The effects of access to health insurance for informally employed individuals in Peru*

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Abstract

In many countries large parts of the population do not have access to health insurance. Peru has made an effort to change this in the early 2000's. Exploiting a regression discontinuity design we study the effects of access to free health insurance on take-up, health care utilization and self-reported health. We find that a substantial fraction of the population signs up and makes use of the services provided. We then provide evidence in favor of two arguments that are less common in economics. First, access to health care centers leads to increased awareness about health problems; and second, this even generates a willingness to pay for services that are not covered, which in the context of Peru is a potentially desirable form of supplier-induced demand.

Key words: Public health insurance, informal sector, health care utilization, regression discontinuity design, supplier-induced demand.

JEL-classification: I13, O12, O17.

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1 Introduction

In developing countries, a large number of individuals is not covered by health insurance (Banerjee et al., 2004; Banerjee and Duflo, 2007). The reasons for this are manifold. On the one hand, individuals are often used to relying on informal forms of risk-sharing instead of being covered by formal health insurance and therefore do not demand insurance.[1] On the other hand, in the past it has not been seen as the role of the government to provide health insurance. Moreover, the World Health Organization and the World Bank stress that even when there is public health insurance then it often does not reach large parts of the population and especially not the poorest families because it is only provided to the minority of employees in the formal sector (WHO, 2010; Hsiao and Shaw, 2007). For instance, until the early 2000's, less than 20 percent of the individuals in Peru had health insurance.

This may be a cause of concern, because health insurance does not only protect individuals against catastrophically high health expenditures (Wagstaff and Doorslaer, 2003). It also encourages them to see a doctor instead of simply buying medication, and thereby promotes appropriate treatment of illnesses that is often argued to be absent (Commission on Macroeconomics and Health, 2001; International Labour Office et al., 2006).

In reaction, many low and middle income countries have recently introduced Social Health Insurance (SHI) targeted to the poor, with the goal to improve their health and to provide them with financial protection against the financial consequences of health shocks. Typically, coverage by SHI may or may not be free and implies that individuals receive medical attention from a service provider. The costs are usually paid out of a designated government budget that is completely or partially funded by taxes.

However, to date, it is not well understood through which channels health insurance coverage contributes to the well-being of individuals and how this relates to the incentives provided to health care providers and patients.[2] Important questions in this context are to what extent it is possible to encourage individuals to invest into preventive care and to seek medical attention rather than simply buying medication, and what the effects of preventive care and medical attention are on health outcomes.

One reason why we lack a deeper understanding is because it is challenging to quantify the effects of insurance coverage at the individual level. There are two main reasons for this. First, we lack detailed data on health care utilization and health outcomes, and second, it is challenging to control for selection into insurance. The second problem means that a regression of utilization or outcome measures on insurance coverage will yield biased results and will not estimate the causal effects of health insurance. In this paper, we make progress in both directions. We use rich survey data from the National Household Survey of Peru ("Encuesta Nacional de

[1] See for instance Fafchamps (1999), Jowett (2003), Chankova et al. (2008), Giné et al. (2008) and Dercon et al. (2008).

[2] See for instance Abel-Smith (1992), International Labour Office et al. (2006), Pauly et al. (2006), and Acharya et al. (2013).

Hogares", ENAHO) for the year 2011 to evaluate the impact of access to the Peruvian Social Health Insurance called "Seguro Integral de Salud" (SIS) for individuals outside the formal labor market on a variety of measures for health care utilization, self-reported health indicators, and out-of-pocket expenditures.

The Peruvian case is interesting because SIS resembles European public health insurance systems in that it covers health care expenditures, but does not strongly incentivize individuals to invest into preventive care. Coverage is free for eligible individuals, and those who are not covered by SIS typically lack insurance coverage.[3] SIS was created in 2001 and subsequently reformed. *Prima facie*, these reforms have been successful, as coverage by SIS is substantial and enrollment has increased from 20 percent in 2006 to more than 40 percent of the total population in 2011, reaching a relatively high enrollment rate among the SHI programs in low and middle income countries (Acharya et al., 2013). Yet, even though aggregate data suggest that some health outcomes improved since the program has been implemented—between 2000 and 2010 total maternal and child mortality rates decreased from 185 to 93 and 33 to 17, per 100,000 and 1,000 thousands of children born alive, respectively[4]—to date there is no study evaluating the effects of insurance coverage on preventive care, health care utilization, out of pocket expenditures and health outcomes at the micro level that controls at the same time for selection into insurance.[5]

1.1 Contribution

In this paper, we use rich individual-level data to provide such an evaluation. We control for selective uptake of insurance by exploiting the institutional setup in Peru that gives rise to a Regression Discontinuity Design (RDD). This is based on a reform that was agreed upon in 2009. Since the end of 2010, a household is eligible for the program if a welfare index called Household Targeting Index (Índice de Focalización de Hogares, IFH) that is calculated by Peruvian authorities from a number of variables is below a specific threshold. Variation

[3]The latter may, however, seek medical attention on a pay-as-you-go basis and buy medication without a prescription.

[4]National Institute of Statistics and Informatics (INEI)-National series, http://series.inei.gob.pe:8080/sirtod-series/. Dow and Schmeer (2003) perform an analysis of the effect of health insurance in Costa Rica on infant and child mortality. They use aggregate level data at the county level and control for fixed effects. As in Peru, increases in insurance coverage over time went along with decreases in infant and child mortality. Gruber et al. (2014) find evidence for similar effects in Thailand.

[5]There are other studies relating enrollment to health care utilization and outcomes. For instance, Parodi (2005) finds that SIS enrollment increases the probability that poor pregnant women give birth in a formal institution. However, he does not control for selection into insurance. Bitrán and Asociados (2009) find that SIS increases utilization for both preventive and curative services (with biggest impacts on treatments for diarrhea and acute respiratory infections for children) and that SIS reduces the likelihood that insured individuals incur in out of pocket health expenditures. The authors control for selection into insurance but they do not use the mean test used by SIS at the period of analysis. Instead, they use consumption per capita to evaluate eligibility. There are also studies that are more policy-oriented. For example, Arróspide et al. (2009) discuss the design and effectiveness of the SIS's institutional budget and provide policy recommendations. Francke (2013) analyzes whether the implementation of the SIS program has played a role in extending health coverage in Peru.

in this index around the threshold provides a natural experiment that we exploit to conduct our analysis. Importantly, households do not know how the index is calculated, and hence the incentive to manipulate it—a common threat to studies based on such a RDD—is not present here. We, however, have access to this information and use it to re-calculate the composite index of economic welfare.

Our analysis is for individuals working in the informal sector. As in many other developing countries, formally employed individuals constitute a smaller group and are covered by a different scheme. For informally employed individuals the IFH index is the most important criterion to determine eligibility. The analysis focuses on individuals from the Lima Province because the regulatory framework mandates that the eligibility evaluation using the IFH index should be first applied in this area. In 2011, almost one third of the population lived in the Lima Province and half of Peru's GDP was generated there. Another advantage of focusing on this part of the country is that it is very densely populated and therefore there are enough health care centers so that we can exclude that either a large distance or absence of the staff explain that individuals do not demand health care.[6]

Exploiting the unusually rich data from the ENAHO of Peru on health care utilization, out of pocket expenditures and self-reported health outcomes, as well as the discontinuity generated by the institutional rules, we find that insurance coverage has positive effects on the utilization of health services. For those who enroll when becoming eligible, the probabilities of visiting a doctor increases by 51.5 percentage points, the probability of receiving medicines increases by 52.7 percentage points, and the probability of requiring medical analysis increases by 20.6 percentage points. Regarding curative use, we find that insured individuals are 56.4 percentage points more likely to seek medical attention (i.e. in public hospitals and health care centers) and 25.7 percentage points more likely to have access to a surgical procedure. SIS does not provide strong incentives to invest into preventive care. Nevertheless, we find that insured women of childbearing age are more likely to control their pregnancy than uninsured women and individuals are more likely to be vaccinated. This is in line with the stark decrease in maternal and child mortality that was observed after the program was introduced. At the same time, as could be expected, we find no effects of insurance coverage on other forms of preventive care. Taken together, these findings are very much in line with the view that the price of health care utilization has decreased and that this has led to increased demand.

It is, however, instructive to interpret our findings in more detail by looking at them through

[6]According to Banerjee et al. (2004) these are two prime reasons why households in Rajasthan in India spend a considerable fraction of their budget on health care, essentially buying drugs. In other parts of Peru, utilization of health services has been limited by supply constraints. The Office of the Ombudsman reports that most of the 4,500 health care centers around the country are not sufficiently equipped to provide inpatient care (Defensoría del Pueblo, 2013). An official technical committee concludes that the biggest challenge faced by the Peruvian health system between 2009 and 2011 is the shortage of supply of health services in many parts of the country, because it lacks adequate capacity infrastructure, equipment and human resources (Comité Técnico Implementador del AUS, 2010). Finally, also statistics from the World Bank shows that, while the average of hospital beds per 1,000 people is 1.83 for Latin America, it is only 1.55 for Peru. This also occurs with other measures of supply health services, including the number of health workers such as physicians, nurses and midwives (World Bank, 2013).

the lens of a simple conceptual framework, or model, that we present in Section 3 below. Guided by this model we provide evidence in favor of two arguments that are less common in economics.[7] First, access to health care centers leads to increased awareness about health problems, because they are more likely to see a doctor; and second, this even generates a willingness to pay for services that are not covered, which in the context of Peru is a potentially desirable form of supplier-induced demand. In line with this, we show that health insurance coverage goes along with increases in health expenditures and their variability. Another way to think of the latter would be a revealed preference for medical care that stems from individuals being better informed about their health care needs. Using an estimator of quantile treatment effects, we find that the effect is particularly pronounced in the top end of the distribution.

Finally, as is common in such studies, we do not find clear effects on health outcomes at the micro level. Our interpretation of this, in part, is that on the one hand these are longer term effects that are not measurable yet. On the other hand, it has to do with the subjectivity of the health report that may be influenced by the increased inclination of insured individuals to see a doctor.

1.2 Related Results

The literature on the impact of SHI for informally employed individuals in low and middle income countries is scarce, but growing.[8] Table 1 provides an overview over a selection of related studies, ordered by country, that are most closely related to ours. Our overall interpretation of the evidence on the effects of insurance is that as of now, more is known about the potential pitfalls than about the effects of a successful SHI program and in particular on how they depend on details of the implementation. The results presented in this paper suggest that SIS in Peru is an exception and belongs to the latter category, as does the Colombian program.[9] Interestingly, the supply-side incentives between those two countries differ in important ways. For that reason, it will be particularly interesting to compare our findings to the ones for Colombia. Also the Thai program seems to be a notable exception.

[7] An exception is Wagstaff and Lindelow (2008) who focus on the effects of health insurance on financial risk in China and find that health insurance coverage increases the risk of incurring high and catastrophic spending, respectively. They argue that this is because insurance encourages individuals to seek care and this ultimately leads to higher expenditures that they then cover themselves.

[8] The selection of papers we discuss here is necessarily incomplete, but we believe it is to some extent representative. Acharya et al. (2013) systematically examine 64 papers on the effects of health insurance and present a review on the 19 papers that correct for selection into insurance. The review concludes that there is little evidence on the impact of insurance on health status, some evidence on utilization, weak evidence on out-of-pocket health expenditures, and unclear effects for the poorest. However, arguably, given the large variation in incentives provided by the respective institutions, it is not surprising that there is heterogeneity in the effect across countries. Giedion et al. (2013) also provide a comprehensive review classifying papers according to findings and research design. They also conclude that specific features of the design have a large impact on the likelihood that specific goals, such as increasing access or improving health, are reached. See also Abel-Smith (1992), International Labour Office et al. (2006), Pauly et al. (2006) and Dercon et al. (2008), and the references therein, for a review of the more policy-oriented literature.

[9] We provide a more in-depth discussion of the institutional details in Section 2.

Table 1: Selected Studies on the Effects of Health Insurance for Informally Employed Individuals in Developing Countries

	country	research design	findings
Thornton et al. (2010)	Nicaragua	field experiment, random assignment of premiums and enrollment location, then instrumental variables estimation	low take-up, substitution towards services provided at covered facilities, reduction in out-of-pocket expenditures, but increase in total individual health expenditures
Barros (2008)	Mexico	use variation in program intensity across time and space	reduction in out-of-pocket expenditures, shift from private to public providers, negligible effect on health
King et al. (2009)	Mexico	random assignment, encouragement to enroll into health insurance program	negative effects on medical spending, no effects on medication spending, utilization and health outcomes; reduction in catastrophic expenditures
Sosa-Rubi et al. (2009)	Mexico	latent class model, parametric identification	positive effect on obstetric utilization; negative effect on utilization in non-accredited state-run clinics, negative effect on private clinics, positive effect on utilization in accredited state-run clinics
Wagstaff (2010)	Vietnam	triple-differencing	reduction of out-of-pocket spending, no impact on utilization
Bauhoff et al. (2011)	Georgia	sharp discontinuities at two regional eligibility thresholds	no effects on utilization, health behavior, management of chronic illnesses, and patient satisfaction; decrease in out-of-pocket expenditures, no reduction of risk of high outpatient expenditures, but reduction of risk of high inpatient expenditures
Miller et al. (2013)	Colombia	fuzzy regression discontinuity design	positive effect on preventive care and health, reduction of financial risk
Gruber et al. (2014)	Thailand	differences-in-differences with ineligibles as control group	increase in health care utilization, reduction of infant mortality
Limwattananon et al. (2015)	Thailand	differences-in-differences with ineligibles as control group	reduction in out-of-pocket expenditures; increase in inpatient and ambulatory care

Turning first to the other countries, Thornton et al. (2010) find that initial take-up of subsidized, but for-pay insurance "Seguro Facultativo de Salud" among informally employed individuals in Nicaragua was as low as 20 percent. Moreover, after the subsidy expired most who previously signed up cancelled their insurance. The specific reason they give for this is that convenience and quality of care were not adequately addressed, which means that at the margin, the price of insurance—the cost side from the perspective of individuals—plays a role, but that the bulk of individuals does not buy insurance because the associated benefits are too low. This could also be because resources were wasted either in the administration or at the health care providers. Another reason why the program did not reach its goal was that over the course of the evaluation of the program, there was a drastic change in government, and with it the design of the program. The results for the few who did sign up and kept their insurance suggest that insurance could have a positive effect in the sense that average health care expenditures, which are generally seen as too low, increased. This could, however, also be the case because those who bought insurance and kept it constitute a negative selection of risks for whom the effect of insurance is particularly high.

All three papers for Mexico investigate the effects of the "Seguro Popular" program, whose aim it is—as the SIS's in Peru—to improve access to health insurance for the poor. Unlike in the Peruvian, but like in the Nicaragua program, coverage in the Mexican program is not for free. Turning to the effects of introducing the program in Mexico, it is remarkable that the findings in all three papers consistently suggest that the demand for medical care has shifted to providers that are part of the system, and in line with this, individuals health care expenditures have been reduced, including catastrophic health expenditures. In that sense, the program was successful in being a transfer program, but less so in encouraging individuals to seek care when ill. Interestingly, as it is the case in Peru with the SIS program, policy makers have also targeted pregnant mothers, and consequently, as in Peru, there is a positive effect on obstetric utilization. At the same time, the findings do not suggest that utilization has increased for other types of care.

The design of the program in Georgia is very similar to the one in Peru. However, and in contrast to our findings, Bauhoff et al. (2011) find no effect of insurance coverage on utilization. They argue that this is due to the fact that individuals were not aware of the fact that they were covered or that there were administrative problems that caused them to indeed not be covered, that they did not make use of the services because the program did not cover drugs, and because the perceived quality of the services was low. Therefore, it is not surprising that their findings are different from ours for Peru.

Turning to Colombia, and comparing the results to the ones in this paper for Peru, it becomes clear that the effects of insurance coverage depend on the design of the system. In Colombia, private insurers mainly receive a capitation fee and therefore have incentives to increase preventive services on the one hand and to limit total medical expenditures on the other. And indeed, Miller et al. (2013) mainly find effects on preventive care. In Peru, SIS covers both preventive and curative services and doctors are reimbursed on the basis of the treatments they provide. Hence, participating hospitals and health care facilities do not have an incentive to discourage curative treatments or medical procedures in favor of preventive services. This explains why in Peru most of the effects are on curative use.

Finally, two recent papers, Gruber et al. (2014) and Limwattananon et al. (2015), investigate the effect of a large-scale increase in health insurance coverage for the poor in Thailand. They find that the program had positive effects on health care utilization, negative effects on out-of-pocket expenditures, and negative effects on child mortality rates. These findings are similar to ours for Peru, except that we find positive effects on health expenditures at the top end of the distribution. Our explanation for this is that individuals, once covered, became aware of additional health care needs and payed for some of them out-of-pocket.

1.3 Plan of the Paper

We proceed as follows. Section 2 discusses the institutional background and provides details on the SIS program. We present our model of demand for health insurance and health care utilization in Section 3. In Section 4 we provide information on our data and in Section 5 we formally describe the econometric approach. Results are presented in Section 6. A number of robustness checks are conducted in Section 7. Section 8 concludes. Additional results are presented in an Online Appendix.

2 Institutional Background

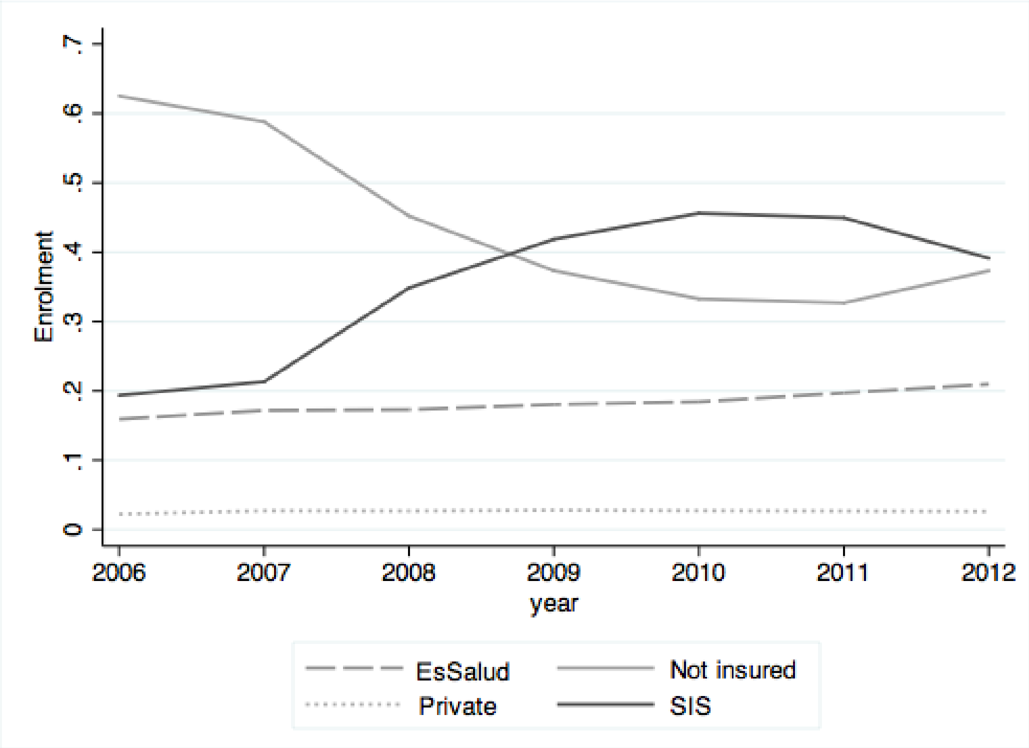
2.1 The Bigger Picture

Before 2001, health services were provided by the Ministry of Health (MINSA), the social security system ("EsSalud"), as well as private clinics and practices. Generally speaking, these providers catered to different groups of the population and did not cooperate with one another (Cetrangolo et al., 2013; Francke, 2013).[10]

MINSA runs a network of hospitals and health care centers that serve the general public. These are the services poor individuals demand and pay for if they are not insured. Next to that, EsSalud provides health insurance to the relatively small group of formally employed individuals and maintains its own facilities for the provision of care. Enrollment into health insurance, either EsSalud or private insurance, is mandatory for dependent employees and voluntary for self-employed. Finally, the private sector offers services at relatively high prices. Consequently, these services are only affordable to more wealthy individuals who are also able to buy private health insurance.

[10] Formally, MINSA is responsible for the regulation of the whole health system. However, in practice, it does so in a relatively passive way (World Bank, 2006).

Figure 1: Health Insurance Coverage in Peru over Time



Notes: Own calculations based on ENAHO survey for the years 2006-2012. See Section 4 for details on the data set and in particular our estimation sample for the year 2011. Here, we use the entire sample and use individual reports on coverage.

The welfare program "Seguro Integral de Salud" (SIS), whose effect we evaluate in this paper, was introduced in 2001. Its goal is to improve access to health care services for individuals who lack health insurance, giving priority to vulnerable groups of the population that live in extreme poverty (Arróspide et al., 2009). In 2009, an important reform took place. There were two goals. The first was to improve the process evaluating eligibility. The second was to expand coverage. To achieve these goals, among others, the budget dedicated to SIS was increased and eligibility rules were changed.[11]

The creation of SIS and subsequent reforms led to a substantial increase of health insurance coverage over time. Bitrán and Asociados (2009) and Francke (2013) provide interesting descriptive analysis of this increase and its relevance within the Peruvian health system in general. In Figure 1, we use data from the ENAHO to characterize the evolution over time. The figure shows that SIS coverage increased from 20.0 percent of the population in 2006 to 44.7 percent in 2011, which means that by then SIS was the main health insurance provider. In contrast, the coverage of EsSalud and private providers remained stable over the years. However, in 2011, 32.4 percent of the population still did not have any type of insurance.

This increase was higher than the one in other countries, such as Colombia. One of the reasons for this could be that the price for insurance was truly zero. Although there is no

[11] Also before April 2009 SIS used a Household Welfare Index ("Índice de Bienestar de Hogares", IBEH) to determine eligibility. However, the IBEH criterion was not strictly applied in practice.

economic reason why there should be a substantial difference between a zero price and a small positive price, behavioral aspects that lead to individuals perceiving a big difference between the two may play an important role (Shampanier et al., 2007).[12]

2.2 Seguro Integral de Salud

If eligible, individuals have the possibility to enroll into SIS at a number of places, including MINSA facilities. They are covered as soon as eligibility is confirmed, which is usually a matter of days. Then, they receive the health services that are offered at MINSA facilities and that are part of the benefit package.

The aim of the government was to target particular, poor groups in the population. For this, ideally, eligibility should be based on accurate information on income at the level of the individual or family. However, such information is typically not available in developing countries because a large part of the population works outside the formal sector and therefore does not pay income taxes and social security contributions. Eligibility for SIS is therefore based on the so-called Household Targeting System ("Sistema de Focalización de Hogares", SISFOH). For this, a unified household registry is maintained and is used to calculate targeting indicators at the level of the family (see SISFOH, 2010). Data are collected by government officials using a standardized form. It includes questions on, amongst other things, housing characteristics, asset possessions, human capital endowments and other factors.

The most important targeting indicator for SIS is the IFH index.[13] It is a linear combination of the variables in the household registry that takes on lower values for households that are more poor. Online Appendix C explains in detail how the IFH is constructed, including the complete list of variables and their weights.

A household is eligible for SIS if the IFH index, water expenditures and electricity expenditures are all below respective regional-specific thresholds.[14] If no information for water and electricity expenditures is available, then a household is eligible if its IFH index is below the

[12]There are several reasons why the uptake in SIS is still far from 100 percent. First, as we explain in more detail in Section 3 below, individuals may perceive the benefits as low compared to the opportunity cost of time it takes to enroll and visit a health care facility instead of simply buying medicines at a pharmacy. This plays a role for our analysis, as we focus on the urban Lima Province. Second, especially in rural areas, cultural reasons or administrative constraints may be important (Parodi, 2005). An example is that individuals do not possess an identity card that they need to enroll.

[13]SISFOH was established in 2004 and, by 2008, three main results were expected: i) a national, complete and updated Household Registry with the corresponding eligibility status using the IFH index; ii) three social programs (including SIS) would fully adopt this criterion to select their beneficiaries and; iii) the rest of social programs would begin using it. However, administrative and political barriers postponed reaching these results as planned. Only in the year of 2010, the Household Registry and eligibility status (including index's weights) were finished and became available for authorities. At the end of that year, SIS was the first social program to adopt the new criterion (see Llanos and Rosas, 2010 and Regulation RJ-N063-2011 for more details).

[14]For Lima, these thresholds are 55 for the IFH, 20 Soles for water expenditures and 25 Soles for electricity expenditures. This corresponds to 7.3 and 9.1 U.S. dollars, respectively. According to the Central Bank of Peru, the average informal exchange rate (Nuevos Soles per U.S. Dollar) in 2011 was 2.755. As a reference, the interbanking rate and the banking rate was 2.754. Table 16 in Online Appendix C provides the complete set of thresholds by geographic areas. Figure 9 shows the relationship between water and electricity expenditures and the IFH index.

threshold. In case one of the household members works in the formal sector, then eligibility is related to income.[15] Moreover, if the monthly wage is greater than 1,500 Soles, or 544.5 U.S. dollars, then the household is not eligible for a social program, unless either water or electricity service expenditures are below their thresholds.

Importantly, potential beneficiaries are not aware of the exact details of the eligibility rules. Whereas they intuit the importance of their answers to the questions of the government official, they do not know how exactly the IFH index is calculated and what their cutoff value for eligibility is. SISFOH does not inform households about the value of their index and only provides the result of the eligibility evaluation.

SIS offers a comprehensive package of health care benefits. It is estimated that SIS covers 65 percent of the total disease burden in the country (Francke, 2013). Table 10 and 11 in Online Appendix A provide a detailed list of services covered by SIS together with the maximum levels of coverage. Coverage includes obstetric and gynecology interventions, pediatric interventions, neoplasm or tumor interventions, transmittable and non-transmittable disease's interventions, chronic and degenerative disease's interventions and emergency care. It also includes outpatient medical-surgical intervention and hospitalization, as well as coverage of high-cost diseases. There are no waiting times or latent periods. But there are maximum levels of coverage in terms of the number of medical attentions. For instance, for preventive care, SIS covers up to 10 treatments to control pregnancy, ultrasounds, lab tests and supplements of iron and folic acid. Regarding curative use of outpatient services, doctor visits and minor surgeries are covered without any limit (including its medications). In the case of inpatient services (with or without surgeries), extra diagnosis and maximum levels are applied.

There are two additional plans for self-employed individuals and to employees of small firms, respectively. The latter are not seen as dependent employees and therefore do not have to be enrolled in EsSalud. Both plans are not free of charge, but involve enrollment at a rate below the actual cost. Moreover, they involve a slightly different benefit package. However, these two additional plans are not important in practice. Administrative statistics from SIS show that the main plan targeted to the poor reaches 12.7 million individuals, or 99.8% of the entire SIS population.[16] In this paper, we focus on the effects of the first plan and refer to it simply as the SIS plan.

MINSA is reimbursed for the services it provides. This is done out of the SIS budget and at fixed rates that are based on estimates of the costs plus a markup. The rates are approved by MINSA in the form of regulation that is updated on a regular basis. This means that, as

[15] One may wonder whether the SIS program creates incentives to transit from formal and informal status. In this context, it is important to note that informality in Peru is not *per se* illegal. We have investigated this possibility in two ways and do not find evidence for this. First, following Card and Shore-Sheppard. (2004), we explore whether there is evidence for SIS crowding out insurance offered by private providers or EsSalud, which would be consistent to the idea of incentives to leave formality due to SIS. Second, we analyze whether SIS enrollment has a significant effect on informality.

[16] See SIS Statistic Report, available at http://www.sis.gob.pe/Portal/estadisticas/index.html, accessed September 2013.

opposed to Colombia, the system offers no incentives to health care providers that are related to preventive care. At the same time, it does also not provide incentives that limit curative use.

In our study period, some of the treatments and services that are covered by SIS suffered from a number of substantial supply limitations. First, there was a lack of equipment in MINSA hospitals. According to Defensoría del Pueblo (2013), which performed a supervision of a sample of hospitals at a national level in 2012, 20 percent of them lack at least one piece of equipment required for inpatient surgery and 15 percent report to have problems with at least one other input needed for performing surgery. Second, there has been a shortage of dentists and ophthalmologists. The rate of odontologists per ten thousand inhabitants is one of the lowest among all medical professionals (Giovanella et al., 2012) and it is even lower when they work as providers for SIS (Defensoría del Pueblo, 2013). Likewise, only a small number of ophthalmologists provides services to SIS participants, which in turn limits the use of ophthalmological care. Only recently, and after our study period, the National Ophthalmological Institute, the largest provider in Peru, joined the list of SIS providers. Third, even though drugs are officially covered by SIS, according to the information in the ENAHO 2011, 37 percent of the covered individuals report to have paid for drugs received at the hospital level and 9.7 percent report to have paid for it at the health care centers level (Defensoría del Pueblo, 2013). This may be related to a cut that SIS experienced in its budget, which resulted in a failure to transfer resources to MINSA, which in turn motivated some hospitals to charge for hospitalization, regardless of insurance status. Patients are referred from health care centers to hospitals when the formers do not have specific medical specialties to perform proper diagnosis or treatments. Once at the hospitals, patients are less aware about the services they are freely entitled to as participants of SIS or they are not able to find all the medications they need. Taken together, the supply limitations imply that some patients were not able to receive some treatments and may have been asked to pay for other treatments that were actually formally included in the SIS package, especially when they received treatment in a hospital. Moreover, they may have had to pay themselves for medicines that are formally covered.

3 Demand for Health Care and Health Insurance

It is instructive to interpret our empirical results through the lens of a simple model of health care demand and insurance choice. The model we present below is based on the one in Einav et al. (2013) and adapted for our purposes. We keep it as simple as possible to focus on what we believe are the main driving forces behind our empirical findings.[17] The primary purpose

[17] We will consider a model with risk neutral individuals. The first order effect of risk aversion will be that individuals are generally more inclined to buy insurance. Zweifel and Manning (2000) present a richer model. See also Cutler and Zeckhauser (2000) on the optimal design of health insurance. Both papers provide excellent reviews of the respective relevant, partially overlapping literatures. We also do not explicitly model health investment (Grossman, 1972), the decision to see a doctor (Gilleskie, 1998), and the relationship between health and wealth (Adams et al., 2003).

of this model is to study the implications the institutional setup has on the demand side, with a focus on individuals not being aware of some of their health care needs before signing up for SIS.

The point of departure is that an individual has health care needs λ_a and λ_u. One can think of them as measured in amounts of health care spending, as will become clear below. Without him seeing a doctor the individual is aware of the former and unaware of the latter, so "a" stands for "aware" and "u" stands for "unaware". Sen (2002) distinguishes in this context between "internal" and "external" views of health and stresses that "the patient's internal assessment may be seriously limited by his or her social experience", such as seeing a doctor or not.[18]

Importantly, and in contrast to what is common in developed countries, the individual can buy all drugs at the pharmacy. That is, there are no prescription drugs. Therefore, the baseline case is that he buys drugs at the pharmacy to treat his health care needs λ_a and pays for this himself. This was common practice for a long time and may of course ultimately have adverse effects on health. However, evidence on this is scarce.[19]

As discussed in Section 2, individuals may enroll into social health insurance. If they are sufficiently poor, i.e. if a welfare index is below a certain threshold, then this is for free. Otherwise, they can buy coverage for a monthly premium. In any case, it involves effort and costs time to sign up. In our model the sum of the effort cost, time cost, and premium are denoted by p, and we think of it as standing for "premium". Social insurance covers a list of treatments at specified locations. Therefore, in our model the prime reason for buying insurance is that it provides access to care and changes its price.[20]

We specify utility to be quadratic in the difference between health care consumption m and health care needs. It is quasi-linear in money, which is given by income y minus the fraction $c \cdot m$ that is paid out of pocket, minus the insurance premium p when insurance is bought. In our model, c will be one if the individual has no insurance for his health care needs, meaning that the individual pays himself, and equal to zero if the individual has insurance and the health care need is covered. In practice, some of the needs of the individual will be covered and other will not, but we keep this implicit here, as we want to focus on our main argument. Formally,

[18] See also the discussion of various biases in self-assessed health measures that are discussed in Murray and Chen (1992).

[19] Laing et al. (2001) discuss this scarce evidence and provide suggestions on how to improve the use of medicines in developing countries.

[20] Another reason to enroll and that we abstract from is risk-aversion. Alderman and Paxson (1992) provide an early synthesis of the related literature. Gertler and Gruber (2002) analyze the extent to which poor households in Indonesia are able to smooth consumption when they are hit by a health shock. They infer that health problems have large welfare costs, and conclude that public disability programs and subsidized healthcare could improve consumption insurance. Chetty and Looney (2006) present a model that illustrates that consumption fluctuations can underestimate the welfare costs of health shocks if households are highly risk averse. Pauly et al. (2008) use data from the World Health Survey for 14 developing countries and show that risk averse individuals may benefit from having access to health insurance, out of a pure consumption motive. Mohanan (2013) shows that households faced with shock-related expenditures are able to smooth consumption on food, housing, and festivals, with small reductions in educational spending, and that debt was the principal mitigating mechanism households used, leading to significantly larger levels of indebtedness.

utility is of the form

$$u(m) = (m - \lambda_a - \lambda_u) - \frac{1}{2\omega}(m - \lambda_a - \lambda_u)^2 + y - c \cdot m - p$$

and the individual will perceive λ_u to be zero before buying insurance.

In the baseline case the individual buys no insurance and utility is given by

$$u_0(m) = (m - \lambda_a) - \frac{1}{2\omega}(m - \lambda_a)^2 + y - m$$

so that he optimal level of health care consumed follows from the first order condition and is[21]

$$m_0 = \lambda_a.$$

This shows that the model is formulated in a way such that optimal consumption from the individual perspective, without insurance, is given by λ_a. If there are no externalities, then this consumption is also welfare optimal. The associated indirect utility is

$$u_0^* = y - \lambda_a.$$

Notice that this optimal consumption does not depend on the parameter ω.

Suppose now that the individual considers buying health insurance with premium p and co-payment rate c. Before buying he is only aware of his health care needs λ_a. Hence, he perceives his utility function to be

$$u_1^{unaware}(m) = (m - \lambda_a) - \frac{1}{2\omega}(m - \lambda_a)^2 + y - c \cdot m - p$$

and he expects to consume

$$m_1^{unaware} = \lambda_a + \omega \cdot (1 - c).$$

Now, health care expenditures depend on the parameter ω. Suppose the treatment is covered by insurance such that $c = 0$. Then it follows that ω is the amount individuals consume in addition if they are covered by insurance. Following Einav et al. (2013) we will think of this as

[21] Here and in the following it is easily verified that the second order conditions hold.

moral hazard.[22]The associated indirect utility is

$$u_1^{unaware*} = \omega \cdot (1-c) - \frac{1}{2\omega} \cdot (\omega \cdot (1-c))^2 + y - c \cdot (\lambda_a + \omega \cdot (1-c)) - p.$$

Individuals buy insurance if $u_1^{unaware*} > u_0^*$. This is the case if

$$\frac{\omega}{2} + y - p > y - \lambda_a$$

or

$$p < \frac{\omega}{2} + \lambda_a.$$

From this we can see that individuals buy insurance if the opportunity cost of time that it takes to enroll and see a doctor is smaller than the health care expenditures they save, λ_a, plus the value they associate with the additional free health care consumption, $\omega/2$.

One reason not to enroll is the perception that even though health insurance buys individuals access to doctors this is is not valuable because advice obtained from them is often of low quality, and therefore insurance is not worth its (opportunity) cost, including the time it takes to enroll.[23] One way to think about this in our model is in terms of high values of p relative to λ_a.[24]

If individuals are heterogeneous in their λ_a and ω, then this will mean that there is adverse selection in the sense that those individuals who buy insurance are aware of higher health care needs λ_a, are more responsive to the decrease in the price of care (have high ω), or face a low p.

Health expenditures for those buying insurance and visiting a doctor who makes them aware of their health care needs λ_u are given by $m_1^{aware} = \lambda_a + \lambda_u + \omega \cdot (1-c)$ in the general case and

[22]This increase in the demand for medical care once we control for the risk is commonly termed *ex post* moral hazard. In contrast, a reduction of preventive effort or care that is due to them being covered by health insurance is termed *ex ante* moral hazard. If higher risk types, in the absence of moral hazard, buy insurance, then one speaks of adverse selection, following Akerlof (1970). See for instance Zweifel and Manning (2000). The empirical literature on moral hazard and adverse selection is still scarce, but growing. Chiappori (2000) provides a broad review of the early literature. Chiappori and Salanié (2000), Abbring et al. (2003), and Abbring et al. (2003) investigate moral hazard in the market for car insurance. Finkelstein and Poterba (2004), Bajari et al. (2006), Fang et al. (2006), Aron-Dine et al. (2012) and Einav et al. (2011) study adverse selection and moral hazard in the context of health insurance in developed countries. Einav et al. (2013) study the interrelation between adverse selection and moral hazard and term it "selection on moral hazard".

[23]Das et al. (2008) provide evidence pointing towards such low quality advice, at least in other low-income countries.

[24]Individuals can always buy private insurance that may or may not be more generous. Regular dependent employees are covered by another social insurance scheme, independent of whether or not they are poor. However, in our empirical analysis we focus on individuals who sign up for public insurance when becoming eligible. Therefore, we abstract from this in our model. Here, we also abstract from the fact that individuals may choose not to enroll for other, non-economic reasons. Non-enrollment into free (net of the opportunity cost of time) state-provided schemes is a well-documented phenomenon in the U.S. See, for instance, Blank and Card (1991), Blank and Ruggles (1996), and Currie and Gruber (1996). Also in other contexts, it is argued that individuals make dominated choices (see for example Choi et al., 2011, and the references therein). In our empirical analysis, we allow individuals not to sign up for insurance when becoming eligible.

for $c = 0$ we get

$$m_1^{aware} = \lambda_a + \lambda_u + \omega.$$

This is a form of what has been termed supplier-induced demand (McGuire, 2000). Strauss and Thomas (1998) argue that this is an important potential determinant of health care expenditures in developing countries. These additional expenditures may or may not be covered by their health insurance. In the latter case, going to the doctor may go along with an increase in out-of-pocket expenditures that may or may not be beneficial to the individual. However, one can make the argument that spending money reveals the preference of the individual for these increased expenditures and that the supplier-induced demand is therefore beneficial to the individual.

Turning to the empirical predictions of the model, we now add a subscript i to make variation across individuals explicit. Denoting whether or not individuals sign up for health insurance by the indicator d_i, this means that in our data we observe

$$m_i = \lambda_{ai} + (\lambda_{ui} + \omega_i) \cdot d_i.$$

There is selection on unobservables because

$$d_i = 1\left\{\lambda_{ai} > p_i - \frac{\omega_i}{2}\right\}$$

is positively correlated with ω_i and λ_{ai}. For treatments and medication that are covered by public insurance we have that the ordinary least squares estimator will estimate

$$\beta^{OLS} = \mathbb{E}\left[\lambda_{ai} + \lambda_{ui} + \omega_i | \lambda_{ai} > p_i - \frac{\omega_i}{2}\right] - \mathbb{E}\left[\lambda_{ai} | \lambda_{ai} \leq p_i - \frac{\omega_i}{2}\right],$$

which exceeds the population average effect of insurance, $\mathbb{E}[\lambda_{ui} + \omega_i]$.

In Section 5 below we provide and discuss conditions such that variation in the welfare index around the eligibility threshold identifies the local average treatment effect. This is the effect of insurance coverage for those individuals whose welfare index is in a small neighborhood around the eligibility threshold (formally $z_i = 0$) and enroll when becoming eligible,

$$\beta^{LATE} = \mathbb{E}\left[\lambda_{ai} + \lambda_{ui} + \omega_i | \lambda_{ai} > p_i - \frac{\omega_i}{2}, z_i = 0\right] - \mathbb{E}\left[\lambda_{ai} | \lambda_{ai} > p_i - \frac{\omega_i}{2}, z_i = 0\right].$$

Notice that the baseline in the second expression now is that they would want to enroll but are not allowed to.[25] In general, the local average treatment effect will not be equal to the average treatment effect, also not for individuals whose welfare index is equal to the eligibility threshold.

[25] Here we abstract from the fact that they can buy insurance at a premium higher than p_i. In our empirical analysis this will lead to some individuals buying insurance when they are ineligible. The local average treatment effect is then still the effect for those individuals who enroll when becoming eligible. The reason for this is that the decision of the individuals who buy insurance while not being eligible will not be altered by crossing the eligibility threshold and will therefore not be reflected in a discontinuity in the amount of spending at the eligibility threshold. At the individual level, when buying insurance when not eligible, becoming eligible means that he does not have to pay the insurance premium himself anymore.

It is likely higher because for those who choose not to enroll we have $\lambda_{ai} \leq p_i - \frac{\omega_i}{2}$, unless the health care needs they are unaware of, λ_{ui}, exceed the ones of the individuals who enroll. Importantly, the local average treatment effect—unlike in other contexts—is highly policy-relevant here. In our empirical application below we will estimate the fraction of individuals who enroll when becoming eligible and the effects of insurance for them. Our estimates are therefore informative about the likely effects of increasing coverage by moving the insurance threshold marginally, for those individuals who then become eligible and enroll.

Finally, when asked about their health, individuals will base their answer on λ_{ai} and $m_{1i}^{unaware}$ when they are not covered by insurance and λ_{ai}, λ_{ui} and m_{1i}^{aware} when they are. Thus, it is an empirical question whether the effect of insurance coverage on their subjective health report is positive or negative. It may be positive because health care needs are satisfied and the individual even receives more treatment than he would buy himself. But it may just as well be negative because exposure to a health care professional has made the individual aware of his health care needs, even if they have been treated.

To summarize, in the simple model outlined above, not all individuals may enroll into health insurance. Once covered, they are likely to see a doctor more often and consume more medical care, which is the result of a pure price and the effect of them being better informed about their medical needs. By the same token, we also expect utilization of other services to increase, including inpatient care. The effect of insurance coverage on subjective health reports may either be positive or negative.

4 Data

The paper uses cross-sectional data from the ENAHO for the year 2011, which is representative at the level of each of the 24 departments that comprise the country. This survey fits our purpose because it provides information on health care utilization, health expenditures, health outcomes, insurance status, and the information needed to re-compute the IFH index. Data are collected using face-to-face interviews with one or more respondents per household, who are also asked to provide information on the other household members.

SIS is targeted to individuals who work in the informal sector. Therefore, for our analysis, we select individuals that belong to a household in which no member is formally employed.[26] This group comprises approximately 60 percent of the entire sample. We focus on individuals from the Lima Province because, as described in Section 2, the regulatory framework mandates that the IFH targeting rule should already be applied in this area in 2011 and only afterwards

[26]We define formality as having monetary income from any wage activity. This does not include any other monetary income or income from self-employment. This definition is closest to the one used by the authorities. They distinguish between those individuals whose wage is observed, who are mainly employees with a formal contract, and others. We have also explored other definitions, including being a wage worker in the main occupation, any indication of having a formal contract in the main occupation, and working in an enterprise that keeps accounting books and is affiliated to a pension system. Results remain qualitatively the same.

to the rest of the country. Our sample contains information on 4,161 individuals after the two exclusions criteria are applied.

We construct our treatment variable using information on enrollment in SIS and in EsSalud. The reason is that some individuals who were actually enrolled in SIS may have wrongly stated to have been enrolled in EsSalud, because both are public insurance programs. While in principle SIS enrollment is at the household level, there are households in our data in which some members state that they are enrolled and other members state that they are not. For the results presented here we use this information as stated by the individuals, because we believe that this corresponds most closely to what individuals actually base their decisions related to health care utilization on.[27] Participation in EsSalud is also recorded in the survey. Similar as in the case of SIS, we consider individuals (not households) enrolled into EsSalud as it is reported in the survey.

Table 2 and 3 provide summary statistics for the main variables that we use in the analysis. We distinguish between three sets of variables. The first one is the participation variable defined as having public health insurance. The second set contains variables related to utilization of health services including health expenditures, and the third set comprises variables of health report. The columns in the two tables contain the summary statistics for the whole sample and for the sample broken down by participation status and eligibility.

In 2011, 38.0 percent of the sample population was either enrolled in SIS or EsSalud. On average, individuals in the sample are 33.0 years old, half of them are woman, individuals have around 8 years of education, and average annual household income is 30,620 Soles, or 11,114.3 U.S. dollars. Participants are slightly older, more likely to be female, and are less educated than nonparticipants. This is not surprising since the SIS program is targeted to the poor. When we compare eligibles to ineligibles, we find similar patterns.

Turning to utilization of health services, we find that, on average, 31.9 percent of the individuals have visited a doctor in the last month, 45.6 percent have received medicines and 6.3 percent have had medical analysis in the same period. 4.1 percent of the individuals have received an intervention or have undergone surgery in the last 12 months. Focusing on women, we observe that those who received pregnancy care in the last 12 months represent 7.4 percent of the sample of the women who are in fertile age. Utilization is generally higher for individuals who are covered by health insurance and for eligible individuals.

Shifting attention to health reports, 39.6 percent of the individuals provide an affirmative answer when asked whether they have experienced any symptom in the last month. At the same

[27] We also explored another variable for participation status in SIS. The variable was constructed at the household level and was a dummy equal to one for individuals that belong to a household where at least one member reported to be enrolled to SIS. The consequence of this is that insurance coverage is estimated to increase more at the eligibility threshold. The main results, which we discuss in Section 6 below, did not change qualitatively. However, the magnitude was smaller. This is related to the econometric approach, which essentially calculates the local average treatment effect as the change in the outcome, which was not affected by using a different definition, divided by the change in the fraction of individuals who were insured, which was affected. See also Section 5 for a more formal discussion.

Table 2: Descriptive Statistics 1/2

Variable	Dummy	(1) Total $N = 4,161$		(2) Participants $N = 1,581$		(3) Non-participants $N = 2,580$		(4) Eligibles $N = 1,786$		(5) Ineligibles $N = 2,375$	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Participation											
Health Insurance	D	0.380	-	1.000	-	0.000	-	0.400	-	0.365	-
Demographics											
Woman	D	0.511	-	0.533	-	0.498	-	0.507	-	0.514	-
Age		33.014	22.250	34.366	24.737	32.185	20.540	28.292	20.695	36.564	22.718
Years of education		8.126	4.854	7.758	5.068	8.351	4.705	6.633	4.485	9.248	4.819
Number household members		4.607	2.101	4.491	1.992	4.678	2.163	4.661	1.917	4.566	2.229
Woman head of household	D	0.251	-	0.256	-	0.248	-	0.254	-	0.250	-
Annual household income (thousand Soles) 1/.		30.62	27.07	31.94	28.69	29.74	25.93	20.33	14.40	38.19	31.39
Utilization											
Any doctor visits	D	0.319	-	0.372	-	0.287	-	0.339	-	0.305	-
Medicines	D	0.456	-	0.507	-	0.426	-	0.465	-	0.450	-
Analysis	D	0.063	-	0.091	-	0.047	-	0.059	-	0.067	-
X-rays	D	0.037	-	0.054	-	0.028	-	0.033	-	0.041	-
Other tests	D	0.013	-	0.019	-	0.009	-	0.010	-	0.016	-
Dental care	D	0.118	-	0.125	-	0.113	-	0.096	-	0.134	-
Ophthalmological care	D	0.054	-	0.054	-	0.053	-	0.025	-	0.075	-
Glasses	D	0.041	-	0.040	-	0.041	-	0.019	-	0.058	-
Vaccines	D	0.109	-	0.133	-	0.094	-	0.138	-	0.087	-
Kids check 2/.	D	0.263	-	0.270	-	0.258	-	0.253	-	0.276	-
Birth control	D	0.060	-	0.063	-	0.058	-	0.065	-	0.056	-
Other treatments	D	0.234	-	0.255	-	0.222	-	0.201	-	0.259	-
Hospital	D	0.060	-	0.088	-	0.042	-	0.057	-	0.062	-
Intervention/Surgery	D	0.041	-	0.055	-	0.032	-	0.039	-	0.042	-
Pregnancy care 3/.	D	0.074	-	0.129	-	0.044	-	0.102	-	0.052	-
Child birth 3/.	D	0.033	-	0.067	-	0.014	-	0.045	-	0.023	-
Any of the above	D	0.687	-	0.739	-	0.655	-	0.677	-	0.695	-
Other medical attention	D	0.199	-	0.258	-	0.162	-	0.195	-	0.201	-

Notes: Data from the ENAHO 2011. See Table 12 in the Online Appendix for variable definitions. 1/. Question applied at household level: total $N = 1,129$, $N = 449$ participants, $N = 680$ non-participants, $N = 479$ eligible, $N = 650$ ineligible. 2/. Question applied for kids under age of 10: total $N = 649$, $N = 289$ participants, $N = 360$ non-participants, $N = 363$ eligible, $N = 286$ ineligible. 3/. Question applied for women in fertile age: total $N = 1,182$, $N = 417$ participants, $N = 765$ non-participants, $N = 532$ eligible, $N = 650$ ineligible.

Table 3: Descriptive Statistics 2/2

Variable	Dummy	(1) Total		(2) Participants		(3) Non-participants		(4) Eligibles		(5) Ineligibles	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Health report											
Any symptom	D	0.396	-	0.394	-	0.397	-	0.444	-	0.356	-
Illness	D	0.144	-	0.156	-	0.136	-	0.147	-	0.141	-
Chronic illness	D	0.415	-	0.457	-	0.390	-	0.351	-	0.464	-
Relapse	D	0.097	-	0.123	-	0.080	-	0.086	-	0.104	-
Accident	D	0.023	-	0.025	-	0.022	-	0.026	-	0.020	-
num. days with symptom		0.134	1.122	0.159	1.299	0.118	0.998	0.162	1.263	0.112	1.003
num. days with illness		0.144	1.099	0.154	1.126	0.137	1.083	0.151	1.069	0.138	1.122
num. days with relapse		0.250	2.295	0.345	2.701	0.191	2.004	0.208	1.987	0.281	2.501
num. days with accident		0.069	1.123	0.124	1.567	0.035	0.727	0.079	1.111	0.061	1.133
Health expenditures											
Any health expenditures	D	0.571	-	0.547	-	0.586	-	0.548	-	0.588	-
Health expenditures		401.133	1154.340	0.547	1294.957	394.735	1059.202	248.033	710.470	516.265	1387.277
Var expenditures		539.212	1020.595	568.610	1163.354	521.197	922.040	429.187	586.629	621.951	1245.203
Abs expenditures		530.172	1007.187	559.612	1144.685	512.132	912.521	324.440	629.826	684.883	1193.124
Sqre expenditures		1295264	1.16e+07	1622640	1.52e+07	1094651	8778272	501719	5000706	1892010	1.47e+07
Expenditures 50	D	0.495	-	0.488	-	0.499	-	0.448	-	0.530	-
Expenditures 75	D	0.250	-	0.250	-	0.249	-	0.196	-	0.290	-
Share expenditures		0.057	0.187	0.057	0.191	0.057	0.184	0.056	0.187	0.058	.187
Var share		0.076	0.170	0.077	0.174	0.075	0.168	0.076	0.171	0.076	.170
Abs share		0.076	0.170	0.077	0.174	0.075	0.168	0.073	0.172	0.078	.170
Sqre share		0.035	0.478	0.036	0.488	0.034	0.472	0.035	0.483	0.035	.475
Share 50	D	0.500	-	0.500	-	0.500	-	0.485	-	0.511	-
Share 75	D	0.250	-	0.250	-	0.250	-	0.246	-	0.253	-
Catastrophic 5%	D	0.231	-	0.223	-	0.235	-	0.227	-	0.233	-
Catastrophic 10%	D	0.136	-	0.131	-	0.140	-	0.135	-	0.137	-
Catastrophic 15%	D	0.096	-	0.094	-	0.098	-	0.092	-	0.100	-
Catastrophic 20%	D	0.069	-	0.067	-	0.071	-	0.065	-	0.072	-
Catastrophic 25%	D	0.051	-	0.051	-	0.051	-	0.046	-	0.055	-

Notes: Data from the ENAHO 2011. See Table 13 in the Online Appendix and Section 6.2.3 for variable definitions.

time, only 14.4 percent report that they suffered from illnesses. Regarding health expenditures, Table 3 shows that 57.1 percent of the individuals had some health expenditures in the last 12 months. The average annual expenditures are around 401.1 Soles, or 145.6 U.S. dollars.

5 Econometric Approach

In this paper, we estimate the impact of SIS coverage on a host of variables characterizing health care utilization, expenditures and health. Based on the institutional setup described in Section 2.2 we do this by means of a fuzzy RDD using the IFH index as the continuous forcing variable.[28] An individual is eligible for public insurance if she lives under poor conditions, which is measured at the household level. In the Lima Province, the condition for this is that the IFH index is below or equal to a value of 55. The usual assumption we will make is that variation in this variable around its threshold provides a natural experiment that randomly assigns eligibility to households and thereby individuals. This assumption is obviously motivated by the cutoff value of 55 for the index and the institutional rules in general. We will formalize it below.

As explained in Section 4, our treatment is coverage by public health insurance, which is defined as being enrolled in either SIS or EsSalud. It follows from the institutional rules that there is no reason to expect EsSalud coverage to change discontinuously when the threshold is crossed. Based on this, we will attribute such discontinuous changes to enrollment in SIS.

As described in Section 2.2, the IFH index is not the only variable that is related to eligibility. Other variables that are important in that respect are labor income, as well as water and electricity consumption. However, the IFH index is the most important criterion for eligibility. Moreover, and importantly, as for EsSalud enrollment, we do not expect a discontinuity in any of those variables when crossing the eligibility threshold for the IFH index. Therefore, discontinuities around the eligibility threshold are plausibly related to the IFH index only.[29]

Once we impose linearity, we can estimate the effects using the standard two-stage least squares instrumental variables estimator. Formally, we specify the first-stage equation that describes the relationship between enrollment into health insurance for individual i, d_i, as a linear probability model

$$d_i = \beta_0^d + \beta_1^d z_i^c + \beta_2^d elig_i + \beta_3^d z_i^c elig_i + \varepsilon_i^d,$$

where z_i^c is the IFH index centered at its threshold and $elig_i$ is an indicator for eligibility. The second-stage equation for outcome variables y_i is, accordingly,

$$y_i = \beta_0^y + \beta_1^y z_i^c + \beta_2^y elig_i + \beta_3^y z_i^c elig_i + \varepsilon_i^y.$$

[28]This approach goes back to at least Thistlethwaite and Campbell (1960). See Hahn et al. (2001) for a more modern exposition and Imbens and Lemieux (2008) for a discussion of practical issues.

[29]See Figure 9 in the Online Appendix for the relationship between water and electricity expenditures and the IFH index.

This is advantageous, as it will allow us to obtain more precise estimates. In our sensitivity analysis in Section 7 we show that this does not affect the point estimates in qualitatively important ways.

When we use the two-stage least squares instrumental variables estimator with $elig_i$ as the instrument for d_i and controlling for the index z_i^c and its interaction $z_i^c elig_i$ with eligibility, then we will estimate the ratio β_2^y/β_2^d. This can then be interpreted as a local average treatment effect, as proposed by Imbens and Angrist (1994), provided that three assumptions hold. We discuss these assumptions below. As explained in the context of the model that is presented in Section 3, the local average treatment effect is the average effect of insurance coverage on the outcome, for those individuals who enroll when becoming eligible by crossing the threshold. It is policy-relevant because it is directly related to the question what the effects of expanding insurance coverage through lowering the threshold value would be. In the model, the effects of insurance coverage are a combination of *ex post* moral hazard (ω) and increased awareness about medical needs (λ_u). Formally, we will not be able to separately quantify the two. However, estimating them for a host of different outcome variables and interpreting the results in light of the institutional rules will allow us to conclude that most of the effects are likely related to the latter.

The first assumption we need to make for our analysis is that if no insurance would be assigned to everybody around the threshold, then the distribution of the outcome conditional on the index would be smooth in the index z_i around zero.[30] This assumption cannot be tested directly and is therefore the main assumption we will make. As we have argued before, the institutional rules suggest that it holds, as no other programs or rules are based on these eligibility thresholds. This is supported by further supportive evidence that we present in Section 7 below.

The second assumption is that insurance status is monotone in eligibility. This holds by construction, as changing from a value of the index slightly higher than the threshold value to a value lower than the threshold value will make an individual eligible for insurance coverage.[31] The final, third assumption is an exclusion restriction. It is that in a small neighborhood around the eligibility threshold, the value of the index, z_i, is independent of the outcomes, and in particular ε_i^y.[32] It would be violated if households would manipulate their answers to the government official in order to influence the value of the IFH index. As discussed in Section 2 this is unlikely to be the case. We nevertheless test for manipulation in Section 7.1.

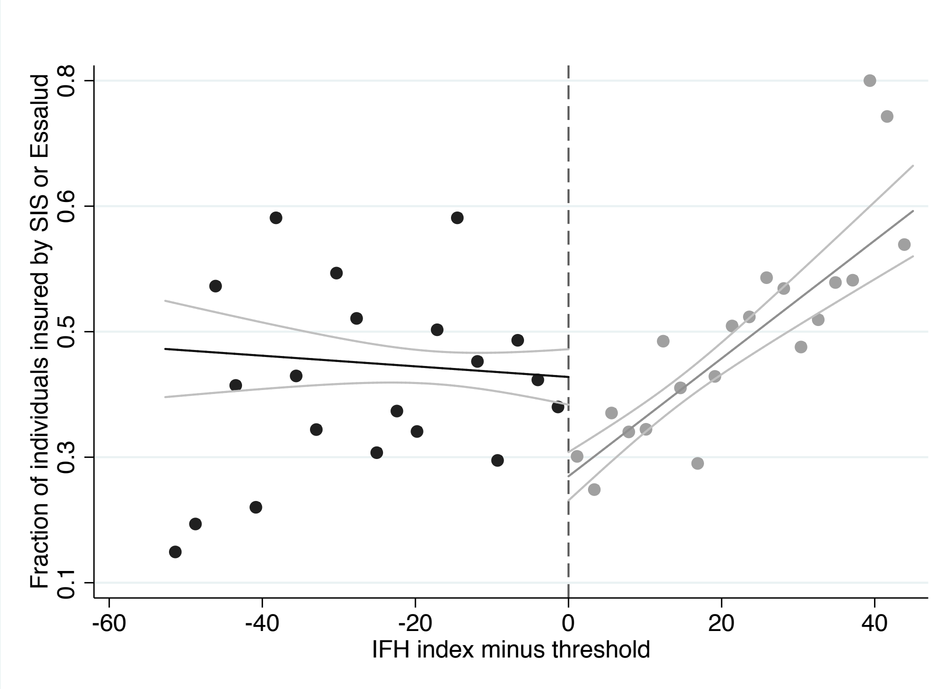
Under the same assumptions, it is also possible to estimate quantile treatment effects, as described in Frandsen et al. (2012). In Section 6.2.3 we estimate the quantiles of the distribution of expenditures with and without insurance. The underlying idea is straightforward. While the

[30]This is slightly stronger than needed. Usually, it is enough to assume that the conditional expectation of y_i given z_i is smooth around the threshold. We make a slightly stronger assumption here in order to be able to estimate quantile treatment effects as well, as described below.

[31]The assumption would be violated if an individual would buy insurance if he is not eligible, but not if he is eligible. See Battistin and Rettore (2008) and Klein (2010) for related discussions.

[32]Again, for the same reason as above, mean independence usually suffices, but we make a stronger assumption in order to also estimate quantile treatment effects.

Figure 2: Health Insurance Coverage



Notes: This and the following figures are based on ENAHO data for the year 2011 for the Lima Province. See Section 4 and Online Appendix C for details on the data and on how the IFH index is computed. The dots denote averages and the regression lines with corresponding 95 percent confidence intervals stem from separate linear regressions to the left and to the right of the threshold using the individual-level data.

local average treatment effect is an average, the quantile treatment effect is the change in, say, the median of the distribution an outcome that results from being covered by public health insurance for those who select to enroll when becoming eligible.

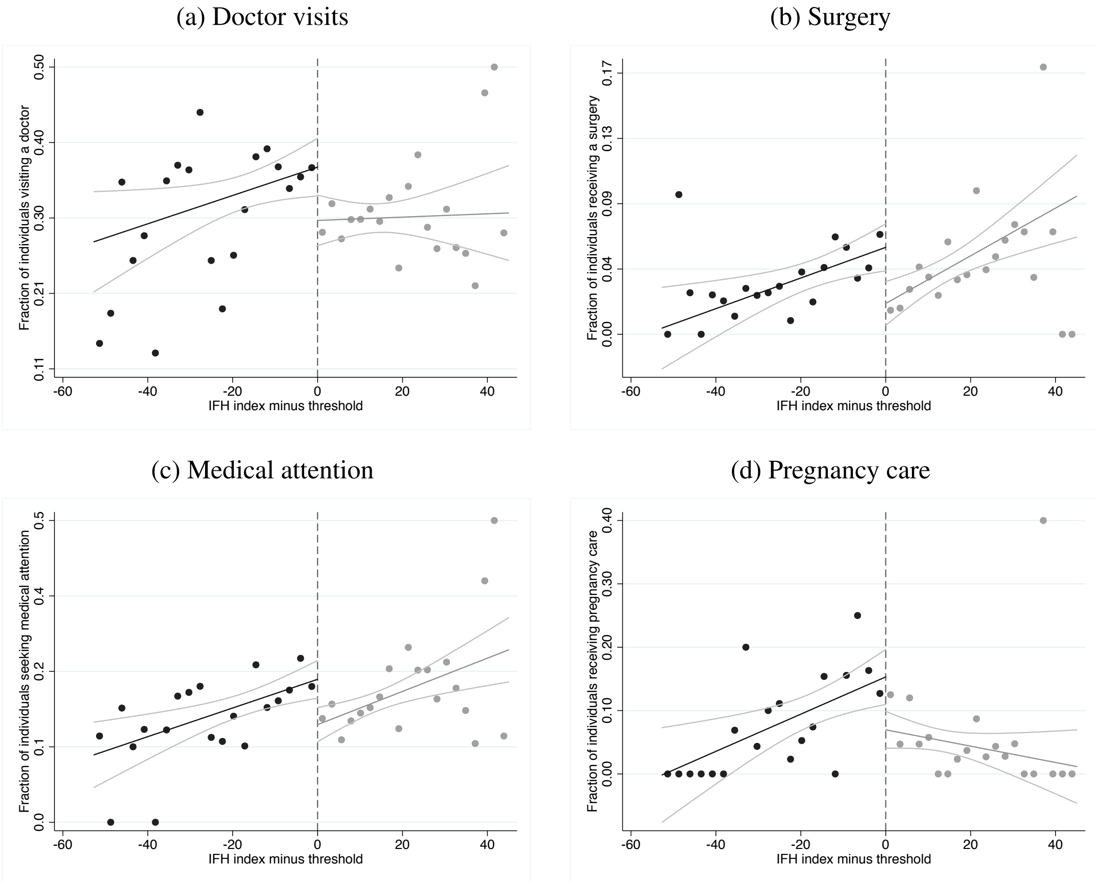
6 Results

6.1 Graphical Analysis

We first graphically examine how enrollment into public health insurance is related to the IFH index. Figure 2 shows the fraction of individuals enrolled into either SIS or EsSalud plotted against the IFH index centered at its threshold.[33] Recall that individuals are eligible for SIS

[33] As explained before, we use this definition because individuals may have confused those two public insurance programs when answering the respective survey questions. It follows from the institutional rules that any discontinuity in the probability to be enrolled in either of those, at the threshold, can be attributed to individuals becoming eligible for SIS. It is, however, likely that even if insurance status was perfectly measured we would not observe that the probability to be insured in only SIS is zero for individuals with a welfare index above the threshold. There are two reasons for this. First, there is a certain level of leakage in the targeting strategy of SIS, which means that some individuals who are formally ineligible may still be able to obtain insurance. What is important for our identification strategy, however, is that there is a discontinuity in this probability at the threshold. This is the case if at least some individuals are properly classified according to our index. Second, we construct the IFH index using survey data from the ENAHO rather than using the official data collected by SISFOH that is used to determine eligibility in practice. This may give rise to measurement error in the running variable. Also this is not a cause of concern as long as there is a positive probability for each individual that the index is measured correctly. Battistin

Figure 3: Health Care Utilization



if the IFH index is below the eligibility threshold. The figure shows a discrete increase in the probability to be covered at the SIS eligibility threshold, when moving from the right to the left and thereby provides direct evidence on the importance of the IFH index as a criterion to determine whether an individual is eligible for the SIS program.

The figure also shows that the probability to be enrolled into one of the two public insurance systems is slightly decreasing in the welfare index among eligible individuals to the left of the threshold. This means that poorer individuals might be slightly more likely to be enrolled, which is in line with the government's goal to target the poor. To the right of the threshold, we see that the probability to be covered by public insurance is increasing in the welfare index. This is due to the fact that dependent employees are more likely to have a higher value of the index and are more likely to be covered by EsSalud. Besides, EsSalud offers voluntary paid plans for self-employed, which is a more common choice among individuals with a higher value of the welfare index.

Next, we explore whether the discontinuity in the probability to be insured translates into discontinuities in the expectations of four of the most important measures of health care uti-

and Rettore (2008) show that then, the observed discontinuity can be attributed to those individuals for whom the index is observed without error. See also Hullegie and Klein (2010) for an alternative parametric approach to estimating treatment effects in a regression discontinuity design with measurement error.

lization.[34] Figure 3a plots the probability that an individual has visited a doctor in the last four weeks against the welfare index. We see that becoming eligible for health insurance, that is moving from the right to the left of the threshold, is related to an increase in utilization. Figure 3b, 3c and 3d show that also the probability to undergo surgery, to receive medical attention and to receive pregnancy care increase, respectively.

6.2 Main Analysis

Next, we analyze more formally how insurance status and outcome variables are related to eligibility. As described in Section 5 above, we do this by means of two-stage least squares instrumental variables regression. The endogenous variable is enrollment into public insurance and the instrument is eligibility according to the welfare index. Throughout, we control for the value of the index (separately to the left and to the right of the eligibility threshold), age, gender, whether the head of the household is female, the number of household members, and years of education.[35]

Table 4 shows the results. We estimate the effect of becoming eligible, at the threshold, to be a 14 percent increase in enrollment into public health insurance. This corresponds to the size of the discontinuity in Figure 2. The effect is highly significantly different from zero, with an F statistic of 29.8.

6.2.1 Health Care Utilization

The table also shows estimates of the effect of SIS on the utilization of 16 health services, including those in Figure 3. The effect on six of them is estimated to be sizable and statistically significant. In particular, being covered by health insurance increases the probability of visiting a doctor in the four weeks prior to the interview by 51.5 percentage points. The probability of receiving medicines in the same four weeks increases by 52.7 percentage points. Moreover, health insurance coverage increases the probability of performing at least some medical analysis by 20.6 percentage points. This suggests that covered individuals who sign up for health insurance when becoming eligible are more likely to see a doctor who then performs an analysis or prescribes a drug, in line with the idea that covered individuals receive medical care that caters better to their needs. This is remarkable because Peru is a country in which poor individuals are accustomed to not receiving any professional diagnosis and where drugs can also be bought in a pharmacy without a prescription.[36]

[34] The survey contains a wealth of variables related to health care utilization and outcomes. Our formal analysis below is more comprehensive.

[35] See Section 7 for results without controlling for covariates and more local analyses.

[36] However, importantly, when interpreting these results we should keep in mind that only 14 percent of the individuals in our sample actually sign up for health insurance when becoming eligible. These are the individuals the program is able to reach. 30 percent of the individuals are covered by public insurance, for the reasons given above, which means that about 56 percent of the individuals do either consciously decide not to enroll because they are healthy or are not aware of their health care needs, as described in the model in Section 3.

Table 4: Effect of Health Insurance on Health Care Utilization

		Estimates	Ste.
Participation (first stage)			
0	Health Insurance	0.1403***	(0.0257)
			$F = 29.8023$
Utilization			
1	Any doctor visit	0.5149***	(0.1954)
2	Medicines	0.5271***	(0.2045)
3	Analysis	0.2056**	(0.0921)
4	X-rays	0.1297*	(0.0712)
5	Other tests	0.0508	(0.0413)
6	Dental care	0.0660	(0.1231)
7	Ophthalmological care	0.0356	(0.0841)
8	Glasses 1/.	-0.0305	(0.0693)
9	Vaccines	0.2884**	(0.1317)
10	Kids check 2/.	0.0678	(0.2610)
11	Birth control	-0.1443	(0.0934)
12	Other treatments	0.1763	(0.1616)
13	Hospital	0.1484	(0.0931)
14	Surgery	0.2567***	(0.0881)
15	Pregnancy care 3/.	0.6504**	(0.2931)
16	Child birth 3/.	0.1900	(0.1593)
1-16	Any of the above	0.4377**	(0.1860)

Notes: See Table 12 for variable definitions. $N = 4,161$, except for kids check, pregnancy care and child birth. 1/. Not covered by SIS. 2/. Question applied for kids under age 10, $N = 649$. 3/. Question applied for women in fertile age, $N = 1,182$. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

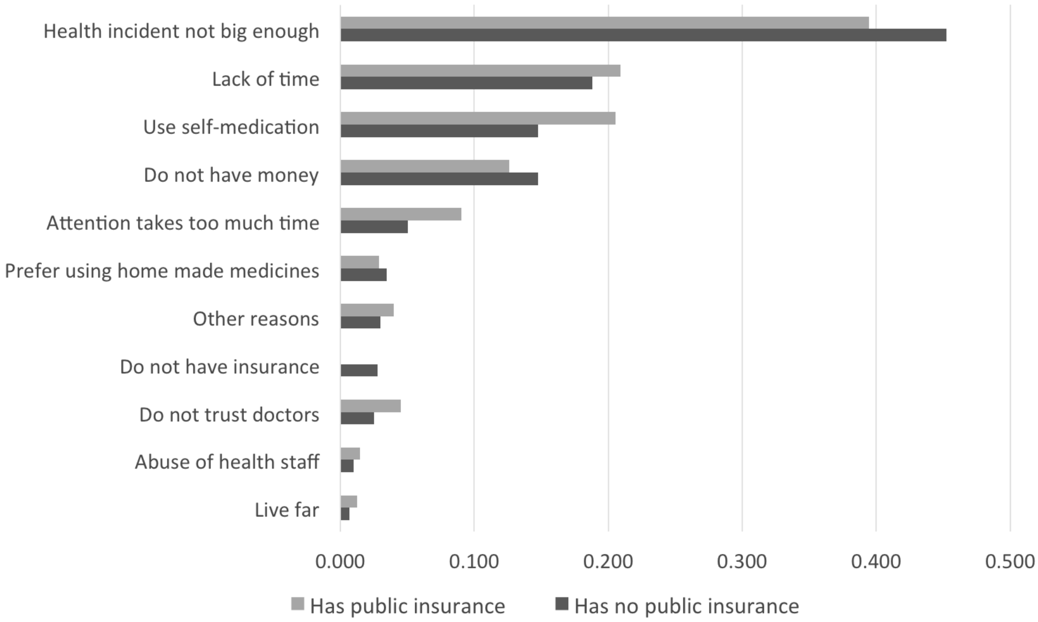
We also find health insurance coverage to have significantly positive effects on two measures of preventive care. The probability of being vaccinated in the three months prior to the interview increases by 28.9 percentage points, and women at fertile age are 65.0 percentage points more likely to control their pregnancy in the previous twelve months.[37]

The likelihood to receive surgery is estimated to increase by 25.7 percentage points. In Section 6.2.3 below we show that at least some individuals pay themselves for the treatments they receive, which suggests that health insurance coverage increases the likelihood that they find it worthwhile to do so. This shows that insurance coverage leads to increased awareness about the individual's health care needs, which is an important additional effects, as we have argued in Section 1 and 3 above.

Table 4 also shows that health insurance coverage has no significant effects on utilization of dental and ophthalmological care during the previous three months, and also not on hospitalization. This can be explained by the supply limitations described in Section 2.1. The MINSA health care centers provide only basic services. Individuals are sent to hospitals in order to visit

[37] We do not observe whether a woman is pregnant. Therefore, in principle, this includes the effect of insurance on becoming pregnant.

Figure 4: Stated Reasons for not Visiting a Health Care Center



a specialist, which also includes dentists and ophthalmologists. The shortage of dentists and ophthalmologists therefore explains at least part of our finding. In Section 2.1, we also explain that hospitals lacked equipment and were plagued by budget problems. This resulted in them charging for services that are formally covered by public health insurance and could explain why we do not find any significant effect of insurance coverage on hospitalization.

Eyeglasses are not part of the benefit package. We nevertheless estimated the effects of insurance on the probability to obtain glasses, because being insured has an effect on seeing a doctor who could advise the individual to get new glasses when performing another treatment. We find that insurance coverage has no significant effect on the probability to obtain eyeglasses.[38]

It is interesting to complement these results with statistics on reasons stated by individuals for not visiting a health care center even though they had a health incident, which is recorded in our data. Out of the 4,161 individuals in our sample, 2,418 report that they had a health incident. These are 60.9 percent of the individuals who are covered by health insurance and 56.4 percent of the individuals who are not. Out of the ones who had an incident and are covered, 35 percent did not visit a health care center. This compares to 40 percent of the individuals who are not covered, meaning that insurance coverage has a positive effect. Figure 4 shows that insurance status does not play a role for the reason why individuals do not see a health care professional. The most important stated reasons for not visiting a health care center were that individuals consider the health incident not big enough, lack time and do not have money. Instead, they seem to resort to self-medication, which likely means that they buy some drugs at the pharmacy. A lack of trust into the system does not seem to be an important reason. Overall,

[38]One can also see this as a placebo test in addition to the tests we perform in Section 7 below.

these numbers suggest that it is still not common to seek medical attention for many individuals. Unfortunately, the nature of the health incident is not recorded, but our interpretation of these results, together with the strong positive effects of public insurance on curative use presented above, is that public health insurance motivates individuals to see a doctor only if the health incident is sufficiently big in their eyes.

6.2.2 Curative versus Preventive Use

In Section 2 we have argued that health insurance coverage may have positive effects on the use of curative and preventive care and that the institutional details and circumstances suggest that in Peru, the main effects will be on curative use.

Ideally, in order to test this hypothesis, we would observe the exact reason why, for instance, a doctor was visited, as 5 out of the 12 measures of utilization in Table 4 may either have a curative purpose or a preventive one: doctor visits, medicines, analysis, X-rays and other tests. Besides, there is a second group of variables that are more likely related to curative use: hospitalization, receiving surgery and birth delivery. A third group of four variables clearly has a preventive nature: reception of vaccines, growth controls of healthy children, reception of birth control methods and pregnancy care (variables 9-11 and 15 in Table 4). On top of that, the survey includes specific questions on preventive uses in the last 3 months. It is related to family planning for women in fertile age, reception of iron supplements for pregnant women and children under three years old, and information on prevention of sicknesses.

In order to tell apart curative from preventive use, we construct an indicator for experiencing a health problem and interact it with the first five variables in Table 4.[39] This means that the outcome is the joint event of experiencing a health problem and going to the doctor. Proceeding in that way allows us to only consider doctor visits, for instance, for those individuals with health problems, which we then interpret as curative use. Panel A in Table 5 shows the results. Those individuals who sign up for insurance when becoming eligible are 56.4 percentage points more likely to receive medical attention than uninsured ones. Coverage also increases the probability of visiting a doctor with curative purposes by 55.5 percentage points, the probability of obtaining medicines by 51.4 percentage points and the probability to conduct medical analysis by 17.9 percentage points. When we group these variables together, then we find that insurance increases the probability of using at least one curative service by 74.0 percentage points.

In line with our expectations, effects on preventive care are weaker. We do, however, find positive effects on pregnancy care and on receiving vaccines. We find that women in fertile age who sign up for insurance when becoming eligible are 65.0 percentage points more likely to

[39] We say that individuals experienced a health problem if at least one of the first 5 questions in Table 13 was answered with “yes”. See Table 3 for summary statistics. To be precise, in the questionnaire, individuals are asked whether they saw a doctor, for instance. On top of that, they are asked whether they experienced health problems and then, if they answer with "yes", again whether they saw a doctor. In our data, the answer to the first, general question is always equal to the one to the third question. Outcome 1’ to 5’ in Table 4 are equal to outcome 1 to 5 in Table 5 if individuals state that they experienced health problems. Otherwise, they are zero.

Table 5: Effect of Health Insurance on Curative and Preventive Use

		Estimates	Ste.
A. Curative			
0'	Medical attention	0.5635***	(0.1741)
1'	Any doctor visit	0.5554***	(0.1729)
2'	Medicines	0.5135***	(0.1676)
3'	Analysis	0.1788**	(0.0863)
4'	X-rays	0.0926	(0.0667)
5'	Other tests	0.0382	(0.0319)
13	Hospital	0.1484	(0.0931)
14	Surgery	0.2567***	(0.0881)
16	Child birth	0.1900	(0.1593)
1'-5',13,14,16	Any of the above	0.7402***	(0.1981)
B. Preventive			
9	Vaccines	0.2884**	(0.1317)
10	Kids check	0.0678	(0.2610)
11	Birth control	-0.1443	(0.0934)
15	Pregnancy care	0.6504**	(0.2931)
6'	Planning 1/.	-0.0412	(0.2447)
7'	Iron 2/.	0.6127	(0.4954)
8'	Preventive campaign 3/.	0.0344	(0.0696)
6'-8', 9-11,15	Any of the above	0.2743*	(0.1626)

Notes: See main text for details on how we distinguish between curative and preventive care. $N = 4,161$, except for kids check: $N = 649$, pregnancy care: $N = 1,182$, planning: $N = 1,181$, iron: $N = 343$. Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. 1/. Family planning for women at fertile age. 2/. Reception of iron supplements for pregnant women and children less than three years old. 3/. Information on prevention of sickness.

control their pregnancy relative to their uninsured peers. Moreover, we find a 28.8 percentage point increase in the probability to be vaccinated.[40]

To summarize, in line with expectations formed by our discussion of the institutional details in Section 2, the effect of insurance coverage on preventive care is much less pronounced that on the utilization of curative services. It is interesting to compare these results to the ones by Miller et al. (2013) for Colombia, where the system provides larger incentives to invest in preventive care, as already discussed in Section 1. And indeed, Miller et al. find stronger positive effects on preventive care and actually no effect on curative use. Nonetheless, it is encouraging that we do find at least some effects on preventive care, in particular on the probability to be vaccinated and to receive pregnancy care, as both are especially important in developing countries.

[40]The last variable indicates whether there was any preventive use. Clearly, in theory, the effect on this probability has to be at least as big as the effect on vaccines, say, because an effect on vaccines implies an effect on any use. We did not impose this here and indeed find that the effect on any use is slightly smaller than the effect on receiving vaccines. However, the difference could also be due to sampling error.

Table 6: Effect of Health Insurance on Health Expenditures

		Estimates	Ste.
1	Any health expenditures	0.2916	(0.1955)
2	Health expenditures	1018.8250**	(440.8071)
3	Absolute deviation expenditures	809.5140**	(385.2883)
4	Absolute value residual expenditures	608.7793*	(369.3996)
5	Squared residual expenditures	8.555E+06*	(4.77E+06)
6	Expenses exceed median	0.2862	(0.1958)
7	Expenses exceed 75th percentile	0.2716	(0.1655)
8	Share expenditures	0.1107	(0.0799)
9	Absolute deviation share	0.0702	(0.0730)
10	Absolute value residual share	0.0698	(0.0730)
11	Squared residual expenditures	0.1422	(0.2277)
12	Share exceeds median	0.5308**	(0.2107)
13	Share exceeds 75th percentile	0.3474**	(0.1760)
14	Catastrophic 5%	0.4059**	(0.1777)
15	Catastrophic 10%	0.2907**	(0.1407)
16	Catastrophic 15%	0.1750	(0.1148)
17	Catastrophic 20%	0.1448	(0.0998)
18	Catastrophic 25%	0.0485	(0.0856)

Notes: See Table 13 for variable definitions. N=4,161. Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

6.2.3 Expenditures

Given our previous findings of strong positive effects on health care utilization, it is interesting to ask what the effect of health insurance coverage is on out-of-pocket expenditures. We have argued in Section 3 that it is an empirical question whether the effect is negative or positive. Obviously, it could be negative because coverage means that individuals do not have to pay for certain treatments anymore. But importantly, it could also be positive if receiving medical attention convinces individuals to actually spend more on their health themselves because they become aware of additional health care needs.

A number of different outcome measures related to health expenditures have been used in other studies. These either attempt to measure expected health expenditures, their variability—interpreted as health risk—, or the likelihood to incur catastrophic health expenditures.[41]

Table 6 presents the effect of SIS on a number of variables constructed from annual health expenditures at the individual level.[42] The first dependent variable is an indicator for incur-

[41]Most studies measure the cross-sectional variability of health expenditures and then interpret it as health risk at the individual level. This is only valid if there is no persistence in health expenditures. Otherwise, health risk is overestimated. See for instance French and Jones (2004) for evidence in favor of such persistence in the U.S.

[42]See also the variable definitions in Table 13. We also experimented with more sophisticated variability measures and found similar results.

ring health expenditures. We find no significant effect on this outcome, suggesting that health expenditures are, if at all, mainly affected at the intensive margin.

Turning to the intensive margin, the second variable is the level of annual health care expenditures. The results suggests that insurance coverage leads to an increase of annual spending by about 1,000 Soles on average, which corresponds to around 363 U.S. dollars,—in line with the idea that individuals are motivated to spend more on their health when using medical services more often. This is about 5 percent of the average income among the poor.

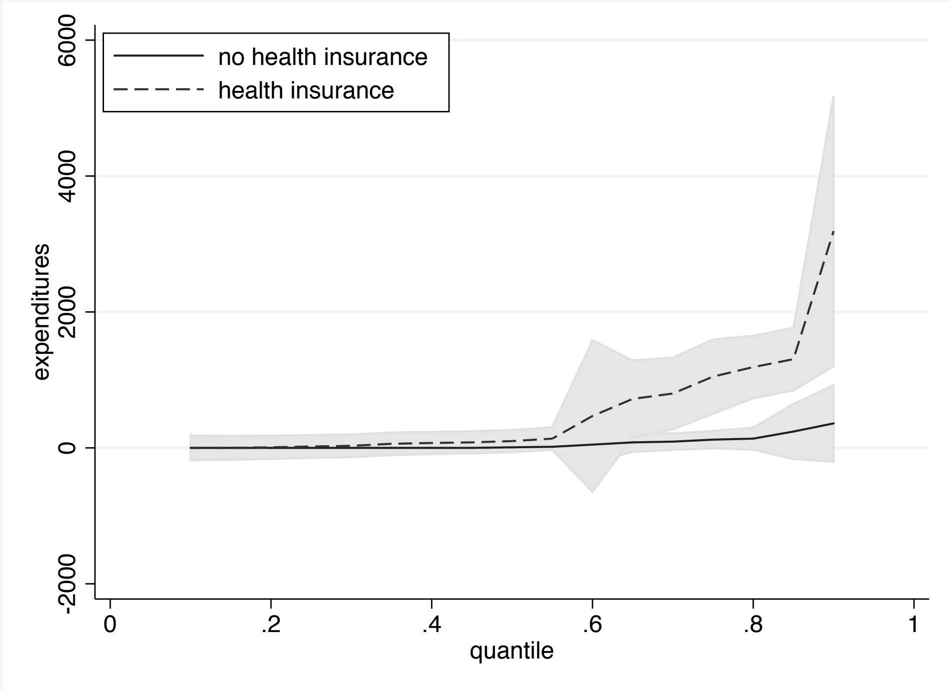
We also examine a possible effect on the variability of medical spending. Our variability measure in the third specification, similar to the one used by Miller et al. (2013), is the mean absolute deviation of health expenditures, calculated separately by insurance status. Specification 4 and 5 are based on residuals obtained from a regression of health expenditures on the value of the index, insurance status and the interaction of these two variables. The idea here is that this allows us to isolate the change in health expenditures around the eligibility threshold on which our analysis is based. The former specification then uses the absolute value of the residual and the latter its square. Effects are only significant at the 10 percent level. Looking at the results for the next two outcome measures, we find no effects on the probability that health expenditures exceed the median or the 75th percentile of the distribution of health expenditures in the entire population.

In order to control for a possible income difference between the control and treatment groups, we also analyze the effect of insurance on the share of annual health expenditures at the individual level, relative to the annual household income per capita. For the last two outcomes, we calculate the 50th and 75th percentile of the distribution of the share and find that SIS increases the probability that this share exceeds the 50th and 75th percentile by 53.1 and 34.7 percentage points respectively. The results are presented in row 8 to 13 and correspond to those in row 2 to 7 of Table 5. Now we find a positive effect on the probability to incur high expenditures.

Finally, we look into whether SIS changes the probability of an individual incurring catastrophic health expenditures. Health spending is defined as catastrophic if the share of the expenditures relative to per capita household income exceeds pre-defined threshold values. This means that here the cutoff values do not depend on the spending of the other individuals in the sample, which is the case for outcome 12 and 13. We follow Wagstaff and Lindelow (2008) and use the thresholds 5, 10, 15, 20 and 25 percent. We find that for those individuals who sign up for health insurance when becoming eligible, the probability that individual health expenditures exceed 5 and 10 percent of the per capita household income increases by 40.6 and 29.1 percentage points, respectively. We do not find significant effects for higher cutoffs. These results are similar to those obtained by Wagstaff and Lindelow (2008) for China.

Overall, it is remarkable that we never find a negative effect on either expected health expenditures or measures of variability or risk of high expenditures. Miller et al. (2013), in contrast, find for Colombia that insurance lowers both mean inpatient medical spending and its vari-

Figure 5: Health Expenditures by Quantile



Notes: The figure shows the percentiles of the distribution of expenditures with and without health insurance, along with 95 percent confidence intervals. See Frandsen et al. (2012) for details on the implementation.

ability. Likewise, Limwattananon et al. (2015) find that health insurance coverage leads to a decrease in out-of-pocket spending in Thailand.

In addition, we quantify the effects of health insurance coverage on the entire distribution of out of pocket expenditures. Figure 5 shows the estimates of the quantiles of the distribution of health expenditures with and without health insurance coverage and corresponding confidence intervals. We do not show this for higher quantiles than the 90th because for those the effects are too imprecisely estimated. It is remarkable that throughout, expenditures are very low when individuals are not insured. As explained in Section 3, our interpretation is that uninsured individuals are not aware of their health status. At the same time, we find that insurance has only a positive effect on the higher end of the distribution: when individuals become eligible for health insurance and enroll, then they receive free medical care, which explains why there is no increase in out of pocket expenditures at the lower end of the distribution. As the same time, as we have argued in Section 3, they may become aware of their health problems when visiting a health care center and can then be convinced to pay for some expensive treatments that are not covered themselves, which explains the increase at the top end of the distribution. This interpretation is also in line with our finding of stark differences in health care utilization—uncovered individuals do simply not receive much attention or treatment of any kind, while curative use increases substantially for those individuals who become eligible and enroll.

To explore this further, we have conducted the analysis underlying Figure 5 separately for each type of health expenditures. Figure 10 in the Online Appendix shows the results for the two types of health expenditures for which we have found an effect, spending on medicines and on other treatments. The former is likely related to the supply limitations we have described in Section 2, namely that health care centers charged for medicines that were formally covered by public insurance. The same might also be true for the latter, but we cannot explore this further because we lack information on what other treatments are precisely.

To complement this systematic evidence with more direct one, we have conducted a small survey in two health care facilities, in October and December 2014. We asked 19 individuals about their experiences. Their answers revealed that the facilities did not have enough drugs in 2011, so that they bought them themselves at private pharmacies, in line with the effect on expenditures for drugs we estimate. They also confirmed that the lack of equipment meant that certain treatments could not be undertaken, which resulted in patients paying themselves for treatment that was received elsewhere. For instance, one person needed to receive prostate surgery and said that he will probably get it elsewhere instead of waiting until the next year.

Such rises in health care expenditures are usually seen in a critical way, especially if some treatments are formally covered but individuals have to pay for them regardless. However, one may question whether this is justified here. On the one hand, this increase in expenditures can be seen as an additional burden to the individuals, possibly also increasing the volatility of expenditures. On the other hand, the alternative could also be that individuals are not treated at all because they are not aware of their health care needs. In that sense the increase in spending for medicines and other treatments could also be seen as a desirable consequence of insurance coverage, which leads to increased accessibility, and thereby gives individuals the idea of using medical services in response to being insured. Moreover, looking at it in yet another way, some treatments are at least partly covered by SIS so that the overall price of a treatment is generally lower, which means that the law of demand (that lower prices mean more demand) would also predict an increase in usage. So also in that sense our findings could be less worrying than they may first seem.

6.2.4 Effects on Health

We have argued in Section 3 that it is unclear how the effect of health insurance on self-reported health measures can be interpreted. The reason for this is that individuals who are covered and who see a doctor more often are more aware of their health problems. Therefore, even if the effect on objective health measures is positive, it could be that the effect on subjective health measures is negative of not significantly different from zero.

Table 7 reports our estimates of the effects of insurance coverage on health reports. We do find positive effects on reports of illnesses and a less strong effect on the number of days individuals could not perform normal activities due to an illness. These results are well in line with the literature (see for instance Acharya et al., 2013), but we—unlike the literature, and for the reasons given above—feel inclined to interpret them as indicating increased awareness of health problems.

Table 7: Effect of Health Insurance on Health

		Estimates	Ste.
1	Any Symptom	0.2655	(0.1942)
2	Illness	0.3158**	(0.1465)
3	Chronic illness	0.0754	(0.1736)
4	Relapse	0.0601	(0.1113)
5	Accident	0.0714	(0.0591)
6	Num. days with symptom	0.4004	(0.4898)
7	Num. days with illness	0.6078*	(0.3607)
8	Num. days with relapse	0.8262	(0.9162)
9	Num. days with accident	0.5295	(0.4494)

Notes: $N = 4,161$. Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

7 Sensitivity Analysis

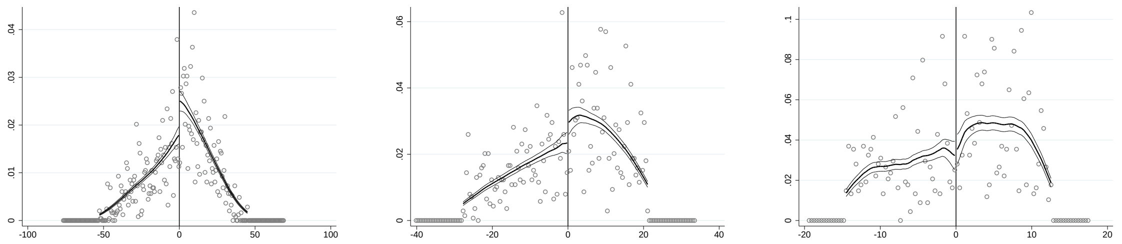
In this section, after having presented the main results, we assess whether they are sensitive to the particular specifications we have used, and whether the identifying assumptions we have made can be supported by additional empirical evidence. We start by examining whether individuals may have manipulated the IFH index in order to become eligible for public insurance. If this was the case, then the magnitude of our estimates would likely be too big, as individuals for whom insurance coverage would have the biggest effects would have the biggest incentive to manipulate the index. Thereafter, we assess whether there were discontinuities at other values of the welfare index. This would raise concerns, as our approach builds on the premise that there is only one discontinuity of the expected outcomes in the welfare index, at least locally. Third, we conduct more local analyses by selecting subsamples of observations that are closer to the threshold. After that, we conduct a non-parametric analysis. And finally, we assess whether the existence of other programs could challenge the validity of our results.

7.1 Manipulation Tests

A common threat to studies based on a RDD is the incentive to manipulate the running variable. For this, individuals need information on how the IFH is calculated. Then, they need to use this knowledge to manipulates their answers to the questions posed by the government official in order to qualify for SIS. This is unlikely to be the case for two reasons. First, even though the information on how the index is computed is, technically speaking, public, it is not easy to obtain and process it. Second, the set of variables included in the IFH construction are verified by the government officials and therefore difficult to manipulate. In this context, the manipulation of the running variable would at most be partial.

We nevertheless analyzes this potential thread. We use the McCrary (2008) test for this. If manipulation takes place, then the density of the running variable will be discontinuous at the

Figure 6: McCrary Test



(a) Full Sample (b) Sample 75 (c) Sample 50

Notes: The figures show estimates of the density of the IFH index around the threshold. The left figure is for the full sample. The figure in the middle is for the sample in which we keep the 75 percent of the observations that are closest to the threshold in terms of the IFH index, separately to the right and to the left. In the right figure we do the same for the 50 percent closest observations to the left and to the right. Full sample: bin size of 0.59 and bandwidth of 23; sample 75: bin size of 0.44 and bandwidth of 12 and sample 50: bin size of 0.32 and bandwidth of 4.8.

cutoff. In our context, the density function would show many individuals barely qualifying for SIS, that is, to the left of the cutoff, and surprisingly few failing to qualify, that is, to the right of the cutoff. The formal procedure is twofold: firstly a finely gridded histogram is obtained and then this histogram is smoothed with a local linear regression for each side of the cutoff.

Figure 6 presents the results. The three panels show the results for the full sample, and for a sample of respectively 75 and 50 percent of the individuals with an IFH index closest to the threshold, separately on each side. Formally, the test for the full sample rejects smoothness of the density around the threshold. However, the result is not robust to choosing smaller subsamples and in any case would hint at manipulation towards becoming ineligible, as the density is higher above the threshold.[43] Taken together with the fact that it is unlikely that individuals are actually able to manipulate the value of the index, this points towards no manipulation and thus speaks in favor of the assumptions made in the main analysis.

7.2 Jumps at Non-Discontinuity Points

Our analysis implicitly assumes that the only discontinuities occur at the eligibility threshold, 55, as we have specified conditional expectations to be linear in the forcing variable, separately to the left and to the right of this threshold. Following Imbens and Lemieux (2008) we conduct separate additional RDD analyses for the subsamples of eligible and ineligible individuals and use the respective medians of the index as the threshold values. For example, the subsample at the left of the threshold would be comprised by those with $z_i(IFHindex) < 55$ and we test for a discontinuity at the median, to maximize the power of the test. By only using data on the left of the official threshold, we avoid conducting the regressions at a point where it is known to have a discontinuity.

[43] It could be that, for budgetary reasons, the government set the threshold low enough such that a bulk of individuals is just not eligible for SIS. Then, the density would be higher to the right of the threshold. We are, however, not able to test this hypothesis. Importantly, it would not threaten our identification strategy as long as the variation in the index around the threshold is still random.

Results are presented in Table D in the Online Appendix. In general, we observe no significant effects on health outcome variables when we run the regressions at the medians of the subsamples. The only exception is, however, the participation variable (health insurance) in the subsample at the right of the official threshold; there is a significant jump when we use the IV-2SLS regressions on the 75 percent observations closer to the median. However, this turns out to be an artifact and disappears when we use local linear regressions.[44]

The picture that emerges is that, with a few non-robust exceptions, there seem to be no discontinuities at points other than the true eligibility threshold. This is important because it supports out choice of imposing linearity in order to obtain more precise estimates of the effects of interest, as described in Section 5.

7.3 More Local Analysis

It can also be argued that the linearity assumption is strong even if there are no discontinuities, and that therefore the analysis should be conducted on the population with IFH index values closer to the threshold. To see whether results are sensitive to that, we reduce the sample to the 75 and 50 percent of the population with IFH index values closest to the threshold, separately for each side.

Table 18, again in the Online Appendix, shows the results for these reduced samples. Some of the coefficient estimates increase in magnitude while the precision of the estimates decreases. For instance, for the 75 percent sample, we find that the effects on the likelihood to visit a doctor, receiving medicines, conducting analysis and having access to surgery increase from 51.5, 52.7, 20.6 and 25.7 reported in Table 4 to 76.1, 88.3, 36.3 and 44.1 percentage points, respectively. At the same time, due to the decreased number of observations, the precision of the estimates decreases, as expected. The estimates of the effects of insurance on receiving vaccines and pregnancy care are therefore no longer significantly different from zero.

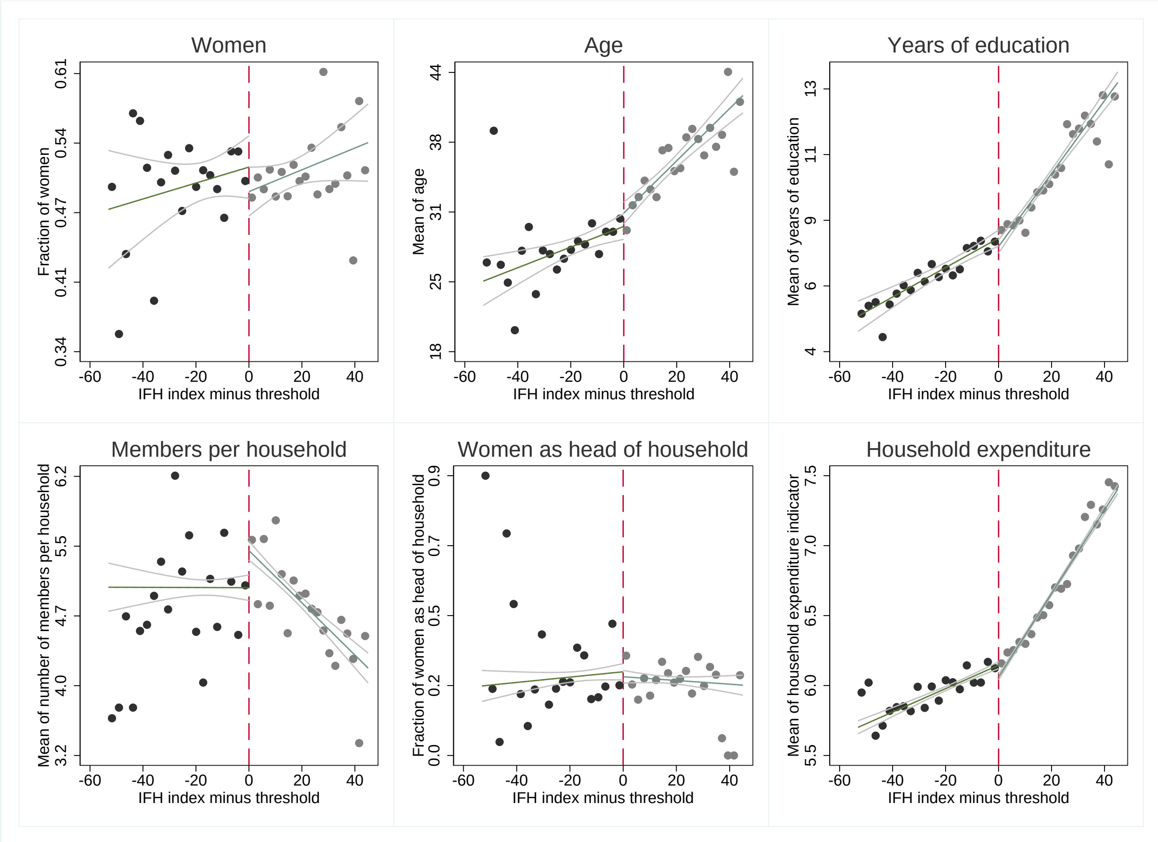
Importantly, however, the picture remains qualitatively the same: the effects on utilization are strongest, in particular for curative use, health expenditures increase, and if anything, individuals report to be in worse health.

7.4 Controlling for Covariates

It is standard practice to test whether the expectation of covariates such as age or gender is a continuous function in the welfare index around the eligibility threshold. When it it is found not to be, then one may be concerned that the assumptions underlying our analysis do not hold,

[44] We also conduct a reduced form analysis (regressions of outcomes on the index, eligibility, its interaction and controls) to see whether any outcome jumps discontinuously at the fictitious thresholds described before. We find no significant effects in general, except for vaccines. There is a negative effect on the subsample to the left and a positive one on the subsample at the right of the original threshold. However, these effects disappear when we use local linear regressions. The rest of the variables, especially those related to curative services, do not exhibit any significant jump at those thresholds.

Figure 7: Graphical analysis of covariates



unless this could be related to the institutional rules. Otherwise, one may then be concerned that the variation in the index around the eligibility threshold is non-random, which would be a violation of an important identifying assumption and could not easily be addressed. Moreover, one may then also be concerned that there are other discontinuities at the same threshold and therefore the estimated effect cannot be attributed to SIS only.

To address those potential concerns, we first conduct both a graphical and a formal analysis in which we replace the dependent health variables by the observed covariates age, gender, whether the woman is the head of the household, the number of household members, years of education and household expenditures. In Section 6.2, we use the first five covariates as controls in order to be able to obtain more precise estimates.

Figure 7 and Table 8 summarize the results. The latter reports instrumental variables estimates of the effect of insurance on the covariates. We do not find evidence for a discontinuity in the expectation of the covariates except for one, which is the number of household members. Figure 7 shows that the expected number of household members changes by about 0.5, or 10 percent, which (roughly) gives the estimated effect in Table 8 if we divide it by the change in the probability of about 0.14 reported in the first column of Table 18 in the Online Appendix. However, Figure 7 shows that this is likely due to the relationship between the welfare index and the expected number of household members being nonlinear (concave) to the right of the

Table 8: Effect of Insurance Coverage on Covariates

IV-2SLS	(1) Full sample		(2) Sample 75%		(3) Sample 50%	
	Estimates	Ste.	Estimates	Ste.	Estimates	Ste.
Woman	-0.0438	(0.1956)	-0.2057	(0.3028)	0.0769	(0.4240)
Age	-7.3244	(8.4632)	6.9167	(12.6805)	-0.5141	(17.9161)
Years of education	2.1508	(1.8593)	0.1840	(2.7045)	-6.5433	(4.5075)
Number household members	-3.5275***	(1.0520)	-5.5418***	(1.9892)	-3.8927	(2.3943)
Women as head of household	-0.0149	(0.1692)	0.3951	(0.2793)	0.6886	(0.4523)
Household's expenditure 1/.	0.2645	(0.1736)	0.0281	(0.2403)	-0.5288	(0.4069)

Notes: $N = 4,161$. Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.00.

eligibility threshold.[45]

To gain confidence into our results we also conducted the main analysis without controlling for covariates, hence also not for the number of household members. Tables 18, **??** and **??** in the Online Appendix show that the main conclusions we have drawn remain the same.

7.5 Non-Parametric Analysis

To address the concern that linearity is too strong of an assumption even in smaller subsamples we conduct a non-parametric analysis. For this, we use local linear and local quadratic regressions to predict the expected outcome and the probability to be covered by insurance using only data to the left or to the right of the discontinuity, respectively. We then calculate the difference between the prediction for the outcome from the right and from the left and divide it by the difference in the probability to be covered by SIS. This leads an estimate of the local average treatment effect that can be compared to the ones reported above.[46]

Table 9 shows the results for a selection of dependent variables and for different bandwidths. We chose the dependent variables out of the ones in Table 4 and Table 6 for which we found significant effects at the 5 percent level or lower. Generally speaking, estimates are less precise, but point estimates are similar. This suggests that the point estimates presented in Section 6 are not driven by the linearity assumption.

[45] One may nevertheless wonder why we could find such an effect. In principle, it could be that the number of household members is an outcome that is negatively affected by having insurance because insurance has a positive effect on using birth control products, which leads to reduced fertility. We, however, do not find such effects that could explain the reduction of birth control methods, also not in the specifications that do not control for covariates. Another possibility is that after being covered by insurance, respondents to the survey use a more strict definition of the household that includes only those members that are covered by health insurance.

[46] It is in principle possible to also control for covariates. This, however, would involve estimating partially linear models where we impose that they enter linearly. We do not do so here because this goes along with a large increase in the computational burden when we bootstrap the standard errors. Therefore, the results reported here are closest to the ones in Table 18 in the Online Appendix. Arguably, since these have in turn be close to the main results where we control for covariates and since we have found that only one covariate exhibits a moderate jump at the discontinuity, this seems a reasonable way to proceed given that this is meant to be a robustness check.

Table 9: Local Linear Regressions

corresponding result			Local Linear				Local Quadratic			
			10	20	50	100	10	20	50	100
Table 4	0	Health Insurance	0.0831**	0.1282***	0.1373***	0.1382***	0.1171**	0.0986**	0.1033***	0.1032***
			(0.0368)	(0.0280)	(0.0247)	(0.0248)	(0.0492)	(0.0400)	(0.0287)	(0.0327)
Table 4	1	Any Doctor visit	0.7595	0.5358	0.5007***	0.4983**	0.4633	0.8347	0.7054	0.6970
			(0.5882)	(0.3286)	(0.1938)	(0.2163)	(86.7429)	(0.7480)	(8.4927)	(0.4620)
Table 4	2	Medicines	1.0387	0.6290***	0.5168**	0.5074**	0.5701	1.0279	0.9759	0.9744*
			(2.1575)	(0.2328)	(0.2605)	(0.2141)	(0.6690)	(1.1001)	(0.7157)	(0.5811)
Table 4	3	Analysis	0.3332	0.2225**	0.2088**	0.2069**	-0.0970	0.3367	0.3416	0.3429
			(0.2437)	(0.1130)	(0.1010)	(0.0900)	(0.2369)	(1.2037)	(0.2940)	(3.4432)
Table 4	9	Vaccines	0.5348	0.3151*	0.2890**	0.2882**	0.5700	0.4987	0.3622	0.3534
			(3.7619)	(0.1642)	(0.1319)	(0.1331)	(1.1554)	(2.2913)	(0.3966)	(1.3567)
Table 4	14	Surgery	0.5280	0.3180***	0.2694**	0.2650***	0.3862	0.4717	0.4726	0.4745*
			(1.4463)	(0.1063)	(0.1068)	(0.0980)	(1.3371)	(2.8475)	(0.8522)	(0.2608)
Table 4	15	Pregnancy care	0.7876	0.6095	0.6033	0.6030	0.0445	0.5770	0.5082	0.5066
			(5.4355)	(1.6750)	(0.5286)	(0.5409)	(1.8262)	(3.0906)	(35.4400)	(6.5831)
Table 6	2	Illness	0.4034	0.3207	0.3139**	0.3140*	0.5729	0.4906	0.3933	0.3852
			(0.6860)	(0.2060)	(0.1374)	(0.1806)	(1.0985)	(0.6135)	(1.7819)	(0.4200)

Note: See also notes to Table 4 and Table 6. Local average treatment effects are reported for bandwidths 10, 20, 50 and 100 and for a procedure based on local linear and local quadratic regressions, respectively. Bootstrapped standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.00.

7.6 Juntos and Food Aid Program

Our identification strategy is based on the assumption that discontinuities at the eligibility threshold can be attributed to SIS. There are some programs whose presence could in principle challenge this assumption.

One of them is Juntos, a conditional cash transfer program. It combines a geographic targeting of the poorest districts with individual targeting, based on the IFH index and the presence of children up to the age of 14. However, Juntos is a rural program and our study focuses on the Lima Province, and our data confirm that no individual in the sample belongs to Juntos.

Besides, there is a number of food aid programs oriented to the poor. To be precise, they are oriented to different groups of the population, such as mothers, children and school students. Our data show that 29 percent of the individuals of our sample receive at least support from one of them.[47] Importantly, since these programs do not use SISFOH's targeting rules and in particular not the IFH index, it is unlikely that a discontinuity at the eligibility threshold can be attributed to them. Our finding in Section 7.4 that household expenditures do not exhibit a discontinuity at the insurance threshold provides additional support for this interpretation.

8 Conclusions

Until recently, large parts of the population in developing countries did not have access to public health insurance. While it is commonly believed that the effects of health insurance

[47] The percentage of individuals that receive food aid is 29 percent among those not covered by SIS and 51 percent among those who are covered. There is no information on the reception of food aid for 874 individuals, or 20 percent of our sample.

coverage are positive, we still lack empirical evidence on its impact on health care utilization, health expenditures, and health outcomes. Besides, it is not yet understood enough through which channels health insurance coverage ultimately leads to better health outcomes and to what extent it is possible to encourage individuals to invest into preventive care.

In this paper, we use rich survey data from Peru to study the effects of the large-scale social health insurance program called "Seguro Integral de Salud" (SIS). The SIS program is targeted to poor individuals working in the informal labor market. Coverage has increased since 2006 and by now about 40 percent of the population are covered by SIS. We make use of the institutional details that give rise to a regression discontinuity design. We estimate the effect of insurance coverage on a wealth of measures for health care utilization, health expenditures and health.

We find strong effects of insurance coverage on measures of health care utilization, such as visiting a doctor, receiving medication and medical analysis. We also find effects on preventive care, but they are much less pronounced. This is not surprising, as the system does not provide any incentives to actually do so. Furthermore, we find positive effects on health care expenditures, mostly at the high end of the distribution, and no clear effects on self-reported health measures.

We thereby provide evidence in favor of two arguments that are less common in economics. First, access to health care centers leads to increased awareness about health problems; and second, this even generates a willingness to pay for services that are not covered, which in the context of Peru is a potentially desirable form of supplier-induced demand.

We formalize this interpretation of our findings using a simple model in which individuals are not aware of some of their health care needs. They sign up for health insurance if the health care needs they are aware of are big enough, then learn about the needs they were unaware of and pay themselves for some of the treatments that are not covered by the health insurance or are in short supply.

Overall, the evidence suggests that when compared to health care systems in other developing countries, the Peruvian one is a notable exception. It seems to reach its goal to provide access to medical care to a sizable fraction of the poor. A key determinant of this success seems to be that the monetary cost of enrolling is zero, instead of being small but positive, which it is elsewhere. This ultimately leads to individuals getting in touch with health care professionals and even developing a willingness to pay for health services. As of now, there is no evidence on the effects this will have on objectively measured health, but it is imaginable that increased access will ultimately lead to better health outcomes. We discuss in the paper why it remains a challenge for the future to measure those, but the institutional features make this a more promising endeavor than it is in many other countries.

References

Abbring, J., P. Chiappori, and J. Pinquet (2003). Moral hazard and dynamic insurance data. *Journal of the European Economic Association 1*(4), 767–820.

Abbring, J., J. Heckman, P. Chiappori, and J. Pinquet (2003). Adverse selection and moral hazard in insurance: Can dynamic data help to distinguish? *Journal of the European Economic Association 1*(2-3), 512–521.

Abel-Smith, B. (1992). Health insurance in developing countries: Lessons from experience. *Health policy and Planning 7*(3), 215–226.

Acharya, A., S. Vellakkal, F. Taylor, E. Masset, A. Satija, M. Burke, and S. Ebrahim (2013). The impact of health insurance schemes for the informal sector in low and middle income countries. Policy Research Working Paper, The World Bank.

Adams, P., M. D. Hurd, D. McFadden, A. Merrill, and T. Ribeiro (2003). Healthy, wealthy, and wise? tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics 112*(1), 3–56.

Akerlof, G. A. . (1970). The market for lemons: Quality uncertainty and the market mechanism. *Quarterly Journal of Economics 84*, 488–500.

Alderman, H. and C. H. Paxson (1992). Do the poor insure? a synthesis of the literature on risk and consumption in developing countries. In E. L. Bacha (Ed.), *Economics in a Changing World: Proceedings of the Tenth World Congress of the International Economic Association*, Economics in a Changing World. St. Martin's Press.

Aron-Dine, A., L. Einav, A. Finkelstein, and M. Cullen (2012). Moral hazard in health insurance: How important is forward looking behavior? NBER Working Paper No. 17802. National Bureau of Economic Research, Cambridge, MA, U.S.A.

Arróspide, M., K. Rozas, and J. Valderrama (2009). Evaluated budget: Integrated health insurance. Ministry of Economics and Finance, Peru.

Bajari, P., H. Hong, and A. Khwaja (2006). Moral hazard, adverse selection and health expenditures: A semiparametric analysis. NBER Working Paper 12445. National Bureau of Economic Research, Cambridge, MA, U.S.A.

Banerjee, A., A. Deaton, and E. Duflo (2004). Wealth, health, and health services in rural rajasthan. *The American Economic Review 94*(2), 326–330.

Banerjee, A. V. and E. Duflo (2007). The economic lives of the poor. *The journal of economic perspectives: a journal of the American Economic Association 21*(1), 141.

Barros, R. (2008). Wealthier but not much healthier: Effects of a health insurance program for the poor in mexico. Working Paper, Stanford University, Stanford, CA.

Battistin, E. and E. Rettore (2008). Ineligible and eligible non-participants as a double comparison group in regression-discontinuity designs. *Journal of Econometrics 142*(2), 715–730.

Bauhoff, S., D. Hotchkiss, and S. O. (2011). The impact of medical insurance for the poor in georgia: A regression discontinuity approach. *Health Economics 20*, 1362–1378.

Bitrán and Asociados (2009). Impact of health insurance on access to health services, health services use and health status in the developing world. Global Health Financing Initiative - The Brrokings Institution.

Blank, R. M. and D. E. Card (1991). Recent trends in insured and uninsured unemployment: is there an explanation? *The Quarterly Journal of Economics 106*(4), 1157–1189.

Blank, R. M. and P. Ruggles (1996). When do women use aid to families with dependent children and food stamps? the dynamics of eligibility versus participation. *Journal of Human resources*, 57–89.

Card, D. and L. Shore-Sheppard. (2004). Using discontinuous eligibility rules to identify the effects of the federal medicaid expansions on low-income children. *Review of Economics and Statistics 86(3): 752-66.*

Cetrangolo, O., F. Bertranou, L. Casanova, and P. Casali (2013). The health system in peru: Current situation and strategies to extend contributive coverage. International Labour Organization.

Chankova, S., S. Sulzbach, and F. Diop (2008). Impact of mutual health organizations: evidence from west africa. *Health policy and planning 23*(4), 264–276.

Chetty, R. and A. Looney (2006). Consumption smoothing and the welfare consequences of social insurance in developing economies. *Journal of Public Economics 90*(12), 2351–2356.

Chiappori, P. (2000). Econometric models of insurance under asymmetric information. In G. Dionne (Ed.), *Handbook of Insurance*, Huebner International Series on Risk, Insurance, and Economic Security, pp. 365–393. Boston, MA, U.S.A.: Kluver.

Chiappori, P. and B. Salanié (2000). Testing for asymmetric information in insurance markets. *Journal of Political Economy 108*(1), 56–78.

Choi, J. J., D. Laibson, and B. C. Madrian (2011). $100 bills on the sidewalk: Suboptimal investment in 401 (k) plans. *Review of Economics and Statistics 93*(3), 748–763.

Comité Técnico Implementador del AUS (2010). Avances del proceso de implementación del aseguramiento universal en salud (2009-2011).

Commission on Macroeconomics and Health (2001). Macroeconomics and health: investing in health for economic development. World Health Organization, Geneva, CH.

Currie, J. and J. Gruber (1996). Health insurance eligibility, utilization of medical care, and child health. *The Quarterly Journal of Economics 111*(2), 431–466.

Cutler, D. and R. Zeckhauser (2000). The anatomy of health insurance. handbook of health economics, vol i, ch 1. aj culyer and jp newhouse.

Das, J., J. Hammer, and K. Leonard (2008). The quality of medical advice in low-income countries. *The Journal of Economic Perspectives 22*(2), 93–114.

Defensoría del Pueblo (2013). Serie Informes Defensoriales - Informe Defensorial No. 161.

Dercon, S., M. Kirchberger, J. W. Gunning, and J. P. Platteau (2008). Literature review on microinsurance. Microinsurance Paper No. 1. International Labor Office, Geneva.

Dow, W. H. and K. K. Schmeer (2003). Health insurance and child mortality in costa rica. *Social science & medicine 57*(6), 975–986.

Einav, L., A. Finkelstein, S. Ryan, P. Schrimpf, and M. Cullen (2011). Selection on moral hazard in health insurance. NBER Working Paper No. 16969. National Bureau of Economic Research, Cambridge, MA, U.S.A.

Einav, L., A. Finkelstein, S. P. Ryan, P. Schrimpf, and M. R. Cullen (2013). Selection on moral hazard in health insurance. *American Economic Review 103*(1), 178–219.

Fafchamps, M. (1999). Risk sharing and quasi-credit. *Journal of International Trade & Economic Development 8*(3), 257–278.

Fang, H., M. Keane, and D. Silverman (2006). Sources of advantageous selection: Evidence from the medigap insurance market. NBER Working Paper No. 12289. National Bureau of Economic Research, Cambridge, MA, U.S.A.

Finkelstein, A. and J. Poterba (2004). Adverse selection in insurance markets: Policyholder evidence from the uk annuity market. *Journal of Political Economy 112*(1), 183–208.

Francke, P. (2013). Peru's comprehensive health insurance and new challenges for universal coverage. Universal Health Coverage Studies, The World Bank.

Frandsen, B., M. Frolich, and B. Melly (2012). Quantile treatment effects in the regression discontinuity design. *Journal of Econometrics* (168), 382–395.

French, E. and J. B. Jones (2004). On the distribution and dynamics of health care costs. *Journal of Applied Econometrics 19*(6), 705–721.

Gertler, P. and J. Gruber (2002). Insuring consumption against illness. *The American Economic Review 92*(1), 51–70.

Giedion, U., E. Andrés Alfonso, and Y. Díaz (2013). The impact of universal coverage schemes in the developing world: a review of the existing evidence. Universal Health Coverage Studies Series No. 25.

Gilleskie, D. B. (1998). A dynamic stochastic model of medical care use and work absence. *Econometrica 66*(1), 1–45.

Giné, X., R. Townsend, and J. Vickery (2008). Patterns of rainfall insurance participation in rural india. *The World Bank Economic Review 22*(3), 539–566.

Giovanella, L., O. Feo, M. Favia, and S. Tobar (2012). Instituto Suramericano de Gobierno en Salud ISAGS.

Grossman, M. (1972). On the concept of health capital and the demand for health. *The Journal of Political Economy 80*(2), 223–255.

Gruber, J., N. Hendren, and R. M. Townsend (2014). The great equalizer: Health care access and infant mortality in thailand. *American economic journal. Applied economics 6*(1), 91.

Hahn, J., P. Todd, and W. van der Klaauw (2001, January). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica 69*(1), 201–209.

Hsiao, W. C. and P. Shaw (2007). Social health insurance for developing countries. The World Bank.

Hullegie, P. and T. J. Klein (2010). The effect of private health insurance on medical care utilization and self-assessed health in germany. *Health Economics 19*(9), 1048–1062.

Imbens, G. and T. Lemieux (2008). Regression discontinuity designs: A guide to pratice. *Journal of Econometrics 142*, 615 – 635.

Imbens, G. W. and J. D. Angrist (1994, March). Identification and Estimation of Local Average Treatment Effects. *Econometrica 62*(2), 467–475.

International Labour Office, Deutsche Gesellschaft für technische Zusammenarbeit, and World Health Organization (2006). Berlin recommendations. International Conference on Social Health Insurance in Developing Countries Berlin, 05-07 December 2005. Final version 3 July 2006.

Jowett, M. (2003). Do informal risk sharing networks crowd out public voluntary health insurance? evidence from vietnam. *Applied economics 35*(10), 1153–1161.

King, G., E. Gakidou, K. Imai, K. Lakin, T. Moore, C. Nall, N. Ravishankar, M. Vargas, M. Tellez-Rojo, J. Hernandez Avila, M. Hernandez Avila, and H. Hernandez Llamas (2009). Public policy for the poor? a randomized assessment of the mexican universal health insurance programme. *The Lancet 373*, 1447–1454.

Klein, T. J. (2010). Heterogeneous treatment effects: Instrumental variables without monotonicity? *Journal of Econometrics 155*(2), 99–116.

Laing, R., H. Hogerzeil, and D. Ross-Degnan (2001). Ten recommendations to improve use of medicines in developing countries. *Health policy and planning 16*(1), 13–20.

Limwattananon, S., S. Neelsen, O. O'Donnell, P. Prakongsai, V. Tangcharoensathien, E. van Doorslaer, and V. Vongmongkol (2015). Universal coverage with supply-side reform: The impact on medical expenditure risk and utilization in thailand. *Journal of Public Economics*.

Llanos, D. and N. Rosas (2010). Cry over spilled milk: Improving targeting outcomes in social programs in peru.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics 142*(2), 698–714.

McGuire, T. G. (2000). Physician agency. *Handbook of health economics 1*, 461–536.

Miller, G., D. Pinto, and M. Vera-Hernandez (2013, October). Risk protection, service use, and health outcomes under colombia's health insurance program for the poor. *American Economic Journal: Applied Economics 5(4)*, 61–91.

Mohanan, M. (2013). Causal effects of health shocks on consumption and debt: Quasi-experimental evidence from bus accident injuries. *Review of Economics and Statistics 95*(2), 673–681.

Murray, C. J. and L. C. Chen (1992). Understanding morbidity change. *The Population and Development Review*, 481–503.

Parodi, S. (2005). Evaluating the effects of the integrated health insurance over maternal health equity within the context of non-economics barriers on service access. CIES, GRADE.

Pauly, M., F. E. Blavin, and S. Meghan (2008). Is there a market for voluntary health insurance in developing countries? Technical report, National Bureau of Economic Research.

Pauly, M. V., P. Zweifel, R. M. Scheffler, A. S. Preker, and M. Bassett (2006). Private health insurance in developing countries. *Health Affairs 25*(2), 369–379.

Sen, A. (2002). Health: Perception versus observation. *British Medical Journal 324*(7342), 860–861.

Shampanier, K., N. Mazar, and D. Ariely (2007). Zero as a special price: The true value of free products. *Marketing Science 26*(6), 742–757.

SISFOH (2010). Methodology to calculate the household targeting index, ifh. Ministry of Economics and Finance, Peru.

Sosa-Rubi, S. G., O. Galarraga, and J. E. Harris (2009). Heterogeneous impact of the "seguro popular" program on the utilization of obstetrical services in mexico, 2001–2006: a multinomial probit model with a discrete endogenous variable. *Journal of health economics 28*(1), 20–34.

Strauss, J. and D. Thomas (1998). Health, nutrition and economic development. *Journal of Economic Literature 36*, 766–817.

Thistlethwaite, D. and D. Campbell (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational Psychology 51*, 309–317.

Thornton, R., L. Hatt, E. Field, M. Islam, F. Solis Dias, and M. Gonzales (2010). Social security health insurance for the informal sector in nicaragua: A randomized evaluation. *Health economics 19*, 181–206.

Wagstaff, A. (2010). Estimating health insurance impacts under unobserved heterogeneity: the case of vietnam's health care fund for the poor. *Health economics 19*(2), 189–208.

Wagstaff, A. and E. v. Doorslaer (2003). Catastrophe and impoverishment in paying for health care: with applications to vietnam 1993–1998. *Health economics 12*(11), 921–933.

Wagstaff, A. and M. Lindelow (2008). Can insurance increase financial risk?: The curious case of health insurance in china. *Journal of health economics 27*(4), 990–1005.

WHO (2010). World health statistics 2010. World Health Organization.

World Bank (2006). *A New Social Contract for Peru: An Agenda for Improving Education, Health Care, and the Social Safety Net*. Washington, DC, USA: World Bank.

World Bank (2013). World development indicators.

Zweifel, P. and W. G. Manning (2000). Moral hazard and consumer incentives in health care. *Handbook of health economics 1*, 409–459.

Online Appendix

This Online Appendix contains additional information on the health insurance plan (Appendix A), detailed variable definitions (Appendix B), a detailed description of the way the welfare index is calculated (Appendix C), results related to the sensitivity analysis in Section 7 (Appendix D), and additional results related to health expenditures (Appendix E).

A Plan Characteristics

Table 10: Basic Plan of Health Insurance - PEAS

Variables 1/.				Type		Treatment	Coverage	Maximum Coverage
				PREVENTIVE SERVICES				
MA		A	M	KC	1	CRED check on Children	Materials, supplies.	1 month 2 checks 1 year 11 checks 2 years 6 checks 4 years 8 checks
MA		A	I	KC	2	Check on newborn weighted less than 2,500 gr.	Consultations, dosage of hemoglobin, iron supplementation.	15 days 5 checks 3 months 4 checks 1 year 9 checks
			M	I	3	Micronutrient supplementation	Provision of Vitamin A, Iron supplement. Consultation, Printed educational material.	1 year 3 checks 2 years 4 checks
	OT	A		PC	4	Pregnancy diagnosis	Laboratory procedure.	No limit
MA			M	PC	5	Prenatal Care	Materials, supplies.	10 checks
	OT	A		PC	6	Complete laboratory tests of pregnant women	Full set of laboratory tests.	No limit
	OT	A		PC	7	Treatment for pregnant women w/ HIV	ELISA test for HIV during pregnancy, childbirth and postpartum. Prophylactic treatment to HIV positive pregnant women.	No limit
	X		M	PC	8	Obstetric ultrasound examinations	Materials, supplies.	No limit
MA		A	M	D	9	Oral health	Supplies.	2 checks/year
MA			M	D	10	Prevention of tooth decay	Materials, supplies.	Dental prophylaxis 2 checks Topical flour coating 4 checks Destartraje 1 check Topical flour gel 2 checks Sealants application 1 checks Restoration practice 4 pieces Ionomer inactivation 4 pieces
DV		BC	M	P	11	Family planning	Guidance and counseling session. Delivery of contraceptives.	Not decided 4 checks Decided checks
DV				O	12	Visual acuity impairment detection	Full benefit. Excludes provision of lenses. Children and Adolescents.	1 check/year
MA			M		13	Normal postpartum care	Checks. Includes supplies used in care.	2 checks
MA			M		14	Prophylactic treatment kids HIV	Provision of artificial milk for 6 months. Monitoring.	No limit

Notes: 1/. Variables observed in the ENAHO. Doctor Visits (DV); Medical Attention (MA); Medicines (M); Analysis (A); Kids Check (KC); Iron (I); Planning (P); Other tests (OT); Surgery (S); Pregnancy Care (PC); Birth Control (BC); Child Birth (CB); Dental (D); Ophthalmology (O); Hospital (H). See R.M. N° 240-2009/MINSA for more details.

Table 11: Basic Plan of Health Insurance - PEAS (continued)

Variables 1/.					Type	Treatment	Coverage	Maximum Coverage
					RECUPERATIVE AND REHABILITATION SERVICES			
MA		A	M		15	Immediate attention to the normal newborn	Supplies, drugs, lab tests.	No limit
MA	OT		M	H	16	Newborn's inpatient care without surgical procedure	Drugs, auxiliary tests, inputs during stay in the health facility.	No limit
MA	OT		M	H	17	Newborn's inpatient care with surgical procedure	Drugs, auxiliary tests, inputs during stay in the health facility.	No limit
MA			M	CB	18	Vaginal birth care	Drugs, materials, supplies.	No limit
MA			M	CB	19	Caesarean section	Drugs, auxiliary tests, supplies, materials.	No limit
DV			M		20	Specialized medical consultation	Drugs, supplies, diagnostic support.	No limit
DV			M	D	21	Ambulatory care: doctor	Drugs, supplies, diagnostic support in health facilities.	No limit
MA			M	D	22	Dental restoration	Materials, portion for replacement equipment and instrumentation.	3 dental restorations/year
MA			M	D	23	Dental extraction	Materials, portion for replacement equipment and instrumentation.	3 extractions/year
MA			M		24	Ambulatory care	Materials, supplies. In health facilities: Level I & II 2/.	No limit
MA			M		25	Emergency care	Drugs, auxiliary tests, materials, supplies.	No limit
		A	M		26	Diagnostic support	Diagnostic support. No diagnostic capabilities include support not tariffed.	No limit
MA			M	S	27	Medical outpatient surgery	Drugs, auxiliary tests, materials, supplies during surgery and patient's stay in the facility.	No limit
MA			M		28	Inpatient in health facility without surgery	Drugs, materials, supplies during surgery and patient's stay in the facility.	No limit
	OT		M	S	29	Inpatient with surgery	Auxiliary tests, drugs during surgical procedure, expenditures incurred during patience stay until discharge.	No limit
			M	H	30	Admission in ICU	Materials, supplies, drugs. Only in facilities where service can be verified.	No limit
MA				D	31	Specialized dental care	Procedures pulpectomy, pulpotomy access opening, direct and indirect pulp capping, fixation or splinting of the tooth with composite, Gingivectomy localized extraction of retained piece, enucleation or marsupialization.	3 checks/year
					32	Rehabilitation care	Rehabilitation of fracture or sprain in Level I care. Level II care only for enrolled population.	No limit
					ADMINISTRATIVE SERVICES			
					33	Emergency Transfer	Displacement road or air according to recognized medical indication. Unrecognized exam for the diagnosis in outpatients.	No limit
					34	Food Allocation	Recognized until a day after discharge.	No limit
					35	Burial	Niche services, casket, shroud, funeral chapel and transfer of the deceased to the cemetery.	"Directiva de Sepelios"

Notes: 1/. Variables observed in the ENAHO. 2/. Level I: Health facility & health center. Level II: Doctor Visits (DV); Medical Attention (MA); Medicines (M); Analysis (A); Kids Check (KC); Iron (I); Planning (P); Other tests (OT); Surgery (S); Pregnancy Care (PC); Birth Control (BC); Child Birth (CB); Dental (D); Ophthalmology (O); Hospital (H). See R.M. N° 240-2009/MINSA for more details.

B Variable Definitions

Table 12: Variable Definitions

Variable	Definition
Participation	
Health Insurance	Are you enrolled in SIS or EsSalud?
Demographics	
Woman	
Age	
Years of education	
Number household members	
Woman head of household	
Annual household income (thousand Soles)	
Utilization	
Any doctor visits	Have you visited the doctor in the last 4 weeks?
Medicines	Have you received medicines in the last 4 weeks?
Analysis	Have you had analysis in the last 4 weeks?
X-rays	Have you had X-rays in the last 4 weeks?
Other tests	Have you had other tests in the last 4 weeks?
Dental care	Have you had dental care in the last 3 months?
Ophthalmological care	Have you had ophthalmology care in the last 3 months?
Glasses	Have you bought glasses in the last 3 months?
Vaccines	Have you received vaccines in the last 3 months?
Kids check	Has your child's health been checked in the last 3 months?
Birth control	Have you received birth control products in the last 3 months?
Other treatments	Have you received other care in the last 3 months? (i.e. orthopedic services)
Hospital	Have you been hospitalized in the last 12 months?
Intervention/Surgery	Have you had a surgery in the last 12 months?
Pregnancy care	Have you received pregnancy care in the last 12 months?
Child birth	Have you had child birth care in the last 12 months?
Other medical attention	Have you had medical attention in the last 4 weeks?

Notes: Table 2 in the main text reports summary statistics.

Table 13: Variable Definitions (continued)

Variables	Definition
Health report	
Any symptom	Have you had a symptom or health problem in the last 4 weeks?
Illness	Have you been ill in the last 4 weeks?
Chronic illness	Do you have a chronic illness or health problem?
Relapse	Have you had a relapse in your chronic illness in the last 4 weeks?
Accident	Have you had an accident in the last 4 weeks?
Num. days with symptom	Number of days you could not perform normal activities because of a relapse
Num. days with illness	Number of days you could not perform normal activities because of a symptom
Num. days with relapse	Number of days you could not perform normal activities because of an illness
Num. days with accident	Number of days you could not perform normal activities because of an accident
Health expenditures	
Any health expenditures	Any annual health expenditures
Health expenditures	Annual health expenditures
Absolute deviation expenditures	Variability of annual health expenditures
Absolute value residual share	Absolute value of residual from regressions for annual health expenditures
Sqre residual expenditures	Square of residual from regressions for annual health expenditures
Expenditures 50	Annual health expenditures exceed 50th percentile (median)
Expenditures 75	Annual health expenditures exceed 75th percentile (third quartile)
Share expenditures	Share annual health expenditures of annual household per capita income
Absolute deviation share	Variability of Share annual health expenditures of annual household per capita income
Abs share	Absolute value of residuals from regression for Share annual health expenditures of annual household per capita income
Sqre share	Square of residuals from regression for share of annual health expenditures on annual household per capita income
Share 50	Share annual health expenditures of annual household per capita income exceed 50th percentile (median)
Share 75	Share annual health expenditures of annual household per capita income exceed 75th percentile (third quartile)
Catastrophic 5%	Share annual health expenditures of annual household per capita income exceed 5%
Catastrophic 10%	Share annual health expenditures of annual household per capita income exceed 10%
Catastrophic 15%	Share annual health expenditures of annual household per capita income exceed 15%
Catastrophic 20%	Share annual health expenditures of annual household per capita income exceed 20%
Catastrophic 25%	Share annual health expenditures of annual household per capita income exceed 25%

Notes: See also Section 6.2.3 for further explanations. Table 3 in the main text reports summary statistics.

C IFH Index

C.1 Variables and Weights for IFH Construction

The IFH index is constructed such that it takes on values between 0 and 100. Higher values indicate better living conditions. In the following, we explain how the index is calculated. SISFOH (2010) provides more details.

First, the ENAHO for the year 2009 was used to determine the set of variables that enters into the IFH computation. The Sommers test was used to identify correlation between candidate explanatory variables and a measure of poverty. Then, significant variables were selected and a Principal Component analysis for discrete variables was applied to reduce dimensions and to focus on those variables that mainly explain the variability of the data. The weights that are used to construct the index correspond to the contribution of the respective variables to the first principal component. This was done separately for three geographic areas, the Lima Province, the other urban areas, and all rural areas.

Table 14 and 15 show the variables, the mutually exclusive alternatives and the corresponding weights. There are three independent sets of weight that correspond to households living in different geographic areas. For instance, consider a household from Lima that cooks with carbon, uses water from outside the house and lives in a house with brick walls. Then, the first three addends of the IFX index are -0.33, -0.35 and 0.10.[1]

Using those weights a raw index ifh_{ij} is calculated as a linear combination of household characteristics with cluster-specific weights. Then, it is standardized so that it lies between 0 and 100 in each cluster. The standardized index is

$$ifh'_{ij} = 100 * \frac{ifh_{ij} - ifh_j^{min}}{ifh_j^{max} - ifh_j^{min}},$$

where ifh'_{ij} is the adjusted IFH that lies in the interval $[0,100]$ and ifh_j^{min} and ifh_j^{max} are the minimum and the maximum values of the original IFH index in cluster j, respectively.

[1] Importantly, the number of members of the household with health insurance does not include those with either SIS or EsSalud. This is important because otherwise, our third assumption in Section 5, the exclusion restriction, would likely be violated.

Table 14: Variables and weights for IFH construction

Variables	Metropolitan Lima	remaining urban areas	rural areas
Fuel used to cook			
Do not cook	-0.49	-0.67	-0.76
Other	-0.40	-0.50	-0.38
Firewood	-0.37	-0.33	0.05
Carbon	-0.33	-0.22	0.36
Kerosine	-0.29	-0.19	0.37
Gas	0.02	0.12	0.52
Electricity	0.43	0.69	0.52
Water supply in the home			
Other	-0.78	-0.58	
River	-0.65	-0.42	
Well	-0.62	-0.37	
Water tanker	-0.51	-0.34	
Pipe	-0.41	-0.32	
Outside	-0.35	-0.25	
Inside	0.10	0.12	
Wall material			
Other	-0.70	-0.80	
Wood or mat	-0.48	-0.55	
Stone with mud	-0.44	-0.46	
Rushes covered with mud	-0.41	-0.43	
Clay	-0.39	-0.38	
Sun-dried brick or adobe	-0.37	-0.20	
Stones, lime or concrete	-0.33	-0.07	
Brick	0.10	0.25	
Type of drainage			
None	-0.89	-0.68	
River	-0.75	-0.49	
Sinkhole	-0.59	-0.40	
Septic tank	-0.46	-0.30	
Drainage system outside the house	-0.39	-0.21	
Drainage system inside the house	0.10	0.20	
Number of members with health insurance			
None	-0.26	-0.25	-0.10
One	-0.04	0.06	0.50
Two	0.06	0.17	0.59
Three	0.14	0.27	0.66
More than three	0.32	0.48	0.86
Goods that identify household wealth			
None	-0.47	-0.35	-0.11
One	-0.17	0.05	0.64
Two	0.02	0.25	0.83
Three	0.15	0.40	0.90
Four	0.25	0.52	1.09
Five	0.47	0.75	1.09
Has fixed phone			
Yes	-0.32		
No	0.20		

Notes: Taken from SISFOH (2010).

Table 15: Variables and weights for IFH construction (Continued)

Variables	Metropolitan Lima	remaining urban areas	rural areas
Roof material			
Other	-0.86	-0.90	
Straw	-0.74	-0.72	
Mat	-0.67	-0.62	
Woven cane	-0.38	-0.23	
Tiles	-0.23	0.03	
Wood or mat	-0.21	0.07	
Concrete	0.17	0.32	
Education of the Household head			
None	-0.51	-0.57	-0.59
Preschool	-0.43	-0.25	-0.08
Primary	-0.28	0.01	0.35
Secondary	-0.06	0.19	0.59
Vocational education (VET)	0.10	0.33	0.68
Undergraduate	0.22	0.55	0.88
Postgraduate	0.40	0.55	0.88
Floor material			
Other	-0.97	-1.12	
Land	-0.60	-0.47	
Concrete	-0.16	-0.01	
Wood	0.08	0.30	
Tiles	0.16	0.40	
Vinyl sheets	0.28	0.51	
Parquet	0.51	0.71	
Overcrowding			
More than six	-0.68		
Between four and six	-0.51		
Between two and four	-0.31		
Between one and two	-0.07		
Less than one	0.24		
Highest level of education in the house			
None			-0.35
Primary			0.11
Secondary			0.41
Vocational education (VET)			0.62
Undergraduate			0.83
Electricity			
No			-0.29
Yes			0.22
Floor made of earth			
Yes			-0.17
No			0.47

Notes: Taken from SISFOH (2010).

C.2 Thresholds for IFH by Cluster

Table 16: Eligibility Thresholds by Cluster

Cluster	Threshold	Population	Per capita income 1/.	Per capita spending 1/.	Poverty status
1	33	208,101	2,184	1,815	0.5159
2	36	1,907,122	2,116	1,697	0.5994
3	34	2,284,876	2,332	1,937	0.5404
4	38	2,646,680	2,282	1,916	0.5389
5	35	634,472	2,067	1,595	0.6410
6	34	212,723	5,941	4,045	0.2606
7	52	2,544,448	5,141	4,260	0.2565
8	42	2,134,993	5,667	4,428	0.2397
9	44	3,740,611	6,403	5,050	0.1352
10	50	2,229,638	5,997	4,673	0.1620
11	44	490,207	5,498	4,015	0.2725
12	43	101,993	8,632	4,638	0.1645
13	43	1,636,740	5,045	4,024	0.2116
14	33	93,527	8,961	6,178	0.0261
15	55	9,342,700	8,712	6,612	0.1546
Peru	-	30,208,831	5,793	4,501	0.2764

Notes: Based on SISFOH (2010), own calculations using the ENAHO 2011. There is no threshold at the national level. 1/. Soles.

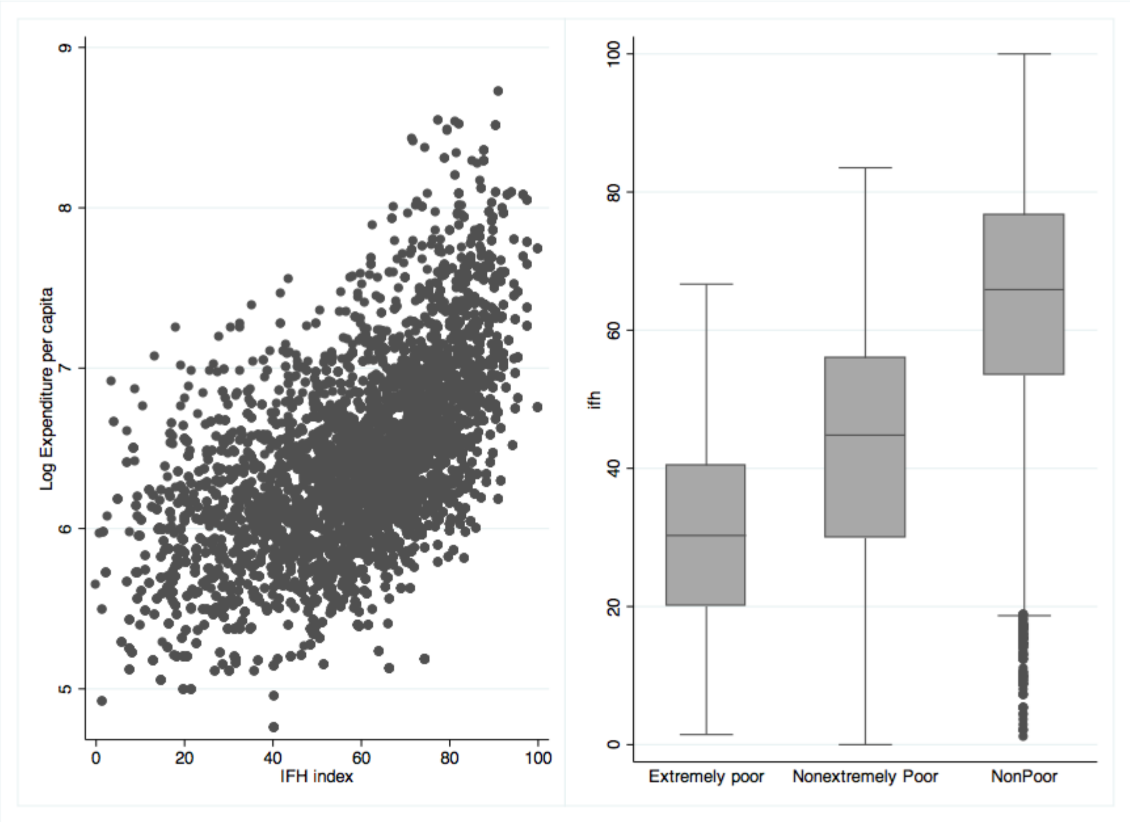
To determine eligibility, there are thresholds for the IFH index by cluster. Individuals and households with an index below or equal to the threshold are eligible for SIS. Table 16 shows the thresholds by cluster. The 15 clusters were defined by identifying areas with similar monetary poverty in the year 2009. In general, each cluster includes several unconnected geographic areas.[2] As an example, consider cluster 2, which includes the rural areas of the jungle of the departments of Ayacucho, Junin, Loreto, Puno, San Martin and Ucayali; and also the rural areas of the northern highlands of the departments of Cajamarca and Lambayeque. The thresholds were determined such that poor individuals, in some sense that is not spelled out, were eligible. They are conservative in the sense that they allow for type 2 errors in the sense that an individual might be declared as eligible even though, according to the criteria that are used, is not part of the target population.[3]

Table 16 also provides some economic indicators obtained from the ENAHO for the year 2011. The variation of the thresholds across clusters reflects the variation in income within Peru. The lower thresholds correspond to the poorer clusters, that is, those with the lowest levels of

[2] Only clusters 1, 14 and 15 include connected geographic areas.

[3] The thresholds are set such that the marginal benefit of expanding five percentage points of coverage of the eligible population generated a marginal increase of one percentage point in that error.

Figure 8: Relationship between IFH and Expenditures Per Capita in Lima Province



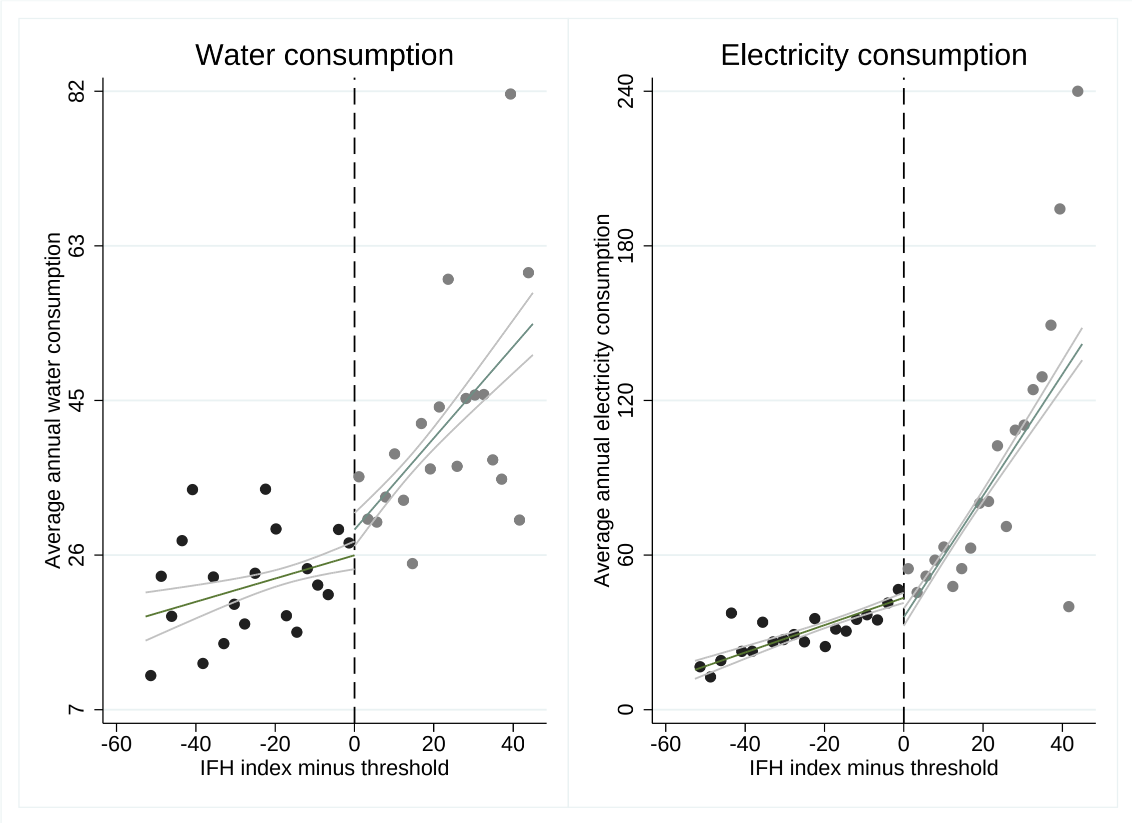
Notes: Based on ENAHO data for the year 2011, See Appendix C for details on how the IFH index is computed. The right figure shows box plots for expenditures by poverty status.

per capita monetary income (or spending) and the highest proportions of poor individuals.[4] The Lima Province, the city under analysis, is in cluster 15, with a cutoff of 55.

We use ENAHO data for the year 2011 as well as the actual weights to re-compute the IFH index for individuals and households in our sample. We cannot directly assess how strongly our index is correlated with the one that was used by the government to determine eligibility. However, as an informal test, we re-produced figures illustrating the correlations between the IFH index and expenditures per capita in SISFOH (2010). Figure 8 shows the figure we obtain for the Lima Province. Generally speaking, the reproduced figures resemble the official ones.

[4]Cluster 14, which corresponds to the urban areas of the jungle of Madre de Dios, is an interesting exception. Informal mining and illegal drugs production have increased income levels during the past years.

Figure 9: Water and Electricity Consumption



D Sensitivity Analysis

Table 17: Subsample of Eligibles and Ineligibles with Hypothetical Threshold equal to Respective Median

		Eligibles		Ineligibles	
		Estimates	Ste.	Estimates	Ste.
First stage: Participation					
0	Health Insurance	-0.0160	(0.0455)	0.0565	(0.0376)
			$F = 0.1237$		$F = 2.2580$
Second stage: Utilization					
1	Doctor visits	3.1152	(9.0213)	0.4775	(0.6780)
2	Medicines	2.5642	(7.5926)	-0.2016	(0.6993)
3	Analysis	0.5863	(2.1066)	-0.5745	(0.5287)
4	X-rays	0.7143	(2.2662)	-0.4274	(0.4173)
5	Other tests	0.0669	(0.6350)	0.0862	(0.1825)
6	Dental care	0.4442	(2.0624)	-0.4177	(0.5419)
7	Ophthalmology	1.6162	(4.6851)	-0.5347	(0.4869)
8	Glasses	1.4392	(4.2278)	-0.2632	(0.3561)
9	Vaccines	4.0881	(11.6414)	1.1538	(0.8391)
10	Kids check	1.3285	(6.1547)	0.4217	(1.5673)
11	Birth control	-1.6099	(4.7842)	0.2812	(0.3760)
12	Others	4.7598	(13.7206)	0.5690	(0.7082)
13	Hospital	1.3865	(3.9999)	-0.0852	(0.3378)
14	Surgery	1.4760	(4.2762)	-0.1892	(0.2907)
15	Pregnancy care	-12.3856	(356.4444)	-0.3562	(1.9939)
16	Child birth	3.9812	(113.6240)	0.0468	(0.7438)
0’	Medical attention	1.3966	(4.2963)	-0.5308	(0.6836)
1’	Doctor visits	1.8136	(5.3320)	-0.4659	(0.6575)
2’	Medicines	2.0428	(5.9121)	-0.5996	(0.7035)
3’	Analysis	0.5004	(1.8910)	-0.4596	(0.4584)
4’	X-rays	0.7582	(2.3646)	-0.2538	(0.3328)
5’	Other tests	-0.1090	(0.4980)	0.0666	(0.1452)
6’	Planning	14.7303	(419.9662)	-1.9868	(8.2431)
7’	Iron	-1.1360	(1.4227)	0.6271	(1.5691)
8’	Preventive campaign	0.5337	(1.9841)	0.1187	(0.2777)
Health report					
1	Symptom	-0.8470	(3.8124)	-0.3881	(0.7074)
2	Illness	0.2594	(2.1987)	0.3262	(0.5334)
3	Chronic illness	1.4699	(4.7893)	0.1146	(0.6412)
4	Relapse	-1.0055	(3.2326)	-0.3406	(0.5205)
5	Accident	1.1493	(3.4220)	-0.1475	(0.2292)
6	Num. days with symptom	2.8030	(9.5805)	0.9274	(1.0469)
7	Num. days with illness	-8.0916	(24.2102)	-1.8098	(1.7281)
8	Num. days with relapse	-3.4676	(12.0192)	-2.5108	(4.1129)
9	Num. days with accident	5.3389	(15.9987)	-2.6958	(2.3248)

Notes: IV-2SLS regressions. Standard errors are denoted by Ste. and reported in parentheses. "* p<0.10 ** p<0.05 *** p<0.01. Eligibles: N=1,786 (total); N=363 (kids check); N=532 (pregnancy care); N=532 (child birth); N=532 (planning); N=177 (iron). Ineligibles: N=2,375 (total); N=286 (kids check); N=650 (pregnancy care); N=650 (child birth); N=649 (planning); N=166 (iron).

Table 18: Effect of Health Insurance on Utilization (No Controls and Reduced Samples)

		Full sample no controls		Sample 75%		Sample 50%	
		Estimates	Ste.	Estimates	Ste.	Estimates	Ste.
First stage: Participation							
0	Health Insurance	0.1385***	(0.0257)	0.1100***	(0.0314)	0.0910**	(0.0409)
			$F = 29.0425$		$F = 12.2723$		$F = 4.9504$
Second stage: Utilization							
1	Doctor visits	0.4975**	(0.1965)	0.7604**	(0.3398)	0.6378	(0.5000)
2	Medicines	0.5044**	(0.2072)	0.8826**	(0.3689)	0.9097	(0.5781)
3	Analysis	0.2063**	(0.0941)	0.3631**	(0.1640)	0.1077	(0.2096)
4	X-rays	0.1220*	(0.0715)	0.2896**	(0.1314)	0.2117	(0.1781)
5	Other tests	0.0476	(0.0420)	-0.0134	(0.0636)	0.0147	(0.1097)
6	Dental care	0.0818	(0.1249)	0.2933	(0.2079)	0.1092	(0.3005)
7	Ophthalmology	0.0269	(0.0850)	0.0255	(0.1314)	-0.2501	(0.2416)
8	Glasses	-0.0405	(0.0705)	0.0042	(0.1026)	-0.2307	(0.1891)
9	Vaccines	0.2880**	(0.1364)	0.3220	(0.2110)	0.4440	(0.3667)
10	Kids check	0.1645	(0.2955)	0.4880	(1.5819)	-0.8043	(2.9582)
11	Birth control	-0.1127	(0.0941)	-0.1493	(0.1500)	-0.0092	(0.2232)
12	Others	0.1859	(0.1653)	-0.0896	(0.2475)	-0.6426	(0.4753)
13	Hospital	0.1347	(0.0952)	0.3110*	(0.1590)	0.3505	(0.2574)
14	Surgery	0.2637***	(0.0902)	0.4407***	(0.1684)	0.4062	(0.2521)
15	Pregnancy care	0.6434**	(0.2942)	0.8070	(0.5415)	0.8604	(1.0486)
16	Child birth	0.1787	(0.1615)	0.0628	(0.2654)	0.1559	(0.5088)
0'	Medical attention	0.5424***	(0.1747)	0.7631**	(0.3076)	0.6714	(0.4532)
1'	Doctor visits	0.5339***	(0.1736)	0.7463**	(0.3038)	0.6081	(0.4373)
2'	Medicines	0.4929***	(0.1683)	0.6930**	(0.2930)	0.5155	(0.4150)
3'	Analysis	0.1794**	(0.0881)	0.2919**	(0.1476)	0.0163	(0.1980)
4'	X-rays	0.0868	(0.0673)	0.2072*	(0.1160)	0.1259	(0.1594)
5'	Other tests	0.0377	(0.0324)	-0.0096	(0.0485)	0.0313	(0.0810)
6'	Planning	-0.0270	(0.2455)	0.0426	(0.3875)	0.5890	(0.8563)
7'	Iron	0.5821	(0.4075)	0.8659	(1.0467)	0.0934	(1.0081)
8'	Preventive campaign	0.0403	(0.0699)	-0.1115	(0.1046)	-0.3091	(0.2045)
Health report							
1	Symptom	0.2655	(0.1977)	0.3459	(0.3118)	0.4221	(0.4981)
2	Illness	0.3140**	(0.1475)	0.4533*	(0.2464)	0.4254	(0.3835)
3	Chronic illness	0.0116	(0.1904)	0.1986	(0.2755)	0.1592	(0.4342)
4	Relapse	0.0295	(0.1157)	0.0756	(0.1804)	0.1869	(0.2917)
5	Accident	0.0773	(0.0603)	0.1947*	(0.1054)	0.1381	(0.1536)
6	Num. days with symptom	0.3740	(0.4603)	0.8116	(0.8134)	1.4127	(1.4355)
7	Num. days with illness	0.6131*	(0.3713)	0.7287	(0.5268)	0.6967	(0.7140)
8	Num. days with relapse	0.7297	(0.9491)	1.3831	(1.5312)	2.2356	(2.5425)
9	Num. days with accident	0.5432	(0.4562)	1.5373*	(0.8913)	1.4919	(1.4427)

Notes: 1/. Not covered by SIS. 2/. Full: N=4,161 (total); N=649 (kids check); N=1.182 (pregnancy care); N=1,182 (child birth). 3/. Sample 75: N=3,124 (total); N=499 (kids check); N=892 (pregnancy care) N=892 (child birth). 4/. Sample 50: N=2,078 (total); N=347 (kids check); N=618 (pregnancy care) N=618 (child birth). 5/. Standard errors in parentheses * p<0.10 ** p<0.05 *** p<0.01.

E Additional Results

Figure 10: Health Expenditures on Medicines (left) and Other Treatments (right)