DVARA RESEARCH

Savings, Portfolio Choice and Healthcare-Seeking Behaviour — An Empirical Analysis Focussing on Women of Reproductive Age (15-49 years) in India

***Reshmi Sengupta**[*] **and Debasis Rooj**[*]*

Abstract

This paper aims to examine the role of financial savings and portfolio choice on the health-seeking behaviour among women in their reproductive age. We have used two nationally representative datasets and applied a matching algorithm to combine the datasets to empirically analyse how savings in finical assets and portfolio diversification impact women's healthcare-seeking behaviour. The empirical analysis is based on a newly developed optimal matching algorithm for multilevel data, which allows us to mimic the cluster-randomised trial for observational studies. We find that both financial savings and portfolio diversification lead to improved health-seeking behaviour. More specifically, we find that women belonging to districts with high savings register their pregnancy early, seek better antenatal care and prefer institutional delivery. On the other hand, we also find that women living in districts with a higher degree of portfolio diversification prefer delivery in private institutions and seek higher postnatal care than their counterparts in districts with a lower portfolio diversification.

[*]Authors email: reshmi.sengupta@flame.edu.in, debasis.rooj@flame.edu.in

Contents

1. Introduction

Financial barriers pose a significant challenge for many women in accessing healthcare during their pregnancy, delivery and postnatal check-ups in India. Although several government initiatives, such as Janani Suraksha Yojna (launched in 2005) and Janani Shishu Suraksha Karyakram (launched in 2011), aim to provide comprehensive and quality antenatal care (ANC) and safe motherhood, healthcare utilisation by women remains low. The National Family Health Survey-4 (2015-16) shows that only 58.6 percent of women accessed ANC during their first trimester of pregnancy, merely 51.2 percent went for at least four ANC visits, only 30 percent of mothers consumed iron and folic acid (IFA) tablets for 100 days or more, only 21 percent received full ANC, and nearly 62.4 percent received postnatal care after two days of delivery. Moreover, almost 11 percent of women's birth was not protected from neonatal tetanus, and nearly 21 percent of women did not go for institutional delivery.

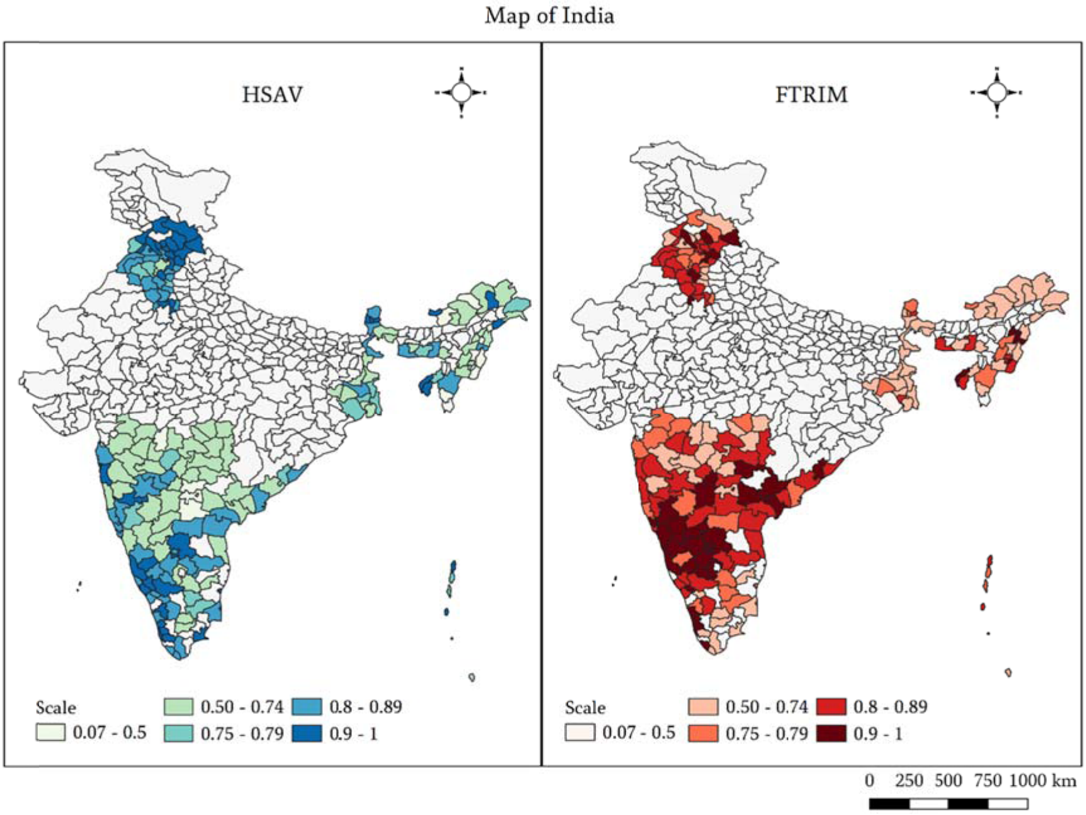
Women belong to a vulnerable group, with low health insurance uptake (including public health insurance) despite high healthcare demand (Sengupta & Rooj, 2019). Women, particularly those in low-income families, may face substantial financial constraints due to high user fees, transportations costs for doctor visits, and other informal payments, especially while accessing pregnancy and childbirth-related healthcare (Dodzo & Mhloyi, 2017; Kananura et al., 2017). Even with social protection, accessing these healthcare services may not always be feasible due to hidden costs and complicated bureaucratic processes. Hence, this may translate into a huge out-of-pocket (OOP) expenditure, ultimately plunging the women into massive financial distress and compelling them to borrow from external sources, thereby leading to huge debts. Thus, in such situations, the household's financial preparedness is crucial to mitigate the risks arising from the healthcare demands of women.

Prudent household savings decisions may help build sufficient economic resources and support individuals in meeting any catastrophic OOP healthcare expenditure, thereby ensuring adequate and timely healthcare access, especially in the short run. Health insurance is one form of savings that can provide this protection. However, in India, the penetration of health insurance is dismal. Moreover, individual (private) health insurance plans may not always cover pregnancy and childbirth-related healthcare expenditures, particularly within the waiting period. In such a scenario, household savings or wealth may act as a safeguard.

Wealth can be accumulated and enhanced through savings and portfolio diversification. Household wealth creation, through the accumulation of savings, is an intrinsically dynamic phenomenon. Each household has a given amount of resources at the beginning of the current period, accumulated from the previous periods, and is used in the health production function to purchase health inputs for better future health (Dowie, 1975). Savings can be in the form of non-risky (safe) and risky financial assets. Household savings may increase the ability and the willingness of the households to pay for healthcare services. For instance, Chiu et al. (2019) found that women who saved had a significantly higher chance of delivering their babies in an institutional setup.

Households in India differ in their access to market-supplied healthcare services and their ability to produce health due to several socioeconomic and demographic differentials. The same is true for savings in financial assets and portfolio choices. A visual depiction of the district-wise distribution of savings behaviour and health-seeking practices by women in their reproductive age shows that, in general, districts with a higher proportion of household savings are also the districts in which women seek more healthcare services, such as antenatal care in the first trimester of their pregnancy (Figure 1), institutional delivery (Figure 2) and postnatal check-up (Figure 3).

Figure 1: District-Wise Distribution of Savings and FTRIM

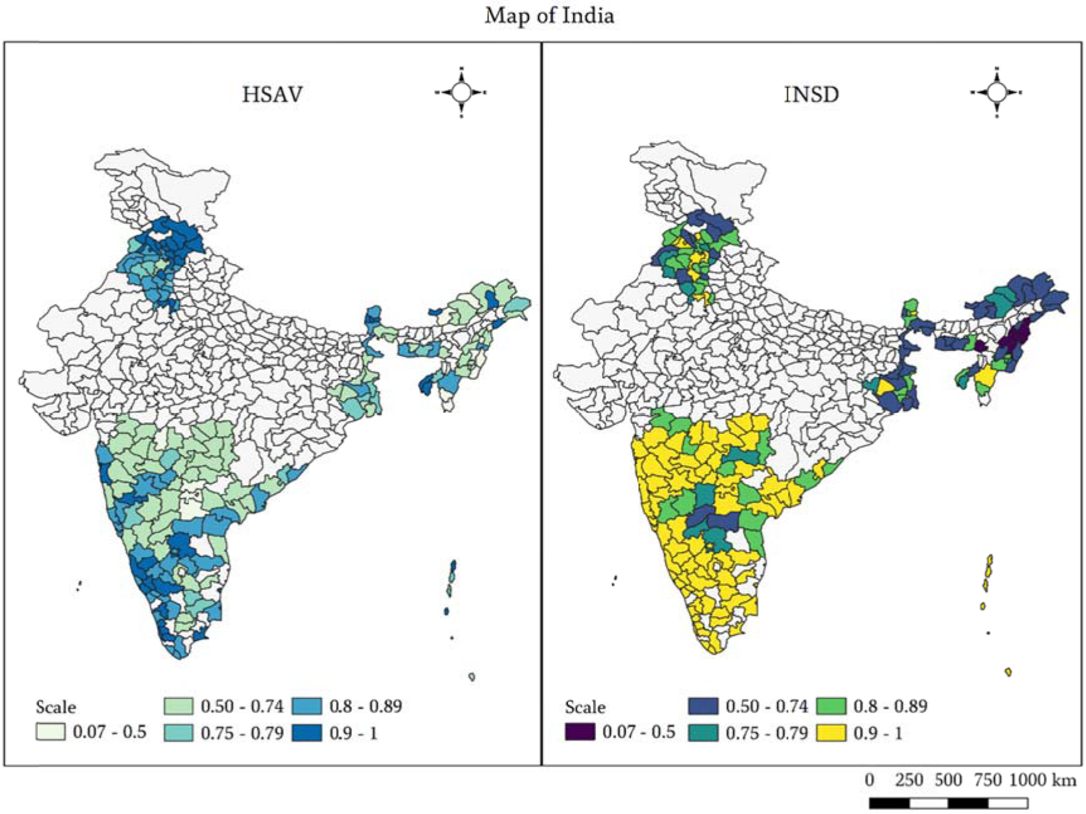


Note: 'Savings' indicates the proportion of households having financial assets, both risk-free and risky, in a district. 'FTRIM' indicates the proportion of women who sought antenatal care during the first trimester (0-3 months) of pregnancy.
Source: Authors' own calculations

In this paper, we argue that financial savings and careful portfolio choice play a strong role in women's demand for health services, potentially protecting the mother, her newborn's health, and the entire family's welfare. This idea can be supported by the fact that 'health' is a fundamental commodity, and consumers undertake health production by combining several inputs, including healthcare services (Dowie, 1975).

Moreover, portfolio choices and healthcare decisions represent investment expenditure and create capital, which can, in turn, improve the welfare of a household. Therefore, it is crucial to understand the connecting dynamics of household savings behaviour, savings and portfolio choice, and their implications on healthcare utilisation. Therefore, in this

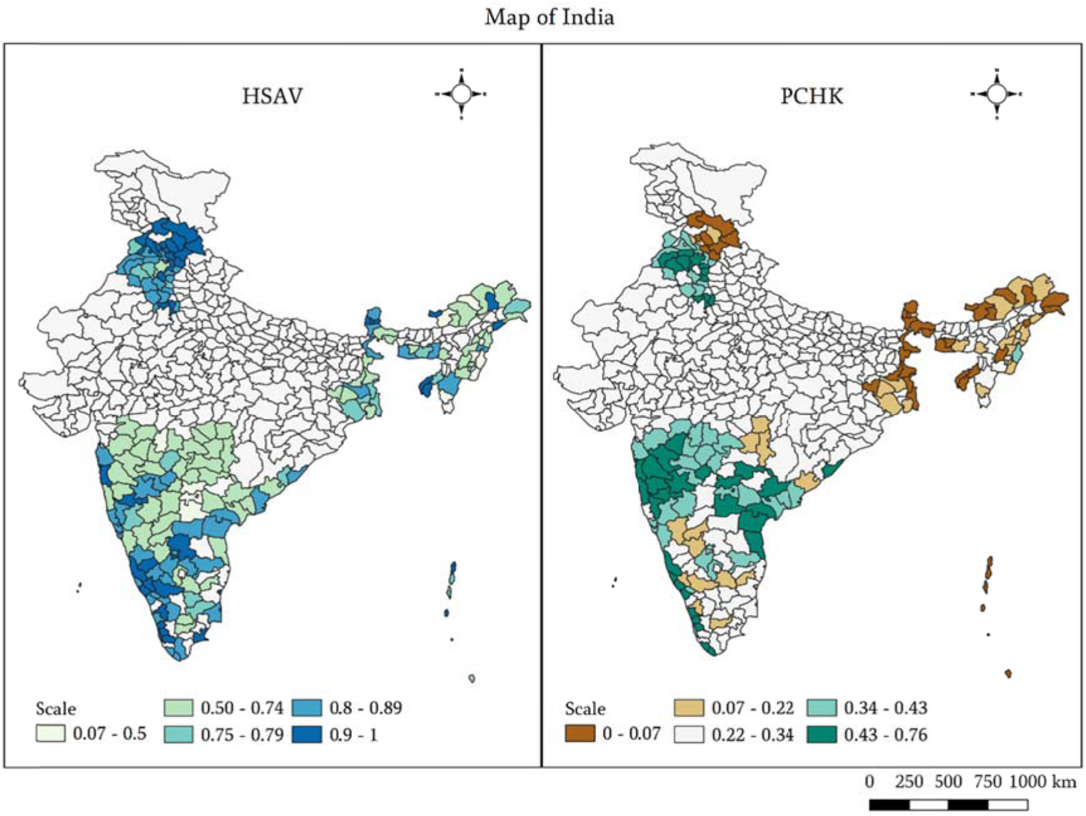
FIGURE 2: District-Wise Distribution of Savings and INSD



Note: 'Savings' indicates the proportion of households having financial assets, both risk-free and risky, in a district. 'INSD' indicates the proportion of women who sought institutional delivery.
Source: Authors' own calculations

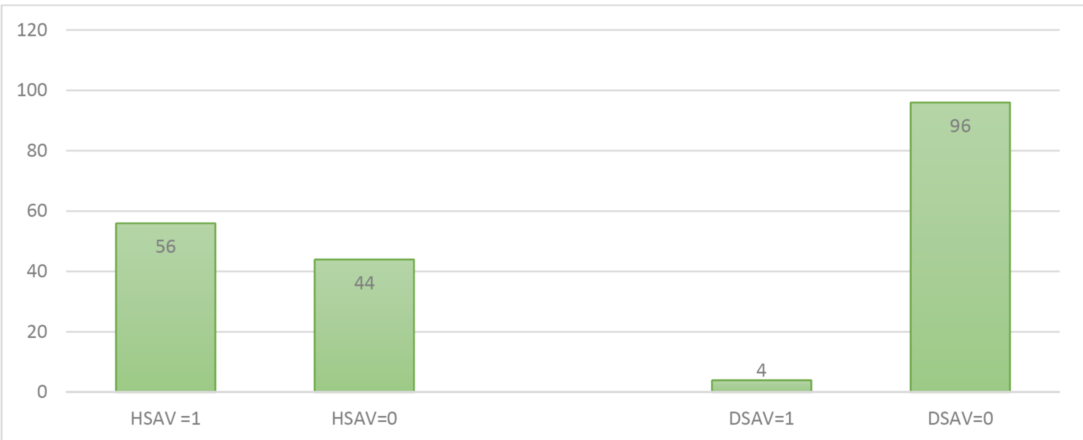
study, we analyse the effect of savings and portfolio diversification on women's health-seeking behavior. Our sample consists of women in their reproductive age (15-49 years). We examine whether higher savings improve health-seeking practices such as antenatal care, intuitional delivery, and postnatal care. We also ascertain the role of portfolio diversification in healthcare use by women. We find that both savings and portfolio diversification have a substantial effect on women's healthcare-seeking behaviour.

FIGURE 3: District-Wise Distribution of Savings and PCHK



Note: 'Savings' indicates the proportion of households having financial assets, both risk-free and risky, in a district. 'PCHK' indicates the proportion of women who sought postnatal check-up within 24 hours of delivery.
Source: Authors own calculations

FIGURE 4: Distribution of Treated and Control Groups



Note: HSAV=1 if the district proportion of savings is greater than or equal to the average district-wise proportion of savings, else 0; DSAV=1 if district proportion of the diversified portfolio is greater than or equal to the average district-wise proportion of diversified portfolio, else 0.
Source: Authors' own calculations

2. Literature Review

Several studies have examined the pathways from wealth (or socioeconomic status) to health or healthcare access (Adams et al., 2003; Hurd and Kapteyn, 2003; Meer et al., 2003; Smith, 2005). In a seminal work by Grossman (1972), later extended by Jacobson (2000), both the authors showed a positive effect of wealth on health. Hurd & Kapteyn (2005) used an ordered logit estimation to find a significant impact of income and wealth on health transition. They showed a stronger effect of wealth on health than income. Meer et al. (2003) used four waves of data from the Panel Study of Income Dynamics to analyse the effect of wealth on an individual's health status. Their results suggested a causal relationship running from wealth to health. They found that wealth had a positive and significant effect on a person's health status.

Michaud & van Soest (2008) used a dynamic panel data model-based test to provide evidence of causal effects from wealth to health. They found no evidence of causal effects of wealth on the health of husbands or wives or one spouse's health on the other spouse's health. On the other hand, Smith (2005) examined the ability of baseline socioeconomic status (SES) to predict the future onset of diseases, after controlling for baseline health measures. In their analysis, they used the significant (unanticipated) increase in wealth during a large stock market run-up during the 1990s (prior wave). Such an increase in wealth can be considered exogenous. Findings from Smith's study indicated that SES failed to predict the future onset of diseases (except arthritis).

Other studies have analysed the impact of wealth on healthcare use. For example, Steinhardt et al. (2009) examined the effect of wealth status on care-seeking patterns and health expenditures in Afghanistan. They found that sick people from all wealth quintiles showed high care-seeking rates, although those in the wealthiest quintile were more likely to seek care than those from the poorest quintile. Arthur (2012) investigated the effect of wealth on maternal healthcare utilisation in Ghana. After controlling for a policy supporting free maternal healthcare, the author found a positive and significant impact of wealth on antenatal care use.

Celik (2000) showed that household assets positively and significantly affected antenatal care use in Turkey. Gage (2007) found that household poverty had a negative effect on the use of maternal healthcare during pregnancy. Abor et al. (2011) showed that individuals in the poorest households in Ghana were less likely to deliver in a healthcare facility and were also less likely to use antenatal services. Vecino-Ortiz (2008) showed that wealthier mothers in Columbia had greater chances of opting for first and multiple antenatal visits than poorer mothers.

Munguambe et al. (2016) studied women's healthcare-seeking practices during pregnancy in Mozambique. In an ethnographic study, they found that in areas where women did not have their income source or did not participate in a community savings scheme and were dependent on their partner's income, they either had delayed treatment or did not seek treatment at all. Bhuiya et al. (2018) showed that participation in microfinance programmes improved healthcare use and health-seeking behaviour (antenatal care, diarrhoea remedy, and immunisation) in Bangladesh.

Adams et al. (2003) examined the causal links between SES and health. The results of this study suggested that SES had no significant effect on the incidence of acute and sudden onset of health conditions. However, SES affected the incidence of some mental, chronic and degenerative conditions. The findings from elderly individuals in the United States also suggested that there could be an SES gradient in seeking treatment, which may influence detection and hence reporting. The study concluded that the ability to pay might be a causal factor in seeking and receiving treatment. Low SES may lead to failure to seek medical care, delay in detecting conditions, reduced access to medical services or less effective treatment.

Using data from a field experiment in Kenya, Dupas & Robinson (2013) showed that simple, informal savings technologies could substantially increase investment in preventive health and reduce vulnerability to health shocks. More recently, Hageman & George (2019) studied whether ownership of health savings account (HSA) was associated with an unmet need for healthcare. They found that HSA ownership was significantly associated with reduced financial barriers to healthcare access.

In a recent study, Lee, Oh, Kim, & Subramanian (2020) used several rounds of National Family Health Survey (NFHS) data, from 1998-1999 to 2015-2016, and found that the utilization of antenatal care (ANC) services remained disproportionately lower among women with poor socioeconomic status. They argued in favour of these women to effectively eliminate any inequality in ANC utilisation in India.

These discussions point towards a positive impact of wealth or savings on health and healthcare use. However, these studies have not used any direct measure of savings but have used either socioeconomic status or wealth index of the households as a measure of their financial ability. Some other studies have used measures of community savings or microfinance. However, the role of financial savings (both safe assets, such as bank deposits or bonds, and risky assets, such as ownership of stocks and debentures) on healthcare use, especially for women in their reproductive age, has not yet been explored. To our knowledge, this study is the first such attempt to examine the role of financial savings and portfolio choice on the health-seeking behaviour of women in India. Moreover, we explore this channel by controlling for the presence of social safety nets, such as health insurance and conditional cash transfer schemes, to discuss and debate public policies, which are often overlooked in India.

We contribute to the literature in several ways. First, we are the first ones to examine the role of financial savings on health-seeking practices by women in India. Second, we examine how portfolio diversification helps in improving these health-seeking practices. Third, we use several measures of health-seeking practices, including prenatal and postnatal healthcare variables. Finally, we use the newly developed matching algorithm for multilevel data akin to clustered experiment design. We find that both financial savings and portfolio diversification positively impact women's health-seeking indicators.

3. Data

This research aims to empirically examine the role of savings and portfolio diversification on the healthcare-seeking practices by women in their reproductive age. However, there is no database that captures both these aspects simultaneously. Therefore, we rely on two separate databases for our analysis.

We combine data from National Sample Survey Office (NSSO) (70^{th} round) and District Level Household and Facility Survey (DLHS-4). The NSSO 70^{th} round (January-December, 2013) survey on 'Debt and Investment' has detailed information on households' financial assets, while DLHS-4 conducted during 2012-13 has detailed information on women's healthcare use.[1]

The outcome variable of interest is women's healthcare utilisation, defined only for women in their reproductive age (15 to 49 years), who were pregnant and/or gave birth during the survey period. The outcome variables on health-seeking behaviour are defined based on whether pregnant mothers seek prenatal care, institutional delivery and postnatal care. A detailed description of these variables is provided in Table 1.

TABLE 1: Variable Definitions

Variables	**Definition**
SAVE	=1 if households save, else 0
RSAVE	=1 if households save in both safe and risky assets, else 0
HSAV (high Savers)	= 1 if district proportion of savings is greater than or equal to the average district-wise proportion of savings, else 0
DSAV (high diversified portfolio)	=1 if district proportion of the diversified portfolio is greater than or equal to the average district-wise proportion of diversified portfolio, else 0
Outcome Variables	
PREG	=1 if last pregnancy is registered within 12 weeks of pregnancy, else 0
TRTS	=1 if sought treatment for health problem during last pregnancy, else 0
FTRIM	=1 if ANC sought during the first trimester (0-3 months) of pregnancy, else 0
ANC8	=1 if at least 8 antenatal visits, else 0
IFA	=1 if at least 100 IFA tablets were taken, else 0

[1] Both these databases have similar rural and urban samples with NSSO having 56 percent of samples from rural areas and 44 percent from urban areas. On the other hand, for DLHS, they are 58 percent and 42 percent, respectively.

INSD	=1 if institutional delivery, else 0
DELPVT	=1 if delivery in private institution, else 0
DELPUB	=1 if delivery in public institution, else 0
PCHK	=1 if check-up within 24 hours of delivery, else 0
CHKPVT	=1 if immediate check-up in private institution, else 0
Control Variables	
AGE	Women's age in years (15-49 years)
SCH	=1 if women attended schooling, else 0
BO	Birth order (0 to 12)
HSCH	=1 if woman's husband attended school
EMP	=1 if woman is currently employed, else 0
RURAL	=1 if region of residence is rural, else 0
HINDU	=1 if religion is Hindu, else 0
MUSLIM	=1 if religion is Muslim, else 0
BPL	=1 if the household is below poverty line, else 0
CHRONIC	=1 if any HH member has undergone diagnosis for chronic illnesses
HOWN	=1 if the household owns a house, else 0
LOWN	=1 if the household owns land, else 0
WEALTH	Household wealth quintile
DHINS	District-wise proportion of having health insurance
DFAST	District-wise proportion of financial assistance for delivery care
DFAR	District-wise proportion of villages with distance to health facility being far away
DBANK	District-wise number of banks during December 2012

Source: Authors' own

The independent variables of interest in our analysis are savings and portfolio diversification. However, given that we are using two separate datasets, we cannot have individual or household level savings indicators directly linked to the individual outcome variables in our analysis. Therefore, we use the household level savings variables from the NSSO data to construct district-level indicators. First, we consider two categories of financial assets.

The first category is the *safe* assets where households save in one or more of the financial assets, such as different types of certificates or securities issued by the government or banks, including National Savings Certificate (NSC), Indira Vikas Patra, Kisan Vikas Patra, RBI bonds, and deposits in post offices, cooperative banks, commercial banks and companies. The other form of the financial asset is *risky,* where households own shares and debentures held in credit or non-credit cooperative societies, commercial banks, financial and non-financial companies, mutual funds from institutions such as Unit Trust of India. Therefore, we define SAVINGS = 1 if households own *safe* financial assets and 0 if they have no financial assets. Further, we define RSAVINGS = 1 if households own both *safe* and *risky* assets and 0 if they own only s*afe* assets or hold no savings.

However, given the nature of our data, these variables need to be converted into district-level constructs for our empirical analysis. Therefore, we define HSAV=1 if the district proportion of savings (SAVINGS) is greater than or equal to the average district-wise proportion of SAVINGS, or else it is 0; DSAV=1 if the district proportion of RSAVINGS is greater than or equal to the average district-wise proportion of RSAVINGS, or else it is 0.

Following past studies (Steinhardt et al. 2009, Bhuiya et al. 2018), we also include several individual, household and district level indicators in our analysis. The individual-level indicators are AGE, SCH, BO, HSCH, EMP, RURAL, HINDU, MUSLIM, BPL, CHRONIC, HOWN, LOW and WEALTH. District-level indicators include DHINS, which is the district-wise proportion of having health insurance; DFAST, which is the district-wise proportion of financial assistance for delivery care (JSY and other social safety nets for pregnant women and children); and DFAR, which indicates the district-wise proportion of villages with distance to health facility being far away. Moreover, in order to capture the financial access, we define a variable DBANK, which is the number of bank branches in the district.[2]

The data for NSSO covered 634 districts from all the states in India. However, DLHS-4 was conducted in the 275 districts. Therefore, our analysis consists of observations from these 275 districts. After deleting the missing observation, finally, our empirical sample consists of 27,282 observations for the HSAV analysis and 20,519 observations for the DSAV analysis.

[2]This data is obtained from the RBI website; we consider the district level branches for the month of December 2012.

4. Empirical Methods

We use a multilevel matching algorithm proposed by Pimentel, Page, Lenard, & Keele (2018). Multilevel data arises when observed units are organised within levels of a hierarchy (clusters) such as class, school or district.

The popular method to adjust for cluster and unit-level covariates uses hierarchical or multilevel regression modelling (Hox, 2002). Multilevel regression models can help recover the causal inference by accounting for the data collection design under certain assumptions, adjusting for unmeasured covariates, and modelling variations in treatment effects (Feller & Gelman, 2015).

A more recent approach to estimate such treatment effects within the multilevel data structure involves propensity score estimation (Grisword, Localio, & Mulrow, 2010; Hong & Yu, 2008; Thoemmes & Kim, 2011). The application of propensity scores in multilevel models stems from the fact that it addresses two major concerns of a quasi-experimental study (Xiang & Tarasawa, 2015). First, it reduces selection bias by matching individuals between the treatment and the control groups based on a set of relevant covariates. Second, it reduces estimation bias by accounting for the random effects across units in a hierarchical data structure (Thoemmes & West, 2011). An excellent example is Hong and Raudenbush (2006), who examine the kindergarten retention policy's effectiveness on students' reading achievement by estimating propensity scores in a multilevel model.

However, in this paper, we use the optimal matching strategy for clustered observational studies proposed by Pimentel et al. (2018) and Zubizarreta and Keele (2017). Thus, our empirical method is akin to a group or cluster-randomized trial (CRT). In a CRT, observed units (for instance, students) are organised into clusters (schools or districts) that are randomised to a treatment or control condition.

However, CRTs may not always be feasible for several reasons (political, cost, or ethical). In such circumstances, a clustered observational study could be used as an alternative. Page et al. (2020) argue that when clustered treatments are non-randomly allocated, the research design may be described as a clustered observational study. Clustered observational studies have a nested or multilevel data structure with observed and unobserved covariates both at the cluster and unit levels. In such a setting, treatment assignment occurs at the group level, while the analytical interest is focussed on unit outcomes. The literature on observational studies for deriving causal inferences is well developed when the selection of treatment happens at the individual level (Rubin 2007, 2008). However, the literature on COS is still underdeveloped.

In clustered observational studies, the data structure is characterised by observed and unobserved covariates at the cluster and unit levels. Therefore, in such a context, if we want to examine the effect of cluster-level treatment on unit-level outcomes, this effect may be confounded by differences in the distributions of covariates across the treatment groups at both levels (Zubizarreta & Keele, 2017).

Randomisation occurs at the cluster level in a CRT, ensuring that the treatment and control clusters are equivalent in expectation. Moreover, at the point of randomisation, we can also assess the balance in expectation in terms of unit-level covariates and further assume balance on all unobserved setting characteristics. Therefore, when an intervention is randomly assigned, differences in the outcomes between clusters that are not treated can be causally attributed to the intervention. This balancing can be achieved by conducting multilevel matching, similar to individual-level matching, to mimic an individual-level RCT (Page et al., 2020). The idea is to create pairs of comparable treated and control clusters. Examples include Steiner et al. (2013), Stuart (2007), and Stuart and Rubin (2008). However, these studies consider matching based on individual-level characteristics only, rendering them less relevant to clustered observational studies in which cluster-level covariates are critical (Page et al., 2020). Therefore, we use the newly developed optimal matching strategy for clustered observational studies. This matching method mimics a CRT by creating comparable treated and comparison clusters and units within clusters to remove overt bias at the individual and group levels.

Following Pimentel et al. (2018), we conceptualise districts with above-average savings (high savers) as a group-level treatment applied to a set of women in their reproductive age. Such allocation allows us to examine whether women in districts with high saving (high savers) observationally have better health-seeking practices than women in districts with below-average savings (low savers), which act as our control group. The findings, therefore, might indicate that savings are effective in enhancing health-seeking practices.

We also investigate whether women in districts with an above-average proportion of savings having both safe and risky assets (high portfolio diversification) use more healthcare services than their counterparts living in districts with a below-average proportion of both safe and risky assets (low portfolio diversification). We find that individuals belonging to the treatment group typically practise better health-seeking behaviour.

5. Results

In this section, we present the results from our empirical analysis.

5.1 Summary statistics

We find that 56 percent of our sample belong to districts with high savings (HSAV=1), but only 4 percent of those are in districts with a diversified portfolio (S treatment and the control groups. Table 3 provides the results from the two-sample t-tests for the two cases considered in our analysis–HSAV, and DSAV.

TABLE 2: Descriptive Statistics

	HSAV		DSAV	
Variables	Mean	SD	Mean	SD
PREG	0.81	0.39	0.82	0.38
TRTS	0.27	0.44	0.27	0.44
FTRIM	0.79	0.41	0.8	0.40
ANC8	0.24	0.42	0.25	0.43
IFA	0.42	0.49	0.44	0.50
INSD	0.83	0.37	0.85	0.36
DELPVT	0.31	0.46	0.32	0.47
DELPUB	0.52	0.50	0.52	0.50
PCHK	0.69	0.46	0.71	0.45
CHKPVT	0.26	0.44	0.27	0.44
AGE	26.52	4.98	26.48	4.90
SCH	0.84	0.37	0.85	0.36
BO	1.98	1.11	1.96	1.07
HSCH	0.87	0.34	0.87	0.33
EMP	0.18	0.38	0.17	0.37
RURAL	0.62	0.48	0.62	0.48
HINDU	0.70	0.46	0.72	0.45
MUSLIM	0.12	0.33	0.12	0.33
BPL	0.39	0.49	0.40	0.49
CHRONIC	0.25	0.43	0.23	0.42
HOWN	0.85	0.36	0.85	0.36

LOWN	0.38	0.48	0.37	0.48
WEALTH	3.02	1.35	2.98	1.34
DLAND	1.21	0.85	1.19	0.87
DHINS	0.23	0.19	0.24	0.19
DFAST	0.27	0.13	0.27	0.14
DFAR	0.14	0.09	0.14	0.09
DBANK	197.7	213.78	223.92	232.67

Note: Total number of observations for HSAV is 27,282; total number of observations for DSAV analysis is 20,519.

Source: Authors' own calculations

We find a clear difference among the healthcare-seeking variables between the treatment and the control groups. More specifically, we find that the treatment group (HSAV=1 and DSAV=1) exhibits a higher mean for most of the health-seeking behaviour variables. For instance, last pregnancy registration (PREG) is 4 percent higher for high savers than low savers. Similarly, ANC sought during the first trimester (FTRIM) is 2 percent more for high savers than low savers. On the other hand, the difference between highly diversified portfolio holders with respect to PREG is not statistically significant. However, for FTRIM, the difference is almost 11 percent and is statistically significant. The t-statistics for most of the other indicators are also statically significant, indicating the presence of a significant difference in the outcome variables between the treatment and control groups.

5.2 Matching

To draw the causal inference on the role of financial savings, we rely on the matching algorithm. We begin by analysing the balance at the district and individual levels. Table 4 contains the standardized differences before and after the matching. The standardized differences are the differences in means divided by the standard deviation. They are calculated before matching for the unmatched sample and after matching for the matched sample. We observe that the imbalances at the individual level covariates are small, indicating that the selection process of our individuals based on our district classification is uniform across treated and control groups, i.e., districts (Page, Lenard, & Keele,2020). However, the standardised differences for the district level variables are considerably large. For example, the standardised difference for DFAST is -0.2 and -0.4 for HSAV and DSAV samples, respectively (Table 4). It indicates that the proportions of individuals receiving financial assistance for pregnancy related health variables are higher for high saving and highly diversified districts than their counterparts in the control groups.

TABLE 3: Two-Sample T-Tests

Variables	Low savers (HSAV=0)	High savers (HSAV=1)	t-test	Low portfolio diversification (DSAV=0)	High portfolio diversification (DSAV=1)	t-test
	Mean	Mean	Mean difference	Mean	Mean	Mean difference
PREG	0.79	0.83	-0.04*** (0.000)	0.83	0.82	0.01 (0.706)
TRTS	0.26	0.27	-0.01** (0.020)	0.26	0.28	-0.02 (0.139)
FTRIM	0.77	0.79	-0.02*** (0.000)	0.79	0.9	-0.11*** (0.000)
ANC8	0.19	0.25	-0.06*** (0.000)	0.25	0.25	0.00 (0.787)
IFA	0.37	0.46	0.09** * (0.000)	0.45	0.4	0.05 *** (0.001)
INSD	0.79	0.86	-0.07*** (0.000)	0.86	0.83	0.03*** (0.005)
DELPVT	0.27	0.35	-0.08*** (0.000)	0.34	0.42	-0.08*** (0.000)
DELPUB	0.53	0.52	0.01* (0.055)	0.52	0.41	0.11*** (0.000)
PCHK	0.67	0.7	-0.03*** (0.000)	0.69	0.84	-0.15*** (0.000)
CHKPVT	0.23	0.28	-0.05*** (0.000)	0.27	0.41	-0.14*** (0.000)

Source: Authors' own calculations

Next, we use matching to address baseline imbalances across the treatment and the control groups. Given that we apply the matching algorithm on multilevel data, the optimal match first considers all the possible individual pairings before matching on districts. In other words, it first compares the differences in the individual level covariates between each treated district and every control district. Then it uses this individual-level information in the district-level match. Finally, once districts are matched using this covariate information, we can match individuals within district pairs.

We use individual and district-level covariates as discussed by Pimentel, Page, Lenard, & Keele (2018). The matching algorithm is iterative, where we first perform a match, assess the resulting balance, and then we finetune the resulting match until the balance is acceptable. Just as outcome measures are not available at the time of randomisation in an experimental study, we cannot examine outcomes when doing implementing matching. The CRT analog to this process is conducting randomisation, assessing balance on baseline measures, and re-randomising if the baseline equivalence is not satisfied (Morgan & Rubin, 2012). The general rule of thumb is that the matched standardised differences should be less than 0.20 and preferably 0.10 (Rosenbaum, 2010). Table 4 reports the standardised differences before and after matching.

Table 4: Standardised Differences Before and After Matching

Variables	HSAV		DSAV	
	Sdiff before	Sdiff after	Sdiff before	Sdiff after
AGE	0.048	0.005	0.012	0.034
SCH	0.192	0.028	0.129	-0.003
BO	-0.202	-0.069	0.025	0.031
HSCH	0.189	0.019	0.144	0.004
EMP	-0.187	-0.011	0.037	0.032
RURAL	0.009	0.008	-0.118	-0.044
HINDU	0.181	0.088	-0.102	-0.033
MUSLIM	-0.111	-0.004	0.225	0.032
BPL	-0.145	-0.018	-0.075	-0.057
CHRONIC	0.087	-0.004	0.029	-0.058
HOWN	0.017	-0.016	0.074	-0.032
LOWN	-0.100	-0.090	0.303	0.075
WEALTH	-0.380	-0.100	-0.201	0.037
DHINS	0.077	0.045	-0.082	-0.011
DFAST	-0.202	-0.055	-0.6	-0.075
DFAR	-0.177	-0.089	0.467	0.027
DBANK	0.382	0.091	0.279	0.279

Source: Authors' own calculations

We observe that the standardised differences for all the individual- and district-level covariates are smaller than 0.1 for HSAV. However, for DSAV, the standardised differences become less than 0.1 for all the covariates, except for DBANK. For DBANK, the standardized differences remain unchanged at 0.279 even after matching.

5.3 Outcome estimates

Next, we assess the role of HSAV and DSAV for improving the health-seeking practices in our matched sample. Once matching is complete, we can estimate the treatment effects. We use a multilevel model with a random intercept, clustering at the district levels, and regressing the outcome on the treatment indicator (Pimentel et al., 2018; Zubizarreta and Keele, 2017). A major advantage of regression-based estimation stems from the fact that we can add any baseline covariate to the model. However, even after matching, some imbalances may still remain for certain covariates. Therefore, to completely remove

TABLE 5: Average Treatment Effects

Outcome variables	Average treatment effects	
	Treatment: HSAV	Treatment: DSAV
PREG	0.001 (0.944)	-0.012(0.628)
TRTS	-0.005 (0.756)	-0.050 (0.018)**
FTRIM	0.046 (0.013) **	0.019 (0.422)
ANC8	0.031 (0.235)	0.090 (0.029)**
IFA	0.100 (0.002) ***	0.033 (0.419)
INSD	0.038(0.059)*	0.047 (0.035)**
DELPVT	0.029 (0.263)	0.0106(0.033)**
DELPUB	0.008 (0.760)	-0.064 (0.165)
PCHK	0.043 (0.097)*	0.067 (0.086)*
CHKPVT	0.023 (0.379)	0.0103(0.020)**

Source: Authors' own calculations

the remaining bias from the imbalance in these covariates, we use these covariates as additional control variables in our model, which is the case for our DSAV sample. This representation is useful when some covariates show imbalances even after the match.

The matching exercise shows that we can reduce the standardised differences below 0.10 for all the covariates for the HSAV sample in our example. However, we are unable to do so for the DBANK variable in the DSAV sample.

Therefore, the resulting regression equation for HSAV is given as:

$$y_{ij} = \alpha + \beta_1 HSAV_j + z_j + \in_{ij}, \quad \mathrm{i} = 1, \ldots\ldots \mathrm{n}; \mathrm{j} = 1, \ldots\ldots, d \tag{1}$$

where y_{ij} is the health-seeking indicators for individual i in jth district, z_j is the random effect and β_1 is the treatment effect for HSAV.

Similarly, the resulting regression equation for DSAV is:

$$y_{ij} = \alpha + \theta_1 DSAV_j + \theta_2 DBANK + \theta_3 z_j + \in_{ij}, \quad \mathrm{i} = 1, \ldots\ldots \mathrm{n}; j = 1, \ldots\ldots, d \tag{2}$$

where y_{ij} is the health-seeking indicators for individual i in jth district, z_j is the random effect, θ_1 is the treatment effect for DSAV, and θ_2 is the coefficient related to the imbalanced covariate, DBANK. It is important to note here that we have clustering both within matched pairs and within districts. In other words, after matching, we treat districts as nested within matched pairs of treatment and control sets and individuals as nested within districts (Pimentel, Page, Lenard, & Keele, 2018).

Table 5 presents estimates from Equations 1 and 2. We find no evidence of any impact of HSAV on PREG and TRTS. The estimated coefficients of these outcome variables are statistically insignificant. The results, therefore, indicate that financial savings play no role in either pregnancy registration or seeking treatment for health problems during the last pregnancy. However, we find that the treatment effects of DSAV on FTRIM, IFA, INSD and PCHK are positive and statistically significant. For instance, the estimated coefficient for FTRIM is 0.46 and is statistically significant at less than 5 percent. It implies that women living in districts with higher financial savings tend to seek more antenatal care during the first trimester of their pregnancy than their counterparts in districts with lower financial savings. The same trend is valid for women taking at least 100 iron and folic tablets during their pregnancies. The estimated coefficient for INSD is also positive and statistically significant at less than 10 percent. This finding indicates that women belonging to high saving districts prefer institutional delivery than those in districts with relatively lower financial savings. However, we find no evidence that women in the treatment group choose either private or public institutions for delivery of their babies. With respect to postnatal care, we find that women in the treatment group seek more check-up within 24 hours of delivery than those in the control group. However, there is no evidence that they seek these postnatal cares in a private facility.

The findings, therefore, imply that after controlling for individual and district-level heterogeneities, including financial access and social security benefits, women living in the districts with a higher proportion of savings seek more healthcare than their counterparts in districts with lower-than-average savings. Thus, the results provide evidence that higher financial savings can improve health-seeking behaviour among women in their reproductive age. Moreover, financial saving also removes the barriers to accessing institutional delivery.

Similarly, for the DSAV analysis, we find no evidence that higher diversification leads to higher pregnancy registration (PREG). However, interestingly, the treatment effect of TRTS is negative and significant. This finding indicates that women belonging to districts with higher portfolio diversification seek lower treatment for health problems during last pregnancy compared to their counterparts in the control group. However, we also find that the treatment effects of ANC8, INSD, DELPVT, PCHK and CHKPVT are positive and statistically significant. Higher portfolio diversification leads to more use of antenatal facilities. The treatment effect of higher portfolio diversification also leads to higher institutional delivery and delivery in a private facility. The estimated coefficient of DELPUB for DSAV is negative but not statistically significant. The estimated coefficients for both the postnatal variables PCHK and CHKPVT are positive and statistically significant for the treatment group.

The results from this section, therefore, indicate that, after controlling for individual-level and district-level heterogeneity, including financial access and social security benefits, women living in districts with a higher proportion of portfolio diversification prefer delivery in private institutions and also seek higher postnatal care compared to women in districts with lower portfolio diversification. Thus, on the one hand, higher portfolio diversification indicates better financial knowledge, which may also translate to improved health practices (willingness to access improved health care). However, on the other hand, portfolio diversification also indicates better financial preparedness among the households, leading to improved health-seeking practices.

6. Conclusion

The decision to save and the decision to use healthcare services are multifaceted aspects for a household. Several factors can influence both these decisions. The process is often dynamic. However, policymakers often ignore these dynamics and look at policy in isolation. A vast majority of Indians are excluded from formal financial services; so they are denied basic healthcare facilities. Health is a significant risk for the members of a household, especially pregnant women, in India. Given the continuous rise in healthcare costs and the ever-increasing out of pocket expenditure, mere health insurance coverage may not be enough. Prudent financial planning can help the household mitigating these challenges. Nonetheless, policymakers have never considered building a coherent policy, which can alleviate both these problems simultaneously.

This paper explores how household savings can influence health-seeking behaviour among Indian women in their reproductive age. We examine the impact of financial savings and portfolio diversification on prenatal care, institutional delivery and postnatal care. We find that greater financial savings have a positive impact on prenatal care and institutional delivery. More specifically, we find that women in districts with high savings seek antenatal care in the first trimester of their pregnancy. High savers also take at least 100 IFA tablets and prefer institutional delivery compared to low savers. The target population of women population also ensure postnatal check-up within 24 hours of delivery if they belong to a district with high-savings.

Similarly, portfolio diversification leads to improved health-seeking practices. For instance, we found that individuals belonging to districts with highly diversified portfolios had at least 8 antenatal visits during their pregnancy. This group of women also preferred institutional delivery and chose private facilities compared to women belonging to districts where portfolio diversification was low. In addition, women in districts with highly diversified portfolios also sought postnatal care. For example, the treatment group sought immediate postnatal check-up within 24 hours of delivery and chose to do so in a private institution.

Thus, the findings indicate that financial savings and portfolio diversification allow the members of households to opt for better health-seeking practices.

Thus, our empirical research provides a broader understanding of the link between two crucial aspects of household decision-making in asset allocation and the inter-linkage between asset allocation and health-seeking behaviour, especially with respect to women in their reproductive ages. A prudent strategy to improve household finance opportunities can play a crucial role in mitigating the challenges arising due to health shocks. A financially well-prepared household can absorb the adverse health shocks and invest in health behaviour that can potentially improve the household's welfare.

References

1. Abor, P. A., Abekah-Nkrumah, G., Sakyi, K., Adjasi, C. K. D., & Abor, J. (2011). The socioeconomic determinants of maternal healthcare utilization in Ghana. *International Journal of Social Economics*, *38*(7), 628—648. https://doi.org/10.1108/03068291111139258

2. Adams, P., Hurd, M. D., McFadden, D., Merrill, A., & Ribeiro, T. (2003). Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics*, *112*(1), 3—56. https://doi.org/10.1016/S0304-4076(02)00145-8

3. Arthur, E. (2012). Wealth and antenatal care use: Implications for maternal healthcare utilisation in Ghana. *Health Economics Review*, *2*(1), 1—8. https://doi.org/10.1186/2191-1991-2-14

4. Bhuiya, M. M. M., Khanam, R., Rahman, M. M., & Nghiem, H. S. (2018). The relationship between access to microfinance, health-seeking behaviour and health service uses: Evidence from Bangladesh. *Economic Analysis and Policy*, *60*, 9—17. https://doi.org/10.1016/j.eap.2018.08.004

5. Celik, Y. (2000). The socioeconomic determinants of alternative sources of antenatal care in Turkey. *International Journal of Health Planning and Management*, *15*(3), 221—235. https://doi.org/10.1002/1099-1751(200007/09)15:3<221::AID-HPM592>3.0.CO;2-A

6. Chiu, C., Scott, N. A., Kaiser, J. L., Ngoma, T., Lori, J. R., Boyd, C. J., & Rockers, P. C. (2019). Household saving during pregnancy and facility delivery in Zambia: A cross-sectional study. *Health Policy and Planning*, *34*(2), 102—109. https://doi.org/10.1093/heapol/czz005

7. Dodzo, M. K., & Mhloyi, M. (2017). Home is best: Why women in rural Zimbabwe deliver in the community. *PLoS ONE*, *12*(8), 1—23. https://doi.org/10.1371/journal.pone.0181771

8. Dowie, J. (1975). The Portfolio Approach to Health Behaviour. *Social Science & Medicine*, *9*, 619—631.

9. Kananura, R. M., Wamala, R., Ekirapa-Kiracho, E., Tetui, M., Kiwanuka, S. N., Waiswa, P., & Atuhaire, L. K. (2017). A structural equation analysis on the relationship between maternal health services utilization and newborn health outcomes: A cross-sectional study in Eastern Uganda. *BMC Pregnancy and Childbirth*, *17*(1), 1—12. https://doi.org/10.1186/s12884-017-1289-5

10. Lee, H. Y., Oh, J., Kim, R., & Subramanian, S. V. (2020). Long-term trend in socioeconomic inequalities and geographic variation in the utilization of antenatal care service in India between 1998 and 2015. *Health Services Research*, *55*(3), 419—431. https://doi.org/10.1111/1475-6773.13277

11. Sengupta, R., & Rooj, D. (2019). The effect of health insurance on hospitalization: Identification of adverse selection, moral hazard and the vulnerable population in

the Indian healthcare market. *World Development*, *122*, 110—129. https://doi.org/10.1016/j.worlddev.2019.05.012

12. Dodzo, M. K., & Mhloyi, M. (2017). Home is best: Why women in rural Zimbabwe deliver in the community. *PLoS ONE*, *12*(8), 1—23. https://doi.org/10.1371/journal.pone.0181771

13. Dowie, J. (1975). The Portfolio Approach to Health Behaviour. *Social Science & Medicine*, *9*, 619—631.

14. Feller, A. and Gelman, A. (2015). Hierarchical models for causal effects. Working Paper

15. Gage, A. J. (2007). Barriers to the utilization of maternal healthcare in rural Mali. *Social Science and Medicine*, *65*(8), 1666—1682. https://doi.org/10.1016/j.socscimed.2007.06.001

16. Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, *80*(2), 223-255

17. Hong, G., & Raudenbush, S. W. (2006). Estimating kindergarten retention policy. Journal of the American Statistical Association, 101(475), 901—910.

18. Hox, J. (2002). Multilevel analysis: Techniques and applications. New York: Erlbaum

19. Hurd, M., & Kapteyn, A. (2005). M . Hurd and a . Kapteyn. In S. H. De Gijsel P. (Ed.), *Multidisciplinary Economics, Springer, Boston, MA*. https://doi.org/https://doi.org/10.1007/0-387-26259-8_28

20. Kananura, R. M., Wamala, R., Ekirapa-Kiracho, E., Tetui, M., Kiwanuka, S. N., Waiswa, P., & Atuhaire, L. K. (2017). A structural equation analysis on the relationship between maternal health services utilization and newborn health outcomes: A cross-sectional study in Eastern Uganda. *BMC Pregnancy and Childbirth*, *17*(1), 1—12. https://doi.org/10.1186/s12884-017-1289-5

21. Jacobson, L. (2000). The family as producer of health–an extended Grossman model. *Journal of Health Economics*, *19*(5), 611-637. https://doi.org/10.1016/S0167-6296(99)00041-7

22. Meer, J., Miller, D. L., & Rosen, H. S. (2003). Exploring the health-wealth nexus. *Journal of Health Economics*, *22*(5), 713—730. https://doi.org/10.1016/S0167-6296(03)00059-6

23. Michaud, P. C., & van Soest, A. (2008). Health and wealth of elderly couples: Causality tests using dynamic panel data models. *Journal of Health Economics*, *27*(5), 1312—1325. https://doi.org/10.1016/j.jhealeco.2008.04.002

24. Munguambe, K., Boene, H., Vidler, M., Bique, C., Sawchuck, D., Firoz, T., . . . Sevene, E. (2016). Barriers and facilitators to healthcare seeking behaviours in pregnancy in rural communities of southern Mozambique. *Reproductive Health*, *13*(1). https://doi.org/10.1186/s12978-016-0141-0

25. NSS (2014). Social Consumption: Health, 71st round, (KI/71.25.0), http://mospi.nic.in/sites/default/files/national_data_bank/ndb-rpts-71.htm

26. Page, L. C., Lenard, M. A., & Keele, L. (2020). The Design of Clustered Observational Studies in Education. *AERA Open*, *6*(3), 233285842095440. https://doi.org/10.1177/2332858420954401

27. Pimentel, S. D., Page, L. C., Lenard, M., & Keele, L. (2018). OPTIMAL MULTILEVEL MATCHING USING NETWORK FLOWS: AN APPLICATION TO A SUMMER READING INTERVENTION. *The Annals of Applied Statistics*, *12*(3), 1479—1505.

28. Sengupta, R., & Rooj, D. (2019). The effect of health insurance on hospitalization: Identification of adverse selection, moral hazard and the vulnerable population in the Indian healthcare market. *World Development*, *122*, 110—129. https://doi.org/10.1016/j.worlddev.2019.05.012

29. Smith, J. P. (2005). Consequences and Predictors of New Health Events. *Analyses in the Economics of Aging*, (August), 213—237. https://doi.org/10.7208/chicago/9780226903217.003.0008

30. Steiner, P., Kim, J.-S., & Thoemmes, F. (2013). Matching strategies for observational multilevel data. In JSM proceedings (pp. 5020—5032). American Statistical Association.

31. Stuart, E. A. (2007). Estimating causal effects using school-level data sets. Educational Researcher, 36(4), 187—198. https://doi.org/10.3102/0013189X07303396

32. Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. Statistical Science, 25(1), 1—21. https://doi.org/10.1214/09-STS313

33. Stuart, E. A., & Rubin, D. B. (2008). Matching with multiple control groups with adjustment for group differences. Journal of Educational and Behavioral Statistics, 33(3), 279—306. https://doi.org/10.3102/1076998607306078

34. Steinhardt, L. C., Waters, H., Rao, K. D., Naeem, A. J., Hansen, P., & Peters, D. H. (2009). The effect of wealth status on care seeking and health expenditures in Afghanistan. *Health Policy and Planning*, *24*(1), 1—17. https://doi.org/10.1093/heapol/czn043

35. Vecino-Ortiz, A. I. (2008). Determinants of demand for antenatal care in Colombia. *Health Policy*, *86*(2—3), 363—372. https://doi.org/10.1016/j.healthpol.2007.12.002

36. Xiang, Y., & Tarasawa, B. (2015). Propensity Score Stratification Using Multilevel Models to Examine Charter School Achievement Effects. *Journal of School Choice*, *9*(2), 179—196. https://doi.org/10.1080/15582159.2015.1028862

37. Zubizarreta, J. R., & Keele, L. (2017). Optimal Multilevel Matching in Clustered Observational Studies: A Case Study of the Effectiveness of Private Schools Under

a Large-Scale Voucher System. *Journal of the American Statistical Association*, *112*(518), 547—560. https://doi.org/10.1080/01621459.2016.1240683