The pathways from medical insurance to health in the US: Evidence from Medicare
(Pathways from insurance to health)

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1 Introduction

Although substantial shares of national income are devoted to health insurance programs around the world, there is comparatively little causal evidence on how much, or how coverage improves health. Part of the problem lies in a dearth of appropriate control groups resulting from absence of uninsured populations in some countries, or non-random selection into insurance when they do exist. Insured individuals can differ from the uninsured in a range of individual and socioeconomic traits, and better health can be pinned to insurance when the mediator may really be higher education, lower time preferences, or other factors positively associated with coverage. In the opposite direction, an observed negative association between insurance and health can result from moral hazard or adverse selection.

Causal inference requires a setting whereby insurance is exogenous and in absence of such opportunities, instrumental variable techniques have been employed to attempt to terse out the appropriate variation. As it is difficult to assess whether instruments are valid, the identification strategy often falls short of being strongly convincing. The transition to the old age insurance program known in the United States as Medicare offers grounds for applying regression discontinuity methods since insurance coverage increases abruptly and exogenously at age 65. If individuals right before and right after age 65 differ only with respect to insurance with Medicare, appropriate treatment and control groups are generated, with causal inference following from the quasi-experimental data design.

Card et al. (2004) finds insurance to be causally tied only to small and statistically insignificant positive effects on self-rated health, although Card et al. (2009) establishes reduced mortality among individuals admitted to hospitals with non-deferrable conditions. Putting aside the issue of whether the evidence is commensurate with programs that consume large amounts of social resources—close to half a trillion dollars for Medicare in the US—important questions remain. Do effects extend beyond declining mortality among severely ill populations? Are other health-related measures such as activity limitations affected? Also, how is health impacted by insurance and are benefits broadly based or limited to certain medical procedures or conditions? Is there evidence of better disease management?

Answers to these questions have important implications. Aging populations around the world will place increased stress on social budgets and in this context, tough choices await. These could include limiting coverage, increasing out of pocket costs, or curtailing access to certain covered procedures, among other possibilities. Optimal social choice depends on cost and benefit considerations that in turn require information on how old age insurance works, that is, how it impacts health. The transition to Medicare in the United States provides a valuable setting for gathering evidence, although as one of the largest insurance programs in the world, program evaluation can be an important objective in itself.

Results show that among the near-elderly, a small increase in the share covered by health insurance generates self-reported health improvements that are strongest but not restricted to the population diagnosed with heart conditions. Health is also enhanced among that diagnosed with diabetes, cancer, hypertension, lower back pain, and in more general terms, coverage is related to a fall in the share of the population in poor or fair health. Furthermore, the program results in a reduction of activity limitations related to a large set of medical conditions that include depression and lung disease. It is also associated with increased testing, prevention, with a reduction in risky behaviors, and with improved diabetes management. Strikingly, effects show up right at or right after age 65 and produce changes that in most cases are still evident a decade after treatment.

2 Background

Although there is robust evidence of positive coverage effects on health of infants and young children, evidence is mixed or non-supportive regarding consequences on older populations (Levy and Meltzer, 2008). Instrumental variable and matching model techniques have established a positive link (Dor, Sudano, and Baker, 2006; Hadley and Waidmann, 2006; Daysal, 2012), but results hinge on the validity of instruments or controls for covariates of insurance. Outcome comparisons of insured and previously uninsured individuals have revealed positive consequences in the form of increased access, improved health, and reduced disparities among individuals with diabetes and heart disease (McWilliams et al., 2003; 2007; 2009). Using a similar strategy, Polsky et al. (2009) does not find mortality effects.

Causal interpretation, however, relies on effectively controlling for relevant individual characteristics other than treatment into insurance. In the same manner that a comparison of outcomes between insured and uninsured individuals need not reveal treatment effects, the same can result from comparisons between the insured and the previously uninsured. Finkelstein et al. (2013) takes on the problem exploiting random assignment to low-income health insurance, and finds widespread effects ranging from better primary and preventive care to improved mental and physical self-rated health. Results stand in contrast to Medicaid expansions that did not impact health of older children (Currie, Decker and Lin, 2008), conceivably resulting either from low marginal benefits accruing to this population group, or from low take-up rates (Card and Shore-Sheppard, 2004).

Evidence based on random assignment may constitute a marked improvement in assessment of effects, but it is not devoid of problems. External validity of results can be limited by the fact that a sample of those interested in participating in a lottery to gain access to low-income health insurance may not be a reflection of the general or of the uninsured population (Finkelstein et al., 2013). In search of additional evidence, research has also turned to program inception studies and to exploiting discontinuities generated by program rules or rule changes. Among an older population, transition to Medicare at age 65 has been tied to improved access to health care and to a decline in late-stage breast cancer diagnoses (Decker, 2005; Card et al., 2008). Yet, translating access to improved health outcomes has proved to be a more difficult task. Card et al. (2004) only finds small and statistically insignificant effects on self-rated health. Mortality effects do not obtain in Finkelstein and McKnight (2008) or in Card et al. (2008), but Card et al. (2009) does find substantially reduced mortality among a population of severely ill individuals.

Discontinuity designs have yet to shed light on other health-related outcomes beyond these important results. Little is known about the impact of coverage on risky behaviors and disease management. Also, if robust and precisely estimated effects on self-rated health can be obtained, it is still unclear how changes are achieved. This study aims to contribute by evaluating an extended range of outcomes, at the same time providing insight on the channels through which insurance affects health. Coverage effects have proved difficult to identify (Card et al., 2009), and focus will therefore be placed on medical conditions and on health at the lower end of the distribution, where insurance is more likely to play a role.

3 Method

Regression discontinuity research designs exploit rules or procedures that generate abrupt changes in treatment levels associated with a variable that forces a discontinuity at a known threshold. When rules are arbitrary, treatment can be taken as randomly assigned and under relatively mild assumptions, outcome differences in a neighborhood of the jump can be interpreted as causally-based (Lee and Lemieux, 2010). Rules related to admission to Medicare provide such an opportunity, where age forces a discontinuous jump in medical coverage at age 65. The program's cutoff age is arbitrary and generates a pseudo experiment where individuals just before and just after age 65 are likely to be similar in all respects but treatment into the program. If factors relevant to the outcome other than treatment evolve smoothly with respect to the forcing variable, treatment effects can be established by comparing outcomes of treated individuals with those of untreated ones, the latter arrived at through extrapolation. In Figure 1, where abrupt increases in coverage and medical checkups at 65 can be ascertained, the effect of increased coverage on access to checkups is established by comparing checkups at 65 with the counterfactual of what they would have been without Medicare, where the counterfactual is the function coming from the left evaluated at age 65.

[Figure 1]

The expectations of outcome under treatment (Y_1) and under no treatment (Y_0) conditioned on a forcing variable x can be modeled with pth-order polynomials:

$$E[Y_{0i}|x_i] = a + b_{01}x_i + b_{02}x_i^2 + b_{03}x_i^3 + \ldots + b_{0p}x_i^p$$
$$E[Y_{1i}|x_i] = a + \tau + b_{11}x_i + b_{12}x_i^2 + b_{13}x_i^3 + \ldots + b_{1p}x_i^p,$$

where the treatment or causal effect τ is equivalent to the difference in intercepts when x is centered at the cutoff. Alternatively, the treatment effect and its standard error can be obtained directly from:

$$Y_i = a+b_{01}x_i+b_{02}x_i^2+b_{03}x_i^3+\ldots+b_{0p}x_i^p+\tau D_i+b_1x_iD_i+b_2x_i^2D_i+b_3x_i^3D_i+\ldots+b_px_i^pD_i+e_i,$$

where $D_i = 1(x \geq x_{cutoff}), b_1^* = (b_{11}-b_{01}), b_2^* = (b_{12}-b_{02}), b_3^* = (b_{13}-b_{03}), b_p^* = (b_{1p}-b_{0p})$, and x is centered at the cutoff, following from the fact that since treatment is a deterministic function of the forcing variable:

$$E[Y_i|x_i] = E[Y_{0i}|x_i] + (E[Y_{1i}|x_i]–E[Y_{0i}|x_i])D_i.$$

The conditional expectation function can be modeled in other ways, examples being global polynomials or more restricted versions of the piecewise polynomial presented above. However, unbiased estimation of the treatment effect hinges on the use of the correct functional form. Nonparametric approaches such as kernel regressions or mean comparisons in small neighborhoods around the cutoff reduce the importance of the correct form requirement, but introduce another type of bias related to the fact that they do not take into account the slope in the forcing variable. As a solution to the problem, Hahn, Todd and van der Klaaw (2001) suggests the use of local linear regressions.

In order to evaluate robustness of results, both parametric and non-parametric approaches will be employed in estimating treatment effects. In the case of the former, the choice of polynomial order involves a trade off between fit and precision and a statistical test (Lee and Card, 2008) is used for identifying the lowest order polynomial whose fit is statistically indistinguishable from that of a completely unrestricted model. In the case of non-parametric estimators, choices involve kernel and bandwidth and following Imbens and Lemieux (2008), a rectangular kernel is selected and a variety of windows employed to see how results change with width around the cutoff point. The forcing variable is discrete, non-integer width choices make little sense, and therefore widths are chosen in discrete steps. The approach is both transparent and intuitive since widening width around the cutoff is equivalent to evaluating how results change as individuals farther from the cutoff age are deemed as comparable in all ways but treatment. Finally, in all cases statistical inference is based on errors clustered by age (Lee and Card, 2008).

Internal validity depends on the remarkably weak and plausible assumption of local continuity (Hahn, Todd and van der Klaaw, 2001), requiring that all factors other than treatment evolve smoothly around the cutoff threshold and imprecise control of the forcing variable (Lee, 2008). Card et al. (2008) evaluates the assumption by testing whether variables relevant to the determination of the outcome variable show discontinuities at age 65. These include family structure, income, mobility, and employment, with special concern in the latter as the possibility of a discontinuity in retirement at 65 could result in increased access to medical services through increased time available for medical procedures. Taken as a whole and using a variety of datasets, the authors find that the variables trend smoothly at 65. A further test (McCrary, 2008), fails to reject the null of no violation of the imprecise control assumption.

4 Data

Data are drawn from the 1997 to 2008 National Health Interview Surveys (NHIS), chosen for being well suited to the question under study as well as the methodology. They reflect more substantial jumps in access to insurance at age 65 than post-national health care reform data, and offer a comprehensive set of variables that includes a variety of health outcomes, inputs, and medical diagnoses. Their size is also a valuable asset in a research method that often focuses on a subset of sample observations, in this case being individuals between the ages of 55 and 75. Aggregated over 1997–2008, observations in this age range and in NHIS person files total some 155,000 records with complete age information, while those drawing from sample adult files total 80,000 records. The information is complemented by 1998–99 to 2005–06 National Health and Nutrition Examination Surveys, offering the additional possibility of examining how coverage affects objective measures of health. Aggregation over four surveys produces datasets with around 2,000 to 5,000 observations depending on the size of the examination or laboratory test files. Finally, measures of diagnostic procedures, preventive measures, and risky behaviors are drawn from 2001 to 2008 Behavioral Risk Factor Surveillance System (BRFSS) surveys that generate a sample of some 850,000 observations in the 55–75 age range.[1]

5 Results

5.1 Self-reported health

Trends in the share of individuals in very good, excellent, poor, or fair health status shown in Figure 2 bear out a rapid deterioration in self-reported health between age 55 and 75. In a 20-year span the population share in the top two categories falls from 55% to 36% while that in the bottom two grows from 15% to 27%. However, the rising prevalence of poor or fair health appears to break, shifting down immediately after age 65 to a level from which the trend resumes its upward trajectory at a lower intercept. The top right

[1] www.cdc.gov/nchs/nhis/quest_data_related_1997_forward.htm;www.cdc.gov/brfss/annual_data/annual_data.htm;www.cdc.gov/nchs/nhanes/nhanes_questionnaires.htm.

panel shows what becomes of the group, in displaying a concurrent discontinuity in good health immediately after age 65. Therefore, rather than halting a decline in top health, coverage appears to improve the lot of those in worst shape, restoring health to what could be considered an acceptable level (good health). Positive coverage effects seem fully manifested right after rather than right at age 65, and discontinuities are therefore estimated with D=1(x>65).

[Figure 2]

Regression results in Table 1 confirm the appreciations, as statistically significant discontinuities occur both in the bottom and in the middle health categories. In the case of the noted outcomes, treatment effects are estimated through use of a first order piecewise polynomial as tests do not reject the null that its fit is statistically indistinguishable from that of a completely unrestrictive specification.[2] These establish a 2.1 percentage point decline in the share of individuals in poor or fair health and a concurrent increase of 2 percentage points in the share in good health right after age 65. Results are robust to a parametric specification that includes controls for gender, education, race, Hispanic ethnicity, geographic region, survey year as well as to local linear regression estimations, where precision increases with window width.

[Table 1]

Results are remarkable for a number of reasons. In principle, positive effects on health are bound to appear only to the extent that there are medical conditions to be treated and even then, the causal link between coverage, access, and ultimately health, is not necessarily straightforward. Coverage facilitates access, but medical services need not result in better health if effective treatments or palliatives are unavailable. In some instances services may even result in deteriorated health when treatment is ineffective and related to complications. A challenge more specific to the method in use is that

[2]Throughout the remainder of the paper, test results regarding specification tests will be alluded to only when they reject the first order piecewise polynomial specification.

effects must show up immediately or in very specific windows in order to be tied to care. It is therefore striking to find such sharp evidence of impacts that not only take hold so quickly, but also last so long.

[Figure 3]

In examining the relationship between insurance and access, Card et al. (2004) decomposes the sample population into subgroups ranging from less educated minorities to more educated whites. Breaks in self-reported health are evaluated and although discontinuity estimates are not statistically significant, the general pattern is one of larger jumps for minorities and the less educated than for whites and the more educated. Graphical evidence reproduced in Figure 3 does not manifest obvious discontinuities (Card et al., 2009), as the decomposition into racial and schooling groups and the measurement of age in quarters results in a high degree of variability. In contrast, this study concentrates on decompositions by health conditions, where effects are less likely to be masked by aggregation, and measures age in years, since requiring a response within three months of admission to Medicare may be too stringent a test in the case of health as the outcome.

[Table 2]

To that end, Table 2 presents estimates of incidence of health conditions among the population aged 55 to 75. The most common diagnoses in the age range are hypertension, high cholesterol, arthritis, and low back pain that impact 32% to 50% of the population, followed by aggregated heart conditions, cancer, and diabetes afflicting 10% to 15% of individuals in the age group. Less prevalent are emphysema, stroke, kidney, and liver disease, although it should be stated that the reference period for the last two medical conditions is 3 and 12 months, respectively, rather than any time in the past as in the case of all others. In terms of severity, diseases associated with the lowest levels of self-rated health include those affecting the kidneys, lungs, liver, and the heart. Seventy percent of patients with weak or failing kidneys and 67% of individuals with congestive heart failure find themselves in a state of poor or fair health. In contrast, diagnoses of arthritis, hypertension, and high cholesterol are associated with rates of poor or fair health status in the order of 25% to 30%.

[Table 3]

Regression discontinuity results in Table 3 establish strong positive coverage effects especially on ailments related to the heart. Their degree, immediacy, and durability can be appreciated in Figure 4, where the share of individuals with any type of heart condition and in poor or fair health is plotted against age. Up to age 65 the share hovers in the low 50s. After that age the share declines abruptly to the low 40s where it stays in the remainder of the age window. Parametric discontinuity estimates establish a statistically significant break after age 65 in the order of an 8 percentage point fall, and local linear regression estimates are in the 7 to 9 point range.

[Figure 4]

Table 3 also shows that coverage is effective in improving health of those with specific cardiovascular conditions such as angina pectoris, coronary heart disease, and hypertension. In the case of the former, the share of individuals in poor or fair health declines by 13 percentage points after age 65, translating to about a 25% fall relative to pre-coverage levels that hover in the mid-50s (Figure 4). Effects on patients with coronary heart disease are almost as great and translate to a 9 percentage point reduction after age 65. Health among the much larger population of individuals diagnosed with hypertension also improves, with the share in the bottom two self-rated categories falling by 4 percentage points. Among individuals 60 to 70, the two most common hospital group procedures are cardiac catheterization and removal of artery obstructions, the two most common hospital admission diagnoses are ischemic heart disease and acute myocardial infarction, and both increase abruptly at 65 (Card et al., 2008). Results are also consistent with findings placing acute treatment and improved risk management at the center of cardiovascular disease mortality reductions that in turn explain the bulk of the considerable increase in life expectancy taking place between 1960 and 2000 (Cutler, Deaton, Lleras Muney, 2006; Cutler et al., 2007). Treatment is highly effective and appears to be the clinical mediator between increased coverage and improved health in the population affected by the disease.

Positive coverage effects, however, are not circumscribed to heart disease. Health of those *without* heart disease, as a class, is positively affected by coverage, with effects ranging from a 2 to a 2.5 percentage point fall in frequency of the bottom two health categories (Table 3). They also extend to specific conditions such as cancer, diabetes, and low back pain. Among individuals diagnosed with cancer, the share in poor or fair health falls by 3 percentage points and among those with diabetes it drops by 6 percentage points. Treatment effects arrived at through local linear regressions are in line with parametric results in the case of diabetes, and are about twice as large in that of cancer, suggesting effects that are concentrated in the neighborhood of age 65 in the case of the latter condition. The less serious but much more prevalent condition of lower back pain is also positively affected by coverage at 65 when the share of individuals in poor or fair health declines by 3 to 5 percentage points.

5.2 Activity limitations

NHIS sample adult files contain information regarding existence of limitations related to physical, mental, or emotional problems. These include whether respondents need assistance with personal care or routine needs, have difficulty walking or remembering, whether they are unable or limited in the amount and kind of work that can be performed, or are limited in any other way. In case of a positive answer, interviewers ask about the medical conditions associated with the limitations, opening other dimensions for evaluating consequences of coverage and reducing co-morbidity confounding effects. That is, a diabetic with heart disease, for example, has the choice of heart disease, diabetes, both, or some other condition as the source of her limitations.

[Table 4]

Activity limitations are not uncommon among the population under study and rise from age 55 when 17% of the sample is impacted, to about twice the level by age 75.

Their causes are varied, with the top three being arthritis, back problems, and heart conditions, affecting 6.4%, 5%, and 4.8% of the sample, respectively (Table 4). Diabetes, hypertension and lung problems follow in limiting 2.9% to 3.5% of the population, while others such as cancer, stroke, and depression limit 1.4% to 1.8%. Regression results presented in Table 5 establish statistically significant relationships between coverage and a wide range of afflictions that include cancer, depression, hypertension, nervous system problems, and lung disease. Local linear regressions support all the stated relationships.

[Table 5]

Graphs provide additional information in depicting the nature of the discontinuities. Limitation rates related to depression trend slightly downward as individuals reach age 65 but then fall abruptly right at that age, settling at a level close to half of that evident in ages 55 to 64 (Figure 5). Limitations related to cancer rise steadily with age, fall abruptly by about 25% between age 64 and 65, and continue their upward trend thereafter at a lower intercept. Similar trends occur with limitations caused by hypertension and lung disease, although not as marked in degree. Positive coverage effects are evident right at rather than right after age 65, a phenomenon perhaps related to the fact that limitations may identify more severe cases of medical conditions. Diagnosis and treatment could be expedited with effects manifested shortly thereafter.[3]

[Figure 5]

Coverage effects on arthritis are statistically significant, but only when using regressions with large windows and a visual inspection of the evidence does not support a break at 65. Limitations appear to begin declining at 64. The phenomenon could be related to statistical variation or to treatment other than Medicare, but it could also be related to early admission to Medicare through the Social Security Disability Insurance program. Musculoskeletal disorders account for over a quarter of all awards (Autor and Duggan, 2006), joint replacement surgeries are effective therapies for arthritis, and are very sensitive to Medicare insurance (Card et al., 2008). Small increases in coverage before 65

[3]Therefore, discontinuities are estimated with $D=1(x \geq 65)$.

could therefore have large impacts on limitations if concentrated on populations with severe cases of the condition.

Few other limitations do not respond to increased coverage in any sort of way. In some cases they are related to medical events with limited treatment options such as stroke or visual impairment, to uncovered care as in limitations related to weight problems, or to non-deferrable treatment such as that related to fractures. In other cases, responses are evident only in parametric specifications as in limitations related to bone, joint, and muscle problems. These may reflect instances where relationships are absent in the population or cases where they are present but cannot be estimated with great precision. Lack of any evidence linking coverage to reductions related to diabetes is unexpected, but perhaps due to the fact that it is through the co-morbidities associated with the disease that the welfare of diabetics is improved. Potential channels of coverage on diabetes are explored in the next section.

5.3 Diagnostics, prevention, and management

Evidence so far presented is consistent with coverage improving self-rated health as well as with reducing limitations related to a variety of medical conditions. The range of mediating channels can be wider, as it could also result in prevention of disease, in a reduction in risky behaviors, and in better management of chronic conditions. Causal effects on health cannot be established without counterfactuals of how it would have behaved otherwise, but tests can evaluate whether Medicare is associated with abrupt changes in diagnostic procedures, preventive services, and a reduction in risky behaviors.

[Figure 6]

Checkups, mammograms, colonoscopies, prostate exams, vaccinations, and cholesterol testing are examined first, and most show discontinuities right at or right after age 65 (Figure 6). Checkup rates follow a smooth upward trend up to age 65 when they jump abruptly by 2 to 3 percentage points, continuing their trajectory thereafter at a higher intercept. More variability is evident in both colonoscopies and mammograms but both rise at 65. The effect of the latter test is small and wears off around age 70, but the pattern is consistent with the diminishing benefits of cancer screening procedures with respect to life expectancy. Evidence of vaccinations is striking, particularly pneumonia, as a smooth upward pattern is interrupted at age 65 when the vaccination rate rises from 34% at age 64 to 48% at age 66. Even what could be considered routine and inexpensive procedures as cholesterol checks show a discontinuity occurring right after age 65. Results in Table 6 establish that all effects are statistically significant in both parametric and non-parametric model specifications. Goodness of fit tests do not reject parametric second order piecewise polynomial specifications for mammograms and flu shots, third order for pneumonia vaccine, and first order for the remaining services. Parametric models are estimated accordingly.[4]

Modifying risky behaviors may be much more costly to the individual, but two of the highest risk factors impacting health are positively affected at age 65: smoking and obesity. The share of smokers having given up the habit rises abruptly by 1.5–1.8 percentage points at that age and the share of overweight or obese individuals, defined as those with a body mass index over 25, drops by 1.8–2.2 percentage points. Relative to pre-intervention levels, percentage effects translate to about a 2% reduction in smoking and a 6% one in the obesity rate. The mechanisms producing such changes are unknown but could include greater physician contact, testing, and eventful experiences such as hospital procedures, all of which rise at that age.

[Table 6]

Results build on previous work in three ways. First, they provide robust relationships between coverage and cholesterol checks, mammograms, and flu shots, whose absence in Card et al. (2004) was correctly attributed by the authors to lack of statistical power rather than to lack of potential relationships between coverage and access to these services. Currently available larger datasets address the problem. Secondly, preventive coverage effects are extended to a number of other services with comparatively sharper and stronger

[4] Regression discontinuities are estimated through the functional forms suggested by the tests and with the knot suggested by the graphs, either $D=1(x>65)$ or $D=1(x\geq 65)$.

discontinuities. The association between Medicare and colonoscopies is of particular importance as cancer screening procedures have been established as the most important factor behind the drop in cancer mortality that has taken place in the US since the last decade of the past century (Cutler, 2008). Pneumonia vaccines can also have significant health benefits in lowering the likelihood of a condition that is among the most common hospital admission diagnoses among the near elderly (Card et al., 2008). Third, a link is established between coverage and a reduction in risky behaviors.

[Figure 7 and Table 7]

Preventive measures could also take the form of limiting the consequences of chronic conditions such as diabetes, and Figure 7 shows that age 65 is associated with an abrupt decline in glycosylated hemoglobin among diabetics that estimators establish as statistically significant and equivalent to a 7% to 12% reduction relative to pre-intervention levels. High glucose levels progressively impair organ function and curtailing them is the single most important factor for limiting the negative consequences of diabetes. Often an associated condition, management of heart disease can take the form of reductions in cholesterol and blood pressure levels. Estimates in Table 7, however, show that age 65 is not linked to abrupt declines in total cholesterol, fasting LDL cholesterol, or mean diastolic or systolic blood pressure levels. Effects could nevertheless be manifested in other ways or be concentrated in specific population subgroups, as research establishes a link between Medicare and a reduction in disparities of measures of control of cardiovascular disease and diabetes across ethnic-racial-schooling groups (McWilliams et al., 2009).

6 Discussion

There can be other explanations for the discontinuities established in this paper. Mere contact with the medical care system and the greater stability or security offered by Medicare as an insurer could result in appreciations of self-rated health. The effect is not devoid of value, but it would be useful to distinguish it from other channels of improvement such as prevention, management, and acute treatment. Current data, however, do not allow for an evaluation, but it is suggestive to find that health improvements at 65 are evident among individuals with conditions with effective therapies such as cardiovascular disease and not among those with less effective options such as those related to strokes or liver disease.

Medicare contact could also increase diagnoses, with effects on self-rated health and activity limitations results that would depend on their information content. Identification or confirmation of medical conditions could bias insurance effects downward as they could result in downward revisions of self-rated health at 65. On the other hand, individuals may learn that previously unidentified health problems are minor or treatable, resulting in bias in the opposite direction. Changes in population composition could also be having an impact on results on self-rated health by medical condition. That is, if diagnoses of (say) cardiovascular disease increase at 65 and the newly diagnosed are in relatively good shape, self-rated health improvements among those with the condition could result from changes in the composition of that population. A priori, it is difficult to say what kind of individual would be more likely to receive a diagnosis resulting from acquisition of Medicare coverage. More intensive use of detection procedures could result in identification of diseases at early stages and addition of relatively healthy individuals to the diagnosed population, but use along the extensive dimension could result in addition of relatively sick ones, undiagnosed until 65 due to lack of previous access to care. The question may not have an easy answer, but empirical evidence suggests that diagnoses do not rise abruptly at 65.[5]

Results may also be influenced by the fact that coverage can generate effects other than the short-term and abrupt that are examined in this paper. Therapies for cardiovascular disease, for example, can have immediate consequences on health and mortality, but they can also result in longer life expectancy. Effects can also take hold over time rather than abruptly and in other cases result in an attenuation of progression of disease. In principle, alternative consequences could be evaluated by testing for changes in slopes in (say) the relationship between age and arthritis or blood pressure at age 65. Such an analysis, however, would require further assumptions regarding stability over time of relationships

[5]Regression discontinuity results and graphs are available from the author.

between age and medical conditions, and therefore are likely to be best examined through use of data that is not aggregated over time.

7 Conclusion

The regression discontinuity approach has been successfully applied to obtain credible and robust evidence regarding the relationship between medical insurance and access to care. Chances of establishing a positive causal link between coverage and health rather than access would not necessarily seem promising a priori. In general, there need to be medical conditions and effective therapies or palliatives in order for coverage to result in improved health. More specific to the method, results must show up at precise time frames in order to be tied to care. In light of this, it is then surprising to find coverage effects that are so widespread, manifested through such a large range of outcomes, and in many cases evident years after treatment.

Medicare was associated with substantially improved self-rated health of individuals diagnosed with heart disease, evidence that is consistent with hospital procedures that also increase abruptly at age 65, such as cardiac catheterization and removal of artery obstructions. Coverage was also associated with improved health among those suffering from cancer, and among those with chronic but treatable conditions such as diabetes, hypertension, and low back pain. An abrupt decline in blood sugar levels among diabetics provided evidence tying coverage to better management of disease.

Assessment of health outcomes through the lens of activity limitations furthered widened the range of medical conditions positively affected by coverage at 65. Limitations related to depression, lung disease, nervous system problems, cancer, and hypertension all decline right at that age. These reductions can reflect health improvements among those suffering from particularly acute cases of disease, and in reducing difficulties and need for assistance with personal care and routine needs, could also reflect quality of life improvements attributable to coverage. Insurance was also associated with outcomes that could result in ulterior positive effects, either through better health or reduced costs in treating afflictions. Preventive and diagnostic services such as cholesterol checks, flu shots, and pneumonia vaccines were found rising abruptly at 65. Important behavioral risk factors such as smoking and being overweight also decline.

In evaluating the consequences of health insurance, the question of essence was not about the effectiveness of medical procedures. Rather, it was about the implications of lowering the marginal cost of access to care of a given quality and the channels through which insurance improves health. An 8% increase in coverage among the near-elderly generates health improvements especially associated with treatment of acute procedures with clear therapies, a decline in activity limitations associated with a wide range of medical conditions, better chronic disease management, increased testing, and a reduction in risky behaviors. Whether the outcomes are achieved through intensive or through extensive means is a question that remains as an important subject of future work.

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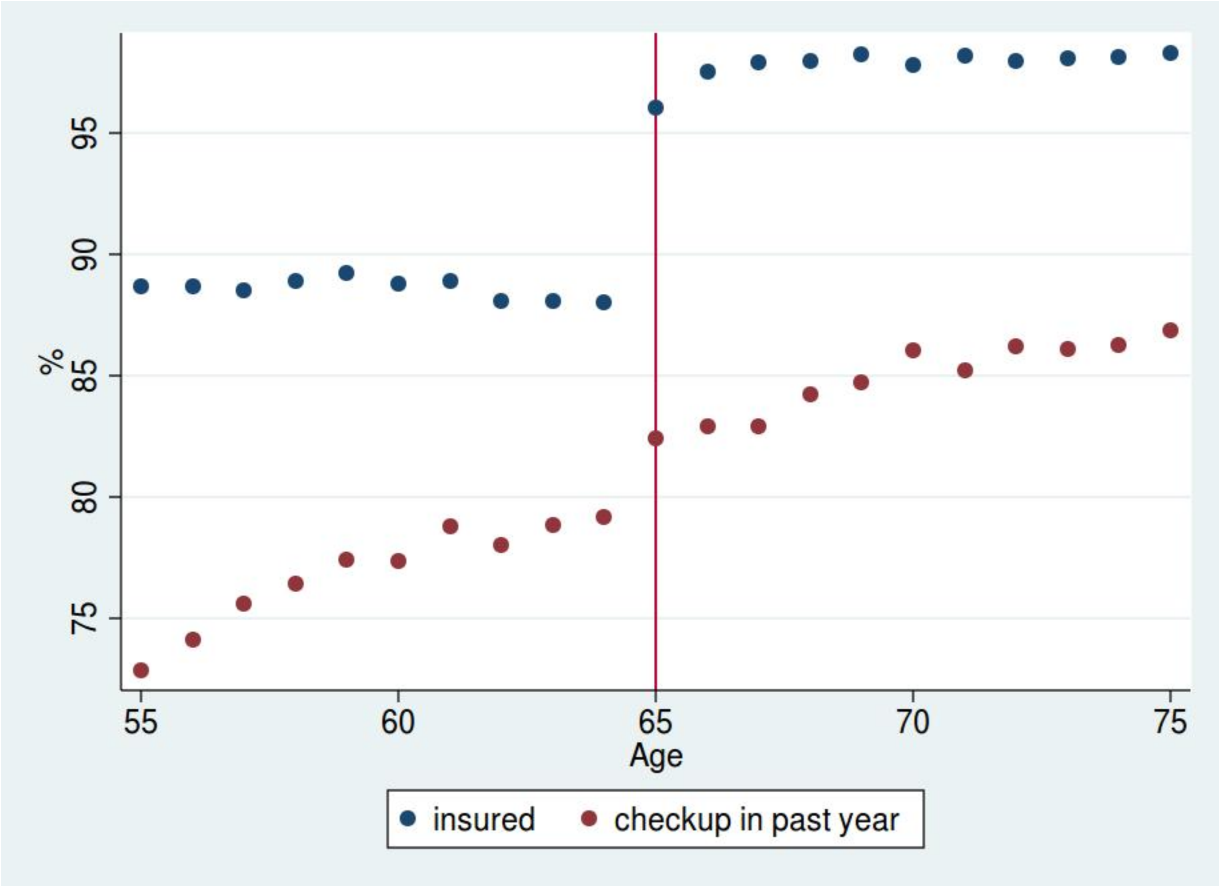

Figure 1: Share of the population covered by medical insurance and with a checkup in the past year by age

Microdata source: BRFSS

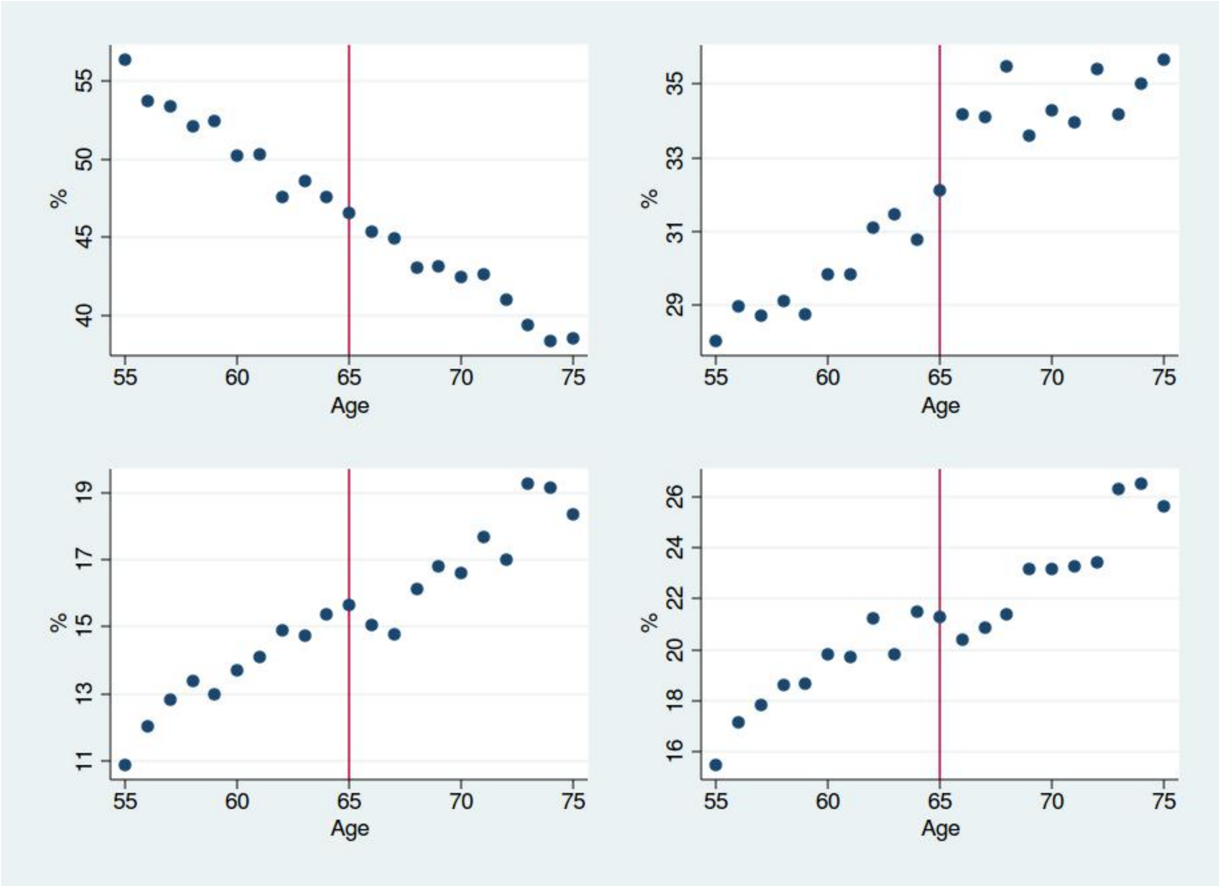

Figure 2: Share of population in self-rated excellent or very good health (top left), in good health (top right), fair health (bottom left), and in fair or poor health (bottom right)

Microdata source: NHIS

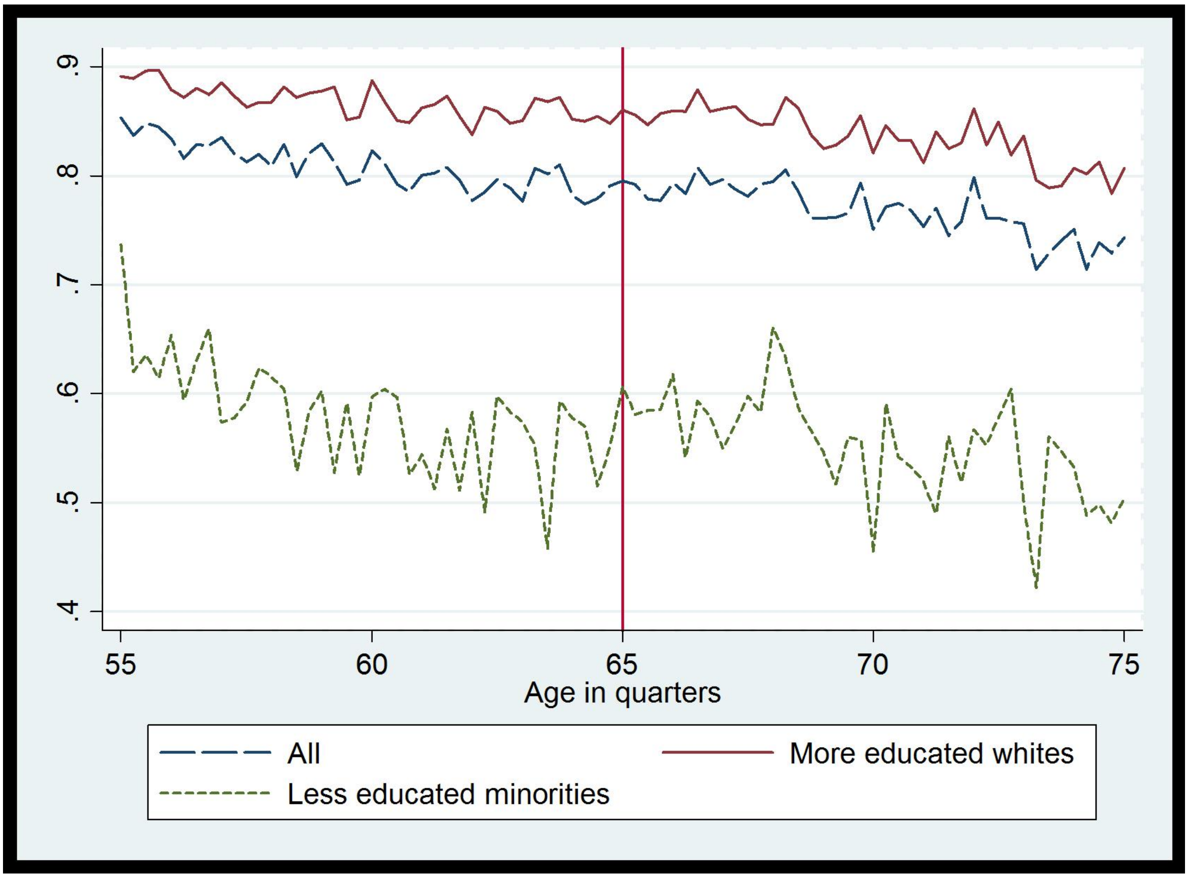

Figure 3: Share of population in excellent, very good, or good health by race-schooling groups and age in quarters

Data source—NHIS

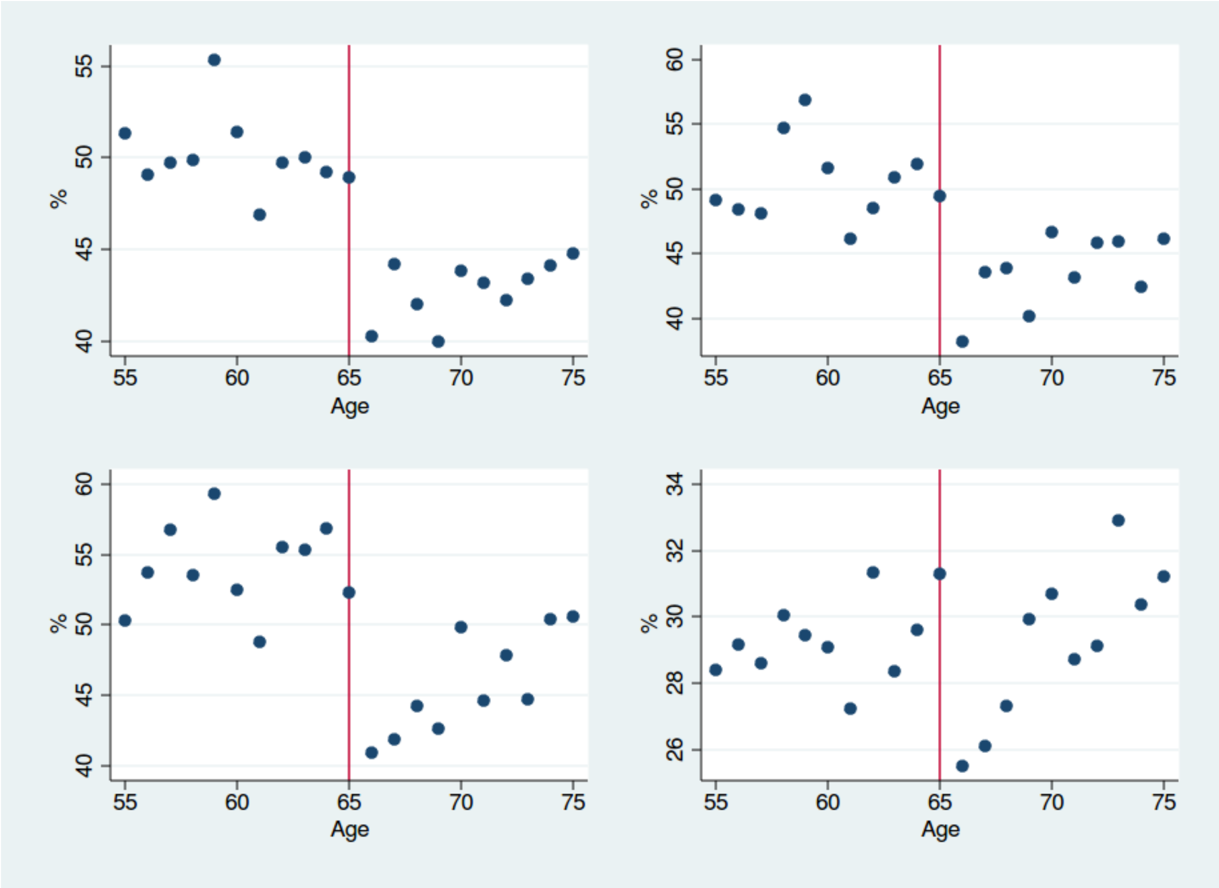

Figure 4: Share of population in fair or poor health among diagnosed with any heart condition (top left), coronary heart disease (top right), angina pectoris (bottom left), and hypertension (bottom right)

Microdata source: NHIS

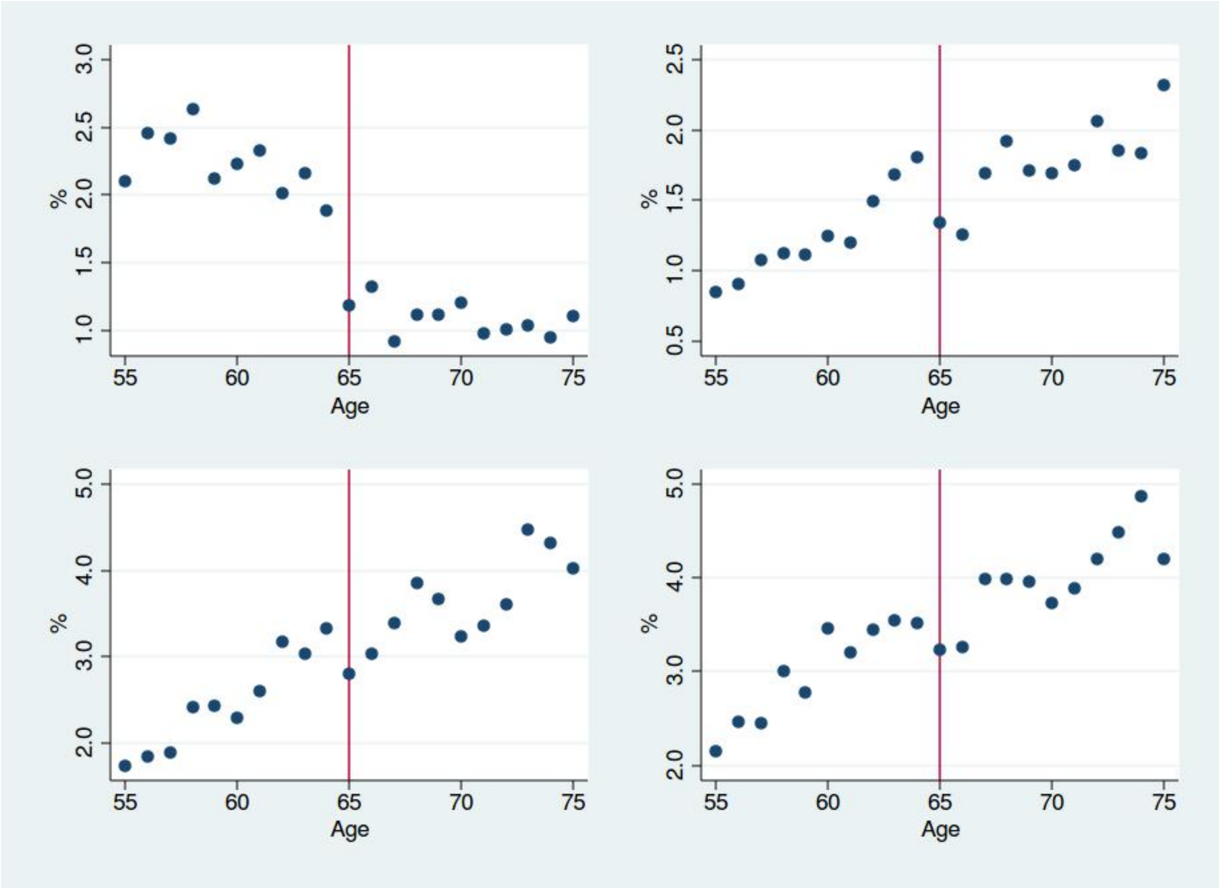

Figure 5: Share of population with activity limitations related to depression (top left), cancer (top right), lung disease (bottom left), and hypertension (bottom right)

Microdata source: NHIS

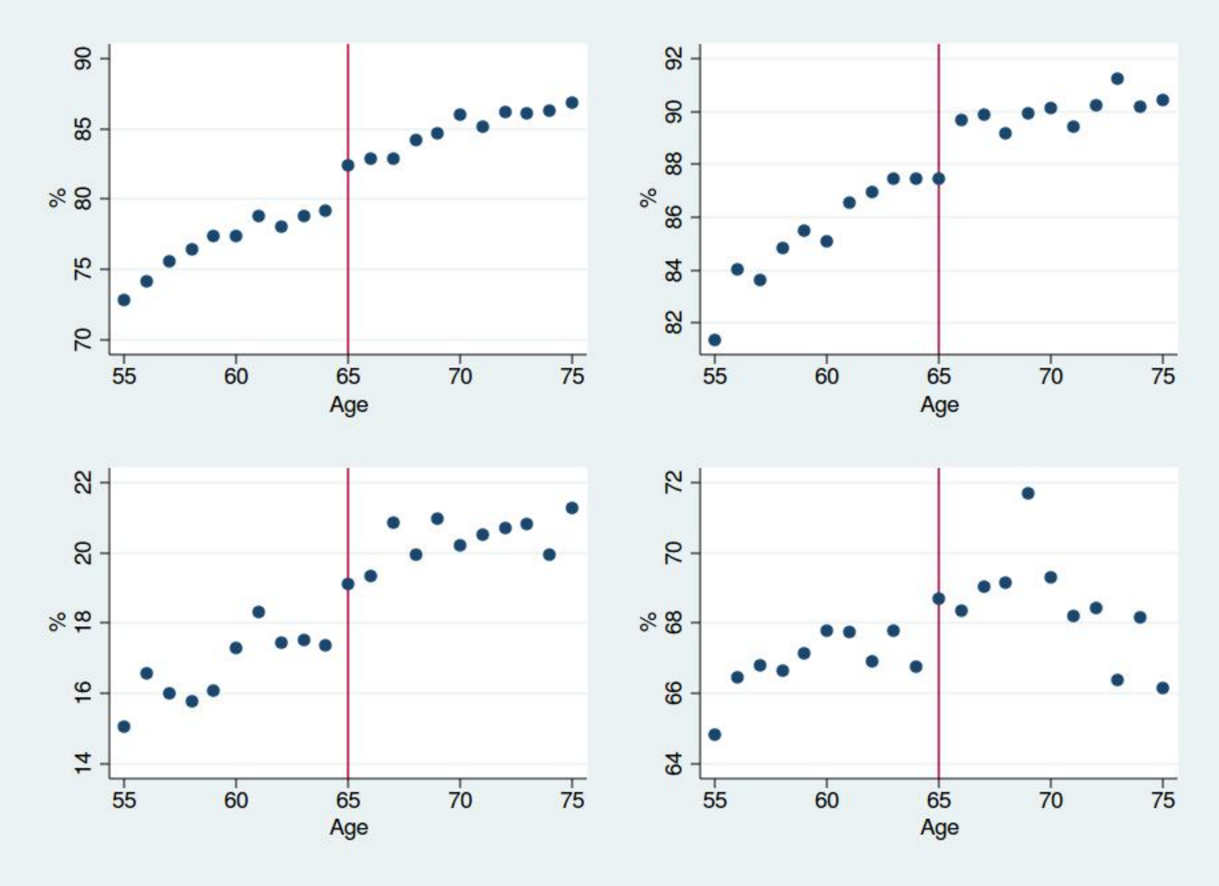

Figure 6: Share of the population with check up (top left), cholesterol check (top right), colonoscopy (bottom left) and mammogram (bottom right) in the past year

Microdata source: BRFSS

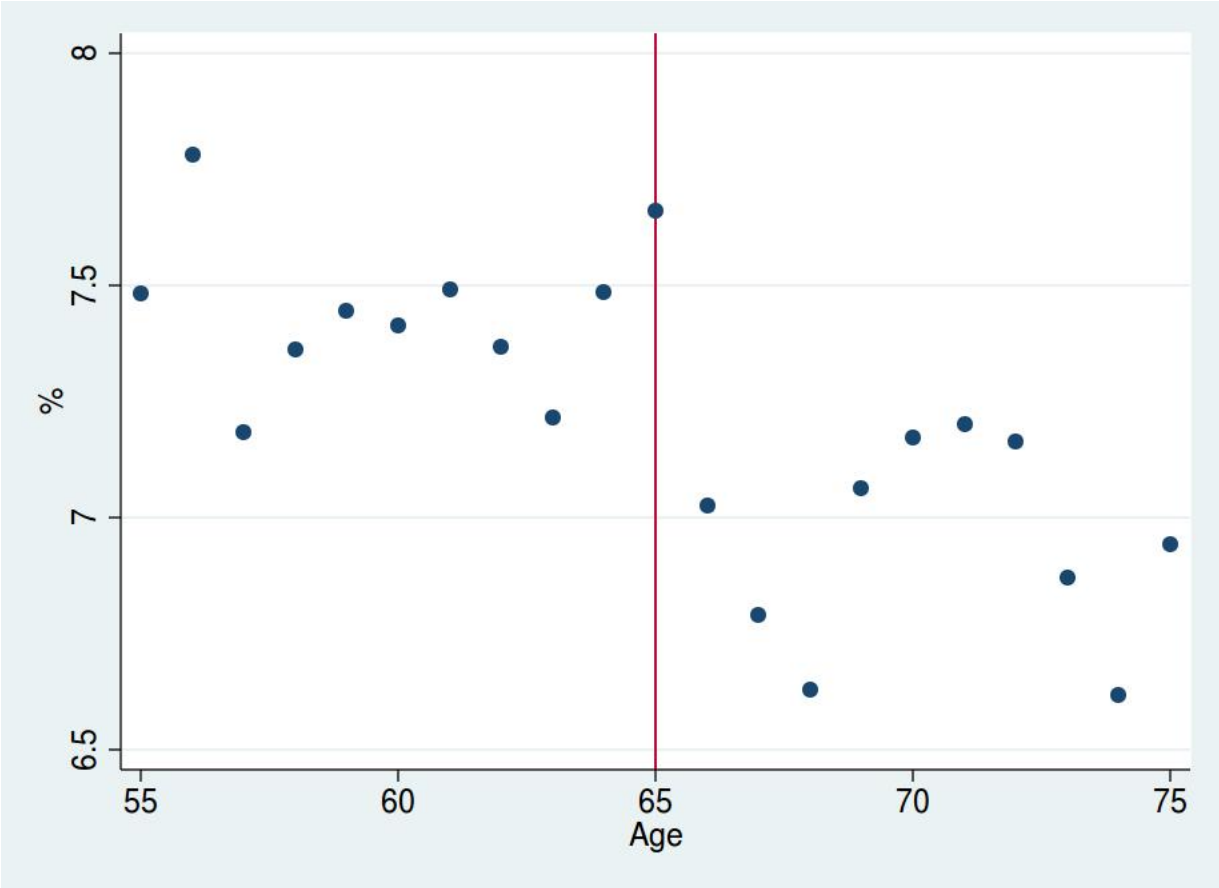

Figure 7: Percent glycosylated hemoglobin among diabetics

Microdata source: NHANES

Table 1–Discontinuity coefficient estimates and standard errors of sample share in health status by category and model specification

	Poor or fair health		Good health		VG or excellent health	
Specification	τ	SE	τ	SE	τ	SE
Parametric						
w/o controls	-2.1	0.51	2.0	0.45	0.13	0.52
w/control	-2.1	0.58	2.1	0.44	0.03	0.05
Local linear						
width=3	-2.0	0.56	1.8	0.67	0.09	0.28
width=4	-1.3	0.45	2.4	0.64	-1.2	0.63
width=5	-1.5	0.39	2.0	0.54	-0.52	0.43

Microdata source: NHIS

Note: Parametric models are estimated without and with controls for year effects, race, Hispanic ethnicity, education, gender, and region. All figures have been multiplied by 100.

Table 2–Incidence of medical condition and self-reported health by diagnosis

	Incidence (%)	Share in poor or fair health (%)		
Diagnosis	Ages 55-75	Ages 55-75	Age 64	Age 66
Angina pectoris	6.1	50	57	41
Arthritis	42.5	30	30	30
Asthma	9.9	38	38	37
Back pain	31.8	34	33	31
Cancer	14.4	28	29	24
High cholesterol	41.5	25	27	25
Congestive heart	3.4	67	72	69
Coronary heart	9.3	47	52	38
Diabetes	14.7	45	46	42
Emphysema	4.2	58	63	57
Heart (all)	10.1	46	49	40
AMI	8.0	49	52	42
Hypertension	47.6	29	30	26
Kidney	2.6	70	71	70
Liver	1.8	56	58	51
Stroke	5.1	56	60	50
Ulcer	12.2	37	37	33

Microdata source: NHIS

Table 3–Discontinuity coefficient estimates of sample share in poor or fair health by medical diagnosis and model specification

Diagnosis	Parametric specification	LLR by window width 3	4	5	Mean at 65 vs. 66
Angina	-13.3	-11.1	-11.8	-15.9	-11.4
	(-1.8)	(-1.9)	(-2.1)	(-3.3)	(-5.0)
Arthritis	-2.1	-0.13	1.5	-1.3	0.5
	(-1.3)	(-0.89)	(-1.2)	(-1.6)	(-2.4)
Asthma	-4.3	2.9	-0.23	-2.5	1.2
	(-2.2)	(-0.92)	(-2.3)	(-2.6)	(-4.1)
Cancer	-3.3	-5.7	-7.3	-7	-5.9
	(-1.1)	(-0.41)	(-0.89)	(-0.56)	(-3.1)
Cholesterol	0.95	-2.9	3.6	2.8	2.1
	(-2.4)	(-3.7)	(-2.6)	(-2.3)	(-4 .0)
Congestive	-6.2	21.7	0.92	1.1	8.2
	(-7.3)	(-2)	(-9.5)	(-6.9)	(-16)
Coronary	-9.1	-10.1	-10.6	-12.4	-11.2
	(-1.8)	(-1.5)	(-2.7)	(-2.4)	(-4 .0)
Diabetes	-6.4	-6.9	-6.1	-8.4	-5.7
	(-1.7)	(-0.13)	(-2.2)	(-2.5)	(-3.2)
Emphysema	-2.2	-3.4	-4.3	-7.2	-3.2
	(-2)	(-1.5)	(-1.6)	(-2.4)	(-6.2)
Heart (all)	-7.7	-7	-6.6	-8.5	-8.7
	(-1.1)	(-1.3)	(-1.7)	(-1.5)	(-3.3)
AMI	-5.1	-7.9	-5.7	-6.7	-9.9
	(-2.5)	(-2.3)	(-3.9)	(-3.6)	(-4.4)
Hypertension	-3.9	-7.3	-5.3	-6.4	-5.8
	(-0.97)	(-0.17)	(-1.4)	(-0.83)	(-1.6)
Kidney	0.22	-10	-1.4	-1.2	-2.5
	(-3.1)	(-2.4)	(-3)	(-2.6)	(-7.4)
Liver	5.5	-1.2	9.7	2.5	6.9
	(-7.3)	(-12.2)	(-7.4)	(-9.8)	(-9.4)
Low back pain	-5.3	-4.2	-2.8	-4.6	-5.4
	(-1.2)	(-2.2)	(-2.4)	(-1.8)	(-2.3)
Stroke	-2.4	-3.3	-0.35	-3.3	-2.8
	(-1.6)	(-1.7)	(-1.2)	(-2.3)	(-5.5)
Ulcer	-4.3	-3.5	-2.1	-4.1	-5.3
	(-1.7)	(-1.9)	(-2.1)	(-2.2)	(-3.5)
W/o heart conditions	-2	-2.5	-2.2	-2.2	-1.7
	(-0.53)	(-0.28)	(-0.48)	(-0.38)	(-0.9)

Microdata source: NHIS
Note: All figures are multiplied by 100 and standard errors are in parenthesis. Tests of differences in mean outcome levels at 65 and 66 are provided in the last column.

Table 4–Incidence of activity limitations in sample by medical condition

Condition	Share (%)	Condition	Share (%)
Arthritis	6.4	Hearing	0.9
Back problems	5.0	Heart	4.8
Bone, joint, muscle	2.0	Hypertension	3.4
Cancer	1.4	Lung	2.9
Circulation	0.8	Nervous system	1.6
Depression	1.8	Stroke	1.7
Diabetes	3.5	Vision	1.8
Fractures	2.2	Weight	0.7

Microdata source: NHIS

Table 5–Discontinuity coefficient estimates of sample share with activity limitations by medical diagnosis and model specification

Diagnosis	Parametric specification	LLR by window width 3	4	5	Mean at 65 vs. 66
Arthritis	-1	-0.18	-0.28	-0.72	-0.09
	(-0.24)	(-0.14)	(-0.19)	(-0.29)	(-0.4)
Back	-0.64	-0.45	-0.21	-0.73	-0.82
	(-0.31)	(-0.24)	(-0.34)	(-0.35)	(-0.36)
Cancer	-0.39	-0.71	-0.81	-0.65	-0.46
	(-0.11)	(-0.1)	(-0.12)	(-0.09)	(-0.21)
Circulation	-0.13	-0.14	-0.01	-0.12	-0.11
	(-0.08)	(-0.06)	(-0.09)	(-0.07)	(-0.15)
Depression	-0.86	-0.62	-0.57	-0.67	-0.69
	(-0.14)	(-0.16)	(-0.11)	(-0.12)	(-0.2)
Diabetes	-0.25	0.65	0.34	0.07	0.31
	(-0.24)	(-0.19)	(-0.19)	(-0.21)	(-0.32)
Fractures	-0.11	0.07	0.02	-0.16	0.08
	(-0.12)	(-0.1)	(-0.09)	(-0.15)	(-0.24)
Hearing	-0.17	-0.19	-0.1	-0.18	-0.09
	(-0.07)	(-0.08)	(-0.05)	(-0.1)	(-0.15)
Heart	-0.53	-0.25	-0.13	-0.15	-0.23
	(-0.27)	(-0.46)	(-0.41)	(-0.36)	(-0.39)
Hypertension	-0.53	-0.44	-0.52	-0.31	-0.28
	(-0.18)	(-0.13)	(-0.13)	(-0.12)	(-0.29)
Lung	-0.46	-0.56	-0.81	-0.82	-0.53
	(-0.16)	(-0.13)	(-0.1)	(-0.12)	(-0.29)
Muscle	-0.4	0.06	-0.11	-0.24	-0.17
	(-0.13)	(-0.19)	(-0.12)	(-0.13)	(-0.25)
Nervous sys.	-0.35	-0.32	-0.25	-0.34	-0.39
	(-0.1)	(-0.12)	(-0.12)	(-0.09)	(-0.21)
Stroke	-0.04	-0.26	-0.1	-0.16	-0.09
	(-0.11)	(-0.06)	(-0.12)	(-0.15)	(-0.22)
Vision	-0.22	-0.52	-0.48	-0.4	-0.37
	(-0.11)	(-0.07)	(-0.07)	(-0.08)	(-0.2)
Weight	-0.17	-0.26	-0.24	-0.27	-0.33
	(-0.1)	(-0.07)	(-0.11)	(-0.38)	(-0.14)

Microdata source: NHIS
Note: All figures are multiplied by 100 and standard errors in parentheses.

Table 6–Discontinuity coefficient estimates of sample share receiving diagnostic, preventive procedure, or with associated risk behavior

	Parametric	LLR by window width			Mean at
		3	4	5	65 vs. 66
Checkup	2	2.7	3.1	2.7	3.2
	(-0.52)	(-1.7)	(-0.3)	(-0.23)	(-0.75)
Cholesterol check	2	2.4	2	1.7	2.2
	(-0.33)	(-0.18)	(-0.18)	(-0.25)	(-0.82)
Colonoscopy	1.4	1.6	2.3	1.8	1.8
	(-0.5)	(-0.22)	(-0.26)	(-0.28)	(-0.66)
Flu shot	3.4	3.1	2.5	3.6	5
	(-0.34)	(-0.26)	(-0.26)	(-0.49)	(-0.72)
Mammography	2.1	1.5	1.7	1.3	1.9
	(-0.47)	(-0.62)	(-0.46)	(-0.6)	(-0.99)
Non-smoker rate	1.5	1.8	1.6	1.8	2.4
	(-0.48)	(-0.29)	(-0.22)	(-0.38)	(-0.82)
Overweight rate	-2.2	-2.3	-1.8	-1.9	-2.1
	(-0.78)	(-0.46)	(-0.41)	(-0.46)	(-0.69)
Pneumo. vaccine	4.8	4.8	5.3	5.5	6.7
	(-0.65)	(-0.76)	(-1.1)	(-1)	(-0.66)
PSA test	0.24	0.64	3.2	1.7	2.9
	(-1.1)	(-0.33)	(-1.4)	(-0.83)	(-1.5)
Rectal exam	-0.05	-0.65	1.1	0.38	1.4
	(-1.1)	(-0.67)	(-1.3)	(-1)	(-1.4)

Microdata source: BRFSS
Note: Statistical tests point to first order piecewise polynomial parametric specifications for checkups, colonoscopies, prostate specific antigen test, and digital rectal exams, second order for mammograms, cholesterol check, flu shots, and smoking, third order for pneumonia vaccine, and fourth order for obesity rates. The time frame for pneumonia vaccine is any time in the past while that for all other preventive services is the past year. All figures are multiplied by 100 and standard errors are shown in parentheses.

Table 7–Discontinuity coefficient estimates of blood pressure, blood sugar, and cholesterol levels among diabetics

	Parametric	LLR by window width			Mean at
		3	4	5	65 vs. 66
Glycosilated hemoglobin	-0.54	-0.88	-0.84	-0.8	-0.64
(%)	(-0.16)	(-0.03)	(-0.14)	(-0.19)	(-0.32)
Total cholesterol	-2.5	-42.1	-26.4	-21.3	-26.9
(mg/dL)	(-10.7)	(-3.3)	(-7.7)	(-8.1)	(-11.6)
LDL cholesterol	14.9	-8.1	-1.5	-3.8	-1
(mg/dL)	(-7.7)	(-4.7)	(-4)	(-5.4)	(-13.5)
Systolic pressure	9	7.5	6.3	9.4	7.7
(mm Hg)	(-3.3)	(-3.7)	(-4.3)	(-3.2)	(-4.5)
Diastolic pressure	0.13	3.61	1.79	1.17	0.21
(mm Hg)	(-2.2)	(-2.6)	(-2.7)	(-2.7)	(-2.3)

Microdata source: NHANES