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Measuring pure health inequality and mobility during a health insurance expansion: Evidence from Mexico

Joan Costa-Font[1,2] | Frank A. Cowell[3] | Belen Saenz de Miera[1]

[1]Department of Social Policy, London School of Economics and Political Science (LSE), London, UK

[2]Department of Health Policy, London School of Economics and Political Science (LSE), London, UK

[3]Department of Economics, London School of Economics and Political Science (LSE), London, UK

Correspondence
Belen Saenz de Miera, Department of Social Policy, London School of Economics and Political Science (LSE), Houghton St, London WC2A2AE, UK.
Email: b.saenzdm@uabcs.mx

Present address
Belen Saenz de Miera, Department of Economics, Universidad Autonoma de Baja California Sur, Carretera al Sur Km 5.5, 23080, La Paz, Baja California Sur, Mexico.

Abstract

The association of insurance expansions and the distribution of health status is still a matter we know little about. This paper draws upon new measures of pure (univariate) inequality and mobility which accommodate categorical data to understand how an expansion of public insurance may be related to both health inequality and mobility. These measures require a definition of individual's status that is either “downward looking” or “upward looking”. Using data from the Mexican Family Life Survey, a nationally representative longitudinal survey, we find that the distribution of health has worsened in Mexico between 2002 and 2009, although the change is only consistent for an upward looking definition status. Together with the lack of mobility in self-reported health, we can thus conclude that Mexico has become more rigid over time despite the rapid public health expansion that took place over the 2000s decade. While further research on the potential drivers of health inequalities is needed, our findings suggest that insurance coverage alone may be not enough to reduce health disparities and promote health mobility. Indeed, health inequality and mobility likely depend on a myriad of factors beyond health care.

KEYWORDS

health, inequality, mobility, public health insurance

1 | INTRODUCTION

The distribution of overall health attainment has become an important indicator to evaluate countries' health system performance (WHO, 2000), and especially the success of policy interventions to extend insurance coverage. Nonetheless, measuring shifts in the distribution of health, and specifically changes in inequality and mobility in a population is far from straightforward. A growing number of studies have focused on both developing measurement tools and providing evidence for specific countries or groups of countries (Van Doorslaer & Van Ourti, 2011). However, most of these studies have only addressed health disparities across socioeconomic status through concentration indices. While this approach has been helpful in drawing attention to dimensions of well-being other than income, it raises some conceptual and methodological concerns that we attempt to address in this paper.

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Approaches that focus on measuring socioeconomic inequalities in health are problematic on a number of grounds. First, it may well be argued that all health inequalities should be a cause of concern and not only those related to socioeconomic status (Gakidou et al., 2000). Second, the analysis of health-related inequalities often draws on unsatisfactory cardinalisation procedures to deal with ordinal variables such as self-assessed health (SAH). Finally, socioeconomic measures do not address the fact that income and health might be codetermined, as evidence suggests. With few exceptions (Contoyannis et al., 2004), studies on health mobility also tend to focus on socioeconomic mobility. Alternative distributional measures of *pure* health inequality and mobility are less problematic and more suitable to evaluate associations with policy interventions. This paper employs a recently developed class of indices suitable for ordinal data (Cowell & Flachaire, 2017, 2018) to analyse the pattern of pure health inequality and mobility between 2002 and 2009 in Mexico.

The Mexican case provides an especially convenient setting, as an ambitious health reform took place over that period through the implementation of Seguro Popular (SP), a public health insurance programme created to provide access to a generous package of health services to those previously excluded from insurance. Indeed, by the beginning of the 2000s decade health insurance coverage was segmented by labour status in Mexico. Before the introduction of SP only formal sector workers and their families had access to health care and other social security benefits, so about half of the population were unprotected. According to administrative records, the health insurance extension managed to attain full universal health care coverage by 2012 (Knaul et al., 2012).

Insurance coverage, whether public or private, provides financial security and specifically reduces the risk of unpredictable medical costs that households would otherwise absorb. If such costs are too high, individuals go without health care, which can have undesirable consequences for their health. Health insurance provides access to primary care and preventive services too. In particular, if coverage is provided to the entire population, it can reduce pre-existing disparities in access to health care inputs and so reduce pure health inequalities. At the same time, if health disparities across the population are reduced and specifically the health of those with poorest health is improved, pure health mobility would be expected to improve.

Nonetheless, the production of health depends on a large list of inputs in addition to health care access. Moreover, the universalisation of health insurance alone guarantees neither use of, nor access to needed health care, especially preventative services. Whether increased access takes place, in particular to high-value health care that improves health status, is an empirical question. Overall, the consensus from recent studies drawing on insurance extensions in the United States is that coverage improves individuals' perceived health (Sommers et al., 2017). This is exemplified by the Oregon study, a key and paradigmatic randomised expansion of health insurance in the United States that found a 25% increase in the likelihood of individuals reporting good or very good health after one year (Finkelstein et al., 2012). The evidence on the effects of SP is more limited, but Teruel Belismelis et al. (2012) also found that the programme increased the probability of reporting good health by 6%. However, little is known about the effects on the distribution of health. Evidence for China, a country that has also undergone important reforms to increase insurance coverage, suggests that health insurance is associated with reductions in health inequalities, but the overall trend seems to be largely driven by factors outside the health system (Wang and Yu, 2016). In fact, health inequalities have increased in China between 1997 and 2009 in both rural and urban areas. We expect to provide new evidence on the potential association between health insurance expansions and the distribution of health.

This paper also exploits the information on individual changes in health status between points in time to analyse short-run mobility in health using a class of indices for ordinal variables (Cowell & Flachaire, 2018). Mobility has been conceptualised and measured in different ways; the measures we employ are concerned with the interpretation of mobility as an abstract concept that indicates how likely it is for individuals to change their position in the distribution across periods (also known as positional mobility; Jäntti and Jenkins, 2015). While Jenkins and Van Kerm (2006) used a rather different approach—namely a decomposition of the Gini index that can be employed with cardinal variables—they were able to explain the apparent paradox of substantial income inequality increase in the United States in the 1980s paired with progressive income growth by explicitly looking at the contribution of mobility to the evolution of inequality over time. The analysis of both inequality and mobility in health thus provides a better understanding of the evolution of well-being over time.

The rest of the paper is organised as follows. Section 2 provides the background, while section 3 explains the institutional setting. Sections 4 and 5 describe the data and methods, respectively. Section 6 presents the results, and a final section discusses the main findings.

2 | BACKGROUND

2.1 | Health inequalities

The study of health inequalities has been the focus of numerous studies over the past decades. Most analytic tools employed in these studies have been inspired by the income inequality literature. But there are salient differences between the nature of income—an unbounded, cardinal variable—and health—commonly measured with a categorical variable, for which the real distance between the categories is unknown. In particular, concentration indices of health on income (CI) are the most popular tool to measure income related health inequalities (Wagstaff and van Doorslaer, 2000; Van Doorslaer & Van Ourti, 2011). One of the features that makes this measure attractive is that it can be decomposed into the contributions of a set of characteristics, provided the relevant outcome can be written as a linear function of these characteristics (Wagstaff et al., 2003). But as the CI should not be used with ordinal variables, arbitrary cardinalisation methods have been commonly applied. For example, Van Doorslaer and Jones (2003) use an ordered probit model to convert SAH categories into a continuous index that is then employed to measure inequality. In general, frequent cardinalisation procedures include ordinal and interval regression, but these rely on non-neutral assumptions on the value and the distribution of health status that are not theoretically grounded. Moreover, Erreygers and Van Ourti (2010) show that the CI should not be employed with bounded cardinal variables—as it fails to satisfy important properties such as the Mirror property—, and only the modified CI should be employed with unbounded cardinal variables. This includes any transformation of ordinal variables into cardinal variables.

Another aspect that makes the CI approach problematic is that the analysis is based on a measure of status that ranks individuals according to socioeconomic level, that is, individual status is given by their position in the income (or consumption) distribution, as opposed to a natural health ranking akin to pure health inequalities. Therefore, the use of CI ignores the fact that some income differences across individuals may be a matter of choice itself or may reflect variations in preferences (Fleurbaey & Schokkaert, 2011), and that income and health may be co-determined. The latter is particularly relevant in the context of health insurance expansions, as such reforms are expected to affect both socioeconomic status and health. Furthermore, the CI approach neglects other aspects of inequalities in health. While health disparities due to demographics such as age and sex are normally considered legitimate (hence the demographic standardisation of health status is a common practice), the role of other factors as a source of (legitimate/illegitimate) inequalities is ignored. Systematic health disparities have been found with respect to race, ethnic origin, place of residence, and other characteristics, however (Cook et al., 2010; King et al., 2009b). Hence, it has been argued that all health inequalities should be a cause of concern and not only those related to socioeconomic status (Gakidou et al., 2000).

In this study, we use an approach to measure pure health inequalities before and after the Mexican health insurance expansion that overcomes the technical and conceptual difficulties outlined above. In particular, we estimate a class of indices that do not require any cardinalisation and use a similar status concept to those used in poverty and relative deprivation analyses (Cowell & Flachaire, 2017).

While the analysis of income inequalities has evidenced that Mexico is one of the most unequal countries (Esquivel, 2015), little is known about the distribution of health. A few studies that have addressed this issue, have employed the most common CI approach and have mainly focused on health care (Barraza-Lloréns et al., 2013; Urquieta-Salomón & Villarreal, 2016). In the case of China, a country that has also recently increased health insurance coverage, the study of the distribution of health has received much more attention (Baeten et al., 2013; Tang et al., 2008), but again most analyses have focused on income-related health inequalities. The study by Wang and Yu (2016) is an exception that finds that health inequality considerably increased between 1997 and 2009 in China. The authors argue that this is likely related to factors outside the health system, such as increasing income inequality and poverty, and environment deterioration. In fact, their results suggest that health insurance contributed to the reduction of health inequalities, although the overall pattern was in the opposite direction. This study will help to shed light on this finding using data for Mexico.

2.2 | Health dynamics

Health dynamics have been much less studied than health inequalities. Hauck and Rice (2004) and Contoyannis et al. (2004) are relatively recent exceptions that rely on measurement tools employed in the income dynamics literature and data from the British Household Panel Survey (BHPS). Hauck and Rice (2004) use a linear dynamic regression model where the dependent variable is health at time *t*, measured with a cardinal indicator of mental health, and the independent variables are the lagged health variable and a set of time-varying and time-invariant variables. In this specification, the estimated coefficient of the lag (β) indicates the extent of mobility. Therefore, low mobility ($\beta = 1$ or $1 - \beta = 0$**)** would imply that it is much more difficult to move far away from their initial state than to remain close. They find, however, there is considerable mobility in mental health, although this varies across socioeconomic groups. In particular, the incidence and persistence of mental illness is higher among low income individuals. Similarly, Contoyannis et al. (2004) use a dynamic regression approach, but their specification is nonlinear as their health measure is a categorical indicator of SAH. Unlike Hauck and Rice (2004), they provide evidence of substantial health persistence and hence limited pure health mobility.

Yet, this pragmatic approach to mobility of dynamic models is problematic at least for two reasons. On the one hand, although this measure is taken from the literature on intergenerational income mobility in which the main interest has been in the concept of positional mobility, it also reflects structural mobility (Jäntti and Jenkins 2015). On the other hand, while large values of $1 - \beta$ imply substantial mobility, low values do not necessarily provide evidence of low mobility, as shown by Cowell and Flachaire (2018). The class of measures we employ to compare rank mobility during the first half of the Mexican health insurance expansion with mobility during the second half of the expansion overcome these difficulties. At the same time, they are suitable for ordinal variables and clearly separate the definition of an individual's status and the aggregation method.

3 | THE EXPANSION OF HEALTH INSURANCE IN MEXICO

Before the most recent reform, health insurance coverage in Mexico resulted from formal employment. As a consequence, informal sector workers and their families, who account for approximately half of the population, were uninsured. In contrast, formal sector workers and their families had access to health services provided by social security institutions. These institutions have their own facilities and are centrally managed by the federal government. Their funding comes from payroll taxes, employer contributions, and general revenues. The uninsured, on the other hand, had access to Ministry of Health (MoH) facilities that are funded through general revenues and are administered by state governments, but a scheme of fees based on self-reported income applied.

Although the government is the provider of health services through both social security institutions and MoH facilities, public resources were historically skewed towards the former. In 2000, public per capita expenditure for the uninsured was \$1482.4 (Mexican pesos of 2011), while the corresponding figure for social security beneficiaries was more than double (\$3197.5) (Secretaría de Salud, 2013). This resulted in large differences in quality and large out-of-pocket expenditures.

SP was created in the 2000s decade to guarantee access to health care as a universal right. Accordingly, the only eligibility criterion for SP is not being beneficiary of social security, and the benefit package guarantees access to a wide range of preventive and treatment interventions. The government estimates that these interventions cover 100% of primary care demand and 85% of the demand for hospitalisation and surgery (CNPSS, 2015).

The allocation of health care funding also radically changed. According to the rules of the programme, it should be financed through federal contributions, state contributions, and progressive contributions from beneficiaries. In practice, however, SP is essentially financed with general revenues, as contributions from beneficiaries account for less than 1% its annual budget (CNPSS, 2015). By 2011, the gap in public per capita expenditure between those with and without social security beneficiaries had narrowed. Also, public health expenditure grew from 2.6% of GDP in 2000 to 3.1% in 2011 (Secretaría de Salud, 2013).

SP started as a pilot in 2002 with 1.1 million beneficiaries distributed across 341 municipalities in 20 states. By 2007, all municipalities had at least one affiliate, and the total coverage had increased to 21.8 million individuals. In 2012, it was formally announced that the country had reached universal coverage (Knaul et al., 2012); the programme records indicate that coverage reached 52.9 million beneficiaries in that year.

The studies that have analysed various aspects of SP typically indicate that it has reduced health expenditures; there is also some evidence on the positive effects on utilisation and health (see a comprehensive review in Knaul et al., 2012). Specifically, Teruel Belismelis et al. (2012) show that the programme increased SAH by 6%. Distributional aspects have received little attention, however, except for the assessment of financial impacts (e.g., King et al., 2009a). In general, the analysis of health disparities is scarce in Mexico despite being an important topic in the political agenda. To examine whether SP is associated with changes in the distribution of health in the Mexican population is the main purpose of this study. Given that the expansion of SP grew steadily during the 2000s decade, this potential association should be visible either in the first and second half, or throughout the entire period. Yet, this will depend on the contribution of universal access to health care to reducing baseline health disparities, and on the interaction with other factors that determine the shape of the health distribution in the short and medium term.

4 | DATA

4.1 | The Mexican Family Life Survey

The Mexican Family Life Survey (MxFLS) is a longitudinal survey covering the 2000s decade. Three waves are publicly available. The first was collected in 2002, before the formal onset of health insurance expansion in Mexico; the second was collected between 2005 and 2006, when coverage levels of SP were between 11% and 15%; and the third wave was collected between 2009 and 2010, when the programme's coverage had reached nearly 40% of the population.

The MxFLS employed probabilistic, stratified, and multi-staged sampling design, and is representative at the national level. The first wave included approximately 8440 households and more than 35,000 individuals. The information collected covers a wide variety of topics. Some indicators such as expenditure are provided at the household level, while other indicators such as health status are provided at the individual level.

The MxFLS interviews were implemented as follows. One or two adults reported all the information related to socioeconomic status and demographic composition of the household. In parallel, each household member 12 years and older was interviewed to collect information at the individual level. The information for children under 12 years was provided by an adult member of the household. If any adult 15 years and older was not present at the moment of the interviews, proxy information was collected from other household members. This information is reported in a separate book so it can be easily identified.

4.2 | Measures

The health variable employed is the response to the question *currently, do you consider your health is...?*, coded as very good (5), good (4), regular (3), bad (2), and very bad (1). This information is available for individuals 15 years and older, which constitute the basic unit of analysis.

SAH information has been widely used in the literature that analyses the relationship between health and socioeconomic status (Adams et al., 2003), as well as in studies that focus on the relationship between health and lifestyles (Contoyannis & Jones, 2004). While SAH is a simple subjective indicator that provides an ordinal ranking of perceived health status, previous studies have shown that it is a good predictor of subsequent use of medical care (Van Doorslaer et al., 2002) and subsequent mortality (Burström & Fredlund, 2001). However, some studies have suggested that SAH may be measured with error if different groups of the population systematically consider different cut point levels when reporting SAH (Groot, 2000). Using SAH information from Canada, Lindeboom and van Doorslaer (2003) found that cut points varied with sex and age, although not with income and education. Our analysis of inequalities is therefore stratified by sex, age, and type of residence area. Proxy information of SAH was used if available to maximise the sample size. Since this could be a potential source of bias due to the subjective nature of the variable, the implications are discussed below.

Other variables employed in the analyses include sociodemographic characteristics at baseline, namely binary variables to indicate whether the individual was female, lived in rural areas, and was active in the labour market in the past 12 months. Region of residence, age group (15–30 years, 31–45 years, and 46 or older), education level as defined by the highest level of education completed (none, primary, secondary, high school, and university), marital status (cohabitating couple, separated or divorced, single, and widowed), and household size were also used.

4.3 | Sample description

Like other longitudinal surveys, the MxFLS suffers from different types of non-response, namely attrition and item non-response. As it is unlikely that both types of non-response are completely random (Rubin, 1987), this constitutes a potential source of bias that must be addressed. In practice, weighting and imputation methods are the most common ways of dealing with attrition and item non-response, respectively (Jenkins, 2011). Many studies on income inequality and mobility have found that differential attrition does not have a substantial impact on the conclusions (Jenkins, 2011). Using the BHPS and the European Community Household Panel to analyse socioeconomic determinants of health, Jones et al. (2006) also show that health-related attrition has little impact on the results. Frick and Brabka (2005), on the other hand, show that using only non-imputed data from Germany significantly underestimates income mobility.

Overall, the MxFLS has relatively low levels of attrition. In particular, 9.2% of the participants 15 years and older at baseline was lost to follow-up at Wave 2, while an additional 7.3% was lost to follow-up at Wave 3 (Table S1). Similar longitudinal surveys for other low- and middle-income countries have attrition rates above 16% (Falaris, 2003). General response rates of the MxFLS are also good but vary across books. For example, the book that contains information about household consumption has a response rate of 95% at baseline, but non-response in SAH is relatively high. If no proxy responses are considered, between 17% and 22% of the participants have missing SAH information; only after considering proxy responses the item non-response decreases to 11% approximately (Table S1).

If we consider both participation in all three waves and complete SAH information (including proxy responses), we end up with a balanced sample of 15,088 individuals or 45,264 wave-individual observations, which constitutes the main analytic sample. The weights of the MxFLS provided are used in the main analysis, as these adjust for non-response. However, we also explore other specifications to assess the robustness of the results, including unweighted estimates, multiple imputation, non-proxy information only, and unbalanced sample inequality estimates.

Finally, it is worth reporting that most of the individuals in the sample have regular or good health (Table S2). About half were female, active in the labour market, and lived in rural areas at baseline. Their education level was generally low (54% with primary education or less), and nearly two thirds lived with their couple. The sample is roughly equally distributed across five country regions.

5 | METHODS

5.1 | Measuring inequality in health

To study inequality in health status, we employ the Cowell and Flachaire (2017) inequality measure specifically developed to deal with ordinal variables such as SAH. Let n_k be the number of persons in each SAH category $k = 1, 2,\ldots, 5$, where one is the least desired category (very bad health) and five is the most desired category (very good health). Then, the status of individual i who is in category $k(i)$ must be a function of either:

$$\sum_{l=1}^{k(i)} n_l \text{ or } \sum_{l=k(i)}^{K} n_l$$

Normalising by total population size, $n = \sum_1^K n_k$, so that individual's status is between 0 and 1 we have:

$$s_i = \frac{1}{n}\sum_{l=1}^{k(i)} n_l \text{ or } s_i{}' = \frac{1}{n}\sum_{l=1k(i)}^{K} n_l$$

where s_i and $s_i{}'$ are the downward and upward looking definitions of individual's status, respectively. If there was perfect equality, all the individuals would be in the same category and both expressions would be equal to one; this maximum-status is the reference point.

Based on a set of elementary axioms, Cowell and Flachaire (2017) show that inequality must take the form of an index in the following class:

$$I_\alpha(s) = \frac{1}{\alpha[\alpha-1]}\left[\frac{1}{n}\sum_{i=1}^{n} s_i^\alpha - 1\right],\ \alpha \in \mathbb{R},\ \alpha \neq 0, 1$$

where $\alpha < 1$ indicates the sensitivity of the index to different parts of the health distribution. In particular, high values of α produce indices that are more sensitive to high-status inequality, while low and negative values produce indices that are more sensitive to low-status. The use of different definitions of status s_i or $s_i{}'$ to calculate $I_\alpha(s)$, gives rise to an index of ordinal inequality based on a downward or upward looking status concept. The index is undefined for $\alpha = 1$, but the limiting form for the case where $\alpha = 0$ is:

$$I_0(s) = -\frac{1}{n}\sum_{i=1}^{n} logs_i$$

Therefore, in the case of perfect equality where everybody is at the same SAH category, both upward and downward versions of the index would be equal to zero. Any departure from this point, for example, a move of 10% of the individuals to other category, would increase inequality. The resulting size of the index would depend on the definition of status and the parameter α. However, there is no natural threshold to assess whether the index is "high" or "low"; instead, the estimates make sense when they serve to rank countries or distinguish trends within a country, as in this case.

As can be seen in these equations, the Cowell and Flachaire class of indices is actually similar to the well-known generalised entropy class of inequality measures GE_α (Cowell, 1980; Shorrocks 1980):

$$GE_\alpha(s) = \frac{1}{\alpha[\alpha-1]}\left[\frac{1}{n}\sum_{i=1}^{n}\left[\frac{s_i}{\mu(s)}\right]^\alpha - 1\right],\ \alpha \in \mathbb{R},\ \alpha \neq 0, 1$$

$$GE_0(s) = \frac{1}{n}\sum_{i=1}^{n} log\frac{s_i}{\mu(s)}$$

$$GE_1(s) = \frac{1}{n}\sum_{i=1}^{n} \frac{s_i}{\mu(s)} log\frac{s_i}{\mu(s)}$$

The GE_α, however, takes the mean $\mu(s)$ as the reference point, which makes sense only if the measure of status is cardinal. Therefore, when estimated with ordinal variables such as SAH, a common approach is to use an arbitrary cardinalisation. We follow this approach in section 6.3 to test whether these results differ from those obtained using the Cowell and Flachaire inequality measures.

Percentile bootstrap with 1000 replications is used to calculate confidence intervals, that is, we generate 1000 bootstrap samples by resampling with replacement from the observed data, and then we estimate I_α^b (or GE_α^b), with b = 1,...,1000, for each bootstrap sample. The percentile confidence interval is then:

$$CI_{percentile} = \left[c^b_{0.025}, c^b_{0.975}\right]$$

where $c^b_{0.025}$ and $c^b_{0.975}$ are the 2.5th and 97.5th percentiles of the empirical distribution function of the bootstrap statistics. All the routines to estimate the Cowell and Flachaire indices were programmed in Stata 14.2.

5.2 | Measuring mobility in health

Transition matrices or contingency tables provide a simple alternative to explore mobility. These matrices have been widely used to analyse mobility with categorical data such as employment status, educational attainment, or income quintiles (e.g., Ferrie, 2005). Let S denote the set of all possible health status values, with $S = [0,1]$ and subsets $S_1,\ldots,S_k \subset S$ such that $U_{k=1}^{K} S_k = S$. Also, let n_{kl} be the number of individuals in S_k at time t_0 and S_l at time t_1. The transition matrix P is therefore a $K \times K$ array with elements

$$p_{kl} = \frac{n_{kl}}{\sum_{j=1}^{K} n_{kj}}$$

If nobody remains in the same position (perfect mobility), all the elements in the diagonal are equal to zero; if everybody stays in the same position (no mobility), all the elements in the diagonal are equal to one.

Mobility indices, however, provide a more useful approach that takes advantage of all the available information at the individual level. In particular, we use the Cowell and Flachaire (2018) mobility index that has at least two important advantages compared to other commonly used mobility measures, namely it is able to capture nonlinear relationships, and it separates the definition of individual's status from the definition of mobility.

Let u_i and v_i denote the status of individual i at time t_0 and time t_1, respectively, where $u_i, v_i \in S$ and $S = [0,1]$, then the profile $z = \{(u_i,\ v_i)_{i=1,\dots,n}\}$ contains all the information about mobility for the population of n individuals. Based on a set of axioms on mobility orderings over all possible pairs z, Cowell and Flachaire (2018) derived the following class of mobility measures that are independent of the population size and the scale of status:

$$M_\alpha = \frac{1}{\alpha[\alpha-1]n} \sum_{i=1}^{n} \left[\left[\frac{u_i}{\mu_u}\right]^{\alpha} \left[\frac{v_i}{\mu_v}\right]^{1-\alpha} - 1 \right],\ \alpha \in \mathbb{R},\ \alpha \neq 0, 1$$

where μ_u and μ_v are the means of u ad v, respectively, and α is a sensitivity parameter that characterises the particular members of the class. Positive values of α produce indices that are sensitive to downward movements, while negative α's produce indices that are sensitive to upward movements. The limiting forms for the cases where $\alpha = 0$ and $\alpha = 1$ are, respectively:

$$M_0 = -\frac{1}{n} \sum_{i=1}^{n} \frac{v_i}{\mu_v} ln\left(\frac{u_i}{\mu_u} \Big/ \frac{v_i}{\mu_v}\right)$$

$$M_1 = \frac{1}{n} \sum_{i=1}^{n} \frac{u_i}{\mu_u} ln\left(\frac{u_i}{\mu_u} \Big/ \frac{v_i}{\mu_v}\right)$$

Since we are employing an ordinal measure of health, proportions are used to define status:

$$u_i = \hat{F}_0(x_{0i}),\ \text{and}\ v_i = \hat{F}_1(x_{1i})$$

where $\hat{F_K}(x) = \frac{1}{n}\sum_{i=1}^{n} I(x_{kj} \leq x)$ is the empirical distribution function of individual health in periods $k = 1$, 2, and $I(.)$ is an indicator function equal to one if its argument is true and equal to zero otherwise. Percentile bootstrap with 1000 replications is also used to calculate confidence intervals.

6 | RESULTS

6.1 | Inequality in health

We begin by comparing the distribution of SAH across waves using first- and second-degree dominance criteria that provide evidence of partial orderings (Aaberge & Brandolini, 2015). While the cumulative share of those reporting at most good health is the highest for the first wave (96.0% in 2002 vs. 93.3% in 2009; left axis in panel A of Figure 1 and Table S3), this is not the case for those reporting at most regular health (50.6% in 2002 vs. 52.8% in 2009). Consequently, the cumulative distributions for 2002 and 2009 intersect, which indicates they cannot be ordered based on the first-degree dominance criterion. The same applies for 2005–2009, although 2002 first-degree dominates 2005.

If we consider a weaker dominance criterion, however, 2002 and 2005 second-degree upward dominate 2009 (panel B of Figure 1). In other words, if we put more weight on those with worst health and start aggregating from below, it seems that the distribution worsens over the period: the higher proportion of individuals with very poor health in the

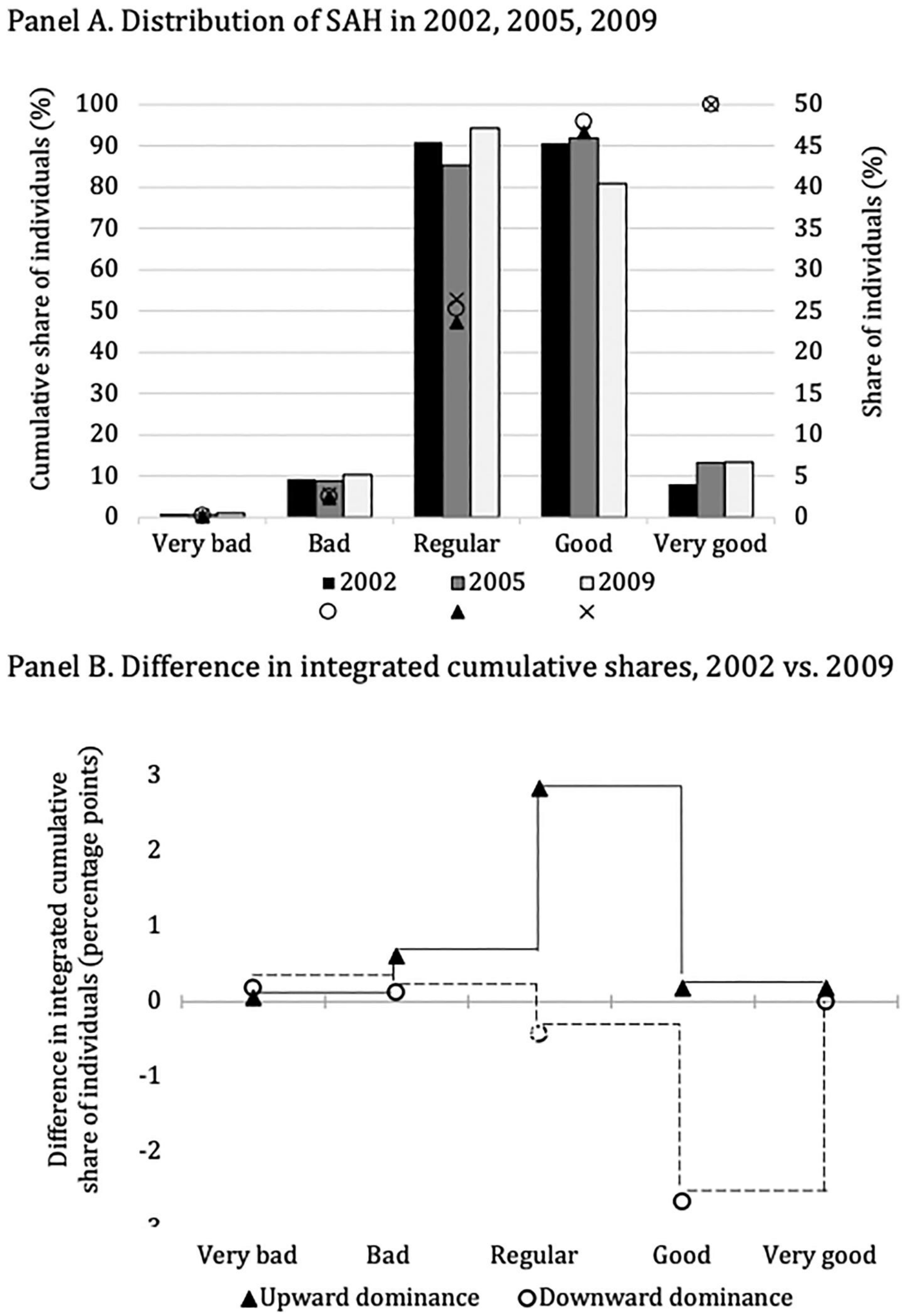

FIGURE 1 The distribution of self-assessed health during the public insurance expansion in Mexico (weighted figures). (a) Distribution of self-assessed health in 2002, 2005, and 2009. (b) Difference in integrated cumulative shares, 2002 versus 2009

last wave provides a disadvantage that is not offset by better performance in very good health. Graphically, this is seen as an always positive difference in the integrated cumulative distribution. On the other hand, no second-degree downward dominance is observed. If we first consider those with highest health and continue integrating going down, the difference in the integrated cumulative distribution changes sign. A recent extension of second-degree stochastic dominance that seeks to provide a general framework for ordering distribution functions with applications for cardinal attributes (namely income) can be found in Aaberge et al. (2013). Extensions of dominance criteria for ordinal variables that use quantiles to characterise inequality comparisons are also available (e.g., Zheng 2011), but this approach may be problematic if quantiles are not well defined (Cowell & Flachaire, 2017). We move now to consider the Cowell and Flachaire ordinal index, which can provide a complete ordering.

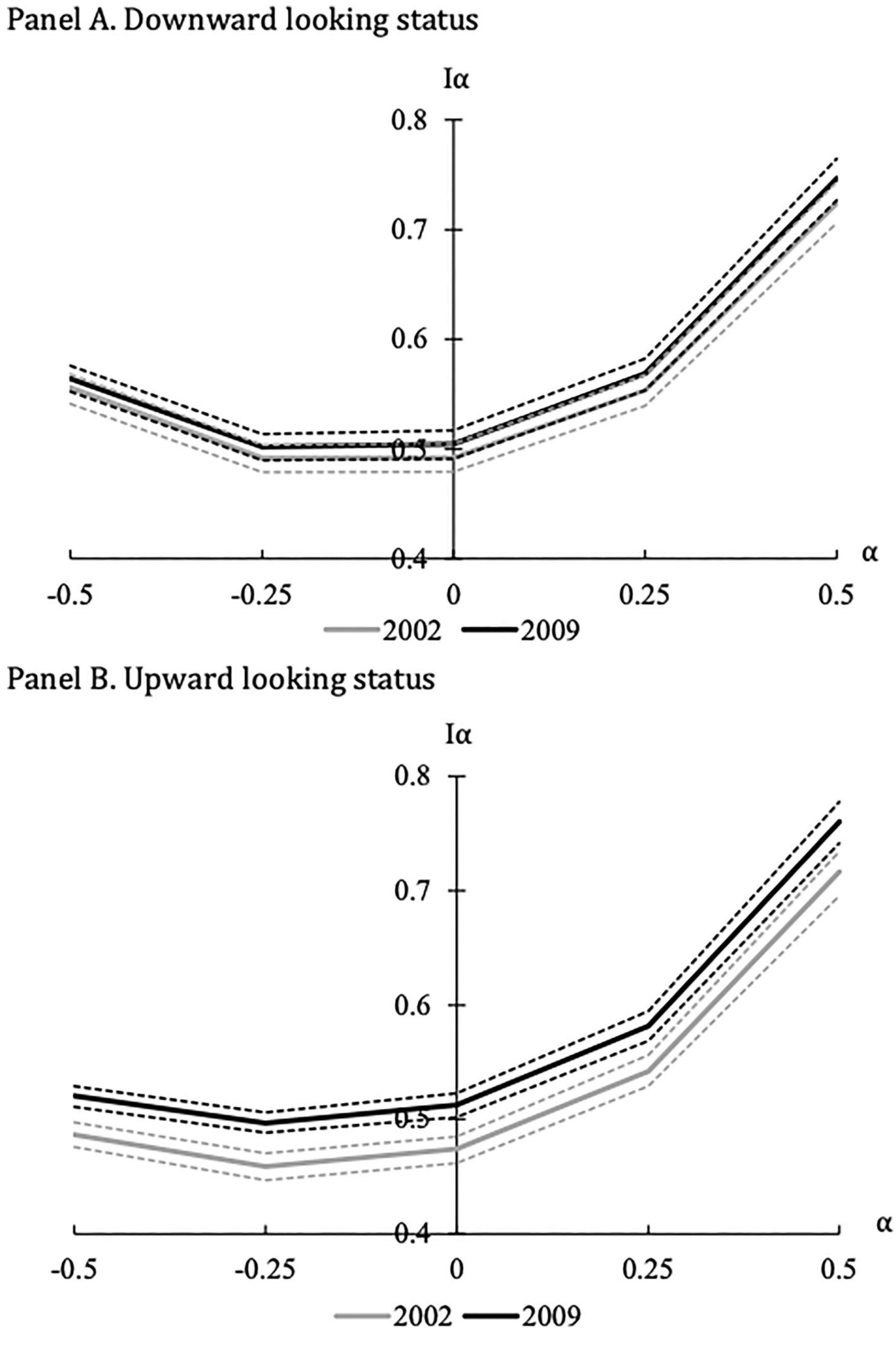

FIGURE 2 Health inequality during the public insurance expansion in Mexico (balanced sample, weighted estimates). (a) Downward looking status. (b) Upward looking status. Dotted lines represent 95% confidence intervals

Figure 2 shows the results of the Cowell and Flachaire inequality index using both the downward (Panel A) and upward (Panel B) looking definitions of status. In this context, the term upward (downward) implies that the status of each individual is determined by those above (below). Analysing the two versions provides more information about the underlying distribution. In both cases, the point estimates indicate a sustained increase in health inequality from 2002 to 2005 to 2009, but this change is only statistically significant for the whole period when the upward looking definition is used, that is, only medium-term changes are observed. In addition, if we hold the sensitivity parameter at $\alpha = 0$, the downward version of the index is higher than the upward version for 2002 ($I_0^{down} = 0.492, I_0^{up} = 0.474$), indicating that individuals tend to report higher categories at baseline. In contrast, the opposite is observed for 2009 ($I_0^{down} = 0.474, I_0^{up} = 0.513$), indicating that the distribution at the end of the study period is skewed towards the lowest

TABLE 1 Health inequality during the public insurance expansion in Mexico by baseline characteristics (balanced sample, weighted estimates; sensitivity parameter $\alpha = 0$)

	Downward looking status			Upward looking status			
	2002	**2005**	**2009**	**2002**	**2005**	**2009**	***n***
Total	0.492 (0.479, 0.505)	0.503 (0.490, 0.515)	0.504 (0.491, 0.516)	0.474 (0.461, 0.485)	0.497 (0.484, 0.508)	0.513 (0.502, 0.524)	15,088
Area of residence							
Urban	0.485 (0.469, 0.500)	0.504 (0.487, 0.519)	0.507 (0.492, 0.523)	0.471 (0.455, 0.486)	0.499 (0.484, 0.513)	0.514 (0.501, 0.527)	7934
Rural	0.497 (0.481, 0.512)	0.499 (0.483, 0.514)	0.492 (0.476, 0.509)	0.473 (0.458, 0.487)	0.485 (0.470, 0.499)	0.505 (0.491, 0.518)	7154
Sex							
Male	0.489 (0.469, 0.506)	0.500 (0.482, 0.517)	0.510 (0.490, 0.527)	0.466 (0.446, 0.483)	0.485 (0.467, 0.501)	0.511 (0.494, 0.527)	6790
Female	0.490 (0.472, 0.508)	0.501 (0.483, 0.518)	0.497 (0.480, 0.516)	0.477 (0.460, 0.493)	0.502 (0.486, 0.516)	0.511 (0.494, 0.525)	8298
Age							
15–30 years	0.452 (0.430, 0.470)	0.481 (0.461, 0.502)	0.487 (0.467, 0.507)	0.439 (0.417, 0.460)	0.462 (0.442, 0.481)	0.485 (0.464, 0.503)	5913
31–45 years	0.474 (0.448, 0.496)	0.483 (0.458, 0.505)	0.470 (0.442, 0.494)	0.465 (0.442, 0.486)	0.497 (0.474, 0.516)	0.508 (0.490, 0.527)	4597
46+ years	0.500 (0.475, 0.524)	0.491 (0.465, 0.514)	0.496 (0.470, 0.521)	0.493 (0.472, 0.512)	0.496 (0.474, 0.514)	0.503 (0.482, 0.521)	4578

Note: Inequality is measured with the Cowell and Flachaire inequality index; 95% confidence intervals are in parenthesis.

categories. On the other hand, if we hold constant the definition of status, the conclusion is the same for different values of the sensitivity parameter α. Therefore, only the adoption of different status definitions affects the conclusions.

Table 1 further analyses health inequality among population subgroups holding $\alpha = 0$. As explained above, this is to account for the possibility that different groups of the population consider different cut point levels when reporting SAH, but also to assess whether inequality patterns vary among these population groups. The results obtained are similar to the results for the total population. If the downward looking definition of status is employed, inequality in health seems stable across both rural and urban areas, males and females, and cohorts, but increasing if the upward looking version is considered—except for the older cohort.

6.2 | Mobility in health

The results presented so far indicate that the distribution of health worsen according to one of the definitions of status employed. Now we exploit individual changes in health between points of time to analyse mobility. In particular, we are interested in the extent to which health status in the previous period affects the distribution of health in the current period.

Figure 3 shows the distribution of SAH at Wave 2 (or 3) by SAH at Wave 1 (or 2). It seems clear that it is more likely to stay in the same state than to transition to another, especially if we look at the extreme categories. Those with very good health at Wave 1, for example, are more likely to have very good health at Wave 2. Similarly, those with very bad health at Wave 2 are more likely to have very bad health at Wave 3. The transition matrices in Table S4 present an alternative way of portraying this. In general, the larger percentages are located in the diagonal or close to the diagonal, which is also an indicator of persistence in health. Additionally, we can see that the values in the diagonal that correspond to lower categories of health increased, but those that correspond to upper categories decreased. This suggests that overall mobility was likely stable.

Next, we use the Cowell and Flachaire mobility index (Figure 4). One can think of this index as a summary of the transition matrices that takes advantage of individual history. While the point estimate of the index indicates a decrease

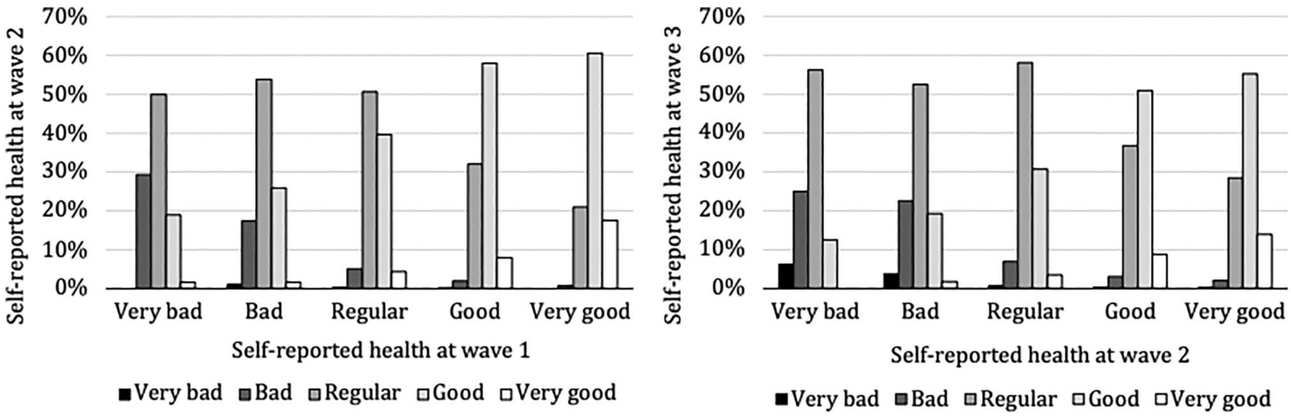

FIGURE 3 Self-assessed health at wave t by self-assessed health at wave $t-1$ (balanced sample, unweighted estimates)

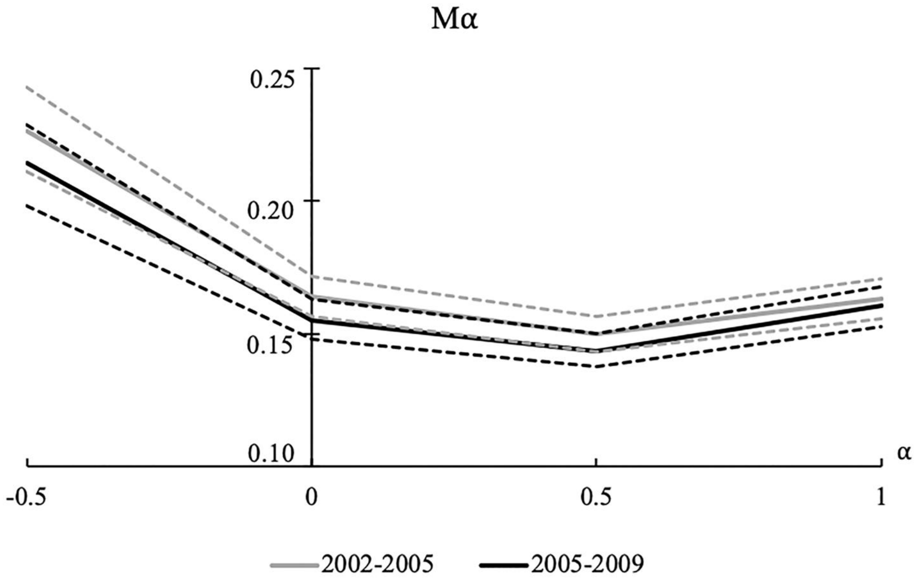

FIGURE 4 Mobility in health during the public health insurance expansion in Mexico (balanced sample, weighted estimates; dotted lines represent 95% confidence intervals)

in mobility (from $M_0^{2002-2005} = 0.164$ to $M_0^{2005-2009} = 0.155$ at $\alpha = 0$), the change is not statistically significant (confidence intervals overlap). This result holds for different values of the sensitivity parameter α. We can thus confirm the conclusions drawn from the transition matrices: mobility remained unchanged during the 2000s decade, that is, it is more likely for those with poor health to remain in the same position. While we cannot compare the sizes of the inequality and mobility indices—as they measure different concepts—, overall patterns of both suggest that the large expansion of health insurance coverage was not enough to improve the distribution of health. Moreover, if low mobility persists, it is unlikely to see important reductions in inequality.

6.3 | Robustness checks

This section examines whether some of the assumptions made to obtain the results in the previous section are likely fulfilled. In particular, we have a better look at the potential effects of non-response and the choice of the inequality measure.

6.3.1 | Reconsidering non-response

To assess whether attrition may be biasing inequality estimates, we recalculated the Cowell and Flachaire index using the unbalanced sample. Table S5 shows that these estimates are consistent with the main results discussed above. In sum, they suggest that health inequality increased between 2002 and 2009, although the changes are only statistically significant if the upward looking status concept is adopted. This conclusion holds, however, for both negative and positive values of the parameter α.

Next, we recalculated the Cowell and Flachaire indices for the balanced sample without weights (Figure S1). While the results are again similar, these estimates provide stronger evidence of an increase in health inequality between 2002 and 2009, as this change is not only statistically significant for the upward looking definition of status but also for the downward looking definition. The unweighted estimates of health mobility, on the other hand, confirm that it remained stable over the period studied (Table S6).

As noted before, proxy information of SAH was considered to avoid missing observations due to item non-response. If individuals with proxy information, however, are systematically different from the rest of the sample, the results would be biased. Hence. we recalculated the indices using only information directly reported by the individual. Table S7 shows that the magnitude of these estimates is only slightly lower, but the pattern is the same.

Finally, since attrition is not a threat to our conclusions, we conducted a test focused on item non-response using non-proxy information from individuals who participated in all three waves of the MxFLS (n = 19,971; see Table S1). In particular, we used multivariate imputation with chained equations (MICE) to take advantage of SAH information available for individuals with missing values for some waves. The model specified was an ordered logistic regression, with sex, age group, area and region of residence, marital status, education, household size, and participation in the labour market as independent variables. The number of imputations was set to five to simplify the computation procedure of bootstrapped confidence intervals. According to Schafer (1999) there is normally no practical benefit to using more than five imputations. The estimated values of the index for each bootstrap sample were combined using Rubin's rule (1987), which basically amounts to calculating an average. Table S8 shows that the results obtained for the parameter $\alpha = 0$ are similar to those presented above. An increase in health inequality between 2002 and 2009 is noted, although the increase is statistically significant for both the downward and upward looking definition of status.

6.3.2 | Measuring inequality with the generalised entropy index

Although the generalised entropy measures (GE_α) are only suitable for cardinal variables, we assess whether the results obtained using this indicator substantially vary from the results obtained using the Cowell and Flachaire index. The GE_α index was calculated with the status of individual i, s_i, simply indicated by the category number of SAH.

Table S9 shows that the generalised entropy estimates are consistent with those obtained using the upward looking definition of status. For $\alpha = -1,0,1$, this measure indicates that inequality in health increased over the period studied. These results hold for the balanced and unbalanced panel, with or without weights, except for some alphas for the weighted figures where the change between 2002 and 2009 is not statistically significant.

In summary, this analysis shows that the two indices can give consistent results in certain settings. However, Costa-Font and Cowell (2016), who previously analysed the correlation between health inequality rankings across 70 countries using the Cowell and Flachaire index and the GE index for different values of the sensitivity parameter α, showed that both measures resulted in similar patterns of inequality across countries only for the extreme case of $\alpha = 0.99$. Therefore, the choice of inequality measures should always take into account the nature of the variables. More specifically, we conclude that the analysis of ordinal variables such as SAH does not require arbitrary cardinalisation procedures, as the Cowell and Flachaire index is specifically designed for this type of variables.

7 | DISCUSSION

The main objective of this study was to analyse the evolution of pure (or univariate) health inequality in Mexico over the 2000s decade. We used a class of measures appropriate to deal with categorical indicators of SAH to analyse pure health inequalities. The results indicate that the distribution of health worsened in Mexico between 2002 and 2009, although the change is only consistent for the upward looking definition of status. Importantly, the choice of the inequality-sensitivity parameter α does not affect the conclusions. Together with the lack of mobility in health observed, we can thus conclude that Mexico is becoming more rigid.

While short study periods could be expected to provide little opportunity for movement in general, Hauck and Rice (2004) found evidence of large mobility in mental health in the United Kingdom over the 1990s decade. In contrast, Contoyannis et al. (2004) found strong persistence in self-reported health status in the UK in the same period. Our findings are in line with the latter.

Teruel Belismelis et al. (2012) previously analysed the effects of increased coverage through SP on perceived health status. They used data from the MxFLS and propensity score matching to create a suitable comparison group drawn from those still uninsured at the time of collection of the third wave. At baseline, those who gained insurance through SP were more likely to report bad health than the comparison group, but the analysis showed that a 6% increase in the probability of reporting good health among the former can be attributed to the programme. How can we reconcile this result with ours? While SP may helped improve SAH among beneficiaries, it seems that other factors shape the overall distribution of health.

Unfortunately, available data for Mexico do not allow analysing the extent to which different economic, institutional, and environmental factors affect health disparities. Evidence for China suggests that income inequality is an important determinant of health disparities. In particular, Baeten et al. (2013) argue that the contribution of income inequality to health inequality is between 25% and 30%. Wang and Yu (2016) also show that common indicators of income inequality such as the Gini coefficient and the Theil index are positively associated with health disparities. Income inequality in Mexico declined over the 2000s decade, however (Esquivel, 2015; OECD, 2014). This decline has been attributed to increases in remittances among low income households, and reductions in labour income and non-labour income (government transfers) inequalities (Esquivel, 2015; Esquivel et al., 2010). Costa and Cowell (2016), on the other hand, document that institutional performance, in particular better government effectiveness, is associated with health inequality declines. According to the Worldwide Governance Indicators (Kaufmann et al., 2010), government effectiveness in Mexico declined from 0.24 in 2002 to 0.17 in 2009. Other indicators of governance such as regulatory quality, control of corruption, and political stability and absence of violence present much larger drops. Therefore, these factors could be key to explain the pattern of health disparities in Mexico. Lifestyle indicators should be considered too. Specifically, Mexico has been subject to an obesity epidemic in the period, which has affected more deprived population groups.

From a policy standpoint, if the distribution rather than just overall levels of health is indeed a concern, a first step should be to start monitoring health inequality using univariate inequality measures. While international organisations such as the WHO and the OECD normally include Mexico in their endeavour to monitor inequality in health (e.g., OECD, 2014; WHO, 2000), there is no clear initiative at the national level. The National Council for the Evaluation of Social Development Policy (Coneval) currently estimates some inequality indicators, but these only include the Gini coefficient and two inter-decile ratios to measure income disparities. Furthermore, there is limited coordination between public health and health care system initiatives, which can explain why measures of health equity do not show major shifts since the expansion of health insurance.

In sum, while further analysis on the potential drivers of health inequalities is needed, the Mexican e suggests that insurance coverage can improve health levels but may be not enough to reduce health disparities and promote health mobility. In fact, health inequality and mobility likely depend on a myriad of factors beyond health care.

CONFLICT OF INTEREST

None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://urldefense.com/v3/__http://www.ennvih-mxfls.org/english/__;!!N11eV2iwtfs!-pw2i8Bf7xLrzwCgyPbvZPhaGCPYx93B-KFFqoltBp-sOe1rFZBy6Pe2dZUe0sXs$

ORCID

Joan Costa-Font https://orcid.org/0000-0001-7174-7919
Belen Saenz de Miera https://orcid.org/0000-0003-3117-0734

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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