ECONOMICS

# Working Paper Series

## No. 13-2024

# Income shock and Women's Health Spending: Evidence from India*

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JEL codes: 111, 112, 114, 115
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30 September 2024

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*Keywords*: Income, Health Spending, Gender

JEL Codes: I11; I12; I14; I15

*This paper has benefited from comments and suggestions from Indrajit Adhikary, Farzana Afridi, Shilpa Aggarwal, Chon-Kit Ao, Parasuram Balasubramanian, Sourav Bhattacharya, Joseph Flavian Gomes, Samarth Gupta, Rajshri Jayaraman, Tanmoy Majilla, Barsha Saha, Maika Schmidt, Aparajita Dasgupta, Soham Sahu, Arnab Mujherjee, Aditya Srinivas, Deepshikha Bhateja, Tirthatanmoy Das participants in the IHOPE Research Brown Bag Seminar Series, Samvad Series-Inclusion Economics India, Department of Economics Seminar at University of Sussex, Economics Seminar at National Cheng-Kung University in Taiwan, 17th Annual Conference on Economic Growth and Development, Department of Economics at IIM Bangalore, Centre for Monitoring Indian Economy seminar and Annual Conference on Contemporary Issues in Development Economics. The authors acknowledge funding from Wellcome Trust/DBT India Alliance grants Indian Health Outcomes, Public Health and Economics Research Centre (IHOPE). The views expressed herein are those of the authors and the usual disclaimers apply. We thank LV Prasad Eye Institute for their generous support and for providing access to their data. The statements, findings, conclusions, views, and opinions contained and expressed in this article are based in part on hospital electronic medical records data obtained from LV Prasad Eye Institute and have been approved by the ethics committee and IRB administration under the IRB approval number: LEC-BHR-R-05-22-876. Research assistance from Krsna Singh is gratefully acknowledged. We also thank Dr. Raja Narayanan and Dr. Anthony Vipin Das at the L V Prasad Eye Institute.

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# 1. Introduction

Steady rise in healthcare expenditure during economic expansion is notably a common trend across many countries around the world (Hall & Jones, 2007; Murphy & Topel, 2003, 2006; Nordhaus, 2003). This undoubtedly aids the familiar conjecture that healthcare expenditure expansion is a consequence of economic growth as healthcare is a luxury good. Acemoglu, Finkelstein, and Notowidigdo (2013) and Blomqvist and Carter (1987) cites The Economist magazine declaring this as "conventional wisdom" in 1993 and stating, "As with luxury good, health spending tends to rise disproportionately as countries become richer." Figure 1 plots World Bank data on health spending trends across different countries and country groups over the period 2000 to 2020. Indeed, it showcases steady increase in health expenditure as a share of GDP in advanced economies such as the United States and OECD. Emerging economies such as China and Indonesia also demonstrate similar trends during a period when their economies expanded steadily. Healthcare expenditure in Sub Saharan Africa remains flat and could be due to uneven economic progress. In contrast, healthcare expenditure relative to GDP in India falls at a time when the Indian economy expands at an annual rate of 6%.

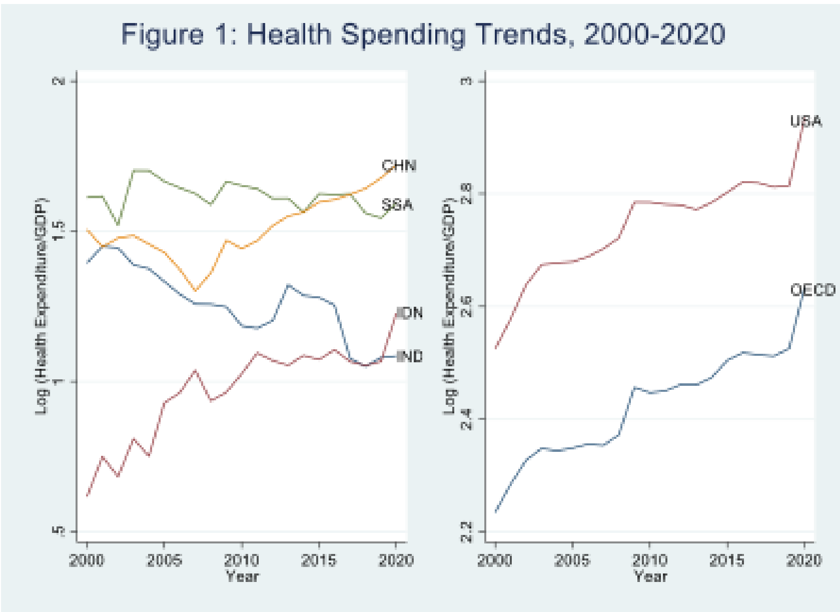


**Figure 1: Note:** The figure represent the health expenditure as a share of GDP

Despite the macro trends seemingly supporting convention wisdom of healthcare as a luxury good, the relationship between income and healthcare could be context specific. Acemoglu et al. (2013) find healthcare to be a necessity rather than a luxury. A negative relationship could emerge in the event of dynamic preferences whereby preferences tilt in favour of non-healthcare goods following an income shock (De Rock, Potoms, & Tommasi, 2022). Negative preference tilting effect on healthcare could dominate over any positive income effect.[1]

We examine this curious contrarian macro trend even further by taking it to the micro Consumer Pyramid Household Survey (CPHS) data in India in Figure 2. In particular, we correlate healthcare expenditure share with household total income and wage income in two separate specifications and find negative partial effects even though the coefficient on total income is insignificantly different from zero. Admittedly the trend plots and the estimates are not causal. Nevertheless, it is logical to ask why India appears to be an outlier in relation to the "conventional wisdom"?

In particular, this paper estimates the causal effect of income shock on healthcare expenditure at the micro level and for female led households. We are able to exploit an unanticipated policy shock in the form of a reduction in mandated employees' provident fund contribution for women to identify the effect of income on healthcare expenditure in female led households. We use CPHS and hospital electronic medical records to this end. CPHS is longitudinal household survey data covering the period 2016-2020 whereas the hospital electronic medical records offer administrative data for a cross-section of patients visiting a leading chain of eye hospitals in India over the period 2016-2020. We find that an unanticipated increase in take-home salary for women is associated with a decrease in overall spending on healthcare in female led households even after controlling for improved health outcomes for women, health-status, healthcare utilization at the intensive margin (i.e., hospital visits to seek treatment). Our results do not seem to support the "conventional wisdom" that healthcare is a luxury good and preferences towards it are uniform across gender, geographies and cultures. It indicates that the effect of income on healthcare could be context specific. It is suggestive that gendered effects of healthcare in India and the global south could be guided by social norms. Therefore, it is not obvious that the income elasticity would always be positive across gender and space.

A large literature examines the empirical relationship between income and healthcare

[1] See section 6 for details.

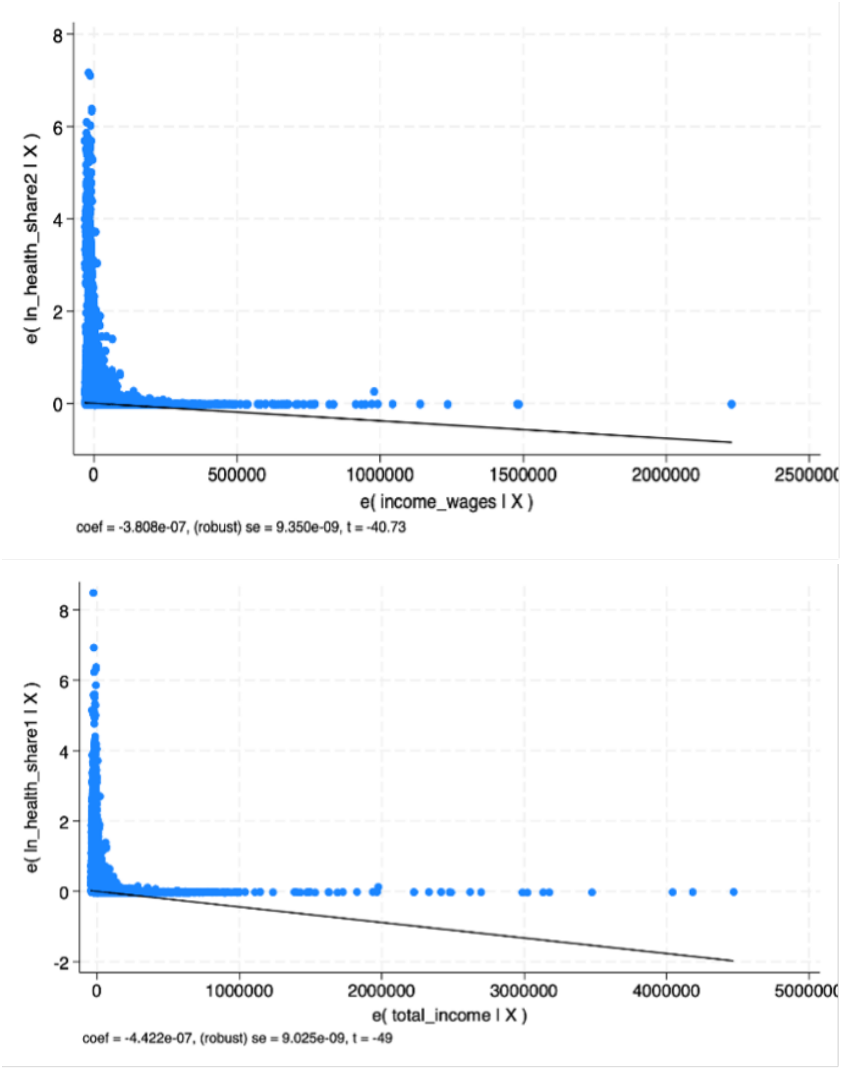


**Figure 2: Household Income, Wages and the Share of Healthcare Expenditure** Source: Consumer Pyramid Household Survey Data 2016-2020

expenditure yet causal estimates are rare. Large majority of empirical studies offer correlations using cross-national, individual cross-sectional, and time series datasets for OECD and advanced economies. Hall and Jones (2007) articulates this well by concluding, "Our model makes the strong prediction that if one looks hard enough and carefully enough, one ought to be able to see income effects [with elasticities above 1] in the micro data. Future empirical work will be needed to judge this prediction." (also cited in Acemoglu et al. (2013)). Needless to add that causal estimates using large longitudinal household survey datasets and patient level cross-sectional administrative datasets for developing countries are even more rare. We contribute to this literature by offering estimates of the causal relationship between income and health spending in a large developing country using a large micro dataset. We also identify gender heterogeneity of this effect which is contrary to the "conventional wisdom" and what is typically observed in high income countries. To the best of our knowledge, these contributions are novel and our paper is the first to offer causal estimates of the effects of income on health spending using developing country large micro datasets.

Our paper is related to Acemoglu et al. (2013) to the extent that they also offer causal estimates of income elasticity of health spending. However, they use state level panel data for the US covering the southern states and oil price shocks as an identifier. In contrast, we are able to exploit household and patient level variation in large micro datasets for a developing country which is a significant step forward in this literature. Our identification strategy for estimating the causal effect relies on the February 2018 announcement by the finance minister of India that mandatory pension contribution by women in formal employment would be reduced from 12% to 8% for the first three years of their employment. This led to an increase disposable income for women compared to the counterfactual. In other words, the cross-sectional variation generated by women in formal employment and the variation generated by the timing of policy onset offers a quasi-experimental setting for identification. We use various alternative definitions of formal employment to identify women working in formal sectors to avoid issues of endogenous selection.

The CPHS dataset is high-frequency, nationally representative, large, and covers the period 2016-2020. It is produced by the Centre for Monitoring Indian Economy (Gupta, Malani, & Woda, 2021; Parker, Souleles, & Carroll, 2014; Sabelhaus et al., 2013). We find that in response to the unanticipated positive income shock, women tend to increase their expenditure on health enhancement activities such as gym membership and nutritionist consultation that could potentially lead to better health outcomes. The overall negative expenditure is driven by significant reductions in doctor consultation expenditure and medications. Two latent channels through which reduced healthcare spending could operate are: a) an improvement in overall health with higher income and b) a potential change in preference for healthcare following the income shock. It is however difficult to distinguish between the two seemingly competing channels. We also find significant changes in the overall expenditure composition and in particular an increase in human capital investments and a decrease in temptation consumption and recreation. We check whether the human capital investments are driven by female led households who are also mothers by restricting the sample. The effect for this sample is positive but not significantly different from zero thus indicating that non-mothers also invest in human capital following a positive unanticipated income shock.

To explore the change in preference for healthcare channel, we supplement our main analysis by collecting hospital-level administrative data on electronic medical records of all women visiting any of the healthcare delivery centers of a leading chain of eye hospitals in India between 2016-2020 and perform a similar empirical exercise. The advantage of this administrative dataset is that it allows us to study expenditure at the intensive margin and also control for ex-ante health status of patients. A woman is only part of this dataset if she had some adverse health condition meriting hospital visit. Among all these women we compare the difference in expense related outcomes before and after the policy for women employed in formal sector from those engaged in non-formal employment. This exercise effectively rules out the 'better health explains decline in health expenditure' channel and we still get a negative impact of income on health spending after controlling for confounding variables. This is suggestive that the effect is driven by heterogeneous preference.

Our paper is related to a large empirical literature on income elasticity of demand for healthcare spending and human capital. Gallardo-Albarrán (2018) focus on human capital and economic development whereas Dreger and Reimers (2005), Magsi, Memon, Sabir, Magsi, and Anwar (2021), Malecki and Jewell (2003), Deering (1981), Gerdtham, Søgaard, Andersson, and Jönsson (1992), and Newhouse (1977) focus on estimating income elasticity. Majority conclude that healthcare is a luxury good but more recent studies report income elasticity to be less than one for the US and OECD member countries and therefore a necessity (Acemoglu et al., 2013; Blazquez-Fernandez, Cantarero, & Perez, 2014; Di Matteo, 2003; Freeman, 2003; Sen, 2005). It is also related to a literature on how income elasticity of healthcare varies by the level of income (Baird, Friedman, & Schady, 2011; Bastagli et al., 2016; Bustamante & Shimoga, 2018; Chauvet & Guillaumont, 2009; Deaton, 2003; Di Matteo, 2003; Dubey et al., 2020; Farag et al., 2012; Preston, 1975) and by unit of analysis (household or individual) (Banerjee, Duflo, Postel-Vinay, & Watts, 2010; Diez-Roux, 1998; Forni, Lippi, et al., 1997; Getzen, 2000;

Susser, 1994).

The paper also speaks to the literature on gender identity and resource allocation as women are the recipients of our unanticipated income shock. Banerjee, Niehaus, and Suri (2019) show that the gender identity of the recipient of money can significantly influence the allocation of monetary resources within a household. Banerjee and Duflo (2019) document that major anti-poverty transfer programs in developing countries are targeted towards women as women's investment decision and resource allocation appear to be more efficient (Goodman & Kaplan, 2019) and women are agents for change (Luke & Munshi, 2011).

Finally, the paper speaks to conditional and unconditional cash transfer in developing countries literature. It suggests that transfers to women increase their assertiveness in household decision-making dealing with expenditure allocations (Attanasio, Battistin, Fitzsimons, & Vera-Hernandez, 2005; Banerjee & Duflo, 2019; Gitter & Barham, 2008; Holvoet, 2005; Rubalcava, Teruel, & Thomas, 2009), has a positive impact on nutritional status of the household (Bouillon & Yáñez-Pagans, 2011; Hazarika & Guha-Khasnobis, 2008; Rubalcava et al., 2009; Yanez-Pagans, 2008) positively affects household human capital investment decisions (Cahyadi et al., 2020; Chatterjee & Poddar, 2021; Handa et al., 2015; Skoufias, Davis, & De La Vega, 2001; Standing, 2013), and has a negative impact on consumption of intoxicants (Doepke & Tertilt, 2019; Evans & Popova, 2017; Team, 2012).

The rest of the paper is organized as follows. Section 2 presents the institutional context behind the unanticipated income shock. Section 3 describes the two datasets and presents descriptive statistics. Sections 4 and 5 present empirical strategy and results. Section 6 concludes.

# 2. Background

This section introduces the institutional setting for the unanticipated income shock. The Employees Provident Fund Act of 1952 established the Employees' Provident Fund Organization in India. This fund administers a defined benefit contribution employees' provident fund for formal sector employees across India. Individual payroll contributions to the fund are made both by employers and employees and they are realised with interest payment upon the termination of the service at an organization. It is a large pension fund in India, and "at present it maintains 24.77 crore (247.7 million) [member] accounts (Annual Report 2019-20)".[2]

On 1 February, 2018, the Government of India announced a reduction in contribution to the employees' provident fund by new women workers joining formal employment from the initial 12% to 8%.[3] The aim of this reduction was to increase the take-home-pay of women while encouraging an increase in labour market participation through the incentive. As per the rules, employees drawing less than Rs 15000 per month at the time of joining an organization had to become members of the EPF.[4] "An employee drawing pay above the prescribed limit (at present Rs 15,000) could also become a member with permission of Assistant PF Commissioner, through mutual agreement between the employee and the employer." Therefore, the policy targeted female workers employed in the formal sector in India. This EPF cut was applicable for the first three years of employment across all occupation class in the formal sector. Such a policy undoubtedly increased disposable. income of families that had women working in the formal sector This would have relaxed the budget constraint of these households and allowed cash to be directed towards healthcare, education, family well-being or consumption of other goods and services.

# 3. Data

## *3.1. Economy-wide Data: Consumer Pyramid Household Survey*

Data on monthly consumption expenditure of households across India covering the period Jan 2016 to Feb 2020 is sourced from Center for Monitoring Indian Economy's (CMIE) Consumer Pyramid Household Survey (CPHS). CPHS is a rich dataset representing 98.5% of the India's population geographically (Afridi, Mahajan, & Sangwan, 2022; Beyer, Franco-Bedoya,

[2] https://www.epfindia.gov.in/siteen/index.php

[3] https://economictimes.indiatimes.com/wealth/personal-finance-news/budget-2018-proposal-new-women-workers-take-home-pay-to-go-up-as-epf-contribution-capped-at-8/articleshow/62737570.cms

[4] Employee whose 'pay' was more than Rs. 15,000 per month at the time of joining was called non-eligible employee.

& Galdo, 2021; Gupta et al., 2021; Vyas, 2020).[5] It covers more than 160,000 households spread across 28 states and 514 districts. The households are interviewed three times a year at the interval of four month (i.e. waves) and are required to report itemised monthly expenditure on multiple categories of goods & services.[6] Combining the data from each wave gives us a panel on monthly expenditure of households for these multiple categories.

The main outcome variable for our study is the monthly expenditure of households on total healthcare.[7] We delve deeper to understand the division of budget on healthcare by including dependent variables for monthly expenditure on medicines, doctor's consultation fees, medical tests, hospitalisation fees, contribution to insurance premiums and health enhancement. To examine the income allocation decision of a household beyond healthcare, we look at the log of monthly expenditure on 15 other categories of goods and services including food, clothing, intoxicants, education etc.

As a next step, to facilitate our empirical analysis that follows, we identify the beneficiary group that receives the treatment and the control group that does not receive the treatment in the CPHS data. The variables in the dataset capture information on demographic indicators of a household such as gender, age, occupation, education and family size. The survey procedure uses a grouping strategy for these variables. This facilitates easier classification of similar households into a group and also helps to understand the characteristics of an individual household as a unit. For example, using the gender group variable one can easily identify if a household has majority of female or male members at a particular point in time.[8]

Given our policy intervention was directed at female workers employed in the formal sector, we work with the sample of households which have more female members than male members (female majority + female dominant + only female). We use this sample of female households in our study to be able to capture the true nature of decision making of women in a household.

[5]The CPHS uses a muti-stage survey design where towns and villages from the 2011 census form the primary sampling unit and households comprise the ultimate sampling unit. The districts and states are grouped into 110 homogeneous regions based on agro-climatic conditions, female literacy rate, number of households and the urbanization levels.

[6]The response rates between 2014 to 2019 in the CPHS varied between 80-87% (Sinha Roy & Van Der Weide, 2022).

[7]We convert all the dependent variables in our study into log-linear form obtained by taking their natural logarithm and adding one. This makes it convenient for us to analyse the percentage change in the outcome due to the effect of the policy.

[8]Refer to Table A1 in appendix.

To further classify this sample of female households into the treatment and control group, we assign a dummy variable equal to one if the occupation group of a household falls under the formal sector in the period before the policy shock. The household becomes a beneficiary of the policy if it had maximum members working in the formal sector without any dynamic shifts in the pre-shock period. The dummy for treatment takes a value of zero if a household has maximum number of members in the non-formal sector in the pre-shock period.[9] Table 1 reports sample means for the main outcome variables in the pre-treatment period for beneficiary and non-beneficiary households.[10] The table indicates similarity between two groups before the assignment of treatment.[11]

Existing studies have identified some limitations with the panel structure of the CPHS dataset (Sinha Roy & Van Der Weide, 2022; Somanchi, 2021). There is regular attrition in the sample, a large number of households drop out and new households are added frequently to maintain the sample size. The dataset appears to be under-representative of women and children while over-representative of well-educated households in the later waves. Consequently, to avoid sample selection bias, we follow only those households in the panel for which we have response beginning from Jan 2016.[12] We do not consider households added in a later wave throughout the analysis. [13]

## 3.2. *Hospital System Micro Data: EyeSmart*

To analyze the micro level health expenditure by females in a hospital system, and to examine how women spend on health conditional on them accessing healthcare, we refer to

[9]Figure A1 and Figure A2 plots the expenditure distribution on total healthcare by beneficiary households across India before and after the policy announcement of reduction in EPF contribution from 12% to 8%.

[10]The similarity in the outcomes before the assignment of treatment ensures that the sample is as good as random. Thus, any variation that we see in expenditure results from the policy shock. The health expenditure and other associated expenses including expenditure on medicines, hospitalisation fees, doctors' fees are largely similar for the beneficiary and the non-beneficiary households. The differences are mainly visible in the contribution to insurance premiums for the two groups. Similarly, the expenditure on other goods and services are fairly similar for other outcomes.

[11]The distribution of our sample into the occupations groups has been presented in Table A2 in the appendix.

[12]Our study uses CPHS instead of the PLFS as the main dataset for analysis. The PLFS data is a pooled cross-section which restricts us from following the same household, it's consumption expenditure and employment status over time (Jha & Basole, 2022) This prohibition can lead to compositional changes in the sample and prevent the identification strategy from capturing the true effects. Thus, the panel nature of CPHS is more suitable and beneficial for our study

[13]The descriptive statistics for the CPHS data have been presented in the Table A4 in the appendix.

**Table 1:** Pre-Treatment Sample Mean of Outcomes for Economy-Wide Data

| Average Monthly Expenditure in Pre-Treatment Period (INR) | | |
|---|---|---|
| Outcomes | Beneficiary HH | Non-Beneficiary HH |
| *Health Outcomes* | | |
| Total Health | 348.25 | 316.61 |
| Medicines | 144.09 | 145.97 |
| Doctors fees | 14.80 | 15.58 |
| Medical test | 17.71 | 30.27 |
| Hospitalisation Fees | 6.89 | 7.00 |
| Insurance Premium | 11.52 | 3.80 |
| Health Enhancement | 153.23 | 113.99 |
| *Other Outcomes* | | |
| Food | 5425.96 | 4626.11 |
| Intoxicants | 333.85 | 253.20 |
| Clothing & Footwear | 790.74 | 594.76 |
| Appliances | 154.91 | 95.04 |
| Restaurants | 240.43 | 156.57 |
| Recreation | 101.71 | 62.81 |
| Bills & Rent | 156.02 | 106.09 |
| Power & Fuel | 1853.76 | 1443.48 |
| Communication | 539.31 | 424.25 |
| Education | 718.09 | 487.85 |
| Hygiene & Beauty | 563.62 | 431.76 |
| Misc | 1348.94 | 998.61 |

Notes: The table represents the pre-treatment sample means of outcome of beneficiary households and non-beneficiary households for the economy-wide data the administrative electronic medical records of patients visiting the LV Prasad Eye Institute (LVPEI) between Jan 2016 to Feb 2020 (we restrict the sample here to avoid contamination from Covid-19 effects). LVPEI has a wide network of hospitals in the form of primary, secondary and tertiary centers across four states of India.[14] It witnesses an influx of patients for eye-care from all socio-economic backgrounds due to its pyramid structure. It's zero-cost services encourage visit from economically disadvantaged sections while exclusive treatments, specialty packages and world-renowned doctors attracts the better-off sections. This widely representative dataset of a hospital system consists of 0.5 million medical records across 23 centers (Das & Basu, 2021; Mehta, Narayanan, Aretz, Khanna, & Rao, 2020).

We have in our data the information on expenditure of an individual in a particular month at a center for eye investigation and surgical treatment. These remain the main outcome variables for our analysis at the hospital level. Out-of-pocket expenditure is the difference between the surgery amount and the financial assistance received by a patient.[15] The amounts have been adjusted for inflation using the monthly consumer price index as deflator. For our regressions, we use logarithmic transformations of these variables to limit the effect of potential outliers.

We are also able to identify the gender, age, marital status, occupation, disease condition and measure of visual acuity of a patient from the dataset.[17] Given that the unanticipated income shock is directed towards females in formal sector employment, we only analyse the sample of 0.2 million female patients visiting the center between Jan 16 to Feb 2020. About 75% of the females in our sample are married and are 51 years old on average. A female patient is classified as an employee of the formal sector if she is employed in government or private service.[18] Thus, she is referred as a beneficiary of the policy in our study as these females are eligible for the EPF reduction.[19]

[14] Primary centers are located in rural settings and provide basic services, secondary centers are and tertiary centers cater to the metropolitan cities and provide advanced surgeries.

[15][16]

[17] The measure of visual acuity is the ability of the eye to distinguish shapes, numbers, objects from a certain distance (see https://en.wikipedia.org/wiki/Visual_acuity).

[18] About 3.12% of females visiting the center are employed in the formal sector and unfortunately we can't identify when they started working in this sample, and therefore our reduced form regression coefficients are likely to be underestimated. Consequently, we expect the actual effect sizes to be larger in magnitude.

[19] The descriptive statistics - the difference-in-differences of raw means for the EyeSmart data have been presented in the Table A5 in the appendix. We also represent the pre-treatment sample means on characteristics of beneficiaries and non-beneficiaries in Table A6

# 4. Empirical Specification

## *4.1. Empirical Specification for the Economy Wide Case*

The institutional structure of the EPF reform defining the eligibility rules for acquiring benefits from the changes in the mandated contribution rates, represents a useful quasi-experiment setting. To identify causal effects, we employ an identification strategy exploiting this quasi-experimental framework and provide reduced form intent-to-treat (ITT) effects of the reform on outcomes of interest. As per the policy rules, females employed in the formal sector were eligible for a reduction in the contribution to EPF from 12% to 8%; effectively increasing their take-home pay and disposable income.

For policy schemes such as these, an eligibility rule can exclude non-beneficiaries but cannot force the eligible individuals into taking the benefit (Chatterjee & Poddar, 2021). Thus, our estimates identify the intent-to-treat (ITT) or the changes in the outcome of being offered the treatment. Such a strategy is used in case of imperfect compliance where all those randomized out do not get the treatment; while those randomized in can choose not to take the treatment (Angrist, Imbens, & Rubin, 1996; Duflo, Glennerster, & Kremer, 2007). We identify the female households exposed to the treatment post-Feb'2018 by observing the occupation group that the household belongs to in the period before the policy shock. [20]

Using a difference-in-differences framework, we study the causal relationship between additional income and changes in a household's monthly expenditure by using the following regression specification:

$$\mathbf{y_{hm}} = \beta_0 + \beta_1\,\mathbf{Beneficiary_h} + \beta_2\,\mathbf{Post\ Feb'18_m} + \beta_3\,\mathbf{Beneficiary_h} \times \mathbf{Post\ Feb'18_m} \\ + \theta_{hm} + \delta_m + \gamma_h + \epsilon_{hm} \tag{1}$$

where $y_{hm}$ is the outcome variable observed at the household-month level. It represents

[20] We check for any sample selection that may change the household composition in response to the announcement of the policy. We do not find any significant effect, mitigating our concerns. The results are presented in Table A7 in the appendix.

the expenditure of a household in a month on healthcare and other goods & services (in log). $Beneficiary_h$ equals one when a female household has been predominantly classified into the occupation group of formal sector pre-Feb'18 and zero if a female household has been predominantly classified into the occupation group of non-formal sector pre-Feb'18. $Post\ Feb'18_m$ is a dummy which takes value one if the month-year is after February 2018, zero otherwise. $\delta_m$ and $\gamma_h$ are fixed effects controlling for monthly and household level unobservable including seasonal variations. Standard errors are clustered at the household level.

A literature on two-way fixed effects highlight limitations with weighting paradigm that lead to spurious inferences in the conventional difference-in-differences (Callaway & Sant'Anna, 2021; De Chaisemartin & d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Note that this is not relevant here because the canonical model performs well in this setting. It is likely to face challenges only if there are multiple periods of treatment or variations in treatment timing or in the presence of non-parallel pre-trends (Roth, Sant'Anna, Bilinski, & Poe, 2022). None of these appear to be a challenge here.

Household specific time varying shocks could be a confounding factor in the relationship between income and health spending. For instance, households dominated by older members would likely spend more on medicines, hospital bills and doctor's consultations as opposed to younger households. Educated households could also have different spending preferences relative to less educated households. Such potential confounding factors are captured by $\theta_{hm}$.

The main coefficient of interest in this specification is $\beta_3$. It captures the effect of unanticipated income shock on the beneficiary household's health and associated expenditure. In other words, it measures the change in monthly expenditure on healthcare and other goods and services by households that receive an additional income post-Feb'2018 as compared to households that do not receive the income shock. $\beta_1$ measures the difference between the average outcomes of the beneficiary and the non-beneficiary households. $\beta_2$ captures any permanent difference in expenditure(outcomes) between the two periods i.e. pre and post-Feb'18.

Note that, our identification strategy is based on exploiting the eligibility rule in assignment to treatment. Therefore, we conduct a trend analysis of the main outcome variable in Figure 3. Figure 3 presents an event study plot that demonstrates insignificant coefficient on health ex-

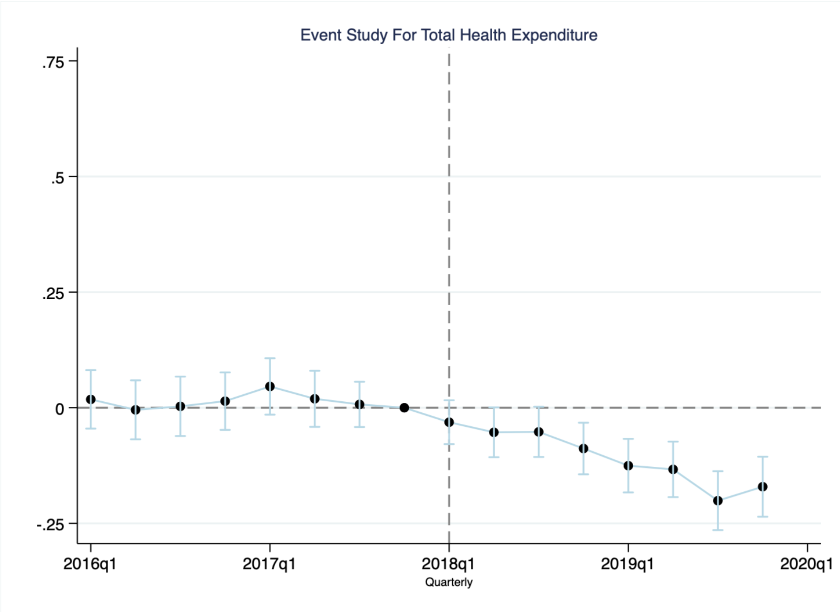


**Figure 3: Event Study Estimates: Expenditure on Healthcare** The figure plots the point estimates for the expenditure on healthcare for the entire span of our study period. The coefficients have been estimated using the specification including fixed effects and controls. The vertical light blue lines indicate the 95% confidence intervals. The x-axis plots the distance in quarters. The coefficients are insignificant before the event and become negative after the shock.

penditure pre-2018. In other words, mean differences in the outcomes between beneficiary and non-beneficiary households prior to treatment exposure are statistically insignificant. Thus, it is reasonable to conclude that the identifying assumption is meaningful and is identifying the true causal effect.

## *4.2. Empirical Specification for the Micro Case*

For the exercise at the intensive margin, we use hospital system data as described above and estimate the following regression specification:

$$\mathbf{y_{imc}} = \beta_0 + \beta_1\,\mathbf{Beneficiary_i} + \beta_2\,\mathbf{Post\ Feb'18_m} + \beta_3\,\mathbf{Beneficiary_i} \times \mathbf{Post\ Feb'18_m} + \theta_m + \delta_s + \gamma_c + \nu_{imc} + \epsilon_{imc} \tag{2}$$

where $y_{imc}$ is the outcome variable observed at the individual-month-centre level. It rep resents the expenditure of a female patient in a month at a hospital on surgical treatment and eye investigation. The out-of-pocket expenditure (in log) has been included as the third dependent variable. $Beneficiary_i$ equals one when a female visiting the hospital is an employee of the formal sector and zero otherwise. $PostFeb'18_m$ is a dummy which takes value one if the month-year is after February 2018, zero otherwise. $\theta_m$, $\delta_s$ and $\gamma_c$ are fixed effects for time, state of residence and the centre of the hospital visited. $\nu_{imc}$ corresponds to a vector of controls for age, marital status, paying category, hospital location, hospital centre category, dummies for disease condition and dummies for the measurement of visual acuity.

Note that health expenditure is affected by the health condition (disease/eye condition) of the patient and is also correlated with the income shock. Therefore, disease condition is a potential confounding factor for our estimates. This is addressed in the specification by the dummies for eye conditions. The coefficient of interest is $\beta_3$ and it captures the difference in the average expenditure of eligible females and ineligible females post-Feb '18 who visit the hospital. Using this as the baseline equation, we also estimate the change in outcomes for a sample of married females.

# 5. Evidence

## 5.1. *Economy Wide Results*

### 5.1.1. *Unanticipated Income Shock and Health Expenditure: Economy-wide Results*

Table 2 presents baseline estimates for Equation 1 for our main dependent variable, total health expenditure. Column(1), reports estimated effect of EPF cut on monthly expenditure of households that receive an additional income compared to the non-beneficiary households. In other words, it shows the change in monthly health expenditure of female households with members largely employed in the formal sector receiving the income shock. Column (1) captures the benchmark results, the coefficient of interest $Post\ Feb'18 \times Beneficiary_h$ remains negative and significant in all four columns. We see a 11.6% decline in monthly expenditure of beneficiary households on total health expenditure following an increase in take-home pay.[21]

[21] To address concerns around differences in healthcare expenditure based on socio-economic background, we also estimated the regression specification for the sample of households in rural areas ($Beta$= -0.13) and urban

**Table 2:** Change in Health Expenditure and Associated Variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| DV (in log) | Health Expenditure | Medicines | Doctors fees | Medical test | Hosp. fees | Ins. Premium | Health Enh |
| Post Feb'18 x Beneficiary HH | -0.116*** | -0.091** | -0.102*** | -0.007 | 0.011* | 0.007 | 0.067*** |
| | [0.020] | [0.037] | [0.018] | [0.008] | [0.006] | [0.007] | [0.020] |
| Observations | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 |
| R-squared | 0.401 | 0.360 | 0.245 | 0.291 | 0.289 | 0.285 | 0.539 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variable in all columns is log of expenditure on healthcare.The estimation includes fixed effects for time and household and controls for age, education and household size. Standard errors are clustered at household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. We find a decrease of 11.6% on total health expenditure. We observe a decrease on expenditure on medicine (9%) and doctor's consultation fees (10%). This decline can partly be explained by improved health conditions of women as they seem to be spending more on health enhancements.

Health spending is not a monolith and one would expect significant heterogeneity in the incidence of the income shock effect across multiple categories of health expenditure. Thus, we expand the analysis by breaking down health expenditure into multiple categories. Columns 2-7 in Table 2 include estimated effects of the income shock on expenditure on medicine, doctor's consultation fees, medical tests, hospitalisation fees, contribution to insurance premiums and health enhancement. The estimate in column (2) for expenditure on medicine is negative and significant. It shows a 9.1% decline in monthly expenditure of beneficiary households relative to non- beneficiary households post-Feb'18. We observe a 10.2% reduction in expenditure on doctor's consultations while a statistically insignificant 0.7% reduction in expenditure on medical tests. We also find a positive and significant increase of 6.7% in expenditure on health improvement by the female households that receive additional income. The interaction term for $Post\ Feb'18 \times Beneficiary_h$ remains insignificant for expenditure on insurance premiums. Broadly our findings suggest that female households that receive additional income do not prioritize health spending when the income is not conditional to be spent upon a specific outcome.[22] Also, they do not spend on the purchase of medicines, tests or doctor consultations. We explore these results further by looking at the case of change in expenditure by females

areas ($Beta$= -0.10). The estimates are negative and significant for both samples. (Results with authors, available upon request.)

[22] To address concerns around differences in healthcare expenditure based on socio-economic background, we also estimated the regression specification for the sample of households in rural areas (Beta= -0.13) and urban areas (Beta= -0.10). The estimates are negative and significant for both samples. (Results with authors, available upon request.)

in a hospital system. From these results, we can infer that females demonstrate precautionary behaviour by allocating income towards health enhancement of the household i.e. visits to the gym or hiring nutritionists rather than increasing health expenditure in general.

### 5.1.2. *Impact on Other Expenditure*

It is expected that an unanticipated income shock would also have an impact on non-health expenditure. Table 3 presents such estimates. Note that, we are estimating the change in the monthly expenditure of beneficiary households on food, clothing, communication, intoxicants etc. as compared to non-beneficiary households, post-Feb'2018. The estimates are obtained using the baseline specification Equation 1 which includes fixed effects and controls.

**Table 3:** Change in Expenditure on Other Goods and Services

| Change in Expenditure on Other Goods and Services | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Expenses on Regular Consumption | | | | | |
| DV (in log) | Food | Power & Fuel | Education | Home Appliances | Clothing | Bills & Rent |
| Post Feb'18 x Beneficiary HH | 0.002 | 0.047*** | 0.082** | 0.025 | 0.086*** | -0.100*** |
| | [0.005] | [0.012] | [0.037] | [0.026] | [0.028] | [0.026] |
| Observations | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 |
| R-squared | 0.704 | 0.448 | 0.558 | 0.270 | 0.276 | 0.592 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| | Expenses on Discretionary Goods | | | | | |
| DV (in log) | Intoxicants | Restaurants | Recreation | Misc. | Comm. & Media | Hygiene & Beauty |
| Post Feb'18 x Beneficiary HH | -0.006 | -0.212*** | -0.044* | -0.039*** | -0.086*** | 0.021** |
| | [0.038] | [0.038] | [0.026] | [0.010] | [0.013] | [0.009] |
| Observations | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 | 469,652 |
| R-squared | 0.539 | 0.433 | 0.310 | 0.555 | 0.584 | 0.588 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variables are log of the outcomes in each column. The estimation includes fixed effects for time and household and controls for age, education and household size. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. We find significant changes in the overall composition of expenditure with increases in human capital investments and decreases in temptation consumption of the households such as recreation and restaurant dining

The top panel represents the estimates for change in monthly expenses on regular consumption such as food (basic items such as pulses, vegetables dairy products etc) in Column (1), power and fuel (petrol and diesel for vehicles, electricity, cooking fuel) in Column (2), education (school fees tuition fees, books) in Column (3), home appliances in column (3), clothing (clothes, footwear, jewellery) in column (5) and bills and rent (monthly house rent, society charges) in column (6). The estimates indicate that female beneficiary households spend more on food items, power and fuel, appliances and clothing while cutting down expenses on bills and society charges. This suggests that women allocate income towards meeting household necessities which cater to basic requirements. Moreover, we find that the income shock translates to an increase in expenditure on education by 8.2%. It echoes the findings of past works Baird, McIntosh, and Özler (2011); Benhassine, Devoto, Duflo, Dupas, and Pouliquen (2015); Chatterjee and Poddar (2021) which suggest that transfers increase investments in education even when they are not conditional on attending school.

We explore the education expenditure result a bit further and focus on a sample of households headed by a female who is a mother (around 32,000 HHs) and compare it with a sample of households headed by a female who is not a mother (around 2,400 HHs). The intention is to check whether the positive education expenditure effect is driven by mothers. We find that while there is an 11.4% increase in expenditure on education for the former sample, the effect is not statistically significant. Results are not reported here but are available upon request.

In the bottom panel of Table 3, the estimates highlight the change in expenditure on discretionary goods by the beneficiary households due to the income shock. The negative coefficients in Columns (1) to (5) of the bottom panel indicate a reduction in expenditure on recreation (movies, clubs, games), restaurant visits, miscellaneous expenses (domestic help, repairs, social obligations, vacations) and communication and media(TV, radio, internet). Our findings also reveal a negative coefficient for expenses on intoxicants (alcohol, tobacco). This is in line with existing evidence on transfer programs and intoxicant consumption (Doepke & Tertilt, 2019; Evans & Popova, 2017; Team, 2012). Estimates in column (6) highlight that female beneficiary households allocate income towards the purchase of beauty products, cosmetics, toiletries, parlours etc. (Beta = 0.021), as indicated by the positive and significant coefficient.

#### *5.1.3. Impact on Healthcare Expenditure as a Share of Income from Wages*

It could be argued that the effect of income shock is on expenditure relative to the size of the household as opposed to aggregate expenditure. Table 4 presents these estimates where the dependent variable is total health expenditure as a share of income from wages. Using the income data from CMIE's CPHS, we merge the monthly income of households from wages with the expenditure data. The main DV has been constructed by dividing the monthly total expenditure of a household on health by the monthly income of the household from wages. Using this outcome, we report the effect of EPF reduction on the monthly expenditure on health for households that receive additional income as compared to those who do not witness a change in their income.

**Table 4:** Expenditure on Health as a Share of Income from Wages

| | (1) | (2) | (3) |
|---|---|---|---|
| DV (in log) | Exp. on Health as a Share of Income | | |
| Post Feb'18 x Beneficiary | -0.003*** | -0.001* | -0.001* |
| | [0.000] | [0.001] | [0.001] |
| Observations | 343,602 | 343,082 | 343,082 |
| Controls | 0.001 | 0.264 | 0.264 |
| Fixed Effects | No | No | Yes |
| R-squared | No | Yes | Yes |

Notes: The dependent variable is expenditure on total health as a share of income from wages in the household. The DV has been converted to log in each column. Controls for age, education and household size have been included in column (1). The estimation in column (2) includes fixed effects for time and household. The main results are in column (3) which includes fixed effects and control. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. We find a 0.1% decrease in healthcare expense as a share of income from wages for beneficiary households as compared to non-beneficiaries.

The coefficient in column (1) has been obtained using a simple OLS regression estimation. The negative and significant coefficient suggests that an increase in income led to a 0.3% reduction in health expenses when accounted as a share of income. Column (2) estimates the regression with fixed effects. The coefficient in column (3) has been obtained using the baseline equation with fixed effects and controls. Broadly our findings indicate that beneficiary households spend 0.1% less on health expenses when accounted as a share of income as compared to non-beneficiary households.[23] This estimation provides a link between income elasticity and the effect of the policy shock.

[23] We also conducted a first-stage regression exercise to estimate the impact of policy intervention on income from wages. Results broadly align with our findings in this section (Results with authors, available upon request)

#### 5.1.4. *Impact on Healthcare Expenditure by excluding Insurance Effects*

Access to health insurance or contributions towards health premiums can affect the decision of a household to increase or decrease their expenditure on healthcare. We conduct an estimation exercise by redefining expenses on healthcare to adjust for any insurance effects. To rule out this alternative mechanism, we compute total health expenditure by adding all monthly expenses on healthcare and subtracting the expense that goes towards contribution to insurance premiums. We estimate the baseline specification (Equation 1) for the computed DV and associated healthcare expenses by including expenditure on healthcare premiums as a control instead of an outcome. The regression includes fixed effects for time and household as well as controls for age, education and household size. Table 5 presents the coefficient obtained from this regression estimation.

**Table 5:** Change in Health Expenditure and Associated Variables

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| DV (in log) | Total Health Exp. | Medicines | Doctors fees | Medical test | Hosp. fees | Health Enh |
| Post Feb'18 x Beneficiary HH | -0.115*** | -0.091** | -0.101*** | -0.007 | 0.011* | 0.067*** |
| | [0.020] | [0.037] | [0.018] | [0.008] | [0.006] | [0.020] |
| Observations | 4,69,652 | 4,69,652 | 4,69,652 | 4,69,652 | 4,69,652 | 4,69,652 |
| R-squared | 0.4 | 0.36 | 0.245 | 0.292 | 0.289 | 0.539 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variables are logs of the outcomes given in each column. The estimation includes fixed effects along with a set of controls. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. Total health expenditure in column (1) has been computed by adding all monthly expenses on healthcare and subtracting the expense that goes towards contribution to insurance premiums. In this estimation exercise, expenses on health insurance have been included as a control. We find a decrease of 11.5% in expenditure on total health by the beneficiaries, a similar estimate to the baseline. This finding rules out the role of insurance.

Column (1) indicates a negative and significant coefficient for the main outcome of interest. It suggests that the monthly expenditure on healthcare reduces by 11.5% for female beneficiary households as compared to female non-beneficiary households when controlling for insurance effects. This estimate is more or less similar to our baseline estimate for healthcare expenses in Table 2. Columns (2)-(6) highlight the point estimates for associated variables in healthcare. In line with baseline results, we find that female beneficiary households spend less on medicines and doctor's consultations while reallocating income towards healthcare expenses. These findings provide additional support to our main results by ruling out the alternative mechanism of the insurance effect.

#### *5.1.5. Impact for a Sub-National Sample*

To account for institutional factors that may affect the expenditure decision of beneficiary and non-beneficiary households at the time of intervention, we run additional regressions. The launch of Pradhan Mantri Jan Arogya Yojna (PM-JAY) in Sep'2018 guaranteed a sum of Rs 5 lakh as health insurance coverage for secondary and tertiary care to poor households across the states of India.[24] Given the presence of a safety net in the form of insurance coverage, a scheme such as this can potentially induce families to spend more on healthcare. Thus, we estimate our baseline regression specification by taking the sample of states where PM-JAY was functional. Column (1) in Table 6 reports the coefficient obtained from this exercise. We observe a decline of 13.3% on expenditure on healthcare for beneficiary households as compared to the non-beneficiary households post our intervention, which is a very close estimate to our baseline finding. This suggests that the launch of PM-JAY does not confound or meddle with the effect of the EPF reduction.

Further, in Column (2) we estimate the baseline specification for the sample of households from states covered under the hospital system data. This exercise enables us to observe the expenditure decision of beneficiary households as compared to the non-beneficiary households for the states of Telangana, Andhra Pradesh, Karnataka and Odisha. The coefficient suggests a decline of 30.7% in total health expenditure. This estimate is very close to our findings from the hospital records data, adding robustness. It implies that differences in expenditure are deeper in these states of India, suggesting a need for better policy intervention.

[24] This scheme covered approximately 12 crore beneficiary families that fall under the bottom 40% of the income bracket in India. The program was applicable across all states except Odisha, West Bengal and National Capital Territory or Delhi.

**Table 6:** Sub-National Sample Check: Change in Expenditure on Health

| | (1) | (2) |
|---|---|---|
| | States covered by PMJAY | States covered by LVPEI |
| DV (in log) | Total Health Expenditure | |
| Post Feb'18 x Beneficiary HH | -0.133*** | -0.307*** |
| | [0.022] | [0.072] |
| Observations | 399,363 | 76,185 |
| R-squared | 0.386 | 0.350 |
| Controls | Yes | Yes |
| Fixed Effects | Yes | Yes |

Notes: The dependent variable in all columns is log of expenditure on healthcare. It includes fixed effects for time and household and controls for age, education and household size. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. Column (1) highlights the change in health expenditure for households in states(all except Delhi, Odisha and West Bengal) covered under PMJAY. Column (2) reports the coefficient for change in health expenditure for beneficiary households in states where LVPEI hospitals operate (Telangana, Odisha, Karnataka and Andhra Pradesh).

#### *5.1.6. Robustness Checks*

In this section, we identify the potential threats to our identification strategy and conduct a falsification test, providing additional evidence in support of our findings.

*Heterogeneity Check:* We account for two caveats in our study of the economy-wide data and try to address these issues. First, our period of the analysis is restricted to the pre-pandemic period only i.e. from January 2016 to February 2020. We argue that the budgetary decisions of a household may get confounded by the onset of the pandemic. However, the reduction in the contribution towards the employee provident fund was applicable for the first three years across all formal sectors. To address this concern regarding the duration of treatment, we estimate Equation 1 by extending the period of our analysis till March 2021.[25] The results for health outcomes are presented in panel A in Table 7. Our findings are similar to the benchmark estimates, it suggests that post an increase in the budget of beneficiary households, the monthly expenditure on total health, medicines and doctor's consultation declined significantly as compared to non-beneficiary households. The stronger negative coefficient ($beta$= -0.121) in Column (4) represents the bias as compared to the benchmark coefficient ($beta$= -0.116).

[25]In India the financial year is from April to March.

**Table 7:** Heterogeneity Groups and Robustness Checks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| DV (in log) | Health Expenditure | | | |
| Extended Time Period: Jan'2016- Mar'2021 | | | | |
| Post Feb'18 x Beneficiary HH | -0.181*** | -0.133*** | -0.164*** | -0.121*** |
| | [0.010] | [0.021] | [0.010] | [0.020] |
| Observations | 553,395 | 552,956 | 553,395 | 552,956 |
| R-squared | 0.016 | 0.362 | 0.065 | 0.367 |
| Controls | No | No | Yes | Yes |
| Fixed Effects | No | Yes | No | Yes |
| Alternate Sample: Households with only female members | | | | |
| Post Feb'18 x Beneficiary HH | -0.246*** | -0.435*** | -0.306*** | -0.374** |
| | [0.074] | [0.158] | [0.073] | [0.151] |
| Observations | 58,985 | 58,928 | 58,985 | 58,928 |
| R-squared | 0.036 | 0.368 | 0.083 | 0.372 |
| Controls | No | No | Yes | Yes |
| Fixed Effects | No | Yes | No | Yes |
| Falsification Test: Households with male members(only + majority + dominant) | | | | |
| Post Feb'18 x Beneficiary HH | -0.002 | -0.004 | 0.002 | -0.001 |
| | [0.008] | [0.015] | [0.008] | [0.015] |
| Observations | 617,846 | 616,941 | 617,846 | 616,941 |
| R-squared | 0.026 | 0.330 | 0.036 | 0.331 |
| Controls | No | No | Yes | Yes |
| Fixed Effects | No | Yes | No | Yes |

Notes: The dependent variable in all columns is log of expenditure on healthcare. Column (1) gives the estimates from OLS regression, column (2) includes fixed effects for time and household and column (3) includes the controls for age, education and household size. Column (4) gives the main results from our specification. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. In panel A, we see that the estimates in column (4) are in line with the benchmark finding. As indicated in panel B, we find a decrease in total health expenditure of 37% for beneficiary households with only female members. In panel C, the value of beta is close to zero, insignificant and negative. This shows that the policy did not have an effect on the sample of male households i.e. the group that was not targeted.

Another cause of concern with our identification strategy can be the selection of the heterogeneous sample of households with more female than male members. We would expect larger effects on households that have only female members. Such households will reflect the true nature of the decision on budgetary allocation by females. We change our sample of assessment by defining the treatment group as the households with only female members that had a maximum number of members employed in the formal sector throughout the pre-period. Panel B in Table 7 highlights the estimates from the difference-in-differences framework for this specification. The coefficient of interest estimated using the baseline equation is in Column (4). Our finding suggests that beneficiary households spend 37.4% less on total health expenditure post an increase in income as compared to non-beneficiary households. Again, the magnitude of the effect is stronger for only female households as compared to our baseline sample. Both heterogeneity checks are in line with the benchmark findings.[26]

*Falsification Test:* Another possible concern with our findings can be that the reduction in expenditure on healthcare by beneficiary households may not be due to the receipt of additional income per se. Our strategy is based on identifying the households that have female members (Only + Majority + Dominant). It is based on the hypothesis that the outcomes for the beneficiary households will not be significantly different from zero as compared to non-beneficiary households for this sample as an effect of the policy shock. However, it can be argued that the intervention may not be affecting the targeted group (i.e. households with more female members) and its choices, rather the change in outcomes was a consequence of some other reason. To check whether our strategy captures the true effect of the intervention, we set the target group as the sample of households with more male members (Only + Majority + Dominant). As part of this falsification exercise, we estimate the results using the baseline specification i.e. Equation 1 for this cohort.

We use a difference-in-differences framework where we compare households with male members that were in the formal sector in the pre-period to the male households with members in the non-formal sector. The findings from this exercise have been presented in Panel C in Table 7. The value of beta is close to zero, insignificant and negative. This shows that the policy

[26]Refer to Table A8 and Table A9 in the appendix for additional robustness checks estimated through assignment of treatment status in an alternate way.

did not have an effect on the sample of male households i.e. the group that was not targeted. Thus, we can infer that our identification strategy captures the true effect of the income shock on the consumption expenditure for the beneficiary households.

### *5.2. Micro Case Eyesmart Findings*

We have shown that at the economy level, households with more female members spend significantly less on health outcomes when they receive additional income. As a next step, we analyse the income allocation at the individual level in a hospital system. This micro-level analysis gives us an understanding of the budgetary decision that a female makes in consideration of her healthcare. Here, we look at the specific case of eye treatments that a female seeks at a private healthcare facility when she receives additional income.

Figure 4 gives the estimates from the regression specification i.e. Equation 2 for the three main outcome variables- investigation amount, surgical amount and out-of-pocket expenditure (in log). The results for the difference in differences framework are estimated at the individual-month-centre level with fixed effects and controls.[27] Our findings indicate that female beneficiary visiting the eye hospital spend significantly less on surgical treatments as compared to female non-beneficiaries ($beta$= -0.431). The out-of-pocket expenditure for the treated group declines by 49.3% post an increase in take-home pay. As indicated in Column (1), the coefficient of expenditure on eye investigation is positive but insignificant ($beta$= 0.069). These results are in line with our economy-wide findings suggesting that females receiving additional income spend less on healthcare as compared to non-beneficiary females and even when they have had to actually access healthcare as manifest in their hospital visits.[28]

Following the baseline analysis, we study the heterogeneity in expenditure by females in the hospital system based on demographic characteristics. We also analyse the difference in expenditure across multiple surgical treatments. The idea for the latter in particular is that more inelastic surgical treatment areas (acute care for example) will exhibit a different elasticity of health expenses with respect to income compared to more elastic surgical treatment areas

[27] See Table A10 in appendix for tabular representation of coefficient estimates

[28] As a part of robustness check, we estimated the results for the hospital system micro case using Coarsened Exact Matching, the coefficient for expenditure on surgery and OOP remains negative and significant. Results are available on request.

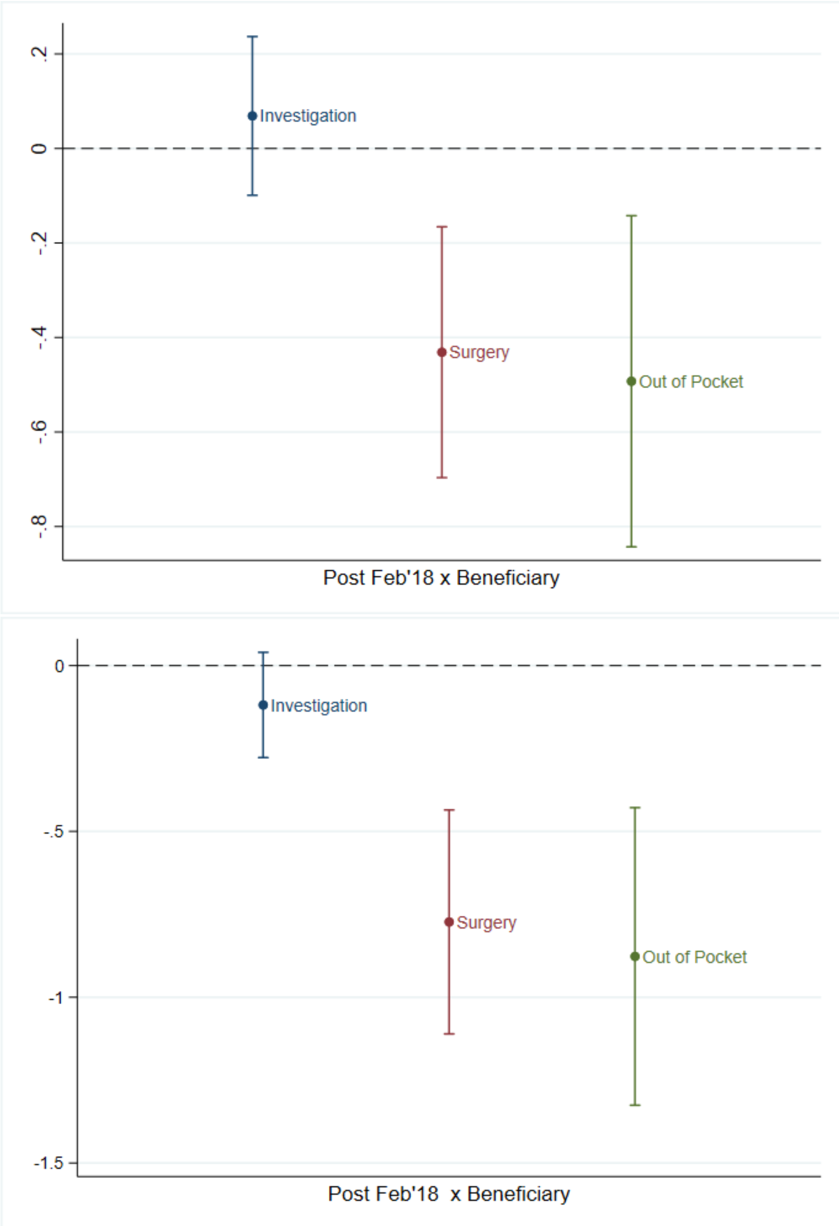


**Figure 4: Impact of Additional Income on Health Expenditure for Beneficiaries** The figure in the first panel represents the impact of additional income on expenditure for healthcare conditional on access to health for female beneficiaries. The second panel presents the estimates for the sample of married females.

(optional treatments for example).

First, we estimate the baseline regression for the sample of married females as indicated in Figure 4. We find a decrease of 77% in expenditure on surgical treatments and 87.7% on out-of-pocket expenditure post-Feb'18, for beneficiary-married females as compared to non-beneficiary-married females. Our results suggest that the marital status of a female leads to a stronger negative impact on healthcare expenditure which can mean that the additional income is being allocated elsewhere. These findings are in line with Mondal and Dubey (2020) who also find that there exists a large gender gap in hospital expenses, especially in the case of currently married females. This suggests that married females might be contributing the additional income towards family welfare which has also been echoed in past works (Doepke & Tertilt, 2019).

**Table 8:** Heterogeneity Check: Change in Expenditure across Surgery Types in LVPEI

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| DV (in log) | Anterior Segment | Cataract | Cornea | Glaucoma | Occular Surface |
| Post Feb'18 x Beneficiary | 0.927 | -0.403* | 1.341 | -0.882 | -0.792 |
| | (1.683) | (0.233) | (0.847) | (0.647) | (0.798) |
| Observations | 2,936 | 130,234 | 5,133 | 3,115 | 11,014 |
| R-squared | 0.511 | 0.546 | 0.313 | 0.356 | 0.649 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| FE | Yes | Yes | Yes | Yes | Yes |
| DV (in log) | Occuloplasty | Refractive Surgery | Retinal | Strabismus | Trauma |
| Post Feb'18 x Beneficiary | -1.286*** | -0.0767 | -0.475** | -0.229 | 1.400 |
| | (0.352) | (0.0990) | (0.234) | (0.716) | (0.914) |
| Observations | 16,077 | 6,693 | 25,400 | 3,061 | 899 |
| R-squared | 0.423 | 0.084 | 0.316 | 0.303 | 0.695 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| FE | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variables are logs of the outcomes given in each column. The estimation includes fixed effects for the time, state of residence and centre of the hospital along with a set of controls. Standard errors are clustered at the district level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. We observe that the coefficient of interest is negative and significant for cataract, occuloplasty and retinal surgery. This suggests that female beneficiaries spend less on expensive surgeries post an increase in income as compared to non-beneficiaries.

Finally, Table 8 highlights the heterogeneity in expenditure across eleven types of surgery. We observe that the coefficient of interest is negative and significant for cataract, occuloplasty and retinal surgery (doctors at LVPEI point out the elective nature of these surgeries to us, highlighting how patients may defer care here in contrast to acute care, especially if they are expensive and patients are paying instead of non-paying patients). This also suggests that female beneficiaries spend less on expensive surgeries post an increase in income as compared to non-beneficiaries. Our results resonate with the findings of Dupas and Jain (2021) who also suggest that women spend significantly less on expensive healthcare procedures.

# 6. Unanticipated Income Shock and Women's Health Spending: Explaining the Negative Effect

Our empirical examinations rely on the hypothesis that a change in income for women in developing countries, all else equal, does not necessarily lead to an increase in healthcare spending and in some cases may lead to a decline. Given that we are able to rule out that this is entirely due to better health outcomes, our findings presented below indicates that health care appears to be a non-normal good for women in these settings. In this section, we try to motivate this hypothesis borrowing from the theoretical literature on household decision making. We heavily borrow insights from the very recent and relevant work of De Rock et al. (2022) who motivate their analysis of household responses to cash transfers using a household collective decision model.

Intra-household collective decision making in various contexts have been widely studied in the economic theory literature (Browning & Chiappori, 1998; Chiappori, 1988, 1992; Chiappori & Ekeland, 2006). As De Rock et al. (2022) point out, this framework is useful to study the distributional effects of public policies. They find that based on testing and rejecting the distribution factors of the testable model, the impact of the cash transfer program in their context was indicative of a change in preferences of women, over and above the income effect. This is particularly true for secondary effects of the cash transfer program, especially if women have skewed preferences towards consumption of certain types (De Rock et al., 2022).

In our case, if women in developing countries have a strong preference towards contributing to the household public good, a marginal increase in their income may not lead to an increase in individual consumption expenditure. In line with De Rock et al. (2022) and Hoddinott and Skoufias (2004), this may result in a change in preferences for women. Consequently, if women's preferences in response to the income shock change in a way that health care expenditure is ranked lower and other consumption is ranked higher in the preference ordering, it is not surprising that an increase in income does not translate to increase in health care demand. This type of skewed preferences in favor of household public good can be due to social factors such as family or peer pressure in households in developing countries (Anukriti, Herrera-Almanza, Pathak, & Karra, 2020; Anukriti, Kwon, & Prakash, 2022; Karim, Kwong, Shrivastava, & Tamvada, 2022) or may just simply reflect a revealed preference among women consumers (Caplin & Dean, 2011; Kline & Tartari, 2016). Further, there is evidence in the literature that households are non-unitary and that small transfers to women may often "be appropriated by men and diverted to other purposes" (Banerjee et al., 2019; Chiappori & Mazzocco, 2017; De Mel, McKenzie, & Woodruff, 2009; Lin, Chen, Chiang, & Zhang, 2021). This would also be consistent with our findings that an increase in women's disposable incomes need not necessarily lead to an increase in demand for goods that are otherwise considered 'normal' with respect to their income elasticity.

Finally, Luke and Munshi (2011) point out the somewhat counter-intuitive finding that historically disadvantaged women may be relatively more assertive in terms of their household choices but the more advantaged ones, such as women in our sample who work in formal sectors, are likelier to be bounded and constrained more by traditions, customs and societal ties. The development economics literature on gender discrimination within households also suggests that resource allocation within household for men and women follow very different patterns. Björkman-Nyqvist (2013) discusses these issues in the context of gender gap and income shocks in Uganda, Rosenzweig and Schultz (1982) show that in India gender-based selective allocation of resources in prevalent and Foster (1995) shows that welfare of females are more sensitive to income fluctuations compared to a smoother relationship for males. Taken together, these seem to provide a background on why a shock to earned income can lead to a change in preferences for women and consequently spending on health care may decrease and the estimated elasticity with respect to income may appear to be negative. The main take-away from the theoretical literature is that women's preferences are not constant with respect to income shocks. Allowing for preferences to be dynamic in their response to earnings can lead to empirical findings in line with our study.

# 7. Concluding Remarks

While the existing literature on income elasticity of demand for healthcare overwhelmingly concludes that healthcare is a normal good with positive elasticity and depending on the context can be classified as necessary goods or luxury goods based on the magnitude of the estimated elasticity, we offer new evidence in this paper that the relationship between income and health may depend on gender identity. We show that an increase in women's take-home salary does not necessarily translate into increased healthcare spending, suggesting that healthcare products and services are non-normal goods for women, in a developing country context.

We exploit an exogenous shock to women's take-home salary incomes generated by an institutional change in the mandated rates of employee contribution to the provident fund for women. Using household survey data as well as administrative data on hospital electronic medical records, we are able to show that the potential increase in women's disposable incomes owing to the higher take-home salaries is correlated with lower healthcare expenses. While the obvious channel for this result could be that women have better health outcomes due to higher income, our hospital data allow us to control for pre-existing health conditions and compare expenditure at the intensive margin of healthcare utilization. Specifically, a woman is only a part of this administrative dataset if she had some health condition for which she sought hospital treatment. We find that our results hold even in this situation suggesting that the selection into better health outcomes do not necessarily drive our average estimates. Studies that focus on cash transfers and public programs have largely documented the impact of receiving additional money on health outcomes, healthcare visits and nutritional status per se rather than healthcare expenditure itself. While a majority of research documents a positive impact on direct health outcomes, some have reported no significant association between additional income and healthcare. Thus, our estimate of an 11.2% reduction in healthcare expenditure presents new evidence towards understanding the relationship.[29]

We conjecture that women's preferences in developing countries for household budget allocations are strongly driven by social and cultural norms. A marginal increase in the income

[29] See Table A11 in the appendix for estimates in the existing literature.

of a male member of the household is not necessarily treated in the same way as a marginal increase in the income of a female member. For instance, the female member may be expected to disproportionately contribute to the household public good, relative to the male. Ironically, this may also include contributing to the health care expenses on family members rather than the individual herself. We find some suggestive evidence along these lines where we show that the composition of spending within the household is impacted by this income shock. Women seem to be spending more on health enhancements and the education of their children. Since the simple correlation between healthcare spending and income does not account for potential substitution between components of healthcare spending; at face value it appears that healthcare demand responds non-normally to income shocks for women, although certain components of healthcare spending may still increase. Overall, our results indicate the relationship between income and healthcare spending is much more nuanced than expected. They seem to vary across gender, cultural norms, and income level. Needless to say further research is merited to explore these issues carefully.

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# A. Appendix

## A.1. *Descriptive Analysis for CPHS data*

The survey procedure uses a grouping strategy for the socio-demographic variables including gender, age, occupation, education and family size. This facilitates easier classification of similar households into a group and also helps to understand the characteristics of an individual household as a unit. The distribution of our sample into the gender groups (See Table A1) and the occupation groups (See Table A2) are presented in the tables below.

**Table A1:** Classification of Economy Wide Data by Gender Group

| **HH Group** | **Gender Groups** | **Definition** |
|---|---|---|
| Female Households | Female Dominated | The number of females is more than males but not more than twice |
| | Female Majority | The number of females are twice the number of males in the household |
| | Only Female | Does not have any male members |
| Male Households | Male Dominated | The number of males is more than females but not more than twice |
| | Male Majority | The number of males are twice the number of females in the household |
| | Only Male | Does not have any female members |
| | Balanced Gender | The number of male and female members is equal |

Notes: The table represents the classification of the gender groups for the households in our sample.

Table A3 presents the summary statistics of the main outcome variables for our sample from the economy wide CPHS data. The average total expenditure of households during our period of study was INR 372 (1 USD = INR 69.51 on an average during the period of our sample) with a high deviation. This indicates that while some households spent as high as INR 0.5 million on healthcare, other households did not allocate any income towards health. Figure A1 and Figure A2 plots the expenditure distribution on total healthcare by beneficiary households across India before and after the policy announcement of reduction in EPF contribution from 12% to 8%.

Table A3 provides further information on the six sub-categories of health indicators. It

**Table A2:** Classification of Economy Wide Data by Occupation Group

| **Classification of Occupation Group into Formal and Non-Formal Sector** | |
|---|---|
| Occupation Group | Percentage of the sample |
| ***Formal Sector*** | **36.68** |
| Business & Salaried Employees | 1.58 |
| Industrial Workers | 3.67 |
| Legislators/Social Workers/Activists | 0.03 |
| Managers/Supervisors | 0.46 |
| Non-industrial Technical Employees | 1.64 |
| Organised Farmers | 2.71 |
| Qualified Self-employed Professionals | 0.41 |
| Wage Labourers | 14.38 |
| White-collar Clerical Employees | 5.92 |
| White-collar Professional Employees | 6.91 |
| ***Non- Formal Sector*** | **63.32** |
| Agricultural Labourers | 6.76 |
| Entrepreneurs | 8.38 |
| Home-based Workers | 1.19 |
| Miscellaneous | 5.83 |
| Retired/Aged | 7.5 |
| Self-employed Entrepreneurs | 13.63 |
| Small Traders/Hawkers | 3.47 |
| Small/Marginal Farmers | 9.5 |
| Support Staff | 6.03 |

Notes: This table includes the summary on distribution of the macro economy wide sample into occupation groups

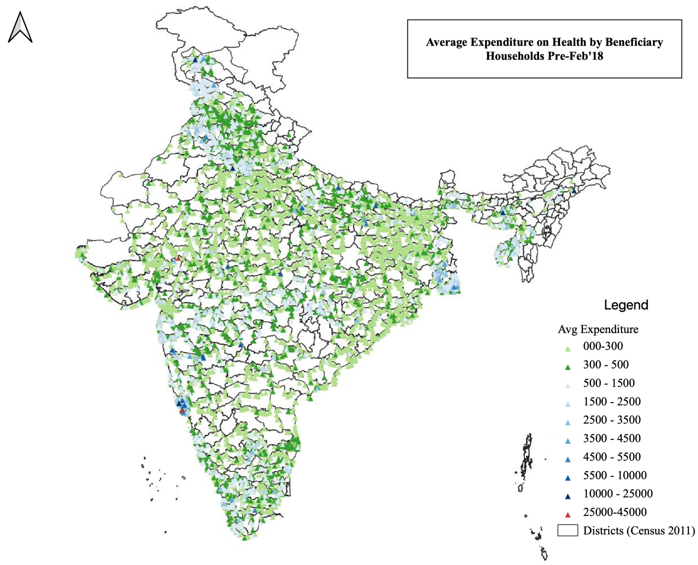


**Figure A1: Expenditure Distribution on Health by Beneficiary Households Across India**
The map represents the average expenditure by beneficiary female households across India before the policy announcement of EPF reduction in Feb 2018

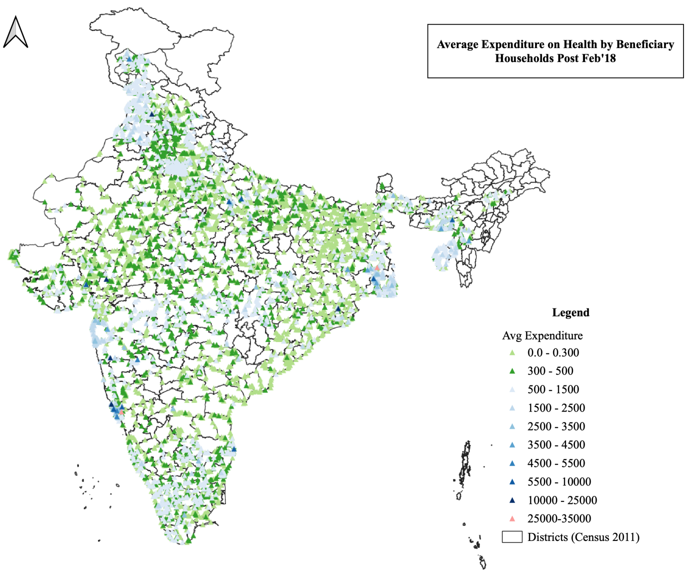


**Figure A2: Expenditure Distribution on Health by Beneficiary Households Across India**
The map represents the average expenditure by beneficiary female households across India after the policy announcement of EPF reduction in Feb 2018

is observable that households in our sample prioritised expenditure on health enhancement through means such as gym subscriptions, nutritionist consultation etc. As a next step, we report the mean and other relevant statistics for expenditure on fifteen other categories of goods and services. On an average households spend the maximum amount of there income on the consumption of food items followed by expenses for power and fuel. The miscellaneous category has a mean value of INR 1333 which includes expenditure on festivals, marriages, vacations etc. by the female households.

**Table A3:** Descriptive Statistics: Main Outcome Variables

| **Average Monthly Expenditure in INR** | | | | |
|---|---|---|---|---|
| DV (Avg Exp) | Mean | Std. Dev | Min | Max |
| ***Health Outcomes*** | | | | |
| Total Health | 372.22 | 2336.46 | 0.00 | 535150 |
| Medicines | 166.91 | 511.79 | 0.00 | 150000 |
| Doctors fees | 21.32 | 128.73 | 0.00 | 50000 |
| Medical test | 8.81 | 204.30 | 0.00 | 30000 |
| Hospitalisation Fees | 28.68 | 2166.32 | 0.00 | 500000 |
| Insurance Premium | 7.50 | 167.95 | 0.00 | 25000 |
| Health Enhancement | 138.98 | 180.54 | 0.00 | 8150 |
| ***Other Outcomes*** | | | | |
| Food | 5060.50 | 2230.41 | 0.00 | 56448 |
| Intoxicants | 311.03 | 405.33 | 0.00 | 22140 |
| Clothing & Footwear | 145.03 | 1961.52 | 0.00 | 360008 |
| Appliances | 145.03 | 873.11 | 0.00 | 112500 |
| Restaurants | 217.47 | 353.07 | 0.00 | 33000 |
| Recreation | 83.30 | 289.37 | 0.00 | 23000 |
| Bills & Rent | 108.71 | 440.23 | 0.00 | 100000 |
| Power & Fuel | 1752.19 | 1515.40 | 0.00 | 31410 |
| Communication | 484.63 | 363.91 | 0.00 | 11650 |
| Education | 588.95 | 1749.04 | 0.00 | 500000 |
| Hygiene & Beauty | 495.94 | 446.94 | 0.00 | 82126 |
| Misc | 1333.80 | 3456.96 | 0.00 | 701250 |

Notes: The table represents the summary statistics for the main outcome variables used in the Macro Case.

## *A.2. Descriptive for Hospital System Data*

We present the difference-in-differences of raw means for the three main outcome variables of the hospital system microdata, as highlighted in Table A4. The estimate for investigation amount observes an increase in the mean value whereas the average value of surgery amount and out-of-pocket expenditure declines. This indicates that females employed in the formal sector spent INR 1311 less on surgical treatments post an increase in income as compared to women in the non-formal sector when visiting the eye hospital. Additionally, for this sample the out-of-pocket expenditure decreased INR Rs 1729 after the policy shock. In order to check the significance of difference in the means, we conducted a simple t-test and obtained the p-values. As indicated, the estimates are significant for all three outcome variables. These preliminary results indicate a negative effect of the income shock.

**Table A4:** Descriptives in Difference-in-Differences Framework

| Exp. on Investigation | Pre | Post | Difference | |
|---|---|---|---|---|
| Beneficiary | 469.69 | 535.27 | First Difference | 65.58 |
| Non-Beneficiary | 96.99 | 112.00 | Second Difference | 15.01 |
| | Difference in Differences (t=5.19, p=0.000) | | | 50.57 |
| Exp on Surgery Amount | Pre | Post | Difference | |
| Beneficiary | 26227.53 | 25454.34 | First Difference | -773.19 |
| Non-Beneficiary | 7298.72 | 7836.73 | Second Difference | 538.01 |
| | Difference in Differences (t=3.65, p=0.000) | | | -1311.20 |
| Out of Pocket Exp. | Pre | Post | Difference | |
| Beneficiary | 24043.88 | 22585.77 | First Difference | -1458.11 |
| Non-Beneficiary | 6445.24 | 6717.04 | Second Difference | 271.81 |
| | Difference in Differences (t=5.16, p=0.000) | | | -1729.92 |

Notes: The table represents the summary statistics from simple difference-in-differences framework for three main outcome variables for the Micro Case.

Table A5 highlights the sample mean values of the characteristics of women visiting the hospital employed in the formal sector and non-formal sector. As the table, the characteristics including age, marital status, visual acuity and location of beneficiaries and non-beneficiaries are more or less similar. This suggests that the sample is as good as random before the assignment of treatment.

*Sample Selection:* We check for sample selection of households into the data by regressing our baseline equation on a dummy variable which takes value equal to 1 for female households. Column (1) gives the estimates from OLS regression, column (2) gives the main results by including fixed effects and controls and column (3) provides the estimates in log form. We obtain a positive but insignificant coefficient in all three columns. These results indicate that household composition does not change in response to the policy.

## *A.3. Additional Results*

*Alternate Treatment Status for Economy-Wide Case:* As part of the validity checks, we include some additional results by defining the treatment status in two other ways. First, we estimate

**Table A5:** Pre-Treatment Sample Mean of Characteristics for Micro Data

| Pre-Treatment Sample Means | | |
|---|---|---|
| | Beneficiary | Non-Beneficiary |
| Age | 51.593 | 52.907 |
| Marital Status | 0.745 | 0.781 |
| Rural | 1.627 | 1.617 |
| Center Category | 1.615 | 1.608 |
| Patient Category | 1.569 | 1.633 |
| Mild or No Visual Impairment 0 | 0.195 | 0.242 |
| Moderate Visual Impairment | 0.191 | 0.176 |
| Severe Visual Impairment | 0.061 | 0.040 |
| Blindness 3 | 0.254 | 0.236 |
| Blindness 4 | 0.072 | 0.080 |
| Blindness 5 | 0.003 | 0.004 |

Notes: The table represents the pre-treatment sample means of characteristics of beneficiaries and non-beneficiaries for the hospital system microdata

**Table A6:** Sample Selection

| **Test for Sample Selection** | | | |
|---|---|---|---|
| | OLS | Linear | Log |
| Post Feb'18 x Beneficiary HH | 0.002 | 0.004 | 0.003 |
| | [0.001] | [0.002] | [0.002] |
| Observations | 1,796,586 | 1,795,660 | 1,795,660 |
| R-squared | 0.004 | 0.838 | 0.838 |
| Controls | No | Yes | Yes |
| Fixed Effects | No | Yes | No |

Notes: Column (1) gives the estimates from OLS regression, column (2) gives the main results by including fixed effects and controls, column (3) provides the estimates in log form. Standard errors are clustered at the household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. The coefficient are positive but insignificant coefficient in all the three columns.

the expenditure on health outcomes using Equation 1 by assigning the treatment status as 1 if a female household had maximum members employed in the formal sector at least once in the pre-period. The control group consists of female households with maximum members in the non-formal sector at least once in the pre-period. In the second specification, we estimate the expenditure on health outcomes by assigning the treatment status as 1 if a female household had maximum members employed in the formal sector consistently through our period of analysis. The control group consists of female households with maximum members in the non-formal sector consistently through our period of analysis. These results are presented Table A7. The coefficient of interest is reported in Column (1). In support of the benchmark findings, we observe a 10% decline in the expenditure on healthcare by the beneficiary households as compared to non-beneficiary households as indicated in Panel A and B.

**Table A7:** Change in Health Expenditure: Alternate Treatment Status

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Treatment Status: HH's formal atleast once in pre-period | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| DV (in log) | Health Expenditure | Medicines | Doctors fees | Medical test | Hosp. fees | Ins. Premium | Health Enh |
| Post Feb'18 x Beneficiary HH | -0.094*** | -0.081** | -0.049*** | -0.008 | 0.008 | -0.008 | -0.010 |
| | [0.016] | [0.032] | [0.015] | [0.007] | [0.005] | [0.007] | [0.016] |
| Observations | 1,281,054 | 1,281,054 | 1,281,054 | 1,281,054 | 1,281,054 | 1,281,054 | 1,281,054 |
| R-squared | 0.359 | 0.319 | 0.208 | 0.196 | 0.218 | 0.225 | 0.449 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Treatment Status: HH's formal consistently from Jan'16 to Feb'20 | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| DV (in log) | Health Expenditure | Medicines | Doctors fees | Medical test | Hosp. fees | Ins. Premium | Health Enh |
| Post Feb'18 x Beneficiary HH | -0.108*** | 0.012 | -0.076*** | 0.004 | 0.012 | 0.019* | 0.146*** |
| | [0.026] | [0.050] | [0.024] | [0.011] | [0.008] | [0.011] | [0.025] |
| Observations | 290,762 | 290,762 | 290,762 | 290,762 | 290,762 | 290,762 | 290,762 |
| R-squared | 0.419 | 0.387 | 0.252 | 0.289 | 0.285 | 0.303 | 0.590 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variable in all columns is log of expenditure on healthcare. Column (1) gives the estimates from OLS regression, column (2) includes fixed effects for time and household and column (3) includes the controls for age, education and household size. Column (4) gives the main results from our specification. Standard errors are clustered at the household level."***','**', and '*' indicate significance at 1%, 10% and 5% respectively. Panel A represents the change in outcome for beneficiary households that had atleast one member employed in the formal sector in the pre-policy shock period. Panel B represents the change in outcome for beneficiary households that had maximum members employed in the formal sector throughout our period of analysis. The negative and significant coefficient in column (1) for panel A and B corroborates our benchmark findings.

*Alternate Occupation Groups for Economy-Wide Case:* As a robustness check, we estimate the expenditure on health outcomes by varying the classification of occupation group into the formal and non-formal sector using Equation 1. In this variation, the non-industrial technical employees and qualified self-employed professionals are considered a part of the non-formal sector. Table A8 highlights the results for this estimation. The coefficient of interest remains negative and significant ($Beta$=-0.126), thus supporting our benchmark findings.

**Table A8:** Change in Health Expenditure: Variation in Classification of Occupation Group

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| DV (in log) | **Total Health Expenditure** | | | |
| Post Feb'18 x Beneficiary HH | -0.147*** | -0.133*** | -0.143*** | -0.126*** |
| | [0.011] | [0.020] | [0.011] | [0.020] |
| Observations | 491,398 | 490,956 | 491,398 | 490,956 |
| R-squared | 0.029 | 0.397 | 0.085 | 0.402 |
| Controls | No | No | Yes | Yes |
| Fixed Effects | No | Yes | No | Yes |

Notes: We estimate the expenditure on health outcomes by varying the classification of occupation group into the formal and non-formal sector. In this variation, the non-industrial technical employees and qualified self-employed professionals are considered a part of the non-formal sector. The dependent variable in all columns is log of expenditure on healthcare. Column (1) gives the estimates from OLS regression, column (2) includes fixed effects for time and household and column (3) includes the controls for age, education and household size. Column (4) gives the main results from our specification. Standard errors are clustered at household level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively.

*Baseline Result for Micro Case:* Table A9 indicates the coefficient estimates from baseline regression of the micro case (see Equation 2). These results are the tabular representation of the coefficient plots in Figure 4. Using the medical records data from hospital visits in the LV Prasad network, we find a negative impact of the income shock on the healthcare spending of female beneficiaries. In the top panel, we find a decline of 43% on surgical expenditure for female beneficiaries visiting the eye hospital as compared to female non-beneficiaries. In the bottom panel, we find that married beneficiary women spend 77% less on surgical expenditure.

## *A.4. Estimates from Existing Studies*

Table A10 summarises the estimates from existing studies that capture the association between transfer programs, insurance schemes and direct healthcare outcomes such as nutritional status, height, weight etc. CCTs conditioned on healthcare have reported a positive

**Table A9:** The Micro Case: Impact of Additional Income on Health Expenditure for Beneficiaries

| | (1) | (2) | (3) |
|---|---|---|---|
| Sample: All Females Visiting the Hospital | | | |
| DV (in log) | Investigation Amt. | Surgery Amt. | Out of Pocket Exp. |
| Post Feb'18 x Beneficiary | 0.0690 | -0.431*** | -0.493*** |
| | (0.0855) | (0.135) | (0.178) |
| Observations | 223,106 | 223,106 | 223,106 |
| R-squared | 0.273 | 0.486 | 0.445 |
| Controls | Yes | Yes | Yes |
| FE | Yes | Yes | Yes |
| Sample: Married Females Visiting the Hospital | | | |
| DV (in log) | Investigation Amt. | Surgery Amt. | Out of Pocket Exp. |
| Post Feb'18 x Beneficiary | -0.119 | -0.773*** | -0.877*** |
| | (0.0808) | (0.172) | (0.228) |
| Observations | 168,491 | 168,491 | 168,491 |
| R-squared | 0.219 | 0.489 | 0.443 |
| Controls | Yes | Yes | Yes |
| FE | Yes | Yes | Yes |

Notes: The dependent variables are log of the outcomes given in each column. The estimation includes fixed effects for time, state of residence and center of the hospital along with a set of controls. Standard errors are clustered at the district level.'***','**', and '*' indicate significance at 1%, 10% and 5% respectively. The negative and significant coefficient for out-of-pocket expenditure and surgical expenses in the top panel indicates that female beneficiaries visiting the eye hospital spend significantly less on surgical treatments as compared to female non-beneficiaries. In the bottom panel, the coefficient estimate suggests that the marital status of a woman leads to a stronger negative impact on healthcare expenditure.

impact on height-for-age of children (0.96 cm taller; Progressa-Mexico, 0.44 cm taller boys; FA-Colombia), assisted childbirth (increase from 16 to 23% in six years; PKH-Indonesia), haemoglobin levels (11.12 g/dL; Progressa-Mexico), stunting (23-27% reduction; PKH-Indonesia; 8.6% reduction; Progressa-Mexico) and illness among infants (39.5% reduction; Progressa-Mexico) (Attanasio et al., 2005; Cahyadi et al., 2020; Gertler, 2004; Rivera, Sotres-Alvarez, Habicht, Shamah, & Villalpando, 2004). While these studies document a positive outcome, another strand in the literature has reported no significant effect of similar policy shocks.

**Table A10:** Estimates on Direct Health Outcomes from Existing Studies

| Name of Program | Country | Indicator | Estimate for treated group compared to control | Reference |
|---|---|---|---|---|
| Progressa | Mexico | Stunting | Children are 8.6% less likely to be stunted. | Gertler (2004) |
| | | Illness | Exposure to intervention for 24 months led to a 39.5% reduction in illness for children | Gertler (2004) |
| | | Haemoglobin | Mean haemoglobin level (11.12 g/dL) in children | Rivera et al (2004) |
| | | Height | Infants under 6 months of age are 1.1cm higher | Rivera et al (2004) |
| Program Keluarga Harapan (PKH) | Indonesia | Stunting | 23 to 27 percent reduction in the probability of being stunted | Cahyadi et al (2020) |
| | | Assisted Childbirth | Increase from 16 to 23% in six years | Cahyadi et al (2020) |
| | | Immunization Rate | No significant effect | Cahyadi et al (2020) |
| Bolsa Alimentacao | Brazil | Weight | An additional month of exposure to the program was associated with a 31g less weight gain | Morris et al (2004) |
| Familias en Accin | Colombia | Heigh-for-age | 12-month-old boys grew 0.44 centimetres more, negligible effects for children older than 2 years | Attanasio et al (2005) |
| | | Healthcare Visits | Increased from 17.2% to 40.0% | Attanasio et al (2005) |
| Credit Transfer Program (Gender-Disaggregated) | Bangladesh | Body Mass Index | No significant effect | Pitt et al (2003) |
| | | Height-for-age | Credit to women leads to increase in height for boys (1.53) and girls (1.14), | Pitt et al (2003) |
| | | Contraceptive Use | No significant effect | Pitt et al (1999) |
| Medicaid (Coverage of Asian and Hispanic Community) | USA | Hospitalization | Increasing the number of children with Medicaid 10% results in a 2-3% percent decline in avoidable hospitalizations among children | Aizer (2007) |

Notes: The table represents the coefficient estimates on direct healthcare outcomes from existing studies in the literature.

Studies by Pitt, Khandker, McKernan, and Latif (1999) and Pitt, Khandker, Chowdhury, and Millimet (2003) on credit programs in Bangladesh report the impact of gender-segregated decisions on intra-household allocations. Credits to women have no significant effect on the body mass index of children and the usage of contraceptives but a positive effect on the height of children. Similarly, Morris, Olinto, Flores, Nilson, and Figueiró (2004) found a negative association between CCT conditioned upon seeking preventive healthcare in Brazil on weight gain of infants. Finally, a study by Aizer (2007) reported that increasing the coverage of insurance programs (Medicaid) by 10% for children in the USA resulted in a 2-3% decline in avoidable hospitalizations.