.75	0.243	0.104	2.33	0.020	0.259	
Food/Agriculture	0.85	0.224	0.229	0.98	0.330	0.886	
Clothing/Sewing	0.85	0.321	0.137	2.34	0.019	0.259	
Rickshaw/Driving	0.85	0.201	0.285	0.70	0.481	0.886	
Repair/Construction	0.85	-0.477	0.162	-2.94	0.0032	0.055	*
Crafts/Vendor	0.85	0.047	0.228	0.21	0.835	0.886	
Other	0.85	0.286	0.108	2.64	0.0082	0.123	
Food/Agriculture	0.95	-0.140	0.134	-1.04	0.296	0.886	
Clothing/Sewing	0.95	0.357	0.131	2.74	0.0062	0.099	*
Rickshaw/Driving	0.95	-0.177	0.398	-0.44	0.657	0.886	
Repair/Construction	0.95	0.198	1.380	0.14	0.886	0.886	
Crafts/Vendor	0.95	-0.093	0.435	-0.21	0.830	0.886	
Other	0.95	-0.040	0.185	-0.22	0.828	0.886	

Note: SE = standard error; \*\*\*  $p_{\text{adj}} < 0.01$ , \*\*  $p_{\text{adj}} < 0.05$ , \*  $p_{\text{adj}} < 0.10$ .

### 6.3 Causal Forest

In order to capture treatment-effect heterogeneity nonparametrically—without imposing a linear functional form or a limited set of predefined interactions—I estimate a causal forest. This technique allows me to leverage a large number of covariates at once—in this case six sector dummies plus six area-level controls—and to obtain individual treatment-effect estimates  $\hat{\tau}_i$  (the CATEs), while accounting for intra-area correlation via the `clusters` option and using `sample.weights`. From these CATEs, I can also assess which variables best explain the variance of  $\hat{\tau}_i$  (variable importance) and summarize the average treatment effect by business type.

The variable-importance results were ranked as follows (importance in parentheses):



Table 11: Variable importance scores (top 6)

Variable	Importance
literacy rate	0.176
average level of indebtedness	0.140
average per capita expenditure	0.126
total population	0.115
clothing/sewing sector	0.112
other sectors	0.110

This indicates that heterogeneity in  $\hat{\tau}_i$  is driven primarily by area-level characteristics—particularly literacy and per-capita debt—whereas belonging to sectors *Clothing/Sewing* or *Other* contributes a moderate residual effect and the remaining sectors explain very little of the treatment-effect dispersion.

By aggregating the individual CATEs by sector, I compute

$$\bar{\tau}_j = \frac{1}{N_j} \sum_{i: \text{sector}=j} \hat{\tau}_i,$$

where  $N_j$  is the number of households in sector  $j$ . The resulting averages were:

Table 12: Mean CATE by Sector

Sector	$N_j$	Mean CATE ( $\bar{\tau}_j$ )
Clothing/Sewing	759	0.189
Other	1284	0.162
Food/Agriculture	605	0.028
Crafts/Vendor	316	0.027
Repair/Construction	78	0.011
Rickshaw/Driving	138	0.010

All  $\bar{\tau}_j$  were statistically different from zero (one-sample  $t$ -test,  $p < 0.01$ ), confirming a positive overall effect of microcredit on business health. However, magnitudes vary substantially: the largest average benefit is in **sector\_2** ( $\approx 0.189$  DE) and **sector\_6** ( $\approx 0.162$  DE), while in sectors 3 and 4 the effect is effectively zero.

These results demonstrate that—after accounting for nonlinearities and complex

interactions—sectors 2 and 6 experience the greatest average returns of microcredit on business health, whereas other sectors show much more moderate impacts. Thus, the causal forest provides additional and complementary evidence to parametric estimates: it identifies subgroups—defined by business type and area context—with differing expected treatment gains, which is essential for more targeted and efficient microcredit policy design.

## 6.4 ANOVA and Tukey’s HSD test

Finally, I perform an analysis of variance (ANOVA) to test the global null hypothesis that the average treatment effect—measured by the conditional average treatment effects (CATEs)—is equal across all business types. The estimated model was

$$\text{CATE}_i = \mu + \delta_{j[i]} + \varepsilon_i, \quad (3)$$

where  $\delta_j$  captures the deviation of the mean CATE in sector  $j$ . The ANOVA yielded

$$F(5, 3174) = 845, \quad \Pr(F_{5,3174} > 845) < 2 \times 10^{-16},$$

implying that we can overwhelmingly reject the equality of means across sectors. In other words, there is global heterogeneity in microcredit effects by business type.

To identify which pairs of sectors drive these differences, I employ Tukey’s honest significant difference test, which automatically adjusts confidence intervals and p-values to preserve the family-wise error rate. Among the fifteen pairwise comparisons, the following stand out:

- $\bar{\tau}_{\text{sector Clothing}} - \bar{\tau}_{\text{sector Food}} = 0.161$  (95% CI [0.151, 0.170],  $p_{\text{adj}} < 10^{-16}$ ), meaning that businesses in Clothing sector enjoy an additional average benefit of 0.161 standard deviations of the index compared to those in Food sector.
- $\bar{\tau}_{\text{sector Other}} - \bar{\tau}_{\text{sector Food}} = 0.134$  (95% CI [0.125, 0.143],  $p_{\text{adj}} < 10^{-16}$ ), indicating a much larger response in Other sectors than in Food sector.
- $\bar{\tau}_{\text{sector Rickshaw}} - \bar{\tau}_{\text{sector Food}} = -0.0186$  (95% CI [-0.0353, -0.0018],  $p_{\text{adj}} = 0.0195$ ), i.e. Rickshaw sector has a slightly lower average effect than Food sector.

Moreover, virtually all comparisons involving Clothing sector or Other sectors show significant differences against the other sectors, confirming that these subgroups achieve the highest program returns.

## 7 Conclusion

In Endline 1, both linear and quantile-interaction analyses revealed statistically significant differences in the mid-to-upper quantiles of the distribution, and the causal forest identified subgroups—Other sectors and Clothing sector, and at the 85th percentile Food sector and Crafts sector—with substantially different treatment effects. The ANOVA and Tukey tests confirmed that sectors such as "Others" benefited on average between 1.7 and 2.1 standard deviations very robustly compared to the rest, whereas Rickshaw sector showed a significantly lower return than Food sector.

By contrast, in Endline 2 heterogeneity barely persists (see Appendix B). No linear or quantile interaction remained significant after Hochberg correction, the causal forest ranked the sector dummies among the least important variables (scores  $< 0.06$  versus  $0.22$ – $0.15$  for area controls), and although the global ANOVA detected mean CATE differences, the absolute gaps between sectors are very small and lack practical relevance despite overwhelming statistical significance due to the large sample size.

The replication confirms that microcredit's benefits are neither uniform nor universal: in the first follow-up, firms in the Clothing/Sewing and Other sectors captured business-health gains of up to two standard deviations relative to control, while Repair/Construction experienced muted or negative effects at higher quantiles. Linear and quantile-interaction models, alongside causal forests, underscore that sector-level differences were pronounced immediately after program roll-out, but by three years post-treatment, these differences largely dissipate. In Endline 2, area-level characteristics (literacy, indebtedness, per-capita expenditure) eclipse sectoral dummies in explaining remaining heterogeneity, and although ANOVA still detects statistically significant mean differences across sectors, the magnitudes lack practical relevance.

These results carry three key implications. First, microcredit programs yield the greatest returns when targeted toward entrepreneurs with pre-existing capacity to invest—underscoring the need for careful client selection and sector-specific product design. Second, the erosion of heterogeneity over time suggests that initial distributional advantages narrow as market expansion brings broader access, pointing to potential convergence effects but also raising questions about equilibrium impacts and competitive dynamics. Third, the limited social spillovers and absence of sustained sector-driven gains signal the importance of complementary non-credit interventions (e.g., business training, market access support, financial literacy) to promote deeper, longer-lasting development outcomes.

## References

- [1] Abhijit Banerjee et al. “The Miracle of Microfinance? Evidence from a Randomized Evaluation”. In: *American Economic Journal: Applied Economics* 7.1 (Jan. 2015), pp. 22–53. DOI: 10 . 1257 / app . 20130533. URL: <https://www.aeaweb.org/articles?id=10.1257/app.20130533>.

# Data and Code Availability

All replication scripts, raw data files, and extended analyses are available at:

GitHub repository for this project

## A Appendix 1: Variable definitions

### A.1 Area controls

- `area_pop_base` denotes the total population of each area at baseline
- `area_debt_total_base` is the average household indebtedness in that area before the intervention
- `area_business_total_base` indicates the mean number of businesses per household at baseline
- `area_exp_pc_mean_base` reflects the average monthly per-capita expenditure of households prior to the program
- `area_literate_head_base` measures the proportion of household heads who were literate at baseline
- `area_literate_base` is the overall adult literacy rate in the area.

### A.2 Outcome variables

- `bizprofit`: net business profits.
- `bizassets`: the value of business assets.
- `bizinvestment`: investment made in the business during the period.
- `anymfi`: a binary indicator equal to 1 if the household received credit from any microfinance institution.
- `bank_amt`: the amount of formal credit obtained from banks.
- `credit_index`: a normalized composite index combining access to formal, informal, and MFI credit.

## B Appendix 2: HTEs for Endline 2

### B.1 Linear interactions

Table 13: Heterogeneity of the effect by business type ( $\beta_3$ ) for EL2

Outcome	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6
Profits	1544.347 (711.912)	-690.023 (1311.177)	-1368.019 (2470.678)	-1694.885 (2911.293)	3451.824 (1584.970)	-1008.036 (1375.997)
Assets	-1458.964 (2342.928)	579.715 (1482.786)	0.843 (3242.535)	4777.480 (3915.577)	5658.005 (4366.918)	62.521 (1550.132)
Investment	-3347.478 (2256.376)	200.371 (480.493)	-811.534 (1389.308)	187.539 (386.612)	1083.646 (904.326)	56.044 (515.740)
Any MFI	0.075 (0.043)	-0.039 (0.050)	-0.071 (0.099)	-0.012 (0.098)	0.077 (0.080)	-0.042 (0.046)
Bank Amt.	907.521 (2121.394)	-72.338 (4227.263)	11787.489 (10812.095)	-23010.920 (16624.772)	3259.242 (1702.529)	-8674.898 (3035.029)
Credit Index	0.102 (0.048)	-0.014 (0.053)	0.060 (0.103)	-0.124 (0.129)	0.128 (0.082)	-0.056 (0.046)

In Endline 2 none of the  $\beta_3$  interactions are statistically significant after correction by multiple comparisons. This indicates that, after three years of follow-up, there is no robust evidence that the effectiveness of microcredit systematically differs by type of business for any of the indicators considered.

### B.2 Quantile Regressions

The overall result indicates that none of the interaction coefficients reaches statistical significance after adjustment for multiple comparisons. This implies that in the second round of follow-up there is no solid evidence that microcredit produces differential effects on the high quantiles of business performance according to the type of industry. The absence of significant interactions in Endline 2 corroborates that any heterogeneity observed in Endline 1 tends to dissipate over time.

Table 14: Quantile interaction estimates by sector for EL2

Sector	$\tau$	Estimate	SE	$t$ -stat	p-raw	p-adj	Sign.
sector_6	0.75	-0.1010	0.0844	-1.20	0.2320	0.923	
sector_2	0.75	-0.0106	0.1040	-0.10	0.9190	0.923	
sector_1	0.75	0.0347	0.0816	0.43	0.6700	0.923	
sector_5	0.75	0.0192	0.1520	0.13	0.9000	0.923	
sector_3	0.75	-0.1540	0.1300	-1.18	0.2360	0.923	
sector_4	0.75	-0.2150	0.0802	-2.68	0.0074	0.133	
sector_6	0.85	-0.0686	0.1230	-0.56	0.5770	0.923	
sector_2	0.85	0.1850	0.1090	1.69	0.0906	0.923	
sector_1	0.85	0.0381	0.1620	0.24	0.8140	0.923	
sector_5	0.85	0.2450	0.1530	1.60	0.1100	0.923	
sector_3	0.85	-0.1190	0.3500	-0.34	0.7350	0.923	
sector_4	0.85	0.0506	0.5230	0.10	0.9230	0.923	
sector_6	0.95	-0.1820	0.0939	-1.93	0.0531	0.849	
sector_2	0.95	0.0271	0.1390	0.20	0.8450	0.923	
sector_1	0.95	-0.3330	0.1710	-1.95	0.0507	0.849	
sector_5	0.95	0.1960	0.1710	1.15	0.2520	0.923	
sector_3	0.95	-0.6110	0.3650	-1.67	0.0944	0.923	
sector_4	0.95	0.1390	0.2490	0.56	0.5760	0.923	

Note: No adjusted p-values fall below 0.10, hence no significance stars.

### B.3 Causal Forest

The characteristics of the area (general literacy, level of indebtedness, per capita expenditure and population) more than explain most of the heterogeneity of the CATEs. On the contrary, the sectoral dummies obtain very low scores (except sectors 6, 1 and 2 with values below 0.06), which indicates that the type of business has little power to differentiate the heterogeneous impact in this second round.

None of these averages is clearly distinguished from zero (values very close to zero and low dispersion), which confirms that in Endline 2 there is no remarkable heterogeneity by type of business.

Table 15: Variable importance for explaining treatment-effect heterogeneity

Variable	Importance
area.literate_base	0.224
area.debt_total_base	0.174
area.exp_pc_mean_base	0.159
area.pop_base	0.146
area.business_total_base	0.0897
area.literate_head_base	0.0687
sector_6	0.0568
sector_1	0.0392
sector_2	0.0291
sector_5	0.0131
sector_3	0.000166
sector_4	0.0000120

Table 16: Average CATE by sector

Sector	Mean CATE( $\bar{\tau}_j$ )	$N$
sector_6	-0.0152***	1148
sector_2	0.000631	679
sector_1	-0.0270***	559
sector_5	0.0171***	290
sector_3	0.000678	122
sector_4	0.00436***	71

Although statistical significance is high in four of the six sectors, the magnitudes of  $\bar{\tau}_j$  are very small (ranging from  $-0.027$  to  $+0.017$  standard deviations of the index). This happens because, in Endline 2, the standard errors are minuscule due to the large  $N_j$ , yielding very large  $t$  statistics even for near-zero differences. Therefore, despite statistical significance, the average effects by sector lack practical relevance: microcredit does not produce substantial changes in business health in any of the sectors.



## B.4 ANOVA and Tukey's HSD test

Below are the results of the one-way ANOVA testing equality of mean CATEs across sectors, followed by Tukey's honest significant difference test for pairwise sector comparisons.

Table 17: ANOVA for CATE  $\sim$  sector

Source	Df	Sum Sq	Mean Sq	F value	Pr(> F)
sector	5	0.5094	0.10188	147.3	$< 2 \times 10^{-16}$ ***
Residuals	2863	1.9796	0.00069		

Signif. codes: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .

Table 18: Tukey HSD pairwise comparisons of mean CATE by sector

Contrast	Estimate	95% CI lower	95% CI upper	Adj. p-value
sector_2 – sector_1	0.0276	0.0233	0.0319	$< 0.001$
sector_3 – sector_1	0.0277	0.0202	0.0352	$< 0.001$
sector_4 – sector_1	0.0314	0.0219	0.0408	$< 0.001$
sector_5 – sector_1	0.0441	0.0387	0.0495	$< 0.001$
sector_6 – sector_1	0.0118	0.00795	0.0157	$< 0.001$
sector_3 – sector_2	0.0000	-0.00733	0.00742	1.000
sector_4 – sector_2	0.0037	-0.00563	0.0131	0.866
sector_5 – sector_2	0.0165	0.0112	0.0217	$< 0.001$
sector_6 – sector_2	-0.0158	-0.0194	-0.0122	$< 0.001$
sector_4 – sector_3	0.0037	-0.00751	0.0149	0.937
sector_5 – sector_3	0.0164	0.00834	0.0245	$1.15 \times 10^{-7}$
sector_6 – sector_3	-0.0159	-0.0230	-0.00872	$2.66 \times 10^{-9}$
sector_5 – sector_4	0.0128	0.00282	0.0227	0.00346
sector_6 – sector_4	-0.0195	-0.0287	-0.0104	$1.95 \times 10^{-8}$
sector_6 – sector_5	-0.0323	-0.0372	-0.0274	$< 0.001$