# Is Universal Health Care in Brazil Really Universal? (preliminary draft)

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Since Brazil's adoption of a universal health care policy in 1988, the country's health care has been delivered by a mix of private providers and free public providers. We examine whether income-based disparities in medical care usage still exist after the development of the public network using a nationally representative sample of over 44,000 Brazilians from 2003. We find robust evidence of a positive association between income and doctor visits, private doctor visits, and private medical expenditures. Interestingly, we also find evidence of a positive relationship between income and *public* doctor visits that disappears after including local area fixed effects to account for variation in availability and quality of medical services across localities. Additionally, we estimate income elasticities of private doctor visits and medical expenditures of well below one, suggesting that private care remains a necessity despite the availability of free public care. These results together suggest that the public health care system in Brazil is not effectively reaching everyone.

**Keywords:** Universal health care; Brazil; Income elasticity of demand for health care; Family Health Program.

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# 1 Introduction and Background

In 1988, Brazil adopted a universal health care policy that created a network of public providers to deliver a full range of health services free of charge. Subsequently, the government expanded the public network and created the Family Health Program (*Programa Saúde da Família*; PSF), which assigns a team composed of a doctor, a nurse, a nurse's assistant and several health workers to provide free health care to all families in a particular area. This paper presents evidence that significant income-based disparities in health care utilization – in both the private and public sectors – exist in Brazil despite the country's commitment to universal health care. We also estimate the income elasticities of private doctor visits and private medical expenditures and conclude that private sector care remains a necessity.

Brazil's health care system consists of both public and private sub-systems. The public system – called *sistema único de saúde* (SUS) – was created and defined in the Federal Constitution of 1988 and the 1990 Organic Health Law. Three main principles of universality, integrality, and decentralization guide the system. Universality means that health care is a universal right; it is the state's duty to provide health care to all citizens free of charge. Integrality means that public health assistance must comprise primary, secondary, and tertiary levels of care. Decentralization means that the management and organization of health services is the responsibility of the municipalities.

Brazil is the fifth largest country in the world in both land area and population, and the SUS is one of the world's largest public health care systems. Its ambulatory system consists of 56,640 units and assists 350 million cases annually, while 6,493 hospitals and 487,058 hospital beds are part of the SUS network. In 2001, the SUS conducted 250 million consultations, 200 million laboratory tests, and 70 million high complexity procedures (Rehem de Souza, 2002).[1] The SUS network consists of a mix of public, non-profit, and for-profit providers, but all services are paid by the federal, state, and municipal governments (Uga and Santos,

[1]High complexity procedures include tomography, magnetic resonance imaging, hemodialysis, and chemotherapy sessions.

2007).

The private health care system – called *sistema suplementar de saúde* (SSS) – comprises those private institutions that do not belong to the SUS. Patients are responsible for their own medical bills in the private system. Individual and group health insurance plans are available to help defray the costs, but coverage rates are low.[2] Though only 20% of the population participates in the SSS, it accounts for approximately half of the country's medical expenditures.

Brazil exhibits striking geographic variation in both health and access to health care. The infant mortality rate of 35.5 per 1,000 in the Northeast – the country's least economically developed region – is more than double the rate of 15.6 per 1,000 in the country's most developed region the Southeast. Endemic and transmittable diseases are notoriously persistent in the less developed North, Northeast and Center-West regions (Pan American Health Organization, 2008). In some states, more than 50% of all registered deaths are attributed to uncertain causes, potentially reflecting a lack of health care services (Lobato, 2000).

Access to SUS hospitals varies widely between municipalities. Wherever the population is highly concentrated (typically wealthier areas), several hospitals are present and the average distance from households to their closest establishment is short. Where population groups are scattered along a extensive territory (typically poorer areas), hospitals are scarce and obtaining care usually requires traveling long distances. Figure 1 illustrates this discrepancy by showing the distribution of hospitals affiliated with the SUS network in the northeastern state of Bahia.[3] Despite their large land area, most municipalities in the northwestern area

[2]There are four types of health insurance plans: self-managed health plans, prepaid group practice plans, medical cooperative plans, and health insurance company plans. Self-managed health plans offer services for the employees of a given firm. Prepaid group practice plans (17 million enrollees) offer different services, depending on the contract signed. The services may be through a network of facilities and professionals or free choice with reimbursement. Medical cooperative plans (10 million enrollees) are similar to prepaid group practices but the health services are strictly from a network of facilities and professionals. Health insurance company plans (6 million enrollees) consist of free choice of professionals and facilities combined with reimbursement to the user (Lobato, 2000).

[3]Bahia is fourth and fifth among Brazilian states in terms of population and territory, respectively. Its economy represents a 5% of Brazil's total GDP, which makes it the richest state in the northeastern region (http://www.sidra.ibge.gov.br).

of the state have 6 or fewer hospitals, while much smaller municipalities in the eastern area of the state have 16 or more hospitals.

These geographic differences highlight the need for empirical research to examine whether Brazil's public health care network is adequately reaching those in need. As a whole, the literature to date suggests that universal health care coverage in Brazil has improved health but that the extent of public sector provision remains insufficient. Macinko et al. (2006 and 2007), Rasella et al. (2010), and Morsch et al. (2001) documented a negative association between PSF coverage and infant or five-year mortality rates. However, in a study of health expenditure that also includes dental care and medicines, Xu et al. (2003) found that Brazil had the second-highest prevalence of catastrophic medical expenditures out of 59 countries despite the availability of free public care. Rodriguez et al. (2009) found that less than half of elderly individuals with chronic conditions had a medical visit in the preceding six months. Using a sample of elderly individuals from southern Brazil, Bos (2007) estimated a positive relationship between the number of public outpatient clinics in a municipality and residents' probability of using the public system. Goldbaum et al. (2005) compared two areas of São Paulo City and found that disparities in health care utilization on the bases of income and education were more evident in the area that was not covered by the PSF. Barros and Bertoldi (2008) examined a sample of 869 households and found that the proportion of income spent on private health services was similar across economic groups. In a study of the northeastern state of Ceará, where PSF covers practically the whole population, Maciel et al (2010) find that the need of physicians to have multiple jobs is a major obstacle to SUS efficacy.

We contribute to this growing literature in three ways.[4] First, to our knowledge we are the first to use a large nationally representative sample to test for income-based disparities in health care utilization in Brazil. Second, we examine whether these disparities are purely

[4] More broadly, we contribute to the extensive literatures on disparities in health care utilization and the income elasticity of health care. See Wagstaff and Van Doorslaer (2000), Goddard and Smith (2001), and Rannan-Eliya and Somanathan (2006) for reviews of the former. See Gerdtham and Jonsson (2000) and Getzen (2000) for reviews of the latter.

driven by differences in the private sector or whether disparities exist in the free public sector as well. Third, we compute the first estimates of the income elasticities of doctor visits (private, public, and overall) and private sector medical expenditures in Brazil.

We estimate a positive relationship between income and doctor visits, private doctor visits, and private medical expenditures that persists even after including demographic, health, living condition, and religion controls as well as state or local area fixed effects. Interestingly, we also find evidence of a positive association between income and *public* doctor visits that persists after adding the control variables but disappears when we include local area fixed effects. This is consistent with the pro-rich disparity in public sector utilization being driven by differences in medical care access and quality between rich and poor areas. Additionally, we estimate income elasticities of private doctor visits and medical expenditures of well below one, so private care remains a necessity in Brazil despite the availability of free public care. Together, these results suggest that the public health care system in Brazil is not effectively reaching everyone. More broadly, our findings underscore the difficulty of implementing a universal health care system in a country with an extensive geographic territory.

## 2 Data

We use the publicly available 2003 *Pesquisa de Orçamentos Familiares* (POF; Survey of Family Budget), a nationally representative dataset of 48,470 households collected by the Brazilian Institute of Geography and Statistics. The survey contains detailed information on all types of income and expenditure in a one year period, as well as socioeconomic and demographic characteristics of the household members. Health expenditures are divided into two broad categories: pharmacy and health care access. Our analysis focuses on the latter, and more specifically expenditures on medical visits. For each medical visit, the survey specifies the type of doctor, amount spent, payment method, and type of provision. Type of provision includes public sector, health insurance company (HIC), or private agent other than a HIC.[5] For those individuals that reported receiving care free of charge, the survey stipulates an estimate of the value of the services.

Table 1 provides summary statistics for the income and medical variables. Table 2 presents summary statistics for the demographic, health, living condition, and religion variables used as controls in our analysis. After dropping observations with missing data, our sample consists of 44,007 observations. In 47.8% of households, at least one member visited a doctor at least once in the reference year. 38.8% of households made at least one visit to a public doctor, while only 13.5% of households made at least one visit to a private doctor. Only 19.6% of household had a member enrolled in a private health insurance plan. Among those households who spent money on private medical care, the average expenditure was R$71.4, or 4.8% of household income.

Figure 2 illustrates the relationship between household income and doctor visits, estimated nonparametrically. Figure 3 plots the relationship between income and expenditures on private care.[6] As expected, both graphs show a positive association between income and private sector utilization that persists throughout the income distribution. A more surprising finding is the positive association between income and *public* sector utilization that persists until approximately the mean household income of R$1,492. Also noteworthy is the overall low level of utilization, particularly for the poor. The poorest households make only 0.4 doctor visits per year; for an average-sized household of 4 members, this equates to only 0.1 visits per year per individual. Even households at the high end of the income distribution only make approximately 1 doctor visit per year, or 0.25 per individual. These observations provide preliminary evidence that Brazil's universal health care system is not effectively reaching everyone. We next turn to regression analysis for a more thorough investigation.

[5]Private agents other than a HIC typically refers to physicians established in particular consultories charging a flat fee per visit.

[6]Neither figure excludes households with no doctor visits/medical expenditures. For ease of viewing, we exclude the top 1% of the income distribution from the figures.

# 3 Doctor Visits

## 3.1 Models

We begin our regression analysis by analyzing the relationship between household income and the number of doctor visits – overall, public, and private – by household members. We estimate Poisson models since the three dependent variables are counts with a significant number of zeroes. In unreported regressions we verified that the results are similar using negative binomial and linear models (results available upon request). The regression equation is

$$\ln(E(visits|\mathbf{X}) = \beta_0 + \beta_1 \ln(income) + \mathbf{X}'\boldsymbol{\beta} \qquad (1)$$

where *visits* is the number of overall, public, or private doctor visits, income is household income, and **X** is a vector of control variables. We take the log of income because of the skewness of the income distribution. This also gives the coefficient for income a straightforward interpretation: the approximate percentage effect on doctor visits of a 1% increase in income. We compute heteroskedasticity-robust standard errors that allow for clustering within each of the 3,984 local geographic areas defined by the POF.[7]

We use several different variations of the vector of controls **X**, starting with a regression with no controls in which $\mathbf{X} = \varnothing$ and then gradually adding groups of variables. We begin by adding a set of demographic characteristics consisting of the gender, age, education, race, and family size variables from Table 2. For family size, we use a flexible specification consisting of a set of dummy variables representing the different numbers of household members.[8] A common challenge in identifying the ceteris paribus relationship between income and health care utilization is controlling for systematic differences in health status between socioeconomic groups. The next two sets of covariates address this issue. First is set of

[7] The POF's local geographic areas are defined specifically for the survey and do not correspond exactly to more commonly-used geographic units. Brazil consists of 5,560 municipalities, so the POF's geographic areas are on average slightly larger than a municipality (Pan American Health Organization, 2008).

[8] Specifically, we include a dummy variable for whether the family size is 1, another for 2, another for 3, etc. Since few households have 10 or more members, we combine these households together into one category.

health variables that includes the body mass index (BMI) and health insurance indicators from Table 2. Unfortunately the POF does not contain more detailed health information, so we also add an extensive set of controls for living conditions consisting of number of rooms in the family's home plus the indicators for dwelling type, water source, toilet type, electricity, and floor type. Though these are not specifically health variables, they should capture many (though obviously not all) of the mechanisms through which a low socioeconomic status would adversely affect health. We next add the religion variables to proxy for cultural differences that might impact medical care usage. Our last two models include fixed effects – first for each of the 27 states and then for each of the 3,984 local geographic areas.[9] Given the substantial within-state variation in SUS network accessibility shown in Figure 1, the area-level fixed effects are vital to capturing differences in physician supply.

## 3.2 Results

Table 3-5 presents the results from the regressions for number of overall, private, and public doctor visits, respectively. Column (1) represents the simple regression with ln(income) as the only explanatory variable. The remaining columns gradually add the sets of controls, building up to the state and local area fixed effects models in columns (6) and (7). In column (8), we estimate the full area fixed effects model excluding the 15% of households in which at least one member has private health insurance, thereby restricting the sample to those who would face the full cost of private care. We report the coefficient estimates and standard errors for the income variable. To conserve space, we do not report the full regression output for the control variables but instead present F statistics from tests of the joint statistical significance of the variables in each group.

We begin the discussion with the results for overall number of doctor visits (sum of

[9] For the Poisson regression with area fixed effects, we use the Stata module xtpqml by Simcoe (2007). This module does not support sampling weights, and we are not aware of a Poisson fixed effects module that does. We therefore do not use the POF sampling weights in our analysis. In unreported regressions (available upon request), we verified that the results from the regressions without area fixed effects – in which weighting is possible – are not sensitive to the use of sampling weights.

private and public) from Table 3. The coefficient for ln(income) is positive and statistically significant at the 0.1% level in all specifications. The magnitude of the estimate is generally stable across columns (1)-(6), ranging from 0.16 to 0.21. This implies that a 1% increase in income is associated with approximately a 0.16% to 0.21% increase in doctor visits. However, columns (7) and (8) show that adding local area fixed effects reduces the estimate to under 0.1. Part of the relationship between income and doctor visits therefore operates through community-specific factors, such as the availability of physician services. For the controls, the sets of demographic and living condition variables are highly jointly significant in all regressions, while the religion variables are marginally jointly significant and the health variables are jointly insignificant.

Table 4 turns to the results for private doctor visits. Ln(income) is statistically significant at the 0.1% level in all specifications, with coefficient estimates ranging from 0.4 to 0.52. A 1% increase in income therefore increases private visits by approximately 0.4% to 0.52%. Importantly, these results suggest that the income elasticity of private doctor visits is well below 1, so private care is still a necessity despite the availability of free public care. The fact that private doctors are a necessity and not a luxury suggests inadequate access or quality in the public sector. For the controls, the demographic and living condition variables are jointly significant in all specifications. The health controls are jointly significant until the insured are dropped from the sample, which necessitates the exclusion of the health insurance variable from the list of regressors. The religion controls are generally jointly insignificant but become jointly significant when those with health insurance are dropped. Importantly, columns (7) and (8) show that adding local area fixed effects does not reduce the effect of ln(income) on number of private doctor visits.

Table 5 presents the results for public doctor visits. Despite the fact that public doctor visits are free, income is still positively and significantly associated with number of these visits in columns (1)-(6). A 1% increase in income is associated with an approximate increase in public doctor visits of 0.09%-0.14%. However, this effect disappears completely when the local area fixed effects are added in columns (7) and (8). This is consistent with the income-based disparity in utilization of free care being driven by the relative scarcity of public health clinics in poor, sparsely-populated areas, or by the quality of public care being lower in these areas. At first glance, these results also fit with a demand-side explanation in which rich and poor areas differ systematically in their demand for health. However, if demand-side factors were driving the results then we would also expect to see the effect of income on *private* doctor visits disappear after adding local area fixed effects, which – as discussed with the results from Table 4 – is not the case. Multicollinearity is another possible explanation, as adding detailed location controls could potentially eliminate too much of the variation in income to obtain meaningful estimates of its effects. The evidence, however, seems to strongly rule out this possibility. First, there is no loss in precision when area fixed effects are added – in fact, the standard error actually decreases slightly from column (6) to (7). Second, if multicollinearity in the income variable were a problem in an analysis of public visits then it should also be a problem with private visits, but Table (4) showed that adding area fixed effects made almost no difference in the estimated income effect on private visits. Third, the variance inflation factor (VIF) for income in the local area fixed effects regression is only 2.829, well below the typically-accepted level of 10 at which the extent of multicollinearity is considered to be problematic (Wooldridge, 2006:99).[10] Turning to the controls, the demographic, living condition, and religion variables are jointly significant in all regressions, while the health variables are jointly significant until the insured are dropped.[11]

To summarize, Tables 3-5 present two pieces of evidence that the network of free public health care providers is not effectively reaching everyone in Brazil. First, private doctor visits are a necessity instead of a luxury. Second, there is a positive relationship between income and public sector utilization that persists through the addition of the individual-level

[10] $VIF = 1/(1 - R_j^2)$, where $R_j^2$ is the $R^2$ from a linear regression of ln(income) on the control variables plus the local area fixed effects.

[11] Another conceivable explanation for the positive relationship between income and public doctor visits is if the "free" public clinics charge patients an informal fee – effectively a bribe – in order to be seen. While there is evidence of such behavior in some developing countries (Ensor and Thompson, 2006), we are not aware of any anecdotal or empirical evidence that these practices are common in Brazil.

controls but disappears when area fixed effects – which capture local factors such as number of public clinics – are added.

# 4 Private Medical Expenditures

## 4.1 Models

We next turn to an analysis of the relationship between income and total household out-of-pocket expenditures on private medical care. This analysis requires dealing with a cluster of observations with zero expenditure. There is a controversy over whether Heckman's sample selection model or the two-part model is the most appropriate when *potential* expenditure is the main outcome of interest (see Madden, 2008 and Jones, 2000). However, our main outcome of interest is *actual* expenditure – we are interested in the expenses Brazilians actually spent on health care, rather the expenses they would spend had they sought health care. Dow and Norton (2003) underscore that the appropriate model in this case is the two-part model as no selection bias is actually present in the sample.[12]

We therefore estimate the effect of ln(income) on ln(medical expenditures) using the following two-part model:

$$\Pr[y > 0|income, \mathbf{X}] = \alpha_0 + \alpha_1 \ln(income) + \mathbf{X}'\boldsymbol{\alpha}_2 \tag{2}$$

$$E[\ln(y)|y > 0, income, \mathbf{X}] = \gamma_0 + \gamma_1 \ln(income) + \mathbf{X}'\boldsymbol{\gamma}_2 \tag{3}$$

where $y$ is out-of-pocket household medical expenses while *income* and $\mathbf{X}$ again represent household income and the vector of controls. To avoid the incidental parameters problem with fixed effects probit and logit models (Hsiao 1996, Kalbfleisch and Sprott 1970), we estimate a linear probability model in the first part (equation 2). In unreported regressions

[12] Sometimes this is referred as the "true zeros" case in the literature, since a zero expenditure observation represents no consumption, and not an unobserved value.

(available upon request), we verified that the marginal effects in the first part are virtually identical using probit or logit models. We estimate the second part (equation 3) with ordinary least squares (OLS) using the 7,479 observations with $y > 0$. By combining the results from the two parts we can compute the marginal effect of ln(income) on the expectation of ln(expenditures) conditional on $X$ for the whole sample as follows:

$$\frac{dE\left[\ln(y)\right]}{d\ln(income)} = \alpha_1 \left(\ln(y)|y > 0\right) + \gamma_1 \left(\Pr[y > 0]\right),$$

where $\Pr[y > 0]$ is the proportion of the sample with non-zero expenditures, which is 0.17. This derivative can be interpreted as the approximate income elasticity of medical expenditures. which we evaluate at the sample mean for $\ln(y)|y > 0$, which is 5.48.[13]

As with doctor visits, with estimate our model first with no control variables and then gradually build up to the area fixed effects models. We again also estimate the area fixed effects model dropping those household where at least one individual has health insurance, which restricts the sample to those households for whom all expenditures are out-of-pocket costs.

## 4.2 Results

Table 6 reports the results. Panel A presents the results from the participation equation 2, while panel B presents the results from the expenditure equation 3. The last row of the table combines the estimates from Panels A and B to obtain the income elasticity.

Panel A shows a positive and statistically significant relationship between income and probability of having any medical expenditures in all specifications. The addition of the first three sets of control variables attenuates this relationship somewhat, but from columns (4) to (8) the coefficient estimate for ln(income) remains very similar – a 1% increase in income

[13] In unreported regressions we verified that our estimated elasticities are very similar to the coefficient estimates from a log-log model with the full sample. (In order to estimate a log-log model with the full sample, we add 1 to y so than ln(y) is defined even for those with no medical expenditures.)

increases the probability of participation by 0.063 to 0.067 percentage points, or 0.37% to 0.39% of the sample participation rate. For the controls, the demographic and living condition controls are consistently highly jointly significant across specifications, while the health variables are jointly significant until the insured are dropped and the religion variables are marginally jointly significant.

Panel B shows that additional income leads to a statistically significant increase in medical expenditures among participators in all regressions. As in Panel A, after the living condition controls are added in column (4) the coefficient estimate for ln(income) is stable across specifications, ranging from 0.16 to 0.18. A 1% increase in income therefore increases medical expenditures by 0.16% to 0.18% among those who participate in the private health care sector.

As shown in the last row of Table 6, the income elasticity of private medical expenditures implied by the participation and expenditure regressions is well below 1 in all regressions. After the living condition controls are added in column (4), the elasticity remains within the 0.38-0.4 range regardless of whether additional controls or fixed effects are included or those with health insurance are dropped from the sample. Private medical spending is therefore a necessity instead of a luxury. This is consistent with our results for private doctor visits from Section 4, and provides further evidence to support the hypothesis that individuals living in poor (generally remote) areas spend money on private care because of a lack of access or quality in the public sector.

# 5 Disparities and the Family Health Program

We close our empirical analysis by examining whether income-based disparities in health care utilization are systematically different in states with higher rates of Family Health Program (PSF) coverage.[14] The Brazilian government created the PSF in 1994 in an effort to

[14]Ideally, we would like to test for differeneces on the basis of local area PSF coverage, but data limitations prevent such an analysis because we do not know which specific areas are represented by each local area

improve primary health care access and reduce service inequality. The PSF assigns a geographical area inhabited by an average of 3,450 and a maximum of 4,500 people to a team composed of one physician, one nurse, one nurse assistant, and four or more community health workers. While PSF physicians and nurses typically provide care at health facilities, community workers provide prevention and education services during household visits. Although the program was initiated at a national level in 1994, its expansion has occurred gradually over time since then (Macinko et al., 2006). According to official data from the Brazilian Department of Health, by our survey year, 2003, the PSF covered 29% of Brazilian families. Some studies suggest the PSF has improved health care access to vulnerable sectors of the population such as the poor and elderly (Macinko et al., 2006; Thume et al., 2010; Goldbaum et al., 2005; Fernandes et al., 2009), while others have been unable to find evidence that the PSF has reduced health service inequality (see for example Morsch et al., 2001; Barros and Bertoldi, 2008).

Testing for systematic differences in disparities on the basis of PSF coverage is important for two reasons. First, the PSF has continued to expand since 2003 with the intention of eventually achieving full coverage of the Brazilian population. If income-based disparities in health care utilization have been eliminated in areas covered by the PSF, then once the entire country is covered the disparities observed in this paper will disappear. Verifying that the disparities are similar in states with high and low PSF coverage rates would therefore provide evidence that our estimates are not outdated. Second, it is unclear whether POS respondents count the in-home medical services provided by PSF community health workers as doctor visits. This creates the potential for measurement error in the overall and public doctor visits variables in areas covered by the PSF. Showing that the disparities are similar in states with high and low PSF coverage rates would increase our confidence that this measurement error is not leading to biased estimators.

We test for heterogeneity on the basis of state PSF coverage in two ways. First, we re-

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indicator.

estimate our Poisson and two-part models adding an interaction term for ln(income)*state PSF coverage rate. A positive (negative) coefficient on the interaction term would indicate that disparities are larger (smaller) in states with extensive PSF coverage. Second, we split Brazil's 27 states into three categories: the 9 with the lowest PSF coverage rates, the 9 with the highest PSF coverage rates, and the 9 in the middle. We then estimate our Poisson and two-part models for each of the three subsamples. Our official data on 2003 state PSF coverage rates come from the Brazilian Ministry of Health.[15] The proportion of families covered by PSF in the average state is 0.29. This coverage rate ranges from a minimum of 0.07 in the Federal District to a maximum of 0.76 in Piauí. The proportion of families covered averages only 0.17 in the 9 states with the lowest coverage rates, compared to 0.38 in the 9 with medium coverage rates and 0.62 in the 9 with high coverage rates.

Tables 7 and 8 present the results for the regressions with the interaction term and the regressions for the subsamples. To conserve space we report only the results including all the control variables plus state fixed effects, as these are most complete specifications for which disparities persisted for all the dependent variables in Sections 3 and 4. The conclusions reached are similar using the other specifications (results available upon request). In Table 7, the interaction term is highly insignificant in all regressions and its effect is small. In Table 8, there is no clear evidence of systematic differences in disparities on the basis of PSF coverage.

# 6 Conclusion

In its Constitution of 1988, Brazil adopted a universal health care policy with the goal of guaranteeing public health care to the most vulnerable sectors of the population. To implement this policy, the government expanded the public service network and created the Family Health Program. Previous research suggests that Brazil's universal health care system has improved health and access to health care (Macinko et al., 2006 and 2007; Rasella et al.,

[15]The data is publicly available at http://www2.datasus.gov.br/DATASUS/index.php

2010; Morsch et al., 2001; Goldbaum et al., 2005). Despite this progress, our paper presents two pieces of evidence that the public health care network is still not effectively reaching everyone. First, we find a pro-rich disparity in doctor visits not only in the private sector but also in the free public sector. The disparity in the public sector disappears after adding local area fixed effects, suggesting it is driven by inadequate quantity or quality of public health care providers in poor remote areas. Second, we estimate the income elasticities of private doctor visits and private medical expenditures and find that private sector care remains a necessity despite the availability of free public care, again pointing to inadequate access to high-quality public care.

Our results point to possible improvements to Brazil's health care system. Considering that hospitals, clinics, and even basic health units may not be cost-effective in the least densely-populated areas, the deployment of health workers to those areas seems to be the key. Whether the PSF is the appropriate model remains an open question, the answer to which requires further research using data at a finer geographical level. Were the PSF found insufficient, community-based interventions would need to be reformulated. This could be done by either reducing the geographical area assigned to each PSF team or by targeting the most vulnerable groups within each area exclusively, instead of attempting to cover all households. Programs destined to increase participation and educate the population on the benefits of the PSF are another valuable strategy. Finally, improved efficacy could be achieved by integrating private doctors with offices in remote areas to the SUS network.

Our findings also contribute to the broader debate over the government's role as a provider and payer of medical services by showing that universal coverage does not automatically lead to universal care. Even if a population is shielded from medical bills, high transportation costs can still prevent the poor from obtaining care. Government efforts to achieve equal access should not only focus on subsidizing medical care for the poor but also ensuring a sufficient supply of providers in underserved areas. This is especially difficult in countries with a large geographic territory and limited tax revenue, such as Brazil.

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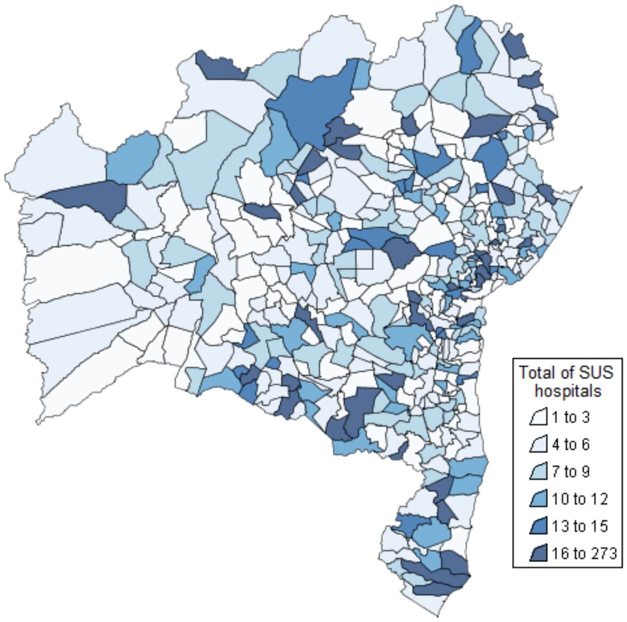
Figure 1 – Hospitals affiliated with the SUS network in the state of Bahia




Source: Ministério da Saúde do Brasil, www.datasus.gov.br.

Figure 2 – Nonparametric Estimation of Relationship Between Income and Doctor Visits

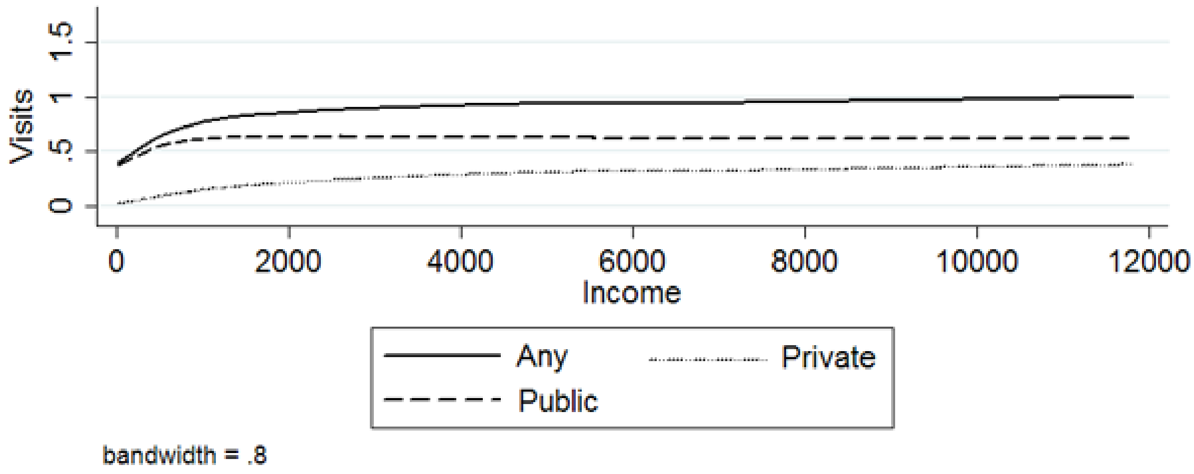


Figure 3 – Nonparametric Estimation of Relationship Between Income and Expenditures

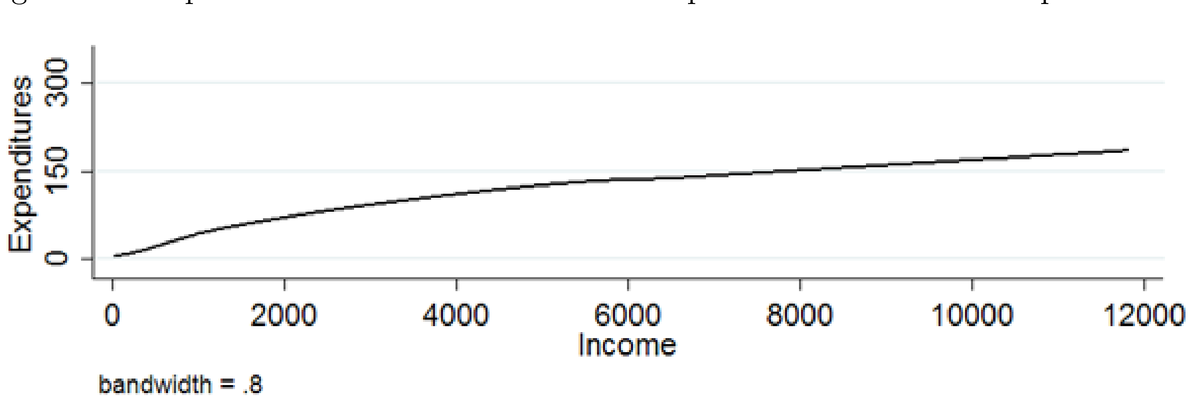


Table 1 – Summary Statistics for Income and Medical Variables

| Variable | Description | Mean (St.Dev.) |
|---|---|---|
| Income | Household income | 1492.310 (3165.195) |
| Visits | Number of doctor visits by household members in past year | 0.789 (1.172) |
| | Fraction with visits>0 | 0.457 (0.498) |
| | Visits among those with visits>0 | 1.726 (1.177) |
| Public Visits | Visits to public doctors by household members in past year | 0.629 (1.082) |
| | Fraction with public visits>0 | 0.370 (0.483) |
| | Public visits among those with public visits>0 | 1.701 (1.158) |
| Private Visits | Visits to private doctors by household members in past year | 0.160 (0.467) |
| | Fraction with private visits>0 | 0.129 (0.335) |
| | Private visits among those with private visits>0 | 1.246 (0.584) |
| Expenditures | Household out-of-pocket expenditures for private medical care | 66.834 (303.406) |
| | Fraction with expenditures>0 | 0.170 (0.376) |
| | Expenditures among those with expenditures>0 | 393.255 (642.913) |
| | Expenditures as fraction of household income | 0.052 (0.245) |
| Health Insurance | Whether anyone in the household had private health insurance | 0.146 (0.353) |

Table 2 – Summary Statistics for Control Variables

| Variable | Description | Mean (St.Dev.) |
|---|---|---|
| Female | Indicator for respondent is female | 0.296 (0.456) |
| Age | Age of respondent in years | 44.139 (16.932) |
| Education | Highest grade completed by respondent | 5.232 (4.527) |
| White | Indicator for respondent's race is white | 0.489 (0.500) |
| Black | Indicator for respondent's race is black | 0.063 (0.244) |
| Mixed | Indicator for respondent's race is mixed | 0.439 (0.496) |
| Family Size | Number of members in household | 3.745 (1.891) |
| Underweight | Indicator for respondent is underweight (BMI$\leq$ 18.5) | 0.056 (0.229) |
| Overweight | Indicator for respondent is overweight (25 $\leq$BMI$<$ 30) | 0.310 (0.462) |
| Obese | Indicator for if respondent is obese (BMI$\geq$ 30) | 0.080 (0.272) |
| Rooms | Number of rooms in home | 5.793 (2.226) |
| Dwelling Type (omitted category is other type of house) | | |
| Dwelling 1 | Indicator for rudimentary house | 0.062 (0.241) |
| Dwelling 2 | Indicator for apartment | 0.053 (0.224) |
| Dwelling 3 | Indicator for single-room dwelling | 0.007 (0.081) |
| Water Source (omitted category is public network with home plumbing) | | |
| Water 1 | Indicator for well with home plumbing | 0.132 (0.339) |
| Water 2 | Indicator for other source with home plumbing | 0.014 (0.119) |
| Water 3 | Indicator for public network without home plumbing | 0.046 (0.210) |
| Water 4 | Indicator for well without home plumbing | 0.063 (0.244) |
| Water 5 | Indicator for other source without home plumbing | 0.067 (0.251) |

(Continued on next page)

Table 2 – Summary Statistics for Control Variables (Continued)

| Variable | Description | Mean (St.Dev.) |
|---|---|---|
| Sewage (omitted category is sewage network) | | |
| Sewage 1 | Indicator for septic tank | 0.202 (0.401) |
| Sewage 2 | Indicator for rudimentary tank | 0.337 (0.473) |
| Sewage 3 | Indicator for infiltration trench | 0.024 (0.153) |
| Sewage 4 | Indicator for river, lake or sea | 0.024 (0.154) |
| Sewage 5 | Indicator for other source | 0.006 (0.076) |
| Sewage 6 | Indicator for no sewage | 0.095 (0.293) |
| Electricity (omitted category is utility company) | | |
| Electricity 1 | Indicator for generator | 0.005 (0.071) |
| Electricity 2 | Indicator for other source | 0.007 (0.085) |
| Electricity 3 | Indicator for no power source | 0.058 (0.234) |
| Floor Type (omitted category is carpet) | | |
| Floor 1 | Indicator for ceramic, tile, or stone | 0.380 (0.495) |
| Floor 2 | Indicator for treated wood | 0.010 (0.098) |
| Floor 3 | Indicator for cement | 0.427 (0.495) |
| Floor 4 | Indicator for untreated wood | 0.010 (0.098) |
| Floor 5 | Indicator for soil | 0.047 (0.212) |
| Floor 6 | Indicator for other floor type | 0.007 (0.085) |
| Religion (omitted category is atheist) | | |
| Religion 1 | Indicator for Catholic | 0.779 (0.415) |
| Religion 2 | Indicator for evangelical missionary | 0.049 (0.217) |
| Religion 3 | Indicator for evangelical Pentecostal | 0.087 (0.282) |
| Religion 4 | Indicator for other envangelical | 0.015 (0.122) |
| Religion 5 | Indicator for Jehovah's witnesses | 0.006 (0.079) |
| Religion 6 | Indicator for spiritualist | 0.010 (0.098) |
| Religion 7 | Indicator for Judaism or Buddhism | 0.001 (0.038) |
| Religion 8 | Indicator for esoteric | 0.003 (0.054) |
| Religion 9 | Indicator for other religion | 0.0001 (0.012) |

Table 3 – Poisson Results for Overall Number of Doctor Visits

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ln(Income) | 0.213 (0.009)*** | 0.210 (0.010)*** | 0.196 (0.010)*** | 0.160 (0.011)*** | 0.159 (0.011)*** | 0.181 (0.011)*** | 0.099 (0.010)*** | 0.098 (0.011)*** |
| Demographic Controls | – | 1156.93*** | 1210.98*** | 1178.14*** | 1177.30*** | 1181.20*** | 1281.22*** | 1105.03*** |
| Health Controls | – | – | 28.90*** | 23.78*** | 24.23*** | 11.23* | 8.29 | 3.38 |
| Living Condition Controls | – | – | – | 270.24*** | 270.56*** | 129.61*** | 31.61 | 30.43 |
| Religion Controls | – | – | – | – | 37.11*** | 55.21*** | 38.80*** | 31.62*** |
| State Fixed Effects | NO | NO | NO | NO | NO | YES | NO | NO |
| Area Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES |
| Drop Insured | NO | NO | NO | NO | NO | NO | NO | YES |

Notes: Heteroskedasticity-robust standard errors, clustered by area, are in parentheses. *** statistically significant at 0.1% level; ** 1% level; * 5% level. Results for sets of controls are F statistics from a test of their joint significance.

Table 4 – Poisson Results for Number of Private Visits

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ln(Income) | 0.515<br>(0.012)*** | 0.475<br>(0.016)*** | 0.513<br>(0.016)*** | 0.400<br>(0.019)*** | 0.399<br>(0.019)*** | 0.410<br>(0.019)*** | 0.425<br>(0.022)*** | 0.459<br>(0.025)*** |
| Demographic Controls | – | 206.11*** | 200.99*** | 120.82*** | 118.53*** | 116.93*** | 112.05*** | 124.34*** |
| Health Controls | – | – | 63.15*** | 65.66*** | 66.39*** | 68.09*** | 70.44*** | 1.13 |
| Living Condition Controls | – | – | – | 160.21*** | 158.91*** | 180.74*** | 106.93*** | 97.41*** |
| Religion Controls | – | – | – | – | 12.45 | 11.88 | 12.13 | 209.46*** |
| State Fixed Effects | NO | NO | NO | NO | NO | YES | NO | NO |
| Area Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES |
| Drop Insured | NO | NO | NO | NO | NO | NO | NO | YES |

See notes for Table 3.

Table 5 – Poisson Results for Number of Public Visits

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ln(Income) | 0.129 | 0.136 | 0.107 | 0.091 | 0.091 | 0.112 | −0.001 | −0.011 |
| | (0.011)*** | (0.012)*** | (0.012)*** | (0.013)*** | (0.013)*** | (0.013)*** | (0.012) | (0.014) |
| Demographic Controls | – | 1079.71*** | 1186.27*** | 1201.45*** | 1200.81*** | 1217.34*** | 1345.02*** | 1162.35*** |
| Health Controls | – | – | 81.98*** | 73.80*** | 75.31*** | 54.38*** | 51.36*** | 3.65 |
| Living Condition Controls | – | – | – | 302.99*** | 303.93*** | 122.45*** | 39.31* | 36.48* |
| Religion Controls | – | – | – | – | 33.33*** | 47.68*** | 31.19*** | 25.63** |
| State Fixed Effects | NO | NO | NO | NO | NO | YES | NO | NO |
| Area Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES |
| Drop Insured | NO | NO | NO | NO | NO | NO | NO | YES |

See notes for Table 3.

Table 6 – Two-Part Model Results

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| Panel A | ln(Income) | 0.103 (0.002)*** | 0.088 (0.003)*** | 0.081 (0.003)*** | 0.063 (0.003)*** | 0.063 (0.003)*** | 0.066 (0.003)*** | 0.064 (0.003)*** | 0.067 (0.003)*** |
| Participation | Demographic Controls | – | 15.59*** | 13.74*** | 7.76*** | 7.66*** | 8.17*** | 7.34*** | 7.29*** |
| (n=44007) | Health Controls | – | – | 21.82*** | 18.80*** | 18.62 | 18.57*** | 12.77*** | 0.43 |
| | Living Condition Controls | – | – | – | 6.63*** | 6.53*** | 5.89*** | 4.44*** | 4.07*** |
| | Religion Controls | – | – | – | – | 2.14* | 2.04* | 2.28* | 1.89* |
| | State Fixed Effects | NO | NO | NO | NO | NO | YES | NO | NO |
| | Area Fixed Effects | NO | NO | NO | NO | NO | NO | YES | YES |
| | Drop Insured | NO | NO | NO | NO | NO | NO | NO | YES |
| Panel B | ln(Income) | 0.273 (0.012)*** | 0.237 (0.014)*** | 0.232 (0.015)*** | 0.176 (0.016)*** | 0.176 (0.016)*** | 0.157 (0.016)*** | 0.165 (0.022)*** | 0.156 (0.027)*** |
| ln(Expenditures) | Demographic Controls | – | 3.21*** | 3.11*** | 2.12** | 2.11** | 8.17*** | 1.75* | 1.20 |
| (n=7479) | Health Controls | – | – | 0.96 | 0.60 | 0.57 | 18.57*** | 1.06 | 1.07 |
| | Living Condition Controls | – | – | – | 2.69*** | 2.68*** | 5.89*** | 0.93 | 1.02 |
| | Religion Controls | – | – | – | – | 6.93*** | 2.04* | 5.60*** | 1.07 |
| | State Fixed Effects | – | – | – | – | – | YES | NO | NO |
| | Area Fixed Effects | – | – | – | – | – | – | YES | YES |
| | Drop Insured | NO | NO | NO | NO | NO | NO | NO | YES |
| Estimated Income Elasticity | | 0.611 | 0.522 | 0.483 | 0.375 | 0.375 | 0.388 | 0.379 | 0.394 |

Notes: Heteroskedasticity-robust standard errors, clustered by area, are in parentheses. *** statistically significant at 0.1% level; ** 1% level; * 5% level. $^{+}$ sample restricted to those with Expenditures>0 in the ln(Expenditures) equation (n=7479).

Table 7 – Results Adding ln(Income)*State Family Health Program Coverage Rate Interaction

| | Poisson: Doctor Visits | | | Two-Part | |
|---|---|---|---|---|---|
| | Overall | Private | Public | Participation | Expenditures |
| ln(Income) | 0.193 (0.022)*** | 0.389 (0.033)*** | 0.125 (0.028)*** | 0.073 (0.005)*** | 0.188 (0.029)*** |
| ln(Income)*PSF Coverage Rate | −0.030 (0.049) | 0.055 (0.070) | −0.033 (0.061) | −0.017 (0.012) | −0.082 (0.061) |
| Demographic Controls | 1181.72*** | 117.04*** | 1217.86*** | 8.14*** | 2.95*** |
| Health Controls | 11.11** | 67.50*** | 54.25*** | 18.29*** | 0.94 |
| Living Condition Controls | 129.91** | 175.80*** | 122.68*** | 6.06*** | 1.91*** |
| Religion Controls | 55.33** | 11.90*** | 47.83*** | 2.03** | 2.27** |
| State Fixed Effects | YES | YES | YES | YES | YES |

See notes for Table 3.

Table 8 – Results Stratifying by State Family Health Program Coverage Rate

| | | Poisson: Doctor Visits | | | Two-Part | |
|---|---|---|---|---|---|---|
| | | Overall | Private | Public | Participation | Expenditures |
| Panel A | ln(Income) | 0.190<br>(0.018)*** | 0.443<br>(0.033)*** | 0.119<br>(0.022)*** | 0.080<br>(0.005)*** | 0.213<br>(0.028)*** |
| Low Coverage Rate | Demographic Controls | 438.36*** | 63.61*** | 465.40*** | 3.95*** | 1.42 |
| (n=12982) | Health Controls | 10.03** | 34.88*** | 33.20*** | 8.10*** | 0.92 |
| | Living Condition Controls | 99.19*** | 63.47*** | 99.79*** | 2.27*** | 1.98*** |
| | Religion Controls | 26.94*** | 429.18*** | 21.84*** | 2.80*** | 1.84* |
| | State Fixed Effects | YES | YES | YES | YES | YES |
| Panel B | ln(Income) | 0.156<br>(0.018)*** | 0.393<br>(0.032)*** | 0.078<br>(0.022)*** | 0.060<br>(0.004)*** | 0.123<br>(0.027)*** |
| Medium Coverage Rate | Demographic Controls | 460.77*** | 53.01*** | 461.11*** | 3.41*** | 1.60* |
| (n=16761) | Health Controls | 3.75 | 27.04*** | 7.23 | 4.58*** | 0.36 |
| | Living Condition Controls | 64.02*** | 53.73*** | 80.07*** | 2.56*** | 2.31*** |
| | Religion Controls | 36.37*** | 17.07** | 33.31*** | 1.43 | 2.10** |
| | State Fixed Effects | YES | YES | YES | YES | YES |
| Panel C | ln(Income) | 0.190<br>(0.019)*** | 0.391<br>(0.037)*** | 0.133<br>(0.022)*** | 0.058<br>(0.005)*** | 0.125<br>(0.030)*** |
| High Coverage Rate | Demographic Controls | 356.93*** | 26.41** | 382.27*** | 2.62*** | 2.20*** |
| (n=14264) | Health Controls | 6.41 | 14.25*** | 23.07*** | 7.00*** | 2.30* |
| | Living Condition Controls | 55.97*** | 120.37*** | 46.29*** | 4.90*** | 2.21*** |
| | Religion Controls | 12.15 | 6.40 | 12.10 | 0.63 | 10.96*** |
| | State Fixed Effects | YES | YES | YES | YES | YES |

See notes for Table 3. For the expenditures regressions in which individuals with zero expenditures are dropped, the sample sizes fall to 2643, 2679, and 2157 in Panels A, B, and C, respectively.