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The Effect of Health Insurance on Health Care Utilization: Evidence from the Medical Expenditure Panel Survey 2000-2005

by

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Abstract

This paper exploits the fact that insurance eligibility in the United States changes abruptly at age 65 due to universal coverage provided by Medicare. In that way, we adopt a regression discontinuity design to analyze the effect of health insurance coverage on health care access and utilization. The main findings suggest that groups with lower pre-65 coverage gain higher increases in the probability of being insured at 65. For instance, less educated persons (less likely to have pre-65 health insurance) appear to increase their likelihood of being insured at age 65 by more than their more highly educated counterparts. Furthermore, this increased insurance coverage appears to be associated with reductions in intergroup disparities in health care access. Therefore, the findings suggest that insurance matters in order to access health care services in a way that could potentially reduce inequalities between different ethnic groups.

Keywords: Medicare, Regression Discontinuity, Health Insurance, Health Care Utilization

Introduction

Approximately 20% of Americans below the age of 65 lack any kind of medical insurance, particularly if they belong to households below the median of the income distribution. The ongoing discussion on health care reform has shown long debates arguing that unequal health coverage causes disparities in health care utilization and ultimately in health outcomes. However, disentangling causality between health coverage and utilization is difficult, given that health insurance decisions might be correlated with unobservable characteristics affecting health outcomes. Therefore, observational comparisons between people with different levels of insurance coverage may yield biased estimates of the true effects. For instance, an upward bias might arise if persons with coverage were healthier or exercised more caution with their health. Alternatively, a downward bias would arise in the presence of adverse selection where sick people become insured because they know they will need health care in the near future.

Hence, understanding the causal relation among health insurance, utilization, and outcomes is of material importance for policymakers. A causal estimation may serve to determine the optimal level of publicly provided medical insurance in order to maximize health care access. Accordingly, this paper analyzes the effect that health insurance coverage has on health care access and utilization. In doing so, the paper contributes to the limited literature that analyzes whether better insurance causes better health outcomes (Brown, Bindman, & Lurie, 1998; Levy & Meltzer, 2001; Card, Dobkin, & Maestas, 2008). Specifically, the paper extends previous research by examining different effects for heterogeneous groups regarding ethnicity, education, and gender, using an unexploited dataset, the Medical Expenditure Panel Survey (MEPS).

Causal estimates are isolated by the adoption of an

empirical strategy that exploits the fact that insurance coverage in the United States changes abruptly at age 65. In contrast to the nonelderly population, almost every American over age 65 is insured. This abrupt change is the result of universal Medicare eligibility at this age. In this regard, we use the Medicare eligibility age threshold as an exogenous variation in insurance status within a regression discontinuity (RD) design.

The main findings suggest that groups with lower pre-65 coverage gain higher increases in the probability of being insured at 65. For instance, less educated persons (less likely to have pre-65 health insurance) appear to increase the likelihood of being insured at age 65 by more than their more highly educated counterparts. Furthermore, it appears that this increased insurance coverage is associated with reductions in intergroup disparities in health care access. Therefore, the findings suggest that insurance matters in order to access health care services in a way that could potentially reduce inequalities between different ethnic groups.

The organization of the document is as follows: Section 2 presents the econometric framework. Section 3 describes the data set. Section 4 presents results regarding changes in insurance coverage at age 65. Section 5 provides tests for the identification assumption. Section 6 presents reduced form results of health outcomes with respect to changes in age. Section 7 presents instrumental variables (IV) results regarding the effect of insurance coverage on health outcomes. Finally, the paper concludes with Section 8.

The Econometric Framework

Consider the following regression equation relating health outcomes to insurance status:

$$h_{it}=\alpha+f(age_{it})+\gamma' X_{it}+\beta C_{it}+V_{it}+\varepsilon_{it} \quad (1)$$

where $f(age_{it})$ is a quadratic function of age for individual i at time t, X_{it} is a K x 1 vector of individual observable characteristics, C_{it} is an indicator variable for health insurance coverage, V_{it} is a J x 1 vector of unobservable individual characteristics, and ε_{it} is an iid disturbance. The coefficient of interest that measures the effect of insurance on health is therefore β. However, if we estimate (1) say by ordinary least squares (OLS) and V_{it} were correlated with C_{it}, then the estimated β will be biased in an unknown direction[4]. In that way, in order to obtain an unbiased estimate for β, we need an exogenous variable related to C_{it} but unrelated to V_{it} and ε_{it}. In other words, we need an instrument for C_{it}.

In the United States, persons reaching the age of 65 become automatically eligible for Medicare coverage. Conseguently, the age threshold of 65 is useful as an exogenous explanatory variable for insurance status. In this context, an RD design taking the age 65 cutoff as the discontinuity point is suitable if other factors affecting health evolve smoothly around this threshold. Specifically, consider the following regression equation relating coverage status to a discontinuity at age 65:

$$C_{it}=\alpha+g(age_{it})+\gamma' X_{it}+\eta_1 * D_{65}+\eta_2 * D_{65} * age_{it}+\eta_3 * D_{65} * age^2_{it}+\psi_{it} \quad (2)$$

where D_{65} is an indicator taking the value of 1 if $age_{it} \geq 65$ and zero otherwise. In estimating (2), we are arguing that persons just below age 65 are a suitable counterfactual for persons just above that threshold. What we are exploiting is an arbitrary rule that provides health insurance when someone turns 65. In that way, the key identification assumption is that the rule is not related to other characteristics that may systematically affect health outcomes. Hahn, Todd, & Van Der Klaauw (2001) proposed the RD technique, which requires an arbitrary rule determining eligibility for some treatment. Under this setting, treatment is as good as randomly assigned for subjects just below and above the eligibility threshold, and consistent treatment effects can be estimated.

Specifically, in terms of (2), the average insurance rate for persons just below age 65 will be given by

$$E(C_{it}|age < 65, X) = \alpha_1 + g(age_{it}) + \Gamma_1' X_{1t} \quad (3)$$

while the average insurance rate for persons just above age 65 will be given by

$$E[C_{it}|age \geq 65, X]=\alpha_1+g(age_{it})+\Gamma_1' X_{1t}+\eta_1+\eta_2 * age_{it}+\eta_3 * age^2_{it} \quad (4)$$

Then, the additional insurance coverage due to the, presumably exogenous, Medicare eligibility threshold is given by

$$E[C_{it}|age \geq 65, X]-E[C_{it}|age \geq 65, X]=\eta_1+\eta_2 * age_{it}+\eta_3 * age^2_{it}|_{age_{it}=65} \quad (5)$$

The expression (5) constitutes the RD estimated effect on the outcome of interest (insurance coverage in this case) taking the group just below the arbitrary cutoff for treatment eligibility as a counterfactual for the group just above the cutoff. The underlying assumption is that, given the presumably arbitrary cutoff, groups just below and above the threshold are very similar with respect to other characteristics that may also affect the outcome of interest. Therefore, the group below the cutoff serves as an appropriate control to isolate causal treatment effects on the outcome of interest.

Researchers in the social sciences have been increasingly using this relatively new econometric technique with stimulating results. For example, Carpenter and Dobkin (2009) used the minimum legal drinking age in the United States (21) as an exogenous threshold to analyze the effect of alcohol consumption on mortality. They found a 21% increase in recent drinking days and a discrete 9% increase in the mortality rate at age 21 (primarily due to motor vehicle accidents, alcohol-related deaths, and suicides). Yanez-Pagan (2008) used the eligibility age

for a cash transfer program in Bolivia (65) to analyze the effects of this income shock on children's human capital investments. The main findings suggest that women are more effective at promoting human capital investments and that, on average, indigenous households tend to prioritize boys' education. For instance, having an eligible woman in the household increases children's schooling expenditures by approximately 56- 91%, depending on the ethnicity of the recipient. Finally, the study shows that pension income in the hands of indigenous people has a smaller impact on human capital investments than analogous income in the hands of nonindigenous people.

In our setting, if the Medicare eligibility threshold is indeed an exogenous rule; that is, if $Cov(D_{65};\varepsilon_{it}+V_{it})=Cov(D_{65}*age_{it};\varepsilon_{it}+V_{it})=Cov(D_{65}*age^2_{it};\varepsilon_{it}+V_{it})$, then (2) can be seen as the first stage equation of a two-stage least squares (2SLS) estimation for (1). If these assumptions hold, the 2SLS estimate of β will be consistent. In this way, for the validity of this method, the discontinuity at age 65 should not affect variables that might be correlated with health outcomes. Therefore, in Section 5, we analyze whether the discontinuity is significantly associated with changes in employment measures, risk attitudes, economic status, and marital status.

The Data

The analysis will be performed using pooled samples of the Household Component (HC) of the Medical Expenditure Panel Survey (MEPS) for years 2000 through 2005. All of the estimations are restricted to persons between ages 55 and 75 as of December of the sample year. All of the variables are also taken to be the end-of-year values.

The MEPS, which began in 1996, is a set of large-scale surveys of families and individuals, their medical providers (doctors, hospitals, pharmacies, etc.), and employers across the United States. MEPS collects data on the specific health services that Americans use, how frequently they use them, the cost of these services, and how they are paid for, as well as data on the cost, scope, and breadth of health insurance held by and available to U.S. workers.

The HC collects data from a sample of families and individuals in selected communities across the United States, drawn from a nationally representative subsample of households that participated in the prior year's National Health Interview Survey (conducted by the National Center for Health Statistics).

During the household interviews, MEPS collects detailed information for each person in the household on the following: demographic characteristics, health conditions, health status, use of medical services, charges and source of payments, access to care, satisfaction with care, health insurance coverage, income, and employment.

Changes in Coverage Results

We begin estimating the following restricted version of (2):

$$C_{it} = \alpha_2 + g(age_{it}) + \Gamma_2' X_{it} + \delta D_{65} + \xi_{it} \qquad (2')$$

The parameter of interest is δ. This parameter gives the associated discontinuity in insurance coverage at age 65. It can be interpreted as the increased likelihood of having insurance due to the event of reaching age 65. The four measures of insurance coverage are Medicare, any insurance, private insurance, and multiple insurance.[6] The dependent variable C_{it} is a dummy taking the value of 1 if person *i* has the analyzed coverage at time *t* and zero otherwise.

It is worth noting that the dependent variables are dichotomous. Therefore, while consistent estimates for δ will be obtained under the assumption of age threshold exogeneity, disturbances obtained from linear probability models will be heteroskedastic. In that way, we estimate the linear model using a two-step feasible generalized least squares (FGLS) procedure. First, the model is estimated via OLS and the predicted dependent variable, $\hat{C}_{it}$, is obtained. Second, each observation is weighted by $\left[\hat{C}_{it}\left(1-\hat{C}_{it}\right)\right]^{-\frac{1}{2}}$ and the model estimated via weighted least squares (WLS). This procedure provides consistent and efficient estimates (robust to heteroskedasticity) provided that Medicare eligibility is exogenous to other variables affecting health coverage and utilization.

Another possibility is modeling the relation of interest with a nonlinear specification like a *probit* model, for example. While this option ensures that predicted coverage rates will be inside the interval [0,1], consistency of estimated marginal effects will be achieved if the unknown conditional mean was correctly specified. As a result, given that we are interested in the effect of the Medicare discontinuity at age 65 (i.e. the δ parameter) rather than the predicted coverage rate, it is safer to rely on the FGLS estimation procedure. However, we will also report *probit* estimated marginal effects as a robustness check.

Table 1 displays the proportion of persons aged 63-64 having each of the four coverage measures. It also shows estimates of δ obtained from (2'). In addition, (2') is estimated for different groups classified by ethnicity and education as detailed in Table 1. All of the estimated regression discontinuities (RD) for the entire sample are significant and not sensitive to the exclusion of the X_{it} vector as evidenced in line 1. Estimated RD for Medicare, any insurance, and multiple insurance are positive and significant for the great majority of subgroups considered. By contrast, only a few subgroups show negative and significant RD for private insurance.

Table 1

Insurance Characteristics Before Age 65 and Estimated Discontinuities at Age 65 (Allowing Only for Differential Intercept at Age 65)

	On Medicare			Any Insurance			Private Insurance			Medicare and Private		
	Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
1. Whole Sample	11.2	77.3	77.4	79.6	18.0	18.3	61.8	-9.0	-7.8	3.0	43.7	44.7
		0.6	0.6		0.8	0.7		1.2	1.1		0.8	0.8
By Ethnicity and Education:												
White Non-Hispanic:												
2. Some High School	18.8	72.0	72.0	74.2	22.3	22.4	50.7	-6.1	-5.5	4.7	36.9	37.0
		2.5	2.5		2.6	2.6		4.2	4.1		3.2	3.2
3. High School Graduate	9.7	82.7	82.6	85.9	15.1	15.3	74.7	-10.2	-9.7	4.2	54.3	54.4
		1.1	1.1		1.3	1.3		2.2	2.1		1.6	1.6
4. Some College	8.2	83.5	83.6	83.5	13.6	13.4	72.6	-6.3	-7.1	3.5	58.6	58.3
		1.4	1.4		1.8	1.8		3.0	2.9		2.2	2.2
5. College Graduate or More	2.8	85.5	85.4	90.9	8.3	8.5	86.8	-8.1	-7.8	1.9	65.7	65.7
		1.1	1.1		1.4	1.4		2.3	2.2		1.7	1.7
Black Non-Hispanic:												
6. Some High School	16.8	66.5	67.5	65.5	30.4	31.2	29.2	-0.4	-1.7	0.9	24.6	24.2
		4.2	4.2		4.5	4.5		5.7	5.6		3.6	3.5
7. High School Graduate	18.4	68.6	68.6	78.0	22.2	23.0	49.6	-3.1	-2.7	2.1	34.2	34.3
		3.4	3.4		3.8	3.8		5.7	5.5		3.6	3.6
8. Some College	24.1	61.6	60.6	84.5	10.4	9.1	58.6	-5.1	-4.9	6.9	39.9	39.9
		5.4	5.3		5.5	5.5		8.3	8.2		5.3	5.3
9. College Graduate or More	8.6	84.6	83.5	82.9	13.2	12.9	74.3	-1.8	0.0	2.9	65.5	65.8
		3.9	3.9		6.3	6.1		9.2	8.8		5.7	5.6
Hispanic:												
10. Some High School	9.1	86.6	87.2	63.6	31.8	33.3	37.9	-16.8	-15.6	3.0	20.5	20.1
		4.2	4.1		6.5	6.4		8.1	7.9		4.5	4.5
11. High School Graduate	7.2	76.6	76.6	72.3	24.9	25.0	54.2	-18.8	-19.3	0.0	29.0	28.5
		3.9	3.9		5.7	5.7		7.2	7.1		3.9	3.9
12. Some College	9.5	86.9	87.3	66.7	32.0	33.1	42.9	-19.7	-18.9	4.8	26.7	24.3
		5.4	5.3		9.4	9.5		12.4	12.5		6.6	6.8
13. College Graduate or More	0.0	63.6	64.1	81.5	9.6	5.8	77.8	0.1	-5.9	0.0	52.2	53.1
		6.3	6.5		10.0	9.7		12.8	12.5		6.5	6.6
By Ethnicity:												
14. White Non-Hispanic	9.8	81.5	81.5	84.7	14.5	14.5	72.0	-8.1	-7.9	3.6	53.6	53.9
		0.7	0.7		0.8	0.8		1.3	1.3		1.0	1.0
15. Black Non-Hispanic	18.4	68.2	68.1	75.9	22.3	22.1	44.5	-0.7	-2.5	3.0	34.0	34.0
		2.0	2.0		2.2	2.2		3.2	3.0		2.0	2.0
16. Hispanic	11.5	70.8	71.5	60.6	32.3	33.3	33.5	-13.5	-12.5	1.0	15.8	16.4
		1.8	1.8		2.6	2.5		2.9	2.8		1.5	1.5
Hispanic Sub-Categories:												
17. Puerto Rico	18.2	72.6	77.3	84.1	14.9	16.1	47.7	-34.9	-30.6	2.3	11.4	11.6
		6.0	6.3		7.2	7.5		9.9	9.7		4.7	4.7
18. Cuba	5.7	77.1	75.7	65.7	41.6	39.4	45.7	-18.3	-24.0	0.0	20.5	15.3
		5.0	5.2		8.8	8.8		10.7	10.6		6.1	6.3
19. Mexico	12.4	71.7	72.7	51.3	40.5	40.6	26.6	-5.6	-6.3	1.1	16.3	16.7
		2.2	2.1		3.1	3.1		3.5	3.3		1.8	1.8
20. Dominican	9.1	59.1	38.4	81.8	25.0	13.2	18.2	19.7	10.4	0.0	19.5	.--
		13.5	15.3		15.9	15.0		18.8	17.3		8.7	.--
21. Central-South America	11.5	59.2	58.4	80.8	-0.8	2.7	42.3	-30.1	-26.2	0.0	14.3	13.3
		8.4	8.0		10.8	10.6		11.7	11.1		4.3	4.1
By Sex:												
22. Male	0.1	76.2	76.2	0.8	16.8	17.1	0.7	-8.2	-6.9	0.0	46.2	47.3
		0.9	0.9		1.1	1.1		1.7	1.5		1.2	1.2
23. Female	0.1	78.3	78.3	0.8	19.0	19.3	0.6	-9.7	-8.5	0.0	41.6	42.5
		0.8	0.8		1.0	1.0		1.6	1.4		1.1	1.1
Other Controls		NO	YES		NO	YES		NO	YES		NO	YES

Note: Heteroskedasticity robust standard errors below the estimates. Bolded estimates are not significant at the 10%, 5% or 1% levels. Entries in columns [1], [4], [7] and [10] are percentages of age 63-64 with insurance type on heading. Remaining columns show estimated regression discontinuities at age 65. All models include quadratic control for age and a dummy for age 65 or older (without interactions with age controls). Other controls include gender, race, ethnicity, education, region, marital status and sample year. Estimates based on linear probability models fit to pooled samples of 2000-2005 MEPS.

While estimates in Table 1 provide initial evidence of RD in insurance at age 65, the specification in (2') only allows for a differential intercept at age 65. Therefore, we estimate (2) because its specification not only allows for a differential intercept at 65, but also allows for differential slope and curvature in age. When using (2), the discontinuity is given by the following expression:

$$\left.\frac{\partial c_{it}}{\partial D_{65}}\right|_{age=65} = \eta_1 + \eta_2 * age + \eta_3 * age^2 = \Pr(C=1 \mid X, age \geq 65) - \Pr(C=1 \mid X, age < 65) \quad (6)$$

Table 2 displays estimated RD using specification (2) for different groups. Notice first that Table 2 estimates are very similar to Table 1 estimates. However, the more flexible specification (2) allows a better fit. In addition, as a robustness check, Table 3 reports estimated marginal effects on the RD using a *probit* specification. Results are materially unchanged, providing further robustness for the estimates. Nevertheless, as explained above, we prefer the flexible FGLS linear probability model estimates to avoid the risk of inconsistency arising from incorrect functional form assumptions. In that way, the analysis will focus on Table 2.

Medicare estimated RD are significant and not sensitive to the exclusion of the X_{it} vector. The proportion of persons aged 63-64 with Medicare is only 11.2%, but the estimated RD at age 65 is 72%. This implies that the likelihood of having Medicare jumps by 72 percentage points at age 65. In general, pre-65 Medicare enrollment appears to be inversely related to education level across different ethnic groups. For instance, 18.8% of Whites with some high school education were enrolled in Medicare at ages 63-64, while only 2.8% of college graduates were enrolled. The same (but less clear) pattern is evident for Blacks and Hispanics. Another feature is that more highly educated persons gain more in the likelihood of having Medicare at 65. The RD for highly educated Whites is 79 percentage points, while it is only of 68.3 percentage points for Whites with a lower level of education.

The likelihood of having any insurance jumps by 17.3 percentage points at age 65. The proportion of persons aged 63-64 covered by some insurance is about 80%. Estimated RD are almost entirely significant among subgroups. However, contrary to Medicare, the likelihood of being insured prior to age 65 increases in relation to education. In addition, estimated RD are higher for people with less education (less likely to be covered prior to age 65). This implies that discontinuities at age 65 are reducing the gap in coverage between different groups. Figure 1 illustrates this fact. The figure shows fitted coverage rates for the whole sample, for the group with the highest pre-65 coverage rate (highly educated Whites), and for the group with the lowest pre-65 coverage rate (Hispanics with low educational status). Clearly, prior to age 65 (260 Quarters), highly educated Whites are over the sample average, while Hispanics with low educational status are below average (showing higher dispersion). However, at age 65, Hispanics gain relatively more coverage than Whites, and pre-65 differences in coverage are virtually equated across these groups.

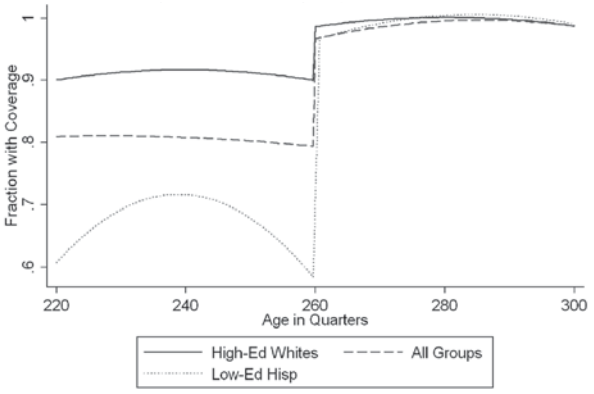

Figure 1. Coverage by Any Insurance

With respect to the ethnicity analysis, Hispanics are the group with the lowest likelihood of being insured prior to age 65. Only 60.6% of 63-64-year-old Hispanics are insured. However, this group shows the largest estimated RD (31.5 percentage points). Furthermore, if we break down the Hispanic group into different subcategories, we observe that the only group showing a significant discontinuity is the Mexican (40 percentage points). The Mexican group is also the one showing the lowest rate of insurance coverage at ages 63-64 (only 51.3 %). Consequently, it appears that the age 65 discontinuity reduces the gaps in coverage not only between groups but also within groups. The gender analysis also suggests a reduction in pre-65 disparities. Males had a higher pre-65 coverage rate (82.7% versus 77.4% for women) and gain a lower increase in post-65 coverage (15.8 percentage points versus 18.6 percentage points for women).

Private coverage shows a negative and significant RD of -5.7 percentage points for the whole sample. This estimate is smaller in magnitude if compared with the positive RD of the other insurance measures. A plausible interpretation for this finding is that with free insurance at 65, some people with a utility function that values consumption relatively more than health services, will substitute costly private insurance with the free public insurance. Notice, however, that only a few subgroups show significant effects on private insurance decline. In particular, Whites with middle and high education and women appear to drive the aggregate effect. Therefore, this effect is not only small in magnitude but is also attributable to some segments of the population and is far from being pervasive.

Multiple insurance also shows significant RD for the whole sample of 42.4 percentage points. Nevertheless, the pre-65 multiple coverage incidences are very low (3% in aggregate). The subgroup analyses show that, for each ethnic group, persons with higher education gain more in multiple coverage incidence at age 65.

Table 2

Insurance Characteristics Before Age 65 and Estimated Discontinuities at Age 65 (Allowing for Differential Intercept, Slope and Curvature at Age 65)

	On Medicare			Any Insurance			Private Insurance			Medicare and Private		
	Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
1. Whole Sample	11.2	71.9	72.0	79.6	17.5	17.3	61.8	-5.1	-5.7	3.0	42.3	42.4
		0.9	0.9		1.1	1.1		1.7	1.6		1.2	1.2
By Ethnicity and Education:												
White Non-Hispanic:												
2. Some High School	18.8	68.4	68.3	74.2	23.0	23.1	50.7	2.1	2.2	4.7	39.1	39.1
		3.7	3.7		3.8	3.8		6.3	6.1		4.8	4.7
3. High School Graduate	9.7	79.2	79.1	85.9	12.5	12.5	74.7	-11.0	-10.6	4.2	51.2	51.4
		1.6	1.6		2.0	1.9		3.3	3.2		2.4	2.4
4. Some College	8.2	76.3	76.4	83.5	17.3	16.9	72.6	0.9	0.2	3.5	54.1	54.0
		2.1	2.1		2.7	2.7		4.5	4.4		3.3	3.3
5. College Graduate or More	2.8	78.9	79.0	90.9	8.8	8.7	86.8	-7.3	-7.6	1.9	59.0	58.9
		1.6	1.6		2.1	2.1		3.4	3.3		2.5	2.5
Black Non-Hispanic:												
6. Some High School	16.8	67.9	68.5	65.5	34.5	35.6	29.2	1.3	-2.0	0.9	16.9	15.8
		6.1	6.2		6.6	6.6		8.4	8.3		5.3	5.3
7. High School Graduate	18.4	54.4	54.9	78.0	19.5	19.8	49.6	5.7	6.1	2.1	35.2	35.9
		5.0	5.0		5.6	5.6		8.3	8.1		5.3	5.3
8. Some College	24.1	58.5	57.6	84.5	17.2	17.5	58.6	-0.3	-2.3	6.9	37.4	36.7
		8.0	7.9		8.1	8.1		12.3	12.1		7.9	7.9
9. College Graduate or More	8.6	73.6	72.1	82.9	10.1	6.8	74.3	-3.7	-5.7	2.9	57.0	56.4
		5.9	5.9		9.6	9.5		14.0	13.6		8.7	8.6
Hispanic:												
10. Some High School	9.1	85.8	89.9	63.6	39.1	42.3	37.9	-13.2	-13.0	3.0	18.9	19.1
		6.5	6.3		9.9	9.8		12.4	12.0		6.9	6.8
11. High School Graduate	7.2	74.3	75.3	72.3	25.4	27.4	54.2	-6.5	-7.4	0.0	33.1	31.8
		6.0	6.0		8.8	8.7		11.0	10.9		5.9	5.9
12. Some College	9.5	84.0	85.3	66.7	35.1	31.7	42.9	-7.2	-9.4	4.8	33.1	29.3
		8.3	8.2		14.6	14.7		19.1	19.2		10.2	10.5
13. College Graduate or More	0.0	81.3	79.4	81.5	8.5	0.8	77.8	-12.7	-18.6	0.0	62.9	64.8
		9.9	10.1		15.7	15.2		20.0	19.5		10.1	10.2
By Ethnicity:												
14. White Non-Hispanic	9.8	75.9	76.0	84.7	14.2	14.0	72.0	-5.0	-5.6	3.6	50.7	50.6
		1.0	1.0		1.2	1.2		2.0	1.9		1.5	1.5
15. Black Non-Hispanic	18.4	62.4	62.4	75.9	22.1	22.8	44.5	-0.3	-1.8	3.0	28.4	28.8
		2.9	3.0		3.2	3.3		4.8	4.5		3.0	3.0
16. Hispanic	11.5	64.4	65.8	60.6	28.5	31.5	33.5	-11.3	-8.6	1.0	18.0	19.0
		1.2	1.2		1.6	1.5		2.4	2.2		1.6	1.6
Hispanic Sub-Categories:												
17. Puerto Rico	18.2	76.6	81.8	84.1	19.4	19.8	47.7	-25.0	-20.7	2.3	21.1	21.0
		9.2	9.4		11.0	11.3		15.1	14.6		7.2	7.0
18. Cuba	5.7	56.7	58.0	65.7	23.6	26.9	45.7	-6.7	-17.2	0.0	38.0	30.6
		8.1	8.1		14.7	14.1		17.7	17.0		10.1	10.1
19. Mexico	12.4	65.8	66.5	51.3	38.6	40.0	26.6	-5.6	-4.7	1.1	16.3	16.9
		3.2	3.1		4.6	4.5		5.0	4.8		2.7	2.7
20. Dominican	9.1	21.8	13.7	81.8	22.6	4.6	18.2	0.4	8.4	0.0	4.8	.---
		17.3	19.2		22.7	20.4		26.6	23.3		12.1	.---
21. Central-South America	11.5	27.3	37.8	80.8	-34.0	-19.5	42.3	-34.0	-23.2	0.0	11.7	13.4
		12.6	12.4		16.6	16.4		18.1	17.3		6.6	6.5
By Sex:												
22. Male	12.6	70.5	70.8	82.1	15.7	15.8	65.1	-3.9	-4.0	3.6	44.9	45.4
		1.4	1.3		1.6	1.6		2.5	2.3		1.8	1.7
23. Female	10.0	73.2	73.1	77.4	19.1	18.6	58.8	-6.1	-7.1	2.5	39.9	39.8
		1.2	1.2		1.6	1.5		2.4	2.2		1.6	1.6
Other Controls		NO	YES		NO	YES		NO	YES		NO	YES

Note: Heteroskedasticity robust standard errors below the estimates. Bolded estimates are not significant at the 10%, 5% or 1% levels. . Entries in columns [1], [4], [7] and [10] are percentages of age 63-64 with insurance type on heading. Remaining columns show estimated regression discontinuities (in percentages) at age 65. All models include quadratic control for age, fully interacted with dummy for age 65 or older. Other controls include gender, race, ethnicity, education, region, marital status and sample year. Estimates based on linear probability models fit to pooled samples of 2000-2005 MEPS.

Table 3
Insurance Characteristics Before Age 65 and Estimated Discontinuities at Age 65 (PROBIT marginal effects)

	On Medicare			Any Insurance			Private Insurance			Medicare and Private		
	Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
1. Whole Sample	11.2	90.6	92.5	79.6	16.4	14.0	61.8	-8.9	-9.2	3.0	30.3	28.2
		1.7	1.8		0.9	0.8		1.2	1.3		0.9	0.9
By Ethnicity and Education:												
White Non-Hispanic:												
2. Some High School	18.8	75.6	77.0	74.2	10.1	9.6	50.7	-6.1	-5.9	4.7	38.0	38.4
		5.6	5.7		3.3	3.2		4.2	4.3		4.0	3.9
3. High School Graduate	9.7	103.4	104.2	85.9	9.4	8.8	74.7	-10.0	-9.7	4.2	44.8	44.9
		3.9	3.9		1.7	1.7		2.2	2.2		2.3	2.3
4. Some College	8.2	96.0	98.7	83.5	14.3	12.7	72.6	-6.2	-7.3	3.5	39.5	39.1
		5.9	6.0		2.2	2.0		3.0	3.0		3.1	3.0
5. College Graduate or More	2.8	91.8	91.2	90.9	10.7	10.0	86.8	-8.0	-7.6	1.9	41.1	41.0
		4.4	4.4		1.7	1.6		2.2	2.2		2.9	2.9
Black Non-Hispanic:												
6. Some High School	16.8	73.9	76.4	65.5	22.3	22.1	29.2	0.0	-1.0	0.9	17.9	15.2
		8.3	8.5		6.1	6.0		5.7	5.7		3.3	3.1
7. High School Graduate	18.4	69.7	72.2	78.0	24.9	25.3	49.6	-3.0	-2.6	2.1	23.1	22.2
		7.6	7.7		4.9	4.8		5.7	5.9		3.4	3.3
8. Some College	24.1	60.5	62.6	84.5	13.9	13.0	58.6	-5.1	-5.2	6.9	20.0	19.1
		11.1	11.9		7.0	6.7		8.4	8.6		5.1	5.0
9. College Graduate or More	8.6	79.8	86.0	82.9	10.1	6.8	74.3	-2.7	-0.2	2.9	7.5	3.7
		15.9	16.0		9.6	9.5		9.3	9.5		9.4	6.2
Hispanic:												
10. Some High School	9.1	127.6	141.3	63.6	40.3	39.5	37.9	-17.6	-17.2	3.0	2.5	1.3
		16.7	19.0		10.3	10.7		8.4	8.7		3.1	1.8
11. High School Graduate	7.2	74.1	71.8	72.3	38.3	38.2	54.2	-19.1	-20.9	0.0	13.2	11.6
		8.5	23.2		8.2	8.2		7.5	7.7		3.4	10.3
12. Some College	9.5	91.6	88.0	66.7	35.1	31.7	42.9	-20.0	-20.4	4.8	4.0	2.8
		17.7	36.3		14.6	14.7		13.0	13.5		4.4	3.6
13. College Graduate or More	0.0	41.5	41.1	81.5	3.2	-3.9	77.8	1.6	-6.8	0.0	62.9	64.8
		11.6	12.4		11.4	9.8		13.6	14.3		10.1	10.2
By Ethnicity:												
14. White Non-Hispanic	9.8	99.6	102.9	84.7	12.4	10.6	72.0	-7.9	-8.2	3.6	41.4	41.4
		2.3	2.4		0.9	0.9		1.3	1.4		1.4	1.3
15. Black Non-Hispanic	18.4	73.6	74.5	75.9	20.8	19.2	44.5	-0.4	-2.3	3.0	20.3	18.5
		4.4	4.5		2.7	2.7		3.3	3.5		2.0	1.9
16. Hispanic	11.5	75.0	76.6	60.6	32.8	34.3	33.5	-14.7	-14.9	1.0	6.6	4.8
		2.3	2.4		1.2	1.1		1.6	1.7		1.3	1.2
Hispanic Sub-Categories:												
17. Puerto Rico	18.2	87.0	97.4	84.1	19.4	19.8	47.7	-39.5	-42.1	2.3	3.2	0.0
		17.0	20.9		11.0	11.3		11.0	12.0		3.5	0.1
18. Cuba	5.7	74.4	76.9	65.7	43.6	11.1	45.7	-20.4	-29.5	0.0	12.6	4.7
		17.8	21.6		11.4	11.6		11.7	13.7		5.8	5.6
19. Mexico	12.4	78.4	78.4	51.3	41.3	43.1	26.6	-6.4	-7.1	1.1	7.2	4.2
		4.8	18.8		4.1	4.2		3.6	3.8		1.7	82.2
20. Dominican	9.1	32.5	14.9	81.8	22.6	4.6	18.2	22.1	13.9	0.0	4.8	.---
		21.7	84.1		22.7	20.4		19.1	12.3		12.1	.---
21. Central-South America	11.5	51.5	57.9	80.8	-3.0	3.1	42.3	-32.5	-37.1	0.0	11.7	13.4
		10.7	36.8		11.2	12.3		13.2	15.6		6.6	6.5
By Sex:												
22. Male	12.6	87.5	90.3	82.1	15.1	12.2	65.1	-8.1	-8.0	3.6	30.8	29.5
		2.5	2.6		1.3	1.3		1.7	1.8		1.4	1.4
23. Female	10.0	93.2	94.9	77.4	17.3	15.1	58.8	-9.6	-10.1	2.5	29.9	27.1
		2.3	2.4		1.2	1.1		1.6	1.7		1.3	1.2
Other Controls		NO	YES		NO	YES		NO	YES		NO	YES

Note: Standard errors below the estimates. Bolded estimates are not significant at the 10%, 5% or 1% levels. Entries in columns [1], [4], [7] and [10] are percentages of age 63-64 with insurance type on heading. Remaining columns show estimated regression discontinuities (from PROBIT marginal effects) at age 65. All models include quadratic control for age, fully interacted with dummy for age 65 or older. Other controls include gender, race, ethnicity, education, region, marital status and sample year. Estimates based on PROBIT models fit to pooled samples of 2000-2005 MEPS.

Figure 2 illustrates this for the Black group. Clearly, the figure shows that prior to age 65, all subgroups had very small incidence of multiple coverage. However, at age 65, highly educated persons show a greater RD with respect to people with lower educational status. This finding suggests that persons with higher education (and presumably higher resources) do not entirely substitute their private coverage with Medicare. By contrast, they maintain their private coverage and supplement it with the Medicare coverage.

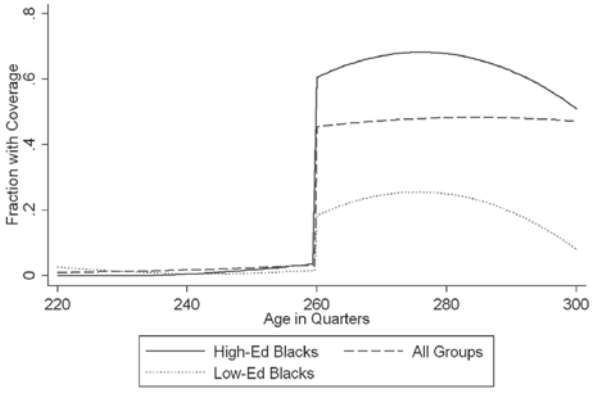

Figure 2. Coverage by Multiple Insurance

In summary, the evidence suggests that RD estimates at age 65 are highly significant in explaining changes in coverage. Therefore, if the onset of age 65 were uncorrelated with other factors affecting health outcomes, we could use RD at 65 as an instrument for insurance coverage in order to identify the effect of insurance on health outcomes. Clearly, we cannot test if RD for age 65 are correlated with unobservable factors, but we could check if observable factors that presumably affect health evolve smoothly at age 65. The next section deals with this issue.

Testing the Identification Assumption

As previously stated, we cannot test whether unobservable factors affecting health show abrupt discontinuities at age 65, given that we do not observe them. However, we do observe some factors that might be correlated with health outcomes. Thus, we can test if these factors evolve smoothly at the age 65 threshold. By doing this, we cannot ensure that the identification assumption holds, but at least, we could say that that there is no evidence to suggest that it does not hold. In that way, we are testing a necessary but not sufficient condition for the identification assumption to hold.

Having said that, we test whether employment, risk attitudes, and economic and marital status evolve smoothly at age 65. To do so, we use an estimator analogous to equation (2) but having the factors being tested as dependent variables. After that, we compute the estimated RD at age 65 for each one of the factors. If these factors evolve smoothly at age 65, the estimated RD should be insignificant. Table 4 shows the estimated RD for each of the dependent variables displayed at the top of each column. As shown in line 1, only two estimated RD are significant at the 5% level. These are the estimated RD for annual income and for being single. The estimates suggest that reaching age 65 is associated with a 19.8% increase in annual income. When we look at the breakdown by ethnicity and education for this variable, it appears that highly educated Blacks account for a huge part of the aggregate RD estimate. For instance, this group shows a highly significant RD estimate of 238.7 percentage points. A possible explanation is that Blacks are resuming their education by the end of their careers, when (presumably) the productivity of their colleagues is declining or most of them are retiring. Confirming this observation, when we look at the ethnicity breakdown, only Blacks show a significant RD estimate of 64.5 percentage points for annual income.

Furthermore, the aggregate significant RD estimate of -1.7 percentage points in the likelihood of being single is also heavily concentrated within the Black sector. In the ethnicity breakdown, the Black group is the only one showing a significant RD estimate of -6.2 percentage points in the probability of being single. It is worth noting that in the ethnicity breakdown, neither Whites nor Hispanics show significant RD estimates at the 5% level. Hence, it appears that the Black group is the only one that violates the identification assumption with respect to the two variables that were significant in aggregate. For that reason, the subsequent IV results of the effects of insurance on health outcomes should be interpreted with caution for Blacks.

Reduced Form Estimates for Health Outcomes

Before the IV estimation, reduced form regressions are performed. Note that by substituting equation (2) into equation (1) we get the following expression:

$$h_{it}=\lambda_0+h(age_{it})+\lambda_1 'X_{it}+\lambda_2 *D_{65}+\lambda_3 *D_{65}*age_{it}+\lambda_4 *D_{65}*age^2_{it}+\omega_{it} \quad (7)$$

where $\lambda_0 = \alpha + \beta\alpha_1$, $\lambda_1 = \gamma + \beta\gamma_1$, $\lambda_2 = \beta\eta_1$, $\lambda_3 = \beta\eta_2$, $\lambda_4 = \beta\eta_3$, and $\omega_{it} = \beta\psi_{it} V_{it} + \varepsilon_{it}$. Therefore, the reduced form RD is given by $\left.\frac{\partial h_i}{\partial D_{65}}\right|_{age=65} = \lambda_2 + \lambda_3 * age + \lambda_4 * age^2$.

Table 5 displays estimated reduced form RD for several measures of access to health care. When taking the whole sample, we find a significant RD of 3.6 percentage point increase in the likelihood of having had a cholesterol check during the previous year. We also find a marginally significant 3.8% percentage point increase in the likelihood of obtaining health care when needed. In addition, no significant RD estimates are found for either Whites or Blacks. However, an interesting feature arises among Hispanics. Hispanics show significant increases in the likelihood of having had a routine check and a cholesterol check in the previous year of 10.4 and 11 percentage points respectively. Both of these activities are preventive measures.

Table 4

Estimated Discontinuities in Employment Measures, Risk Attitudes, and Economic and Marital Status at Age 65

	On Medicare			Any Insurance			Private Insurance			Medicare and Private		
	Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65		Age 63-64	RD at Age 65	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
1. Whole Sample	2.9+	1.5	2.4	-0.4	-1.8	-1.4	-1.7	0.6	19.8*	1.5	-0.3	.-1.7*
	1.6	1.7	2.7	2.4	2.9	1.1	1.3	0.9	9.0	1.7	1.2	0.8
By Ethnicity and Education:												
White Non-Hispanic:												
2. Some High School	6.2	0.2	-8.6	-7.5	.-21.5+	5.7	1.1	.-10.0**	-25.7	0.3	1.5	-0.5
	5.5	5.3	10.5	10.1	11.4	4.7	5.1	3.5	32.5	6.0	4.6	1.7
3. High School Graduate	7.8*	1.9	2.5	7.0	4.2	.-4.2+	2.0	1.9	2.7	-0.6	-0.5	-1.6
	3.2	3.1	5.3	4.6	5.8	2.4	2.3	1.2	15.7	3.3	2.3	1.2
4. Some College	2.6	2.6	14.4*	-0.8	7.5	-1.0	.-5.6+	-1.5	43.5*	7.4	-2.7	.-4.2*
	4.6	4.6	7.3	6.5	7.4	2.9	3.0	1.5	21.5	4.7	3.2	1.9
5. College Graduate or More	-0.7	4.0	-0.5	-7.1	-2.1	-2.2	-1.1	1.1	13.2	1.3	0.6	-1.9
	3.8	4.2	5.6	5.7	6.8	2.1	2.1	0.9	15.1	3.8	2.0	2.1
Black Non-Hispanic:												
6. Some High School	3.7	-3.8	18.9	-16.4	1.1	-8.0	-12.0	-5.2	35.4	12.4	7.2	-8.3
	8.0	11.5	17.1	11.7	12.8	6.4	9.0	7.5	52.6	8.7	7.8	5.7
7. High School Graduate	7.0	-0.6	-9.7	6.4	-16.6	2.8	-8.0	-7.7	73.8	-2.8	2.4	-7.8
	7.9	6.6	13.6	9.9	12.1	5.4	7.4	5.1	51.3	8.0	6.2	5.1
8. Some College	-5.5	-4.6	12.7	-21.6	4.5	-4.5	9.0	3.4	-4.8	6.0	8.6	-2.4
	12.0	10.9	17.1	14.6	17.7	6.5	10.4	7.9	72.9	12.1	9.1	6.2
9. College Graduate or More	9.8	-5.5	12.7	45.4**	21.7	6.4	-1.8	-3.2	238.7**	10.8	-7.0	-10.2
	14.3	16.5	22.1	17.2	20.3	8.7	9.1	4.5	79.7	15.4	10.3	8.8
Hispanic:												
10. Some High School	-13.2	36.4*	.-52.6*	-1.0	.-42.1*	4.9	8.6	0.6	-48.4	-10.1	-3.6	-5.9
	11.5	16.2	25.8	23.1	21.1	6.3	11.6	8.3	81.7	12.4	8.3	6.2
11. High School Graduate	-4.4	-5.0	-17.7	37.2*	.-30.0*	-1.3	0.7	10.8+	5.6	18.6	-8.5	-0.6
	10.2	9.6	16.8	14.3	13.7	6.5	8.8	5.8	69.5	10.5	6.9	4.6
12. Some College	35.5*	-4.5	21.2	23.3	15.2	11.1	.-25.9*	-5.9	183.5+	23.5	-0.7	-6.8
	17.8	15.5	26.1	24.8	31.8	8.0	12.9	7.3	108.7	17.2	9.9	8.3
13. College Graduate or More	20.5	-21.6	1.7	.-52.7*	22.2	-14.5	-11.1	-12.8	181.4	-25.4	24.0*	-4.4
	18.9	23.6	28.9	26.1	30.1	10.4	14.6	8.6	122.1	19.5	10.3	12.1
By Ethnicity:												
14. White Non-Hispanic	3.1	2.0	1.7	-1.6	-1.0	-1.8	-1.3	0.1	9.0	0.3	-0.4	-1.2
	1.9	2.0	3.1	2.9	3.5	1.4	1.4	0.8	9.4	2.0	1.3	0.8
15. Black Non-Hispanic	4.1	-2.3	8.3	-3.3	0.6	-1.1	-5.7	-4.0	64.5*	2.8	3.3	.-6.2*
	4.5	4.8	7.9	6.0	7.1	3.2	4.4	3.4	28.3	4.7	3.8	3.0
16. Hispanic	1.9	-1.9	-2.4	3.8	-4.0	-1.7	-1.1	4.9+	39.3	6.4	.-5.6+	0.3
	2.2	2.6	4.4	3.3	4.5	1.3	1.9	1.3	13.1	2.4	1.9	1.1
Hispanic Sub-Categories:												
17. Puerto Rico	16.8	-29.7	39.7	-0.6	0.7	11.3	4.2	33.9**	72.1	-7.7	-7.3	-5.0
	14.0	24.6	34.9	21.7	33.7	9.7	14.8	11.7	103.6	15.4	10.4	9.8
18. Cuba	-11.6	5.8	37.0	89.4**	36.7	-12.5	-1.9	6.1	72.5	15.0	.-23.3*	-3.7
	16.7	13.5	25.9	30.2	27.7	12.2	16.9	13.1	114.8	18.0	11.8	9.6
19. Mexico	3.9	-0.1	-1.4	1.6	-4.6	-3.8	-0.7	3.6	52.4	5.7	-3.8	-1.4
	4.9	5.6	10.1	8.4	9.9	3.1	5.0	3.3	38.0	5.2	3.8	2.5
20. Dominican	39.0	-40.3	25.5	-44.4	34.9	46.8*	-41.6	19.6	-103.8	-17.5	2.5	3.5
	28.0	98.0	124.8	96.5	75.8	20.2	31.3	29.8	231.1	31.3	18.4	12.4
21. Central-South America	-3.1	-8.4	13.9	-42.8	30.7	.-26.2**	7.8	-9.2	49.9	35.0*	-20.9	11.1
	16.1	20.7	32.6	26.2	28.9	10.5	15.7	10.8	142.6	17.4	12.8	11.7
By Sex:												
22. Male	2.3	1.3	-0.2	0.4	-3.6	-2.6	.-3.4+	0.0	26.1*	4.2+	.-1.8+	-1.8
	2.3	2.2	3.3	3.6	3.6	1.8	1.8	1.1	11.9	2.2	1.1	1.1
23. Female	3.0	1.8	4.6	-1.9	-0.6	-0.2	-0.2	1.1	12.7	-0.8	1.1	-1.6
	2.2	2.6	4.4	3.3	4.5	1.3	1.9	1.3	13.1	2.4	1.9	1.1

Note: Heteroskedasticity robust standard errors below the estimates. + significant at 10%; * significant at 5%; ** significant at 1%. Table shows estimated regression discontinuities (in percentages) at age 65. All models include quadratic control for age, fully interacted with dummy for age 65 or older. Other controls include gender, race, ethnicity, education, region, marital status, and sample year. Estimates of all columns (except [5] and [9]) based on linear probability models fit to pooled samples of 2000-2005 MEPS. Dependent variables in columns [5] and [9] are the natural log of hours/week and annual income respectively.

Table 5

Measures of Access to Health Care Before Age 65 and Estimated Discontinuities at Age 65 (Allowing for Differential Intercept, Slope, and Curvature at Age 65)

	All		Whites		Blacks		Hispanics	
	Age 63-64	RD at Age 65	Age 63-64	RD at Age 65	Age 63-64	RD at Age 65	Age 63-64	RD at Age 65
	[1]	[2]	[3]	[4]	[6]	[7]	[10]	[11]
Preventive (ex-ante) Activities:								
1. Routine Check during last year	76.9	1.2	78.7	-1.1	78.3	4.6	67.3	10.4*
		1.5		1.9		4.1		4.2
2. Cholesterol Check during last year	77.2	3.6*	79.2	1.5	76.3	7.9	69.1	11.0**
		1.5		1.8		4.2		4.2
3. Dental Check during last year	54.2	-0.2	60.5	-1.9	42.3	1.3	39.9	4.1
		1.7		2.0		4.7		4.5
4. Flu Shot during last year	45.4	2.0	48.7	3.4	36.9	-3.8	38.4	5.2
		1.7		2.1		4.7		4.5
5. Breast Exam during last year	67.9	0.4	69.9	-1.5	72.5	1.5	58.5	8.3
		2.3		2.8		6.4		6.1
6. Mammogram during last year	63.7	-0.5	65.0	-0.4	67.5	-1.4	58.4	1.5
		2.4		2.9		6.6		6.3
7. Made Appointment Routine last year	79.4	0.3	83.1	0.3	75.7	-4.1	66.2	6.7
		1.5		1.7		4.7		4.6
Curative (ex-post) Activities:								
8. Number of Emergency Room Visits in last year	2,058	0.1	1,920	-0.2	2,088	5.1	2,585	-4.2
		1.1		1.4		3.4		2.9
9. Number of Inpatient Hospitalizations in last year	1,815	-0.8	1,839	0.0	1,892	-0.7	1,715	.-5.6*
		1.1		1.3		3.1		2.6
10. Number of Outpatient Hospitalizations in last year	1.1	0.4	1.3	-0.6	1.2	5.7	0.6	3.5
		2.3		3.0		6.3		4.7
Health Care Utilization Measures:								
11. Got Medical Appointment when Wanted	87.1	2.0	89.0	2.7+	87.3	-1.8	80.9	2.8
		1.4		1.6		4.4		4.8
12. Got Health Care when Needed	86.5	3.8+	90.0	3.4	86.5	-1.4	73.4	10.9+
		2.1		2.4		6.0		6.7
13. Number of Office-Based Physician Visits in last year	5.6	-2.7	5.8	.-6.6+	4.8	7.2	5.4	11.6
		3.3		4.0		9.0		9.3
14. Total Health Care Expenditure during last year	5,826.2	2.4	6,206.7	0.2	5,755.6	27.9	4,431.5	16.3
		8.7		9.7		26.7		27.6
Doctor's Service Quality with Patients:								
15. Doctor Listened	92.9	-1.5	93.1	-0.9	94.1	-4.6	90.4	-1.1
		1.1		1.3		3.4		3.5
16. Doctor Explained so Understood	91.8	0.6	92.9	1.1	88.9	0.3	89.3	-3.4
		1.1		1.2		3.5		3.9
17. Doctor Showed Respect	93.5	-0.5	93.5	-0.5	93.8	-3.4	93.4	0.8
		1.1		1.2		3.2		3.2

Note: Heteroskedasticity robust standard errors below the estimates. + significant at 10%; * significant at 5%; ** significant at 1%. Table shows estimated regression discontinuities (in percentages) at age 65. All models include quadratic control for age, fully interacted with dummy for age 65 or older. Other controls include gender, race, ethnicity, education, region, marital status, and sample year. Estimates of all rows (except 8, 9, 10, 13, and 14) based on linear probability models fit to pooled samples of 2000-2005 MEPS. Dependent variables in rows 8, 9, 10, 13, and 14 are the natural log of the respective measure.

In addition, Hispanics show a significant -5.6 percentage point's reduction in the number of inpatient hospitalizations during the previous year. Therefore, these results suggest that Hispanics are significantly increasing their preventive health care activities at 65, while reducing curative activities. This could suggest that before reaching age 65, since Hispanics are more likely to be uninsured, they engage in fewer preventive activities. As a result, they seek health care only when they become aware of a bad state of health. However, after age 65, they are more likely to be insured and engage in more preventive activities reducing the realization of extreme bad health states requiring hospitalization. In that way, Hispanics require fewer hospitalizations after age 65.

While reduced form estimates suggest some significant estimated RD for Hispanics, this framework does not allow the identification of the β parameter. Then, in order to estimate a measure of the effect that insurance has on

health access measures, IV regressions are necessary. The next section focuses on this issue.

Measuring the Effect of Insurance on Health Care Access

In this section, we estimate the system of equations given by expressions (1) and (2) using 2SLS. Clearly, equation (2) is the first stage regression, while equation (1) is the second stage. Columns 1 to 4 of Table 6 display IV estimates of β. For these estimations, we take Cit to be 1 if person i reported having any insurance at time t and zero otherwise. Column 1 shows that having insurance is significantly associated with a 17.4 percentage point increase in the likelihood of having had a cholesterol check during the previous year. It is also associated with a 32.6 percentage point increase in the likelihood of having a flu shot in the last year and with a 17.5 percentage point increase in the number of outpatient hospitalizations. Furthermore, it appears that having insurance also affects the attitudes of doctors towards patients. For instance, having insurance is significantly associated with an 11.3 percentage point increase in the likelihood that the doctor explained the diagnostic to the patient so that it was understood.

When looking at Whites (column 2), we find significant effects of insurance only on the likelihood of having a flu shot. For Whites, insurance is associated with a 41.5 percentage point increase in the likelihood of getting a shot. Consequently, it appears that having insurance does not affect health care access for whites Whites in a pervasive manner. This finding is not very surprising since Whites are the ethnic group with the highest access to health care prior to age 65. This is clear from observation of columns 5 and 6. These columns display the pre-65 White-Black and White-Hispanic gaps in health care access respectively. In the majority of measures, the gap is positive, implying that Whites enjoy relatively better health care access than other groups.

Column 3 suggests that for Blacks, insurance is significantly associated with higher likelihoods of routine and cholesterol checks (28.4 and 33.8 percentage points respectively). In addition, having insurance implies a significant 23.2 percentage point increase in the number of emergency room visits and a 30.6 percentage point increase in the likelihood of obtaining care when needed. Therefore, having insurance appears to significantly improve Blacks' access to health care.

The impact of having insurance on health care access appears to be largest among Hispanics. Column 4 suggests that having insurance is significantly associated with higher probabilities of getting routine checks, cholesterol checks, flu shots, breast exam and health care when needed. In addition, insurance is associated with an increased number of doctor visits and health care expenditures. As a result, health insurance matters more in increasing access to health care for Blacks and Hispanics than for Whites.

Next, we ask whether the estimated increased access to health insurance at age 65 has diminished the gaps in health care access between different groups. To answer this question, we compute measures of changes in health access disparities at age 65. Let β^j be the IV estimate of the effect of insurance on health access for group $j \in \{whites; blacks; hispanics\}$. Let $RD^j_{65} = \frac{\partial \hat{c}^j_{it}}{\partial D_{65}} = \hat{\eta}_1 + \hat{\eta}_2 * 65 + \hat{\eta}_3 * 65^2$ be the estimated RD at age 65 in any insurance coverage for group j.[8] Therefore, the estimated change in health care access disparities between groups j and h due to changes in insurance coverage at age 65 is given by:

$$\left[\hat{\beta}^j * RD^j_{65}\right] - \left[\hat{\beta}^h * RD^h_{65}\right] \qquad (8)$$

Columns 8 to 10 of Table 6 show estimated changes in health access disparities at age 65 using (8) for Whites-Blacks, Whites-Hispanics, and Blacks-Hispanics. Most of the estimates are negative, implying a reduction in the pre-65 gaps between groups. For example, column 7 shows a pre-65 gap of 11.1% between Blacks and Hispanics in the likelihood of getting a routine check. Column 10 then shows that Hispanics have increased 1.1 percentage points more the likelihood of routine checks than blacks due to increased insurance coverage at age 65. Therefore, the pre-65 gap has been reduced as a result of increased insurance. All but one of the preventive activities show a positive pre-65 gap between Blacks and Hispanics. In addition, for these activities, the gap is reduced due to increased coverage at 65. However, flu shots had a negative pre-65 gap (meaning that Hispanics were more likely to get a flu shot than Blacks). Moreover, this gap is exacerbated with the increased coverage at 65. Similarly the pre-65 White-Black gap in flu shots was 11.8%, and this gap is also exacerbated with the increased insurance access at 65. Thus, it appears that Blacks may be reluctant to take flu shots and that the lower likelihood of getting them is not due to insurance coverage.

When comparing White-Black pre-65 gaps in preventive activities, only breast examinations and mammogram incidence have a negative sign. Furthermore, this gap is exacerbated by changes in insurance coverage at 65. Therefore, Blacks appear to have a greater preference for this kind of preventive activity than Whites do. In the same way, the pre-65 gap in emergency room visits and inpatient hospitalizations suggests higher utilization of these services by Blacks. Besides, changes in the disparities at age 65 exacerbate this gap. This could mean that Blacks have a lower level of health and need intensive treatments more often than Whites.

The pre-65 gaps between Whites and Hispanics are all positive except for emergency room visits. Furthermore, all but two of the gaps are reduced with the increased insurance coverage at 65. Gaps that are exacerbated at 65 are the likelihood of dental checks and of the doctor explaining so as to be understood. Therefore, it appears that

Table 6

Instrumental Variables Regressions of Access to Health Care Measures on Any Insurance

	All	Whites	Blacks	Hispanics	Disparities at Ages 63-64			Percent Change in Disparity Due to Change in Coverage at 65		
	Coefficient on Coverage	Coefficient on Coverage	Coefficient on Coverage	Coefficient on Coverage	Whites - Blacks	Whites - Hispanics	Blacks - Hispanics	Whites - Blacks	Whites - Hispanics	Blacks - Hispanics
Outcomes	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Preventive (ex-ante) Activities:										
1. Routine Check during last year	7.4	-7.2	28.4*	24.2**	0.4	11.5	11.1	-7.5	-8.6	-1.1
	5.6	8.8	12.2	8.5						
2. Cholesterol Check during last year	17.4**	9.1	33.8**	28.2**	2.9	10.1	7.2	-6.4	-7.6	-1.2
	5.6	8.4	12.8	8.5						
3. Dental Check during last year	-2.1	2.4	-20.2	-3.3	18.2	20.5	2.4	4.9	1.4	-3.6
	6.0	9.1	14.4	9.1						
4. Flu Shot during last year	32.6**	41.5**	-0.5	38.7**	11.8	10.3	-1.5	5.9	-6.4	-12.3
	6.5	10.0	14.4	9.4						
5. Breast Exam during last year	3.0	-10.0	14.4	23.1*	-2.6	11.3	14.0	-4.7	-8.7	-4.0
	7.9	12.3	18.3	11.7						
6. Mammogram during last year	10.1	4.2	15.3	11.5	-2.5	6.5	9.0	-2.9	-3.0	-0.1
	8.2	12.5	18.8	12.1						
7. Made Appointment Routine last year	1.4	1.9	-10.5	11.8	7.4	16.9	9.5	2.7	-3.5	-6.1
	5.8	8.2	14.1	9.4						
Curative (ex-post) Activities:										
8. Number of Emergency Room Visits in last year	1.3	-1.7	23.2*	-4.7	-168.3	-664.4	-496.1	-5.5	1.2	6.8
	4.1	6.2	10.5	6.0						
9. Number of Inpatient Hospitalizations in last year	0.3	-0.6	8.3	0.7	-52.6	124.3	176.9	-2.0	-0.3	1.7
	3.9	6.0	9.1	5.2						
10. Number of Outpatient Hospitalizations in last year	17.5*	17.0	26.2	18.0+	0.1	0.7	0.6	-3.6	-3.3	0.3
	8.4	13.5	18.8	9.4						
Health Care Utilization Measures:										
11. Got Medical Appointment when Wanted	7.1	11.8	-22.2	14.2	1.8	8.1	6.4	6.7	-2.8	-9.5
	6.2	8.9	14.9	10.5						
12. Got Health Care when Needed	16.2+	7.5	30.6*	28.8*	3.6	16.6	13.0	-5.9	-8.0	-2.1
	8.6	13.3	18.1	14.3						
13. Number of Office-Based Physician Visits in last year	14.4	7.2	22.7	45.2*	1.0	0.4	-0.7	-4.2	-13.2	-9.0
	12.0	18.3	26.7	18.2						
14. Total Health Care Expenditure during last year	46.7	16.3	119.4	117.8*	451.1	1775.3	1324.1	-24.9	-34.8	-9.8
	31.3	44.1	78.0	53.9						
Doctor's Service Quality with Patients:										
15. Doctor Listened	1.3	4.5	-5.7	9.0	-1.0	2.7	3.7	1.9	-2.2	-4.1
	5.0	7.1	11.5	8.4						
16. Doctor Explained so Understood	11.3*	13.2+	18.6	2.4	4.0	3.6	-0.4	-2.4	1.1	3.5
	5.0	6.9	12.1	9.4						
17. Doctor Showed Respect	3.9	5.8	6.4	4.1	-0.3	0.0	0.4	-0.6	-0.5	0.2
	4.7	6.9	10.6	7.8						

Note: Heteroskedasticity robust standard errors below the estimates. + significant at 10%; * significant at 5%; ** significant at 1%. Columns 1-4 show 2SLS estimated coefficients (in percentages) on any insurance. Any insurance is instrumented with dummy for 65 years or more and its interactions with age and age squared. Other controls include gender, race, ethnicity, education, region, marital status, and sample year. Estimates of all rows (except 8, 9, 10, 13, and 14) based on linear probability models fit to pooled samples of 2000-2005 MEPS. Dependent variables in rows 8, 9, 10, 13, and 14 are the natural log of the respective measure. Columns 5-7 show disparities between groups at ages 63-64 obtained from Table 4. Columns 8-9 show relative changes in disparities (in percentages) between groups due to changes in coverage at 65 calculated as detailed in text.

the increased insurance coverage has greatly contributed to reducing the gaps between the group with the highest pre-65 health care access (Whites) and the group with the lowest pre-65 health access (Hispanics). We also estimate the system of equations (1)-(2) but using multiple coverage as the insurance measure. Table 7 provides 2SLS estimates. Although the estimated magnitudes are different, the qualitative results are unchanged. We find significance

Table 7
Instrumental Variables Regressions of Access to Health Care Measures on Multiple Insurance

	All	Whites	Blacks	Hispanics	Disparities at Ages 63-64			Percent Change in Disparity Due to Change in Coverage at 65		
	Coefficient on Coverage	Coefficient on Coverage	Coefficient on Coverage	Coefficient on Coverage	Whites - Blacks	Whites - Hispanics	Blacks - Hispanics	Whites - Blacks	Whites - Hispanics	Blacks - Hispanics
Outcomes	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Preventive (ex-ante) Activities:										
1. Routine Check during last year	3.1	-1.7	18.2*	47.3**	0.4	11.5	11.1	-6.1	-9.9	-3.7
	2.3	2.3	7.8	17.2						
2. Cholesterol Check during last year	7.1**	2.5	19.9*	55.2**	2.9	10.1	7.2	-4.5	-9.2	-4.7
	2.3	2.2	7.8	16.9						
3. Dental Check during last year	-1.1	0.7	.-15.5+	-3.9	18.2	20.5	2.4	4.8	1.1	-3.7
	2.5	2.4	9.0	18.0						
4. Flu Shot during last year	12.9**	11.1**	0.3	63.8**	11.8	10.3	-1.5	5.5	-6.5	-12.0
	2.6	2.6	9.0	18.4						
5. Breast Exam during last year	1.7	-2.9	12.0	59.9*	-2.6	11.3	14.0	-4.9	-12.9	-7.9
	3.6	3.5	12.5	29.9						
6. Mammogram during last year	4.4	0.9	15.3	29.8	-2.5	6.5	9.0	-4.0	-5.2	-1.2
	3.7	3.6	13.0	29.8						
7. Made Appointment Routine last year	0.4	0.5	-6.5	18.5	7.4	16.9	9.5	2.1	-3.3	-5.4
	2.2	2.1	8.9	19.0						
Curative (ex-post) Activities:										
8. Number of Emergency Room Visits in last year	0.3	-0.7	14.7*	-12.5	-168.3	-664.4	-496.1	-4.6	2.0	6.6
	1.7	1.7	6.7	11.9						
9. Number of Inpatient Hospitalizations in last year	-0.1	-0.3	6.2	-9.1	-52.6	124.3	176.9	-1.9	1.6	3.5
	1.6	1.6	5.9	10.3						
10. Number of Outpatient Hospitalizations in last year	6.9*	4.3	18.1	31.4+	0.1	0.7	0.6	-3.0	-3.8	-0.8
	3.5	3.7	12.2	18.8						
Health Care Utilization Measures:										
11. Got Medical Appointment when Wanted	2.2	2.3	-12.9	20.6	1.8	8.1	6.4	4.9	-2.8	-7.6
	2.0	1.9	8.4	17.9						
12. Got Health Care when Needed	5.8+	0.6	24.2+	46.4	3.6	16.6	13.0	-6.6	-8.5	-1.8
	3.5	3.2	14.1	35.8						
13. Number of Office-Based Physician Visits in last year	6.2	2.3	15.3	79.3*	1.0	0.4	-0.7	-3.2	-13.9	-10.6
	5.0	4.9	17.5	37.8						
14. Total Health Care Expenditure during last year	18.6	4.7	76.0	169.3	451.1	1775.3	1324.1	-19.5	-29.8	-10.3
	13.0	12.0	51.8	111.5						
Doctor's Service Quality with Patients:										
15. Doctor Listened	0.2	0.6	-4.2	11.3	-1.0	2.7	3.7	1.5	-1.9	-3.4
	1.6	1.5	6.8	13.8						
16. Doctor Explained so Understood	3.5*	2.7+	11.9+	1.5	4.0	3.6	-0.4	-2.1	1.1	3.1
	1.6	1.5	7.0	15.7						
17. Doctor Showed Respect	1.2	1.0	3.7	7.9	-0.3	0.0	0.4	-0.6	-1.0	-0.4
	1.5	1.4	6.4	12.8						

Note: Heteroskedasticity robust standard errors below the estimates. + significant at 10%; * significant at 5%; ** significant at 1%. Columns 1-4 show 2SLS estimated coefficients (in percentages) on multiple insurance. Multiple insurance is instrumented with dummy for 65 years or more and its interactions with age and age squared. Other controls include gender, race, ethnicity, education, region, marital status, and sample year. Estimates of all rows (except 8, 9, 10, 13, and 14) based on linear probability models fit to pooled samples of 2000-2005 MEPS. Dependent variables in rows 8, 9, 10, 13, and 14 are the natural log of the respective measure. Columns 5-7 show disparities between groups at ages 63-64 obtained from Table 4. Columns 8-9 show relative changes in disparities (in percentages) between groups due to changes in multiple coverage at 65 calculated as detailed in text.

in the same health access measures and implied disparity changes suggesting a general reduction in pre-65 gaps. In summary, these IV estimates provide significant evidence that increased insurance provides better health care access. In particular, the improved access is more strongly observed for groups with weaker ex-ante access.

Conclusion

In this paper, the age threshold for Medicare eligibility has been exploited as an exogenous variation for health insurance coverage in a regression discontinuity (RD) framework. RD estimates imply a large and significant increase in the likelihood of being insured at age 65. The estimates imply that groups with lower pre-65 coverage

incidence gain higher increases in the likelihood of being insured at 65. In particular, persons with less education (less likely to have pre-65 health insurance) appear to increase the probability of being insured at age 65 by more than their more highly educated counterparts.

The disparity in coverage is also reduced among ethnic groups. For instance, the group with the lowest likelihood of being insured prior to age 65 (Hispanics) showed the largest estimated effect (31.5 percentage points' increase). Furthermore, when analyzing different Hispanic subcategories, the group showing the largest coverage increase was the one with the lowest pre-65 coverage (Mexicans, with 40 percentage points' increase in the likelihood of being insured after age 65). Therefore, the evidence strongly suggests that Medicare contributes to reducing coverage disparities between and within ethnic groups in the United States.

On the other hand, private coverage showed a negative effect equivalent to -5.7 percentage points for the whole sample. This estimate is smaller in magnitude if compared with the positive effects on the other insurance measures. Hence, the possibility of a crowding out effect from private towards public insurance after universal eligibility is far from being pervasive. Overall, the provision of universal health insurance at age 65 has been shown to reduce coverage disparities across education and ethnic groups without unintended crowding out effects.

Reduced form and IV estimates show that Hispanics, the group with the lowest pre-65 access to health care, appear to have increased health care access in a differentially higher proportion than other groups. For instance, they show significant increases in the likelihood of having had a routine check and a cholesterol check of 10.4 and 11 percentage points respectively. They also show a significant -5.6 percentage point reduction in the number of inpatient hospitalizations during the previous year. Therefore, it appears that insurance coverage is influencing the decision to take more preventive care leading to a reduction in curative care.

In addition, IV estimates combined with RD estimates on insurance coverage show that the increased access to health insurance at age 65 has contributed to reducing the pre-65 gaps in health care access between different ethnic groups. Specifically, the estimates suggest that the increased insurance coverage has greatly contributed to reducing the gaps in health care utilization between the group with the highest pre-65 health care access (Whites) and the group with the lowest pre-65 health access (Hispanics).

As a consequence, it appears that increased insurance coverage is associated with reductions in intergroup disparities in health care access. Most importantly, this effect has not been associated with reduced private coverage. In that way, it appears that the great majority of government resources are being directed towards persons without the possibility of health coverage before universal eligibility. As a result, the evidence shows that health insurance matters in order to access health care services. Moreover, the improved coverage appears to reduce inequalities between different ethnic groups in U.S. society with an adequate overall targeting efficiency.

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Footnotes

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2 Medicare is a publicly provided health insurance which any American above age 65 is eligible to receive without any payment.

3 Age is defined in quarters.

4 An upward bias would arise if persons with insurance were healthier or exercised more caution with their health. Alternatively, a downward bias would arise in the presence of adverse selection where sick people become insured because they know that they will need health care in the near future.

5 Age 65 is understood as 260 quarters.

6 The Multiple Insurance indicator takes the value of 1 for individuals having Medicare and private insurance, while it takes the value of zero otherwise.

7 In the MEPS, "Whites" refers to the group commonly denoted as "Caucasian".

8 Note that since age is measured in quarters, 65 years is understood as 260 quarters.

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