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Analyzing disparity trends for health care insurance coverage among non-elderly adults in the US: evidence from the Behavioral Risk Factor Surveillance System, 1993–2009

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Abstract

Objective—To explore the changing disparities in access to health care insurance in the United States using time-varying coefficient models.

Data—Secondary data from the Behavioral Risk Factor Surveillance System (BRFSS) from 1993 to 2009 was used.

Study design—A time-varying coefficient model was constructed using a binary outcome of no enrollment in health insurance plan versus enrolled. The independent variables included age, sex, education, income, work status, race, and number of health conditions. Smooth functions of odds ratios and time were used to produce odds ratio plots.

Results—Significant time-varying coefficients were found for all the independent variables with the odds ratio plots showing changing trends except for a constant line for the categories of male, student, and having three health conditions. Some categories showed decreasing disparities, such as the income categories. However, some categories had increasing disparities in health insurance enrollment such as the education and race categories.

Conclusions—As the Affordable Care Act is being gradually implemented, studies are needed to provide baseline information about disparities in access to health insurance, in order to gauge any changes in health insurance access. The use of time-varying coefficient models with BRFSS data can be useful in accomplishing this task.

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Keywords

Health insurance; Disparities; Health surveillance data; Temporal trends; P-splines; Varying coefficient model

JEL Classification

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Introduction

Despite improvements in some health measures of Americans in the last decades and the increase in life expectancy [30, 36], disparities persist across certain groups—who continue to have poorer access to health care services as well as poorer health outcomes than their counterparts. Several factors have emerged and been identified in the literature as being key to being healthy and having access to health insurance. These factors include socioeconomic status and health insurance coverage [35, 39, 40]. The US stands alone among the industrialized countries in not providing health care coverage to all its citizens [33]. In the first 3 months of 2014, it was estimated by the US National Health Interview Survey (NHIS) that 18.4 % of persons aged 18–64 were uninsured [8]. In addition, earlier studies using data from the US Behavioral Risk Factor Surveillance System (BRFSS) have found an increasing trend of being uninsured among individuals aged 18–64 [1, 34].

The aim of this study is to identify disparities in health insurance coverage for adults aged 18–64 years across different demographic and socioeconomic groups over time using US BRFSS data from 1993 to 2009. The results, therefore, can be used as a baseline for future studies. The interest here is not to study the trends in health care insurance coverage, but to study the how disparities are changing over time–an analysis, to our knowledge, that has yet to be done.

This study's analytical approach is new to BRFSS applications; it used time-varying coefficient models (VCM) that allow the coefficients of the variables in a regression model —for instance, a logistic regression as in those applied here—to vary over time, which therefore allows the study of the trends of the coefficients (readable as odds ratios in logistic regression models). This approach provides a method that treats time as a continuous variable while taking into consideration the relationship between the variables. Therefore, observing the trends in the odds ratio (OR) plots can highlight the trends in the disparities, since we are observing how the odds of a certain category of a variable are changing in terms of the reference category for that variable. Since the BRFSS is a cross-sectional study that is performed each month on a new random sample, it is not longitudinal, and the observations are not necessarily dependent. Therefore, longitudinal data analysis would not be appropriate and classical time series analysis presents several limitations. Instead, the use of the VCM does not require the aggregation of observation for each unit of time as in time series or cohort trend analysis, therefore minimizing the loss of information in the variability between the observations. The VCM offers a flexible statistical approach for studying a very rich data source such as the BRFSS that has the advantage of spanning a large period of time with large sample sizes [4].

This paper suffers from two major limitations: first, even though the varying coefficient model (as an extension of classical linear models) allows capturing the dynamic feature which may exist in the data, our statistical analysis was essentially descriptive and does not provide the possibility to unequivocally identify a causal relationship between the health insurance coverage and the dependent variables. Second, this study is based on cross-sectional data. However, where panel data do exist, they often lack the details about health and health insurance coverage. Hence, despite the limitations of the cross-sectional data, BRFSS is the world's largest cross-sectional telephone survey and provides rather detailed information about health insurance coverage, health status, diseases, income, education, and other individual characteristics useful at least to provide first evidence for these types of studies.

Institutional background

One way that the US health care system is characterized–as with health systems in most countries—is by the ratio of private and public insurers funding the system. What is unique about the US system is the dominance of the private element over the public one: coverage is provided mainly through private health insurance that is the largest component of the health care system. In the first 3 months of 2013, it was estimated that 23.9 % of the US population under the age of 65 was covered by a public health plan [2]. These programs include Medicare, Medicaid, the Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plans, and military plans [2]. This leaves 60.3 % of those under the age of 65 covered by private health care plans, and 17.1 % uninsured [2]. The primary public US health coverage program is Medicare, a federal program enacted in 1965 and funded through Social Security payments. It provides health coverage mainly to people 65 years of age and older, some disabled people under 65 years of age, people with end-stage renal disease, and amyotrophic lateral sclerosis. Medicare has provided elderly Americans with basic health insurance coverage, with a number of gaps. Medicare does not cover the full range of health services needed by many elderly people: preventive care coverage is incomplete, and it lacks dental-, hearing-, and vision-related benefits [2]. In addition, Medicare does not cover chronic long-term care (LTC), most notably nursing home care for the disabled elderly [31]. In addition, over time, other "holes" in coverage have been identified such as that of varying rates of coverage for prescription drugs [25]. To have additional coverage for these needs, most Medicare enrollees buy their own supplemental insurance coverage (i.e., Medigap insurance also known as Medicare supplement insurance). Medicaid is funded jointly at the federal and state levels and is available for individuals of all ages and families with a low income and limited resources who cannot afford proper medical care. Each state sets its own rules about eligibility and covered services. The eligibility depends on several factors, such as age, pregnant status, disability, income and resources, as well as citizen/legal immigrant status. With the ACA, Medicaid has been expanded to include all nonelderly citizens and eligible legal residents whose family income does not exceed 133 [23]. Medicaid-ineligible people with incomes up to 400 % of the poverty line can receive premium subsidies through tax credits for health plans offered through state health insurance exchanges. Most non-elderly US citizens obtain health insurance through their employers or organizations such as unions, professional associations, or other groups to which they belong; people who may not have access to group insurance (e.g., self-employed or people to whom employers do not offer health insurance plan) may choose to purchase their own individual health insurance directly from an insurance company [2]. Individual insurance plans are traditionally much more expensive than group insurance since individuals will be responsible for paying the entire premium rather than sharing the cost with an employer and because of the type of the risk pool. Indeed, in the individual market, individuals tend to be more heterogeneous in their risk level than those who have access to group insurance. Not surprisingly, they tend to face explicit variation in premiums that depends on characteristics thought to be predictive of expected benefits among which health risk is probably the most important. Approximately 5 % only purchase insurance on the private non-group individual market [2]. In the wake of the Great Recession in the late 2000s, the United States saw a crisis in the labor market with escalating unemployment that today stands at 4.9 % [37]. Since employers provide health insurance as part of the benefits package for employees, the loss of a job has resulted in the loss of health benefits for millions of Americans, exposing individuals and families to potentially catastrophic health care costs in the event of a serious illness. Currently, workers who lose their job-based health benefits have few affordable insurance options. Unemployed individuals with incomes that are modest (but too high to qualify for Medicaid) can buy health insurance through the individual insurance market but the majority of those who seek coverage in this market do not end up buying a plan because of the prohibitive cost. Under the COBRA (Consolidated Omnibus Budget Reconciliation Act), unemployed individuals, who are employed by a firm with 20 or more workers, have the right to temporary continuation of health coverage at group rates (for up to 18 months). Few people, however, decide to continue their coverage through COBRA since the participants are generally required to pay the entire premium themselves and plans tend to be too expensive. The new ACA legislation does not make any changes in COBRA; however, unemployed individuals may have expanded health insurance options, including subsidies to purchase insurance through exchanges, and expanded access to Medicaid coverage. At this time, however, 32 of the states have indicated that they will implement the Medicaid expansion for 2016. In states that choose not to expand Medicaid, persons below 100 % of FPL will not be eligible for either Medicaid or subsidies on the exchanges. Even though losing or changing jobs may create a gap in health insurance coverage between employed and unemployed individuals [26], disparities in health care coverage also exist among other groups, especially younger and less-educated individuals and racial/ethnic minority groups. In general, those with lower income, younger age, less education, and being of Hispanic ethnicity were found to have higher percentages of having no health insurance [1, 34, 34]. These disparities can also be quite large, for instance it was estimated from the US National Health Interview Survey in 2013 that 42.6 % of 18–64 adults with no high school diploma were uninsured compared with 14.0 % with more than a high school education, and an estimated 41.4 % of uninsured Hispanics were found compared with 15.2 % uninsured non-Hispanic whites [1]. The same survey also found an estimated 39.1 % of the poor (defined as those with an income below the poverty threshold given the family household size) were uninsured compared with 11.7 % of the not-poor (defined as 200 % above poverty threshold) in the 18–64 age category

[1]. In addition, [1] have found an increase in uninsuredness for those with high school or less education, those aged 18–34, Hispanics, and the employed from 2001 to 2006, although the method used did not control for other variables and is not able to assess the gaps between the categories. The ACA reform envisions important changes from 2014 for workers, younger adults, those with a low income, and those at high health risk. As far as access is concerned, in exchange for tax cuts, employers with over 50 employees are obliged to supply their employees insurance coverage, a provision enforced by a fine of 2000 USD-per employee for each year of missed coverage. In view of this, therefore, there may be a real improvement in access to health care for many workers although this is not guaranteed as employers may find it more cost-effective to pay the fine rather than provide insurance coverage. Again concerning access, an extension of the Medicaid program is envisaged from 2014 and changes in the implementation are happening, particularly where this, as mentioned before, was left to state-level decisions. Moreover, the “Obamacare” reform will not allow insurance companies to fix premiums based on a patient’s clinical history (i.e., pre-existing conditions). This substantially limits companies dumping or rather refusing to cover high-risk individuals through price policies [23]. Insurers will not be allowed to turn away people with pre-existing health conditions, cancel coverage when beneficiaries need expensive treatment, or charge women higher premiums than men. Beginning in 2014, all individuals will be required, with exceptions, to have health insurance or pay 695 USD per person, up to 2850 USD per family. Comprehensive coverage will be mandated, with caps on annual out-of-pocket costs. In the USA, young adults have represented, until today, one of the largest segments of the US population without health insurance. Thanks to Obama’s reform, young adult children can stay on their parents’ policies up to age 26 (an increase from age 18) [10, 21]. Also, college students who go to college full time are now able to be covered through their parents’ insurance policies until age 26. Upon graduation, however, they lose their eligibility for family coverage. The current high unemployment rates across the country tend to exacerbate the difficulties young adults face in obtaining employment-sponsored health insurance. Moreover, the number of standard full-time permanent jobs in the last decade has decreased, while the non-standard work arrangements (temporary work, contingent, part-time contract etc.) have become much more common, especially for young adults. Even when employed, young adults are typically employed through low-wage or temporary jobs that generally do not offer health insurance benefits [9].

Methods

Data

BRFSS began collecting data in 1984; by 1993 it had become a nationwide system with a total sample size that exceeded 100,000 a year [6, 27]. Sampling is conducted by taking a new random sample every month using random digit dialing from a land-line sampling frame for a telephone interview. The US territories were not included in the analysis, as these data-collection sites had very few observations, particularly in the earlier years of the survey.

Data from the BRFSS from 1993 to 2009 were combined for performing the analysis. An advantage of the BRFSS is that most of the questions required for this analysis do not change significantly; therefore, a continuous data set can be created by combining data from several years of collection. The data from 2010, 2008, and 2006 were excluded because participants were not asked questions on high blood pressure and high cholesterol status during these surveys, and these questions were required for this analysis. This study, therefore, is based on 15 years of data. The outcome variable is having no health insurance plan, which is taken from a question on whether the respondent currently has a health care plan. Seven independent variables were also constructed from the data, mainly to represent socio-demographic variables. These were age, sex, race, income, education level, work status, and number of health conditions. Only those aged 18–64 were included in the analysis; individuals aged 65 and over were excluded, as most members of this age group have health coverage through Medicare.[1] The categories for the age variable, therefore, were those 18–34, 35–49, and 50–64 years of age. Race categories included non-Hispanic white, non-Hispanic black, Hispanic, and "other" race category, which includes all non-Hispanic minorities. Education is assessed in the BRFSS by asking the respondent, "What is the highest grade or year of school you completed?" Responses were placed on a six-point ordinal scale: (1) never attended school; (2) grade 1–8; (3) grade 9–11; (4) grade 12 or GED; (5) some college (1–3 year of college); and (6) college graduate or more. Because very few people were categorized in the first two groups, we collapsed categories 1, 2, and 3. Hence, the highest grade or year of school completed by the respondent was categorized into four mutually exclusive levels: less than high school graduate (or less than grade 11 education level), high school diploma, some college, and college graduate or more.[2] Work status contained three categories: working, not working, and student.

All the variables except for income and number of health conditions were taken directly from one question in the BRFSS dataset. The income variable was constructed by considering BRFSS household information on earnings and number of household members, as well as the poverty threshold for each year taken from the Department of Health and Human Services [38]. Survey participants found to be earning less than the poverty threshold—for that year and number of household members—were considered to be in the low-income category. Those earning three times more than the poverty threshold were categorized as high income, and the remaining participants earning amounts between these two categories were placed in the median income category. Responses to the household earnings question were often missing (approximately 14 %), and therefore, after constructing the income variable using this question with the available data, the missing values were imputed from an ordered logistic regression model with income as the outcome variable and sex, age, race, education level, and work status as the independent variables. The final sample size after imputing the missing values for income is 1,327,808 observations.

The number of health conditions variable was constructed by adding the responses to three questions in the BRFSS data set that asked participants if a doctor had ever told them that

[1]The nature of the question in the BFSS survey simply asks the respondent if they are currently enrolled in a health care plan. There is no follow-up question on what type of insurance that they hold and therefore it would not be possible to identify who would be using Medicaid.

[2]The 12th grade of secondary schools is typically the last year of high school.

they have diabetes or high blood pressure or high cholesterol. Combining the responses from these questions resulted in four categories, which represent having no, one, two, or three health conditions.[3]

Statistical analysis

A VCM was constructed in order to observe how the coefficients (or ORs) changed over time in order to study the trends of these disparities.[4] VCMs were first discussed by [16] and the description and estimation are well established in the literature. The analysis of trends using time-varying coefficients has been discussed mainly for use with longitudinal data [17–19]. The VCM is a direct extension of the generalized linear model. A generalized VCM with a response variable Y having a distribution from an exponential family, and independent variables $X_1, \ldots, X_p$, can be written as

$$\eta = a_0 + X_1 a_1(U_1) + \cdots + X_p a_p(U_p),$$

with the canonical link η and link function $g()$, which provides the relationship between the linear predictor and the mean of the distribution function. The coefficients $a_1, \ldots, a_p$ vary with the new variables $U_1, \ldots, U_p$, which are referred to as the effect modifiers [16]. Therefore, while in a generalized linear model the coefficients are constant, in a VCM we have coefficients that are a function of another variable (the effect modifier). The effect modifier can also be one single variable, U, such as time, in the case of time-varying coefficients. This case was used in this analysis, as we are interested in one effect modifier of time that is a variable constructed from the month and year of the interview for each observation.

To construct the VCM, it is necessary to test whether these coefficients are constant or actually vary with time, which was performed using two main steps. The first step is to fit a VCM for each independent variable while leaving all other independent variables with constant coefficients and then testing against the null hypothesis, which contains the model where all the variables have constant coefficients. This involves a likelihood ratio test between these two nested models, which shows whether the independent variable being tested has time-varying or constant coefficients. This test is performed for each independent variable used in the analysis.

The second step involves the building of the model by testing if the varying coefficients for a certain variable should remain in the model when other varying coefficients for another variable are already present. This involves a test between the two models:

[3]BRFSS includes among the "health variables" also the self-assessed health (SAH). Even though SAH has been widely used in previous studies examining the relationship between health and socioeconomics, SAH is a subjective measure of health that may involve biases in the measurement of disparities (see [5, 11, 20] for a discussion of biases associated with self-assessed health). In order to support the reliability of our measure of health insurance disparities, we employed a more objective (even though self-reported) functional measure of health: the number of health conditions.

[4]Although BRFSS is complex survey data, this analysis did not use weights to adjust for this. The addition of weights was very computationally heavy for the model and sample size used and would not have been feasible. However, since we are interested in coefficient or OR trends, the weights are not essential, particularly since the weighing variables are present in the model. A check of a simple model (with only one time-varying coefficient) with weights has shown very little effect on the results of the VCM (results are not shown). Descriptive statistics presented in Table 1 are consistent with this choice and consequently should be taken as references to better understand the models here proposed and not as unbiased estimates of the variables reported.

$$H_0: \text{logit}(nohplan) = \sum_{j=1}^{p} b_j Z_j + a_1(t) X_1,$$

$$H_1: \text{logit}(nohplan) = \sum_{j=1}^{p} b_j Z_j + a_1(t) X_1 + a_2(t) X_2 .$$

where "`nohplan`" is the outcome variable for having no health plan and Z_j are the variables with constant coefficients b_j. The null hypothesis includes the time-varying coefficient $a_1(t)$, which was found to be significant in step one. The alternative hypothesis is now testing whether to include the time-varying coefficient $a_2(t)$ for another variable X_2. These tests are performed in a stepwise manner for all the variables in the analysis until the final model is reached. To determine which variable should be added next, the residuals of the previous model is fit with each of the remaining variables, and the variable from the model that provides the best explanation for these residuals (i.e., highest deviance explained) is added next. This procedure was repeated at each step in the step-wise process of building the model. An alternative procedure would be to fit the full model with all the varying coefficients in the model and remove terms that are not significant. However, fitting a full model may greatly increase computation time and especially for big data applications such as the BRFSS.

The method described above involves using non-parametric techniques using splines (special piecewise polynomials) to fit the models. Using parametric techniques, while simpler, is not favored, as the strong assumptions they require lack flexibility and could create misspecification of the data and large bias [14, 16]. There are several non-parametric techniques that could be used; the present analysis used P-spline estimation, a type of penalized spline estimation method. This estimation method does not require selection of knots (the specific position points required to define the spline) and has a type of penalty, a difference penalty, that is not computationally expensive [12, 13, 22]. P-spline estimation also allows for the selection of the degree of the spline (quadratic, cubic, etc.) and the degree of the difference penalty to be used in the model. The models used a third-degree B-spline and a second-order difference penalty, as recommended by [13]. A total of 45 knots were used (three for each year for the 15 years of observation).[5]

When the final time VCM is found, OR plots could then be produced to easily interpret the results and trends. These OR plots show the trends of the ORs for each population subgroup. The OR plots are constructed to include the base effect (or the constant coefficient) and the time-varying coefficient for each subgroup. The reference category does not have an OR plot; it does still, however, have a time-varying coefficient, the significance of which can be found in the model summary.

[5]The models were fit using the `R` software program version 3.0.1 with the `mgcv` package and the `bam` function, which is designed for fitting models with big data [41].

Results

The disparities in terms of access to a health care plan can first be seen from the proportions as described in Table 1. Perhaps the most apparent differences are for the education and income variables. Disparities can also be seen between the race, age, and work-status categories, but less so for the participants' sex and number of health conditions categories. A Chi-squared contingency table test for each of the variables gave a significant *p* value, which was expected with such a high sample size, and indicates, therefore, that all the observed differences are also statistically significant.

Following the steps required for building of the time VCM resulted in a model in which all the independent variables had significant time-varying coefficients. This final model can be written as:

$$\begin{aligned}\operatorname{logit}(nohplan) &= \sum_{j=1}^{p} b_j Z_j + a_0(t) + a_1(t)\text{age} + \mathrm{a}_2(\mathrm{t})\text{sex} \\ &+ a_3(t)\text{edu} + \mathrm{a}_4(\mathrm{t})\text{work} + \mathrm{a}_5(\mathrm{t})\text{race} \\ &+ a_6(t)\text{income} + \mathrm{a}_7(\mathrm{t})\text{healthcond},\end{aligned}$$

where the variable abbreviations are found in Table 1. The time-varying coefficients $\sum_{i=1}^{7} a_i(t)$ were found for all the independent variables used in the model. The coefficient $a_0(t)$ is the time-varying intercept, which was also tested for inclusion in the model. Table 2 summarizes the estimates with the non-parametric component represented by the splines of each category with time. Looking at the constant estimates, we can observe that in general, younger age, male gender, lower education, not working, non-white race, and having lower income increase the odds of having no health plan. The greatest disparities were found in the income and education variables. The *p* values of the spline estimates can provide an initial idea of whether the coefficients are significantly varying over time. The table shows that almost all the coefficients are significantly time-varying except for age 50–64, male, student, white race, and having three health conditions. These *p* values can be underestimated [41], however, so *p*-value interpretation should be done with caution, especially if they are borderline significant. Therefore, although the only borderline significant *p* value was for the black race category, to observe trends, it is better to rely on the reading and interpretation of the plots.

The OR plots in Figs. 1, 2, 3, 4, 5, 6, and 7 show the change in the ORs over time for each category of a certain variable compared with the reference category of that variable. The plots contain confidence intervals produced by the mgcv R package, which are represented by the dotted lines. These plots clearly show which ORs change over time and which are constant. In general, we observed that all of the OR plots are exhibiting a non-constant trend over time, except for the categories male, students, and having three health conditions, which have constant ORs over time. Many of the plots suggest an improving situation in which there is a closing of the gap between the categories (i.e., decreasing disparities) for having a health care plan. This possibility can be seen for the age categories, the income levels, and the does-not-work category, in which there is a decreasing OR trend compared with their respective reference categories (i.e., the groups are becoming more similar over time).

For the other variables, education and race, the disparities appear to be increasing. For education, we observe that OR trends are increasing for all the education categories compared to the reference (university graduate or more category). For race, the OR trends are less clear, but seem to be increasing at a slower rate and at time overlap with the OR of one. For the other race category (which includes non-Hispanic minority groups), the OR began from below one (i.e., higher odds of having a health plan compared with white race), and increased to an OR above one before plateauing approximately after the year 2000. For the Hispanic race, which has the highest odds of having no health care plan compared to white, the OR appear to overlap with one in the earlier period of analysis but then increase after approximately the year 2000. The number of health conditions and the trends are even subtler, and there was a constant OR trend for those having three or more health conditions.

Discussion

The results clearly show that great disparities existed in health care coverage, and that these disparities have increased over time for certain socioeconomic groups. The driving factors of the increased disparities seem to be related to education and race. Ahluwalia and Bolen [1] have also shown an increase in uninsuredness for certain socio-demographic groups from 2001 to 2006, for the less educated, and among Hispanic groups, as was found in this analysis. Overall, the trends are positive, but gaps still remain: while the low-income category shows a decreasing OR trend, this disparity remained quite large by the end of 2009 (OR of approximately 6, compared with that of the high-income category).

The VCM also appears to control for demographic changes. For instance, while further descriptive analysis has shown that the proportion of the population in the 50–64 age groups increase significantly in the 15-year analysis period, the coefficient spline for this age category was not significant, indicating that the coefficient was constant with time. The remaining two age categories, however, had significant and decreasing OR trends compared to the 50–64 reference age category. The VCM was therefore able to identify which subgroups exhibited changing trends in their access to health insurance over time but without further analysis and the possible inclusion of interaction terms, for instance with education or income. The reasons for this change are unclear. One possible explanation for the decrease in the odds of uninsuredness in the 18–34 age group is the increase in the increase in the proportion of students in this age group, therefore allowing access to health care coverage through universities and other educational institutions. The results show that students and workers do not significantly differ in their access to health care coverage and therefore interactions between age and work status or education may explain these findings. The present model is an exploratory one that was able to identify which subgroups have shown a change, further analysis can then explain why this change occurred.

While income is the indicator that most directly measures material resources, education is perhaps the most basic socioeconomic component: lower education level may represent lifetime effects of socioeconomic limitations, and may influence future occupational opportunities and earning potential. Higher educational degrees are typical prerequisites for highly compensated work, which allows affordability of health insurance coverage and access to high-quality care [29].

Similar to the finding of the previous literature, our results show that non-Hispanic whites are more likely than any other race/group to have insurance coverage [1, 29]. The results from the VCM showed that there is an increased OR trend (although less clearly for the Hispanic category) for not having a health plan for African Americans and Hispanics compared with the white race reference group, indicating, therefore, that the disparities are increasing. The racial disparities in health insurance are strongly associated with socioeconomic factors: African Americans and Hispanics face greater economic and educational barriers than other groups and have less access to high-paying jobs that facilitate access to health care and health care coverage. Compared to non-Hispanic whites, non-Hispanic blacks and Hispanics tend to have higher rates of unemployment and under-representation in good-paying jobs that include health insurance as part of the benefit package [29]. Furthermore, individuals from racially or ethnically diverse backgrounds make up a great majority of the uninsured population [3, 15]. Since the nation’s population continues to become increasingly diverse (people of color are projected to comprise more than 50 % of the US population by 2050), this disparity in insurance coverage is likely to grow if left unaddressed [3].

The results fit in a rapidly changing scenario. Health insurance coverage has long been regarded as a facilitator to health care access; eliminating disparities in health insurance coverage is certainly one necessary component to reducing disparities in health outcomes, especially for the most vulnerable groups. In the USA, there have been several healthcare reform proposals with the aim of improving health care coverage, and consequently health care access to address this vulnerability: the most ambitious of recent legislation, the Affordable Care Act, became law in March of 2010. As is implied in the title of the ACA, one of the key provisions in the law is the expansion of coverage to the socially and economically disadvantaged population and making health care more affordable. It is still too early to evaluate the ability of ACA to reduce disparity in health insurance and health care access. Some authors have already pointed out some elements of weakness in the ACA [23, 24, 28].

Moreover, the extension of Medicaid and the subsidies available to economically disadvantaged individuals may not be utilized if the low-income individuals and families are not aware of these options. Individuals with low education (historically, black and Hispanic adults also have been much more likely than whites to have a low level of education and to live in poverty) not only have difficulty reading printed health materials, they also struggle to understand technical terms, jargon, and complex concepts that are often embedded in the Medicaid insurance program [32]. Therefore, states should be more aggressive in facilitating outreach efforts to effectively reach health care consumers and educate them about the ACA, ensuring that materials such as enrollment and claim information and financial disclosures are in plain language.

The challenge still remains in “closing the gap” and inverting the negative trends we have clearly shown in our analysis. Much is left to accomplish in order to prevent and reduce deep-seated historical inequities and pervasive cultural barriers that make it difficult to obtain basic health care coverage and medical care. In the era of big reforms addressing these issues, surveillance programs such as BRFSS can provide useful data for monitoring and evaluating their effectiveness.

Conclusions

Our study indicates that the disparities as well as temporal trends exist in many of the socioeconomic factors that are associated with health care access. The use of the VCM method was able to show how these disparities are changing over time and whether the gaps in the access to health care coverage have been improving or not. This provides significantly more information than observing changes in proportions between two periods of time for instance. The trends can be used to understand which subgroups of the population may require specific attention. Future work should focus on the impact of the other factors such as geographic variation and the interaction with the socioeconomic status on healthcare access, and how the effect of ACA is changing these disparities.

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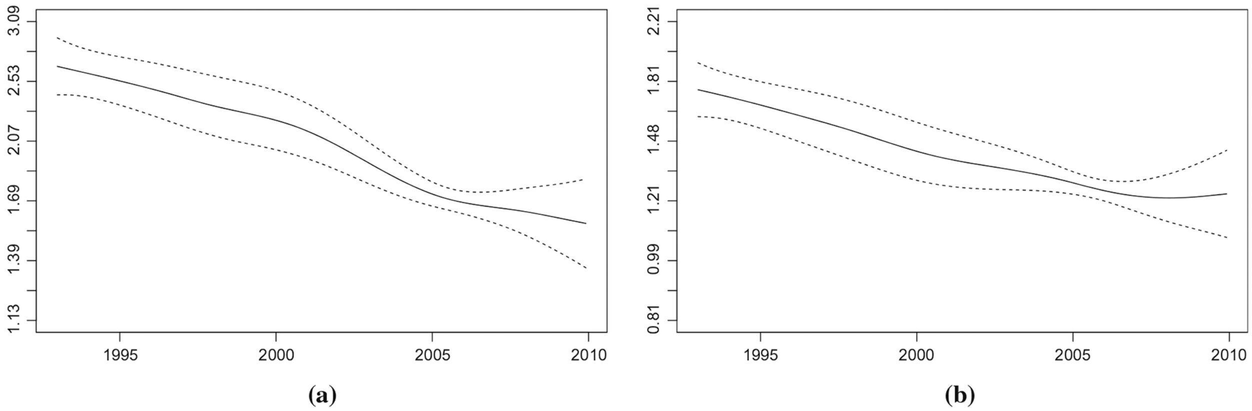

Fig. 1.

Odds-ratio plots for the age categories with the age category 50–64 as the reference category. **a** Age 18–34 and **b** 35–49

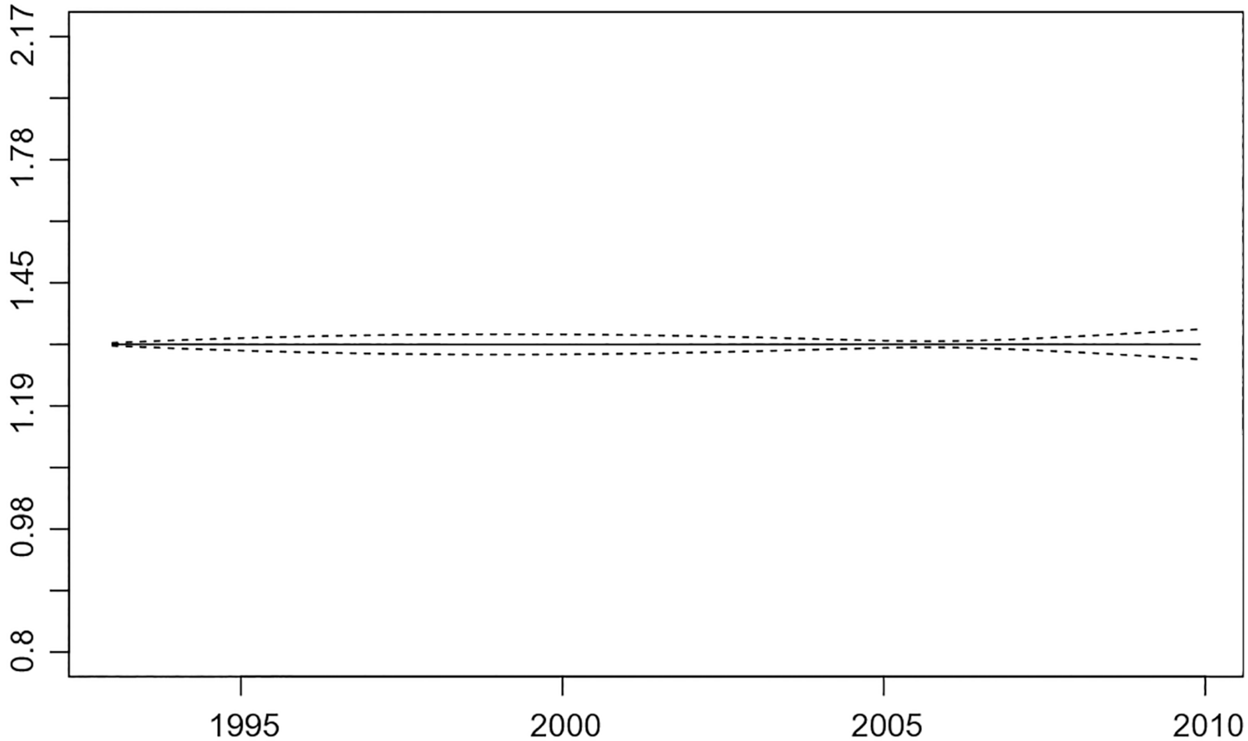

Fig. 2.
Odds-ratio plot for the male category with females as the reference category

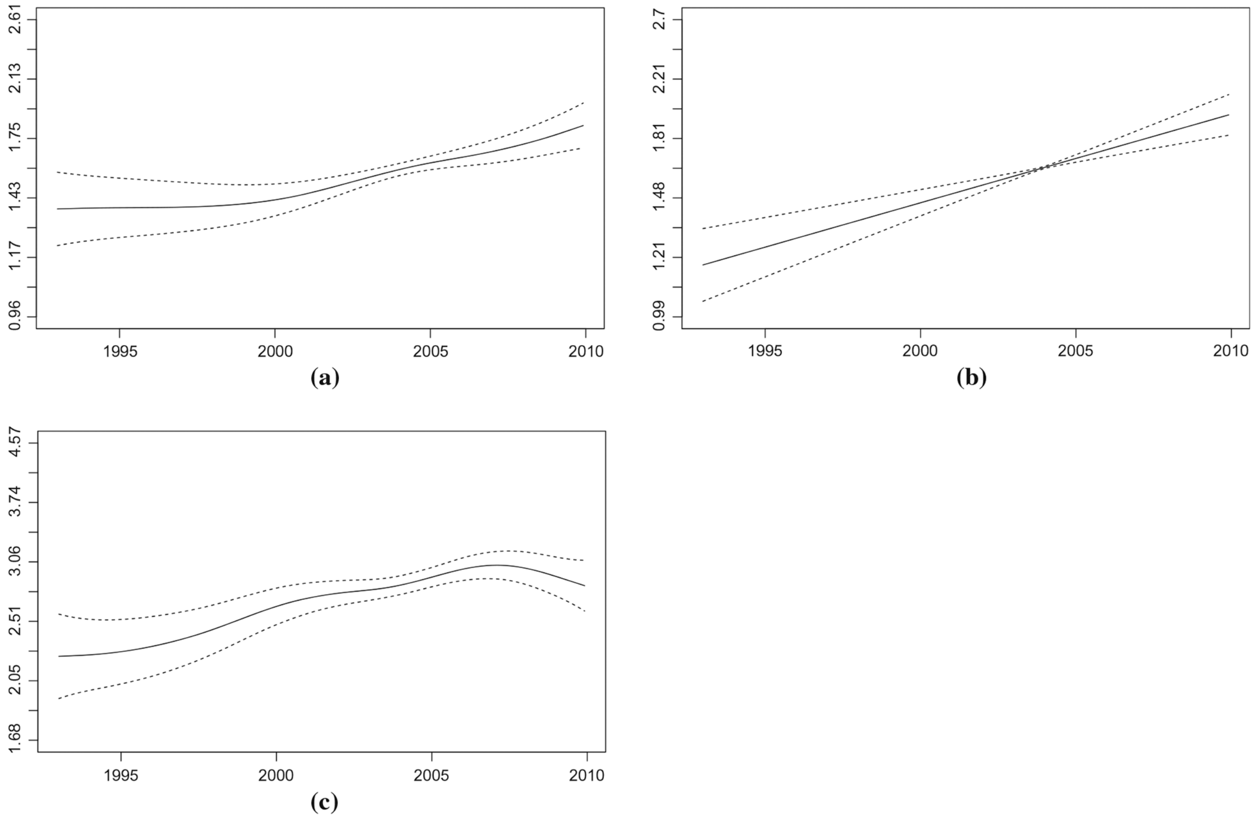

Fig. 3.

Odds-ratio plots for the education categories with the university education or above as the reference category. **a** Some college, **b** high school and **c** grade 11 or less

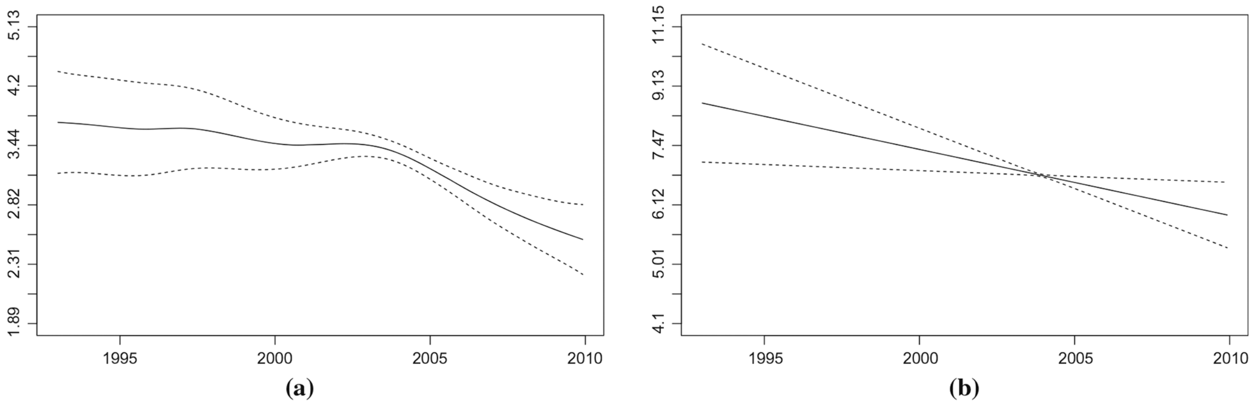

Fig. 4.

Odds-ratio plots for the income categories with high income as the reference category. **a** Median income and **b** low income

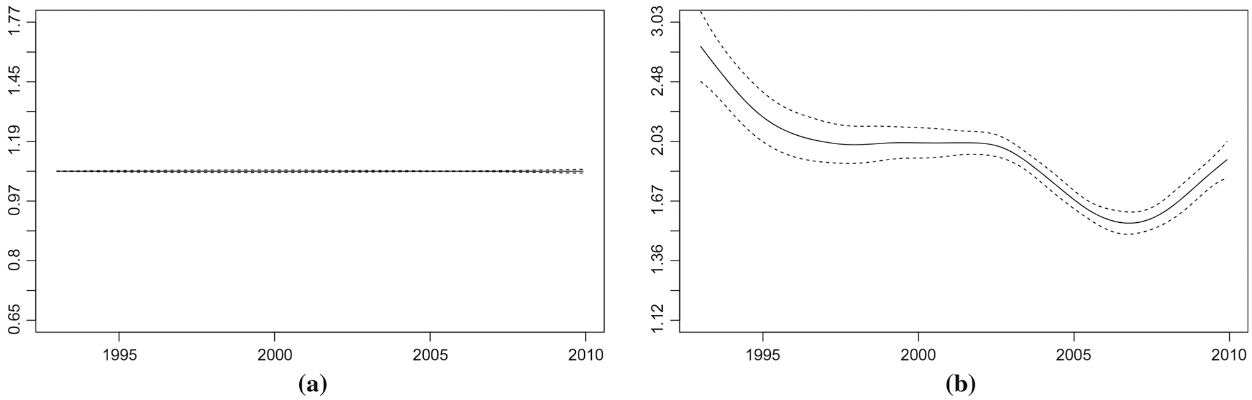

Fig. 5.

Odds-ratio plots for the work categories with works as the reference category. **a** Student and **b** does not work

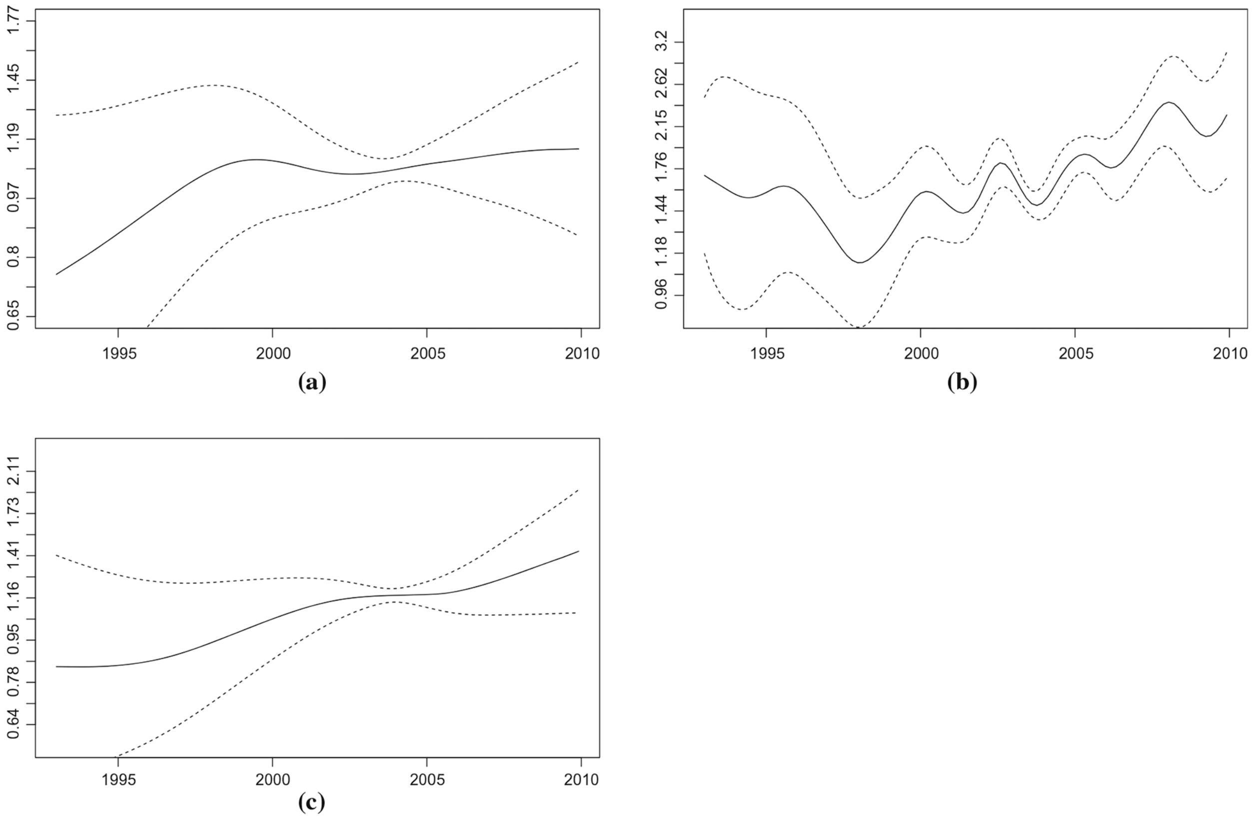

Fig. 6.

Odds-ratio plots for the race categories with white as the reference category. **a** Other, **b** Hispanic and **c** black

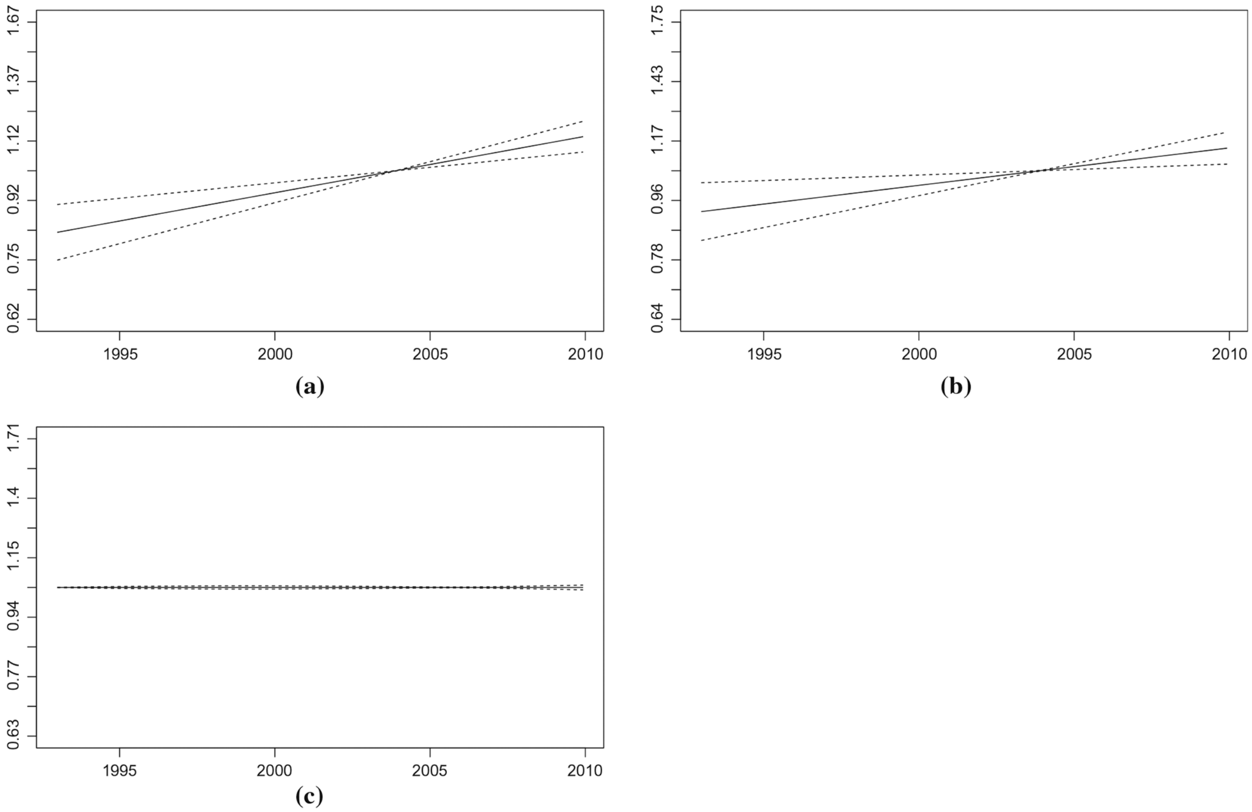

Fig. 7.

Odds-ratio plots for the number of health conditions categories with no health condition as the reference category. **a** One health condition, **b** two health conditions and **c** three health conditions

Table 1

Descriptives of variables and proportion of non-elderly adults having no health insurance by socio-demographic variables and number of health conditions in the USA from 1993–2009

Variable (abbreviation)	Total (%)	No health care plan (%)	χ^2 test*
	–	**11.1**	
Age (age)			
18–34	19.0	14.9	<0.001
35–49	39.0	10.4	
50–64	42.0	9.9	
Sex (sex)			
Female	60.8	11.1	0.002
Male	39.2	11.0	
Education (edu)			
University+	37.2	5.3	<0.001
Some university	28.4	11.1	
High school	27.6	15.0	
<Grade 11	6.8	26.7	
Income (income)			
High	39.8	4.5	<0.001
Median	53.7	13.5	
Low	6.5	31.3	
Work status (work)			
Works	72.3	9.2	<0.001
Student	2.1	18.0	
Does not work	25.6	15.9	
Race (race)			
White	79.4	9.4	<0.001
Black	8.7	16.8	
Hispanic	6.7	20.5	
Other	5.3	14.4	
No. of health conditions (healthcond)			
None	52.8	11.3	<0.001
One	30.4	10.2	
Two	13.6	11.5	
Three	3.2	12.6	

Sample size 1,327,808

*Test of independence between categories. Due to the large sample size, the confidence intervals are not reported, as they are very narrow

Table 2

Summary of the estimates for the final time-varying coefficient model for having no health care plan in the US from 1993–2009

Variable	OR (95 % CI)	*p* value
Age (reference: 50–64)		
18–34	1.87 (1.70–2.07)	<**0.001**
35–49	1.34 (1.23–1.47)	<**0.001**
s(time):18–34	–	<**0.001**
s(time):35–49	–	<0.001
s(time):50–64	–	0.518
Sex (reference: female)		
Male	1.32 (1.19–1.46)	<**0.001**
s(time):male	–	0.997
s(time):female	–	<0.001
Education (reference: university or more)		
Some university	1.58 (1.41–1.78)	<**0.001**
High school	1.64 (1.47–1.83)	<**0.001**
Less grade 11	2.77 (2.40–3.19)	<**0.001**
s(time):university or more	–	**0.002**
s(time):some university	–	**0.004**
s(time):high school	–	<**0.001**
s(time):less grade 11	–	<**0.001**
Work status (reference: working)		
Student	1.08 (1.00–1.15)	0.094
Does not work	1.84 (1.63–2.08)	<**0.001**
s(time):working	–	<**0.001**
s(time):student	–	0.984
s(time):does not work	–	<**0.001**
Race (reference: White		
Other	1.08 (0.92–1.27)	0.456
Hispanic	1.76 (1.09–2.84)	0.054
Black	1.16 (1.03–1.30)	**0.034**
s(time):white	–	0.510
s(time):other	–	**0.010**
s(time):Hispanic	–	<**0.001**
s(time):black	–	**0.024**
Income (reference: high)		
Median	3.11 (2.65–3.66)	<**0.001**
Low	6.76 (5.63–8.11)	<**0.001**
s(time):high	–	<**0.001**
	–	
s(time):median	–	<**0.001**

Variable	OR (95 % CI)	*p* value
s(time):low	–	**0.015**
Number of health conditions (reference: none)		
One health condition	1.01 (0.95–1.08)	0.715
Two health conditions	1.06 (0.99–1.14)	0.195
Three health conditions	1.04 (0.93–1.16)	0.601
s(time):none	–	<**0.001**
s(time):one	–	<**0.001**
s(time):two	–	**0.005**
s(time):three	–	0.983