The Health Consequences of Subsidized Health Insurance: Evidence from Iran

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Abstract

In 2014, the Iranian government introduced Salamat Universal Insurance Program (SUIP) that offered almost free primary health insurance to every uninsured individual. Consequently, more than 10 million individuals were given primary health insurance by SUIP, and primary health insurance coverage rose by nearly 15 percentage points among the urban population. We assess the impact of SUIP on healthcare utilization and mortality of various age-groups among the urban population. The results indicate that the introduction of SUIP has been effective in improving the utilization of outpatient healthcare and reducing infant mortality. However, no discernible impact is found on the utilization of inpatient services and mortality of other age-groups. We attribute these findings to the insufficient coverage of primary insurance in the inpatient sector and the extremeness of mortality as a health indicator for these age-groups.

1 Introduction

In recent decades, expanding health insurance coverage through publicly funded programs has been a popular policy in low and middle-income countries (LMIC). In these countries, even subsidized private health insurance is unaffordable for the poor. Therefore, a considerable portion of the population is left uninsured in the absence of an affordable public program.

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As a result, many LMICs such as China, Colombia, Costa Rica, Georgia, Mexico, Nicaragua, Thailand, etc, have implemented programs to extend the health insurance coverage to the poor Acharya et al. (2012); Erlangga et al. (2019). Such programs, due to their inherent large scales, require considerable financial resources to implement. Therefore, in LMIC, where public resources are most limited, it is extremely important to know whether the public health insurance expansion programs are likely to meet their primary goals, which are increasing access to healthcare, improving health outcomes, and provideing financial protection against adverse health shocks.

In mid 2014, the Iranian government launched "Salaamat Universal Insurance Program" (SUIP), which granted almost free primary health insurance to all uninsured citizens. Between 2015 to 2017 SUIP provided health insurance to more than 10 million individuals. In this paper, we are trying to investigate whether the introduction of SUIP has been successful in promoting healthcare utilization and reducing mortality among the urban population. To overcome the problem of self-selection in enrolling in the program, we study the changes in the aggregate measures of utilization and mortality rates (MR) across 183 districts in Iran, comprising more than 54 million individuals out of the total 59 million urban population (based on census 2016).

The results from our cross-district analysis suggest that SUIP has promoted the utilization of outpatient healthcare services. However, we have not found strong evidence suggesting that this program has had an impact on hospital care use. We believe that the structure of primary health insurance in Iran, which offers limited financial coverage for the services in the inpatient sector, could be responsible for these results. Our study also reveals that SUIP has been successful in reducing infant mortality. However, we cannot detect any impact on the mortality of other age groups.

Up to our knowledge, this is the first study that evaluates the impact of SUIP on utilization and mortality. Beyond evaluation of an ambitious health policy in Iran, we believe this study has broader applicability that provides valuable insights into the vast literature of consequences of health insurance expansion (HIE) programs.

First, most LMICs adopt targeted HIE programs that offer subsidized or free health insurance to a specific population, and there are fewer countries that have chosen to adopt universal or near-universal HIE programs. Although it is not always possible to draw a line between the two, the main distinction between universal and targeted programs are in the sense that the latter "targets" its subjects and provide insurance for the subset of population that are deemed to need it most. However, the scope of universal HIE programs are generally wider and they aim to expand the coverage for the general public or a considerable fraction of the population. Subsequently, this aspect of difference between these two types of programs, might hints out that their impact on the the relevant outcomes might differ as well. While , there are many studies that evaluate consequences of targeted HIE programs on healthcare utilization and health outcomes Bauhoff et al. (2011); Bernal et al. (2017); Thornton et al. (2010); Sood et al. (2014), there are relatively few that evaluate outcomes universal or near-universal HIE programs. The latter set of research mostly includes studies on NCMS program in china Hou et al. (2014); Wagstaff et al. (2009), and studies on Seguro Popular health insurance in Mexico King et al. (2009); Pfutze (2014). Our study provides additional evidence on the impact of an almost universal HIE on healthcare utilization and health outcomes on low and middle-income countries, and thus adds to the depth of this literature

Moreover, the number of studies that evaluate the impact of HIE programs in LMIC on health outcomes is considerably smaller than the number of studies that investigate their impact on financial protection and healthcare utilization. Although there is an overall consensus in the literature on the positive impact of HIE programs on financial protection and healthcare utilization, the results are greatly contrasting on their impact on health outcomes Giedion et al. (2013); Acharya et al. (2012). This lack of consensus might be due to the fact that HIE programs could only have an indirect effect, through increased utilization, on health outcomes. But, it is also the case that their impact on health outcomes is much harder to detect. Giedion et al. (2013) mention three factors that are essential to detect the impact of HIE programs on health outcomes: first, considering the outcomes that can be affected by access to care, second, allowing for sufficient lag between program implementation and evaluation, and third, availability of good data.

We believe that this study overcomes these challenges, and, therefore, provide additional evidence on the impact of HIE programs on health outcomes. We have studied the impact of SUIP on mortality rates of various age groups starting from infants and ending with 70-74. Mortality is the most extreme outcome and it might not be the most suitable indicator for evaluating the impact of HIE programs on health outcomes. However, in the context of this study, it might be the best available option for a few reasons: it is a definite outcome with a clear description, it incorporates health outcomes of all of the population and not just a specific subset of it, and most importantly, it is the most reliable data on health outcomes in Iran. Besides, some studies have shown that HIE programs could have a discernible impact on mortality of infants Pfutze (2014) and adults with health conditionSood et al. (2014). Therefore, there are evidence to assume that SUIP could have affected mortality of different age groups.

Whether, we have allowed for sufficient lag between intervention and evaluation is a more serious concern. It seems reasonable to assume that our period of evaluation, which starts nine months after SUIP implementation and lasts for three years, is sufficient for evaluating mortality of infants and under-five children. However, we acknowledge that a longer time frame might be needed to estimate the impact on MR of older age groups. But, unfortunately, since the program went through major changes since 2018, it would have been impossible to do so. Finally, our data on mortality comes form the main organization responsible for recording vital statistics. Therefore, our data on mortality is comprehensive and reliable.

Finally, the experience of SUIP might have several important lessons for LMICs that want to design a HIE program. SUIP offered nearly free[1] health insurance for every individual that was uninsured at the time of enrollment. On the upside, this ambitious program dramatically increased insurance coverage among the population, and, as the results in this paper point out, it has been successful in promoting access to healthcare and improving health outcomes. However, the downside was that the government only anticipated that six million people would enroll in this insurance, and it could not manage the healthcare expenses of more than 10 million enrollees in SUIP. Underestimating the pool of uninsured population, a flawed process of checking for enrollment in other insurance funds, and switching from other funds to SUIP, all resulted that the actual enrollment figure was well above the government expectation.

As a result, the government was forced to step down from its promise of providing free insurance coverage in 2018, when it declared that only poor families would be given free insurance, and tried to prevent SUIP enrollees from seeking care from the private sector. This experience shows that while universal programs might have an advantage in providing universal coverage and improving outcomes, their tremendous and uncertain financial burden might be too challenging for many LMICs to handle. Especially in a country like Iran, in which the government's financial power sharply fluctuates from year to year.

The rest of this paper proceeds as follows. In the next section, we provide a concise description of the SUIP and the context of health insurance in Iran. The third section describes our data. We present our empirical methodology and results in the fourth and fifth section,

[1]With a fixed cost of less than 1$ for every household.

respectively. Finally, in the last section, we discuss the threats to our identification and evaluate the robustness of our results.

2 Context

Health insurance in Iran is provided through a two-pillar system. The first pillar is often employer-provided mandatory primary health insurance with government-regulated premiums, fees and coverage. The second pillar is supplementary health insurace usually purchased as a group, e.g. through the employer. Primary insurance covers the cost of primary and secondary level healthcare services. Supplementary insurance provides coverage for tertiary services as well as additional coverage for the first two levels of healthcare services[2]. Healthcare services are provided by private and public health centers in Iran with no referral system in place. Therefore, individuals could directly visit specialists in public and private centers. Coinsurance rates vary between 30 percent for doctor visits to 10 percent for inpatient services. However, not all services are covered by primary insurance; particularly many inpatient services and surgeries are excluded. Furthermore, insurance payments are based on government-set service fees which are far below what private centers charge. In conclusion, although primary health insurance provides first-dollar coverage with no deductibles, its coverage, especially for inpatient and para-clinical services is capped and limited. Therefore, the two biggest insurance providers, covering for more than 90% of the insured population, have only paid 28% of all healthcare expenses in 2015 (Goudarzi et al. (2017)).

To increase health insurance coverage, the fifth five-year development plan (2011-2015) obliged the government to expand coverage to all citizens. SUIP was introduced in May 2014 to provide free primary health insurance for all uninsured Iranians. This program mostly affected the urban population because another initiative existed for the rural population and the residents of small cities since 2005. SUIP resulted in an increase of health insurance in urban areas from 76.4 percent in 2010 to 91.7 percent in 2016. The percentage of the rural population with coverage rose from 92.8 percent to 96.7 percent during the same period (Ahmadnezhad et al. (2017)). Households could register for SUIP by completing an online form and attending a public services office to pay a small fee (less than 1$ for each household). Iran Health Insurance

[2]Supplementary insurance premiums are substantially higher than primary insurance. Therefore, only a small sub-sample of the population purchases supplementary health insurance. In 2010 around 16 percent of the urban population had supplementary health insurance. Since our focus in this paper is on the expansion of primary health insurance we do not discuss the details of the supplementary health insurance in Iran.

Organization (IHIO) was responsible for controlling lack of prior coverage. Nevertheless, the generousity of the scheme led to higher than expected take-up. Therefore, in 2018, IHIO started charging half of the regular primary insurance premiums to manage costs. This change, however, falls outside our study period.

The final point of this section is that, beside SUIP, the Ministry of Health simultaneously launched another program known as HTP, or “Health Transformations Plan”. This program was mainly aiming to improve the quality of health care delivered in the public hospitals. We will get back to this issue on Section5.3 where we discuss more thoroughly about the specific details of this program, and their possible consequences on our identification strategy. However, in brief, we can say that the our empirical approach does not seems to be greatly endangered by the simultaneous execution of the HTP.

3 Data

We combine three data sources to evaluate the impact of SUIP in the form of a balanced panel of 183 districts, with population greater than 50,000, over 3 years before (2011-2013) and after (2015-2017) SUIP introduction. First, we measure SUIP take-up rate by dividing the official number of insured individuals from IHIO in each district from 2015 to 2017 by the urban population from the population census 2016. Second, we use individual records from Household Expenditure and Income Survey (HEIS) rounds for 2011 to 2017 (excluding 2014, the year of introduction) to construct district-level healthcare utilization variables. HEIS is a standard expenditure and income survey with detailed information on various cost and income items. Specifically, HEIS records household spending on outpatient and inpatient healthcare services respectively over the past month and over the past year. Since we do not know the quantity of the healthcare services and that our main focus is on access to health services, we construct dummy variables that indicate whether a specific healthcare service is used by the household when the relevant expenditure item is non-zero. For outpatient services we use doctor visits (both general practitioners and specialists), and medical treatments which includes prescription drugs, medical tests and scans. Hospital care is a dummy for any inpatient healthcare service used during last year. A similar variable is defined for use of denistry services. Like other primary health insurance, SUIP offers negligible coverage for dentistry services. Hence this is used as a placebo test in our analysis. All household-level utilization dummy variables are collapsed to district-level variables that show the percentage of households that used the given healthcare service. We use reported expenditures on insurance from HEIS to measure the percentage of households with primary health insurance coverage before the introduction of SUIP (2011 to 2013). Unfortunately, HEIS does not distinguish between SUIP and Rural Insurance, another scheme introduced in 2005 for rural areas and small cities.

Infants are the most vulnerable group and their survival could be a measure of the adequacy of health services and treatments. Therefore, the main health outcome we use is infant mortality rate (IMR). The third data source in our study comes from Iran National Organization for Civil Registration (NOCR) and reports the total number of registered births and deaths in each district for the duration of our study. IMR is calculated by dividing total number of deaths for infants under age of one year old by total registered births for each district-year[3]. We also estimate the impact of SUIP on the mortality rate of other age-groups. The first age-group is 1-4 (more than one year and less than five), and the rest of them are five-year-interval age groups, starting from 5-9 and ending with 70-74[4]. The mortality rate of these age groups is calculated by dividing total number of deaths to the estimated population of that age group. Estimated population is calculated by using linear interpolation from the reported population of the age-groups in census 2011 and census 2015.

We restrict our study to 183 districts with more than 50,000 urban population in the 2011 population census. There are in total 331 districts in Iran at the sample base year and the included districts comprise of 92 percent of urban population in 2011. The main reason for this restriction is the small number of observations for small districts in HEIS which results in imprecise estimates for the aggregate proportions constructed above. The reults are, however, robust to changing this population threshold (section 5.3).

Table 1 shows summary statistics for insurance coverage (panel A), healthcare utilization (panel B), health outcomes (panel C), and control variables (panel D) for several subsamples of districts. We categorize districts into four groups based on the quartile of average primary health insurance coverage before the introduction of SUIP (2011- 2013). Prior insurance coverage captures the intensity of SUIP treatment because districts with a higher number of uninsured individuals would benefit more from SUIP. The first five columns show averages for

[3]One consideration is that the IMR calculated from the NOCR data sources underestimates actual infant mortality rate. This underestimation results from the fact that NOCR only records deaths for registered births. Parents must apply for registration within 15 days from birth date, and NOCR reports that 95% of registrations are recorded in the legal interval. Therefore, our data excludes still births and newborn deaths without birth registration.

[4]This type of grouping the death records is done because our data source gives us the number of deaths in each county in the aforementioned age-groups

the period before SUIP introduction (2011-2013) and the rest of columns show averages after SUIP introduction (2015-2017). Insurance coverage rate rises from 70 percent to 85 percent after SUIP introduction (column (5) vs. (10) in panel A). Looking across quartiles we observe a smaller increase in insurance coverage for districts with higher prior coverage. For example, coverage in the first quartile moves from 52 to 78 percent (column (1) vs. (6)). But for fourth quartile it moves from 84 to 90 percent (column (4) vs. (9)). Similarly official SUIP take-up rates are higher for districts with smaller prior insurance coverage. Therefore, we conclude that SUIP targeting was effective in reaching out the uninsured individuals.

Panel B of Table 1 reports healthcare utilization variables. Prior to the introduction of SUIP, average utilization of outpatient services (visit and treatment) has a positive correlation with average primary insurance coverage with a substantial gap between quartiles. However, after the introduction of SUIP, this gap is narrowed[5]. The pattern for hospital care is different and we do not see a clear correlation between average primary insurance coverge and inpatient care before or after the introduction of SUIP. Panel C shows that IMR is not correlated with average primary insurance coverage. However, the significant reduction in IMR is more pronounced for lower quartiles. Figure 1 shows that distribution of IMR shifts to the left after the introduction of SUIP. These patterns suggest that SUIP might have been effective in improving utilization and outcomes.

Finally, panel D shows summary statistics of three control variables used in our study. Real per capita income increases slightly both within a period for quartiles and over time. Percent of population in small cities is higher for higher quartiles of prior insurance. Also the per capita number of physicians is negatively correlated with insurance coverage. It is worth noting that per capita income is calculated from HEIS data while percent of population in small cities and physicians are from administrative sources that correspond respectively to 2016and 2011 population census [6].

Deprivation-Level is a variable defined by the Iran ministry of health, which divides districts into five groups based on various factors that, in overal, represent deprivation in terms of

[5]One point, which is worth mentioning here, is that this narrowing down of the gap seems to be as a result of declining utilization in the upper quartiles whereas in the first quartile utilization has been either steady across the two periods (Visit) or it has increased moderately (Treatment). In general, outpatient health care utilization in 2011-2017, with respect to the measures that we adopt in this study, had a declining trend. The reason is not particularly clear to us, but the very poor economic performance of Iran in the past decade might play the key role here.

[6]Unfortunately the occupation title had been dropped from the 2016 census, and we could not get a measure of number of physicians in each district in 2015-2017 period.

access to medical care.

4 Empirical Method

Comparing outcomes for SUIP takers and non-takers is problematic as many factors influence takeup and health outcomes. Uninsured individuals receiving SUIP coverage are different than those who already have insurance. For example, labor regulation requires provision of primary health insurance for workers.

Furthermore, we do not have individual-level data on the intensity of healthcare utilization (e.g. number of doctor visits). Therefore, we analyze the data at district-level. Even at aggregate level we expect SUIP takeup to be correlated with unobservables that affect outcomes.

In order to rely on the quasi-random variation created by the program, we use pre-SUIP insurance coverage interacted by post program years dummy as an instrument for SUIP takeup. SUIP targetted individuals without prior insurance. Therefore, we expect a negative correlation between prior coverage and SUIP takeup. Figure A.1 in the appendix shows that there is indeed a negative correlation between the two. However, in order to have a valid instrument, we need to make sure both relevance and exclusion restriction are satisfied. While the raw correlation is encouraging we need to look partial correlations to test for relevance. Specifically, we run the following first stage regression:

$$\text{SUIP}_{dt} = \psi \text{Post}_t \times \text{Ins}_{d,0} + \xi_t \text{Depr}_d + \zeta \text{Post}_t \times X_d + \alpha_d + \delta_t + \eta_{dt} \tag{1}$$

here SUIP_{dt} shows the percentage of households in district d and year t covered by SUIP program. Post_t is a dummy variable for years after implementation of SUIP. $\text{Ins}_{d,0}$ is the average insurance coverage in district d for the period before SUIP. α_d and δ_t are district and year fixed effects which respectively control for time-invarient district features that influence SUIP takeup and country-wide effects that have a similar impact across districts. We also allow year fixed effects to vary with categories of deprivation level ($\xi_t \text{Depr}_d$) and include interaction of Post_t with three district-level control variables in X_d. The control variables are (i) high income dummy (above median per capita income), (ii) percentage of population residing in cities with less than 20,000 individuals, and (iii) per capita number of physicians (GP and specialists) in 2011. Relevance condition is tested by looking at the significance of ψ.

In the IV estimation process, we use the prediction of SUIP from 1 in the second stage regression specification as follows

$$y_{dt} = \beta\widehat{\text{SUIP}}_{dt} + \lambda_t \text{Depr}_d + \kappa \text{Post}_t \times X_d + \nu_d + \gamma_t + \epsilon_{dt} \tag{2}$$

here y_{dt} is the outcome variable which is either of four healthcare utilization variables or mortality rates for different age groups. $\widehat{\text{SUIP}}_{dt}$ is the predicted SUIP takeup, and the rest of variables are similar to the first stage regression. The coefficient of interest is β which shows the change in the outcome of interest as a result of a one percentage point increase in SUIP coverage holding other variables constant. This causal interpretation is valid when the instrument does not impact outcomes directly or through variables not included as controls. In other words, ϵ_{dt} and $\text{Post}_t \times \text{Ins}_{d,0}$ must be uncorrelated.

Our estimation strategy relies solely on residual variation in SUIP takeup that is correlated with pre-SUIP insurance coverage. Healthcare utilization and mortality might be trending due to gradual improvement in access and economic growth. Furthermore, districts might have persistent gaps in outcomes due to pre-existing disparities. Inclusion of year and district fixed effects would correct for these issues.

Even after controling for district and year fixed effects, we might expect differential trends based on initial endowments. Inclusion of $\lambda_t \text{Depr}_d$ and $\kappa \text{Post}_t \times X_d$ in 1 and 2 address such differential trends as follows. First, districts with low service utilization and poor health might be on a positive trend even without SUIP expansion due to mean-reverting processes or other government interventions. Our specification allows districts with different levels of deprivation to have completely different trends. Second, the interaction of high income dummy with Post_t allows for heterogeneity in outcome trends based on income[7]. Third, Ministry of Health implemented HTP almost at the same time as SUIP. This program targetted cities with a population of less than 20,000 . Therefore, we include the interaction of the Post_t variables with the percentage of population in these cities out of total urban population to control for the likely impacts of HTP. Fourth, we allow for differential trends based on the initial number of physicians (GP and specialists) per capita in district because HTP intended to equalize supply of doctors across districts.

[7]We prefer using this variable instead of including adjusted per capita income of districts for two reasons. First, the size of the samples in smaller districts might not be adequate to find a percise estimate of per capita income in a single year. Second, including annual per capita income induces a bias due to the correlated sampling error between utilization and income in the sample taken from each district.

A final issue in the estimation of SUIP impact is dependency on initial outcomes. Figure 2 shows a negative correlation between changes in infant mortality rates (IMR) and initial IMR[8]. This means that the decline in IMR is faster for districts with higher initial IMR. Since health insurance coverage prior to SUIP is negatively correlated with IMR, the exclusion restriction is violated. Dow and Schmeer (2003) also discuss IMR convergence across Nicaraguan provinces. One approach to address this issue is to control for indicators of development, such as GDP or access to sanitation that might be correlated with IMR. We included similar variables in 2. Another method is to include time trends that vary with initial IMR. This approach effectively allows a differential trend in the outcome variable based on the initial value of that variable. Equation 3 presents this specification

$$y_{dt} = \beta \widehat{\text{SUIP}}_{dt} + \theta \text{Post}_t \times y_{d,0} + \lambda_t \text{Depr}_d + \kappa \text{Post}_t \times X_d + \nu_d + \gamma_t + \epsilon_{dt} \tag{3}$$

here, $y_{d,0}$ denotes the initial value of the outcome variable which is based on the first year of our data (2011). In the estimation of this regression we remove this year to prevent spurious identification. Given that we only have 6 years of data, removing the first year and adding another trend variable reduce statistical power. Therefore, if the results sustain this specification we would have good confidence that the causal effect is estimated.

5 Results

In this section we first look at the impact of SUIP expansion on healthcare utilization. Then we present results for mortality rates for different age groups. Finally, we conduct several robustness checks.

5.1 Healthcare Utilization

Table 2 displays the results of panel fixed effects IV regression estimation of Equation 2. The percentage of the SUIP take-up rate for district c and in years after the start of the

[8]For instance, as a part of this study, we evaluated pattern for changes in IMR for provinces based on their initial values of IMR. Provinces with a higher initial level of IMR are the ones that experienced more reduction in IMR. In addition the results point out there is a negative and statistically significant and negative correlation between the IMR in one year and IMR in the subsequent years.

program has been instrumented by the average coverage rate of primary insurance in 2011-2013 ($Ins\,Cov^{T_0}$). In addition to presenting the estimation results for indicators of healthcare utilization, we have displayed the result of the first-stage regression of our 2SLS estimator.

The results indicate that the program has been quite successful in increasing the utilization of the two outpatient healthcare services (Visit and Treatment). The results in the first two columns indicate that, on average, one percent additional SUIP take-up has been associated with 0.76 and 0.66 percentage point increased in utilization of Visit and Treatment, respectively. Moreover, including additional controls, in columns 5 and 6, substantially intensifies our estimates. The only controlling variable which has both economic and statistical significance, regarding these two variables, is the $Post \times High\,Income$. The estimated coefficient of this variable is positive, which implies that, on average, utilization of these three outpatient services have increased more in wealthy districts relative to the poor ones. The estimated coefficients of the two other controls have the expected signs, but they all fail to find statistical significance at the 95% confidence interval. Our finding that controlling other variables that represent access to healthcare strengthen the estimates of SUIP impact is particularly reassuring since a rival hypothesis for the results of columns 1-2 is that the effects other policies, which aimed to improve the access to healthcare in the deprived districts, are deriving our results. However, we have found that by controlling the factors that represent access to healthcare, the estimates of SUIP impact only intensify further.

The results also suggest that the SUIP had no discernible impact on hospital care use and utilization of dentistry services. For the latter, this result comes as expected, since the primary insurance offers almost no coverage for dentistry services. However, the lack of a significant impact on hospital care requires further scrutiny. We can offer several explanations for this observation. First, as we have discussed in section 2, primary health insurance provides ineffective coverage for services in the inpatient sector. So, it is not surprising to find that the expansion of primary insurance, through the implementation of the SUIP, has been impotent in affecting hospital care use. Second, if the demand for the inpatient services is much more inelastic than outpatient services, finding no evidence of the SUIP impact on this measure would be justified. However, this hypothesis is rejected by the results of Kermani et al. (2008) for the Urban households in Iran, and Manning et al. (1987) in their study of the RAND experiment, where they both calculate comparable elasticities for outpatient and inpatient services. Finally, the third explanation is that the increased utilization of preventive care through expanded utilization of outpatient services has offset the increased hospital care use, caused by the SUIP implementation. Although we are not aware of any evidence on this subject for Iran, the results of Currie and Gruber (1996); Dafny and Gruber (2005); **?**); Trujillo (2003), where all studies find positive impacts of the same magnitude of HIE programs on utilization of inpatient and outpatient care, undermine the possibility of this hypothesis. Therefore, we conclude that the most probable explanation for finding no impact on hospital care use is that primary health insurance provides limited and ineffective coverage for these services in Iran.

5.2 Mortality

Table 3 presents, the IV panel regression results of Equation 3 for IMR and MR 1-4. $Post \times IMR^{2011}$and $Post \times MR^{2011}1-4$ are the variable inserted to control for the initial level of outcomes, to capture the possible effects of convergence. The other controls are defined as same as the last section.

The results indicate that SUIP had a positive impact on the reduction of infant mortality, and this impact has been profound. The estimated result of our preferred specification in column (4) imply that a ten percent SUIP take-up has been, on average, associated with a 1.7 reduction in IMR (per 1000 live births). Moreover, inline with the results for healthcare utilization, including the set of controls and Deprivation-Level dummies magnifiies the estimates. This fairly assures us that our estimates of the impact of the SUIP do not stem from the effects of other simultaneous programs. Another interesting point is that the estimates of column (2) and (4) are very close to each other. This means that our controlling variable are effective to capture the pattern of convergence in IMR, which points out to their efficacy to controll for unequal trends among districts with different levels of development. The estimates of the impact of SUIP on MR 1-4, however, display a different picture. Although all of the estimates are negative, none of them are statistically or even economically significant. Besides, including the set of controls and mortality rate in 2011 do not meaningfully change the results. However, there is still evidence for convergence in moratlity rates in this age group because the estimated coefficients of $Post \times MR^{2011}1-4$ are negative and statistically different from zero. Figure 3 shows the impact of SUIP takeup on mortality rates of age groups older than 4 years. Dots show point estimates for the given age group and the interval is 95 percetn confidence interval. These are estimated from a specification similar to 3. We do not find a significant impact on any of the age groups. We have omitted the estimated impact on 70-74 age group as the confidence interval spans -0.15 to +0.15 but we do not find an impact on the oldest individuals either.

Generally, the results are in line with our expectations and findings of the literature on evaluating the impact of health insurance expansion programs on mortality. Although infant mortality seems to be greatly influenced by the implementation of SUIP, we have found no evidence suggesting this program also affected mortality in other age groups. As it has been frequently discussed in the literature, the absence of impact in mortality rate of the age groups presented in Figure 3is most probably due to the fact that mortality is an extreme and very unlikely event in these age groups, and a considerable portion of mortality in these ages occur for reasons other than health conditions. However, infants are a considerably more vulnerable group and the majority of their deaths happen due to health conditions. Therefore, it is not surprising that we find a significant impact of SUIP on their mortality. This is in line with the findings of J Hanratty (1996); Gruber et al. (2014); Cesur et al. (2017); Pfutze (2014), in advanced and developing countries, that health insurance expansion programs can significantly reduce infant mortality.

5.3 Robustness Analysis and Threats to the Identification

5.3.1 Threats to the Identification

Pre-existing Trends A significant hazard to the validity of results is the possibility of pre-existing trends. In this case, this hazard implies that when we are attributing the change in the outcomes to the initial coverage rate of primary insurance, we might be capturing the effects of a pre-existing trend in which districts with lower primary insurance coverage were experiencing higher growth of healthcare utilization and more reduction in infant mortality. To check for this threat, we investigate the data prior to the introduction of the SUIP to find out whether there has been a correlation between initial coverage rate of primary insurance in one district, and the changes of our intended outcomes, prior to the start of the SUIP.

To investigate the presence of pre-existing trends, we compare the correlation between initial insurance coverage and the change in outcomes (utilization and IMR) in two periods: one in which the SUIP takes place and the one completely prior to it. For Visit and Treatment, we use HEIS data for 2008-2013, hypothetically assuming that 2011-2013 are post-program years. We then estimate the reduced-form regression of Equation 2, and compare the estimates of coefficient of $Post \times InsCov_d^{T_0}$(the instrument in Equation 2) for 2011-2017 (actual SUIP) and 2008-2013 (hypothetical program). For IMR we only have six years of data, therefore, we have to compare two three-years periods: first, 2011-2013, hypothetically assuming that

2013 is post-program year, and, second, 2012,2013 and 2015, in which 2015 is the actual post-program year. Similarly, we compare the estimates of coefficient of $Post \times InsCov_d^{T_0}$(the instrument in Equation 3) for the hypothetical and actual program[9].

The results of this analysis are presented in Table 4. For Visit and Treatment, the estimated coefficients for the period of the SUIP introduction are **negative** and significantly different from zero. However, estimated coefficients for the period of the prior to the SUIP introduction, are all **positive** and statistically significant. This result points out the presence of divergent trends in healthcare utilization. This means, in 2008-2013, districts with higher initial primary insurance coverage had, on average, increased their utilization of healthcare services relative to the districts with lower coverage. This finding explains why we find considerably larger estimates of SUIP impact when we include the set of controls and $Year \times DepLevel$ fixed effects in section 5.1. This happens because controlling for these variables disentangles the downward trend in healthcare utlization of deprived counties, which also had lower insurance coverage, from the impact of SUIP.

For IMR, the estimated coefficient of $Post * Inscov^0$ is positive and statistically significant, when we consider the period of the actual program. In line with our main results, this finding indicates that, controlling for other factors, IMR in districts with **lower** initial insurance coverage has **reduced** relative to districts with higher initial insurance coverage, and we attribute this finding to the impact of SUIP. However, we find no significant correlation between initial insurance coverage and change in IMR in hypothetical post-program year (2013), which rules out the possibility of pre-existing trends between these variables.

5.3.2 Population Cutoffs

So far, we have only studied the districts with urban population>50,000, in 2011, due to the scarcity of observations in the HEIS in smaller districts. However, it is important to evaluate the sensitivity of the results to this threshold. The results, estimated from considering different thresholds are displayed in Table 5. The upshot is that the results do not show sensitivity to imposing various thresholds.

[9] We forgo including initial IMR to control for the possibility of convergence because we only have 3 years of data for each regression and controlling for this issue requires elimination of the first years in each period. However, since the results of Table 3 show that including initial IMR into the regression does not considerably changes the estimated coefficient of SUIP impact once we have included the set of controls, we are not concerned about this issue.

5.3.3 Contemporaneous Shocks

The other threat to the validity of our results derives from the possible effects of contemporaneous shocks that could have affected the outcomes of this study, and were correlated with the initial coverage of primary insurance. The only possible candidate which we think is capable of creating a serious threat is the "Health Transformation Plan"(HTP). Although the HTP and the SUIP originate from different legislation, they were both implemented at the same time. The HTP concerned all public hospitals in the country, and its goal was to improve the supply of inpatient and outpatient healthcare services, provide financial support for the hospitalized patients and patients with refractory diseases, and to promote vaginal delivery. Nonetheless, we have discussed more details of the HTP in the appendix.

Although the simultaneous execution of the HTP might have reinforced the impact of the SUIP, there are several reasons to believe that the results have not been deriven by the implementation of the HTP. First, the impact of the HTP on the outcomes of this study does not seem to be directly correlated with the coverage of primary insurance in years prior to its introduction. However, an indirect correlation, through the general level of access to healthcare in districts, might exist between these variables. The focus of the HTP was to improve access to healthcare in deprived districts, and the additional controls that we have used in estimations (Deprivation-Levels, High_Income dummy, Fraction U20, and per capita number of physicians) could all be considered as indicators for the level of access to healthcare. So, paying attention to how their incorporation into the estimations changes the results might be insightful in this regard. Considering the results in Table 2 and Table 3, we observe their inclusion does not reduce the estimated impact of SUIP. Instead it almost doubles the impact suggesting presence of a downward bias due to other confounding deprivations. In addition, the estimated coefficients of these controls, except High_Income dummy (which is positive!), are rarely statistically or economically significant. The insignificance of these variables display that the indirect link between initial coverage of primary insurance and the size of the HTP impact, through the initial level of access to healthcare, is too weak to be a source of concern.

Moreover, when we consider larger urban population cutoffs, we observe that the estimated effect of a one additional percentage of the SUIP take_up on the changes of outcomes (utilization and infant mortality) varies minimally. By restricting the number of districts to the more populated ones, we are excluding a set of more deprived districts from our primary sample. This exclusion would have probably resulted in much greater volatility in the results, if the correlation between the SUIP take-up with the magnitude of improvements in outcomes had been mostly caused by the HTP.

6 Conclusion

In this paper, we have investigated the consequences of implementing a major health insurance expansion program (SUIP) in Iran, on various measures of healthcare utilization and mortality rates of different age groups. Our cross-district analysis demonstrates that the program was successful in promoting access to outpatient healthcare utilization. However, the program did not have any discernible impact on hospital care use. We attribute this finding to the fact that primary health insurance in Iran provides ineffective coverage for inpatient services. Our analysis also reveals that SUIP had an important role in reducing infant mortality. However, we found no evidence supporting that mortality rates of other age groups have also decreased as a result of SUIP. The results display robustness toward changing the sample of districts. Besides, we discovered that pre-existing trends in utilization and IMR across districts cannot be responsible for our estimates on the impact of SUIP. We have also discussed why we do not believe that simultaneous effects of other programs have been driving our results. However, there is no denying that these programs could have reinforced the impact of SUIP.

Based on our study, we can address several issues that might be of importance from the academic and policymaking perspective. First, although near-universal and universal health insurance expansion programs might have an advantage over targeted programs in attracting the pool of uninsured population and improving the general access to healthcare and health outcomes of the public, their tremendous and highly unpredictable costs pose a serious threat to the sustainability of the program. SUIP experience in Iran provides an example in this case, as the government had significantly underestimated the number of individuals that would seek SUIP coverage. This resulted in facing level of costs were well above the initial expectation of the government.Consequently, the government was forced to set back from the promise of providing free health insurance for all the uninsured.

Second, in line with the majority of the literature, we find that health insurance expansion programs can improve the utilization of healthcare if insurance provides sufficient coverage for the costs of these services. In Iran, primary insurance, although it seems to have a generous coinsurance rate, offers limited and capped coverage for inpatient healthcare expenses. Therefore, it is not surprising to find out that SUIP did not have a discernible impact on the utilization of inpatient healthcare. A similar situation might arise in other low and middle-income countries, where insurance funds might formally or informally restrict their coverage in many ways. Consequently, it seems important to consider whether insurance provides reasonable coverage for healthcare expenses before evaluating the effectiveness of an insurance expansion program.

Finally, our finding that SUIP had substantially reduced IMR corroborates with the finding of other studies that investigate the impact of health reform programs on infant mortality. Besides, our inability to find a discernible impact of SUIP on the mortality rate of other age groups is not surprising. Mortality is the most extreme outcome, which is quite rare among the majority of age-groups. Therefore, we should not conclude that our finding that SUIP had no significant impact on the mortality rate of these age groups means that it did not improve the health outcomes of this population. However, we believe that further research is required to investigate why IMR tends to be substantially affected by health reform programs. Specifically, it should be figured out what kind of health conditions that are behind infant mortality, tend to be largely reduced by expanding health insurance coverage. The answer to this question might be of extreme importance from the public health policy perspective.

References

Arnab Acharya, Sukumar Vellakkal, Fiona Taylor, Edoardo Masset, Ambika Satija, Margaret Burke, and Shah Ebrahim. The impact of health insurance schemes for the informal sector in low-and middle-income countries: a systematic review. *The World Bank Research Observer*, 28(2):236–266, 2012. ISSN 1564-6971.

Elham Ahmadnezhad, Zhaleh Abdi, and Seyed Reza Majdzadeh. *Assessment of Health System toward Universal Health Coverage*, book section 8, pages 149–161. National Institute for Health Research, Iran, 2017.

Sebastian Bauhoff, David R Hotchkiss, and Owen Smith. The impact of medical insurance for the poor in georgia: a regression discontinuity approach. *Health economics*, 20(11): 1362–1378, 2011. ISSN 1057-9230.

Noelia Bernal, Miguel A Carpio, and Tobias J Klein. The effects of access to health insurance: evidence from a regression discontinuity design in peru. *Journal of Public Economics*, 154: 122–136, 2017. ISSN 0047-2727.

Resul Cesur, Pinar Mine Gunes, Erdal Tekin, and Aydogan Ulker. The value of socialized medicine: The impact of universal primary healthcare provision on mortality rates in turkey. *Journal of Public Economics*, 150:75–93, 2017. ISSN 0047-2727.

Janet Currie and Jonathan Gruber. Health insurance eligibility, utilization of medical care, and child health*. *The Quarterly Journal of Economics*, 111(2):431–466, 1996. ISSN 0033-5533. doi: 10.2307/2946684. URL `https://doi.org/10.2307/2946684`.

Leemore Dafny and Jonathan Gruber. Public insurance and child hospitalizations: access and efficiency effects. *Journal of Public Economics*, 89(1):109–129, 2005. URL `https://EconPapers.repec.org/RePEc:eee:pubeco:v:89:y:2005:i:1:p:109-129`.

William Dow and Kammi Schmeer. Health insurance and child mortality in costa rica. *Social science & medicine (1982)*, 57:975–86, 2003. doi: 10.1016/S0277-9536(02)00464-1.

Darius Erlangga, Marc Suhrcke, Shehzad Ali, and Karen Bloor. The impact of public health insurance on health care utilisation, financial protection and health status in low-and middle-income countries: A systematic review. *PloS one*, 14(8), 2019.

Ursula Giedion, Eduardo AndrÃ©s Alfonso, and Yadira DÃaz. *The impact of universal coverage schemes in the developing world: a review of the existing evidence*. World Bank, Washington, DC, 2013.

Zahra Goudarzi, Mohammad R. Mobinizadeh, Alireza Olyaee Manesh, Mussa Tabatabaei, and Saied Maanavi. *Health System Financing in Iran*, book section 3, pages 56–82. National Institute for Health Research, Iran, 2017.

Jonathan Gruber, Nathaniel Hendren, and Robert M. Townsend. The great equalizer: Health care access and infant mortality in thailand. *American Economic Journal: Applied Economics*, 6(1):91–107, 2014. doi: 10.1257/app.6.1.91. URL `http://www.aeaweb.org/articles?id=10.1257/app.6.1.91`.

Zhiyuan Hou, Ellen Van de Poel, Eddy Van Doorslaer, Baorong Yu, and Qingyue Meng. Effects of ncms on access to care and financial protection in china. *Health economics*, 23(8): 917–934, 2014. ISSN 1057-9230.

Maria J Hanratty. Canadian national health insurance and infant health. *American Economic Review*, 86:276–84, 1996.

Majid S Kermani, Hossein Ghaderi, and Ayoub Yousefi. Demand for medical care in the urban areas of iran: an empirical investigation. *Health economics*, 17(7):849–862, 2008. ISSN 1057-9230.

Gary King, Emmanuela Gakidou, Kosuke Imai, Jason Lakin, Ryan T Moore, Clayton Nall, Nirmala Ravishankar, Manett Vargas, Martha Maria Tellez-Rojo, and Juan Eugenio Hernandez Avila. Public policy for the poor? a randomised assessment of the mexican universal health insurance programme. *The lancet*, 373(9673):1447–1454, 2009. ISSN 0140-6736.

Willard G. Manning, Joseph P. Newhouse, Naihua Duan, Emmett B. Keeler, and Arleen Leibowitz. Health insurance and the demand for medical care: Evidence from a randomized experiment. *The American Economic Review*, 77(3):251–277, 1987. ISSN 00028282. URL `http://www.jstor.org/stable/1804094`.

Tobias Pfutze. The effects of mexico's seguro popular health insurance on infant mortality: An estimation with selection on the outcome variable. *World Development*, 59:475–486, 2014. ISSN 0305-750X.

Neeraj Sood, Eran Bendavid, Arnab Mukherji, Zachary Wagner, Somil Nagpal, and Patrick Mullen. Government health insurance for people below poverty line in india: quasi-experimental evaluation of insurance and health outcomes. *Bmj*, 349:g5114, 2014. ISSN 1756-1833.

Rebecca L Thornton, Laurel E Hatt, Erica M Field, Mursaleena Islam, Freddy SolÃs Diaz, and Martha Azucena GonzÃ¡lez. Social security health insurance for the informal sector in nicaragua: a randomized evaluation. *Health economics*, 19(S1):181–206, 2010. ISSN 1057-9230.

Antonio J Trujillo. Medical care use and selection in a social health insurance with an equalization fund: evidence from colombia. *Health economics*, 12(3):231–246, 2003. ISSN 1057-9230.

A Wagstaff, M Lindelow, G Jun, X Ling, and Q Juncheng. Extending health insurance to the rural population: an impact evaluation of china's new cooperative medical scheme. *Journal of health economics*, 28(1):1, 2009. ISSN 0167-6296.

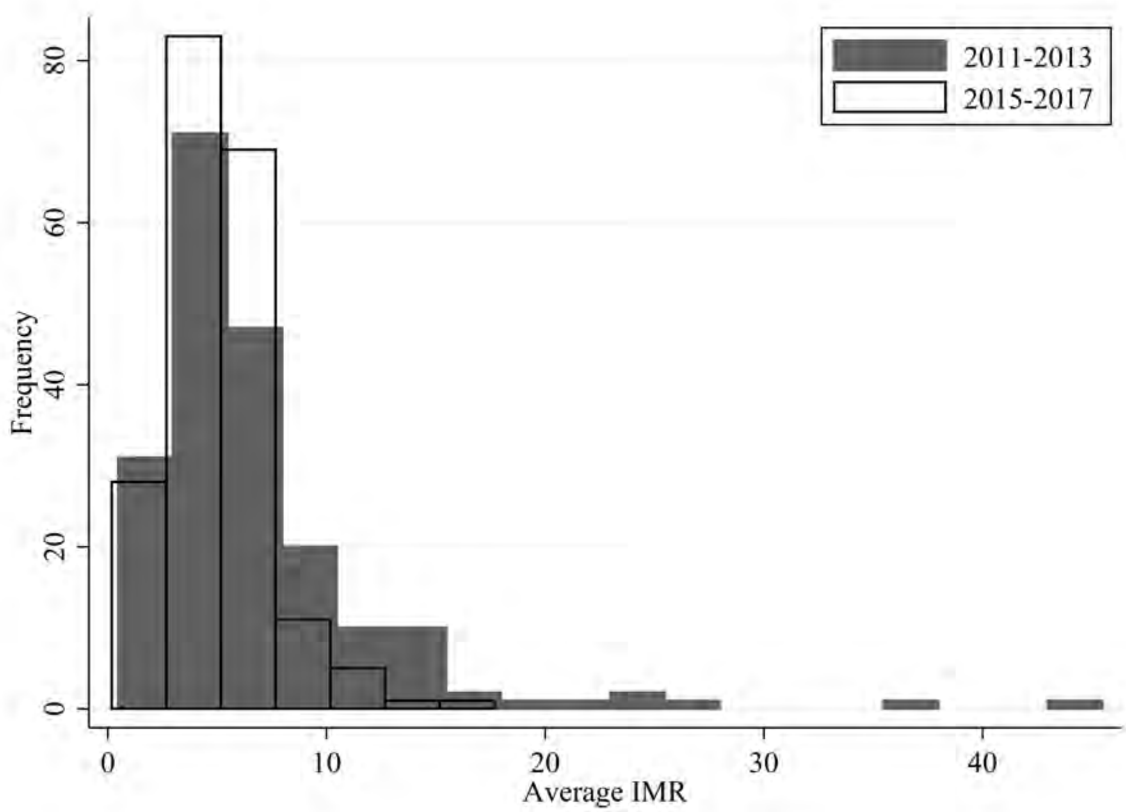

Figure 1: Distribution of infant mortality rate before and after SUIP

Note: Figure presents histgram of average infant mortality rates for 183 districts, in two periods, 2011-2013 (before SUIP) and 2015-2017 (after SUIP).

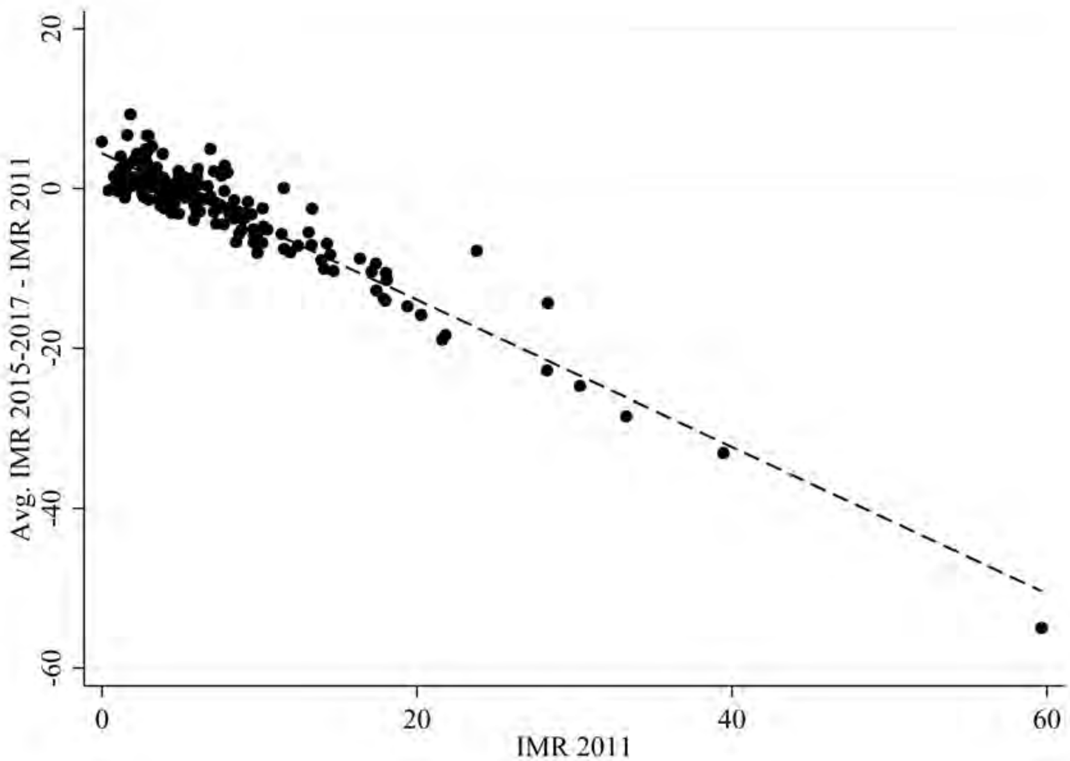

Figure 2: Relation between changes in IMR and initial IMR

Note: Figure shows the correlation between change in IMR and its initial level. The Y-axis is the difference between average IMR in 2015-2017 and the IMR in 2011. The X-axis is IMR in 2011. Mortality rates are reported per 1000 registered births.

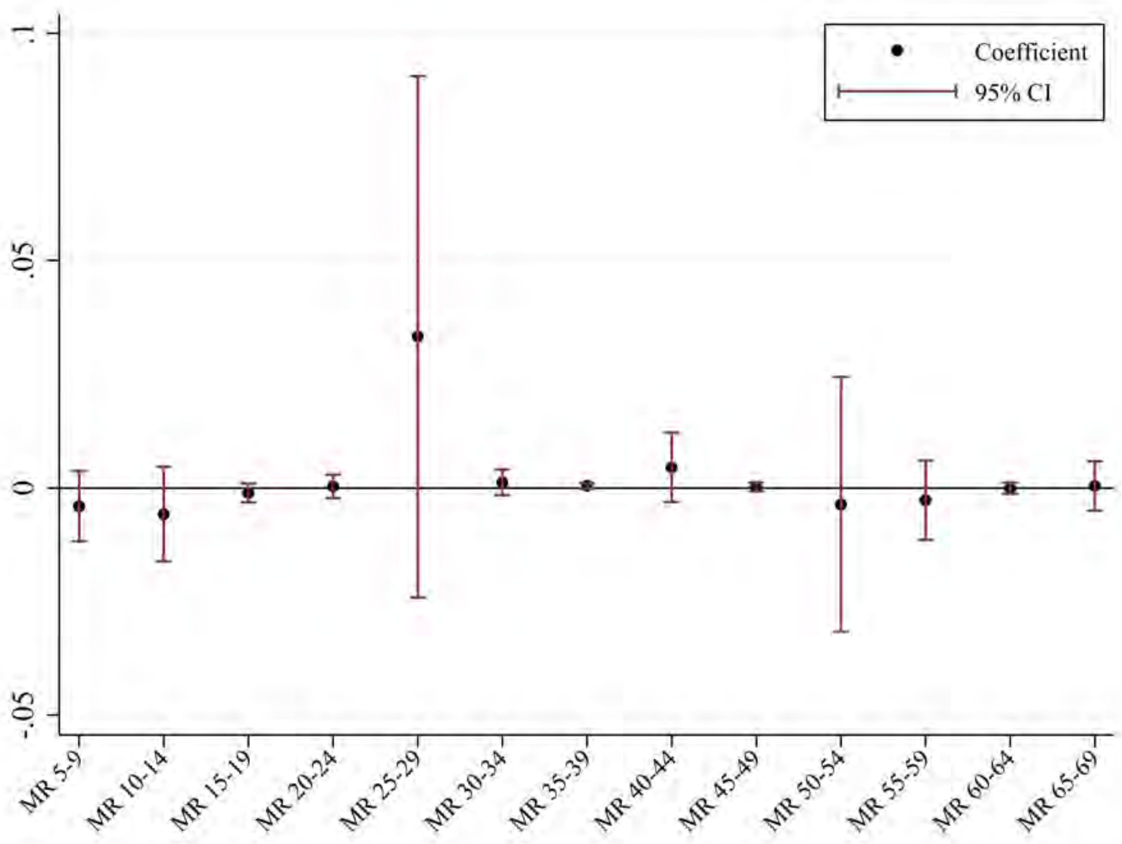

Figure 3: Impact of SUIP on Mortality Rates of Various Age Groups

Note: The figure presents the estimated coefficients and their corresponding confidence intervals of the impact of SUIP on mortality rate of various age groups. SUIP take-up is measured in percentage of the population who have enrolled in the program, and mortality rates are expressed per 1000 population of that age group.

Table 1: Summary Statistics

	Before (2011-2013)					After (2015-2017)				
Quart. health insurance (2011-2013)	q1	q2	q3	q4	All	q1	q2	q3	q4	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Insurance coverage										
Insurance coverage	52	68	75	84	70	78	86	87	90	85
	(1.60)	(0.33)	(0.32)	(0.56)	(0.96)	(2.8)	(1.4)	(1.2)	(0.97)	(0.93)
SUIP Take-up	-	-	-	-	-	28	22	18	15	21
	-	-	-	-	-	(1.9)	(1.2)	(1.4)	(1.1)	(0.79)
Panel B: Healthcare utilization										
Visit	42	48	55	57	51	42	45	49	44	45
	(2.1)	(2.0)	(1.5)	(2.0)	(1.1)	(2.5)	(2.1)	(1.7)	(2.5)	(1.1)
Treatment	51	61	67	67	61	55	62	63	59	60
	(2.5)	(2.2)	(1.4)	(2.0)	(1.1)	(2.6)	(2.4)	(1.8)	(2.5)	(1.2)
Hospital Care	13	14	15	13	14	16	18	18	17	17
	(1.0)	(1.2)	(0.95)	(0.81)	(0.5)	(1.1)	(1.0)	(1.2)	(1.1)	(0.55)
Dentistry	5.6	6.2	7.3	6.0	6.3	4.3	6.3	6.6	6.7	6
	(0.67)	(0.76)	(0.61)	(0.67)	(0.34)	(0.49)	(0.57)	(0.74)	(0.87)	(0.34)
Panel C: Health outcome										
IMR	5.9	7.8	6.4	6.6	6.7	4.2	5.7	4.5	5.7	5.0
	(0.67)	(0.93)	(0.60)	(0.68)	(0.37)	(0.35)	(0.38)	(0.27)	(0.39)	(0.18)
MR 1-4	0.81	0.86	0.71	0.9	0.82	0.60	0.69	0.59	0.63	0.63
	(0.07)	(0.05)	(0.06)	(0.07)	(0.03)	(0.06)	(0.05)	(0.05)	(0.06)	(0.03)
Panel D: Other variables										
Real per capita income	2.1	2.3	2.6	2.5	2.4	2.3	2.4	2.7	2.7	2.5
	(0.06)	(0.08)	(0.07)	(0.07)	(0.04)	(0.08)	(0.09)	(0.10)	(0.10)	(0.047)
% Population in small cities (<20,000)	-	-	-	-	-	9.2	15	15	22	15
	-	-	-	-	-	(1.7)	(2.1)	(2.6)	(2.7)	(1.2)
Physician per 10000 population	3.6	4.1	6.4	5.3	4.9	-	-	-	-	-
	(0.35)	(0.40)	(0.72)	(0.56)	(0.27)	-	-	-	-	-
No of districts	46	46	46	45	183	46	46	46	45	183

Note: The table displays means and standard errors of selected variables for four groups of districts. districts are divided into quartiles by their average insurance coverage in 2011-2013. Insurance Coverage and SUIP Take-up is the percentage of the population with any primary insurance and SUIP insurance, respectively. Visit and Treatment show percentage of the population who have utilized these services in the past month. Hospital Care denotes the percentage of the population having inpatient services utilization in the past year. IMR represents infant mortality rate in 1000 live births. % Population in small cities is obtained from the results of 2016 census. Real per capita income is reported in 2011 ten million Rials.

Table 2: IV Regression Results of Impact on Healthcare Utilization

VARIABLES (%)	Visit	Treatment	Hospital	Visit	Treatment	Hospital	Dentist	SUIP Take-UP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SUIP Take-up (%)	0.755***	0.658**	-0.0558	1.506**	1.280**	0.007	-0.008	
	(0.278)	(0.268)	(0.114)	(0.609)	(0.561)	(0.197)	(0.115)	
$Post \times High\,Income$				13.06***	9.951***	2.958*	1.374	-2.302
				(3.979)	(3.547)	(1.542)	(1.010)	(1.402)
$Post \times Percentage\,U20$				0.400*	0.330*	-0.050	0.0676*	-0.256***
				(0.213)	(0.195)	(0.074)	(0.0376)	(0.040)
$Post \times pc\,Physicians$				0.0276	0.267	-0.255	-0.0189	-0.489**
				(0.585)	(0.564)	(0.199)	(0.131)	(0.191)
$Post \times Ins.Cov^0$								-0.263***
								(0.066)
Observations	1,098	1,098	1,098	1,098	1,098	1,098	1,098	1,098
Number of districts	183	183	183	183	183	183	183	183
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Dep FE	No	No	No	Yes	Yes	Yes	Yes	Yes

Note: Table presents panel fixed-effects IV regression estimation of Equation 2. The SUIP Take-up is the percentage of households under the SUIP coverage in year t after the program. In all specifications, the SUIP Take-up rate has been instrumented by the average primary insurance coverage in the 2011-2013 period. The results of the first-stage regression of this 2SLS IV regression is presented in column (9). Cluster robust standard errors has been reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3: Impact of SUIP on Mortality

Variables	IMR (per 1000 births)				MR 1-4 (per 1000 population)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SUIP Take-UP(%)	-0.034	-0.162*	-0.079**	-0.167**	-0.003	-0.007	-0.004	-0.007
	(0.036)	(0.098)	(0.033)	(0.080)	(0.006)	(0.012)	(0.006)	(0.012)
$Post \times IMR^{2011}$			-0.361***	-0.359***				
			(0.041)	(0.044)				
$Post \times MR^{2011} 1-4$							-0.160**	-0.151*
							(0.073)	(0.082)
Observations	915	915	915	915	915	915	915	915
Number of districts	183	183	183	183	183	183	183	183
Year FE	X	X	X	X	X	X	X	X
Year×Dep FE	-	X	-	X	-	X	-	X
Controls	-	X	-	X	-	X	-	X

Note: The table presents regression results of the impact of the SUIP on infants mortality rate (IMR), expressed per 1000 registered births. SUIP Take-UP is the percentage of population under the coverage of the SUIP in years after the program started. The set of controls are $Post \times High\,Income$, $Post \times Percentage\,U20$,and $Post \times pc\,Physicians$. Cluster robust standard errors has been reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: Investigating Pre-existing Trends in Utilization

VARIABLES	Visit	Treatment	IMR	Visit	Treatment	IMR
	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Program			Hypothethical Program		
$Post * Ins\, Cov^{T_0}$	-0.373***	-0.307***	0.0506**	0.182**	0.181**	0.0182
	(0.117)	(0.110)	(0.0241)	(0.0794)	(0.0799)	(0.0338)
Observations	1,098	1,098	549	1,092	1,092	1,092
R-squared	0.121	0.053	0.118	0.121	0.076	0.084
Number of districts	183	183	183	182	182	183
Year FE	X	X	X	X	X	X
Year*Dep FE	X	X	X	X	X	X
Controls	X	X	X	X	X	X

Note: Table presents the fixed effects panel regression results for the correlation between initial insurance coverage and outcomes of interest for the period in which SUIP is implemented and a period completely prior to it. $Ins\, Cov^{T_0}$ denotes the percentage of primary insurance coverage in the base period. The set of controls are $Post \times High\, Income$, $Post \times Percentage\, U20$,and $Post \times pc\, Physicians$. Cluster robust standard errors has been reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: Comparing the Estimated Impact of the SUIP for Different districts Population Cutoffs

Variable	Visit	Treatment	Hospital	Dentist.	IMR
	(2)	(3)	(4)	(5)	(6)
Panel A: Urban Population>50,000					
SUIP Take-UP(%)	1.506**	1.280**	0.007	-0.008	-0.167**
	(0.609)	(0.561)	(0.197)	(0.115)	(0.0805)
Number of districts	183	183	183	183	182
Panel B: Urban Population>75,000					
SUIP Take-UP(%)	1.226**	1.295***	0.030	0.073	-0.134**
	(0.507)	(0.495)	(0.155)	(0.116)	(0.0667)
Number of districts	123	123	123	123	123
Panel C: Urban Population>100,000					
SUIP Take-UP(%)	1.620***	1.685***	0.042	0.065	-0.158*
	(0.626)	(0.638)	(0.148)	(0.153)	(0.0873)
Number of districts	98	98	98	98	98
Panel D: Urban Population>100,000 & <1,000,000					
SUIP Take-UP(%)	1.408**	1.503***	-0.054	0.048	-0.149*
	(0.570)	(0.575)	(0.141)	(0.144)	(0.0805)
Number of districts	90	90	90	90	90

Note: The controls used in all of the specifications are year fixed effects, year and Deprivation-Levels interactions, $Post \times High\,Income$, $Post \times Percentage\,U20$,and $Post \times pc\,Physicians$. IMR in 2011 have also been controlled in Column (8), and subsequently 2011 has been excluded from the panel regression of this specification .Cluster robust standard errors has been reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

A Online Appendix

A.1 Description of SUIP

Concerned of affordability of health insurance to poorer citizens, Iranian government aimed to provide affordable health insurance with substantial subsidies for the population. Consequently two major programs were introduced to achieve this goal. The first program, implemented in 2005, provided free health insurance for the entire rural population and residents of small cities. As a result, health insurance coverage in rural areas increased substantially so that by 2010 more than 92% of the rural population had health insurance coverage. The second program, the Salamat Universal Insurance Program (SUIP), was launched in 2014. Its aim was to provide free primary health insurance coverage for every Iranian who had not been under insurance coverage.

SUIP had a fairly simple registration with two step. In the first step, heads of households had to register for the program on a designated website. After online registration, in the second step, they had to attend a public services office to handout the identification requirements and fill out the required forms. Charges required for the registration were small, less than 1$ for each individual. Since the rural population and residents of small cities with less than 20,000 population had been previously covered by free rural insurance, SUIP was most influential in expanding primary health insurance coverage for the urban population. Subsequently, reports express that primary insurance coverage, among the urban population, rose from 76.4% in 2010 to more than 90% in 2015 . Our data, from Salamat Insurance Organization, for 2015-2017, show that roughly ten million individuals have been under cover of Salamat insurance. However, due to the lack of a solid database for identifying enrollees who had other primary insurances, multi-insurance coverage was a key issue.

In Iran, the health insurance system is made of two levels, primary health insurance, and complementary health insurance. Primary health insurance is usually acquired through employment. The fees and the details of coverage are regulated by the government, and there are mainly a few large primary insurance providers, typically associated with the public sector. Primary insurance covers roughly 70% of the expenses in the public outpatient services and 90% of it in the public inpatient services. The co-payment rate in the private health sector is the same but with the cap of payment in equivalent public services. Charges in both public and private sector are set each year by the government[10], and the prices in the private sector

[10] Iran's the fifth five-year plan of development, Chapter 3, Article 38

are considerably higher (more than twice for the outpatient services). However, because there are many costly services, especially in inpatient and Para-clinical sector, which are excluded from primary insurance coverage, primary insured individuals can contract complementary insurance providers (mainly through their employer) to provide insurance cover for additional services.

The number of enrollees in the Salamat insurance was much more than the government had initially anticipated. Therefore, the costs of providing free insurance for more than ten million people created substantial financial difficulties for the government. Trying to keep down the expenses, the government decided to restrict the Salamat insured people to seek care from the public sector in November 2017 (which overlap the last six months of our study period). Finally, in March 2018 (not included in our study period), the government decided to provide free insurance only to those who could prove themselves needy and gave a 50% discount in primary health insurance fees to the rest[11] .

A.2 Description of HTP

The Salamat insurance, although originated differently and years earlier, was launched simultaneously with another major health reform plan. The "Health-Sector Transformation Plan" (HTP) contained seven programs to improve the supply side of public health sector in Iran.[12]. Three of these programs aimed to improve the access and quality of services delivered in public hospitals across the country. Specifically, their targets were reducing out-of-pocket expenditures, improving the quality of hostelling services, and increasing number of in-call specialists in public hospitals. Another one's goal was to improve financial protection to the patients with special and hard-to-cure diseases such as MS and hemophilia. One other program was aiming to promote vaginal delivires by providing incentives for the mothers and doctors to disregard C-section in favor of a vaginal delivery.

The last two programs might have more relevance with the outcomes of our study. One program aimed to improve the quality of outpatient visits in public hospitals, and the other one intended to encourage specialist to stay in the public hospitals in deprived areas permanently. The former program, was implemented uniformly across the country, and, after allowing for seperate trends in outcomes based on variables that are correlated with access to healthcare

[11]Act 37991/54048 of council of ministers in 2017/06/24

[12]Iran ministry of health, The set of instructions for the health sector reform plan, Administrative version 1.00

(income, number of physicians, and Deprivation-Level) we are not much concerened that this program can invalidate our IV approach. In the latter case, the Ministry of Health defined the Deprivation-Level variable to assign specialists to public hospitals in the deprived areas. Five categories were defined where one category considered to be not deprived, and therefore, ruled out of the program. For the others, incentive packages were designed to encourage doctors to join the program. Unfortunately, we don't have the data on the actual assignment of doctors, but, we try to address this issue with considering separate trends for each category of Deprivation Level.

A.3 Further results

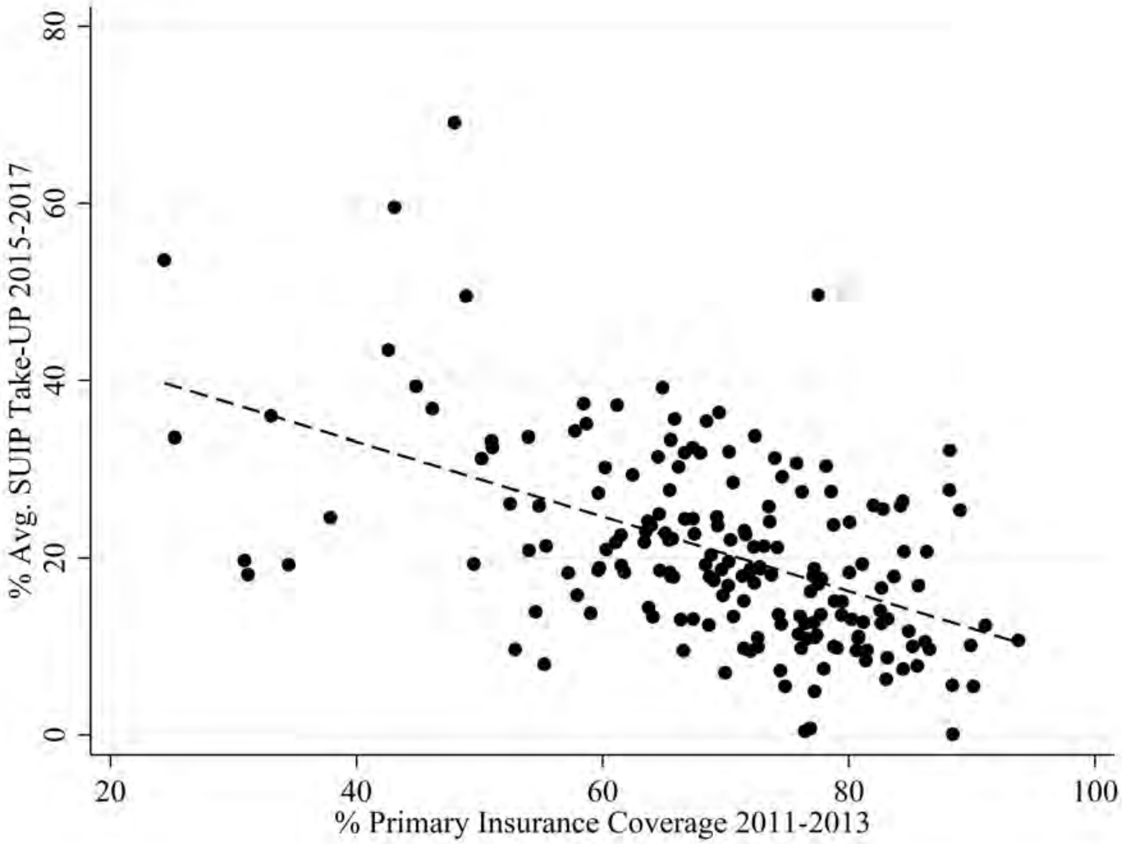

Figure A.1: Relation between SUIP coverage and pre-SUIP insurance coverage

Note: The graph plots average SUIP Take-up rate in the post SUIP years versus average prime insurance coverage in the pre SUIP period.

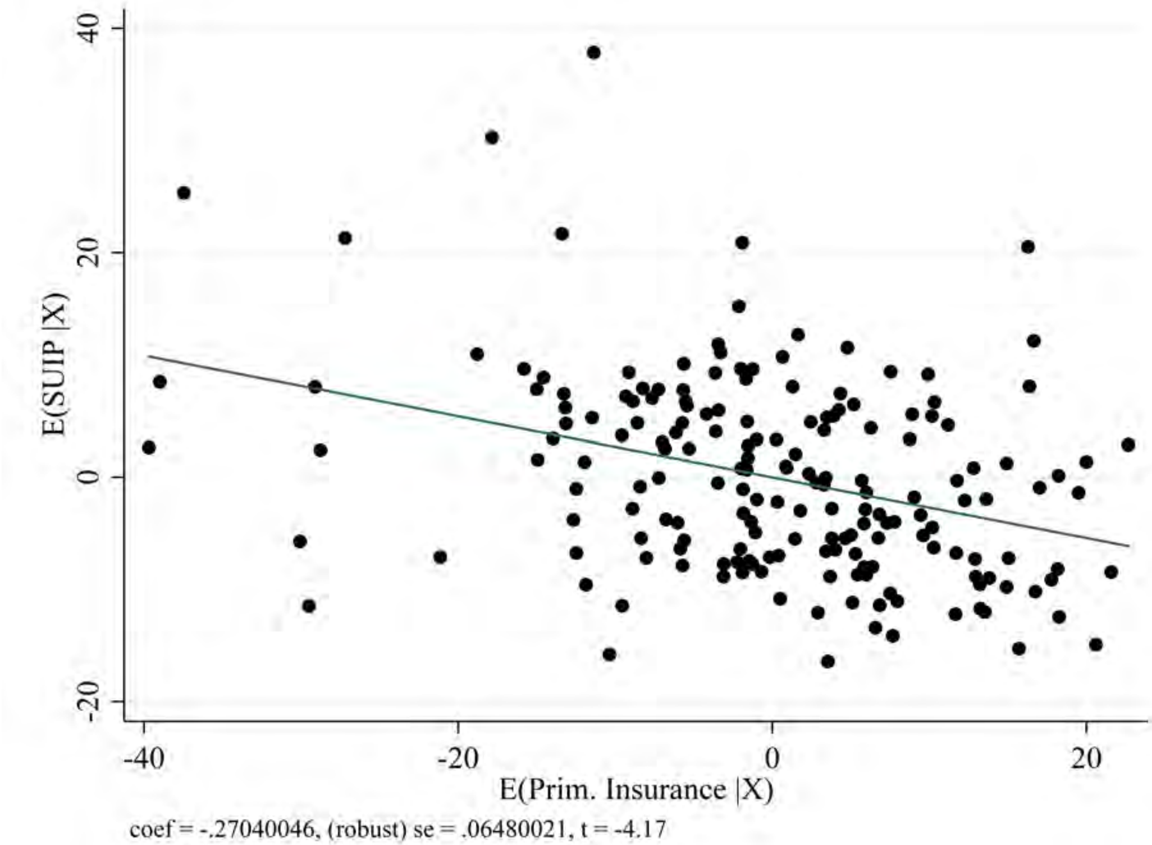

Figure A.2: Partial Correlation Plot

Note: The graph presents the partial correlation plot between average SUIP take-up(%) in 2015-2017 and average primary insurance coverage (%) in 2011-2013. Controls are High_Income dummy, percentage living in cities<20,000 population, and per capita number of physicians in 2011.

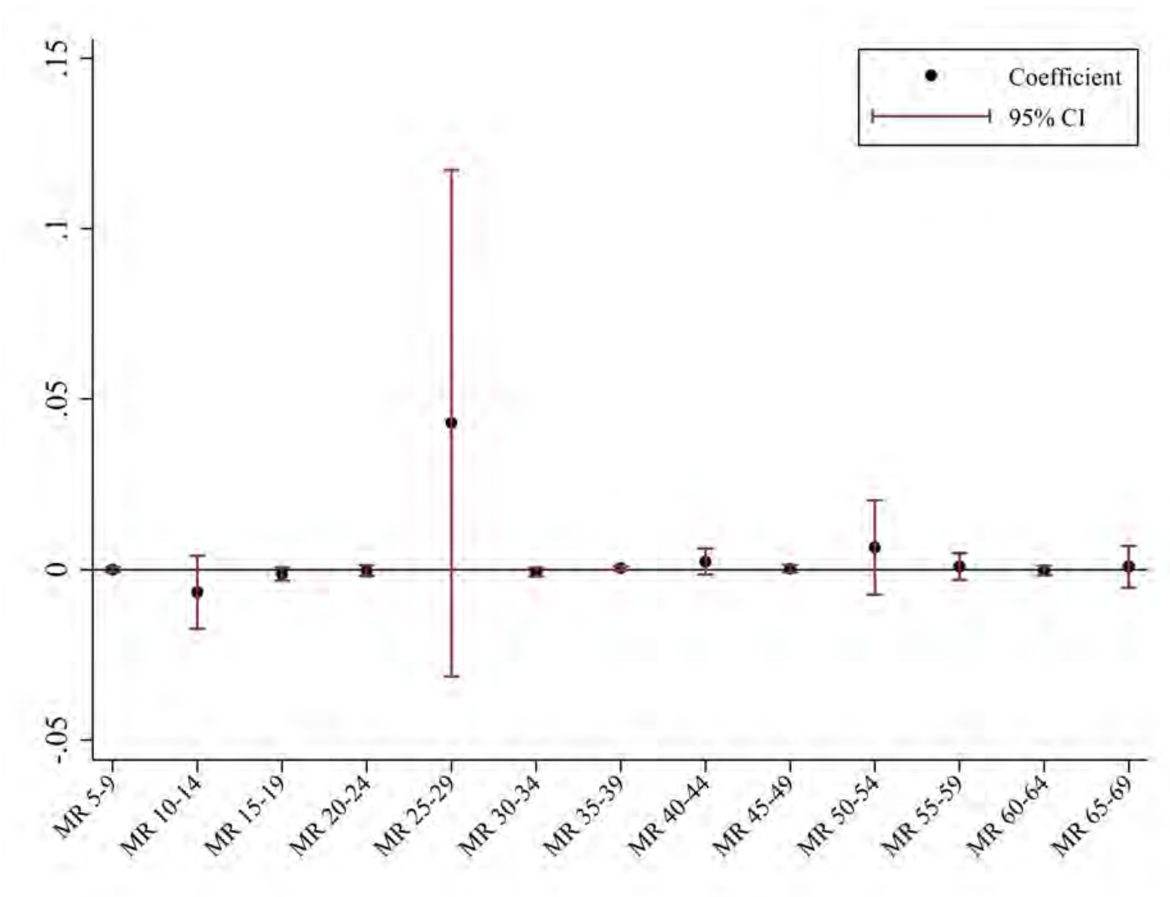

Figure A.3: Impact of SUIP on Mortality Rates of Various Age Groups_(pre MR controlled)
Note: Impact of SUIP on the mortality rates of other age groups, controlled by 2011's mortality rate.

Table 6: Results for Hospitalization

	OLS with controls				IV with controls			
Sample(population)	All	>75k	>100k	100k-1000k	All	>75k	>100k	100k-1000k
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SUIP Takeup	-0.198***	-0.141**	-0.149**	-0.157**	0.007	0.030	0.042	-0.054
	(0.068)	(0.067)	(0.075)	(0.077)	(0.197)	(0.155)	(0.148)	(0.141)
$Post \times High\,Income$	2.161	3.038**	3.205**	1.422	2.958*	3.512**	3.913**	1.716
	(1.405)	(1.479)	(1.585)	(1.714)	(1.542)	(1.509)	(1.593)	(1.726)
$Post \times Percentage\,U20$	-0.116***	-0.059	-0.030	-0.027	-0.050	0.004	0.042	0.012
	(0.038)	(0.059)	(0.074)	(0.071)	(0.074)	(0.086)	(0.102)	(0.092)
$Post \times pc\,Physicians$	-0.391***	-0.503***	-0.451***	-0.372*	-0.255	-0.399**	-0.339	-0.300
	(0.147)	(0.149)	(0.171)	(0.221)	(0.199)	(0.189)	(0.207)	(0.254)
Observations	1,098	738	588	540	1,098	738	588	540
NO. Districts	183	123	98	90	183	123	98	90
R-squared	0.063	0.012	0.113	0.026	0.112	0.041	0.142	0.051
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year×Dep FE	No	No	No	No	Yes	Yes	Yes	Yes