Racial Segregation and the Effectiveness of Expanding Public Health Insurance for Children

November 2004

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PRELIMINARY and INCOMPLETE
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JEL Codes: I1, HO

ABSTRACT

Between 1990 and 2001, changes in eligibility standards for Medicaid and the creation of the State Child Health Insurance Programs enormously expanded the availability of public health insurance for children in the United States. The goal of these expansions was to reduce the number of uninsured children and improve child health outcomes. However, it is not clear that expanding public health insurance has reduced the number of uninsured in the way that policymakers had intended, at least at the national level. This paper explores the heterogeneity of health insurance coverage rates and sociodemographic characteristics of metropolitan areas within the states and finds that Medicaid and SCHIP expansions seem to have had differential impacts depending upon city characteristics. Metropolitan areas with lower levels of racial segregation were more likely than other areas to have seen improvements in overall insurance coverage for children following public health insurance expansions.

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‡I am grateful to the Robert Wood Johnson Scholars in Health Policy Research and the Economic Research Initiative on the Uninsured at the University of Michigan for financial support. Karen Conway, Christopher Carpenter, Rucker Johnson, Julie Cullen, Mike Chernew, Jonathan Ketcham and Mark Pauly provided valuable comments on an earlier draft.

I. Introduction

Since the late 1980s there has been an enormous expansion in the public health insurance system for the children in the United States. A series of laws passed between 1986 and 1990 required states to expand both income and categorical eligibility standards for the Medicaid program. More recently, the creation of State Child Health Insurance Programs (SCHIPs) has further expanded the availability of public health insurance nationwide, particularly for older children, while still giving states flexibility in setting their own standards. However, although the expansions have significantly increased public health insurance coverage, it is not clear that they have reduced the number of uninsured children in the way that policymakers had intended. In fact, although the fraction of children without health insurance nationwide increased from 12.9 percent in 1987 to 15.4 percent in 1998 before falling back to 11.6 percent in 2002 (U.S. Census Bureau 2003).

A factor that may be helpful in understanding the effectiveness of Medicaid expansions is that health insurance coverage patterns in the United States vary dramatically by geographic area. Table 1 shows that fewer than 2 percent of children in Harrisburg, PA wee uninsured during the 1990s, while more than 30 percent of children in El Paso and McAllen, TX lacked coverage. As Cunningham and Ginsburg (2001) show that a substantial portion of geographic heterogeneity is explained by neither individual characteristics nor differences in health care markets. Marquis and Long (2002) note a 35 percentage point spread in the fraction of the U.S. population covered by employer-sponsored insurance across metropolitan areas, and build a model to explain variation in the probability that firms offer health insurance coverage across local labor markets. They find evidence that several market characteristics, including unemployment rates, labor market concentration, unionization and firm size have significant effects on the probability that employers in a given area offer health insurance to their employees.

However, availability of employer-sponsored health insurance is only one factor that is likely to affect the impacts of Medicaid and SCHIP eligibility expansions. Adding labor market variables to a model similar to that of Cunningham and Ginsburg still leaves a substantial amount of unexplained variation across MSAs.[1] A growing body of literature in economics is recognizing what has already been pointed out in the sociological and public policy literatures – that policy implementation factors such as ease of enrollment and outreach campaigns play an important part in determining the success of a new program. This seems especially likely to be true in the case of public health insurance expansions for children, where take-up has been far from universal.

Selden et al. (1998) find that in 1996, after most of the Medicaid expansions had been phased in, 10 million children remained uninsured and half of them appeared to be Medicaid eligible. Kenney et al. (2003a) find that by 2002, after SCHIP had taken effect, the number of uninsured children in the U.S. had fallen to 7.8 million, but more than half still appeared eligible for either SCHIP or Medicaid. A comparison of 1999 and 2002 survey data from the National Survey of America's Families reports that parental awareness of the SCHIP program rose by 23 percentage points to 71 percent in 2002; however, only about half of parents of low-income children in 2002 understood that families did not need to be receiving welfare in order to enroll children in SCHIP (Kenney et al., 2003b).

Aizer (2003b) argues that information networks are an important determinant of whether or not eligible children are enrolled in Medicaid. She finds that outreach and publicity campaigns in California in the late 1990s had the effect of both increasing Medicaid

[1] These results are available from the author upon request.

coverage and improving health outcomes, and that this effect was largely confined to Hispanic children in communities exposed to Spanish-language outreach and advertising. Because of the importance of information dissemination in the Medicaid and SCHIP enrollment processes, it seems probable that the impacts of eligibility expansions according to demographic characteristics of the city. Specifically, these effects may have differed by the degree to which minority populations are residentially segregated from whites and from one another.

The goal of this paper is to examine the degree to which effectiveness of Medicaid and SCHIP expansions at improving the child health insurance rate varied within the states at the MSA level based upon racial segregation in residential housing patterns. The following section describes the Medicaid and SCHIP programs and their recent eligibility expansions. Section III develops hypotheses about the relationship between segregation patterns, outreach and health insurance program enrollment. Section IV describes the data used in the empirical analysis and Section V presents the results of the analysis. Finally, Section VI discusses the results and summarizes the main findings of the paper.

II. The Medicaid and SCHIP Programs

Medicaid was created in 1965 by Title XIX of the Social Security Act as the American public health insurance program for the poor. It was originally available only to women and children receiving Aid to Families with Dependent Children (AFDC) welfare benefits, as a supplement to Medicare for elderly and disabled individuals with extremely low income, and to others in the social welfare system.[2] Until the early 1990s, the structure of the program was similar to that of AFDC. Each state administered its own Medicaid program, with some discretion as to choosing which services to cover, setting reimbursement rates for participating health care providers, and deciding whether or not to extend eligibility to very poor non-AFDC populations, such as the "medically needy."[3] The federal government shared the cost of each state's Medicaid program using a cost-sharing formula based upon the state's per capita income relative to the national average. In return, the federal government required that states offer all Medicaid recipients a standardized minimum set of benefits without cost sharing to categorically needy recipients, including welfare recipients. The basic required benefit package in Medicaid includes inpatient and outpatient hospital services, physician visits, prenatal care, laboratory and x-ray services and preventive care services for children.

Although Medicaid was widely regarded as the American public health insurance program for the poor, it was by no means available to all poor children. For most children outside of the foster care system, Medicaid coverage was directly linked to welfare eligibility and participation. Because there was both a categorical eligibility requirement for AFDC – living in a single parent household – poor children living in two parent households did not usually qualify for Medicaid. Additionally, income eligibility limits for single parent families

[2] This would include foster children and Supplemental Security Income recipients.
[3] This is a program for families who were categorically ineligible for welfare (two-parent families) and had medical expenses so high that they had "spent down" to poverty level.

were extremely low in many states, so that many children in families well below the federal poverty line were eligible for neither AFDC nor Medicaid. In 1990 the national average maximum income for AFDC eligibility in 1988 was only $5,000 (or 46.9 percent of the federal poverty line). No state offered AFDC to families with incomes higher than 80 percent of the federal poverty line, and eligibility was cut off as low as 20 percent of poverty ($2,200) in Texas (National Governor's Association 1990).

During the mid-1980s, lawmakers became concerned about evidence showing high infant mortality and other poor health outcomes for young children in the U.S., relative to other industrialized countries. Congress passed a series of six laws between 1986 and 1990 that first encouraged and later required the states to expand the eligibility criteria for children in their Medicaid programs using only age and family income as eligibility criteria, in essence "de-linking" AFDC and Medicaid eligibility by removing categorical eligibility requirements. Consistent with concerns about infant mortality, the initial expansions targeted pregnant women and infants. The first mandatory expansion of Medicaid, passed under the Medicare Catastrophic Coverage Act of 1988, required that all infants living in families with income below 75 percent of the federal poverty line (regardless of their eligibility for AFDC) be covered by Medicaid by July 1989. Shortly thereafter, mandatory coverage was expanded by the Omnibus Budget Reconciliation Act of 1989 to include all children under the age of 6 living in families with income below 133 percent of the federal poverty level.

As the expansions progressed, the federal government required expanded coverage for older and older children. In July 1991 states were required to begin phase in coverage for children under 18 living in families with incomes below the federal poverty level, starting with the youngest children, so that by 2001 all children living in poverty were Medicaid-eligible. As a result of the expansions, the number of children eligible for Medicaid nearly doubled in eight years, so that by 1996 one in every three American children was eligible for the program.

The Balanced Budget Act (BBA) of 1997 encouraged states go even further by creating new public health insurance programs for children that could be completely independent of the social welfare system. OBRA 1997 authorized $40 billion in block grants to the states over ten years to create State Child Health Insurance Programs (SCHIPs). States were given the choice of using SCHIP funding to either create new public health programs independent of Medicaid or to use existing Medicaid programs to expand coverage. As of October 2003, 18 states have chosen the SCHIP-only expansion, 13 have expanded entirely through Medicaid and the remaining 19 have adopted a hybrid approach (CMS 2003).

In part because of the different state/federal cost sharing arrangement, states enjoy considerably more freedom in administering their SCHIP programs than they do under Medicaid. The program was designed to provide coverage for "target" children with family incomes of below 200 percent of the federal poverty line who are ineligible for Medicaid, but some states have chosen to set eligibility levels even higher. Under SCHIP, states also have greater flexibility in setting a benefits package and can require cost sharing of certain higher-income families, subject to federal guidelines. This means that the cost and quality of Medicaid and SCHIP benefits in some states may differ, but the BBA 1997 provisions still represents a significant expansion in the availability of subsidized public health insurance for children, beyond what had been authorized under the Medicaid expansions.

III. Race and the Expansion of Public Coverage

The few papers that exist in the literature on race and public health insurance coverage tend to focus on differential impacts of program expansion by the race of the child. Racine et al. (2001), for example, analyze health care utilization and outcomes for children in the National Health Interview Survey over the period of major Medicaid expansions (1989-1995). They find that black and Hispanic children were significantly more likely to gain health insurance, to get medical care and to have improved health outcomes after the expansions had taken place. All of these effects were measured through changes over time in national averages by race group, and did not exploit either variation at the state level in Medicaid policy or variation at the community level in sociodemographic characteristics.

Given that Medicaid eligibility is determined at the federal and state level, why might it be informative to look at local variation in coverage changes? As Figures 1A and 1B illustrate for two large states, California and Pennsylvania, health insurance coverage patterns vary widely within many states. In California, a very low employer-based coverage rate in Fresno is largely compensated for by higher-than-average Medicaid coverage. In San Diego, on the other hand, there is a higher employment-based coverage rate but also a larger fraction of children uninsured. As is documented by Cunningham and Ginsburg (2001) a large portion of this variation is not explained by either individual characteristics or health care market conditions. The sociological and public policy literatures have recently placed a great deal of emphasis on the role of community-level outreach and information networks. Several authors in the economics literature (Remler et. al 2001, Aizer 2003a and 2003b) have started to pick up on these ideas. There are several ways in which segregated housing patterns could affect child health insurance coverage through outreach and information networks.

A priori, it is impossible to say whether racial and ethnic segregation will lead to larger or smaller effects of the expansions. However, we can form several working hypotheses. To a large extent, the impacts of segregation on coverage changes (if there are any) should depend upon both the racial and geographic distribution of uninsured children across each metropolitan area. One possibility is that uninsured children in the early 1990s were disproportionately non-white and living in segregated neighborhoods. If black and Hispanic children were more likely to be eligible for public health insurance coverage, residential concentration could have lead to more effective outreach and enrollment campaigns. The concentration of eligible populations could have also improved the likelihood that information about eligibility and enrollment procedures traveled by word of mouth. On the other hand, if segregation patterns were particularly pronounced, information (either formal or informal) may never traveled into minority neighborhoods in the first place.

Another possibility is that uninsured children at the beginning of the expansion period were not predominantly non-white and located in segregated neighborhoods. If program enrollment and outreach efforts were not targeted geographically, then segregation patterns should have made no difference in how Medicaid and SCHIP programs affected health insurance coverage at the MSA level. However, if program outreach was targeted at segregated and possibly centralized neighborhoods, then the presence of these types of housing patterns would have lead to less effective enrollment campaigns. One way in which to try to separate the possible negative effects of segregation on coverage increases is to use an individual-level child race interaction term to see if segregation patterns affected all children or only children in the segregated race group.

V. Data

A dataset for the analysis was constructed by pooling the first waves of each of the six panels of the Survey of Income and Program Participation (SIPP) conducted since 1990. American households are sampled independently for each SIPP panel, so this produces a pooled cross section of children in the years 1990, 1991, 1992, 1993, 1996 and 2001. Information is available about each family's demographic characteristics, family income and employment behavior, as well as the child's health insurance coverage status. State and metropolitan statistical area (MSA) of residence are also identified for 67 major MSAs in 35 different states[4], creating a nationally representative sample of just over 58,000 children living in non-rural settings. Table 1 contains descriptive statistics for this sample.

Data on Medicaid generosity are matched to the microdata by state of residence and year. Because of difficulties associated with capturing something as complex as the generosity of a state's public health program in one variable, three different variables are used in the empirical analysis. Each of these measures varies by year, both within and across states. The first variable is simply the maximum income (measured as a fraction of the federal poverty line) at which an infant[5] is eligible for either Medicaid or SCHIP in a given state or year. The second variable is the maximum age at which a child is eligible for either Medicaid or SCHIP in a given state and year[6].

The final variable used is a "simulated instrument" similar to the one developed by Currie and Gruber (1996). Using a 1996 national sample of children under nineteen and Medicaid eligibility data from the National Governor's Association, I calculate the fraction

[4] The SIPP groups the lowest-population states in most survey years for purposes of confidentiality, but this coding does not pose a major problem for this analysis since these contain very few MSAs.
[5] An infant is a child under the age of one.
[6] Note that the maximum income eligibility standard for older children will be lower than that for younger children in most states, especially before 1996.

that would be eligible for Medicaid or SCHIP under each state's rules for a given year. This measure varies within and across states over time based upon the legislative generosity of a state's policy, but because the same national sample is used to calculate each state's measure, it does not capture any state-level differences in income and age distributions of children that might have independent effects on insurance coverage.

Graphs of the changes in each of the three public health insurance variables between 1990 and 2001 are presented in the Appendix. Generosity of the state Medicaid programs expanded enormously during these twelve years, encouraged by both the mandated and the optional expansions of coverage legislated at the federal level. For each of the measures, there is a noticeable increase in eligibility over the 12 years being considered. There is also variation over time in the diversity of state policy which is only partially captured in the graphs by changes in the minimum and maximum values of the measures. The simulated instrument variables demonstrates no only the most pronounced average increase over time, but also the most variation within states over time. In the average state in 1990, only 3.9 percent of children were eligible for Medicaid through an expansion (non-AFDC recipients), and by 1996 this had grown to 24.1 percent of all children. With the inclusion of SCHIP in the late 1990s, the fraction of children in the average state eligible for some type of public health insurance coverage grew to almost two thirds.

In order to measure differences in racial housing patterns between cities and over time, set of segregation indices is matched to the child sample by MSA of residence. A number of detailed measures of racial housing segregation have been calculated by the Census Bureau[7] using census data from 1990 and 2000. Two measures of segregation for blacks[8] are used in

[7] Source: http://www.census.gov/hhes/www/housing/resseg
[8] Future research will also consider residential segregation patterns for Hispanics.

this analysis: interaction and centralization indices[9]. The interaction index measures the extent to which minority group members are exposed to the majority group. It is defined as minority-weighted average of the majority proportion of the population in each area, or:

$$\text{INTERACTION} = \sum_{i=1}^{n}\left[\left(\frac{y_i}{t_i}\right)\left(\frac{x_i}{X}\right)\right]$$

where n is the number of census tracts in a given metropolitan areas, y is the non-Hispanic white (majority) population, t is the total population, x is the minority population, and X is the sum of all minority populations across all census tracts. This measure varies between zero and one, with values closer to one indicated more interaction, or less segregation.

The centralization index measures the extent to which minority group members reside in the center of an urban area. It is defined as relative share of the minority population that would have to change their area of residence to match the centralization pattern of the majority population, or:

$$\text{CENTRALIZATION} = \sum_{i=1}^{m}\left(X_{i-1}Y_i\right) - \sum_{i=1}^{m}\left(X_iY_{i-1}\right)$$

where m is the number of census tracts in a given metropolitan area ranked by increasing distance from the Central Business District. This measure varies between -1 and 1, with positive values indicating a tendency for minority group members to reside closer to the city center, or more segregation. These indices are only calculated every ten years, so values for the years between 1990 and 2000 are filled in by linear interpolation[10].

Finally, in order to control for differences in economic conditions between cities, a set of variables describing local labor markets is matched to the child sample by year and MSA

[9] Detailed descriptions and definitions of these variables are available at http://www.census.gov/hhes/www/housing/resseg/app_b.html.
[10] Given that trends in housing patterns move very slowly, the assumption of linearity seems to be a fair one.

of residence. The fraction of employment in each MSA is broken down into ten major industry groups (2-digit SIC codes) using data from the Bureau of Economic Analysis[11]. The BEA also provides data on the number of employers in each metropolitan area, which can be used with geographic area to calculate employment density. Local unemployment rates are taken from Bureau of Labor Statistics calculations[12]. The lower portion of Table 1 provides descriptive statistics for the MSA-level data.

Table 2 ranks the metropolitan areas in the sample by fraction of children uninsured. Estimates for each city using pooled 1990-2001 data range all the way from 1.3 to more than 45 percent of children without health insurance. Perhaps more interesting is the fact that coverage patterns also vary significantly within a number of states. Although the state of Texas has a relatively high fraction of uninsured, this fraction varies from 15 percent in Austin to 24 percent in Houston to 45 percent in McAllen. In Cleveland 5 percent of children are uninsured while in Toledo that number is almost 15 percent. There is also statistically significant within-state variation in Pennsylvania, Michigan, California and Florida.

Tables 3 and 4 list the Interaction and Centralization Indices for each of the cities. Lower values of the interaction index indicate that housing patterns limit the interaction of black and white families. By this measure, New York and Detroit are the two most segregated metropolitan areas in the sample, followed by Chicago, Miami and Cleveland. The cities with higher interaction values tend to be smaller and to have smaller black populations, although this is not always the case. Phoenix, Seattle, Minneapolis and San Diego are among the least segregated large cities in the sample. The centralization index in

[11] Source: U.S. Department of Commerce, Bureau of Economic Analysis, Regional Economic Information System (RCN 0316), May 2003.

[12] Unemployment rates in March of each year, not seasonally adjusted. Source: Author's data extracts from www.bls.gov/lau/home.htm

Table 4 takes a positive value to reflect the degree to which blacks would have to move out from the city center in order to have similar housing patterns to whites. Negative values of this index, as are observed for six sample cities including West Palm Beach, San Diego and Raleigh, indicate that whites are more likely to live in the city center. Large cities that have relatively centralized black populations include Boston, Detroit, Cincinnati and Cleveland.

VI. Analysis

The regression model estimated as a baseline for the empirical analysis is as follows:

$$U_{imst} = a_m + a_t + bMED_{st} + g_1 X_{msti} + g_2 Z_{mt} + e_{imst} \qquad (1)$$

where U is a dummy variable indicated whether or not the child is uninsured, MED is an indicators of Medicaid/SCHIP program generosity that varies within states over time, X is a vector of child and family sociodemographic characteristics. The vector Z contains MSA-level variables, including the unemployment rate, the fraction of employment in manufacturing, services and government, and employment density. These measures vary within MSAs over time. Year and MSA-level fixed effects are included. The estimates presented in the paper are for linear probability models; probit models give similar results. The standard errors used to calculate t-statistics are clustered at the MSA level to account for potential heteroskedasticity. I estimate this model (and each of the ones to follow) using each of the three Medicaid variables in turn.

The results presented in Table 3 do not provide any evidence that increasing eligibility for Medicaid and CHIP significantly reduced the fraction of children without health insurance at the national level. Coefficients on the Income Eligibility for Infants and Maximum Age variables are negative but not statistically significant. The coefficient on the Simulated

Instrument variable is actually positive, but is not estimated precisely. Several child and family characteristics do emerge as strong predictors of whether or not a child is uninsured. With each additional year of age, children are one-quarter of a percentage point more likely to be uninsured. This result is consistent with most states' policies of providing more generous Medicaid coverage for younger children. Children in female-headed household families are significantly less likely than their peers in two-parent households to be uninsured, presumably because female-headed families are more likely to receive AFDC/TANF or to have connections to the social welfare system. Education of the household head also has a significant effect on a child's insurance status. Compared to a reference group of individuals with exactly 12 years of education, children of high school dropouts are 12 percentage points more likely to be uninsured and children of individuals with at least some college education are 8 percent less likely to be uninsured. While none of the coefficients on the MSA level variables are statistically significant at conventional levels, there seems to be at least a marginally significant effect [p= 0.12 in Column 2] of a three-quarter percentage point rise in the uninsurance rate for every percentage point increase in the share of employment in manufacturing. In Column 3, greater employment density is also associated [p=0.06] with higher child health insurance coverage rates, all else equal.

Table 4 presents results for a model identical to the first one except for the addition of MSA-level racial segregation variables. Two distinct measures of housing segregation within metropolitan areas are considered: an index that represents the degree to which blacks and whites live in similar areas (Interaction Index) and an index that represents the degree to which black homes are disproportionately located toward the center city of a metropolitan area (Centralization Index). Interestingly, both higher levels of interaction between blacks and whites (indicating less segregation) and higher levels of centralization (indicating more centralization) are significantly associated with lower levels of health insurance coverage for children. As was true in the previous model, there is no significant individual-level effect of a child being black, although being in the other nonwhite group (Native American, Asian) is associated with lower coverage levels.

The models discussed so far merely replicates the type of analysis done in previous studies by estimating the average effect of expanding public health insurance across *all* metropolitan areas in the country. In order to test that the effects of Medicaid and SCHIP expansions differed by community, interactions between MSA-level economic conditions and state-level Medicaid generosity variables are added. The empirical model is as follows:

$$U_{imst} = \alpha_m + \alpha_t + \beta_1 MED_{st} + \beta_2 MED_{st} * R_{mt} + \gamma_1 X_{imst} + \gamma_2 R_{mt} + \gamma_3 Z_{mt} + \varepsilon_{imst} \qquad (2)$$

where the only modification is that now the two racial segregation variables (interaction, centralization) are interacted with the Medicaid generosity variable. Statistically significant estimates of the β_2 coefficients would indicate that the impact of expanding public health insurance on reducing the number of uninsured varies by metropolitan area according to local housing patterns conditions.

Table 5 provides estimates for the interacted model (Equation 2). Adding racial concentration interactions to the model does not fundamentally change the finding that expanding Medicaid and SCHIP eligibility on average has no significant effect in reducing the number of uninsured children. Again, the significant coefficients on the segregation measures indicate that cities with less isolated but more centralized black populations have higher percentages of uninsured children, independent of both individual and family characteristics and local economic conditions.

The coefficients for the Interaction*Medicaid terms in all three columns are negative but not statistically significant. By constrast, the estimated Centralization*Medicaid coefficients are estimated much more precisely and are positive, showing that eligibility expansions were significantly less likely to be effective in metropolitan areas with very centralized black populations.

One might expect that if racial segregation is directly affecting access to and use of public health insurance programs, that it should predominantly affect black children. The models for which results are reported in Table 6 include an additional interaction between the Medicaid*Segregation terms and a dummy variable for whether or not a child is black in order to test this hypothesis. Surprisingly, the coefficients on the new interaction term are not statistically significant, while the coefficients on the original Medicaid*Centralization interactions remain significant. This pattern would suggest either that racial segregation affects access to health insurance for children of all races more or less equally, or that a MSA-level characteristic correlated with racial concentration has been omitted from the model.

VII. Discussion

The results presented in the previous section provide evidence that while the expansion of public health insurance availability through Medicaid and SCHIP between 1990 and 2001 may not have significantly reduced the number of uninsured children in all parts of the country, it did so in metropolitan areas with particular socioeconomic characteristics. Expansions were more likely to have been successful in areas with lower levels of racial segregation, and more specifically less concentration of the black population in the city center.

This result could be consistent with two effects of segregation. First, segregated neighborhoods could be undesirable targets for enrollment campaigns and information about eligibility might not be well-communicated to eligible families. Second, states or localities might be targeting outreach and enrollment efforts on segregated neighborhoods, but eligible children are not disproportionately located in these neighborhoods. If the first effect is the true one, we would expect that the reduced coverage to be concentrated among black children. However, based on the results of the Individual Race*Segregation*Medicaid interaction model, it seems that segregation patterns affect not only the insurance coverage patterns of black children, but of whites and other minority groups as well. This result is consistent with the hypotheses that outreach and information campaigns may be mis-targeted geographically.

Although this conclusion can only be drawn extremely tentatively at this point, there may be good reasons to believe that racial concentration and the geographical distribution of poverty and health insurance coverage are not as well correlated as we might intuitively believe. An examination of the data used in this study reveals that in the highly segregated city of Detroit, for example, the child poverty rate for blacks is dramatically higher than that for whites, and yet a significantly greater fraction of white children are uninsured.[13]

One of the goals of future work on this topic are to further explore the issue of geographic distributions of poverty and health insurance coverage, an analysis that would most likely require restricted access zip code or Census tract neighborhood data. I will also be incorporating measures of segregation for Hispanics in the next revision of the paper.

[13] Formal results will be available in a revised version of the paper. (The log file currently resides on the hard drive of a crashed computer.)

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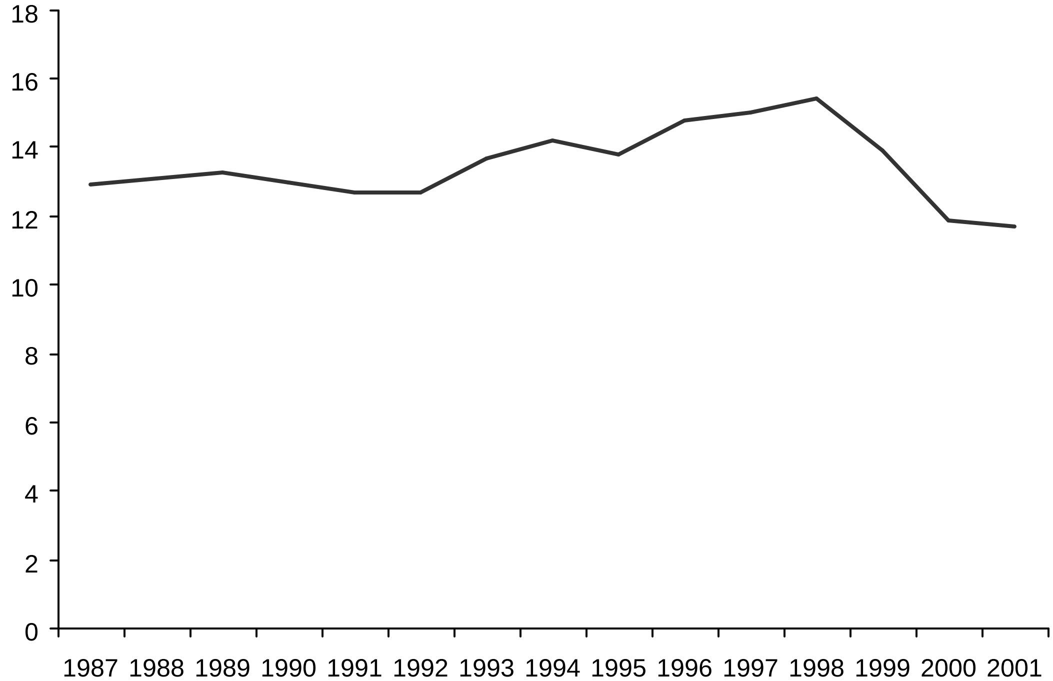
Figure 1
Fraction of Children without Health Insurance
1987-2001



Source: U.S. Census Bureau (2003)

Figure 1A
Distribution of Health Insurance Coverage For Children, California, 1990-2001 Average

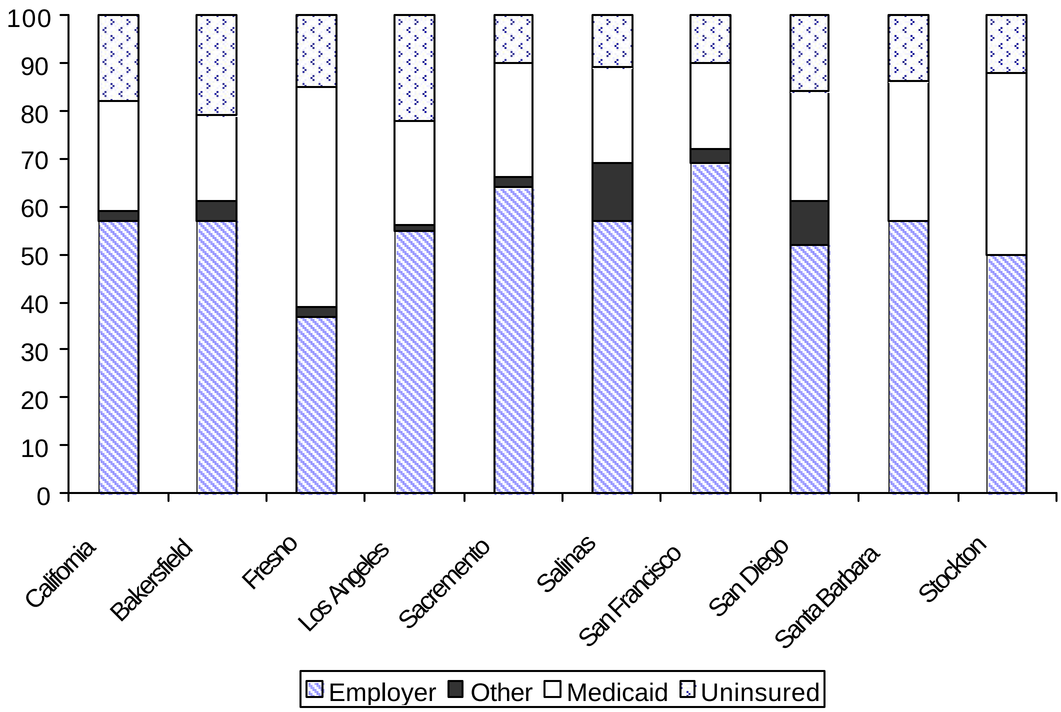


Figure 1B
Distribution of Health Insurance Coverage For Children, Pennsylvania, 1990-2001 Average

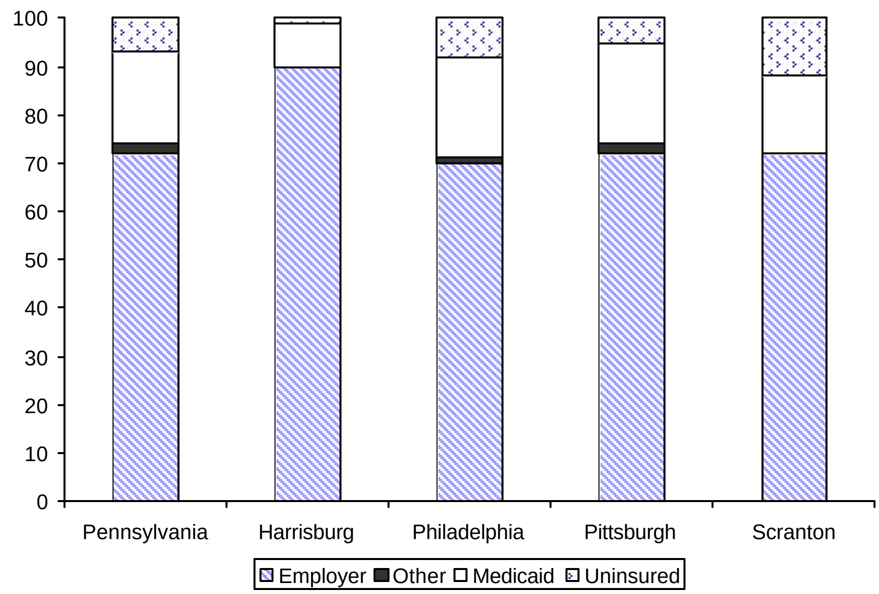


TABLE 1: MSAs Ranked by % Children Uninsured

Rank	MSA	% Uninsured	95% Confidence Interval	
1	Harrisburg	0.013	-0.001	0.026
2	Lansing	0.023	0.004	0.043
3	Minneapolis	0.028	0.019	0.038
4	Honolulu	0.032	0.013	0.051
5	Milwaukee	0.050	0.033	0.067
6	Worcester	0.050	0.022	0.078
7	Cleveland	0.051	0.038	0.064
8	Detroit	0.060	0.050	0.070
9	Melbourne	0.064	0.030	0.098
10	Greensboro	0.069	0.044	0.095
11	Madison	0.075	0.041	0.108
12	Boston	0.077	0.064	0.089
13	Fort Wayne	0.084	0.056	0.112
14	Dayton	0.085	0.056	0.113
15	Philadelphia	0.085	0.075	0.096
16	Columbus	0.087	0.065	0.109
17	Norfolk	0.087	0.065	0.109
18	Rockford	0.087	0.055	0.119
19	Fayetteville	0.090	0.056	0.123
20	Memphis	0.096	0.068	0.124
21	San Francisco	0.097	0.085	0.109
22	Cincinnati	0.100	0.076	0.124
23	Charlotte	0.103	0.074	0.133
24	Chicago	0.107	0.097	0.116
25	Tulsa	0.114	0.079	0.149
26	Seattle	0.115	0.096	0.134
27	Raleigh	0.118	0.082	0.153
28	St. Louis	0.118	0.098	0.138
29	Stockton	0.119	0.084	0.155
30	Scranton	0.124	0.085	0.164
31	Denver	0.125	0.100	0.149
32	New York	0.126	0.118	0.134
33	Indianapolis	0.134	0.108	0.160
34	Nashville	0.144	0.111	0.176
35	Toledo	0.148	0.107	0.190
36	Atlanta	0.149	0.130	0.168
37	Pensacola	0.149	0.105	0.193

TABLE 1 (Continued): MSAs Ranked by % Children Uninsured

Rank	MSA	% Uninsured	95% Confidence Interval	
38	Fresno	0.150	0.120	0.180
39	Austin	0.150	0.114	0.187
40	Knoxville	0.154	0.107	0.200
41	Phoenix	0.158	0.136	0.181
42	San Diego	0.164	0.143	0.185
43	Tampa	0.167	0.139	0.195
44	Albuquerque	0.168	0.115	0.222
45	Colorado Springs	0.171	0.127	0.215
46	Birmingham	0.176	0.134	0.218
47	Oklahoma City	0.179	0.142	0.216
48	Corpus Christi	0.180	0.129	0.231
49	Jacksonville	0.182	0.147	0.217
50	Orlando	0.185	0.152	0.218
51	Lakeland	0.204	0.142	0.266
52	Fort Myers	0.208	0.140	0.277
53	Eugene	0.211	0.155	0.267
54	Bakersfield	0.212	0.174	0.250
55	W. Palm Beach	0.213	0.163	0.263
56	Los Angeles	0.217	0.208	0.227
57	New Orleans	0.217	0.183	0.252
58	Dallas	0.221	0.203	0.239
59	Baton Rouge	0.222	0.171	0.273
60	Greenville	0.224	0.174	0.273
61	Houston	0.243	0.225	0.261
62	Mobile	0.255	0.205	0.306
63	San Antonio	0.258	0.225	0.291
64	Beaumont	0.268	0.213	0.324
65	Miami	0.278	0.255	0.302
66	El Paso	0.307	0.258	0.356
67	McAllen	0.452	0.407	0.497

Source: Author's calculations with 1990-2001 panels of the Survey of Income and Program Participation.

TABLE 2: MSAs Ranked by Racial Interaction Index

Rank	MSA	Interaction Index	Rank	MSA	Interaction Index
1	New York	0.18	35	Harrisburg	0.52
2	Detroit	0.18	36	Raleigh	0.53
3	Chicago	0.21	37	Orlando	0.54
4	Miami	0.24	38	Rockford	0.54
5	Cleveland	0.25	39	San Francisco	0.54
6	Memphis	0.25	40	Oklahoma City	0.57
7	New Orleans	0.28	41	Fort Myers	0.57
8	Milwaukee	0.28	42	Lakeland	0.58
9	Birmingham	0.29	43	Springfield	0.59
10	Philadelphia	0.30	44	Pensacola	0.60
11	St. Louis	0.32	45	Knoxville	0.60
12	Los Angeles	0.33	46	San Antonio	0.60
13	Atlanta	0.34	47	Denver	0.61
14	Beaumont	0.34	48	Greenville	0.62
15	Baton Rouge	0.35	49	Austin	0.62
16	Mobile	0.35	50	Corpus Christi	0.62
17	Houston	0.36	51	Fresno	0.63
18	Dayton	0.39	52	Stockton	0.64
19	W. Palm Beach	0.39	53	Bakersfield	0.64
20	Cincinnati	0.40	54	San Diego	0.65
21	Indianapolis	0.42	55	Minneapolis	0.70
22	Toledo	0.43	56	Melbourne	0.72
23	Dallas	0.44	57	Lansing	0.73
24	Norfolk	0.45	58	Seattle	0.74
25	Jacksonville	0.45	59	El Paso	0.78
26	Greensboro	0.47	60	Phoenix	0.78
27	Boston	0.48	61	Honolulu	0.81
28	Columbus	0.49	62	Colorado Springs	0.83
29	Fort Wayne	0.50	63	Madison	0.88
30	Nashville	0.50	64	Albuquerque	0.89
31	Charlotte	0.50	65	McAllen	0.89
32	Tampa	0.51	66	Scranton	0.91
33	Tulsa	0.52	67	Eugene	0.98
34	Fayetteville	0.52			

TABLE 3: MSAs Ranked by Racial Centralization Index

Rank	MSA	Centralization Index	Rank	MSA	Centralization Index
1	W. Palm Beach	-0.11	35	Charlotte	0.30
2	McAllen	-0.07	36	Orlando	0.31
3	San Diego	-0.04	37	New Orleans	0.32
4	Melbourne	-0.04	38	Eugene	0.35
5	Raleigh	-0.02	39	Denver	0.36
6	Lakeland	-0.01	40	Madison	0.38
7	Baton Rouge	-0.01	41	San Francisco	0.38
8	Greenville	0.03	42	Houston	0.38
9	Honolulu	0.04	43	Toledo	0.38
10	Chicago	0.05	44	Nashville	0.39
11	Miami	0.06	45	Springfield	0.40
12	Colorado Springs	0.09	46	Oklahoma City	0.40
13	El Paso	0.10	47	Atlanta	0.41
14	Memphis	0.13	48	Corpus Christi	0.42
15	Fayetteville	0.14	49	Birmingham	0.43
16	Albuquerque	0.15	50	Los Angeles	0.44
17	Dallas	0.18	51	Knoxville	0.45
18	Greensboro	0.19	52	Stockton	0.46
19	Jacksonville	0.19	53	St. Louis	0.48
20	Dayton	0.20	54	Mobile	0.51
21	Tampa	0.21	55	Rockford	0.53
22	New York	0.21	56	Philadelphia	0.56
23	Seattle	0.21	57	Minneapolis	0.58
24	Tulsa	0.22	58	Milwaukee	0.58
25	Scranton	0.23	59	Boston	0.60
26	Austin	0.24	60	Lansing	0.61
27	Fort Myers	0.24	61	Cincinnati	0.61
28	Beaumont	0.26	62	Detroit	0.61
29	Pensacola	0.26	63	Columbus	0.63
30	Phoenix	0.26	64	Indianapolis	0.66
31	Bakersfield	0.27	65	Cleveland	0.66
32	San Antonio	0.28	66	Harrisburg	0.71
33	Norfolk	0.29	67	Fort Wayne	0.72
34	Fresno	0.30			

TABLE 4
Descriptive Statistics

	Mean	Standard Deviation
Child Age	8.6	3.8
Girl	48.8%	50.0
Female Headed HH	22.2%	41.6
Family Income (Monthly)	$3,554	3150
Size of Family	4.4	1.6
Household Head Age	38.3	9.4
Black	18.0%	38.4
Other Non-White	6.2%	24.0
< HS Education	21.3%	42.7
College Education	23.9%	42.6
Unemployment Rate	6.8%	2.7
% Manufacturing	12.6%	4.1
% Services	31.1%	3.9
% Government	14.4%	4.7
Employment Density (Firms/Square Mile)	254.3	387.7
Racial Concentration Interaction Index	0.41	0.19
Racial Concentration Centralization Index	0.34	0.19
Maximum Income Eligibility for Infants	163%	31
Maximum Age Eligibility	8.9	3.8
Simulated Instrument	14.5%	7.5

Sample: Children living in 67 Metropolitan Statistical Areas from the first waves of the 1990, 1991, 1992, 1993, 1996 and 2001 panels of the Survey of Income and Program Participation. N=58,710.

TABLE 5: Baseline Regression Models

	(1)	(2)	(3)
Infant Eligibility	0.0000		
	(0.21)		
Maximum Age		-0.0024	
		(1.22)	
Simulated Instrument			0.0582
			(1.34)
Child Age	0.0025	0.0025	0.0025
	(4.05)**	(4.05)**	(4.05)**
Girl	-0.0013	-0.0013	-0.0013
	(0.48)	(0.47)	(0.46)
Female_Headed Family	-0.0131	-0.0131	-0.0130
	(2.24)*	(2.23)*	(2.23)*
Family Size	0.0084	0.0085	0.0084
	(3.49)**	(3.51)**	(3.50)**
HH Head's Age	-0.0004	-0.0004	-0.0004
	(1.19)	(1.19)	(1.19)
Black	0.0037	0.0036	0.0037
	(0.34)	(0.33)	(0.34)
Other Non-White	0.0331	0.0329	0.0330
	(1.75)*	(1.74)*	(1.75)*
HH Head < HS Grad	0.1232	0.1233	0.1232
	(8.46)**	(8.48)**	(8.46)**
HH Head College Grad	-0.0847	-0.0847	-0.0847
	(13.20)**	(13.25)**	(13.25)**
No Workes in HH	-0.0501	-0.0500	-0.0501
	(5.51)**	(5.52)**	(5.52)**
2+ Workers in HH	-0.0438	-0.0438	-0.0438
	(5.80)**	(5.84)**	(5.80)**
Unemployment Rate	0.0046	0.0049	0.0051
	(0.90)	(0.99)	(1.00)
% Manuf. Employment	0.7083	0.7347	0.7135
	(1.50)	(1.55)	(1.53)
% Services Employment	0.0837	0.1171	0.1088
	(0.31)	(0.45)	(0.42)
% Gov Employment	0.0735	0.0879	0.0906
	(0.15)	(0.19)	(0.19)
Employment Density	-0.0001	-0.0001	-0.0001
	(1.13)	(1.32)	(1.87)*

*Robust z-statistics in parentheses. * significant at 5% level; ** significant at 1% level All models include MSA and year fixed effects. N = 58,710.*

TABLE 6: Models Including Segregation Variables

	(1)	(2)	(3)
Infant Eligibility	-0.0001		
	(0.49)		
Maximum Age		-0.0021	
		(1.15)	
Simulated Instrument			0.0639
			(1.40)
Interaction Index	0.7604	0.7538	0.7396
	(2.50)**	(2.50)**	(2.51)**
Centralization Index	0.4057	0.3985	0.4189
	(3.43)**	(3.46)**	(3.55)**
Child Age	0.0025	0.0025	0.0025
	(4.05)**	(4.05)**	(4.05)**
Girl	-0.0016	-0.0015	-0.0015
	(0.56)	(0.55)	(0.54)
Female-Headed HH	-0.0133	-0.0133	-0.0132
	(2.27)*	(2.26)*	(2.25)*
Family Size	0.0083	0.0083	0.0083
	(3.43)**	3.44)**	(3.43)**
HH Head's Age	-0.0003	-0.0003	-0.0003
	(1.17)	(1.17)	(1.17)
Black	0.0035	0.0035	0.0035
	(0.32)	(0.32)	(0.32)
Other Non-White	0.0329	0.0328	0.0328
	(1.74)*	(1.73)*	(1.75)*
HH Head < HS Grad	0.1233	0.1234	0.1233
	(8.44)**	(8.46)**	(8.45)**
HH Head College Grad	-0.0845	-0.0844 -	0.0845
	(13.23)**	(13.27)**	(13.27)**
No Workers in HH	-0.0500	-0.0499	-0.0500
	(5.53)**	(5.54)**	(5.55)**
2+ Workers in HH	-0.0440	-0.0440	-0.0440
	(5.82)**	(5.85)**	(5.83)**
Unemployment Rate	0.0016	0.0020	0.0022
	(0.58)	(0.75)	(0.82)
% Manuf. Employment	0.6066	0.6245	0.5984
	(1.63)	(1.70)*	(1.65)*
% Services Employment	-0.0105	0.0198	0.0125
	(0.04)	(0.08)	(0.05)
% Gov. Employment	0.4313	0.4374	0.4594
	(0.93)	(0.94)	(1.02)
Employment Density	0.0000	0.0000	-0.0001
	(0.27)	(0.56)	(1.15)

*Notes: Robust z-statistics in parentheses. * significant at 5% level; ** significant at 1% level. All models include MSA and year fixed effects. N = 58,710* .

Table 7: Models Including Segregation Interactions

	(1)	(2)	(3)
Infant Eligibility	-0.0002		
	(1.06)		
Maximum Age		-0.0046	
		(1.87)*	
Simulated Instrument			0.0117
			(0.17)
Interaction Index	0.7797	0.5513	0.5975
	(2.41)**	(1.92)*	(1.98)*
Infant*Interaction	-0.0006		
	(1.49)		
Age * Interaction		-0.0031	
		(1.16)	
SimInst*Interaction			-0.0404
			(0.60)
Centralization Index	0.2007	0.2887	0.3606
	(1.50)	(2.40)**	(2.83)**
Infant*Centralization	0.0010		
	(2.46)**		
Age*Centralization		0.0086	
		(3.40)**	
SimInst*Centralization			0.1691
			(2.04)*
Black	0.0036	0.0034	0.0034
	(0.33)	(0.31)	(0.31)
Other Non-White	0.0326	0.0325	0.0327
	(1.72)*	(1.72)*	(1.73)*

*Notes: Robust z-statistics in parentheses. * significant at 5% level; ** significant at 1% level. All models include the set of control variables in Tables 3 and 4 as well as MSA and year fixed effects. N = 58,710.*

Table 8: Models Including Race/Segregation Interactions

	(1)	(2)	(3)
Infant Eligibility	-0.0002		
	(1.05)		
Maximum Age		-0.0048	
		(1.96)*	
Simulated Instrument			0.0057
			(0.08)
Interaction	0.7795	0.5525	0.6097
	(2.42)**	(1.93)*	(2.01)*
Infant*Interaction	-0.0007		
	(1.52)		
Infant*Interaction*Black	0.0000		
	(0.08)		
Age*Interaction		-0.0030	
		(1.15)	
Age*Interaction*Black		0.0021	
		(0.81)	
SimInst*Interaction			-0.0331
			(0.48)
SimInst*Interaction*Black			0.1045
			(1.06)
Centralization Index	0.1997	0.2807	0.3450
	(1.49)	(2.36)**	(2.74)**
Infant*Centralization	0.0010		
	(2.54)**		
Infant*Centralization*Black	-0.0002		
	(0.96)		
Age*Centraliation		0.0086	
		(3.35)**	
Age*Centralization*Black		0.0000	
		(0.02)	
SimInst*Centralization			0.1588
			(1.79)*
SimInst*Centralization*Black			0.0454
			(0.56)
Black	0.0161	-0.0058	-0.0104
	(1.23)	(0.36)	(0.81)
Other Non-White	0.0325	0.0327	0.0330
	(1.72)*	(1.74)*	(1.75)*

*Notes: Robust z-statistics in parentheses. * significant at 5% level; ** significant at 1% level. Models include set of control variables in Tables 3 and 4 as well as MSA and year fixed effects. N = 58,710.*

APPENDIX
Medicaid Generosity Variables

Figure B1: Maximum Income Level for Infant Eligibility

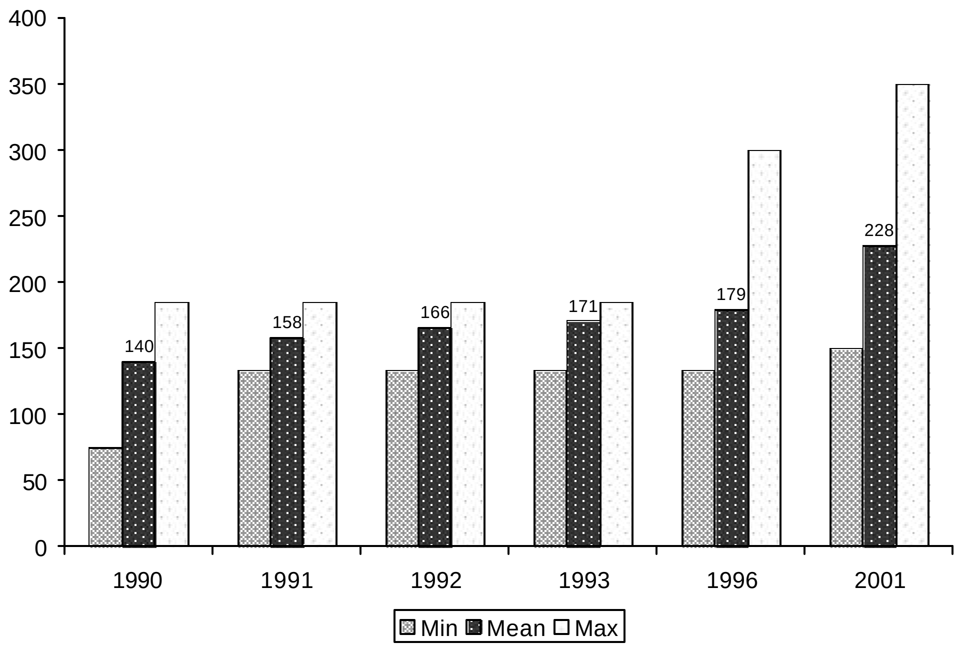


Figure B2: Maximum Age Limit for Eligibility

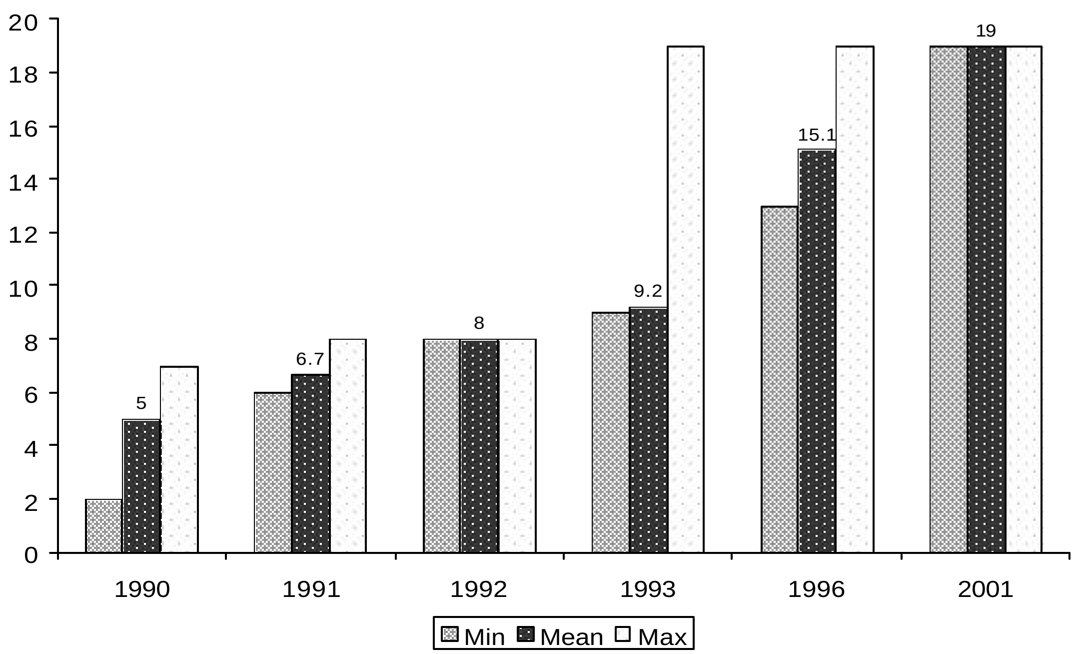


Figure B3
Simulated Instrument