Heterogeneous and Distributional Effects of Mexico's Health Insurance for the Poor on the Supply of Healthcare Services

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Abstract

We analyze the effects that the expansion of Seguro Popular (SP), Mexico's universal health insurance program, has had on the human and material resources needed to meet the new demand. Unlike previous evaluations, we use Sanitary Jurisdictions (SJs) as units of analysis and operationalize SP's intervention as a continuous treatment indicator (relative number of recipients). Estimates using a variety of propensity score approaches suggest that, on the average, SP has effectively had a positive impact on Mexico's health resources. However, quantile and interaction treatment effects suggest that the program may be leaving behind some of the most vulnerable geographical areas.

Keywords: generalized propensity score methods, continuous treatments, quantile treatment effects, interaction treatment effects, Mexico, Seguro Popular, causal inference.
JEL code: I38, C21, I13

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1 Introduction

By the end of 2012 Mexico reached a landmark in its journey towards universal health insurance coverage. Some 50 million uninsured people in 2001, basically all informal workers and their families, are now covered via the public health insurance system Seguro Popular (SP). This is the most important financial effort to provide health insurance for the uninsured the country has made since the creation of its social security system in 1943. However, achieving universal health coverage, as it has been referred to (Knaul et al. 2012; Frenk et al. 2006), does not automatically imply that the human and material resources needed to meet the new demands for health services are available. Since the program's funding goes without strict earmarking, whether the financial resources managed to translate into resources associated with the provision of health services is an important matter that deserves attention. In this paper we examine the degree to which the key resources, in particular the numbers of doctors' offices and of physicians and nurses with day-to-day contact with patients, have been expanded following SP entitlement.

We use data from publicly available sources of the Ministry of Health to analyze the impact that different treatment levels – different levels of SP coverage in 2009 – have had on the growth in the density of human and material resources between 2001 and 2010, conditioning on a set of covariates that describe the available infrastructure prior to the start of the implementation of SP. We estimate dose-response functions using an OLS-based Generalized Propensity Score method (Hirano and Imbens 2004) to calculate Inverse Probability of Treatment Weights (Robins et al. 2000), and we also use a robust estimation procedure estimating three different weights (Fong et al. 2015a) that extends the Covariate Balancing Propensity Score methodology (Imai and Ratkovic 2014) to continuous treatments. These approaches are flexible enough to permit the analysis not only of average impacts, but also of their heterogeneity through quantile analysis and looking for distributional effects by estimating interactions of the treatment indicator with the initial conditions.

Being a single-shot treatment analysis based on propensity score methods, all of our results are predicated on the validity of the unconfoundedness assumption, also known as selection-on-observables or ignorability; that is, that we have identified and measured all the variables whose effects may be confounded with that of SP coverage.

We make four distinct contributions to the existing SP evaluation literature. Firstly, we consider a facet for which little work has been done: the actual expansion of available health professionals and infrastructure in reaction to the newly created potential demand for services. The large body of the existing SP evaluation literature focuses on the individual financial impacts – out-of-pocket payments, catastrophic health expenditures – and on the use of health services and health improvements while also labor market incentives have been studied, but only Bosch and Campos-Vázquez (2010) have analyzed the expansion of the infrastructure. Secondly, we analyze the effects of SP coverage as a continuous variable, avoiding the implications of turning to a number of simplifying statistical and causal assumptions such as dichotomizing a

continuous treatment variable in order to apply traditional propensity score methods. Moreover, unlike all previous work, we focus on the Sanitary Jurisdiction (SJ) as unit of analysis. The SJ is the most basic regional administrative division in charge of the operation of healthcare services and programs. It is well known that the chosen unit of analysis and the way researchers operationalize the treatment play an important role in the nature of the findings (Pearl 2009).

By directly using the number of persons affiliated to the program in each SJ relative to the size of the open population (those who lack the health insurance provided by law through the social security system) as our treatment indicator, we stay closer to the actual causal process behind SP's intervention. Thirdly, we estimate Quantile Treatment Effects (QTE) thereby contributing to the analysis of SP's heterogeneous treatment effects (Sosa-Rubí et al, 2009; Wirtz et al, 2012) across segments of the population that remain masked when only Average Treatment Effects (ATEs) are estimated. Lastly, by estimating Interaction Treatment Effects (ITE) we also contribute to the analysis of SP's distributional effects (García-Díaz and Sosa-Rubí, 2011) assessing the effect SP has had on the distribution of health resources across the country.

Our estimates suggest that, on the average, a greater expansion of the human and material resources occurred in geographical areas with higher degrees of SP coverage. Whereas that finding may be considered expected and even desirable, analyzing the heterogeneity behind these ATEs using the QTEs and ITEs indicate that the SP program has had distributional effects on said resources, leaving behind some of the most vulnerable parts of the country and thereby generating more inequality. By implication, a different kind of public health policy is needed to attend to the most vulnerable part of the population in the country.

The paper proceeds as follows. Section 2 briefly reviews the history of Seguro Popular and presents the data that is used along with the decisions regarding units and years of analysis. Section 3 discusses the methods we apply in the analysis of the causal effect of SP coverage on the expansion of key human and material resources. In Section 4 we present the corresponding estimates, and in Section 5 we conclude with a brief discussion of our results.

2 Seguro Popular, Previous Evaluations, and the Data

Seguro Popular (Popular Health Insurance, SP) was launched as a pilot program in 2002 and remained so until the end of 2003. At that time, it covered roughly 2.2 million people previously uninsured in a total population of about 100 million of which over 50 percent lacked any health insurance coverage, leaving them effectively outside the social health protection system. At the same time, the new Ley General de Salud (General Health Law, LGS) launched the Sistema de Protección Social en Salud (System of Social Protection in Health, SPSS) and just over 10 years later SP covers more than 55 million people (Fig. 1) – covering the full population without access to the social security institutes (such as IMSS, ISSSTE, Pemex, the Ministry of Defense or the Navy). Enrollment in the program is voluntary, and is granted to all legal residents in

Mexican territory who lack work-related health insurance, offered to formal sector workers through social security institutions, ascertained with the mere declaration of the applicant.[1]

The LGS specified that the Federal Government and the States were to share the responsibility, being the latter responsible for managing the resources allocated by the Federation for the service delivery in general. The funding of SP has a tripartite structure: a social contribution, covered annually by the federal government directly proportional to the number of beneficiaries (the main source of funding), a solidarity contribution, covered both by the federal government and states according to health indicators such as infant and adult mortality, and family contributions, a fee introduced to replace out-of-pocket payments made at the time of the delivery of services (although families can be classified into a non-contributory regime based on the household's income). By 2012, the beneficiaries had access to a package of 284 health services and interventions listed in the Catálogo Universal de Servicios Esenciales de Salud (Universal List of Essential Health Services, CAUSES).

An abundant literature of evaluations of the impacts of SP exist, but not on the particular aspect of the expansion of the infrastructure. Key findings of the evaluations of SP include that SP affiliates see their out-of-pocket health expenditures reduced (Teruel Belismelis et al. 2012; Gakidou et al. 2007; Barros 2008; King et al. 2009; Grogger et al. 2011; Parker and Ruvalcaba 2010; Ávila-Burgos et al. 2013; Gakidou et al. 2006; Scott 2006; Knaul and Frenk 2005; Knaul et al. 2006; García-Díaz and Sosa-Rubí 2011; Galárraga et al. 2010; Hernández-Torres et al. 2008) and also of catastrophic health expenses (Hernández-Torres et al. 2008). The evidence regarding these explicit objectives of the program covers such a wide range of data sources and methodologies that there is little doubt as regards this important achievement of the program. Increments in the use of services have also been reported (Knox 2016; Teruel Belismelis et al. 2012; Gakidou et al. 2007; Parker and Ruvalcaba 2010; Gakidou et al. 2006; Scott 2006; Sosa-Rubí et al. 2009; Harris and Sosa-Rubí 2009), as well as positive effects not just on the self-reported health of the beneficiaries (Teruel Belismelis et al. 2012), but also in some biomarkers (Parker and Ruvalcaba 2010). However, the impacts on this front are still being debated, not everybody finds the same positive results on health outcomes (Gakidou et al, 2006; Scott, 2006; Knaul et al, 2006; Aguilera and Marrufo, 2009).[2] Another strand of the evaluation literature has focused on its impact on the labor market, as the program might be creating perverse incentives to work in the informal sector; however, the evidence here is mixed. Some studies find negligible or no effects (Duval Hernández and Smith Ramírez 2011; Arias et al. 2010; Campos-Vazquez and Knox 2013; Azuara and Marinescu 2013), while others find that SP actually has a negative

[1] Nowadays, written proof of the absence of any affiliation to social security institutions is required in major cities.

[2] Note that all SP's evaluations assume the intervention behind the program consists in receiving a publicly funded health insurance policy from the government, that is, becoming a beneficiary by being included in the program's roster. From there to "effective access" to healthcare services is, however, a different matter: the assumption that the necessary means to provide such services have been made available often remains implicit.

effect on the creation of formal jobs, especially in small and medium sized firms (Bosch and Campos-Vázquez 2010).

Despite this large body of evaluations, and even though the evidence suggests that the effect of SP on healthcare access is larger in areas with greater supply of health professionals (Bleich et al, 2007), so far, only Bosch and Campos-Vázquez (2010) have addressed the effect of SP on the supply of human and material resources used in the provision of health services. They followed a differences-in-differences approach, analyzing the expansion of resources during the years 2001-2009, using a dichotomized treatment indicator considering municipalities as 'treated' when more than 10 individuals were affiliated to SP. They encountered a positive effect of SP on the number of doctors and nurses, but hardly any effect on the number of clinics.

For the analysis presented in this paper we have merged the administrative records of SP from 2002-2010, containing the number of families and individuals affiliated, with the federal records of infrastructure and human resources employed by the Secretaría de Salud (Ministry of Health, SSA). These are the primary resources used in providing healthcare services to the population not insured by any of the traditional social security institutions. The SSA data is available at an annual frequency disaggregated at the health establishment (service outlet) level.[3]

Figure 1 shows the (aggregate) evolution of key resources along with the coverage of the SP program. We see that the increased coverage of the SP program seems to be associated with a growing number of physicians and nurses in day-to-day contact with patients (providing clinical care) as well as with the number of doctors' offices. We analyze the impact of SP coverage on these three variables since they seem to be the most fundamental elements in the provision of healthcare services.

[Insert Figure 1 about here]

Only 19% of the municipalities in Mexico register an SSA health establishment, which suggests that it is not the best unit of analysis for our purposes. The monetary flows from the Federal Government to the States were assigned to Sanitary Jurisdictions, who were the responsible entity to assure the provision of healthcare services. In all our estimates we use the Sanitary Jurisdiction (SJ) as the unit of analysis and aggregate the data accordingly. There are 242 SJs in Mexico, none of them crossing state borders. However, 9 out of 2,457 municipalities form part of two sanitary jurisdictions. For lack of better data access, in aggregating the data we have treated these municipalities as a sanitary jurisdiction in themselves, leaving us with 233 units available for our analysis. Given the variation in size and population across SJs, we work with the densities of SSA's material and human resources instead of their absolute numbers, in all cases relative to the population that lacks labor-related health insurance coverage provided by

[3] The data can be retrieved from the Sistema Nacional de Información en Salud (National Health Information System, SINAIS) website: http://www.dgis.salud.gob.mx/contenidos/sinais/estadisticas.html.

the traditional social security institutions. The same reference population is used for the SP coverage, only this time expressed as a proportion.

Looking at Figure 1, we see that by 2009 SP had reached 31 million affiliates, thus roughly 50% of the population without traditional health insurance was covered by that year. Figure 2 shows the distribution of this coverage in 2009 across SJs, exhibiting a fair number of observations on every treatment level in a relatively symmetric distribution around 0.5. This unique symmetry in SP coverage makes 2009 ideal for our purposes. The reason for using outcome variables from 2010 instead of 2009 is that the budget of the Federal Government is earmarked annually and that the increase in a given year's affiliation roster does not reflect on the budget and expansions of the existing infrastructure and personnel until the next year.

[Insert Figure 2 about here]

3 Empirical Strategy

Ideally, we would analyze the exact path followed by the SP implementation and its impact on the available resources over time. Moreover, we would need to allow for mutual interactions between the two pathways: the implementation of SP may have reacted to the initially available resources as well as the expansion path that was followed. Although for binary treatments, progress has been made that allows for the mutual interactions between the paths followed by treatment and outcomes (Robins et al. 2000), similar techniques for dynamic continuous treatments are not readily available.

We essentially abstract from the precise paths that have been followed, and instead decide to relate the observed growth of the resources over the period from 2001 to 2010 – that is, since before the pilots of SP started – to the (relative) number of SP affiliates in 2009. Both measures are the cumulative result of efforts shown over time: the accumulation of services over time and the SP implementation level reached until then. Doing this overlooks the possibility that different coverage paths may have resulted in different outcome paths and final outcomes, but with continuous treatments the number of different pathways is intractable in practice.

Given that we analyze the impact of SP coverage at a single moment in time on the growth of the resources, Propensity Score (PS) methods are appropriate to assess whether human and material resources followed the new entitlement and are effectively expanded to meet the new potential demand for services. Under an unconfoundedness or selection-on-observables assumption, PS methods allow removing all biases in assessing the treatment effect by adjusting for differences in a set of covariates.

It is important to note that, by considering the treatment as a continuous treatment at a single moment in time, we implicitly assume that the path that was followed to reach the observed coverage level is irrelevant for the growth of resources reported in 2010. Our basic assumption is that the infrastructure and personnel of the SSA that were already on the ground in

2001 before affiliation started, explain why some SJs make the most of SP, both in terms of affiliation and making new investments.

We control for a set of 7 variables that describe the available infrastructure and personnel in 2001: the density (relative number) of doctors' offices, staffed and non-staffed hospital beds, and physicians and nurses, both with and without day-to-day contact with patients (with and without clinical duties). Specifically, in using the densities of these resources as covariates in a PS framework, we are assuming that, conditioning them, the SP coverage can be considered as good as randomly assigned, independent of potential outcomes, and the treatment assignment mechanism is said to be ignorable. A covariate balance test will be used to assess the credibility of this assumption.

We consider the existing resources in 2001 as indicators of the difficulties each SJ faced to translate financial means into an expansion of the basic resources needed to provide healthcare services, difficulties that are also likely to be behind the roll-out of the SP program itself. We do not condition on recent values of our variables since they cannot be considered strictly pre-treatment covariates.

The maps in Figure 3 gives a sense of the phenomenon we are aiming to disentangle. There we can see the geographical distribution of the 2010-2001 increment in the density (per 1000 people without work related health insurance) of SSA's nurses with day-to-day contact with patients, according to their distribution of both the density observed in 2001 and the level of SP coverage reached by 2009. On the one hand, going from left to right, we can see that SJs that were better off in terms of the density of nurses in 2001 exhibit greater increments in said density by 2010. On the other hand, going from bottom to top, we can see that these increments also followed the SP coverage accordingly, showing the greater increments in the upper right corner, and the lesser in lower left. Indeed, it would seem that there are good reasons to think that SP has had positive impacts on the density of health resources in the SJs, but to what degree are these increments related to preexistent levels of said resources?

[Insert Figure 3 about here]

3.1 Propensity Score Methods

The classic PS approach has focused on the case where units of analysis are exposed to one of two possible values of the causal variable, treatment or control, at a given point in time, and values for an outcome are assessed some time subsequent to exposure (Rosenbaum and Rubin 1983, 1984; Rubin and Thomas 1992). To apply these methods in assessing SP's effects on the SJs, it is necessary to operationalize SP coverage as a dichotomous variable for every SJ, just as Bosch and Campos-Vázquez (2010) did for municipalities and Sosa-Rubí et al. (2009) for localities.

However, it is important to note that every estimate obtained following this traditional design implicitly assumes that every treated SJ has been exposed to the same treatment regime. Figure 2 shows that any chosen rule to dichotomize the underlying continuous treatment will hide the large variation that exists in SP coverage rates.

Moreover, we cannot expect that the estimates obtained from a dichotomized SP coverage correspond to the average treatment effect of full SP coverage. By definition, the causal effect of the dichotomized coverage is null; the results of this approach would quantify the association between the dichotomized coverage and the outcome variables, mediated through their common cause: the original continuous SP coverage (Hernán and VanderWeele 2011; VanderWeele and Hernan 2013). Compounding different levels of a continuous treatment variable into one single, dichotomized, regime misses the opportunity to exploit the information contained in the variability of SP coverage across SJs.

Furthermore, this interpretation of the effects of the dichotomized treatment is predicated on the assumption that we have adequately controlled for confounding not just for the dichotomized version of the treatment variable, but for the underlying continuous version as well. In this regard, it is important to note that balancing covariates with respect to the dichotomized SP coverage does not necessarily achieve balance across different values of the original continuous causal variable.[4]

In short, if we are not to compromise possible insights discarding valuable data in aggregating coverage levels, we need to resort to other propensity score methods, different from those designed for binary causal variables, and directly use the continuous coverage of SP as the treatment variable.

3.2 Generalized Propensity Score

Several researchers have proposed generalizations of the PS methodology for non-binary treatments (Robins et al. 2000; Imbens 2000; Imai and Van Dyk 2004), coined Generalized Propensity Score (GPS) by Hirano and Imbens (2004).

As in the case with the binary treatment, in estimating the GPS, researchers model the distribution of the observed treatment assignment given pre-treatment covariates using a parametric model. In the practical implementation of this methodology, researchers often fit Gaussian distributions to continuous treatments such as the SP coverage by means of Ordinary Least Squares (OLS), evaluating the observed treatment exposure t and a set of covariates $\mathbf{x}$, $f_{T|X}(t,\mathbf{x})$. There are several GPS methods to estimate the causal response of a continuous treatment

[4] Dichotomized SP coverage may not be considered a random event even after controlling for pretreatment covariates, casting doubts on the basic assumption of selection-on-observables (Sosa-Rubí et al, 2009; Galárraga et al, 2010; Rivera-Hernandez et al, 2016). Estimations with our data, dichotomizing on the median SP coverage in 2009, suggest that the use of a binary approximation instead of the "true" (that is, continuous) treatment variable has important consequences for the causal inference. These results are available from the authors upon request.

(Hirano and Imbens 2004; Flores et al. 2012; Robins 2000; for a comparison of the empirical performance of these methods see Zhao et al. (2013).

In order to be able to extend our analysis to quantile treatment effects, we follow the GPS version of the Inverse Probability of Treatment Weights (IPTW) suggested by Robins et al. (2000). They pointed out that using $1/ f_{T|X}(t,\mathbf{x})$ as weights can lead to very unstable estimates, and proposed using a more stable version of the weights: $W(t,\mathbf{x})= f_{T|}(t)/ f_{T|X}(t,\mathbf{x})$, where the numerator corresponds to an estimate of the empirical distribution of the treatment.

In estimating the stabilized weights, as a first approach, we have regressed the (continuous) SP coverage in 2009 against our 7 covariates corresponding to the year 2001: doctors' offices, staffed and non-staffed hospital beds, physicians and nurses with and without day-to-day contact with patients, along with all two-way interactions between these variables, i.e.,

$$f_{T|\mathbf{x}}(t,\mathbf{x}) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2\sigma^2}[t-(\mathbf{x}'\beta)]^2\right\},$$

where $\mathbf{x}$ thus contains 35 variables in total, and β is the vector of regression coefficients. The numerator, $f_{T|}(t)$, is estimated in the same fashion, only this time using an empty model.

Besides these OLS-based stabilized weights, we have also used a robust estimation procedure to estimate three different weights as proposed by Fong et al. (2015a), which is an extension of the Covariate Balancing Propensity Score (CBPS) methodology to continuous treatments. The CBPS (Imai and Ratkovic 2014) models treatment assignment while optimizing the covariate balance in a Generalized Method of Moments (GMM) framework. The idea behind the CBPS is simple and consists of adding, to the usual score vector of the treatment assignment model, the differences in means between the treatment and control groups of every covariate as moment conditions. As with the CBPS for dichotomous treatments, the continuous extension automates covariate balance optimization, which in this case implies minimizing the correlation between the covariates and the treatment.

We estimate three different weights following this methodology (Fong et al. 2015b): two parametric models, one that gives equal importance to both correctly predicting treatment assignment and balancing covariates (CBPS-OVER), a second one that privileges covariate balance over the probabilistic model (CBPS-EXACT), and the non-parametric approach that dispenses with the treatment assignment model altogether only minimizing covariate balance (NP-CBPS) by means of Lagrange multipliers.[5] It is important to note that none of the three CBPS weights use interactions, unlike the OLS stabilized weights, since our main concern is balancing our 7 covariates.

We can test the performance of the four proposed stabilized weights given that, if covariates are indeed balanced across the different levels of SP coverage in the different OLS

[5] The latter is a limit case and can help in gaining insight into what is to be expected from achieving a better balance.

and CBPS pseudo-samples, we would expect that regressing each covariate against SP coverage results in a non-significant coefficient.

3.3 Heterogeneous Treatment Effects

Under ideal conditions, the ATE as estimated by the methods introduced in Section 3.2 provides a complete description of the relationship between the treatment and the outcome distribution across beneficiaries. However, averages may mask important subgroup differences, making it necessary to look into the conditions under which the same exposure to the treatment has a differential effect across segments of the population. This is of particular importance for social development programs attempting to reach those in greater need.

Quantile Treatment Effects

In exploring heterogeneous treatment effects, QTEs give us the effect of the treatment, not on the mean, but on any given quantile of the outcome distribution. Thus, looking at the effect that a treatment has on different quantiles, researchers can go beyond the mean and assess the effect of the treatment on the shape of the entire outcome distribution. Knowing whether the treatment has changed the skewness in the outcome distribution or not, allows researchers to address questions about who are making the most of social programs, uncovering the best practices and possible undesired effects on inequality.

A nice feature of the IPTW approach is that it can easily be modified to analyze the impact of a treatment on non-central parts of the outcome distribution. The idea remains basically the same, only this time, instead of estimating the (conditional mean) outcome model by OLS, we have estimated several conditional quantiles of the outcome variables by means of Quantile Regressions (Koenker 2005), using the same inverse probability weighting as before. In other words, we apply Quantile Regression to the pseudo-sample where the correlation between the covariates and the treatment is broken using IPTW, just as in Section 3.2. Hence, the causal inferences are predicated on the validity of the same unconfoundedness or selection-on-observables assumption as usual in a PS framework.

Interaction Effects

Also in the IPTW framework, investigating the interaction between the treatment and pre-treatment covariates can help in profiling recipients unable to benefit from the program as intended (see Bleich et al. (2007) for a similar approach). The idea is to test, in a regression framework, whether the effect of SP coverage varies with the density of healthcare resources observed before the roll-out of SP started. A statistically significant positive coefficient for the

interaction between SP coverage and a pre-SP covariate would suggest a stronger effect of SP as SJs are better off in terms of the covariate in question.

4 Results

Before we present and interpret our results, we address the issue known as common support to make sure that we include only "comparable" units. In order to compare only SJs alike in everything but their SP coverage, following King and Zeng (2006; 2007), we have dropped the least comparable (furthest away in the covariate space) SJs according to Gower's (1966; 1971) metric from the analysis. We use only the 194 SJs with the smallest mean distance to the rest of the observations in the data, dropping the 17% least comparable SJs. This trimming results in a more compact, less model dependent data set that allows better comparisons across SJs (Fig. 4, Appendix Table A.1).

[Insert Figure 4 about here]

4.1 Average Treatment Effects

Applying a covariate balance test valid for continuous treatments to evaluate the credibility of the treatment ignorability assumption for the SP coverage in 2009, we can see (Fig. 5, Appendix Table A.2) that the pseudo-samples generated using the several weighting algorithms (described in Section 3.2), indeed break the association observed between the covariates and the SP coverage in the unweighted sample (UM). The estimated coefficients regressing each covariate against SP coverage are not statistically significantly different from zero in the weighted samples, although the CBPS-OVER algorithm leaves room for doubt at the 90% confidence level (Appendix Table A.2). As expected, the non-parametric CBPS achieves the best covariate balance.

[Insert Figure 5 about here]

Looking at the change in the density of doctors' offices, physicians and nurses from 2001 to 2010 using the pseudo-samples generated for the continuous SP coverage, we see (Fig. 6, Appendix Table A.3) that these estimates suggest that SP has had a positive impact on SSA's resources: all estimates are statistically different from zero. Unlike previous evaluations of SP that used dichotomized treatment variables, we can interpret these parameters, which in the linear outcome model estimated correspond to the slopes of dose-response functions, as the ATE of full SP coverage on the SJs. Attending to the smallest numbers, which also correspond to the best balanced sample (generated by NP-CBPS), our estimates suggest that on average, for our

trimmed sample, full coverage of SP translates into roughly 2 doctor's offices, 6 physicians and 8 nurses, both in day-to-day contact with patients, per ten thousand population.

These numbers may seem small, but keep in mind that in 2001, in these same 194 SJs, the average density of these same resources was 4.5, 8 and 10 per ten thousand people, respectively. It is also important to note that these figures differ substantially from the "naive" OLS estimates obtained when using the unmatched – unweighted – sample (UM). The latter overestimates the impact of SP on doctors' offices by 26%, and underestimates the impact on physicians and nurses in day-to-day contact with patients by 23% and 34% respectively.

[Insert Figure 6 about here]

4.2 Heterogeneous and Distributional Effects

All of our previous estimates belong to the average, that is, not to a SJ in particular, and hide that some SJs may be doing better than others in expanding these resources for different reasons. As noted in Section 3.3, IPTW methods can easily be modified to go beyond the ATEs and into the QTEs and ITEs (Bleich et al. 2007) to profile segments of the population with heterogeneous responses to full SP coverage.

Looking at the QTEs, we see that the effect of full SP coverage is smaller in the lower part of the outcome distributions (Fig. 7, Appendix Table A.4). This suggests that SP has had more than a central location effect, as would correspond to similar magnitudes across quantiles. On the contrary, treatment effects are quite heterogeneous along the distribution of the outcome variables, being clearly larger as we move towards the upper quantiles in the case of doctors's offices and the third quartile for physicians and nurses. That is to say that the QTEs show that the SP program has widened the spread of the outcome distributions. The increment in the density of health workforce and infrastructure is larger for SJs that were better off making progress on this front. This is particularly so for doctors' offices, where the effect of SP is statistically indistinguishable from zero for the first decile, and grows steadily up to twice the mean for the highest decile. It is important to note that physicians and nurses also exhibit the smallest coefficients in the first two deciles of their respective distributions, being mostly non-significant for the first decile, with the third quartile roughly 1.5 times the average impact.

It is important to remember that the outcome variables examined correspond to the growth in the densities of SSA's resources between 2001 and 2010, and not the densities of the resources themselves. Whether SP has contributed or not to a more unequal distribution of healthcare resources in Mexico depends on which SJs are reaping the most benefits from program. If the SJs benefiting the least from the program were precisely those less advantaged in terms of healthcare resources in 2001, then the SP program would likely have contributed to the inequality in the distribution of these resources. If, on the other hand, the least advantaged SJs were making the most of the program, it would have contributed to alleviate this same inequality.

In this regard, our estimates of the ITEs (Fig. 8, Appendix Table A.5), allowing for distinct effects of SP coverage at different baseline levels of the resources, suggest that SP has had stronger effects boosting the investment in physicians and nurses in day-to-day contact with patients as the density of physicians without day-to-day contact with patients in the SJs in 2001 was larger. Bear in mind that, in 2001, more than half of the physicians without day-to-day contact with patients were engaged in administrative tasks, with the rest dispersed among educational activities, epidemiologists and anatomic-pathologists. That is to say that the number of physicians without day-to-day contact with patients is closely related to institutional development and higher-level healthcare services. In 2001, 64% of the physicians without day-to-day contact with patients worked at Specialized (Inpatient) Hospitals.

Looking closely at the distribution of our estimates for physicians and nurses in Figure 8, we can also see that SP seems to have a larger effect on SJs with lesser densities of doctors' offices, which indicates that poorer SJs favor the investment in health workers providing clinical care. Taken together, the heterogeneity in SP treatment effects suggests that the SJs making the most of SP are precisely those better off in terms of the material and human resources examined. These results provide evidence of the apparent inability of SP to work against the inequality in the distribution of resources associated with the provision for healthcare services.

Regrettably enough, the distribution of health resources is just another dimension of inequality in less developed regions, where people are more likely to experience inadequate educational services, social support systems, and transportation. The maps in Figure 9 show the geographical distribution of our main findings regarding the observed heterogeneity in the effects of full SP coverage. There we see from left to right, three (latent) classes[6] of the estimated effects of SP on the density of nurses with day-to-day contact with patients according to the order of magnitude. Similarly, on the vertical cells, from bottom to top, we see classes of effects on the density of physicians. In all the maps, in colors going from blue to red, we can see quartiles of the 2000 Marginality Index (MI) of the Mexican National Population Council (CONAPO).

In Figure 9 we can see how the bluish colors, belonging to SJs with lesser MI, and therefore better off, concentrate on the maps closer to the upper right corner, where they coincide with the larger effects of SP on both nurses and physicians with day-to-day contact with patients, while reddish colors can be found in the lower left corner map exhibiting the exactly opposite case mostly in southeastern Mexico, the poorest region in the country.

[Insert Figures 7, 8 and 9 about here]

[6] Latent class analysis (LCA) is a subset of structural equation modeling used to find groups or subtypes of cases in multivariate categorical data.

5 Conclusions and Discussion

We have analyzed the effects the introduction of Seguro Popular (SP) has had on the growth of healthcare infrastructure. Although at a first glance our results point in the same general direction as those of Bosch and Campos-Vázquez (2010) and Bleich et al. (2007), that is, that on the average the SP program has resulted in increases in the resources allocated to provide healthcare services, our analysis differs from previous evaluations on a number of aspects with important implications for the results. In this paper, on the one hand, in assessing the impact of SP on the human and material resources of the SSA – something not analyzed frequently –, instead of the municipalities, we have used as units of analysis the basic regional administrative unit in charge of the operation of healthcare services and programs, the Sanitary Jurisdiction (SJ). On the other hand, the use of the SP coverage as a continuous causal variable has allowed us to gain insight into the effects of SP that cannot be obtained when presuming it can be dichotomized.

We have shown evidence that average results hide a great deal of information regarding the heterogeneity of the effects of SP. In particular, estimating Interaction Treatment Effects (ITEs) shows us that quite probably SP has had distributional effects on the resources involved in the provision of healthcare services. Our results suggest that the SJs that were better off in terms of these resources before the roll-out of SP started are precisely the ones making the most of the program. Perhaps this finding is less surprising than we might have hoped for. Geographical and other differences between states and regions imply that the provision of health care services faces important challenges that vary throughout the country. The variety of challenging circumstances, of which the differences between urban and rural areas is perhaps the easiest to imagine, also imply large differences in costs. These geographical differences have always existed, and can explain both the better starting position – a consequence of historical advantages – as well as the better advancement – making more of new investments in health – being concentrated in the same regions.

The fact that SP may be leaving behind the most vulnerable geographic areas in the country is of major concern from a public policy perspective, and it points to the need for complementary public health policies if Mexico is to keep moving towards the establishment of universal healthcare services of high quality (Franzoni and Sánchez-Ancochea, 2016). We are not the first to notice the lack of a territorial approach in the Mexican Health Policy (López and Aguilar, 2004).

We have argued how different assumptions regarding the nature of the treatment may affect inferences, a problem that generally cannot be eliminated entirely in making causal inference, but that is important when informing about public policy. Future research should, moreover, consider the dynamics of both treatment and outcome variables. For example, as long as two sanitary jurisdictions exhibit the same SP coverage in 2009, our approach treats them as if they had the same amount of treatment exposure, which may not be true if the path towards reaching the 2009 treatment level was very different. Also, overlooking treatment histories has

led us to omit their possible interaction with confounders at different points in time. By conditioning on covariates from 2001, the year prior to the implementation of the SP program in its pilot phase, we have implicitly assumed SP coverage in 2009 as a fixed, time-independent (non-dynamic) treatment. However, it is quite possible that SP's roll-out strategy reacted to the changing conditions SP itself helped to bring about. By implication, covariates from 2002 to 2008 are not strictly pre-SP covariates with respect to the coverage history that led to the coverage attained by 2009, and we would be mistaken in including them in our estimation of the Generalized Propensity Score (GPS). On the other hand, by not including them, we are leaving out from the analysis potentially relevant confounding information. Generalizations of the GPS methodology exploit the time-series cross-sectional nature of data sets (Blackwell 2013; Robins et al. 2000; Fong et al. 2015b) but so far they have focused on dichotomous treatments, and have yet to reach the case of continuous time-varying treatments needed for a more complete analysis of SP.

Improvements in the availability of doctors, nurses and health establishments (service outlets) are undoubtedly good news, but they are only part of the story. These resources are a necessary but not a sufficient condition for the effective access to healthcare services of the quality that permits significant health improvements of the population at large. Tracing the impact of SP along the whole – far from linear – causal path from affiliation to health outcomes, as the conventional theory of change would suggest, remains a pending and challenging task in which the GPS approach of our paper can make an important contribution while further generalizations of the techniques will be useful.

Acronyms

ATE	Average Treatment Effect
CBPS	Covariate Balancing Propensity Score
CONAPO	National Population Council
GM	Genetic Matching
GMM	Generalized Method of Moments
GPS	Generalized Propensity Score
IMSS	Instituto Mexicano del Seguro Social
IPTW	Inverse Probability of Treatment Weights
ISSSTE	Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado
LGS	Ley General de Salud –General Health Law–
MI	Marginality Index
OLS	Ordinary Least Squares
PEMEX	Petróleos Mexicanos
PS	Propensity Score

QTE	Quantile Treatment Effect
SINAIS	Sistema Nacional de Información en Salud –National Health Information System–
SJ	Sanitary Jurisdiction
SP	Seguro Popular
SPSS	Sistema de Protección Social en Salud –System of Social Protection in Health–
SSA	Secretaría de Salud –Ministry of Health–

References

Aguilera N, Marrufo GM (2009) Assessing the effect of "Seguro Popular" on health outcomes. UIA, Instituto de Investigaciones sobre Desarrollo Sustentable y Equidad Social

Arias J, Azuara O, Bernal P, Heckman JJ, Villarreal C (2010) Policies to promote growth and economic efficiency in Mexico. Working Paper 16554, National Bureau of Economic Research, URL http:// www.nber.org/papers/w16554

Ávila-Burgos L, Serván-Mori E, Wirtz VJ, Sosa-Rubí SG, Salinas-Rodríguez A (2013) Efectos del Seguro Popular sobre el gasto en salud en hogares mexicanos a diez años de su implementación. Salud Pública de México 55:S91-S99

Azuara O, Marinescu I (2013) Informality and the expansion of social protection programs: Evidence from Mexico. Journal of Health Economics 32(5):938-950

Barros R (2008) Wealthier but not much healthier: Effects of a health insurance program for the poor in Mexico. Discussion Paper 09-002, Stanford University, URL http://economics.stanford. edu/files/JMP_RBarros.pdf

Blackwell M (2013) A framework for dynamic causal inference in political science. American Journal of Political Science 57(2):504-520

Bleich SN, Cutler DM, Adams AS, Lozano R, Murray CJ (2007) Impact of insurance and supply of health professionals on coverage of treatment for hypertension in Mexico: Population based study. British Medical Journal 335(7625):875

Bosch M, Campos-Vázquez RM (2010) The trade-offs of social assistance programs in the labor market: The case of the "Seguro Popular" program in Mexico. Documento de Trabajo DT-2010-12, El Colegio de México, URL http://cee.colmex.mx/documentos/documentos-de-trabajo/2010/dt201012.pdf

Campos-Vazquez RM, Knox MA (2013) Social protection programs and employment: The case of Mexico's Seguro Popular program. Economía Mexicana NUEVA ÉPOCA XXII, (2):403-448, URL http://sites.google.com/site/raycampos/CV_Knox_Nov2008_SeguroPopular.pdf

Duval Hernández R, Smith Ramírez R (2011) Informality and Seguro Popular under segmented labor markets. 6th IZA/World Bank conference: Employment and development, IZA Institute for the Study of Labor/ World Bank, URL http://www.iza.org/conference_files/worldb2011/3229.pdf, session A.4: Informality, Crisis and Inequality. ITAM, Mexico City, Mexico.

Flores CA, Flores-Lagunes A, Gonzalez A, Neumann TC (2012) Estimating the effects of length of exposure to instruction in a training program: The case of Job Corps. Review of Economics and Statistics 94(1):153-171, URL http://www.mitpressjournals.org/doi/abs/10.1162/REST_a_00177

Fong C, Hazlett C, Imai K (2015a) Parametric and nonparametric covariate balancing propensity score for general treatment regimes, mimeo. URL https://pdfs.semanticscholar.org/89d0/fe3d3d9a0270a60e368950c14498bd1c051e.pdf

Fong C, Ratkovic M, Hazlett C, Imai K (2015b) Cbps: R package for covariate balancing propensity score. Comprehensive R Archive Network (CRAN) URL https://cran.rproject.org/web/ packages/CBPS/CBPS.pdf

Franzoni JM, Sánchez-Ancochea D (2016) The quest for universal social policy in the South: Actors, ideas and architectures. Cambridge University Press

Frenk J, González-Pier E, Gómez-Dantés O, Lezana MA, Knaul FM (2006) Comprehensive reform to improve health system performance in Mexico. The Lancet 368(9546):1524-1534

Gakidou E, Lozano R, González-Pier E, Abbott-Klafter J, Barofsky JT, Bryson-Cahn C, Feehan DM, Lee DK, Hernández-Llamas H, Murray CJ (2006) Assessing the effect of the 2001-06 Mexican health reform: An interim report card. The Lancet 368(9550):1920-1935

Gakidou E, Lozano R, González-Pier E, Abbot-Klafter J, Barofsky JT, Bryson-Cahn C, Feehan DM, Lee DK, Hernández H, Murray CJ (2007) Evaluación del impacto de la reforma mexicana de salud 2001-2006: un informe inicial. Salud Publica de México 49 supl 1:S88-S109, URL http://www.scielosp.org/pdf/spm/v49s1/10.pdf

Galárraga O, Sosa-Rubí SG, Salinas-Rodríguez A, Sesma-Vázquez S (2010) Health insurance for the poor: Impact on catastrophic and out-of-pocket health expenditures in Mexico. The European Journal of Health Economics 11(5):437-447

García-Díaz R, Sosa-Rubí SG (2011) Analysis of the distributional impact of out-of-pocket health payments: Evidence from a public health insurance program for the poor in Mexico. Journal of Health Economics 30(4):707-718

Gower J (1971) A general coefficient of similarity and some of its properties. Biometrics 27(4):857-871

Gower JC (1966) Some distance properties of latent root and vector methods used in multivariate analysis. Biometrika 53(3-4):325-338

Grogger J, Arnold T, León AS, Ome A (2011) Efectos del Seguro Popular sobre el gasto en salud, utilización de servicios médicos, y nivel de salud, y resultados a largo plazo del experimento del Seguro Popular en México y evidencia de la Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH). Evaluation commissioned by the Comisión Nacional de Protección Social en Salud (CNPPS) 28, Centro de Investigación y Docencia Económicas, URL http://seguropopular.cide.edu/documents/130486/130726/201101_gasto.pdf

Harris JE, Sosa-Rubí SG (2009) Impact of "Seguro Popular" on prenatal visits in Mexico, 2002-2005: Latent class model of count data with a discrete endogenous variable. Tech. Rep. 14995, National Bureau of Economic Research, URL http://www.nber.org/papers/w14995

Hernán MA, VanderWeele TJ (2011) Compound treatments and transportability of causal inference. Epidemiology (Cambridge, Mass) 22(3):368

Hernández-Torres J, Avila-Burgos L, Valencia-Mendoza A, Poblano-Verástegui O (2008) Evaluación inicial del Seguro Popular sobre el gasto catastrófico en salud en México. Salud Publica de México 10 (1):18-32, URL http://www.scielo.org.co/pdf/rsap/v10n1/v10n1a03.pdf

Hirano K, Imbens GW (2004) The propensity score with continuous treatments. In: Gelman A, Meng XL (eds) Applied Bayesian Modeling and Causal Inference from Incomplete-data Perspectives: An Essential Journey with Donald Rubin's Statistical Family, Wiley Series in Probability and Statistics, vol 226164, John Wiley & Sons, Ltd, chap 7, pp 73-84

Imai K, Ratkovic M (2014) Covariate balancing propensity score. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 76(1):243-263

Imai K, Van Dyk DA (2004) Causal inference with general treatment regimes. Journal of the American Statistical Association 99(467):854-866

Imbens GW (2000) The role of the propensity score in estimating dose-response functions. Biometrika 87(3):706-710

King G, Zeng L (2006) The dangers of extreme counterfactuals. Political Analysis 14(2):131-159

King G, Zeng L (2007) When can history be our guide? The pitfalls of counterfactual inference. International Studies Quarterly 51(1):183-210

King G, Gakidou E, Imai K, Lakin J, Moore RT, Nall C, Ravishankar N, Vargas M, Téllez-Rojo MM, Hernández Ávila JE, Hernández Ávila M, Hernández Llamas H (2009) Public policy for the poor? A randomised assessment of the Mexican universal health insurance programme. The Lancet 373(9673):1447-54, URL http://www.sciencedirect.com/science/article/pii/S0140673609602397

Knaul FM, Frenk J (2005) Health insurance in Mexico: Achieving universal coverage through structural reform. Health Affairs 24(6):1467-1476

Knaul FM, Arreola-Ornelas H, Méndez-Carniado O, Bryson-Cahn C, Barofsky J, Maguire R, Miranda M, Sesma S (2006) Evidence is good for your health system: Policy reform to remedy catastrophic and impoverishing health spending in Mexico. The Lancet 368(9549):1828-1841

Knaul FM, González-Pier E, Gómez-Dantés O, García-Junco D, Arreola-Ornelas H, Barraza-Lloréns M, Sandoval R, Caballero F, Hernández-Avila M, Juan M, et al. (2012) The quest for universal health coverage: Achieving social protection for all in Mexico. The Lancet 380(9849):1259-1279

Knox M (2016) Health care reform in a developing country: Transfer program or something more? Impacts of Mexico's Seguro Popular program five years after introduction, URL http://faculty.washington.edu/knoxm/wordpress/wp-content/uploads/2014/11/Knox-Seguro-Popular-2016-1.pdf

Koenker R (2005) Quantile Regression. 38, Cambridge University Press

López F, Aguilar AG (2004) Niveles de cobertura y accesibilidad de la infraestructura de los servicios de salud en la periferia metropolitana de la ciudad de México. Investigaciones Geográficas (53):185-209

Parker S, Ruvalcaba LN (2010) Identificación y análisis de los efectos en las condiciones de salud de los afiliados al Seguro Popular. Evaluation commissioned by the Comisión Nacional de Protección Social en Salud (CNPPS), Centro de Investigación y Docencia Económicas, URL http://seguropopular.cide.edu/documents/130486/130726/201002_efectos.pdf

Pearl J (2009) Causality. Cambridge University Press

Rivera-Hernandez M, Rahman M, Mor V, Galarraga O (2016) The impact of social health insurance on diabetes and hypertension process indicators among older adults in Mexico. Health Services Research 51(4):1323-1346

Robins JM (2000) Marginal structural models versus structural nested models as tools for causal inference. In: Halloran M, Berry D (eds) Statistical models in epidemiology, the environment, and clinical trials, The IMA Volumes in Mathematics and its Applications, vol 116, Springer, chap 2, pp 95-133

Robins JM, Hernán MA, Brumback B (2000) Marginal structural models and causal inference in epidemiology. Epidemiology 11(5):550-560

Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. Biometrika 70(1):41-55

Rosenbaum PR, Rubin DB (1984) Reducing bias in observational studies using subclassification on the propensity score. Journal of the American Statistical Association 79(387):516-524

Rubin DB, Thomas N (1992) Characterizing the effect of matching using linear propensity score methods with normal distributions. Biometrika 79(4):797-809

Scott J (2006) Seguro popular: Incidence analysis. Decentralized service delivery for the poor II:147-166

Sosa-Rubí SG, Galárraga O, Harris JE (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

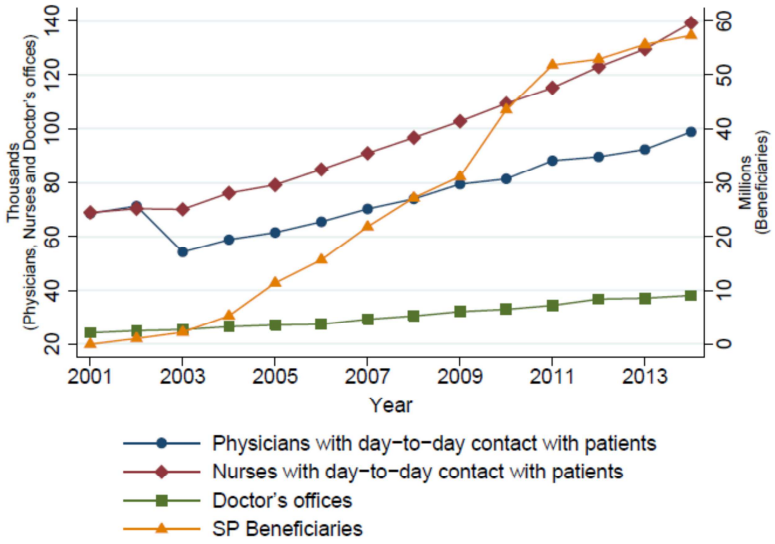
Teruel Belismelis G, Castro M, Guadarrama R (2012) Estudio sobre los efectos del Seguro Popular en la utilización de servicios médicos y en la salud de los afiliados. Evaluation commissioned by the Comisión Nacional de Protección Social en Salud (CNPPS), Centro de Investigación y Docencia Económicas, URL http://seguropopular.cide.edu/documents/130486/130726/201201_efectos.pdf

VanderWeele TJ, Hernan MA (2013) Causal inference under multiple versions of treatment. Journal of Causal Inference 1(1):1-20

Wirtz VJ, Santa-Ana-Tellez Y, Servan-Mori E, Avila-Burgos L (2012) Heterogeneous effects of health insurance on out-of-pocket expenditure on medicines in Mexico. Value in Health 15(5):593-603

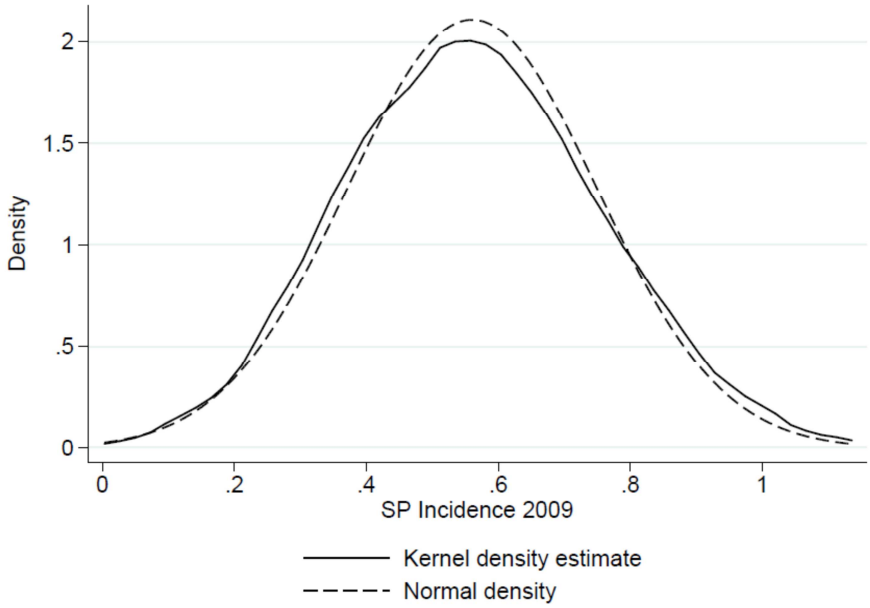
Zhao S, van Dyk DA, Imai K (2013) Propensity-score based methods for causal inference in observational studies with fixed non-binary treatments. mimeo. URL http://imai.princeton.edu/research/files/gpscore.pdf

Figure 1: National Evolution of Key Resources and SP Coverage



Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.

Figure 2: Distribution of SP Coverage Across Sanitary Jurisdictions in 2009

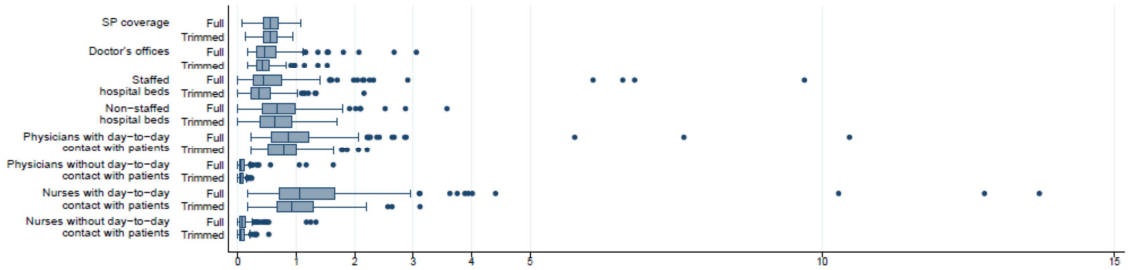


Source: Own elaboration based on data from the administrative records of Seguro Popular.

Figure 3: Geographical Distribution of the 2010-2001 Increment in the Density* of Nurses with day-to-day Contact with Patients.

*SP coverage refers to affiliates as proportion of the population without work-related health insurance (IMSS, ISSSTE, Pemex, the Ministry of Defense or the Navy). Densities are expressed per 1,000 people without this insurance.
Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
Note: The map exhibits, on the horizontal cells, from left to right, quintiles of the density of nurses with day-to-day contact with patients in 2001. Similarly, on the vertical cells, from bottom to top, we see quantiles of 2009 SP coverage. In colors, from blue to red, we see the quantiles of 2010-2001 change in the density of nurses with day-to-day contact with patients.

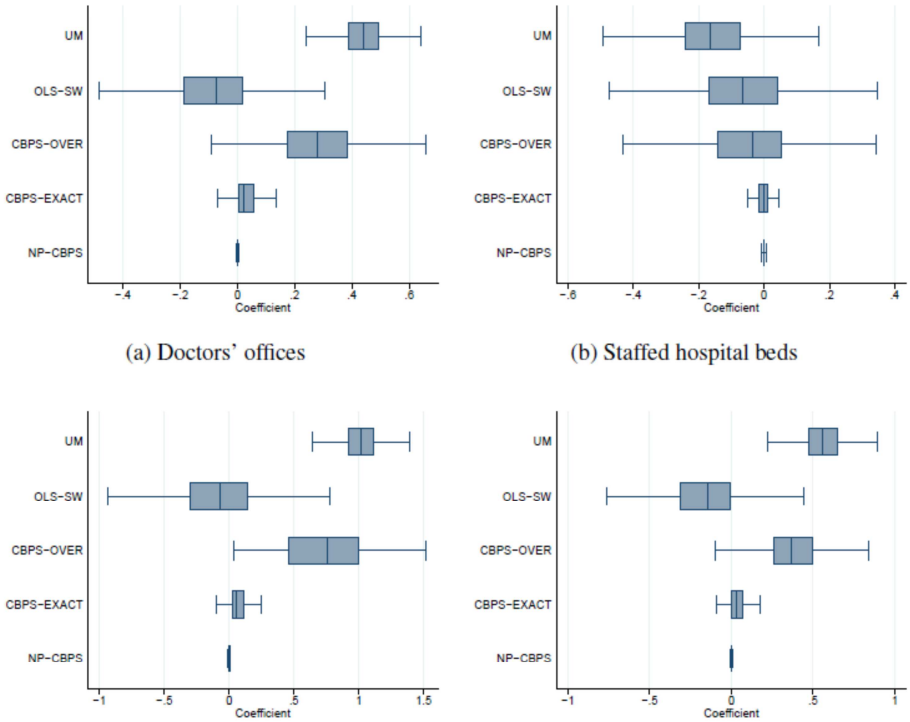
Figure 4: Descriptive Statistics of the Sanitary Jurisdictions [a]



Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
The left and right side of each box are the first and third quartiles, and the band inside is the second quartile (the median). Whiskers represent the smallest observation still within 1.5 Inter Quartile Range of the lower quartile, and the largest observation still within 1.5 Inter Quartile Range of the upper quartile. Outliers as dots.

[a] SP coverage refers to affiliates as proportion of the population without work-related health insurance (IMSS, ISSSTE, Pemex, the Ministry of Defense or the Navy). Other variables are expressed per 1,000 people without this insurance. The trimmed sample results from dropping the farthest away observations in the covariate space according to Gower's metric.

Figure 5: Covariate-Balance for SP coverage [a,b]



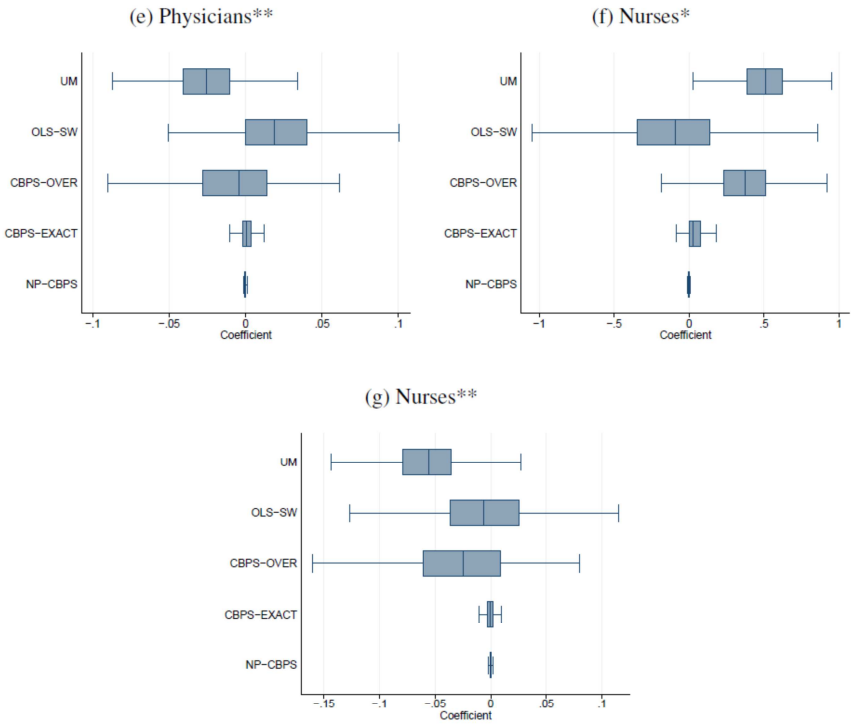
(a) Doctors' offices

(b) Staffed hospital beds

(c) Non-staffed hospital beds

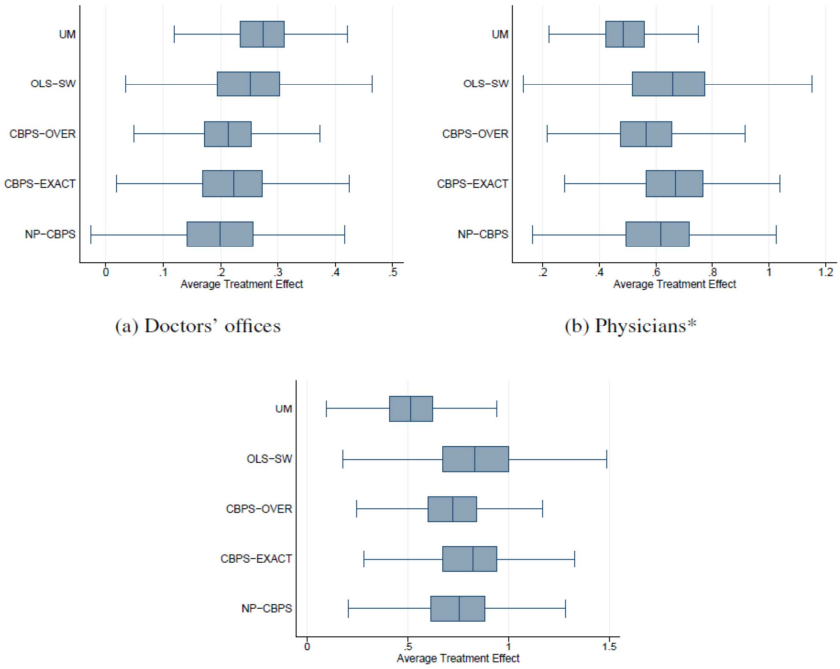
(d) Physicians*

(Figure continues)



Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
The left and right side of each box are the first and third quartiles, and the band inside is the second quartile (the median). Whiskers represent the smallest observation still within 1.5 Inter Quartile Range of the lower quartile, and the largest observation still within 1.5 Inter Quartile Range of the upper quartile. Outliers are not shown..
* In day-to-day contact with patients
** Without day-to-day contact with patients
[a] Coefficients result from linear regressions of each covariate in 2001 on the original SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.
[b] UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NPCBPS = Non-parametric Covariate Balance Propensity Score.

Figure 6: Average Treatment Effects of Full SP coverage on Sanitary Jurisdictions [a,b]



(a) Doctors' offices

(b) Physicians*

(c) Nurses*

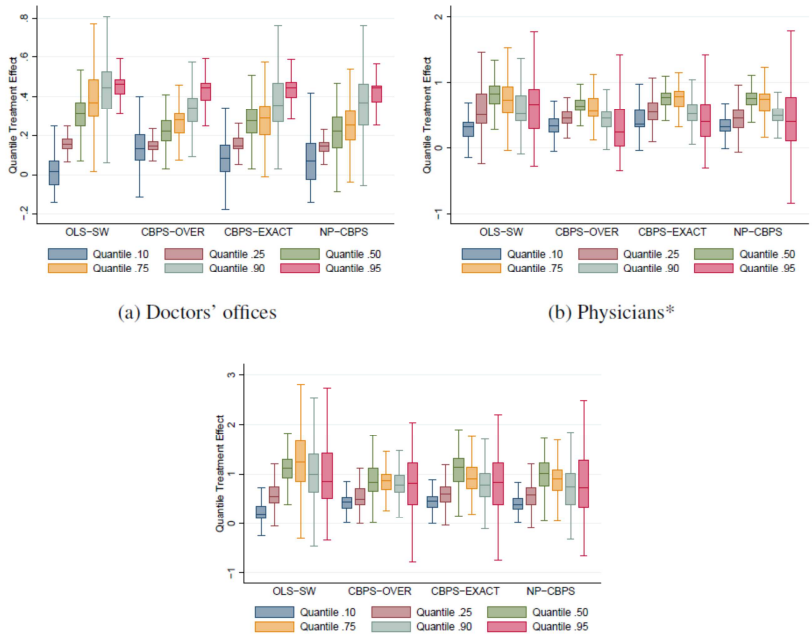
Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
The left and right side of each box are the first and third quartiles, and the band inside is the second quartile (the median). Whiskers represent the smallest observation still within 1.5 Inter Quartile Range of the lower quartile, and the largest observation still within 1.5 Inter Quartile Range of the upper quartile. Outliers are not shown..

* In day-to-day contact with patients

[a] Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from linear regressions of each outcome variable on the original SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.

[b] UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NPCBPS = Non-parametric Covariate Balance Propensity Score.

Figure 7: Quantile Treatment Effects of Full SP coverage on Sanitary Jurisdictions



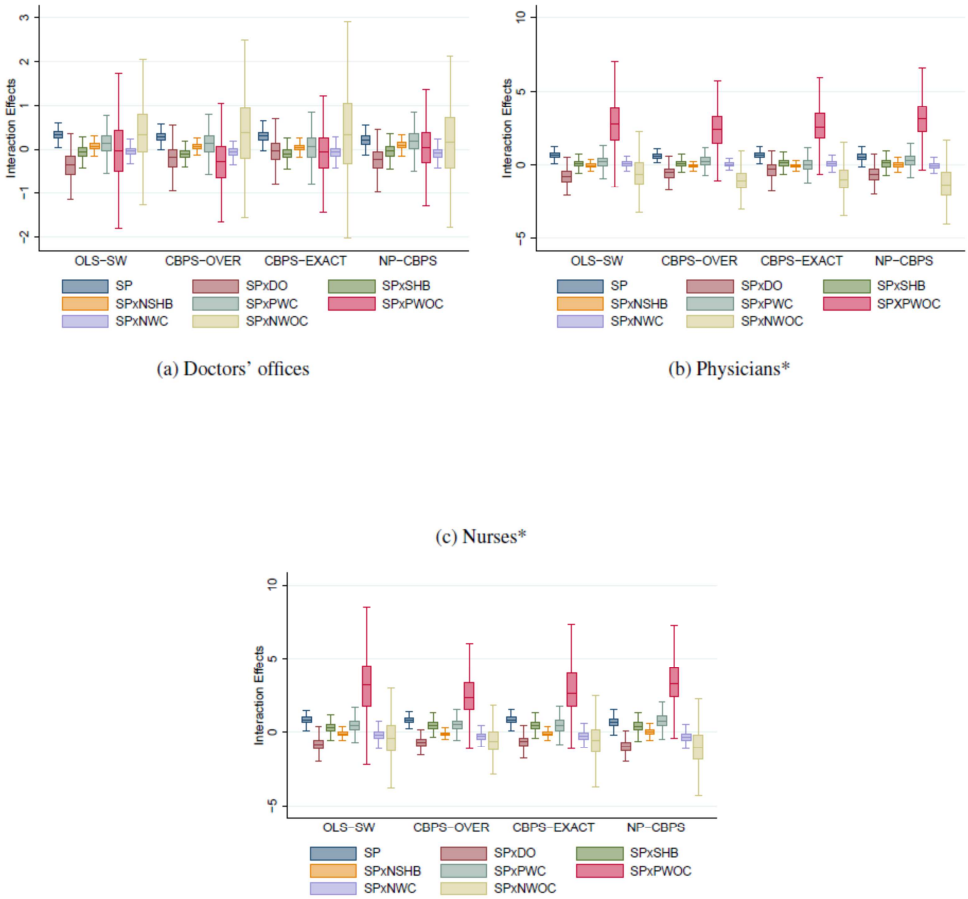
(a) Doctors' offices

(b) Physicians*

(c) Nurses*

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
The bottom and top of each box are the first and third quartiles, and the band inside is the second quartile (the median). Whiskers represent the smallest observation still within 1.5 Inter Quartile Range of the lower quartile, and the largest observation still within 1.5 Inter Quartile Range of the upper quartile. Outliers are not shown..
* In day-to-day contact with patients
[a] Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from quantile regressions of each outcome variable on the original SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.
[b] UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NPCBPS = Non-parametric Covariate Balance Propensity Score.

Figure 8: Interaction Effects of SP coverage with Pre-Treatment Covariates on Sanitary Jurisdictions



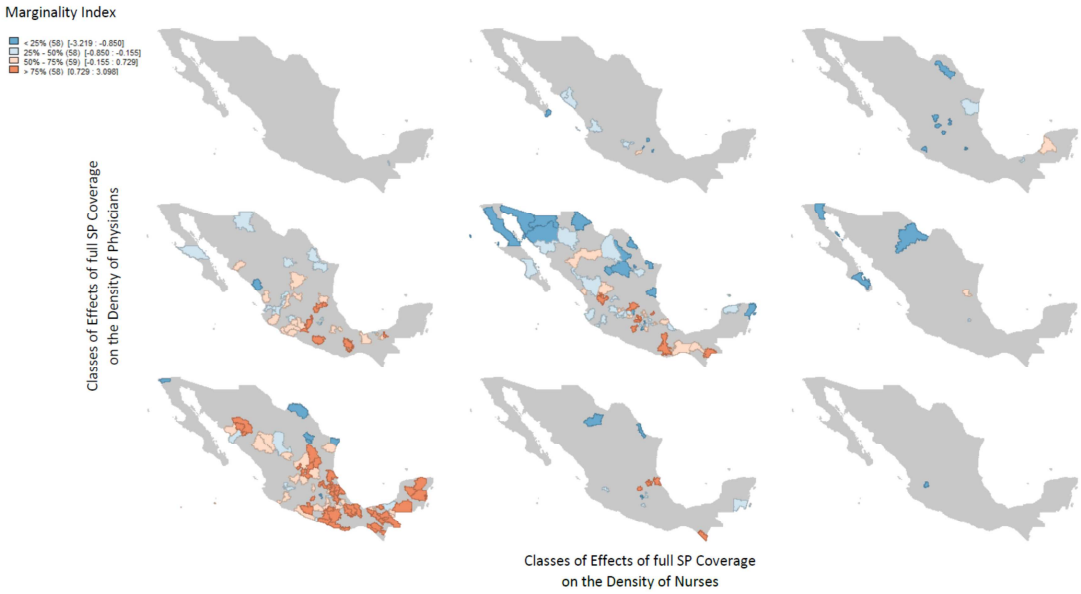
(a) Doctors' offices

(b) Physicians*

(c) Nurses*

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.
The bottom and top of each box are the first and third quartiles, and the band inside is the second quartile (the median). Whiskers represent the smallest observation still within 1.5 Inter Quartile Range of the lower quartile, and the largest observation still within 1.5 Inter Quartile Range of the upper quartile. Outliers are not shown..
* In day-to-day contact with patients
[a] Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from linear regressions of each outcome variable on the original SP coverage in 2009 and its interactoins with all 7 pre-treatment (2001) covariates [DO = doctors' offices; SHB = staffed hospital beds; NSHB = non-staffed hospital beds; PWC = physicians in day-to-day contact with patients; PWOC = physicians without day-to-day contact with patients; NWC = nurses in day-to-day contact with patients; and NWOC = nurses without day-to-day contact with patients.; all variables expressed per 1,000 people without work-related health insurance], weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.
[b] UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NPCBPS = Non-parametric Covariate Balance Propensity Score.

Figure 9: Geographical Distribution of Full SP Coverage Effects on Nurses and Physicians with day-to-day Contact with Patients.



*Densities are expressed per 1,000 people without work-related health insurance (IMSS, ISSSTE, Pemex, the Ministry of Defense or the Navy). Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular. Note: The map exhibits, on the horizontal cells, from left to right, three latent classes (groupings) of the estimated Seguro Popular's full coverage effects on the density of nurses with day-to-day contact with patients according to the order of magnitude. Similarly, on the vertical cells, from bottom to top, we see classes of effects on the density of physicians. In colors the quartiles of the 2000 Marginality Index of the Mexican National Population Council (conapo).

Appendix

Table A.1: Descriptive Statistics of the Sanitary Jurisdictions

Variable [a]	Sample [b]	Mean	Std. Dev.	Min	Max	Obs.
SP coverage	Full	0.56	0.19	0.06	1.08	233
	Trimmed	0.55	0.17	0.13	0.94	194
Doctors' offices	Full	0.54	0.35	0.17	3.05	233
	Trimmed	0.45	0.20	0.17	1.53	194
Staffed hospital beds	Full	0.66	1.01	0.00	9.70	233
	Trimmed	0.42	0.30	0.00	2.16	194
Non-staffed hospital beds	Full	0.76	0.49	0.00	3.58	233
	Trimmed	0.67	0.37	0.00	1.69	194
Physicians with day-to-day with patients	Full	1.06	0.98	0.22	10.47	233
	Trimmed	0.81	0.36	0.22	2.21	194
Physicians without day-to-day with patients	Full	0.09	0.16	0.00	1.63	233
	Trimmed	0.06	0.05	0.00	0.24	194
Nurses with day-to-day contact with patients	Full	1.39	1.47	0.16	13.72	233
	Trimmed	1.02	0.49	0.16	3.12	194
Nurses without day-to-day with patients	Full	0.11	0.16	0.00	1.34	233
	Trimmed	0.07	0.07	0.00	0.53	194

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.

a SP coverage refers to SP affiliates in 2009 as proportion of the population without work-related health insurance (IMSS, ISSSTE, Pemex, the Ministry of Defense or the Navy). Other variables measure the available infrastructure in 2001 before SP, and are expressed per 1,000 people without this insurance.

b The full sample results from aggregating the municipality level data to the sanitary jurisdiction level (242 SJs). The trimmed sample of 194 SJs results from dropping the furthest away observations in the covariate space according to Gower's metric.

Table A.2: Covariate-Balance for SP coverage [a]

	Sample [b]	Coef. [c]	Bootstrap Std. Err.	z	p > z	Normal-based [95% Conf. Interv]	
Doctors' offices	UM	0.44	0.08	5.83	0.00	0.29	0.59
	OLS-SW	-0.06	0.17	-0.35	0.73	-0.39	0.27
	CBPS-OVER	0.17	0.16	1.06	0.29	-0.14	0.48
	CBPS-EXACT	0.03	0.06	0.50	0.62	-0.09	0.15
	NP-CBPS	0.00	0.02	-0.02	0.99	-0.03	0.03
Staffed hospital beds	UM	-0.17	0.13	-1.25	0.21	-0.42	0.09
	OLS-SW	-0.03	0.17	-0.16	0.88	-0.37	0.31
	CBPS-OVER	0.09	0.15	0.65	0.52	-0.19	0.38
	CBPS-EXACT	0.00	0.05	0.00	1.00	-0.11	0.11
	NP-CBPS	0.00	0.01	0.09	0.93	-0.03	0.03
Non-staffed hospital beds	UM	1.01	0.14	7.16	0.00	0.74	1.29
	OLS-SW	-0.08	0.35	-0.22	0.83	-0.75	0.60
	CBPS-OVER	0.44	0.32	1.37	0.17	-0.19	1.06
	CBPS-EXACT	0.05	0.11	0.46	0.64	-0.16	0.26
	NP-CBPS	0.00	0.04	-0.02	0.99	-0.09	0.08
Physicians with day-to-day contact with patients	UM	0.56	0.13	4.28	0.00	0.30	0.81
	OLS-SW	-0.10	0.27	-0.38	0.70	-0.63	0.42
	CBPS-OVER	0.31	0.18	1.70	0.09	-0.05	0.68
	CBPS-EXACT	0.04	0.08	0.52	0.60	-0.11	0.19
	NP-CBPS	0.00	0.02	-0.02	0.99	-0.04	0.04
Physicians without day-to-day contact with patients	UM	-0.03	0.02	-1.13	0.26	-0.07	0.02
	OLS-SW	0.02	0.04	0.71	0.48	-0.04	0.09
	CBPS-OVER	0.02	0.03	0.73	0.46	-0.04	0.08
	CBPS-EXACT	0.00	0.01	0.42	0.67	-0.01	0.02
	NP-CBPS	0.00	0.00	0.06	0.96	-0.00	0.00
Nurses with day-to-day contact with patients	UM	0.51	0.17	2.91	0.00	0.17	0.85
	OLS-SW	0.00	0.37	0.01	0.99	-0.72	0.73
	CBPS-OVER	0.38	0.23	1.68	0.09	-0.06	0.82
	CBPS-EXACT	0.05	0.09	0.52	0.60	-0.13	0.22
	NP-CBPS	0.00	0.02	0.05	0.96	-0.04	0.04
Nurses without day-to-day contact with patients	UM	-0.06	0.03	-1.74	0.08	-0.12	0.01
	OLS-SW	0.01	0.05	0.20	0.84	-0.09	0.12
	CBPS-OVER	0.03	0.05	0.59	0.55	-0.06	0.12
	CBPS-EXACT	0.00	0.01	-0.08	0.94	-0.02	0.02
	NP-CBPS	0.00	0.00	0.07	0.95	-0.01	0.01

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.

a Treatment variable is the continuous Seguro Popular coverage in 2009.

b UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NP-CBPS = Non-parametric Covariate Balance Propensity Score.

c Coefficients result from linear regressions of each covariate in 2001 on the SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.

Table A.3: Average Treatment Effect of Full SP coverage on Sanitary Jurisdictions [a]

Result Variable 2010-2001 (Change in Density)	Sample [b]	Coef	Bootstrap Std. Err.	z	p > z	Normal-based [95% Conf. Interv]	
Doctors' offices	UM	0.27	0.06	4.74	0.00	0.16	0.38
	OLS-SW	0.25	0.08	3.01	0.00	0.09	0.41
	CBPS-OVER	0.20	0.06	3.18	0.00	0.08	0.32
	CBPS-EXACT	0.15	0.09	1.66	0.10	-0.03	0.32
	NP-CBPS	0.19	0.08	2.33	0.02	0.03	0.35
Physicians with day-to-day contact with patients	UM	0.49	0.10	4.72	0.00	0.28	0.69
	OLS-SW	0.68	0.22	3.06	0.00	0.24	1.11
	CBPS-OVER	0.69	0.13	5.28	0.00	0.43	0.94
	CBPS-EXACT	0.70	0.15	4.61	0.00	0.40	1.00
	NP-CBPS	0.64	0.17	3.71	0.00	0.30	0.97
Nurses with day-to-day contact with patients	UM	0.52	0.16	3.26	0.00	0.21	0.83
	OLS-SW	0.87	0.27	3.23	0.00	0.34	1.40
	CBPS-OVER	0.85	0.17	4.89	0.00	0.51	1.19
	CBPS-EXACT	0.93	0.23	4.10	0.00	0.49	1.38
	NP-CBPS	0.79	0.24	3.22	0.00	0.31	1.27

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular.

a Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from linear regressions of each outcome variable on the SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.

b UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NP-CBPS = Non-parametric Covariate Balance Propensity Score.

Table A.4: Quantile Treatment Effect of Full SP coverage on Sanitary Jurisdictions [a]

	/Sample: [b]	UM		OLS-SW		CBPS-OVER		CBPS-EXACT		NP-CBPS	
Res.Var. [c]	Quantile	Coef.	p > z	Coef.	p > z	Coef.	p > z	Coef.	p > z	Coef.	p > z
	.10	0.15	0.07	0.02	0.84	0.16	0.09	-0.02	0.89	-0.02	0.86
	.25	0.16	0.00	0.15	0.01	0.14	0.00	0.15	0.06	0.15	0.02
Doctors' offices	.50	0.26	0.00	0.34	0.00	0.21	0.00	0.26	0.01	0.21	0.07
	.75	0.30	0.00	0.37	0.02	0.22	0.00	0.25	0.03	0.28	0.05
	.90	0.38	0.00	0.39	0.02	0.31	0.00	0.34	0.02	0.36	0.01
	.95	0.45	0.00	0.48	0.00	0.44	0.00	0.44	0.01	0.44	0.00
	.10	0.40	0.00	0.35	0.13	0.40	0.02	0.32	0.24	0.32	0.15
Physicians with	.25	0.43	0.00	0.46	0.14	0.55	0.00	0.53	0.03	0.43	0.07
day-to-day	.50	0.58	0.00	0.87	0.00	0.78	0.00	0.76	0.00	0.73	0.00
contact with	.75	0.50	0.00	0.76	0.02	0.79	0.00	0.81	0.00	0.76	0.00
patients	.90	0.32	0.25	0.50	0.14	0.50	0.03	0.53	0.05	0.46	0.05
	.95	0.00	0.99	0.60	0.23	0.15	0.77	0.30	0.53	0.21	0.74
	.10	0.42	0.02	0.28	0.26	0.47	0.03	0.41	0.14	0.39	0.12
Nurses with	.25	0.33	0.01	0.52	0.06	0.85	0.00	0.74	0.01	0.64	0.02
day-to-day	.50	0.57	0.01	1.21	0.00	1.23	0.00	1.36	0.00	1.15	0.00
contact with	.75	0.73	0.00	1.20	0.06	0.86	0.00	1.02	0.01	0.94	0.04
patients	.90	0.66	0.09	1.00	0.15	0.68	0.03	1.10	0.02	0.84	0.07
	.95	0.30	0.66	0.82	0.16	0.52	0.28	1.12	0.02	0.39	0.47

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular..

a Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from linear regressions of each outcome variable on the SP coverage in 2009, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.

b UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NP-CBPS = Non-parametric Covariate Balance Propensity Score.

c Result variable. Change in density between 2001 and 2010.

Table A.5: Interaction Treatment Effect of SP coverage with Pre-treatment Covariates on Sanitary Jurisdictions [a]

	/Sample: [b]	UM		OLS-SW		CBPS-OVER		CBPS-EXACT		NP-CBPS	
Res. Var. [c]	Terms [d]	Coef.	p > z	Coef.	p > z	Coef.	p > z	Coef.	p > z	Coef.	p > z
Doctors' offices	SP	0.31	0.01	0.33	0.00	0.26	0.02	0.37	0.01	0.19	0.16
	SPxDO	-0.16	0.53	-0.38	0.21	-0.13	0.67	0.33	0.35	-0.26	0.37
	SPxSHB	-0.16	0.13	-0.05	0.72	-0.13	0.25	0.06	0.69	-0.03	0.84
	SPxNSHB	0.03	0.71	0.08	0.40	0.05	0.53	0.09	0.30	0.08	0.41
	SPxPWC	0.20	0.35	0.11	0.66	0.10	0.70	-0.60	0.09	0.28	0.27
	SPxPWOC	-0.65	0.21	-0.10	0.88	-0.18	0.73	0.01	0.99	-0.01	0.99
	SPxNWC	-0.09	0.38	-0.03	0.77	-0.07	0.52	-0.01	0.95	-0.17	0.17
	SPxNWOC	0.49	0.54	0.18	0.77	0.30	0.69	0.48	0.60	0.27	0.72
Physicians with day-to-day contact with patients	SP	0.53	0.00	0.69	0.01	0.64	0.00	0.74	0.00	0.52	0.05
	SPxDO	-0.55	0.20	-0.87	0.10	-0.47	0.34	0.01	0.99	-0.76	0.18
	SPxSHB	0.10	0.66	0.10	0.68	0.10	0.68	0.32	0.27	0.20	0.51
	SPxNSHB	-0.04	0.74	-0.05	0.75	-0.12	0.31	-0.06	0.74	0.02	0.90
	SPxPWC	0.24	0.46	0.20	0.64	0.21	0.57	-0.34	0.47	0.44	0.32
	SPxPWOC	1.72	0.21	2.76	0.11	2.33	0.10	2.52	0.05	3.07	0.05
	SPxNWC	0.05	0.77	0.10	0.58	0.04	0.81	0.03	0.91	-0.11	0.63
	SPxNWOC	-1.13	0.11	-0.98	0.34	-1.15	0.13	-0.96	0.35	-1.48	0.18
Nurses with day-to-day contact with patients	SP	0.61	0.01	0.88	0.01	0.87	0.00	0.79	0.02	0.69	0.06
	SPxDO	-0.64	0.09	-0.79	0.09	-0.69	0.06	-0.85	0.08	-0.99	0.03
	SPxSHB	0.55	0.05	0.25	0.44	0.48	0.12	0.49	0.16	0.46	0.21
	SPxNSHB	-0.01	0.92	-0.12	0.54	-0.15	0.30	-0.12	0.56	0.03	0.89
	SPxPWC	0.40	0.26	0.35	0.46	0.55	0.15	0.93	0.06	0.77	0.11
	SPxPWOC	2.25	0.10	2.56	0.24	1.84	0.18	2.07	0.22	3.11	0.04
	SPxNWC	-0.25	0.39	-0.07	0.83	-0.29	0.29	-0.43	0.23	-0.44	0.18
	SPxNWOC	-1.00	0.25	-0.57	0.66	-0.60	0.53	-0.40	0.75	-0.86	0.49

Source: Own elaboration based on data from the National Health Information System (SINAIS) and the administrative records of Seguro Popular..

a Effects on the 2010-2001 increment in the density of resources, per 1,000 people without work-related health insurance, obtained from linear regressions of each outcome variable on the SP coverage in 2009 and its interactions with all 7 pre-treatment (2001) covariates, weighted accordingly to the pseudo-sample in question. Bootstrapping (1,000 replications) takes into account the matching algorithm.

b UM = unmatched sample (194 SJs); other samples are matched using different techniques: OLS-SW = Robins' OLS-based stabilized weights; CBPS-OVER = Over-identified Covariate Balance Propensity Score; CBPS-EXACT = Exactly-identified Covariate Balance Propensity Score; and NP-CBPS = Non-parametric Covariate Balance Propensity Score.

c Result variable: Change in density between 2001 and 2010.

d SP =Seguro Popular, interacted with: DO = doctor's offices; SHB = staffed hospital beds; NSHB = non-staffed hospital beds; PWC = physicians in day-to-day contact with patients; PWOC = physicians without day-to-day contact with patients; NWC = nurses in day-to-day contact with patients; and NWOC = nurses without day-to-day contact with patients. All variables expressed per 1,000 people without work-related health insurance.