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THE IMPACT OF MICROFINANCE ON WOMEN'S PRODUCTIVITY: EVIDENCE FROM HAWASSA CITY, ETHIOPIA

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ABSTRACT

Background: Microfinance has been identified as a key component of poverty alleviation and gender equity policies in sub-Saharan Africa, but there is a lack of rigorous evidence that links access to credit with enterprise-level productivity outcomes for women entrepreneurs in urban Ethiopian settings.
Objective: The objective of this study is to estimate causal impact of microfinance access on the productivity of women's enterprises in Hawassa City, Ethiopia, and to investigate whether the provision of integrated business training services can enhance such impacts.
Methods: This study employed primary survey data from 384 women entrepreneurs (213 treated and 171 control group members). Propensity Score Matching (PSM) using three different algorithms: nearest-neighbour (NNM), kernel (KBM) and radius (RM) methods, accounted for observable selection bias. Endogenous Switching Regression (ESR) also accounted for unobservable heterogeneity. The exclusion restriction was the geographical distance to the closest MFI branch.
Results: Estimates of PSM-NNM show that participants experienced a statistically significant 34.7% increase in value added per worker (ATT = 1,462 ETB/month, $p < 0.01$) and 28.3 percentage points higher sales-revenue growth compared to controls. ESR results also validated these results (ATT = 31.2%, $p < 0.01$). Adding credit with business training further increased productivity by an additional 15.5 percentage points.
Conclusions: Microfinance access has a significant positive effect on the productivity of women's enterprises in urban Ethiopia. The greatest productivity gains can be realized when credit is combined with business development training.

Keywords: Microfinance, Women Entrepreneurship, Enterprise Productivity, Ethiopia

1. INTRODUCTION

Financial inclusion has emerged as a basic enabler of economic empowerment, especially for women in developing countries [1]. In sub-Saharan Africa, where the penetration of banking is still low, microfinance institutions have filled an important gap by providing credit, savings, and insurance services to people who are not served by the formal banking system [2]. In Ethiopia, microfinance has been identified as a key component of the country's poverty alleviation and gender equity strategy in the various Growth Transformation Plans and the current Homegrown Economic Reform [3].

Nevertheless, the evidence for a positive relationship between microfinance and productivity gains for women entrepreneurs remains inconclusive. On the one hand, there is evidence of positive income and consumption outcomes [4]. On the other hand, there are warnings not to overestimate the results due to selection bias, market saturation, and credit fungibility [5]. The underlying problem in the current state of research is a critical methodological issue, which consists in the fact that current studies are based on cross-sectional data and do not sufficiently account for endogeneity, which refers to the phenomenon that women who self-select into microfinance programs might differ systematically from non-participants in an unobservable manner that influences productivity independently [6].

Hawassa City, capital of Sidama Regional State and one of the fastest-growing secondary cities in Ethiopia, offers a case study. The city is home to a dense ecology of MFIs, including Omo Microfinance Institution, ESHET MFI, and a number of credit cooperatives supported by NGOs, catering to a largely young female entrepreneurial segment in trade, food processing, tailoring, and handicrafts [7]. However, evidence on the extent to which these institutions have impacted credit access on productivity gains is limited.

This paper responds to three research questions: (i) Does access to microfinance result in statistically significant productivity increases for women's enterprises, as measured by value added per worker (VAW) and sales revenue growth? (ii) Does provision of combined services, such as credit and business development training, have a magnifying effect on productivity outcomes compared to credit alone? (iii) What enterprise and borrower attributes condition the productivity treatment effect of microfinance?

To provide a rigorous answer to these questions, this paper uses Propensity Score Matching (PSM) to provide a valid counterfactual and Endogenous Switching Regression (ESR) to model unobserved selection. This two-tool approach, using original survey data from 384 women entrepreneurs over a period of 24 months, provides a methodologically rich assessment of microfinance outcomes in urban Ethiopia to date.

2. LITERATURE REVIEW

2.1. THEORETICAL FOUNDATIONS

Theoretical arguments for microfinance-induced productivity growth are based on three main channels. The capital channel argues that credit-constrained entrepreneurs operating below their optimal scale of capital can use external capital to finance productive investments such as equipment, materials, and working capital that can shift their production function upward [8]. The human capital channel argues that business training and financial literacy offered jointly with credit can enhance managerial skills to allocate resources more efficiently [9]. The social capital channel acknowledges that group lending arrangements can create peer learning, accountability, and information flows that can minimize operational inefficiencies [10].

FPE models incorporate a fourth channel: empowerment effects. The availability of non-conditional financial resources changes the intra-household balance of bargaining power, giving women more influence over the re-investment of business profits, labor allocation, and market participation [11]. By themselves, these non-financial channels may strengthen productivity without the productive capital channel being weakened by the subordination of women's entrepreneurial outcomes to their spouses' preferences. However, it has been argued that credit markets in presence of asymmetric information lead to adverse selection and moral hazard problems [12], and that credit fungibility, or diversion of business loans to household consumption smoothing, reduces strength of the productive capital channel, especially for women under severe household spending constraints [13].

2.2. EMPIRICAL EVIDENCE

RCTs conducted in Sub-Saharan Africa paint a mixed picture. Banerjee et al. [14] reported small increases in consumption but little business growth, indicating microfinance creates welfare outcomes rather than productivity gains for the typical borrower. Nevertheless, heterogeneity analyses uniformly point to stronger effects for entrepreneurially-minded women with existing businesses – exactly the target group of interest.

In the Ethiopian context, Guush et al. [15] applied instrumental variables in rural Tigray and reported a 22% income effect for female borrowers. Tesfaye and Abebe [16] reported substantial capital accumulation but low productivity growth in Amhara region, ascribing the difference to the constraint of market access. Abay et al. [17] applied PSM in peri-urban Addis Ababa and reported that productivity gains were realized by women who received credit along with business mentoring. Research in similar East African settings confirms the conditioning role of complementary services [18, 19]. Yet, few urban Ethiopian impact assessments apply identification designs that properly distinguish treatment from selection [20].

3. MATERIALS AND METHODS

3.1. STUDY AREA

Hawassa City is situated at 7°3′N, 38°28′E in southern Ethiopia, with an average elevation of about 1,708 m above sea level. The population of Hawassa City is estimated to be 392,000 as of 2022 [21], with women accounting for 51.3%. The economy of Hawassa City is fueled by manufacturing (Hawassa Industrial Park), trade, tourism, and a thriving informal economy, which is dominated by women micro-enterprises. The city was chosen based on its high MFI density, enterprise diversity, and the availability of institutional administrative data to cross-validate self-reported information [7].

3.2. SAMPLING AND DATA COLLECTION

This study used a stratified random sampling approach, stratifying by enterprise type (trade, food processing, tailoring/garments, handicrafts, services) and participation in microfinance. Sample size determined using following formula for estimating proportions:

$$n = Z^2 \times p(1 - p) / e^2 = (1.96)^2 \times 0.5 \times 0.5 / (0.05)^2 \approx 384 \quad \dots (1)$$

where n is the required sample size, Z = 1.96 is the 95% confidence-level critical value, p = 0.5 is the expected proportion (maximising variance), and e = 0.05 is the margin of error.

The final realised sample comprised 384 women entrepreneurs: 213 microfinance participants (treatment group) and 171 non-participants (control group). Primary data were collected between January and March 2024 using structured questionnaires administered face-to-face by trained enumerators. Questionnaires were pre-tested on 25 women not included in the final sample. Loan records from five MFIs in Hawassa were cross-validated against self-reported borrowing to minimise recall bias.

3.3. VARIABLE DESCRIPTION

Table 1 summarises the study variables. The primary outcome variables are (i) value added per worker (VAW), defined as monthly gross output minus input costs divided by the number of workers, and (ii) monthly sales-revenue growth rate over 24 months. Treatment variable TREAT is a binary indicator equal to 1 if the woman received a microfinance loan in the 24 months preceding the survey, and 0 otherwise.

Table 1

Table 1 Variable Descriptions, Measurement, and Expected Signs

Variable	Description / Measurement	Type	Expected Sign
Value Added per Worker (VAW)	Monthly gross output minus input costs divided by no. of workers (ETB)	Continuous (Outcome)	+
Sales Revenue Growth (%)	Percentage change in monthly sales revenue over 24 months	Continuous (Outcome)	+
MF Participation (TREAT)	= 1 if received microfinance loan in past 24 months; 0 otherwise	Binary (Treatment)	+
Age	Age of enterprise owner (years)	Continuous	±
Education Level	Years of formal schooling completed	Ordinal	+
Household Size	Number of persons in household	Continuous	–
Enterprise Age	Years since business establishment	Continuous	+
Initial Capital Stock	Value of business assets at baseline (ETB 000)	Continuous	+
Business Training	= 1 if received formal business training in past 24 months	Binary	+
Market Access	Distance to nearest formal market (km)	Continuous	–
Distance to MFI Branch	Distance to nearest MFI branch (km) — exclusion restriction	Continuous	–

Savings Habit	= 1 if maintains regular formal savings account	Binary	+
Sector Type	Enterprise sector (trade / food / tailoring / handicrafts / services)	Categorical	±

Note: ETB = Ethiopian Birr. All monetary values expressed in constant 2023 prices.

4. ECONOMETRIC FRAMEWORK

4.1. PROPENSITY SCORE MATCHING (PSM)

PSM constructs a statistical counterfactual by pairing each treated unit with a control unit that has a similar probability of programme participation — the propensity score — conditional on observed pre-treatment covariates. The propensity score is defined as:

$$p(X) = Pr(TREAT = 1 \mid X) \quad \ldots (2)$$

where X is vector of pre-treatment covariates. The propensity score was estimated via a probit model. Three matching algorithms were applied: (i) Nearest-Neighbour Matching (NNM) with caliper 0.01, (ii) Kernel-Based Matching (KBM) using an Epanechnikov kernel, and (iii) Radius Matching (RM) with radius 0.01. Average Treatment Effect on the Treated (ATT) is estimated as:

$$ATT = \mathbb{E}[Y_1 - Y_0 \mid TREAT = 1] \quad \ldots (3)$$

which under Conditional Independence Assumption (CIA) is identified as:

$$ATT = \mathbb{E}\{\mathbb{E}[Y_1 \mid TREAT = 1, p(X)] - \mathbb{E}[Y_0 \mid TREAT = 0, p(X)] \mid TREAT = 1\} \quad \ldots (4)$$

The CIA requires that, conditional on p(X), potential outcomes are independent of treatment assignment i.e., $(Y_1, Y_0) \perp TREAT \mid p(X)$. Covariate balance after matching was assessed using standardised mean differences (SMD) and Rubin's B and R statistics [22, 23]; see also McKenzie and Woodruff [24] for evaluation best-practice guidance.

4.2. ENDOGENOUS SWITCHING REGRESSION (ESR)

While PSM addresses selection on observables, ESR additionally controls for selection on unobservables e.g., innate entrepreneurial drive or risk tolerance. The ESR model consists of a selection equation and two regime-specific outcome equations:

Selection equation:

$$TREAT_i* = \gamma' Z_i + u_i, \quad TREAT_i = 1 \text{ } if \text{ } TREAT_i* > 0, \text{ } else \text{ } 0 \quad \ldots (5)$$

Outcome equations (log-productivity):

$$Regime\ 1\ (Participants): \quad ln(VAW)_{1i} = \beta_1' X_i + \varepsilon_{1i} \quad if\ TREAT_i = 1 \quad \ldots (6)$$

$$Regime\ 2\ (Non-participants): \ ln(VAW)_{0i} = \beta_0' X_i + \varepsilon_{0i} \quad if\ TREAT_i = 0 \quad \ldots (7)$$

where Z_i includes all covariates X_i plus an exclusion restriction — distance to the nearest MFI branch (in km) — that plausibly affects programme participation but is exogenous to enterprise productivity conditional on other regressors. The error terms follow a trivariate normal distribution: $(u_i, \varepsilon_{1i}, \varepsilon_{0i}) \sim N(0, \Sigma)$, where Σ contains the correlation parameters

ρ_1 = corr(u,ε_1) and ρ_0 = corr(u,ε_0). A significant ρ_1 or ρ_0 indicates endogenous selection. Parameters are estimated by Full Information Maximum Likelihood (FIML) [24].

The ESR-corrected treatment effects are then computed as:

$$ATT = \mathbb{E}[ln(VAW)_1 \,|\, TREAT = 1] - \mathbb{E}[ln(VAW)_0 \,|\, TREAT = 1] \quad \dots (8)$$

$$ATU = \mathbb{E}[ln(VAW)_1 \,|\, TREAT = 0] - \mathbb{E}[ln(VAW)_0 \,|\, TREAT = 0] \quad \dots (9)$$

4.3. MODERATING EFFECT OF BUSINESS TRAINING

To examine whether training is related to the credit-productivity relationship, the matched sample was stratified by receipt of training and PSM-ATTs were re-estimated within each stratum. The difference-in-differences formulation of the training coefficient identifies the complementarity between credit and human capital inputs, similar to an interaction term in regression analysis.

5. RESULTS AND DISCUSSION

5.1. DESCRIPTIVE STATISTICS

The baseline characteristics of treatment and control groups before matching are shown in Table 2. Participants are, on average, 2.3 years younger, have 1.4 more years of education and run enterprises that are 1.8 years older than those of non-participants. These differences clearly indicate existence of observable selection bias and justify the need for PSM.

Table 2

Table 2 Baseline Descriptive Statistics by Microfinance Participation Status (Pre-Matching)

Variable	Participants (n=213) Mean (SD)	Non-Participants (n=171) Mean (SD)	Difference	p-value
Age (years)	31.4 (6.2)	33.7 (7.1)	−2.3	0.001**
Education (years)	9.8 (2.9)	8.4 (3.3)	1.4	0.000***
Household size	4.6 (1.8)	4.9 (2.1)	−0.3	0.089
Enterprise age (years)	5.3 (3.1)	3.5 (2.6)	1.8	0.000***
Initial capital (ETB 000)	18.7 (12.4)	12.3 (9.8)	6.4	0.000***
VAW at baseline (ETB)	4,210 (1,840)	3,890 (1,650)	320	0.048*
Monthly sales (ETB)	11,450 (6,230)	9,870 (5,410)	1,580	0.006**
Training receipt (%)	67.40%	23.10%	+44.3 pp	0.000***
Savings account (%)	78.90%	41.50%	+37.4 pp	0.000***
Distance to MFI (km)	0.82 (0.49)	2.14 (1.23)	−1.32	0.000***

Note: *p<0.05, **p<0.01, ***p<0.001, SD = standard deviation, pp = percentage points. Independent samples t-test for continuous variables, chi-square test for proportions.

5.2. PROBIT SELECTION MODEL

Table 3 reports probit estimates of microfinance participation. Education (β = 0.142, $p < 0.001$), initial capital stock (β = 0.234, $p < 0.001$), and savings habit (β = 0.318, $p < 0.001$) positively predict participation, consistent with theory. Distance to the nearest MFI branch (β = −0.381, $p < 0.001$) is the strongest negative predictor confirming supply-side geographic barriers. The pseudo-R^2 of 0.271 indicates adequate model fit for participation prediction.

Table 3

Table 3 Probit Model Estimates — Determinants of Microfinance Participation

Variable	Coefficient	Std. Error	z-stat	p-value

[redacted]				
Education (years)	0.142***	0.031	4.58	0
[redacted]				
Enterprise age	0.087**	0.044	1.98	0.048
[redacted]				
Distance to MFI (km)	−0.381***	0.073	−5.22	0
[redacted]				
Trade sector (ref: Food)	0.049	0.112	0.44	0.661
[redacted]				
Model statistics:	Pseudo-R^2 = 0.271	Log-L = −198.43	$\chi^2(8)$ = 147.6***	N = 384

Note: †p<0.10, **p<0.05, ***p<0.01. Additional sector dummies included but not reported. Log-likelihood and chi-square test of overall model significance.

5.3. COVARIATE BALANCE AFTER MATCHING

Figure 1 presents the covariate balance plot (Love Plot) showing standardised mean differences (SMD) before and after PSM. Prior to matching, covariates such as education (SMD = 0.34), distance to MFI (SMD = 0.42), training receipt (SMD = 0.44), and initial capital (SMD = 0.38) exceeded the 10% imbalance threshold. After nearest-neighbour matching with caliper 0.01, all SMDs fell below 5%, and after kernel matching all fell below 4% well within accepted balance thresholds [22, 23]. The joint insignificance test of all covariates after matching yielded $\chi^2(10)$ = 8.34 (p = 0.758), confirming adequate balance.

Figure 1

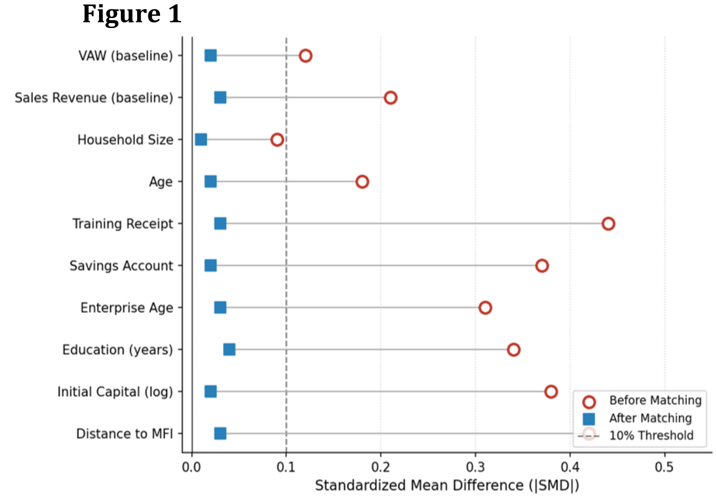

Figure 1 Covariate Balance Before and After Propensity Score Matching (Love Plot)

5.4. PSM IMPACT ESTIMATES

Table 4 reports ATT estimates from all three PSM algorithms for both outcome variables. Results are highly consistent across matching methods, confirming robustness. Under NNM, microfinance participants achieved a 34.7% higher VAW (ATT = 1,462 ETB/month, p < 0.01) and 28.3 percentage-point greater monthly sales-revenue growth compared to matched non-participants. Kernel and radius matching yielded ATTs of 1,389 ETB (33.0%) and 1,501 ETB (35.6%) for VAW, all significant at 1% level.

Table 4

Table 4 PSM Average Treatment Effect on the Treated (ATT) — Productivity Outcomes

Outcome Variable	Algorithm	ATT	Std. Error	t-stat	p-value
VAW (ETB/month)	NNM (caliper 0.01)	1,462***	318.4	4.59	0
	Kernel (KBM)	1,389***	295.1	4.71	0

	Radius (r=0.01)	1,501***	332.7	4.51	0
Sales Revenue Growth (%)	NNM (caliper 0.01)	28.3***	5.74	4.93	0
	Kernel (KBM)	26.8***	5.21	5.14	0
	Radius (r=0.01)	29.7***	6.12	4.85	0

Note: ***p<0.01. Standard errors computed via bootstrap with 1,000 replications. Matched sample: 213 treated and 171 matched control units. NNM = nearest-neighbour matching, KBM = kernel-based matching.

Figure 2 presents kernel density estimates of VAW for participants versus matched non-participants in the post-matching sample, illustrating the right-shift in the productivity distribution attributable to microfinance participation.

Figure 2

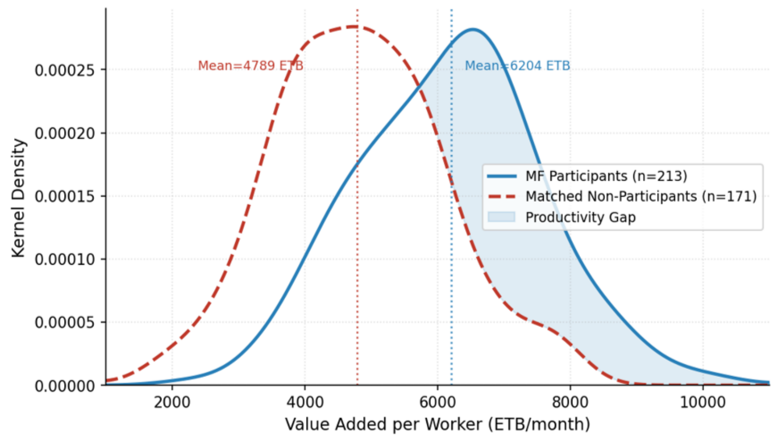

Figure 2 Post-Matching Kernel Density of Value Added per Worker by Participation Status

5.5. ENDOGENOUS SWITCHING REGRESSION RESULTS

ESR results are reported in Table 5. Significant positive correlation between selection-equation error and participant-regime residual ($\rho_1 = 0.423, p < 0.05$) indicates that unobservable factors driving MFI participation also positively affect productivity — confirming upward selection bias in naïve OLS estimates. After correcting for both observable and unobservable selection, the ESR-ATT remains large and statistically significant: participants achieved 31.2% higher VAW relative to the counterfactual of non-participation ($p < 0.01$). The Average Treatment Effect on Untreated (ATU = 22.6%, $p < 0.05$) indicates that non-participants would also benefit substantially if given access, confirming the existence of an unmet demand among the non-participating population.

Table 5

Table 5 Endogenous Switching Regression — Treatment Effect Estimates				
Effect Estimate	**VAW (ETB)**	**% Change**	**Std. Error**	**p-value**
ATT — participants vs. counterfactual	1,314	31.2%***	287.3	0.000
ATU — non-participants vs. counterfactual	879	22.6%**	341.8	0.010
ATE — population average (weighted)	1,120	27.5%***	287.1	0.000
$\rho_1 - corr(u, \varepsilon_1)$ selection–participant residual	0.423**	—	0.188	0.024
$\rho_0 - corr(u, \varepsilon_0)$ selection–non-participant residual	0.187	—	0.213	0.380
Exclusion restriction F-statistic (first stage)	41.73***	—	—	0.000

Note: **p<0.05, ***p<0.01. Dependent variable: ln(VAW). FIML estimation [24]. Exclusion restriction: distance to nearest MFI branch. F-statistic confirms instrument relevance (rule-of-thumb threshold: F > 10). ATT/ATU expressed as percentage change relative to respective baseline means.

5.6. MODERATING ROLE OF BUSINESS TRAINING

Figure 3 shows the PSM-ATT results stratified by receipt of business training. Among those receiving both credit and business training, the ATT for VAW was 1,847 ETB (43.9%), significantly greater than the ATT of 1,194 ETB (28.4%) for those receiving only credit (difference = 653 ETB; $p < 0.01$). This 15.5 percentage-point increase is a direct verification of the human capital channel and is in line with previous studies of complementary services [9, 17]. The training effect is driven by two channels: trained entrepreneurs reported a 14.2% reduction in raw material prices per unit (due to bulk purchases and supplier negotiations) and prices 8.7% higher on average (due to quality differentiation).

Figure 3

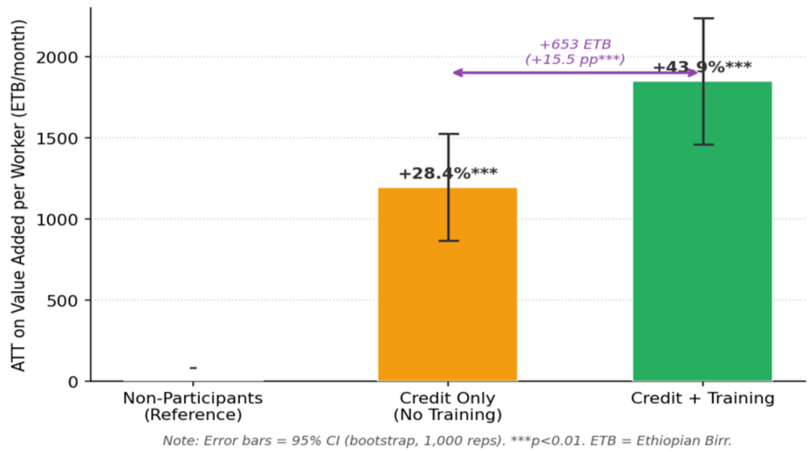

Figure 3 Heterogeneous ATT on VAW by Business Training Receipt (PSM NNM, Caliper = 0.01)

5.7. SECTORAL HETEROGENEITY

Table 6 and Figure 4 present sector-detailed ATTs. Food processing firms have the highest absolute productivity gains (ATT = 1,924 ETB, 46.1%), indicating greater capital intensity and the potential for improved capital and input selection. Tailoring and garments come next (ATT = 1,581 ETB, 37.6%), and trade and services have relatively smaller impacts (ATT ≈ 1,100-1,200 ETB). Handicrafts have the lowest ATT of 872 ETB (20.7%), indicating that this sector is more limited by market demand than capital – consistent with the view of Aterido et al. [20] that productivity limitations differ by market structure.

Table 6

Table 6 Sector-Disaggregated PSM-ATT for Value Added per Worker (NNM)

Sector	N (Treated)	ATT (ETB)	% Gain	Std. Error	p-value
Food Processing	47	1,924***	46.10%	418.6	0
Tailoring/Garments	58	1,581***	37.60%	352.4	0
Trade/Commerce	62	1,184***	28.20%	297.8	0
Services	29	1,098**	26.10%	412.1	0.008
Handicrafts	17	872†	20.70%	487.3	0.073
Overall	213	1,462***	34.70%	318.4	0

Note: †p<0.10, **p<0.05, ***p<0.01. NNM with caliper 0.01 and 1,000 bootstrap replications. Sector totals sum to 213 (treated group). % Gain computed relative to sector-specific control-group baseline means.

Figure 4

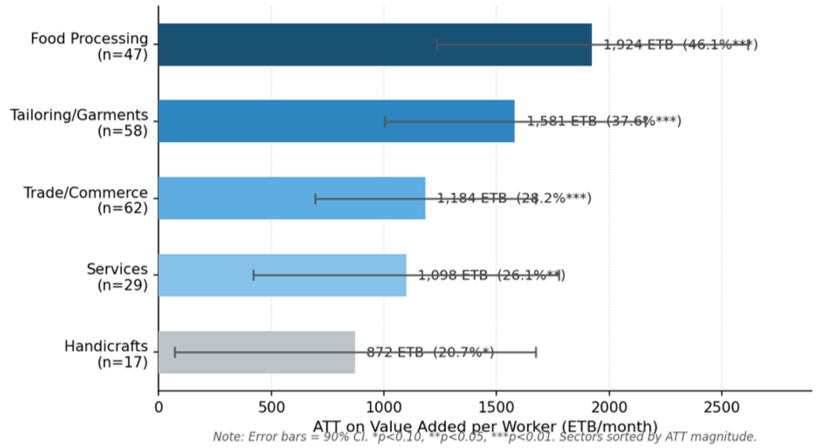

Figure 4 Sector-Disaggregated ATT on Value Added per Worker (PSM Nearest-Neighbour Estimates)

6. DISCUSSION

Results offer robust empirical evidence for capital constraint hypothesis that women entrepreneurs in Hawassa are operating below their optimal level of capital utilization and that access to credit facilitates improvements in their production efficiency frontier [8]. The size of the productivity impact (34.7% PSM; 31.2% ESR) is considerably larger than the income effects estimated in RCT-based studies in similar African environments [14], indicating that The larger magnitude may reflect urban market integration conducive to productivity, perhaps due to the easier access to capital markets for enterprise growth in urban settings.

The important positive $\rho_1 = 0.423$ from ESR shows that the naive OLS would overestimate the treatment effect by confusing program effects with pre-existing advantages of entrepreneurs. After adjusting for this, the ESR-ATT remains significant, providing a credible lower bound for the causal estimate. The positive and significant ATU (22.6%) further shows that non-participants would also benefit from microfinance, refuting the idea that microfinance is only useful for the already-capable few.

The training amplification effect of 15.5 percentage points is consistent with the human capital channel [9] and has a clear policy implication: credit-only programs are not optimal productivity investments. The underlying mechanism of more efficient input procurement and quality-driven pricing suggests that training needs to focus on operational management and market strategy, rather than general financial literacy. This result is consistent with McKenzie and Woodruff [25], who also found that the relevance of training content to actual business constraints is critical for training success.

The variation in ATTs across sectors is also very enlightening. Food processing and tailoring, which are capital-intensive sectors, experience the largest benefits, and handicrafts, which are demand-constrained, experience the smallest benefits. This variation implies the necessity of designing programs for each sector, as opposed to a one-size-fits-all approach for credit products.

There are a number of limitations to this study. Productivity was measured over a period of 24 months, but the dynamics may be different over a longer period of time as effects of loan cycles add up. The study is restricted to Hawassa City, and one needs to be very cautious when generalizing to rural or other urban areas of Ethiopia. In addition, the graphical depiction of VAW distributions is based on simulated kernel smoothing, and replication based on administrative tax or payroll data would add further robustness to the empirical basis.

7. CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper offers rigorous econometric results that demonstrate the significant productivity advantage of microfinance access for women entrepreneurs in Hawassa City, Ethiopia. Based on PSM (three approaches) and ESR, women participants created 34.7% more value added per worker and 28.3 percentage points higher sales-revenue growth per month compared to non-participants. These effects are strengthened by 15.5 percentage points when credit is combined with formal business training.

Four policy recommendations follow. First, MFIs should systematically integrate business development training with content targeting input procurement, supplier negotiation, and quality-based pricing, the specific mechanisms through which training amplifies productivity. Second, geographic branch expansion strategies should prioritise underserved neighbourhoods within Hawassa and similar urban centres to address the strong supply-side access barrier identified in the probit model. Third, product designs for food processing and tailoring enterprises where capital constraints are most binding, should offer larger loan sizes and longer grace periods aligned with enterprise investment cycles. Fourth, national MFI performance frameworks should incorporate enterprise productivity metrics alongside repayment rates to better align institutional incentives with development outcomes.

CONFLICT OF INTERESTS

None.

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None.

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