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EXPLAINING DIFFERENCES IN EMPLOYER SPONSORED INSURANCE COVERAGE BY RACE, ETHNICITY AND IMMIGRANT STATUS

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I. Introduction

It is well known that much higher proportions of non-elderly African-Americans, Hispanics, and immigrants are uninsured compared to U.S. born whites. Much of the difference, especially for Hispanics and immigrants, is due to differences in employer-sponsored insurance (ESI) coverage. For example, recent studies (Nichols, Hadley and Reschovsky 2003; Schur and Feldman 2001; Perry, Kannel and Castillo 2000; Quinn 2000) highlighted substantial differences in both ESI coverage and overall insurance coverage for Hispanics who are primarily Spanish-speaking or recent immigrants relative to both other Hispanics and to Whites. These studies also highlight differences in having a job that offers ESI, rather than differences in either employment status or ESI take-up, and differences in education, wage rates, family income, and family structure that presumably contribute to the differences in overall coverage and in ESI coverage.

Other studies have demonstrated smaller, though statistically significant, widespread and persistent differences in coverage between Whites and African-Americans. (Monheit and Vistnes 2000, Waidmann and Rajan 2000, Ammons 1997, Long 1987). Non-elderly African-Americans have levels of ESI and public coverage slightly higher than Latinos but still substantially lower than Whites. In addition, Monheit and Vistnes (2000) find that rates of uninsurance grew for all groups between the mid 1980s and mid 1990s, but that rates for African-Americans and Latinos grew faster than those of Whites.

Most of the prior research has focused on identifying factors associated with differences in coverage. Only a few studies have attempted to decompose the effects of differences in populations' characteristics from "unexplained" differences in underlying model parameters (Zuvekas and Taliafero 2003; Monheit and Vistnes 2000; Fronstin, Goldberg and Robins 1997).

Virtually no studies have addressed the effects of variations in state policies and local labor markets on differences in insurance coverage. Finally, past research has not looked at the effects of race, ethnicity, immigrant, and citizenship status in an integrated or comprehensive fashion.

The research described here attempts to address these shortcomings. We base our empirical analyses on a theoretical framework that recognizes the interplay between alternative types of insurance coverage, labor market decisions, and family decision-making. This framework motivates an empirical model of ESI coverage and its “pathways” (whether to work, whether to take a job that offers insurance, whether to take up insurance if offered). We then use the empirical model to identify the relative contributions of various factors in explaining gross differences in coverage by race, ethnicity, immigrant, and citizenship status, focusing on key differences in populations’ characteristics, state policies, and local labor market conditions.

II. Data Sources

The primary data for this study are the 1999 and 2002 rounds of the National Survey of America’s Families (NSAF),[1] which collected detailed data on health insurance coverage, employment and other job attributes (establishment size, industry and tenure at the current job), ESI offers, race/ethnicity, citizenship and immigrant status (years in US and country of origin), health, demographic and household characteristics (such as wage rates and family income, education, family structure, general health status, work limitations), and knowledge of public programs (e.g., Medicaid). The 1999 and 2002 rounds of NSAF provide data on over 145,000

[1] NSAF is a household survey, designed and administered by the Urban Institute, that collects economic, household, and health information from about 40,000 families in each round and yields a nationally representative sample of non-institutionalized children and adults from all 50 states and the District of Columbia. The survey over-sampled low-income families, i.e. families with incomes less than 200% of the Federal Poverty Level (FPL). A more detailed overview of the survey is contained in Kenney et al. (1999).

adults, including 17,167 Hispanics and 15,940 African-Americans. There are 17,514 adults who are classified as immigrants across all race/ethnicity groups. In this paper we combine race, ethnicity and immigration status to form four groups for analysis: white non-Hispanic citizens; black non-Hispanic citizens, Hispanic citizens, and Hispanic non-citizens. "Citizens" here include both the native born and naturalized. The two "Hispanic" groups include persons giving any response to the separate race question.

We draw on several additional sources for data related to each adult's area of residence: (1) The Area Resource File (ARF) for county-level data on provider supply and other health care market characteristics; (2) the 2000 Census files for information at the county level on the employment and human capital characteristics of people in the local market; (3) HRSA's Uniform Data System for data on the number of Federally Qualified Health Centers, "look-alikes," and Rural Health Clinics to construct a measure of safety net capacity; and (4) County Business Patterns data to measure local area industry mix and firm size patterns that can affect employer decisions about offering health insurance coverage.

Table 1 gives sources and definitions for the variables used in the analysis and Table 2 presents means of those variables for the four groups studied. [Forthcoming description of differences.

III. Analytic Approach

A. Theoretical Framework

We draw upon several different theories of individual and/or family behavior regarding insurance coverage to motivate our empirical models of pathways to ESI coverage. The main theory of health insurance demand is developed around the concept of expected utility maximization (Phelps 1973, 1976), and typically models individual (rather than family) behavior and takes work decisions as exogenous. An individual's demand for health insurance is made under uncertainty about future health status and subject to a budget constraint that incorporates the costs of alternative insurance options. This framework generally implies that the demand for any insurance option will depend on the price of that option and prices of each of the other insurance options, income, expected health status, and preferences towards risk.

Taking economic theories of household production and family decision-making (Becker 1965, 1981; Bergstrom 1997; Weiss 1997) into consideration involves adding to the insurance choice analysis a role for labor supply choices, emphasizing the joint nature of employment choices and insurance choices, and framing them as family rather than individual decisions. A necessary condition for having access to ESI is that one adult in the family works (usually, full time). The choice of a particular employer simultaneously determines wages, whether health insurance is offered, and the terms at which it is offered. The choice of a parent to work and how many hours to work simultaneously determines income, access to ESI, and (possibly) whether any family members are income-eligible for Medicaid or TANF[2] benefits.

One empirical implication of considering work and insurance decisions together is that employment status, hours, observed wages, and even income are endogenous in modeling insurance choice. Also, two adult families face more complex choices than single adults, and have more complex ways of optimizing over those choices. While the bulk of our analyses pool

[2] Temporary Assistance for Needy Families, which replaced Aid to Families with Dependent Children (AFDC) in 1996.

households with one and two adults, we will also estimate models for these two groups separately as a sensitivity analysis.

This conceptual framework motivates many potentially interesting empirical analyses of insurance choice. The one we examine here is an analysis of ESI coverage specified as the result of multiple stages of decision-making or "pathways." Choosing ESI is conditional on at least one adult family member having an ESI offer, which is conditional on the decision that at least one adult works. Thus, the choice to obtain ESI over other insurance options can be broken down into multiple distinct conditional decisions.

B. ESI Pathway Model Estimation and Identification

The probability of having ESI through one's own employment or a family member's employment can be expressed as the product of three probabilities:

$$\text{(C.1.)}\quad \Pr(\mathit{ESI}{=}1) = \Pr(\mathit{Work}) * \Pr(\mathit{ESI\ Offer}{=}1 \mid \mathit{Work}) * \Pr(\mathit{ESI\ Take\text{-}up}{=}1 \mid \mathit{ESI\ Offer}),$$

where we define ESI offer and work status as any adult in the family having an ESI offer/working. Each factor in this expression represents a step in the pathway to ESI coverage. The preliminary tabulations (Table 2) show these probabilities separately for the four racial/ethnic/citizenship status groups. This simple analysis tells us, in a gross sense, the relative importance of race/ethnicity and citizenship/immigrant status at each step in the pathway. What we find is that at the "work" stage, there are very small differences in the probability of living in a family with at least one worker. The probabilities range from 0.55 for Latino non-citizens and black citizens to 0.59 for white citizens. At the "offer" stage, conditional on living with a worker, the probabilities of having an offer of health employer-sponsored insurance are similar for the three citizen groups (0.84 for Latino citizens, 0.87 for black citizens and 0.90 for white citizens), but substantially lower for non-citizen Latinos (0.61). Finally, at the "takeup" stage, non-citizen Latinos have a 0.66 probability of accepting an offer of insurance compared to white citizens who accept with a probability of 0.95, black citizens who accept with a probability of 0.87 and Latino citizens who accept with probablity 0.84.

Presumably, the different gross probabilities by group at the different steps reflect other individual differences that may vary systematically by group, such as education and health status. Therefore we conduct a more thorough multivariate analysis of these pathways, controlling for group differences in other characteristics. This suggests the following general empirical strategy:

(C.2.) $\Pr(\mathit{Work}=1 \mid X) = \mathrm{F}(\beta_1 X, u_1)$

(C.3.) $\Pr(\mathit{ESI\ Offer}=1 \mid \mathit{Work}=1, X) = \mathrm{F}(\beta_2 X, u_2)$

(C.4.) $\Pr(\mathit{ESI\ Take\text{-}up}=1 \mid \mathit{ESI\ Offer}=1, \mathit{Work}=1, X) = \mathrm{F}(\beta_3 X, u_3)$.

To implement this strategy and obtain unbiased estimates of β_1, β_2, and β_3, we need to address sample selection problems that could potentially arise at each step of the process due to correlations among the unobservables (u_1, u_2, u_3). So long as X is exogenous to u_1, we can obtain unbiased estimates of β_1 in equation (C.2.). From this coefficient, we can compute for different X variables, say the Hispanic indicator variable, the effect of being Hispanic relative to being White on the probability of work. When we are not using a linear probability model, we will need to specify at what values of the other X variables we are evaluating this effect. In all such cases, we will focus on effects of being of a given status for people of that status, i.e., "effects of treatment on the treated." These estimates will reflect causal differences of being Hispanic relative to being White only if there are no omitted factors that affect the likelihood of work that differ systematically by Hispanic status. In general, however, we will interpret our effects as conditional differences (conditional on the things we can and do control for) and not causal effects.

We use a sample selection correction procedure to account for unobserved factors that affect the probability of working that may also be related to the error term in the second stage offer equation. This procedure assumes our model is well specified and that the first stage F(.) is the normal (Gaussian) CDF. When estimating the second stage as a linear probability model, we use the two-step version originally suggested by Heckman (1979). When estimating the second stage as a probit, we use a procedure suggested by Van de Ven and Van Pragg (1981). Even after making this adjustment, there may still be other omitted factors that differ systematically by an X variable of interest (such as Hispanic status). So again, we are estimating conditional, but not necessarily causal, effects of being Hispanic and other X variables on offer among workers (β_2).

If there are elements of β_2 that we know *a priori* or can reasonably assume to be 0, i.e. valid exclusion restrictions (see Table 4), our ability to obtain unbiased estimates of β_2 (or at least account for unobserved factors that affect the probability of working) under potential model misspecifications is greatly enhanced.[3] Likewise, if there are elements of β_3 that we can assume to be 0, then we can use a similar method to obtain unbiased estimates of β_3 in equation (C.4.).[4]

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[3] Specifically, even if the model is well specified, valid exclusion restrictions reduce the potential multicollinearity between the *X* and the Heckman selection term. Further, valid exclusion restrictions allow us to relax the parametric assumption that F is normal using a semiparametric procedure described in Vella (1992) which uses higher order polynomials of the first stage index. (This would need to be implemented outside the HECKPROB command.)

[4] Note that for estimating the conditional take-up model, it is not necessary to use parameters from the unconditional work status model or the conditional offer model. We can simply estimate a reduced-form unconditional offer equation. One implication is that so long as there are exogenous predictors of work status that can be excluded from the conditional offer model to estimate β_2, then we can use these same exogenous predictors in an unconditional offer model to estimate β_3.

Factors that should affect the work decision, but which would be less likely to affect offer or take-up (aside from their effect on work status) include the number of children by age category,[5] the presence of an elderly parent, and TANF policies pertaining to work (e.g. work requirements, earned income exclusions, sanctions). While not strictly necessary, there are additional factors that should affect offer rates and/or work status but which would be much less likely to affect take-up rates given an offer, such as the county industry and firm size mix and county unemployment rates.[6] We will estimate the set of models in C.2.-C.4. separately for married and single adults. In both cases, the models we propose treat the individual as the unit of observation for ESI coverage. However, the opportunity set on which the ESI decision is conditioned is defined at the family level. Thus, we estimate the presence of a worker in a family and the presence of an ESI offer in the family given the presence of a worker. The final step estimates the takeup of an ESI offer by the individual conditional on an ESI offer in the family.

C. Measuring the Contribution of Factors Affecting Coverage Disparities

We first estimate models using pairs of probit analyses (Work, Offer|Work), (Offer|Work, Takeup|Offer,Work) where error terms are assumed to be distributed bivariate normal. These will give estimates of the relative contribution of race/ethnic/immigration status disparities at each stage to the overall disparities in ESI coverage, controlling for differences in personal and market-level characteristics between groups. This set of analyses will tell us how much of the observed differences by race/ethnicity/immigrant/citizenship status at each stage of the ESI

[5] We would include the number of children in all the models, but exclude number of children by age group from the offer and take-up models.
[6] Vella (1992) proposes a test for selection bias in models where the second stage model dependent variable is binary. We will only need to estimate selection-adjusted probit models in the case in which there is evidence of selection bias.

pathway remain "unexplained" after accounting for personal characteristics and policy/market characteristics. The unexplained portion of disparities we attribute to "structural" differences in how members of each group gain access to ESI coverage. These may include differences in preferences of individuals, expectations about health care needs, attitudes of employers, or other unobserved factors. We quantify the net structural effect by applying the estimated coefficients from one group to another group's distribution of characteristics. So for example, we can estimate the rates of labor force participation, ESI offer and takeup if non-citizen Latinos had the personal and market characteristics of citizen whites. The differences between these simulated rates and the actual rates for non-citizen Latinos represent the effect of population differences in observable characteristics. Any remaining disparity we attribute to structural differences.

While these models and simulations allow us to quantify the relative effects of observable and unobservable differences, they will not tell us the relative importance of observable differences in personal, policy, or market characteristics for outcomes on the ESI pathway. Thus, the final phase of the analysis will apply linear decomposition techniques to identify how various observable exogenous factors contribute to insurance coverage disparities by race, ethnicity and immigrant status.

The decompositions proposed by Blinder (1973) and Oaxaca (1973) used a linear model, which allows effects of individual (or groups of) covariates and coefficients to be estimated separately. Thus, for the decomposition analyses we will estimate linear probability models for the decision of interest while using a probit to estimate the sample selection equation.[7] For

[7] To check the validity of our linear model, we would compare the results with the marginal effects and statistical significance from our nonlinear models. In past experience (Shen and Zuckerman, 2003), we obtain extremely close results between the two approaches (the dependent variable in that context was ESI coverage rate).

example, we can decompose differences in the rate of ESI Offer between Hispanics and Whites as $\overline{P}_2^H - \overline{P}_2^W = [(\overline{X}^H - \overline{X}^W)\hat{\beta}_2^H] + [\overline{X}^W(\hat{\beta}_2^H - \hat{\beta}_2^W)]$.[8] The first term measures the differences in the offer rate explained by differences in mean group characteristics ($\overline{X}^j$), while the second term measures the difference in offer rate explained by differences in structural factors ($\hat{\beta}_2^j$).[9]

We decompose the disparity in insurance coverage due to differences in population characteristics by *subsets* of population characteristics and structural factors such as human capital, local labor market conditions, and state policies. This will allow us to isolate the contribution of, say, human capital, to Hispanics' low ESI rates by multiplying regression coefficients for human capital factors with Hispanic-specific values, but White values for the rest of the variables.

IV. Results

Tables 3 through 5b present results from probit and bivariate probit models of each stage in ESI coverage pathway. Our joint estimate of the work and offer decisions found no correlation in the error terms for the two equations, an indication that the selective nature of the worker sample does not bias the estimates of the offer equation. We could not reject the hypothesis that ρ=0 for any group. The smallest *p*-value on any test was 0.44. In addition, in standard Heckman analyses where the offer stage was modeled as a linear probability, we found the selection term insignificant. Thus, the presence of a worker in the household (Table 3) and the presence of an offer to any worker (Table 4) are estimated as simple probits. We did, however, find some

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[8] Several alternative decompositions are possible. One alternative weights the difference in characteristics (first term) using coefficients for whites ($\hat{\beta}_2^W$). That this decomposition produces different results is known as the index number problem. A third alternative used by Neumark (1988) weights the first term by weights calculated on the *pooled* sample of Hispanics and Whites. We will explore the differences produced using alternative decompositions.
[9] In this version of the analysis, we constrain the coefficient vectors to be equal across populations except for the constant terms. Structural differences, therefore are captured in one term. Future work will relax these assumptions.

evidence of potential selection bias in the linear probability takeup model (though not the probit model). For this reason we present results from both simple probits (Table 5a) and bivariate probits (Table 5b).

The simulations based on these models are shown in Table 6. Because of the small raw differences in the work equation, we focus our simulations on the offer and takeup stages. The top panel tabulates the actual probabilities of having an ESI offer (conditional on having a worker in the HIU) for the four study groups and the average predicted probability for each group if the distribution of underlying characteristics were equivalent to that of the reference population (white non-Hispanic citizens). For Latino citizens, shifting underlying characteristics increases the probability of offer, eliminating 3 of the initial 4 percentage point disparity with whites. For black citizens, shifting to the white distribution of characteristics results in a higher offer probability than that of whites. For non-citizen Latinos, however, a shift in characteristics accounts for less than half of the offer disparity (13 of 30 percentage points).

The bottom portion of the panel does the same exercise for the probability of takeup given the presence of an offer in the HIU. Again, the black/white disparity is more than eliminated by the shift in characteristics (indicating that structural factors favor African Americans in both the offer and takeup stages). For Latino citizens, the entire difference is explained by differences in characteristics. Finally, for non-citizen Latinos, about half of the disparity remains after simulating a shift to white characteristics.

We now shift to linear decompositions of the offer and takeup models to allow comparisons across sets of characteristics. Table 7 shows the gross percentage point disparities for three study groups relative to non-Hispanic whites, and the marginal effects of differences in six groups of characteristics. “Demography” includes gender and marital status; “Human Capital” includes age and education, “Spanish Language” is a single variable (not included in group-specific probits) indicating that the NSAF interview was conducted in Spanish; “Labor Market” includes population density and an indicator for counties bordering Mexico, and in the offer model also includes county-level unemployment, educational attainment, industrial mix, and the fraction of workers in small firms (employees<50); “Health Care Market” includes measures of hospital beds, federally qualified health centers, Medicare reimbursement, and HMO penetration; and “State Policies” include indicators for the presence of high risk insurance pools, community rating, welfare eligibility rules and whether the state’s minimum wage exceeds the federal level.

The top panel of Table 7 shows results from selection-corrected models, while the bottom panel presents results based on OLS models. The evidence that selection bias may be present in the takeup models is apparent here. Comparing the total effects of all observed characteristics in the offer models, we see very little difference between the top and bottom panels, but in the takeup models, the corrected models attribute more than twice as much to characteristic differences in the uncorrected models than in the corrected models. For non-citizen Latinos, we find that less than a third of the gross disparity in takeup is explained by characteristic differences in the Heckman models while nearly two thirds is explained in the uncorrected model.

In the offer model, differences in observed characteristics account for more than the gross disparities for African Americans and Latino citizens, but only 74% of the disparity for non-citizen Latinos. For African Americans, differences in demographic characteristics (notably marital status, where whites are more likely to be currently married) alone can account for the entire disparity with whites. For Latino citizens, differences in human capital and language account for the largest portion of the gross disparity. For non-citizen Latinos, language differences account for the largest portion of offer disparity, followed by differences in human capital (age and education). For each group, differences in labor market characteristics and state coverage policies account for small amounts of the disparities.

In the (selection-corrected) takeup model, the observed characteristics explain the only very small portions of the disparities for African American and Latino citizens—a finding somewhat at odds with those from the probit model where half or more of the takeup disparities for these groups could be explained by characteristic differences. For non-citizen Latinos, human capital and language again explain the largest share of takeup disparities.

Finally, to examine where structural differences might exist, we performed tests on several specifications of the bivariate probit models of offer and takeup. In particular, for each "minority" study group we (jointly) tested the hypotheses that the group had coefficients equal to those of "whites" for specific sets of covariates.[10] Table 8 gives the results of these tests. In the offer stage, African Americans differ significantly from whites only in the effect of demographic variables. Latino citizens differ from whites in the effects of labor market and health care market variables. Non-citizen Latinos, however, exhibit significantly different coefficients in every area other than health care market factors. For African American and Latino citizens, more differences are apparent in the takeup model. Further investigation of the quantitative implications of these findings seems warranted.

[10] For each group separately, we pooled the group with whites and tested that sets of interactions were equal to zero.

V. Discussion

Our primary goal was to identify the relative contributions of differences in personal characteristics, state policies, and local labor market conditions in explaining variations in ESI coverage by race, ethnicity, immigrant, and citizenship status.

It has been well documented that Latinos in the U.S. have significantly higher rates of uninsurance than non-Hispanic whites, even after controlling for differences in characteristics. The most striking finding of this research was that Latino citizens look more similar to African Americans in ESI offers and takeup than to non-citizen Latinos. This is true in both the magnitude of gross disparities at each stage and in the size of the net disparities that remain after controlling for differences in characteristics.

In considering the relative importance of work, ESI offers and takeup in the overall ESI disparities, no group is particularly disadvantaged in the probability of having a worker present as a potential source of an offer. For African Americans the bigger disparity seems to be in takeup, while Latinos (both citizen and non-citizen) exhibit disparities in both offer and takeup.

We found that differences in the distribution of age, education and language are important among observable differences in explaining the both offer and takeup disparities for Latinos, but that for non-citizens, structural differences remain in both stages.

To the extent that education and language are mutable factors, these findings imply that policies to increase human capital and improve job skills may be a viable long-term strategy for reducing disparities in insurance coverage. In the short term, however, subsidizing ESI coverage and strengthening the safety-net may need to be considered. However, the apparently large structural differences that exist for non-citizens suggest that there may be legal reasons (including individual perceptions of legal difficulties) for disparities that may require other approaches if reducing disparities is a policy goal. Further research on other non-citizen groups may shed light on whether Latino immigrants face unique problems in obtaining insurance.

Further analysis is also important to assess how much of the difference in ESI coverage is due to less access to public insurance, especially by recent immigrants and non-citizens. For example, an interaction between Medicaid eligibility generosity and whether the person immigrated after 1996 will suggest whether the 1996 changes in Federal law influenced ESI coverage. If recent immigrants are effectively cut off from Medicaid, then it may increase the likelihood of their seeking and obtaining ESI coverage. Another important dimension of public policy is the role played by reliance on the safety net as an alternative to generous public insurance programs.

If these turn out to be significant factors, then they raise important political issues about the decision to allow non-citizens to be eligible for Medicaid coverage, as well as the roles of the federal and state governments in setting Medicaid eligibility and financing Medicaid costs. If states with large racial and ethnic minority populations are unwilling or unable to support more generous Medicaid coverage, then it would suggest that a greater federal role would be needed in order to expand access to public insurance for these subpopulations.

Finally, estimating a set of related models that look at different steps on the pathway to ESI coverage should improve our basic understanding of the interactions between labor market decisions and the demand for health insurance. These models will provide information about the relative importance of the decision to take a job that offers insurance versus the decision to take up insurance, and will also highlight differences between the basic labor-force participation decision and the decision to take a job that offers insurance. Moreover, we hope to illuminate the role played by family decision making by contrasting the behavior of one-adult and two-adult families. In general, a better understanding of these processes will contribute to the formulation of specific policies aimed at reducing insurance disparities by affecting labor market structure.

References

Ammons, L. 1997. Demographic Profile of Health-Care Coverage n America in 1993. *Journal of the National Medical Association* 89(11): 737-744.

Becker, Gary. 1965. A Theory of the Allocation of Time. *Economic Journal* 75:493-517.

Becker, Gary. 1981. *A Treatise on the Family*. Cambridge, MA: Harvard University Press.

Bergstrom, Theodore C. 1997. A Survey of Theories of the Family. In *Handbook of Population and Family Economics*, edited by Mark. R. Rosensweig and Oded Stark. Handbooks in Economics 14, vol. 1A. Elsevier: North Holland.

Blinder, Alan S. (1973), "Wage Discrimination: Reduced Form and Structural Estimates." Journal of Human Resources, 8 (4), 436-455.

Fronstin, Paul, Lawrence G. Goldberg, and Philip K. Robins, 1997. "An Analysis of Trends in Private Health Insurance Coverage, 1988-1992," *Social Science Quarterly* 78(1), March.

Heckman, James, 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47:153-161.

Kenney, G., S. Zuckerman, S. Rajan, N Brennan and J. Holahan. 1999. The National Survey of America's Families: An Overview of the Health Policy Component. *Inquiry* 36(3):353-362.

Long, S. 1987. Public Versus Employment-related Health Insurance: Experience and Implications for Black and Nonblack Americans, *Milbank Quarterly* 65(Supp 1):200-212.

Monheit, A. and J. Vistnes. 2000. Race/Ethnicity and Health Insurance Status: 1987 and 1996. *Medical Care Research and Review* 57(Supp1):11-35.

Nichols, L., J. Hadley and J. Reschovsky. 2003. "Why Are So Many Latinos Uninsured in the United States," unpublished manuscript, Center for Studying Health System Change, Washington DC, presented at the Annual Meeting of the Allied Social Sciences Association, Washington DC.

Oaxaca, R. (1973), "Male-Female Differentials in Urban Labor Markets." *International Economic Review*, 14, 693-709.

Perry, Michael, Susan Kannel and Enrique Castillo. 200. "Barriers to Health Coverage for Hispanic Workers: Focus Group Findings." Commonwealth Fund Report #425, December.

Phelps C. 1976. The Demand for Reimbursement Insurance. in R. Rosett, ed., *The Role of Health Insurance in the Health Services Sector*, New York: National Bureau of Economic Research.

Phelps C., The Demand for Health Insurance: A Theoretical and Empirical Investigation. RAND Research Paper Series No. R-105-OEO, Santa Monica: 1973.

Schur, Claudia and Jacob Feldman. 2001. “Running In Place: How Job Characteristics, Immigrant Status, and Family Structure Keep Hispanics Uninsured” Commonwealth Fund Report #453, June.

Shen, Yu-Chu. and Stephen Zuckerman. 2003. Why Is There State Variations In Employer-Sponsored Insurance? *Health Affairs* 22(1):241-251.

Van de Ven, W.P.M.M. and B.M.S. Van Pragg. 1981. “The Demand for Deductibles in Private Health Insurance: A Probit Model with Sample Selection.” *Journal of Econometrics* 17:229-252.

Vella, F. 1992. Simple Tests for Sample Selection Bias in Censored and Discrete Choice Models. *Journal of Applied Econometrics* 7: 413-421.

Waidmann, Timothy A. and Shruti Rajan. 2000. Race and Ethnic Disparities in Health Care Access and Utilization: An Examination of State Variation. *Medical Care Research and Review* 57(Supp1): 55-84.

Weiss, Yoram. 1997. The Formation and Dissolution of Families: Why Marry? Who Marries Whom? and What Happens upon Divorce? In *Handbook of Population and Family Economics*, edited by Mark. R. Rosensweig and Oded Stark. Handbooks in Economics 14, vol. 1A. Elsevier: North Holland.

Zuvekas, Samuel H. and Gregg S. Taliaferro. 2003. "Pathways to access: Health insurance, the health care delivery system, and racial/ethnic disparities, 1996-1999," *Health Affairs* 22(2):139-153, March/April.

Table 1: Variable definitions

Variable	*Description*
Family Labor Force Participation	A dichotomous indicator of whether either adult (head or spouse) in the family insurance unit worked for pay at least 35 hours per week in their main job.
Family ESI Offer	A dichotomous indicator of whether either adult in the family insurance unit is eligible for insurance offered by their employer, conditional on at least one adult working full time.
ESI Take-Up	A dichotomous indicator of whether the person is covered by an ESI policy, conditional on at least one adult in the family insurance unit being eligible for ESI.
Age	Continuous variable (with age-squared) or set of dichotomous indicators of different age groups
Gender	Interactions between gender and key determinants of labor-force participation will also be included
Race	White, African-American, other race
Ethnicity	Hispanic (distinguish between Puerto Rican, Cuban, Mexican, and other Hispanic ethnicities)
Spanish Interview	NSAF interview conducted in Spanish
Education	Dichotomous variables for years of education: 8 or less, 9-11, 12, some college, college graduate, post-graduate/professional school
Marital Status	Married, spouse present; married, spouse absent; single (never married, divorced, separated, widowed)
Children	Number, by age group
Caregiver Status	Elderly (75+) parent in household
Market Characteristics	
County Unemployment	Area Resource File, 1999 and 2002
Pct. Pop with College Educ.	2000 Census, county
Pct. Workers in 1-digit Industry	2000 Census
Pct. Workers in Small (<50) Establishments	County Business Patterns
FQHC Availability	HRSA Data System for 1998 and 2000; number of FQHC sites within 5 miles, based on latitudes and longitudes of 5-digit zip codes
Public hospital beds	Beds per capita in county, from Area Resource File
HMO Penetration	County, from Area Resource File; affects price of private insurance
Average Medicare Payment per Beneficiary	County, from Area Resource File; affects price of private insurance
Population Size and Density	Control for cost of living and other unmeasured environmental factors
State Characteristics	
Minimum Wage	State minimum wage exceeds federal
Welfare Rules Related to Work Status	Income disregard for typical family;, work requirement exemptions, work requirement sanctions
High Risk Pools	
Community Rating	

Table 2: Sample Characteristics

		White non-Hispanic citizens	African American citizens	Latino citizens	Latino non-citizens
		N = 69,042	**N = 10,393**	**N = 6,437**	**N = 4,143**
Variable Group	*Variable*	*mean*	*mean*	*mean*	*mean*
Dependent Variables	***Family LFP***	*0.59*	*0.55*	*0.56*	*0.55*
	Family Offer	*0.90*	*0.87*	*0.84*	*0.61*
	ESI Takeup	*0.95*	*0.88*	*0.88*	*0.66*
Demographics	Female	0.51	0.57	0.52	0.47
	Married	0.67	0.46	0.60	0.68
	Never married	0.21	0.40	0.29	0.27
	Divorced	0.10	0.12	0.09	0.03
	Widowed	0.02	0.03	0.02	0.02
	Number of kids 0-4	0.19	0.22	0.30	0.47
	. . . 5-12	0.36	0.40	0.50	0.65
	. . .13-18	0.31	0.32	0.38	0.39
	Elderly (75+) parent present	0.01	0.01	0.02	0.00
Human Capital	Age 18-19	0.04	0.06	0.07	0.06
	20-24	0.09	0.12	0.14	0.16
	25-29	0.09	0.11	0.13	0.17
	30-34	0.11	0.11	0.13	0.17
	35-39	0.12	0.12	0.13	0.16
	40-44	0.14	0.14	0.11	0.10
	45-49	0.12	0.11	0.11	0.06
	50-54	0.12	0.10	0.07	0.06
	55-59	0.09	0.07	0.06	0.03
	Education - less than high school	0.02	0.02	0.09	0.40
	. . . some high school	0.05	0.11	0.12	0.12
	. . . high school graduate	0.34	0.38	0.35	0.26
	. . . some college	0.30	0.31	0.29	0.14
	. . . college graduate	0.28	0.16	0.14	0.06
	Spanish interview	0.00	0.00	0.17	0.83
Labor Market (County) Characteristics	Unemployment rate	3.98	4.40	5.05	4.97
	% pop with college education	23.9	24.4	24.6	25.7
	County borders Mexico	0.01	0.01	0.09	0.08
	Population density	1,284	3,293	3,419	3,263
	Share of workers in agriculture	0.005	0.004	0.003	0.003
	. . . in mining	0.003	0.002	0.004	0.003
	. . . in construction	0.106	0.086	0.088	0.085
	. . . in manufacturing	0.052	0.046	0.049	0.052
	. . . in transportation	0.031	0.031	0.031	0.030
	. . . in wholsale trade	0.057	0.063	0.068	0.071
	. . . in retail trade	0.164	0.166	0.155	0.149
	. . . in finance/real estate	0.099	0.106	0.107	0.107
	. . . in services	0.451	0.465	0.461	0.465
	. . . in unclassified estabs	0.011	0.010	0.012	0.011
	. . . in auxiliaries	0.002	0.002	0.002	0.002
	. . . in small estabs (<50)	0.461	0.425	0.450	0.441
Health Care Market	FQHC sites within 5 miles	2.9	5.4	7.1	7.5
	Hospital beds per 1000 (county)	3.4	4.1	3.3	3.3
	HMO penetration (county)	0.27	0.27	0.33	0.33
	Average Medicare pmt (county)	529	571	582	589
State coverage Policies	High-risk pool	0.54	0.48	0.76	0.77
	Community rating for nongroup	0.19	0.14	0.20	0.15
	Minimum wage exceeds Fed.	0.22	0.15	0.36	0.41
	Medicaid eligibility (simulated)	0.09	0.20	0.17	0.18
	Average family income disregard	345	353	307	316
	Restricted work req. exemption	0.08	0.12	0.10	0.11
	Tough work req. exemption	0.76	0.80	0.59	0.58
Income	Total family income / 1000	65.3	48.0	51.1	33.8
	< 50% poverty	0.03	0.08	0.06	0.09
	50 - 99% poverty	0.04	0.10	0.08	0.20
	100 - 149% poverty	0.06	0.11	0.10	0.20
	150 - 199% poverty	0.07	0.09	0.12	0.17
	200 - 299% poverty	0.16	0.17	0.19	0.18
	> 300% poverty	0.65	0.45	0.44	0.16

Table 3: Labor Force Participation Models (Probit)

Variable	White non-Hispanic citizens N = 69,042 Coeff	(std error)	African American Citizens N = 10,393 Coeff	(std error)	Latino Citizens N = 6,437 Coeff	(std error)	Latino Non-citizens N = 4,143 Coeff	(std error)
Female	-0.345	*(0.019)*	-0.102	*(0.058)*	-0.448	*(0.055)*	-0.880	*(0.077)*
Never married	-0.311	*(0.032)*	-0.148	*(0.073)*	-0.260	*(0.086)*	0.058	*(0.097)*
Divorced	0.071	*(0.036)*	-0.058	*(0.078)*	-0.190	*(0.099)*	0.236	*(0.170)*
Widowed	-0.250	*(0.070)*	-0.360	*(0.147)*	-0.519	*(0.132)*	-0.095	*(0.225)*
Number of kids 0-4	-0.254	*(0.021)*	0.042	*(0.054)*	-0.149	*(0.052)*	-0.058	*(0.060)*
. . . 5-12	-0.157	*(0.012)*	0.001	*(0.032)*	-0.072	*(0.032)*	0.015	*(0.044)*
. . .13-18	-0.027	*(0.018)*	0.129	*(0.037)*	0.112	*(0.047)*	0.079	*(0.057)*
Elderly (75+) parent present	-0.214	*(0.090)*	-0.038	*(0.192)*	-0.070	*(0.186)*	-0.852	*(0.559)*
Age 18-19	1.027	*(0.068)*	0.838	*(0.188)*	0.776	*(0.202)*	0.506	*(0.351)*
20-24	0.798	*(0.065)*	0.572	*(0.153)*	0.505	*(0.139)*	0.624	*(0.311)*
25-29	1.088	*(0.050)*	0.942	*(0.163)*	0.745	*(0.129)*	0.576	*(0.303)*
30-34	1.026	*(0.056)*	0.943	*(0.141)*	0.954	*(0.139)*	0.593	*(0.274)*
35-39	0.932	*(0.049)*	1.006	*(0.137)*	0.707	*(0.144)*	0.543	*(0.280)*
40-44	0.897	*(0.046)*	0.966	*(0.124)*	0.715	*(0.143)*	0.772	*(0.274)*
45-49	0.859	*(0.051)*	0.993	*(0.137)*	0.709	*(0.174)*	0.537	*(0.319)*
50-54	0.824	*(0.048)*	0.925	*(0.137)*	0.606	*(0.153)*	0.646	*(0.286)*
55-59	0.617	*(0.053)*	0.816	*(0.134)*	0.619	*(0.159)*	0.408	*(0.298)*
Education - less than high school	-0.405	*(0.121)*	-0.619	*(0.301)*	-0.162	*(0.205)*	0.053	*(0.219)*
. . . some high school	-0.256	*(0.107)*	-0.237	*(0.254)*	-0.265	*(0.206)*	-0.148	*(0.258)*
. . . high school graduate	-0.022	*(0.105)*	0.080	*(0.250)*	0.186	*(0.199)*	-0.024	*(0.236)*
. . . some college	-0.109	*(0.104)*	0.291	*(0.245)*	0.104	*(0.190)*	-0.182	*(0.224)*
. . . college graduate	-0.007	*(0.108)*	0.235	*(0.260)*	0.200	*(0.195)*	0.028	*(0.267)*
Population density	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*
FQHC sites within 5 miles	-0.003	*(0.002)*	-0.001	*(0.004)*	-0.002	*(0.005)*	-0.006	*(0.005)*
Hospital beds per 1000 (county)	5.005	*(5.093)*	-0.968	*(10.918)*	-14.342	*(13.784)*	31.981	*(19.582)*
HMO penetration (county)	0.198	*(0.072)*	0.417	*(0.193)*	0.038	*(0.195)*	0.343	*(0.299)*
High-risk pool	-0.021	*(0.027)*	-0.255	*(0.074)*	-0.176	*(0.114)*	-0.209	*(0.133)*
Community rating for nongroup	0.081	*(0.028)*	0.144	*(0.112)*	-0.010	*(0.101)*	0.083	*(0.132)*
Minimum wage exceeds Fed.	-0.061	*(0.037)*	0.023	*(0.111)*	0.179	*(0.124)*	0.382	*(0.142)*
Medicaid eligibility (simulated)	-1.148	*(0.032)*	-1.347	*(0.060)*	-1.218	*(0.060)*	-0.886	*(0.080)*
Average family income disregard	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*	0.000	*(0.000)*
Restricted work req. exemption	-0.012	*(0.044)*	0.007	*(0.086)*	0.035	*(0.114)*	0.257	*(0.112)*
Tough work req. exemption	0.139	*(0.041)*	0.349	*(0.100)*	0.058	*(0.107)*	0.140	*(0.151)*
Constant	-0.011	*(0.140)*	-0.456	*(0.288)*	0.129	*(0.285)*	-0.191	*(0.441)*

Table 4: ESI Offer Models (Probit)

. . . in construction	[illegible]	[illegible]	[illegible]	[illegible]
. . . in manufacturing	8.306 *(4.110)*	-1.722 *(9.920)*	-4.126 *(8.949)*	10.224 *(10.640)*
. . . in transportation	9.714 *(4.521)*	0.428 *(10.871)*	-6.981 *(7.613)*	8.223 *(8.854)*
. . . in wholsale trade	6.883 *(4.657)*	-3.328 *(10.787)*	-5.896 *(9.338)*	12.525 *(10.439)*
. . . in retail trade	5.489 *(4.025)*	-2.221 *(8.886)*	-5.233 *(7.373)*	11.935 *(9.772)*
. . . in finance/real estate	7.313 *(4.113)*	-4.776 *(9.109)*	-1.009 *(8.766)*	10.442 *(10.526)*
. . . in services	[illegible]	[illegible]	-4.020 *(7.882)*	8.077 *(9.314)*
. . . in unclassified estabs	7.567 *(4.203)*	-1.562 *(9.857)*	-7.659 *(7.854)*	0.785 *(12.085)*
. . . in auxiliaries	43.608 *(14.227)*	-2.817 *(37.046)*	-22.239 *(35.981)*	-31.169 *(40.907)*
. . . in small estabs (<50)	-1.100 *(0.312)*	-1.173 *(0.860)*	-0.097 *(0.748)*	-2.962 *(1.040)*

Table 4: ESI Offer Models (Probit), continued

	White non-Hispanic citizens	African American Citizens	Latino Citizens	Latino Non-citizens
FQHC sites within 5 miles	-0.002 *(0.004)*	-0.003 *(0.009)*	-0.005 *(0.008)*	-0.007 *(0.007)*
Hospital beds per 1000 (county)	6.939 *(7.221)*	-20.962 *(18.269)*	-74.963 *(20.466)*	17.874 *(28.888)*
HMO penetration (county)	0.205 *(0.130)*	0.319 *(0.425)*	0.637 *(0.448)*	-0.461 *(0.466)*
High-risk pool	-0.072 *(0.049)*	-0.062 *(0.125)*	-0.341 *(0.188)*	-0.190 *(0.206)*
Community rating for nongroup	0.077 *(0.049)*	-0.143 *(0.227)*	0.125 *(0.161)*	-0.019 *(0.200)*
Minimum wage exceeds Fed.	-0.154 *(0.077)*	-0.126 *(0.219)*	0.112 *(0.220)*	0.402 *(0.175)*
Medicaid eligibility (simulated)	-0.599 *(0.064)*	-0.677 *(0.165)*	-0.460 *(0.138)*	-0.286 *(0.152)*
Average family income disregard	0.000 *(0.000)*	0.000 *(0.000)*	-0.001 *(0.000)*	-0.001 *(0.000)*
Restricted work req. exemption	0.103 *(0.069)*	0.062 *(0.147)*	-0.183 *(0.181)*	0.011 *(0.205)*
Tough work req. exemption	-0.021 *(0.062)*	-0.196 *(0.150)*	0.143 *(0.221)*	-0.051 *(0.156)*
Constant	-5.848 *(4.031)*	3.783 *(9.314)*	5.645 *(7.497)*	-6.863 *(9.179)*

Table 5a: ESI Takeup Models (Probit)

Hospital beds per 1000 (county)	[illegible]	[illegible]	[illegible]	[illegible]
HMO penetration (county)	0.323 *(0.142)*	0.168 *(0.352)*	1.190 *(0.339)*	-0.190 *(0.360)*
High-risk pool	-0.178 *(0.052)*	0.009 *(0.126)*	-0.599 *(0.188)*	-0.221 *(0.196)*
Community rating for nongroup	-0.014 *(0.060)*	0.211 *(0.221)*	0.062 *(0.136)*	-0.352 *(0.222)*
Minimum wage exceeds Fed.	0.057 *(0.075)*	0.329 *(0.203)*	0.189 *(0.152)*	0.392 *(0.224)*
Medicaid eligibility (simulated)	-0.775 *(0.095)*	-1.122 *(0.142)*	-1.184 *(0.165)*	-0.596 *(0.224)*
Average family income disregard	[illegible]	[illegible]	0.000 *(0.000)*	0.001 *(0.000)*
Restricted work req. exemption	-0.056 *(0.077)*	-0.248 *(0.172)*	-0.040 *(0.187)*	0.044 *(0.299)*
Tough work req. exemption	0.072 *(0.069)*	0.217 *(0.210)*	0.129 *(0.184)*	-0.040 *(0.247)*
Constant	0.879 *(0.280)*	0.269 *(0.515)*	2.185 *(0.490)*	0.283 *(0.506)*

Table 5b: ESI Takeup Models (Bivariate Probit)

Hospital beds per 1000 (county)	[illegible]	[illegible]	[illegible]	[illegible]
HMO penetration (county)	0.286 *(0.142)*	0.103 *(0.323)*	1.125 *(0.391)*	-0.191 *(0.389)*
High-risk pool	-0.169 *(0.056)*	0.022 *(0.111)*	-0.581 *(0.195)*	-0.279 *(0.255)*
Community rating for nongroup	-0.015 *(0.069)*	0.222 *(0.201)*	0.061 *(0.157)*	-0.377 *(0.201)*
Minimum wage exceeds Fed.	0.065 *(0.073)*	0.338 *(0.192)*	0.182 *(0.155)*	0.456 *(0.237)*
Medicaid eligibility (simulated)	-0.701 *(0.131)*	-0.950 *(0.184)*	-1.145 *(0.200)*	-0.640 *(0.192)*
Average family income disregard	[illegible]	[illegible]	0.000 *(0.000)*	0.001 *(0.001)*
Restricted work req. exemption	-0.059 *(0.085)*	-0.249 *(0.148)*	-0.032 *(0.170)*	0.047 *(0.209)*
Tough work req. exemption	0.068 *(0.069)*	0.236 *(0.182)*	0.115 *(0.175)*	-0.003 *(0.222)*
Constant	0.930 *(0.232)*	0.308 *(0.520)*	2.235 *(0.608)*	0.205 *(0.521)*

Table 6: Simulated Offer and Takeup Probabilities

Race	Conditional Offer Probability	Predicted Probability using "White" Data	Effect of Character-istics	Effect of structure
White, non-hispanic citizens	0.90	0.90		
African Americans	0.89	0.92	0.02	-0.02
Latino citizens	0.85	0.89	0.04	0.01
Latino non-citizens	0.60	0.73	0.13	0.17

Race	Conditional Takeup Probability	Predicted Conditional Probability using "White" Data	Effect of Character-istics	Effect of structure
White, non-hispanic citizens	0.95	0.95		
African Americans	0.89	0.92	0.03	0.03
Latino citizens	0.91	0.94	0.03	0.01
Latino non-citizens	0.63	0.76	0.13	0.19

Table 7: Linear Decompositions of Offer and Takeup Disparities

	% Point Diff from Non-hispanic Whites	Effect of Characteristic differences (shift from g to W)						
		Demog-raphy	*Human Capital*	*Spanish Interview*	*Labor Market*	*Health Care Market*	*State Coverage Policies*	***Total***
Heckman								
Offer								
African Americans	-2.1	2	1	0	1	0	1	**5**
Citizen Latinos	-5.8	0	3	2	1	0	1	**7**
Non-Citizen Latinos	-28.4	0	8	12	1	0	1	**21**
Takeup								
African Americans	-7.4	0	0	0	0	0	0	**1**
Citizen Latinos	-7.4	0	1	1	0	0	1	**2**
Non-Citizen Latinos	-29.5	0	4	5	0	0	1	**9**
OLS								
Offer								
African Americans	-2.1	2	1	0	1	0	1	**5**
Citizen Latinos	-5.8	0	3	2	1	0	1	**7**
Non-Citizen Latinos	-28.4	0	8	12	1	0	1	**22**
Takeup								
African Americans	-7.4	1	1	0	0	0	1	**3**
Citizen Latinos	-7.4	0	2	2	0	0	1	**5**
Non-Citizen Latinos	-29.5	0	7	10	0	0	2	**18**

Table 8: Tests for Structural Differences

OFFER

Race	Demography			Human Capital			Labor Market			Health Care Market			State Coverage Policies		
	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value
African Americans	21.38	4	0.000	21.01	14	0.101	22.67	15	0.091	2.86	3	0.414	8.04	7	0.329
Latino citizens	8.29	4	0.082	23.52	14	0.052	36.72	15	0.001	26.10	3	0.000	8.18	7	0.317
Latino non-citizens	27.32	4	0.000	38.87	14	0.000	79.52	15	0.000	2.51	3	0.474	23.47	7	0.001

TAKEUP

Race	Demography			Human Capital			Labor Market			Health Care Market			State Coverage Policies		
	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value	F-statistic	DF	P-value
African Americans	32.90	4	0.000	37.40	14	0.001	2.28	1	0.131	0.43	3	0.934	160.03	7	0.000
Latino citizens	5.64	4	0.228	42.77	14	0.000	1.93	1	0.165	8.12	3	0.044	135.02	7	0.000
Latino non-citizens	19.76	4	0.001	106.70	14	0.000	17.88	1	0.000	6.28	3	0.099	47.58	7	0.000