The Effects of *Seguro Integral de Salud* on Healthcare Utilization, Healthcare Out-of-pocket Expenditures, and Health in Peru

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Giovann Alarcón Espinoza

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Dedication

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Abstract

In this dissertation, I study the effects of *Seguro Integral de Salud* (SIS), a publicly-operated health insurance program in Peru that provides healthcare coverage to poor and vulnerable individuals and complements the subsidies already existing through the nationwide network of public healthcare providers. First, I estimate SIS' effect on healthcare utilization. I find that SIS has had a positive impact on healthcare utilization, especially preventive care, while some implementation problems are likely to be the cause of an estimated negative effect on obtaining corrective lenses. I also find that SIS effect is smaller among poor enrollees, likely because the program is unable to help its enrollees to overcome other barriers to access healthcare (e.g., geographical barriers). In addition, I find some negative effects on people's out-of-pocket healthcare expenditures, especially for some types of preventive care. SIS' debt to providers is likely the reason why it had a positive effect on "other services." Lastly, I find no evidence of an effect of SIS coverage on catastrophic healthcare expenditure and children's health.

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1.1. Introduction

Many countries around the world have achieved or are on their way to reaching universal healthcare coverage. Almost everyone in the developed world has some form of health insurance or healthcare coverage to protect them from the financial risks associated with their health, and in recent years many developing countries have moved towards universal healthcare coverage by implementing government–operated health insurance programs. In September, 2015, 267 economists from 44 countries, including Nobel laureates, signed a declaration calling on policy makers throughout the world to "prioritize a pro–poor pathway to universal health coverage as an essential pillar of sustainable development."[1] Health insurance has proven to be a very attractive policy all over the world.

This trend towards universal coverage is taking place despite inconclusive evidence, mostly from developed countries, on the effects of health insurance. For example, Brook, *et al*. (1983) found that the extra healthcare gained from having a better insurance coverage did not have an effect on people's health in the U.S. On the other hand, increasing the number of people enrolled in Medicaid reduces children's mortality by 34% (Currie and Gruber, 1996). If healthcare obtained through insurance is ineffective, the case for a better use of resources to improve healthcare could be argued. But if it is cost-effective, then the extension of health insurance should be promoted. In either case, governments are making these policy decisions with little or no evidence.

[1] Economists' Declaration (2015, September). Retrieved December 23, 2015, from http://universalhealthcoverageday.org/economists-declaration/#text

One case that exemplifies this lack of evidence in decision making is the *Seguro Integral de Salud* (SIS) in Peru. Implemented in 2002, this program was the National government's response to strong economic barriers to obtaining healthcare (47% of the population that required healthcare did not obtain it due to economic reasons in 2000; Madueño, *et al.*, 2003, p. 95) that coexisted with high levels of idle capacity among public providers (40-53% among providers of outpatient services in 1999; Madueño, *et al.*, 2003, p. 194). With the objective of reducing the economic barriers that "vulnerable people"[2] face when in need of healthcare, but without any formal studies providing technical, objective support for an extension, SIS has progressively increased its number of enrollees. By December, 2019, it enrolled 47.9% of Peru's population.[3]

Considering that the program is the main mechanism to achieve universal coverage in Peru,[4] that it absorbs significant public resources, and that in 2019 22.4% of the population is still uninsured, the main goal of my research is to estimate causal relations between SIS and three outcomes of importance: healthcare utilization, household healthcare expenditures, and health outcomes.

As previously stated, the main objective of SIS is to increase the use of needed healthcare services, especially among the poor. Thus, Chapter 2 will focus on estimating the magnitude of this relationship for the specific case of SIS, i.e., the extent to which SIS

[2] Though vaguely defined, this is the legal term for the program's target population. Most of the time, it is understood that "vulnerable people" refers to the population under the poverty line, though sometimes it refers to specific groups with a higher probability of needing care (such as pregnant women and children under five).

[3] The 2019 *Encuesta Nacional de Hogares* (ENAHO) reports that only 47.9% of its sample is enrolled in SIS. However, official records report 20 million enrollees, which is closer to two thirds of the population.

[4] In 2009, a law was passed that declared Universal Coverage as a national goal. Although a considerable percentage of the population is still uninsured, the rate of health insurance coverage has increased significantly since this law passed, almost exclusively through expansions of SIS enrollment.

has achieved its goal of providing healthcare services to the poor and vulnerable propulation. Chapter 2 will also study the equity effects of this program; SIS was designed to improve access to healthcare among the poor, but not all poor are enrolled,[5] and high rates of leakage to the non-poor have been observed since the early stages of the program's implementation until 2009, when Universal Healthcare Coverage was declared to allow participation by certain groups of the population regardless of their poverty level.

Healthcare is one of the few categories of consumption that can impoverish families, and this is one of the main reasons for the spread of health insurance in the world. One of the core objectives of health insurance is to provide some degree of protection against the financial risk associated with poor health. This relationship is explored in Chapter 3. Does enrollment in SIS reduce the possibility that households spend a high portion of their income on healthcare? The direction of the relationship between health insurance and healthcare expenditure is not as clear as the relationship studied in Chapter 2. It may be that, by enrolling in SIS, people gain coverage and their disposable income (net of expenditures on healthcare) increases as this coverage reduces the price of healthcare. But it may also be the case that, as people enroll, the lower price leads them to seek more care, sometimes not covered by the program, which offsets the initial price reduction and decreases their disposable income.

Ultimately, health insurance should improve health, to the extent that it facilitates access to healthcare services that have a positive effect on health. However, the empirical literature is still inconclusive about this relationship. And that leads to the main objective

[5] The percentage of poor people who are not enrolled in SIS has decreased over time, especially after 2009.

of Chapter 4: estimating the relationship between health insurance and health. I will focus on children's health and evaluate the effect of SIS in short-term illnesses and symptoms (e.g., diarrhea and acute respiratory infections), and children's malnutrition as a proxy to long-term health.

This dissertation will fill some of the gaps in the empirical literature, which are especially large among developing countries, and will provide useful information for the design of future expansions of SIS. It will also provide evidence that policy makers and health officials in Peru can use to adjust the program and increase its effectiveness in reducing inequality. Finally, my results will provide key information to the current debate about universal coverage in Peru, since the effects of health insurance on healthcare utilization, financial protection, and health are decisive factors in this debate.

The remaining sections in this chapter provide some background information: a brief history of health insurance in Peru, and a description of some relevant components of the program.

1.2. Health Insurance in Peru

As with most health systems, the one in Peru is highly complex. With different insurance programs, each with their own provider apparatus, their own revenue sources and financial channels, and with little interaction between these healthcare stakeholders, a patient can have different experiences depending on which sub-system they is tied to. However, the two main insurers, SIS (61.7% of the population with insurance coverage in 2019) and the Social Health Insurance (34.5% of the population with coverage), are operated by the government. Each one of these two institutions funds and operates an exclusive network of providers. SIS works almost exclusively with the different networks from the Ministry of Health (MOH) and the regional governments. The Social Health Insurance system is a public institution that administers the mandated contributions made on behalf of their enrollees[6] and provides them with healthcare through its own network of providers. These two main institutions coexist along with several private insurance plans and providers, who capture a small and decreasing portion of the market (3.9% of the population with coverage).

When SIS was implemented in 2002, the health system already had some major insurers, including the Social Health Insurance, which has been operating since 1936. In this section, I provide a brief review of the history of health insurance in Peru.

1.2.1. The Social Health Insurance

The first major health insurance scheme that was implemented in Peru was the *Caja Nacional del Seguro Social del Obrero* in 1936, which targeted a very specific group of unionized employees. Twelve years later, in response to demands from another union, the government created the *Caja del Seguro Social del Empleado*. These two organizations had similar objectives: to provide outpatient and inpatient care when needed due to illness, pregnancy, injury, or disability; monetary subsidies due to illness, pregnancy, maternal leave, and death; and pensions due to disability or retirement.

[6] Enrollment is restricted to people who are formally employed, which limits the number of enrollees, especially given Peru's high rate of informal employment.

Between the 1970s and 1990s, Peru's Social Health Insurance underwent major changes. First, the *Caja Nacional del Seguro Social del Obrero* and the *Caja del Seguro Social del Empleado* were merged in 1973 to become the new Social Health Insurance, which was modeled after other similar programs in Latin America. Second, in the 1980s there was a series of adjustments to the size of the premium paid by employers, which has always taken the form of a percentage of the employee's paycheck. Third, the pension and health insurance systems were separated in 1992 and the latter was branded as EsSalud. Fourth, in 1997 private companies were allowed to enter the Social Health Insurance market to supplement EsSalud, the government's health insurance, and to provide preventive and ambulatory recovery care to those groups that decided to form their own pools.[7]

EsSalud is financed by a premium equivalent to 9% of most enrollees' paychecks; 78% of EsSalud enrollees pay this contribution and the other 22% pay a discounted premium.[8] This contribution is mandated for everyone who is formally employed and it provides health insurance for the employee and his or her family. EsSalud offers a comprehensive plan that includes prevention, promotion, recovery, and rehabilitation, along with regular curative health services and even economic and social benefits.[9] This plan is offered through a network of clinics and hospitals that EsSalud operates.

[7] Employees of every company can choose to have their ambulatory care be administered by private insurers. These private companies would receive half the premium paid to EsSalud but would receive an additional payment if they estimate a higher premium based on the specific pool of employees.

[8] This contribution is smaller (4-6%) for some groups: retirees, farmers, fishers, and home workers.

[9] These social benefits are mainly disability payments for enrollees when they are on a leave due to an illness that has lasted over 30 days.

The main challenge that the Social Health Insurance faces is how to expand coverage more widely in Peru given the structure of Peru's labor market, which has a high level of informality, a situation that is beyond the control of the health sector.

1.2.2. Subsidized Healthcare

The Ministry of Health (MOH) was created in 1935 as an attempt to organize, modernize, and improve the provision of health services by public facilities.[10] These facilities, organized in territorial networks of clinics and hospitals affiliated with the MOH, were funded by taxes and out–of–pocket payments made by patients. However, in 2002 Peru began to decentralize its government, and these networks were included in that process; they were transferred to the departmental governments, with the sole exception being the National Research Hospitals and the healthcare network in the Metropolitan area of Lima.

The primary objective of these networks has always been to provide comprehensive care to everyone, regardless of their insurance status.[11] Since they receive tax revenue to fund their operations (31% of all health expenditure was funded out of general tax revenue in 2005; MINSA and CIES, 2008), fees in these facilities were subsidized regardless of the socioeconomic status of the patient. However, this was a system of subsidies, not of insurance, until two pilot insurance programs (predecessors of SIS) were implemented.

[10] Originally, the Ministry was in charge of public health, labor, and public assistance issues. In 1942 and 1968 this Ministry transferred its responsibilities on labor and public assistance matters, respectively, to other ministries.

[11] In fact, if an insured person seeks care in one of these facilities, they would be responsible for full payment of the fees as the MOH does not charge insurers for the care of their enrollees.

1.2.3. Health Insurance Pilot Programs

In 1997 and 1998, the MOH established health insurance programs that sought to expand coverage and healthcare use through the demand for these services. The first of such pilot programs was the *Seguro Escolar Gratuito*, which targeted children in public schools and pre-schools between the ages of 3 and 17 years. Although it was mainly a program created to increase the popularity (and votes) of the administration at the time, it was founded on the basis that there was idle capacity in public clinics and hospitals. Thus, in theory, it was a demand subsidy to increase healthcare use among a targeted population.

One year after the creation of the *Seguro Escolar Gratuito*, and under the advocacy and funding of the World Bank and the Inter–American Development Bank, the Mother and Child Insurance program was implemented. This program targeted pregnant women living in pilot districts classified as poor. It provided coverage to women throughout the pregnancy and postpartum, as well as coverage to the child until they turned 5 years old. The program's goal was to reduce the high rates of maternal and infant mortality in Peru.

One of the main differences between these two programs was that whereas the *Seguro Escolar Gratuito* was implemented nationwide, the Mother and Child program operated in pilot areas of the country determined mainly by a targeting criteria based on geographic and socioeconomic barriers to care. This difference was the main reason why some initial analysts deemed the *Seguro Escolar Gratuito* to be a program concentrated in urban, middle class areas, whereas the Mother and Child program was considered as a poverty alleviation and reduction program. Later, this criterion for the implementation of the Mother and child program was used for the implementation of SIS.

1.2.4. Universal Coverage

In April 9th, 2009, the Framework Law declaring Universal Health Insurance Coverage in Peru was passed. This marked a milestone for the Peruvian healthcare system as it implied a major reform that would change the structure of this system. Although this Framework Law did not establish specific enrollment goals, nor did it have a timeline (or a plan) to establish when universality was to be achieved, it did give a start to this reform and defined the general terms and principles that should guide the process.

One of the principles that this Framework Law established was that coverage expansion should be implemented progressively. Despite previous efforts to increase health insurance coverage, mainly implemented through SIS, still almost half the population was uninsured.[12] Given that reaching universality would imply a significant fiscal effort by the government, employers, and families, it was not realistic to declare that universality would be accomplished in the short term.

This Framework Law also defined three regimes that categorized enrollees and administrators of health insurance (IAFAS for the acronym in Spanish). The subsidized regime was targeted to people living in poverty. This regime, which includes a significant percentage of the population, provides a full premium subsidy and is assigned exclusively to SIS. The second regime, or semi-contributory regime, has a partial subsidy and was created to enroll middle income families with unstable jobs or working in small-sized companies. The Law does not define which IAFAS should administer this regime, although at the time the Law was passed only SIS offered plans that were partially

[12] In 2008 the rate of uninsurance in Peru was approximately 47%.

subsidized with public funds. Finally, the third regime, the contributory regime, includes all plans with premiums fully paid by private agents: either employers or families. The main IAFAS in this regime is EsSalud, since it administers the Social Health Insurance program, which is funded by employers. Also, some private insurance companies offer group (although for small pools) and individual plans, but they cover only about 4% of the population.

As stated above, SIS currently administers two regimes: fully and partially subsidized. Although affiliated with the MOH, SIS has some level of (budgetary and operational) independence. Its main function is to administer the funds used to finance individual health benefits of Peruvians who do not have health insurance and meet the eligibility characteristic: the vulnerable population living in poverty.

1.3. The *Seguro Integral de Salud* (SIS)

Increasing health insurance coverage among the poor is one of the most important policies implemented in the last 20 years in Peru, and the only reform initiative during that time in its healthcare system. This reform began when SIS was implemented in 2002 and reached a major milestone when Universal Coverage was declared in 2009. In fact, SIS is the main (and, in practice, the only) strategy that Peru has to achieve universal health insurance coverage.

SIS was implemented in 2002 by merging the two pilot programs described previously, the *Seguro Escolar Gratuito* and the Mother and Child program. The newly created SIS expanded coverage to all children of school age, without requiring enrollment in a public school, all pregnant or postpartum women, and all children under 5 years of age, with no geographical restriction. Although SIS did not define a clear qualifying rule, the program's benefits were meant to reach low-income, vulnerable people only.

SIS was designed as a mechanism for public insurance that fully subsidizes and facilitates access to health insurance among the poor. It is a publicly funded health insurance program that operates at the national level. It finances the costs of most healthcare procedures, prescription drugs, and other complementary services through a nationwide network of publicly managed providers to treat most health conditions, though recently it started funding services provided by other networks. A SIS enrollee is entitled to receive free healthcare, with no copay or deductible, whereas an uninsured person would still have to make (subsidized) out–of–pocket payments to obtain the same care. There is a trivial fee that an enrollee has to pay when applying to join the program, equivalent to $0.3, but this fee can be waived and it is seldom paid by an enrollee.

SIS has four main objectives: i) increase access to healthcare; ii) target healthcare toward the poor and vulnerable; iii) improve the allocation of public resources; and iv) increase investment in public facilities. Yet, in practice, almost all its efforts focus on the first two.

1.3.1. Beneficiaries

The poor are the main population that SIS targets. From 2002 to 2006, SIS operated under five different plans that categorized enrollees based on their demographic characteristics. The two prioritized plans were for pregnant women and children under 5 years of age.

Other plans covered children between 5 and 17 years of age, adults, and people experiencing emergencies.

Also, using the geographical targeting criterion from the Mother and Child program, SIS began its operations by prioritizing seven departments. Based on high rates of socioeconomic and geographic barriers, a more aggressive enrollment was originally planned in Apurimac, Ayacucho, Bagua, Cusco, Huancavelica, Huanuco, and Puno. These departments were the poorest at the time and faced significant geographic barriers, in terms of the average distance to the nearest health clinic.

These two priorities, to pregnant women and children and to seven departments in the country, were changed in 2006, the first change in administration after the program's implementation in 2002. This led to other plans, especially the plans for children between 5 and 17 years of age and for adults, which started accounting for a greater proportion of SIS budget. Similarly, resources began to be allocated to wealthier, urban departments. In addition, SIS began offering basic health plans to working adults who were not eligible for partially subsidized plans. These plans targeted informal workers and offered coverage under a reduced premium.

1.3.2. Cost sharing and network

Government providers, which are grouped into networks of clinics and hospitals, are where SIS enrollees obtain care. This web of networks is mainly funded by: (i) budget allocations made by departmental governments and the MOH; and (ii) out-of-pocket payments made by patients (or by SIS on their behalf through a previously determined fee schedule). The departmental governments and MOH finance the "fixed costs" of healthcare: salaries, equipment, new infrastructure, and maintenance;[13] whereas the patient (or SIS) is responsible for the "variable costs" incurred by providing care to SIS beneficiaries, such as drugs, hospital supplies, tests, and exams. This has been the situation for decades, and having to make out-of-pocket expenditures has been a significant barrier for the poor. Despite having explored other payment mechanisms, SIS has not changed this structure, which was originally designed to reimburse providers using fee-for-service payments and simply replaced the source of funding for its enrollees.[14]

1.3.3. Targeting

At its implementation, SIS did not have a strategy to target its beneficiaries; there was no tool or algorithm used to determine people's eligibility. SIS used a general application form that provided basic data on the family's assets, but these data were not used to determine eligibility. The only piece of information SIS used was the applicant's report of enrollment in EsSalud and later the dataset of enrollees was cross-checked with EsSalud dataset to eliminate people enrolled in both programs.

The closest to a targeting strategy that SIS had at the time was a set of enrollment goals defined by SIS and followed by the departmental health directorates. These goals were determined for four out of five of the health plans that the program offered: children aged 0-5, children aged 6-17, pregnant women, and other adults. Since enrollment in the program was mainly through the network of government-run healthcare providers, SIS

[13] Since these funds are allocated through their budgets, in practice any healthcare provided in these facilities is subsidized regardless of enrollment status. In other words, anyone seeking care through a provider affiliated with the government will receive subsidized healthcare.
[14] SIS has tested other methods, and recently implemented a capitation payment, although it does not affect the period of analysis of this study.

published these goals to promote a planned expansion of the program. Although these goals did not respond to the specific characteristics of the applicants, they were established taking into account geographical concentrations of poverty throughout Peru.

The two pilot programs that preceded SIS provided a base of enrollees, so that since its creation SIS had millions of beneficiaries. However, there was a fundamental difference between enrollment for these two pilots and SIS. *Seguro Escolar Gratuito* was the program with most enrollees. This program was implemented nationwide and it enrolled automatically all students in public schools, following an opt-out enrollment process. In contrast, the Mother and Child program had an opt-in enrollment strategy, and it was implemented only in seven departments: Apurimac, Ayacucho, Cusco, Huancavelica, Huanuco, and Puno, and in the network of Bagua, from the Amazonas department.

SIS followed the Mother and Child program's enrollment strategy but did not limit its beneficiaries to these seven departments since it was a nationwide program. Building on the Mother and Child program, SIS started stronger in these seven localities and that meant that the enrollment goals were higher in these departments. These goals were revised periodically and were made in consultation with the Ministry of Health and local governments throughout Peru. In practice, this meant that after the first year, these goals increased steadily at a similar rate in all departments.

After Peru's administration changed in July of 2006, SIS stopped establishing these enrollment goals. I use these enrollment goals as my the main identification strategy for the estimation of the effect of health insurance, which will be explained in detail in the methodology section of Chapter 2.

Three years after SIS was implemented, a socioeconomic assessment of all enrollees' households was introduced as a filter to determine program eligibility. Despite not being mandatory, this assessment was based on the use of a Socio-Economic Assessment Form (FESE for its acronym in Spanish), which collects data on the applicant's household's assets.

This form was the precursor of the Household Targeting System (SISFOH for its acronym in Spanish), which is an algorithm that uses information on a household's assets to approximate the household's wealth. The experience through the application of the FESE allowed government officials to test and improve the algorithm used to estimate this index. The office responsible for this tool, the Targeting Office of the Ministry of Development and Social Inclusion, standardized this tool as an effort from the national government to homogenize different eligibility criteria for all its social programs and establish a National Targeting System for public programs. This office tested the algorithm in the capital city, Metropolitan Lima, in 2011. In 2012, this tool was rolled out nationwide and it was used as part of the eligibility rules for all social programs from the national government. In 2013, this algorithm was first modified and has since been updated in several occasions.

With the intention to prevent social programs applicants from adjusting the information they provide with hopes of improving their chances of qualifying for social programs, the government has not disseminated the algorithms and the thresholds used to determine wealth eligibility since 2012.

1.3.4. Enrollment

As mentioned above, initially SIS assigned enrollment goals to all public provider networks, which then enrolled people through two main mechanisms: recruitment or accepting applications. When in an expansion stage, or when a specific network is falling behind in its goal, public providers enrolled people through campaigns they conducted with communities, such as immunization campaigns. This way, they could reach people who would not regularly visit their facilities.

The most common way in which SIS has always enrolled beneficiaries is when people seek care through public providers. When people visit a public provider, a social worker offers them the possibility to enroll in SIS. The application process is basically going through a socioeconomic assessment, the SISFOH is currently applied, and one can even get coverage right away and avoid payment for the care they originally were seeking. This introduces a bias when using regular estimation methods to assess the effect of SIS on healthcare utilization, financial protection, and health. This mechanism of enrollment implies that people obtain coverage when they need care, which introduces a problem of selection; assessing the effect of health insurance on healthcare utilization, and the other outcomes, one hypothesizes that getting coverage would increase the use of care, but in this case one also observes that the use of care is what facilitates the decision of enrolling. Thus, some specific econometric methods will be required to isolate the selection bias introduced by this latter relationship as I am interested only in the effect of enrollment in SIS on healthcare utilization, financial protection, and health. One approach is to use the enrollment goals for each provider network as an instrumental variable, since these goals should affect the probability that an individual is enrolled but not their decision to seek healthcare (except through the individual's insurance status).

1.3.5. Coverage expansions

SIS coverage has been steadily extended since its implementation. Out of Peru's total population of over 28 million people, by the end of 2002, its first year of operation, administrative data showed 5.8 million enrollees, and by December, 2019, the figure almost quadrupled, to 20.1 million enrolled.[15]

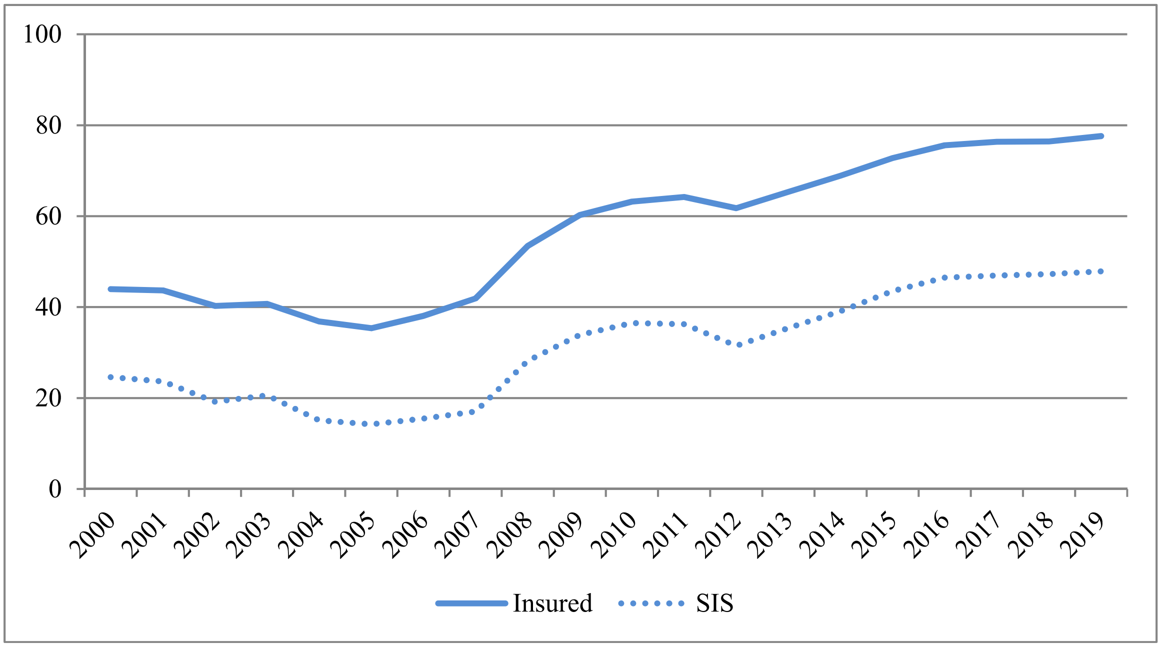
Figure 1.1 shows the insurance rate and SIS enrollment from 2000 to 2019. These estimates show the same trend: approximately 44% of the population was insured prior to 2002, and this increased to 78% in 2019. This figure also shows that the main driver of coverage expansion in Peru has been SIS, which started with an enrollment of 24% of the population before 2002 and grew to almost 50% by 2019.

Although SIS was implemented in 2002, Figure 1.1 (and Figure 1.2) include data of only one of the previous pilot programs for 2000 and 2001, the *Seguro Escolar Gratuito*, which was a program for all students enrolled in a public school, including pre-primary formal school. Thus, between 2001 and 2002, Figure 1.1 shows not only a change in the aggregate number of people enrolled in the program, it also includes a change in the

[15] Administrative data can be different from self-reported data for several reasons. Administrative data can double count some individuals. For example, it can be that some enrollees first enrolled in the emergency plan to receive healthcare services and later enrolled through a more permanent plan based on their demographics. Self-reported data can undercount the total number of enrollees, when individuals do not recollect and report their enrollment in the program.

demographics of these enrollees as health coverage was no longer restricted for public schools students and children and pregnant women from seven departments.

Figure 1.1: Insurance Rate and Enrollment Rate in SIS, 2000-2019

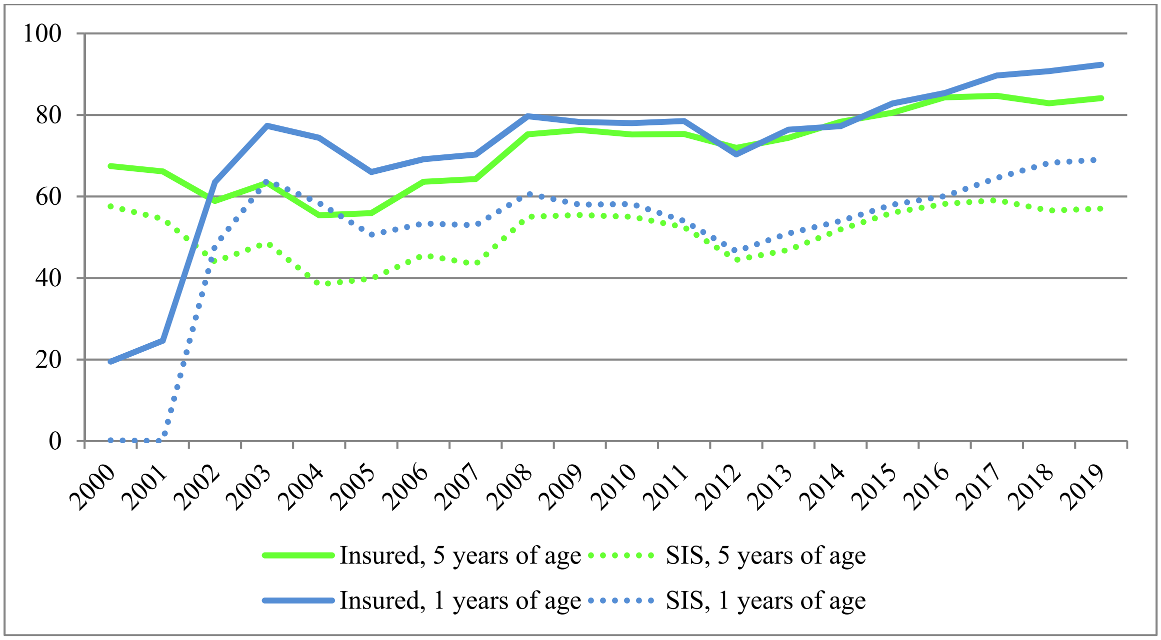


Author's analysis of the 2000-2019 ENAHO.

It is also important to show the trend in enrollment of two specific cohorts, as they are used for the analysis in Chapter 4. In Chapter 4, I study the effect of obtaining SIS coverage on malnutrition among children who were one year old at the baseline and were five years old after they enrolled in SIS. A simple inspection of Figure 1.2 allows the reader to reach the same conclusions stated above: SIS has been expanding coverage and it has been the main driver of the increase in the insurance rate.

However, what is specific to these cohorts is that most of the expansion happened quickly, in the first years after SIS was implemented. As mentioned above, SIS gave a high priority to young children (under five years of age), which affected mainly the cohort of one-year-olds. This cohort reached its highest enrollment rate through SIS in 2003 (64%), although it remained high after that, over 50% in almost all years.

Figure 1.2: Insurance Rate and SIS Enrollment in Peru for Children 1 and 5 year of age, 2000-2019



Author's analysis of the 2000-2019 ENAHO.

In contrast, the cohort of five-year-olds already had a high insurance rate in 2000, mainly through the *Seguro Escolar Gratuito*, as this program reached students in public schools who at five were in kindergarten. Even though the cohort of five year olds had a high enrollment in 2000, it quickly increased its enrollment after 2005 when the government redesigned the program and lowered the priority assigned to pregnant women and children under five years of age.

As mentioned above, prior to 2002 enrollment through SIS, as depicted in Figures 1.1 and 1.2, meant enrollment through the *Seguro Escolar Gratuito* or the Mother and Child

Insurance Program. Although the data source used in these estimations, the ENAHO, collected information on enrollment through the *Seguro Escolar Gratuito*, it did not have a question where people could report enrollment through the Mother and Child Insurance Program, which explains the estimates of zero enrollment for 2000 and 2001 for the cohort of one year olds.

This dramatic expansion of SIS occurred with no rigorous analysis of the program's effects. Based on simple correlations or anecdotal observation, a widespread perception among health officials and experts is that SIS has increased healthcare utilization for enrollees. But there has been no estimation of the causal relationship between the program and people's health. It could be that the government is financing an ineffective program, wasting scarce resources. Or it could be that this expansion should have been more aggressive, if the program creates significant benefits that outweigh the costs.

Chapter 2

How Successful Has SIS Been in Increasing the Use of Healthcare Services and Reducing Inequity in Utilization in Peru?

2.1. Introduction

Prior to the implementation of the health insurance programs in Peru, the healthcare system was one where the population's needs were often unmet, and facilities were significantly underused. Policy makers and officials focused on the barriers to the use healthcare, and the debate emphasized economic barriers over geographic and cultural barriers, perhaps because economic barriers were easier to address, despite the challenges they posed. In fact, having to make (subsidized) out-of-pocket payments to obtain health services was a major hurdle for people in need of healthcare, which exacerbated existing inequities; implementing the payment of user fees in Peru in the 1980s "reduce[d] the access to care proportionally more for the poor than for the rich" (Gertler *et al.*, 1987, p. 67). In this context, health insurance arrived in the 1990s as a possible solution to this problem, as it could facilitate access to healthcare services for people who could not afford these fees.

Of its four strategic goals, SIS focused its operations on two: i) increase access to healthcare; and ii) target healthcare toward the poor and vulnerable. These two goals are where SIS focused most of its efforts, and it is widely believed that SIS has increased healthcare use among its enrollees, although no rigorous evaluation has been conducted to verify this conjecture.

This chapter explores the relationship between obtaining SIS coverage and the use of healthcare services. Since SIS prioritized enrollment of the poor in its early years, I will explore whether this relationship varied by socioeconomic levels. More specifically, this chapter seeks to answer the following questions:

- How did SIS affect the use of healthcare services by the end of its first administration, in 2005?
- Did this effect vary across socioeconomic levels? In particular, did SIS help narrow inequities in the use of healthcare services between poor and non-poor households?

The overall perception of the program's performance is that its effect is positive and significant, that is that SIS has increased the use of health services among its enrollees, focusing the increase in the national rate of healthcare utilization among people who report needing care. In terms of the equity analysis, it is commonly believed that the middle class gained the most from the SIS expansions, rather than the prioritized population: poor and rural households.

The rest of this chapter is organized in six sections. First, I summarize the literature in the developing world, including a few studies about SIS and its predecessors. The next section introduces the data source used in this study: the *Encuesta Nacional de Hogares*. A standard theoretical model of the demand for healthcare is presented in the following section. The estimation methods are then discussed in detail. The following section presents the results of the effect of SIS enrollment on the utilization of healthcare, and on inequity in the use of healthcare services. The final section summarizes the main conclusions and draws policy implications from these results.

2.2. Literature Review

Almost all health economists would agree that health insurance leads to an increase in healthcare consumption. Literature reviews that have focused on this relationship show that most studies find a positive effect of health insurance on healthcare utilization.[16] In fact, as discussed in detail below, economic theory suggests that gaining health insurance makes the individual face a lower price for healthcare services, which increases his or her consumption of these services.[17]

In fact, increasing the use of healthcare services is one of the goals of health insurance. Individuals who purchase health insurance do so in order to increase their consumption of healthcare (in the event of illness), as is assumed by most economic models of health insurance, and governments implement these programs when they intend to facilitate the population's (or, more strictly, the insurance beneficiaries') access to medical care.

2.2.1. Health Insurance Programs in Developed Countries

The effect of health insurance coverage on the use of medical care has been studied in the developed world for many decades. Most notably, the RAND Health Insurance Experiment clearly showed that having different coinsurance rates (i.e. different out–of–pocket prices for each unit of medical services) led to different levels of consumption. In particular, Manning, *et al*. (1987) found that the price elasticity for all types of healthcare utilization was approximately – 0.2. More recently, Finkelstein, *et al*. (2011) also found

[16] Geidion and Diaz (2010), Buchmueller, *et al*. (2005), and Hadley (2003).
[17] Pauly (1968).

that one year after obtaining health insurance through Medicaid, a group of low-income adults in Oregon increased their healthcare utilization for three different types of care: preventive, primary care, and inpatient care.

2.2.2. Health Insurance Programs in Developing Countries

The economic literature about the effects of health insurance in the developing world is more scarce. Several programs in other Latin American countries that are similar to SIS have been studied.[18] For Mexico, Sosa-Rubi, *et al*. (2009) found that enrolling in the *Seguro Popular* program is positively associated with the use of general obstetrical care, and Harris and Sosa-Rubi (2009) found an increase of 1.65 prenatal care visits. This last result from Harris and Sosa-Rubi (2009) is based on a Poisson regression conditional on membership in one of three latent classes: i) women who have had very few or no prenatal visits during their pregnancy; ii) women who sought care, on average, every five weeks during their pregnancy; and iii) women who had some complications detected prior to labor, and thus were required to have a visit, on average, every 2.4 weeks. The authors report that 59% of the overall effect of an increase in 1.65 prenatal visits is due to the increase in prenatal care among women in the first latent class, and the remaining effect is mainly due to an improvement in the detection of pregnancy complications, which results in a shift of some women from the second to the third latent class.

King, *et al*. (2009) evaluated a program that promoted enrolling in *Seguro Popular* and improved healthcare facilities. This evaluation used a randomized experiment that assigned treatment to territorial clusters defined by the healthcare facilities networks. The

[18] For a detailed description of these programs, see the literature review in Chapter 4.

experiment had a high attrition rate, from 74 matched pairs of clusters at the baseline to 50 pairs at the follow-up, and the authors found no effect on utilization of a number of health services: medical procedures, preventive care, outpatient care, inpatient care, eye exams, flu vaccinations, mammograms, cervical exams, and Pap smear testing. This lack of any effect could be explained by the short amount of time between the baseline and the time of the evaluation, only 10 months of treatment.

Another randomized experiment, in Nicaragua, found that obtaining insurance affected neither the probability of seeking care nor the number of visits. Thornton, *et al*. (2010) studied a voluntary health insurance program for workers in Nicaragua's informal sector. The randomization occurred at enrollment locations, and the cost of premiums was also randomly assigned. Two potential problems may have affected these results. First, since coverage was voluntary, the take-up rate was very low (20%). The authors explain that bureaucracy and program costs may have hindered enrollment. Second, the study does not explicitly rule out the possibility of crowding out; the people who enrolled in the program could have had other forms of coverage before enrollment.

In Colombia, where preventive care is essentially free regardless of insurance coverage, Miller, *et al*. (2009) found that enrollment in the subsidized regime is associated with an increase of approximately 29 percentage points in the utilization of preventive care among enrollees. In the case of children, they found that those enrolled had 1.24 more growth monitoring and well-care visits than children who were uninsured. These results are very interesting as they cannot be due to moral hazard, since they are not due to a significant reduction in the price of preventive care. Instead, it likely reflects the supply-side incentives to contain (curative services) expenses, as health insurance creates some incentives that encourage providers to improve the health of enrollees (through the increase of the preventive care), which reduces future expenditures in curative care services.

Similarly, Giedion, *et al*. (2009) find that the probability of having a complete set of immunizations in Colombia increased by six percentage points for covered children between 1995 and 2005. Again, this result is interesting because immunizations are free regardless of children's insurance coverage. These two similar results from different studies suggests that "health insurance in Colombia generates some positive spillover effects that go beyond making services more affordable" (Giedion, Diaz, Alfonso, and Savedoff, 2009, p. 68).

2.2.3. Health Insurance Programs in Peru

Six studies have examined the relationship between obtaining coverage from a public program and the utilization of healthcare services in Peru. All use cross-sectional data, but they use different identification methods and estimation approaches. Although they all find significantly positive associations between public coverage and utilization, only one of them claims to estimate causal relationships.

Three of these studies examine this relationship for the two original pilot programs, the *Seguro Escolar Gratuito* and the Mother and Child Insurance program. Jaramillo and Parodi (2004) conducted an evaluation of these two pilots. This evaluation included an analysis of whether these programs reduce the inequities in coverage and access. In order to study these inequities, the authors use two variables to define socioeconomic quintiles: predicted household expenditures[19] and a wealth index.

Using the Heckman method to correct for selection bias, they found that the *Seguro Escolar Gratuito* was associated with an increase in the probability of visiting a healthcare provider when in (self–reported) need by 16.7%. When evaluating the Mother and Child Insurance program, the authors found an 8% increase in the probability of seeking preventive care during pregnancy.

Their analysis of how the program affects the inequities of access concluded that neither program favored households in the poorest quintile in terms of gaining more access relative to the other quintiles. Moreover, their results suggest that both programs increased these inequities as people in the richest quintile benefited the most from this coverage, with increased benefits for each quintile as one move from the least wealthy to the wealthiest quintile for the *Seguro Escolar Gratuito*.

McQuestion and Velasquez (2006) examined the two programs implemented in the 1990s: the Mother and Child Insurance program and a USAID project in Peru: *Proyecto 2000*. Using variance components logistic models, the authors found that enrolling in the Mother and Child Insurance program increased the probability that a pregnant woman delivered her most recent child in a public facility.

Bitrán, *et al*. (2010) examined the relationship between enrollment in all publicly funded health insurance program in Peru: SIS and its two predecessor pilot programs. They

[19] They use the predicted household expenditure, since one of their data sources, the Demographic and Health Survey, does not have income or expenditure information.

use two data sources – the Demographic and Health Survey (DHS) from 2000 (pilot programs) and a pooled DHS sample for 2004-2007 (SIS);[20] and the 2002-2006 ENAHO panel – to explore the effect of coverage on specific types of healthcare services. The authors find that both programs had a positive association on the probability of young children, (18-59 months of age) being fully immunized, the probability of women (15-49 years of age) receiving a pap-smear exam, the probability of children under 5 years of age being treated for diarrhea, the probability of children under 5 years of age being treated for acute respiratory infections, and the mean percentage of growth monitoring schedule completion among children under 5 years of age. Interestingly, the only health service for which they did not find a significant result was for the probability of pregnant women (15-49 years of age) having their delivery attended by skilled personnel. For SIS only, they found an increase of approximately 6-19% in the probability of seeking care when symptoms, illnesses, or relapses where present.

In addition, Bitrán, *et al*. (2010) explored whether these results varied by income level. They found that the pilot programs had a pro-poor effect on the probability of being fully immunized, although the opposite happened for all the other services they studied. They also found a pro-poor association between the probability of receiving treatment for both diarrhea and acute respiratory infections, and the mean percentage of growth monitoring schedule completed.

[20] The 2004-2007 DHS surveys do not ask the insurance status of children. This study uses the mother's insurance status to impute children's enrollment in SIS.

Using a probit model, Longaray (2010) found a positive effect of SIS coverage on healthcare utilization. Moreover, he predicts that if all uninsured Peruvians were enrolled in SIS, the probability of using health services would increase by 20%.

Parodi (2006) used the 2004 Demographic and Health Survey to estimate the relationship between SIS coverage among pregnant women and their decision to deliver in a public facility. Using a multinomial discrete choice model, he found that women who obtain coverage through SIS increased their probability of delivering their child in a public facility by 27%.

The author found that this association is stronger among the wealthy, with a 56% increase in this probability for women in the richest quintile compared to 27% for those in the poorest quintile. This result is consistent with other studies, and also suggests that SIS expansions are widening inequities in the use of healthcare services.

Parodi also explored how non-economic factors (e.g., geography, ethnicity, cultural practices, and power relationships within the household) affect this relationship. He found that rural, non–Spanish speaking women whose husbands make most decisions in the household have a lower probability of going to a public facility to deliver their child.

Bernal, *et al* (2017) evaluated the effect of SIS on a set of access outcomes for the population of the city of Lima. They used a recent targeting tool introduced by the Peruvian government in 2011 as a pilot. This pilot was implemented only in the city of Lima and later, in 2012, was extended to the overall country. Using the ENAHO data set that is described in detail in the following section, they found large effects of enrollment on utilization of healthcare ranging from 5% to 15% depending on the specific type of service.

Interestingly, the authors find that SIS reduces enrollees' participation in preventive campaigns by 5%, which they attribute to a change in people's behavior once they find financial coverage from the risks of having bad health (i.e., moral hazard).

2.3. Data

The *Encuesta Nacional de Hogares* (ENAHO), which has some similarities to the World Bank's Living Standards Measurement Study surveys and is conducted annually in Peru, is the main source of data for this chapter. This survey is implemented by the *Instituto Nacional de Estadística e Informática*, the government agency responsible for producing the national statistics for leading socioeconomic indicators. Annual cross-sectional datasets are available starting in 1997. A small sub-sample of the participants provide information in consecutive years, which provides a small panel dataset.

The ENAHO has 5 main objectives: i) produce indicators on the evolution of poverty, welfare, and other household characteristics; ii) diagnose the population's living conditions and poverty; iii) assess how social programs are improving living conditions; iv) be a source of information for research; and v) allow comparisons with similar studies and surveys.

Although the sampling unit is the household, data are provided at two levels: household and individual. Wealth and assets are collected at the household level. Modules in the ENAHO that gather data at the individual level are mainly about their education, health, employment and income, and participation in social programs. Expenditures are tracked in detail at both levels, depending on the category. Healthcare expenditures are tracked at the individual level, and for each type of care: curative or routine care visits, drugs and prescriptions, laboratory exams, dental care, optometrist visits, immunizations, inpatient care, and pregnancy check-ups and delivery care.

The health module provides information on: i) people's healthcare needs in the last four weeks (whether they showed symptoms, developed an illness, had an accident, or had a relapse related to their chronic conditions); ii) their treatment (facility used, staff that provided care, type of care, time issues related to the visit, and reasons for not visiting a provider); iii) preventive care (children's check-ups and immunizations, birth control supplies, and nutritional supplement provision); iv) health expenditures; and v) health insurance status and type.

Since the first ENAHO was implemented in 1997, data have been collected annually, although there have been some changes in its design. For example, it was originally implemented quarterly, with the health module included in the fourth quarter, but in 2003 the methodology changed so that the survey is continuously in the field. In 2002 the question about health insurance started gathering information about people's enrollment in SIS, but previous surveys did not collect accurate information on its two predecessor programs.

In Section 2.5, I discuss the identification strategy: instrumental variables. The instrument I use is annual program enrollment goals by geographical jurisdiction, which were used only in the early years of operations, between 2002 and 2006. As mentioned above, cross-sectional datasets are available annually from 1997 to 2019, but I focus on 2005 for two reasons. First, these enrollment goals were used only until July of 2006, which rules out 2006 as a whole. Second, as shown in Table 2.1, 2005 has the largest sample size of households for this period (2002 to 2005). In addition, since the last methodological update to the survey in this period was implemented in 2003, 2005 offers data that should be less affected by the novelty of these changes and subsequent adjustments.

Table 2.1: ENAHO Annual Sample Size, 2000-2006

Year	Households	Individuals
2000	4,447	16,876
2001	16,515	74,644
2002	18,598	83,102
2003	14,892	56,265
2004	23,900	86,455
2005	25,643	86,309
2006	25,807	88,804

Author's analysis of the 2000-2006 ENAHO.

2.4. Theoretical Model

As discussed above, empirical evidence typically shows that health insurance increases the consumption of healthcare. But how does this happen? What are the channels through which health insurance increases healthcare utilization?

This relationship can be represented using one of the most widely applied economic concepts: the demand for healthcare. Theoretical models provide two mechanisms for the effects on consumers who obtain health insurance: i) health insurance produces a movement along the demand curve of health services, since insurance reduces the price of healthcare, and ii) health insurance shifts the demand of healthcare to the right (in addition to causing a movement along the new demand curve), since insurance operates as an income transfer from the rich to the poor or from the healthy to the ill.

Pauly (1968) was one of the first economists to propose a theory of how the demand for healthcare is affected by health insurance. His theory was formulated in the context of analyzing the welfare consequences of consuming health services when insured. He considers health insurance to be a mechanism by which people with coverage face a reduced price for healthcare. The decision to obtain insurance is driven by the consumer's desire to pay a lower price for healthcare. Thus, under Pauly's theory, health insurance leads to a movement along the demand curve for healthcare that, under a full coverage policy, goes all the way to the point where the demand meets the horizontal axis, a price of zero. If the demand for healthcare is downward sloping, as demands for any good or service are almost always expected to be, a lower price will lead to an increase in the optimal level of healthcare utilization. This increase is the effect of insurance on healthcare utilization.[21]

However, Nyman (2005), challenged Pauly's theory to consider health insurance as an income transfer from the rich to the poor (or the healthy to the ill), not only as a price distorting mechanism.[22] In economic terms, this implies that health insurance not only creates a movement along the demand for healthcare, but also causes an outward shift in the demand curve. Specifically, Nyman (2003) suggests that health insurance produces a

[21] Pauly's main conclusion was that by reducing the price of healthcare that consumers face (to a point below its marginal cost), health insurance leads to inefficient and welfare decreasing overconsumption.
[22] Nyman (2003).

positive shift in the demand of healthcare, since health insurance operates like an income transfer when ill.[23]

I argue that the first mechanism, health insurance having an effect on the price of health services, dominates this relationship in the case of SIS. As discussed in the previous chapter, people can benefit from subsidies if they seek care through a public provider. In fact, all SIS does is complement subsidies that are already in place; when an enrollee seeks healthcare in these facilities, SIS is responsible for the payment of (almost) all healthcare expenses incurred by the enrollee, according to a pre-established fee schedule. However, this does not constitute an income transfer; it is just an increase in the level of subsidy that an enrollee receives.

To model the demand for healthcare I use a relatively simple model. Assume that individual i has a utility function that depends on his or her consumption of medical services, M_i, and consumption of other goods, C_i:

$$U_i = U(M_i, C_i) \tag{2.1}$$

subject to:

$$(p+q)M_i + C_i \leq Y_0 \tag{2.2}$$

where p is the out-of-pocket price per unit of medical services, q represents other costs incurred by the individual per unit of medical care (e.g. transportation, direct forgone

[23] Under this new theory, (social) welfare gains can occur when health insurance allows the previously uninsured to obtain healthcare that would otherwise be unaffordable.

earnings, day care for children/siblings), and Y_0 is the individual's disposable income. Notice that, for simplicity, the price of C_i has been normalized to 1.

Notice that I model p to be the out-of-pocket expenditure for a unit of medical services, which implies that

$$p = \begin{cases} p_0 & S_i = 0 \\ 0 & S_i = 1 \end{cases} \tag{2.3}$$

where p_0 is a strictly positive value, and could represent either the market price (at marginal cost per unit of medical services) or a partially subsidized price, and S_i is a binary variable that represents SIS enrollment (taking the value of 1 when enrolled).

Standard assumptions for the individual's preferences, i.e. locally non-satiated, continuous, and rational (which imply the existence of a quasi-concave utility function: $U()$ and the satisfaction of Walras' Law), allow for the derivation of demand functions and the consequent finding of optimal levels of consumption and utility maximization. Equation 2.4 represents the demand for healthcare:

$$M_i = m(p, q, Y_0) \tag{2.4}$$

Recall that the effect of obtaining health insurance through SIS is modeled as a drop in the out-of-pocket price per unit of medical services; i.e., $M_i = m(p(S_i), q, Y_0)$.

However, these assumptions do not lead to an unambiguous effect of a reduction in the price of medical services (which represents the effect of obtaining insurance coverage) on the optimal level of healthcare consumption, as theory still allows for the possibility that this effect is positive. This theoretical peculiarity, known as a Giffen good, is usually related to low-quality (or undesired) goods consumed by low-income individuals, for whom a reduction in the price of this good would have an income effect such that the individuals would be able to exchange the consumption of this good for other higher-quality (or more desired) goods.

If the Weak Axiom of Revealed Preferences is satisfied, in addition to the previous assumptions, then I can argue that the compensated law of demand is also satisfied, so that the Marshalian demand would certainly have a non-positive own-price effect:

$$\frac{\partial m(p(S_i), q, Y_0)}{\partial p} < 0 \tag{2.5}$$

where $\partial M_i / \partial S_i = \partial m(p(S_i), q, Y_0) / \partial p$.

If the Marshalian demand for healthcare services is decreasing in p (and q), as most empirical studies have found, then the effect of SIS enrollment (through a reduction in p to zero) on the consumption of medical services will be positive.

One important feature of this model is the relative importance of both prices that directly affect the consumption of healthcare. Using a similar model, Acton (1976) shows that when comparing the elasticities for p and q in the model, $\varepsilon_p < \varepsilon_q$ if $p < q$. In other words, as p drops due to gaining insurance coverage, the demand for healthcare becomes relatively more sensitive to these other (non-price) costs, so that the decision to seek healthcare (along with other exogenous factors that affect demand) increasingly depends on q.

In the case of SIS, when an individual receives fully subsidized healthcare (i.e., p is zero), the other costs still affect consumption decisions. This prevents the optimal consumption of medical services, at least theoretically, from being extremely high (or at the extreme, infinite).

Now, the decision behind individuals' enrollment in SIS can be incorporated into the model. As mentioned in Chapter 1, enrollment happens mostly at healthcare facilities when individuals seek medical services. This means that the decision to enroll in SIS depends on demand for medical services: $S_i = s(M_i)$. Incorporating this decision into the Marshalian demand previously formulated yields:

$$M_i = m(p(S_i(M_i)), q, Y_0) \tag{2.6}$$

Equation 2.6 depicts a latent problem in the empirical analysis of health insurance: health insurance enrollment and healthcare utilization (or health outcomes or health expenditure) are determined simultaneously. Thus, a simple estimation of equation 2.6 would produce biased results. In words, gaining health insurance could lead the individual to use healthcare when needed, but it could also be that a larger demand for healthcare could lead the individual to seek health insurance. The relationship of interest of this study is the former; it should be isolated from the latter to produce unbiased results.

This simultaneity bias, also known as selection bias, leads some economists to argue that only empirical studies that use randomized controlled trials, or natural experiments, produce credible results to evaluate the effects of health insurance.[24]

[24] Levy and Meltzer (2001)

However, as discussed below, some econometric methods can reduce the risk of this bias without using a Randomized Control Trial.

Note that the decision to enroll in SIS does not depend only on the individual's need for medical services; it also depends on other factors (e.g. satisfying program eligibility). For simplicity, I choose to omit these other factors as they do not affect the discussion presented above.

Although I will use panel data to estimate the relationship of interest, I chose to represent this relationship using a static model. The reason behind this decision is that most dynamic models use a first period to represent the decision to purchase health insurance prior to the revelation of the health state in the second period of time, whereas in the case of SIS this sequence does not apply; the health state is revealed to the individual before he or she or they decides to enroll in the program. Thus, the decision to obtain coverage through SIS affects the current period's consumption of healthcare (and of other goods and services).

One difference between this model and most models that represent the decision to purchase (private) health insurance is that this model does not include a premium that individuals would have to pay for becoming insured. The model above represents the decision to enroll in a public program, which differs significantly from the decision to purchase health insurance. For example, this model does not include a premium payment for enrollment. This is because enrollment in SIS does not require payment, it requires only filling out an application and paying a trivial fee which is waived in most cases.[25]

[25] This fee was approximately $0.30 during the first years of SIS implementation.

Also, since this fee is not actuarially fair and is only meant to cover the administrative cost of determining eligibility, I assume this to be zero.

2.5. Estimation Method

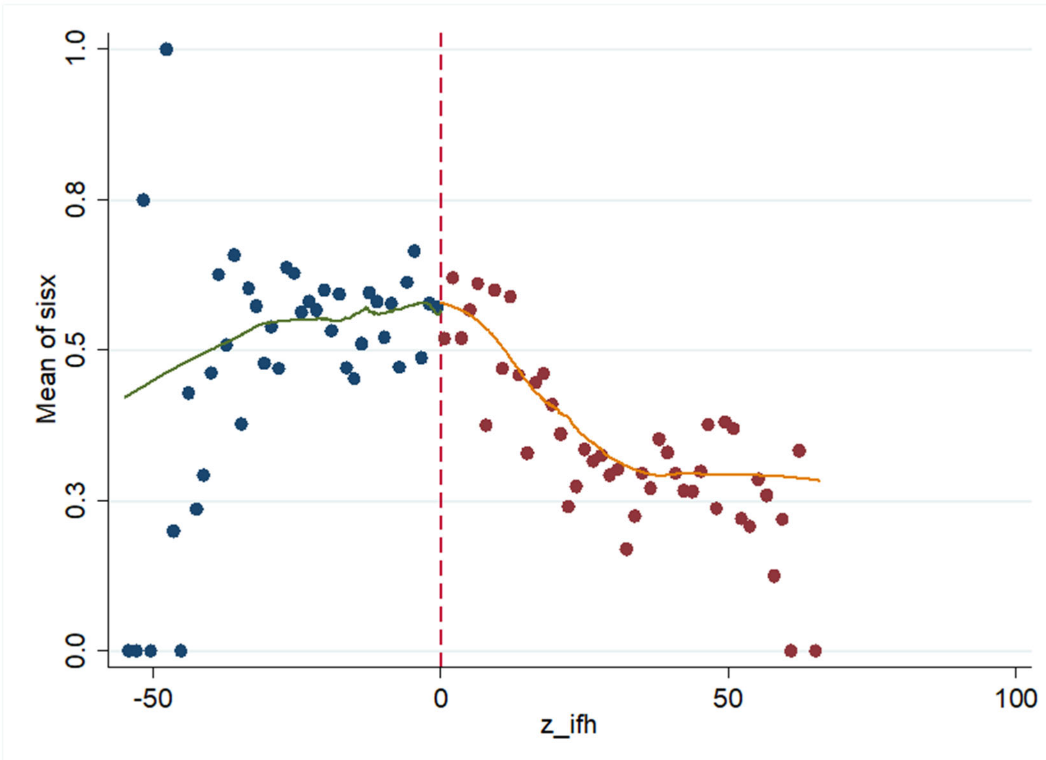
The main problem for estimating the relationship of interest is the presence of selection bias (i.e., the simultaneous determination between having health insurance and seeking healthcare). This refers to the fact that there is dual causality in the relationship between healthcare and insurance status. I am interested in the possibility that someone who is insured is more likely to seek healthcare. But it can also happen that people having a high probability of requiring healthcare in the near future will get insurance, which implies that a high consumption of healthcare (due to having poor health) leads to being insured. This problem may lead to overestimation of the effect of insurance on the use of care. In addition, as explained in the previous chapter, a high percentage of the program enrollment in Peru happens when the eligible patient visits the healthcare provider, which creates the perfect setting for selection problems.

Appropriate estimation techniques are needed to address these issues. Experimental approaches provide the most reliable approach about the relation between healthcare and health.[26] I intended estimating the household assets index used by Bernal, *et al* (2017) for 2012, when eligibility for the program based on this index was extended nationwide. However, I did not find a discontinuity in SIS enrollment at the eligibility threshold. More specifically, I estimated a non-parametric function of the relationship

[26] Levy and Meltzer (2001).

between enrollment in SIS (sisx) and the asset index (z_ifh). Figure 2.1 shows that enrollment decreases at the threshold, but without a discontinuity.

Figure 2.1: SIS Enrollment by Household's Wealth (Measured by SIS' Household Asset Index), 2012



Author's analysis of the 2012 ENAHO.

Given that there is no discontinuity in the probability of being enrolled in the program at the eligibility threshold, a quasi-experimental approach was not feasible for me. Thus, I will use a key element in the program's early implementation strategy, enrollment goals by departments, to apply an instrumental variables approach. In addition, I will use other methods as robustness checks for these results, to minimize the possibility that they are sensitive to the method used. If the results are robust across these different methods, the estimated relationship will have greater credibility.

2.5.1. Instrumental Variables

A common way to address selection bias produced by simultaneity is to use instrumental variables. This implies first modeling the decision of a person to enroll in the program and then modeling the process that determines the use of healthcare.

This approach is credible as long as its assumptions are satisfied. The main challenge is finding a good instrument: a variable that affects the explanatory variable of interest, i.e. health insurance enrollment, but does not directly affect the dependent variables.

As described in section 1.3.3 in Chapter 1, SIS used annual enrollment goals for each geographical jurisdiction to guide the expansion of the program. However, this strategy was applied only from 2002 to 2006. I use these enrollment goals as the instrument for my analyses. The number of enrollees that SIS wanted to achieve is a relevant predictor for enrollment in the program, since it affects the effort that 'recruiters' put into enrolling. Higher enrollment goals drove enrollment in SIS as it affected eligible individual's probability of enrolling. However, these enrollment goals in and of themselves did not change the decision an individual makes about their healthcare utilization, except through an increased probability of being enrolled. And these goals did not affect an individual's perceived healthcare needs.

In total, I aggregated these goals to 25 geographical jurisdictions and the resulting enrollment goals ranged from 14.6% of the overall population in Callao to 61.0% in Huancavelica in 2005.[27]

The first stage of the model, estimating the decision to enroll in SIS, is:

$$S_i = \alpha_1 + \gamma_1 G_i + \tau_1 X_i + \mu_1 \tag{2.7}$$

where S_i represents enrollment in the program, G_i is the enrollment goal set for the individual's department as a percentage of the total population, and X_i is a set of covariates.

Using the probability of enrollment, predicted in the first stage, the decision to seek care is modeled as:

$$Y_i = \theta + \delta \widehat{S_i} + \varphi X_i + \varepsilon_i \tag{2.8}$$

where Y_i is the healthcare outcome under analysis and $\widehat{S_i}$ is the predicted probability of the individual of being enrolled in the program.

The second challenge to using this approach is the possibility that the enrollment goal is a weak instrument. Using a Hausman test, and the routines suggested by Shea (1997) and Angrist and Pischke (2009), I will test for the potential problems caused by a presumably weak instrument. Angrist and Pischke (2009) also suggest a few alternatives in the case of weak instruments (e.g. just-identified estimates).

[27] SIS published its enrollment targets disaggregated by health network, which I aggregated to the corresponding department.

For this analysis, I select 2005 as the year of analysis. This is because 2005 falls within the period in which enrollment goals were used as a strategy to plan the program's expansion and it was the year of highest enrollment within that period.[28] Also, 2005 is the year with the highest sample size within this period.

2.5.2. Equity Analysis of the Effect of SIS on Healthcare Utilization

In order to assess whether the program's effect differs for different sub-groups of the population, I will add a right-hand-side variable to all instrumental variables regressions: the interaction between SIS enrollment and the individual's poverty status.

Since this analysis has two endogenous variables, two instruments are needed for correct identification. As with the endogenous variable, the second instrument is the interaction of the enrollment goals with the individual's poverty stratus.

Thus, equations 2.9 and 2.10 are the new first-stage regressions and equation 2.11 is the new second-stage regression:

$$S_i = \alpha_1 + \gamma_1 G_i + \rho_1 G_i * P_i + \tau_1 X_i + \mu_1 \tag{2.9}$$

$$S_i * P_i = \alpha_2 + \gamma_2 G_i + \rho_2 G_i * P_i + \tau_2 X_i + \mu_2 \tag{2.10}$$

$$Y_i = \theta + \beta \widehat{S_i} + \delta \widehat{S_i * P_i} + \varphi X_i + \varepsilon_i \tag{2.11}$$

where P_i is the individual's poverty status.

[28] While 2006 had a higher aggregate enrollment than 2005, enrollment goals were only used until July of 2006.

From these equations, δ is the estimated effect for the non-poor sub-group, whereas $\delta + \beta$ is the estimated effect for the poor sub-group. I will also focus on the statistical significance of δ, since this is the estimated difference between both effects.

2.5.3. Outcomes and Covariates

I evaluate the effect of SIS on 16 types of healthcare:

- visit to a healthcare professional,
- medications,
- laboratory tests,
- X-rays,
- other exams,
- preventive care,
- dental care,
- eye care,
- corrective lenses,
- immunizations,
- children's wellness checkups,
- birth control supplies,
- other types of care.
- inpatient care,
- pre-natal care, and
- institutionalized delivery.

The first five outcomes are reported for the four weeks prior to when people were interviewed. The following nine and three outcomes are reported for the three and twelve months prior, respectively. Wellness checkups were only reported for children under five years of age. The analysis for birth control supplies includes only individuals between 15 and 50 years of age. Lastly, pre-natal care and institutionalized delivery were only reported by women who gave birth 12 months prior to when they were interviewed.[29]

In addition to estimating the effect of enrollment in SIS on these outcomes, I include a set of ten covariates in these regressions: age, sex, educational level (head of household's education if the individual is a minor), ability to read and write, has an indigenous language as mother tongue, number of household members, sex of the head of the household, poverty level, urbanicity, and region of residence.[30]

2.5.3. Multiple Hypothesis Testing

In this chapter, I assess the effect of SIS in 16 different outcomes for two analyses: the effect of SIS on the overall utilization of these 16 healthcare services and the effect of SIS in the equity in access to healthcare. Chapters 2 and 3 also assess the effect of SIS in a large number of outcomes. Given the high number of outcomes estimated in these analyses, there is a high probability of falsely finding that SIS has an effect on some of these outcomes.

[29] The data set provided information on these 16 outcomes, but did not collect data on other important outcomes, such as emergency services.

[30] These regions were defined by the geographic condition (e.g., coast, highland, and jungle) rather than the political jurisdiction of an area. Thus, some departments, used to define the instrument, have a portion of their population in one of these regions and another potions in a different region.

Considering the case of 16 independent outcomes, and assuming that all null hypothesis are true, the commonly used critical value of 0.05 (i.e., the threshold to reject the null hypothesis that the estimate is statistically zero) would yield a 56% probability of finding at least one false rejection, or error type I.[31] This issue is commonly known as Multiple-Hypothesis Testing.

There are a few different methods that control for Multiple-Hypothesis Testing. One of the most widely used is the sharpened False Discovery Rates (FDR) q-values. These FDR are, as it name suggests, the proportion of false rejections. If we define V as the number of false rejections and S as the number of true rejections, where $R = V + S$, the FDR is $E[Q = V/R]$.

Benjamini and Hochberg (1995) formalize the use of FDR controls. Suppose there are m hypothesis to be tested, where $p_1 < p_2 < \ldots < p_m$, and that there is a number q such that: $q \in (0,1)$. If k is the largest i for which $p_i \leq iq/m$, then hypothesis 1 through k are rejected, which controls the FDR at level q for independent or positively dependent q-values.

Benjamini, *et. al.* (2006) proposed using the FDR controls in a two-stage process that estimates the number of true rejections (m_0) to achieve "sharpened" FDR controls.[32] First, apply the FDR control at level $q' = q/(1+q)$, and stop if k is zero. If not, approximate $\widehat{m}_0$ as m - k, and apply the FDR control at level: $q^* = q'm/\widehat{m}_0$. This process

[31] These probability is estimated as: $1\text{-}0.95^{16} = 0.56$.

[32] If m_0 is known, or approximated, then the q values can be "sharpened" by replacing iq/m with iq/m_0 and greater power would be attained if at least one hypothesis would be false.

further improves the power of the FDR controls by incorporating (an approximation to) the number of true rejections.

Anderson (2008) uses this two-stage procedure to estimate the minimum value of $q*$ at which each hypothesis would be rejected (i.e., the q-value), which provides a "sharpened" controlled alternative to the p-values.

The main advantage of this method is its flexibility around the set of estimates being controlled. For example, in Chapter 3 I will assess the effect of SIS on the probability of incurring an out-of-pocket payment (i.e., a binary variable) and its effect on (transformed) healthcare expenditures (i.e., a set of continuous variables). This method also allows for different outcomes to be estimated using different specifications or identification methods, since it only requires the estimates' p-values.

One disadvantage of this method is that it does not account for the possibility of correlations among the p-values. This is the case of my analyses since I test the effect of SIS in the use of different types of healthcare services – and expenditures on different services in Chapter 3 and health outcomes in Chapter 4. However, Anderson (2008) performed a series of simulations that showed that this method works well when this correlation is positive, such as the case of my analyses.

Compared to other methods, such as the familywise error rate control, the FDR are not too conservative, but they are more conservative that regular p-values, or z-values in the case of Instrumental Variables estimates. However, the value of the sharpened q-values can sometimes be below the value of unadjusted p-values. This is particularly the case when there are many hypotheses rejected, because false rejections can be tolerated if there are many true rejections.

2.6. Results

As explained in the previous section, I use instrumental variables to estimate the relationship between participating in SIS and the use of health services. In particular, I use the program's enrollment goal for 2005 to approximate a participation rate that SIS is expected to achieve. At the time, SIS had five different health plans, which targeted different sub-groups and provided different benefits: children under five years of age, children of school age (6-17), pregnant women, adults, and a plan that covered emergency cases. Since the plan for emergencies did not involve any enrollment goals, I used the four other sub-groups to define enrollment goals for each subgroup in 2005. In addition, I calculated the aggregated enrollment goal as a percentage of the population.

2.6.1. Overall SIS Estimated Effects

Following equations 2.7 and 2.8, Table 2.2 shows the instrumental variable estimates of the effect of the SIS program on different outcomes of healthcare utilization. Although I estimated these results using the enrollment goals for specific sub-groups of the population (e.g., children under 5 years of age) as instruments, I focus on the results obtained all using the expected participation rates for each department for the overall population.

Table 2.2 shows mixed results for the effect of SIS on healthcare utilization; there are positive, significant effects among some types of services, but the opposite is found for other types of care (see Tables A.2-5 in Appendix A for the full regression results).

Table 2.2: Instrumental Variables Estimated Effect of SIS on Healthcare Utilization, 2005

Outcome	Estimated Effect	Standard Error	Statistical Significance	
			z-value	q-value
Utilization in the last 4 weeks				
Visit to a healthcare professional	-0.017	0.211	0.937	0.713
Medication	-0.110	0.285	0.699	0.606
Laboratory	-0.021	0.056	0.707	0.606
X rays	-0.071	0.044	0.101	0.254
Other exams	0.012	0.015	0.430	0.543
Utilization in the last 3 months				
Preventive care	1.726	0.534	0.001	0.007
Dental care	-0.159	0.110	0.148	0.340
Eye care	-0.095	0.057	0.096	0.254
Corrective lenses	-0.111	0.050	0.026	0.093
Immunizations	1.822	0.559	0.001	0.007
Child's checkup (<5 years of age)	0.658	0.188	0.000	0.007
Birth control (individuals 15-50)	1.142	1.839	0.535	0.548
Other	0.213	0.157	0.177	0.362
Utilization in the last 12 months				
Hospitalization	-0.091	0.077	0.234	0.369
Pre-natal care (women who gave birth)	5.070	6.074	0.404	0.543
Institutional delivery (women who gave birth)	2.110	3.128	0.500	0.548

Notes: Statistical significance indicates the probability that the coefficient is zero. Due to estimating the effect of the program on several outcomes, I used the sharpened False Discovery Rate (FDR) q-values to adjust for multiple-hypothesis testing.

Robust standard errors estimated clustered at sampling cluster.

The overall sample size is 64,118; with 7,660 children under 5, 31,157 people aged between 15 and 50; and 3,594 women who gave birth in the previous 12 months.

Author's analysis of the 2005 ENAHO.

Preventive care, including immunizations and children's wellness checkups, showed positive effects. In contrast, the estimates show a decrease in the probability of seeking eye care and purchasing of corrective lenses. Lastly, Table 2.2 does not show any significant effects on visiting a doctor, prescribed medications, having some laboratory exams, dental care, or hospitalizations.

All first-stage regressions pass the tests for underidentification and weak identification, with the exception of 3 services: birth control, pre-natal care, and institutional delivery (see Table A.1 in Appendix A).

As mentioned in section 2.5.3, there is a 56% chance of finding one or more false rejections. To control for Multiple-Hypothesis Testing, I estimate the sharpened q-values following the procedure suggested by Anderson (2008).

The original estimates showed negative effects for visiting an ophthalmologist, but estimating the sharpened q-values following the procedure suggested by Anderson (2008) lead me to disregard this conclusion. The q-value for this relationship is over the 0.1 threshold, suggesting that this estimated negative effect was false. The significance conclusion remain the same (either significant or not statistically different from zero) for all other estimates in Table 2.2 after estimating the sharpened q-values, although the effect of SIS on purchasing corrective lenses goes from being moderately significant ($p<0.05$) to being mildly significant ($q<0.1$).

All future tables ignore the p-values and use the sharpened q-values instead to report on the statistical significance of each estimate, p-values are only shown in the Appendices. Since the "sharpened" q-values are more conservative in assessing statistical significance and less likely to produce false rejections, I use them to provide a better assessment of all estimates' statistical significance.

As a sensitivity analysis, I also used the enrollment rates of specific population sub-groups as instruments. Although there is some correlation between the different alternative instruments, there are also differences in the values and relative differences between one department and another. The results obtained using these other instruments are consistent with those shown in Table 2.2 (see Table A.6-7 in Appendix A for selected outcomes).

2.6.2. Estimated SIS Effects by Poverty Status

The program was intended to provide coverage for vulnerable groups of the population, but it also enrolled some non-poor individuals. In 2005, 17.4% of all SIS enrollees were not poor. In order to assess whether the program had different effects for these sub-groups, I used an interaction term between SIS enrollment and the individual's poverty status, following equations 2.9-2.11. Table 2.3 shows the estimates for β and $\beta+\delta$ in equation 2.11.

Table 2.3 shows that the effect of SIS on healthcare utilization is lower for poor individuals; all estimates of δ in equation 2.11 are highly significant ($q<0.01$), with the exception of access to birth control supplies and institutional delivery ($q>0.1$). Prenatal care is also significant, but only slightly ($q<0.1$). These results imply that individuals living in poverty that are enrolled in SIS show a smaller effect on healthcare utilization, even for services that showed no significant effect in the overall analysis (see Table A.10-13 in Appendix A).

Table 2.3: Instrumental Variables Estimated Effect of SIS on Healthcare Utilization by Poverty Status, 2005

Outcome	Estimated Effect Non-poor (β)	 Poor (β+ δ)	Significance of the difference q-value (δ)
Utilization in the last 4 weeks			
Visit to a healthcare professional	0.522	-0.123	0.001
Medication	0.471	-0.255	0.001
Laboratory	0.155	-0.044	0.001
X rays	0.007	-0.083	0.001
Other exams	0.036	0.013	0.005
Utilization in the last 3 months			
Preventive care	2.201	1.684	0.008
Dental care	0.052	-0.217	0.001
Eye care	-0.042	-0.107	0.007
Corrective lenses	-0.067	-0.120	0.008
Immunizations	2.371	1.777	0.007
Child's checkup (< 5 years of age)	0.843	0.631	0.005
Birth control (individuals 15-50)	1.696	1.364	0.101
Other	0.491	0.174	0.001
Utilization in the last 12 months			
Hospitalization	0.032	-1.087	0.001
Pre-natal care (women who gave birth)	4.794	3.806	0.094
Institutional delivery (women who gave birth)	1.857	1.547	0.128

Notes: Statistical significance indicates the probability that the coefficient is zero, which were estimated using the False Discovery Rate (FDR) control.

Robust standard errors estimated clustered at sampling cluster.

The overall sample size is 64,118; with 7,660 children under 5, 31,157 people aged between 15 and 50; and 3,594 women who gave birth in the previous 12 months.

Author's analysis of the 2005 ENAHO.

As in the overall analysis, all estimates pass the first-stage tests for underidentification and weak identification, with the exception of birth control supplies, pre-natal care, and institutional delivery (see Table A.8-9 in Appendix A). Table A.9 shows that the first-stage of the interaction between SIS enrollment and poverty status passes the test of excluded instruments but does not pass the Sanderson-Windmeijer multivariate Chi-squared test of underidentification.

2.7. Discussion

The results presented in the previous section indicate that SIS improves healthcare access for its enrollees, especially for preventive services. Some implementation and bureaucratic problems are potentially weakening the program's full impact.

SIS, as well as its predecessor pilot programs, was created under the assumption that there was a significant level of unutilized healthcare supply, and that the marginal cost of providing these services was below the marginal benefits for all Peruvians. The main objective of the program was to increase healthcare utilization, in particular through creating a shift in demand for targeted sub-groups of the population who needed these services but could not afford them.

The estimates shown in Table 2.2 suggest that this goal was achieved, at least in part. Even in its early years, SIS increased the use of some healthcare services, mainly preventive services, for its enrollees. This is particularly important as SIS gave priority to preventive care for small children and pregnant women. The positive effects on children's checkups and immunizations are particularly encouraging, as preventing health conditions is especially important for a country with an underdeveloped health system, a general f lack of resources, and wide-spread poverty. Unfortunately, the number of pregnant women in the sample was too small to produce valid results and SIS' effect on services targeted to this sub-group could not be assessed; the estimates for prenatal care and having an institutional delivery did not pass the tests of excluded instruments and underidentification.

However, these results also point to some problems faced by the program. Since its early years, the program has been underfunded, with more enrollees that its resources allows it to serve. Moreover, this gap has increased in time, as the political and social pressures to expand the program have meant that enrollment has grown at a higher rate than its funding. The result of this mismatch has been chronic debt and delays in payments to providers for services received by SIS enrollees. This has led providers to reject these services and the provision of medical equipment for SIS enrollees, since they did not expect to be reimbursed for these. This was especially the case for services and equipment that were not fully subsidized by the providers' own budget (e.g., corrective lenses). Some providers even engaged in the illegal practice of requesting out-of-pocket contributions to cover the cost of services that were included in SIS' plan of benefits.[33] These practices explain the negative results for purchasing corrective lenses, as it was more likely that SIS enrollees would forgo these products when their coverage was rejected. This is one example of how bureaucratic problems undermine SIS' intervention, and why enrollees were less likely to find care when needed.

[33] Alarcón (2004) and Bernal, et al. (2017).

Table 2.3 shows that the effect of the program on most services is not the same for the poor and the non-poor. In fact, SIS has a smaller effect among their poor enrollees, those it is mandated to prioritize. Although 82.6% of SIS' enrollees were poor in 2005, they seem to face more barriers to access healthcare than just having to pay for these services.

As mentioned before, SIS was created under the premise that the public healthcare system was underutilized in Peru, so that boosting the demand for healthcare would produce just a small marginal cost to the public budget while addressing the needs of a sub-group of the population. However, despite the efforts by the national government to expand the healthcare supply in the 1990s, these healthcare clinics and hospitals clustered in urban areas where non-poor families, who could already afford to pay a subsidized fee, reside. Poorer, rural areas still lacked access to these services. Thus, mostly non-poor households were in the best position to gain from the benefits of the program.

Without a comprehensive strategy to expand healthcare supply to rural and remote areas, an initiative like SIS would not likely fulfill its ultimate goal of increasing healthcare access for the poor. Even when SIS can produce a demand expansion for the poor, they still face geographic barriers to access healthcare. In some extreme cases, it can take several hours of rudimentary transportation (e.g., riding an animal, canoeing, or even walking) to get to the nearest healthcare facility for some people living in rural areas, most of whom are poor or extremely poor. Acknowledging this barrier, the Ministry of Health implemented guest houses next to healthcare facilities as a strategy to reduce maternal mortality. But birth is a health event that can possibly be planned, other health shocks cannot and even preventive care would be forgone in these extreme situations.

As SIS improved its targeting strategies, and different levels of government increased their investment in healthcare services, the program may have started to reduce the inequities in access to healthcare. However, in the first few years, up until at least 2005, the program increased these gaps as it was the non-poor who benefited the most from SIS.

Thus, to answer the main question posed in this chapter, I conclude that SIS reached its goal of expanding the demand for healthcare and effectively increasing healthcare utilization for a set of desirable types of care. However, this demand shift is higher among non-poor individuals, which increases the gaps in access to healthcare between the poor and non-poor in Peru.

Chapter 3

The Effect of Health Insurance on Out-of-pocket Healthcare Expenditures and Households' Financial Protection against Catastrophic Healthcare Expenditures

3.1. Introduction

The Peruvian government made a significant investment in expanding the healthcare supply during the 1990s, when the construction of publicly administered hospitals and clinics boomed. These new healthcare facilities across the country provided health services for a subsidized fee, where a doctor's visit would cost approximately between \$0.3 and \$1.7. However, despite these subsidies most people still had unmet healthcare needs, and the use of these new facilities fell short of their full capacity. Health officials, with the support from other branches of the government and multinational agencies such as the World Bank and the Inter-American Development Bank, decided to try a new approach to subsidies. This led to the creation of the two preceding pilot programs, the Mother and Child program and the *Seguro Escolar Gratuito*, and the subsequent implementation of SIS.

The idea behind these programs was that supply-side subsidies were not sufficient to reduce unmet needs for healthcare, and that demand-side subsidies may be more efficient in meeting these needs. These subsidies received through SIS enrollment would add to the already existing supply-side subsidies, so that SIS enrollees would receive a full subsidy for any health service included in that health plan's benefits.

In theory, a full subsidy on all health services included in the generous health plan's benefits of SIS would likely lead to a decrease in healthcare expenditures paid by patients, even if utilization of these services increased, or no change in expenditures (e.g., an individual may not have use a specific service before enrolling in SIS and makes no out-of-pocket expenditures, but after enrolling these services would be free). However, a failed design and some implementation problems meant that, in practice, enrollees had to make out-of-pocket payments for some services that were supposed to be covered by SIS; due to lack of compensation, many public providers restricted access to some services (e.g., medications or lab exams), and SIS enrollees had to find them on the private market where SIS did not provide coverage, and these providers even charged SIS enrollees for some services that were fully covered.[34]

Since enrollees had to make out-of-pocket payments, even for services that were covered by the program, it is important to assess whether SIS produced a decrease in out-of-pocket expenditures. As found in Chapter 2, SIS increased the consumption of some healthcare services, but if the financial coverage of SIS was not effective, its enrollees could have seen an increase in expenditures. And if this was the case, it is useful to identify which types of services had decreased expenditures under SIS, and which had increased expenditures.

The effect of health insurance on healthcare expenditures is an empirical question. For most cases, when the price of healthcare drops for someone when they obtain health insurance coverage, one could expect healthcare expenditures to drop as well. This is particularly the case for covered healthcare that is needed on a regular basis, such as preventive care. Officials in Peru expected this to be the case for all services included in the plan's benefits. However, as mentioned above, implementation problems resulted in SIS enrollees having to make some payments for the services they received. And increases in the consumption of some services may have led to an increase in expenditures, even

[34] Alarcón (2004).

though prices dropped. This is likely the case for services that would not have been consumed without health insurance and for which enrollees had to make some out-of-pocket payments, most notably adjunct services. And for some services, an increase in consumption due to a decrease in out-of-pocket expenditures may have led to healthcare expenditures not changing for individuals.

Thus, this chapter first addresses the following questions: Has SIS reduced the overall out-of-pocket payments made by their enrollees? Is this effect homogeneous across different types of healthcare services?

In addition, I explore the effect of SIS on its enrollees' financial protection against impoverishing healthcare expenditures, that is catastrophic expenditures. Not all health shocks affect a household's financial stability in the same way. In fact, some health events have the capacity to damage this stability and pose such a financial strain on people that they can fall in poverty.

In 2012, healthcare represented over 10% of total expenditures for 18% of all Peruvians.[35] Even more alarming is that 6% of the population spent 20% or more of their total expenditures on healthcare. For people living in extreme poverty, these figures were 9.6% and 4.3%, respectively, which may indicate that SIS is somehow protecting the financial status of the poor, although it may indicate that the poor simply do not seek healthcare since they cannot afford it.

[35] Alarcón (2013).

A severely adverse health shock can harm a household's standard of living in many ways. For example, a household may lose disposable income if this shock directly affects a working adult, either through that person having to recover from a long illness or accident or through that person having to care for another household member who is recovering from this event. Peru's Social Health Insurance could protect families from this income loss, but a very small portion of the labor force in Peru is covered by this benefit since most of the labor force works in the informal sector.[36]

A more direct way by which a severe health shock could affect a household's standard of living is when a high-cost treatment is required to recover from the health shock. In the long term, if the household needs to make high out-of-pocket payments for a prolonged period of time, this event could affect the household's wealth as it may need to incur debt through either formal or informal (e.g., a loan from family or friends) channels, or it may need to liquidate some of their assets to pay for healthcare. In the short term, these high out-of-pocket payments would lead to families having to adjust their consumption and reprioritize their spending, cutting expenses in other areas to pay for healthcare. And for poor households, who are the majority of SIS enrollees, this means cutting spending on basic needs.

This phenomenon complements the previous research questions mentioned above. More specifically, I investigate whether a non-catastrophic health insurance program, has helped poor households in Peru cope with severely adverse health shocks. Has SIS been

[36] Diaz and Valdivia (2012) estimate that only one in four workers have Social Health Insurance benefits.

successful in reducing households' likelihood of incurring in large healthcare expenditures that can lead them to poverty or financial distress?

One of the intrinsic features of health insurance is the protection it provides against the financial risk associated with severe health shocks. Another benefit of having health insurance is that it makes available healthcare that is simply not affordable without it. Some argue that this is the main reason why people seek health insurance, to protect their assets from such risk. But how effective has SIS been in providing such protection to its enrollees?

Many health insurance programs in the developing world were created to help households avoid high healthcare expenditures (e.g. the *Seguro Popular* program in Mexico). They are usually implemented in a context where a large portion of the population is incurring catastrophic healthcare expenditures, the type of expenditures that can compromise the household's ability to maintain its customary standard of living. In contrast, SIS was not created to cover high cost, recurring health services and procedures. Instead, SIS was intended to address the economic barriers to seeking healthcare among the poor. Thus, the main objective of SIS is to increase the use of healthcare through a demand-side subsidy, eliminating any out-of-pocket payments.

In addition, SIS was not explicitly intended to protect families against catastrophic healthcare expenditures. In addition, SIS has had some design and implementation problems that have forced enrollees to decide between either making out-of-pocket payments to obtain access to some services that were covered by the program or forgoing those services.

SIS had generous coverage, including a wide range of health services, but these benefits do not include coverage for high cost, long-term health services and procedures, such as dialysis for kidney failure, bone marrow transplants for leukemia, and some other cancer treatments. Alongside SIS, officials created in 2002 another program to cover these services and procedures: the *Fondo Intangible Solidario de Salud* (FISSAL), but this program did not begin operations until 2013 due to its low level of political priority.[37] Despite this, SIS may still have had an impact on the likelihood of their enrollees experiencing catastrophic healthcare expenditures.

3.2. Literature Review

The economic literature on the relationship between health insurance programs and healthcare expenditures is concentrated on specific cases, mostly those programs for which the goal was to reduce high expenditures of their target population, mainly low–income people. Programs such as *Seguro Popular* in Mexico, FOSYGA in Colombia, the *Seguro Facultativo de Salud* in Nicaragua, and programs in other regions have been the subject of several studies.

3.2.1. *Seguro Popular* in Mexico

The *Seguro Popular* program in Mexico is an exemplar case of a program that was created to address high healthcare expenditures made by the uninsured population. This program

[37] FISSAL (2014).

had the explicit goal of providing financial protection to its beneficiaries against excessive healthcare expenditures.

A randomized controlled trial conducted in rural areas of Mexico allowed King, *et al*. (2009) to study the effect of *Seguro Popular* on catastrophic healthcare expenditures. This experiment was launched in 2005 and it consisted in selecting 50 out of 100 "health local clusters," for a program that promoted enrollment in *Seguro Popular* and upgraded the medical facilities. The definition of health cluster was based on the geographic coverage of healthcare facilities. They estimated an intent-to-treat effect of 23% on the probability of incurring this type of impoverishing expenditure, and a local average treatment effect of 55% on this probability.

Grogger, *et al*. (2009) replicate the analysis done by King, *et al*. (2009) and add administrative data about the status of the supply of healthcare. They also replicate the analysis using a household survey to provide results for the whole population. They reach a similar conclusion and find an important weakness of the program: they conclude that catastrophic healthcare expenditures fell for rural households that have access to "well-staffed facilities," but had no effect for other households. Their analysis of the household survey leads them to argue that the program also reduces catastrophic healthcare expenditures by 2.9 percentage points among urban households.

Galárraga, *et al*. (2010), using an instrumental variable approach, estimate that this program reduced catastrophic expenditures, defined as spending 30% or more of total expenditures on healthcare, by 54% at the national level. Taking advantage of the gradual implementation of the program by Mexican states, the authors use the year a state was incorporated into the *Seguro Popular* as the instrument in this study.

3.2.2. *Fondo de Solidaridad y Garantia* (FOSYGA) in Colombia

Colombia's FOSYGA is a program with two distinct regimes: contributory, for those who can afford to pay a premium, and fully subsidized, for the poor. FOSYGA was designed to provide cross-subsidies from the wealthy to the poor, the healthy to the sick, and the young to the old. Individual choice is embedded in the system as people choose their plan (and insurer) and FOSYGA pays their premium.[38]

Florez, *et al*. (2009), using propensity score matching, found that FOSYGA reduced the probability of incurring a catastrophic healthcare expenditure.[39] The authors use different thresholds, 10%, 20%, 30%, and 40%, to explore differences in this effect by the size of the health shock. Their results suggest that the mitigating effect of health insurance in Colombia decreases with the level of the catastrophic healthcare expenditures. More specifically, they find that the probability of incurring healthcare expenditures that exceed 10% of the household's overall expenditure is reduced by 62%, but this figure drops to only 13% when the threshold is set at 40%.

[38] In practice, most cities have only one available insurer (Miller, *et al*., 2009).
[39] This result holds for all thresholds used in the analysis: 10%, 20%, 30%, and 40%.

3.2.3. *Seguro Facultativo de Salud* in Nicaragua

In 2007, informal sector workers in Nicaragua were offered the *Seguro Facultativo de Salud*. This is a voluntary health insurance program that shares many similarities to health insurance offered by a typical Social Health Insurance.

Thornton, *et al*. (2010) used a randomized control trial to estimate the effect of health insurance on out-of-pocket expenditures.[40] They found that total out-of-pocket expenditures fell for those who took up the insurance after only one year of enrollment. Although the estimate is not statistically significant, they estimate that out-of-pocket expenditures fell by approximately 55%.

Their estimate also implies that the monetary value of this reduction in expenditures is below the average annual premium, which suggests that this program did not provide absolute cost savings mechanism for the average enrollee.

3.2.4. Medicaid in the United States of America

Finkelstein, *et al*. (2011) used an experiment conducted in Oregon to study the effect of a Medicaid expansion that occurred in 2008. The experiment randomly offered a group of uninsured, low-income adults a chance to apply to a fully subsidized health insurance coverage through Medicaid. This randomized controlled trial found that after one year of implementation the group selected by lottery to have health insurance coverage experienced a 20 percentage points decline in the probability of having out-of-pocket medical expenditures, an 18 percentage points decline in the probability of having medical

[40] The experiment consisted in randomizing the costs of premiums as well as enrollment locations.

debts, a 15 percentage points reduction in the probability of having to borrow money or not pay other bills in order to pay for medical expenses, and a 4 percentage points decline in the probability of treatment having been refused due to medical debt.

3.2.5. SIS in Peru

Bitrán, *et al*. (2010) studied the relationship between SIS enrollment and out-of-pocket expenditures for medical services in the four weeks prior to being interviewed. They used a subsample of the 2002-2006 ENAHO panel (only those that provided information in all five years), which is a small subsample of this panel. Using information on prior health insurance (i.e., insurance coverage status two years prior to the survey) as an identifying variable to control for endogeneity, the authors found that gaining SIS coverage reduced the probability of making out-of-pocket expenditures in the past four weeks by over 67% (and possibly by 81%) in 2004.[41]

The study also estimated the effect of enrollment on the amount spent on healthcare and the probability of incurring catastrophic healthcare expenditures, which the authors defined as healthcare expenditure equivalent to 30% or more of all household expenditure in one year. They found no significant effect for these outcomes.

Petrera and Jimenez (2018) study the determinants of out-of-pocket expenditures among poor Peruvians that seek healthcare in public facilities. They found that SIS reduced people's out-of-pocket expenditures between 2010 and 2014. They also found that factors

[41] The authors report that analysis beyond 2004 was not possible due to a very small number of observations that made some out-of-pocket expenditures in healthcare. This is a limitation of the sample and the identification strategy of the study.

associated with higher out-of-pocket expenditures were age, total household expenditures, and type of provider (e.g., hospital),

Bernal, *et al*. (2017) used a regression discontinuity design to estimate the effect of SIS in Metropolitan Lima, the capital of Peru. As described in Chapter 2, the authors use the pilot of a national targeting strategy for social programs implemented in Lima in 2011, which used an asset index for any household applying for SIS coverage.

Using a Regression Discontinuity Design estimation strategy, they find that SIS has no effect on individuals' incurring at least some healthcare expenditure, and no effect on the amount of this expenditures. The authors find that SIS increases healthcare expenditures on medications (by 55%), X-rays (by 17%), and inpatient visits (by 41%). They also find that SIS increases the probability of incurring a catastrophic expenditure, using several thresholds: 5%, 10%, 15%, 20%, and 25%.

3.3. Data

The main data source for this chapter is the one described in the previous chapter: the *Encuesta Nacional de Hogares* (ENAHO). As mentioned in Chapter 2, one of the main goals of the ENAHO is to provide an estimate of the poverty rate, which implies gathering detailed and comprehensive information about households' income and expenditures. These detailed data include information about households' expenditures on healthcare for a selected set of services.

In addition to the information on health and the use of healthcare services, detailed in Chapter 2, the ENAHO also provides detailed information about out-of-pocket expenditures on: i) provider visits, ii) drugs and prescriptions, iii) laboratory analyses, iv) dental care, v) optometrist care, vi) corrective lenses, vii) immunizations, viii) child checkups, ix) contraceptives, x) inpatient care, xi) surgery, xii) pregnancy check-ups, xiii) delivery, and xiv) other healthcare services. This information is available for each individual in the household. If respondents refused to provide this information, it is imputed using a "hotdecking" method.[42]

Using these data, I explore the effect of SIS enrollment on the amount of out-of-pocket expenditures individuals paid for each of these services. In addition, I assess the impact of SIS on making any payment for healthcare, which is defined as having a positive amount in at least one of the individual service categories.

I also focus on the effect that SIS has on the probability of incurring catastrophic (or impoverishing) healthcare expenditures. As mentioned before, catastrophic expenditures are defined as a percent of healthcare expenditures relative to total household expenditures, although the economic literature on the topic has not settled on a standardized threshold for this indicator. I provide more detail about the definition of this variable in the Methods section.

3.3.1. Expenditures on Healthcare

Peru is a country where healthcare represents a small proportion of total consumption expenditures. The Ministry of Health estimate that 4.6% of the Peru's GDP was spent on

[42] Hotdeck is a widely used routine that dataset managers use to impute missing data. In this case, the *Instituto ?Nacional de Estadistica e Informatica* provides these variables already imputed when missing.

healthcare in 2005.[43] Not only is this a low percentage in comparison with the Organization for Economic Cooperation and Development countries, it is also below the average in the South American region (7.6%).[44]

Households are the most important source of healthcare expenditures in Peru; direct payments from households, mostly out-of-pocket and not premium payments, represented 38% of all healthcare consumption in 2005. Employers funded 33% of healthcare expenditures, and the Government, mostly through general funds, contributed 27%. In a country where poverty rates are high (49% of the population cannot afford a basic basket of food and non-food goods and 17% cannot afford the basic food basket), this contribution from households to healthcare is significant.

Using the 2005 ENAHO, I estimate that 52.5% of the population living in a household where no member works in the formal labor market, and thus no one is eligible for coverage through Peru's Social Health Insurance, used healthcare services. However, only 34.7% made out-of-pocket expenditures, which implies that 17.8% received a full subsidy for their use of healthcare services or someone outside of their household paid for them, including an insurer.

Table 3.1 shows the mean of these out-of-pocket expenditures in 2005 for each of the services under analysis. Medications were the largest healthcare expense in Peru in

[43] MINSA (2015).
[44] The World Bank: Data Bank, https://databank.worldbank.org/reports.aspx?source=world-development-indicators. Last accessed 22 August, 2021.

2005, with an overall average of 69.5 *nuevos soles*. This mean increased to 272 *nuevos soles* when considering only those who made any out-of-pocket payment.

Table 3.1: Out-of-pocket Expenditures in Healthcare in Peru, 2005

Outcome	No OOP payment (%)	Mean (S/.)	Percentiles		
			90%	95%	99%
OOP Expenditures in the last 4 weeks					
Doctor's visit	89.3	13.7	23.8	60.9	302.3
Medication	74.4	69.5	121.6	308.5	1,257.9
Laboratory	98.4	7.2	0.0	0.0	214.3
X rays	99.3	4.3	0.0	0.0	0.0
Other exams	99.9	0.7	0.0	0.0	0.0
OOP Expenditures in the last 3 months					
Dental care	94.3	19.5	0.0	39.8	481.1
Eye care	98.4	2.9	0.0	0.0	60.7
Corrective lenses	98.8	5.5	0.0	0.0	273.6
Immunizations	99.3	0.9	0.0	0.0	0.0
Child's check up	97.3	2.0	0.0	0.0	40.5
Birth control supplies	98.6	1.1	0.0	0.0	31.9
Other	93.8	6.4	0.0	7.96	120.37
OOP Expenditures in the last 12 months					
Hospitalization	97.4	16.1	0.0	0.0	352.4
Pre-natal care	93.3	4.7	0.0	15.2	101.7
Institutional delivery	89.6	9.4	5.5	50.8	200.8

Notes: The population of this table was restricted to households with no member employed in the formal labor market.

The average exchange rate in 2005 was: 1 U.S. dollar = 3.29 *nuevos soles*.

Author's analysis of the 2005 ENAHO.

Medications was also the category with the largest expenditure cutoff for the 99th percentile in the 2005 ENAHO: 1,257.9 *nuevos soles*.

The portion of the population that made no out-of-pocket payments for doctor's visits was 89.3%, while those who did not spend any money on medications was 74.4% of the population. However, the percentage of the population that made no out-of-pocket expenditures is very high (over 90%) for other healthcare services included in Table 3.1. For example, almost no individual paid directly for X-rays, immunizations, birth control, and "other exams," all services with over 99% having no out-of-pocket payments.

There can be different underlying factors driving the high percentages of people not spending on services and these are related to the type of service. For example, preventive care is meant to be fully subsidized for all (i.e., immunizations and birth control), and enrollees will not likely find themselves in situations where they are forced to pay for these services. On the other hand, adjunct healthcare services, such as an MRI, are required as a part of another form of treatment (e.g., surgery); if someone cannot afford the surgery and decides not to have this procedure, they are less likely to require these adjunct services.

Table 3.1 also shows the nature of the distribution of healthcare expenditures; skewed distributions, with a high concentration at zero and long tails. The following section discusses how this issue is addressed in this chapter.

3.3.2. Catastrophic Healthcare Expenditures

As discussed above, some health shocks require high-cost treatment that can lead a household to financial strain and even poverty. The economic literature measures this type of expenditures in terms of its proportion of a household's total expenses. Thus, severe health shocks often imply a redistribution of consumption priorities within a household; with limited resources, families have to reduce some expenses or borrow money to pay for this healthcare.

However, in a country where half of the population lives under poverty and almost one in every five cannot afford a basic food basket, this redistribution implies that these families have to forgo some basic goods and services to pay for needed healthcare. And in these cases, any additional amount of out-of-pocket payments for healthcare impacts the household's ability to meet these basic needs.

Table 3.2 shows the incidence of catastrophic healthcare expenditures in Peru. In 2005, 57.9% of the population that were in households where no member worked in the formal labor market faced out-of-pocket healthcare payments that exceeded 10% of the household's total expenditures. This percentage decreases as the threshold is raised, but 32.2% of the population still are part of families where a health shock has made them allocate 40% or more of their total expenses to healthcare. Interestingly, the incidence of catastrophic healthcare expenditures is similar among SIS enrollees; 55.7% for low catastrophic expenditures and 31.4 % for critical catastrophic expenditures.

Table 3.2: Catastrophic healthcare expenditures among Households not Part of Peru's Formal Labor Market, 2005

Outcome	All	Among SIS enrollees
Low, 10+% of household expenses	57.9	55.7
Medium. 20+% of household expenses	46.2	45.1
High, 30+% of household expenses	38.1	37.6
Critical, 40+% of household expenses	32.2	31.4

Notes: These estimates exclude households with a member that works in Peru's formal labor market. Author's analysis of the 2005 ENAHO.

3.4. Methods

The relationship between healthcare expenditures and health insurance coverage is similar to that between healthcare utilization and coverage: they are simultaneously determined. The relationship that I want to assess in this chapter is the impact of having SIS coverage on healthcare expenditures and on the likelihood of incurring a catastrophic expenditure. However, people who expect to have a need for healthcare, and thus to incur healthcare expenditures, may be more inclined to seek SIS enrollment.

I use the same identification strategy used in Chapter 2: instrumental variables. Again, the enrollment goals established by SIS officials are used as the instrument for enrollment in SIS. I expect that these goals influence the likelihood of people being enrolled, but do not directly affect healthcare expenditures or the probability of experiencing a catastrophic expenditure after controlling for some other characteristics of individuals. As in the previous chapters, I mainly use the F-test of excluded instruments and the Sanderson-Windmeijer F-test of excluded instruments to assess the underidentification and weak-identification of the instrument.

In addition to this potential bias problem, I face two other complications when working with the healthcare expenditures data. First, healthcare expenditures have a skewed distribution, being concentrated at a value of zero, with a long tail. To approximate a normal distribution, and reduce the effect of outliers, economists often use a natural logarithmic transformation on the variable of interest. However, as explained below, I find the Inverse Hyperbolic Sine Transformation to be better for my purposes. Second, as mentioned above, there is no standardized definition for a catastrophic healthcare expenditure. As in the existing literature, I use several different definitions of the level of catastrophic expenditures.

3.4.1. Inverse Hyperbolic Sine Transformation

There are many problems associated with estimating relationships where the dependent variable has a right-skewed distribution. One of the main problems is that the distribution of healthcare expenditures in Peru is highly skewed to the right, with most people having zero expenses and a long tail skewed to the right generated from a few outliers. For example, the distribution of out-of-pocket expenditures on prescriptions and other medications has a mean of 73.2 *nuevos soles*, with 72% of the population reporting zero out-of-pocket expenditures on medications.

A simple logarithmic transformation (i.e., taking the logarithm of healthcare expenditures) is commonly used to achieve a better fit of the data. However, since 63.3% of people in the 2005 ENAHO report having no expenditures, I would have to either: i) exclude all those individuals from my analysis, or ii) impute too many observations that report zero expenditure to a very low expenditure.

Instead, I use the inverse hyperbolic sine transformation, also known as *arcsinh*, because it approximates the natural logarithm while being defined at zero and it allows me to keep the healthcare expenditure variables for all observations in my dataset. This transformation is defined as:

$$\widetilde{HE_{ji}} = log\left(HE_{ji} + \sqrt{{HE_{ji}}^2 + 1}\right) \tag{3.1}$$

where HE_{ji} is the healthcare expenditures of individual i on service j.

3.4.2. Catastrophic Healthcare Expenditure

Financial protection from uncertain, high-cost health shocks is at the core of any health insurance scheme. In this case, I aim to identify health events that impose significant expenses on the household and can impact its ability to meet its basic or regular needs or even impoverish it and jeopardize its standards of living.

Although the economics literature does not have one standard indicator for this event, the definition of catastrophic healthcare expenditure is commonly defined in terms of the value of the out-of-pocket expenditures that a household incurs to obtain medical services relative to the household's total expenditure. However, there is no generally accepted threshold for this relative measure. Some studies define this threshold at 10% (e.g., Florez, *et al*., 2009), while others use higher thresholds (e.g., Galárraga, *et al*., 2010, and Bitrán, *et al*., 2010). I consider four thresholds of catastrophic expenditure: 10%, 20%, 30%, and 40%, based on the range of thresholds used in the literature. This set of thresholds will provide a better understanding of the relationship of SIS with different severity levels of health shocks.

One particular feature of catastrophic healthcare expenditure is that it does not only affect the individual, but due to its significant financial strain it also affects the other members of the individual's household. Thus, an individual enrolled in SIS not only protects or themselves financially but also protects all the members of the individual's household from the financial risk associated with such a health shock.

Since households are the unit of analysis for the relationship between having SIS coverage and the probability of incurring a catastrophic health expenditure, I use a different treatment variable for this part of my analyses. Instead of modelling the effect of an individual being enrolled in SIS, as in all other analyses, I model the effect of having one or more household members enrolled in SIS on catastrophic healthcare expenditures.

Similarly, all covariates are aggregated at the household level. Most explanatory variables used in Chapter 2 were defined at the household level (e.g., number of household members), but those that were defined at the individual level in previous analyses (i.e., age, sex, education, ability to write and read, and mother language) indicate the variable level for the head of the household in this part of the analyses.

3.5. Results

3.5.1. Estimated Effects on Out-of-pocket Expenditures

Using administrative data on the enrollment rate goals as the instrument, I first estimate the effect of having SIS coverage on out-of-pocket healthcare expenditures. As discussed above, I transformed these expenditures using the inverse hyperbolic sine transformation.

Table 3.3 shows these estimates for the (transformed) amount of these out-of-pocket expenditures on a set of healthcare services and for the probability of having to make any out-of-pocket expenditure (see Tables B.1-4 in Appendix B for full results of the regressions).[45]

First, Table 3.3 shows that SIS reduces people's probability of having to make any out-of-pocket payments for healthcare, which is a statistically significant result ($p<0.01$).

Second, these results indicate that being enrolled in SIS does not have a significant effect on expenditures for most types of healthcare services. The only healthcare services that SIS enrollment have a decreasing effect on are: dental care, corrective lenses, immunizations, and child's check-ups. Note, however, that less than 5% of all individuals reported having made out-of-pocket expenditures for corrective lenses, immunizations, and child's check-ups, which is a limitation of this analysis.

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[45] The latter is a binary variable indicating if the individual had to make out-of-pocket payments for any service.

Table 3.3: Instrumental Variables Estimated Effect of SIS on Out-of-pocket Healthcare Expenditures, 2005

Outcome	Estimated Effect	Standard Error	q-value
OOP Expenditures in the last 4 weeks			
Visit to a healthcare professional	-0.899	0.763	0.315
Medication	-2.265	1.211	0.114
Laboratory	-0.146	0.254	0.591
X rays	-0.320	0.235	0.287
Other exams	0.000	0.079	0.663
OOP Expenditures in the last 3 months			
Dental care	-1.229	0.545	0.098
Eye care	-0.228	0.214	0.349
Corrective lenses	-0.700	0.314	0.098
Immunizations	-0.513	0.239	0.098
Child's checkup (children <5)	-0.611	0.205	0.045
Birth control (individuals 15-50)	6.487	8.216	0.543
Other	1.426	0.619	0.098
OOP Expendoitures in the last 12 months			
Hospitalization	-0.493	0.383	0.287
Pre-natal care (pregnant women)	0.573	2.586	0.663
Institutional delivery (pregnant women)	1.184	4.292	0.663
Any out-of-pocket expenditure	-0.720	0.259	0.005

Notes: Statistical significance indicates the probability that the coefficient is zero, which were estimated using the False Discovery Rate (FDR) control.

Robust standard errors estimated clustered at sampling cluster.

The overall sample size is 64,118; with 7,660 children under 5, 31,157 people aged between 15 and 50; and 3,594 women who gave birth in the previous 12 months.

Any out-of-pocket expenditure is a binary variable that indicates whether the individual made a payment for any type of service. All other variables are continuous.

Author's analysis of the 2005 ENAHO.

Table 3.3 also shows that SIS appears to increase people's expenditures on "other services." These services are likely to be adjunct services that were not covered by SIS or services for which providers illegally rejected their services or required direct payment for. This result likely reflects an increase in utilization and expenses for provided-induced healthcare that was not covered by the program.

The original estimates suggested that SIS reduced expenditures on medications ($p<0.1$), but this significance was challenged using the FDR control as shown in Table 3.3 ($q>0.1$).

All first-stage regressions pass the tests for underidentification and weak identification, with the exception of 3 services: birth control, pre-natal care, and institutional delivery (see Table A.1 in Appendix A).

As a sensitivity analysis, I transform these variables into binary variables that indicate whether the individual made a payment for the specific service and estimate the effect of SIS on having to make out-of-pocket expenditures for these healthcare services (see Tables B.5-9 in Appendix B). These results show that SIS only has a significantly negative effect on wellness checkups for children. Although the estimates for obtaining dental care, corrective lenses, and immunizations were also negative, but slightly not significant ($q=0.111$).

3.5.2. Estimated Effects on Catastrophic Healthcare Expenditures

Table 3.4 shows the estimated effect of SIS enrollment on incurring catastrophic or impoverishing healthcare expenditure (see Table B.10 in Appendix B for full results of the regressions).

Table 3.4: Instrumental Variables Estimated Effect of SIS on Catastrophic Healthcare Expenditure, 2005

Severity of the Catastrophic Healthcare Expenditure	Estimated Effect	Standard Error	q-value
Low, 10+% of household expenses	-0.758	0.370	0.195
Medium, 20+% of household expenses	-0.557	0.327	0.195
High, 30+% of household expenses	-0.294	0.276	0.216
Critical, 40+% of monetary expenses	-0.332	0.261	0.216

Notes: Statistical significance indicates the probability that the coefficient is zero, which were estimated using the False Discovery Rate (FDR) control.
Robust standard errors estimated clustered at sampling cluster.
The sample is 15,445 households that are excluded from the formal labor market.
: Author's analysis of the 2005 ENAHO.

Almost all estimates are negative but not statistically significant. The negative point estimates suggest that SIS enrollment reduces the chances of incurring in catastrophic healthcare expenditures, regardless of the threshold used. Two of these four thresholds, low and medium catastrophic healthcare expenditures, have a p-value below 0.1. However, these estimates are not significant once the FDR q values are used (q > 0.1), suggesting that those estimates were falsely significant.

All first-stage regressions pass the tests for underidentification and weak identification (see Table B.9 in Appendix B).

3.6. Conclusions and Discussion

SIS was created to eliminate the economic barriers that reduce access to healthcare by making healthcare more affordable for the most vulnerable Peruvians; by complementing the existing subsidy through public providers, SIS aimed to fully subsidize most healthcare services. The results presented in Table 3.3 suggest that SIS accomplished this goal by 2005; people who enrolled in SIS reduced their likelihood of making any out-of-pocket expenditures for healthcare.

When disaggregating this analysis by type of service, I estimate that SIS reduces expenditures on dental care, corrective lenses, immunizations, and children's checkups. These results are important since they indicate that people are consuming more preventive healthcare, as found in Chapter 2, and reducing their expenditures at the same time due to SIS.

Table 3.3 also shows that despite theoretically reducing the price of healthcare to zero, SIS increased expenditures on "other services." This is only marginally significant, but it reflects that some of these services are excluded from the SIS benefit plan and, most importantly, perhaps due to some implementation problems that affected the early years of the program's operations.

SIS did not cover all services, most notably high-cost, catastrophic expenditures were excluded from the SIS plan of benefits. These services were supposed to be covered by another fund created specifically to administer public resources for rare, high cost treatments. However, this plan had low levels of priority and so it was not implemented until 2013 due to lack of resources. In practice, public funds provided only a partial subsidy for these services in 2005; households had to finance directly most of these costs.

However, if SIS had worked according to plan, enrollees would not have had to make any out-of-pocket healthcare expenditures for most services, as the health plan's benefits were quite generous. But this was not the case as the delays in reimbursement for they services provided forced some providers to charge out-of-pocket payments to enrollees for services that were covered by SIS. Some public providers also rejected providing these healthcare services to SIS beneficiaries, which led enrollees to forgo these services or obtain them from private providers, where they had to pay the full cost of the service as SIS was not authorized to reimburse providers outside its network of public providers.

This situation was generated by structural problems that hindered the capacity of SIS to provide financial protection for its enrollees. The program was not created as an insurance program but rather as another public agency. A health insurance program needs a level of flexibility to manage the health risks of its enrollees. Instead, SIS was limited by typical Public Finance Management rules that imposed limits on how the SIS budget was allocated, spent, and accounted for, and so the impact of SIS was affected by these controls.

SIS funds were allocated through the regular budgetary channels that regulated every public agency. SIS funds were, in practice, a line-item budget that was proposed by SIS officials and approved by the Ministry of Finance. Instead of following a budget growth that was the result of a planned expansion of the program and that focused on filling the gaps of unmet healthcare needs among its target population, the Ministry of Finance allocated funds based on a restrictive budgetary growth rate that depended on tax revenues growth.

Within two years, SIS was unable to reimburse providers for the services they provided to SIS enrollees. It is very likely that SIS' budget in 2002 was not based on an actuarial study of its plan of benefits for the number of enrollees it had that year. By the end of 2003, less than 24 months after beginning its operations, debts to providers were estimated to be equivalent to 6 months of claims at the national level.[46]

Consequently, providers began rejecting services for SIS enrollees or asking them to pay out-of-pocket for these services even when they were entitled to receive the service at no cost.[47] In practice, SIS did not provide coverage for services that required additional supplies not covered by the own provider budget. For example, providers that recommended laboratory services for some patients to aid their diagnoses, would require full payment from these patients regardless of their enrollment status.

Thus, despite being theoretically fully subsidized, SIS enrollees had to make some payments that influenced how the program affects their healthcare expenditures. Since the price for some healthcare services was not zero, expenditures did not fall for all services, and even rose in one case. As shown in Table 3.3, individual's expenditures on "other services" increased due to being enrolled in SIS. These "other services" are mostly adjunct services, such as particular diagnostic analyses needed for a surgery procedure. And they

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[46]Alarcón (2004).
[47] Bernal, *et al*. (2017) report that these practices continued in 2011, although by 2011 SIS had placed agents in hospitals to help enrollees get the services covered by the program at no cost.

are also the types of services that providers would restrict access to, and even charge for. The estimated positive effect of having SIS coverage on expenditures of these "other services" suggests that enrollees were not willing to forgo the whole treatment and agreed to make out-of-pocket payments for these adjunct services.

I also find that SIS has no major effect on the probability of incurring a catastrophic healthcare expenditure (see Table 3.4). SIS was not created as a catastrophic health plan; the *Fondo Intagible Solidario de Salud* (FISSAL) had this objective. Treatments such as dialysis for kidney failure or stem cell transplant for some cancers, were meant to be covered by FISSAL. This fund was also established in 2002, as part of a more comprehensive strategy to provide coverage for Peruvians vulnerable to severe health shocks. But despite its legal creation, in practice, it was not implemented due to its low political priority and lack of resources. It took 11 years after its creation for FISSAL to cover the treatment of its first beneficiary.

However, the need for a high-cost treatment is not the only impact on a household's financial stability. There are other situations in which households have to make out-of-pocket payments that can deplete their disposable income and push them to poverty. These situations are at the core of the concept of catastrophic healthcare expenditures. Anyone who is already living in poverty does not have disposable income and is highly vulnerable to most health shocks. In this situation, any additional out-of-pocket payments that a household makes for medical services needed by one of its members implies reducing the consumption of a basic good or service that is needed for its subsistence.

In Peru, the cost of a basket of basic goods and services was 232 *nuevos soles* for an individual in 2005. Basic food consumption, which is used to estimate extreme poverty, was estimated to cost 106 *nuevos soles*. Although only 3.9% of the population was hospitalized in 2005, the average out-of-pocket expenditure for inpatient services was 614 *nuevos soles* (see Table 3.1), although this average was almost half among SIS enrollees, at 284 *nuevos soles*. This means that if a member of a poor household requires hospitalization, it is highly likely that this household will experience a catastrophic healthcare expenditure. Even though SIS did not cover high-cost treatments, there was room for it to provide financial protection against catastrophic healthcare expenditures for its poor enrollees. However, my results show that SIS does not have an effect on the probability of incurring a catastrophic health expenditure for its enrollees.

Since it was first implemented, SIS was intended to focus on the most vulnerable population, which mainly includes people living in poverty. In 2005, 82% of all enrollees were poor. Although SIS enrollees may not have received a full subsidy for their healthcare consumption, either because some services are not covered by their plan of benefits or because providers restrict access to covered services, SIS still reduces their expenditures on the most common types of healthcare services. Yet it does not reduce the probability of incurring a catastrophic healthcare expenditure.

Chapter 4

Does *Seguro Integral de Salud* Have an Effect on Children's Health?

4.1. Introduction

When countries set a goal of improving their population's health outcomes, sometimes they resort to policies that affect the financing rules that govern their healthcare systems through (expanding the eligibility of their) health insurance programs. The underlying idea behind these initiatives is that reducing the financial burden of healthcare will facilitate access to care, which in turn will improve the population's health. However, one may question whether expanding the coverage of publicly-operated health insurance programs affect a country's health outcomes. Do health insurance programs improve health? Internationally, there is no conclusive evidence that supports this hypothesis. Some studies find a positive effect, but evidence showing no effect is also often found, and even the studies that support this relationship find that its impact is small (Levy and Meltzer, 2001 and 2008, and Giedion, Alfonso, and Diaz, 2013).

The most plausible way in which health insurance could affect health outcomes is via an increase in healthcare utilization. Standard economic reasoning argues that when families face a reduced price of care, they increase their consumption of healthcare. The economic literature strongly supports this relationship. In fact, in Chapter 2, I find that those enrolled in Peru's *Seguro Integral de Salud* are more likely to obtain care when needed, especially preventive care. However, these findings are not enough to show that health insurance has a positive impact on health. This hypothesis also requires that the increased utilization of healthcare services will improve people's health. The fact that the international literature remains inconclusive about the effect of health insurance on health suggests that the latter part might be the weak link in the relationship between health insurance and health outcomes; it may seem that more healthcare, obtained through gaining health insurance coverage, is not always better, at least at the margin in aggregate measures.

If evidence about the effects of health insurance on healthcare utilization in the developing world is scarce, the literature studying its effects on health outcomes is even more limited (Giedion, Alfonso, and Diaz, 2013). In this chapter I will explore this relationship for the case of Peru's SIS, focusing on children's health as this was one of the sub-groups of the population prioritized by the program since its creation. In addition, Chapter 2 concluded that SIS had a positive impact on utilization of children's wellness checkups, which is the theoretical mechanism described above as an intermediate step between having health insurance and having better health.

The rest of this chapter is organized as follows. The next section provides a literature review, which explores in detail studies that examine the relationship between public health insurance and health in developing countries; some find a positive effect, but they are not the majority (Giedion, Alfonso, and Diaz, 2013). The data sources used to estimate this relationship are presented in the third section. The fourth section of the chapter discusses the theoretic model that informs the econometric modeling, which is presented in the fifth section. Finally, the main findings and conclusions are presented in sections six and seven.

4.2. Literature Review

As discussed in Chapter 2, almost all economists agree that health insurance leads to an increase in healthcare consumption.[48] But the goals of health insurance programs are not only to increase healthcare utilization and decrease the probability that a financial shock could severely affect disposable income, but also to improve the health outcomes of their beneficiaries. Although it is probably the ultimate goal of any health policy, such as increasing health insurance coverage, improving health is an indirect result of increasing healthcare utilization, one that perhaps can be observed only in the long run. The underlying theory is that people can achieve better health outcomes when effective preventive and curative healthcare services are available to them in a timely manner, which health insurance is intended to facilitate.

Most of the literature that explores this relationship comes from the developed world, where natural experiments, as well as randomized experiments, have been used to investigate it. In the U.S., two major public health insurance programs have been studied: Medicare and Medicaid.

The eligibility rules to qualify for Medicare present a scenario where the elderly benefit from a system that provides them with (nearly) universal coverage. Since one becomes eligible upon reaching 65 years of age, the opportunity to compare the newly eligible with those who are a few months away from eligibility arises. Card, *et al*. (2004) used this approach to perform a set of discontinuity design regressions and explore the changes in mortality and self-reported health status, among other variables, at this age.

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[48] Giedion and Diaz (2010), Buchmueller, *et al*. (2005), and Hadley (2003).

They find small effects on self-assessed health, although they find that the largest effects are observed among the groups that experience the largest gains in coverage at age 65: the less educated minorities and Hispanics; a reduction of about 15% of the gap between the overall population around the age of 65 and each of these groups. These small effects could be interpreted as an indication that changing insurance types would not have a large effect on health status, even if the benefits from Medicare are better than those from a previous type of coverage. However, gaining insurance could yield a perception of improved health in people. Although Card, *et al*. (2004) used different methods and data sources to explore the effects of gaining Medicare coverage on mortality rates, they found no significant effect either at 65 or over the long run; and when they found a change in mortality rates, they argue that they are most likely driven by other factors. However, they were unable to measure changes in mortality rates for specific subgroups, which could experience some improvement hidden by aggregation.

In terms of mortality, Card, *et al*. (2009) found that Medicare-eligible people experience an important absolute decrease and a slower growth in the probability of death at the age of 65. They also found an estimated 0.8-1.0 percentage point decrease in the likelihood that a patient admitted to a hospital dies within a week of admission when compared to patients in a similar condition at admission but who are just under 65 when admitted (Card, *et al*., 2009).[49] This effect persists, in significance and size, for at least nine months after someone becomes 65. The increased healthcare use due to becoming

[49] This reduction of 1 percentage point in the 7-day mortality is equivalent to a 20% reduction in deaths. Other lengths of mortality were also estimated: at 14, 28, 90, 180, and 365 days of admission, but they are relatively less precise than estimates for the 7-day mortality. They estimate a reduction of deaths by 7%-9% and 2%-4% for the 28-day and 365-day mortalities, respectively; however, robustness checks, based on lower bound estimates, performed by the authors are not consistent with these estimates.

Medicare eligible also leads to a reduction in the growth of the probability of death at 65 (Lichtenberg, 2002).

The first channel that may explain the effect of Medicare on health outcomes is the gain of insurance from people who were uninsured just before 65. However, the size of these effects suggests that this is not the only driving factor. Another potential source for these large effects is the increase in healthcare use among patients who were previously insured, either by Medicaid or private insurance, due to more generous benefits. The latter has not been strongly proven empirically (Card, *et al*., 2009).

Medicaid is the other main health insurance program that has been studied in the U.S. Its target population has been low income families, giving clear priority to children and pregnant women. However, expansions from the last decade have favored other adults, including childless adults. Medicaid eligibility is determined by states, and different states have granted eligibility to people at different income levels throughout time. This variation of income levels at which people are eligible across states provides the identification strategy used by some studies to estimate the effect of this program on health outcomes, using methods such as difference-in-differences estimation. Among children, it has been found that increasing the eligibility income cutoff is associated with significant improvements in health outcomes (e.g.,. a decrease in infant mortality and low birth weight (Currie and Gruber, 1996.))[50] Furthermore, expansions that targeted low income women

[50] Although they examine changes in the eligibility criteria among pregnant women aged 15 – 44, they focus on two birth outcomes. Combining the use of state fixed effects and an instrumental variable, which they simulate using the different changes of eligibility criteria throughout states and time, Currie and Gruber (1996) find that a 30 percentage point increase in the income level cutoff for Medicaid is associated with an 8.5 percent reduction in infant mortality and a 1.9 percent reduction in the incidence of low birth weight.

have proven more effective, in terms of their effect on health outcomes, than broader expansions to women with higher incomes.[51]

Among adults, Sommers, *et al*., (2012) found a decrease in mortality and an increase in self-reported health status due to Medicaid expansion. The Medicaid expansion to childless adults with incomes below the federal poverty level that started in 2000 was associated with a reduction in adjusted all-cause mortality of 6.2%, or 19.6 deaths per 100,000 adults. This result was larger among non-whites, adults aged 35-64, and adults residing in counties with high levels of poverty; the adjusted all-cause mortality for these three groups fell by in 41.0, 30.4, and 22.2 deaths per 100,000 adults, respectively. More importantly, this estimate increased over time, with an overall reduction of deaths by 6.5 per 100,000 adults per year. Medicaid expansions to childless adults since 2000 were also found to be associated with an increase in self-reported health status of approximately 2.2 percentage points for adults reporting an "excellent" or "very good" health.

In the case of Canada, a natural experiment approach was used to explore the effects of the Canadian National Health Insurance (NHI) on infant mortality and low birth weight (Hanratty, 1996). The fact that NHI was implemented progressively throughout all Canadian provinces allowed the author to use year effects to reduce the bias due to unobservables. Using a panel of counties for a span of 16 years: 1960-1975, she estimated that the introduction of this system was associated with a decrease of 4% in the infant mortality. Similarly, she used panel data on births between 1960 and 1974 to estimate that

[51] In contrast, De la Mata (2012) found no effect of Medicaid eligibility on children's health in the short and medium run. She uses an RDD approach, which ignores the effect of the program for children whose family income is not close to the eligibility cutoff.

the low-birth-weight rate declined by 1.3 after the implementation of the NHI system, although this finding is only weakly significant. A larger effect, although not significant, of 9% was found for the children of unmarried women.

One factor that may explain the variability of results about the relationship between health insurance and health is that health insurance programs are heterogeneous.[52] Differences in the health system in each country explain why the same program works differently in different countries, e.g., the healthcare supply available (in terms of infrastructure and health professionals) at the time of implementation is very likely to have important differences across countries. Moreover, the heterogeneity of the health insurance programs being introduced in the developing world – in terms of target populations, benefits, levels of subsidies and eligibility criteria, cost-sharing mechanisms, and payment mechanisms to providers – make these programs very difficult to compare. Health insurance programs offered by governments differ with respect to: coverage, as some cover primary care while others are comprehensive; premiums, as some are free while others are only partially subsidized; copays, as some have high copays while others are completely free.

All these variable elements inherent in the design of health insurance programs that address the needs of specific populations bring heterogeneity to the outcome people obtain from being covered. Thus, to explore the different studies, it is important to understand the program under analysis and its specific background before discussing their results; this is done in the remainder of this section.

[52] Levy and Meltzer, 2001 and 2008; Giedion and Diaz, 2009; and Giedion, Alfonso, and Diaz, 2013.

4.2.1. Costa Rica

Costa Rica is a country often referred to as "a health 'success' story" as it has better health outcomes than other countries with a similar income level (Dow, *et al.*, 2003).[53] It was during the 1960s and 1970s that health outcomes improved significantly, for example a reduction in child mortality from a rate of 70 per 1,000 in 1960 to 20 per 1,000 in 1980, which happened to coincide with the expansion of health insurance in that country.

It was in 1971 that Costa Rica introduced its first national health plan, and coverage rates started climbing rapidly in 1973 until the third world debt crisis hit Costa Rica in 1980. During this period, the coverage rate among children increased from 42% in 1973 to 73% in 1984. Most of this increase was led by gains in coverage among the middle class. Households with informal sector workers or unemployed adults were excluded from this expansion and faced barriers to obtain healthcare despite the safety nets implemented by the government.[54]

Other major policy changes introduced in the health sector during the same time period included: i) investment in the expansion of primary care facilities and personnel; ii) nationalization of (almost) all hospitals by the agency that runs the universal insurance program; and iii) introduction of primary healthcare programs targeting the uninsured (mainly for those living in rural areas in 1973, and extended to some urban areas in 1976). Simultaneous with these changes in the health system, other major achievements were reached: high levels of female education, a sharp fertility decline, water supply and

[53] In fact, some of Costa Rica's health outcomes are equivalent to those of the U.S. (e.g., life expectancy).
[54] In theory, uninsured people with very low incomes were eligible for waivers of user fees and premiums.

sanitation expansions, advanced social development, sustained economic growth, and political stability (Dow, *et al.*, 2003, p. 16).

Using individual-level data, and eliminating time-invariant unobserved bias by using fixed effects, Dow *et al*. (2003) found a small effect of health insurance on child mortality. They estimate an insurance-mortality elasticity of -0.10, or that the health insurance expansion in the 1970s explains only about 4% of the decrease in child mortality. Their results show a more modest effect than other estimates of the effect because: i) they were able to differentiate between the expansion of health insurance and other policy changes in the health sector; and ii) they avoided the use of aggregated data by estimating individual-level models (they also argue that aggregation can introduce substantial upward biases when estimating the effects of health insurance on health).

Dow and Schmeer (2003) used aggregated data, with fixed effects to control for unobservables and an instrumental variables approach, to estimate the impact of health insurance on child mortality in Costa Rica. Using the baseline insurance rate for each county as an instrument, they find a small effect of health insurance expansion on child mortality. They conclude that "the proposition[s] that health insurance can lead to large improvements in infant and child mortality [according to the experience in Costa Rica], and that expanding insurance to the poor can substantially narrow socioeconomic differentials in mortality …" are questionable (Dow and Schmeer, 2003, p. 975). They conclude that there is little support for the argument that "health sector reforms focusing on insurance can by themselves address serious health problems such as infant and child mortality" (Dow and Schmeer, 2003, p. 985).

4.2.2. Brazil

Brazil's health system is, in theory, one of universal healthcare coverage. The *Sistema Unico de Saudade* (SUS) is the public system that was "based on the principle of health as a citizen's right and the state's duty" (Paim, *et al.*, 2011, p. 1778) and was implemented in 1988. This system was implemented along with the decentralization of many government functions, which included the transfer of publicly owned healthcare facilities from the federal government to states and municipalities. In a country of high levels of regional and social inequalities, this process led to underfunding in the poorest regions.[55] Thus, despite offering comprehensive care, people face significant barriers when they seek care through SUS.

These barriers to healthcare result in a situation where one would gain access only when willing to pay for it, either by paying out of pocket for private services or purchasing private, supplemental coverage. This was fostered by the government's strong support to the development of an exclusive private sector.

This led to the formation of "a complex network of complementary and competitive service providers and purchasers, forming a public–private mix that is financed mainly by private funds" (Paim, *et al.*, 2011, p. 1785). The Brazilian healthcare system can be divided in three sectors: the public sector (SUS), the private services sector, and the private health insurance sector. Healthcare services in the public sector, SUS, are financed and provided by all levels of government: federal, state, and municipal. The private services sector,

[55] Although the federal government has some redistribution mechanisms to finance care in the poorest regions, these are not enough to overcome the serious inequalities in Brazil.

either for-profit or non-profit, is financed in various ways with a mix of public or private funds. Finally, the private health insurance sector is formed by various forms of health plans, each with different benefits coverage, premiums that correspond to these benefits, and tax subsidies that provide incentives to purchase these plans.

Nyman and Barleen (2005) explored the Brazilian case and addressed the endogeneity problem by restricting their analysis to people who were recently diagnosed with an acute illness or a chronic condition. The restriction on the sample would mitigate the bias produced by endogeneity as it is expected that the insurance status of this population would not change after the diagnosis; for those uninsured previous to the diagnosis it would be (prohibitively) expensive to find private coverage after being diagnosed and, for those insured, the decision to obtain coverage would have been exogenous to this health shock. Using this health shock, they found that health insurance has a positive effect on self-reported health status. Among those with an acute illness, having insurance increases (reduces) the probability of self-reporting a better (worse) health status when compared to the uninsured (Nyman and Barleen, 2005, pp. 11–12, Table 4). Similarly, those with a chronic condition have a higher probability of reporting a better health status if they have some insurance coverage (Nyman and Barleen, 2005, p. 12, Table 7).

4.2.3. Colombia

In the early 1990s, Colombia began a progressive phase of state modernization, which included a package of reforms that affected many sectors. In the health sector, a significant expansion of health insurance coverage was designed with the goal of gradually reaching universal coverage. In fifteen years, Colombia's insurance rate quadrupled. Mainly through expansions of the subsidized regime, the insurance coverage rate grew from 20% in 1993 to 80% in 2007 (Miller, et al., 2009).

A National Fund, Colombia's Solidarity and Guarantee Fund (FOSYGA), was designed to receive funds from two regimes: the contributory, for people who have the ability to pay a premium (in practice, the formally employed and their families), and the fully subsidized, for the poor. Financed by a combination of private (payroll taxes and deductions) and public (general taxation) funds, FOSYGA was designed to provide cross-subsidies from the wealthy to the poor, the healthy to the sick, and the young to the old. Individual choice is embedded in the system as people choose their plan (and insurer) and FOSYGA pays their premium.[56]

In the contributory regime, every formal employee, which includes self-employed people, who contributes 12.5% of his or her salary[57] receives coverage for themselves and their families. In the subsidized regime, everyone who is identified as eligible[58] is granted coverage at no cost. However, in practice, due to budgetary limits not everyone who is eligible for the subsidized regime obtains coverage.[59] Given this constraint, priority is given to pregnant and lactating women, children under five years of age, people with disabilities, and displaced populations (Pinto, 2008).

[56] Although, in practice, most cities have only one available insurer (Miller, *et al*., 2009).
[57] Employers are responsible for a contribution of 8.5% of the employee salary, while the employee contributes the remaining 4%.
[58] Eligibility to the subsidized regime is determined by a system, SISBEN, that uses a proxy means test to approximate family wealth. This system is very similar to Peru's SISFOH.
[59] Also, not everyone who is enrolled is eligible, as enrollment began before the targeting system was implemented.

In this context, Miller, *et al*. (2009) used a regression discontinuity design approach combined with the use of an instrumental variable[60] to explore the effect of enrollment in the subsidized regime on health status. They find that enrollment produces: 1) a 1.3 days reduction in the time a child is absent from usual activities due to illness, and 2) a 35 percentage points reduction in children reporting cough, fever, or diarrhea. They argue that these effects are strongly related to increases in preventive care observed among enrollees, which suggests that the supply–side, cost–containing incentives play an important role in Colombia's results from coverage expansions.[61]

Giedion, *et al*. (2009) used two alternative approaches, propensity score matching and matched double difference, and obtained inconclusive results. They evaluate the effects of the subsidized regime on five different health outcomes, related mainly to newborns and children.[62] Their results find no relationship between health insurance and health, with the exception of an effect on low birth weight. At the national level, they found a lower incidence of extremely low birth weight using the propensity score matching estimator. In rural areas, they found a reduction in the incidence of low birth weight and extremely low birth weight, but only when using the matched double differences estimation method. However, their analysis is based on a cross-sectional survey and limits the checks of robustness of their results, as they cannot find a credible identification strategy.

[60] They use a simulated SISBEN score to predict and instrument for enrollment.
[61] Miller, *et al*. (2009) find that enrollment in the subsidized regime is associated with an increase in the probability of a preventive visit within a year of 29 percentage points. They also find that enrolled children had 1.24 more growth monitoring and well-care visits than uninsured children.
[62] These measures are: 1) survival of children under five; 2) health status perception score; 3) low birth weight; 4) extremely low birth weight; and 5) complications after delivery.

4.2.4. Mexico

Much like in Peru, by the turn of the millennium health insurance in Mexico was limited to formally employed workers (and small group who could pay full premiums to a small private market). The Social Security System guaranteed that every employee in the formal sector would have health insurance coverage for themselves and their families. However, a structural characteristic of the labor market, namely having a high rate of employment in the informal sector, meant that insurance rates were relatively low. Catastrophic health expenditure was a major issue in the country, which led to the introduction of a set of reforms with the objective of providing "social protection in health" to a significant number of people: 50 million uninsured Mexicans (King, *et al*., 2009). One of the most important components of this reform was the implementation of *Seguro Popular* in 2002. This program provides its enrollees with insurance coverage based on a well defined benefits package, which includes coverage for 266 unique health interventions and 312 medicines recommended for treating 95% of the disease burden (Barros, 2008). Within this package, beneficiaries have full coverage for their healthcare; there are no deductibles or co-payments.

Since its design, *Seguro Popular* was planned to have a progressive expansion. The main eligibility criterion for *Seguro Popular* is not being a beneficiary of the Social Security System. Although most families in the informal sector are among the poorest, the program has no explicit targeting system based on poverty at the individual level. However, the program focused its expansion on the poorest regions.

Seguro Popular is administered by states, although it is financed mainly by the Federal government. In 2006, for every family enrolled by the program the federal government transferred to the states approximately $660 per year. States also made a contribution of approximately $130 per family per year (Barros, 2008).

The *Seguro Popular* does not seem to have had a strong effect on health outcomes. Taking advantage of the identification strategy provided by the irregular expansion of the program, Knox (2008) uses a modified difference-in-differences analysis on panel data for 2002, 2003, and 2004. She finds that although small and driven by the effect on a specific group of the population, females aged 31 – 55, there is a slight increase in the number of days that people report as being sick or that they cannot perform their daily activities due to illness. The author argues that this result may be explained by an increased awareness about health that people gain when they increase their use of healthcare services, especially when the analysis uses self-reported measures of health; these results can be driven by individuals' perception of their own health.

Using a triple difference approach,[63] Barros (2008) provides an intention–to–treat estimate of the effect of *Seguro Popular* on a set of outcomes. This approach implies that the control group is defined by people who are *covered* by the Social Health Insurance, instead of people who are *eligible* but chose not to enroll. He provides estimates for two health-related outcomes: the probability of experiencing health problems and reports that the health of a user improved after receiving healthcare, and he finds no significant difference in either outcome. Barros argues that "the program had a negligible effect on

[63] Barros' approach uses a triple-difference analysis taking differences over: 1) the targeted state intensity, a measure of the goal for a state's expansion rate, 2) time, and 3) eligibility to the program.

the health of beneficiaries, perhaps because the quality of care was low" (Barros, 2008, p. 1).

King, *et al*. (2009) studied an outreach program that was implemented using a randomized experiment at the community level: they defined 74 matched–pair clusters. The treatment consisted of encouraging people to enroll a year prior to the planned rollout of *Seguro Popular* in their communities, e.g. informing beneficiaries of *Oportunidades*, a pre-existing conditional cash transfer program, that they were automatically enrolled in *Seguro Popular*. The authors used non–parametric methods to estimate intention–to–treat and complier average causal effects on a set of outcomes, including self–reported health, over a ten-month period. Although they found significant reductions in catastrophic healthcare expenditures and in health expenditure, there was no significant effect on health outcomes (or healthcare utilization).

4.2.5. Summary

As discussed in detail above, empirical studies have not found strong, conclusive evidence about the relationship between health insurance and health; some studies find a positive (but mild) effect, and some studies find no effect at all (Levy and Meltzer, 2001 and 2008; Giedion and Diaz, 2009; and Giedion, Alfonso, and Diaz, 2013). These results suggest that there may not be a strong relationship, but the fact that this is a relationship that is difficult to estimate may also explain this inconclusiveness.

As found in other literature reviews, methodological issues present more challenges for the study of this relationship than for the others studied in Chapters 2 and 3 (Giedion, Alfonso, and Diaz, 2013). First, some studies focused on a health outcome that is not directly related to the intervention or the services that are affected by the coverage expansion. In fact, very few health insurance programs specify goals related to the health of their beneficiaries, and most programs have comprehensive benefits, which makes it more difficult to estimate a causal effect on a single health outcome. Second, some studies conduct evaluations over a relatively short time period that does not allow sufficient time to show some effect of health insurance coverage on health. It seems that health insurance may affect health, but not immediately; it may take many years for someone with health insurance to see their health improved due to this coverage. Third, the data available to study this relationship (using sound methodologies) are relatively scarce, especially in the developing world. Most of these data come from surveys that are cross-sectional; even though these surveys are repeated over time, they do not follow the same individuals. And when longitudinal data are available, they are repeated in rounds that are four or six years apart, which may be too long to study the effects of participating in a program. For example, one individual may not have been enrolled in round 1 of the survey, but then enrolled the following year and disenrolled the year after; the data may omit such information.

In the case of Peru's SIS, although it does not have an explicit goal related to the health of its beneficiaries, the initial priority focused on the enrollment of pregnant women and children, especially young children, and the funds allocated to their care suggest that one goal of the program was to improve the health outcomes for this population (e.g., reduce infant and maternal moralities, reduce malnutrition among children). This priority has implications for the data to be used in this study. Thus, the following section discusses in detail the data used and how to address the second and third issues.

4.3. Data

There are two sources of data for this analysis: i) the *Encuesta Demográfica y de Salud Familiar* (DHS); and ii) the Young Lives Study.

4.3.1. The Demographic and Health Survey

The Demographic and Health Survey (DHS) program has been implementing household surveys throughout the world since 1984. DHS surveys have been collecting information from over 90 countries, and in Peru they are called the *Encuesta Demográfica y de Salud Familiar*. The program is administered by ICF International, and in Peru the survey is collected by the *Instituto Nacional de Estadística e Informática*, the government's statistics agency, which provides official estimates of key socio-economic indicators, such as poverty, maternal and infant mortality, and malnutrition.

The main objective of the DHS is to provide information for a set of indicators relevant to population, health, and nutrition. Although the survey provides information for the entire population in the country, it focuses on and provides more detailed information for women between 15 and 49 years of age and their children born alive in the last 60 months. Topics covered by the DHS include: child health; nutrition and anemia; infant and child mortality; maternal health and mortality; fertility; family planning; HIV prevalence; knowledge, attitudes, and behavior; women's empowerment; gender and domestic violence; education; household composition and basic demographic characteristics of the household members; access to services related to environmental health; and wealth.

In Peru, the DHS is a nationally representative survey, with representative inference at the departmental level.[64] In addition to the domains covered by the standard DHS survey, data on children's and women's insurance status and type are included in Peru's DHS, which allows one to identify SIS enrollment.[65] The first survey was conducted in 1986, and additional surveys were implemented in 1992, 1996, and 2000. Subsequent surveys were collected annually starting in 2004.

The sampling strategy of this survey was changed after the survey that was implemented in 2000. First, although it is not a longitudinal study, starting in 2004 the DHS-Peru has been collected continuously every year; it changed its design from annual to multiannual cross-sections; instead of collecting data for 30,000 households in 2004, the design divided this sample over four years: 2004-2007. This is known as the Interim or Continuous DHS . Datasets are available for every year in the period 2004-2020. The purpose of this change was to be able to have estimates by pooling 3 or 4 years after a few rounds of the survey that could be updated annually.[66] Despite the smaller sample size, each annual cross-section was designed to be nationally representative, although for a smaller set of indicators. Indicators such as infant or maternal mortality and anthropometric data require an aggregation of three to four years of data.

The second change was that in 2008, and later in 2009, the sample size was increased. In 2008, the government made a structural change in the way budgeting is programmed for most agencies, and this change required annual data to follow some key

[64] Peru has 24 departments and an additional province that has administrative autonomy from any department.
[65] The 2000 DHS identifies coverage through the Mother and Child Insurance program, as SIS was not implemented yet.
[66] The plan was to have most indicators annually starting in 2006, the exceptions being indicators that require a big sample (e.g., maternal mortality) and would need the pooled sample of four consecutive surveys.

indicators. Instead of programming the national budget based on a set of activities historically performed, the budget was going to be planned based on a set of national priorities. These priorities were expressed in a group of measurable goals set for every year, reducing malnutrition and maternal and infant mortality among them. Since this budgeting process required continuous, annual data, the sample of the DHS was adjusted to provide this information; the sample was increased in 2008, and the following years, to be able to estimate these indicators at the departmental level.

These two main changes to the sampling strategy had important changes for the sample collected in each survey. Table 0.1 summarizes the changes in sample sizes from 2000 to 2014: i) the reduction of the sample size in 2004, and ii) the increase in sample size in 2008 (and 2009).

These two main changes to the sampling strategy had important changes for the sample collected in each survey. Table 0.1**: DHS Sample Size, 2000 – 2014**

Year	Households	Individuals	Women (15-49)	Children (<5)	Births
2000	33,046	131,062	29,423	13,697	65,453
2004	7,063	27,756	6,251	2,537	13,692
2005	6,148	28,458	6,214	2,631	13,666
2006	7,552	29,879	6,625	2,779	14,258
2007	8,573	29,217	6,399	2,696	14,313
2008	14,469	53,372	11,968	4,835	24,636
2009	27,709	105,225	24,212	10,289	50,084
2010	27,756	101,409	22,947	9,281	46,780
2011	27,709	98,662	22,517	9,146	46,194
2012	28,376	103,211	23,888	9,620	47,261
2013	28,324	99,097	22,920	8,983	44,725

2014	30,361	108,536	24,872	9,610	47,633

Author's analysis of the 2000-2014 DHS-Peru.

Given that I use an Instrumental Variables approach, with the program's enrollment goal as instrument, I am limited to the period of the first administration that ran the program until mid-2006. Thus, I aggregate data from 2004 and 2005 and obtain a universe of 5,168 children born up to 60 months prior to the time their mothers were interviewed for this survey.

As discussed in Chapter 2, SIS intended to provide health insurance to the vulnerable population who could not afford other forms of insurance. This excluded people who were eligible to obtain coverage through the Peruvian Social Health Insurance program: EsSalud. This program covered every employee in the "formal" labor market, and SIS explicitly denied coverage to anyone who was covered by this other program.

I exclude from this analysis children who were eligible for coverage through the Peruvian Social Health Insurance at the time of the survey, as measured by having a household member who was covered by this program. In addition, children included in the dataset who were dead at the time of the interview are also excluded due to lack of information for the main outcomes under analysis. This, leaves a total of 3,940 children under 5 in the sample.

The 2004-2005 DHS has 5 main outcomes to evaluate children's health; whether these children had: i) diarrhea, ii) blood in stools, iii) cough, iv) difficulty breathing, and v) fever in the last 2 weeks.

As mentioned before, the DHS provides information at various levels: household, household members, women aged 15-49, and their children. Using these data, I select 10 variables as covariates for these analyses:

- child's age,
- child's sex,
- mother's education level (i.e., no education, elementary, secondary, some college, or college graduate),
- mother's employment status,
- mother's relationship to the head of the household (i.e., head, head's wife, head's relative, non-relative),
- sex of the head of the household,
- household's wealth level (belonging to one of five quintiles),
- community's altitude (in meters),
- community's natural region (capital city, Coast, Highland, High Rainforest, Low Rainforest), and
- community's urbanicity (large city, small city, or town).

Other variables were included as covariates in previous versions of the analyses but were later discarded due to their lack of contribution in explaining the first or second stage outcomes. Some of these variables were: the source of drinking water in the household, characteristics of the sewage network, a continuous household's wealth index, and a different measure of the community's density.

4.3.2. The Young Lives Study

The Young Lives Study is a longitudinal study focused on the dynamics of childhood poverty. It is being conducted in four developing countries: Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru, and Vietnam. As an international study, this is an initiative that involves a network of organizations, led by the Department of International Development at the University of Oxford. The main partner organization in Peru is the *Grupo de Análisis para el Desarrollo* (GRADE).

This study planned to follow children and their families, with a special focus on the children's caregivers, for about 16 years: from 2002 to 2017. The first round was conducted in 2002 and targeted children who were born either between 2001 and 2002 (6 to 18 months old at the time of the survey) or between 1994 and 1995 (7.5 and 8.5 years of age in 2002). These children were then followed, so that data were gathered again in 2006 and in 2009. However, in 2009 children were not asked about their health insurance status, which means that the 2009 (and 2013 and 2017) data will not be used in my analysis.

In total, the study followed approximately 12,000 children in each of the four countries. The distribution of the sample per cohort was approximately 2:1 favoring the younger children, i.e. the younger cohort has data for approximately 2,000 children aged 1 year in 2002. The younger cohort in Peru started with 2,052 children in 2002, of which 1,963 were re-contacted in the second round (2006). Although this attrition rate is small relative to other longitudinal studies in developing countries, this attrition is not random (Outes-Leon and Dercon, 2008). It has been found that urban, poorer, and less educated households were more likely to attrite. However, there is little evidence of attrition bias when conducting analysis of child anthropometric and school enrollment outcomes, especially when controlling for a set of observable variables (Outes-Leon and Dercon, 2008).

The analysis in this chapter will focus on the younger cohort for two reasons. First, the larger sample provides more power for statistical inference. Second, and more importantly, the effects of having health insurance, and the increased probability in healthcare utilization that comes with it, are generally larger among younger children than among school–aged children. The younger cohort moves from 1 to 5 years of age between Round 1 and Round 2 of the survey, which is a critical age range for children's development, one in which access to healthcare can have a significant effect over many health outcomes, such as malnutrition.

In each round, information was gathered on the child's current and past health, childcare, education and work (if the child was of working age), other daily activities, hopes and aspirations for the future, how they feel they are treated by others, and parental background. In addition, the caregiver was asked for his or her perceptions, attitudes, and aspirations for the child and the family.

Of special interest for this analysis is the information about insurance status and type, and anthropometric measures of the child and his or her caregiver. The anthropometric data allow for the assessment of the child's nutritional status throughout both rounds, as well as control for genetics using the height and weight of the caregiver, who is typically the mother.

It should be noted that the question asking about insurance type changed between the first and second rounds. Specifically, one of the categories in the first round was having an insurance provided by the "Government," which was later changed to having an insurance provided by "*Seguro Integral de Salud*." Despite this slight change, results should be comparable throughout both rounds. It is likely that in 2002, when SIS was implemented as a program that replaced the previous two government insurance programs: *Seguro Escolar Gratuito* and Mother and Child Insurance, it was more convenient to have a vague category as "Government"; even if SIS were already implemented by the time of the interview, people could have not known the new program when asked about it if they were more familiar with the old programs.

In addition to the individual level data, the Young Lives surveys also collect household and community level data. Topics included in the household questionnaires are: demographic composition, assets and financial support, food and non-food consumption and expenditure, socio-economic status, social capital, economic changes, and recent life history. The community data include information about infrastructure and services, health and education facilities, community networks, crime, and environmental changes.

The sampling method used by the Young Lives Study presents a potential limitation for the external validity of this study. First, although the households were randomly selected within each sentinel site, these 20 sentinel sites were not randomly selected. The sample was drawn to oversample poor areas, but also to ensure representation of each country's diversity.

In addition, the sampling strategy in Peru included a country-specific feature: it excluded the districts ranked at the top five percent of the national poverty map developed by the government for the year 2000 (Escobal and Flores, 2008). These issues challenge the data's representativeness of the population in Peru. In fact, the Young Lives Study was not designed to be representative at the national level. However, it has been found that estimates from the Young Lives Study in Peru are similar to those from two nationally representative surveys: the *Encuesta Nacional de Hogares* (ENAHO) and the *Encuesta Demográfica y de Salud Familiar* (DHS). For example, after applying sampling weights, poverty rates were similar for the Young Lives Study and the ENAHO, which is used to measure the official poverty rates in Peru. It is concluded that "while not suited for simple monitoring of child outcome indicators, the Young Lives sample will be an appropriate and valuable instrument for analyzing causal relations and modeling child welfare, and its longitudinal dynamics in Peru" (Escobal and Flores, 2008, p iv).

Finally, since the goal of this study is to explore the effects of gaining SIS coverage, my focus lies on children who were initially uninsured and later gained coverage through SIS. This implies a small sample size because only 586 (30%) of the Young Lives younger cohort are reported as being uninsured in 2002. In particular, of the 1,963 children who were interviewed in Rounds 1 and 2, 1,150 reported in 2002 that they had some form of insurance coverage from the government. One possible explanation is that the study oversampled children in departments where the Mother and Child Insurance program had been previously operating; the interest of the study in exploring the dynamics of poverty led them to focus on the poorest districts of the country which were also targeted by government programs. The main implication from having a high percentage of children enrolled in SIS in Round 1 is that an Average Treatment Effect will not be possible to estimate. Instead, I will focus in estimating the Average Treatment Effect on the Treated as I will try to match those who were uninsured in 2002 and reported having SIS coverage in 2006 with those who reported being uninsured in both rounds.

4.4. Theoretical Model

Some economists argue that a major contribution to the field of health economics is the model of the demand for health by Michael Grossman (1972), the first economic explanation of the characteristics of health and how people make decisions to determine its optimal level (Culyer, 1981; Muurinen, 1982; and Wagstaff, 1986). Grossman presented health as a stock of human capital that depreciates over time but can also be increased. Investments in health can be made through a "household production function" that is determined by the consumption of inputs (e.g., medical care, time inputs, etc.). However, as depicted in traditional economic models, these inputs imply a positive cost to consumers who have limited resources.[67] Thus, consumers find the optimal level of health, along with optimal levels of other desirable goods and services, that maximize their utility given these restrictions and production functions.

Using Grossman's assumption about people's preferences for health, as a desirable good but not necessarily valued above all others, I formulate the average individual's utility function:

[67] In the case of medical services, even when enrolled in SIS there are other costs associated with consuming these services. See the theoretical model in Chapter 2 for a discussion of these costs.

$$U_i = U(H_i, C_i) \tag{4.1}$$

where H_i represents the individual's health status and C_i his or her level of consumption.

Since the individual's preferences are modeled as non–lexicographic, there exists a quasi–concave utility function: *U( )*, which can be maximized by consuming optimal levels of health and other goods.

An individual's health is determined by his or her consumption of health inputs. In his work on child mortality, Schultz (1984) presents an improved model for this health production function. He discusses the idea that there might be some characteristics of the individual, such as biological endowments, that affect simultaneously the demand for health inputs and child health outcomes (see Figure 0.1). Given that these characteristics are unobservable, simple OLS estimation of the health production function using cross-sectional data would yield biased results.

For the purpose of my analysis, I will disaggregate Schultz's demanded inputs into medical care, M_i, other observable health inputs, O_i, such as sanitation, food, etc., biological endowments, B_i, and a random error, e_{1i}:

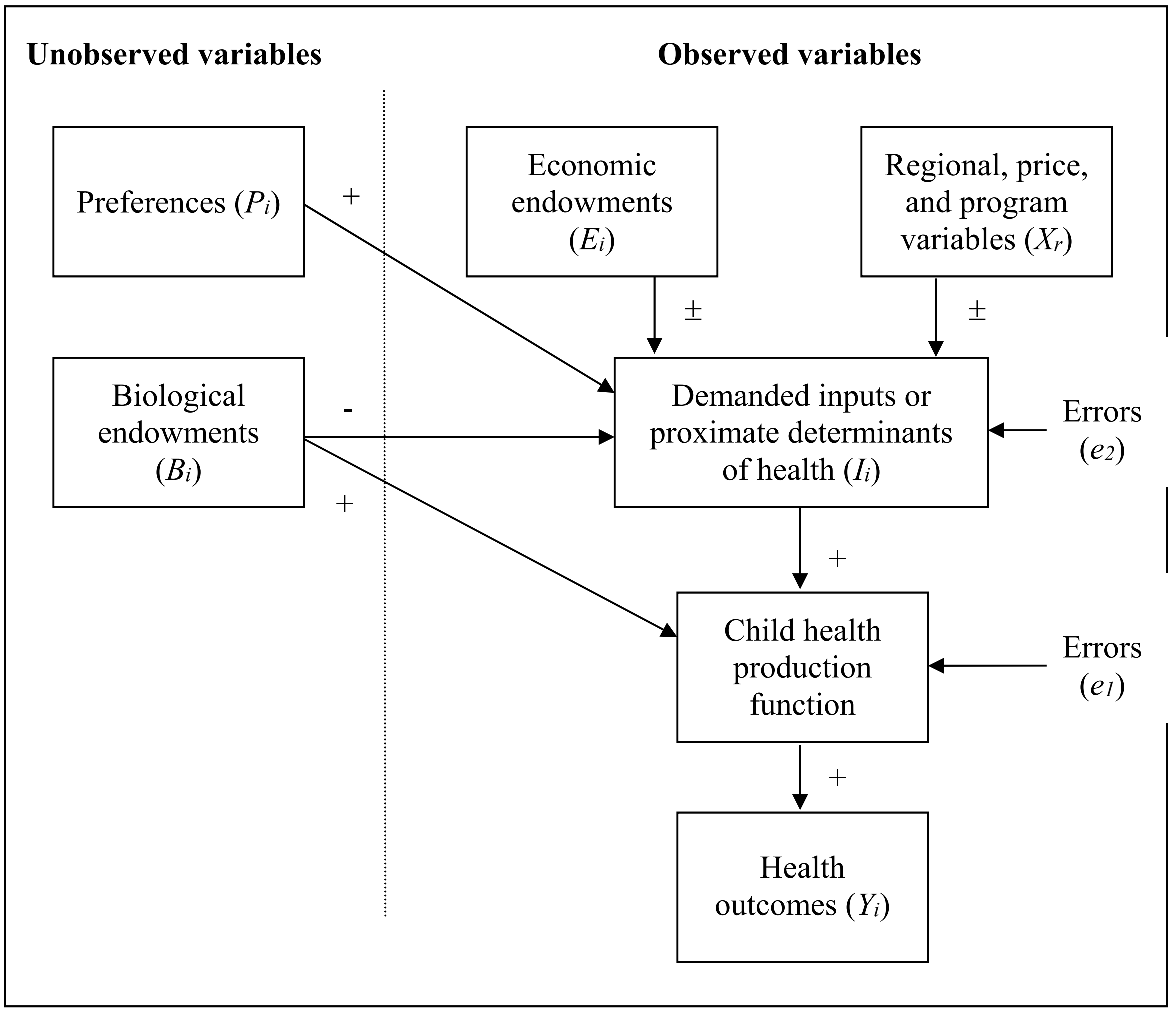
$$H_i = H(M_i, O_i, B_i, e_{1i}) \tag{4.2}$$

I make the assumption that this function is quasi-concave in health inputs: $H'(\,) > 0$ and $H''(\,) < 0$.

Following, Schultz's diagram, aside from the biological endowments, the demand for these health inputs is determined by economic endowments, E_i; regional, price, and program variables, V_i; unobserved preferences, P_i; and other unobserved factors, e_{2Oi}. The following equation represents these relations:

$$O_i = O(E_i, V_i, B_i, P_i, e_{2Oi}) \tag{4.3}$$

Figure 4.1. Schultz's Flow Diagram of Factors Determining Child Health



Source: Schultz (1984).

However, the demand for medical care is also determined by the insurance status of the individual; as observed in Chapter 2, health insurance through SIS increases the demand for medical inputs in Peru:

$$M_i = M(S_i, E_i, V_i, B_i, P_i, e_{2Mi}) \tag{4.4}$$

Using these expressions, the reduced form that corresponds to the health production function can be expressed as:

$$H_i = H(S_i, E_i, V_i, B_i, P_i, e_{2Mi}, e_{2Oi}, e_{1i}) \tag{4.5}$$

Equation 4.5 represents the main relationship to be estimated in this chapter as it depicts the way health insurance enrollment (through SIS) affects health outcomes. As pointed out by Schultz, one needs to be careful when estimating these functions as using ordinary least squares on (4.5) would produce biased estimates due to unobserved determinants (and endogenity): enrollment in SIS is correlated with the health outcomes via the biological endowments, preferences, and other unobserved factors that affect enrollment. Clearly, estimation methods need to address this fundamental issue to estimate the relationship between health insurance (through SIS) and health. The following section discusses these issues in detail.

4.5. Methods

The choice of the econometric methods to estimate equation 4.5 depends on the data source that is used. Thus, for the synthetic panel created using the DHS-Peru 2004-2013, I propose to combine instrumental variables with a first differenced estimation method. For the Young Lives data, I combine propensity score matching with difference-in-differences estimation that compares children who gained insurance through SIS between Rounds 1 and 2 with children who remained uninsured in both rounds.

4.5.1. Instrumental Variables

As in Chapters 2 and 3, I first use an Instrumental Variables approach to address the potential simultaneity existing in the relationship between health and health insurance coverage. To isolate the effect of having health insurance, in particular SIS, on children's health I use the program's enrollment goals as the instrument. I argue that these goals, which are defined by SIS officials, affect the likelihood of people being enrolled in the program, but do not affect children's health directly after controlling for some other children's characteristics and those of their family and household.

4.5.2. Difference-in-differences Matching Estimator

By pairing each individual treated with someone from the non–treated group in the sample, matching methods attempt to create a control group, a group that is equivalent to the treated group in all factors except that of having received the treatment. When used correctly, and when the method's assumptions are satisfied, the control group can be a correct approximation to the counterfactual of the treatment group.

The propensity score is based on the premise that the treatment is not randomly assigned, but rather depends stochastically on a set of observable variables, X_i. This method can be used when treatment is targeted to some population defined by some observable characteristics, which exemplifies the case of SIS using an algorithm that is calculated from a set of observable characteristics of the individual's household, which then determines program eligibility.

The fundamental assumption for any matching method is conditional independence between the dependent variable (health) and program participation (enrollment in SIS): $\left(H_i^T, H_i^C\right) \perp SIS_i \mid X_i$, where H_i^T and H_i^C represent individual i's health when being treated and when not being treated, and SIS_i denotes enrollment. Using the propensity score theorem formulated by Rosenbaum and Rubin (1983), this assumption implies that $\left(H_i^T, H_i^C\right) \perp SIS_i \mid p(X_i)$, where $p(X_i) = P(SIS_i = 1 \mid X_i)$ is the propensity score. In other words, if the conditional independence assumption is valid for X_i, then it is also valid for $p(X_i)$.

One additional assumption that is required by this matching method is that the propensity score falls between 0 and 1 (i.e. $0 < p(X_i) < 1$), which is known as the common support assumption.

The main advantage of using this method is that it simplifies matching since the high dimensionality of the problem makes matching a very difficult process, especially when X_i is a large set of variables. Thus, matching on a scalar, the propensity score, instead of a set of variables reduces the problem to a single dimension and simplifies the matching procedure significantly. This advantage applies only when the propensity score is estimated parametrically, which introduces parametric assumptions about $p(X_i)$. However, one can be very flexible in this parametric specification of the matching model. In addition, using a probit (or logit) model helps satisfy the assumption about the boundaries of the propensity score.

One potential limitation of matching methods is the possibility of not finding a non–treated observation that matches some of the treated observations. This presents a problem, especially when the effect of program participation is heterogeneous.[68] This highly depends on how rich the data are, and the matching method must be adjusted to the specific context of the data and the program under evaluation. Using the propensity score, I will create a control group based on different matching methods: i) nearest neighbor with replacement, ii) nearest 3 neighbors with replacement, iii) kernel matching, and iv) kernel matching where weights depend on the distance between the treated and the control being matched. As detailed in the following section, relatively few observations are lost even when reducing the bandwidth (or caliper) to the lowest level considered (1%), regardless of the matching method used.

Matching will be based on a set of observable variables from the children in the sample that were obtained in the first round of the study (i.e., in 2002). These variables include characteristics of the children, their prenatal experiences (obtained by their mothers' recall), and characteristics of their caregivers and households. In addition, some health outcomes in 2002 will be incorporated as matching variables to produce a control group with similar health, in an attempt to reduce the possibility that the conditional independence assumption is not satisfied. In either case, this procedure implies that both groups: treatment and control, will be matched pre–treatment.

The main limitation of using this approach is that there might be some factors determining participation that are not observable, which implies that the conditional independence assumption is incorrect. However, the problem of selection on

[68] If this effect is assumed to be homogeneous, these unmatched observations could be ignored and estimates would still be unbiased. However, if effects are heterogeneous, strict consistency is achieved only for the population in the common support, the matched sample, and it could be threatened when there is a considerable loss of observations.

unobservables can be reduced by combining this method with difference-in-differences estimation. Using this approach allows one to ignore time-invariant unobservable characteristics that determine participation. Heckman, Ichimura, and Todd (1997 and 1998) and Blundell and Costa-Dias (2000) suggest that when combined with difference-in-differences, the conditional independence assumption for matching can be stated in terms of the pre–post evolution instead of levels of the outcome. In our case, this means that this assumption can be re-expressed as: $H_{i1}^{C} - H_{i0}^{C} \perp SIS_i \mid p(X_i)$, where H_{i0}^{C} and H_{i1}^{C} represent pre- and post-SIS health for individual *i*. "It means that controls have evolved from a pre- to a post-programme period in the same way treatments would have done had they not been treated. This happens both on the observable component of the model and on the unobservable time trend" (Blundell and Costa–Dias, 2009, p. 451).

Furthermore, since I am mostly interested in estimating the average treatment effect on the treated (ATT), where the focus is on those that have been treated and H^T is known, the condition can be weakened to: $\Delta H_i^C \perp SIS_i \mid X_i$. Again, just as in the case of cross–sectional matching, the theorem formulated by Rosenbaum and Rubin (1983) can be applied to reformulate this assumption into $\Delta H_i^C \perp SIS_i \mid p(X_i)$. For the ATT estimation, the support assumption also weakens to $p(X_i) < 1$.

Following the general recommendation of Blundell and Costa-Dias (2009), the estimator for the effect of SIS enrollment on health for those enrolled, when using propensity score matching with longitudinal data, is:

$$\hat{\delta} = \sum_{i \in T} \left[\left(H_{i1} - H_{i0} \right) - \sum_{i \in C} W_{ij} \left(H_{j1} - H_{j0} \right) \right] w_i \qquad (4.6)$$

where $\hat{\delta}$ is the average treatment effect on the treated, W_{ij} is the kernel-weight placed on comparison observation j for individual i, and w_{ij} represents the reweighting that reconstructs the outcome distribution for the treated sample.

4.5.3. Creating the Treatment and Control Groups, Young Lives Study

Even though the first round of the Young Lives Study was implemented in 2002, the same year SIS operations began, 59% of the sample reported being covered by SIS that year. It is possible that a group of children in the study were previously enrolled in the Mother and Child Health Insurance program and their coverage rolled over to SIS, which would justify such a high enrollment rate. In addition, SIS had a major expansion in its first year of operations for young children, which could have increased coverage in the regions were the study focused (see Figure 1.1 in Chapter 1).

In contrast, only 30% of the first round sample reported being uninsured. Given that my main interest is evaluating the effect of gaining SIS coverage on children's nutritional status, I focus on the group of children who gained SIS coverage; those who were uninsured in 2002 and reported being enrolled in SIS in 2006. In total, the Young Lives Study in Peru has information on 172 children who gained SIS coverage, which is the treatment group for this analyses.

A pool of 358 children compose the universe for the control group: children who were uninsured at both time periods, 2002 and 2006. I use Propensity Score Matching to further define the control group by pairing children who gained SIS coverage with those who were uninsured in both time periods using a set of observable characteristics. I perform this matching using 27 variables with information from 2002. The variables I use for matching include characteristics of the child: sex, race and ethnicity, and breastfeeding practices; characteristics of the pregnancy: overall assessment, the month of the first antenatal care visit, place of birth, weight at birth, and number of weeks at birth; a set of the caregiver's characteristics: relationship to the child, weight and height, literacy and education, birth history, race and ethnicity, and marital status; and characteristics of the household: urbanicity, ownership of the house, and water supply and sewage.

Due to the small sample size, I conduct a more robust sensitivity analysis by trying 12 different matching specifications: four propensity score functions and three different bandwidths (or calipers). The four propensity score functions I use to assess the sensitivity of the results to these matching choices are: nearest neighbor, nearest 3 neighbors, kernel-Epanechnikov, and kernel quartic (biweight). I also use 5%, 2.5%, and 1% as bandwidths (or calipers for the kernel functions). In addition, I also estimate the effect of SIS on children's malnutrition without matching at the baseline.

However, the main results I present were obtained using a kernel quartic function and a 1% bandwidth in the matching process. Using this bandwidth, I lose only 11 observations from the treatment group because they lie outside of the common support region. The wider bandwidths of 5% or 2.5% would both result in 7 cases without a match, respectively. An additional 4 cases lost in comparison to the wider bandwidth is an acceptable loss for the gains of having a closer match, especially since 11 observations represent only 6.4% of the treatment group.

In terms of matching functions, the kernel functions seem to perform better; the matching resulting from using these functions yield fewer significant differences between groups post-matching (see Table C.5 in Appendix C). Using these functions and a caliper of 1%, only one variable has a post-matching difference in means between groups with a probability of accepting the null hypothesis below 10%.[69] In contrast, when using nearest neighbor functions a higher number of variables still have different means at the different levels of bandwidths.

Thus, I report the results of using the kernel quartic with a 1% bandwidth for the pre-treatment matching, using data from 2002 when the children in the sample were only 1 year of age. After matching both groups' observations based on children's characteristics in 2002, I study the effect of gaining SIS coverage in 2006 on their nutritional status measured by three outcomes: height-for-age, BMI-for-age, and weight-for-age z-scores.

Using the Young Lives Study, I focus on equation 4.15:

$$(Y_{i1} - Y_{i0}) = \alpha + \delta(S_{i1} - S_{i0}) + \varepsilon_i \tag{4.7}$$

Under the assumptions made above, estimation of equation 4.7 provides consistent estimates of the impact of SIS enrollment on *Y*.

This relationship could vary by the age of the child. For example, the weight-for-age z-scores could differ at 5 months of age and at 14 months for the same child, everything else constant. Thus, I also estimate equation 4.16 to capture this heterogeneity in the impact of SIS enrollment on *Y*.

[69] The hypothesis formulated by this test is that the means of the treatment and control groups are equal after matching.

$$\left(Y_{i1} - Y_{i0}\right) = \alpha + \beta\left(S_{i1} - S_{i0}\right) + \varphi\left(S_{i1} - S_{i0}\right)Age_{i0} + \gamma Age_{i0} + \varepsilon_i \qquad (4.8)$$

When presenting the estimates related to equation 4.8, I will not report estimates of the coefficients (e.g., β), but I rather focus on the marginal effect of SIS enrollment on malnutrition: $\delta_i = \partial(Y_{i1} - Y_{i0}) / \partial(S_{i1} - S_{i0})$.

4.5.4. Children's Health Outcomes

Using the SIS annual enrollment goals for each geographic jurisdiction as an instrument, I estimate the effect of having SIS coverage on five health events and symptoms that are highly prevalent among children in Peru: having had diarrhea, bloody stools, fever, cough, or difficulty/rapid breathing in the last two weeks.

Diarrhea and bloody stools are very common among children and are a leading cause for children's underdevelopment in Peru. Among the population of children in the DHS sample, 15.3% reported having had diarrhea in the last two weeks, and 1.5% reported blood being present in their stools. When this is a frequent event, children cannot retain the nutrients needed for their growth and, even when they have regular access to food and a sufficient, balanced diet, this could lead to delayed growth and stunting. An immediate risk of diarrheas is dehydration, which can be easily treated with liquids, especially an oral rehydration solution (ORS) which is a prepackaged sachet of glucose and electrolytes available in all healthcare facilities.[70]

[70] This rehydration solution can also be made at home diluting six teaspoons of sugar and 0.5 teaspoons of salt in one liter of water.

Fevers are a common symptom indicating a general problem in a person's health, usually the presence of a virus or bacterial infection. Among children, fevers that last over 1-3 days require a healthcare professional evaluation as prolonged fevers are associated with febrile seizures.[71] This symptom was present in almost one out of four children in the population under analysis.

Coughing among children, and especially having difficulty breathing, are symptoms of acute respiratory infections. In fact, rapid breathing can be an indication of pneumonia. Some complications from this are organ failure caused by bacteria in the bloodstream that transmits the infection, lack of oxygen due to the difficulty breathing, fluid accumulation around the lungs, and lung abscesses. In Peru, these symptoms are fairly common, as 37.9% of children in this analyses had a cough in the last two weeks, and 17.7% had short, rapid breaths.

In addition to these five health outcomes, I use three different indicators of children's nutritional status, all measured by z-scores: height-for-age, BMI-for-age (as a substitute for weight-for-height), and weight-for-age. Using the first and second rounds of the Young Lives Study, I focus on children, 6-18 months of age in 2002, who were uninsured in 2002 and compare their z-scores and their different measures of nutritional status[72] at both time periods.

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[71] General recommendations suggest that newborns with a temperature over 30 C (or 100.4 F) should seek care as soon as detected, whereas children over 2 years of age should only seek care when the fever lasts over 3 days.

[72] Consistently with the standard definition, I define stunting, wasting, and underweight as having a height-for-age, BMI-for-age, and weight-for-age z-score, respectively, below –2.

Height-for-age is a long-term measure of malnutrition; it is a measure of cumulative health that is not sensitive to short-term changes in children's nutritional status. When in deficit, this measure indicates chronic or frequent illness (or chronic inadequate nutrition). Cases were the height-for-age z-score of a child is extremely low, below –2, are usually considered to represent pathological shortness. In fact, these cases are commonly interpreted as moderate or severe stunting.

The common measure for current nutritional status is the weight-for-height z-score. However, the Young Lives Study for Peru had a portion of missing data for this variable in round 2. Instead, I use as substitute information on the children's Body Mass Index (BMI) relative to the child's age, another indicator that measures weight relative to height. However, the BMI information cannot be used directly and had to be standardized for children based on their age and sex, as the BMI is very sensitive to age among children. The advantage is that the BMI-for-age z-score is also sensitive to short-term changes in a child's nutritional status. In addition, the BMI z-score can also be used to produce estimates of wasting, a BMI-for-age z-score below –2, and obesity, a BMI-for-age z-score over 2.

The weight-for-age z-score is a relative measure of body mass and age. This z-score can be considered to be a composite measure of height-for-age and weight-for-height (O'Donnell, 2008, p. 40). Thus, it is not straightforward to interpret results related to this measure, as it combines cumulative and current growth and health deficits. Despite this problem, this measure is commonly used for monitoring growth and to assess changes in the magnitude of malnutrition over time.

4.6. Results

In this section, I present estimates of the reduced form of the determinants of health (equation 4.5). More specifically, I estimate the impact of SIS coverage on two categories of children's health outcomes: i) children's health events and health symptoms (i.e., having had diarrhea, bloody stools, fever, cough, or difficulty breathing in the last two weeks), and ii) children's malnutrition (i.e., children stunted, wasted, overweight, and underweight). The choice of these health outcomes is based on data availability and their relevance as these health outcomes affect and are important indicators of children's physical development.

I use the Peru DHS to analyze the effect of SIS on children's health events and symptoms, while the analysis of the Young Lives data is limited to the effect of SIS on children malnutrition.

4.6.1. Health Events and Symptoms

Using an Instrumental Variables approach, I estimate that SIS has no significant effect on these five health events and symptoms. Table 4.2 shows the estimated effect of being enrolled in SIS over this set of health outcomes (see Table C.2 in Appendix C for full results of the regressions).

Although four estimates have a positive sign, suggesting that SIS enrollment would increase the likelihood of children under five years of age reporting these symptoms in the last two weeks, none of these is statistically different from zero. The estimate for having blood in their stools is negative, although it is also not statistically significant. These results suggest that SIS does not affect short-term health among its enrollees under five years of age.

Table 4.2: Instrumental Variables Estimated Effect of SIS on Children's Health Events and Symptoms, 2004-2005

Outcome	Estimated effect	Standard Error	q-value|
Diarrhea	0.0259	0.2217	1.000
Bloody stools	-0.0661	0.1050	1.000
Fever	0.3099	0.3451	1.000
Cough	0.0111	0.3358	1.000
Short, rapid breaths	0.2299	0.2464	1.000

Notes: Statistical significance indicates the probability that the coefficient is zero, which were estimated using the False Discovery Rate (FDR) control.
Robust standard errors estimated clustered at sampling cluster.
The overall sample size is 3,940 children under 5 years of age.
Author's analysis of the 2004-2005 DHS-Peru.

All first-stage regressions of these estimates pass the tests for underidentification and weak identification (see Table C.1 in Appendix C).

In addition, I estimated the effects of SIS on these health outcomes for children under two years of age, which is a sub-group with higher prevalence of these health outcomes.[73] Although these estimates show lower q-values, they are still not statistically significant (see Table C.4 in Appendix C). These estimates are reported in the Appendix

[73] Using the DHS, 2005, I estimate that 15.3% of all children under five reported having diarrhea in the past two weeks, whereas 21.8% of children under two years of age report the problem.

because the tests for excluded instruments and underidentification cannot rule out weakness of the instrument for this smaller sample (see Table C.3 in Appendix C).

4.6.2. Nutritional Status

The estimated marginal effects of gaining SIS coverage on these malnutrition indicators, δ in equations 4.7 and 4.8, are presented Table 4.3. Most estimates are not statistically different from zero, indicating that enrolling in SIS would not improve their nutritional status.

According to the p-values, the only significant relationship is between SIS coverage and children's underweight (i.e., BMI-for-age z-score below -2) (see Table C.12 in Appendix C). However, after adjusting these p-values to account for Multiple-Hypothesis Testing, I find that SIS does not have a significant effect on any of these malnutrition outcomes (see Table 4.3).

Given the small sample size for this analysis resulting from the high enrollment rate of children in SIS at the baseline of the Young Lives Study, I conduct a sensitivity analysis consisting of using 4 different propensity score functions and 3 different bandwidths in the matching process (see Tables C.6-12 in Appendix C). Estimates of not matching the two groups at the baseline are also shown as a reference in all tables. This means that I produce a total of 13 estimates for each health outcome; the one presented on Table 4.3 and 12 estimates to test how sensitive this estimate is to the selection of the matching function and bandwidth.

Despite very few differences in the estimates' sign, the different combinations of matching functions and bandwidths produce similar estimates. In general, there are fewer differences when estimating the effect on relative malnutrition outcomes (i.e., stunting, wasting, obesity, and underweight), than when estimating the effect on the continuous z-scores. However, all estimates are not statistically significant (q<0.1).

Table 4.3: Difference-in-differences Matching Estimator for the Effect of SIS on Children's Malnutrition, 2002-2006

Outcome	**Estimated effect**	**Standard Error**	**q-value**
Height-for-age Z-score			
Base specification	0.0276	0.146	1.000
Age interaction	0.0542	0.122	1.000
Stunting (height-for-age z-score < -2)			
Base specification	0.0454	0.0634	1.000
Age interaction	0.0410	0.0621	1.000
BMI-for-age Z-score			
Base specification	0.0254	0.1330	1.000
Age interaction	0.0223	0.1310	1.000
Wasting (BMI-for-age z-score < -2)			
Base specification	-0.0096	0.0210	1.000
Age interaction	-0.0083	0.0210	1.000
Obesity (BMI-for-age z-score > 2)			
Base specification	-0.0038	0.0455	1.000
Age interaction	-0.0034	0.0455	1.000
Weight-for-age Z-score			
Base specification	-0.0270	0.0913	1.000
Age interaction	-0.0036	0.0889	1.000
Underweight (weight-for-age z-score < -2			

Base specification	-0.0587	0.0258	0.396
Age interaction	-0.0599	0.0271	0.396

Notes: Statistical significance indicates the probability that the coefficient is zero, which were estimated using the False Discovery Rate (FDR) control.

Robust standard errors estimated clustered at sampling site level.

Author's analysis of the Young Lives Study, Peru, rounds 1 and 2 (2002 and 2006).

4.7. Discussion

I do not find strong evidence of a positive effect of being enrolled in SIS on children's health. This is consistent with other studies of the relationship between health insurance coverage and health. My study suffers from two data limitations in estimating the effect of SIS on children's health: one set of indicators is a group of health symptoms assessed by the survey's respondents for a very short referral period (last two weeks), and the small sample size of one data source weakens the statistical power to evaluate small effects on the outcomes.

When assessing whether enrollment in SIS has an effect on having had diarrhea, bloody stools, fever, cough, or difficulty breathing among children under 5 years of age, I find no statistically significant effects. The period for which these symptoms are reported is only the two weeks prior to the survey interview and this small window is likely a very noisy measure of current health for children. However, these results cannot rule out the possibility that SIS coverage could improve children's health if we measured it in a longer period of time.

Thus, I also focus on children's nutritional status using their anthropometric outcomes. Even though a child's nutritional status depends on factors that fall outside of health interventions (e.g., food security), in developing countries these indicators also reflect the health history of a child. For example, frequent episodes of uncontrolled diarrhea in an infant could lead to growth delays and stunting.

However, I do not find significant results of the effect of SIS coverage on children's malnutrition indicators. The significant results for underweight reported in Table C.10 in Appendix C are likely to be false rejections of the null hypothesis; when adjusting for Multiple-Hypothesis Testing, these estimates fall outside of the statistical significance range ($q>0.1$).

These results are limited by small sample sizes and imperfect, self-reported measures of children's health outcomes. The DHS-Peru collects additional data on children's health (e.g., hemoglobin levels and anthropometric outcomes). Unfortunately, this only covers a portion of the 2005 sample that is not considered to be representative for reporting on these outcomes.

Improving children's health involves a deep change in people's behavior, which is only achieved after accessing to abundant information about adequate health practices enforced by parents for a prolonged time. In addition, timely access to needed healthcare, even for minor illnesses and symptoms such as diarrhea and fever, can help prevent further complications, malnutrition (e.g., stunting), and the development of chronic health conditions. If SIS can facilitate continued access to these services, it has of producing an improvement on children's health outcomes. This chapter does not find evidence of this result yet.

Chapter 5

Conclusion

The *Seguro Integral de Salud* (SIS) is a publicly-operated health insurance program in Peru that was created in 2002 to complement the subsidies already existing through the nationwide network of public healthcare providers. Since 2002, SIS has had four main objectives: i) increasing access to healthcare; ii) targeting healthcare toward the poor and vulnerable; iii) improving the allocation of public resources; and iv) increasing healthcare capital and investment in public facilities. This dissertation focuses on assessing SIS' success in achieving its first two objectives. In addition, I estimate the effect of SIS on individuals' out-of-pocket expenditures in healthcare and their probability of incurring catastrophic healthcare expenditures. Lastly, I focus on the effect that SIS had in the health of children under five years of age.

Results from this dissertation make important contributions to the study of the effect of health insurance on health and healthcare utilization and expenditures. First, this is the first rigorous study of SIS, a program that in 2019 provided health insurance for 48% of the population in Peru. All previous analyses are descriptive or focus on statistical associations between SIS enrollment and healthcare outcomes. Second, I use a unique feature of the early stages of the program to define the identification strategy of my analyses. Instrumental Variables is not an approach widely used in the study of the effects of health insurance. I argue that SIS' enrolment goals for each geographic jurisdiction are a valid instrument in this case; SIS' enrollment goals affect individuals' probability of enrolling in the program but do not affect directly their health outcomes or consumption of healthcare. Third, due to the richness of data available about access to healthcare by type of service in Peru, I estimate the effect of SIS on a large number of types of services for each relationship I study. However, the analysis of this number of outcomes has a high chance of finding false rejections to the null hypothesis of the estimate being statistically equal to zero. Thus, I incorporate the estimation of "sharpened" q-values for each estimate to control for Multiple-Hypothesis Testing in my analyses.

In Chapter 2, I assess SIS' success in achieving its first two objectives: increasing healthcare access, and having a bigger impact on the poor and vulnerable. Although consistent with other studies that find a positive effect of SIS on healthcare utilization, this Chapter helps identify the type of services in which SIS has a positive effect: preventive services such as regular annual checkups, immunizations, and children wellness checkups. Interestingly, I also find that SIS decreases the probability of its enrollees of purchasing corrective lenses, which is explained by providers' practices of rejecting these medical equipment to SIS enrollees. As SIS could not timely reimburse these providers for their services, the latter refrained from providing their services.

In addition, I find that SIS' effect on healthcare utilization is greater for non-poor enrollees, even for types of services where SIS does not have an effect on the whole population. Thus, by increasing healthcare utilization more among the non-poor, SIS is widening the gap in access to healthcare by poverty status. This finding highlights the importance of complementing the implementation of any health insurance program with a strategy that expands the healthcare supply. If the poor face geographical barriers to obtain healthcare (e.g., some may reside in an area where the nearest healthcare facility is many hours away), then having health insurance will have a limited effect on their access to healthcare.

In Chapter 3, I estimate the effect of SIS on individuals' out-of-pocket expenditures and households' probability of incurring a catastrophic healthcare expenditure. I find that SIS decreases out-of-pocket expenditures in dental care visits, purchasing corrective lenses, immunizations, and children's wellness checkups. Due to their potential cost savings effects, health insurance programs prioritize preventive care. This is the case of SIS, as enrolling in SIS leads to an increase in utilization of these services and it also leads to decreased out-of-pocket expenditures.

Chapter 3 also provides evidence of the extent in which implementation problems that SIS experienced affect SIS' effects on their enrollees' healthcare expenditures. As mentioned before, SIS persistent debts with healthcare providers forced them to reject covered services for its enrollees, or even illegally charge for these services. These practices have meant that SIS enrollees have increased their out-of-pocket expenditures in adjunct services due to the program. For example, provider could have charged patients for an MRI needed before a surgery, when this was covered by SIS. Individuals enrolled in SIS are willing to make out-of-pocket payments for this type of services in order to avoid forgoing their overall care or treatment.

SIS was created as a fund to cover the most common treatments for its population, but it did not cover high-cost treatments such as dialysis. Another fund was created for this purpose, the FISSAL. Consistently, I find in Chapter 3 that SIS has no effect on individuals' probability of incurring a catastrophic healthcare expenditure.

Chapter 4 provides evidence that, even though SIS increases healthcare utilization and it decreases out-of-pocket expenditures for some types of care, especially preventive care, it does not affect children's health. Although I face some data limitations, this finding is consistent throughout different health outcomes and estimation methods.

In sum, my dissertation provides evidence that: i) SIS was successful in increasing access to healthcare, especially for preventive services; ii) non-poor enrollees have gained more from this effect; iii) SIS has reduced individuals' out-of-pocket expenditures in some types of healthcare, while increasing expenditures of adjunct services; iv) SIS has not affected their enrollees' probability of incurring catastrophic healthcare expenditures; and v) SIS has not changed the health outcomes of their children enrollees.

Chapter 6

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Appendix A

Estimates of the Effect of SIS on Healthcare Utilization

Table A.1: Instrumental Variables Estimates of Enrollment in SIS, 2005, First Stage (Table 2.2)

	Overall population	Children (<5)	15-50 Population	Pregnant Women
Enrollment goals	0.1757***	0.6980***	0.0191	0.0557
	(0.0409)	(0.1271)	(0.0217)	(0.0689)
Age	-0.0072***	-0.0407***	-0.0042***	-0.0034***
	(0.0003)	(0.0040)	(0.0002)	(0.0010)
Sex (male)	0.0103***	0.0317**	0.0180***	
	(0.0034)	(0.0134)	(0.0036)	
Preschool (no school)	-0.0380***	-0.0304	-0.0173*	-0.0090
	(0.0127)	(0.0411)	(0.0103)	(0.0278)
Primary (no school)	-0.0694***	-0.0246	-0.0301**	0.0092
	(0.0143)	(0.0465)	(0.0120)	(0.0327)
Secondary (no school)	-0.1543***	-0.0524	-0.0767***	0.0003
	(0.0149)	(0.0467)	(0.0117)	(0.0354)
Post-secondary (no school)	-0.1563***	-0.1590***	-0.0702***	-0.0421
	(0.0158)	(0.0567)	(0.0120)	(0.0376)
Reads & writes	0.0247**	0.0668**	0.0185**	-0.0138
	(0.0111)	(0.0326)	(0.0083)	(0.0220)
Speaks indigenous language	-0.0510***	0.0183	-0.0135***	0.0074
	(0.0079)	(0.0322)	(0.0046)	(0.0157)
Household members	-0.0023*	-0.0092**	0.0012	-0.0042*
	(0.0013)	(0.0039)	(0.0009)	(0.0025)
Sex of HH head (male)	-0.0173***	0.0043	-0.0053	-0.0064
	(0.0057)	(0.0226)	(0.0043)	(0.0202)
Poor (non-poor)	0.0202***	0.1073***	0.0056	-0.0125
	(0.0061)	(0.0257)	(0.0038)	(0.0244)
Extremely poor (non-poor)	0.0293***	0.0804***	-0.0009	0.0099
	(0.0090)	(0.0287)	(0.0062)	(0.0258)
Urbanicity (urban)	0.0642***	0.1588***	0.0129**	0.0158
	(0.0093)	(0.0260)	(0.0050)	(0.0134)
Central Coast (Northern Coast)	-0.0025	0.0095	-0.0140**	-0.0436**
	(0.0162)	(0.0604)	(0.0063)	(0.0195)
Southern Coast (Northern Coast)	0.0126	0.1489***	0.0057	-0.0469**
	(0.0141)	(0.0509)	(0.0097)	(0.0206)
Northern Highlands (Northern Coast)	-0.0785***	-0.0928**	-0.0216**	0.0266
	(0.0154)	(0.0468)	(0.0099)	(0.0289)
Central Highlands (Northern Coast)	-0.0032	-0.0306	-0.0070	-0.0083
	(0.0144)	(0.0415)	(0.0072)	(0.0227)
Southern Highlands (Northern Coast)	0.0263*	0.0328	0.0079	-0.0254
	(0.0158)	(0.0451)	(0.0076)	(0.0201)
Rainforest (Northern Coast)	-0.0017	-0.0059	-0.0041	-0.0233
	(0.0151)	(0.0415)	(0.0077)	(0.0187)
Metropolitan Lima (Northern Coast)	0.0075	-0.0544	-0.0029	0.0284
	(0.0142)	(0.0487)	(0.0074)	(0.0296)

Constant	0.3665***	0.2682***	0.1822***	0.1883***
	(0.0259)	(0.0748)	(0.0160)	(0.0449)
Observations	64,118	7,660	31,157	3,594
F test for excluded instruments				
F test	18.44	30.16	0.77	0.65
P-value	0.0000	0.0000	0.3804	0.4189
Sanderson-Windmeijer multivariate Chi-squared test of underidentification:				
SW Chi-square test	18.46	30.28	0.77	0.66
P-value	0.0000	0.0000	0.3797	0.417

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.2: Instrumental Variables Estimates of Healthcare Utilization, Services Used in the Last Four Weeks, 2005, Second Stage (Table 2.2)

	Doctor's visit	Medication	Laboratory	X rays	Other exams
Enrollment in SIS	-0.0167	-0.110	-0.0212	-0.0714	0.0121
	(0.211)	(0.285)	(0.0564)	(0.0435)	(0.0154)
Age	0.000227	0.000774	0.000477	-0.000200	0.000130
	(0.00153)	(0.00205)	(0.000411)	(0.000314)	(0.000112)
Sex (male)	0.0304***	0.0550***	0.00483**	0.00612***	0.000985**
	(0.00481)	(0.00611)	(0.00191)	(0.00141)	(0.000484)
Preschool (no school)	0.0311**	0.0248	0.00989*	0.00167	-0.000555
	(0.0125)	(0.0163)	(0.00505)	(0.00375)	(0.00105)
Primary (no school)	0.0261	0.0108	0.00853	-0.00350	0.000270
	(0.0188)	(0.0245)	(0.00660)	(0.00500)	(0.00157)
Secondary (no school)	-0.00708	-0.0290	-0.00300	-0.0103	0.00119
	(0.0358)	(0.0465)	(0.0108)	(0.00820)	(0.00265)
Post-secondary (no school)	0.0132	-0.0249	0.00695	-0.00469	0.00398
	(0.0376)	(0.0484)	(0.0110)	(0.00824)	(0.00299)
Reads & writes	-0.0117	-0.00871	0.00236	0.00405	0.000608
	(0.0107)	(0.0137)	(0.00440)	(0.00331)	(0.000868)
Speaks indigenous language	-0.0201	-0.0398**	-0.00367	-0.00303	-0.000635
	(0.0124)	(0.0160)	(0.00399)	(0.00299)	(0.000861)
Household members	-0.000621	-0.000811	0.00116**	0.000605**	3.00e-05
	(0.00132)	(0.00174)	(0.000517)	(0.000287)	(8.83e-05)
Sex of HH head (male)	0.00506	0.00284	-0.00228	-0.00301	0.000327
	(0.00789)	(0.00965)	(0.00308)	(0.00204)	(0.000664)
Poor (non-poor)	-0.0649***	-0.065***	-0.025***	-0.0124***	-0.00179**
	(0.00782)	(0.0107)	(0.00280)	(0.00198)	(0.000753)
Extremely poor (non-poor)	-0.121***	-0.151***	-0.031***	-0.0146***	-0.0020***
	(0.0104)	(0.0145)	(0.00320)	(0.00219)	(0.000740)
Urbanicity (urban)	-0.0311**	-0.064***	-0.00375	0.00142	-0.000933
	(0.0154)	(0.0206)	(0.00400)	(0.00310)	(0.00117)
Central Coast (Northern Coast)	-0.0334**	-0.083***	-0.012***	-0.0079***	-0.00200
	(0.0170)	(0.0213)	(0.00437)	(0.00269)	(0.00144)
Southern Coast (NC)	0.00660	-0.064***	-0.00416	-0.00153	-0.00126
	(0.0212)	(0.0234)	(0.00581)	(0.00343)	(0.00136)
Northern Highlands (NC)	-0.0221	-0.0176	-0.018***	-0.00645*	-0.00208*
	(0.0169)	(0.0215)	(0.00504)	(0.00332)	(0.00120)
Central Highlands (NC)	-0.0262**	-0.055***	-0.017***	-0.00227	-0.00215**
	(0.0116)	(0.0147)	(0.00374)	(0.00232)	(0.000999)
Southern Highlands (NC)	-0.00604	-0.0463**	-0.0114**	0.00408	-0.00268**
	(0.0152)	(0.0190)	(0.00500)	(0.00354)	(0.00120)
Rainforest (NC)	-0.0297**	-0.0299*	-0.00602	-0.00213	-0.0025***
	(0.0130)	(0.0154)	(0.00396)	(0.00219)	(0.000935)
Metropolitan Lima (NC)	-0.0634***	-0.113***	-5.16e-05	0.000644	-0.00200*
	(0.0123)	(0.0148)	(0.00531)	(0.00301)	(0.00114)

Constant	0.250***	0.447***	0.0284	0.0330*	-0.00253
	(0.0919)	(0.123)	(0.0245)	(0.0188)	(0.00642)
Observations	64,118	64,118	64,118	64,118	64,118
R-squared	0.019	0.021	0.015	-0.038	-0.006

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.3: Instrumental Variables Estimates of Healthcare Utilization, Services Used in the Last Three Months (Part I), 2005, Second Stage (Table 2.2)

	Preventive	Dental	Eyes	Glasses
Enrollment in SIS	1.726***	-0.159	-0.0945*	-0.111**
	(0.534)	(0.110)	(0.0568)	(0.0500)
Age	0.00882**	-0.00113	-7.87e-05	-0.000474
	(0.00387)	(0.000802)	(0.000430)	(0.000361)
Sex (male)	0.0752***	0.00509*	-0.000598	0.00124
	(0.00906)	(0.00300)	(0.00172)	(0.00149)
Preschool (no school)	0.0945***	0.00844	0.00642	0.00118
	(0.0313)	(0.00707)	(0.00392)	(0.00351)
Primary (no school)	0.151***	0.0116	0.00486	-0.00203
	(0.0450)	(0.0100)	(0.00606)	(0.00511)
Secondary (no school)	0.270***	0.0154	0.00240	-0.00582
	(0.0871)	(0.0190)	(0.0106)	(0.00897)
Post-secondary (no school)	0.287***	0.0739***	0.0267**	0.00732
	(0.0878)	(0.0216)	(0.0122)	(0.00934)
Reads & writes	-0.0422*	0.00998*	0.00674**	0.00503*
	(0.0252)	(0.00551)	(0.00329)	(0.00296)
Speaks indigenous language	0.0516*	-0.0114*	-0.0103***	-0.0123***
	(0.0311)	(0.00672)	(0.00381)	(0.00345)
Household members	-0.00155	-0.000743	-0.000125	-0.000274
	(0.00283)	(0.000768)	(0.000439)	(0.000325)
Sex of HH head (male)	0.00103	0.00728	0.00613*	0.000493
	(0.0152)	(0.00556)	(0.00366)	(0.00294)
Poor (non-poor)	-0.0271	-0.0452***	-0.0156***	-0.0124***
	(0.0174)	(0.00558)	(0.00253)	(0.00196)
Extremely poor (non-poor)	-0.0736***	-0.0578***	-0.0125***	-0.00928***
	(0.0254)	(0.00644)	(0.00282)	(0.00249)
Urbanicity (urban)	-0.0927**	-0.00110	0.000137	0.00303
	(0.0431)	(0.00821)	(0.00388)	(0.00357)
Central Coast (Northern Coast)	0.0151	-0.0117	-0.00586	-0.00581*
	(0.0227)	(0.00951)	(0.00408)	(0.00334)
Southern Coast (Northern Coast)	0.0614**	0.0175**	-0.00162	-0.00274
	(0.0304)	(0.00805)	(0.00426)	(0.00318)
Northern Highlands (Northern Coast)	0.0567	0.00662	-0.0110***	-0.00826**
	(0.0397)	(0.00937)	(0.00402)	(0.00357)
Central Highlands (Northern Coast)	0.0960***	0.0174**	-0.000949	0.00284
	(0.0322)	(0.00688)	(0.00331)	(0.00297)
Southern Highlands (Northern Coast)	0.0826**	0.0437***	0.00734	0.00977**
	(0.0369)	(0.00828)	(0.00513)	(0.00456)
Rainforest (Northern Coast)	-0.000814	0.0120*	-0.00241	0.00173
	(0.0309)	(0.00661)	(0.00331)	(0.00293)
Metropolitan Lima (Northern Coast)	0.0282	0.0199**	0.00981*	0.00136
	(0.0243)	(0.00914)	(0.00534)	(0.00374)
Constant	-0.518**	0.124**	0.0372	0.0505**
	(0.230)	(0.0486)	(0.0257)	(0.0218)

Observations	64,118	64,118	64,118	64,118
R-squared	-1.737	-0.009	-0.024	-0.086

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.4: Instrumental Variables Estimates of Healthcare Utilization, Services Used in the Last Three Months (Part II), 2005, Second Stage (Table 2.2)

	Immunization	Child's checkup	Birth control	Other
Enrollment in SIS	1.822***	0.658***	1.142	0.213
	(0.559)	(0.188)	(1.839)	(0.157)
Age	0.0107***	-0.117***	0.00470	0.00262**
	(0.00405)	(0.00856)	(0.00774)	(0.00115)
Sex (male)	0.0133	-0.0434**	0.0736**	0.0308***
	(0.00884)	(0.0186)	(0.0345)	(0.00386)
Preschool (no school)	0.0841**	0.0397	0.0442	0.0325***
	(0.0332)	(0.0394)	(0.0329)	(0.00995)
Primary (no school)	0.137***	0.0548	0.0586	0.0454***
	(0.0481)	(0.0438)	(0.0557)	(0.0148)
Secondary (no school)	0.275***	0.0654	0.103	0.0695**
	(0.0916)	(0.0510)	(0.140)	(0.0274)
Post-secondary (no school)	0.291***	0.114*	0.0922	0.0912***
	(0.0929)	(0.0660)	(0.129)	(0.0302)
Reads & writes	-0.0521*	-0.0199	-0.00796	0.00194
	(0.0268)	(0.0358)	(0.0358)	(0.00748)
Speaks indigenous language	0.0694**	-0.0210	0.0100	-0.00752
	(0.0322)	(0.0302)	(0.0240)	(0.00819)
Household members	0.00184	-0.00441	-0.00370	-0.00127
	(0.00302)	(0.00416)	(0.00254)	(0.000942)
Sex of HH head (male)	0.0284*	-0.0203	-0.0292**	0.00907
	(0.0153)	(0.0255)	(0.0121)	(0.00620)
Poor (non-poor)	-0.0335*	-0.0875***	0.000448	-0.0394***
	(0.0180)	(0.0331)	(0.0121)	(0.00629)
Extremely poor (non-poor)	-0.0825***	-0.0966***	-0.00770	-0.0513***
	(0.0270)	(0.0331)	(0.00991)	(0.00804)
Urbanicity (urban)	-0.106**	-0.0714*	-0.0186	-0.0160
	(0.0450)	(0.0382)	(0.0272)	(0.0123)
Central Coast (Northern Coast)	0.0142	0.0736	0.0231	-0.0869***
	(0.0261)	(0.0636)	(0.0301)	(0.0133)
Southern Coast (Northern Coast)	0.0389	0.0732	0.00639	-0.0913***
	(0.0266)	(0.0487)	(0.0166)	(0.0108)
Northern Highlands (Northern Coast)	0.0746*	0.104***	-0.0279	-0.0112
	(0.0424)	(0.0369)	(0.0366)	(0.0131)
Central Highlands (Northern Coast)	0.120***	0.0707**	-0.0198	-0.0835***
	(0.0340)	(0.0352)	(0.0183)	(0.0108)
Southern Highlands (Northern Coast)	0.0852**	0.0963***	-0.0372*	-0.0440***
	(0.0388)	(0.0348)	(0.0195)	(0.0125)
Rainforest (Northern Coast)	0.00503	-0.0387	0.000618	-0.0372**
	(0.0329)	(0.0413)	(0.0127)	(0.0147)
Metropolitan Lima (Northern Coast)	0.0302	0.142***	-0.0203	-0.0488***
	(0.0255)	(0.0476)	(0.0156)	(0.0124)

Constant	-0.626***	0.420***	-0.184	-0.0184
	(0.242)	(0.105)	(0.345)	(0.0691)
Observations	64,118	7,660	31,157	64,118
R-squared	-2.905	0.064	-0.848	-0.018

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Table A.5: Instrumental Variables Estimates of Healthcare Utilization, Services Used in the Last Twelve Months, 2005, Second Stage (Table 2.2)

	Hospitalization	Pregnancy's checkup	Birth
Enrollment in SIS	-0.0910	5.070	2.110
	(0.0765)	(6.074)	(3.128)
Age	-0.000189	0.0103	0.00124
	(0.000552)	(0.0223)	(0.0113)
Sex (male)	0.0201***		
	(0.00318)		
Preschool (no school)	0.0106*	0.103	0.0212
	(0.00600)	(0.140)	(0.0758)
Primary (no school)	0.00880	-0.0379	-0.0522
	(0.00826)	(0.169)	(0.0952)
Secondary (no school)	0.00278	-0.00120	0.00901
	(0.0133)	(0.169)	(0.0899)
Post-secondary (no school)	0.00309	0.203	0.0851
	(0.0143)	(0.291)	(0.159)
Reads & writes	0.00190	0.102	0.0410
	(0.00562)	(0.139)	(0.0770)
Speaks indigenous language	-0.00599	-0.0661	-0.00775
	(0.00496)	(0.105)	(0.0589)
Household members	0.00191***	0.0341	0.0312**
	(0.000658)	(0.0275)	(0.0147)
Sex of HH head (male)	0.00111	0.0147	0.0218
	(0.00396)	(0.113)	(0.0544)
Poor (non-poor)	-0.0165***	-0.0320	0.0275
	(0.00364)	(0.122)	(0.0608)
Extremely poor (non-poor)	-0.0231***	-0.132	-0.0509
	(0.00450)	(0.148)	(0.0771)
Urbanicity (urban)	-0.00492	-0.106	-0.0858
	(0.00613)	(0.122)	(0.0648)
Central Coast (Northern Coast)	-0.0101**	0.146	0.0587
	(0.00495)	(0.315)	(0.164)
Southern Coast (Northern Coast)	0.00333	0.301	0.105
	(0.00965)	(0.354)	(0.191)
Northern Highlands (Northern Coast)	-0.0197***	-0.208	-0.0287
	(0.00568)	(0.250)	(0.129)
Central Highlands (Northern Coast)	-0.0150***	0.0230	0.0367
	(0.00500)	(0.112)	(0.0635)
Southern Highlands (Northern Coast)	-0.00410	0.109	0.0605
	(0.00635)	(0.175)	(0.0964)
Rainforest (Northern Coast)	-0.000405	0.0211	0.0538
	(0.00513)	(0.138)	(0.0755)
Metropolitan Lima (Northern Coast)	0.00520	-0.164	-0.133
	(0.00537)	(0.157)	(0.0819)

Constant	0.0529	-0.580	-0.153
	(0.0328)	(1.274)	(0.653)
Observations	64,118	3,594	3,594
R-squared	-0.016	-7.179	-1.610

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.6: Instrumental Variables Estimates of Doctor's Visits Using Different Enrollment Goals as Instruments, 2005, Second Stage

	Overall Population	Children <5	Children 5-17	Pregnant Women	Adults
Enrollment in SIS	-0.0167	2.128	0.122	-0.0280	-0.0710
	(0.211)	(4.517)	(0.305)	(0.180)	(0.167)
Age	0.000227	0.0157	0.00123	0.000146	-0.000164
	(0.00153)	(0.0326)	(0.00221)	(0.00130)	(0.00121)
Sex (male)	0.0304***	0.00825	0.0290***	0.0305***	0.0309***
	(0.00481)	(0.0473)	(0.00541)	(0.00467)	(0.00460)
Preschool (no school)	0.0311**	0.119	0.0368**	0.0306***	0.0288**
	(0.0125)	(0.191)	(0.0151)	(0.0117)	(0.0116)
Primary (no school)	0.0261	0.184	0.0363	0.0253	0.0221
	(0.0188)	(0.336)	(0.0244)	(0.0171)	(0.0166)
Secondary (no school)	-0.00708	0.333	0.0149	-0.00887	-0.0157
	(0.0358)	(0.720)	(0.0499)	(0.0311)	(0.0295)
Post-secondary (no school)	0.0132	0.357	0.0354	0.0114	0.00452
	(0.0376)	(0.728)	(0.0515)	(0.0332)	(0.0315)
Reads & writes	-0.0117	-0.0699	-0.0155	-0.0114	-0.0103
	(0.0107)	(0.126)	(0.0120)	(0.0104)	(0.0104)
Speaks indigenous language	-0.0201	0.0761	-0.0139	-0.0206*	-0.0225**
	(0.0124)	(0.204)	(0.0160)	(0.0113)	(0.0109)
Household members	-0.000621	0.00450	-0.000291	-0.000648	-0.000751
	(0.00132)	(0.0109)	(0.00141)	(0.00130)	(0.00130)
Sex of HH head (male)	0.00506	0.0420	0.00745	0.00487	0.00413
	(0.00789)	(0.0806)	(0.00893)	(0.00760)	(0.00752)
Poor (non-poor)	-0.0649***	-0.112	-0.0679***	-0.0646***	-0.0637***
	(0.00782)	(0.100)	(0.00924)	(0.00743)	(0.00729)
Extremely poor (non-poor)	-0.121***	-0.193	-0.125***	-0.120***	-0.119***
	(0.0104)	(0.151)	(0.0126)	(0.00980)	(0.00963)
Urbanicity (urban)	-0.0311**	-0.174	-0.0403*	-0.0304**	-0.0275**
	(0.0154)	(0.301)	(0.0211)	(0.0135)	(0.0129)
Central Coast (Northern Coast)	-0.0334**	0.00371	-0.0310*	-0.0336**	-0.0343**
	(0.0170)	(0.0805)	(0.0169)	(0.0169)	(0.0171)
Southern Coast (NC)	0.00660	0.0349	0.00842	0.00645	0.00589
	(0.0212)	(0.0662)	(0.0208)	(0.0212)	(0.0214)
Northern Highlands (NC)	-0.0221	0.0927	-0.0147	-0.0227	-0.0250
	(0.0169)	(0.243)	(0.0202)	(0.0160)	(0.0158)
Central Highlands (NC)	-0.0262**	-0.0542	-0.0280**	-0.0260**	-0.0255**
	(0.0116)	(0.0677)	(0.0120)	(0.0115)	(0.0115)
Southern Highlands (NC)	-0.00604	-0.0870	-0.0113	-0.00561	-0.00399
	(0.0152)	(0.168)	(0.0176)	(0.0145)	(0.0143)
Rainforest (NC)	-0.0297**	-0.0768	-0.0327**	-0.0294**	-0.0285**
	(0.0130)	(0.107)	(0.0138)	(0.0128)	(0.0127)
Metropolitan Lima (NC)	-0.0634***	-0.00961	-0.0599***	-0.0637***	-0.0648***
	(0.0123)	(0.116)	(0.0135)	(0.0120)	(0.0120)

Constant	0.250***	-0.667	0.191	0.255***	0.273***
	(0.0919)	(1.933)	(0.132)	(0.0785)	(0.0735)
Observations	64,118	64,118	64,118	64,118	64,118
R-squared	0.019	-2.843	0.038	0.016	0.004

Columns are regressions on the same outcome using enrollment goals for different sub-groups
Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05,*p <0.1
Author's analysis of the 2005 ENAHO

Table A.7: Instrumental Variables Estimates of Children's Checkups Using Different Enrollment Goals as Instruments, 2005, Second Stage

	Overall Population	Children <5	Children 5-17	Pregnant Women	Adults
Enrollment in SIS	0.658***	1.970**	0.818***	0.635***	0.538***
	(0.188)	(0.987)	(0.230)	(0.175)	(0.159)
Age	-0.117***	-0.0627	-0.110***	-0.118***	-0.122***
	(0.00856)	(0.0419)	(0.0103)	(0.00809)	(0.00744)
Sex (male)	-0.0434**	-0.0846*	-0.0484**	-0.0427**	-0.0397**
	(0.0186)	(0.0455)	(0.0202)	(0.0183)	(0.0175)
Preschool (no school)	0.0397	0.0886	0.0457	0.0389	0.0353
	(0.0394)	(0.0928)	(0.0435)	(0.0390)	(0.0370)
Primary (no school)	0.0548	0.100	0.0603	0.0540	0.0506
	(0.0438)	(0.102)	(0.0486)	(0.0434)	(0.0410)
Secondary (no school)	0.0654	0.152	0.0759	0.0638	0.0574
	(0.0510)	(0.121)	(0.0560)	(0.0505)	(0.0479)
Post-secondary (no school)	0.114*	0.343	0.142*	0.110*	0.0926
	(0.0660)	(0.220)	(0.0745)	(0.0646)	(0.0606)
Reads & writes	-0.0199	-0.119	-0.0320	-0.0182	-0.0108
	(0.0358)	(0.104)	(0.0402)	(0.0354)	(0.0329)
Speaks indigenous language	-0.0210	-0.0793	-0.0281	-0.0200	-0.0157
	(0.0302)	(0.0740)	(0.0333)	(0.0297)	(0.0284)
Household members	-0.00441	0.00795	-0.00290	-0.00462	-0.00553
	(0.00416)	(0.0126)	(0.00466)	(0.00407)	(0.00384)
Sex of HH head (male)	-0.0203	-0.0267	-0.0211	-0.0202	-0.0197
	(0.0255)	(0.0489)	(0.0277)	(0.0253)	(0.0241)
Poor (non-poor)	-0.0875***	-0.236**	-0.106***	-0.0849***	-0.0740**
	(0.0331)	(0.119)	(0.0384)	(0.0318)	(0.0294)
Extremely poor (non-poor)	-0.0966***	-0.225**	-0.112***	-0.0944***	-0.0850***
	(0.0331)	(0.111)	(0.0381)	(0.0320)	(0.0298)
Urbanicity (urban)	-0.0714*	-0.291*	-0.0981**	-0.0676*	-0.0514
	(0.0382)	(0.172)	(0.0455)	(0.0367)	(0.0335)
Central Coast (Northern Coast)	0.0736	0.131	0.0806	0.0726	0.0684
	(0.0636)	(0.126)	(0.0695)	(0.0628)	(0.0596)
Southern Coast (NC)	0.0732	0.00227	0.0646	0.0745	0.0797*
	(0.0487)	(0.111)	(0.0543)	(0.0479)	(0.0447)
Northern Highlands (NC)	0.104***	0.105	0.104**	0.104***	0.104***
	(0.0369)	(0.0901)	(0.0416)	(0.0363)	(0.0342)
Central Highlands (NC)	0.0707**	0.00194	0.0623	0.0718**	0.0769**
	(0.0352)	(0.0936)	(0.0397)	(0.0346)	(0.0321)
Southern Highlands (NC)	0.0963***	-0.0271	0.0813**	0.0985***	0.108***
	(0.0348)	(0.113)	(0.0396)	(0.0339)	(0.0316)
Rainforest (NC)	-0.0387	-0.156	-0.0530	-0.0367	-0.0281
	(0.0413)	(0.121)	(0.0467)	(0.0399)	(0.0375)
Metropolitan Lima (NC)	0.142***	0.382**	0.171***	0.138***	0.120***
	(0.0476)	(0.191)	(0.0567)	(0.0451)	(0.0415)

Constant	0.420***	-0.243	0.339***	0.431***	0.480***
	(0.105)	(0.522)	(0.127)	(0.0986)	(0.0903)
Observations	7,660	7,660	7,660	7,660	7,660
R-squared	0.064	-2.534	-0.096	0.083	0.155

Columns are regressions on the same outcome using enrollment goals for different sub-groups
Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05,* p<0.1
Author's analysis of the 2005 ENAHO

Table A.8: Instrumental Variables Estimates of Enrollment in SIS, 2005, First Stage (Table 2.3)

	Overall population	Children (<5)	15-50 Population	Pregnant Women
Enrollment goals	0.1102***	0.4591***	0.0071	0.0804
	(0.0416)	(0.1385)	(0.0227)	(0.0847)
Enrollment goals * poverty status	0.0933***	0.2871***	0.0157*	-0.0199
	(0.0147)	(0.0623)	(0.0092)	(0.0460)
Age	-0.0072***	-0.0405***	-0.0042***	-0.0034***
	(0.0003)	(0.0040)	(0.0002)	(0.0011)
Sex (male)	0.0103***	0.0312**	0.0181***	
	(0.0034)	(0.0135)	(0.0036)	
Preschool (no school)	-0.0374***	-0.0325	-0.0170	-0.0103
	(0.0127)	(0.0412)	(0.0104)	(0.0278)
Primary (no school)	-0.0683***	-0.0215	-0.0292**	0.0063
	(0.0144)	(0.0467)	(0.0121)	(0.0327)
Secondary (no school)	-0.1524***	-0.0511	-0.0755***	-0.0027
	(0.0150)	(0.0469)	(0.0116)	(0.0364)
Post-secondary (no school)	-0.1541***	-0.1640***	-0.0694***	-0.0440
	(0.0158)	(0.0558)	(0.0119)	(0.0358)
Reads & writes	0.0248**	0.0669**	0.0189**	-0.0160
	(0.0111)	(0.0326)	(0.0083)	(0.0218)
Speaks indigenous language	-0.0513***	0.0130	-0.0142***	0.0090
	(0.0079)	(0.0325)	(0.0046)	(0.0158)
Household members	-0.0025**	-0.0091**	0.0010	-0.0040
	(0.0012)	(0.0039)	(0.0008)	(0.0027)
Sex of HH head (male)	-0.0167***	0.0052	-0.0052	-0.0064
	(0.0057)	(0.0225)	(0.0043)	(0.0204)
Urbanicity (urban)	0.0621***	0.1461***	0.0113	0.0210
	(0.0094)	(0.0264)	(0.0049)	(0.0128)
Central Coast (Northern Coast)	-0.0029	0.0007	-0.0140**	-0.0428**
	(0.0159)	(0.0592)	(0.0063)	(0.0195)
Southern Coast (Northern Coast)	0.0106	0.1375***	0.0053	-0.0450**
	(0.0142)	(0.0516)	(0.0097)	(0.0204)
Northern Highlands (Northern Coast)	-0.0770***	-0.0951**	-0.0221**	0.0301
	(0.0154)	(0.0472)	(0.0097)	(0.0294)
Central Highlands (Northern Coast)	-0.0029	-0.0352	-0.0075	-0.0059
	(0.0143)	(0.0418)	(0.0071)	(0.0226)
Southern Highlands (Northern Coast)	0.0271*	0.0286	0.0078	-0.0233
	(0.0157)	(0.0446)	(0.0075)	(0.0201)
Rainforest (Northern Coast)	-0.0011	-0.0076	-0.0041	-0.0220
	(0.0151)	(0.0417)	(0.0077)	(0.0186)
Metropolitan Lima (Northern Coast)	0.0042	-0.0668	-0.0037	0.0315
	(0.0141)	(0.0484)	(0.0074)	(0.0302)
Constant	0.3818***	0.3538***	0.1853***	0.1795***
	(0.0260)	(0.0717)	(0.0160)	(0.0494)

Observations	64,118	7,660	31,157	3,594
F test for excluded instruments				
F test	29.66	26.84	1.83	0.47
P-value	0.0000	0.0000	0.1608	0.6282
Sanderson-Windmeijer multivariate Chi-squared test of underidentification:				
SW Chi-square test	17.66	30.17	0.52	0.8
P-value	0.0000	0.0000	0.4722	0.3699

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.9: Instrumental Variables Estimates of the Interaction between Enrollment in SIS and Poverty Status, 2005, First Stage (Table 2.3)

	Overall population	Children (<5)	15-50 Population	Pregnant Women
Enrollment goals	-0.1017	-0.5470	-0.0492	-0.1107
	(0.0364)	(0.1249)	(0.0195)	(0.0676)
Enrollment goals * poverty status	0.3948	1.4556	0.1138	0.1661
	(0.0158)	(0.0503)	(0.0068)	(0.0232)
Age	-0.0055	-0.0290	-0.0032	-0.0034
	(0.0003)	(0.0037)	(0.0002)	(0.0007)
Sex (male)	0.0086	0.0154	0.0136	
	(0.0029)	(0.0120)	(0.0027)	
Preschool (no school)	-0.0195	-0.0197	-0.0157	-0.0066
	(0.0120)	(0.0405)	(0.0097)	(0.0274)
Primary (no school)	-0.0422	0.0032	-0.0232	0.0145
	(0.0135)	(0.0448)	(0.0114)	(0.0311)
Secondary (no school)	-0.1109	-0.0261	-0.0555	0.0090
	(0.0140)	(0.0443)	(0.0112)	(0.0330)
Post-secondary (no school)	-0.0984	-0.0450	-0.0447	-0.0012
	(0.0144)	(0.0500)	(0.0112)	(0.0321)
Reads & writes	0.0238	0.0341	0.0156	-0.0198
	(0.0105)	(0.0312)	(0.0074)	(0.0212)
Speaks indigenous language	-0.0507	-0.0008	-0.0131	0.0132
	(0.0074)	(0.0310)	(0.0037)	(0.0146)
Household members	-0.0016	-0.0069	0.0013	-0.0015
	(0.0011)	(0.0034)	(0.0008)	(0.0020)
Sex of HH head (male)	-0.0092	0.0042	-0.0030	-0.0052
	(0.0054)	(0.0188)	(0.0035)	(0.0140)
Urbanicity (urban)	0.0478	0.1027	0.0081	0.0263
	(0.0086)	(0.0254)	(0.0044)	(0.0113)
Central Coast (Northern Coast)	-0.0039	0.0136	-0.0112	-0.0347
	(0.0119)	(0.0392)	(0.0048)	(0.0174)
Southern Coast (Northern Coast)	-0.0003	0.0771	-0.0022	-0.0376
	(0.0112)	(0.0371)	(0.0071)	(0.0194)
Northern Highlands (Northern Coast)	-0.0664	-0.0797	-0.0171	0.0225
	(0.0146)	(0.0428)	(0.0094)	(0.0293)
Central Highlands (Northern Coast)	0.0059	-0.0227	-0.0080	-0.0178
	(0.0128)	(0.0376)	(0.0061)	(0.0213)
Southern Highlands (Northern Coast)	0.0280	0.0233	0.0054	-0.0259
	(0.0137)	(0.0402)	(0.0060)	(0.0193)
Rainforest (Northern Coast)	-0.0008	-0.0039	-0.0080	-0.0277
	(0.0136)	(0.0357)	(0.0068)	(0.0179)
Metropolitan Lima (Northern Coast)	0.0070	-0.0678	-0.0030	-0.0020
	(0.0129)	(0.0388)	(0.0063)	(0.0237)
Constant	0.2734	0.2767	0.1338	0.1665
	(0.0235)	(0.0635)	(0.0144)	(0.0426)

Observations	64,118	7,660	31,157	3,594
F test for excluded instruments				
F test	313.93	431.39	139.35	25.74
P-value	0.0000	0.0000	0.0000	0.0000
Sanderson-Windmeijer multivariate Chi-squared test of underidentification:				
SW Chi-square test	33.56	64.72	0.67	4.22
P-value	0.0000	0.0000	0.4116	0.0399

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.10: Instrumental Variables Estimates of Healthcare Utilization by Poverty Status, Services Used in the Last Four Weeks, 2005, Second Stage (Table 2.3)

	Doctor's visit	Medication	Laboratory	X rays	Other exams
Enrollment in SIS	0.522*	0.471	0.155**	0.00683	0.0361
	(0.292)	(0.387)	(0.0791)	(0.0599)	(0.0232)
Enrollment in SIS * Poverty status	-0.645***	-0.726***	-0.199***	-0.0896***	-0.0236***
	(0.0952)	(0.118)	(0.0274)	(0.0185)	(0.00815)
Age	0.000638	0.00106	0.000677	-0.000117	0.000171
	(0.00166)	(0.00220)	(0.000448)	(0.000345)	(0.000128)
Sex (male)	0.0310***	0.0560***	0.00489**	0.00618***	0.000939*
	(0.00495)	(0.00639)	(0.00197)	(0.00142)	(0.000486)
Preschool (no school)	0.0394***	0.0330*	0.0130**	0.00309	-0.000150
	(0.0142)	(0.0179)	(0.00527)	(0.00388)	(0.00112)
Primary (no school)	0.0384*	0.0237	0.0127*	-0.00162	0.000816
	(0.0210)	(0.0268)	(0.00694)	(0.00528)	(0.00171)
Secondary (no school)	0.00997	-0.0129	0.00373	-0.00719	0.00208
	(0.0390)	(0.0500)	(0.0115)	(0.00882)	(0.00296)
Post-secondary (no school)	0.0419	0.00300	0.0181	0.000566	0.00523
	(0.0422)	(0.0533)	(0.0121)	(0.00907)	(0.00332)
Reads & writes	-0.00734	-0.00254	0.00323	0.00452	0.000565
	(0.0113)	(0.0143)	(0.00436)	(0.00327)	(0.000889)
Speaks indigenous language	-0.0298**	-0.0534***	-0.00557	-0.00402	-0.000566
	(0.0130)	(0.0164)	(0.00405)	(0.00306)	(0.000907)
Household members	-0.00188	-0.00251	0.000842	0.000412	6.92e-05
	(0.00140)	(0.00180)	(0.000536)	(0.000300)	(0.000102)
Sex of HH head (male)	0.00742	0.00497	-0.00132	-0.00258	0.000471
	(0.00850)	(0.0101)	(0.00322)	(0.00208)	(0.000701)
Urbanicity (urban)	-0.0394**	-0.0752***	-0.00527	0.000775	-0.00107
	(0.0160)	(0.0213)	(0.00408)	(0.00322)	(0.00124)
Central Coast (Northern Coast)	-0.0298*	-0.0793***	-0.0109**	-0.00710**	-0.00198
	(0.0163)	(0.0206)	(0.00448)	(0.00282)	(0.00150)
Southern Coast (NC)	0.00593	-0.0644***	-0.00426	-0.00151	-0.00136
	(0.0203)	(0.0209)	(0.00538)	(0.00352)	(0.00145)
Northern Highlands (NC)	-0.0299	-0.0309	-0.0185***	-0.00667*	-0.00186
	(0.0188)	(0.0227)	(0.00505)	(0.00341)	(0.00126)
Central Highlands (NCt)	-0.0245**	-0.0546***	-0.0158***	-0.00158	-0.00192*
	(0.0124)	(0.0151)	(0.00390)	(0.00236)	(0.000986)
Southern Highlands (NCt)	-0.00459	-0.0455**	-0.0105**	0.00464	-0.00270**
	(0.0160)	(0.0196)	(0.00524)	(0.00368)	(0.00122)
Rainforest (NC)	-0.0314**	-0.0326**	-0.00617	-0.00216	-0.00250***
	(0.0136)	(0.0160)	(0.00412)	(0.00230)	(0.000954)
Metropolitan Lima (NC)	-0.0576***	-0.108***	0.00241	0.00176	-0.00165
	(0.0144)	(0.0156)	(0.00582)	(0.00329)	(0.00117)

Constant	0.178*	0.381***	-0.000678	0.0198	-0.00653
	(0.105)	(0.138)	(0.0279)	(0.0216)	(0.00779)
Observations	64,118	64,118	64,118	64,118	64,118
R-squared	-0.046	-0.034	-0.016	-0.051	-0.023

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Table A.11: Instrumental Variables Estimates of Healthcare Utilization by Poverty Status, Services Used in the Last Three Months (Part I), Second Stage (Table 2.3)

	Preventive	Dental	Eyes	Glasses
Enrollment in SIS	2.201***	0.0519	-0.0415	-0.0665
	(0.724)	(0.153)	(0.0782)	(0.0692)
Enrollment in SIS * Poverty status	-0.517**	-0.269***	-0.0653***	-0.0532**
	(0.208)	(0.0499)	(0.0245)	(0.0217)
Age	0.00939**	-0.00102	-3.31e-05	-0.000427
	(0.00418)	(0.000887)	(0.000469)	(0.000396)
Sex (male)	0.0749***	0.00567*	-0.000460	0.00133
	(0.00960)	(0.00313)	(0.00172)	(0.00149)
Preschool (no school)	0.101***	0.0123	0.00765*	0.00222
	(0.0334)	(0.00787)	(0.00423)	(0.00375)
Primary (no school)	0.161***	0.0168	0.00631	-0.000820
	(0.0487)	(0.0112)	(0.00651)	(0.00548)
Secondary (no school)	0.284***	0.0236	0.00514	-0.00350
	(0.0939)	(0.0211)	(0.0115)	(0.00966)
Post-secondary (no school)	0.307***	0.0898***	0.0320**	0.0117
	(0.0972)	(0.0243)	(0.0132)	(0.0102)
Reads & writes	-0.0408	0.0126**	0.00729**	0.00540*
	(0.0255)	(0.00582)	(0.00339)	(0.00303)
Speaks indigenous language	0.0481	-0.0169**	-0.0114***	-0.0131***
	(0.0317)	(0.00706)	(0.00391)	(0.00352)
Household members	-0.00128	-0.00192**	-0.000477	-0.000526
	(0.00292)	(0.000791)	(0.000454)	(0.000334)
Sex of HH head (male)	0.00322	0.00830	0.00648*	0.000799
	(0.0161)	(0.00577)	(0.00376)	(0.00298)
Urbanicity (urban)	-0.0995**	-0.00360	0.000101	0.00305
	(0.0449)	(0.00861)	(0.00410)	(0.00372)
Central Coast (Northern Coast)	0.0150	-0.00821	-0.00456	-0.00481
	(0.0237)	(0.00966)	(0.00407)	(0.00334)
Southern Coast (NC)	0.0593*	0.0182**	-0.00126	-0.00248
	(0.0327)	(0.00819)	(0.00414)	(0.00315)
Northern Highlands (NC)	0.0532	0.00355	-0.0109**	-0.00799**
	(0.0404)	(0.00972)	(0.00423)	(0.00365)
Central Highlands (Northern Coast)	0.0973***	0.0189***	-6.89e-05	0.00361
	(0.0323)	(0.00713)	(0.00324)	(0.00295)
Southern Highlands (Northern Coast)	0.0810**	0.0463***	0.00846	0.0106**
	(0.0379)	(0.00893)	(0.00523)	(0.00471)
Rainforest (Northern Coast)	-0.00269	0.0119*	-0.00219	0.00191
	(0.0314)	(0.00706)	(0.00335)	(0.00301)
Metropolitan Lima (Northern Coast)	0.0331	0.0227**	0.0108**	0.00223
	(0.0263)	(0.0102)	(0.00544)	(0.00388)

Constant	-0.579**	0.0895	0.0255	0.0406
	(0.260)	(0.0559)	(0.0290)	(0.0247)
Observations	64,118	64,118	64,118	64,118
R-squared	-1.908	-0.043	-0.030	-0.090

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table A.12: Instrumental Variables Estimates of Healthcare Utilization by Poverty Status, Services Used in the Last Three Months (Part II), 2005, Second Stage (Table 2.3)

	Immunization	Child's checkup	Birth control	Other
Enrollment in SIS	2.371***	0.843***	1.696	0.491**
	(0.762)	(0.242)	(2.872)	(0.222)
Enrollment in SIS * Poverty status	-0.594***	-0.212***	-0.332	-0.317***
	(0.221)	(0.0742)	(0.445)	(0.0745)
Age	0.0113**	-0.116***	0.00595	0.00292**
	(0.00441)	(0.00906)	(0.0108)	(0.00126)
Sex (male)	0.0129	-0.0455**	0.0680	0.0309***
	(0.00948)	(0.0193)	(0.0478)	(0.00396)
Preschool (no school)	0.0922***	0.0436	0.0480	0.0374***
	(0.0355)	(0.0389)	(0.0434)	(0.0107)
Primary (no school)	0.149***	0.0598	0.0663	0.0520***
	(0.0522)	(0.0434)	(0.0747)	(0.0161)
Secondary (no school)	0.292***	0.0725	0.124	0.0799***
	(0.0992)	(0.0511)	(0.193)	(0.0298)
Post-secondary (no school)	0.314***	0.142**	0.113	0.109***
	(0.103)	(0.0692)	(0.181)	(0.0332)
Reads & writes	-0.0507*	-0.0259	-0.0128	0.00351
	(0.0273)	(0.0359)	(0.0499)	(0.00770)
Speaks indigenous language	0.0656**	-0.0235	0.0138	-0.0109
	(0.0331)	(0.0303)	(0.0345)	(0.00826)
Household members	0.00216	-0.00488	-0.00347	-0.00183*
	(0.00314)	(0.00434)	(0.00287)	(0.000959)
Sex of HH head (male)	0.0310*	-0.0209	-0.0275*	0.0105*
	(0.0164)	(0.0260)	(0.0160)	(0.00640)
Urbanicity (urban)	-0.113**	-0.0737*	-0.0215	-0.0187
	(0.0471)	(0.0378)	(0.0323)	(0.0130)
Central Coast (Northern Coast)	0.0143	0.0834	0.0266	-0.0845***
	(0.0279)	(0.0657)	(0.0404)	(0.0141)
Southern Coast (Northern Coast)	0.0365	0.0724	0.00308	-0.0914***
	(0.0298)	(0.0518)	(0.0212)	(0.0117)
Northern Highlands (Northern Coast)	0.0713	0.102***	-0.0224	-0.0124
	(0.0435)	(0.0374)	(0.0521)	(0.0137)
Central Highlands (Northern Coast)	0.122***	0.0721**	-0.0188	-0.0814***
	(0.0344)	(0.0349)	(0.0226)	(0.0111)
Southern Highlands (Northern Coast)	0.0836**	0.0958***	-0.0408	-0.0425***
	(0.0401)	(0.0351)	(0.0252)	(0.0131)
Rainforest (Northern Coast)	0.00304	-0.0388	-0.000229	-0.0375**
	(0.0336)	(0.0413)	(0.0141)	(0.0152)
Metropolitan Lima (Northern Coast)	0.0361	0.147***	-0.0183	-0.0451***
	(0.0279)	(0.0503)	(0.0206)	(0.0134)

Constant	-0.699**	0.345***	-0.244	-0.0632
	(0.275)	(0.125)	(0.489)	(0.0786)
Observations	64,118	7,660	31,157	64,118
R-squared	-3.215	0.034	-1.367	-0.065

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Table A.13: Instrumental Variables Estimates of Healthcare Utilization by Poverty Status, Services Used in the Last Twelve Months, 2005, Second Stage (Table 2.3)

	Hospitalization	Pregnancy's checkup	Birth
Enrollment in SIS	0.0323	4.794	1.857
	(0.106)	(4.155)	(2.297)
Enrollment in SIS * Poverty status	-0.141***	-0.988	-0.310
	(0.0345)	(1.169)	(0.598)
Age	-6.13e-05	0.00604	-0.000847
	(0.000607)	(0.0162)	(0.00872)
Sex (male)	0.0201***		
	(0.00314)		
Preschool (no school)	0.0127**	0.0970	0.0197
	(0.00634)	(0.107)	(0.0642)
Primary (no school)	0.0117	-0.0119	-0.0394
	(0.00878)	(0.125)	(0.0791)
Secondary (no school)	0.00724	0.0209	0.0151
	(0.0143)	(0.133)	(0.0769)
Post-secondary (no school)	0.0105	0.206	0.0726
	(0.0157)	(0.208)	(0.127)
Reads & writes	0.00261	0.0874	0.0375
	(0.00567)	(0.111)	(0.0685)
Speaks indigenous language	-0.00755	-0.0591	-0.00648
	(0.00508)	(0.0891)	(0.0549)
Household members	0.00168**	0.0296	0.0295***
	(0.000677)	(0.0189)	(0.0108)
Sex of HH head (male)	0.00174	0.00722	0.0188
	(0.00406)	(0.0935)	(0.0466)
Urbanicity (urban)	-0.00622	-0.0919	-0.0865
	(0.00638)	(0.112)	(0.0648)
Central Coast (Northern Coast)	-0.00913*	0.102	0.0345
	(0.00502)	(0.227)	(0.130)
Southern Coast (Northern Coast)	0.00323	0.253	0.0774
	(0.00930)	(0.254)	(0.153)
Northern Highlands (Northern Coast)	-0.0204***	-0.194	-0.0275
	(0.00576)	(0.199)	(0.111)
Central Highlands (Northern Coast)	-0.0142***	-0.00547	0.0225
	(0.00486)	(0.0877)	(0.0548)
Southern Highlands (Northern Coast)	-0.00354	0.0706	0.0393
	(0.00640)	(0.123)	(0.0762)
Rainforest (Northern Coast)	-0.000591	-0.0182	0.0343
	(0.00514)	(0.0984)	(0.0602)
Metropolitan Lima (Northern Coast)	0.00681	-0.163	-0.131*
	(0.00557)	(0.123)	(0.0671)

Constant	0.0337	-0.395	-0.0395
	(0.0375)	(0.893)	(0.496)
Observations	64,118	3,594	3,594
R-squared	-0.020	-4.366	-0.931

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Appendix B

Estimates of the Effect of SIS on Healthcare Out-of-pocket Expenditures

Table B.1: Instrumental Variables Estimates of Healthcare Expenditures, Services Used in the Last Four Weeks, 2005, Second Stage (Table 3.3)

	Doctor's visit	Medication	Laboratory	X rays	Other exams
Enrollment in SIS	-0.899	-2.265*	-0.146	-0.320	0.000952
	(0.763)	(1.211)	(0.254)	(0.235)	(0.0793)
Age	-0.00290	-0.00386	0.00102	-0.00107	6.70e-05
	(0.00560)	(0.00874)	(0.00185)	(0.00171)	(0.000562)
Sex (male)	0.121***	0.252***	0.0224**	0.0244***	0.00398*
	(0.0198)	(0.0298)	(0.00966)	(0.00658)	(0.00242)
Preschool (no school)	0.0658	0.0615	-0.00431	-0.00657	-0.00494
	(0.0525)	(0.0794)	(0.0243)	(0.0207)	(0.00620)
Primary (no school)	0.0398	-0.0525	-0.0237	-0.0311	-0.00428
	(0.0747)	(0.112)	(0.0318)	(0.0274)	(0.00911)
Secondary (no school)	-0.0724	-0.294	-0.0634	-0.0572	-0.00448
	(0.136)	(0.203)	(0.0495)	(0.0448)	(0.0140)
Post-secondary (no school)	-0.135	-0.409*	-0.0576	-0.0601	-0.000211
	(0.141)	(0.212)	(0.0527)	(0.0443)	(0.0154)
Reads & writes	-0.0501	-0.00773	0.0317	0.0210	0.00320
	(0.0432)	(0.0673)	(0.0210)	(0.0169)	(0.00556)
Speaks indigenous language	0.0258	-0.114*	0.00974	-7.32e-05	-0.00339
	(0.0421)	(0.0692)	(0.0211)	(0.0144)	(0.00496)
Household members	0.00497	0.0110	0.00794***	0.00267	0.000317
	(0.00541)	(0.00846)	(0.00267)	(0.00167)	(0.000460)
Sex of HH head (male)	-0.0113	-0.0480	-0.0134	-0.0134	-0.00156
	(0.0311)	(0.0488)	(0.0144)	(0.0116)	(0.00243)
Poor (non-poor)	-0.279***	-0.418***	-0.0981***	-0.0496***	-0.00619*
	(0.0309)	(0.0555)	(0.0147)	(0.0107)	(0.00360)
Extremely poor (non-poor)	-0.516***	-0.894***	-0.131***	-0.0691***	-0.00873**
	(0.0374)	(0.0711)	(0.0165)	(0.0118)	(0.00348)
Urbanicity (urban)	-0.173***	-0.300***	-0.0136	0.00823	-0.000571
	(0.0538)	(0.0893)	(0.0183)	(0.0171)	(0.00613)
Central Coast (Northern Coast)	-0.225***	-0.378***	-0.0314	-0.0313**	-0.0106**
	(0.0627)	(0.114)	(0.0220)	(0.0137)	(0.00517)
Southern Coast (NC)	-0.191***	-0.491***	-0.0340	-0.0130	-0.00235
	(0.0710)	(0.102)	(0.0243)	(0.0177)	(0.00654)
Northern Highlands (NC)	-0.0943	-0.124	-0.0534**	-0.0148	-0.0105*
	(0.0620)	(0.104)	(0.0222)	(0.0177)	(0.00546)
Central Highlands (NC)	-0.211***	-0.329***	-0.0628***	-0.00987	-0.00597
	(0.0489)	(0.0693)	(0.0169)	(0.0114)	(0.00500)
Southern Highlands (NC)	-0.181***	-0.328***	-0.0558**	0.0151	-0.00584
	(0.0554)	(0.0855)	(0.0218)	(0.0171)	(0.00684)
Rainforest (NC)	-0.192***	-0.0857	-0.0296*	-0.00315	-0.00606
	(0.0494)	(0.0744)	(0.0161)	(0.0110)	(0.00489)
Metropolitan Lima (NC)	-0.307***	-0.502***	0.0218	0.00302	-0.00839
	(0.0544)	(0.0845)	(0.0240)	(0.0152)	(0.00515)

Constant	1.212***	2.573***	0.144	0.158	0.0129
	(0.339)	(0.527)	(0.112)	(0.102)	(0.0318)
Observations	64,064	63,280	64,114	64,114	64,118
R-squared	0.017	-0.010	0.009	-0.026	0.001

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05,* p<0.1
Author’s analysis of the 2005 ENAHO

Table B.2: Instrumental Variables Estimates of Healthcare Expenditures, Services Used in the Last Three Months (Part I), 2005, Second Stage (Table 3.3)

	Dental	Eyes	Glasses
Enrollment in SIS	-1.229**	-0.228	-0.700**
	(0.545)	(0.214)	(0.314)
Age	-0.00663*	0.000344	-0.00279
	(0.00402)	(0.00162)	(0.00226)
Sex (male)	0.0341**	-0.0100	0.00709
	(0.0158)	(0.00938)	(0.00929)
Preschool (no school)	0.0240	0.0313**	0.0152
	(0.0356)	(0.0153)	(0.0208)
Primary (no school)	0.0244	0.0190	-0.00705
	(0.0512)	(0.0235)	(0.0315)
Secondary (no school)	0.0450	0.0339	-0.0318
	(0.0971)	(0.0412)	(0.0561)
Post-secondary (no school)	0.375***	0.150***	0.0629
	(0.108)	(0.0484)	(0.0586)
Reads & writes	0.0665**	0.0182	0.0318*
	(0.0281)	(0.0128)	(0.0181)
Speaks indigenous language	-0.0504	-0.0293**	-0.0785***
	(0.0351)	(0.0144)	(0.0217)
Household members	-0.000764	0.000851	-0.00214
	(0.00405)	(0.00217)	(0.00214)
Sex of HH head (male)	0.0446	0.0277*	0.00256
	(0.0347)	(0.0150)	(0.0195)
Poor (non-poor)	-0.270***	-0.0695***	-0.0790***
	(0.0297)	(0.0124)	(0.0128)
Extremely poor (non-poor)	-0.306***	-0.0605***	-0.0547***
	(0.0333)	(0.0128)	(0.0161)
Urbanicity (urban)	0.0353	-0.00870	0.0181
	(0.0393)	(0.0154)	(0.0222)
Central Coast (Northern Coast)	-0.0987**	-0.0224	-0.0302
	(0.0465)	(0.0169)	(0.0213)
Southern Coast (Northern Coast)	-0.00434	-0.00322	-0.0214
	(0.0384)	(0.0191)	(0.0197)
Northern Highlands (Northern Coast)	0.0148	-0.0332**	-0.0572***
	(0.0449)	(0.0154)	(0.0219)
Central Highlands (Northern Coast)	0.0796**	-0.00148	0.0156
	(0.0359)	(0.0135)	(0.0185)
Southern Highlands (Northern Coast)	0.174***	0.0218	0.0622**
	(0.0461)	(0.0192)	(0.0286)
Rainforest (Northern Coast)	0.0777**	-0.00713	0.0121
	(0.0344)	(0.0132)	(0.0180)
Metropolitan Lima (Northern Coast)	0.100**	0.0379*	0.00976
	(0.0490)	(0.0197)	(0.0237)

Constant	0.686***	0.0995	0.307**
	(0.242)	(0.0977)	(0.137)
Observations	64,065	64,096	64,108
R-squared	-0.028	0.007	-0.079

Reference group in parentheses for categorical variables

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Author's analysis of the 2005 ENAHO

Table B.3: Instrumental Variables Estimates of Healthcare Expenditures, Services Used in the Last Three Months (Part II), 2005, Second Stage (Table 3.3)

	Immunization	Child's checkup	Birth control	Other
Enrollment in SIS	-0.513**	-0.611***	6.487	1.426**
	(0.239)	(0.205)	(8.216)	(0.619)
Age	-0.00426**	-0.0691***	0.0267	0.0157***
	(0.00173)	(0.0126)	(0.0347)	(0.00464)
Sex (male)	0.00576	-0.0158	-0.127	0.0682***
	(0.00714)	(0.0253)	(0.152)	(0.0144)
Preschool (no school)	-0.0223*	-0.0266	0.105	0.135***
	(0.0128)	(0.0333)	(0.151)	(0.0414)
Primary (no school)	-0.0375*	-0.0118	0.193	0.199***
	(0.0207)	(0.0398)	(0.255)	(0.0622)
Secondary (no school)	-0.0712*	-0.0663	0.519	0.360***
	(0.0394)	(0.0462)	(0.629)	(0.113)
Post-secondary (no school)	0.000515	0.0587	0.530	0.477***
	(0.0465)	(0.117)	(0.578)	(0.125)
Reads & writes	0.00979	0.0382	-0.126	0.000770
	(0.00980)	(0.0295)	(0.161)	(0.0305)
Speaks indigenous language	-0.0296*	0.0861***	0.0615	0.0197
	(0.0161)	(0.0265)	(0.107)	(0.0325)
Household members	-0.00209	-0.0160***	-0.00785	-0.00191
	(0.00162)	(0.00518)	(0.0111)	(0.00423)
Sex of HH head (male)	-0.00666	-0.116***	-0.00457	0.0763**
	(0.0103)	(0.0334)	(0.0518)	(0.0298)
Poor (non-poor)	-0.0373***	-0.111**	-0.104*	-0.215***
	(0.00885)	(0.0519)	(0.0560)	(0.0269)
Extremely poor (non-poor)	-0.0273**	-0.137***	-0.0644	-0.251***
	(0.0116)	(0.0498)	(0.0420)	(0.0327)
Urbanicity (urban)	0.0143	0.0727*	-0.124	-0.105**
	(0.0175)	(0.0410)	(0.114)	(0.0500)
Central Coast (Northern Coast)	-0.0215	-0.0381	0.0956	-0.279***
	(0.0138)	(0.0581)	(0.133)	(0.0528)
Southern Coast (Northern Coast)	0.0565	-0.0366	0.0172	-0.350***
	(0.0378)	(0.0474)	(0.0758)	(0.0447)
Northern Highlands (Northern Coast)	-0.0171	0.0247	0.0937	0.0180
	(0.0185)	(0.0407)	(0.159)	(0.0576)
Central Highlands (Northern Coast)	0.0162	0.0502	0.0256	-0.266***
	(0.0124)	(0.0382)	(0.0660)	(0.0416)
Southern Highlands (Northern Coast)	0.0463**	0.0943*	-0.0477	-0.191***
	(0.0199)	(0.0494)	(0.0888)	(0.0504)
Rainforest (Northern Coast)	0.00849	0.0430	0.00394	-0.125**
	(0.0110)	(0.0376)	(0.0534)	(0.0541)
Metropolitan Lima (Northern Coast)	0.00719	0.119	0.0104	-0.0691
	(0.0115)	(0.0733)	(0.0696)	(0.0541)

Constant	0.294***	0.714***	-1.069	-0.421
	(0.105)	(0.133)	(1.550)	(0.285)
Observations	63,811	7,527	31,146	64,045
R-squared	-0.122	-0.028	-5.329	-0.148

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table B.4: Instrumental Variables Estimates of Healthcare Expenditures, Services Used in the Last Twelve Months, 2005, Second Stage (Table 3.3)

	Hospitalization	Pregnancy's checkup	Birth	Any OOP Expenditure
Enrollment in SIS	-0.493	0.573	1.184	-0.720***
	(0.383)	(2.586)	(4.292)	(0.259)
Age	-0.00107	0.00444	0.00939	-0.00276
	(0.00277)	(0.0190)	(0.0317)	(0.00187)
Sex (male)	0.0841***			0.0634***
	(0.0134)			(0.00574)
Preschool (no school)	0.0255	0.0514	0.0392	0.0218
	(0.0274)	(0.0609)	(0.108)	(0.0176)
Primary (no school)	0.00647	0.0317	0.0475	0.00882
	(0.0402)	(0.0705)	(0.118)	(0.0249)
Secondary (no school)	-0.0163	0.0903	0.141	-0.0273
	(0.0653)	(0.215)	(0.355)	(0.0440)
Post-secondary (no school)	-0.0292	0.116	0.133	0.00791
	(0.0695)	(0.196)	(0.328)	(0.0473)
Reads & writes	0.0278	-0.0132	-0.0174	0.0154
	(0.0273)	(0.0319)	(0.0491)	(0.0149)
Speaks indigenous language	-0.0378	-0.0113	0.0371	-0.0385***
	(0.0237)	(0.0367)	(0.0593)	(0.0145)
Household members	0.0124***	0.00473	0.0195***	0.00322*
	(0.00338)	(0.00527)	(0.00686)	(0.00193)
Sex of HH head (male)	0.00179	-0.0511*	-0.0110	-0.0222**
	(0.0223)	(0.0271)	(0.0388)	(0.0112)
Poor (non-poor)	-0.0828***	-0.0341	-0.00685	-0.0881***
	(0.0189)	(0.0437)	(0.0674)	(0.0108)
Extremely poor (non-poor)	-0.125***	-0.0309	-0.000461	-0.184***
	(0.0221)	(0.0193)	(0.0290)	(0.0149)
Urbanicity (urban)	0.0100	-0.0608	-0.0429	-0.0501**
	(0.0311)	(0.103)	(0.172)	(0.0196)
Central Coast (Northern Coast)	-0.0242	-0.0204	-0.0307	-0.127***
	(0.0298)	(0.0836)	(0.135)	(0.0204)
Southern Coast (Northern Coast)	-0.0210	-0.0479	-0.107**	-0.115***
	(0.0349)	(0.0391)	(0.0487)	(0.0202)
Northern Highlands (Northern Coast)	-0.0849***	-0.0298	0.0249	-0.0542**
	(0.0294)	(0.0923)	(0.140)	(0.0227)
Central Highlands (Northern Coast)	-0.0580**	-0.0410	-0.0872**	-0.0904***
	(0.0227)	(0.0274)	(0.0412)	(0.0142)
Southern Highlands (Northern Coast)	-0.0184	-0.0676	-0.149	-0.0342*
	(0.0278)	(0.0565)	(0.0923)	(0.0180)
Rainforest (Northern Coast)	0.00254	-0.0508	-0.0487	-0.0250
	(0.0219)	(0.0382)	(0.0667)	(0.0167)
Metropolitan Lima (Northern Coast)	-0.00179	0.0194	-0.0879*	-0.101***
	(0.0254)	(0.0438)	(0.0524)	(0.0169)

Constant	0.229	-0.107	-0.373	0.654***
	(0.164)	(0.831)	(1.377)	(0.114)
Observations	64,084	17,736	17,728	64,118
R-squared	-0.013	-0.073	-0.242	-0.097

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Table B.5: Instrumental Variables Estimates of Healthcare Expenditures (Binary), Services Used in the Last Four Weeks, 2005, Second Stage

	Doctor's visit	Medication	Laboratory	X rays	Other exams
Enrollment in SIS	-0.0826	-0.497**	-0.0159	-0.0532	0.000545
	(0.154)	(0.242)	(0.0404)	(0.0361)	(0.0117)
Age	5.58e-05	-0.00177	0.000183	-0.000207	1.10e-05
	(0.00113)	(0.00174)	(0.000293)	(0.000262)	(8.28e-05)
Sex (male)	0.0230***	0.0514***	0.00394***	0.00384***	0.000570
	(0.00383)	(0.00554)	(0.00145)	(0.000984)	(0.000352)
Preschool (no school)	0.0185*	0.00993	-0.000134	-0.00107	-0.000551
	(0.0103)	(0.0156)	(0.00368)	(0.00315)	(0.000771)
Primary (no school)	0.0165	-0.0108	-0.00295	-0.00490	-0.000419
	(0.0148)	(0.0220)	(0.00495)	(0.00418)	(0.00123)
Secondary (no school)	0.00202	-0.0605	-0.00874	-0.00916	-0.000530
	(0.0272)	(0.0399)	(0.00780)	(0.00686)	(0.00203)
Post-secondary (no school)	-0.0151	-0.0874**	-0.00718	-0.0101	0.000201
	(0.0280)	(0.0414)	(0.00841)	(0.00682)	(0.00223)
Reads & writes	-0.0136	-0.00532	0.00474	0.00301	0.000369
	(0.00846)	(0.0131)	(0.00323)	(0.00258)	(0.000718)
Speaks indigenous language	0.0130	-0.0252*	0.00125	-0.000223	-0.000462
	(0.00827)	(0.0133)	(0.00318)	(0.00222)	(0.000731)
Household members	0.000826	0.000685	0.00110***	0.000380	3.83e-05
	(0.000981)	(0.00164)	(0.000380)	(0.000252)	(6.64e-05)
Sex of HH head (male)	-0.000626	-0.00999	-0.00207	-0.00215	-0.000224
	(0.00606)	(0.00943)	(0.00227)	(0.00172)	(0.000339)
Poor (non-poor)	-0.0487***	-0.0453***	-0.0150***	-0.00704***	-0.000847
	(0.00622)	(0.0103)	(0.00232)	(0.00163)	(0.000532)
Extremely poor (non-poor)	-0.101***	-0.131***	-0.0205***	-0.0100***	-0.00127**
	(0.00759)	(0.0144)	(0.00260)	(0.00180)	(0.000512)
Urbanicity (urban)	-0.0400***	-0.0584***	-0.00255	0.00139	-3.33e-05
	(0.0109)	(0.0178)	(0.00292)	(0.00263)	(0.000911)
Central Coast (Northern Coast)	-0.0314**	-0.0897***	-0.00551	-0.00467**	-0.00138*
	(0.0127)	(0.0211)	(0.00354)	(0.00206)	(0.000736)
Southern Coast (NC)	-0.0258*	-0.0966***	-0.00427	-0.00164	-7.09e-05
	(0.0141)	(0.0184)	(0.00411)	(0.00272)	(0.000949)
Northern Highlands (NC)	0.00339	-0.0369*	-0.00825**	-0.00242	-0.00144*
	(0.0125)	(0.0202)	(0.00365)	(0.00268)	(0.000797)
Central Highlands (NC)	-0.0264***	-0.0608***	-0.0101***	-0.00115	-0.000768
	(0.00948)	(0.0134)	(0.00271)	(0.00174)	(0.000699)
Southern Highlands (NC)	-0.0226**	-0.0516***	-0.00892**	0.00284	-0.000813
	(0.0106)	(0.0164)	(0.00353)	(0.00262)	(0.000926)
Rainforest (NC)	-0.0262***	-0.0244*	-0.00467*	-0.000222	-0.000776
	(0.00979)	(0.0144)	(0.00264)	(0.00166)	(0.000669)
Metropolitan Lima (NC)	-0.0526***	-0.117***	0.00210	0.000458	-0.00101
	(0.0104)	(0.0154)	(0.00380)	(0.00223)	(0.000724)

Constant	0.187***	0.529***	0.0211	0.0261*	0.00158
	(0.0683)	(0.106)	(0.0179)	(0.0156)	(0.00471)
Observations	64,064	63,280	64,114	64,114	64,118
R-squared	0.030	-0.051	0.009	-0.034	0.001

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table B.6: Instrumental Variables Estimates of Healthcare Expenditures (Binary), Services Used in the Last Three Months (Part I), 2005, Second Stage

	Dental	Eyes	Glasses
Enrollment in SIS	-0.210**	-0.0548	-0.107**
	(0.0957)	(0.0442)	(0.0481)
Age	-0.00125*	-2.78e-05	-0.000427
	(0.000703)	(0.000333)	(0.000347)
Sex (male)	0.00556**	-0.00183	0.00115
	(0.00256)	(0.00175)	(0.00140)
Preschool (no school)	0.00310	0.00554*	0.00262
	(0.00627)	(0.00312)	(0.00327)
Primary (no school)	0.00415	0.00285	-0.000622
	(0.00902)	(0.00478)	(0.00483)
Secondary (no school)	0.00536	0.00522	-0.00443
	(0.0169)	(0.00846)	(0.00862)
Post-secondary (no school)	0.0534***	0.0243***	0.00945
	(0.0186)	(0.00924)	(0.00889)
Reads & writes	0.0121**	0.00359	0.00449
	(0.00503)	(0.00257)	(0.00280)
Speaks indigenous language	-0.00657	-0.00641**	-0.0118***
	(0.00621)	(0.00298)	(0.00331)
Household members	-0.000372	-3.31e-05	-0.000315
	(0.000703)	(0.000370)	(0.000320)
Sex of HH head (male)	0.00635	0.00456*	0.000511
	(0.00566)	(0.00261)	(0.00292)
Poor (non-poor)	-0.0418***	-0.0118***	-0.0116***
	(0.00485)	(0.00237)	(0.00192)
Extremely poor (non-poor)	-0.0520***	-0.0104***	-0.00805***
	(0.00568)	(0.00246)	(0.00241)
Urbanicity (urban)	0.00421	-0.00159	0.00273
	(0.00699)	(0.00313)	(0.00342)
Central Coast (Northern Coast)	-0.0185**	-0.00508	-0.00528
	(0.00840)	(0.00324)	(0.00330)
Southern Coast (Northern Coast)	-0.00524	-0.000215	-0.00335
	(0.00691)	(0.00425)	(0.00309)
Northern Highlands (Northern Coast)	0.00375	-0.00719**	-0.00887***
	(0.00829)	(0.00316)	(0.00343)
Central Highlands (Northern Coast)	0.0115*	-0.000209	0.00215
	(0.00654)	(0.00280)	(0.00286)
Southern Highlands (Northern Coast)	0.0287***	0.00511	0.00922**
	(0.00804)	(0.00404)	(0.00437)
Rainforest (Northern Coast)	0.0112*	-0.00151	0.00175
	(0.00630)	(0.00270)	(0.00280)
Metropolitan Lima (Northern Coast)	0.00999	0.00629	0.00120
	(0.00819)	(0.00383)	(0.00365)
Constant	0.127***	0.0254	0.0467**
	(0.0424)	(0.0199)	(0.0209)

Observations	64,065	64,096	64,108
R-squared	-0.031	-0.001	-0.083

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table B.7: Instrumental Variables Estimates of Healthcare Expenditures (Binary), Services Used in the Last Three Months, 2005, Second Stage

	Immunization	Child's checkup	Birth control	Other
Enrollment in SIS	-0.101**	-0.114***	1.211	0.223
	(0.0438)	(0.0353)	(1.582)	(0.152)
Age	-0.000836***	-0.00747***	0.00499	0.00275**
	(0.000318)	(0.00109)	(0.00668)	(0.00112)
Sex (male)	0.00106	-0.00373	-0.0257	0.0188***
	(0.00133)	(0.00291)	(0.0294)	(0.00325)
Preschool (no school)	-0.00429*	-0.00557	0.0206	0.0260***
	(0.00243)	(0.00507)	(0.0289)	(0.00980)
Primary (no school)	-0.00694*	-0.00110	0.0375	0.0387***
	(0.00387)	(0.00560)	(0.0488)	(0.0147)
Secondary (no school)	-0.0142*	-0.0111	0.0995	0.0642**
	(0.00730)	(0.00692)	(0.121)	(0.0272)
Post-secondary (no school)	-0.00177	-0.00117	0.101	0.0847***
	(0.00855)	(0.0142)	(0.111)	(0.0294)
Reads & writes	0.00174	0.00834*	-0.0245	0.000317
	(0.00188)	(0.00438)	(0.0309)	(0.00711)
Speaks indigenous language	-0.00601**	0.0106***	0.0105	0.00342
	(0.00288)	(0.00372)	(0.0206)	(0.00777)
Household members	-0.000365	-0.00182***	-0.00149	-0.000665
	(0.000300)	(0.000643)	(0.00214)	(0.000859)
Sex of HH head (male)	-0.000837	-0.0157***	-0.000400	0.0111**
	(0.00195)	(0.00431)	(0.00989)	(0.00567)
Poor (non-poor)	-0.00681***	-0.00314	-0.0201*	-0.0392***
	(0.00167)	(0.00661)	(0.0108)	(0.00596)
Extremely poor (non-poor)	-0.00514**	-0.00880	-0.0133*	-0.0517***
	(0.00219)	(0.00631)	(0.00794)	(0.00745)
Urbanicity (urban)	0.00294	0.0133*	-0.0245	-0.0200*
	(0.00330)	(0.00707)	(0.0220)	(0.0116)
Central Coast (Northern Coast)	-0.00419	-0.0100	0.0153	-0.0790***
	(0.00263)	(0.00744)	(0.0256)	(0.0125)
Southern Coast (Northern Coast)	0.0109	-0.0111*	0.00200	-0.0977***
	(0.00726)	(0.00601)	(0.0147)	(0.0109)
Northern Highlands (Northern Coast)	-0.00355	-0.00515	0.0160	-0.00387
	(0.00353)	(0.00616)	(0.0307)	(0.0132)
Central Highlands (Northern Coast)	0.00328	0.000886	0.00482	-0.0786***
	(0.00247)	(0.00551)	(0.0127)	(0.0101)
Southern Highlands (Northern Coast)	0.00906**	0.00813	-0.00818	-0.0506***
	(0.00359)	(0.00702)	(0.0170)	(0.0121)
Rainforest (Northern Coast)	0.00149	0.00276	0.000492	-0.0440***
	(0.00211)	(0.00529)	(0.0103)	(0.0130)
Metropolitan Lima (Northern Coast)	0.000671	0.00565	-0.000924	-0.0450***
	(0.00215)	(0.00953)	(0.0134)	(0.0125)

Constant	0.0574***	0.115***	-0.195	-0.0297
	(0.0192)	(0.0208)	(0.298)	(0.0687)
Observations	63,811	15,324	31,146	64,045
R-squared	-0.140	-0.117	-4.153	-0.055

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table B.8: Instrumental Variables Estimates of Healthcare Expenditures (Binary), Services Used in the Last Twelve Months, 2005, Second Stage

	Hospitalization	Pregnancy's checkup	Birth
Enrollment in SIS	-0.0782	0.204	0.0571
	(0.0571)	(0.808)	(0.782)
Age	-0.000260	0.00153	0.000572
	(0.000414)	(0.00594)	(0.00578)
Sex (male)	0.0136***		
	(0.00212)		
Preschool (no school)	0.00281	0.0171	0.000104
	(0.00429)	(0.0194)	(0.0205)
Primary (no school)	0.000895	0.0107	0.000459
	(0.00619)	(0.0224)	(0.0226)
Secondary (no school)	-0.00339	0.0264	0.00917
	(0.00996)	(0.0674)	(0.0657)
Post-secondary (no school)	-0.00546	0.0274	0.00870
	(0.0105)	(0.0618)	(0.0606)
Reads & writes	0.00419	-0.00421	0.000658
	(0.00422)	(0.00999)	(0.00933)
Speaks indigenous language	-0.00494	-0.00307	0.00576
	(0.00351)	(0.0110)	(0.0107)
Household members	0.00186***	0.00162	0.00424***
	(0.000528)	(0.00121)	(0.00128)
Sex of HH head (male)	0.000985	-0.0111	-0.00380
	(0.00341)	(0.00777)	(0.00689)
Poor (non-poor)	-0.0103***	-0.00883	0.00213
	(0.00295)	(0.0131)	(0.0122)
Extremely poor (non-poor)	-0.0173***	-0.00681	0.00504
	(0.00349)	(0.00525)	(0.00539)
Urbanicity (urban)	-0.000320	-0.0192	-0.00136
	(0.00469)	(0.0324)	(0.0312)
Central Coast (Northern Coast)	-0.00162	-0.000412	-0.0104
	(0.00456)	(0.0260)	(0.0243)
Southern Coast (Northern Coast)	-0.00308	-0.0115	-0.0220**
	(0.00505)	(0.00983)	(0.00882)
Northern Highlands (Northern Coast)	-0.0133***	-0.00685	0.00642
	(0.00455)	(0.0270)	(0.0258)
Central Highlands (Northern Coast)	-0.00973***	-0.00953	-0.0164**
	(0.00347)	(0.00750)	(0.00768)
Southern Highlands (Northern Coast)	-0.00193	-0.0157	-0.0265
	(0.00431)	(0.0177)	(0.0170)
Rainforest (Northern Coast)	0.00173	-0.0139	-0.00526
	(0.00352)	(0.0118)	(0.0123)
Metropolitan Lima (Northern Coast)	-0.000947	0.00308	-0.0205**
	(0.00392)	(0.0110)	(0.00938)

Constant	0.0389	-0.0478	-0.0176
	(0.0246)	(0.260)	(0.251)
Observations	64,084	17,736	17,728
R-squared	-0.015	-0.173	-0.004

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2005 ENAHO

Table B.9: Instrumental Variables Estimates of Households' Enrollment in SIS, 2005, First Stage (Table 3.4)

	Household Member Enrolled in SIS
Enrollment goal	0.21627***
	(0.06395)
Age	-0.00588***
	(0.00032)
Sex (male)	0.01507
	(0.01033)
Preschool (no school)	-0.00596
	(0.02132)
Primary (no school)	0.00983
	(0.02565)
Secondary (no school)	-0.03133
	(0.02574)
Post-secondary (no school)	-0.09365***
	(0.02846)
Reads & writes	0.02328
	(0.02032)
Speaks indigenous language	-0.00837
	(0.01421)
Household members	0.06760***
	(0.00222)
Poor (non-poor)	0.09870***
	(0.01242)
Extremely poor (non-poor)	0.11835***
	(0.01673)
Urbanicity (urban)	0.10614***
	(0.01348)
Central Coast (Northern Coast)	-0.04016
	(0.03025)
Southern Coast (Northern Coast)	-0.01029
	(0.02905)
Northern Highlands (Northern Coast)	-0.08324***
	(0.02785)
Central Highlands (Northern Coast)	-0.03981*
	(0.02414)
Southern Highlands (Northern Coast)	-0.03667
	(0.02478)
Rainforest (Northern Coast)	0.00153
	(0.02385)
Metropolitan Lima (Northern Coast)	-0.06771***
	(0.02594)
Constant	0.19615***
	(0.04105)

Observations	15,445
F test for excluded instruments	
F test	11.44
P-value	0.0008
Sanderson-Windmeijer multivariateChi-squared test of underidentification:	
SW Chi-square test	11.46
P-value	0.0007

Demographic variables refer to the household's head, unless otherwise explicitly defined
Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Table B.10: Instrumental Variables Estimates of Catastrophic Healthcare Expenditures, 2005, Second Stage (Table 3.4)

	Low (>0.1)	Medium (>0.2)	High (>0.3)	Critical (>0.4)
HH Member Enrolled in SIS	-0.758**	-0.557*	-0.294	-0.332
	(0.370)	(0.327)	(0.276)	(0.261)
Age	-0.00340	-0.00179	0.000101	-4.92e-05
	(0.00228)	(0.00202)	(0.00171)	(0.00162)
Sex (male)	0.0113	0.00286	-0.00845	-0.0218
	(0.0194)	(0.0188)	(0.0168)	(0.0149)
Preschool (no school)	0.0727**	0.0606**	0.0561**	0.0418*
	(0.0289)	(0.0267)	(0.0247)	(0.0243)
Primary (no school)	0.0749**	0.0520	0.0392	0.0182
	(0.0348)	(0.0321)	(0.0303)	(0.0293)
Secondary (no school)	0.0694*	0.0519	0.0487	0.0139
	(0.0392)	(0.0377)	(0.0347)	(0.0339)
Post-secondary (no school)	0.0346	0.0167	0.0285	0.00145
	(0.0553)	(0.0531)	(0.0496)	(0.0480)
Reads & writes	-0.00403	0.00385	0.00163	0.0129
	(0.0281)	(0.0261)	(0.0236)	(0.0226)
Speaks indigenous language	-0.0166	-0.00336	-0.00194	-0.00148
	(0.0195)	(0.0178)	(0.0157)	(0.0140)
Household members	0.101***	0.0779***	0.0525***	0.0501***
	(0.0248)	(0.0221)	(0.0188)	(0.0177)
Poor (non-poor)	-0.00578	-0.0298	-0.0509	-0.0443
	(0.0409)	(0.0369)	(0.0317)	(0.0303)
Extremely poor (non-poor)	-0.159***	-0.154***	-0.157***	-0.124***
	(0.0514)	(0.0454)	(0.0389)	(0.0373)
Urbanicity (urban)	-0.0160	-0.00497	-0.00780	0.00903
	(0.0442)	(0.0375)	(0.0326)	(0.0306)
Central Coast (Northern Coast)	-0.119***	-0.122***	-0.0900***	-0.0860***
	(0.0399)	(0.0344)	(0.0287)	(0.0311)
Southern Coast (Northern Coast)	-0.150***	-0.133***	-0.105**	-0.105***
	(0.0378)	(0.0402)	(0.0421)	(0.0394)
Northern Highlands (Northern Coast)	0.0166	0.0317	0.0426	0.0265
	(0.0387)	(0.0339)	(0.0333)	(0.0308)
Central Highlands (Northern Coast)	-0.0740***	-0.0748***	-0.0716***	-0.0677***
	(0.0264)	(0.0238)	(0.0226)	(0.0223)
Southern Highlands (Northern Coast)	-0.0682**	-0.0766***	-0.0769***	-0.0833***
	(0.0281)	(0.0268)	(0.0249)	(0.0238)
Rainforest (Northern Coast)	0.0141	0.0310	0.0258	0.0254
	(0.0271)	(0.0245)	(0.0233)	(0.0240)
Metropolitan Lima (Northern Coast)	-0.166***	-0.152***	-0.120***	-0.121***
	(0.0459)	(0.0417)	(0.0371)	(0.0362)
Constant	0.574***	0.425***	0.286***	0.264***
	(0.113)	(0.102)	(0.0886)	(0.0842)

Observations	15,445	15,445	15,445	15,445
R-squared	-0.253	-0.128	-0.010	-0.037

Demograohic variables refer to the household's head, unless otherwise explicitly defined
Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2005 ENAHO

Appendix C

Estimates of the Effect of SIS on Children's Health

Table C.1: Instrumental Variables Estimates of Enrollment in SIS among Children under Five Years of Age, 2004-2005, First Stage (Table 4.2)

	Enrollment in SIS
Enrollment goals	0.367020***
	(0.11017)
Age	-0.109445***
	(0.00699)
Sex (male)	-0.023047
	(0.01874)
Mother's Education: Primary (no school)	0.023551
	(0.03840)
Mother's Education: Secondary (no school)	0.017832
	(0.01502)
Mother's Education: Some College (no school)	0.015022
	(0.05512)
Mother's Education: College Graduate (no school)	-0.058722
	(0.06625)
Mother Employed	0.062285***
	(0.02186)
Mother is Head's Wife (HH head)	-0.077942
	(0.06418)
Mother is Head's Relative (HH head)	-0.009964
	(0.05697)
Mother is Head's Non-Relative (HH head)	0.213794
	(0.13340)
HH Head's Sex (male)	-0.063365
	(0.04937)
HH Wealth: Poorer (poorest)	0.036751
	(0.02601)
HH Wealth: Middle (poorest)	-0.020614
	(0.04204)
HH Wealth: Richer (poorest)	-0.032500
	(0.04640)
HH Wealth: Richest (poorest)	-0.178604***
	(0.06571)
Cluster Altitude in meters	-0.000039*
	(0.00002)
Coast (Metropolitan Lima)	0.144599**
	(0.06070)
Highlands (ML)	0.181274**
	(0.08067)
High Rainforest (ML)	0.086735
	(0.07107)
Low Rainforest (ML)	0.035129
	(0.06965)
Small city (capital, large city)	-0.069828*
	(0.04148)

Town (capital, large city)	0.017476
	(0.04570)
Constant	0.547849***
	(0.09269)
Observations	3,940
F test for excluded instruments	
F test	11.1
P-value	0.0009
Sanderson-Windmeijer multivariate Chi-squared test of underidentification:	
SW Chi-square test	11.19
P-value	0.0008

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2004-2005 Demographic and Health Survey-Peru

Table C.2: Instrumental Variables Estimates of Health Events and Symptoms among Children under Five Years of Age, 2004-2005, Second Stage (Table 4.2)

	Diarrhea	Bloody Stools	Fever	Cough	Rapid Breathing
Enrollment in SIS	0.0673	-0.0702	0.313	0.0539	0.257
	(0.225)	(0.103)	(0.340)	(0.326)	(0.242)
Age	-0.0263	-0.0108	0.0123	-0.00933	0.0181
	(0.0254)	(0.0119)	(0.0378)	(0.0364)	(0.0264)
Sex (male)	-0.0268*	-0.00746	0.00562	-0.0236	0.00731
	(0.0145)	(0.00527)	(0.0194)	(0.0211)	(0.0165)
Mother Has Primary (no school)	0.0283	0.0182***	0.0215	0.0374	0.0482
	(0.0248)	(0.00698)	(0.0440)	(0.0483)	(0.0335)
Mother Has Secondary (NS)	0.0376	0.00792	0.000959	0.0457	0.0320
	(0.0282)	(0.00613)	(0.0475)	(0.0506)	(0.0364)
Mother Has Some College (NS)	0.00124	0.0211	-0.0276	0.0450	-0.0246
	(0.0392)	(0.0132)	(0.0587)	(0.0683)	(0.0449)
Mother Has College Graduate (NS)	-0.0165	-0.000175	-0.0184	-0.0496	0.00262
	(0.0491)	(0.0100)	(0.0729)	(0.0749)	(0.0568)
Mother Employed	-0.000505	0.0131*	0.0104	0.0280	0.00457
	(0.0221)	(0.00765)	(0.0299)	(0.0310)	(0.0235)
Mother is Head's Wife	-0.0905	0.0165	0.0345	-0.0994	-0.0819
	(0.0580)	(0.0177)	(0.0660)	(0.0719)	(0.0578)
Mother is Head's Relative	-0.0532	0.0267	0.0116	-0.0504	-0.0691
	(0.0534)	(0.0163)	(0.0600)	(0.0616)	(0.0498)
Mother is Head's Non-Relative	0.0459	0.0116	0.00671	-0.00343	-0.0546
	(0.135)	(0.0294)	(0.189)	(0.187)	(0.180)
HH Head's Sex (male)	-0.0430	0.0151	0.0285	-0.0418	-0.0393
	(0.0358)	(0.0153)	(0.0495)	(0.0509)	(0.0366)
HH Wealth: Poorer (poorest)	-0.0168	-0.00203	0.0334	0.0159	-0.00596
	(0.0195)	(0.00897)	(0.0322)	(0.0350)	(0.0265)
HH Wealth: Middle (poorest)	-0.0668***	-0.0105	0.00829	-0.0418	-0.0126
	(0.0249)	(0.00818)	(0.0399)	(0.0398)	(0.0320)
HH Wealth: Richer (poorest)	-0.0588	-0.0130	0.0339	-0.0552	-0.0181
	(0.0395)	(0.00958)	(0.0474)	(0.0521)	(0.0390)
HH Wealth: Richest (poorest)	-0.0772	-0.0319	0.0479	-0.134	0.0351
	(0.0645)	(0.0209)	(0.0865)	(0.0885)	(0.0735)
Cluster Altitude in meters	-2.57e-05*	-4.71e-06	-9.66e-06	-4.21e-05*	8.54e-06
	(1.44e-05)	(5.97e-06)	(2.36e-05)	(2.27e-05)	(1.62e-05)
Coast (Metropolitan Lima)	-0.0585	0.00169	-0.0627	-0.0955	-0.0716
	(0.0586)	(0.0234)	(0.0855)	(0.0842)	(0.0609)
Highlands (ML)	0.0267	0.0193	0.00981	-0.0183	-0.0474
	(0.0746)	(0.0354)	(0.119)	(0.115)	(0.0774)
High Rainforest (ML)	0.0712	0.0306	0.0130	-0.0335	-0.0214
	(0.0736)	(0.0273)	(0.0917)	(0.0917)	(0.0696)
Low Rainforest (ML)	0.0236	0.0251	0.0799	-0.0580	0.0336
	(0.0547)	(0.0207)	(0.0746)	(0.0785)	(0.0545)

Small city (capital, large city)	0.0295	-0.00755	-0.0194	0.0307	0.0124
	(0.0265)	(0.0103)	(0.0450)	(0.0486)	(0.0328)
Town (capital, large city)	0.0321	-0.00453	-0.00514	0.0212	-0.0385
	(0.0356)	(0.00618)	(0.0377)	(0.0412)	(0.0305)
Constant	0.302*	0.0365	0.0303	0.548**	0.0878
	(0.163)	(0.0657)	(0.231)	(0.220)	(0.170)
Observations	3,940	3,940	3,940	3,940	3,940
R-squared	0.045	-0.056	-0.037	0.024	-0.033

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the2004-2005 Demographic and Health Survey - Peru

Table C.3: Instrumental Variables Estimates of Enrollment in SIS among Children under Two Years of Age, 2004-2005, First Stage

	Enrollment in SIS
Enrollment goals	0.4123274**
	(0.16373)
Age	-0.097249***
	(0.03087)
Sex (male)	-0.014805
	(0.02683)
Mother's Education: Primary (no school)	0.1398252**
	(0.05613)
Mother's Education: Secondary (no school)	0.094891
	(0.07289)
Mother's Education: Some College (no school)	0.072892
	(0.08942)
Mother's Education: College Graduate (no school)	0.000304
	(0.11068)
Mother Employed	0.053103
	(0.03341)
Mother is Head's Wife (HH head)	-0.057583
	(0.09787)
Mother is Head's Relative (HH head)	0.013618
	(0.08811)
Mother is Head's Non-Relative (HH head)	0.2874218*
	(0.16203)
HH Head's Sex (male)	-0.063008
	(0.06939)
HH Wealth: Poorer (poorest)	-0.017548
	(0.03849)
HH Wealth: Middle (poorest)	-0.184008***
	(0.06580)
HH Wealth: Richer (poorest)	-0.1958748**
	(0.07874)
HH Wealth: Richest (poorest)	-0.4412666***
	(0.10293)
Cluster Altitude in meters	-0.0000558*
	(0.00003)
Coast (Metropolitan Lima)	0.046499
	(0.10155)
Highlands (ML)	0.137988
	(0.12549)
High Rainforest (ML)	0.014957
	(0.10848)
Low Rainforest (ML)	-0.104902
	(0.11069)
Small city (capital, large city	-0.018475
	(0.06111)

Town (capital, large city	0.048874
	(0.06870)
Constant	0.5878663***
	(0.13251)
Observations	1,631
F test for excluded instruments	
F test	6.34
P-value	0.0121
Sanderson-Windmeijer multivariateChi-squared test of underidentification:	
SW Chi-square test	6.45
P-value	0.0111

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Authors analysis of the 2004-2005 Demographic and Health Survey - Peru

Table C.4: Instrumental Variables Estimates of Health Events and Symptoms among Children under Two Years of Age, 2004-2005, Second Stage

	Diarrhea	Bloody Stools	Fever	Cough	Rapid Breath
Enrollment in SIS	0.500	-0.306	0.650	0.320	0.366
	(0.399)	(0.221)	(0.557)	(0.434)	(0.328)
Age	0.165***	-0.0101	0.147**	0.122**	0.118***
	(0.0490)	(0.0223)	(0.0632)	(0.0544)	(0.0397)
Sex (male)	-0.0319	-0.0159	0.0469	0.0241	0.0479*
	(0.0251)	(0.0127)	(0.0336)	(0.0312)	(0.0271)
Mother Has Primary (no school)	-0.00629	0.0568	-0.0316	-0.0162	0.0172
	(0.0687)	(0.0389)	(0.0976)	(0.0916)	(0.0692)
Mother Has Secondary (NS)	0.00441	0.0288	-0.0882	-0.0280	-0.0488
	(0.0569)	(0.0285)	(0.0869)	(0.0802)	(0.0647)
Mother Has Some College (NS)	0.0191	0.0451	-0.0927	-0.00838	-0.0632
	(0.0783)	(0.0442)	(0.105)	(0.101)	(0.0766)
Mother Has College Graduate (NS)	0.0175	-0.0130	-0.0503	-0.0769	-0.0404
	(0.0872)	(0.0350)	(0.113)	(0.125)	(0.0862)
Mother Employed	-0.0279	0.0323*	-0.0294	-0.00286	-0.0265
	(0.0373)	(0.0191)	(0.0486)	(0.0454)	(0.0345)
Mother is Head's Wife	6.74e-05	0.00965	0.128	0.0777	-0.0525
	(0.107)	(0.0453)	(0.113)	(0.103)	(0.0861)
Mother is Head's Relative	0.0416	0.0413	0.0992	0.0952	-0.0310
	(0.103)	(0.0435)	(0.106)	(0.0951)	(0.0834)
Mother is Head's Non-Relative	0.0344	0.0867	-0.0111	-0.0565	-0.103
	(0.238)	(0.0901)	(0.255)	(0.252)	(0.190)
HH Head's Sex (male)	0.0115	0.00447	0.113	0.124*	0.0223
	(0.0712)	(0.0330)	(0.0832)	(0.0725)	(0.0548)
HH Wealth: Poorer (poorest)	0.0219	-0.00995	0.0677	0.0176	0.0339
	(0.0393)	(0.0162)	(0.0535)	(0.0417)	(0.0365)
HH Wealth: Middle (poorest)	-0.0191	-0.0611	0.117	0.0325	0.111
	(0.0948)	(0.0478)	(0.126)	(0.0939)	(0.0771)
HH Wealth: Richer (poorest)	0.0253	-0.0815	0.159	-0.00927	0.105
	(0.115)	(0.0501)	(0.143)	(0.111)	(0.0901)
HH Wealth: Richest (poorest)	0.0461	-0.166*	0.230	0.0573	0.162
	(0.208)	(0.100)	(0.269)	(0.208)	(0.160)
Cluster Altitude in meters	-1.28e-05	-2.07e-05	1.39e-05	-6.64e-05*	-4.69e-06
	(3.21e-05)	(1.51e-05)	(4.36e-05)	(3.53e-05)	(2.67e-05)
Coast (Metropolitan Lima)	-0.161	0.00142	-0.109	-0.0725	-0.0553
	(0.0994)	(0.0411)	(0.113)	(0.104)	(0.0796)
Highlands (ML)	-0.0940	0.0640	-0.0807	0.0698	0.0491
	(0.142)	(0.0716)	(0.181)	(0.157)	(0.109)
High Rainforest (ML)	0.0311	0.0440	-0.0337	0.0258	0.0480
	(0.118)	(0.0513)	(0.130)	(0.120)	(0.0917)
Low Rainforest (ML)	0.00980	0.0137	0.0720	-0.0151	0.104
	(0.0954)	(0.0370)	(0.0960)	(0.0992)	(0.0782)

Small city (capital, large city	0.0493	-0.00829	0.0326	0.0156	-0.0249
	(0.0542)	(0.0222)	(0.0673)	(0.0577)	(0.0465)
Town (capital, large city	0.0336	0.000442	0.0564	0.0793	-0.0471
	(0.0581)	(0.0250)	(0.0616)	(0.0600)	(0.0599)
Constant	-0.115	0.198	-0.352	0.131	-0.112
	(0.299)	(0.147)	(0.405)	(0.303)	(0.239)
Observations	1,631	1,631	1,631	1,631	1,631
R-squared	-0.171	-0.909	-0.316	-0.044	-0.090

Reference group in parentheses for categorical variables
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Author’s analysis of the 2004-2005 Demographic and Health Survey - Peru

Table C.5: Performance of Matching Methods and Bandwidths

Matching Method	Treatment Observations Off Common Support	Variables Not Statistically Different after Matching		
		<0.1	<0.2	<0.3
Nearest Neighbor				
5.0% bandwidth	7	2	3	4
2.5% bandwidth	7	2	3	4
1.0% bandwidth	11	2	2	5
Nearest 3 Neighbors				
5.0% bandwidth	7	1	2	4
2.5% bandwidth	7	1	2	6
1.0% bandwidth	11	1	2	4
Kernel-Epanechnikov				
5.0% bandwidth	7	0	0	0
2.5% bandwidth	7	0	1	1
1.0% bandwidth	11	1	2	2
Kernel Quartic				
5.0% bandwidth	7	0	0	0
2.5% bandwidth	7	0	1	1
1.0% bandwidth	11	1	2	2

Note: Robust standard errors estimated clustered at sampling site level.
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.6: SIS' Estimated Effect on Height-for-age Z-score, 2002-2006

Matching method		**NN**	**NN**	**NN**	**NN**	**NN**	**NN**
	No	**1**	**1**	**1**	**3**	**3**	**3**
Caliper/Bandwidth	**PSM**	**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.021	-0.024	-0.024	-3.2E-6	0.089	0.073	0.046
	(0.093)	(0.141)	(0.141)	(0.150)	(0.125)	(0.126)	(0.148)
Observations	523	263	263	258	371	370	362
+ Age interaction	0.034	0.0028	0.0028	0.023	0.122	0.108	0.078
	(0.074)	(0.118)	(0.118)	(0.126)	(0.106)	(0.107)	(0.124)
Observations	523	263	263	258	371	370	362

Matching method	**No**	**Kernel**	**Kernel**	**Kernel**	**Kernel**	**Kernel**	**Kernel**
	PSM	**Epa**	**Epa**	**Epa**	**Quartic**	**Quartic**	**Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.021	0.027	0.001	0.020	0.029	-0.002	0.028
	(0.093)	(0.109)	(0.118)	(0.145)	(0.109)	(0.122)	(0.146)
Observations	523	514	512	490	514	512	490
+ Age interaction	0.0341	0.072	0.044	0.046	0.071	0.039	0.054
	(0.074)	(0.094)	(0.100)	(0.122)	(0.094)	(0.103)	(0.122)
Observations	523	514	512	490	514	512	490

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.7: SIS' Estimated Effect on Stunting (height-for-age z-score < -2), 2002-2006

Matching method **Caliper/Bandwidth**	**No PSM**	**NN 1 5.0%**	**NN 1 2.5%**	**NN 1 1.0%**	**NN 3 5.0%**	**NN 3 2.5%**	**NN 3 1.0%**
Base specification	0.014	0.044	0.044	0.039	-0.001	0.005	0.034
	(0.049)	(0.055)	(0.055)	(0.056)	(0.057)	(0.058)	(0.062)
Observations	523	265	265	258	378	382	375
+ Age interaction	0.013	0.040	0.040	0.035	-0.006	0.000	0.028
	(0.049)	(0.054)	(0.054)	(0.055)	(0.058)	(0.059)	(0.061)
Observations	523	263	263	258	371	370	362
Matching method **Caliper/Bandwidth**	**No PSM**	**Kernel Epa 5.0%**	**Kernel Epa 2.5%**	**Kernel Epa 1.0%**	**Kernel Quartic 5.0%**	**Kernel Quartic 2.5%**	**Kernel Quartic 1.0%**
Base specification	0.015	0.014	0.036	0.049	0.016	0.041	0.045
	(0.049)	(0.059)	(0.059)	(0.064)	(0.059)	(0.059)	(0.063)
Observations	523	514	512	490	514	512	490
+ Age interaction	0.013	0.009	0.030	0.045	0.010	0.034	0.041
	(0.049)	(0.059)	(0.059)	(0.063)	(0.059)	(0.059)	(0.062)
Observations	523	514	512	490	514	512	490

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.8: SIS' Estimated Effect on Body Mass Index-for-age Z-score, 2002-2006

Matching method	**No PSM**	**NN 1**	**NN 1**	**NN 1**	**NN 3**	**NN 3**	**NN 3**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.021	-0.009	-0.009	0.019	-0.088	-0.082	0.017
	(0.122)	(0.149)	(0.149)	(0.146)	(0.116)	(0.115)	(0.127)
Observations	523	263	263	258	371	370	362
+ Age interaction	0.022	-0.011	-0.011	0.017	-0.091	-0.086	0.010
	(0.123)	(0.151)	(0.151)	(0.15)	(0.116)	(0.115)	(0.123)
Observations	523	263	263	258	371	370	362
Matching method	**No PSM**	**Kernel Epa**	**Kernel Epa**	**Kernel Epa**	**Kernel Quartic**	**Kernel Quartic**	**Kernel Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.021	-0.087	-0.063	0.017	-0.087	-0.057	0.025
	(0.122)	(0.121)	(0.124)	(0.135)	(0.120)	(0.128)	(0.133)
Observations	523	514	512	490	514	512	490
+ Age interaction	0.022	-0.087	-0.065	0.014	-0.087	-0.060	0.022
	(0.123)	(0.123)	(0.125)	(0.133)	(0.121)	(0.128)	(0.131)
Observations	523	514	512	490	514	512	490

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.9: SIS' Estimated Effect on Wasting (BMI-for-age Z-score < -2), 2002-2006

Matching method	**No PSM**	**NN 1**	**NN 1**	**NN 1**	**NN 3**	**NN 3**	**NN 3**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	-0.012	-0.013	-0.013	-0.013	-0.011	-0.011	-0.011
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)
Observations	523	263	263	258	371	370	362
+ Age interaction	-0.011	-0.011	-0.011	-0.012	-0.009	-0.009	-0.009
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)
Observations	523	263	263	258	371	370	362
Matching method	**No PSM**	**Kernel Epa**	**Kernel Epa**	**Kernel Epa**	**Kernel Quartic**	**Kernel Quartic**	**Kernel Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	-0.012	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	523	514	512	490	514	512	490
+ Age interaction	-0.011	-0.008	-0.008	-0.0083	-0.008	-0.008	-0.009
	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)	(0.021)
Observations	523	514	512	490	514	512	490

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.10: SIS' Estimated Effect on Obesity (weight-for-age Z-score > 2), 2002-2006

Matching method	**No PSM**	**NN 1**	**NN 1**	**NN 1**	**NN 3**	**NN 3**	**NN 3**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	-0.027	-0.082	-0.082	-0.072	-0.051	-0.051	-0.016
	(0.040)	(0.059)	(0.059)	(0.059)	(0.043)	(0.042)	(0.049)
Observations	523	263	263	258	371	370	362
+ Age interaction	-0.026	-0.082	-0.082	-0.071	-0.050	-0.050	-0.016
	(0.041)	(0.059)	(0.059)	(0.058)	(0.044)	(0.043)	(0.048)
Observations	523	263	263	258	371	370	362
Matching method	**No PSM**	**Kernel Epa**	**Kernel Epa**	**Kernel Epa**	**Kernel Quartic**	**Kernel Quartic**	**Kernel Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	-0.027	-0.050	-0.038	-0.004	-0.049	-0.034	-0.004
	(0.040)	(0.045)	(0.046)	(0.047)	(0.045)	(0.047)	(0.046)
Observations	523	514	512	490	514	512	490
+ Age interaction	-0.026	-0.046	-0.036	-0.003	-0.046	-0.032	-0.003
	(0.041)	(0.046)	(0.047)	(0.047)	(0.046)	(0.048)	(0.046)
Observations	523	514	512	490	514	512	490

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.11. SIS' Estimated Effect on weight-for-age Z-score, 2002-2006

Matching method	**No PSM**	**NN 1**	**NN 1**	**NN 1**	**NN 3**	**NN 3**	**NN 3**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.036	-0.056	-0.056	-0.056	0.027	0.027	0.028
	(0.085)	(0.124)	(0.124)	(0.124)	(0.091)	(0.091)	(0.092)
Observations	524	274	274	274	386	386	382
+ Age interaction	0.044	-0.039	-0.039	-0.039	0.045	0.044	0.050
	(0.080)	(0.122)	(0.122)	(0.12)	(0.085)	(0.085)	(0.087)
Observations	524	274	274	274	386	386	382
Matching method	**No PSM**	**Kernel Epa**	**Kernel Epa**	**Kernel Epa**	**Kernel Quartic**	**Kernel Quartic**	**Kernel Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	0.036	-0.021	-0.013	-0.018	-0.021	-0.015	-0.027
	(0.085)	(0.092)	(0.084)	(0.090)	(0.090)	(0.083)	(0.091)
Observations	524	515	514	502	515	514	502
+ Age interaction	0.044	0.008	0.010	0.005	0.006	0.008	-0.004
	(0.080)	(0.090)	(0.081)	(0.086)	(0.087)	(0.080)	(0.090)
Observations	524	515	514	502	515	514	502

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru

Table C.12: SIS' Estimated Effect on Underweight (weight-for-age Z-score < -2), 2002-2006

Matching method	No PSM	NN 1	NN 1	NN 1	NN 3	NN 3	NN 3
Caliper/Bandwidth		5.0%	2.5%	1.0%	5.0%	2.5%	1.0%
Base specification	-0.05**	-0.08**	-0.08**	-0.08**	-0.06*	-0.06*	-0.05*
	(0.024)	(0.032)	(0.032)	(0.032)	(0.029)	(0.029)	(0.029)
Observations	524	274	274	274	386	386	382
+ Age interaction	-0.05**	-0.08**	-0.08**	-0.08**	-0.06*	-0.06*	-0.06*
	(0.024)	(0.034)	(0.034)	(0.034)	(0.031)	(0.031)	(0.031)
Observations	524	274	274	274	386	386	382
Matching method	**No PSM**	**Kernel Epa**	**Kernel Epa**	**Kernel Epa**	**Kernel Quartic**	**Kernel Quartic**	**Kernel Quartic**
Caliper/Bandwidth		**5.0%**	**2.5%**	**1.0%**	**5.0%**	**2.5%**	**1.0%**
Base specification	-0.05**	-0.06**	-0.06**	-0.06**	-0.06**	-0.06**	-0.06**
	(0.024)	(0.027)	(0.025)	(0.026)	(0.026)	(0.025)	(0.026)
Observations	524	515	514	502	515	514	502
+ Age interaction	-0.05**	-0.06**	-0.06**	-0.06**	-0.06**	-0.06**	-0.06**
	(0.024)	(0.027)	(0.026)	(0.027)	(0.026)	(0.026)	(0.027)
Observations	524	515	514	502	515	514	502

Robust standard errors in parentheses (clustered at sampling site level)
*** p<0.01, ** p<0.05, * p<0.1
Author's analysis of the 2002-2006 Young Lives Study, Peru