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Expanding Health Insurance for the Elderly of the Philippines

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Abstract

This paper evaluates a Filipino policy that expanded health insurance coverage of its senior citizens, aged 60 and older, in 2014. Using regression discontinuity and difference- in-differences methods, we find that the expansion increases insurance coverage by approximately 16 percentage points. We show that the compliers, those induced by the policy to obtain insurance, are disproportionately female and largely from the middle of the socioeconomic distribution. Instrumental variables estimates indicate that out-of-pocket medical expenditures more than double among the compliers. We argue that this is most likely driven by an outward shift in the medical demand curve.

Keywords: insurance, medical demand, compliers, Philippines

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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.[2] 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 lower income countries.[3]

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 amendment to the 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 health insurance for the elderly in a lower-middle-income country. Unlike their counterparts in rich nations, many of the individuals affected by this policy 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 compared to similar policies in the developed world, where most people have consistent health insurance coverage throughout their adult lives. This paper conducts a comprehensive evaluation of the ESCA amendment. We investigate how it affects insurance coverage, who is most affected, and how their expenditures and utilization change as a result of the new insurance coverage. To estimate how the ESCA amendment affects insurance coverage, we exploit the age eligibility cutoff and utilize data from both before and after the policy. This allows us to combine regression discontinuity and difference-in-differences methods, 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 increases insurance coverage by 16 percentage points.

Next, we ask who is induced by the policy to take up insurance. That is, who are the "compliers" in this natural experiment? We find that the compliers are disproportionately female and largely from the middle of the income and education distributions. This is

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[2] For excellent reviews, see Giedion et al. (2013) and Acharya et al. (2012).

[3] 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.

consistent with several features of the Filipino insurance system, in which male senior citizens were more likely to be insured in the absence of the policy and individuals at both the bottom and top of the socioeconomic distribution had other channels through which they were likely to be insured before the policy. We also find some evidence of adverse selection. That is, the compliers in our context have higher inpatient utilization (in the absence of the policy) than the never-takers.

Identifying the characteristics of compliers, which is not frequently done in policy evaluations of insurance programs, is a valuable exercise that helps place our study in the context of the broader literature.[4] In particular, our results highlight the unique nature of this policy compared with other programs implemented in similar countries, which largely target the poor. In this sense, our study could be useful for policymakers considering expansions of their national insurance programs to broader (higher-income) populations. In addition, we estimate the impact of insurance on expenditures and utilization, thereby providing important insights into how the impact of insurance might change as incomes increase in the developing world.

In order to obtain these estimates, we use an instrumental variables strategy. We use the regression described above, which estimates the effect of the policy on insurance coverage, as the first stage of our instrumental variables specification. We find that insurance actually *increases* household per capita health expenditures. This is in contrast with the majority of evidence in both the developed and developing world (Acharya et al., 2012; Finkelstein et al., 2012; Giedion et al. 2013; Shigeoka 2014), with a few important exceptions from China, Indonesia, and Peru (Wagstaff and Lindelow 2008; Sparrow et al. 2013; Bernal et al. 2017). Interestingly, the increase we document is driven by expenditures on outpatient services and medicines, which are not typically included in the primarily inpatient benefits of the insurance coverage in this context.

We argue that the increase in expenditures is driven by an outward shift in the demand for medical care, rather than just a movement along the curve. This is consistent with our finding that insurance increases the likelihood of being diagnosed with a chronic condition, specifically, hypertension. In a setting where these chronic diseases are vastly underdiagnosed, an increase in diagnoses is likely indicative of an increase in testing, which could explain why insured individuals end up spending more on outpatient services (like laboratory tests) and drugs (for treatment). Importantly, this could also mean that the shift in the demand curve is beneficial for health, although we are unable to examine health outcomes in this study.

This outward shift in demand could have been the result of insured individuals' increased contact with the healthcare system, or complementarities between inpatient services and non-covered outpatient services or drugs. If this explanation is correct, we should also see increases in healthcare utilization. Although we do not detect any significant effects of insurance on the probability of visiting a health facility in the last month or having a hospital stay in the past year, we note that these estimates are imprecisely estimated and that the 95% confidence intervals cannot rule out large positive effects on utilization. In addition, these simple measures of utilization do not capture the

[4] See Kowalski (2018) and Kowalski (2016) for important exceptions. Unlike the present study, these utilize data from a true experiment rather than a natural experiment.

frequency of health visits or hospital stays. Indeed, we find some evidence suggesting that insurance increases intensive margin utilization.

The striking finding that insurance can change the demand for medical care is related to a large literature on physician-induced demand (Johnson 2014). While this literature has primarily focused on more detrimental forms of physician-induced demand in rich countries, our findings provide evidence that insurance can change demand in ways that could be beneficial for patients. Our results therefore speak to the small set of studies documenting potentially beneficial forms of physician-induced demand in lower-income countries (Wagstaff and Lindelow 2008; Sparrow et al. 2013; Bernal et al. 2017).

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 policy on health insurance coverage, the characteristics of the compliers, and the effect of this expansion in insurance coverage on expenditures and utilization. Finally, we conclude.

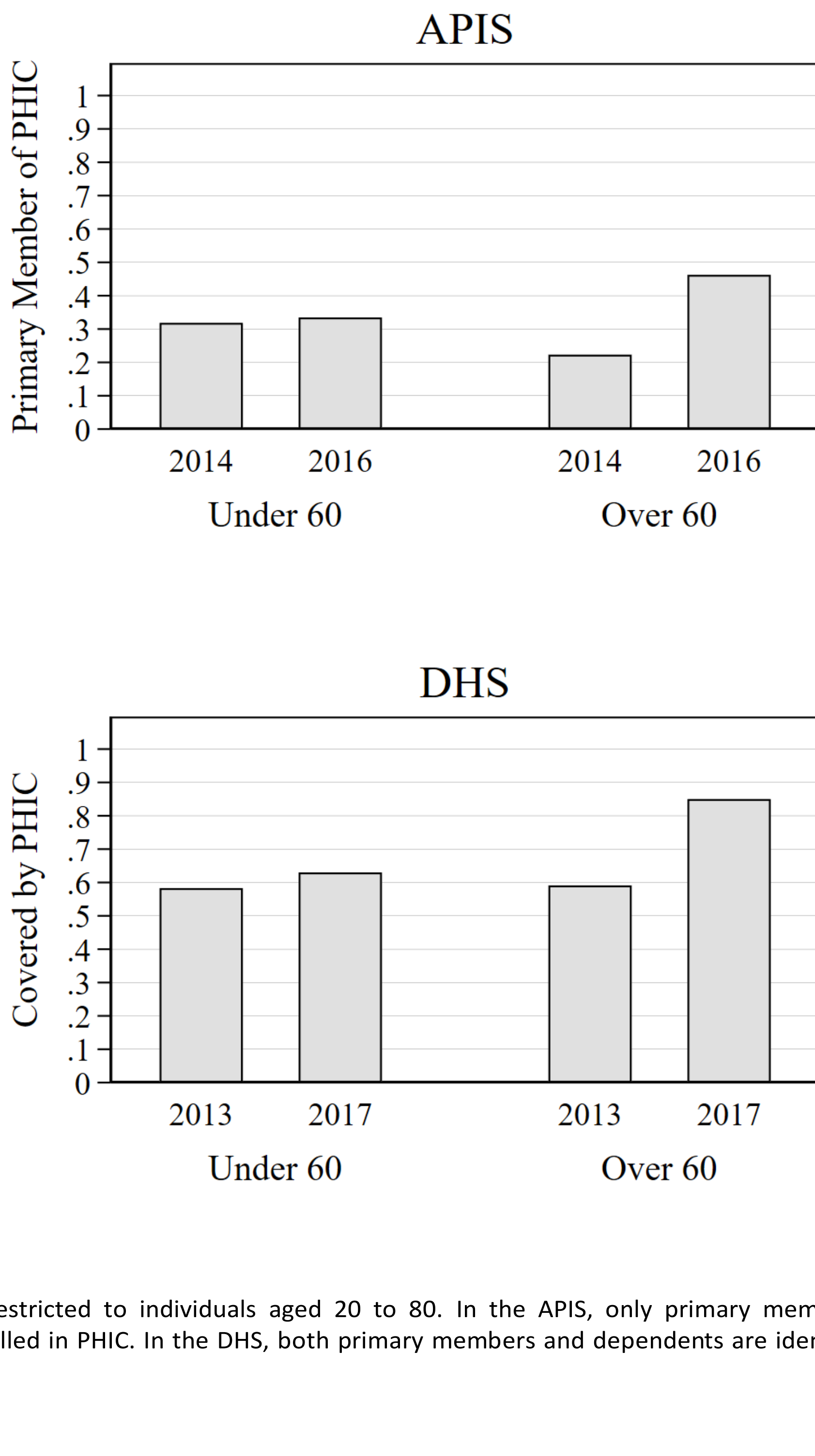
2. Health Insurance in the Philippines

Since the 1960s, the Philippines has had a tradition of providing health insurance coverage to portions of its citizenry. 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%.

In our study period, there are three types of membership to the PHIC: paying, lifetime, and sponsored.[5] 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

[5] With the adoption of the Philippine Universal Health Care Act in 2019, the NHI primary membership types were reduced to two: direct contributors, whose insurance premiums are paid directly by members with their employers, if applicable, and indirect contributors, whose premiums are paid by the national government through general taxes and other government incomes.

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.

depending on their income.[6] 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 2013 NHIA, the national government was tasked to fully subsidize the premium contributions of households identified as poor by a proxy means test (many of whom were already eligible for PHIC benefits since 2010 through a conditional cash transfer program). In addition, a corollary law from 2014 that applied to the elderly population, the Republic Act 10645, which amends an earlier law, the Expanded Senior Citizens Act (ESCA), was instituted. Because of this amendment to ESCA, which we refer to simply as ESCA throughout the remainder of the paper, 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.[7] 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 the PHIC, unless they are included as part of 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.[8] To enroll, individuals are required to fill out a two-page form and provide proof of identification. This can be done at local PHIC offices, the Office of Senior Citizen Affairs, and hospitals.

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.[9] 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.

[6] 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.

[7] In addition, parents of PHIC members who were over 60 years old and below a non-specified income threshold were technically considered to be covered dependents, prior to 2014. However, the data seems to suggest that knowledge of this law was limited, as we see see no jump in coverage rates at age 60 prior to 2014, which is what we would expect if senior citizen parents were enrolling as dependents.

[8] As we show in Appendix Table A1, "general" outpatient expenditures (which include consultations, physical check-ups, and basic laboratory services) account for only 7% of total expenditures.

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

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 basic information on individual utilization which is not available in the APIS.[10]

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. This includes spending on inpatient care, outpatient care, medicines, therapeutic gadgets, and equipment.

Importantly, the APIS has information on PHIC membership at the individual level.[11] 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 for each year. First, in the year 2014, we see that about 34% of people ages 50-59 and only 26% of people ages 60-69 are enrolled in the PHIC. 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 are members and 46% of those ages 60-69 are members in 2016. The next row displays statistics on household OOP medical expenditures (per person). In both years, households of individuals younger than 60 spend less than households with individuals aged 60 and older. The health expenditure share of total income is also higher for households with senior citizens in both years.

The next three rows contain information about three different categories of health expenditures: inpatient, outpatient, and medical product expenditures. We first note that there are some data quality issues related to these variables in the 2014 survey. Specifically, for 30% of individuals in the 2014 survey, there are discrepancies between total health expenditures and the sum of the three expenditures categories. This is due to respondents reporting a value for total health expenditures but being uncertain about expenditures on one or more of the categories. Instead of being coded as missing, these values are coded as zeros, resulting in a total health expenditure value that exceeds the sum of the expenditure categories. This problem does not exist in the 2016 survey. We describe in section 4.2 how we deal with this data issue in our analysis.

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

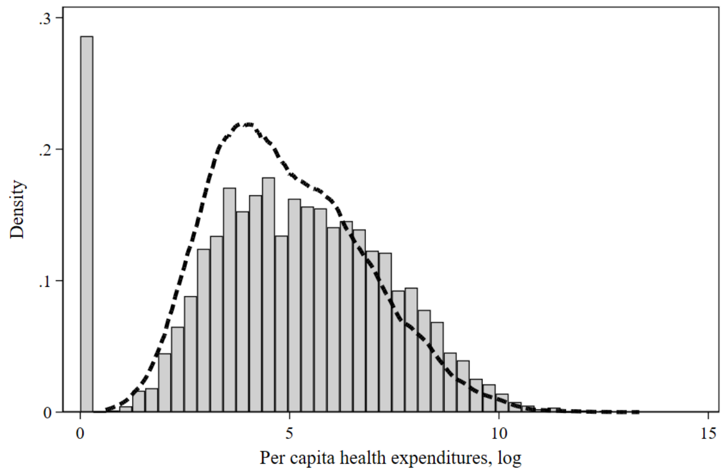
[11] As we discuss later, individuals are only recorded as members if they are the primary member of PHIC, not if they are qualified dependents.

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)
Inpatient exp. per capita (pesos)	519.77	592.38	424.17	482.58
	(6337.35)	(5071.41)	(4665.57)	(3806.97)
Outpatient exp. per capita (pesos)	140.21	169.57	100.65	284.58
	(1413.12)	(932.85)	(754.49)	(2895.45)
Medical products exp. per capita (pesos)	266.04	369.58	550.50	1164.08
	(1150.56)	(1424.41)	(1954.64)	(3646.46)
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.

Average spending for inpatient expenditures and medical products is much higher than for outpatient expenditures. In the 2016 survey (in which total expenditures equal the sum of the parts), the highest average expenditures are for medical products. For all categories, spending is higher for households with senior citizens. It is important to note that the ratio of average spending on each category to average total spending does not provide an accurate estimate of the average share of health spending on each category at the household level. We therefore report in Appendix Table A1 the average shares of health expenditures going to each of the three categories at the household-level. Again focusing on 2016, we see that households spend more than 80% of their health expenditures on medical products on average. We also complement this information with data from another source, the 2015 Family Income and Expenditures Survey (FIES), which provides an even more detailed breakdown of the health expenditure categories.[12] In the second column of Table A1, we show that the vast majority of spending on medical products is on pharmaceuticals; very little is spent on other products (like bandages or knee braces). In addition, we show that while over half of (the small share of) outpatient spending is on "general" services like consultations, a non-trivial portion goes to specialized services like X-rays or electrocardiograms.

In addition to these expenditure variables, 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 con- struct dummies for three income categories: the 3rd decile and below, the 4th to the 7th deciles, and the 8th decile and higher. Descriptive statistics for these categorical variables and gender are also reported in Table 1.

Finally, in Figure 2, we display a histogram of the log of per capita medical expenditures. To address zeros, we add one to the per capita expenditure variable before taking logs. The

[12] Unfortunately, the FIES does not have information on the insurance status or ages of individual household members and therefore cannot be used in the main analysis.

figure reveals that approximately 9% of our sample have zero health expenditures (the width of each bin is approximately 0.3). 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 also includes individuals who are covered under the PHIC as dependents of primary members.[13] 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 are covered by the PHIC, while a slightly smaller share, 61%, of those aged between 60 and 69 are. 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 increases 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 had a hospital stay. This may be a consequence of the higher prevalence of diagnosed chronic and acute conditions among the elderly, also documented in this table.

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 income information 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.

[13] Spouses and children count as qualified dependents and can also avail of benefits. However, they are not automatically enrolled and have more limited benefits than the primary member.

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.

4.2.1. 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:

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

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 $p_1 - p_0$.

4.2.2. 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

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

Where $\widehat{D}_{iat}$ 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 acquire insurance coverage as a consequence of the ESCA.

As discussed above, there are some data quality issues related to the expenditure category variables in 2014. In all expenditure-related regressions, we control for an indicator equal to one for households with total health expenditures that exceed the sum of their inpatient, outpatient, and medical product expenditures. We also run specifications that exclude these households from the analysis.

Importantly, the use of an instrumental variable helps alleviate typical endogeneity concerns that would arise from an OLS regression of utilization (or expenditures) on insurance coverage. Adverse selection could lead to a positive correlation between the error term and the insurance indicator (unhealthy people choose to get insurance and also have higher utilization), while advantageous selection would result in the opposite (people who care about their health choose to get insurance and have lower utilization because they are healthier in general). Another potential source of endogeneity is reverse causality; individuals may not know they are eligible for free insurance until they go to a health facility. If senior citizens only find out about the ESCA when they visit a facility, this would lead to a causal link from utilization to insurance coverage. Using an instrument helps alleviate these concerns. We argue that the instrument, the interaction between $SENIOR_a$ and $POST_t$, is uncorrelated with the error term after we control for the main effects of $SENIOR_a$, $POST_t$, and a flexible function of age that varies above and below age 60. Senior citizens might have systematically different utilization from non-seniors, individuals in post-ESCA years might have systematically different utilization from those in pre-ESCA years, and utilization might vary (flexibly) with age – all for reasons unrelated to the ESCA. However, we argue that any *differential* difference in outcomes across years, right at the cutoff between seniors and non-seniors, can only be due to the ESCA's expansion of insurance to the elderly. Under this assumption, θ_1 provides us with a consistent estimate of the LATE.

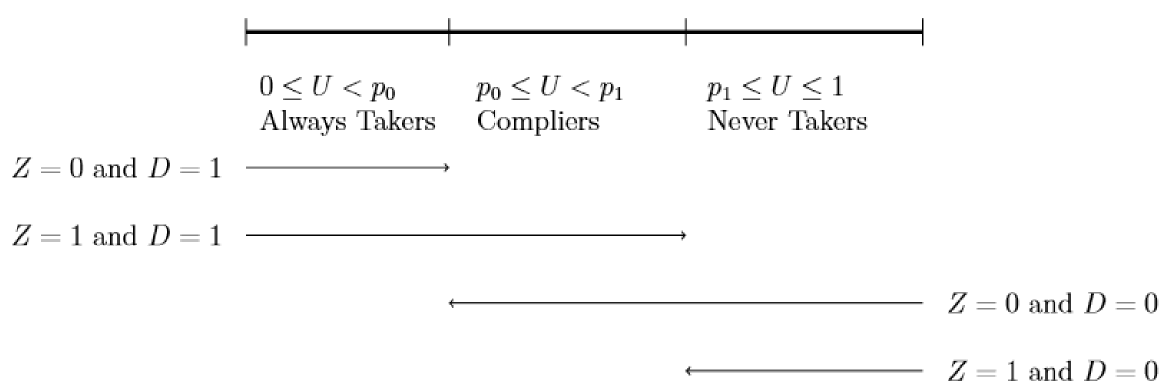
4.3. Complier Characteristics

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 is most impacted by the ESCA. This is a policy-relevant question that will provide guidance on what lessons can be applied to other contexts.

4.3.1. Identification

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 $p_0 \leq U < p_1$. For these individuals,

Figure 3. Identifying the Compliers



we will have that $Z = D$. 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. Similarly, 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. 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.

We calculate the characteristics of the compliers using methods similar to those used in the existing literature (Imbens and Rubin, 1997; Katz et al., 2001; Abadie, 2002, 2003; Kowalski, 2016). Identification entails computing $E[X|D = d, p_0 \leq U < p_1]$ 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

$$\mu x(0) \equiv E[X|D = 0, p_0 \leq U < p_1] = \tag{3}$$

$$\frac{1}{p_1 - p_0}[1 - p_0)E[X|D = 0, Z = 0] - (1 - p_1)E[X|D = 0, Z = 1]].$$

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

$$\mu x(1) \equiv E[X|D = 1, p_0 \leq U < p_1] = \tag{4}$$

$$\frac{1}{p_1 - p_0}[p_1 E[X|D = 1, Z = 1] - p_0 E[X|D = 1, Z = 0]].$$

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

$$\pi * = \frac{V(\widehat{\mu x(1)}) - C(\widehat{\mu x(0)}, \widehat{\mu x(1)})}{V(\widehat{\mu x(0)}) + V(\widehat{\mu x(1)}) - 2C(\widehat{\mu x(0)}, \widehat{\mu x(1)})}.$$

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

4.3.2. 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 individual characteristic, then a simple way to estimate characteristic averages is to estimate the following regression:

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

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 1,000 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 (and controlling for age). 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

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

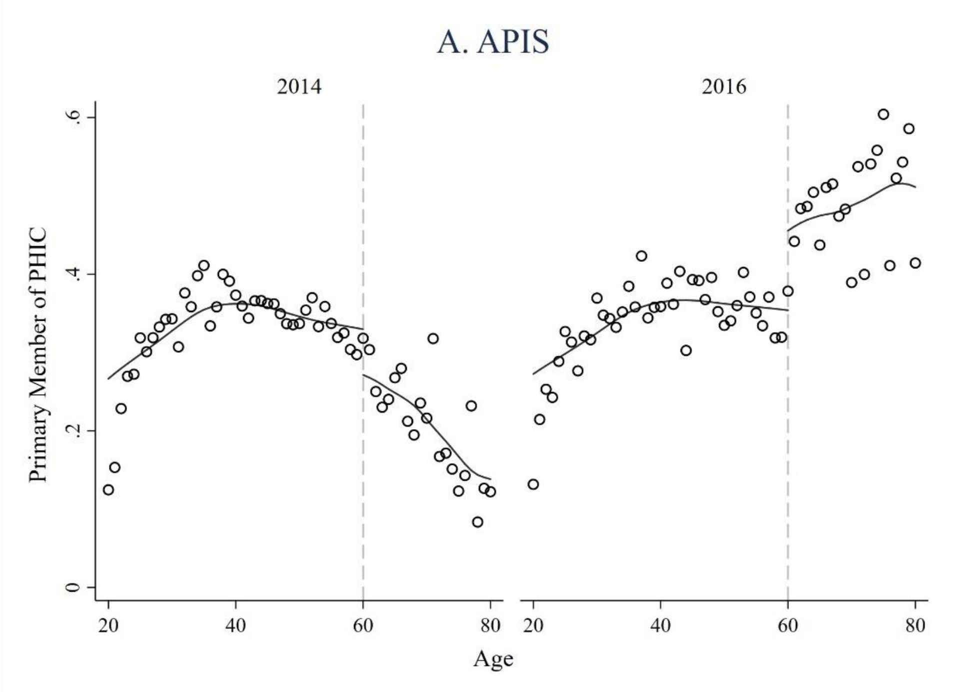
The first term is the average of the outcomes for the never takers and the untreated compliers. The second is the average of the outcomes for the never takers. Because both groups are untreated, differences between the two cannot be due to heterogeneous treatment effects (which could be the case in a comparison of λ_{AT} and λ_{AT+TC}). If λ_{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, and graph the lowess-smoothed relationship 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 is 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 has been 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, sign-up time costs, or low perceived benefits of insurance may have served as 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 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 has 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 differ across the DHS and APIS, the estimates of the marginal impacts of the ESCA are almost identical across datasets.

Figure 4. Insurance Coverage by Age and Year



Notes: Dots represent age-specific means, and lines represent the lowess-smoothed age-coverage relation- ship, 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.

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 describe above. Each panel contains four box plots corresponding to means for the always takers, compliers, never takers, and the full sample, computed from 1,000 bootstrapped re-samples. Because the means of the compliers involve 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.

Results from both datasets indicate that the compliers are 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 are less likely to be in the low education and SES categories than the never takers (and in some cases, the always takers). They are 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 are far less likely to be male than the always and never takers.

Why is 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. 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.[14] 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 are 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.

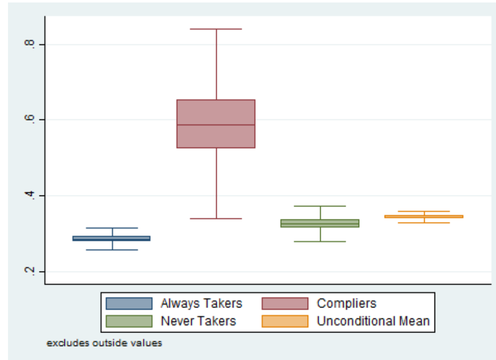
The link between employment and insurance also explains why the compliers are more likely to be women, who have lower labor force participation than men do and are therefore less likely to be insured, either as paying or lifetime members once they turn 60 (in the absence of the policy). Although married women can be covered as dependents if their spouses are PHIC members, this is not automatic and benefits are slightly less generous if there are additional dependents involved.

[14] 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.

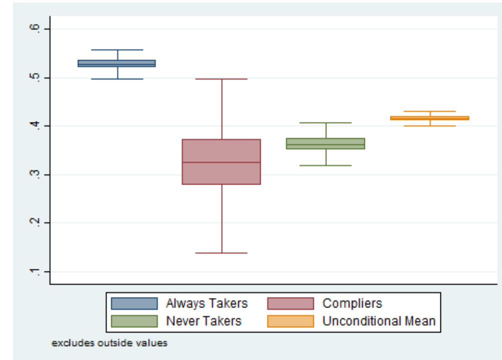
Figure 5. Observable Characteristics for Always Takers, Compliers, and Never Takers in APIS

A. Low Education

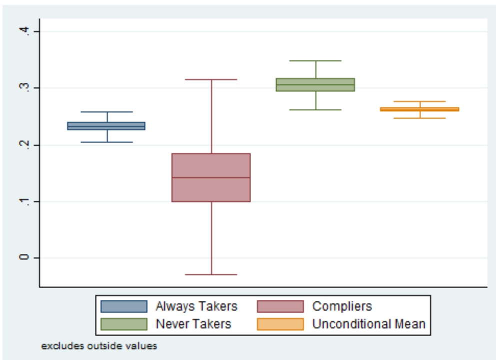
B. Middle Education



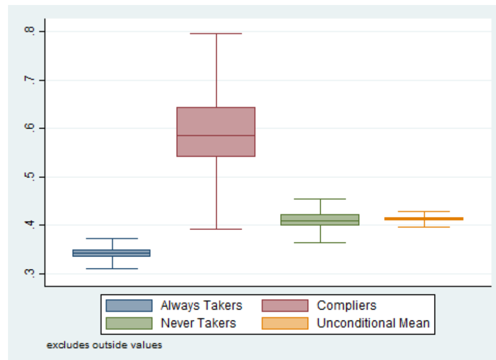
C. High Education



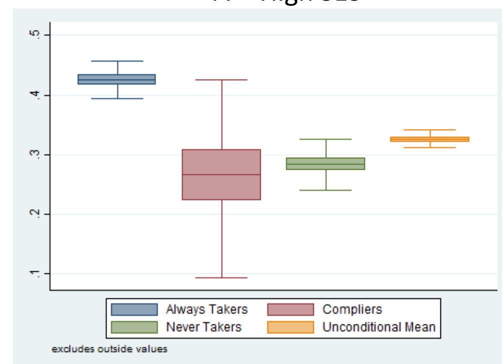
D. Low SES



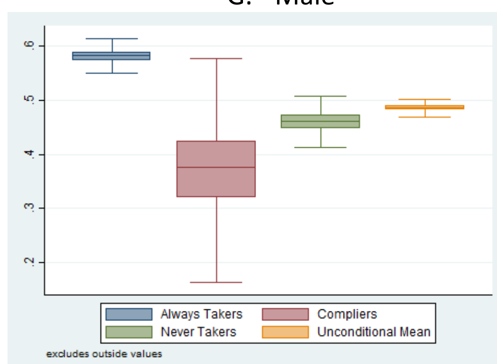
E. Middle SES



F. High SES

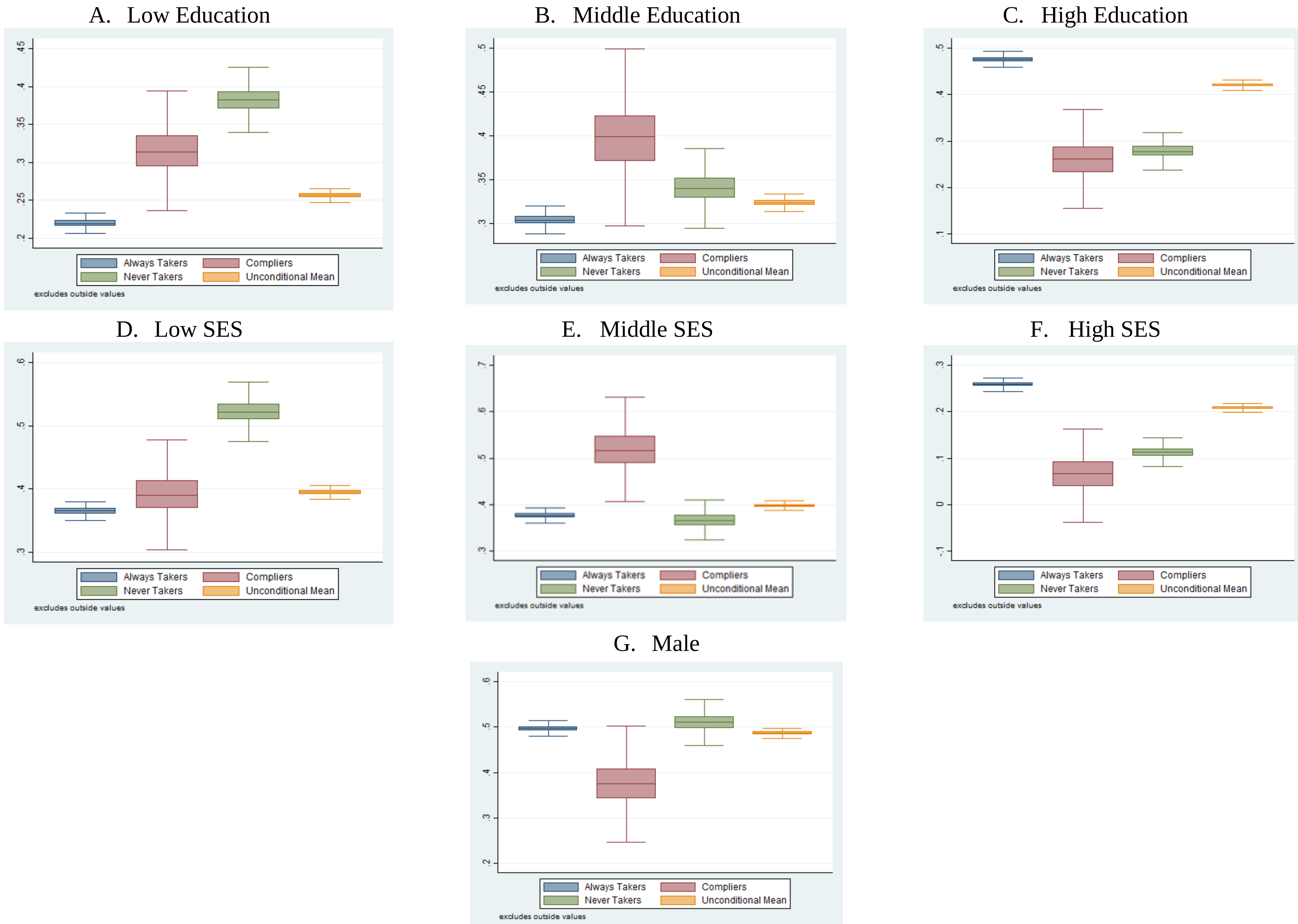


G. Male



Notes: Box plots were computed from 1,000 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 1,000 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.

6.2. Testing for Selection

We now test whether there is 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), 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 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 variables. We also 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 interaction parameters (which are α_1 in equation (1)) are zero.

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. Expenditures and Utilization Results

In Table 6, we report second-stage IV estimates of the effect of insurance on various expenditure variables. 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

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.

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. In the appendix, Table A2 shows that results are very similar when we exclude individuals with data quality issues (that is, with total health expenditures that exceed the sum of the three expenditure categories).

The first outcome of interest is household per capita medical expenditures from the APIS. This outcome includes OOP spending on inpatient and outpatient services, as well as medical products (which, as shown in Table A1, are primarily drugs). Strikingly, despite households facing *lower* OOP prices, we see that total expenditures *increase*. The estimate from the 10-year bandwidth is 1.230, which indicates that insurance coverage more than doubles medical expenditures. When we investigate the expenditure share spent on health as an outcome variable, we see positive coefficients that are large relative to the mean in both specifications, and a statistically significant coefficient for the 10-year bandwidth, indicating that health insurance leads to a 4.6 percentage point increase in the health share of expenditures.

Table 6. IV Estimates: Effect of Health Insurance on Expenditures (APIS)

	Log Health Expenditures		Health Expenditure Share		Log Inpatient Expenditures		Log Outpatient Expenditures		Log Medical Product Exp.	
Bandwidth	5	10	5	10	5	10	5	10	5	10
Enrolled in PHIC	1.416*	1.230**	0.027	0.046**	-0.523	0.105	1.751**	1.541***	1.534**	1.822***
	(0.770)	(0.523)	(0.025)	(0.019)	(0.677)	(0.472)	(0.716)	(0.494)	(0.712)	(0.495)
Weak identification F	43.320	100.382	43.320	100.382	43.320	100.382	43.320	100.382	43.320	100.382
Underidentification F	42.872	98.983	42.872	98.983	42.872	98.983	42.872	98.983	42.872	98.983
Polynomial Order	1	2	1	2	1	2	1	2	1	2
Mean of Dep. Var.	4.99	4.94	0.036	0.036	0.62	0.62	1.23	1.25	3.77	3.69
N	6707	13116	6707	13116	6707	13116	6707	13116	6707	13116

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*, a flexible polynomial for age that varies above and below the cutoff, and data quality indicator equal to one for individuals from households whose total health expenditures exceed the sum of their inpatient, outpatient, and medical product expenditures.

Table 7. IV Estimates: Effect of Health Insurance on Utilization (DHS)

	Hospital Stay Last Year		Health Visit Last Month		Hospital Stay Last Month		
Bandwidth	5	10	5	10	5	10	15
Enrolled in PHIC	0.006	0.004	0.051	0.016	0.244	0.196	0.241*
	(0.060)	(0.034)	(0.079)	(0.046)	(0.348)	(0.167)	(0.134)
Weak identification F	66.615	190.617	66.615	190.617	4.569	20.410	32.715
Underidentification F	65.926	186.954	65.926	186.954	4.573	20.250	32.298
Polynomial Order	2	3	2	3	2	3	3
Mean of Dep. Var.	0.060	0.056	0.11	0.10	0.13	0.14	0.14
N	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.

It is notable that newly enrolled individuals in the PHIC spend more on medical expenditures despite gaining insurance coverage. This finding adds to mounting evidence that health insurance can increase OOP spending for households in developing countries (Wagstaff and Lindelow 2008; Sparrow et al. 2013; Bernal et al. 2017). Importantly, if the only effect of the ESCA is 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 often 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 and therefore caution against using these estimates to compute elasticities.

If the rise in expenditures were only reflecting movement along the demand curve, then we should see the largest increases in expenditures for inpatient services, as the ESCA's main benefit is coverage of inpatient services. On the contrary, the remaining columns of Table 6 show large and statistically significant increases in expenditures for outpatient services and drugs,[15] and not for inpatient expenditures. This provides further evidence that insurance in this context does not simply move individuals along the demand curve but rather, shifts the demand curve out.

What could have caused this shift in the demand curve for primarily non-covered healthcare? One explanation is that insured individuals spend more time with doctors and the healthcare system in general, which results in better knowledge about their health status and/or higher demand for healthcare. This could happen if increased interactions with doctors reveal new information about insured patients' health, or if insured patients use more inpatient services that have complementarities with outpatient services and drugs. To examine the plausibility of this hypothesis, we investigate utilization measures from the DHS. In Table 7, we investigate whether insurance increases the likelihood of an individual using inpatient services in the past year or visiting any health facility in the past month. We see no significant effects of insurance coverage on either of these variables, but note that the coefficients are imprecisely estimated (95% confidence intervals cannot rule out large positive effects on both outcome variables).

We do, however, find some evidence of increased intensity of utilization. In the last three columns of Table 7, 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 outward shift in the demand curve, through the mechanisms described above.

In the Appendix, we also show results from conditional quantile IV regressions, which provide estimates of the effect of insurance on total health expenditures at different deciles of the expenditure distribution. We show that the effect of insurance is increasing across

[15] Notably, Bernal et al. (2017) also find that access to health insurance in Peru increases OOP expenditures on medications.

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. This is exactly what we would see if insurance changes the intensive but not the extensive margin of utilization (though it could also be indicative of individuals going from very low to very high spending as a result of insurance). In short, these results are consistent with our argument that insurance is increasing utilization primarily on the intensive margin.

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

We have interpreted our results thus far as evidence that insurance causally increases health expenditures for individuals who gain insurance coverage as a result of the ESCA. However, the positive coefficients that we estimate in Table 6 could also be the result of individuals just below the age cutoff of 60 *reducing* expenditures in anticipation of gaining free coverage at age 60; in fact, we see in Table 1 that individuals under age 60 have lower health expenditures in 2016 than 2014. If this is indeed the case, we are still be able to causally identify the effect of the ESCA on insurance coverage, as well as the reduced form effect of the ESCA on expenditures, but we are not able to interpret our IV estimates as the LATE of insurance on expenditures. We therefore investigate the plausibility of this alternate explanation. In Appendix Figure A1, we plot average log health expenditures by age and graph the lowess-smoothed relationship separately for 2014 and 2016. Consistent with our estimates in Table 6, we see a positive discontinuity at age 60 that is larger in 2016 than in 2014. In addition, we make two important observations. First, total health expenditures are lower in 2016 than 2014 for all age groups – not only for those slightly younger than age 60.[16] Second, for those aged 50-59 in 2016, it is not the case that those closest to age 60 are the ones with the lowest expenditures. Conversely, it appears to be those in their early fifties with the lowest expenditures in 2016. These observations are not what we would expect to see if individuals close to the cutoff age are indeed "saving" their utilization for after turning 60.

7.3. Chronic Conditions Results

In Table 8, we explore one specific reason why insurance might be leading to higher spending, by investigating how insurance affects chronic condition diagnoses using the DHS. We first note that the share of individuals with a chronic disease diagnosis are very low (7% overall, 5% for hypertension, 2% for diabetes, and less than 0.2% for cancer), not because actual prevalence is this low but because of severe underdiagnosis.[17] True prevalence rates for hypertension, for example, are estimated to be 35-40% for this age group (FNRI-DOST, 2013). In this setting of drastic underdiagnosis, changes in the share

[16] This is likely due to sampling variation, as other sources do not show decreases in OOP health expenditures over this time period.
[17] Measurement error could also contribute to the low rates in this context, as the survey respondent may not have full information about all household members.

of individuals with a chronic disease diagnosis should be interpreted as a change in the share that have been tested (rather than a change in actual prevalence).

Because chronic condition diagnoses are so rare, 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 are 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 which is, generally, not covered by the PHIC. This could be an important reason for the increase in drug spending that we document. In addition, the finding that individuals are more likely to be tested for various conditions could also explain the increase in outpatient spending, which includes various types of medical tests.

8. Discussion

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. We find that the policy has 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 are largely drawn from the middle of the income distribution. This is in contrast with most recent insurance expansions in the developing world, which have tended to explicitly target the poor.

Interestingly, our IV estimates reveal that this increase in insurance coverage leads to an increase in out-of-pocket expenditures. We estimate that insurance more than doubles medical spending for those who are induced by the policy to take up insurance. This increase in spending is driven by increases in outpatient and drug expenditures, which are typically not covered by this insurance. We argue that these large expenditure increases are due to an outward shift of the demand curve, rather than movements down the curve in response to reductions in price.

This outward shift could be due to insurance increasing the amount of contact that individuals have with the healthcare system. Increased interaction with doctors might provide insured patients with more information about their own health or cause them to value health more, therefore increasing their demand for healthcare. We find evidence consistent with this story: the insurance expansion increases diagnoses of hypertension, a condition that is often treated with medication and could therefore result in higher drug expenditures.

Another related explanation is the possibility that insured patients use more covered (inpatient) services, which have complementarities with non-covered services. This could result in higher utilization of both outpatient services and drugs. Consistent with this explanation, we find evidence of increased utilization of inpatient services on the intensive margin. Both of these explanations describe a potentially beneficial form of provider-induced demand, quite different from the types of provider-induced demand studied in rich countries.

There are two other related explanations for our results. First, it could be the case that doctors treat insured patients differently, recommending more aggressive treatments or medication that may or may not be covered by insurance. Another possibility is that insured patients make different health spending decisions due to the knowledge that potentially large future inpatient costs will be covered. We acknowledge that some combination of all of these explanations may be in play.

This study highlights 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. Importantly, other work also has shown that health insurance can increase OOP spending for households in developing countries (Wagstaff and Lindelow 2008; Sparrow et al. 2013; Bernal et al. 2017). This mounting evidence has important policy implications. It suggests that government officials should ensure that the increased expenditures reflect higher use of necessary care. In addition, policy makers should ensure that physicians are not charging higher prices to newly insured patients who have a less elastic demand.

Table 8. Effect of Health Insurance on Chronic and Acute Conditions (DHS)

	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 (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). 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.

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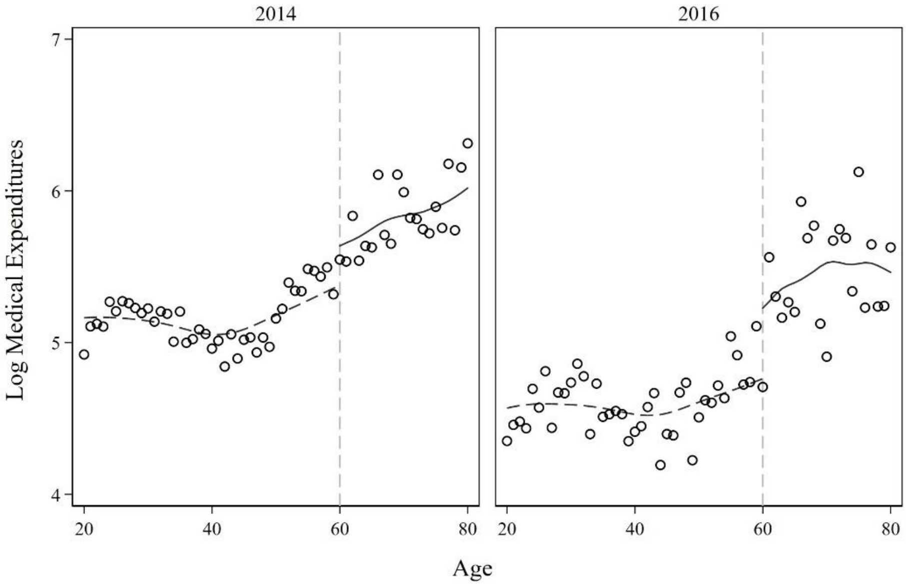
Appendix

A. Appendix Figures and Tables

Figure A1. Health Expenditure by Age and Year



Notes: Dots represent age-specific means of log per capita health expenditures, and lines represent the lowess-smoothed age-expenditure relationship, above and below age 60.

Table A1. Health Expenditures Shares by Expenditure Type, APIS and FIES

	2014 APIS	2015 FIES	2016 APIS
Inpatient expenditure share	0.07	0.08	0.06
	(0.22)	(0.24)	(0.22)
Outpatient expenditure share	0.09	0.11	0.09
	(0.21)	(0.21)	(0.22)
General outpatient		0.07	
		(0.17)	
Other outpatient		0.04	
		(0.13)	
Medical product expenditure share	0.65	.81	.85
	(0.48)	(0.31)	(0.30)
Pharmaceutical products		0.78	
		(0.32)	
Other products		0.03	
		(0.11)	

Notes: Sample includes all households in the 2014 APIS, 2015 FIES, and 2016 APIS. General outpatient services include consultations, physical check-ups, and laboratory services. Other outpatient services include specialized medical services (analysis and interpretation of X-rays, etc.), dental services, and paramedical services (freelance acupuncturists, optometrists, etc.). Other medical products include thermometers, bandages, corrective eye glasses, dentures, etc.

Table A2. IV Estimates: Effect of Health Insurance on Expenditures (APIS), Restricted Sample

	Log Health Expenditures		Health Expenditure Share		Log Outpatient Expenditures		Log Inpatient Expenditures		Log Medical Product Exp.	
Bandwidth	5	10	5	10	5	10	5	10	5	10
Enrolled in PHIC	1.435*	1.131*	0.054**	0.073***	1.601**	1.728***	-0.020	0.480	1.195	1.134**
	(0.870)	(0.594)	(0.022)	(0.017)	(0.670)	(0.475)	(0.561)	(0.392)	(0.802)	(0.554)
Weak identification F	37.391	84.908	37.391	84.908	37.391	84.908	37.391	84.908	37.391	84.908
Underidentification F	37.004	83.865	37.004	83.865	37.004	83.865	37.004	83.865	37.004	83.865
Polynomial Order	1	2	1	2	1	2	1	2	1	2
Mean of Dep. Var.	4.60	4.53	0.027	0.026	0.73	0.75	0.38	0.37	4.53	4.46
N	5584	10860	5584	10860	5584	10860	5584	10860	5584	10860

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. All regressions exclude individuals from households whose total health expenditures exceed the sum of their inpatient, outpatient, and medical product expenditures.

B. 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 $U \in [p0, p1]$. In addition, we will assume that $Z \perp (U, X)$. First, we note that

$$\mu_X(0) =$$

$$E[X|D = 0, p_0 \leq U < p_1] =$$

$$E[X|Z = 0, p_0 \leq U < p_1] =$$

$$\frac{1}{p_1 - p_0}[(1 - p_0)E[X|p_0 \leq U \leq 1] - 1(1 - p_1)E[X|p_1 \leq U \leq 1]] =$$

$$\frac{1}{p_1 - p_0}[(1 - p_0)E[X|Z = 0, p_0 \leq U \leq 1] - 1(1 - p_1)E[X|Z = 1, p_1 \leq U \leq 1]] =$$

$$\frac{1}{p_1 - p_0}[(1 - p_0)E[X|D = 0, Z = 0] - (1 - p_1)E[X|D = 0, Z = 1]]$$

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

$$\mu_X(1) =$$

$$E[X|D = 1, p_0 \leq U < p_1] =$$

$$E[X|Z = 1, p_0 \leq U < p_1] =$$

$$\frac{1}{p_1 - p_0}\left[p_1 E[X|0 \leq U < p_1] - p_0 E[X|0 \leq U < p_0]\right] =$$

$$\frac{1}{p_1 - p_0}\left[p_1 E[X|Z = 1, 0 \leq U < p_1] - p_0 E[X|Z = 0, 0 \leq U < p_0]\right] =$$

$$\frac{1}{p_1 - p_0}\left[p_1 E[X|D = 1, Z = 1] - p_0 E[X|D = 1, Z = 0]\right]$$

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).

B. 2. Quantile IV Regressions

In this section, we 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 can shed 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. That said, we also note that movement at the upper end of the expenditure distribution and not the lower end could also be indicative of individuals going from very low to very high spending as a result of PHIC.

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 10% of the medical expenditure observations were zeros. Hence, estimation of the model for τ = 0.1 is informative of the effects of the PHIC at the extensive margins, whereas estimation for τ > 0.1 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.

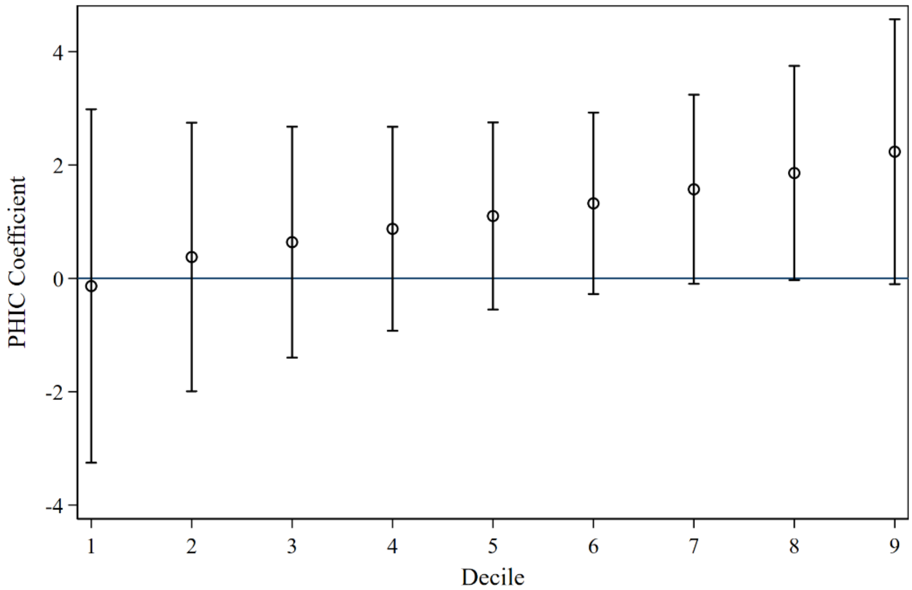
In Table B1, we present the estimations of $\alpha(\tau)$ from the SQF for $\tau \in \{0.1, 0.2, ..., 0.9\}$, estimated using the methods proposed by Machado and Santos Silva (2018). In Figure B1, we also plot the estimates from the table along with their 95% confidence intervals. It is clear that the 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.

Table B1. 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 B1. 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* × *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.