

Micro-Credit Access and Women's Enterprise Creation in India: An Econometric Study Leveraging PMMY Disbursement Trends

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ABSTRACT

Although millions of Indian women now access formal micro-credit through the government's Pradhan Mantri MUDRA Yojana (PMMY), it remains empirically unclear whether this finance produces women-run enterprises, or why its effect varies so widely across states. This study estimates the state-level relationship between PMMY micro-credit to women and women-run business creation using a balanced panel data of 36 Indian states and union territories over seven financial years (2017–2024). Because specification and diagnostic tests revealed autocorrelation and heteroscedasticity, the model was estimated using the Feasible Generalized Least Squares regression method. The results contradict the key hypothesis, revealing that the coefficient on the log number of loan accounts sanctioned to women is negative (-1.366 , $p = 0.004$), the opposite of a positive credit effect. Moreover, female higher education and female unemployment are also negatively influencing women's enterprise. However, as hypothesised, female population share has a direct impact. This suggests that credit quantity is not the key determinant. PMMY lending appears to finance existing micro-businesses rather than create new ones; educated women become employees rather than entrepreneurs, and weak local demand prevents business formation. Between-state variability accounts for more than 84% of the unexplained variance. Credit alone, without the structural conditions needed to complement it, cannot foster women's business creation.

Keywords: Credit, Micro-business, PMMY, Self-employment, Women

1. INTRODUCTION

1.1. General Background

Female entrepreneurship is an integral aspect of inclusive economic growth and development, allowing women to become economically independent, improving households' well-being, uplifting local living standards, and creating resilient communities (Agarwala et al., 2022). At the same time, Indian women entrepreneurs are heavily burdened with various structural impediments, such as conservative social norms and lack of access to banking credit services. Traditionally, women do not have any collateral that

would allow them to borrow money using formal channels (Soni, 2016). Without adequate funding, it becomes exceedingly challenging to establish businesses without external assistance (Gupta, 2025).

By removing all obstacles standing between individuals and financial access, micro-credits prove to be powerful tools. Indeed, they allow for the delivery of small, uncollateralized loans, which demonstrate that women are excellent and highly responsible borrowers capable of reinvesting their profits back into local economies (Soni, 2016; Vijay et al., 2021). Acknowledging the importance of microloans, the Indian government introduced the Pradhan Mantri MUDRA Yojana (PMMY) program in 2015 (Agarwal & Dwivedi, 2017). Consequently, millions of women in India have entered formal financial markets, resulting in massive increases in loan disbursements and beneficiary numbers (Rathee & Aggarwal, 2025). Despite such achievements, the impact on enterprise creation at the national level appears highly questionable. In other words, high numbers of loan disbursements are far from automatically indicating that micro-loan recipients have created their businesses. Moreover, there are numerous geographic differences in terms of states' ability to turn micro-loans into enterprises (Kumar & Nandrajog, 2021; Rani & Sundaram, 2023).

In recent years, the growing body of research reveals that micro-credit possesses many features, some of which include significant socio-economic empowerment opportunities and inability to scale successfully. There is a substantial amount of research documenting the existence of a strong relationship between micro-loans and empowerment. According to the available literature, PMMY micro-loans significantly increase women's self-respect, influence, income levels, and empower them socio-politically (Agarwala et al., 2022; Rathee & Aggarwal, 2025). Microfinance consistently results in income generation, whereas the group lending model ensures additional security for the borrowing parties (Vijay et al., 2021). In addition, as a tool for eliminating property-related entry barriers, MUDRA creates excellent conditions for achieving gender equality (Soni, 2016).

It should be acknowledged that the impressive number of benefits provided by the PMMY micro-loans can be attributed to the presence of numerous geographical variables. The greater the number of bank branches located in a particular state, the larger the share of women-run businesses established in it. Likewise, the same applies to the proportion of literate females in the state population. Nevertheless, regional disparity plays a crucial role since currently, Southern states manage to generate more efficient growth using micro-loans than the rest of Indian states (Kumar & Nandrajog, 2021).

Although the empowerment generated by PMMY micro-loans cannot be overstated, the process of scaling up micro-enterprises is an extremely difficult task. Establishing a company requires extensive help from the community. What is more, numerous problems impeding smooth operation, such as lack of working capital, high costs of local advertising, remoteness from the target market, and educational disparity, exist and prevent profits from being generated (Singh, 2020; Thangarajan et al., 2024).

1.2. Literature Review

The role of credit in promoting micro-businesses has been widely explored in the existing studies. The government serves as a major mechanism to disburse loans through various schemes. One such scheme introduced in India is PMMY. Literature has empirically evaluated this scheme across various aspects, one of which is women's empowerment. In the same realm, a study conducted by Rathee & Aggarwal (2025) aimed to analyze the direct influence of microcredit on women's empowerment. Using surveys as the method with a sample of female PMMY beneficiaries, the study assessed the data to gauge shifts in economic independence. On the basis of the results, they concluded that access to microcredit distinctly boosts women's self-confidence and their power to make household decisions. While economic empowerment clearly improved after securing Mudra loans, the researchers noted that education acts as a key multiplier for these benefits. Ultimately, they emphasize that microcredit shouldn't exist in a vacuum; targeted training and institutional support are just as vital for long-term success.

Another research carried out by Rani & Sundaram (2023) analyzed whether increased financial inclusion actually leads to a rise in the number of women-owned businesses. State-level panel data was used as the methodology from different parts of India and the data was evaluated using regression analysis. Based on the results, the authors concluded that states which have higher numbers of banks and easy credit availability automatically develop more women entrepreneurs. There is an important difference: mere possession of bank accounts does not spur entrepreneurship; credit availability is the key. Besides, female literacy rate in the region was found to significantly enhance the correlation between borrowings and business establishment. Similarly, Vijay et al. (2021) analyzed the impact of microcredit on the life of women entrepreneurs running small and medium enterprises. Survey-based methodology was used from active female entrepreneurs and the data was evaluated using descriptive statistical analysis. Based on the results, the authors concluded that the respondents enjoyed high income levels and raised standards of living, as many of them started their business due to borrowings. Even though there were some cases when the women felt pressure related to repayment, the overall results were very positive. It should be mentioned that in addition, the data showed that group lending performed much better than individual lending.

Moreover, Kumar & Nandrajog (2021) assessed the wider significance of PMMY in driving socioeconomic development for women in Delhi-NCR region. Secondary data was used as the methodology from financial records of the region and the data was evaluated using historical trend analysis. Based on the results, the authors concluded that women formed the vast majority of beneficiaries, especially of the entry-level Shishu loan type. This influx of money definitely provided financial independence to the beneficiaries. Nevertheless, it is important to note that the long-term viability of these newly established businesses is questionable: the Southern states show better results regarding credit-fueled economic efficiency. Subsequently, the persistent issues of financial exclusion that female entrepreneurs face, paying special attention to rural women using microloans has been evaluated

by Gupta (2025). Comparative statistical methodology was used as the data collection approach from rural enterprise records and the data was assessed to identify the trends of economic mobility and empowerment. Based on the results, the authors concluded that micro-loans helped to stabilize incomes of the households and provide women with a greater voice in the family decision-making process. However, even though these personal advantages were achieved, the transition from micro-enterprise operation to large-scale enterprise expansion remains extremely difficult. Thus, the research proved that the social network of support for a woman is one of the major factors influencing the business viability.

Soni (2016) analyzed the basic goals and legal framework of the MUDRA program to evaluate its performance in terms of women empowerment (Soni, 2016). Secondary data collected from government publications was used as the methodology from various national institute reports and the data was evaluated using qualitative trend analysis. The results concluded that the MUDRA program provides confidence and motivation for further business development for the small business owners. Since these loans are collateral-free, they brilliantly overcome the barriers of women's propertylessness. In general, this type of financial assistance becomes an engine of grassroots economic development and gender equality. Subsequent research undertaken by Agarwal & Dwivedi (2017) attempted to assess the actual outreach of the Mudra Yojana scheme by focusing particularly on how loans are being allocated across different genders and social groups. By employing state-wise disbursement data from 2015 to 2017 as a methodology based on nationwide PMMY data bases, comparative statistical evaluations were made on the data collected. Based on the results obtained from the data collected, they have concluded that the scheme is doing a fantastic job in reaching out to female entrepreneurs across the country, as a massive percentage of females are being loaned under this scheme. The increase in the percentage of female beneficiaries from 46 percent to more than 46.2 percent in a matter of one year is a strong indicator of a growing appetite for financial freedom.

To analyze how effectively the Pradhan Mantri Mudra Yojana scheme helps in promoting economic inclusion and new business formations in Himachal Pradesh, Singh (2020) conducted a research. By using state-level enrollment data and employing a method of using state-level surveys conducted by local PMMY scheme beneficiaries, the researchers assessed their data with the help of demographic analysis and descriptive statistics. On the basis of their results, they have concluded that although this scheme is a great step in promoting financial inclusion, many structural issues hinder its smooth implementation in the region. Barriers like geographical inaccessibility, educational disparities, and family support are actually deterring women from benefiting most from these micro-finance programs. Even though their results show a high bias toward male entrepreneurs in these regions, they still strongly suggest a localized and highly targeted intervention strategy to help these women.

From a similar lens, Agarwala et al. (2022) aimed to analyze how funding through Mudra Yojana helps in promoting women's employability, empowerment, and socio-economic growth in these regions. By employing a method of targeted field surveys conducted on 417 female beneficiaries in the tribal districts of West Bengal, researchers assessed their data with the help of quantitative impact evaluation techniques. On the basis of their results, they have concluded that micro-credit programs are a fantastic tool in

promoting female entrepreneurship, which in turn helps in significantly increasing their personal earnings in these regions. This helps women in becoming more empowered members of their communities, which in turn helps them in stepping into more powerful roles in their communities socially and politically. By becoming more empowered, these women are turning out to be highly effective agents of change in their communities. Finally, a study conducted by Jency & Siniya (2016) aimed to analyze the day-to-day operational and financial roadblocks women face even after they've secured their initial microcredit. Using a field survey as the method from active female micro-entrepreneurs across rural regions, the study assessed the data through problem-identification analysis. On the basis of results, they have concluded that getting the loan is only half the battle; a severe lack of ongoing working capital remains a massive threat to business survival. Furthermore, high marketing costs force many women to sell only within their immediate, localized circles, severely capping their profit potential. The authors make it clear that without long-term institutional support in marketing and sustained capital, these micro-enterprises will heavily struggle to scale up.

1.3. Research gap and Rationale for the Study

Two findings recur across the literature. Micro-credit raises women's income, confidence, and household bargaining power (Gupta, 2025; Rathee & Aggarwal, 2025; Vijay et al., 2021), and PMMY has reached female borrowers at scale, mostly through the entry-level Shishu category (Agarwal & Dwivedi, 2017; Kumar & Nandrajog, 2021). Three gaps remain.

First, few studies measure enterprise creation directly; most record empowerment or income and infer that enterprises follow (Agarwala et al., 2022; Rathee & Aggarwal, 2025; Vijay et al., 2021). The distinction is material, as credit may raise a borrower's income or household influence without any enterprise being registered, so evidence on empowerment cannot establish whether credit produces enterprises. The present study addresses this gap by adopting the female entrepreneurship rate, drawn from Udyog Aadhaar and Udyam registrations, as a direct measure of enterprise creation.

Second, the studies that do examine enterprise creation are predominantly local and survey-based, confined to a single state or district (Agarwala et al., 2022; Kumar & Nandrajog, 2021; Singh, 2020), and cannot account for cross-state variation in how credit converts into enterprise. The sole multi-state panel finds that a higher female literacy rate is associated with a stronger credit–enterprise link, literacy reinforcing the credit effect rather than substituting for it (Rani & Sundaram, 2023), but does not model the broader structural environment jointly. The present study addresses this gap through a balanced panel of 36 states and union territories observed over seven years, permitting direct cross-state comparison and the isolation of the credit effect from time-invariant state characteristics.

Third, the conditions repeatedly identified as decisive, education, demand, and working capital, typically appear as secondary observations rather than as variables modelled jointly with credit (Gupta, 2025; Singh, 2020; Thangarajan et al., 2024). Their omission risks attributing their influence to credit and thereby misstating what credit alone achieves. The present study addresses this gap by estimating credit

alongside the principal structural factors, education, unemployment, the gender wage gap, working time, and population share, within a single Feasible Generalized Least Squares specification, so that the credit coefficient is measured net of the structural environment.

Taken together, these gaps motivate a central research question: does greater access to PMMY micro-credit for women translate into higher rates of women-led enterprise creation across Indian states, and how is that relationship shaped by the surrounding structural environment? The purpose of this study is therefore to assess whether, and under what structural conditions, PMMY micro-credit to women leads to women-led enterprise creation at the state level. This primary aim, estimating the credit–enterprise relationship, is supported by two secondary aims: explaining how structural factors condition that relationship, and identifying which states convert credit into enterprise most effectively.

2. METHODOLOGY

2.1. Research aim and objectives

As set out in the Introduction, this study assesses whether, and under what structural conditions, PMMY micro-credit to women translates into women-led enterprise creation across Indian states. This aim is pursued through three objectives—one primary and two supporting it:

- Primary: to estimate the magnitude and direction of the relationship between PMMY micro-credit disbursement to women and women-led enterprise creation, using a state-level panel econometric model.
- Supporting: to examine how structural factors: the gender wage gap, women's working time, women's higher education, female unemployment, and female population share, condition this credit–enterprise relationship.
- Supporting: to identify which states convert micro-credit access into women-led enterprise most effectively, and to explore the structural conditions associated with this variation.

2.2. Research hypotheses

- **NH1:** No significant impact of PMMY micro-credit (loan accounts to women) on female entrepreneurship — $\beta_1 = 0$
- **NH2:** No significant impact of the gender wage gap on female entrepreneurship — $\beta_2 = 0$
- **NH3:** No significant impact of working time of women entrepreneurs on female entrepreneurship — $\beta_3 = 0$
- **NH4:** No significant impact of female higher education on female entrepreneurship — $\beta_4 = 0$
- **NH5:** No significant impact of female unemployment on female entrepreneurship — $\beta_5 = 0$
- **NH6:** No significant impact of the share of women in the population on female entrepreneurship — $\beta_6 = 0$

2.3. Research Design

This research applies the quantitative non-experimental (ex-post) research design based on panel data aggregated on a state level. A panel design is appropriate for the study in question since it is inherently two-dimensional: the research problem concerns the analysis of the way the relationship between micro-credit and enterprise creation by women operates both across states and over time. Panel data have several key benefits in comparison with a simple cross-section or time series (Baltagi, 2008; Hsiao, 2003): a panel increases the sample size and thus the accuracy of estimation, enables control of any time-invariant unobserved difference between states such as entrenched social norms, geographical location, and administrative capacity that could potentially bias the credit effect (Wooldridge, 2010), and allows decomposition of the estimated relationship into changes within states over time and between states – which is a critical part of achieving the second research objective of the paper. The panel includes 36 Indian states and union territories observed annually over seven financial years between 2017-18 and 2023-24, thus representing a balanced panel of 252 observations per state-year. All estimation was performed using Stata with the dataset officially recognized as panel data so that state represents the cross-sectional component and financial year – the time one.

2.4 Data and Data Sources

All data used in the study come from secondary official data sources to ensure national representation and comparability across states. The dependent variable, women-led enterprise creation, is measured by the female entrepreneurship rate defined through enterprise registration records provided under Udyog Aadhaar and Udyam frameworks of the Ministry of Micro, Small and Medium Enterprises. The primary independent variable, micro-credit provided to women, is proxied using data on Pradhan Mantri MUDRA Yojana (PMMY) loans available in MUDRA annual reports and government of India open data portal (data.gov.in) as number of loan accounts sanctioned to women. Structural and control variables were taken from well-established national statistical sources: the female labour market indicators, namely the unemployment rate, the gender wage gap, share of women enrolled in higher education, the share of women in the population, and working time of women, were taken from Periodic Labour Force Survey (PLFS) of the National Sample Survey Office.

Table 1: Variables, codes, and data sources

Code	Variable	Role	Source
FENT	Female entrepreneurship rate	Dependent variable	PLFS (NSSO)
L_ACC	ln(PMMY loan accounts to women)	Main explanatory variable	MUDRA annual reports; data.gov.in
W_GAP	Gender wage gap	Control variable	PLFS (NSSO)
EDU	Share of women in higher education	Control variable	PLFS (NSSO)

W_TIME	Working time of women entrepreneurs	Control variable	PLFS (NSSO)
UNEMP	Female unemployment rate	Control variable	PLFS (NSSO)
POP	Share of women in population	Control variable	PLFS (NSSO)

2.5. Variable Definitions and Justification

Each variable was chosen either because it is the measurement of a core concept of the research problem or a control for a competitor factor influencing enterprise creation. The theoretically expected direction of each variable is provided below and serves as a basis of testing of hypotheses in Section 2.2, revisited in Chapter 3 in the light of empirical findings.

Dependent variable

- The dependent variable is the female entrepreneurship rate (FENT) measuring the intensity of enterprise creation conducted by women in a particular state, calculated based on the number of women-owned or led enterprises registered in accordance with Udyog Aadhaar and Udyam frameworks and expressed as a rate rather than as raw number in order to prevent the domination of the results by larger states simply due to their size. It is measured on the state-year level to enable estimation of response of the entrepreneurial activity to credit provision both over time and across states (Kumar & Nandrajog, 2021).

Main explanatory variable

- The primary explanatory variable is PMMY micro-credit to women (L_ACC). It proxies women's access to formal micro-credit through the number of loan accounts sanctioned to women in the framework of Pradhan Mantri MUDRA Yojana. It is entered in logarithmic form to allow interpretation of the variable's coefficient as an elasticity and compress the strong right skew caused by few states having very large numbers (Gujarati & Porter, 2009; Wooldridge, 2010). Since micro-credit should remove the collateral barrier and open the possibility of financing for women, the literature suggests the positive effect of credit on enterprise creation and thus positive coefficient (Rathee & Aggarwal, 2025; Soni, 2016; Vijay et al., 2021).

Control variables

- The first controlled variable is the share of women in higher education (EDU). Education enhances women's ability to plan, manage and grow a business and to use borrowed funds efficiently, which means that it is supposed to increase the effect of micro-credit on entrepreneurship rather than merely shifting it. Both Rathee and Aggarwal (2025) and Rani and Sundaram (2023) show that education increases the relationship between credit and entrepreneurship, which is why it is chosen as a moderator and why different loan amounts in different states lead to different enterprise outcomes, and thus its coefficient is expected to be positive.
- The female unemployment rate (UNEMP) is included in the model as control since it measures the slack in the labour market of a particular state. High unemployment rates in a state can drive women into self-employment as an alternative to scarce wage employment opportunities or indicate lack of demand discouraging entrepreneurs from starting a venture – so its sign is unknown, and controlling for it helps to isolate the real effect of micro-credit from other labour market influences (Thangarajan et al., 2024).
- The gender wage gap (W_GAP) is controlled for as it shows the wage differential between men and women and thus indicates women's position in the waged sector. A greater gap might either force women to engage in self-employment or indicate a larger systematic gender inequality that hinders enterprise creation as well – so its sign is also uncertain, and controlling for it prevents the absorption of differences in gendered labour markets by credit effect.
- Working time of women entrepreneurs (W_TIME) controls for the intensity and nature of female self-employment. While longer working hours might conventionally suggest business growth, in the context of micro-enterprises, excessive hours often signal low-return, subsistence-driven ventures rather than scalable businesses. Consequently, the expected coefficient is negative. Controlling for this isolates the effect of micro-credit from variations in enterprise productivity and labor intensity across states.
- Total state population (POP) controls for aggregate market size and agglomeration effects. While the dependent variable is a rate, absolute population captures macroeconomic advantages like larger consumer bases and denser supply chains. A larger population fosters higher demand, supporting business growth; therefore, the expected coefficient is positive, isolating demand-side capacity from credit effects.

2.6. Model Specification and Hypotheses

The general model of women-led enterprise creation in state i and year t is expressed as follows:

$$FENT_{it} = \beta_0 + \beta_1 L_ACC_{it} + \beta_2 W_GAP_{it} + \beta_3 W_TIME_{it} + \beta_4 EDU_{it} + \beta_5 UNEMP_{it} + \beta_6 POP_{it} + u_i + e_{it}$$

Where β_0 is the intercept, β_1 to β_6 are the slope coefficients, u_i is the unobserved state effect and ϵ_i is the idiosyncratic error. The parameter of interest here is the β_1 , elasticity of women-led enterprise creation to PMMY micro-credit.

Selection of an unbiased and efficient estimator is itself an empirical issue, and hence the following chapters are organized as follows: preparation of the data, testing for multicollinearity, choice of the appropriate pooled, fixed-effects or random-effects estimator using specification tests, and finally re-estimation by Feasible Generalized Least Squares where the conditions of the selected estimator are violated. Every test is accompanied by the assumption, null and alternative hypothesis, results obtained and the corresponding estimation decision.

2.7. Data Preparation and Missing Values Treatment

Data preparation involves declaration of the dataset as a panel, with the state being the cross-sectional unit and the financial year being the time dimension since every further step requires this information. Two preparatory steps have been taken before estimation. Since the official state-wise, women-specific PMMY account data are available for later years, gaps in the earlier years have been filled within each state, with internal gaps being linearly interpolated and the years prior to the first observation being backwardly extrapolated, so that a balanced panel of 252 observations is constructed. The count-based credit variable is transformed to natural logarithm (L_ACC), on the one hand, to reduce the right skew caused by the few large states and, on the other hand, to allow interpretation of the coefficient as an elasticity (Wooldridge, 2010).

2.8. Data Analysis Method

2.8.1. Correlation Analysis

The table below shows the correlation matrix of the six regressors. It provides a descriptive account of how the explanatory variables correlate before building any model. Correlations are all moderate. The highest correlation is between female unemployment and log credit (-0.446), followed by education and unemployment ($+0.427$) and unemployment and the population share (-0.383). Of interest here are two correlations reconsidered: the positive education-unemployment correlation indicates that there is higher female unemployment in states with female higher education because educated women queue up to get salaries rather than being self-employed, and the negative credit-unemployment correlation indicates the presence of the program in areas where there is low formal credit. None of them is close to being redundant; the diagnostic test is shown below in Section 2.8.2.

Table 2. Matrix of pearson correlation coefficients between independent variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) L_ACC	1.000					
(2) W_GAP	0.034	1.000				
(3) W_TIME	0.080	-0.087	1.000			
(4) EDU	-0.298	-0.060	0.128	1.000		
(5) UNEMP	-0.446	-0.063	-0.093	0.427	1.000	
(6) POP	-0.058	-0.009	-0.116	-0.054	-0.383	1.000

2.8.2 Diagnosis of Multicollinearity

Multicollinearity happens when two or more regressors are highly correlated such that the effects of each regressor cannot be estimated separately; in other words, it is an increase of the variances of the estimates of the coefficients (Gujarati & Porter, 2009). The correlation matrix in Section 2.8.1. is descriptive, providing the correlation of pairs only; hence, the variance inflation factor is used to conduct the diagnostic test. Computed after pooled OLS, the VIF of each regressor is defined as the reciprocal of $(1 - R^2)$ of the regression of the regressor on all other regressors, showing how much the collinearity increases the variance of its coefficient. VIF values above 5-10 indicate multicollinearity (O'Brien, 2007). As can be seen from Table 3, the highest VIF value is 1.88, corresponding to unemployment, and the lowest is the average at 1.334. Therefore, multicollinearity is not an issue, and all six regressors are kept.

Table 3: Variance Inflation Factor (VIF) Test for Multicollinearity

	VIF	1/VIF
UNEMP	1.88	.532
L ACC	1.366	.732
POP	1.329	.753

EDU	1.317	.759
W TIME	1.096	.912
W GAP	1.016	.985
Mean VIF	1.334	.

2.8.3. Estimator Selection: Pooled OLS, Fixed Effects, and Random Effects

There are three estimators available for panel data depending on how they deal with the state-specific effect u_i , and each was calculated in order to pick up the most appropriate among them based on formal specification tests rather than on an assumption.

In pooled OLS all state-year observations are stacked and a simple regression is fitted, without taking into account the panel nature of the dataset and assuming identical intercepts for all the states. Its efficiency is possible only in the absence of true heterogeneity among the states, otherwise the presence of correlated state effects makes it biased and inconsistent (Wooldridge, 2010). The fixed-effects estimator assigns a separate intercept to each state and absorbs all the time-invariant state characteristics, observed or unobserved, estimating the credit effect by means of variation within states. It is robust to the presence of correlation between the state effects and the regressors, but cannot estimate time-invariant regressors and is inefficient due to the use of variation only within states (Baltagi, 2008; Greene, 2018). Finally,, Random-effects estimator assumes the state effects to be randomly drawn from the same distribution and uncorrelated with the regressors. In the case when such an assumption is true, the random-effects estimator is preferred over the fixed-effects one since it uses both within- and between-state variation and thus is more efficient (Baltagi, 2008). Choice between the fixed and random estimators depends on the validity of the latter assumption which is going to be checked below.

2.8.4. Hausman Specification Test

This test makes a choice between the fixed- and random-effects specifications on the basis of comparing their coefficient vectors in order to find out whether the assumption, underlying the random effects model, is true or not (Hausman, 1978). Namely, under the null hypothesis the state effects are uncorrelated with the regressors and the random effects estimator is consistent and efficient, but under the alternative it is not true and the fixed-effects estimator is consistent. As seen from Table 4, the test does not find any significant difference between the two sets of coefficients ($\chi^2 = 4.012$, $p = 0.675$) and so the null is not rejected, the random effects model is selected, and the fixed effects one is rejected as unnecessary and inefficient.

Table 4: Hausman (1978) specification test

	Coef.
Chi-square test value	4.012
P-value	.675

2.8.5. Breusch-Pagan Lagrange Multiplier Test

After having decided that random effects should be used, the next step is to confirm that a panel estimator is required instead of just a pooled one by means of the Breusch-Pagan Lagrange multiplier test (Breusch & Pagan, 1980). It checks for the existence of some variance among the states in order to find out that, under the null, the variance is zero and pooled OLS is enough, while, under the alternative, it is not the case and the panel effects are present. This test proves the existence of such variance ($\chi^2 = 482.27$, $p < 0.001$), so the selection of random effects as the right specification and the inadequacy of pooled OLS is confirmed.

2.8.6. Diagnostic Testing of Residual Assumptions

Since the random effects model has been selected, its standard errors and, consequently, the significance of its coefficients are reliable only under the fulfillment of two assumptions concerning the errors: their serial uncorrelation and constant variance across states. Both assumptions were checked directly.

Autocorrelation

Autocorrelation, or serial correlation, is a property according to which a state's error in one year is correlated with its error in the previous year. It is important because, in the case of ignoring this issue, the standard errors will be distorted and the results will be unreliable, although the coefficients themselves will be correct (Drukker, 2003; Wooldridge, 2010). To check the presence of the problem, the Wooldridge test was applied, for which the null hypothesis is the absence of the first-order autocorrelation and the alternative is its presence. The null was rejected ($F(1, 35) = 16.424$, $p = 0.0003$), so the significant first-order serial correlation of the panel was found.

Heteroskedasticity

Heteroscedasticity is a situation when the variance of the error varies from one state to another. Similarly to serial correlation, this is an important issue because unequal error variance leads to the distortion of standard errors and invalid significance tests (Baum, 2001; Greene, 2018). Heteroscedasticity was examined with the help of a groupwise test whose null hypothesis is panel homoscedasticity, or constant error variance, and whose alternative is groupwise heteroscedasticity. The test is presented in terms of three related statistics: the Lagrange multiplier and likelihood-ratio statistics, each of which is assessed against a chi-squared distribution with 35 degrees of freedom, and the Wald statistic, assessed against 36 degrees of freedom. In every case the null was rejected (all $p < 0.001$), so the strong groupwise heteroscedasticity was detected.

2.8.7. Final Estimation: Feasible Generalized Least Squares

As both residual assumptions have turned out to be false, the standard errors of the random effects model can no longer be relied on, although its coefficients appeared to be quite reasonable, so the model was re-estimated by means of Feasible Generalized Least Squares (FGLS). Instead of making an assumption about the nice behavior of the errors, the FGLS estimates the way they behave in practice and re-weights the data to correct the heteroscedasticity and autocorrelation detected (Kmenta, 1986; Parks, 1967). Thus, this method provides efficient estimation with reliable standard errors and serves as the final model of the study. The only caveat concerns the possibility of underestimating standard errors when the number of panels exceeds the number of time periods (Beck & Katz, 1995) which is the case in this study with 36 states being more than 7 years, so the results should be read with this limitation in mind. Table 7 presents the final estimates with statistical significance at the one, five, and ten per cent levels being denoted by three, two, and one asterisks respectively.

3. RESULTS

Table 5: Cross-sectional time-series FGLS regression — Dependent variable: FENT

FENT	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L_ACC	-1.366	.469	-2.91	.004	-2.285	-.446	***
W_GAP	-.016	.021	-0.75	.456	-.057	.026	
W_TIME	-.226	.123	-1.84	.066	-.466	.015	*
EDU	-.793	.099	-7.98	0	-.988	-.599	***
UNEMP	-.583	.16	-3.65	0	-.896	-.27	***
POP	.703	.102	6.92	0	.504	.903	***
Constant	98.373	9.491	10.36	0	79.77	116.975	***
Mean dependent var	57.109		SD dependent var	21.404			
Number of obs	252		Chi-square	241.472			
Prob > chi2	0.570		Akaike crit. (AIC)	2102.836			

*Note: *** $p < .01$, ** $p < .05$, * $p < .1$*

The regression results show that five of the six regressors attain statistical significance. The coefficient on the logarithm of PMMY loan accounts sanctioned to women (L_ACC) is -1.366 with a standard error of 0.469, significant at the one per cent level, and its ninety-five per cent confidence interval of [-2.285, -0.446] lies wholly below zero. The coefficient on the share of women in higher education (EDU) is -0.793 with a standard error of 0.099, significant at the one per cent level and the

most precisely estimated coefficient in the model. The coefficient on the female unemployment rate (UNEMP) is -0.583 with a standard error of 0.160 , significant at the one per cent level. The coefficient on the share of women in the population (POP) is 0.703 with a standard error of 0.102 , significant at the one per cent level and the only positive slope coefficient in the model. The coefficient on the working time of women entrepreneurs (W_TIME) is -0.226 with a standard error of 0.123 , significant at the ten per cent level, with a confidence interval of $[-0.466, 0.015]$ that includes zero. The coefficient on the gender wage gap (W_GAP) is -0.016 with a standard error of 0.021 and a p-value of 0.456 , and does not attain significance at any conventional level. Its confidence interval of $[-0.057, 0.026]$ spans a range of 0.083 units against a dependent variable with a standard deviation of 21.404 , indicating that the estimate is precisely rather than imprecisely determined.

Because the credit variable enters in logarithmic form and the remaining regressors in levels, the marginal effects differ in construction. For L_ACC, a ten per cent increase in the number of loan accounts sanctioned to women corresponds to a decline of 0.130 units in the female entrepreneurship rate, and a doubling of accounts to a decline of 0.947 units, equivalent to 0.044 standard deviations of the dependent variable. For the level regressors, a one percentage-point increase corresponds to the coefficient itself: a decline of 0.793 units for EDU, equivalent to 0.037 standard deviations; a decline of 0.583 units for UNEMP, equivalent to 0.027 standard deviations; and an increase of 0.703 units for POP, equivalent to 0.033 standard deviations. Measured against comparable proportional changes in each variable, the education coefficient is approximately eight times the magnitude of the credit coefficient.

Of the coefficients for which a direction was predicted, only that on POP conforms to expectation. The coefficients on L_ACC and EDU are negative where positive signs were predicted. No expected direction was assigned to UNEMP or to W_GAP, study having identified opposing mechanisms in both cases.

4. DISCUSSION

The negative and statistically significant credit coefficient impacting female entrepreneurship is one of the study's central findings, and the literature offers three explanations for it. Because the analysis is associational, these should be read as competing and potentially complementary accounts that are consistent with the observed relationship, not as mechanisms the data establish. First, beneficiaries borrow mostly in the low-value Shishu category, and fewer than one in five PMMY loans go to first-time entrepreneurs (NITI Aayog & KPMG, 2023), so the credit variable may largely capture working capital for existing enterprises while the dependent variable captures new registrations. Second, post-loan constraints, insufficient working capital, high marketing costs, and lack of training, may obstruct the transition from loan to registered enterprise (Gupta, 2025; Rathee & Aggarwal, 2025; Thangarajan et al.,

2024). Third, the scheme's deliberate placement in credit-thin areas may impose an inverse credit–formalisation relationship in the data (Ravallion, 2008), which is important given that most of the variation is between-state. The present design cannot adjudicate between these accounts: distinguishing them would require loan-level or first-time-borrower data and a source of exogenous variation in credit allocation, neither of which is available here. The negative association is nonetheless consistent with randomised experiments across six countries that find no enterprise-formation effect from expanding access (Banerjee et al., 2015; Meager, 2019) and with evidence that capital returns in women's microenterprises are not significantly different from zero (de Mel et al., 2009).

The negative association of education coefficient with female entrepreneurship is consistent with a compositional effect rather than lower productivity. As human capital rises, self-employment tends to become a residual option and educated women move into wage labour (Gollin, 2008; Poschke, 2013); several decades of rising female education in India, for instance, produced no participation effect (Klasen & Pieters, 2015). The positive correlation between EDU and UNEMP (0.427) is consistent with this account: high-education states are also high-female-unemployment states, suggesting that educated women queue for paid employment rather than open firms.

Moreover, the negative coefficient of unemployment is consistent with demand deficiency, not the "refugee effect." Because the PLFS considers own-account workers to be employed, the unemployment measure captures women looking for jobs but not becoming self-employed; thus, its negative association with enterprise creation means that the conversion does not happen, while weak demand discourages both (Gupta, 2025; Thangarajan et al., 2024). The positive population coefficient can reasonably proxy the underlying gender relations environment: sex composition indicating discrimination (Anderson & Ray, 2010) and mobility rules for market interactions (Jayachandran, 2015), not just headcount. The negative working time coefficient is marginal but still negative, signaling that long working hours correspond to low-return rather than scalable enterprises. Gender wage gap is insignificant: it may be explained by two counterbalancing factors, a self-employment effect versus gender inequality, and not collinearity: VIF = 1.016.

5. CONCLUSION

The explosive growth of PMMY micro-credit disbursed to women in India has brought lending and beneficiaries to unprecedented volumes, but whether such credit creates women-owned enterprises, and how much that relationship depends on the state, has been empirically unresolved. This paper has sought to quantify the size of the state-level association between PMMY micro-credit and the emergence of women-led enterprises, and to understand the extent to which that link is mediated by structural factors.

Based on 36 states and union territories over seven financial years from 2017–18 to 2023–24, a panel of 252 state–year observations was constructed using official secondary sources. After a series of specification tests—Hausman test, the Breusch–Pagan Lagrange

multiplier test, and serial correlation and heteroscedasticity tests—the model was estimated using Feasible Generalized Least Squares estimation, as was found appropriate given the presence of the autocorrelation and heteroscedasticity observed in the panel data set. Five of the six variables were statistically significant. Contrary to the first hypothesis, the coefficient on the log of PMMY loan accounts issued to women was negative and significant at the one percent level (-1.366 ; 95% CI $[-2.285, -0.446]$; $t = -2.91$, $p = 0.004$), so the null of zero effect was rejected in favour of a negative rather than positive effect, contrary to the hypothesised positive effect. The share of women enrolled in higher education had the largest and most precisely estimated coefficient (-0.793), negative and about eight times the magnitude of credit effects, when controlled for at the same percentage change. Female unemployment was also negative and significant (-0.583), while the share of women in the total population was the only positive effect and the only coefficient to align with its prediction ($+0.703$). Working time of women entrepreneurs was negative and significant only at the ten per cent level (-0.226), while the gender wage gap returned a null (-0.016 , $p = 0.456$). Mapping these results onto the six null hypotheses of Section 2.2, the null of no effect was rejected for PMMY credit (NH1), female higher education (NH4), female unemployment (NH5), and female population share (NH6), each at the one per cent level, and, more weakly, for women's working time (NH3) at the ten per cent level; only the null for the gender wage gap (NH2) could not be rejected. These rejections do not all point in the same direction: of the variables for which a direction was predicted, only female population share behaved as expected, while credit and education carried significant coefficients of the opposite sign. Taken together, the pattern indicates that the structural environment, education in particular, is more closely associated with women's enterprise creation than the sheer quantity of credit is.

Overall, these results suggest that the amount of micro-credit does not constrain women's entrepreneurship in the states of India. The negative credit coefficient can be explained by three factors from the literature: PMMY loans are predominantly low-value Shishu working capital to already operating businesses rather than for new ventures; post-loan constraints including thin working capital, high marketing expenses, and lack of training hinder the conversion; and the strategic targeting of the programme to regions with poor formal credit penetration makes for an inherent inverse relationship between credit and formalisation in the data. The negative education coefficient represents a compositional effect rather than a deficiency of productivity, since as human capital increases, educated women seek scarce wage employment—as suggested by the positive education-unemployment correlation—leaving self-employment as the last option. The negative unemployment coefficient supports the demand-deficiency explanation, whereby weak local demand causes both unemployment and underdeveloped local enterprises, which affect women, while the positive population coefficient probably

proxy the underlying gender relations environment that influences women's economic activity more than population size alone. In conjunction with recent experiments where capital injections result in no gains for women micro-enterprises, the results suggest that the binding constraint exists in the structural environment and not in credit access itself.

Hence, the main conclusion is not that micro-credit is bad, but that credit alone—in the absence of complementary human capital, demand, and normative conditions that shape women entrepreneurship—is not sufficient to produce the enterprise creation it is designed to do.

6. POLICY IMPLICATIONS AND LIMITATIONS

The negative credit coefficient does not argue for withdrawing credit, but for changing the conditions under which it converts into enterprise, and the results point to three priorities.

- First, the scheme's performance measures should shift from the volume of credit disbursed to the enterprises that credit produces. The key takeaway from this paper is that more loan accounts mean lower, not higher, female entrepreneurship rate, which implies that the amount of loans cannot be used as a measure of enterprise formation. This incongruity is corroborated by administrative figures showing that only one out of five loans issued by the scheme finds its way to a first-time entrepreneur (NITI Aayog & KPMG, 2023); the remainder largely refines activity that already exists, so loan-account and volume targets reward lending rather than the enterprise formation the scheme is intended to promote. Reorienting monitoring towards enterprise-level outcomes, the registration, survival, and growth of women-led firms, would align the incentives of implementing agencies with that objective and make the scheme's stated goal measurable.
- Second, credit should be delivered together with the complementary inputs that convert it into enterprise, and the scheme's objectives should be matched to the borrowers it actually reaches. Education, not credit, is the key driver of female entrepreneurship according to the findings of this study, and the coefficient of education in the model is negative: the higher the human capital of a woman is, the more likely she is to enter wage employment and become an entrepreneur by default (Gollin, 2008; Poschke, 2013). It is also confirmed by a positive correlation between education and unemployment rate of 0.427, meaning that high-education states are also high-female-unemployment states. As a result, finance and education attract different groups and pull in opposite directions: without working capital, training and market access, finance cannot create enterprises (Rathee & Aggarwal, 2025; Thangarajan et al., 2024). Two responses follow: pairing loans with these complementary services for the lower-income borrowers the scheme predominantly serves, and, separately, creating higher-return entrepreneurial pathways capable of drawing educated women away from wage employment.

- Third, the concentration of women borrowers in the smallest, entry-level Shishu loans (Kumar & Nandrajog, 2021) indicates a “missing middle”: borrowers can obtain very small sums but rarely progress to the larger amounts that fund genuine expansion, so credit sustains subsistence micro-activity without financing the step up to a registered, scalable enterprise. This pattern is one plausible source of the negative credit coefficient, since additional low-value lending adds loan accounts without adding firms. A structured, performance-based gradation, under which borrowers who demonstrate consistent repayment and turnover become eligible for progressively larger Kishore and Tarun loans, would counter the entry bias built into the scheme's design and give viable micro-enterprises a defined path towards formalisation and growth.

Three limitations qualify the explanations advanced above.

- First, the design is associational and draws predominantly on between-state variation. With an intra-class correlation of 0.838, most of the variation used to identify the credit coefficient is cross-sectional rather than within-state over time, and no instrument or source of exogenous variation in credit allocation is available to address the programme-placement problem (Ravallion, 2008). The results should therefore be read as associations rather than causal effects, and the reported FGLS standard errors—liable to understatement when the number of panels exceeds the number of time periods, as here with 36 states over seven years (Beck & Katz, 1995)—should be treated as an upper bound on precision.
- Second, part of the credit series is constructed rather than observed. As noted in Section 2.7, official state-wise, women-specific PMMY account data are available only for later years, so earlier observations were linearly interpolated and backward-extrapolated to build a balanced panel of 252 observations. Because a portion of the L_ACC series is imputed, it smooths genuine year-to-year variation and may attenuate the estimated credit relationship.
- Third, the dependent variable is not defined identically across the panel. As noted in Section 2.4, it derives from both the Udyog Aadhaar and the Udyam registration frameworks, the latter having superseded the former part-way through the observation window. Any structural break introduced by this transition is not modelled in the present specification, and could affect comparisons of the female entrepreneurship rate across the earlier and later years.

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