Does Income Affect Women's Health Spending? Evidence from India's Formal Sector

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Abstract

This paper examines how women's control over income affects household health investment decisions by exploiting a 2018 policy change in India that increased take-home pay for women in the formal sector. Using household-level panel data from 2016-2019, I implement a difference-in-differences strategy comparing female-majority households in formal versus informal employment. Results show that beneficiary households increased health expenditure by 1.9% following the policy change. This increase was primarily driven by preventive care, with a 5.9% rise in health enhancement spending and a 3.4% increase in health insurance premiums, while spending on immediate medical needs showed minimal changes. The effects were strongest immediately following the policy implementation but declined over time. Analysis of household characteristics reveals that education levels strongly influence health spending patterns, with high-education households spending 24% more than basic-education households. These findings suggest that while increased income prompts higher health investments by women, the sustainability of these changes may depend on household characteristics and competing consumption priorities.

Introduction

Traditional economics has largely focused on understanding and modeling individual decision-making, in that they assume rational consumers base their decisions in order to maximise their objective function, given their budget constraint (Almås et al., 2023). However, some of the most important decisions on allocation of resources are not taken individually, but within the family. As Agarwal et al. (2022a) points out, research on intra household decision making exists in various contexts, and is useful to study the distributional effects of public policies in developing country contexts. We extend this framework by arguing that public policies can serve as a lens to examine how increased resource control affects household health investment decisions.

Understanding how households allocate additional income to health investments is crucial for policy design in developing countries. While extensive research has examined the relationship between income and health spending, less attention has been paid to how gender shapes these investment decisions. This gap is particularly relevant in contexts where women's healthcare access and decision-making power are constrained by social and economic factors (Agarwal et al., 2022b). Maxwell and Vaishnavi (2011) point out that one of the ways to determine the degree of agency a woman holds is by studying the extent of their influence in household resource allocation. They find that there is a positive association between working women and household decision making.

Building on this literature linking women's employment to household decision-making power, we examine how formal sector employment—and specifically, changes in women's take-home pay—affects health investment decisions. The formal sector context is particularly relevant as it provides both increased income and potentially greater autonomy in spending decisions.

This paper examines how women's health spending responds to increased income by exploiting a 2018 policy change in India that effectively raised take-home pay for women in the formal sector. Our analysis focuses on three key dimensions: the types of health investments women prioritize when given additional resources, how household characteristics like education and age composition influence these choices, and how spending patterns evolve over time after an income shock.

Several features make this setting particularly suitable for examining women's health investment decisions. First, India's mixed healthcare system, with both public and private options, allows us to observe discretionary health spending choices. Second, the formal sector context provides a well-defined treatment group with clear policy exposure. Third, our detailed household-level data enables analysis of different types of health spending, from preventive care to curative treatments.

We find that, given an increase in income, female-headed households in the formal sector increase their health expenditure by 1.9% compared to households in the informal sector, with a focus on preventative, long-term health expenditure, although we see a declining effect over time. Our findings contribute to understanding how income changes translate into health investments, particularly in contexts where women's healthcare decisions intersect with formal employment, education, and household dynamics. This has important implications for policies aimed at improving women's health outcomes through economic empowerment.

Institutional Context and Policy

One of the key constraints that persist poverty for households is the inability to invest in human capital and productive activities (Macours & Vakis, 2009). In developing countries, cash transfers is a popular social protection strategy to alleviate poverty and improve social outcomes, particularly for health and education. These cash transfer programmes fundamentally aim at increasing the budget constraint of households either under “specific behavioural conditions” or without any stipulations (World Bank, 2018). Whether these strategies go beyond just relieving immediate liquidity constraints and result in upward mobility is still under question, since any policy targeting household resource allocation impinges on the complex, interrelated dynamics of household behavior. Existing literature on cash-transfers emphasize that the beneficiary of the cash transfer is a “mediator” for better nutrition and health (Gram et al., 2018). Beneficiary spending often results in an increase in paying for “higher quality meals, increased preventative and curative health visits, transportation to health facilities and medical supplies” (Gram et al., 2018). Gram et al. (2018) further argue that beneficiary spending does not exist in a vacuum, rather an outcome of “individual beliefs, attitudes and relationships to other household members”. The effectiveness of such interventions thus depends on how these individual and household dynamics shape the allocation of additional income toward key investments.

Our study examines these dynamics through a different lens: a policy change that effectively increased women's disposable income through reduced mandatory savings. Following Agarwal et al. (2022a), we analyze the February 2018 amendment to India's Employee Provident Fund Act of 1952, which reduced EPF contributions for women in the formal sector from 12% to 8%, to incentivise more women to join the formal sector (Nanda, 2018). This policy change provides an ideal natural experiment to study how women's health investment decisions respond to increased take-home pay, while working through existing formal sector institutions rather than direct transfers.

Methods

Data Sources

Consumer Pyramid Household Survey

The study uses longitudinal household level survey data from Consumer Pyramid Household Index from the Center for Monitoring Indian Economy which comprises 174,000 sample households all across 28 states and 514 districts in India collected triannually. The paper obtains data from January 2016 to December 2019, providing both pre and post-policy implementation periods. The CPHS offers several advantages for our analysis. It has detailed expenditure data across multiple categories including health, leisure, and education, and includes rich household characteristics including age composition, education levels, and region type. Particularly, it provides granular health expenditure data broken down into components such as medical treatments, preventive care, and health enhancement which is helpful for our analysis.

The study focuses on households with significant female representation in decision-making, specifically, female-majority households, female dominant households and all female households. Female majority households have more females than male members, and female-dominant households are households where females form not only the numerical majority but also play primary roles in decision-making, income generation, or caregiving. This grouping is done to understand the nature of decision-making of women in a household (Agarwal et al., 2022).

Treatment and control group construction

The identification strategy leverages the 2018 policy affecting formal sector employment. Households were split into formal and informal employment based on the definition of formal employment characterised by regular pay, return contracts, and social security (International Labor Organization, n.d). This grouping was used in Agarwal et al.'s (2022) paper as well. Households that have a majority of females in the formal sector before the policy shock were assigned a dummy value of 1 and took the value of 0 if the household had majority females in the informal sector prior to the shock. This assignment enables us to implement a difference-in-differences strategy to estimate the causal effect of increased income on health expenditure patterns.

Two-way fixed effects Difference in Difference Approach

This study employs a two-way fixed effects difference-in-differences (DiD) design to estimate the causal effect of increased income on health expenditure. The baseline specification is:

$$\text{Log(Health Expenditure)}_{i\square} = \beta_0 + \beta_1\text{Beneficiary}_i + \beta_2\text{Post2018}_\square + \beta_3(\text{Beneficiary} \times \text{Post2018})_{i\square} + \delta_i + \gamma_\square + \varepsilon_{i\square}$$

Where *i* indexes households and *t* indexes time (months), $\textit{Beneficiary}_i$ indicates formal sector employment which takes the value of 1 for households with majority of females in the formal sector and 0, otherwise. $\textit{Post2018}_\square$ indicates periods after the policy implementation and takes the value of 1 where data is prior to February 2018, and 0 otherwise. δ_i represents household fixed effects, and $\gamma_\square$ represents time fixed effects. The main coefficient of interest is β_3, measuring the differential change in health expenditure for beneficiary households after the policy was implemented. The household fixed effects (δ_i) control for time-invariant household characteristics that might affect health expenditure patterns. The time fixed effects ($\gamma_\square$) account for temporal shocks affecting all households. The study uses logarithmic transformation of the dependent variable to address skewness in expenditure data and interpret coefficients as percentage changes.

The baseline model is further augmented with household characteristics:

$$\text{Log(Health Expenditure)}_{i\square} = \beta_0 + \beta_3(\text{Beneficiary} \times \text{Post2018})_{i\square} + \beta_4\text{EduGroup}_{i\square} + \beta_5\text{AgeGroup}_{i\square} + \delta_i + \gamma_\square + \varepsilon_{i\square}$$

Drawing from prior literature and a DAG approach, we include household education and age composition as key covariates. Our DAG analysis reveals that both education and household age composition act as confounders in the relationship between income and health expenditure. This specification includes education group fixed effects to control for variation in health awareness and decision-making capacity, age group composition to account for lifecycle differences in health needs (Vikram and Vanneman, 2019; Parinduri, 2016; Chowdhury et al., 2018). The importance of controlling for these confounders is evident in our model progression, where the treatment effect changes from -1.3% to +2.1% after including age controls, suggesting significant omitted variable bias in the baseline specification (see Table A2 in Appendix). This underscores the necessity of including these covariates for reliable causal inference.

We consolidate the original CPHS categories into broader groups to improve interpretability while maintaining its theoretical relevance. Age group categories included in the model are *young-dominated* households (combining households with majority children, and Young-dominated), *adult-dominated* (households with working-age majority) and *senior-present* (households with significant elderly presence). Education Groups included are *high-education* (graduate-dominated, graduate-majority, graduate minority households), *medium-education* (All matriculates, matriculate-dominated, matriculate majority, matriculate-minority households), *basic-education* (Households of some literates, and literate households), and *low-education* (illiterate households).

While our main difference-in-differences model estimates the average treatment effect, it masks potential temporal heterogeneity in how households respond to increased income. To examine the dynamic effects of the policy, we estimate:

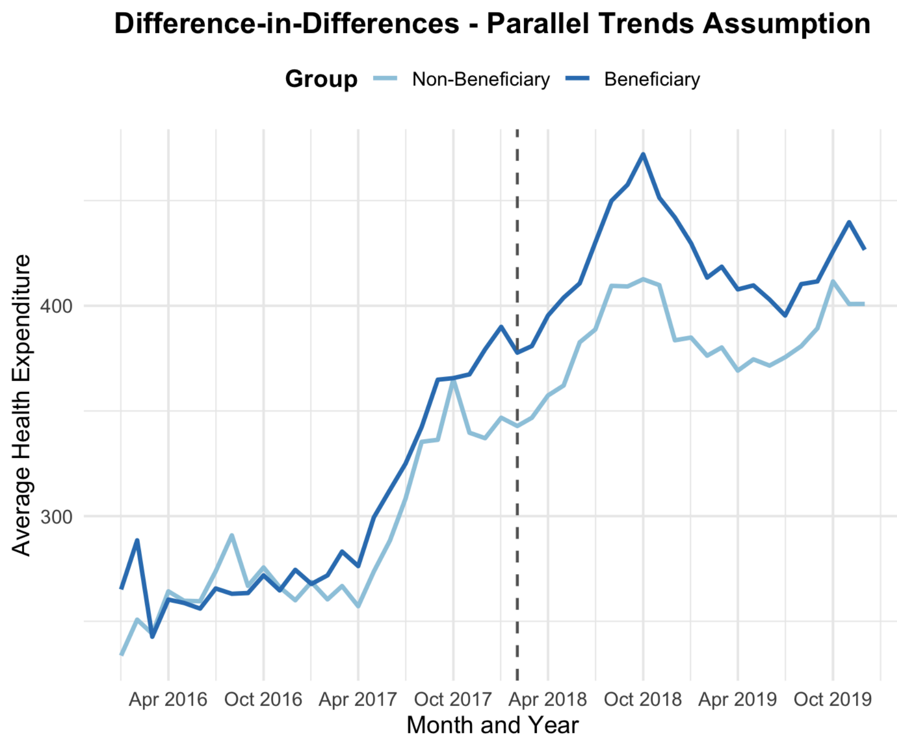
$$\text{Log(Health Expenditure)}_{i\square} = \beta_0 + \Sigma_{\square}\beta_{\square}(\text{Beneficiary} \times \text{Quarter})_{i\square} + \beta_4\text{EduGroup}_{i\square} + \beta_5\text{AgeGroup}_{i\square} + \delta_i + \gamma_{\square} + \varepsilon_{i\square}$$

where *Quarter* represents quarterly time periods after policy implementation, allowing us to trace the evolution of the treatment effect over time. This model will help assess whether the income shock had immediate effects or if households took time to adjust spending patterns and reveal whether initial changes in health expenditure were sustained over time.

Our difference-in-differences strategy relies on several key assumptions. We argue that the Stable Unit Treatment Value assumption is likely satisfied in this context because of the clear sectoral separation that operates in the distinct labor markets with different regulatory environments for the formal and informal sector, minimizing spillover effects. Since the policy specifically targets formal sector wages, we assume that it does not affect informal sector workers. Upon visual inspection of pre-treatment periods from 2016 to 2017 (See Figure 1), we can confirm parallel

movement in average health expenditure between the treatment and control groups supporting the crucial parallel trends assumptions.

Figure 1: Parallel trends plot (beneficiary vs non-beneficiary health spending)



While both fixed and random effects specifications were considered, a Hausman test strongly rejected the consistency of random effects estimators ($p < 0.05$). This supports our use of fixed effects to control for unobserved household characteristics that might correlate with both formal sector employment and health spending decisions. The two-way fixed effects approach also accounts for time-invariant household characteristics and temporal shocks that could confound our estimates.

Results

As shown in Table 1, we see that 60% of the female households are employed in the informal sector, with self-employed entrepreneurs (street vendors, shop owners, etc.) making up the highest population, and formal sector workers primarily concentrated in wage labor.

The data also reveals important patterns in household health expenditure from 2016 to 2019. Total monthly health expenditure shows a substantial increase over the study period, rising from Rs. 26,306 in 2016 to Rs. 39,634 in 2019 - a 50% increase.

Table 1: Percentage of Female Workers by Employment and Occupation Group

Characteristic	**N = 1,703,983**
employment_type	
Informal Employment	1,028,598 (60%)
Formal Employment	675,385 (40%)
occupation_group	
Wage Labourers	311,309 (18%)
Self-employed Entrepreneurs	251,374 (15%)
Support Staff	154,911 (9.1%)
Small/Marginal Farmers	141,031 (8.3%)
Entrepreneurs	110,704 (6.5%)
White-collar Professional Employees	96,311 (5.7%)
Retired/Aged	85,961 (5.0%)
White-collar Clerical Employees	85,284 (5.0%)
Agricultural Labourers	83,673 (4.9%)
Industrial Workers	74,923 (4.4%)
Organised Farmers	62,814 (3.7%)
Miscellaneous	61,760 (3.6%)
Non-industrial Technical Employees	58,997 (3.5%)
Small Traders/Hawkers	58,025 (3.4%)
Business & Salaried Employees	34,581 (2.0%)
Home-based Workers	18,345 (1.1%)
Qualified Self-employed Professionals	7,078 (0.4%)
Managers/Supervisors	5,902 (0.3%)
Legislators/Social Workers/Activists	1,000 (<0.1%)

Breaking down this expenditure by category, we see that health enhancement is consistently the largest component of health spending accounting for approximately 40-43% of total health expenditure, increasing from Rs. 11,273 in 2016 to Rs. 15,880 in 2019. In terms of medical service expenditures, spending on doctors fees increased significantly from Rs. 1,121 in 2016 to Rs. 2,911 in 2019. Spending on hospital fees fluctuated, peaking at Rs. 1,734 in 2018 before declining, and medical tests doubled from Rs. 432 to Rs. 877 per month from 2016 to 2019.

Expenditure on health insurance premium, representing the smallest share of health expenditure, shows modest but increasing adoption, rising from Rs. 371 to Rs. 469 per month in 2019. Figure 2 shows the breakdown of the monthly health expenditure components for female-headed households over the years 2016 to 2019.

Figure 2: Breakdown of Components of Monthly Health Expenditure

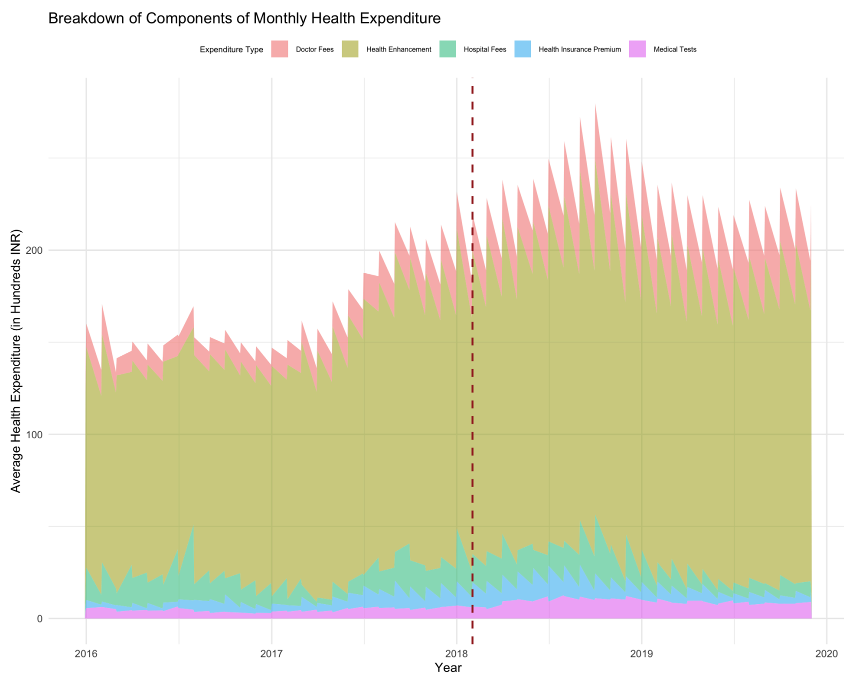


Table 2 reports the estimates of equation 2 for the main dependent variable, Log of monthly total health expenditure. The interaction term Beneficiary:Post_2018 is positive and statistically significant at the 0.01 level, indicating that female households in the formal sector experienced a 1.9% higher growth in health expenditures post-2018 relative to female households in the informal sector, after accounting for household age and education composition. This suggests that the income shock from the 2018 policy had a measurable impact on the health spending behavior of beneficiary households.

Among the age-related categories, female-headed households with seniors-present exhibit the largest positive associations with health expenditures compared to the reference group, households with adults, with an increase of 2.7% ($p < 0.01$) in monthly health expenditure compared to adult households.

Table 2: Final Model

	Dependent variable:
	log_m_exp_health
as.factor(age_group_simple)Senior-present	0.027*** (0.006)
as.factor(age_group_simple)Young-dominated	0.023*** (0.004)
as.factor(edu_group_simple)High-education	0.239*** (0.007)
as.factor(edu_group_simple)Low-education	−0.088*** (0.005)
as.factor(edu_group_simple)Medium-education	0.139*** (0.005)
Beneficiary:Post_2018	0.019*** (0.003)
Observations	1,703,983
R^2	0.001
Adjusted R^2	−0.038
Note:	*p<0.1; **p<0.05; ***p<0.01

Notes: Coefficients shown are relative to the base category of Adult-dominated households, and Basic-education, for age group and education group variables, respectively.

Young-dominated households see an associated increase of 2.3% ($p < 0.01$), compared to adult-dominated households, closely following households with seniors present.

In terms of education, female-headed households with majority highly educated individuals exhibit the highest health expenditures, with a substantial 23.9% higher spending compared to the reference group, households with basic-education, significant at the 0.01 level. Similarly, households with medium-education see an associated 13.9% ($p < 0.01$) increase in health expenditure compared with households with basic education. On the other hand, households with low education spend 8.8% ($p < 0.01$) less than the reference group.

Table 3 gives the estimates for equation 3 reporting the temporal trends in how the policy shock affected health expenditure. Immediately following implementation, beneficiary households showed a significant 3.9% increase in health spending, highly significant at the 0.01 level.This initial effect remained relatively stable through Q2 2018 before showing a slight uptick to 1.3% in Q3 2018, though this increase was not statistically significant. However, starting in Q1 2019, we observe a significant decline in the treatment effect. Health expenditure decreased by 1.8% ($p < 0.05$) in Q1 2019, with this downward trend continuing and strengthening through subsequent quarters. By Q4 2019, beneficiary households were spending 3.3% less on health compared to the initial impact ($p < 0.01$).

Table 3: Dynamic Treatment Effects Model

	Dependent variable:
	log_m_exp_health
Beneficiary	0.039*** (0.006)
Beneficiary:factor(post_quarter)2018_Q2	−0.001 (0.008)
Beneficiary:factor(post_quarter)2018_Q3	0.013 (0.008)
Beneficiary:factor(post_quarter)2018_Q4	0.009 (0.008)
Beneficiary:factor(post_quarter)2019_Q1	−0.018** (0.008)
Beneficiary:factor(post_quarter)2019_Q2	−0.033*** (0.008)
Beneficiary:factor(post_quarter)2019_Q3	−0.030*** (0.009)
Beneficiary:factor(post_quarter)2019_Q4	−0.033*** (0.009)
Beneficiary:factor(post_quarter)pre_2018	0.003 (0.006)
Observations	1,703,983
R^2	0.001
Adjusted R^2	−0.038
Note:	*p<0.1; **p<0.05; ***p<0.01

In order to examine the individual effects of the components of total health expenditure in a household, two way fixed effects models were run with the log of each component of total health expenditure as the dependent variable (See Table 4). Examining the components of health expenditure reveals heterogeneous effects of the income increase across different categories of health spending.

The strongest effects are observed in preventive and health enhancement-related categories. Health enhancement expenditure, which includes spending on wellness and preventive care, shows the largest increase of 5.9%, significant at the 0.01 level, among beneficiary households.

Table 4: Change in Associated Health Expenditure Variables

	Dependent variable:				
	log_m_exp_doc Doctor	log_m_exp_medtest Tests	log_hosp_fee Hospital	log_health_ins Insurance	log_health_enh Enhancement
	(1)	(2)	(3)	(4)	(5)
Treatment Effect	0.003	0.001	−0.0002	0.034***	0.059***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,703,983	1,703,983	1,703,983	1,703,983	1,703,983
R^2	0.0001	0.00002	0.00003	0.001	0.004
Adjusted R^2	−0.039	−0.040	−0.040	−0.039	−0.036
Note:					*p<0.1; **p<0.05; ***p<0.01

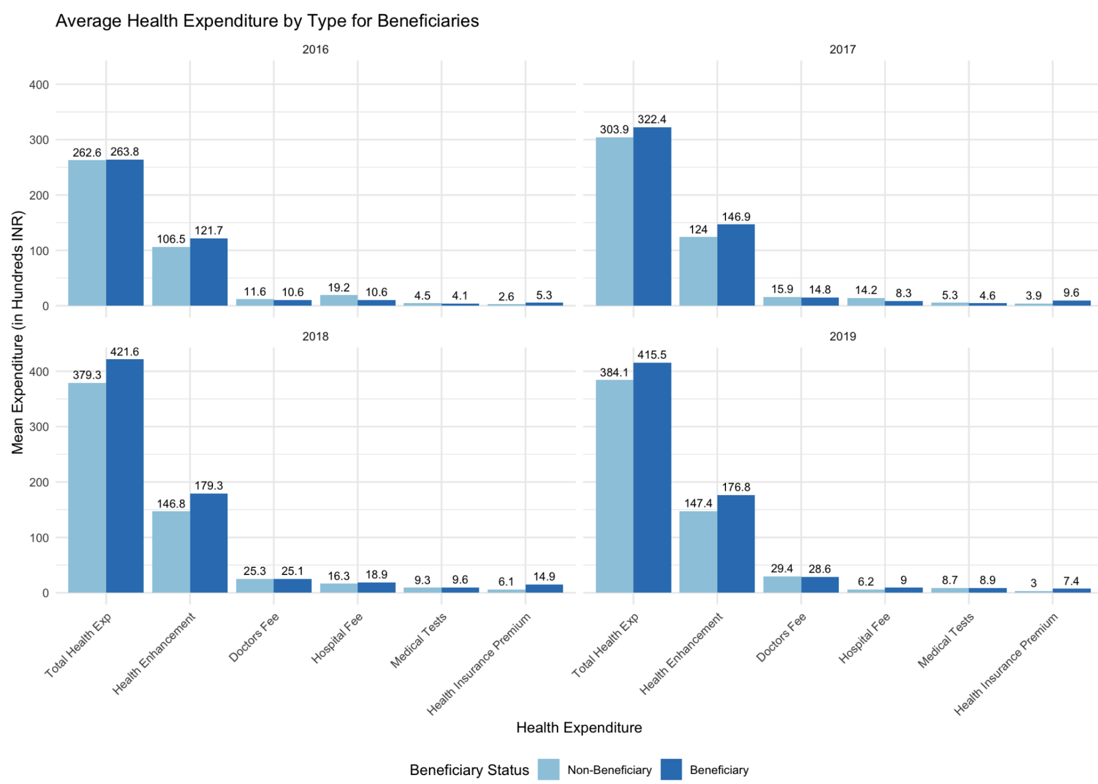
Similarly, health insurance premium spending increased by 3.4%, also significant at the 0.01 level. In contrast, we find minimal effects on direct medical care expenses. Doctor fees show a small, insignificant increase of 0.3%, while medical tests show an even smaller increase of 0.1%, statistically insignificant as well. Hospital fees actually decreased marginally by 0.02%, though this effect is also not statistically significant.

Discussion

Following the 2018 policy that increased take-home pay for formal sector employees, our findings suggest that female-headed households in formal employment increased their health expenditure by 1.9% compared to similar households in informal employment. This differential response to the policy-induced income change demonstrates that women's health spending decisions are responsive to changes in available resources. This finding is similar to studies in anti-poverty cash transfer literature that show that women as recipients of cash transfers improve the health status of children, as well as larger increases in spending on health, and nutrition (Duflo, 2003, Thomas, D. 1990 Gertler and Boyce, 2003).

Breaking down this effect by type of health spending reveals an important pattern: the increase was primarily driven by preventive and long-term care choices (See Figure 3). Specifically, we find a 5.9% increase in health enhancement spending and a 3.4% increase in health insurance premiums, while spending on immediate medical needs like doctor visits and hospitalizations showed minimal changes. This spending pattern coincides with India's broader push toward preventive healthcare and insurance coverage during this period, including the launch of Ayushman Bharat in 2018, a nation-wide government initiative which aimed to increase health insurance coverage.

Figure 3: Bar Chart breakdown of Health Expenditure by Type

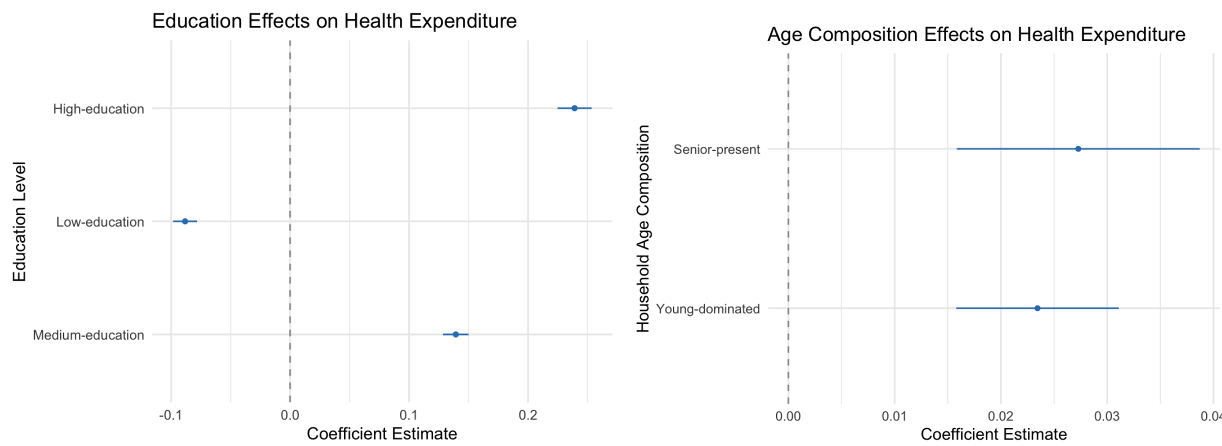


The stronger response in preventive care compared to curative care might reflect both gender-specific healthcare seeking behaviors and socio-cultural constraints. While women often face barriers in accessing hospital-based or curative care due to household pressures and social norms in India (Agarwal et al., 2022b), they tend to be more proactive in preventive healthcare decisions. Research by Hallyburton and Evarts (2014) shows that women are more likely than men to seek health information and coordinate healthcare decisions for their families. This pattern is particularly pronounced among educated women - our finding that high-education households showed the largest increase in health expenditure aligns with Dluhos-Sebesto et al. ‘s (2021) evidence that education plays a crucial role in health information seeking and disease prevention.

The gender role of women as primary health care coordinators for their families might explain these spending patterns. Studies have documented that women are more likely to consult diverse healthcare resources, including formal and informal networks, and often search for health information both for themselves and family members (Rowley et al., 2014; Warner and Procaccino, 2007). This broader engagement with health information, combined with increased resources from formal sector employment, might facilitate greater investment in preventive care even when cultural barriers to hospital-based care persist.

Figure 4 reveals that household composition significantly influences health expenditure patterns in female-headed households, with senior-present households spending 2.7% more on health compared to adult-dominated households. This age-composition effect is particularly relevant in India's demographic context, where population aging intersects with healthcare needs and household financial decisions. Chowdhury et al. (2018) document that households with elderly members face substantially higher healthcare burdens, particularly in managing chronic conditions. This burden is especially pronounced given that over 60% of India's aged population suffers from at least one non-communicable disease (Mini and Thankappan 2017).

Figure 4: Coefficient plots for education and age effects



Notes: Coefficients shown are relative to the base category of Adult-dominated households, and Basic-education. The dots represent point estimates and horizontal lines show 95% confidence intervals. All estimates are from the two-way fixed effects model controlling for household education levels.

The higher spending in senior-present households might reflect both health needs and resource allocation decisions. Dhak (2014) as cited in Chowdhury et al. (2018) finds that Indian households often prioritize elderly healthcare needs, even under financial constraints. This prioritization becomes more feasible when households have access to formal sector income, as suggested by our findings.

Finally, our temporal analysis shows that while the policy had an immediate positive effect on health spending, the impact was not sustained long-term. Households appear to have initially allocated their increased income to health expenditure but adjusted their spending patterns downward over time. This could reflect either a reallocation of the additional income to other priorities after meeting initial health needs, as evidenced by the women's spending on other expenditure including food, recreation and clothing (see Table A3 in Appendix) or possibly suggest that the income shock led to a one-time increase in health investments rather than a permanent change in health spending patterns. This pattern has important implications for understanding how income shocks translate into sustained health investments, particularly in developing country contexts where households face multiple resource constraints.

Conclusion

This paper examines how increased income affects women's health expenditure patterns by exploiting a 2018 policy change that increased take-home pay in India's formal sector. We find that female-headed households in formal employment increased their health expenditure by 1.9% compared to informal sector households, with this increase primarily driven by preventive care and health insurance spending. The stronger response in preventive rather than curative care, combined with the significant role of education in health spending decisions, suggests that both resource constraints and information access influence women's health investment choices. However, the declining effect over time raises questions about the sustainability of income-driven health investments.

These findings have important policy implications. While income increases can prompt higher health investments by women, the temporal pattern suggests that one-time income shocks might not sustain long-term changes in health spending behavior. This points to the potential value of combining income-based interventions with health education and sustained support for preventive care access.

This paper has several limitations that warrant consideration. The CMIE data has been criticized for underrepresenting women, young adults, and having a bias towards urban, middle-class, educated households, potentially limiting the generalizability of our findings (Das et al., 2024). Our short observational window, particularly post-policy, constrains our ability to assess longer-term effects. Additionally, our treatment group includes all women in the formal sector rather than just new entrants post-2018, potentially diluting the estimated treatment effect. The lack of access to a detailed codebook also created challenges in precise variable interpretation. Future research with longer time horizons and more representative data could help address these limitations and further illuminate the relationship between women's income and health investment decisions.

Appendix

Table A1: Average Monthly Household Health Expenditure in Hundreds INR

Health Outcome	2016	2017	2018	2019
m_exp_health	263.06	311.18	396.03	396.34
m_exp_doctors_physio_fee	11.21	15.43	25.21	29.11
m_exp_medical_tests	4.32	5.00	9.39	8.77
m_exp_hospitalisation_fees	15.64	11.90	17.34	7.29
m_exp_health_ins_premium	3.71	6.16	9.57	4.69
m_exp_health_enhancement	112.73	133.00	159.68	158.80

Table A1 presents the average monthly household health expenditure (in hundreds INR) from 2016 to 2019. Total health expenditure increased from Rs. 263.06 in 2016 to Rs. 396.34 in 2019. Health enhancement consistently represents the largest component after total health expenditure, increasing from Rs. 112.73 in 2016 to Rs. 158.80 in 2019. Other components show varying patterns: doctor fees more than doubled from Rs. 11.21 to Rs. 29.11, while hospitalization fees decreased from Rs. 15.64 to Rs. 7.29 over the study period.

Table A2: Model progression showing how adding covariates changed effects

	Dependent variable:		
	log_m_exp_health		
	(1)	(2)	(3)
Beneficiary:Post_2018	-0.013^{***} (0.003)	0.021^{***} (0.003)	0.019^{***} (0.003)
Observations	1,703,983	1,703,983	1,703,983
R^2	0.0002	0.00004	0.001
Adjusted R^2	-0.039	-0.040	-0.038
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A2 shows how the treatment effect evolves with the addition of different controls. The baseline model without controls shows a decrease of 1.3% in health expenditure. Adding age group controls changes the direction and magnitude of the effect to a 2.1% increase, suggesting significant confounding by household age composition. The addition of education controls stabilizes the effect at 1.9%, which remains robust. This progression demonstrates the importance of controlling for household characteristics in isolating the policy's impact.

Table A3 examines changes in non-health expenditure categories following the policy change. All coefficients are statistically significant at the 0.01 level. Beneficiary households increased spending on food, clothing and footwear, recreation, and transportation compared to non-beneficiary households, while decreasing expenditure on bills and rent. These patterns suggest the policy led to broader changes in household consumption patterns beyond health spending.

Table A3: Changes in other expenditure categories

	Dependent variable:				
	Food	Bills and Rent	Clothing and Footwear	Recreation	Transportation
	(1)	(2)	(3)	(4)	(5)
Beneficiary:Post_2018	0.015***	−0.014***	0.052***	0.026***	0.053***
	(0.001)	(0.003)	(0.005)	(0.003)	(0.003)
Observations	1,703,983	1,703,983	1,703,983	1,703,983	1,703,983
R^2	0.007	0.0001	0.0002	0.0003	0.0003
Adjusted R^2	−0.032	−0.039	−0.039	−0.039	−0.039
Note:					*p<0.1; **p<0.05; ***p<0.01

Notes: Two-way fixed effects difference-in-difference models were run with the logarithmic transformation of each expenditure category as the dependent variable, and is controlled for age group and education composition.

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