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Expanding Health Insurance for the Elderly of the Philippines

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Abstract

The Philippines expanded health insurance coverage of its senior citizens, aged 60 and older, in 2014. Employing data from two separate sources, we find that the expansion increased insurance coverage by approximately 16 percentage points. Instrumental variables estimates indicate that out-of-pocket medical expenditures more than doubled among the newly insured. We argue that this is most likely driven by an outward shift in the medical demand curve due to physician-induced demand. Quantile regression estimates indicate that these effects were the most pronounced among high utilizers. We show that the compliers, defined as those induced by the policy to obtain insurance, are disproportionately female and largely from the middle of the socioeconomic distribution. Finally, tests for selection indicate only moderate adverse selection into the treatment.

Key Words: Insurance, Medical Demand, Compliers, Philippines

JEL Codes: I10, I13, I14

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1 Introduction

There is a large, well-established literature that investigates how health insurance affects health-related decisions and outcomes in developed countries (Card et al., 2008; Manning et al., 1987; Shigeoka, 2014; Levy and Meltzer, 2008; Finkelstein et al., 2012). As low- and middle-income countries begin to establish and expand their various nationally-sponsored health insurance programs, we have seen the rapid emergence of a similar literature that focuses on the developing world. For excellent reviews, see Giedion et al. (2013) and Acharya et al. (2012). The vast majority of programs in developing countries, however, have targeted the poor, which means that little is known about how health insurance affects people from higher up in the socioeconomic distribution of low and middle income countries.[1]

Notably, it is also the case that very few programs make special provisions for the elderly, a vulnerable group who face frequent and often serious health shocks. One exception is the 2014 Expanded Senior Citizens Act (ESCA) in the Philippines, which granted free health insurance to all individuals aged 60 and older. This policy provides us with the unique opportunity to study the effects of heath insurance for the elderly in a lower-middle-income country. Unlike their counterparts in rich nations, many of the individuals affected by ESCA have been uninsured, and therefore without regular access to medical care or advice, for large portions of their lives. Expansion of insurance to a group of people that has had relatively little access to the health care system might have very different effects on utilization compared to similar policies in the developed world, where most people have consistent health insurance coverage throughout their adult lives.

To estimate how the ESCA affected insurance coverage, we exploit the age eligibility cutoff and utilize data from both before and after the policy. This allows us to combine

[1]The "30 Baht" program in Thailand did expand insurance coverage to the middle class. However, Gruber et al. (2014) discuss how this program provided supply-side incentives for care for the poor and show how this aspect of the policy may have mattered the most. In keeping with this, they show that a major impact of the policy was to reduce infant mortality for the poor.

a regression discontinuity design with a difference-in-differences framework, comparing individuals just above and below the age cutoff of age 60, before and after the policy was implemented. Using data from the Annual Poverty Indicators Survey (APIS) and the Demographic and Health Survey (DHS), we find that the policy increased insurance coverage by 16 percentage points.

Next, we use this analysis as the first stage for an instrumental variables specification, to estimate the effect of insurance coverage on various outcomes of interest. We find that, in our context, insurance actually *increased* household per capita health expenditures, contrary to the majority of evidence in both the developed and developing world (Giedion et al., 2013; Acharya et al., 2012). The magnitude of this increase is not trivial – insurance appears to have more than doubled per capita health expenditures.

This increase in expenditures is not driven by increases in the number of people seeking inpatient or outpatient care. On the contrary, it seems to be driven by increases in the intensity of treatment, conditional on seeking care, and increases in the demand for drugs and other medical products. We therefore argue that the increase in health expenditures may be indicative of an outward shift in the demand curve, driven by physician-induced demand. Similar arguments have been made in the (very few) studies that also find insurance leading to higher out-of-pocket expenditures. (Wagstaff and Lindelow, 2008; Sparrow et al., 2013).

This hypothesis is consistent with our investigation into distributional effects. We find that the positive effects of insurance coverage on health expenditures are concentrated at the upper end of the expenditure distribution. Insurance expansion had no effect on the lower quantiles but positive effects on the highest quantiles of the distribution of out-of-pocket expenditures. This argument is also consistent with our finding that insurance increased the likelihood of a chronic condition diagnosis, particularly, hypertension.

Our instrumental variables estimate identifies a local average treatment effect; specifically, the effect of insurance on those induced to become insured as a consequence of the ESCA. These individuals are typically called the compliers. We compute the average characteristics of the compliers using the methods outlined in Kowalski (2016). We find that the compliers are disproportionately female and are largely from the middle of the income and education distributions. These results highlight the uniqueness of this policy, compared with other programs implemented in similar countries which largely target the poor. In this sense, our findings could be useful for governments considering expansions of their national insurance programs to broader (higher-income) populations. They also provide important insights into how the impact of insurance might change as incomes increase in the developing world.

The balance of this paper is organized as follows. In the next section, we provide a brief overview of health insurance in the Philippines. After that, we discuss the data sources that we use, followed by a discussion of our research design. The next two sections discuss the impacts of the ESCA on health insurance coverage, who was most affected by the ESCA, and the effect of this expansion in insurance coverage on expenditures and utilization. Finally, we conclude.

2 Health Insurance in the Philippines

The Philippines has a tradition of providing health insurance coverage to portions of its citizenry that dates back to the 1960s. Initially, the country's National Health Insurance (NHI) maintained separate programs for employees in the formal sector and for the rest of the population. However, only the program for employees, which was managed by the public pension system, was successful in its early years. This prompted the restructuring of the NHI program in 1995. At this time, the Philippine Health Insurance Corporation (PHIC) was created to build on and expand the successful components of the original NHI program with the aim of eventually achieving more comprehensive health insurance coverage throughout the country. The initiative has had some success. In 2017, over 60%

of individuals aged 20 to 80 report being covered by PHIC in the DHS (see Figure 1). However, official estimates claim a higher coverage rate of 90%.

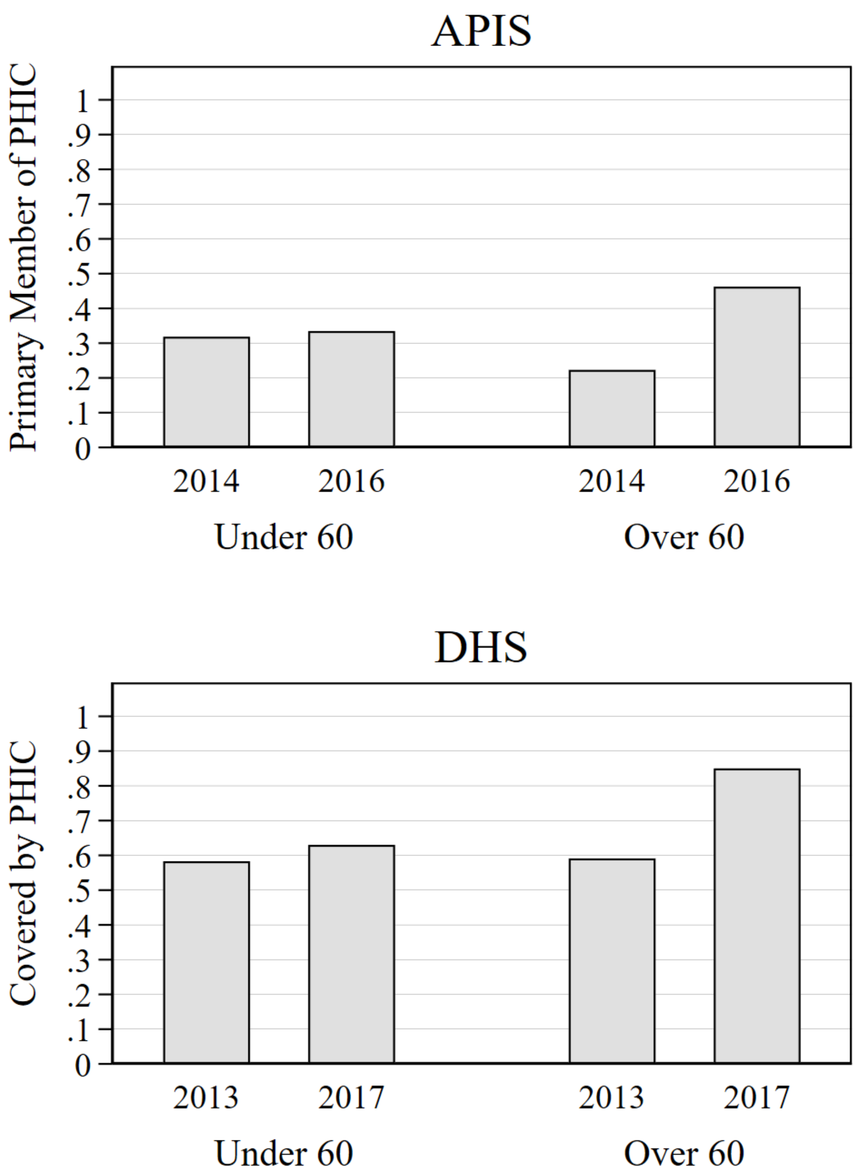
Currently, there are three types of membership to the PHIC: paying, lifetime, and sponsored. Paying members pay their own premiums either in their entirety or shared with their employers, who are required by law to contribute. These premiums range between four and 17 USD per month depending on the employee's salary and are typically split by the employee and employer. In addition, own-account workers are encouraged to become members of the PHIC by contributing between four and seven USD per month depending on their income.[2] Next, lifetime members are those who have paid at least 120 monthly premiums and have reached the official minimum age of retirement of 60. Finally, sponsored members have their premiums paid by a third party such as a local or the national government.

The Philippines expanded health insurance coverage in 2013 with the passage of the National Health Insurance Act (NHIA) (see Pantig (2013) for additional details). Under the NHIA, the national government agreed to pay the premium contributions for households identified as poor by a proxy means test. In addition, a corollary law from 2014 that applied to the elderly population, the Republic Act 10645 or the Expanded Senior Citizens Act (ESCA), was instituted. Because of this law, all individuals aged 60 and above were automatically eligible for the PHIC's sponsored program. Previously, senior citizens were only guaranteed coverage if they were lifetime members of the PHIC or if they were indigent. As a result of this policy change, coverage of the elderly greatly expanded.

For seniors who gained coverage as a result of the ESCA, the main benefit is the coverage of inpatient care. Basic inpatient services are fully covered for sponsored elderly members. Drugs are generally not covered by PHIC, unless they are included as part of

[2] The PHIC maintains a separate membership class for self-paying non-employer-sponsored individuals, which include migrant workers, informal sector employees, self-earning individuals, Filipinos with dual citizenship, naturalized Filipino citizens, and foreign citizens working and/or residing in the Philippines.

Figure 1: PHIC Membership: APIS and DHS



Notes: Sample restricted to individuals aged 20 to 80. In the APIS, only primary members of PHIC are recorded as enrolled in PHIC. In the DHS, both primary members and dependents are identified as enrolled in PHIC.

an inpatient stay. Sponsored senior members can also obtain free primary care benefits, though these are also fairly accessible and inexpensive for those who do not have insurance. To enroll, individuals are required to fill out a two-page form and provide proof of identification. This can be done at PHIC offices, as well as at health facilities.

The ESCA by-and-large achieved its goal of increasing coverage rates among elderly Filipinos. Before investigating this more rigorously in the remainder of the paper, we provide some descriptive evidence in Figure 1. Here, we report PHIC enrollment rates from two datasets: the APIS and DHS, both before and after the policy was implemented.[3] Although the two datasets measure coverage slightly differently (as we discuss below), they both show very similar patterns. Among those younger than age 60, PHIC coverage increased only slightly (less than 5 percentage points) after the implementation of the ESCA, whereas for those 60 and older, coverage increased by over 20 percentage points. In a very short period, the ESCA substantially increased insurance coverage rates among elderly Filipinos.

3 Data

We employ data from two different sources. The first is the Annual Poverty Indicators Survey (APIS), which is a nationally representative consumption survey. The second is the Demographic and Health Survey (DHS), which collects information on demographic and health indicators. The APIS has good quality expenditures data, while the DHS has information on individual utilization which is not available in the APIS.[4]

[3]Note that the ESCA did not go into effect until after the 2014 APIS was conducted.

[4]Features of the expenditures questions in the DHS make it difficult to separately identify total and out-of-pocket expenditures.

3.1 APIS

The APIS contains information on household expenditures, including out-of-pocket (OOP) medical expenditures, income, demographics, education, and access to government programs. Our main outcome of interest is OOP medical expenditures, which we divide by household size in order to obtain expenditures per capita. Importantly, the APIS has information on PHIC membership at the individual level.[5] We employ the APIS from survey years 2014 and 2016. The APIS is conducted in July of those years. The 2014 round of the APIS serves as pre-policy data since the mandatory coverage for senior citizens did not pass in Congress until September of 2014 and was only officially implemented in November of that year.

In Table 1, we report summary statistics from the APIS. We do so separately for people between age 50 and 59 and between age 60 and 69 separately for each year. First, in the year 2014, we see that about 34% of people ages 50-59 were enrolled in the PHIC but that only 26% of people ages 60-69 were. We presume that this reflects strong ties between insurance coverage and employment; many people who retire (and who are not lifetime members) lose insurance coverage. In the year 2016, however, we see a substantial jump in PHIC membership at age 60. Specifically, 36% of people ages 50-59 were members in 2016 but 46% were members in 2016. The next row displays statistics on household OOP medical expenditures (per person). In both years, households of individuals younger than 60 spent less than households with individuals aged 60 and older.

In addition, we also employ data on education, income, and gender from the APIS. We construct separate dummies for three educational categories: incomplete primary, complete primary, and complete secondary. We also construct dummies for three income categories: the 3^{rd} decile and below, the 4^{th} to the 7^{th} deciles, and the 8^{th} decile and higher. Descriptive statistics for these categorical variables and gender are also reported

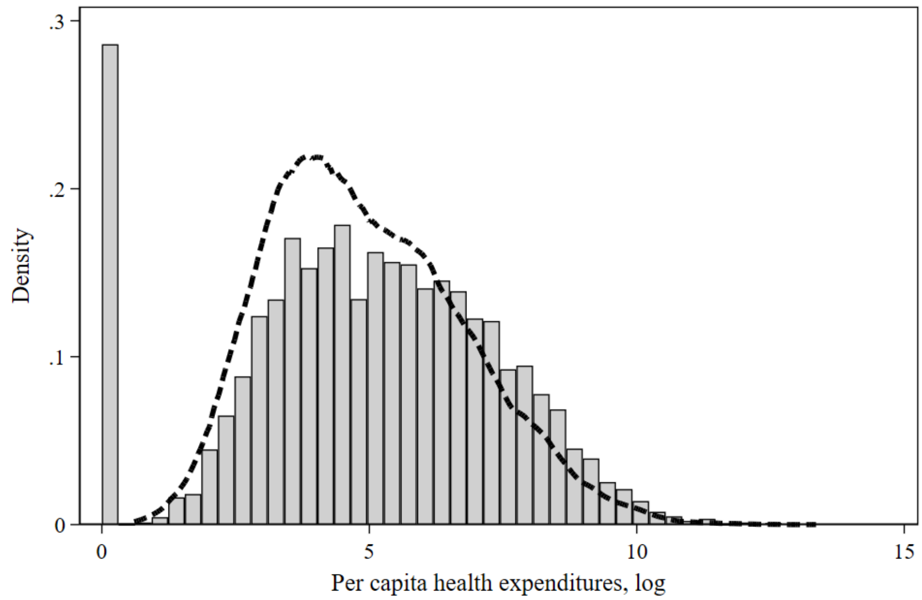
[5] As we discuss later, individuals are only recorded as members if they are the primary member of PHIC, not if they are qualified dependents.

Table 1: Summary Statistics, APIS

	2014		2016	
	Age 50-59	Age 60-69	Age 50-59	Age 60-69
Primary member of PHIC (=1)	0.34	0.26	0.36	0.46
	(0.47)	(0.44)	(0.48)	(0.50)
Health expenditure per capita (pesos)	1378.99	1874.15	1075.33	1931.24
	(7369.51)	(9026.70)	(6088.83)	(6745.78)
Health expenditure share	0.03	0.04	0.03	0.04
	(0.07)	(0.08)	(0.07)	(0.09)
Male (=1)	0.49	0.47	0.49	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Education: Incomplete Primary (=1)	0.19	0.29	0.21	0.29
	(0.39)	(0.45)	(0.41)	(0.45)
Education: Complete Primary (=1)	0.35	0.38	0.31	0.32
	(0.48)	(0.48)	(0.46)	(0.47)
Education: Complete Secondary (=1)	0.46	0.34	0.48	0.39
	(0.50)	(0.47)	(0.50)	(0.49)
Low-income household (=1)	0.28	0.27	0.28	0.26
	(0.45)	(0.45)	(0.45)	(0.44)
Middle-income household (=1)	0.41	0.41	0.41	0.40
	(0.49)	(0.49)	(0.49)	(0.49)
High-income household (=1)	0.31	0.31	0.31	0.34
	(0.46)	(0.46)	(0.46)	(0.47)

Notes: Low, middle, and high income correspond to the 1st to 3rd, 4th to 7th, and 8th to 10th deciles of the national per capita income distribution, respectively.

Figure 2: Distribution of PC Medical Expenditures (log)



Notes: Sample includes individuals aged 50 to 69 in the 2014 and 2016 waves of the APIS.

in Table 1.

Finally, in Figure 2, we display a histogram of the log of per capita medical expenditures. To address zeros, we added one to the per capita expenditure variable before taking logs. The figure reveals that almost 30% of our sample have zero health expenditures. For the non-zero observations, we have overlaid a kernel density plot which reveals a distribution with a slight right skew for individuals with positive spending.

3.2 DHS

The DHS contains information on medical utilization, PHIC membership, and other demographics. For the period prior to the ESCA, we employ the DHS from 2013. For the post-period, we employ the DHS round fielded in 2017.

In Table 2, we report summary statistics from the DHS. As in the previous table, we provide separate estimates for individuals aged 50 to 59, and those aged 60 to 69, separately for each year. Unlike in APIS, where PHIC enrollment refers only to primary members, the DHS includes individuals who are covered under the PHIC as dependents of primary members. This accounts for the higher percentages of people covered by the PHIC in the DHS than the APIS. In 2013, 63% percent of people aged between 50 and 59 were covered by the PHIC, while a slightly smaller share, 61%, of those aged between 60 and 69 were. In 2017, however, we see a substantial jump in PHIC coverage among those aged 60 to 69 to 83%, while coverage in the younger group increased only slightly to 67%. We also present inpatient use and outpatient use by age group and year. In both years, we see that individuals aged 60 to 69 are more likely to have visited a health facility or been confined in a hospital. This may be a consequence of a higher prevalence of chronic and acute health conditions among the elderly.

As with the APIS, we also employ information on socioeconomic status and gender from the DHS. We employ three categorical education dummies corresponding to the same categories from the APIS: incomplete primary, complete primary, and complete secondary. However, the DHS does not have comparable information on household income to the APIS. Instead, we employ a wealth index that is constructed from a Principal Components Analysis of a battery of questions on asset ownership. We construct three wealth categorical variables corresponding to the 1st and 2nd quintiles, the 3rd and 4th quintiles, and the highest quintile. Descriptive statistics for these categorical variables and gender from the DHS are also reported in Table 2.

Table 2: Summary Statistics, DHS

	2013		2017	
	Age 50-59	Age 60-69	Age 50-59	Age 60-69
Covered by PHIC (=1)	0.63	0.61	0.67	0.83
	(0.48)	(0.49)	(0.47)	(0.37)
Hospital stay last year (=1)	0.05	0.07	0.05	0.07
	(0.21)	(0.26)	(0.21)	(0.26)
Health visit last month (=1)	0.10	0.13	0.09	0.12
	(0.30)	(0.34)	(0.28)	(0.33)
Illness: Chronic condition (=1)	0.06	0.11	0.05	0.10
	(0.24)	(0.34)	(0.23)	(0.33)
Illness: Acute condition (=1)	0.12	0.14	0.09	0.11
	(0.33)	(0.35)	(0.29)	(0.32)
Male (=1)	0.49	0.46	0.49	0.47
	(0.50)	(0.50)	(0.50)	(0.50)
Education: Incomplete Primary (=1)	0.22	0.28	0.22	0.29
	(0.41)	(0.45)	(0.42)	(0.46)
Education: Complete Primary (=1)	0.31	0.35	0.29	0.33
	(0.46)	(0.48)	(0.46)	(0.47)
Education: Complete Secondary (=1)	0.47	0.37	0.48	0.38
	(0.50)	(0.48)	(0.50)	(0.48)
Low-wealth household (=1)	0.37	0.35	0.43	0.41
	(0.48)	(0.48)	(0.49)	(0.49)
Middle-wealth household (=1)	0.40	0.41	0.38	0.39
	(0.49)	(0.49)	(0.49)	(0.49)
High-wealth household (=1)	0.23	0.24	0.19	0.20
	(0.42)	(0.43)	(0.39)	(0.40)

Notes: Low, middle, and high wealth correspond to the 1st and 2nd, 3rd to 4th, and 5th quintiles of the wealth index distribution, respectively.

4 Research Design

4.1 Conceptual Framework

We consider the impact of health insurance coverage on medical utilization and other outcomes within the framework first discussed by Heckman and Vytlacil (1999) and Vytlacil (2002) and subsequently applied to the context of health insurance by Kowalski (2016). We let Y_T and Y_U denote potential outcomes both with and without the treatment (insurance coverage in our case). Treatment status is denoted by $D \in \{0, 1\}$ where unity represents treatment. As is standard, the econometrician observes

$$Y = DY_T + (1 - D)Y_U.$$

Consistent with the previous literature, treatment status is determined by a latent variable of the form

$$I = p_Z - U.$$

Here, p_Z (which enters the expression positively) can be interpreted as the benefits of treatment and U (which enters negatively) as the costs of treatment, so that individuals with lower values of U will take up treatment prior to those with higher values. We normalize U to be a uniform random variable on the unit interval without loss of generality. In our context, p_Z depends on a binary instrumental variable (IV) denoted by $Z \in \{0, 1\}$. Accordingly, p_Z can take on one of two values: p_1 (the probability of treatment for those with $Z = 1$) and p_0 (the probability of treatment for those with $Z = 0$). We will assume that the vector (Y_T, Y_U, U) and Z are distributed independently. Without loss of generality, we assume that $p_1 \geq p_0$. Participation is then determined by the relation $D = 1(I \geq 0)$.

We are interested in $\Delta = Y_T - Y_U$ which is the individual-specific treatment effect.

Because we cannot simultaneously observe Y_T and Y_U for the same individual, we cannot identify (without random assignment or further assumptions) the average treatment effect which is denoted by $E[\Delta]$. However, the IV research design discussed in the next subsection will allow us to identify the local average treatment effect (LATE) which is defined as

$$LATE = E[\Delta | p_0 \leq U \leq p_1].$$

This corresponds to the average treatment effect for the subpopulation whose participation is affected by the IV. These individuals will be treated when $Z = 1$, but untreated when $Z = 0$. This group of people is typically called the compliers and constitutes $100 \times (p_1 - p_0)\%$ of the population.

4.2 Instrumental Variables Estimator

To estimate the effect of health insurance coverage on utilization, we employ a two stage least squares (2SLS) estimator which is equivalent to the IV estimator in our case since our model is just identified. In the first stage, we estimate $p_1 - p_0$ which corresponds to the effects of the IV on participation, as discussed above. To do this, we will exploit the regression discontinuity created by the ESCA in which all people 60 and older were able to enroll in the PHIC after November of 2014. In the second stage, we compute the 2SLS or IV estimator which, as discussed by Imbens and Angrist (1994) and Lee and Lemieux (2010), identifies the LATE.

First Stage

In the first stage, we estimate the effects of the ESCA on PHIC membership. Building on earlier notation, we let D_{iat} denote whether individual i of age a at time t is insured by PHIC. Next, we define an indicator for being age 60 or older (which we denote using $SENIOR_a$). Throughout the rest of this paper, we will use the variable $POST_t$, which is a dummy variable that is turned on in survey years after the ESCA was implemented. In the APIS, this year is 2016 and in the DHS, it is 2017. As previously discussed, because the ESCA was implemented between the 2014 and 2016 waves of the APIS, we should see effects in 2016 but null effects in 2014. Similarly, we should see impacts in the 2017 wave of the DHS but not the 2013 wave. Restricting the estimation to individuals within some bandwidth b of age 60, we then estimate the following regression:

$$D_{iat} = \alpha_0 + \alpha_1 SENIOR_a \times POST_t + \alpha_2 SENIOR_a + \alpha_3 POST_t + g(a-60) + \nu_{iat}, \quad (1)$$

where $g(a-60)$ is a flexible polynomial in $a-60$ that allows for different polynomials below and above 60. The variable $SENIOR_a \times POST_t$ is equal to one for individuals who are 60 or older in the post-ESCA period. This variable, which we will refer to as Z_{at} in subsequent discussions, is our IV. The parameter α_1 governs the strength of our IV and determines the magnitude of $p_1 - p_0$.

Second Stage

In the second stage, we estimate the effects of PHIC membership on medical expenditures, hospital stays, and outpatient visits. Building on earlier notation, we let Y_{iat} denote the outcome of interest for individual i of age a at time t. Our second stage regression can then be written as

$$Y_{iat} = \theta_0 + \theta_1 \hat{D}_{iat} + \theta_2 SENIOR_a + \theta_3 POST_t + f(a-60) + \mu_{iat}, \quad (2)$$

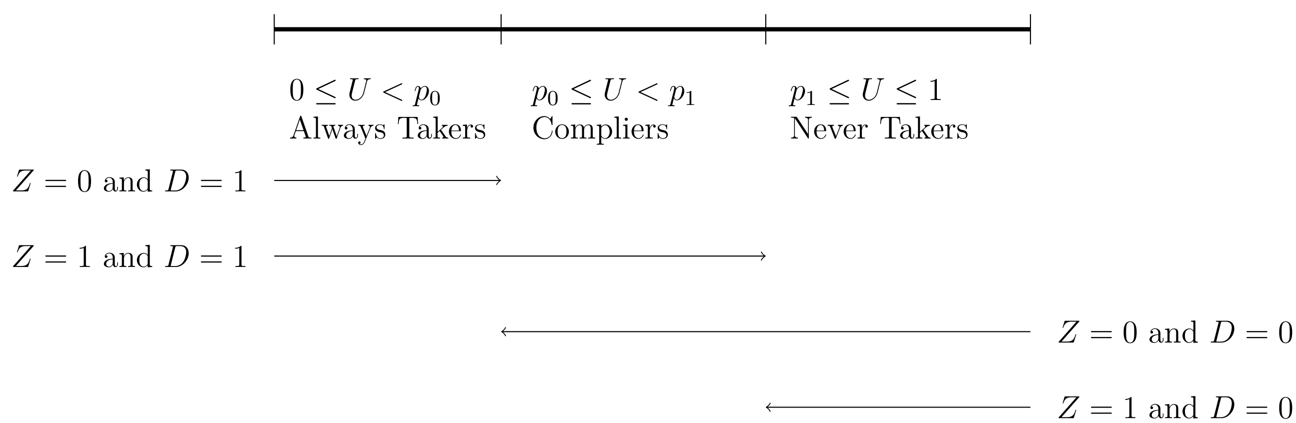
where $\hat{D}_{iat}$ is predicted coverage obtained from our first stage in equation (1) and $f(a-60)$ (similar to $g(a-60)$) represents flexible polynomials on either side of the age cutoff. The parameter θ_1, identifies the LATE provided that Z_{at} affects PHIC membership monotonically and satisfies the usual exclusion restriction. This estimator identifies the effect of health insurance coverage on the compliers: the subset of the population that acquired insurance coverage as a consequence of the ESCA.

4.3 Complier Characteristics

As mentioned above, our IV estimator identifies the effect of insurance for a very specific group, the compliers, in our natural experiment. In order to properly interpret the LATE and understand the mechanisms behind the estimated effects, it is important to think carefully about who the compliers are. The compliers cannot be identified in any experiment with non-compliance. However, means of their observable characteristics, which we denote as X, can be identified. Computing means of these characteristics will shed light on who was impacted by the ESCA. This is a policy-relevant question that will provide guidance on what lessons can be applied to other contexts.

Identification

Figure 3: Identifying the Compliers



Before we proceed, we use Figure 3 to discuss how the take-up of treatment, or insurance in our case, varies across the population in our research design. This is very similar to the discussion in Kowalski (2016). First, individuals with $0 \leq U < p_0$ will always obtain treatment. These are the *always takers*, and in our context, they are individuals who take up insurance even if they are not affected by the ESCA. In the data, these individuals have $Z = 0$ and $D = 1$. Second, the *compliers* have $p_0 \leq U < p_1$. These individuals obtain insurance if they are eligible for ESCA ($Z = 1$) but do not if they are not eligible ($Z = 0$). Unlike the always takers, the compliers cannot be separately identified in the data. Individuals with $Z = 1$ and $D = 1$ are comprised of always takers and treated compliers. Third, individuals with $p_1 \leq U \leq 1$ will never seek treatment in this experimental design; these are the *never takers*. These individuals do not have insurance ($D = 0$) despite being eligible for ESCA ($Z = 1$) and can be identified accordingly. Finally, the set of individuals for whom $Z = 0$ and $D = 0$ (who are not insured while ineligible for ESCA) contains both the never takers and the untreated compliers.

Applying similar arguments as in Kowalski (2016), average characteristics of the compliers can be identified. Identification entails computing $E\left[X|D = d, p_0 \leq U < p_1\right]$ for $d \in \{0, 1\}$ and then taking a weighted average. In the Appendix, we show that the average characteristics of the untreated compliers will be given by

$$\begin{aligned}&\mu_X(0) \equiv E\left[X|D = 0, p_0 \leq U < p_1\right] = \\&\frac{1}{p_1 - p_0}\left[(1 - p_0)E[X|D = 0, Z = 0] - (1 - p_1)E[X|D = 0, Z = 1]\right].\end{aligned} \tag{3}$$

The same formula appears in Kowalski (2016). We restate it for the sake of being comprehensive. Similarly, we also show that the average of the characteristics for the treated compliers is given by

$$\begin{aligned}&\mu_X(1) \equiv E\left[X|D = 1, p_0 \leq U < p_1\right] = \\&\frac{1}{p_1 - p_0}\left[p_1 E[X|D = 1, Z = 1] - p_0 E[X|D = 1, Z = 0]\right].\end{aligned} \tag{4}$$

Next, we can take a weighted sum of the averages of the untreated and treated compliers to recover the overall averages of the compliers' observables. Note that $Z = D$ for the compliers and so, $\mu_X(0) = \mu_X(1)$. This is essentially a balance test. Therefore, for any $\pi \in [0, 1]$, we will have that

$$E[X|p_0 \leq U < p_1] = \mu_X(0)\pi + \mu_X(1)(1 - \pi). \tag{5}$$

The parameter π can be chosen optimally given estimates of $\mu_X(0)$ and $\mu_X(1)$ by setting it equal to

$$\pi^* = \frac{V\left(\widehat{\mu_X(1)}\right) - C\left(\widehat{\mu_X(0)}, \widehat{\mu_X(1)}\right)}{V\left(\widehat{\mu_X(0)}\right) + V\left(\widehat{\mu_X(1)}\right) - C\left(\widehat{\mu_X(0)}, \widehat{\mu_X(1)}\right)}.$$

Setting $\pi = \pi^*$ minimizes the variance of the estimate of $E[X|p_0 \leq U < p_1]$.

Estimation

We now discuss the estimation of the complier characteristics. Estimates of the conditional expectations in the above equations can be calculated directly from the data. If we let X_{iat} denote some personal characteristic, then a simple way to estimate characteristic averages is to estimate the following regression:

$$X_{iat} = \lambda_{NT} + \lambda_{AT}1(AT_{iat}) + \lambda_{AT+TC}1(ATTC_{iat}) + \lambda_{NT+UC}1(NTUC_{iat}) + u_{iat}, \qquad (6)$$

where NT identifies the never takers, AT identifies the always takers, $ATTC$ identifies the composite of the always takers and treated compliers, and $NTUC$ identifies the composite of the never takers and the untreated compliers. Note that λ_{NT} is the constant in this model. The different subgroups can be identified in the data as discussed in Figure 3. Each coefficient provides us with one of the conditional expectations needed for the calculations in equations (3) and (4). We then obtain that

$$\mu_X(0) = \frac{1}{p_1 - p_0}[(1-p_0)(\lambda_{NT} + \lambda_{NT+UC}) - (1-p_1)\lambda_{NT}]$$
$$\mu_X(1) = \frac{1}{p_1 - p_0}[p_1(\lambda_{NT} + \lambda_{AT+TC}) - p_0(\lambda_{NT} + \lambda_{AT})].$$

The λ-parameters come from an estimation of equation (6) and the probabilities are the propensity scores evaluated at $Z = 1$ and $Z = 0$.

Estimation involves several steps. First, we estimate equation (6). Because the instrument Z is partially determined by age (and because we do not control for age in this regression), we limit to a small bandwidth (5 years) to minimize the potential bias from excluding age. Second, we calculate p_Z by estimating equation (1). Specifically, we predict the probability of treatment in equation (1) just below and just above the cutoff age in the post-ESCA year. We then use these estimates to compute the quantities in equations (3) and (4). Note that estimation of equation (6) also allows for estimation of the average characteristics of the always takers and the never takers.

To conduct inference, we use the bootstrap to estimate the expectation in equation (5) using 1000 replications. We then compute box plots of the bootstrapped estimates for the always takers, compliers, never takers, and the grand mean. We employ the optimal weight, π^*, for all computations of the average complier characteristics.

4.4 Testing for Selection

As in any study of health insurance, it is important to ask who selects into insurance. Are those with the highest potential utilization or the lowest potential utilization selecting in first? This question can be answered by estimating equation (6), using outcomes such as medical expenditures or utilization as the dependent variable. This essentially compares average outcomes across always-takers, always-takers with treated compliers, never-takers with untreated compliers, and never-takers. The parameter λ_{NT+UC} identifies selection into the treatment because a non-zero value for this parameter indicates a difference in average outcomes across compliers and never takers. To see this, note that

$$\lambda_{NT+UC} = \underbrace{E[Y_U|p_0 \leq U \leq 1]}_{\text{Never Takers + Compliers}} - \underbrace{E[Y_U|p_1 \leq U \leq 1]}_{\text{Never Takers}}.$$

The first term is the average of the outcomes for the never takers and the untreated compliers. The second is the average of the outcomes for the never takers. Because both groups are untreated, differences between the two cannot be due to heterogeneous treatment effects (which could be the case in a comparison of λ_{AT} and λ_{AT+TC}). If

$\lambda_{NT+UC} = 0$ then there are no differences between the two groups and therefore there is no selection into treatment. If, on the other hand, $\lambda_{NT+UC} > 0$, this indicates that never takers have lower utilization than the compliers, which indicates adverse selection. Finally, $\lambda_{NT+UC} < 0$ indicates lower utilization among the compliers which indicates advantageous selection.

5 The Effect of ESCA on Insurance Coverage

We begin with a graphical illustration of the effects of the ESCA on PHIC membership. In Panel A of Figure 4, we use the APIS survey to plot the share of individuals enrolled in the PHIC, by age, separately for 2014 and 2016. In Panel B, we repeat the same exercise using the DHS data for the years 2013 and 2017. Although the two surveys capture slightly different measures of PHIC coverage (described in section 3), both figures depict similar patterns. Before the policy was implemented, the relationship between coverage and age appears to be fairly smooth through age 60. In contrast, in the post-ESCA years for both the APIS and the DHS, there is a large discontinuous increase in insurance coverage at age 60 which is consistent with the ESCA being in place by this time. A comparison of the age patterns before and after the policy offers evidence that the ESCA was quite effective at increasing coverage rates for those over 60 years old. However, it is worth noting that, in principle, the ESCA could have increased coverage rates of elderly Filipinos to 100%. In actuality, coverage rates are on par with 50% in the APIS in 2016 and 80% in the DHS in 2017. Limited awareness or sign-up time costs may have served as significant barriers to enrollment.

In Table 3, we report estimates of the corresponding regressions presented in equation (1), which serves as the first stage equation for the subsequent IV analysis. Every cell in this table reports the coefficient on the age 60 discontinuity interacted with the post dummy, which we have denoted by $Z_{at} = POST \times SENIOR$. This is the effect of

Figure 4: Insurance Coverage by Age and Year

Notes: Dots represent age-specific means, and lines represent the lowess-smoothed age-coverage relationship, above and below age 60. In the APIS, only primary members of PHIC are recorded as enrolled in PHIC. In the DHS, both primary members and dependents are identified as enrolled in PHIC.

the ESCA on PHIC membership. This variable is also our instrument for insurance coverage. Each column uses a different bandwidth of either 2, 5 or 10 years around the cutoff. Each row uses a different order for the polynomial $g(a-60)$. We also report the optimal order for each bandwidth. Consistent with the graphical evidence above, these results demonstrate that the policy had a sizable effect on insurance coverage rates, with estimates ranging from nine to 19 percentage points depending on the bandwidth. Within each bandwidth, our estimates are consistent across different polynomial orders. Across bandwidths, estimates do vary, but they are fairly consistent across the 5 and 10-year bandwidths. Importantly, despite the fact that estimates of the levels of coverage rates differ across the DHS and APIS, the estimates of the marginal impacts of the ESCA are almost identical across datasets.

Table 3: First Stage Estimates: Effect of Policy on Insurance Coverage

	APIS			DHS		
Bandwidth	2	5	10	2	5	10
Polynomial Order						
Zero	0.088**	0.16***	0.18***	0.12***	0.15***	0.19***
	(0.036)	(0.024)	(0.018)	(0.027)	(0.018)	(0.014)
One	0.091**	0.16***	0.18***	0.12***	0.15***	0.19***
	(0.036)	(0.024)	(0.018)	(0.027)	(0.018)	(0.014)
Two		0.16***	0.18***		0.15***	0.19***
		(0.024)	(0.018)		(0.018)	(0.014)
Three		0.16***	0.18***		0.15***	0.19***
		(0.024)	(0.018)		(0.018)	(0.014)
Optimal Order	0	1	2	1	2	3
N	2811	6707	13116	5435	13650	27356

Notes: Standard errors, clustered at the household level, reported in parentheses ($^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$). Each cell represents a different regression, defined by the specified bandwidth and polynomial order. The dependent variable in all regressions is an indicator for PHIC membership. We only report the coefficient (and standard error) for the $POST \times SENIOR$ interaction, but all regressions control for the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff.

6 Describing the Compliers

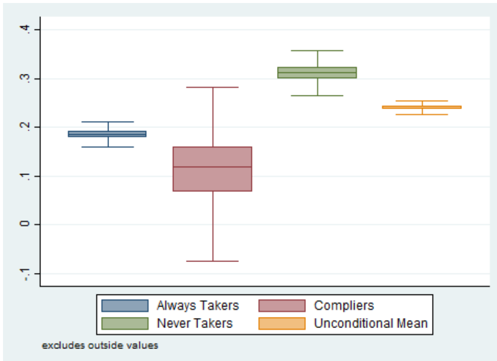
6.1 Complier Characteristics

Before moving on to estimate the effect of increased insurance coverage on healthcare utilization, we discuss the characteristics of the compliers. This is an important exercise because the IV estimates we discuss later will provide us with a local average treatment effect which (as already discussed) is the effect of insurance coverage on the compliers. Specifically, we estimate the parameter in equation (5) so that we can better understand the demographic composition of the compliers, who cannot be directly identified in any experiment with non-compliance. We also compute the averages of the same characteristics for the never takers and the always takers using the regression parameters from equation (6). We employ a 5-year bandwidth throughout this analysis, which we conduct using both the APIS and DHS. Finally, inference is conducted per the discussion at the end of Section 4.3.

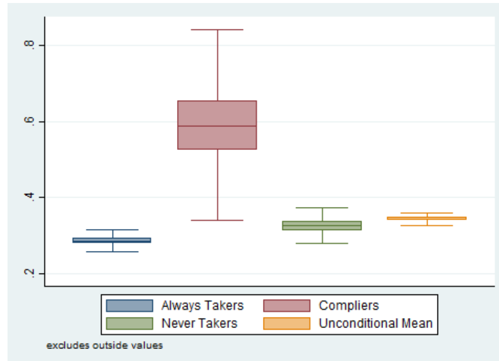
We present the results in Figure 5, which uses the APIS, and Figure 6, which uses the DHS. Each figure displays seven panels corresponding to seven outcome variables: indicators for low, middle, and high education; low, middle, and high socioeconomic status (SES); and a male dummy. In the APIS, SES is measured by household income and in the DHS, it is measured with a wealth index which we described above. Each panel contains four box plots corresponding to means for the always takers, compliers, never takers, and the full sample, computed from 1000 bootstrapped re-samples. Because the means of the compliers involved the computation of many auxiliary parameters and because compliers make up a smaller share of the sample, these estimates are far noisier than those for the always and never takers.

Figure 5: Observable Characteristics for Always Takers, Compliers, and Never Takers in APIS

A. Low Education

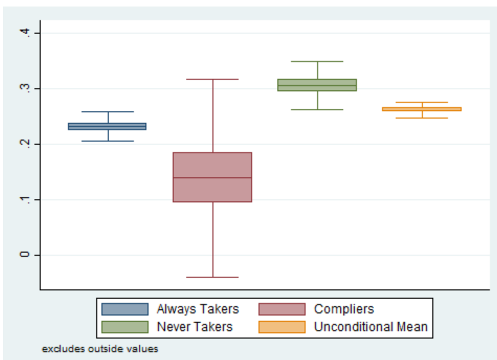


B. Middle Education

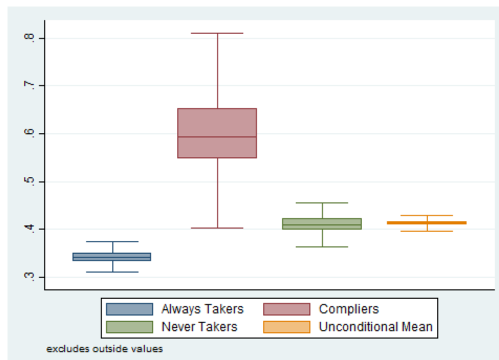


C. High Education

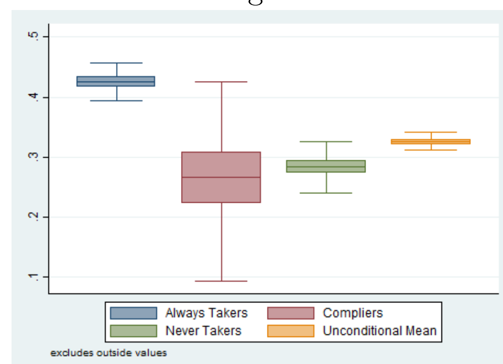
D. Low SES



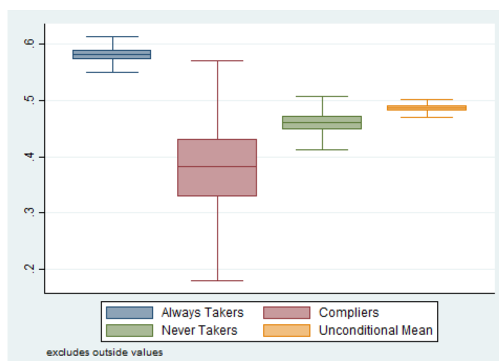
E. Middle SES



F. High SES

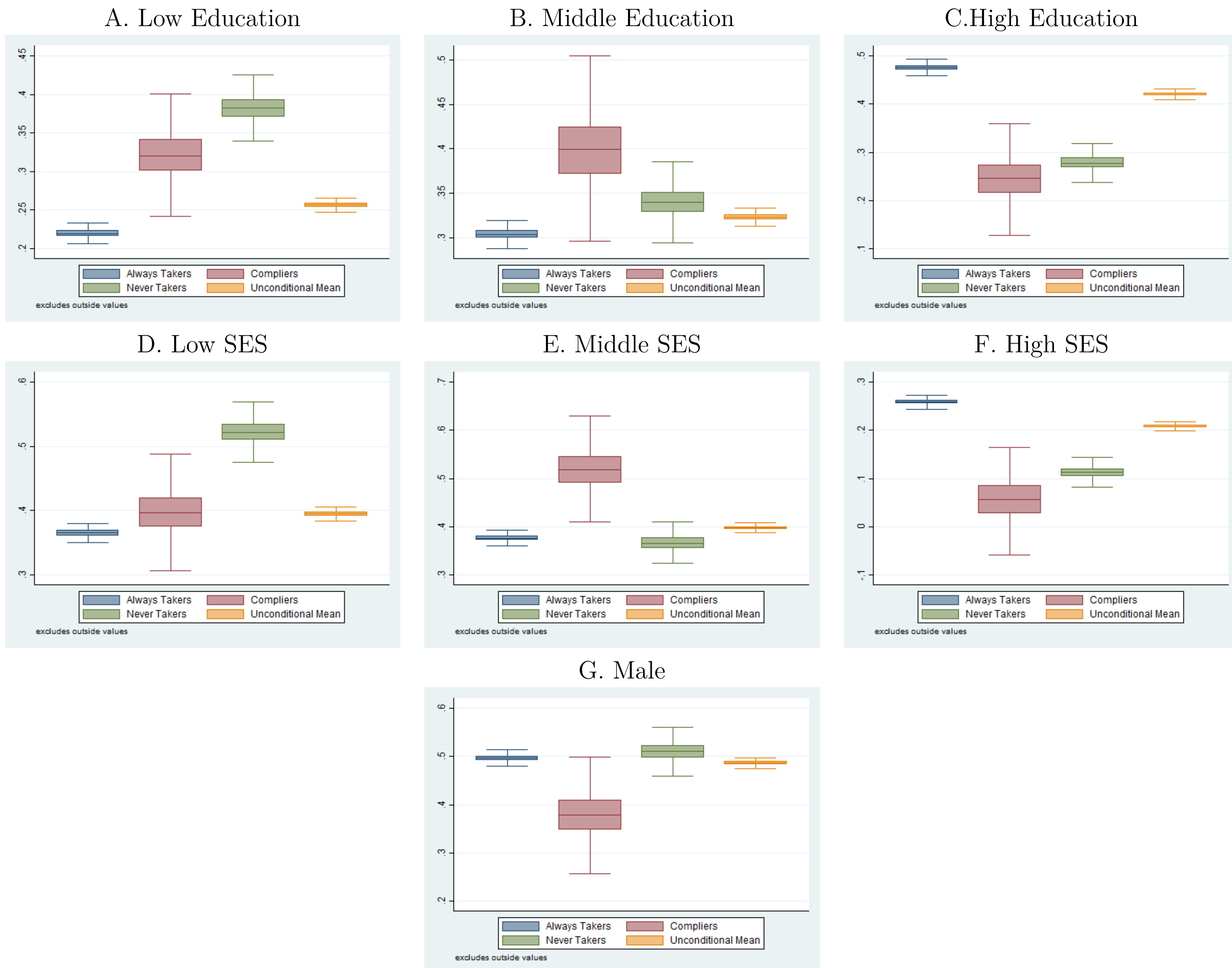


G. Male



Notes: Box plots were computed from 1000 bootstrapped re-samples. They denote the median, 75th and 25th percentiles, and upper and lower adjacent values. Low, middle, and high education correspond to incomplete primary, complete primary, and complete secondary education, respectively. Low, middle, and high SES correspond to the 1st to 3rd, 4th to 7th, and 8th to 10th deciles of the national per capita income distribution, respectively.

Figure 6: Observable Characteristics for Always Takers, Compliers, and Never Takers in DHS



Notes: Box plots were computed from 1000 bootstrapped re-samples. They denote the median, 75th and 25th percentiles, and upper and lower adjacent values. Low, middle, and high education correspond to incomplete primary, complete primary, and complete secondary education, respectively. Low, middle, and high SES correspond to the 1st and 2nd, 3rd to 4th, and 5th quintiles of the wealth index distribution, respectively. The box plots were computed from 1000 bootstrapped re-samples.

Results from both datasets indicate that the compliers were by-and-large from the middles of the education and SES distributions and disproportionately female. The first point is most evident in Panels B and E, where the complier means for the middle education and SES indicators are higher than the means of the always takers and never takers. We also see that the compliers were less likely to be in the low education and SES categories than the never takers (and in some cases, the always takers). They were also less likely to be in the high SES and education groups than the always takers. Finally, in Panel G of both Figures 5 and 6, we see that the compliers were far less likely to be male than the always and never takers.

Why was the middle class most impacted by this policy? Prior to the ESCA, the Philippines already provided health insurance coverage to the poor, though the low insurance enrollment rates among the lowest income group suggest that many were not aware of this policy. In addition, health insurance in the Philippines is strongly tied to employment, which means that individuals in the highest socioeconomic categories already had high coverage rates – substantially higher than the rest of the population – prior to the policy.[6] In short, the rich already had insurance, while the poor either already had insurance or were unaware of their eligibility for it. This helps explain why the compliers were less likely to be drawn from the lowest socioeconomic groups than the never takers, and less likely to be from the highest socioeconomic groups compared to the always takers.

6.2 Testing for Selection

We now test whether there was any selection into health insurance as a consequence of the ESCA. That is, are those with the highest potential utilization the ones that choose to obtain insurance first? In Table 4, we report the results of estimating equation

[6] As described above, individuals who have paid at least 120 monthly premiums and are at least 60 years old become lifetime members of PHIC. Those in the highest socioeconomic groups are likely to fall in this category simply from being consistently employed in jobs where employers helped subsidize their premiums.

(6), where we regress expenditure and utilization measures on indicators for each of the following groups: always takers, always takers with treated compliers, and never takers with untreated compliers, which leaves never takers only as the omitted category. We estimate this regression using a 5-year bandwidth and the optimal polynomial orders identified in Table 3.

Table 4: Selection Tests

	Log Health Expenditures (APIS)	Hospital Stay Last Year (DHS)	Health Visit Last Month (DHS)
Always-Takers	0.277*	0.064***	0.038***
	(0.151)	(0.009)	(0.014)
Always-Takers & Treated Compliers	0.518***	0.065***	0.044***
	(0.140)	(0.007)	(0.011)
Never-Takers & Untreated Compliers	-0.109	0.026***	0.007
	(0.141)	(0.009)	(0.015)
Polynomial Order	1	2	2
Mean of Dep. Var.	4.990	0.0597	0.108
N	6707	13650	13650

Notes: Standard errors, clustered at the household level, reported in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$). All regressions utilize a 5-year bandwidth. The omitted category is the Never-Taker only group. All regressions include the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff.

As previously discussed, selection into the treatment is identified by the coefficient on the never taker/untreated complier indicator. This parameter is informative of how the untreated compliers compare to the never takers. This is informative of selection because the compliers select into insurance before the never takers. Importantly, it is not tainted by treatment effect heterogeneity. For medical expenditures and outpatient health visits, we see no significant difference between the never-takers and compliers, suggesting that there is limited selection into insurance based on these two outcomes. For hospital stays, however, we see a significant difference between the never takers and the group comprised of never-takers and untreated compliers. This indicates that, compared to the never takers, compliers are significantly more likely to have had a hospital stay in the past year. That is, those who are more likely to select into insurance (the compliers), had higher hospital utilization prior to being eligible for PHIC, which provides some evidence of adverse selection. Finally, we see that the groups with insurance (always takers and always takers with compliers) have significantly higher expenditures and utilization than those without insurance (never takers and never takers with compliers), which could be due to the treatment effect of insurance as well as selection into insurance.

7 The Effect of Insurance Coverage on Utilization

We now discuss our IV estimates. First, we provide some evidence of the validity of our IV. Next, we present IV estimates of the LATEs on expenditure and utilization. After that, to provide some insight into the distributional effects of this insurance expansion, we estimate quantile IV models. Finally, we investigate chronic and acute diagnoses as outcomes.

7.1 Instrument Validity

We begin with a simple test to investigate the validity of our instrument. In RD studies, one common test is to estimate a parallel RD specification using covariates as the dependent variables of interest, to ensure that there are no discontinuities for characteristics that should not have been affected by the policy. In our context, we are primarily concerned with differential discontinuities across the two years of data that we use. To check for these differential discontinuities, we estimate a variant of equation (1) in which we replace PHIC membership with different covariates as our dependent variable. We employ dummies for being male and the lowest and middle education and SES categories as dependent variables for a total of five equations. We estimate the system as a Seemingly

Unrelated Regression model. We then compute an F-test of the null that all of the RD parameters (which are α_1 in equation (1)) are zero.

Table 5: Instrument Validity Tests

	APIS			DHS		
Bandwidth	2	5	10	2	5	10
Dependent Variable:						
Male	0.016	0.030	0.0068	-0.020	-0.021	0.013
	(0.038)	(0.025)	(0.018)	(0.028)	(0.018)	(0.013)
Low SES	0.022	-0.011	-0.011	-0.0032	0.00015	0.0034
	(0.033)	(0.022)	(0.016)	(0.028)	(0.018)	(0.013)
Middle SES	-0.035	-0.029	-0.019	0.0039	0.00031	0.0038
	(0.037)	(0.024)	(0.018)	(0.028)	(0.018)	(0.013)
Low Education	-0.026	-0.023	-0.024	-0.038	-0.00092	0.0010
	(0.033)	(0.021)	(0.015)	(0.025)	(0.016)	(0.011)
Middle Education	-0.031	-0.011	-0.0094	0.022	0.022	0.0042
	(0.036)	(0.023)	(0.017)	(0.027)	(0.017)	(0.012)
Polynomial Order	0	1	2	1	2	3
F-statistic	3.99	5.61	5.63	3.05	3.39	1.47
p-value	0.55	0.35	0.34	0.69	0.64	0.92
N	2811	6707	13116	5424	13624	27309

Notes: Standard errors, clustered at the household level, reported in parentheses ($^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$). Each cell represents a different regression, defined by the specified dependent variable, bandwidth, and polynomial order. We only report the coefficient (and standard error) for the $POST \times SENIOR$ interaction, but all regressions control for the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff. In both datasets, low and middle education correspond to incomplete primary and complete primary, respectively. In the APIS, low and middle SES correspond to the 1st to 3rd and 4th to 7th deciles of the national per capita income distribution, respectively. In the DHS, low and middle SES correspond to the 1st to 2nd and 3rd to 4th quintiles of the wealth index distribution, respectively.

The results of this exercise are reported in Table 5 where we report the estimates from the 2-year, 5-year, and 10-year bandwidth specifications using both the APIS and DHS. For each bandwidth, we choose the optimal polynomial order according to standard information selection criterion. Across all specifications, none of the five estimates is individually significant at conventional levels. Using the F-test, we also fail to reject the null that all five estimates are zero. All told, these estimates are consistent with the exogeneity of the instrument.

7.2 IV Results

Expenditures and Utilization

In Table 6, we report second-stage IV estimates of the effect of insurance on expenditures and utilization. The corresponding first stage estimates can be found in Table 3. We study five outcomes of interest, and we report estimates from a 5-year and 10-year bandwidth for each outcome, using the optimal polynomial orders identified in Table 3. We also report test statistics of weak and under identification based on Kleibergen and Paap (2006) below each of the point estimates.

The first outcome of interest is household per capita medical expenditures from the APIS. This outcome includes OOP spending on outpatient and hospital services, as well as drugs, medical products, therapeutic appliances, and equipment. Strikingly, despite households facing *lower* OOP prices, we see that total expenditures *increased*. The estimate from the 10-year bandwidth is 1.123, which indicates that insurance coverage more than doubled medical expenditures.

It is notable that newly enrolled individuals in the PHIC spent more on medical expenditures despite gaining insurance coverage. Importantly, if the only effect of the ESCA was to move consumers down their demand curves, then this estimate implies that the elasticity of demand for medical care is greater than unity, which is much larger than existing estimates in the literature. For example, the oft-cited elasticity from the RAND Health Insurance Experiment is -0.2 (see Keeler and Rolph (1988)). Consequently, we suspect that our large coefficient estimates could reflect an outward shift of the demand curve, driven by some form of physician-induced demand, and therefore caution against using these estimates to compute elasticities.

The following two columns report the effects of PHIC membership on health expen-

Table 6: IV Estimates: Effect of Health Insurance on Expenditures and Utilization

	Log Health Expenditures (APIS)		Health Expenditure Share (APIS)		Hospital Stay Last Year (DHS)		Health Visit Last Month (DHS)		Hospital Stay Last Month (DHS)		
Bandwidth	5	10	5	10	5	10	5	10	5	10	15
Enrolled in PHIC	1.460*	1.123**	0.028	0.043**	0.006	0.004	0.051	0.016	0.244	0.196	0.241*
	(0.823)	(0.561)	(0.027)	(0.019)	(0.060)	(0.034)	(0.079)	(0.046)	(0.348)	(0.167)	(0.134)
Weak identification F	43.384	99.939	43.384	99.939	66.615	190.617	66.615	190.617	4.569	20.410	32.715
Underidentification F	42.928	98.543	42.928	98.543	65.926	186.954	65.926	186.954	4.573	20.250	32.298
Polynomial Order	1	2	1	2	2	3	2	3	2	3	3
Mean of Dep. Var.	4.99	4.94	0.036	0.036	0.060	0.056	0.11	0.10	0.13	0.14	0.14
N	6707	13116	6707	13116	13650	27356	13650	27356	1469	2827	4081

Notes: Standard errors, clustered at the household level, reported in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$). Each cell represents a different regression, defined by the specified dependent variable, bandwidth, and polynomial order. We report the results of instrumental variables regressions, with 1(Enrolled in PHIC) as the endogenous variable of interest, and $POST \times SENIOR$ as our instrument. All regressions control for the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff.

ditures as a share of total household expenditures. On average, medical expenditures are 3.6% of household expenditures regardless of whether we use a five or ten year bandwidth. Using the five year bandwidth, we see that PHIC membership increased the share of medical expenditures by 2.8 percentage points, but this estimate is not statistically significant. Using the ten year bandwidth, the estimate increases to 4.3 percentage points and is significant at the 95% level. This suggests that the ESCA about doubled the share of medical expenditures in the household's budget, which is consistent with its effects on log medical expenditures in the first two columns.

The next two outcomes we study are utilization measures from the DHS. Specifically, we investigate whether insurance increased the likelihood of an individual using inpatient services in the past year or visiting any health facility in the past month. We see no effects of insurance coverage on either of these variables.Total health expenditures increased, but outpatient and inpatient utilization did not change at the extensive margin.

This could be the case for two reasons. First, increases in spending on drugs and other medical products (which are included in expenditures but not accounted for in our outpatient and inpatient utilization indicators), could be driving the increases in total expenditures. Drugs are not typically covered by PHIC and could therefore be an important reason for the higher expenditures. Second, if insurance changed the intensity of utilization without changing the extensive margin, this could also be responsible for the higher spending.

We explore the second hypothesis in the remaining columns of Table 6. Here, the outcome variable is an indicator for individuals who went to a hospital after visiting a health facility. Note that this outcome is conditional on having visited a health facility in the past month. Because of the substantially smaller sample size available for this variable (which results in lower first-stage F-statistics), we also report the results from a 15-year bandwidth. Across all three specifications, estimated coefficients are around 0.2, which represents a large magnitude relative to the dependent variable mean of 0.14. Although these estimates are not significant in either the 5 or 10-year bandwidth specifications (likely due to the small sample size), the estimate in the 15-year bandwidth specification is significant at the 10% level. Consistent with the hypothesis outlined above, insurance does appear to be increasing the intensity of utilization, which could be driving the increases in expenditures documented in the first two columns of Table 6.

Quantile IV

We now investigate the effects of PHIC membership on medical expenditures at various points in its distribution, using a quantile IV estimator developed by Chernozhukov and Hansen (2008). We index the quantile of the medical expenditure distribution with τ. This procedure delivers $\sqrt{N}$-consistent estimates of the parameters of the model

$$S_Y(\tau|D,X) = \alpha(\tau)D + X'\beta(\tau) + f_\tau(a-60)$$

where $X = [SENIOR, POST]'$ and the function $S_Y(\tau|D,X)$ is what Chernozhukov and Hansen (2008) refer to as the *structural quantile function* or SQF.

The interpretation of the SQF is that it describes the quantile function of a latent variable $Y_d = \alpha(U)d + X\beta(U)$ where the treatment is fixed at $D = d$ and U is sampled from a uniform on $[0,1]$ conditional on X. The treatment variable, which is PHIC membership in our case, is potentially correlated with U. Identification of $\alpha(\tau)$ requires an IV that impacts PHIC membership, is independent of U, but satisfies an exclusion restriction. Accordingly, we re-purpose the same IV that we used for estimation of equation (2), $Z_{at} = POST \times SENIOR$, for the identification of the parameters of the SQF.

Quantile IV estimation is useful because it sheds light on whether the impacts of the PHIC were at the extensive or intensive margins. If insurance is changing the intensive but not the extensive margin of utilization, we should see movements in the upper end of the expenditure distribution, not at the lower end. That is, we should see higher spending as a consequence of PHIC membership among individuals who were already spending on healthcare as opposed to individuals who were not spending at all.

Related, quantile regression is also useful because it provides another way of addressing the presence of many zeros in medical expenditure data. Recall that in Figure 2, close to 30% of the medical expenditure observations were zeros. Hence, estimation of the model for $\tau \leq 0.3$ is informative of the effects of the PHIC at the extensive margins, whereas estimation for $\tau > 0.3$ is informative of the intensive margins. Finally, note that the commonly used two-part model in health economics discussed in Mullahy (1998) cannot be modified to handle endogenous regressors without relatively stringent parametric assumptions.

In Table 7, we present the estimations of $\alpha(\tau)$ from the SQF for $\tau \in \{0.1, 0.2, ..., 0.9\}$, estimated using the methods proposed by Machado and Santos Silva (2018). In Figure 7, we also plot the estimates from the table along with their 95% confidence intervals. It is clear that the effect of insurance is increasing across deciles, with magnitudes higher than unity between the 5th to 9th deciles. In fact, the effects are only significant (at the 10% level) for the top 3 deciles of the expenditures distribution, implying more movement at the upper end of the distribution.

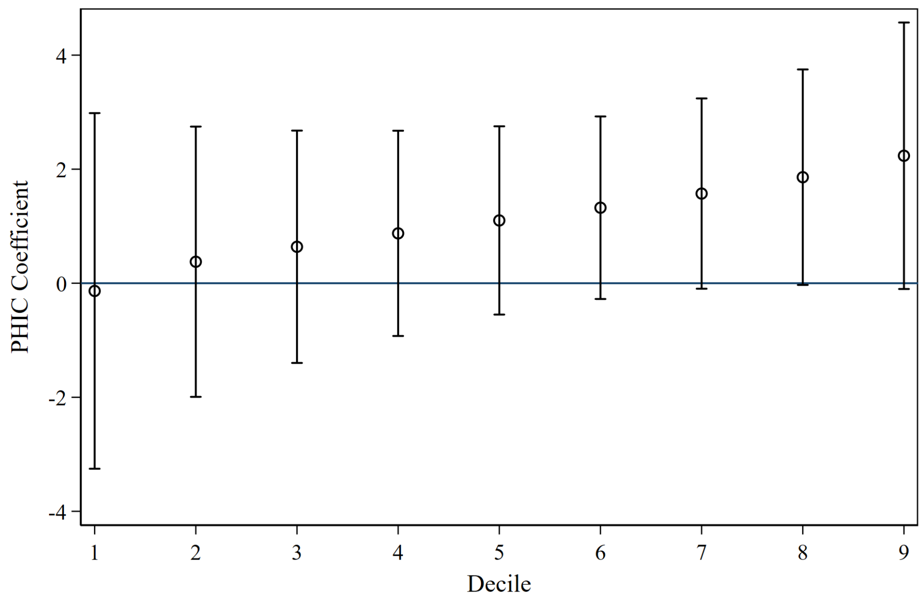
The results in Table 6, Table 7, and Figure 7 suggest that individuals are not more likely to see a provider because of insurance, but they do obtain more intensive treatment (conditional on seeing a provider at all) and do spend more on health. This is consistent with some form of provider-induced demand. This pattern of results is precisely what we would see if providers were more likely to recommend intensive treatment or follow-up care for insured individuals, or if insured patients were more likely to act upon these types of of provider recommendations. It is worth noting that these results are also consistent with our earlier characterization of the compliers as coming from the middle of the socioeconomic distribution. Low-income individuals are unlikely to have the means to pay for follow-up treatments or care, while higher-income individuals are more likely to have been receiving this higher-intensity care prior to the policy. Finally, previous

Table 7: Quantile IV Estimates: Effect of Health Insurance on Log Expenditure Deciles

	Decile								
	1	2	3	4	5	6	7	8	9
Enrolled in PHIC	-0.135	0.377	0.639	0.875	1.101	1.324	1.572*	1.860*	2.236*
	(1.591)	(1.209)	(1.040)	(0.918)	(0.842)	(0.817)	(0.851)	(0.964)	(1.192)
Polynomial Order	2	2	2	2	2	2	2	2	2
Mean of Dep. Var.	4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94	4.94
N	13116	13116	13116	13116	13116	13116	13116	13116	13116

Notes: Standard errors reported in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$). All regressions use the APIS. We report the results of quantile instrumental variables regressions on log per capita medical expenditures, with 1(Enrolled in PHIC) as the endogenous variable of interest, and $POST \times SENIOR$ as our instrument. All regressions control for the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff.

Figure 7: Quantile Regression Coefficients



Notes: Each point represents the coefficient estimate (and 95% confidence interval) of the effect of PHIC membership on per capita medical medical expenditures from an IV quantile instrumental regression for the specified decile. All regressions use $POST \times SENIOR$ as the instrument and control for the main effects of $POST$, $SENIOR$, and a flexible polynomial for age that varies above and below the cutoff.

results from Table 4 indicated that the untreated compliers were more likely to have been hospitalized relative to the never takers, once again indicating that the compliers were likely to have had some medical utilization even in the absence of PHIC membership.

Chronic Conditions

In Table 8, we explore one specific reason why insurance might be leading to higher spending, by investigating how insurance affected chronic condition diagnoses using the DHS. Because chronic condition diagnoses are so rare (with prevalence rates of 5% for hypertension, 2% for diabetes, and less than 0.2% for cancer), we use a more parsimonious, reduced-form approach and estimate two separate regression discontinuity specifications for 2013 and 2017. The results in Table 8 show that after the implementation of the policy, individuals above the age of 60 were significantly more likely to be diagnosed with a chronic condition. This relationship does not exist prior to the policy, and does not exist for acute conditions (before or after the policy). When we disaggregate the different types of chronic conditions, the effect appears to be driven by increases in hypertension diagnoses (the most common of the three). Hypertension, like the other two chronic conditions, are often treated with expensive medication (generally not covered by insurance) that could be an important reason for the increase in health spending that we document.

8 Conclusion

This paper evaluates the effect of a health insurance expansion in the Philippines, which provided free health insurance to all individuals ages 60 and older starting in 2014. The policy had a substantial impact on coverage, increasing insurance rates by roughly 16 percentage points. We explore the characteristics of the compliers in this natural experiment and find that they were largely drawn from the middle of the income distribution. This is in contrast with most recent insurance expansions in the developing world, which have largely explicitly targeted the poor.

Table 8: Effect of Health Insurance on Chronic and Acute Conditions

	Chronic Condition		Acute Condition		Hypertension		Diabetes		Cancer	
Age 60 and Older	-0.015	0.015*	-0.000	0.012	-0.012	0.013**	-0.003	0.000	0.000	0.001
	(0.012)	(0.009)	(0.014)	(0.010)	(0.010)	(0.007)	(0.006)	(0.004)	(0.002)	(0.001)
Year	2013	2017	2013	2017	2013	2017	2013	2017	2013	2017
Mean of Dep. Var.	0.074	0.067	0.13	0.10	0.054	0.050	0.019	0.015	0.0017	0.0017
N	9410	17946	9410	17946	9410	17946	9410	17946	9410	17946

Notes: Standard errors, clustered at the household level, reported in parentheses ($^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$). All regressions use the DHS. Each cell reports the coefficient on $POST$ from a different regression, defined by the specified year and outcome variable. All regressions use a 10-year bandwidth, control for the main effects of $POST$, $SENIOR$, and a first-order polynomial for age that varies above and below the cutoff.

Interestingly, our IV estimates reveal that this increase in insurance coverage led to an increase in out-of-pocket expenditures. We estimate that insurance more than doubled medical spending for those who were affected by the policy. This was not driven by increases in inpatient or outpatient utilization on the extensive margin. Rather, it appears to be driven by increases in the intensity of treatment (conditional on seeking care) and possibly in the demand for drugs and other medical products.

As evidence for the latter, we show that the insurance expansion also increased diagnoses of hypertension, which is often accompanied by increased use of medications. We argue that these findings reflect a shift outward in the demand curve, due to provider-induced demand. Results from quantile IV estimation are also consistent with this argument. We find that most of the increase in expenditures is driven by movements at the upper third of the expenditure distribution. These findings highlight important policy considerations for low- and middle-income countries considering providing free health insurance for the elderly, or – given the characteristics of the compliers – expanding national insurance programs to higher-income groups.

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A Appendix

A.1 Average Complier Characteristics Derivations

We now derive the formulas given in equations (3) and (4). We will exploit the fact that $Z = D$ for $U \in [p_0, p_1]$. In addition, we will assume that $Z \perp (U, X)$. First, we note that

$$
\begin{aligned}
&\mu_X(0) = \\
&E\left[X|D = 0, p_0 \leq U < p_1\right] = \\
&E\left[X|Z = 0, p_0 \leq U < p_1\right] = \\
&\frac{1}{p_1 - p_0}\left[(1 - p_0)E[X|p_0 \leq U \leq 1] - (1 - p_1)E[X|p_1 \leq U \leq 1]\right] = \\
&\frac{1}{p_1 - p_0}\left[(1 - p_0)E[X|Z = 0, p_0 \leq U \leq 1] - (1 - p_1)E[X|Z = 1, p_1 \leq U \leq 1]\right] = \\
&\frac{1}{p_1 - p_0}\left[(1 - p_0)E[X|D = 0, Z = 0] - (1 - p_1)E[X|D = 0, Z = 1]\right].
\end{aligned}
$$

Per Figure 3, the second term nets out the contribution of the never takers from the composite of the untreated compliers and never takers. Similar arguments deliver that

$$
\begin{aligned}
&\mu_X(1) = \\
&E\left[X|D = 1, p_0 \leq U < p_1\right] = \\
&E\left[X|Z = 1, p_0 \leq U < p_1\right] = \\
&\frac{1}{p_1 - p_0}\left[p_1E[X|0 \leq U < p_1] - p_0E[X|0 \leq U < p_0]\right] = \\
&\frac{1}{p_1 - p_0}\left[p_1E[X|Z = 1, 0 \leq U < p_1] - p_0E[X|Z = 0, 0 \leq U < p_0]\right] = \\
&\frac{1}{p_1 - p_0}\left[p_1E[X|D = 1, Z = 1] - p_0E[X|D = 1, Z = 0]\right]
\end{aligned}
$$

where, similar to above, the second term nets out the effects of the always takers from the first term which is a composite of the treated compliers and always takers (per Figure 3).