Banking on Love:
How Migrant Children Impact Parental Health Seeking Behaviour[*]

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Abstract

Rural populations in the Global South continue to face barriers to healthcare access due to weak infrastructure and low incomes. While adult children's migration can enhance household resources, its impact on parents' healthcare utilization remains uncertain. Using data from the *Longitudinal Aging Study in India (LASI)*, this paper identifies the causal effect of children's migration on parental healthcare use, instrumenting migration with historical negative rainfall shocks (1950–2016). Results show that a higher share of migrant children increases outpatient visits and related expenditures, particularly when parents have fewer children. Migration also raises private healthcare use in villages lacking accessible or quality public primary care, but has no effect on tertiary care, indicating limited insurance against catastrophic health costs. These findings highlight the dual role of migration in supporting elderly health while exposing service gaps, underscoring the need to strengthen public primary healthcare and social protection in low-migration rural areas.

Keywords: Health Utilization, Health Financing, Migration, Elderly, India

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1. Introduction

A significant portion of the world's population still lacks access to vital healthcare services with the global south still besotted by poor health care. (UN-SDG 3)[1] These problems are likely to multiply as the global elderly population is projected to rise from 1 billion in 2019 to 2.1 billion by 2052 with low- and middle-income countries (LMIC) accounting for a large proportion of this increase. This is likely to lead to rising morbidity burden and high health care costs in the global south (Belachew et al. 2024). Issues regarding financing this cost are therefore of utmost importance. There have been calls for Universal Health Coverage, through publicly funded health insurance as well as through better access to public hospitals and clinics (Sadana et al. 2018). However, the burden of these costs still remains largely private, with substantial out of pocket expenditure (OOPE), especially through catastrophic health expenditures (Brinda et al. 2015, Wagstaff et al 2020). In the face of such financial burden, households are likely to use myriad strategies to fund this expenditure. In this paper, we ask what is the impact of migrant children- a potential source of funds- on healthcare utilization and expenditures of middle aged and elderly parents.

The impact of migration of children on health expenditures of parents is ambiguous. On the one hand, some studies show that the parents who are left behind suffer from mental depression, sometimes even leading to suicides, and worse physical health due to lack of supportive care when children migrate (Antman, 2010). On the other hand, other studies point out to the benefits of remittances that can fund better nutrition (Bohme et al 2015). In the first case, this would lead to potentially rising health expenditures, while in the latter case, the better health due to nutrition is likely to lower health expenditures. Even these simple directional flows are not immediately apparent-lacking caregivers, elderly parents may be unable to seek healthcare, thus lowering health expenditures, whereas remittances can reduce budget constraints and can increase health expenditures. In our paper, we attempt to provide an empirical answer to this question using a large representative data set for India.

[1] https://www.un.org/sustainabledevelopment/health/
[2] https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

The context of India is an especially relevant one since India is undergoing a demographic transition with the elderly population in many states of India poised to cross 15–20 % population share by 2036 (MoHFW, 2016). A whopping 71 percent of those 60 and above live in rural India (LASI, 2020), with relatively poor public primary healthcare access. In 2020, there were 24,918 Primary Health Centres (PHCs) operating in India, with each expected to cater to a population of 20,000 in hilly/tribal areas and 30,000 in the plains. Subcentres-smaller primary health care units-are more numerous but they too cater to around 5000 people and of varied quality and are often bypassed (Rao and Sheffel, 2018; Rao et al., 2023). While access to quality public care is poor, chronic diseases like diabetes and hypertension are rampant; for example, almost 50 percent of the elderly are found to be hypertensive (Kothavale et al., 2022). Given poor access of public primary facilities and high morbidity, national surveys[3] estimate that 80 % of households use their household income and savings as the major source of health financing and only 17 % of the citizens have health insurance. The costs are not borne for catastrophic expenditures only. According to Gupta et al. (2016), the cumulative annual expenditures on out-patient care, in addition to hospitalizations, are especially large for households that have the elderly. Hence, in this paper we look at the impacts on health expenditures on both outpatient visits as well as hospitalization.

To estimate the impact of migration of children on parental health expenditures, we use the Longitudinal Survey of the Aged in India (LASI)-a large representative survey of adult individuals who are 45 years and above in India, along with their spouses, irrespective of age. The survey collected data on individuals between 2017 to 2019. We focus on 32,050 individuals aged 45 and above and living in rural India the setting for this study.

While the motivation for this study are the elderly (who are typically aged 60 and above), existing studies point out to poor health for those who are middle aged (ages 45-

[3] National Sample Survey report 2017–18.

59).[4] Ghosh et al (2023) finds that 16.2% of those in the middle-aged group are *frail*, an indicator often associated with elderly, with a strong evidence of gender difference: 21.4% of the middle-aged females are frail as compared to 9.6% among males. Health in this age group is especially relevant for what follows when an individual turns 60; for example, Lefebvre et al (2025) find that later detection of hypertension in middle age (post the age of 55) correlates with higher occurrence of Stage 2 hypertension post the age of 60. For a holistic understanding of issues relating to health of those 60 and above, we take the stand that it is important to understand the health seeking behaviour of the middle-aged. Further, migration of adult[5] children, the impact of which this paper seeks to address, is also common in the age group 45-59; for those middle aged who have children, almost 21 % of adult children have migrated away outside the village (sourced from LASI). This is lower than the analogous proportion for those 60 and above, which stands at 31.5%, but not by much. Hence, the middle aged already experience migration of children and are vulnerable healthwise. Hence, instead of focusing only on the elderly, this paper includes those in the middle-ages as well, though we do provide separate results for those who are aged 60 and above.

Our analysis of healthcare seeking behaviour looks at multiple indicator variables that reflect whether a parent (45 and above) is likely to seek care for any ailment, whether a parent goes for outpatient care, whether a parent is hospitalized. Further we examine health expenditures: separately for out-patient care and hospitalization. These are the main dependent variables of interest. We analyze the impact of the proportion of children, aged 18 and above, who live outside the village (referred to as migrant children) on the various healthcare seeking indicators. Using the sample described above, and controlling for a rich set of covariates, including state fixed effects, we find that a higher proportion of migrants among adult children is associated with a higher probability that an individual seeks care and visits a facility for outpatient care (OPD) but has no significant association in being hospitalized. Moreover, we find that the log of expenditures on outpatient care is higher when the proportion of migrants among

[4] Where we draw the line when we think of the elderly is subjective. If we define threshold of being elderly on the basis of economic dependence, then it is important to note that 62 percentage of rural males are working in the age group 60-69.
[5] In India, a person is considered an adult at the age of 18.

children is higher, but there is no correlation between having migrant children and the log of expenditure on hospitalization. Interpreting these associations as causal is likely to be wrong, as households with migrant children are likely to be different in unobservable characteristics from those where such migration is low, or does not happen.

We tackle the aforementioned identification problem by using an instrumental variable (IV) approach. The objective is to use exogenous variation in proportion of migrants among children for identification, one that is not induced by omitted variables that affect health seeking outcomes. We use the number of historical weather shocks for the districts where the parents live; instances where rainfall falls below the bottom 20 per cent of the empirical distribution generated by the time series of district-level rainfall (we call these droughts).[6] Such an instrument has to satisfy two conditions: It has to correlate with the endogenous variable. However, while the data set has a full count of children who have migrated, it has no information on when they migrated. To get around this problem, we follow a data driven approach to choose our best first stage regression: we estimate many specifications where we regress proportion of migrants among children on cumulative number of lagged shocks in different periods, starting in 1950 and none after 2016, and use the F stats of these regressions to decide what periods best predict our endogenous variable. We find the specification with two shock periods: total droughts in the period 1950-1988 and total droughts in the period 1989-2016, when taken together provides us the best fit (F stats of around 15). The second condition that needs to be met for these variables to be a valid IV is that they should not correlate with the omitted variables in the regression. The literature on rainfall shocks has pointed out that contemporaneous rainfall shocks affect households through many channels. (Mellon, 2025) Therefore, we use lagged rainfall shocks. Further, using the categories of variables pointed out by Mellon (2025) which are affected by rainfall, we undertake an exercise that regresses all these variables with our two instruments-we show that our IVs do not correlate with demographic variables- age, years of education, whether an

[6] Another common instrumental variable in the migration literature is the network of migrants from the past. However, information on migration is available at the district level, and only from the census. Further, the census accounts for migrants only at the destination and not the source. We did experiment with this instrument as well, but it has a very low first stage, even for the main specification.

individuals is Scheduled Caste (SC) or Scheduled Tribe (ST)[7], marital status, religion, their mental health index, their physical health index, household size, number of children, including a wealth index; they are also orthogonal to village level variables: village infrastructure index, distance to health facilities; they do not also correlate with district level variables: literacy rates, access to banking services, area of the district, average labour earnings. Interestingly, while these IV do not correlate with any of the scales to measure current mental or physical health, one of them does correlate negatively with height, thus pointing to possibilities of long run effects due to insufficient nutrition when parents were young. Further we find that droughts happen in bigger districts (population-wise) and in villages where sex ratio (females to males) is higher. In order to ensure that none of these variables confound our analysis, we control for all of them (except mental and physical health index, which could be potentially endogenous) in the second stage of our regression: our argument then is that conditional on these variables, the induced variation in the proportion of migrants among children due to cumulative history of droughts, is orthogonal to the residual unobserved factors that affect health-seeking outcomes.

Our instrumental variables estimator results show that a 10 percentage point higher migrants among children (a third of 1 standard deviation) raises the probability of outpatient visits by 13.8 percentage points (an 18 percent effect size), but it has no effect on seeking care of hospitalization. The marginal effect from a similar change in migrant children on outpatient expenditure is 46 percent, but there is no effect on hospitalization. Diving deeper, we find that parents who have a higher proportion of migrant children show increase in both private OPD usage.

A disaggregation of the OPD expenditures yields that increase in OPD expenditures are due to increase in the medicinal expenses, tests and investigations and transport expenditures. We find that there is a higher OPD usage, even when there are health facilities in the village, but the expenditures accrue when the nearest health facilities are

[7] SC denotes *Scheduled Castes* and ST denotes *Scheduled Tribes*, the official classifications used by the Government of India for historically disadvantaged social groups entitled to affirmative action.

not in the village. We find the significant results of migrant children come from relatively poorer households but accrue to both male and female parents.

Interestingly, when we stratify parents into those who are middle-aged (45-59) and elderly (60 and above), we find that while a higher proportion of migrant children increases OPD visits in both age groups, it increases expenditure only for the middle-aged. However, we find that expenditures do go up for the elderly if there is no health facility in the village. This suggests that when children migrate, the middle-aged get quality private healthcare, whereas the elderly living in places with less access to healthcare facilities are now more likely to get healthcare. When we consider the sex of the migrant children, we find that both male and female children are likely to increase such health usage, but the effects of male children are much higher (almost double). We also find such migration impacts to be much larger for parents with fewer than 4 children as compared to parents with more than 4 children.

We conduct a battery of robustness checks- in particular controlling for mental and physical health indices, as well as other variables like Crime, social security, health schemes, irrigation, disease environment, district-level male and female wages. We find both the results on OPD visits and OPD expenditures are robust to inclusion of all these other potential confounders.

Our results contribute to two strands of literature. First, we contribute to the literature that investigates the impact of migration on the health of left behind elderly. The results, as pointed above, are ambiguous with some studies finding negative effects on parents physical and mental health (Antman, 2010; Antman, 2012; Ao et al 2016; Carr, 2019) where as others (Bohme et al 2015, Kahn et al 2003, Lu, 2013) find that migration leads to better elderly health due to remittances. We deviate from these studies in that we look at health-seeking outcomes including the financial implications of such a migration. Our results, which also cover the middle-aged, point out that the overall effect of such migration is an increase in health expenditure, which pays for out-patient health visits outside the village, to private health providers and for expenditures that individuals bear even if they go to public health facilities (tests, medicines). These results are true even if

we control for measures of physical and mental health, that are found in the literature cited above, to be affected by child migrating. Interestingly, we show this expenditure is not necessarily funded out of remittance, which has a positive but weak correlation with proportion of migrant children. This implies that parents consume health from their own income and savings, with the assurance of the larger pooled income of the migrant children. We do not find evidence that migrant children fund hospitalization and its expenditures.

The second literature we connect to is the literature on the health of the elderly and issues around funding their healthcare. A large literature exists on issues of pensions and social insurance to fund health expenditures of the elderly with its implication on debt, but it is typically on developed countries (Cylus et al 2022, Elmendorf and Sheiner, 2017; Nishiyama and Smetters 2014). In the literature that calls for more global attention (Harper, 2014), the discussion on developing countries focuses on the impending crisis. The issue of financing ultimately boils down to who will fund the health care of the old and the mode of delivery-whether through insurance payouts for visits to private healthcare or through providing public healthcare. In the context of India, this discussion (Poddar, 2025) has been around a large public health insurance program (PM-JAY) and upgrading existing public primary healthcare centres (called Health and Wellness Centres: HWCs). Our paper explores issues of financing through private sources. Our results point out that some household funding mechanisms that rely on migrating children are already in place. But they do a better job at funding outpatient visits that cater more to primary health care and not tertiary healthcare that typically involve hospitalization. This private primary healthcare funding compensates for 'missing' quality[8] public primary healthcare, funding expenditures when there is no Primary Health Centre in the village. However, this also points out that there is a health care expenditure that is not funded, when there are no migrating children-hence, quality primary health care needs to be funded for such households.

[8] We consider Primary Health Centres to be quality healthcare. Small public sub-centres are often of varied quality and are still focused on maternal and child health services, though there has been a recent move to use them for screening the elderly. There is relatively less evidence on the efficacy of these centres for health of the elderly.

The paper is organized as follows. In section 2, we provide details about the dataset used for this analysis and provide summary statistics. Section 3 discusses the empirical model used for estimation, and discusses how we identify the impact of migrating children. In Section 4, we provide the main results. We provide some robustness checks in section 5, including assuaging some concerns about exclusions restrictions. We provide a rich heterogeneity analysis in section 6 and conclude with a discussion in section 7.

2. Data and Descriptive Statistics

This study relies on three primary sources of data. The core individual and household-level information are drawn from Wave 1 of the Longitudinal Aging Study in India (LASI), a nationally representative panel survey conducted in 2017 and 2018.[9] LASI covers 73,396 adults aged 45 and above across all Indian states and union territories. It is designed to examine ageing, health, and socio-economic outcomes among older adults. There are 43,240 individuals aged 45 and above in the rural sample of the survey. LASI does not report the district or village of the respondent. However, in its early release, it provided information on 9 village-level demographic variables from census 2011. Matching the data state-wise yielded an exact match of 1302 out of 1502 villages. When we merge the climate data (described below), we lose 38 districts from 640 districts. This gives us a sample size of 37,533. Missing values for variables for our analysis, especially the height of an individual, an important indicator for long run health, leaves us with a sample size of 32,050 observations.

The LASI contains details on all hospitalization visits and details of the most recent out-patient visit (OPD) in the 12 months prior to the survey. These include the kind of facility a person goes to (public, private) and the expenditures (and its constituent parts). These help us define an elaborate set of indicators for health-care utilization and

[9] Data was collected by the following academic institutions - International Institute of Population Sciences, Mumbai (India), Harvard T.H. Chance School of Public Health, Cambridge (USA), and the University of Southern California (USC), in collaboration with the National Pogramme for the Healthcare of the Elderly, India's flagship programme for geriatric care and management of health needs of an ageing population.

expenditures, which serve as dependent variables for our analysis. 71 percent of sampled individuals sought some health care in the last 12 month, though the footfall in formal care was slightly lower: 56 percent for OPDs and 6 percent for hospitalizations. While the mean outpatient expenditure was ₹ 373 ($ 4.2), there is large variation with a standard deviation of ₹1769 ($ 20.07) and a max of ₹112,850 ($ 1280.27). The average hospital expenditures in our data set is ₹851 with a standard deviation: ₹7,965. Given these magnitudes of expenditure, it is likely that outpatient visits cater mostly to primary care where as hospitalization in-patient care are about tertiary care. Therefore, we refer to primary and tertiary care synonymously with OPD visits and hospitalization respectively.

The main independent variable of interest is the proportion of adult children who live away from the village.[10] Among those who have children, we calculate the number of adult children (above the age of 18) who live away from the village: we call them migrant adult children and refer to the proportion inter-changeably as proportion migrant children. On an average, 26% of children reside outside the village where their parents reside (standard deviation: 32%), with considerable variation ranging from parents with no migrant children to those whose adult children have all migrated.[11]

LASI also contains detailed measures of long-run health status (height), socio-demographic characteristics (sex, age, education, marital status, caste, religion), household size, number of children. It also contains information on ownership of assets. We conduct principal component analysis and create three quintiles. Further, since we look at health expenditures, it is important to account for whether a household is insured, which the survey allows us to do. For auxiliary analysis, we also create two indices base

[10] While we could drop the sample of those who don't have children, this may lead to selection bias-hence we create a variable that indicates that a person has at-least one child (only 3 percent of parents don't have children in our sample).

[11] 28% of children live within the same village but maintain separate households. While we know the location of the district where the child has migrated to, we do not know if it is rural or urban.

on standardized scales and questions in LASI: one for physical health[12] and one for mental health[13]. The summary statistics of our sample are given in Table 1.

For reasons we discuss below, we conduct an intra-state analysis. This means we are comparing geographic settlements within a state-hence there may be differences in health care access, infrastructure as well as other development indicators. To account for this spatial heterogeneity, we incorporate a set of village-level and district-level control variables. At the village level, we account for health access: distance to a sub-centre, distance to a Primary Health Centre (PHC), distance to a private clinic and distance to a private hospital. These are sourced from the community module of the LASI. Further, the module also reports whether a village has access to an all-weather road, piped water, drainage, a chemist shop, government and private schools at various levels (pre-primary to high school), college, Madarasa, Post Office, Library, Police Station, Bank and general provision store. We create a village-level development index by conducting principal component analysis on indicators of aforementioned infrastructural facilities and predicting the first factor. We define the village as developed if it above the median and underdeveloped if it below the median. At the district level, we include various demographic indicators: sex ratio, dependency ratio, and literacy rate; economic and infrastructural indicators such as total population, access to formal banking services (all from Census of India 2011), average labour earnings (National Sample Survey-Employment Unemployment Survey 2011-12), road length (Open Street Map 2015[14]); and remotely sensed measures such as per capita night-time light intensity (DSMP-OLS Radiance Calibrated Nighttime Lights (RCNTL), National Oceanic and Atmospheric Administration's National Geophysical Data Center (NGDC), which serve as proxies for local economic development.

[12] This is based on a scale of mobility that asks individuals if they can do various activities-walking 100 yards, sitting for 2 hours or more, getting up from a chair after sitting for a long period, climbing one flight of stairs without resting, stopping kneeling or crouching, reaching or extending arms above shoulder, pulling or pushing large objects, lifting and carrying weights over 5 kilos, picking up a coin from a table and questions as a part of ADL index (https://hign.org/sites/default/files/2020-06/Try_This_General_Assessment_2.pdf)

[13] This is based on a self reported scale of depression (CESD), that has been validated by https://www.apa.org/pi/about/publications/caregivers/practice-settings/assessment/tools/depression-scale

[14] https://www.openstreetmap.org

The last dataset we use is historical rainfall data from 1950 to 2016, sourced from the Temperature and Precipitation Gridded Data for Global and Regional Domains. This dataset is produced by the Copernicus Climate Change Service (C3S) and made available through the Climate Data Store (CDS). It offers high-resolution gridded observations of precipitation and temperature, based on a combination of ground-based meteorological stations and satellite-derived measurements.

3. Empirical Model and Identification

We describe here the empirical model that we use to test whether migrant children impact healthcare utilization. Let y_{ihvds} represent, generically, an indicator of health care utilization of an ith person belong to the h th household, living in village v situated in district d of the state s. The primary binary indicators we consider are: whether an individual sought care in any formal or informal (e.g. quacks, pharmacy) health facility in the last 365 days, whether an individual went for primary care to an out-patient department (OPD) of formal health facility, whether an individual went to a hospital for tertiary care. Further we consider the logarithm of health expenditures on OPD and the logarithm of expenditures on hospitalization as two additional variables for health care utilization costs. To avoid endogenous sample selection based on falling sick or recognizing that they are suffering from an ailment or making any expenditure, we consider the full sample-hence, in this paper, we consider the impacts on the unconditional expected value of y. In the case of expenditures, we add 1, so as to be able to take a logarithmic transformation.

The main independent variable of interest is the proportion of children who live away from the village ($prop\_mig_{ihvds}$) which varies at the individual level; in the case when both parents are in the sample, this value repeats. In India, boys typically migrate for employment, whereas girls migrate away after being married away. While we consider this proportion gender-wise in a later section, we consider all children, irrespective of their gender for our main results. As pointed out before, we do not know the timing of the migration. The only restriction we impose is that the children should be at-least 18 years at the time of the survey.

To begin our analysis, we note the bivariate association between some indicators of healthcare utilization and ($prop\_mig_{ihvds}$). As Table 2 shows, the proportion of individuals who seek OPD care rises monotonically from 0.51 when no child above 18 has migrated away to around 0.64 when more than three-quarters of the children (though not all) have migrated away. There is a slight fall when all adult children have migrated away but the proportion is still higher at around 0.58. The gradient on seeking care is not so sharp, indicating use of informal sources of care. There is hardly any difference in terms of hospitalization though. Similarly, log of OPD expenditure rises from 1.76 when no children have migrated away, as compared to 2.15 when all children have migrated away. Like before, there is no clear-cut direction in terms of hospitalization expenditure.

The relationship between ($prop\_mig_{ihvds}$) and healthcare utilization outcomes is confounded by many other factors. To parse the impact of some of the potentially observable variables, we take into account individual variables: whether an individual has a child, total number of children, an indicator for sex (a dummy if one is a female), age, two dummies for education (whether the person has studied up-to matriculation-class X; whether the person has studied higher secondary level and above), the individual's caste (three dummy variables, each indicating if the person is from Scheduled Caste, Schedule Tribe or Other Backward Caste community), marital status (three dummy variables indicating whether the person is currently married, whether the person is a widow/widower and whether the person is divorced/separated), the individual's religion (three dummy variables indicating if the person is a Hindu, Muslim or Christian respectively), a dummy variable indicating whether the person has health insurance and an indicator of long term health: the height (in cms) of the individual. Let us denote all these individual variables by the vector Ind_{ihvds}. Further, we consider household variables-household size, two dummies for the top two wealth terciles based on the predicted first factor. Let us denote these variables by $House_{hvds}$. Migration can depend on the level of development of the village-we account for this through three dummy variables that represent the top 3 quartiles based on the infrastructure index described above (the least developed village being the reference category). Since health

seeking behaviour depends on access to health facilities, we account for the distance to the nearest subcentre, distance to the nearest Primary health centre and the distance to the nearest private hospital. For reasons describe below, we will use the intra state variation to identify our marginal effect of interest. Hence we account for differences between the districts by taking into account district level rural Sex Ratio (ratio of the number of females to the number of males), rural Dependency Ratio (ratio of the nonworking-age (0-14; 65+) population to the working-age population), the district rural literacy rate, the log of the population of the rural district, the proportion of the rural district that has intense night lights (aggregating 1-kilometer resolution grids of area, within the rural district, with night-time light intensity of 13-digit numbers or higher), average rural district level wage earnings per day, and district level total rural road intensity. We denote these village and district variables by $VillDist_{ds}$.

Given these variables, the empirical model we estimate is:

$$y_{ihvds} = \alpha_s + \beta prop\_mig_{ihvds} + \gamma' Ind_{ihvds} + \delta' House_{hvds} + \mu\, VillDist_{vds} + \varepsilon_{ihvds}$$

Here α_s denotes that we estimate with state fixed effects, which implies that we use intra-state variation in our analysis. We estimate this linear specification by Ordinary Least Squares. Further, all standard errors are robust and clustered at the level of the district (more on that below).

Identification

While the specification above accounts for various observable factors and takes into account state-level differences, concerns still remain about unobserved variables that correlate with both migration of children and healthcare-seeking behaviour. In particular migration is an endogenous decision with the literature finding ambiguous results in what role wealth plays: while the poor have a higher push pressure to migrate, the rich have better means to migrate. If the former is true, then OLS will be biased downwards if wealth has a positive association with health-seeking behaviour; on the other hand, if the rich tend to have more migrant children, then the bias will be upwards. It is not possible to control for the wealth levels of the households when the migration decision

happened; we do control for current wealth levels-however, such indicators always miss out dimensions of wealth. There are also likely to be other unobservable variables that confound our OLS estimators.

To identify our relationship, we take an instrumental variables approach. The instruments use the number of droughts that the district (where households reside) has experienced over the period 1950-2016. Recall though that the dataset does not contain information on when the children have migrated. Hence, we take a data-driven approach to find the exact instrumental variables. To be more precise, we consider two instruments defined by the total number of droughts and separately floods in the year intervals [1950,x] and [x,2016]. We choose x so as to maximize the F-Statistics of the first stage of instrumental variable estimation. Figure 1 presents the F-Statistics for all integer values of x. We find that the cumulative history of droughts is more predictive of migration decisions and not floods. The two instruments: the cumulative drought shocks in the years 1950-1988 and the cumulative drought shocks for the years 1989-2016 provide the highest F-Statistics of 14.5. If we restrict the analysis to use only one instrumental variable, we find that the cumulative number of droughts till 2016 gives the F-Statistics of 14.52. The association is negative, with more droughts leading to smaller proportion of children migrating. We use the 2 instruments for our main results, while we show results with 1 instrument in the robustness section. The instrumental variables demonstrate variation across districts within states, with historical drought episodes averaging 5.8 during 1950-1988 and 7.7 during 1989-2016. In some cases, when we consider subsample analysis, our F-Statistics fall below 10 and there is then a possibility that we have a weak instrument problem. To assuage concerns on this front, we provide the Anderson-Rubin *p*-values for weak instrument inference as advocated by the literature (for example, see Enikolopov et al, 2020).

The most important assumption that allows a potential instrument to identify a relationship is exclusion. In other words, the instruments should not correlate with the error term in the estimation model. At first pass, given the rich literature of how rainfall shocks affect a myriad of outcomes, it may be contended that our instruments are weak on meeting exclusion assumptions. Mellon (2025) provides a list of variables that

correlate with weather shocks in his criticism of why weather shocks may not be a good instrument. We contend with this criticism in three ways. First, we note that most of the argument made are about contemporaneous weather shocks (though the article does make a general point about all kinds of weather shocks). Hence we consider the history of shocks. Second, in Table 3, we regress our instruments on the covariates that we consider important for health utilization. We find that only four variables, out of a large set, have an association with the drought variables we consider. Most importantly, those living in districts with more past droughts show lower height. We also find that district sex ratio (defined by females to male ratio) is higher when there are more cumulative droughts. Paradoxically we find that villages are marginally more developed if there are more droughts: the proportion of individuals in Quartile 2 goes down for one of the variables, whereas the proportion in Quartile 3 goes up for the other drought variable. There is no association of the instruments with proportion of individuals in Quartile 4. The last variable that is significant is the probability of being separated. Besides this, a whole set of variables including wealth, night-lights, health access is uncorrelated to the instruments. We include all these variables in our specification, to partial out their impact, so that we can contend that the error term in the empirical model is uncorrelated to our instruments-a claim of conditional exogeneity. Third, in our robustness section, we control for a set of variables that have been shown to correlate with rainfall shocks. This set of variables is given by Mellon (2025) and we show that controlling for these sets of variables does not statistically change the coefficient of interest that we estimate. Hence, these variables are unlikely to confound our analysis.

4. Main Results

In this section, we present the core empirical results examining how adult children's migration influences healthcare utilization and expenditure among individuals, including the elderly in India. As stated above, we employ both Ordinary Least Squares (OLS) and Instrumental Variable (IV) strategies, and proceed in stages—first documenting the average effect, then disaggregating by gender, location, wealth, and health service type in Section 5.

Table 4 reports OLS estimates capturing the association between the proportion of migrant children and elderly individuals' healthcare utilization and expenditure. The dependent variables include indicators for any outpatient visit, any hospitalization, and the log of outpatient and hospitalization expenditures.

The main coefficient of interest—percentage of adult children living outside the village—shows a positive and statistically significant association with outpatient visits. A 10-percentage point increase in the proportion of migrant children is associated with a 0.5 percentage point increase in the probability of seeking outpatient care. This relationship holds even after adjusting for household composition, socioeconomic status, and district-level fixed effects. However, the association with hospitalization is weak and statistically insignificant, suggesting that migration is correlated with discretionary forms of care (like outpatient visits) rather than acute episodes necessitating hospitalization. There is also no significant relationship between migration and logged hospitalization expenditures, reinforcing the idea that the effects of migration are more pronounced at the margins of preventive or lower-intensity care.

For reasons explained above, OLS estimates are likely to be inconsistent; hence we turn to IV estimates. Recall that the instrument leverages long-term district-level historical drought exposure (1950–2016), exploiting its predictive power for adult children's migration while assuming that historical climate shocks do not directly affect current elderly health-seeking behaviour, conditional on controls and location. The first stage results in Table Appendix A1 suggest that drought variables significantly reduce the probability of children being away from the village by 2-3 percentage points. The second stage IV results, reported in Table 5, suggest that a 10-percentage point increase in the percentage of migrant children leads to a 13.8 percentage point increase in the likelihood of an outpatient visit. The coefficient on log outpatient expenditure also increases, with a magnitude of 0.045 (45 percent for a 10 pp change in migrant children), indicating that migration improves not only access to care but also willingness or ability to pay for it. There is no significant effect on hospitalization or inpatient expenditure, echoing the earlier finding that migration's impact is primarily seen in outpatient behaviour. This suggests that having children's away leads to increase in expenditures

for primary care, but has less influence on large expenditures that come with tertiary care.

While our results confirm that migration of children increases healthcare utilization, it is equally important to understand where individuals seek this care. We explore whether migration influences the choice between public and private providers, offering insight into how financial support may shape care-seeking preferences. This distinction is critical in the Indian healthcare system, where public facilities are heavily subsidized but often suffer from poor accessibility and quality, while private providers charge user fees but offer better availability and responsiveness. Our results reveal that children's migration leads to an increase in the probability of seeking care from private providers (Column 2 in Table 6). If a parent has 10 percentage point higher proportion of children outside, the probability of going to a private provider rises by 0.08, an increase of around 27 percent. In contrast, the coefficient on public sector usage is smaller and statistically insignificant. This suggests that the migration-induced increase in care utilization is not simply a shift from non-use to public care, but rather reflects a movement toward private healthcare, which is more expensive but generally preferred when households can afford it. The effect on hospitalization remains insignificant across provider types, reinforcing the notion that migration's impact is concentrated in outpatient behaviours.

Next, we unpack the increase in expenditure on out-patient care by examining specific medical components: consultation fees, medicines (both provided by providers[15] and purchased outside), diagnostic tests, and hospital/nursing home charges. This disaggregation allows us to assess which elements of outpatient spending are most responsive to migration of children. We find that among these components (Panel A in Table 7), only spending on medicines bought outside medical facilities, diagnostic tests and investigations shows a statistically significant increase.

We look at other expenditures in Panel B of Table 7. These are some aspect of medical expenditures done as an outpatient- surgeries, getting blood/oxygen and other non-

[15] Note that patients can seek care from the outpatient departments of hospitals.

medical and indirect expenses associated with outpatient visits, such as transport, food, caregiver escort support. The indirect expenditures often pose significant barriers to care, especially in rural or underserved areas. Of these categories, transport expenditure is the only one that shows a statistically significant increase. This finding highlights a key mechanism through which migration influences healthcare utilization: by providing the means to overcome spatial barriers, enabling individuals to access care that would otherwise be logistically challenging. We explore issues of access in the next section.

The significance of increased spending on medicines, diagnostic tests and transport underscores the role of relaxation of budget constraints in addressing both clinical and logistical barriers to healthcare. These findings suggest that children's migration not only enables individuals to access care more frequently, but may also enhance the effectiveness and completeness of treatment by supporting the uptake of critical services such as diagnostic investigations and facilitating travel to healthcare facilities that may otherwise be difficult to reach.

Taken together, Tables 6 and 7 provide consistent evidence that children's migration leads to improved outpatient healthcare access among parents. The effects are particularly pronounced in the uptake of private sector services, accompanied by modest increases in health expenditure—suggesting enhanced quality and completeness of care.

Plausible Mechanisms

The effects we observe can come from three possible channels-first, migrant children may send remittance. We do observe a positive significant association between the probability that there is a remittance from children when a larger proportion of them are away (Appendix Table A2). The occurrence of such transfers is however low; only 3.9 percent receive such transfers in our dataset. So, this is likely to explain part of our results, albeit only marginally.[16] The second channel that is likely to be at play is that a parent needs to save less when children are away-if there is a large shock, they expect children

[16] Since the dummy signifying that the household has received a remittance has a very low correlation with the instruments, we cannot undertake an IV estimation.

to remit money. Hence, their budget sets expand and they can spend more on healthcare, especially amounts that are not catastrophic. Third, in the context of migrant daughters, households often save money to pay the dowry expenditures for their daughters; once their daughters are married off, this saving incentive is lower-hence there may be a greater expenditure on healthcare. We are unable to show direct evidence for mechanisms 2 and 3 since we do not have savings data; however, as we will see later, a heterogeneity by the gender of children who have migrated throws some light on the relative importance of the last mechanism. We come back to this point in section 5.4.

An issue that one needs to take cognizance of at this stage is that higher use of private health care may signal worse health outcomes. Some worsening of health, when children leave, has been noted in the literature discussed above. We do not explicitly control for contemporaneous health outcomes-both physical and mental-in our regressions due to potential issues of endogeneity and reverse causality. But later in a robustness sun-section 6.1, we explore and argue that this is not what drives our result.

Our main result points out to higher outpatient care usage in private facilities and on expenditures on diagnostic tests and care. There can be many reasons ailing parents may seek private care. First, local public care may be poor or absent and private care, which is often perceived as better, may be distant. Relaxing budget constraints may allow a parent to seek such care. However, this may also require caregivers in the family, often children, to take out time. If such children are fewer in number or absent, then the relaxation of budget constraints may not suffice. Second, relaxation of budget constraints may induce parents to seek opinion of those they consider better, even if public facilities are available in the village. To tease out some of these dimensions, we explore some of the issues in the next section that explores heterogeneity.

But before, we move to next section, it is important to point out that in no heterogeneity analyses, we find a causal effect of migration of children on hospitalization

and hospitalization expenditure.[17] Hence, before delving into understanding outpatient visits and expenditures during these visits (for which we have over all results), we note that we find no evidence to suggest that migration of children impacts hospital visits or hospitalization expenditure in any sub-group analysis. This is suggestive evidence that while migration of children can facilitate access to primary outpatient care, we find no evidence that it does so for tertiary care.

5. Heterogeneity Analysis

In this section, we show results regarding OPD visits and expenditures, disaggregating by healthcare access, gender, location, wealth, and health service type. We do not present in the tables the first stage coefficients for our IVs using every sub-sample used for heterogeneity analyses (though we provide the F stats in the tables). However, in the discussion below, there is at-least one instrument that is always significant at 10 percent in each first stage regression. We start first with issues of access as it addresses issues raised above.

5.1 Distance to Nearest Health Facility

Table 8 explores whether the effect of children's migration on outpatient healthcare utilization varies with proximity to the nearest health facility (both public and private). The analysis splits the sample into households with a facility within the village (distance = 0) and those without one (distance > 0). The results reveal that migration has a statistically significant effect on outpatient utilization in both contexts, though with some variation in intensity. Among households without a facility in the village, a 10-percentage-point increase in the share of migrant children leads to a 9-percentage point increase in the likelihood of any OPD visit and a 67.4% increase in outpatient expenditure. Among households with a facility within the village, the effect on OPD visits is also positive and statistically significant and the point estimate is larger, though statistically not different from the coefficient when the village does not have a health facility. The effect on outpatient expenditure in this group is not statistically significant, though.

[17] Results are available on request.

These findings suggest that while the impacts of children's migration are not limited to overcoming geographical constraints, they do overcome access issues, when health facilities are not in the village. The latter in particular points out to positive welfare effects, absent local healthcare. These results are similar when we consider plausibly better quality public care, which are typically available at Primary health centres (PHCs). While PHCs cater to a larger area and hence are unlikely to be in a village, when choose a 5 km cut off (based on the median distance), we find higher probability of visits in response to children's migration, for distances on both sides of the threshold (Table 9). The coefficients of OPD visits are statistically the same, though the point estimate when PHCs are closer are larger. However, as before, the expenditure impacts ensue only when PHCs are more than 5 km away. These echo the results above, that migration of children can overcome healthcare access issues to an extent.

5.2 Age group

As individuals age, their health needs intensify while mobility and financial independence often decline, making them more reliant on support for accessing care. Disaggregating the effects of migration by age helps reveal whether its impact is stronger among older cohorts who face greater barriers to healthcare utilization.

Table 10 examines whether the impact of children's migration on healthcare utilization varies across two age groups: the middle aged (45–59 years) and the elderly (60+ years). The results indicate that migration has a strong effect among the middle aged. Specifically, for individuals aged 45–59, a 10-percentage-point increase in migrant children leads to a 18.8 percentage point increase in the probability of any outpatient visit and a 77.5% increase in outpatient health expenditure. In contrast, for those aged 60 and above, the analogous effect on outpatient visits is 9.9 percentage point and only marginally significant, and there is no statistically significant change in expenditure.[18] Further, narrowing the analysis to the elderly (aged 60 and over), we find that the impacts

[18] What is striking though, is that outpatient usage among the two age groups is very similar, with more than 50 % of parents in each group going for OPD visits. This may point out that the definition of 60 as a threshold for being "elderly" may be an artificial one, at least for health seeking behaviour.

on expenditure depends on whether or not the village has a health facility (Table 11). Among this more vulnerable age group, results show that migration has a stronger effect on outpatient expenditure when no health facility is present within the village. These results suggest that migration plays a compensatory role in contexts with institutional gaps, enabling older adults to afford quality (proxied by expenditure) outpatient visits (catering mostly to primary care) that may only be available at a distance. Overall these results suggest that when children migrate, the middle aged get quality private healthcare, whereas the elderly living in places with less accessible health care are now more likely to get quality healthcare.

5.3 Wealth Quintile

Our explanations have so far relied on the easing of budget constraints to seek private health care. If this is a plausible explanation, then the results should be stronger for households that are relatively poor. Results reported in Table 12, which stratify the effects for lower-income households (bottom two wealth terciles) and higher-income households (top third tercile) show evidence for our explanation. Among poorer households, a 10-percentage-point increase in migrant children leads to a 14.6 percentage point increase in the probability of any outpatient visit and a 58 percent increase in outpatient health expenditure. In contrast, for richer households, the estimated effects are statistically insignificant. This pattern suggests that wealthier households may already enjoy more stable access to healthcare and face fewer liquidity or credit constraints. As a result, the marginal utility of additional income from migration is lower in this group. These findings support the view that migration can have equity-enhancing effects by relaxing financial barriers among the poor and improving their access to outpatient care.

5.4 Gender: Parents and Migrant Children

Parents

Given evidence of gender discrimination in mortality and health (Anderson and Ray 2010), explore if the impact of migrating children impact mothers and fathers differentially. Our results suggest that there are no differences. Point estimates, reported

in Table 13, for the sample of fathers (men) is similar to that of the mothers (female), both for OPD visits and OPD expenditure. Hence, we find no differential effect across gender of parents.

Migrant Children

We alluded to earlier on different mechanism at play which alleviate the household budget. One of the channels was through migration of women-post marriage, households may not have to accumulate assets and can spend more on healthcare. This is distinct from being able to spend more, due to the insurance from children-both male and female, who have access to resources. To look at this, we explore impacts of higher proportion of male (and female in a separate specification) children who have migrated out.[19] Results in Table 14 that have proportion of male children as the relevant endogenous variable, find that 10 percent higher proportion of male children away from the parents increases OPD visits by 24.8 percentage points. The impact on outpatient expenditure is large at 76 percent though it has a *p* value of 0.102. Analogous results for female children migrated out show an impact of 1.04 percentage points in probability of OPD visit and an impact of 35% on OPD expenditures (Table 15). While statistical tests can't rule out the coefficients are same, the point estimate differences are large and the lack of a verdict is likely to be driven by the high standard errors that IV estimators produce. The plausibly larger coefficient for migrant sons is consistent with the idea that parents feel more secure about accessing their son's income.

5.5 *Number of Children*

We want to capture if children going way has a heterogeneous effect when the number of children vary.[20] The effects can go both ways. If parents have very few children, a child going away can have a substantial negative effect in caregiving: for example, a parent may need to be taken to the hospital and absence of a child to accompany the parent to a healthcare facility may put stress on other remaining few children, leading to a fall in health care usage. If parents have a lot more children, this

[19] We control for a dummy that indicates if there are any male (and female) children for the parent.
[20] A separate hypothesis is whether the incremental impacts of prop of migrant children depend on the initial value. One could potentially test this using a quadratic specification. However, the F stats of the regression are poor and our first stage fails. Hence, we do not report results from this exercise.

stress may be less. On the other hand, a migrant childs' earning potential may be far more important to buy healthcare for a parent in family with few children as a compared to a family with many children, many of whom are potentially working. Columns 1 and 2 in Table 16 present results using our baseline specification when the number of children is less than 4 (the mean being 3.74 for family with children) and when it is higher than 4. The estimated marginal effects do not vary by number of children. However, this specification is not ideal to test this heterogeneity. A 1 percentage point increase in a larger family is a much higher change in the number of children as compared to a smaller family. Hence in columns 3 and 4, we run the same specification but instead of proportion of migrant children, we include the number of migrant children as the endogenous variable. Results show that the marginal positive impact of one migrant child is far greater when the parent has few number of children. This suggests that the importance of the child's earnings outweighs their care-giving role, even in smaller families. When we run an analogous regression with log of out-patient expenditure, we find that the migration of one child increases expenditure by 66 percent when there are more than 4 children, as compared to 140 percent when there are less than 4 children. (results available on request).

6. Robustness: Exclusion Restriction

A key identifying assumption of the instrumental-variable (IV) strategy is that historical drought exposure affects elderly health-seeking behaviour only through children's migration, and not through any other local characteristics that independently shape healthcare use or spending.

While the exclusion restriction cannot be directly tested, we evaluate its plausibility by sequentially adding potential confounders to the instrumental-variable specification and examining whether the estimated effect of children's migration remains stable. We assess robustness for two outcome variables—the probability of an OPD (outpatient department) visit, capturing the extensive margin of healthcare utilization, and OPD expenditure, reflecting the intensity of healthcare spending conditional on use.

Tables 18A–18B present robustness checks for the probability of an OPD visit, while Tables 19A–19B report parallel specifications for OPD expenditure. Each table pairs the baseline regression (without additional controls) with an extended specification that includes one potential confounder. The stability of the migration coefficient across these models provides evidence supporting the exclusion restriction.

6.1 *Mental Health and Physical Health*

Extant literature, discussed above, explores the impact of children's migration on both physical and mental health. We have noted that the results can go in both directions. Our identification strategy should ideally take care of any impacts on health from migrating children. Further our balance tables show that our instruments do not correlate with these current measures of health. However, we give further evidence here that controlling for these variables does not affect our results. To do so, we construct two indices of mental and physical health for the parents and control for them in our IV estimation. If what we have estimated is indeed confounded by health, then our coefficients should change. If our results remain robust to their inclusion, then we can contend that these effects are not driven by health as an omitted variable.

To implement this, we construct measures of mental and physical health for the parents. The LASI contains 10 questions as a part of a CES-D-R10 scale to construct a mental health (depression) measure.[21] When we control for this in our regression, our coefficient remains unchanged both for OPD visits (Table 18A; Column 1) as well as Log of Expenditure (Table 19A; Column 1). Similarly, we construct a measure of physical health based on mobility (see Appendix Table A3), questions regarding activities of daily living (ADL) and questions regarding instrumental activities of daily living (IADL)[22], and question that asks if they use aids or supportive devices for doing daily list of activities (as defined in ADL). We construct a principal component analysis using indicator variables take the value 1 if an individual can do an activity (or does not use any aids to do any activity). We use the standardized value of the first predicted factor as our index

[21] This is based on Andresen et al (1994) depression scale used by the centre of epidemiological studies.
[22] For a list of activities see: https://my.clevelandclinic.org/health/articles/activities-of-daily-living-adls. We do not use ailments to define our index as detection is a function of whether a person goes to a health provider.

of physical health. Controlling for this variable does not change our results (Table 18A and 19A; Column 2). This gives credence to our argument that the increase in usage of OPD and expenditures are due to a relaxation of the budget constraint and not due to health issues.

For a list of other potentially confounding variables, we use Mellon (2025) to draw up a list of variables for which we have data. They are driven by the apprehension that the instruments (drought variables) correlate with this list of variables and it is possible that they also affect our outcomes. We show that this is not the case.

6.2 Crime Quantile

Local crime rates and policing quality can influence health-seeking behaviour by shaping perceptions of safety. High crime or weak law enforcement may deter elderly individuals from visiting clinics, reducing both the probability of OPD visits and associated spending. If historical drought exposure weakened local institutions or governance capacity, rainfall shocks might affect healthcare outcomes through security conditions rather than through children's migration.

Our crime variable is measured at the village levels and is an indicator of whether a given list of crimes occur in the village.[23] We conduct a principal component analysis using these variable and construct an indicator on whether the crime is more or less than median. When the crime control variable is introduced in Tables 18A and 19A (Column 3), the coefficient on the share of migrant children remains unchanged in magnitude and significance. This suggests that variation in local security conditions does not mediate the relationship between historical drought and elderly healthcare behaviour, lending support to the exclusion restriction.

[23] List of crimes are petty crimes (like pickpocketing, purse snatching), burglary, abuse against the elderly, kidnapping, violence against women, killings/murders, drug related crimes and other miscellaneous crimes.

6.3 Social Security Coverage

Social security programmes can improve financial security and healthcare access among older adults, thereby increasing both the probability of visiting health facilities and healthcare spending. If historical drought shaped the spatial rollout of social protection schemes, rainfall variation might affect healthcare use through institutional coverage rather than migration. We construct an index that uses principal component analysis and which takes as input whether the village has access to a list of 22 government social schemes (excluding health). We define a variable based on whether a village has more (or less) than median value on the first predicted factor. When social security coverage variable is included in Tables 18A and 19A (Column 4), the migration coefficient remains stable across specifications. This implies that programmatic targeting or benefit access does not confound the IV relationship.

6.4 Health Scheme Coverage

Public health insurance schemes reduce the effective cost of care, increasing the likelihood of OPD visits and total spending per episode. If drought-affected regions were later prioritized for health insurance expansion, rainfall shocks could influence healthcare behaviour through subsidized healthcare access rather than through migration.

We use an analogous procedure to construct the health scheme variable (the community questionnaire of LASI lists 13 health schemes). Controlling for health scheme coverage (*Health scheme coverage)* in Tables 18A and 19A (Column 5) leaves the migration coefficient nearly identical to the baseline estimates, ruling out health insurance penetration as an alternative mechanism.

6.5 Irrigation Coverage

Irrigation intensity captures agricultural productivity and economic resilience to weather shocks. Areas with greater irrigation coverage are likely to have higher and more stable incomes, which could enhance both healthcare utilization and expenditure. If rainfall variability historically influenced irrigation investments, the instrument could

predict healthcare outcomes via long-term income rather than migration. Including irrigation coverage (total amount of village land that is irrigated) in the regressions reported in Tables 18A and 19A (Column 6) leaves the migration coefficient virtually unchanged across both outcomes, indicating that agricultural income stability is not an alternative channel through which rainfall shocks affect elderly health-seeking behaviour.

6.6 Disease Environment

A higher incidence of infectious disease increases healthcare needs, raising both utilization and expenditure. If historical drought affected local ecological or sanitary conditions that continue to influence disease prevalence, rainfall could shape healthcare outcomes through morbidity risk rather than migration.

LASI records for a village if any of the following diseases broke out in the village in the year leading up to the survey: Malaria, Cholera, Black Fever, Dengue, Diarrhea, Chikunguniya, Chicken pox, Plague, Tuberculosis, Any other disease. The binary indicators are combined as an index using principal component analysis and this is used as the disease outbreak variable. Adding disease outbreak variables to the regressions in Tables 18B and 19B (Column 2) does not alter the estimated migration effect for either outcome, suggesting that differences in disease prevalence do not confound the IV estimates.

6.7 Natural Disaster Exposure

Exposure to disasters can affect infrastructure, mobility, and healthcare access. If historical drought exposure correlates with contemporary disaster frequency, rainfall variation might predict healthcare outcomes through environmental vulnerability rather than migration. The LASI lists various natural disasters: earthquake, flood, cyclone, drought, landslide, locust/pest attack, fires, and any other natural disaster in the last 5 years. We use indicator variables to undertake a principal component analysis. The first predicted factor used is our index of natural disaster exposure. When the natural disaster exposure index is controlled for in Tables 18B and 19B (Column 2), the migration

coefficient remains stable for both the probability of an OPD visit and OPD expenditure, indicating that disaster-related vulnerability does not mediate the observed relationship.

6.8 Wages

Male and Female wage levels reflect local earnings and purchasing power, which can influence both healthcare utilization and spending. If historical drought had persistent effects on male employment opportunities or labour productivity, rainfall shocks might influence current healthcare outcomes through long-run income differences rather than migration. Controlling for village level male wage in Tables 18B and 19B (Column 3) does not attenuate the migration coefficient, suggesting that male income effects are not driving the results. Including female wage controls in Tables 18B and 19B (Column 4) also leaves the estimated migration coefficient unchanged for both outcomes, indicating that gendered income variation is not a confounding channel.

Across all robustness checks reported in Tables 18A–18B and 19A–19B, the estimated effect of children's migration on both the probability of an OPD visit and OPD expenditure remains consistent in sign, magnitude, and statistical significance. This stability provides strong evidence that historical drought shocks influence elderly health-seeking behaviour only through their effect on children's migration, not through alternative socioeconomic, institutional, or environmental pathways.

7. Conclusion and Discussion

The age distribution in developing countries is likely to get more skewed towards the elderly. Health costs are likely to rise and developing countries will have to deal with issues of health financing. What makes issues complicated in regions like rural India (still accounting for around two-thirds of the population of India) is that the middle-aged also show signs of being frail; while they (in-particular males) are still working, quality public healthcare is not always accessible and private healthcare (perceived by the population to be superior) is expensive. Given this background, this paper explores issues of how both the middle aged and elderly (adults 45 and above) fund their healthcare-in particular it examines if having migrant children can allow parents to fund their health

expenditures. Using instrumental variables estimation techniques that deal with the endogeneity of a migration decision made by children, we show that parents with a higher proportion of migrant children show higher outpatient visit usage which is primarily for primary care. These visits are to private providers and therefore lead to a rise in outpatient expenditures. Importantly, we do not find evidence that having migrant children leads to higher hospitalization usage or higher expenditure for hospitalization. Thus, migration of children may be a strategy that can fund primary care and its expenditure but there is no evidence that it can take care of tertiary care. This is consistent with the evidence on remittances-very few children remit; hence the mechanism at play is likely to be an easing of the budget constraint of parents when children migrate or an increase in consumption of health from parental budgets as a response to know that the total family incomes is higher post migration. We find the result come from the relatively poor households. Hence, such easing of the parental budget constraints can only be small and is likely to explain why there is a rise in OPD expenditures that are not catastrophic to begin with. Hence, our result points to a mixed bag-one where primary care is partially improved but not tertiary.

The increased usage of private Outpatient as a response to migrant children is true irrespective of whether or not there are providers in the village or quality public providers like Primary Health Centres close by (within 5 km or beyond). However, expenditures on OPD care are driven by visits to providers when there are no nearby health providers. This is consistent with the breakdown of the expenditures which show a rise in transport expenditures, in addition to rise in expenditure on tests and medicines. These results also imply that lack of local health facilities can be compensated by rising family incomes. This is especially true in the case of the elderly pointing out to a possibility that income effects for the elderly may be sufficient to "buy" private health away from the village. The other side of the coin points out to unrequited demand for private health care that cannot be funded for the parents (including the elderly) if they do not have migrant children. Hence, it makes a case for out migration rates of children (and possibly close family members) as a basis on which newer investments of public health services access should be prioritized.

The link between migration of children and health utilization suggests that between two equally under-developed areas, one could prioritize quality public health care services like public primary health centers for regions that have very low migration rates. In particular, any money-metric welfare calculation on the impact of providing public health funds-either insurance or public health facility- must bear in mind, that it will cover part of expenditures for migrating households that are already funded privately. This observation can be useful if there is a priority needed in locating additional Primary Health Centres-our paper shows that the full value of investment may come from locating in places with very low migration rates.

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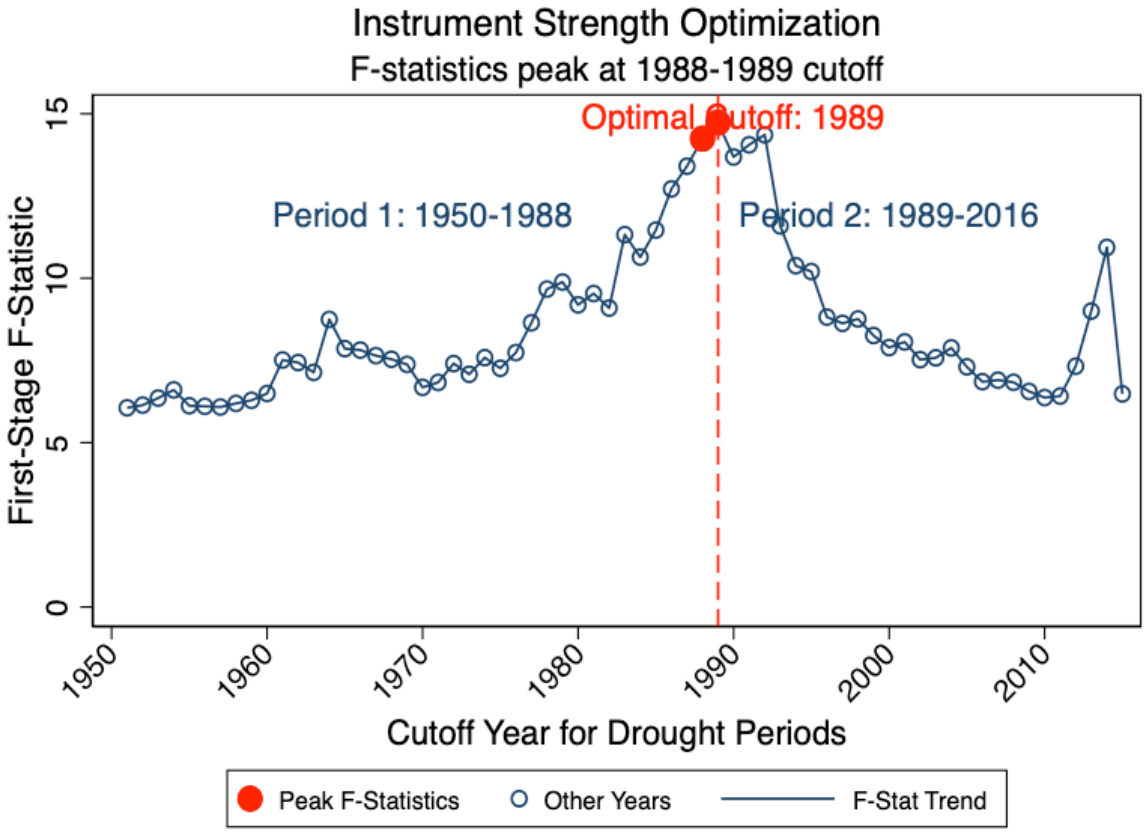
FIGURES

Figure 1



TABLES

Table 1: Descriptive Statistics

	Mean	SD	Min	Max	N
% of children 18+ living outside village	25.34	31.58	0.00	100.00	32050
Sought health care	0.70	0.46	0.00	1.00	32050
Opd Visit in last one year	0.55	0.50	0.00	1.00	32050
Hospitalised	0.07	0.25	0.00	1.00	32050
Outpatient Expenditure	373.75	1762.46	0.00	112850.00	32050
Hospital Expenditure	856.80	8014.95	0.00	418000.00	32050
Public Opd Facility	0.16	0.37	0.00	1.00	32050
Private Opd Facility	0.30	0.46	0.00	1.00	32050
Public Hospital Facility	0.03	0.16	0.00	1.00	32050
Dummy:Female	0.53	0.50	0.00	1.00	32050
Age	59.75	10.48	45.00	116.00	32050
Dummy:Matr and Lower	0.38	0.49	0.00	1.00	32050
Dummy:High Sec and above	0.05	0.22	0.00	1.00	32050
Dummy: Hindu	0.79	0.41	0.00	1.00	32050
Dummy: Muslim	0.10	0.30	0.00	1.00	32050
Dummy:Scheduled Caste	0.20	0.40	0.00	1.00	32050
Dummy:Scheduled Tribe	0.16	0.37	0.00	1.00	32050
Dummy: Other Backward Castes	0.40	0.49	0.00	1.00	32050
Dummy:Curr Married	0.76	0.43	0.00	1.00	32050
Dummy:Widow/Widower	0.22	0.41	0.00	1.00	32050
Dummy: Have Child	0.97	0.17	0.00	1.00	32050
Total Number of Children	3.63	1.88	0.00	18.00	32050
Household size	5.12	2.69	1.00	35.00	32050
Dummy:Wealth Tercile 2	0.33	0.47	0.00	1.00	32050
Dummy:Wealth Tercile 3	0.33	0.47	0.00	1.00	32050
land	3.43	7.50	0.00	200.00	32050
Height (cm)	155.61	9.12	103.30	195.80	32050
Dummy:Has Health insurance	0.25	0.43	0.00	1.00	32050
Distance to PHC (km)	6.48	6.68	0.00	60.00	32050
Distance to Sub-center (km)	2.44	4.67	0.00	65.00	32050
Distance to Private Hospital (km)	18.06	24.62	0.00	303.00	32050
Villag Dev Quart 2	0.23	0.42	0.00	1.00	32050
Villag Dev Quart 3	0.24	0.43	0.00	1.00	32050
Villag Dev Quart 4	0.26	0.44	0.00	1.00	32050
Sex ratio (2011)	95.54	5.76	69.00	117.70	32050
Dependency ratio (2011)	57.02	12.45	35.90	98.00	32050
Literacy rate (7+ years)	69.20	10.03	43.90	96.50	32050
Log Population (2011)	7.08	0.88	3.37	8.71	32050
Access to banking services (%)	55.35	18.61	10.00	94.30	32050
Log of Area (sq. km.)	8.00	1.13	0.00	10.62	32050
Road length (km)	480.98	718.75	0.00	4497.00	32050
Labour earnings (USD/day)	4.02	2.13	1.40	16.10	32050
Total drought 1989-2016	5.75	1.95	1.00	11.00	32050
Total drought 1950-1988	7.80	2.22	2.00	13.00	32050
Health care provider fees (consultation charges)	37.74	311.11	0.00	32000.00	32050
Medicines from hospital	67.70	777.74	0.00	110000.00	32050
Medicines from outside	145.19	674.64	0.00	40000.00	32050
Tests/investigations	49.20	418.72	0.00	25000.00	32050
Hospital and nursing home charges	5.58	156.98	0.00	10000.00	32050
Operation theater/surgery charges	6.88	274.31	0.00	25000.00	32050

Blood, Oxygen, Cylinder	1.97	111.56	0.00	15000.00	32050
Transport	39.91	217.05	0.00	10000.00	32050
Expenses of accompanying person(s)	11.00	124.38	0.00	10000.00	32050
Other expenditure not elsewhere reported	8.57	187.70	0.00	25000.00	32050
% of children 18+ living inside village	27.65	32.89	0.00	100.00	32050

Table 2:Association between Child Outmigration and Health Seeking Behaviour

% of children 18+ living outside village	Sought health care	OPD Visit in last one year	Hospitalised	Log Outpatient Expenditure	Log Hospital Expenditure
0%, No Child	0.64	0.50	0.06	1.54	0.33
0%	0.67	0.51	0.06	1.76	0.4
1-25%	0.71	0.57	0.07	1.98	0.44
26-50%	0.74	0.6	0.07	2.27	0.5
51-75%	0.75	0.62	0.07	2.28	0.47
76-99%	0.74	0.64	0.06	2.31	0.42
100%	0.72	0.58	0.07	2.15	0.45

Table 3:Association between Past Droughts and Covariates

	Droughts: 1989-2016	Droughts 1950-88
Dummy: Have Child	-0.00373	-0.00233
Total Number of Children	-0.0738	-0.06
Wealth Tercile 2	0.00795	0.00688
Wealth Tercile 3	-0.0206	-0.0249
Height (cms)	-0.460**	-0.424**
Mental Health Index	0.0340	0.0442
Physical Health Index	-0.0157	-0.0111
Villag Dev Quart 2	-0.0412	-0.0487*
Villag Dev Quart 3	0.0625**	0.0408
Villag Dev Quart 4	-0.0213	-0.00139
Age	-0.0495	-0.116
Education less than 10th	0.0159	0.00829
Education more than 10th	0.00391	0.00205
Dummy: Hindu	0.00548	-0.00817
Dummy: Muslim	-0.0031	0.0127
Dummy: Christian	-0.00629	-0.00288
Dummy: SC	0.00312	0.00241
Dummy: ST	-0.00433	0.00475
Dummy: OBC	0.00125	-0.0103
Dummy: Curr Married	-0.00768	-0.000922
Widow/Widower	0.00465	0.0000843
Dummy: Separated	0.00388**	0.00264*
Dummy: Female	0.00858	0.00702
Dummy: Has Health Insurance	0.0208	0.0186
Household Size	0.0566	0.00073
Distance to PHC	-0.64	-0.64
Distance to Subcenter	-0.178	-0.136
Distance to Pvt Hospital	-1.083	-1.766
Rural District Sex Ratio (2011)	2.711***	2.415***
Rural District Dependency Ratio (2011)	0.226	0.54
Rural District Literacy Rate (2011)	0.122	-0.845
Log District Rural Population (2011)	0.0692	0.0124
District Prop of Rural District Banked	1.431	-0.247
Rural District Prop of Area with Bright Night Lights	-0.0468	-0.0588
Rural District Lab Earnings (USD/day)	-0.0875	-0.109
Rural District Road Length 2011 (Kms)	54.09	59.91

Table 4: Association between Child Outmigration and Healthcare Utilization

	Healthcare Utilization				
	Sought Care	Outpatient Visit	Hospitalization	Log Outpatient Expenditure	Log Hospital Expenditure
Percentage of children 18 and above living outside village	0.0002**	0.0005***	0.0000	0.0013*	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0008)	(0.0004)
Mean of dep. var	0.70	0.55	0.07	1.97	0.44
Observations	32,050	32,050	32,050	32,050	32,050
R-squared	0.1030	0.1114	0.0137	0.1885	0.0141

Sample consists of individuals aged 45 and above from rural households. Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, mental and physical health marital status, having health insurance, household size, have children indicator variable, number of children, village resource quantile, distance to sub-centre, PHC , 2011 district controls (sex ratio, dependency ratio, literacy level, population, bank facilities, night light area, road length and labour earnings) and state fixed effect. Expenditure variables are in log form (log(expenditure + 1)).

* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 5: Impact of Children's Out-migration on Healthcare Utilization

	Healthcare Utilization				
	Sought Care	Outpatient Visit	Hospitalization	Log Outpatient Expenditure	Log Hospital Expenditure
% of children 18+ living outside village	0.0032	0.0138***	-0.0003	0.0446**	0.0015
	(0.0029)	(0.0044)	(0.0011)	(0.0205)	(0.0085)
Mean of dep. var	0.70	0.55	0.07	1.97	0.44
Observations	32,050	32,050	32,050	32,050	32,050
First-stage F-stat	14.52	14.52	14.52	14.52	14.52
Hansen P-value	0.311	0.930	0.236	0.699	0.123

Notes: Instrumental variable estimates using historical drought exposure as instruments for children's out-migration. Sample consists of individuals aged 45 and above from rural households. Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, marital status, mental and physical health, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects. First-stage F-statistic tests instrument strength. Hansen P-value tests instrument validity (overidentification).
Expenditure variables are in logarithmic form.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 6: Impact of Children's Out-migration on Healthcare Utilization by Facility Type

	Healthcare Utilization			
	Public OPD	Private OPD	Public Hospitalization	Private Hospitalization
% of children 18+ living outside village	0.0045	0.0088***	-0.0000	-0.0006
	(0.0030)	(0.0034)	(0.0006)	(0.0008)
Mean of dep. var	0.16	0.30	0.03	0.04
Observations	32,050	32,050	32,050	32,050
First-stage F-stat	14.52	14.52	14.52	14.52
Hansen P-value	0.351	0.369	0.230	0.507

Notes: Instrumental variable estimates using historical drought exposure as instruments for children's out-migration. Sample consists of individuals aged 45 and above from rural households. Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, marital status, health insurance, household size, have children indicator variable ,number of children, village resource quintile, distance to health facilities, 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects.
First-stage F-statistic tests instrument strength. Hansen P-value tests instrument validity (overidentification).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: IV Results- Outpatient Expenditure Components

Panel A

Log of…	Fee Consult	Medicines from Hospital	Medicines from Outside	Tests/Investigations	Hospital Charges
% of children 18+ living outside village	0.0144	0.0073	0.0385**	0.0144*	-0.0028
	(0.0105)	(0.0109)	(0.0184)	(0.0079)	(0.0025)
Mean of dep. var	0.87	0.56	1.23	0.43	0.05
Observations	32,050	32,050	32,050	32,050	32,050
First-stage F-stat	14.52	14.52	14.52	14.52	14.52
Hansen P-value	0.423	0.563	0.523	0.144	0.817

Panel B

Log of…	Surgery Charges	Blood/Oxygen	Transport	Accommodation	Other Expenses
% of children 18+ living outside village	-0.0012	0.0005	0.0249**	-0.0093	-0.0070
	(0.0010)	(0.0008)	(0.0117)	(0.0068)	(0.0049)
Mean of dep. var	0.01	0.01	0.97	0.23	0.13
Observations	32,050	32,050	32,050	32,050	32,050
First-stage F-stat	14.52	14.52	14.52	14.52	14.52
Hansen P-value	0.105	0.515	0.759	0.546	0.328

Notes: The dependent variable is the log of various expenditures. When they take the value 0, we add 1 to be able to make log transformations. Instrumental variable estimates using historical drought exposure as instruments for children's out-migration. Sample consists of individuals aged 45 and above from rural households. Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, marital status, health insurance, household size, have children indicator variable,number of children, village resource quintile, distance to health facilities, 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects. First-stage F-statistic tests instrument strength. Hansen P-value tests instrument validity (overidentification). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: IV Results - Healthcare Utilization by Distance to Health Facilities

	Healthcare Utilization by Distance to Facilities			
	OPD Visit (Dist > 0)	OPD Visit (Dist = 0)	Log OPD Exp (Dist > 0)	Log OPD Exp (Dist = 0)
% of children 18+ living outside village	0.0099**	0.0178**	0.0674***	0.0177
	(0.0043)	(0.0083)	(0.0219)	(0.0272)
Mean of dep. var	0.55	0.55	1.95	1.97
Observations	10,692	21,358	10,692	21,358
First-stage F-stat	10.77	5.50	10.77	5.50
Hansen P-value	0.307	0.678	0.415	0.249
AR P-value		0.021		0.355

Notes: Instrumental variable estimates examining heterogeneous effects by distance to nearest health facility (Dist). Sample consists of individuals aged 45 and above from rural households. Dist > 0: Households with positive minimum distance to any health facility. Dist = 0: Households with zero minimum distance (facility in village). Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, have children indicator variable, number of children, village resource quintile, distance to health facilities, 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects. First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Healthcare Utilization by Distance to PHC

	Healthcare Utilization by PHC Distance			
	OPD Visit (Dist ≥ 5km)	OPD Visit (Dist < 5km)	Log OPD Exp (Dist ≥5km)	Log OPD Exp (Dist < 5km)
% of children 18+ living outside village	0.0088**	0.0163**	0.0391*	0.0245
	(0.0042)	(0.0078)	(0.0214)	(0.0288)
Mean of dep. var	0.55	0.56	1.96	1.98
Observations	17,629	14,421	17,629	14,421
First-stage F-stat	11.23	5.30	11.23	5.30
Hansen P-value	0.829	0.338	0.884	0.321
AR P-value		0.005		0.255

Notes: Instrumental variable estimates examining effects by distance to Primary Health Centre (PHC) using 5km threshold. Sample consists of individuals aged 45 and above from rural households. Dist ≥ 5km: Households located more than equal to 5km from nearest PHC. Dist < 5km: Households located within 5km of nearest PHC.Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects. First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 10: IV Results - Healthcare Utilization by Age Group

	Healthcare Utilization by Age Group							
	Age≥ 60			Age < 60			Age ≥ 60	Age < 60
	OPD Visit	Pub OPD Visit	Pvt OPD Visit	OPD Visit	Pub OPD Visit	Pvt OPD Visit	Log OPD Exp	
% of children 18+ living outside village	0.0099**	0.0045	0.0066*	0.0188***	0.0048	0.0112**	0.0193	0.0775**
	(0.0040)	(0.003)	(0.004)	(0.0067)	(0.004)	(0.005)	(0.019)	(0.0315)
Mean of dep. var	0.57	0.16	0.32	0.53	0.15	0.29	2.03	1.91
Observations	15,535	15,535	15,535	16,515	16,515	16,515	15,535	16,515
First-stage F-stat	10.91	10.91	10.91	8.57	8.57	8.57	10.91	8.57
Hansen P-value	0.934	0.347	0.275	0.837	0.606	0.519	0.700	0.720
AR P-value				0.002	0.304	0.027		0.019

Notes: Instrumental variable estimates examining heterogeneous effects by age group. Sample consists of individuals aged 45 and above from rural households. Age >= 60: Elderly individuals (traditional retirement age and above) Age < 60: Younger adults (ages 45-59) Robust standard errors clustered at the district level are reported in parentheses.
All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, number of children, have children indicator variable, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects.
First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 11: IV Results - Healthcare Expenditure for Elderly (60+) by Distance to Health Facilities

	Log OPD Exp	
	Nearest Health Facility Distance > 0	Nearest Health Facility Distance = 0
% of children 18+ living outside village	0.0436**	-0.0172
	(0.0181)	(0.0308)
Mean of dep. var	2.01	2.04
Observations	5,218	10,317
First-stage F-stat	15.33	2.98
Hansen P-value	0.214	0.196
AR P-value		0.395

Notes: Instrumental variable estimates for elderly individuals (age ≥60) by distance to health facilities. Sample consists of individuals aged 60 and above from rural households. Distance > 0: Households with positive minimum distance to any health facility. Distance = 0: Households with health facility in village (zero distance). Robust standard errors clustered at the district level are reported in parentheses.
All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, number of children, have children indicator variable, village resource quintile, distance to health facilities, 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects.
First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 12: IV Results - Healthcare Utilization by Wealth Group

	Healthcare Utilization by Wealth Group			
	OPD Visit (Top Wealth)	OPD Visit (Mid & Bottom Wealth)	Log OPD Exp (Top Wealth)	Log OPD Exp (Mid & Bottom Wealth)
% of children 18+ living outside village	0.0081	0.0146***	-0.0011	0.0579***
	(0.0061)	(0.0045)	(0.0275)	(0.0217)
Mean of dep. var	0.59	0.53	2.26	1.82
Observations	10,680	21,370	10,680	21,370
First-stage F-stat	5.25	15.14	5.25	15.14
Hansen P-value	0.896	0.846	0.789	0.987
AR P-value	0.367		0.964	

Notes: Instrumental variable estimates examining heterogeneous effects by wealth group.
Sample consists of individuals aged 45 and above from rural households. Top Wealth: Wealth Tercile 3. Mid & Bottom Wealth: Wealth terciles 1-2. Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects.
First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: IV Results - Healthcare Utilization by Gender

	Healthcare Utilization by Gender			
	OPD Visit (Female)	OPD Visit (Male)	Log OPD Exp (Female)	Log OPD Exp (Male)
% of children 18+ living outside village	0.0131***	0.0140***	0.0428**	0.0453*
	(0.0041)	(0.0052)	(0.0204)	(0.0234)
Mean of dep. var	0.57	0.53	2.04	1.89
Observations	16,994	15,056	16,994	15,056
First-stage F-stat	14.75	12.53	14.75	12.53
Hansen P-value	0.480	0.513	0.347	0.730

Notes: Instrumental variable estimates examining heterogeneous effects by gender.
Sample consists of individuals aged 45 and above from rural households.
Robust standard errors clustered at the district level are reported in parentheses.
All regressions include controls for age, gender, caste, religion, wealth, mental and physical health, marital status, health insurance, household size, number of children, have children indicator variable ,village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects.
First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: IV Results-Healthcare Utilization by Prop of Male Children Out-migrated

	Healthcare Utilization				
	Sought Care	Outpatient Visit	Hospitalization	Log Outpatient Expenditure	Log Hospital Expenditure
Prop of Male Children	0.0113	0.0248**	0.0002	0.0761%	0.0107
	(0.0095)	(0.0119)	(0.0023)	(0.0465)	(0.0185)
Mean of dep. var	0.70	0.55	0.07	0.44	0.44
Observations	32,050	32,050	32,050	32,050	32,050
First-stage F-stat	3.79	3.79	3.79	3.79	3.79
Hansen P-value	.	0.495	0.200	0.426	0.140
AR P-value	0.134	0.003	0.434	0.073	0.302

Notes: Instrumental variable estimates using historical drought exposure as instruments for children's out-migration. Sample consists of individuals aged 45 and above from rural households.
Robust standard errors clustered at the district level are reported in parentheses.
All regressions include controls for whether household has a male child, age, gender, caste, religion, wealth, marital status, mental and physical health, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, Private Hospital), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects. First-stage F-statistic tests instrument strength. Hansen P-value tests overidentification. AR P-value is Anderson-Rubin test for weak instruments.
% p <0.102 * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 15: IV Results-Healthcare Utilization by Prop of Female Children Out-migrated

	Healthcare-Seeking Behaviour				
	Sought Care	Outpatient Visit	Hospitalization	Log Outpatient Expenditure	Log Hospital Expenditure
% of Female children 18 and above living outside village	0.0018	0.0104***	-0.0004	0.0349**	-0.0010
	(0.0022)	(0.0033)	(0.0008)	(0.0150)	(0.0062)
Mean of dep. var	0.70	0.55	0.07	0.44	0.44
Observations	32,050	32,050	32,050	32,050	32,050
First-stage F-stat	12.40	12.40	12.40	12.40	12.40
Hansen P-value	0.228	0.667	0.284	0.993	0.140

Notes: Instrumental variable estimates using historical drought exposure as instruments for children's out-migration.Sample consists of individuals aged 45 and above from rural households.
Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, marital status, mental and physical health, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects First-stage F-statistic tests instrument strength. Hansen P-value tests instrument validity (overidentification). Expenditure variables are in logarithmic form. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 16: IV Results- OPD Visits by Children's Outmigration Intensity

	Healthcare Utilization by total number of children			
	Opd Visit # Child > 4	Opd Visit # Child ≤ 4	Opd Visit # Child > 4	Opd Visit # Child ≤ 4
% of children 18+ living outside village	0.0137***	0.0138***		
	(0.005)	(0.0059)		
Number children 18 and above living outside village			0.215***	0.45***
			(0.083)	(0.165)
Mean of dep. var	0.56	0.54	0.56	0.54
Observations	8,975	23,075	8,975	23,075
First-stage F-stat	9.53	9.93	9.66	11.49
Hansen P-value	0.49	0.65	0.37	0.83
AR P-value	0.010	0.012	0.013	

Notes: Instrumental variable estimates using historical drought exposure as instruments for children's out-migration.Sample consists of individuals aged 45 and above from rural households.
Robust standard errors clustered at the district level are reported in parentheses. All regressions include controls for age, gender, caste, religion, wealth, marital status, mental and physical health, health insurance, household size, number of children, village resource quintile, distance to health facilities (sub-center, PHC, government dispensary), 2011 district controls (sex ratio, dependency ratio, literacy level, population, banking facilities, nighttime lights, road infrastructure, labour earnings), and state fixed effects First-stage F-statistic tests instrument strength. Hansen P-value tests instrument validity (overidentification). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Robustness: : Exclusion Restriction Validity: Probability of OPD Visit

Panel A

	With Mental Health	With Physical Health	With Crime	With Soc Sec	With Health Insurance	With Irrigation
% of children 18+ outside village	0.0137***	0.014***	0.0154***	0.0138***	0.0138***	0.0150***
	(0.004)	(0.004)	(0.0053)	(0.0045)	(0.0044)	(0.0052)
Observations	32050	32050	29,107	32,050	32,050	28,169

Panel B

	With Disease	With Disaster	With Wage Male	With Wage Fem
% of children 18+ outside village	0.0144***	0.0136***	0.0137***	0.0135***
	(0.0046)	(0.0044)	(0.0044)	(0.0043)
Observations	30,828	31,891	31,989	31,917

Notes: Sample consists of individuals aged 45 and above from rural households. Each pair of columns presents IV regression results with and without controlling for the potentially confounding variable (using same sample). Testing whether inclusion of contextual variables affects the main relationship, which could indicate violation of exclusion restriction. Robust standard errors clustered at the district level are reported in parentheses. All regressions include district-level controls and state fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table18: Robustness: : Exclusion Restriction Validity: Log OPD Expenditure

Panel A

	With Mental Health	With Physical Health	With Crime	With Soc Sec	With Health Insurance	With Irrigation
% of children 18+ outside village	0.045**	0.045**	0.050**	0.045***	0.045***	0.049**
	(0.021)	(0.021)	(0.023)	(0.021)	(0.021)	(0.023)
Observations	32050	32050	29,107	32,050	32,050	28,169

Panel B

	With Disease	With Disaster	With Wage Male	With Wage Fem
% of children 18+ outside village	0.049**	0.045**	0.044**	0.043**
	(0.021)	(0.021)	(0.020)	(0.020)
Observations	30,828	31,891	31,989	31,917

Notes: Each pair of columns presents IV regression results with and without the contextual variable (using same sample) Sample consists of individuals aged 45 and above from rural households.Testing whether inclusion of contextual variables affects the main relationship, which could indicate violation of exclusion restriction. Robust standard errors clustered at the district level are reported in parentheses. All regressions include district-level controls and state fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix

Appendix Table A1: First Stage

	% of children 18+ living outside village
Total drought 2016-1988	-3.6415***
	(0.7092)
Total drought episodes (1988)	-2.6918***
	(0.6805)
Has children (dummy)	20.8353***
	(1.0374)
Total children living	2.2369***
	(0.1681)
Dummy: Wealth tercile 2	3.3571***
	(0.5796)
Dummy: Wealth tercile 3	7.0558***
	(0.6672)
Height	0.1389***
	(0.0297)
Village Quart 2	0.4288
	(0.7981)
Village Quart 3	0.1442
	(0.9001)
Village Quart 4	0.6897
	(0.9265)
Age	0.5144***
	(0.0276)
Dummy:Matr and Lower	1.4172***
	(0.4461)
Dummy:High Sec and above	-1.5208*
	(0.7899)
Dummy: Hindu	-1.0118
	(1.3647)
Dummy: Muslim	-5.6860***
	(1.7870)
Dummy: Christian	3.1786*
	(1.9015)
Dummy:Scheduled Caste	-3.3680***

	(0.8329)
Dummy:Scheduled Tribe	-4.4965***
	(1.0788)
Dummy: Other Backward Castes	-2.0559***
	(0.7818)
Dummy:Curr Married	-4.7812**
	(1.9652)
Dummy:Widow/Widower	-7.2959***
	(1.9897)
Dummy:Separated	-2.8716
	(2.4132)
Female	5.3658***
	(0.4961)
Dummy:Has Health insurance	1.1271
	(0.6849)
Household size	-2.6594***
	(0.1297)
Distance to PHC	-0.0163
	(0.0412)
Distance to sub-center	0.1004*
	(0.0608)
Distance to Private Hospital	-0.0430***
	(0.0133)
Sex ratio (2011)	0.6846***
	(0.1202)
Dependency ratio (2011)	0.2499***
	(0.0746)
Literacy rate (2011)	0.1978***
	(0.0720)
Log Population (2011)	1.6002
	(1.1693)
Access to banking services (%)	0.0218
	(0.0406)
Log of Area (sq. km.) with Bright Night lights	-0.6325
	(0.7852)
Labour earnings (USD/day)	0.0730
	(0.3634)

Road length (km)	0.0001
	(0.0007)
Mean of dep. var	
Observations	32,050
R-squared	0.195
F-statistic	.

Notes: Dependent variable is the percentage of children aged 18 and above living outside the village.
Sample consists of individuals aged 45 and above from rural households. Robust standard errors clustered at the district level are reported in parentheses. State fixed effects are included but not reported. F-statistic tests the strength of the instrumental variables. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix Table A2: Association of Children's Out-migration on Healthcare Utilization

	Financial support from son and daughter
% of children 18+ outside village	0.000847 ***
	(0.00009)
Mean of dep. var	0.039
Observations	32,050
R-squared	0.067

Sample consists of individuals aged 45 and above from rural households.
Robust standard errors clustered at the district level are reported in parentheses.All regressions include controls for age, gender, caste, religion, wealth, mental and physical health marital status, having health insurance, household size, have children indicator variable, number of children, village resource quantile, distance to sub-centre, PHC , 2011 district controls (sex ratio, dependency ratio, literacy level, population, bank facilities, night light area, road length and labour earnings) and state fixed effect
Expenditure variables are in log form (log(expenditure + 1)).
* p < 0.10, ** p < 0.05, *** p < 0.01.

[Mobility]

HT303 – HT311. Because of physical or health problems, do you have difficulty doing any of the activities? Exclude any difficulties that you expect to last less than three months.

	Do you have difficulty with…?	
HT303	Walking 100 yards	1. Yes 2. No
HT304	Sitting for 2 hours or more	1. Yes 2. No
HT305	Getting up from a chair after sitting for long period	1. Yes 2. No
HT306	Climbing one flight of stairs without resting	1. Yes 2. No
HT307	Stooping, kneeling or crouching	1. Yes 2. No
HT308	Reaching or extending arms above shoulder level (either arm)	1. Yes 2. No
HT309	Pulling or pushing large objects	1. Yes 2. No
HT310	Lifting or carrying weights over 5 kilos, like a heavy bag of groceries	1. Yes 2. No
HT311	Picking up a coin from a table	1. Yes 2. No