# (De)accumulating Savings to Borrow? The Impact of Women's Provident Fund Contribution on Debt

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**Abstract**

Automatically enrolling in a retirement savings plan is one of the most widespread policy nudge to boost retirement readiness. However, little is known about its effect on mortgage loans. We study the effect of savings in an automatic enrollment plan using a quasi-natural experiment created when, in February 2018, the Government of India reduced women employees' contribution to Employee Provident Fund, a statutory automatic enrollment retirement savings plan with defined contribution, for the first three years of employment, from the existing rate of 12 percent to 8 percent. Using a synthetic difference-in-differences technique on a nationally representative household panel data, we could show that the reduction of women's contribution to the provident fund is associated with an increase in the equated monthly instalment of mortgage and vehicle loans by 4.12 percent and 3.80 percent, respectively, among women households primarily engaged in formal sector occupations. Furthermore, our results suggest that policy nudges—even when well-targeted—are guided by educational attainment and occupational volatility to produce differential behavioural responses. Our findings are fairly robust to alternative specifications.

**Keywords**: Household finance; retirement scheme; gender; policy nudge

**JEL**: D14; D90; G51; H24; H55; J78

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# 1 Introduction

Incentivization women employees to enroll in retirement savings plans is becoming increasingly popular worldwide to deepen female labour force participation in the formal sector and reduce the gender gap in retirement readiness.[1] Without exception, in February 2018, the Ministry of Labour & Employment in India reduced women employees' contribution to the Employee Provident Fund (EPF),[2] India's statutory automatic enrollment[3] retirement savings plan with defined contribution,[4] for the first three years of employment from the existing rate of 12 percent to 8 percent. While the objective of the policymakers was to encourage the women, newly employed in the formal sector, to join the retirement savings plan, the effectiveness of such incentives might also depend on specific unintended impacts of this policy on the household balance sheet. For example, Agrawal et al. (2024) find that the beneficiaries of this policy intervention increase investment in school and professional education. However, no study to date has explored the possibility that slashing women's contributions to the defined contribution plan for a limited period might impact the household debt. This latter plausibility is the key focus of this paper.

We augment the existing literature[5] by studying the household co-holding of savings accounts and debt. We explore the effect of the slashing of newly joined women employees' contribution to EPF on long-, medium-, and short-term debt. We, following Arkhangelsky et al. (2021), exploit a quasi-natural experimental design by incorporating plausible exogenous variations in the policy implementation, specifically cohort-temporal differences in a synthetic difference-in-differences setup. The policy's implementation timing in February 2018, unknown to potential beneficiaries, makes the treatment exogenous. As the policy intervention is intended for women in the formal workforce, we work with a sample of households

[1] https://www.oecd.org/content/dam/oecd/en/publications/reports/2021/03/towards-improved-retirement-savings-outcomes-for-women_c6b33e1/f7b48808 − en.pdf

[2] https://www.epfindia.gov.in/site_docs/PDFs/CBT_Files/220CBT_AGENDA22.pdf

[3] Employees are automatically enrolled in the retirement savings plan unless they opt out.

[4] In defined contribution plan both the employers and employees contribute their mandated share. In India, salaried employees, besides EPF, can also save in Public Provident Fund (PPF), another government-backed savings instrument. While EPF is a mandatory retirement scheme for salaried employees, PPF is a voluntary savings scheme open to all Indian citizens. The cap to PPF is pegged at INR 1,50,000.

[5] Gomes et al. (2021) and Gathergood & Olafsson (2024) outline a detailed review.

in which the number of female members exceeds that of male members to better capture women's decision-making dynamics within the household. We refer to such households as 'women-households'.[6] For differences arising from cohort variation, our study defines a treatment group consisting of women-households primarily employed in the formal sector during the pre-intervention period, and a control group comprising women-households primarily engaged in non-formal occupations in the pre-intervention period. The variation along the temporal dimension is ensured by including one year of monthly household data before and one year after the policy implementation, drawn from the nationally representative Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE). The introduction of a reduction in women's contributions to the provident fund in February 2018 led to a higher disposable income for women employed in the formal sector compared to the counterfactual, i.e., women working in the non-formal sector. We aim to capture the effect of this higher disposable income on household debt.

Our main results measure the effect of a reduction in women's contribution to the provident fund on the equated monthly instalment (EMI) of house loans, vehicle loans, and loans for durables of women's households. In India, house loan or mortgage loan is extended for 10 to 25 years (i.e., long-term debt), vehicle loan[7] is for three to seven years (i.e., medium-term debt), and loan for consumer durables (i.e., unsecured loans), such as television, refrigerator, mobile, is due within three to 11 months (i.e., short-term debt). We find that post-reduction of women's contribution to the provident fund, the monthly debt obligations of house loans and vehicle loans increased by 4.12 per cent and 3.80 per cent, respectively, among women households predominantly employed in the formal sector. The findings of our heterogeneity analysis indicate that the policy's effect on home loans is stronger among more educated women households with relatively stable income sources. We use robustness checks, including inverse probability weighting matching and randomized inferences, to restore confidence in our results.

The observed effect of women employees' reduced provident fund contribution on house-

[6]See Table 1 for further details.
[7]In general, the vehicle is hypothecated to the lender.

hold debt is an example of policy nudge leading to wide-scale unintended consequences. A wide body of literature suggests that the incremental contribution to retirement savings plans due to automatic enrollment[8] is primarily financed by reduced consumption (Thaler, 1994; Beshears et al., 2006), crowding out of private savings (Feldstein, 1974; Attanasio & Brugiavinni, 2003; Chetty et al., 2014) and unsecured debt such as credit card borrowing (Beshears et al., 2024; Choukhmane & Palmer, 2024). A limited literature (e.g., Beshears et al., 2024; Choukhmane, 2024) has studied the unintended consequences of policy nudges regarding changes in the enrollment status in retirement savings plans. Our study is related to Beshears et al. (2024), who study the effects of automatic pension enrollment on household debt using a natural experiment created by the enactment of the UK Pensions Act 2008, which required all UK firms to enrol their employees in workplace pensions. Although our study uses an entirely different empirical setting, they are qualitatively similar to that of Beshears et al. (2024). While Beshears et al. (2024) find that automatic pension enrollment causes an increase in mortgage debt balances, we find that a reduction in provident fund contributions by newly joined women employees in the formal sector significantly increases the monthly debt obligations of house loans for these women households. However, while there is no increase in vehicle debt balances in Beshears et al. (2024) our results suggest statistically significant evidence of an increase in monthly debt obligations for vehicle loans in women households.

Our paper is related to the literature (Morrison, 1998; Gross & Souleles, 2002; Choi & Laschever, 2018; Gorbachev & Luengo-Prado, 2019; Medina & Pagel, 2021; Choi, 2022; Vihriala, 2025) that highlights households' intention to co-hold low-yield liquid assets and high-cost debt (i.e., borrower-saver puzzle). Our findings also relate to the extensive literature (e.g., Berniell et al., 2020; Reboul et al., 2021) on gendered relationship between income shock and debt that suggests that women's borrowing to income ratio is far more than men

[8]Literature documents managers who are willing to increase employees' savings in a retirement plan, changing employees' default enrollment status from non-participation (i.e., zero default contribution) to participation (i.e., a positive contribution by the employee) (Thaler, 1994). Several investigations (Beshears et al., 2006; Blumenstock et al, 2018; Choi et al., 2004; Friedberg et al., 2024; Madrian & Shea, 2001) have shown that default contribution boosts the fraction of employees contributing to a retirement savings plan. Among recent investigations, Beshears et al. (2022) estimate that the automatic enrollment of U.S. Army civilian employees in a defined contribution plan has a positive impact on their cumulative savings.

and they primarily borrow for social purposes and to repay debt. In terms of methodology, our paper is closely related to Agrawal et al. (2024), although not identical. Similar to Agrawal et al. (2024), we also exploit the exogenous variation in the policy exposure by the women employed in the formal sector.

The rest of the paper is arranged as follows. Section 2 outlines the institutional context. Section 3 describes the data and compares the two cohorts of our analysis. Section 4 explains our identification strategy to assess the impact of slashing women's contribution to EPF on household debt. We present the main results of our analysis in Section 5, followed by the heterogeneity analysis in Section 6. Robustness test results are reported in Section 7. The final section concludes.

## 2 Background

### 2.1 Institutional context

In India, the Employees' Provident Fund, a defined contribution plan, was launched through the establishment of Employees' Provident Fund Organization (EPFO) by the Ministry of Labour & Employment, Government of India, under the Employees' Provident Funds and Miscellaneous Provisions Act, 1952. The Central Board of Trustees administers the pan-India operation of EPFO. An establishment belonging to a defined class of industries, with a minimum of 20 employees, should register with EPFO; however, others might also voluntarily register. Employees are automatically enrolled in the EPF unless they opt out. The upper limit of monthly EPF contributions by the employer is 12 percent on a maximum wage ceiling of INR 15,000 (USD 232).[9] In addition to mandatory contributions of 12 percent, employees can make voluntary contributions to their EPF account, but these contributions also need to be within the monthly ceiling of INR 15,000, which includes both the employee's and employer's contributions. Given the contributory nature of the plan, the employer is expected to transfer to the EPFO the contributions payable to the fund by itself and employees at

[9]Currency exchange rate in May, 2018 at 1 USD = 64.80 INR https://www.thomascook.in/blog/our-services-forex/1-usd-to-inr-from-1947-to-2024/

the rate specified under the Act. On a change in employment, the member needs to transfer her EPF account to her present establishment. The employee realizes the accumulated fund with EPFO and with interest upon retirement or cessation of service. As of March 31, 2023, the EPF is subscribed to by 298.83 million members.[10]

In the 2018-19 Union budget, the Finance Minister announced to reduce the EPF contribution for the first three years of women joining the formal sector from 12 percent to 8 percent without any change in the employer's contribution. The primary aim of this policy was twofold: first, to incentivize women employees to join a defined contribution retirement plan, and second, to allow higher take-home pay for the initial three years of employment in the formal sector. Hence, the policy of reduced contribution to the EPF was intended to cover the women formal sector employees across industries.

### 2.2 Borrower-saver puzzle

Based on the extent of co-holding of assets and liabilities, Gorbachev and Luengo-Prado (2019) divide individuals into four broad groups: (a) borrower-saver with positive holding in both savings and debt, (b) borrowers, with positive debt but no savings (c) savers, with positive savings but no debt, and (d) neutral, with neither savings nor debt. Our paper falls within the first group (i.e., borrower-saver) that simultaneously holds a savings account and debt, as we explore the effect of the slashing of contributions to the retirement savings plan on household debt on a sample of women-households who co-hold an Employee Provident Fund account (retirement savings plan) and debt.

The borrower-saver puzzle is rooted in Hicks (1935) who wrote, "So long an interest rates are positive, the decision to hold money rather than lend it, or use it to pay off old debts, is apparently an unprofitable one." Reasons surfaced in the literature for simultaneously accumulating savings and debt include liquidity preferences (Gross & Souleles, 2002; Telyukova & Wright, 2008; Telyukova, 2013) to ensure availability of cash to make certain future payments, precautionary savings (Fulford, 2015; Druedahl & Jorgensen, 2018) to address any

[10] www.epfindia.gov.in/site$_d ocs/Annual_R eport/Annual_R eport_2022-23.pdf$

unforeseen shock, perceived risk of future access to credit (Gorbachev & Luengo-Prado, 2019), preference for risk aversion (Barsky et al., 1997; Druedahl & Jorgensen, 2018), education and financial literacy (Bartaut et al., 2009; Gathergood & Weber, 2014) for better allocation of resources across financial assets to prevent default in paying debt obligations, and anticipated future income volatility based on past experience (Gorbachev, 2006; Feigengaum & Li, 2012).

The policy announcement of slashing the provident fund contribution from the existing 12 percent to 8 percent for newly joined women employees in the formal occupation after February 2018 offers us a quasi-natural experimental setting to estimate the effect of reduced contribution to the pension plan on household debt. However, such a setting offers us limited possibilities to explore the reason or mechanism of the effect through the lens of the borrower-saver puzzle. Saying so, given data limitations, we could only explore the heterogeneity of the policy effect with respect to the education/ financial literacy and anticipated future income volatility.

## 3 Data

For empirical analysis, this study uses the CMIE-CPHS monthly panel data spreading over March, 2017 to February, 2019. CPHS geographically covers 98.5 percent of India's population (Vyas, 2020). It surveys around 160,000 households from 514 districts of 28 Indian states at a four-month interval and collects information on monthly income and expenditure across multiple categories of goods and services that include food, clothing, financial services, energy, among others. The primary dependent variable of this study is the equated monthly instalment of the house, vehicle, and durables loans of the household. Combining monthly data from various rounds of surveys allows us to build a panel of monthly expenditure on the above-stated debts. The study examines the effect of the reduction in women's contribution to the retirement plan on the log of EMIs of three broad debt categories. The CPHS also collects demographic information on household members, such as age, gender, occupation,

education, household size, etc.

To streamline analysis, in CPHS, the individual responses are collapsed into household-level typologies to facilitate easier classification of similar households into a group. This allows for a better understanding of the characteristics of an individual household as a unit. For example, under the gender group variable, according to the majority sex of its members,[11] each household is assigned to one of seven categories (refer to Table 1). This enables one to classify a sample household based on gender dominance. Likewise, a similar strategy is used for the occupation group: Occupation is categorized into 20 mutually exclusive groups, with each household classified based on the predominant employment profile of its members.[12] This classification forms the basis for our distinction between the formal and non-formal sectors (refer to Table 2).

**Table 1:** ***Gender group classification***

| **Household group** | **Gender group** | **Narration** |
|---|---|---|
| Women households | Only female | No male in the household |
| | Female majority | Number of males is half the number of females in the household |
| | Female dominated | Number of males is less, but not less than half the number of females in the household |
| Men households | Only male | No female in the household |
| | Male majority | Number of females is half the number of males in the household |
| | Male dominated | Number of females is less, but not less than half the number of males in the household |
| | Balanced gender | Equal number of males and females in the household |

*Notes:* The table presents the classification of households in our sample based on CPHS defined gender groups.

**Table 2:** ***Occupation group classification***

| **Sector** | **Occupation Groups** |
|---|---|
| **Formal Sector** | Business & Salaried Employees; Industrial Workers; Legislators/Social Workers/Activists; Managers/Supervisors; Non-industrial Technical Employees; Organised Farmers; Qualified Self-employed Professionals; Wage Labourers; White-collar Clerical Employees; White-collar Professional Employees |
| **Non-formal Sector** | Agricultural Labourers; Entrepreneurs; Home-based Workers; Miscellaneous; Retired/Aged; Self-employed Entrepreneurs; Small Traders/Hawkers; Small/Marginal Farmers; Support Staff |

*Notes:* The table presents the classification of households in our sample based on CPHS defined occupation groups.

[11] CPHS does not explicitly identify transgender respondents; any such cases are coded as male in the dataset.

[12] This rule relies on every member's work status, not just that of the household head, and is therefore more accurate when different members do different kinds of work.

### 3.1 Data Description

As the reduction in EPF contribution is only restricted to newly joined women in the formal sector, this study uses households with more women than men (referred to as "women-households"), defined as households where the gender composition is exclusively female, female-majority, or female-dominated. In the next step, the women household is divided into two groups: the households receiving the treatment and the control group. The treatment group is isolated from the control group with a treatment dummy that takes the value one if the women household's occupation group is formal. The control group, with the value of treatment variable equal to zero, comprises the women household whose occupation group is non-formal. However, recent investigations (Somanchi, 2021; Sinha Roy & Van Der Weide, 2022; Agrawal, 2024) suggest that while in the early waves of survey to compensate large attrition new households were added, the later waves were under-represented by women. Therefore, for avoiding sample selection bias, this study includes household responses from March 2017 to February 2019.

**Table 3:** ***Descriptive Statistics: Outcome Variables***

| | Treatment Group | | | | | Control Group | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Var** | **Obs** | **Mean** | **Std. Dev** | **Min** | **Max** | **Obs** | **Mean** | **Std. Dev** | **Min** | **Max** |
| **Panel 1: Dependent Variable (Equated monthly installment in INR)** | | | | | | | | | | |
| House EMI | 391,704 | 119.9921 | 986.4119 | 0 | 80000 | 482,901 | 68.02942 | 982.5836 | 0 | 500000 |
| Vehicle EMI | 391,704 | 110.5556 | 870.7249 | 0 | 70000 | 482,901 | 81.18469 | 1020.732 | 0 | 280100 |
| Durable Goods EMI | 391,704 | 24.8047 | 371.9814 | 0 | 70000 | 482,901 | 20.18126 | 237.1587 | 0 | 50000 |
| **Panel 2: Dependent Variable (Log Equated monthly installment)** | | | | | | | | | | |
| House EMI | 391,704 | 0.2372395 | 1.36033 | 0 | 11.28979 | 482,901 | 0.1507453 | 1.083211 | 0 | 13.12236 |
| Vehicle EMI | 391,704 | 0.2549463 | 1.403217 | 0 | 11.15627 | 482,901 | 0.2094687 | 1.266077 | 0 | 12.54291 |
| Durable Goods EMI | 391,704 | 0.0989707 | 0.8472772 | 0 | 11.15627 | 482,901 | 0.0870117 | 0.7922921 | 0 | 10.8198 |

*Notes:* The table presents summary statistics for the main outcome variables—Equated Monthly Installments (EMIs) for House, Vehicle, and Durable Goods. Panel A reports the outcome variables in Indian Rupees (INR), and Panel B reports their log-transformed values. Columns 2 to 6 correspond to the treatment group, while Columns 7 to 11 correspond to the control group.

The study is conducted on 874,605 women households. While the treatment group comprises 391,704 women households, 482,901 women households are taken as control. Table 3 offers the descriptive statistics of three outcome variables, equated monthly instalment on house loan, vehicle loan, and loan for durable goods. On an average, women household

members in the treatment group spend INR 119.99 per month for repaying house loan as compared to INR 68.02 per month in the control group. On an average, women household member in the treatment group spend INR 110.55 per month and INR 24.80 per month for repaying vehicle loan and durable goods loan, respectively.

### 3.2 Comparison of Pre- and Post-Policy women households in formal occupation

To estimate the effect of the reduction in provident fund contributions by newly employed women in the formal sector on household debt, in this subsection, we compare the monthly household debt obligations of this policy-affected cohort (i.e., women households) before and after the policy implementation. Specifically, we compare their monthly debt obligations prior to February 2018 (before the policy implementation) with those observed since March 2018 (following the introduction of the provident fund contribution reduction for women employed in the formal sector). Table 4 presents a comparison of the policy-affected cohort before and after the policy's introduction, based on their monthly debt obligations for long-term loans (i.e., house loans), medium-term loans (i.e., vehicle loans), and short-term loans (i.e., loans for durable goods). In terms of monthly debt obligations across all three categories of loans, the post-policy equated monthly instalment is higher compared to the pre-policy equated monthly instalment. Although the differences between the pre- and post-policy monthly debt obligations are statistically significant due to the large sample size, the magnitudes of these differences in monetary terms are relatively small.

**Table 4:** ***Comparision of Pre- and Post-Policy in INR***

| | **Pre-Policy** | **Post-Policy** | **Difference** | **p-value** |
|---|---|---|---|---|
| House EMI | 86.77 | 149.78 | 63.01 | 0.0000 |
| Vehicle EMI | 80.24 | 137.73 | 57.49 | 0.0000 |
| Durable Goods EMI | 16.20 | 32.52 | 16.31 | 0.0000 |
| Observations | 185,166 | 206,538 | | |

*Notes:* The table presents a pre- and post-policy comparison of women households where the majority of members are employed in the formal sector. EMI and INR refer to Equated Monthly Instalment and Indian Rupee, respectively.

# 4 Identification strategy

The government of India amended the Employees' Provident Funds and Miscellaneous Provisions Act, 1952, in February 2018. As per the amendment, women employees entering the formal sector after April 2018 became eligible for a reduced provident fund contribution from the existing 12 percent to 8 percent. Notably, while the policy targeted a specific beneficiary group, it did not mandate uptake, which means that eligibility enabled the participation but did not enforce it. Therefore, this study adopts an intent-to-treat framework rather than estimating the average treatment effect. Under an intent-to-treat approach, those randomized out are excluded from receiving the treatment, while those randomized in may choose not to comply (Angrist et al., 1996; Duflo et al., 2007). In this context, women newly employed in the non-formal sector are automatically excluded from policy coverage. However, eligible women in the formal sector may opt not to participate and continue contributing at the 12 percent. Since the policy was targeted at women in formal employment, the analysis in this paper focuses on households with a predominance of women members—classified as women households (i.e., female-majority, female-dominant, or female-only), as defined in Table 1. This household-level approach is used to better capture the decision-making dynamics of women within the household.

To establish a quasi-natural experimental design, we divide this sample of women households into treatment and control groups based on pre-policy employment characteristics. The treatment group includes households where the majority of working members were employed in the formal sector prior to February 2018, with no dynamic shifts observed in the pre-policy period. The control group comprises households with most members engaged in the non-formal sector during the same pre-policy period. This setup allows for a robust comparison of the policy's effects across groups differentially exposed to the reform. To estimate the causal relationship, we, following Angrist & Pischke (2009, 233), use the following difference-in-differences specification for each women household $h$ during the month $m$ to

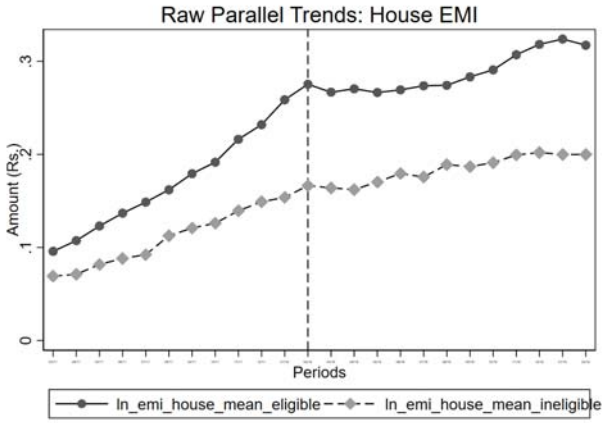
capture the intent-to-treat effect of the policy:

$$\mathbf{Y_{hm}} = \alpha + \beta \mathbf{Women_h} + \gamma \mathbf{PostFeb2018_m} + \delta(\mathbf{Women_h} * \mathbf{PostFeb2018_m}) + \mathbf{X_{hm}} + \mu_h + \omega_m + \epsilon_{hm} \quad (1)$$

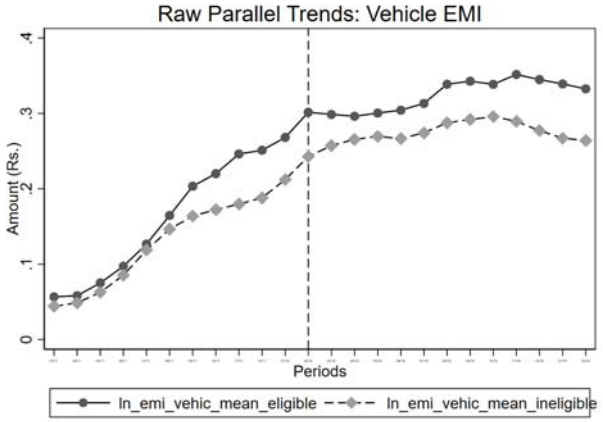
where subscripts $h$ and $m$ refer to households and month, respectively. $\boldsymbol{Y_{hm}}$ is the logarithm of the equated monthly instalment of the debt obligation of household $h$ at the end of month $m$. $\boldsymbol{Women_h}$ is a dummy variable that takes the value 1 if the women household (as defined in Table 1) is primarily engaged in formal employment (as defined in Table 2) prior to February 2018; it takes the value 0 if the women household is primarily employed in the non-formal sector during the same period. $\boldsymbol{PostFeb2018_m}$ is a dummy variable that takes the value 1 for month-year after February 2018 when the reduction in provident fund contribution for the newly joined women in the formal sector was implemented, and zero otherwise. The variable of interest, $\boldsymbol{Women_h * PostFeb2018_m}$, is an interaction term that takes the value 1 for women households engaged in formal occupation during the implementation of the reduced provident fund contribution policy, and zero otherwise. The household-level control variables, viz, education, age, household size, and region, are represented by $X_h$. The time invariant household level heterogeneity is captured by $\mu_h$. $\omega_m$ represents the time-varying common shock. A statistically significant positive $\delta$ captures the extent of the variation caused by the provision of a reduction in the provident fund contribution by the women workforce in the formal occupation on the debt obligations of the women households. Alternatively, it measures the variations in the equated monthly instalments of house loan, vehicle loan, and debt for durable goods by the women households in formal occupation that received additional disposable income from reduced provident fund contribution from 12 percent to 8 percent.

**Figure 1:** ***Trends in Outcomes for Treated and Control Group***

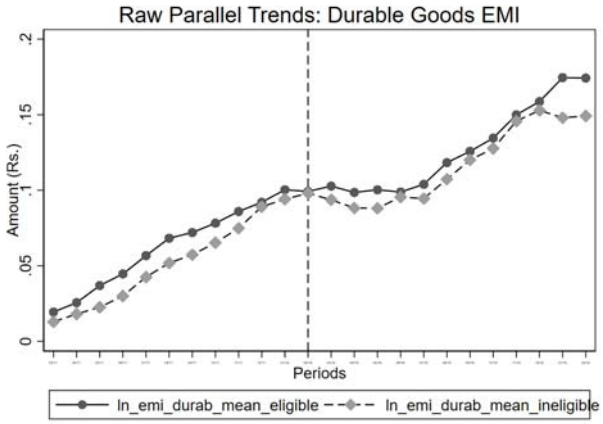
**(a)** ***Log House EMI***




**(b)** ***Log Vehicle EMI***




**(c)** ***Log Durable-Goods EMI***




Note: The figure above depicts the trends in our outcomes of interest for both treated group and control group. In all the sub-figures, the solid line is for treated group and dashed line is for control group. The vertical line represents the implementation time of the policy.

The identification strategy of the difference-in-differences approach relies critically on the assumption of parallel trends; that is, in the absence of treatment, the treatment and control groups would have exhibited similar trends in the outcome variable. In the context of our study, this implies that, in the absence of provision to reduce the women's contribution towards provident fund, household debt among women households employed in the formal sector would have evolved similarly to that of women households in the non-formal sector. To assess the validity of this assumption, we provide graphical evidence of common pre-treatment trends in the outcome variables for the treated and control groups, as illustrated in Figure 1. Figure 1 presents three panels depicting the monthly coefficients of the logarithm of debt obligations for house loans, vehicle loans, and durable goods loans. These plots trace the evolution of debt across time for women households in formal versus non-formal employment, and they demonstrate parallel trends in all three debt categories prior to the policy intervention. This evidence of consistent pre-treatment trajectories reinforces confidence in the validity of our identification strategy.

One potential concern in difference-in-differences analysis is ensuring comparability of the control and treatment groups. To address this concern, we, following Arkhangelsky et al. (2021), undertake a synthetic difference-in-differences analysis to estimate the effect of a reduction in provident fund contributions on monthly debt obligations for women households. Synthetic difference-in-differences combines the strength of the synthetic control method with the conventional difference-in-differences identification strategy to establish causality in a panel setting. Under synthetic difference-in-differences, control groups are designed synthetically to ensure that the treatment and the control group follow a similar trend in the dependent variable, a modelling assumption for any difference-in-differences analysis. Here, by leveraging synthetic control method, synthetic difference-in-differences method builds a synthetic control group that re-weighs and matches the pre-treatment trend of the treatment group to weaken the assumption of parallel-trend, and then administers difference in differences for comparing the variations in dependent variable of the treatment group with its synthetic control counterpart both before and after February 2018, the month of the in-

troduction of provident fund reduction for the newly joined women workforce in the formal occupation.

# 5 Results

## 5.1 Evidence using difference-in-differences identification strategy

This section, following equation (1), presents the primary results from the difference-in-differences identification strategy. Table 5 reports the estimated effects on equated monthly instalments for house, vehicle, and durable goods loans. The coefficients capture the impact of the February 2018 reduction in provident fund contributions — from 12 percent to 8 percent - on monthly debt obligations among women households experiencing an increase in disposable income. In other words, it captures the change in monthly debt obligations after the policy implementation among women households primarily employed in formal occupations, relative to those mainly engaged in non-formal sectors.

The estimate in Column (1) is positive and statistically significant. It suggests that the monthly debt obligation of house loans for women households engaged in formal occupation increased by 3.77 percent after a reduction in provident fund contribution in February 2018. Columns (2) and (3) show that the equated monthly instalments of vehicle loans and loans for durable goods have increased by 1.51 percent and 0.09 percent, respectively, though these estimates are imprecisely measured. All regressions include time fixed effects and household-level controls—education, age, household size, and region—and report robust standard errors clustered at the household level. The results broadly indicate that women households with members primarily employed in the formal occupation in the period before policy have higher debt obligation after the increase in their disposable income from reduction in provident fund contribution.

**Table 5:** ***Policy's Impact on Log of Various EMI Categories***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | 0.0377*** | 0.0151 | 0.0009 |
| | (0.0098) | (0.0109) | (0.0072) |
| Observations | 874,605 | 874,605 | 874,605 |
| R-squared | 0.5371 | 0.4669 | 0.3529 |
| Controls | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes |

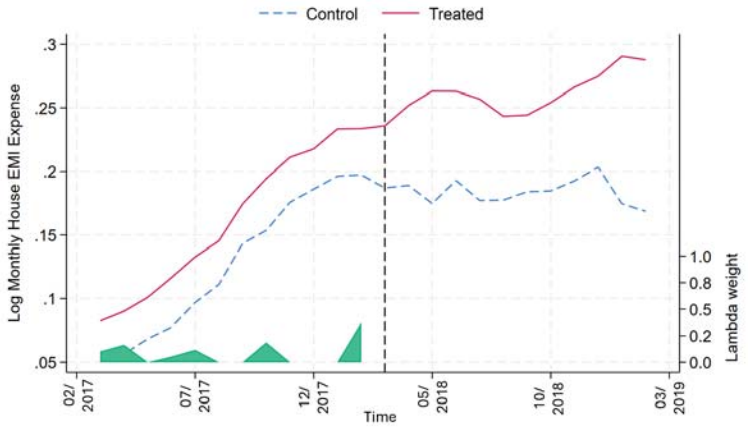
*Note:* This table reports the results from regression equation (1), analyzing the impact of the policy on various outcome variables: log values of Equated Monthly Installments (EMIs) for House (column 1), Vehicle (column 2), and Durable Goods (column 3). All regressions include household and time fixed effects, and control for age, education, household size, and region. Robust standard errors clustered at the household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

## 5.2 Evidence using synthetic difference-in-differences identification strategy

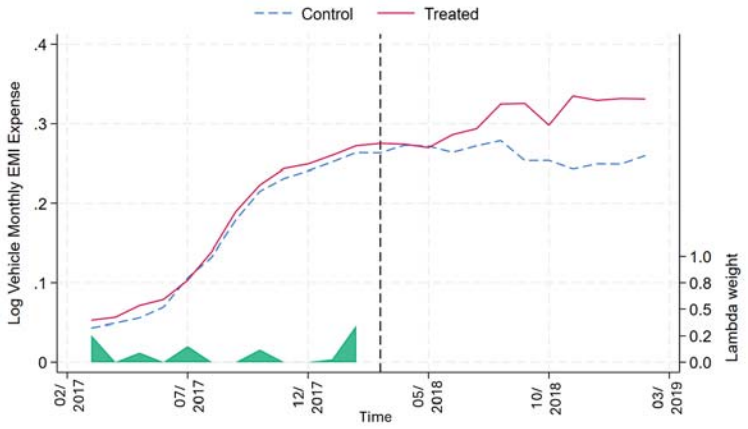
Figure 2 shows the plots of synthetic difference-in-differences of the logarithm of monthly debt obligations for house loans (panel a), vehicle loans (panel b), and loans for durable goods (panel c) from March 2017 to February 2019 on the balanced panel version of our dataset. The vertical dotted line marks the beginning of the treatment period after February 2018. Immediately after the provident fund contribution slashes from February 2018, the red line representing the treated and the blue line indicating the control diverge noticeably in both panels (a) and panel (b). Thus, the slashing of the provident fund contribution leads to a positive change in the monthly debt obligations of women households. The results of synthetic differences-in-difference are reported in Table 6. Columns (1) and (2) show an increase of 4.12 percent and 3.80 percent in monthly debt obligations for house loans and vehicle loans, respectively, for women households predominantly employed in formal sector after the slashing of the provident fund contribution in February 2018, confirming the baseline results of this paper.

**Figure 2:** ***Synthetic Difference in Differences***

**(a)** ***Log House EMI***




**(b)** ***Log Vehicle EMI***




**(c)** ***Log Durable-Goods EMI***

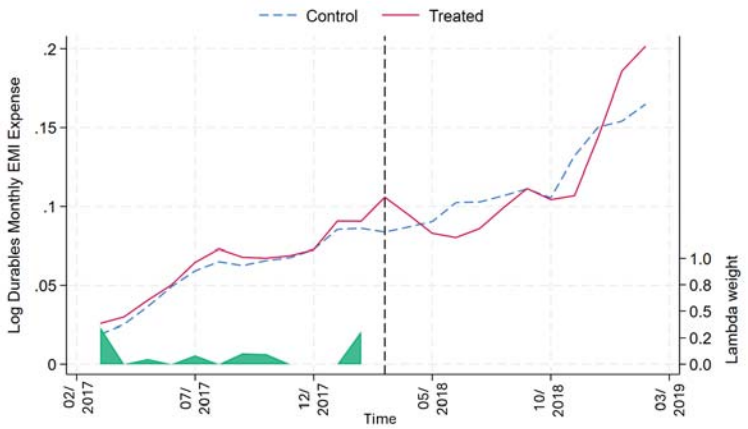


**Table 6:** ***SDID Estimate of Policy's Impact on Log of Various EMI Categories***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | 0.0412*** | 0.0380** | -0.0039 |
| | (0.0145) | (0.0180) | (0.0110) |
| Observations | 292,272 | 292,272 | 292,272 |
| R-squared | 0.5371 | 0.4669 | 0.3529 |
| Controls | Yes | Yes | Yes |

Note: All columns report results from the synthetic difference-in-differences methodology (Arkhangelsky et al., 2021), using CMIE-CPHS monthly household-level panel data for the period March 2017 to February 2019. The dependent variables in columns (1), (2), and (3) are the log values of Equated Monthly Installments (EMIs) for House, Vehicle, and Durable Goods, respectively. Bootstrapped standard errors based on 100 simulations are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

# 6 Heterogeneity Analysis

To deepen our understanding of the aggregate effects of the EPF policy reform documented in Section 5, we examine whether the policy induced rise in long term debt obligations varies systematically with two household characteristics that proxy for financial resilience and planning capacity: (i) occupational volatility and (ii) educational attainment. Both characteristics feature prominently in the literature on the borrower saver puzzle, which emphasises that households' simultaneous use of low yield liquid assets and high cost debt can be rational if they face liquidity shocks, credit access risk, or limited financial sophistication (Gross & Souleles, 2002; Telyukova & Wright, 2008; Gorbachev & Luengo Prado, 2019).

Households with members in stable (non-volatile) occupations and higher educational profiles are more likely to exhibit behavior consistent with forward-looking financial planning, thereby aligning with the conceptual framing of borrower-saver types. These households may possess the institutional literacy, risk appetite, and financial flexibility to strategically reallocate savings and credit in response to shifts in disposable income. In contrast, households with lower education levels or more volatile employment situations may face liquidity constraints, greater income uncertainty, and limited access to formal credit, all of which may

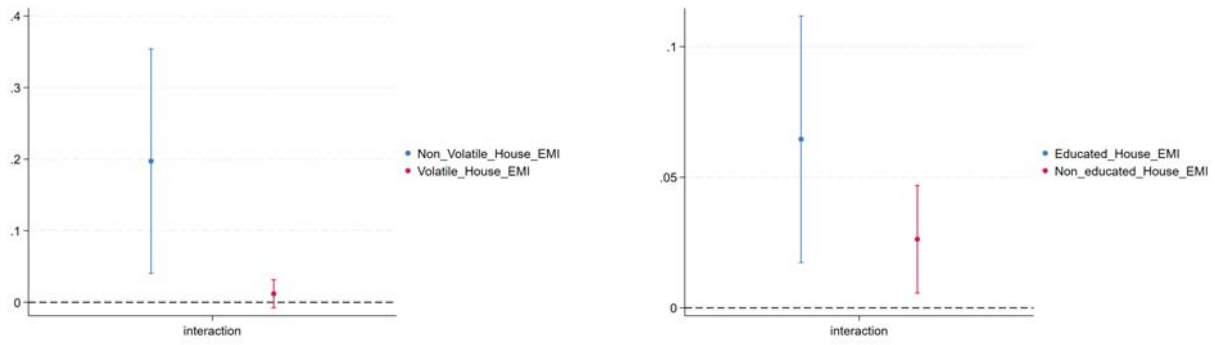
mute their responsiveness to the policy.

For the occupational volatility heterogeneity analysis, we classify occupations as volatile or non-volatile using the CPHS-provided household-level occupation group variable, which is based on the predominant occupations of its members (refer to Table A1 in the Appendix). We then re-estimated the primary difference-in-differences specification (equation 1) separately for both groups, keeping the full battery of women household and month fixed effects and covariates. Also, to look at heterogeneity by education, we used the CPHS household-level education group variable to classify households as more educated or less educated according to the highest educational attainment among members aged 25 and older (refer to Table A2 in the Appendix). Again, we estimated the difference-in-differences model separately for both categories using equation 1.

Based on the primary results reported in Table 5, only the mortgage channel is statistically significant among the three debt horizons (house, vehicle, and durables). Consequently, Figures 3(a) and 3(b) present the heterogeneity analysis of house loan EMIs along the dimensions of occupational volatility and educational attainment, respectively.

**Figure 3:** ***Heterogeneity***

**(a)** ***Occupational Volatility*** **(b)** ***Educational Attainment***




Note: Figures (a) and (b) depict the heterogeneity results along the occupational volatility and educational attainment dimensions, respectively.

Figure 3(a), indicating occupational volatility, shows that the policy-induced increase in house loan EMIs is significantly more pronounced among women households in non-volatile

occupations. These households may perceive lower career-related income volatility, and are therefore more likely to increase borrowing for long-term investments, such as housing, in response to a temporary rise in disposable income. This behavior is consistent with the borrower-saver framework, wherein households maintain retirement savings while simultaneously increasing long-term borrowing, reflecting a strategy to smooth consumption and optimize asset accumulation over the lifecycle.

Our heterogeneity findings on the educational attainment dimension (Figure 3(b)) indicate that the policy's effect on house loan EMI is considerably stronger among the more educated group. This suggests that educational attainment enhances a household's ability to process and respond to changes in income, possibly through greater financial literacy, credit access, or long-term planning behavior. These results echo the literature that emphasizes the role of education in enabling financially optimal co-holding behavior, i.e., borrowing while maintaining some savings (Bartaut et al., 2009; Gathergood & Weber, 2014). Taken together, the heterogeneity analysis reinforces the relevance of the borrower-saver puzzle in our empirical setting. While the overall post-policy increase in long-term household debt obligations among women households employed in the formal sector reflects a shift in financial behaviour in response to a retirement savings contribution cut, the subgroup results show that this shift is most pronounced among those with more stable employment and higher educational attainment. These characteristics likely signal lower financial uncertainty and greater financial capacity, enabling such households to adjust their saving and borrowing strategies in a more responsive and strategic manner. In contrast, less educated and more occupationally volatile households may remain constrained by liquidity risks, credit market frictions, or precautionary motives that discourage increased debt obligations, even when disposable income rises. Thus, our findings suggest that policy nudges—even when well-targeted—interact with underlying household characteristics to produce differential behavioral responses, revealing hidden layers of inequality in financial literacy and adaptability.

# 7 Robustness

## 7.1 Falsification

A plausible concern with the outcome of the difference-in-differences analysis is that the change in monthly debt obligations of the women households majorly employed in the formal sector after February 2018 might not solely be attributed to the slashing in provident fund contributions. This paper's empirical strategy is rooted in identifying the change in the monthly debt obligations among the women households comprising households belonging to the only female, majority female, and dominant female classes, as indicated in Table 1. To assess whether our identification strategy can capture the true effect of the reduced provident fund contribution of the newly joined women workforce in the formal occupation, households with only male members (refer to Table 1) are set as the target group.

This paper estimates equation 1 on the male-only cohort to administer the falsification test. The idea behind this falsification exercise is fairly straightforward. Since the male-only households working in the formal sector are not expected to benefit from the reduced provident fund contribution, they are not expected to experience any significant increase in monthly debt obligations. A difference-in-differences analysis compares the male-only households employed in formal occupations in the pre-treatment period with the male-only households engaged in the non-formal sector. If the primary results of this analysis hold, then the difference-in-differences estimator of the falsification exercise should not be statistically significant. The results are reported in Table 7. The coefficient of the policy effect (interaction term in equation 1) in column (1) is negative, not statistically significant, and close to zero. This indicates that the reduction in provident fund contribution didn't affect male-only households, i.e., households that the government of India did not target by the said policy. This suggests that our empirical strategy is reasonably successful in capturing the true effect of the reduced provident fund contribution for the target households.

**Table 7:** ***Policy's Impact on Log of Various EMI Categories (Log Values, Only Males)***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | -0.0039 | 0.0524 | 0.0155 |
| | (0.0361) | (0.0479) | (0.0266) |
| Observations | 56,089 | 56,089 | 56,089 |
| R-squared | 0.4906 | 0.4637 | 0.4182 |
| Controls | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes |

Note: This table reports the results from estimating regression equation (1) for households composed exclusively of male members. All regressions include household and time fixed effects, and control for age, education, household size, and region. Robust standard errors clustered at the household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

### 7.2 Alternate Sample - Extended Period

The baseline results are estimated by using equation (1) of the difference-in-differences framework on a monthly panel ranging from March 2017 to February 2019, one year before and after the policy shock. Two reasons for selecting the time frame: first, new households were added to compensate for considerable attrition in the early waves of the survey, and second, women, the beneficiaries of the reduced provident fund contribution, were underrepresented in the later waves. We run equation (1) on a monthly panel from January 2016 to December 2019[13] to ensure that a particular time range does not drive our results. The results are reported in Table 8. Results suggest that the monthly debt obligation of house loans for the women households engaged in formal occupation has increased by 4.31 percent after a reduction in provident fund contribution in February 2018. The magnitude of the treatment effect estimated using the extended panel is close to our baseline difference-in-differences estimates. It confirms that our main results hold even in the extended panel and are not sensitive to the time frame.

[13]We restricted to December 2019 to ensure that the desired effect of reduced provident fund contribution is not diluted from the COVID-19 pandemic, which was reported in India on January 30, 2020 (Andrews et al., 2020).

**Table 8:** ***Policy's Impact on Log of Various EMI Categories (Alternate Sample)***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | 0.0431*** | 0.0366*** | 0.0109* |
| | (0.0097) | (0.0101) | (0.0063) |
| Observations | 1,714,939 | 1,714,939 | 1,714,939 |
| R-squared | 0.4171 | 0.3524 | 0.2507 |
| Controls | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes |

Note: This table reports the results from estimating regression equation (1) on an extended monthly panel covering the period from January 2016 to December 2019. All regressions include household and time fixed effects and control for age, education, household size, and region. Robust standard errors clustered at the household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

### 7.3 Inflation adjusted results

Another concern could be that our results are biased by changes in the price level of the dependent variable over time. We address such potential bias by conducting a robustness test for inflation adjustment. In our analysis, we use the inflation-adjusted equated monthly instalments for house loans, vehicle loans, and loans for durables. Specifically, inflation is controlled for in the regression specification (1) of the difference-in-differences using the Consumer Price Index provided by the Central Statistics Office (India).[14] The inflation-adjusted results are reported in Table 9. The results are consistent with our main findings.

### 7.4 Inverse probability weighting

Another primary concern in observational studies is that non-randomized treatment assignment might result in confounding, where pre-treatment characteristics related to both treatment and outcome yield biased estimates of the treatment effect. Following Abadie (2005), we use an inverse probability weighting estimator in a difference-in-differences framework to adjust for possible confounding. Inverse probability weighting ensures a balanced comparison between the treatment and control group by weighting each observation in the analysis by the inverse probability of receiving the treatment.

[14] See here: https://cpi.mospi.gov.in

**Table 9:** ***Policy's Impact on Log of Various EMI Categories (Female HH Sample w/ Inflation)***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | 0.0377*** | 0.0151 | 0.0009 |
| | (0.0098) | (0.0109) | (0.0072) |
| Observations | 874,605 | 874,605 | 874,605 |
| R-squared | 0.5371 | 0.4669 | 0.3529 |
| Controls | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes |

Note: This table reports results from regression equation (1), including the same household-level controls (age, education, household size, and region) as well as an additional control for inflation using the Consumer Price Index. Robust standard errors clustered at the household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We use the household-level controls - education, age, and household size - as observable covariates for matching, as these variables are least likely to be influenced by the reduced provident fund contribution. Furthermore, stabilized weights are used to improve the estimator's efficiency. The results, reported in Table 10, suggest an increase in monthly debt obligation for house loans, confirming our baseline results.

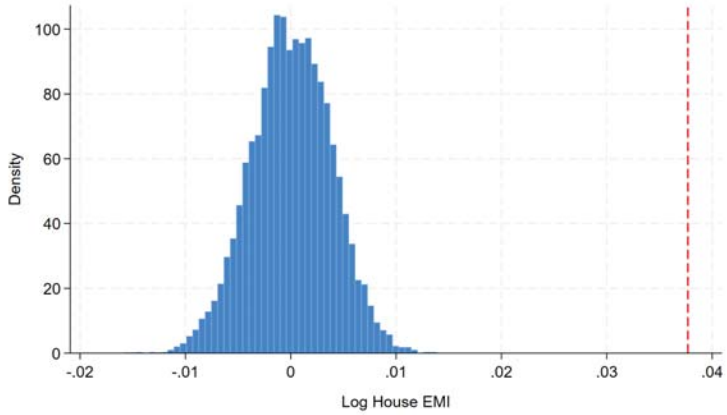
**Table 10:** ***Policy's Impact on Log of Various EMI Categories (Female HH Sample w/ IPW Weights)***

| | **Log House EMI** | **Log Vehicle EMI** | **Log Durable Goods EMI** |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Policy Effect (interaction)* | 0.0253** | 0.0009 | -0.0034 |
| | (0.0099) | (0.0111) | (0.0073) |
| Observations | 874,605 | 874,605 | 874,605 |
| R-squared | 0.5398 | 0.4677 | 0.3569 |
| Controls | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes |

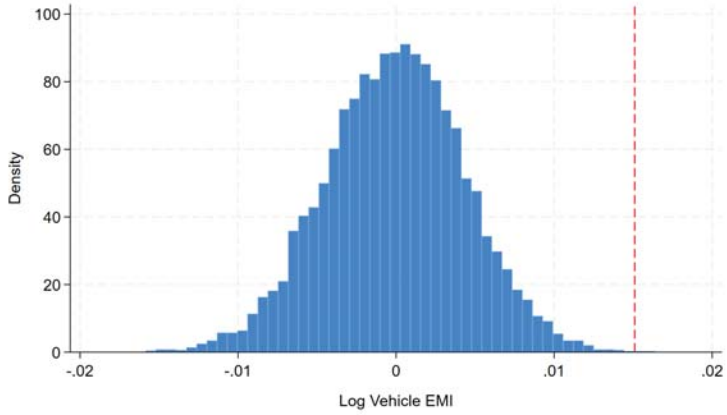
Note: This table reports the results from estimating regression equation (1) with inverse probability (stabilized) weights. All regressions include household and time fixed effects and control for age, education, household size, and region. Robust standard errors clustered at the household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Figure 4:** ***Randomized inference***

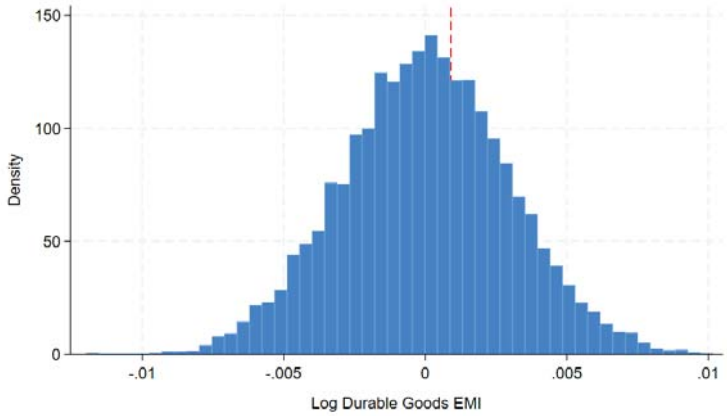
**(a)** ***Log House EMI***




**(b)** ***Log Vehicle EMI***




**(c)** ***Log Durable-Goods EMI***




Note: The figure depicts the results of randomized inference. The dependent variables in panels (a), (b), and (c) are the logarithm of monthly debt obligations of house loans, vehicle loans, and loans for durable goods, respectively. The horizontal axis indicates coefficients estimated through 1000 simulated regressions, and the vertical axis represents the density of the estimated coefficients. The dashed vertical red line represents the actual value of $\gamma$ as reported in Table 5. All regressions use district and time fixed effects and use education, age, and household size as controls.

### 7.5 Randomized inference

We use a randomized inference test to proclaim that the outcome of the difference-in-differences is the effect of slashing newly joined women employees' contributions to the provident fund and not a matter of chance. Primarily proposed by Fisher (1936) and latter extended by Rosenbaum (2002), randomized inference is more and more employed in quasi-natural experiments (see for example, Bharadwaj et al., 2014; Chakraborti et al., 2018; Chatterjee & Kamal, 2021; Chatterjee & Poddar, 2021) as a falsification test.

The final sample of women households is randomly assigned to either the treated group, i.e., predominantly engaged in the formal occupation, or the control group, i.e., primarily employed in the non-formal sector without considering whether the women household is employed in the formal sector or not and a beneficiary of the policy intervention. Equation (1) is re-estimated with these pseudo-treated and control groups after each random assignment and conducting 1000 simulations. The objective of this test is if the differences-in-differences estimation is capturing some random variation between the actual women households predominantly occupied in the formal sector (treatment group) and the women households employed in non-formal occupation (control group), it would identify identical effects in a few simulations with random treatment assignment. The treated group not significantly differing from the control group in terms of the dependent variables after random assignment would indicate that the results are likely to be arbitrary. Alternatively, simulated findings significantly deviating from the actual results in terms of magnitude and significance would repose confidence in our identification strategy.

Figure 4 shows the density plot of 1000 simulated coefficients $\gamma$ of the interaction term $\boldsymbol{Women_h * PostFeb2018_m}$, each with a separate randomly assigned women household in the treated group. Panels (a), (b), and (c) correspond to the dependent variables - logarithm of monthly debt obligations of house loan, vehicle loan, and loan for durable goods, respectively. While the horizontal axis plots the simulated coefficients, the vertical axis indicates the density of the estimated coefficients. The dashed vertical red line represents the actual value of $\gamma$ as reported in Table 5. All regressions use district and time fixed effects

and use education, age, and household size as controls. With reference to panels (a) and (b), we find that the distribution of the simulated coefficients is concentrated at zero and far away from the dashed vertical red line, i.e., the actual coefficient. This indicates that the systematic differences in household monthly debt obligations between the treatment and control groups are induced by the slashing of provident fund contributions instead of random variation.

## 8 Conclusion

The existing literature on retirement savings plans unanimously concludes that automatic enrollment augments retirement readiness and is primarily financed by reduced consumption, crowding out of private savings, and unsecured debt. However, little is known regarding the effect of automatic enrollment on mortgage loans. In this paper, through the lens of the borrower-saver puzzle, we offer novel evidence that the relationship between savings in an automatic enrollment retirement plan with defined contribution and monthly obligations for long-term debt may depend on the level of educational attainment and occupational volatility.

We study the effect of savings in an automatic enrollment plan using a quasi-natural experiment created when, in February 2018, the Government of India reduced women employees' contribution to Employee Provident, a statutory automatic enrollment retirement savings plan with defined contribution, for the first three years of employment, from the existing rate of 12 percent to 8 percent. Using a synthetic difference-in-differences technique on a nationally representative household panel data, we could show that post-reduction of women's contribution to the provident fund, the equated monthly instalment of house loans and vehicle loans increased by 4.12 percent and 3.80 percent, respectively, among women households primarily engaged in formal sector occupations. Our findings are fairly robust to alternative specifications.

Borrowing from the borrower-saver puzzle of the credit card literature, we conjecture that

formal sector women employees' increased take-home pay, due to the exogenous policy shock, would be strongly driven by educational attainment and occupational volatility while borrowing. Households with members in stable (non-volatile) occupations and having higher educational attainment may possess the institutional literacy, risk appetite, and financial flexibility to strategically reallocate savings and credit in response to any change in disposable income. Over all, our findings suggest that policy nudges—even when well-targeted—interacts with underlying household characteristics to produce differential behavioural responses and is intrinsically guided by hidden layers of inequality in financial literacy and adaptability.

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# Appendix

**Table A1:** ***Volatility group classification***

| Volatility group | Occupation Groups |
|---|---|
| **Volatile** | Salaried employees in small businesses; Industrial workers; Managers; Qualified self-employed professionals |
| **Non-volatile** | Legislators; Organised farmers; Non-industrial technical employees in the public sector; White-collar clerical employees; Wage labourers; Agricultural labourers; Entrepreneurs; Home-based workers; Small Traders/Hawkers |

*Notes:* The table presents the classification of occupations into volatile and non-volatile groups based on the CPHS household-level occupation variable.

**Table A2:** ***Education group classification***

| Education group | Household education categories |
|---|---|
| **More educated** | All Graduates household; Graduates dominated household; Graduates majority household; Graduates minority household |
| **Less educated** | All Matriculates household; Households of all illiterates; Households of all literates; Households of some literates; Matriculates dominated household; Matriculates majority household; Matriculates minority household |

*Notes:* The table presents the classification of households by highest educational attainment (age>25) into more-educated and less-educated groups using the CPHS education variable.