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Does social health insurance spillover to student performance? Evidence from an RDD in Peru

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Abstract

The literature on the effects of Social Health Insurance focuses on its stated goals, namely health status and financial protection; but little work exists on its effect on education. In this paper, we examine the effect of the Peruvian program on student performance by means of a sharp regression discontinuity design. We use a unique individual-level database built from the merger of detailed data from a household survey and standardized test scores from a national census. We find large effects of health insurance on mathematics and reading scores. Moreover, we analyze the main potential mechanisms: health of child, health of family members, and status of household finances. The clearest channel is a lower incidence of anemia among children and mothers, probably due to better nutrition. Finally, we explore whether the effect of health insurance on test scores is heterogeneous by sex to the extent that the data allow. We find it is mostly driven by girls who are better off across the entire score distribution.

JEL codes: D04 I18 I21 I38.

Keywords: social health insurance, test scores, anemia, Peru.

1 Introduction

A large fraction of the population in the developing world faces health deficiencies because this population pays health services out-of-pocket (Banerjee and Duflo, 2007). In reaction, many countries have introduced Social Health Insurance (SHI), in which service providers are paid from a fund that the government finances through taxes. The goals of the SHI are to improve the health of the targeted population and to protect them against the financial consequences of health shocks. In this context,

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the empirical literature has extensively studied the effect of SHI on health and financial protection.[1] However, the SHI spills over to another important dimension: education. In particular, health insurance has a potential effect on student performance in primary school. The mechanisms for this effect are manifold. The most direct is the better health of children that affects academic skills and school attendance. Another mechanism is the better health of parents that affects the provision of educational inputs (i.e., school supplies, books, personal computers) and the time used to provide instruction to children. The financial protection provided by insurance is another mechanism. A reduction in the level and variability of out-of-pocket expenses frees up household resources that can be devoted to educational inputs. Hence, the causal effect of SHI on education has a strong theoretical background; however, the evidence is scarce. Increasing the knowledge on this spillover may help to optimize the design of SHI schemes and to assess their social welfare effects beyond the stated goals.

The estimation of the causal effect of SHI on education is challenging for two reasons. First, as health care requires time to affect educational outcomes, the estimation requires detailed individual data on health care and posterior educational outcomes. Developing countries typically lack this kind of dataset. Second, the endogeneity between health insurance and education at the household level poses challenges to the causal estimation. On the one hand, there is a reverse causality problem. More educated households better understand the benefits of health insurance. On the other hand, a number of omitted variables may arise. For instance, more responsible parents dedicate resources to both health insurance and education services. These problems yield biased results in a regression of educational outcomes on insurance coverage.

In this study, we examine the causal effect of SHI on student performance that is measured by standardized test scores for children of primary school age. We focus on the Peruvian SHI called "Seguro Integral de Salud" (SIS). We make progress on the two challenges. On the one hand, we face the lack of individual data by merging the data from the National Household Survey of Peru ("Encuesta Nacional de Hogares", ENAHO) and the Census Student Assessment ("Evaluación Censal de Estudiantes", ECE) that reaches the universe of Peruvian students. In particular, we complement the information for each child from three to six years old that participated in the survey with the test scores obtained when the child attains primary school. On the other hand, we account for the endogeneity of health insurance and education by means of a sharp Regression Discontinuity Design (RDD) for the Peruvian institutional setup. The basic idea is simple. A welfare index that is computed by authorities from a set of characteristics of the household is the only eligibility criterion for a large fraction of the population. Households with a welfare index below a specific threshold are eligible, while households with a welfare index above this threshold are not.

[1] A large body of evidence confirms that the SHI increases insurance coverage, access to preventive and curative services, and self-reported health status. See Acharya et al. (2013) for a review on 19 early articles on the effects of SHI that correct for selection into insurance. A burgeoning literature studies the effect of SHI on objective measures of health status. See Limwattananon et al. (2015) for Thailand, Beuermann and Garzon (2016) for Jamaica, Conti and Ginja (2016) and Celhay et al. (2019) for Mexico, and Cesur et al. (2017) for Turkey. The evidence is ambiguous for financial protection. A number of papers, like Wagstaff (2010) and Limwattananon et al. (2015), finds that insurance coverage led to a reduction in out-of-pocket spending. However, other studies, like Thornton et al. (2010) and especially Bernal et al. (2017) find a positive effect on out-of-pocket spending.

In particular, we use a non-parametric technique to estimate the local average treatment effects of insurance coverage. We start by replicating the welfare index for the households of the ENAHO. We then restrict the sample to the households for which this welfare index is the only eligibility criterion.[2] Meeting the eligibility threshold means insurance coverage for this subsample because the SIS affiliation process is free, takes place where the health service is provided, and lasts a couple of days at most. Further, we apply the non-parametric technique proposed by Calonico et al. (2014b) and use the test scores from the ECE as the dependent variable and the welfare index built from ENAHO as the forcing variable.

We find large and highly significant effects of health insurance coverage on student performance. In particular, health insurance coverage increases the children's scores in the standardized reading test by 86.3 points that corresponds to 0.92 times of the standard deviation of the score of the unrestricted sample. It also leads to an increase of 172.9 points in the standardized math test that represents 1.43 times the corresponding standard deviation. The size of these effects are remarkable and so are the significancy of the coefficients.

We then turn examining the potential mechanisms through which SHI improves student performance. First, we explore whether children have better health. As the ENAHO does not include objective measures of health status, we use the rich data from the Survey on Demography and Health of Peru ("Encuesta Demográfica y de Salud Familiar", ENDES) to analyze this potential mechanism. We start by replicating the welfare index for the households covered by this survey; we then restrict the sample to the households for which the welfare index is the only eligibility criterion; and we then apply the non-parametric RDD. While the samples of the ENAHO and ENDES are different, the universes from which they come are the same: households in Peru during 2011. We find that health insurance coverage is associated with a reduction of 41 percentage points in the probability of anemia (moderate or severe). According to Nokes et al. (1998), a healthy level of hemoglobin affects student performance through normal academic skills and regular school attendance. In fact, we find that insurance coverage increases the probability of attending school by 53 percentage points. Second, we explore a possible effect on other members of the household. Using the ENDES again, we find a reduction of 20 percentage points in the probability of anemia of women of fertile age. Third, we explore financial protection. Insurance coverage is associated with a reduction in the level and variability in out-of-pocket health expenses, but we do not emphasize this channel as the RD plots are not clear and the results are not robust. Moreover, we fail to find a positive effect on educational household expenses. Overall, the evidence points to a lower incidence of anemia in both children and women as important channels that effect test scores. We then finish this analysis of potential mechanisms by looking for other insurance effects that are consistent with this finding. We focus on household nutrition and examine whether SHI has an effect on the consumption of 50 food categories available in the ENAHO. We find it increases the annualized purchases of fresh fish (8.57 kilograms); decreases those of cakes and pastries (-2.08 kilograms); noodles (-6.79 kilograms); candies, chocolates and honey (-0.46 kilograms); prepared meals to consume at home

[2]Households with high water and electricity consumption are not eligible. Households with low water or electricity consumption are evaluated by means of the welfare index. Hence, we focus on this last group.

(-7.84 kilograms); and has no significant effect on other categories.

We finish by exploring whether the effect of SHI on test scores is heterogeneous by sex. We find that this effect is mostly driven by girls. Moreover, using an estimator of quantile treatment effects, we find that the effect on girls' test scores is relatively uniform across the entire distribution. Unfortunately, the low number of observations does not allow us to analyze the effect of SHI on potential channels by sex.

Our study contributes to the small amount of studies that examines how SHI spills over to education. On the one hand, all other studies focuses on the effect of expansions of health insurance. Levine and Schanzenbach (2009), Chen and Jin (2012), Cohodes et al. (2016) and Alcaraz et al. (2016) apply difference-in-differences methods over aggregate data at the state, village or municipality level. Hence, they rely on the assumption that these expansions are not correlated with underlying trends in educational outcomes at the correspondent aggregation level, nor with policies that might affect them. To our knowledge, our study is the first to estimate the spillover effect of SHI on education by means of an RDD or by using individual-level data. We argue that it is instructive to observe an estimate that does not require holding the same critical assumptions. On the other hand, most of the above-mentioned studies focus on Medicaid in the United States. A valuable exception are Chen and Jin (2012) who study the effect of the Chinese SHI, and Alcaraz et al. (2016) who focus on the Mexican SHI. Hence, this is the second study to explore this spillover effect on low- and middle-income countries. The coverage of SHI should have greater effects in these countries in which sizable informal labor markets cause high social vulnerability. Finally, this study has crucial policy implications related to the fight against multidimensional poverty. We show that a poverty program aiming to affect one dimension reaches another one equally important in a remarkably effective way. Policy-makers should take note that multidimensional poverty alleviation does not necessarily require multidimensional programs.

The rest of the study proceeds as follows: Section 2 provides detailed information on our institutional setup. Section 3 presents the database we exploit. In Section 4, we explain our identification strategy. Section 5 presents our main results and the proposed mechanisms. Section 6 presents a battery of robustness tests. And Section 7 concludes.

2 Institutional framework

2.1 Education in Peru and the SIS program

Pre-school and school are mandatory in Peru. Public schools are free, and there is a strong supply of private schools in urban areas, particularly in Lima. The Peruvian educational system performs relatively well from the point of view of access and graduation (Guadalupe et al., 2017). However, the results are not good in terms of the performance of the students. The Programme for International Student Assessment (PISA) shows that out of the 70 evaluated countries in 2015, Peru was 63rd in reading comprehension and 62nd in mathematics.

The Peruvian SHI, called SIS, was created in 2001. Its stated goal is to provide health-care services and financial protection to individuals who lack health insurance, and it gives priority to the extremely poor. The SIS program is the main health insurance provider in Peru. After a series of reforms, its coverage has increased substantially, from 20 percent of the total population in 2006 to about 54 percent in 2018.[3]

The SIS program provides free coverage for health services. Eligible individuals receive medical care at public health facilities that comprise health centers and hospitals. They have to pay neither coverage nor services, that is, there are no premiums, copays or deductibles. Public health facilities are paid per treatment from a government fund that is financed through taxes.[4] Reimbursement rates are supposed to finance variable costs plus a markup, while independent direct government transfers cover fixed costs. Ineligible individuals have access to public health facilities subject to paying for the provided services, that is, subject to out-of-pocket expenses.

The benefit package of SIS is comprehensive. It covers ambulatory, inpatient and emergency care such as medicines and high-cost treatments. The benefit package is composed of a basic plan (*Plan Esencial de Aseguramiento en Salud* - PEAS) and two supplementary plans. PEAS establishes a wide list of needs and the number of times an individual can receive each listed benefit. According to Francke (2013), PEAS covers 65% of the total burden of illness. However, the supplementary plans can provide discretionary needs that go beyond the established limits. Hence, the benefit package of SIS is theoretically very generous. However, the public health facilities face severe limitations (e.g. numbers of health professionals, beds, and intensive care units) that translate into long waiting lists or no effective coverage in some cases.[5]

The benefit package includes key services that the economic development literature has linked to improvements in educational performance, such as treatment for anemia (Bobonis et al., 2006; Chong et al., 2016), elimination of intestinal parasites (Miguel and Kremer, 2004; Baird et al., 2016), and obesity (Taras and Potts-Datema, 2005). As for anemia, SIS covers the diagnosis and treatment of deficiencies in iron and vitamin A in children. Every child diagnosed with anemia is treated with iodized salt and a check-up is scheduled monthly for three months. SIS also covers prevention of these deficiencies through the supplementation of micro-nutrients. In the case of intestinal parasites that infect the digestive system, SIS includes diagnosis by ova and parasite tests, treatment with antibiotics, and monitoring of the nutritional state. As for obesity, SIS covers a wide range of diagnosis tests (e.g., lipidic profile, blood glucose test, and liver profile).

2.2 Eligibility for SIS

The identification of SIS beneficiaries has historically been based on the lack of insurance coverage and income level. In order to identify individuals living in poor conditions, SIS follows an eligibility rule

[3]The SIS indeed is a generic name that refers to two schemes: a fully subsidized plan and partially subsidized plan. However, the former achieves 99 percent of the population. We refer to the fully subsidized scheme of SIS simply as SIS.

[4]In the year of analysis, SIS did not have capitation fees.

[5]See Bernal et al. (2017) and Bauhoff and Oroxom (2019) for more characteristics of the SIS plan.

that is largely based on a proxy-means test at the household level. Hence, a formal algorithm is used to identify households' income through information on their characteristics, and people are eligible if their index falls below a specific threshold.

Like most large-scale SHI programs, SIS was rolled out in several phases. The first algorithm was used until 2011. However, the government found that the authorities were motivated by personal criteria and had started declaring some households eligible whose index was above the threshold. A new algorithm was introduced in 2011 as part of a reform intended to assess eligibility more rigorously.

Since 2011, household eligibility has relied on two criteria. First, one or both expenditures on water and electricity must be below 20 and 25 Soles respectively. If this criterion is fulfilled, the second one applies: the new welfare index has a range from 0 to 100 and must be below a regional-specific threshold.[6] The welfare index is a linear combination of variables that are related to the living conditions of the household. Online Appendix A provides the complete list of variables and their weights. Importantly, potential beneficiaries do not know how the welfare index is computed, nor the cutoff values for eligibility (Bernal et al., 2017).

This new set of rules was introduced in an attempt to assess eligibility more rigorously, that is, to avoid leakage. It was applicable to Lima from 2011 on, and to the whole country from 2012 on. This schedule was actually met. However, over the years, the evaluation lost its rigor.

An important feature of SIS is that eligibility means coverage. An individual may conduct the affiliation process when healthy or when medical attention is needed. The enrollment process takes place at SIS facilities or at public health facilities. The individual must fill in a form and wait one or two days for the official answer on eligibility. The process is short because authorities have already collected socioeconomic information for households throughout the country regardless of whether they had applied for SIS or not. Once the answer is ready (yes or no, with no further information), the individual is subject to SIS benefits, that is, there are no exclusions, waiting times or latent periods.

2.3 The research on SIS

The literature finds large positive effects of SIS on access to health-care services and, contrary to the typical expectation, a positive effect on out-of-pocket expenditures. There are three studies on the effect of SIS that control for selection into insurance. First, Neelsen and O'Donnell (2017) estimate the impact of a 2007 reform that expanded SIS coverage. A difference-in-differences strategy compares individuals covered for the first time and individuals already covered by employment-based insurance. They find positive effects on access to ambulatory care, medication, and diagnostic tests. Second, Bernal et al. (2017) estimate the effect of SIS by means of a semi-parametric RDD that exploits the same threshold in the welfare index that we use for our non-parametric RDD. Even though the estimations are not directly comparable, they confirm the positive effects found by Neelsen and O'Donnell (2017) (ambulatory care,

[6] When government authorities have income records on households members, a slightly different set of rules applies. However, the level of informality is very high in Peru, especially among the targeted population. Hence, government authorities do not have income records for most of the SIS applicants.

medication, and diagnostic tests), and they also find positive effects on other services, like hospitalization and surgery. They go further by analyzing the effect of SIS for each of health service by financing source. Surprisingly, they find that relatively low-cost services related to diagnosis (doctor visits, analysis) are financed by SIS, while relatively high-cost services related to treatment (medicines, hospitalization and surgery) are paid by covered individuals themselves. They posit that the information on health status that the diagnostic services provide would increase the willingness to pay for the treatment services, which are typically in short supply. This is confirmed by a positive SIS effect on out-of-pocket expenditures. Finally, Bauhoff and Oroxom (2019) estimate the impact the ID requirement introduced as part of the 2011 reform. A difference-in-differences strategy compares infants eligible for SIS prior to the requirement, who could retain their coverage, versus ineligible infants whose inclusion in SIS could be compromised by the new requirement. Using data from ENDES, they find no effect on access to health-care services or health outcomes.

3 Data

We use data from three different sources. First, we use the ENAHO household survey that covers the 24 regions in Peru. The survey is conducted by the National Institute of Statistics and Informatics (*Instituto Nacional de Estadística e Informática*, INEI). We focus on the ENAHO 2011, survey that comprises 24,809 households with a total of 99,776 individuals. The ENAHO has detailed information that we use to reconstruct the welfare index. This reconstruction is direct because all the questions used by authorities to compute the welfare index come from the ENAHO. In fact, the phrasing of the questions and the corresponding categories are the same. We also take from this survey outcomes on schooling, health-care use, and expenditures.

Second, we use the ECE census that covers Peruvian students. The Ministry of Education conduct this census that consists of a test that is designed to assess the levels of reading comprehension and math. The test is applied every year to children in the second grade. A Rasch model then uses the students' answers to produce two independent scores.[7]

We exploit a unique database that was generated based on the merger of these two sources. At our request, the INEI and the Ministry of Education merged the data on each child from three to six years old in the ENAHO 2011 survey with the test scores obtained in the ECE when the child had reached primary school. They executed this merger privately using the ID numbers that are not publicly available. Out of the 7,397 children between three and six years old covered by the ENAHO 2011 survey, the ECE test scores are available for 5,992. This sample represents a success rate of 81%.[8] We preserve the anonymity of the children when accessing these data.

[7]The Peruvian system for measuring learning achievements is based on two tools: the census evaluations from the ECE and the sample evaluations. The first has been applied to every student in second grade annually since 2007 and to eighth grade students since 2015. The test was also applied to children in the fourth grade in some specific years. The second allows for a deeper evaluation.

[8]Table C.1 in the Online Appendix C shows the distribution of these children by age in the ENAHO 2011 survey and the year of evaluation.

We restrict the analysis to individuals from Lima Province for three reasons. First, the new welfare index was used in Lima from 2011 on and in the whole country from 2012 on. Hence, Lima Province in 2011 is the place and time where the discontinuity is clearest. Second, Peru has two large conditional cash transfers programs that use the same welfare index and thresholds as SIS: the JUNTOS and PENSION 65 target the poor and the elderly, respectively. Importantly, they both exclude Lima Province and therefore the RDD assumption of smoothness around the threshold holds. Third, to the extent that Lima Province concentrates schools and teachers, the difference in student performance that we exploit is not driven by large distances between home and school, or by the number of teachers. Hence, out of the 5,992 children with available test scores at the national level, we end up with 420 living in Lima Province.

A third source is the ENDES household survey that is representative at the level of each region in Peru. The survey is also conducted by the INEI. Most of the questionnaire is targeted at children and at women of childbearing age. We focus on the ENDES 2011, survey that covers 10,605 children ages 0-5 and 22,952 women ages 15-49. The ENDES includes information to reconstruct the welfare index similarly to the ENAHO; however, it provides child and maternal objective measures of health status that the ENAHO does not (e.g., hemoglobin levels). The ENDES lacks ID numbers and therefore we could not request the INEI and the Ministry of Education to merge children from this survey to their test scores from the ECE. In order to confidently draw conclusions from either sample, the ENAHO and the ENDES should be representative of the same universe. Hence, we restrict the analysis of the ENDES to individuals living in Lima Province as we do with the ENAHO. Our sample then contains 712 children ages 0-5 and 2,024 women ages 15-49.

4 Method

The empirical analysis aims to identify the effect of health insurance coverage on student performance. Estimating this effect by means of an ordinary least squares neglects two sources of endogeneity. First, insurance coverage and education are codetermined, with each affecting the other. While insurance coverage determines education through the mechanisms pointed out in Section 1, education also determines insurance coverage in several ways. For instance, more educated households are able to understand the benefits of health insurance. Second, comparing children covered and uncovered by SHI neglects differences between these two groups. Coverage is driven by economic, social, and cultural conditions that are largely unobserved. These two problems, simultaneity and omitted variables, can confound our estimates.

To address these concerns, we exploit the unique features of the Peruvian SHI. Eligibility is assessed at the household level and relies on two criteria. First, water and electricity expenditures cannot exceed 20 and 25 Soles, respectively. Second, provided that water or electricity expenditures are not high, the welfare index cannot exceed a specific threshold, which equals 55 in the case of Lima Province. The usage of the discontinuity in water and electricity expenditures is not possible with the databases at hand. The ENAHO directly collects this information, but the respondents of the surveys typically are imprecise (they do not have to show a receipt); the ENDES does not ask for these expenditures. In contrast, the second discontinuity can be exploited because the welfare index is computed from a set of characteristics of the household that are verifiable by field authorities because both surveys use this set. Hence, the welfare index we construct from the answers to the survey is highly precise.

We start by selecting individuals from households with low consumption of water or electricity. In the case of the survey coming from the merge of ENAHO and ECE, we directly use the information provided by the respondent for the household. Out of the 420 children living in Lima Province, we end up working with 203. In the case of the ENDES, we estimate water or electricity expenditures from available household characteristics. The Online Appendix B contains a detailed explanation of these calculations. Out of the 712 children and 2,055 women living in Lima Province, we end up working with 187 children and 594 women with low water and electricity consumption, and information on hemoglobin levels. Table C.2 in the Online Appendix C presents the summary statistics of our main variables.

We estimate the effect of health insurance coverage by using a sharp RRD. We define the assignment variable w_i as the welfare index for individual i. The regression discontinuity estimate is then defined as:

$$\tau_{RDD} = \lim_{w_i \to 0} E\left[y_i | z_i = 1, w_i\right] - \lim_{w_i \to 0} E\left[y_i | z_i = 0, w_i\right], \tag{1}$$

where y_i is the observed outcome of individual i, and z_i equals one if individual i is eligible (i.e. $w_i \leq 0$) and zero otherwise. We estimate τ_{RDD} with local linear regressions. In particular, we compute the conventional estimate (calculated based on a first order polynomial) with the data-driven bandwidth selector suggested by Calonico et al. (2014b).

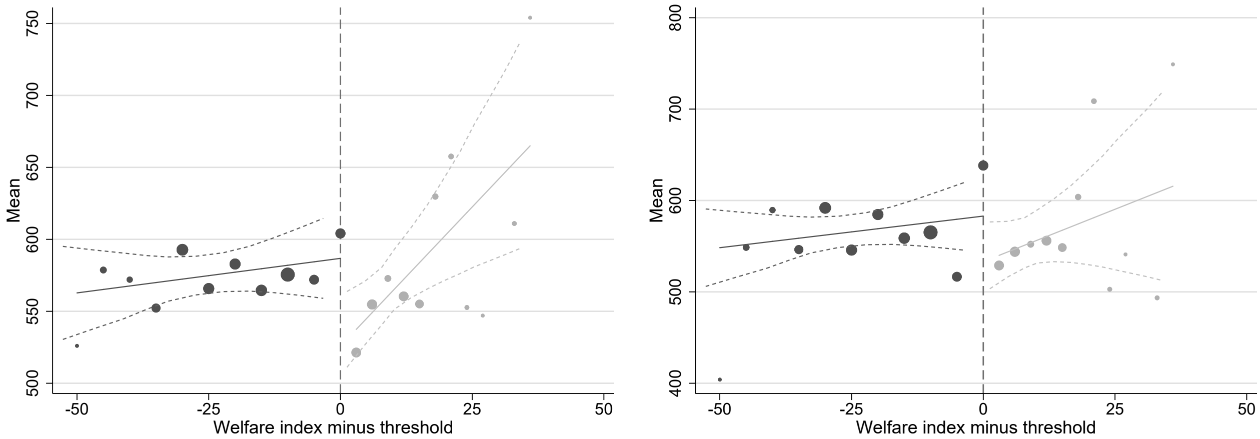
Our identification strategy relies on three assumptions. First, we need the conditional expectations to be smooth around the threshold (Imbens and Lemieux, 2008). We require $E(y_t|z = 1, w = 0) = E(y_t|z = 0, w = 0)$ and $E(y_c|z = 1, w = 0) = E(y_c|z = 0, w = 0)$, where y_t and y_c are the outcomes under treatment and control conditions, respectively. While this assumption cannot be tested directly, it arguably holds as no other social program uses the welfare index or the eligibility threshold in Lima Province (see Section 3). Second, insurance status needs to be monotone in eligibility. This assumption holds by construction. In our institutional setup, an uncovered individual with a welfare index slightly above the threshold will be covered by the SHI if this index changes to a value slightly below the threshold. Third, we need no sorting around the discontinuity. Sorting could occur if households manipulate the answers collected by the field authority to influence the value of the welfare index.

5 Results

5.1 Basic results

We start by showing graphically the relation between the welfare index of children from three to six years old in the ENAHO 2011 survey and their test scores when they reach primary school. In Figure 1, Panels A and B show plots for the average test scores of reading comprehension and math, respectively, in each case against the welfare index minus the eligibility threshold. Every dot denotes the average score for a specific bin and its size represents the number of observations. Since individuals are covered by SHI when the index is below the eligibility threshold, we observe a downward jump of scores to zero. The interpretation is that health insurance coverage has a positive effect on both test scores.

Figure 1: Test scores on welfare index



Panel A: Reading

Panel B: Math

Notes: The figure shows the insurance effect on student performance. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province. The dots denote averages, where the bin width is five to the left of the threshold and three to the right. Their size represents the number of observations. The regression lines with corresponding 95% confidence intervals stem from separate linear regressions to the left and to the right using individual-level data.

We now examine these results more formally. Table I presents the RD estimates for the test scores, according to Equation 1. Following Calonico et al. (2014a), we report the conventional estimate of τ_p^{RD} and the standard errors, but present the robust bias-corrected p-value levels. In order to get more precise estimations, we control for age, gender, and years of education and for two variables at the household level: the number of members and whether the head is female.[9] Columns 1 and 2 show that health insurance coverage increases the score of the standardized test for reading by 86.28 points and is 0.915 times the standard deviation of the whole sample, respectively. Columns 3 and 4 show it also leads to an increase of 172.9 points in the standardized test of math and is 1.429 times the standard deviation.

Table I: The effect of health insurance coverage on test scores: non–parametric RDD estimates

	Reading		Math	
	Score	Sd. score	Score	Sd. score
	(1)	(2)	(3)	(4)
Insurance coverage	86.28**	0.915**	172.9***	1.429***
	(38.59)	(0.409)	(71.20)	(0.589)
Observations	203	203	203	203
BW right	13.29	13.29	9.852	9.852
BW left	12.72	12.72	11.80	11.80
Controls	Yes	Yes	Yes	Yes
Mean	572.93	6.08	564.41	4.67
S.D.	81.80	0.87	105.99	0.88

Notes: The table shows the insurance effect on student performance. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial, and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

The effects we report are large. As a reference point, Alcaraz et al. (2016) find that going from no coverage to having all the targeted population registered in the Mexican SHI would translate into an increase of 0.156 times the standard deviation of the average across municipalities. Our results for the effects on SHI should be compared with this reference with caution. We estimate the average effect of the sub-population with a welfare index close to the cutoff, while the references are related to the overall average treatment effect.

[9]The estimator is implemented by the STATA package *rdrobust*.

5.2 Potential mechanisms

We analyze possible mechanisms for the effect of health insurance coverage on student performance. The natural candidates are the stated goals of SHI, namely better health of the targeted population and protection against the financial consequences of health shocks. Table II displays each of these mechanisms by presenting the RD estimates for a number of dependent variables. Our selection of these variables is guided by the two-period model of child health and schooling outcomes of Glewwe and Miguel (2007) and particularly by their production function that measures academic skills, as we do, by test scores when the child is of primary school-age (time period 2).

Child health status is the first potential mechanism we analyze. Panel A shows that the data from the ENDES 2011 survey reflect whether children have better health. These are not the children of the ENAHO 2011 survey for which we have test scores, but both surveys use the same sample. We find that SHI leads to an increase in hemoglobin of 0.32 that unfortunately is not precise. However, we do find that health insurance has a negative and statistically significant effect on the probability of moderate or severe anemia equal to -40.7 percentage points. Iron deficiency is related to lower cognitive function, memory, and attention span that explain the effect of SHI on test scores. Moreover, iron deficiency, which means less oxygen in the blood, is also related with less aerobic capacity and general weakness. For this reason, anemia relates to school attendance. We find that health insurance coverage increases school attendance by 52.6 percentage points. These results are consistent with the studies on the effect of programs to provide iron supplements on school participation (Bobonis et al., 2006), schooling attainment (Chong et al., 2016), and test scores (Halterman et al., 2001). Panel A of Figure 2 presents the relation between the welfare index of children between three and six years old and their hemoglobin level.

The health status of parents is another potential mechanism. In the production function for academic skills, the health status is directly related to parent's provision of educational inputs such as the pedagogical value of time spent by parents with the child and school supplies. Panel B of Table II uses data from the ENDES 2011 survey that reflects whether women have better health. We find that health insurance coverage leads to an increase in hemoglobin of 1.392, and a subsequent reduction in the probability of moderate or severe anemia of 19.7 percentage points. A higher aerobic capacity may increase both the time shared with children in educational activities and the income to buy school supplies. Panel B of Figure 2 presents the relation between the welfare index of women and their hemoglobin level.

Household financial protection is the third potential mechanism. Parents face an intertemporal budget constraint. Health insurance protects households against the financial consequences of health shocks that allows parents to dedicate more resources to the provision of educational inputs or to smooth the consumption of such inputs (or both). Panel C of Table II uses data from the ENAHO 2011 survey to explore whether health insurance changes the household financial status of the tested children. First, we find that insurance coverage decreases annual out-of-pocket spending for health care by on average 52.5 Soles, which corresponds to 19 US dollars. Second, we find evidence of a reduction in the variability

Table II: The effect of health insurance coverage on mechanisms: non-parametric RDD estimates

	Effect	Mean	Observations	BW right/left	Source	Unit analysis
Panel A: Health status of children						
Hemoglobin	0.320		187	17.70	Endes	Children
	(0.739)			8.041		
Anemia	-0.407**		187	9.093	Endes	Children
	(0.241)			6.470		
School attendance	0.526**		203	9.295	Enaho	Children
	(0.207)			10.670		
Panel B: Health status of women						
Hemoglobin	1.392**		594	9.809	Endes	Mother
	(0.592)			6.971		
Anemia	-0.197**		594	8.781	Endes	Mother
	(0.105)			7.183		
Panel C: Financial protection						
Level of health expenses	-52.50***	278.54	203	8.037	Enaho	Children
	(61.20)	(781.91)		6.786		
Variability of health expenses	-131.9.7***	410.21	203	7.909	Enaho	Children
	(39.24)	(664.13)		6.335		
Level of cultural and teaching expenses	-170.9	413.11	203	9.008	Enaho	Children
	(143.9)	(619.405)		6.703		
Panel D: Years of schooling						
School delay (dummy)	-0.232**	0.099	203	10.67	ECE	Children
	(0.119)	(0.113)		11.75		
School delay (number of years)	-0.330**	0.113	203	11.09	ECE	Children
	(0.171)	(0.361)		11.10		

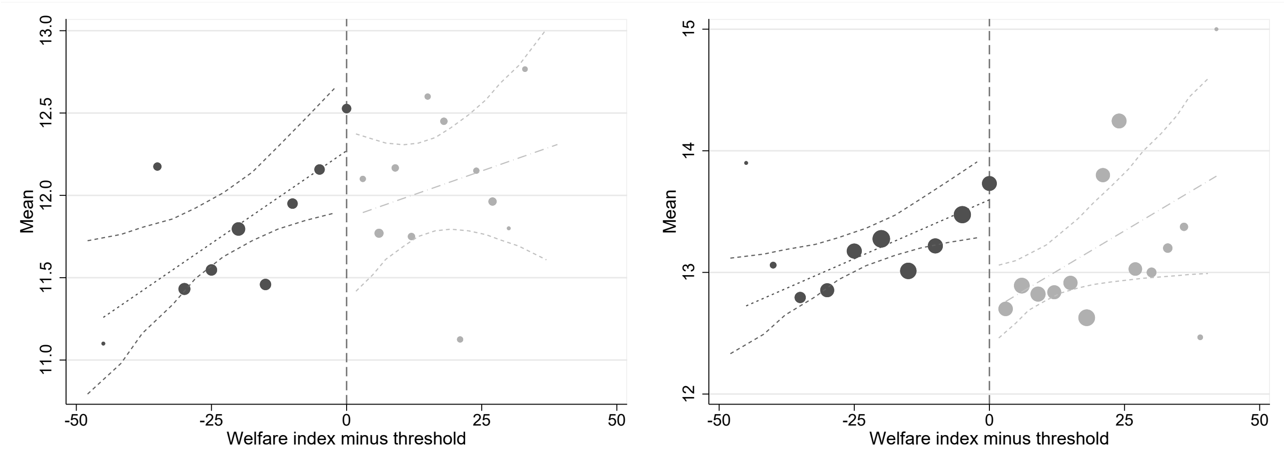
Notes: The table shows the insurance effect on health and spending outcomes. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial, and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

of this spending. This variability measure, following Miller et al. (2013), is the mean absolute deviation in health-care expenditures that is calculated separately by insurance status. We take the first result with caution because the size of the coefficient changes by method of estimation.[10] Moreover, we fail to find an insurance effect on educational household expenses. However, this transfer could have taken place between 2011 and the year of application of the exam, which we are not able to test.

The production function of Glewwe and Miguel (2007) includes child health and parents' provision of educational inputs for both time periods 1 and 2. Our identification strategy, based on a discontinuity that existed only in 2011, and our cross-sectional surveys preclude us from exploring the effect of health insurance on health status and financial protection beyond 2011. However, the production function

[10] Table C.6 in the Online Appendix C presents the full set of RD estimators, that is, conventional, bias-corrected and robust.

Figure 2: Hemoglobin level on welfare index



Panel A: Child Panel B: Woman

Notes: The figure shows the insurance effect on the hemoglobin level. In Panel A, the sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province. In Panel B, the sample includes all women from households with low consumption of water and electricity and who are residents of Lima Province. The dots denote averages in which the bin width is five to the left of the threshold and three to the right. Their size represents the number of observations. The regression lines with corresponding 95% confidence intervals stem from separate linear regressions to the left and to the right using individual-level data.

includes an additional input for time period 2 for which we do have information: the accomplished years of schooling. As we have the age of the evaluated children from the ENAHO 2011 survey and the year of schooling when the test was applied from the ECE, we construct an indicator variable for whether the child is delayed by age (extensive margin) and a discrete variable for the years the child is delayed (intensive margin). Panel D shows that health insurance coverage decreases the probability of being delayed by 23.2 percentage points and the number of years of school delay by 0.33.[11]

In sum, we have shown that the better health of children and women are likely mechanisms for the effect of health insurance coverage on student performance. We now go further to analyze how health insurance effects the health status. There are many potential mechanisms (e.g., access to health services, local health environment, and innate healthiness).[12] However, to provide a picture that is both parsimonious and innovative in the framework of social health insurance, we focus on household nutrition. The database of the ENAHO 2011 survey includes the quantities purchased by the household that are measured in kilograms, annualized, and grouped into 50 categories. We compute the per capita purchased quantities of these 50 categories and use them as dependent variables. Table III presents the RD estimates for those categories that are significant at the 0.05 level (Table C.3 in the Online Appendix C includes the results for the whole set of categories).

[11]The effect of health insurance on years of education is indirect. The coverage affects health and financial statuses, and these variables in turn affect years of education. The model of Glewwe and Miguel (2007) goes deeper on the distinction between direct and indirect effects.

[12]See Glewwe and Miguel (2007) for a production function for child health.

Table III: The effect of health insurance coverage on per capita food purchased by the household

	Effect	Mean	Observations	BW right/left	Source	Unit of analysis
Cakes and pastries	-2.079**	2.51	203	11.70	Enaho	Children
	(1.024)	(4.09)		9.856		
Noodles	-6.785**	12.51	203	8.492	Enaho	Children
	(3.683)	(8.73)		10.44		
Fresh fish	8.565**	9.97	203	10.01	Enaho	Children
	(3.942)	(13.08)		8.889		
Candies, chocolates, honey	-0.463*	0.59	203	8.200	Enaho	Children
	(0.279)	(1.31)		7.983		
Prepared meals to consume	-7.843***	6.47	203	5.634	Enaho	Children
at home	(3.098)	(18.45)		9.159		
Other foods to consume	8.129***	3.32	203	11.56	Enaho	Children
at home	(3.312)	(6.95)		10.59		

Notes: The table shows the insurance effect on amount of kilograms of product purchased by the household (annualized, per capita). The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

On the one hand, health insurance coverage increases the annualized purchases of fresh fish (8.57 kilograms) that is an important source of proteins and micro-nutrients (e.g., omega-3 acids, iodine, vitamin D, calcium). The research has shown that fish consumption benefits cognitive performance and school performance. Lehner et al. (2020) find a statistically significant association between an intake of 8 grams of fish per day and the probability of increasing grades in German and mathematics by one point, compared to no or limited fish consumption. For female students, the effect was larger than average. Likewise, De Groot et al. (2012) associate a higher intake of fish with better grades in reading comprehension and final grades at the end of the academic period, with a slightly greater effect on female students.

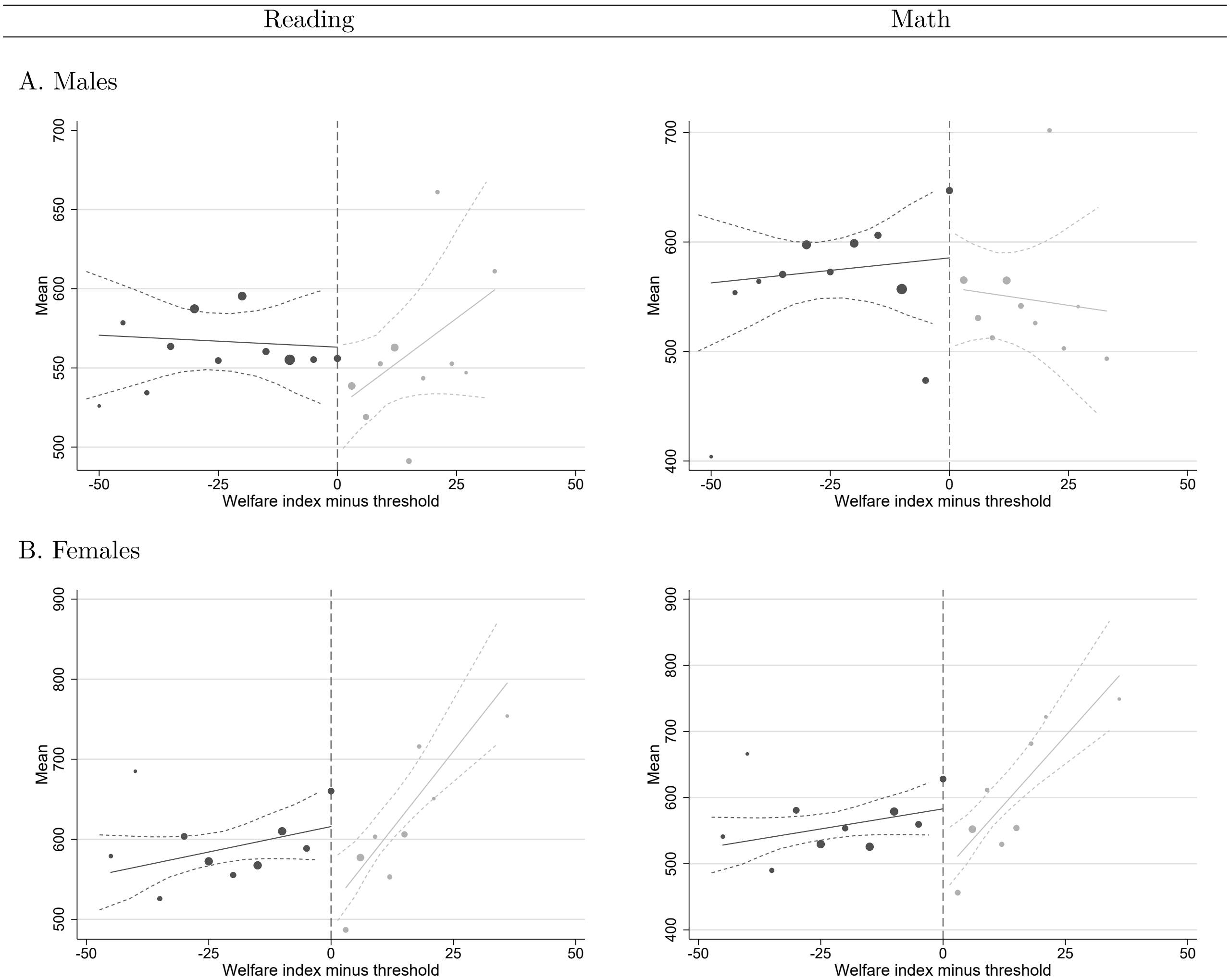
On the other hand, health insurance coverage decreases the annualized purchases of four categories whose excessive consumption over time can lead to the development of chronic diseases, namely cakes and pastries (-2.08 kilograms); noodles (-6.79 kilograms); candies, chocolates, and honey (-0.46 kilograms)[13]; and prepared meals to consume at home (-7.84 kilograms). This last category refers to meals bought in commercial establishments to take out, and it includes mainly five typical Peruvian dishes with a high content of saturated fat. We find that health insurance coverage increases the annualized purchases of other foods to consume at home, but the assessment of the nutritional content of the components of this category is not clear.

[13] Although it is not statistically significant at the 5% level, we have included the RD estimate for candies, chocolates and honey because its significance is very high when we consider the sum of purchases and donations. This regression is available in Table C.3 in the Online Appendix C.

5.3 The effect of health insurance by sex

The economic development literature shows that males perform relatively better than females from early years of schooling on. This gender gap occurs with a particular emphasis on mathematics test scores. In this context, a natural question is whether the effect of SHI on test scores that we report is heterogeneous by sex. Figure 3 shows the plots for the average test scores against the welfare index minus the eligibility threshold. Panels A and B show the plots for males and females, respectively. We observe that the downward jump of scores to zero is much clearer for girls than for boys. The interpretation is that the positive effect of health insurance coverage on test scores is mainly driven by girls.

Figure 3: Test scores on welfare index



Notes: The figure shows the insurance effect on test scores. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province. The dots denote averages in which the bin width is five to the left of the threshold and three to the right. Their size represents the number of observations. The regression lines with corresponding 95% confidence intervals stem from separate linear regressions to the left and to the right using individual-level data.

We now present more formal evidence. Table IV shows the non–parametric RD estimates for the effect of social health insurance on tests scores. Columns 1 and 2 show the baseline results for math and reading comprehension, respectively. We want to obtain exactly the same RD estimates as in Tables II and III by sex, but the *rdrobust* command in Stata of Calonico et al. (2017) cannot compute them due to the limited number of observations. What we do then is exclude the control variables to facilitate the calculations. Columns 3 and 4 show the same previous non–parametric RD estimates but without controls. The results are roughly the same, but this time the effect of reading comprehension and math are closer. Columns 5 and 7 show the RD estimates for the effect of health insurance on reading comprehension scores for males and females, respectively. The estimated effect is 2.58 times greater for girls than for boys. This huge difference indicates that social health insurance may help to alleviate a potential gender gap in developing countries. Columns 6 and 8 show the RD estimates for the effect of health insurance on math scores for males and females, respectively. This time the estimates are close, but the precision of the coefficient is much higher for girls than for boys. All these results are consistent with the graphical analysis in Figure 3. Overall, we confirm that the positive effect of health insurance coverage on both test scores is mainly driven by girls.

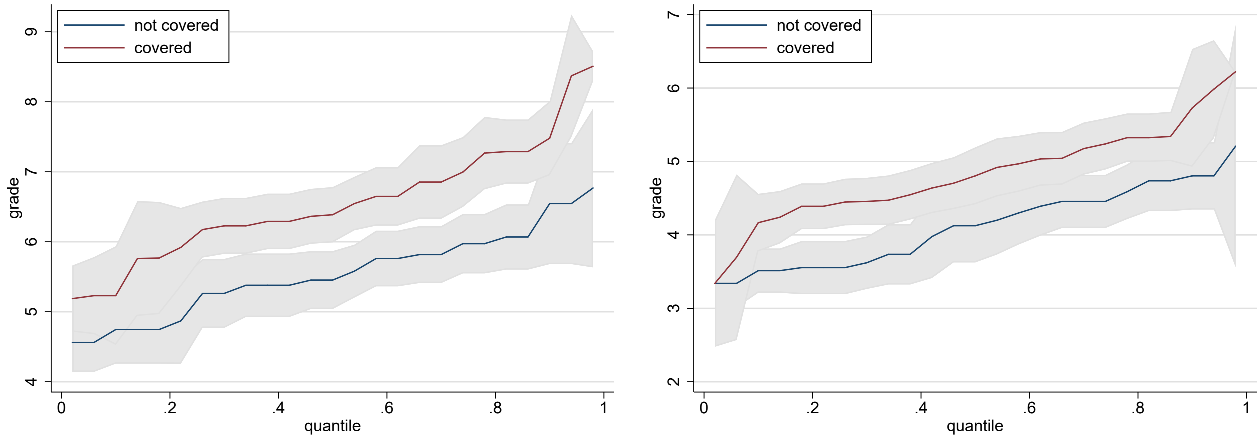
Table IV: The effect of health insurance coverage on test scores: non–parametric RDD estimates

	Overall (baseline)		Overall		Males		Females	
	Reading (1)	Math (2)	Reading (3)	Math (4)	Reading (5)	Math (6)	Reading (7)	Math (8)
Insurance coverage	86.28**	172.9**	112.8**	159.8**	77.58	232.7	199.2***	240.1***
	(38.59)	(71.20)	(44.92)	(77.35)	(79.48)	(142.9)	(63.42)	(49.58)
Observations	203	203	203	203	118	118	85	85
BW right	13.29	9.852	12.17	10.71	11.65	8.997	13.53	10.46
BW left	12.72	11.80	10.44	11.56	15.02	14.69	5.177	3.874
Controls	Yes	Yes	No	No	No	No	No	No
Mean	572.93	564.41	572.93	564.41	560.96	567.61	589.54	559.96
S.D.	81.80	105.99	81.80	105.99	80.27	119.53	81.46	84.13

Notes: The table shows the insurance effect on student performance by sex. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

We now use our same RD setting to estimate the quantile treatment effects as described in Frandsen et al. (2012) for females. Figure 4 displays the estimates of the quantiles for the distribution of reading and math test scores with and without social health insurance coverage. We find that health insurance roughly has a positive effect throughout the whole distribution.

Figure 4: Effect of SHI on the distribution of tests scores of females



Panel A: Reading

Panel B: Math

Notes: The figure shows the percentiles of the distribution of expenditures with and without health insurance, along with 90% confidence intervals. The sample includes all females from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province. See Frandsen et al. (2012) for details on the implementation.

6 Robustness checks

In this section, we present robustness checks in order to support our identification strategy. First, we compare children for those who we have test scores with those who do not have test scores. Second, we investigate the manipulation of the targeting index by the households to increase the likelihood of being eligible. Third, we explore whether there are discontinuities around the threshold in the covariates. Fourth, we show the full set of RD estimates.

6.1 Selection to merge

The causal effect of health insurance on test scores was estimated for 203 children from 3 to 6 years old in the ENAHO 2011 survey whose test scores were available in the ECE 2012-2016. However, the match between ENAHO and ECE was not perfect. There are some possible explanations. First, individuals surveyed by ENAHO may give inaccurate names and ID numbers. This can be random, but we cannot rule out that some people may want to preserve anonymity. In a context of high informality and crime, individuals do not want their socioeconomic situation to be known by tax authorities, social programs or common criminals. Second, children surveyed by ENAHO may not be enrolled in school in the year of the test or may be absent for health reasons the day of the test. If there is a systematic difference between the children with available and unavailable test scores, our results may be biased.

In order to evaluate this concern, we compare the 203 children with 50 children that satisfy the same restrictions (i.e., residents of Lima Province, and low consumption of water and electricity), but whose test scores are not available in the ECE. Table C.4 in the Online Appendix C presents this comparison.

It assesses the balance across all our covariates: women, age, education, and household members as well as whether the household head is a woman. We do not observe any statistically significant difference that raises concern about a bias in our estimations. The table also compares four socioeconomic variables: welfare index, household expenditure, water consumption and electricity consumption. The number of observations is lower for these last variables because they change at the household level, and therefore we make the evaluation at this level.

We complement this evidence with an additional RD estimation using Equation 1. The unit of analysis is the 253 children in the ENAHO 2011 survey that satisfy our restrictions, the dependent variable is a dummy equal to one if the test score is available in ECE (and zero otherwise), and the running variable is the welfare index. A significant estimator (positive or negative) means that the probability of being in our sample discontinuously changes at the threshold. We obtain -0.220 with a standard error equal to 0.179 (bandwidth equal to 14.92 to the right and 9.86 to the left).

6.2 Manipulation of the running variable

A crucial condition for identification in the RD design is continuity of the conditional expectation of counterfactual outcomes in the running variable. This continuity may not be assumed if agents are able to manipulate this variable. In our framework, this manipulation would require individuals with knowledge on how the welfare index is calculated by authorities, and individuals capable of successfully lying in the face of questions from government officials who administer the house-to-house questionnaire. We argue that this is not likely for two reasons. First, the algorithm for calculating the welfare index is not widely known by the population and it is difficult to understand for the average resident. Second, the variables that compose the welfare index (see Table A.1 in the Online Appendix A) were chosen by authorities precisely with the purpose of being verified by government officials who apply the house-to-house questionnaire.

Although manipulation is unlikely in the Peruvian framework, we evaluate this possibility using the McCrary (2008) test. The main objective of this test is to estimate the difference in the running variable, which in our case is the welfare index, at the left and at the right of the threshold. Then, we test whether this difference is statistically different from zero. If households manipulate the index around the threshold in order to become eligible, then the density function should show several households to the left of the cutoff and few households to the right of it. Figure D.1 in the Online Appendix D shows an estimate of the density of the welfare index that allows for a discontinuity at the threshold. In Panel A, the sample is composed by all households from Lima Province with one child between three to six years old in the ENAHO 2011 survey. As throughout the analysis, we exclude households with a high consumption of water or electricity. The size of the discontinuity difference at the threshold is $T_q = -0.3574$ and has a p-value of 0.7208. In Panel B, the sample is all households in Lima Province in the ENDES 2011survey but excluding households with high consumption of water or electricity. The size of the discontinuity difference at the threshold is $T_q = 0.1328$ and has a p-value of 0.8944. Therefore, there is no statistical evidence of systematic manipulation of the running variable (the shape of the distribution is not smooth due to the small number of observations).

6.3 Testing for discontinuities in household characteristics

In order to explore whether the relation between the health insurance and test scores is not driven by factors other than the targeting index, the standard practice is to test whether the expectation of the covariates is a continuous function in the welfare index around the eligibility threshold. Table C.5 in the Online Appendix C presents the RD estimations from using Equation 1 in which this time every covariate is the dependent variable. We do not observe any discontinuity in the proportion of women, age, years of education, and number of household members as well as whether a woman is the household head.

6.4 Robustness to estimation method

Although the survey provides little power, the magnitude of the estimated SIS effect is robust to a number of alternative methods. Table C.6 in the Online Appendix C presents the full set of RD estimators, that is, conventional, bias-corrected and robust. The results are qualitatively the same.

7 Conclusions

This study provides evidence that SIS, a social health insurance program in Peru, has a positive, large, and statistically significant effect on the test scores of children between three and six years old when they attain primary school. We argue that the health status of children and their families are the main channels for this effect. In particular, the evidence shows that SIS lowers the incidence of anemia for children and for women of childbearing age, which is likely related to better nutritional intake. Moreover, this study shows the effect of SIS on academic performance is driven by girls, who benefit from the program throughout the entire test score distribution. To the best of our knowledge, these are the first estimates of the spillover effect of public health insurance to student performance by means of an RD design.

Our results have several implications that are important for public policy. First, impact evaluations of SHI programs must not only be limited to direct objectives, but must also include spillovers to objectives not initially considered. Otherwise, the contribution of social health insurance will be strongly underestimated. Second, the design of poverty alleviation programs must consider that moving one dimension (e.g., consumption, education, or health) effectively affects other dimensions, at least in the medium term. Third, the gender gap in academic results, reported in several developing countries, is sensitive to health insurance coverage.

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Online appendices

A Welfare index construction

Table A.1: Variables and weights for welfare index construction in Metropolitan Lima

Variables	Weights	Variables	Weights
Fuel used to cook		*Roof material*	
Do not cook	-0.49	Other	-0.86
Other	-0.40	Straw	-0.74
Firewood	-0.37	Mat	-0.67
Carbon	-0.33	Woven cane	-0.38
Kerosine	-0.29	Tiles	-0.23
Gas	0.02	Wood or mat	-0.21
Electricity	0.43	Concrete	0.17
Water supply in the home		*Education of the Household head*	
Other	-0.78	None	-0.51
River	-0.65	Preschool	-0.43
Well	-0.62	Primary	-0.28
Water tanker	-0.51	Secondary	-0.06
Pipe	-0.41	Vocational education (VET)	0.10
Outside	-0.35	Undergraduate	0.22
Inside	0.10	Postgraduate	0.40
Wall material		*Floor material*	
Other	-0.70	Other	-0.97
Wood or mat	-0.48	Land	-0.60
Stone with mud	-0.44	Concrete	-0.16
Rushes covered with mud	-0.41	Wood	0.08
Clay	-0.39	Tiles	0.16
Sun-dried brick or adobe	-0.37	Vinyl sheets	0.28
Stones, lime or concrete	-0.33	Parquet	0.51
Brick	0.10	*Overcrowding*	
Type of drainage		More than six	-0.68
None	-0.89	Between four and six	-0.51
River	-0.75	Between two and four	-0.31
Sinkhole	-0.59	Between one and two	-0.07
Septic tank	-0.46	Less than one	0.24
Drainage system outside the house	-0.39	*Has fixed phone*	
Drainage system inside the house	0.10	Yes	-0.32
Number of members with health insurance		No	0.20
None	-0.26		
One	-0.04		
Two	0.06		
Three	0.14		
More than three	0.32		
Goods that identify household wealth			
None	-0.47		
One	-0.17		
Two	0.02		
Three	0.15		
Four	0.25		
Five	0.47		

Notes: Taken from Bernal et al. (2017). The original Spanish version corresponds to SISFOH (2010).

B Consumption of water and electricity

Households with high water and electricity consumption are not directly eligible for SIS, while households with low water or electricity consumption are evaluated by means of the welfare index. In the case of Lima, households with water expenditures above 20 Soles (7.3 U.S. dollars) and electricity expenditures above 25 Soles (9.1 U.S. dollars) are directly ineligible from SIS. In order to apply our RD design that is based on the welfare index, we need to exclude these high consumption households. ENAHO includes information on household expenditures on water and electricity, but ENDES does not. Hence, we approximate these expenditures at the household level with the available information.

In the case of water expenditure, we start by multiplying the number of household members, available in the ENDES, and the average water per capita consumed by district. The public agency that regulates the use of drinking water at the national level publishes this information (SUNASS, 2010), which we replicate in Table B.1.

Table B.1: Annual average per capita consumption of water in Lima by district

District	Consumption (m3)	District	Consumption (m3)
Lima-Cercado	12.62	Pucusana	7.7
Ancón	6.7	Pueblo Libre	12.65
Ate	12.5	Puente Piedra	7.05
Barranco	13.1	Punta Hermosa	14.52
Breña	11.55	Punta Negra	14.52
Carabayllo	8.43	Rímac	12.1
Chaclacayo	9.27	San Bartolo	6.45
Chorrillos	12.5	San Borja	13.23
Cieneguilla	10.06	San Isidro	13.03
Comas	9.77	San Juan de Lurigancho	10.1
El Agustino	10.89	San Juan de Miraflores	10.49
Independencia	4.88	San Luis	12.15
Jesús María	12.67	San Martín de Porres	10.79
La Molina	13.37	San Miguel	12.79
La Victoria	12.52	Santa Anita	11.51
Lince	12.2	Santa Rosa	8.77
Los Olivos	11.58	Santiago de Surco	12.99
Lurigancho	10.31	Surquillo	12.96
Lurín	8.54	Ventanilla	7.51
Magdalena	12.75	Villa El Salvador	9.59
Miraflores	13.09	Villa María del Triunfo	6.86
Pachacamac	9.21		

Notes: Data from SUNASS (2010).

Once we estimate the water consumption level by household, we compute the water expenditures by using the official rates of the Peruvian state company that provides drinking water and sewerage services to Lima. These rates vary according to the level of consumption.

Table B.2: Tariff of water in Lima by consumption level

Consumption (m3)	Tariff
0-9	0.94
10-24	1.091
25-49	2.414
more than 50	4.095

Notes: Data from RGG No. 0408-2011-GG of Sedapal.

In the case of electricity expenditure, we start by listing the home appliances of each household according to ENDES. We then calculate the consumption of kilowatts of each home appliance by multiplying its average kilowatts per hour consumption (information available from the public agency that regulates the use of electricity (Osinergmin, 2018)) and the average hours of usage (information available from a private consultant company (CONCORTV, 2011). We add up the kilowatt consumption per available home appliance to obtain the household consumption of electricity.

Table B.3: Annual average consumption of electricity in Lima by home appliance

Appliance	Consumption (Kw per hour)	Hours of use
TV	0.12	3.72
Refrigerator[1/]	0.35	24
Washing machine[2/]	0.5	1.5
Computer	0.3	2.97
Radio	0.8	3
Blender	0.3	1
Microwave	1.1	1
Electric kitchen	4.5	3
Light bulbo	0.25	8

Notes: Data from Osinergmin (2018) and CONCORTV (2011). 1/. We assume that the refrigerator stays plugged in all day. 2/. We assume that the duration of an average cycle of a washing machine is 1.5 hours.

Table B.4: Tariff of electricity in Lima by consumption level

Consumption (Kw)	Northern Lima		Southern Lima	
	Fixed charge	Variable charge	Fixed charge	Variable charge
under 30	2.46	0.3785	2.35	0.2426
31-100	2.46 + 11.36	0.5047	2.35 + 7.28	0.3234
more than 101	2.56	0.5249	2.41	0.3315

Notes: Data from Osinergmin (2018).

Once we have the level of electricity consumption, we compute electricity expenditures. The two companies divide the districts of Lima for electricity supply: *Enel* (formerly *Edelnor*) for the northern districts and *Luz del Sur* for the southern districts. We use the maximum tariff schedule of the public electricity service for these companies according to their regulator (Osinergmin, 2018) (BT5B, residential). Table B.4 presents the tariff by area.

C Tables

Table C.1: Children of ENAHO 2011 with available test score in ECE, by age and year of evaluation

Year of evaluation	Age at the Enaho 2011: 3	4	5	6	Total
2011	6	2	17	283	308
2012	4	5	252	960	1,221
2013	7	163	867	230	1,267
2014	75	465	183	67	790
2015	864	345	73	43	1,325
2016	423	423	182	53	1,081
Total	1,379	1,403	1,574	1,636	5,992

Notes: The table shows the children surveyed by the ENAHO 2011 whose test scores are available in the ECE. We exclude children from zero, one and two years old in 2011 because ECE are not available for most of them.

Table C.2: Summary statistics

Variable	Total N=203		Covered[1/.] N=139		Not covered N=64		Source	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Survey	Year
Socio economic status								
Welfare index	43.52	18.34	33.54	12.07	65.19	7.92	Enaho	2011
Education status of children								
Reading score	572.93	81.80	576.48	79.64	565.21	86.45	ECE	2012-16
Reading sd. score	6.08	0.87	6.12	0.84	6.00	0.92	ECE	2012-16
Math score	564.41	105.99	568.08	102.81	556.42	113.01	ECE	2012-16
Math sd. score	4.67	0.88	4.70	0.85	4.60	0.93	ECE	2012-16
School delay (dummy)	0.10	0.30	0.10	0.30	0.09	0.29	Enaho	2011
School delay (number of years)	0.11	0.36	0.11	0.33	0.13	0.42	Enaho	2011
Health status of children								
Hemoglobin[2/.]	11.89	1.12	11.81	1.13	12.07	1.08	Endes	2011
Anemia[2/.]	0.05	0.21	0.06	0.23	0.03	0.18	Endes	2011
Health status of women								
Hemoglobin[3/.]	13.16	1.87	13.24	1.32	13.09	2.25	Endes	2011
Anemia[3/.]	0.03	0.17	0.02	0.13	0.04	0.20	Endes	2011
Financial protection of household								
Level of health expenses	278.54	781.91	223.18	675.01	398.77	969.94	Enaho	2011
Variability of health expenses	410.21	664.13	345.64	583.30	550.45	799.87	Enaho	2011
Level of cultural and teaching expenses	413.11	619.41	244.62	260.54	779.06	939.57	Enaho	2011
Per capita food purchased by household								
Cakes and pastries	2.51	4.09	2.58	4.41	2.35	3.31	Enaho	2011
Noodles	12.51	8.73	13.42	8.98	10.53	7.87	Enaho	2011
Fresh fish	9.97	13.08	10.21	12.76	9.44	13.84	Enaho	2011
Candies, chocolates, honey	0.59	1.31	0.50	1.22	0.80	1.48	Enaho	2011
Prepared meals to consume at home	6.47	18.45	6.95	21.60	5.42	8.23	Enaho	2011
Other foods to consume at home	3.32	6.95	3.62	7.64	2.67	5.15	Enaho	2011

Notes: The sample from the ENAHO 2011 survey includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, with available test score. The sample from the ENDES 2011 survey includes individuals from households with low consumption of water and electricity and who are residents of Lima Province. 1/. Coverage is defined by welfare index criterion. 2/. Question applied for children in ENDES 2011: total N = 187, covered N = 127, non-covered N = 60. 3/. Question applied for women in fertile age in ENDES 2011: total N = 595, covered N = 281, non-covered N = 314.

Table C.3: Per capita purchased food

N	Variables	Conventional		Obs.	Bandwidth	
		Coefficient	Std. Err.		Right	Left
1	Bread	4.325	(4.629)	203	13.48	10.39
2	Cakes and pastries	-2.079**	(1.024)	203	11.70	9.856
3	Rice	19.91	(16.89)	203	11.36	7.744
4	Milk	11.89*	(10.05)	203	8.377	12.39
5	Potato	39.28*	(23.23)	203	12.62	6.469
6	Sugar	-4.593	(10.27)	203	10.41	8.223
7	Eggs	1.122	(2.594)	203	15.03	9.742
8	Beef and other red-meat	-1.468	(3.115)	203	10.32	10.38
9	Chicken and other poultry-meat	-6.563	(6.603)	203	8.640	9.021
10	Poultry offal	5.020	(3.458)	203	13.59	11.01
11	Meat by-products	-0.284	(1.365)	203	12.10	10.33
12	Cow liver	-0.546	(0.652)	203	8.617	9.429
13	Beef tripe	0.663	(0.700)	203	14.41	8.452
14	Other offal	0.106	(0.477)	203	9.152	7.614
15	Corn, cornmeal, and toasted corn	-0.103	(3.317)	203	11.92	11.83
16	Wheat, wheat flour, and oats	-6.812	(4.330)	203	10.48	10.45
17	Quinoa, quinoa flour	1.650*	(0.994)	203	9.073	8.260
18	Pea flour, beans	1.436*	(0.873)	203	7.595	9.289
19	Noodles	-6.785**	(3.683)	203	8.492	10.44
20	Fresh fish	8.565**	(3.942)	203	10.01	8.889
21	Tuna, sardines, and others canned fish	0.842*	(0.568)	203	9.139	5.315
22	Seafood	-0.0662	(0.803)	203	8.815	4.191
23	Oil	0.453	(1.593)	203	9.779	7.874
24	Fresh cheese	-0.401	(0.926)	203	11.77	11.21
25	Margarine	-0.119	(0.478)	203	7.896	11.27
26	Butter	0.0687	(0.0780)	203	18.27	5.009
27	Others dairy products	-5.651	(3.971)	203	15.47	8.773
28	Iodized salt	-0.917	(1.300)	203	7.028	9.549
29	Fresh and whole chili	1.814	(1.182)	203	17.16	4.528
30	Spices and seasonings	2.095	(1.909)	203	14.31	10.79
31	Lentils, beans and peas	-3.391	(2.852)	203	8.856	8.621
32	Onion	-2.085	(4.885)	203	11.51	13.49
33	Tomato	3.519	(3.460)	203	14.95	9.717
34	Carrot, pumpkin	0.154	(4.495)	203	9.117	8.232
35	Corn	0.760	(1.953)	203	8.613	8.191
36	Sweet potato, yucca, and ullucus	1.887	(4.881)	203	17.64	9.016
37	Other vegetables and legumes	-4.382	(6.015)	203	10.15	7.648
38	Lemmon	0.612	(1.909)	203	9.233	8.621
39	Tangerine, orange and papaya	-0.810	(7.736)	203	14.03	10.50
40	Banana	-5.173	(11.13)	203	14.63	7.722
41	Other fruits	-1.918	(12.94)	203	10.52	8.107
42	Coffee, tea, cacao, and herbs	0.584*	(0.327)	203	6.930	8.522
43	Candies, chocolates, and honey	-0.463*	(0.279)	203	8.200	7.983
44	Alcoholic beverages	-0.694	(1.346)	203	11.59	7.347
45	Sodas	-14.09*	(8.725)	203	8.013	13.26
46	Water and juice	8.690	(13.68)	203	16.40	9.242
47	Prepared meals to consume at home	-7.843***	(3.098)	203	5.634	9.159
48	Other foods to consume at home	8.129***	(3.312)	203	11.56	10.59
49	Pet and domestic animals' food	-2.258	(4.631)	203	6.375	9.149
50	Other foods consumed out of home	-14.64	(13.18)	203	5.109	8.747

Notes: The table shows the insurance effect on amount of kilograms of product purchased by the household (annualized, per capita). The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

Table C.4: Selection into merge

Variables	Obs.	Full sample			Match	No match	Diff
		Mean	Min	Max	Mean	Mean	Mean
Women	253	0.435	0	1	0.419	0.500	-0.081
		0.031			0.035	0.071	0.078
Age	253	4.565	3	6	4.581	4.500	0.081
		0.073			0.082	0.160	0.183
Years of education	253	0.099	0	2	0.103	0.080	0.023
		0.020			0.023	0.039	0.049
Household members	253	4.767	1	11	4.739	4.880	-0.141
		0.104			0.111	0.267	0.260
Women is head of household	253	0.209	0	1	0.187	0.300	-0.113
		0.026			0.027	0.065	0.064
Welfare index	233	44.229	2.3	89.0	44.338	43.749	0.589
		1.161			1.322	2.372	2.999
Log household expenditures	233	7.516	6.2	9.1	7.535	7.432	0.104
		0.030			0.032	0.079	0.078
Log water consumption	233	2.483	0	5.0	2.492	2.441	0.051
		0.078			0.086	0.188	0.202
Log electricity consumption	231	3.107	0	5.4	3.126	3.023	0.103
		0.081			0.088	0.209	0.209

Notes: In the case of the socioeconomic outcomes, the table compares the 241 children under six years old residents of Lima Province with available test scores and the 193 similar children without available test scores. In the case of the educational outcomes, the table compares the 203 children from three to six years old residents of Lima Province with available test scores and the 50 similar children without available test scores. As throughout the analysis, we exclude households with high consumption of water and electricity. The unit of analysis is the household for the socioeconomic variables and children between three and six years old for the educational variables. T-tests computed using the *ttest* command in Stata. Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

Table C.5: Testing for discontinuities in covariates

	Women	Age	Years of education	Household members	Women is head of household
	(1)	(2)	(3)	(4)	(5)
Insurance coverage	0.364 (0.319)	-0.328 (0.587)	-0.0344 (0.0741)	-0.908 (0.772)	-0.103 (0.195)
Observations	203	203	203	203	203
BW right	11.42	14.20	5.883	17.13	14.45
BW left	7.877	11.13	7.606	10.71	10.63

Notes: The table shows the insurance effect on covariates. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional RD estimates that are calculated based on a first-order polynomial and the bias-corrected significance levels following Calonico et al. (2014a). Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01.

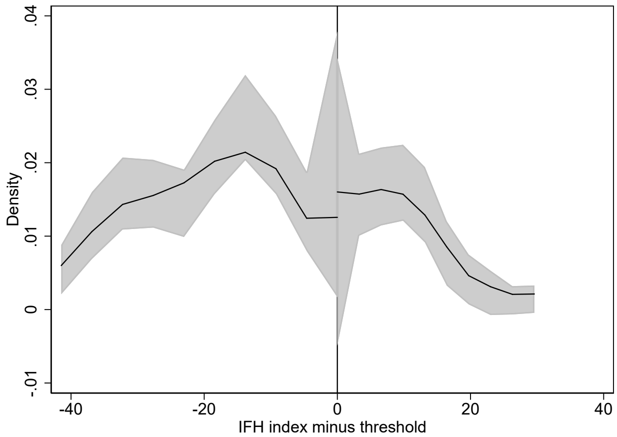
Table C.6: RD estimates using local polynomial regression by method

Variables	Conventional		Bias-corrected		Robust		Obs.	Bandwidth	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.		Right	Left
Reading score	86.28**	(38.59)	91.98**	(38.59)	91.98**	(45.67)	203	13.29	12.72
Reading sd. score	0.915**	(0.409)	0.976**	(0.409)	0.976**	(0.484)	203	13.29	12.72
Math score	172.9**	(71.20)	193.3***	(71.20)	193.3**	(82.84)	203	9.852	11.80
Math sd. score	1.429**	(0.589)	1.598***	(0.589)	1.598**	(0.685)	203	9.852	11.80
Level of health expenses	-52.50	(61.20)	-164.6***	(61.20)	-164.6*	(93.95)	203	8.037	6.786
Variability of health expenses	-131.9***	(39.24)	-205.9***	(39.24)	-205.9***	(72.36)	203	7.909	6.335
Level of cultural and teaching expenses	-170.9	(143.9)	-127.0	(143.9)	-127.0	(173.6)	203	9.008	6.703
School delay (dummy)	-0.232*	(0.119)	-0.250**	(0.119)	-0.250*	(0.137)	203	10.67	11.75
School delay (number of years)	-0.330*	(0.171)	-0.374**	(0.171)	-0.374*	(0.197)	203	11.09	11.10
Cakes and pastries	-2.079**	(1.024)	-2.308**	(1.024)	-2.308*	(1.187)	203	11.70	9.856
Noodles	-6.785*	(3.683)	-7.769**	(3.683)	-7.769*	(4.448)	203	8.492	10.44
Fresh fish	8.565**	(3.942)	8.111**	(3.942)	8.111*	(4.659)	203	10.01	8.889
Candies, chocolates, honey	-0.463*	(0.279)	-0.484*	(0.279)	-0.484	(0.349)	203	8.200	7.983
Prepared meals to consume at home	-7.843**	(3.098)	-9.101***	(3.098)	-9.101**	(3.821)	203	5.634	9.159
Other foods to consume at home	8.129**	(3.312)	8.994***	(3.312)	8.994**	(3.556)	203	11.56	10.59
Candies, chocolates, honey[1/.]	-2.531**	(1.286)	-3.081**	(1.286)	-3.081*	(1.632)	203	7.711	8.037
Reading score[2/.]	112.8**	(44.92)	126.2***	(44.92)	126.2**	(53.20)	203	12.17	10.44
Math score[2/.]	159.8**	(77.35)	183.1**	(77.35)	183.1**	(91.12)	203	10.71	11.56
Reading score (males)[2/.]	77.58	(79.48)	91.30	(79.48)	91.30	(97.03)	118	11.65	15.02
Math score (males)[2/.]	232.7	(142.9)	259.1*	(142.9)	259.1	(161.9)	118	8.997	14.69
Reading score (females)[2/.]	199.2***	(63.42)	212.9***	(63.42)	212.9***	(80.50)	85	13.53	5.177
Math score (females)[2/.]	240.1***	(49.58)	264.4***	(49.58)	264.4***	(61.33)	85	10.46	3.874
Hemoglobine children [3/.]	0.320	(0.739)	0.364	(0.739)	0.364	(0.924)	187	17.70	8.041
Anemia children [3/.]	-0.407*	(0.241)	-0.553**	(0.241)	-0.553*	(0.303)	187	9.093	6.470
Hemoglobine women [3/.]	1.392**	(0.592)	1.447**	(0.592)	1.447**	(0.715)	594	9.809	6.971
Anemia women [3/.]	-0.197*	(0.105)	-0.225**	(0.105)	-0.225*	(0.124)	594	8.781	7.183

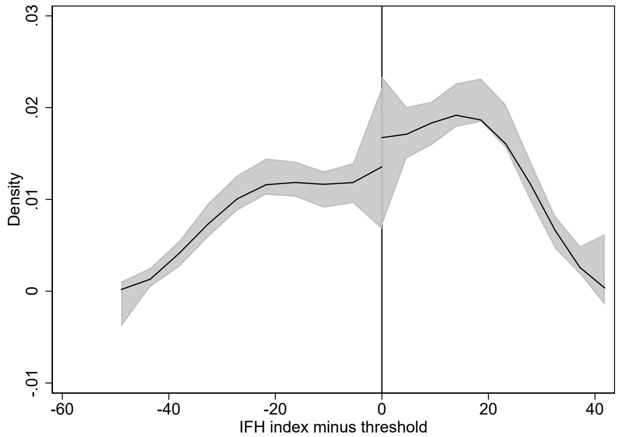
Notes: The table shows the insurance effect on the full set of dependent variables. The sample includes all children from three to six years old from households with low consumption of water and electricity and who are residents of Lima Province, within the two different MSE-optimal bandwidth selectors (to the left and to the right of the cutoff). The table presents the conventional, the bias-corrected and the robust RD estimates, that are calculated based on a first-order polynomial. Standard errors are reported below the coefficients in parentheses. *p<0.10 **p<0.05 ***p<0.01. 1/. This variable includes purchases and donations. 2/. These RD estimates are calculated with no baseline covariates. 3/. These variables come from Endes.

D Figures

Figure D.1: McCrary test



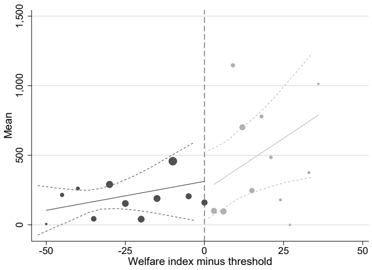
Panel A



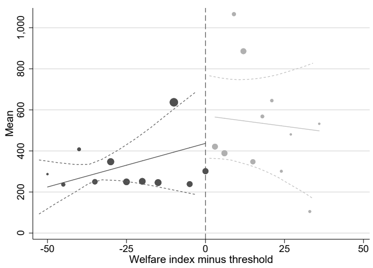
Panel B

Notes: The figure shows an estimate of the density of the welfare index that allows for a discontinuity at the threshold. It uses the local polynomial density estimators proposed in Cattaneo et al. (2018). Panel A includes households of the ENAHO 2011 survey, residents of Lima Province, with low consumption of water and electricity, and with children from three to six years old. $T_q = -0.3574$, p-value=0.7208, number of observations = 233. Panel B includes households of the ENDES 2011 survey, residents of Lima Province, and with low consumption of water and electricity. $T_q = 0.1328$, p-value=0.8944; number of observations = 775.

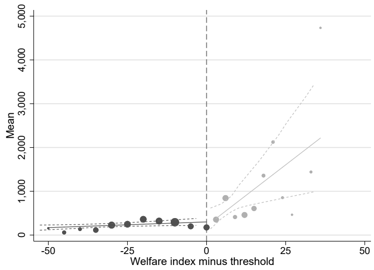
Figure D.2: The effect of health insurance coverage on mechanisms: RD plots



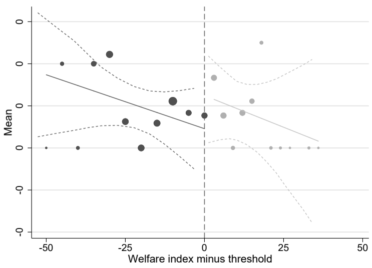
Level of health expenses



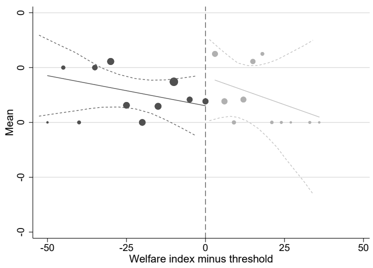
Variability of health expenses



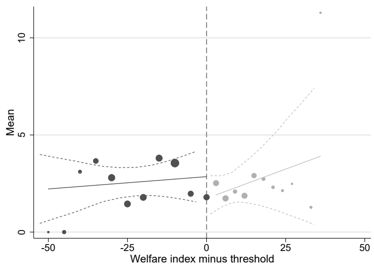
Level of cult.and teaching expenses



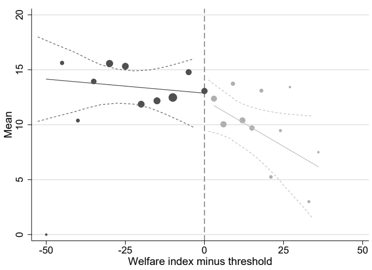
School delay (dummy)



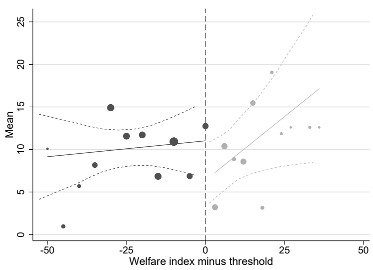
School delay (number of years)



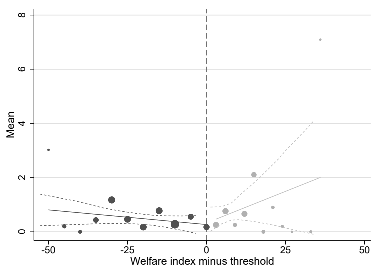
Cakes and pastries



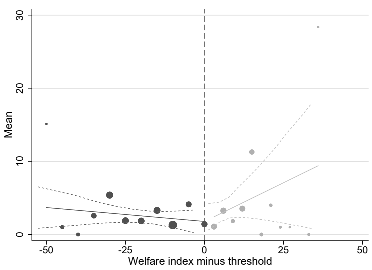
Noodles



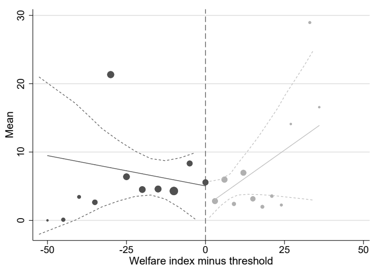
Fresh fish



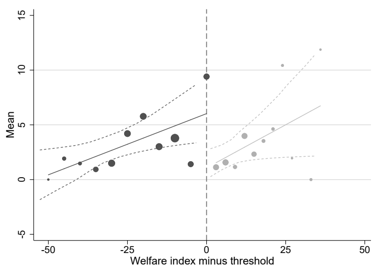
Candies, chocolates, honey



Candies, choc., honey (reception)



Prepared meals to consume at home



Other foods to consume at home

Notes: The figure shows the insurance effect on the full set of dependent variables, except for those already shown. The sample includes all children from three to six years old from households with low consumption of water and electricity who are residents of Lima province. The dots denote averages in which the bin width is five to the left of the threshold and three to the right. Their size represents the number of observations. The regression lines with corresponding 95% confidence intervals stem from separate linear regressions to the left and to the right using individual-level data.