

Health Insurance and Access to Care for the Near Elderly

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The vast majority of Americans become eligible for Medicare at age 65. This results in 7 percent of the near elderly transitioning from uninsurance to insurance and 60 percent switching from some source of insurance to Medicare. We develop an extension of two-sample IV to estimate the effect of uninsurance on access to care while accounting for the effects of the other transitions. We find that not having insurance results in much lower probabilities of having a medical provider or receiving inpatient care. The foregone hospitalizations are for life-threatening emergent conditions and elective surgeries that increase quality of life.

* We thank Kevin Friedman for outstanding research assistance and seminar participants at UC Santa Cruz, Louisiana State University, University of Illinois Urbana-Champaign, UC Riverside, University of Notre Dame, Purdue University, UC Merced, Stanford University, University of Pennsylvania, and City University of London for their comments and advice. We gratefully acknowledge funding from the National Institute on Aging (R01AG026290). Affiliations: Anderson: University of California, Berkeley, mlanderson@berkeley.edu. Dobkin: University of California, Santa Cruz, cdobkin@ucsc.edu. Maestas: Harvard University, maestas@hcp.med.harvard.edu. Rose: Stanford University School of Medicine and Department of Veterans Affairs Palo Alto Health Care System, liamrose@stanford.edu.

The near-elderly are an important yet understudied population. Compared to individuals aged 18-54, those 55-64 have a much higher burden of illness, characterized by multiple chronic conditions and functional impairments (Baker et al., 2001; McWilliams et al., 2004; Fowler-Brown et al., 2007; Baker et al., 2006; Freid, Bernstein and Bush, 2012; Case and Deaton, 2015; Villarroel and Cohen, 2016), which for many limit their ability to participate in the labor force. As a result, a significant share of Americans in their late-50s and early-60s lack access to employer-sponsored health insurance, the most common source of affordable health insurance for people who have not reached the Medicare eligibility age of 65.¹ Nationwide, 8.5 percent of people aged 55-64 were uninsured in 2019, with wide variation across states (Kaiser Family Foundation, 2020).² Understanding the effect of insurance on access to care for this population is particularly important because their need for medical care is great yet they are vulnerable to coverage gaps (Baker et al., 2001).

Although a large literature has documented the benefits of public and private health insurance for various groups across a broad range of health and financial outcomes,³ this literature lacks a credible causal estimate for the near-elderly *uninsured*. The challenge with estimating the causal effect of health insurance for any population is that selection into insurance coverage on the basis of unobserved

¹Not coincidentally, the near elderly have the highest rate of disability benefit receipt, which is a route to obtaining health insurance coverage through Medicare or Medicaid.

²The uninsurance rate among people aged 55-64 was 13.4 percent in 2009, prior to the passage of the Affordable Care Act (ACA) (Center for Financing, Cost Trends and Quality: Medical Expenditure Panel Survey Household Component, 2009). Although the ACA reduced the number of uninsured Americans, the coverage expansion has been incomplete because many states chose not to expand their Medicaid programs, and because some individuals have opted not to purchase individual coverage due to the high cost of premiums and the removal of the individual mandate (Kaiser Family Foundation, 2020).

³The most recent literature has focused on the effects of Medicaid expansions that occurred prior to and because of the Affordable Care Act. Studies find Medicaid improves access to medical care (Finkelstein et al., 2012; Sommers, Long and Baicker, 2014; Sommers et al., 2015, 2016; Wherry and Miller, 2016; Sommers et al., 2017), increases service utilization (Finkelstein et al., 2012; Miller, 2012; Taubman et al., 2014; Smulowitz et al., 2014; Golberstein et al., 2015; Loehrer et al., 2016; Finkelstein et al., 2016; Wherry and Miller, 2016; Simon, Soni and Cawley, 2017; Cole et al., 2017; Sommers et al., 2017), reduces financial risk (Finkelstein et al., 2012; Baicker et al., 2013; Mazumder and Miller, 2016), in some cases improves self-reported health outcomes (Finkelstein et al., 2012; Miller, 2012; Baicker et al., 2013; Courtemanche and Zapata, 2014; Sommers, Long and Baicker, 2014; Sommers et al., 2015, 2016, 2017; Simon, Soni and Cawley, 2017), and reduces mortality (Sommers, Baicker and Epstein, 2012; Sommers, Long and Baicker, 2014; Sommers et al., 2017; Goldin, Lurie and McCubbin, 2021; Miller, Johnson and Wherry, 2021).

characteristics confounds observational comparisons of people with and without insurance coverage (Levy and Meltzer, 2004, 2008).⁴ In the quasi-experimental literature, numerous papers have solved the selection problem by leveraging age-based eligibility rules or expansions of public health insurance, but these designs do not recover the causal effect of health insurance for the uninsured. Rather, they recover the reduced-form effect of the policy on all affected groups. This is because health policy changes tend to initiate multiple treatments simultaneously, and any one treatment can itself induce heterogeneous responses across the population. An expansion of public health insurance at a given age or point in time may result in coverage gains for the uninsured, but it may also induce coverage *changes* for insured individuals who switch from private to public coverage. This “crowd-out” effect complicates estimation of the causal effect of health insurance, since the estimated effect of the policy change conflates the effects on the uninsured and the insured. Often, the insured are a much larger group than the uninsured, raising the possibility that the crowd-out effect is as large or larger than the treatment effect for the uninsured.

In this paper, we estimate the causal effect of insurance on access to health care and health care utilization for the uninsured near-elderly. We do so by leveraging the sharp changes in insurance coverage that occur when people turn 65 and become eligible for Medicare. It is well documented that there is a large increase in health care utilization when people turn 65 (Card, Dobkin and Maestas, 2008, 2009). However it is not clear how large the increase in utilization is for the near-elderly *uninsured* (as opposed to all-near elderly), and how much age-based Medicare eligibility closes the gaps in access to health care between the insured and the uninsured. As explained in Card, Dobkin and Maestas (2008,

⁴Two of the three major randomized controlled trials evaluating the causal effects of health insurance, the RAND Health Insurance Experiment (Manning et al., 1987) and the Oregon Health Insurance Experiment (Finkelstein et al., 2012), enrolled limited numbers of near elderly individuals and were therefore under-powered to examine this population. In addition, the RAND experiment was not designed to estimate the effect of insurance for the uninsured since it did not include an uninsured control group. The third experimental study was the Social Security Disability Insurance (SSDI) health insurance demonstration project (Weathers II and Stegman, 2012), which included large numbers of near-elderly individuals who had newly qualified for SSDI but had not yet fulfilled the waiting period for Medicare eligibility.

2009), reaching age 65 triggers multiple transitions in insurance coverage across the population, all of which may contribute to estimated changes in access and utilization at age 65. In the context of instrumental variables (IV) estimation with a single instrument, this is the well-known multiple channels problem, which can lead to violations of the exclusion restriction. Using panel data to trace out usage patterns for individuals undergoing different insurance transitions is challenged by the lack of *large-scale* panel data sets that contain detailed information about both health insurance and health outcomes. Thus far, the literature has only been able to estimate the reduced-form effects of turning 65, which combine the effect of gaining insurance for the uninsured with the effect of changes in insurance type among the insured. For example, as we document below, at age 65, 13.5 percent of the population transitions from some insurance (other than Medicare) to Medicare and 46.5 percent transitions from some insurance (other than Medicare) to Medicare and a second source of coverage. Although the effect of gaining insurance is likely much larger than the effects of changes in the type of insurance coverage, approximately nine times as many people experience a change in type of insurance coverage as newly gain insurance coverage at age 65, so these other transitions cannot be ignored. Furthermore, this reduced-form literature predates the Affordable Care Act (ACA), which lowered uninsurance rates for people under 65 to varying degrees across states.

To address the possibility that these other changes in insurance coverage might also affect healthcare utilization we extend the standard two-sample IV approach to allow for multiple channels. Our method leverages the considerable cross-state and temporal variation in the size of the changes in insurance coverage that occur at age 65. This variation allows us to estimate both the effects of becoming insured and the effects of changes in the type of insurance people have.

We implement the multi-channel two-sample IV approach in several steps. We begin by using a regression discontinuity design and data from the American Community Survey (ACS) to estimate the change at age 65 in the fraction of

the population covered by different types of insurance in each state, before and after the implementation of the ACA. The ACS allows people to report up to six different kinds of insurance coverage, yielding a large number of possible transitions in coverage when people become eligible for Medicare. We consolidate the transitions into three groups of transitions that individuals are likely to face. The first group consists of transitions from not having insurance to having Medicare. The second group consists of transitions from having some insurance other than Medicare to Medicare. The third group is transitions from some insurance other than Medicare to being covered by both Medicare and another insurer.

We estimate the changes in access to care and utilization in each state using the Behavioral Risk Factor Surveillance System (BRFSS) and administrative hospital records. Then, for each state and time period we pair the estimates of the changes in insurance at 65 with the changes in access and utilization. This allows us to regress the change in care at age 65 on the fraction of the population in a state that experiences each of the three types of insurance transitions. This in turn enables us to estimate three local average treatment effects (LATEs): the effect of becoming insured, the effect of transitioning from one type of insurance (other than Medicare) to Medicare, and the effect of transitioning from one type of insurance (other than Medicare) to Medicare and a second payer. The multi-channel IV design requires one assumption beyond the standard IV assumptions — the state and period LATEs must be uncorrelated with the observed state and period changes in insurance types. This assumption is not innocuous, but we show that violations of it have testable implications and derive a straightforward test.

We find that gaining health insurance has enormous effects on access to care and health care utilization. For the uninsured, becoming insured reduces the probability of foregone care by 53.9 percentage points, increases the probability of having a regular medical provider by 32.8, and the probability of having had a checkup in the last year by 41.2 percentage points. Gaining insurance also

results in 13.2 additional hospitalizations per 100 people. Of these, 3.6 are for emergencies and 7.4 are for elective inpatient procedures.⁵ These are very large increases, from base rates of 4.0 and 0.5 for emergencies and elective procedures, respectively. Many of these emergency hospitalizations are for conditions such as sepsis, cardiac arrhythmia, and renal failure, which can be fatal if medical care is delayed. The elective procedures include large numbers of hip and knee replacements, which have been shown to increase quality of life, and heart procedures, which likely increase both quality of life and life expectancy. In contrast, the effects of changes in the type of insurance on access and utilization are much smaller. The only statistically significant effects are a reduction in the probability of foregone care and an increase in the probability of a checkup for people transitioning onto Medicare from a another type of insurance.

Given the novelty and complexity of the multi-channel two-sample IV approach and the fact that it reveals that the increases in access and utilization at age 65 are primarily due to the uninsured gaining health insurance, we compare our multi-channel estimates to the standard two-sample IV estimates that implicitly assume a single channel (uninsured to Medicare). For some of the access to care measures, the estimates of the effect of insurance from the multi-channel approach are larger than the estimates from the two-sample IV approach, however the magnitudes are broadly similar, and the multi-channel estimates are not statistically distinguishable from the two-sample IV estimates. Across all outcomes, the multi-channel approach generates estimates that are less precise than the two-sample IV approach. Both research designs reveal that for the near-elderly population, gaining insurance results in very large increases in healthcare utilization that close much of the gap in access to care that existed between the insured and uninsured prior to becoming eligible for Medicare.

This paper makes at least three contributions to the literature. First, we develop a solution to the multiple channels problem that commonly arises when

⁵Emergency hospitalizations are hospital admissions that are coded as being due to an emergency.

researchers use policy variation to identify the effects of health insurance in the population. Our new method allows us to recover the causal effects of health insurance for the uninsured specifically, while also estimating the effect of changes in the type of insurance coverage people have. Our approach complements the more structural approach of a selection model, applied previously in the context of disentangling the effects of Head Start from alternative preschool programs using a single lottery instrument (Kline and Walters, 2016). Kline and Walters (2016) adopts a control function approach because overidentification tests suggest that treatment effects are heterogeneous in its context. In comparison our approach is similar in spirit to covariate or site interactions with a single instrument, but the identifying variation is more transparent than with interacted IVs, and our falsification test specifically tests the mean independent LATEs assumption that we require. Although we determine that for the near-elderly in 2008-2017 changes in insurance type have at most small effects on access to health care and utilization, this need not be the case for other outcomes, other periods, other sub-populations or other policies.

Second, we provide new evidence on the disease burden present among the near elderly, and particularly those who lack insurance coverage. The small literature on the effects of health insurance among the near elderly finds mixed results. On one hand are studies that leverage the age-65 Medicare eligibility threshold in either a regression discontinuity or differences-in-differences design, often with panel data such as the Health and Retirement Study (HRS). Several studies find positive effects of Medicare eligibility on an array of access, utilization, and health outcomes, including mortality (McWilliams et al., 2003, 2004, 2007^{a,b}; Card, Dobkin and Maestas, 2008, 2009),⁶ while other studies find no effect on health and mortality (Polsky et al., 2009; Black et al., 2017). By design, the age-65 studies are not able to distinguish effects for the near elderly uninsured from the previously

⁶In addition, studies find that Medicare eligibility leads to narrowing of racial and ethnic health disparities (Card, Dobkin and Maestas, 2008; Wallace et al., 2021) and protection from financial risk (Barcellos and Jacobson, 2015).

insured and they may be uninformative about the value of insurance coverage in the post-ACA era; the HRS-based studies use longitudinal information to make observational comparisons between the previously uninsured and insured.⁷

Third, because our new approach makes use of massive samples across states and years, we obtain much greater statistical power than most previous studies of the effects of health insurance. The added precision enables us to recover the condition-level health benefits that arise when the near-elderly uninsured gain coverage, particularly for a host of emergency and inpatient conditions. The patterns of access and treatment gains that arise when Medicare coverage begins are indicative of severe under-provision of care, as opposed to wasteful or otherwise unnecessary care. This suggests that an expansion in Medicare coverage would have very high value for the near elderly uninsured (which needs to be weighed against potential crowd-out of employer-sponsored and other forms of insurance). On the other hand, retrenchment of coverage could have very high costs for those elderly individuals who are ages 65 and 66 and who would otherwise lack access to employer-sponsored or other forms of insurance.

In the next section, we provide brief background about the Medicare program. This is followed by a presentation of our empirical strategy, results, and conclusion.

I. Background

The federal Medicare program provides health insurance coverage to people aged 65 and older, younger people who receive Social Security Disability Insurance (SSDI) benefits, and people with End-Stage Renal Disease (ESRD). Coverage consists of hospital insurance (Part A), medical insurance (Part B), and prescription drug coverage (Part D). Part C refers to Medicare Advantage (MA),

⁷Studies of the effect of Medicaid expansion on low-income, near-elderly individuals also find evidence of positive effects on health, particularly reductions in metabolic syndrome, gross motor skill difficulties and other activity limitations (McInerney et al., 2020) as well as reductions in mortality (Miller, Johnson and Wherry, 2021). These studies note crowd-out effects are potentially important since the increase in Medicaid coverage post-ACA was substantially larger than the increase in insurance coverage, indicating that many who transitioned to Medicaid did so from another form of insurance rather than uninsurance.

under which beneficiaries can opt to obtain the services covered under Parts A, B, and sometimes D through a private managed care plan. Parts A and B are referred to as Original Medicare. People enrolled in Original Medicare have the option to purchase supplemental coverage through a private “Medigap” plan.

Because Medicare coverage is nearly universal for the aged, the vast majority of the U.S. population experiences an important shift in health insurance coverage and related financial incentives in the month they turn 65.⁸ The sign and magnitude of the shift depends on both the generosity of their pre-65 health insurance coverage—if they had coverage—and the choices they make for Medicare coverage.

Medicare beneficiaries pay no premium for hospital insurance as long as they paid Medicare payroll taxes for at least 10 years (or their spouse did).⁹ All beneficiaries are required to pay the federal premium for Part B medical insurance (\$134 per month in 2018). Part D prescription drug benefits are provided through private drug plans, which are allowed to tailor premiums (and drug formularies) as long as they cover certain drugs. The average premium for basic drug coverage was \$34 per month in 2018 (Centers for Medicare & Medicaid Services, 2018). Similarly, private managed care plans operating under Part C often include prescription drug benefits and extra benefits not covered by Medicare (e.g., vision or dental). The average MA premium was \$30 per month in 2018 (Centers for Medicare & Medicaid Services, 2018), though, importantly, it is possible to select a managed care plan with drug benefits for no additional premium beyond the federal premium. People who are employed have the option of deferring enrollment (and associated premium payments) in Parts B/D if they are actively employed and their employer offers health insurance coverage. Since there are no premiums associated with enrollment in Part A hospital insurance, there is

⁸SSDI beneficiaries and people with ESRD are a notable exception; they qualify for Medicare before age 65 and their coverage continues unchanged at age 65.

⁹Those with insufficient tax contributions can obtain Medicare hospital insurance by paying a prorated premium (e.g., an individual who contributed for less than 7.5 years would pay a monthly premium of \$422 in 2018).

no reason not to enroll in Part A upon turning age 65. By law, if an individual has both employer-sponsored coverage associated with active employment and Medicare, then the employer plan is the primary payer, while Medicare acts as the secondary payer.¹⁰

For many people, Medicare is a better financial deal than the insurance they had prior to turning 65. This is increasingly true as employer plans have become less generous, with greater employee cost-sharing and restrictive provider networks.¹¹ That said, Original Medicare’s deductibles, co-insurance, and co-payments are large, and may result in greater out-of-pocket expenses, particularly for those who had relatively generous private plans.¹² For this reason, many Medicare beneficiaries (39 percent in 2018) choose to enroll in private Medicare Advantage plans or purchase supplemental Medigap policies from private insurers (21 percent in 2018) (Koma, Cubanski and Neuman, 2022). Medigap policies reduce out-of-pocket expenses for services covered by Medicare to a lesser degree than Medicare Advantage plans, but typically have no restrictions on the provider network; Medigap premiums are much larger than the typical Medicare Advantage plan.¹³ Low-income individuals can obtain supplemental coverage through Medicaid, which in most states does not require premiums or cost-sharing. Also relevant is that because Medicare sets payment rates for services, health care providers also experience a shift in financial incentives as their patients transition to Medicare from other sources of coverage.¹⁴

In all likelihood, because of their high out-of-pocket costs and poor health the group that experiences the most consequential transition of all is the near-elderly

¹⁰An exception is people who work for small employers. Employers with fewer than 20 employees can require their employees who are 65 or older to enroll in Medicare as their primary insurance coverage.

¹¹For example, in 2018, 29 percent of participants with employer-based coverage were enrolled in a high-deductible health plan. The average deductible in these plans was \$2,349 (for single coverage) (Claxton et al., 2018)

¹²In 2018 the deductible for Original Medicare was \$1,340 for Part A and \$183 for Part B, and the coinsurance on hospital stays was \$335 per day for the 61st through 90th day of hospitalization (Centers for Medicare & Medicaid Services, n.d.).

¹³The average annual Medigap Plan F premium was \$2,293 in 2018 (Weiss Ratings, 2018). Some individuals have the option to enroll in supplemental coverage through their former employers.

¹⁴In general, Medicare pays providers less than private insurers but more than state Medicaid programs.

uninsured. Table 1 compares the near-elderly who lack health insurance with the privately-insured across several measures of health status, health care utilization, and access to care. The near-elderly uninsured self-report substantially worse health than those with private insurance. For instance, 24.6 percent of the uninsured report “Fair” or “Poor” health, compared to just 11.9 percent of the privately insured. They are also significantly more likely to have various forms of functional and activity limitations. More than twice as many uninsured as privately-insured report being unable to work due to their health problems, which explains the lack of insurance coverage for many individuals. Despite this greater need for health care, 31.5 percent of the uninsured forewent care due to costs compared to only 4.0 percent of those with private insurance, and were also more likely to forego (24.5 percent) or delay (26.7 percent) medications due to cost compared to 5.1 percent and 7.8 percent of the privately insured, respectively. Just as striking are the stark differences in utilization by insurance status. The uninsured were 30 percent less likely to have had one or more office visits than the privately insured (63.2 percent versus 90.8 percent) and were 29.7 percent less likely to have had an overnight hospital stay (6.4 percent versus 9.1 percent). For completeness, we show the same statistics for near-elderly individuals receiving Medicaid, and those with other insurance (primarily SSDI beneficiaries who automatically qualify for Medicare).

Low-income near-elderly individuals have access to Medicaid in some states but not others, depending on their state’s income and other eligibility rules.¹⁵ As we show in the next section, this causes the proportions of individuals transitioning from uninsurance to Medicare or from some insurance (other than Medicare) to Medicare to vary widely across states and over time, providing motivation for our empirical strategy to address the multi-channel problem.

¹⁵Even among states that chose to expand Medicaid (before or after the ACA), there is wide variation in coverage levels across services that are deemed optional.

II. Empirical Strategy

When people become eligible for Medicare upon turning 65, seven percent of the population transitions from not having insurance to being covered by Medicare. There are also large and abrupt changes in health care utilization at this age (Card, Dobkin and Maestas, 2008, 2009). One approach to estimating the effect of insurance on health care utilization is to rescale the change in utilization by the change in the fraction of the population with health insurance. However, the estimates generated by this two-sample IV (fuzzy regression discontinuity) approach may be inconsistent. The problem is that at age 65 not only does seven percent of the population gain insurance, but as detailed in Section I, other subpopulations experience significant changes in the structure and generosity of their insurance coverage. If these other changes in insurance coverage result in changes in healthcare utilization then the two-sample IV estimates will be inconsistent.

To estimate the effect of the different changes in the structure and generosity of health insurance, we implement an extension of the standard instrumental variables approach. This extension allows us to estimate not only the effect of moving from being uninsured to insured but also the effects of other changes in insurance coverage, such as transitioning from private insurance to Medicare. To implement this approach, we use variation across states and time periods in the proportion of a state's population experiencing each type of insurance transition.

We begin with a stylized example to illustrate the intuition underlying our approach. Suppose 64-year olds in State A circa 2009 (pre-ACA) are 90% privately covered and 10% uninsured, while 65-year olds are 100% Medicare covered. With only a single instrument, the age-65 discontinuity, we cannot parse out the effects of transitioning from no insurance to Medicare versus the effects of transitioning from private insurance to Medicare. To separately identify these two channels we interact the instrument with temporal or spatial variation. For example, suppose the ACA results in near-universal coverage. Then 64-year olds in State A

circa 2014 (post-ACA) are 100% privately insured, while 65-year olds are 100% Medicare covered. We can estimate the effects of transitioning from private insurance to Medicare using the post-ACA sample and then back out the effects of transitioning from no insurance to Medicare using the pre-ACA sample under the assumption that the effects of transitioning from private insurance to Medicare are stable in State A over time. Note, however, that this assumption in our stylized example is stronger than the one we apply in practice. Alternatively, suppose we have data from State B, where 64-year olds are 80% privately covered and 20% uninsured circa 2009, while 65-year olds are 100% Medicare covered. The RD effect of turning 65 in State A (State B) equals 0.1 (0.2) times the effect of transitioning from no insurance to Medicare plus 0.9 (0.8) times the effect of transitioning from private insurance to Medicare. With two equations and two unknowns we can solve for the effects of each of the two transitions under the assumption that the effects are similar in both states (again, this assumption is more restrictive than we need in practice).

In practice we have many states and more than two transitions. While our stylized example is just-identified, our actual data yield an over-identified system of equations, which we exploit later in robustness checks. We start by grouping the changes in insurance coverage that occur when people become eligible for Medicare into three categories that broadly capture the changes in generosity and incentives faced by patients and providers. The three focal types of transitions are: 1) no insurance to Medicare; 2) one type of insurance (other than Medicare) to Medicare; and 3) one type of insurance other than Medicare to two or more types of insurance coverage (one of which is Medicare). Then, we estimate the frequency of each of these three insurance transitions at age 65 in every state, both before and after the implementation of the ACA. We also estimate the changes in health care utilization at age 65 in each state-period pair. Finally, to estimate the effect of insurance on health care utilization we regress the estimated changes in health care utilization at age 65 on the changes in the three types of health

insurance coverage for each state-period pair. We describe each of these steps in detail in the following subsections.

A. Identification of the Insurance Transitions

To directly estimate the fraction of the population experiencing each of the three transitions in insurance coverage described above we would need to observe the insurance coverage of each individual before and after they become eligible for Medicare. There is no panel data set large enough to precisely estimate these transitions at the state level. For this reason we turn to the American Community Survey (ACS), which is the largest nationally representative survey with detailed questions about health insurance coverage (US Census Bureau, 2008–2017*a*).

Since the ACS is a repeated cross-section, it is not possible to observe changes in insurance coverage for individuals. However, we can back out the proportion of the population experiencing each transition under the assumption that when people become eligible for Medicare at age 65, they either take up Medicare, possibly in combination with other insurance, or they do not change their insurance coverage. This assumption would be violated if becoming eligible for Medicare induced an individual to switch from, say, private insurance to Medicaid alone, or, as another example, to become uninsured.

The ACS questions allow respondents to report any combination of six possible insurance types, or to indicate that they have no health insurance. The six insurance types are: Medicare, Medicaid, employer/union, directly purchased, Veterans Administration care or TRICARE, and other. This results in 64 distinct combinations of insurance coverage.¹⁶ We reduce the large number of possible combinations into four mutually exclusive groups based on the similarity of the financial incentives faced by patients and health care providers. The four groups are no insurance, one type of insurance that is not Medicare, Medicare alone, and

¹⁶Since people can choose up to 6 types of insurance there are $\sum_{i=0}^6 \binom{6}{i}$ possible combinations.

two or more sources of health insurance (which may include Medicare).¹⁷

Panel (a) of Figure 1 shows the transitions in health insurance coverage that individuals are likely to experience after they turn 65. Although there are 16 (i.e., 4^2) possible transitions, nine of them represent changes in insurance coverage that are unlikely to be caused by becoming eligible for Medicare (e.g., via the independence of irrelevant alternatives), or otherwise occur with very low probability. For example, becoming eligible for Medicare should not induce people to drop their current insurance coverage and transition to being uninsured. These are the nine pairs of nodes not linked by arrows. The seven remaining transitions we label (a) through (g), and we represent their respective probabilities as p_a through p_g . The three red diagonal lines labeled (d) (no insurance to Medicare), (e) (one type of insurance to Medicare), and (f) (one type of insurance to two or more types of coverage) denote the changes in insurance coverage Medicare eligibility is likely to cause.¹⁸ The four horizontal lines denote people who do not change their insurance coverage when they become eligible for Medicare. For instance, the transition group labeled (c) (Medicare to Medicare) includes SSDI recipients who initiate Medicare coverage prior to age 65.

To estimate the insurance transition rates using the ACS, we leverage the fact that the proportion experiencing each transition can be inferred from the fractions of the population just under and just over age 65 with each type of insurance coverage. For example, Panel (a) of Figure 1 shows that an individual just under 65 with no insurance may continue after 65 with no insurance (a) or transition to Medicare (d), yielding $\lim_{age \uparrow 65} P(\text{No Insurance} \mid \text{age}) = p_a + p_d$ (i.e., uninsured 64 year olds consist of those that either remain uninsured or gain Medicare). In-

¹⁷We assign Medicare Advantage participants to the “Medicare only, over 65” category, even though MA is sometimes more comparable in risk protection to “two or more sources of health insurance,” where the two sources are Medicare plus Medigap. We assign Medicaid recipients to the “One Insurer Not Medicare, Under 65” category even though they experience minimal out-of-pocket costs compared to other insured individuals in this group (e.g., those with employer/union or directly purchased insurance).

¹⁸Transition (f) includes those transitioning from Medicaid to Medicare plus Medicaid as well as those moving from private or government insurance to Medicare plus supplemental insurance. Although near-elderly individuals with Medicaid have lower out-of-pocket costs than most other groups, their out-of-pocket costs do not change when they transition to Medicare plus Medicaid at 65.

dividuals under 65 with one type of non-Medicare health insurance may continue with this coverage (*b*), transition to Medicare alone (*e*), or move to having two or more sources of coverage (such as Medicare plus Medigap or Medicare plus Medicaid) (*f*). Individuals on Medicare before 65 will continue with Medicare after turning 65 (*c*). Finally, those with two or more sources of coverage, one of which is typically Medicare, will not change their coverage (*g*). Similar reasoning can be used to characterize the fraction of the population over 65 with each type of insurance coverage.

Panel (b) of Figure 1 presents the full set of equations relating each observable statistic to one or more of the (unobserved) transition probabilities. The system of equations in Panel (b) can be solved to obtain estimates of the full set of transition probabilities, which are shown in Panel (c) of Figure 1. We can estimate four of the transition probabilities via single conditional means approaching age 65 from above or below, and we can estimate the remaining three via differences in two or more conditional means in a neighborhood around age 65.¹⁹

B. Estimating the Insurance Transitions at Age 65

To estimate the seven transition probabilities on the left-hand side of Panel (c) in Figure 1, we need consistent estimates of the proportion of the population just over and just under 65 with each type of insurance. We estimate these proportions using the following regression:

$$(1) Y_a = \beta_0 + \beta_1 Over_a + \beta_2 Age_a + \beta_3 Age_a^2 + \beta_4 Over_a Age_a + \beta_5 Over_i Age_a^2 + \varepsilon_a$$

¹⁹In Panel (b) the limits on the left side of each of the columns can be directly estimated from the ACS. The unobserved insurance transition probabilities p_a , p_b , p_c , and p_g each correspond to the observed proportion of the population just under or just over 65 with a particular type of insurance. The three other unobserved transition probabilities, p_d , p_e , and p_f are combinations of observed proportions of the population above or below 65 with various types of coverage. The transition probabilities can be solved for via substitution. For example to solve for p_d we start with $\lim_{age \uparrow 65} P(\text{No Insurance} | \text{age}) = p_a + p_d$ and substitute in for p_a . This gives us $p_d = \lim_{age \uparrow 65} P(\text{No Insurance} | \text{age}) - \lim_{age \downarrow 65} P(\text{No Insurance} | \text{age})$. A similar approach allows us to solve for the transition probabilities p_e and p_f .

where Y_a is the proportion of people in age cell a that have a particular insurance type. The variable $Over_a$ is an indicator variable that takes on a value of unity when an age cell is 65 or greater. We recenter the variable Age at 65 so the parameter β_0 is $\lim_{age \uparrow 65} E[Y \mid age]$ and $\beta_0 + \beta_1$ gives $\lim_{age \downarrow 65} E[Y \mid age]$. Using the ACS, we estimate this regression for each of the four insurance categories, separately for each state, before and after the implementation period of the ACA.²⁰ We estimated and examined the optimal bandwidths for each state and time period pair using the approach developed in Calonico, Cattaneo and Titiunik (2014). We then picked a bandwidth of 10 years, which is near the center of the distribution of recommended bandwidths, to use for all state, time period, and dependent variable combinations. We picked a single bandwidth as it lets us implement a simple and transparent approach to documenting the robustness of the estimates to the choice of bandwidth. We then combine the parameter estimates from these regressions using the equations in Panel (c) of Figure 1 to obtain estimates of the seven transition probabilities. To compute the variances and covariances of the transition probabilities we re-sample 1,000 times with replacement from each state-time period combination and compute the variance-covariance matrix of the seven transition probabilities.

We empirically assess the validity of our identifying assumptions and approach to estimating the transition probabilities by comparing national level estimates from the ACS with estimates from the Medical Expenditure Panel Survey (MEPS) (Agency for Healthcare Research and Quality, 2008–2017). The panel structure of the MEPS allows us to directly estimate the fraction of the population experiencing each of the 16 possible transitions in insurance coverage between survey rounds.²¹ Table 2 presents the results of this analysis. The table reveals that between the survey round before they turn 65 and the survey round after they turn 65, only 5 percent of survey respondents report experiencing one of the nine

²⁰Examples of the age profiles of insurance for two states before and after the implementation of the ACA are presented in Figures ??, ??, ??, and ??.

²¹Estimates based on the MEPS are similar to estimates based on the HRS but a bit more precise because MEPS surveys individuals multiple times per year while HRS surveys individuals biennially.

transitions that we assume are not caused by Medicare availability. This is close to the fraction (3.6 percent) that report one of these nine transitions between ages 62 and 63 (Table ??), suggesting that the small share of people experiencing these transitions in the months around their 65th birthdays reflects natural variability in insurance coverage between survey rounds, rather than a causal effect of Medicare eligibility. This represents evidence in support of our identifying assumptions. Table 2 also reveals that despite the substantial differences between the two surveys in how insurance coverage is measured, the size of the transitions that were indirectly estimated from the ACS are fairly similar to those directly estimated from the MEPS, further validating our approach.²²

C. Estimating the Change in Health Care Utilization at Age 65

We estimate changes in access to care at age 65, using the BRFSS 2008-2017 (Centers for Disease Control and Prevention, 2008–2017). Among other topics, BRFSS respondents are asked whether they have a regular medical provider, if they have had a check up in the last year, and if they have foregone medical care due to cost in the past year. To estimate the changes at age 65 in each of these three measures of access to health care, we fit Equation (1) separately for each of the 102 state pre/post ACA combinations using a bandwidth of 10 years.²³

We also investigate inpatient care, arguably the most intensive and expensive form of care. We use individual-level administrative hospital records from 23 states for the 2008-2017 time period from the Healthcare Cost and Utilization Project (HCUP, 2008-2017).²⁴ For each state we have the universe of hospital discharges that occurred during the calendar year. To compute hospitalization rates by age we divide counts of hospital admissions by population estimates

²²The largest exception is the “transition” from two or more insurers to two or more insurers. We note that the ACS produces systematically higher levels of people reporting two or more insurers than the MEPS and HRS.

²³Examples of the age profiles of access to care for two states before and after the implementation of the ACA are presented in Figures ??, ??, ??, and ??.

²⁴We received hospital discharge records directly from state agencies in California and Florida (California Office of Statewide Health Planning and Development, 2008–2017; Florida Agency for Health Care Administration, 2008–2017).

from the Census (US Census Bureau, 2008-2017b). Working in rates is essential for generating precise estimates as there is substantial variation in the size of the age cohorts in our sample due to the sharp increase in birth rates just after the end of the Second World War, known as the Baby Boom. In addition to overall admissions rates, we also compute rates for elective, urgent and emergency admissions. Examining these separately is important because elective admission rates are likely to be very sensitive to insurance coverage, given the high cost of a hospitalization for the uninsured. On the other hand, emergency admissions are likely to be less sensitive to insurance coverage due to the Emergency Medical Treatment and Active Labor Act (EMTALA), which requires hospitals to treat emergency medical conditions regardless of insurance status. Due to changes over time in states' participation in the HCUP program, hospitalization data is not available for every state in every year.²⁵ We use Equation (1) to estimate both the overall change in the hospitalization rate at age 65 and the change in elective, urgent or emergency hospitalizations separately for each of the 36 state-pre/post ACA combinations for which we have hospital discharge records.²⁶

D. Estimating the Effect of Insurance Coverage on Access to Health Care and Utilization

To estimate the effect of changes in insurance coverage on health care utilization we leverage rich variation across states and years in the rate at which people transition between different types of insurance coverage at age 65. We first estimate Equation (1) as described in Section II.B to determine the fraction of the population in state s during period t that becomes insured upon turning 65 ($I1_{st}$) and the fractions that transition onto Medicare from another insurance type ($I2_{st}$)

²⁵The analysis includes a near census of hospital records from Arizona 2009-2017, Arkansas 2009, California 2008-2017, Colorado 2008-2012, Florida 2008-2017, Hawaii 2009, Iowa 2008-2009, Kentucky 2008-2017, Maryland 2008-2017, Massachusetts 2008-2014, Michigan 2008-2017, Minnesota 2014-2016, Nevada 2009-2015, New Jersey 2008-2017, New York 2008-2015, North Carolina 2008-2017, Oregon 2008-2015, South Dakota 2009, Utah 2009, Vermont 2009, Washington 2008-2017, and Wisconsin 2008-2010.

²⁶Examples of the age profiles of hospitalization rates for two states before and after the implementation of the ACA are presented in Figures ??, ??, ??, and ??.

or onto Medicare and a secondary payer ($I3_{st}$). We then estimate Equation (1) as described in Section II.C to determine the change in health care utilization for each state s in period t (H_{st}). For the analysis, t enumerates two periods: pre-ACA and post-ACA.

Under the exclusion restriction, changes in utilization at the RD threshold are, in expectation, due solely to insurance transitions. We can thus express the estimated change in utilization for state s in period t as the sum of the insurance transitions in state s in period t times the local average treatment effect for each insurance transition in state s in period t (plus a residual):

$$(2) \quad H_{st} = \tau_{1st}I1_{st} + \tau_{2st}I2_{st} + \tau_{3st}I3_{st} + u_{st}$$

If we decompose $\tau_{jst} = \bar{\tau}_j + \tilde{\tau}_{jst}$, then we can estimate Equation (2) using a linear regression with no intercept to recover mean treatment effects for each of the three insurance transitions (i.e., $\bar{\tau}_1, \bar{\tau}_2, \bar{\tau}_3$). As we show in Appendix ??, this estimation strategy gives us consistent estimates of the three treatment effects under the standard instrumental variables assumptions and the additional assumption that any heterogeneity in treatment effects is uncorrelated with the fraction of the population in a state experiencing a transition in insurance coverage. The intuition is straightforward: if the treatment effect heterogeneity is uncorrelated with the magnitudes of the insurance transitions, then the random component of the treatment effects does not bias the estimates. The zero intercept result comes from the exclusion restriction — a unit that has no first stage should demonstrate no reduced form effect. Formally we assume:

$$(3) \quad \text{Exclusion restriction: } E[u_{st} \mid I1_{st}, I2_{st}, I3_{st}] = 0$$

$$(4) \quad \text{Mean independent LATEs: } E[\tilde{\tau}_{jst} \mid I1_{st}, I2_{st}, I3_{st}] = 0$$

Note that treatment effects need not be homogeneous in order for Equation (2)

to estimate $\bar{\tau}_j$; per Equation (4) we only need the treatment effect heterogeneity across states and periods, $\tilde{\tau}_{jst}$, to be uncorrelated with the insurance transitions across states and periods, Ij_{st} . In practice this implies that treatment effects in states where a large fraction of the population transitions from uninsured status to Medicare (e.g., pre-ACA Southern states) do not have systematically different treatment effects than those where a small fraction of population transitions from uninsured status to Medicare.

In Appendix ?? we derive a falsification test for the mean independent LATEs assumption (Equation 4). Specifically, if the heterogeneity in treatment effects is correlated with the fraction of the population experiencing an insurance transition, the relationship between H_{st} and $I1_{st}, I2_{st}, I3_{st}$ becomes nonlinear. We assess this possibility by estimating a version of Equation (2) that includes quadratic terms and interactions of the insurance transitions and testing the joint hypothesis that the coefficients on the nonlinear terms are zero.

The use of estimated first-stage coefficients, rather than “true” first-stage coefficients, raises an additional complication — the right-hand side variables in Equation (2) are measured with error (the estimation error). This sampling error has the potential to attenuate estimates of τ , and we address the issue in two ways. First, rather than estimating reduced-form and first-stage coefficients at the state-by-year level, we estimate them at the state-by-pre/post ACA level, increasing the sample size for each estimate. Second, we estimate an error in variables (EIV) model, described in Appendix ??, as a robustness check.

It is instructive to compare our multi-channel approach with others that have been applied in different contexts. For example, Kline and Walters (2016) estimates the effects of transitioning to the Head Start preschool program from either home care or an alternative preschool program. It uses a Head Start lottery as an instrument, but the lottery simultaneously increases Head Start enrollment and decreases enrollment in alternative preschool programs. With only a single instrument, it considers interacting the instrument with covariates or site indicators.

However, doing so generates a weak instruments problem for the second channel of interest; the partial F -statistic in the first stage for enrollment in alternative preschool programs is only 1.8. Furthermore, overidentification tests reject the null hypothesis of homogeneous treatment effects, so it is unclear whether generating additional instruments using covariate or site interactions with the lottery variable yields consistent estimates of LATEs. As an alternative, the paper implements a Heckman-style selection model that relies on an additive separability functional form assumption. This approach accommodates different LATEs for different interacting subgroups, under the assumption that these LATEs vary parametrically with the propensity to enroll in different treatments. It finds that Head Start enrollment is the only statistically significant channel through which the lottery affects outcomes, though it lacks power to draw any conclusions regarding the effectiveness of alternative preschool programs.

Our multi-channel approach complements the more structural approach of a selection model. It is similar in spirit to covariate or site interactions, but the identifying variation is more transparent. Critically, our falsification test actually tests the mean independent LATEs assumption that we require. In contrast, conventional overidentification tests may reject based on the presence of *any* treatment effect heterogeneity (Parente and Silva, 2012), which is more restrictive than what our identification strategy requires. In that sense the estimation strategy and falsification test are well-tailored for each other.

It is also informative to consider potential scenarios that could bias our estimates. For example, Medicare Advantage (MA) penetration rates vary across states. Suppose that states with high rates of MA penetration also have low shares of individuals transitioning from no insurance to Medicare and higher shares of individuals transitioning from private coverage to Medicare. If MA restrains healthcare utilization relative to other insurance plans, then our approach might attribute drops in utilization at age 65 to the some-coverage-to-Medicare transition when in fact it is an artifact of Medicare Advantage that would apply

to any transition. Alternatively, the ACA set minimum standards for individual plans, which could increase utilization among under-65 individuals in the post-ACA period. Such an increase would attenuate any utilization growth at age 65 post-ACA, and the multi-channel estimator might overestimate the effect on utilization of transitioning from no insurance to Medicare. A third source of bias could arise from variation across states in the for-profit hospital share, which if it were positively correlated with the uninsured rate across states, would attribute utilization changes at age 65 due to the presence of for-profit hospitals to individuals transitioning from no insurance to Medicare.

We perform several robustness checks, in addition to the falsification test discussed above, to investigate these possible biases. First, we test whether our estimates survive the inclusion of state fixed effects when estimating Equation (2). These fixed effects remove any cross-state variation in insurance transition probabilities. Next, we test whether our estimates change when using only pre-ACA data to estimate Equation (2). This change removes any ACA-induced variation in insurance transition probabilities.²⁷ Finally, since potential biases involve a systematic relationship between the LATE and the size of the relevant insurance transition (i.e., first-stage coefficient), we test for such a relationship by plotting the IV coefficient against the size of the uninsured-to-Medicare transition for each state-by-pre/post-ACA combination. If there is no systematic relationship, we expect a flat gradient. To perform this test we estimate the IV coefficients under the exclusion restriction that the uninsured-to-Medicare transition is the only transition that has nontrivial effects on utilization. The exercise thus represents a test of the joint null hypothesis of mean independent LATEs and a single-channel exclusion restriction.

²⁷In a standard panel data context we would consider adding both state and time fixed effects to the model simultaneously. In this context, however, the “data” for our panel regressions consist of RD coefficients. This fact has two important implications. First, the data have already been purged of some potential biases. Second, each observation (i.e., RD coefficient) contains substantial measurement error, quantified by its standard error. This measurement error limits how much variation we can remove from the data without generating a highly unfavorable signal-to-noise ratio.

III. Results

The near elderly who lack health insurance report being in substantially worse health than those with private insurance, and are also much more likely to report having foregone medical care or medicine due to cost (see Table 1). Gaining Medicare coverage substantially reduces the cost of medical care for this uninsured population and likely leads to substantial increases in health care utilization. Even among the insured, a non-trivial fraction report foregoing care due to cost. It is possible that this group also gains from Medicare eligibility.

To determine how much of the change in health care access and utilization is due to the uninsured becoming insured, as opposed to other differences between the uninsured and the insured, we leverage the fact that the majority of the near elderly uninsured become eligible for Medicare when they turn 65. Figure 2 presents the age profile of insurance coverage for the 2008-2017 period in the United States. The figure reveals that at age 65 there is a sharp reduction in the fraction of the population that is uninsured. This seven-percentage-point reduction in the share uninsured estimates p_d , the probability of transition type (d) from Figure 1. Intuitively, individuals gaining insurance when turning 65 are doing so because of the availability of Medicare, so reductions in the share uninsured correspond to transitions from no insurance to Medicare. However, there are also large changes in the type of insurance coverage held by people who were insured prior to age 65. Figure 1 reveals a large decline in individuals with non-Medicare single coverage (-60 percentage points), accompanied by a large increase in individuals with two types of insurance. The $+47$ percentage point increase in individuals with two types of insurance estimates p_f , the probability of transition type (f) from Figure 1. There is also an increase in individuals with Medicare-only coverage ($+21$ percentage points); when combined with the decrease in individuals with no insurance (i.e. $21 - 7 = 14$) it estimates p_e , the probability of transition type (e) from Figure 1 (i.e. transitioning from non-Medicare single coverage to two types of insurance).

We use the approach described in Section II.D to estimate what fraction of the population experiences each of three major changes in insurance coverage. As described above, Table 2 shows that, nationally, 7.0 percent of the population transitions from no insurance to Medicare, 13.5 percent switch from (non-Medicare) single coverage to Medicare, and 46.5 percent change from (non-Medicare) single coverage to having two types of insurance. As can be seen in Figures ??, ??, and ?? there is substantial variation across states and time periods in the fraction of the population experiencing each of these changes in insurance coverage. The figures also reveal that though the insurance transitions are correlated, there is significant independent variation due to the fact that many people do not experience a change in insurance. We leverage this variation to estimate the effect of each type of insurance transition on health care utilization.²⁸

The changes in insurance coverage documented above result in substantial changes in health care utilization at age 65. Figure 3 reveals a 3.4 percentage point reduction in the fraction of the population reporting that they have foregone care due to cost. There are also statistically significant increases in the fraction of the population that has a medical provider or had a check-up in the last year. These reduced-form findings are compelling evidence that Medicare eligibility significantly increases access to and utilization of the medical system. The figure also reveals that Medicare eligibility leads to a persistent change in levels for these outcomes, particularly for foregoing care due to cost.

Figure 4 presents the age profile of hospitalization rates. The figure reveals that the increase in access to the health care system results in an increase in the rate at which people get treated on an inpatient basis at the hospital. The increase is largest for elective admissions, but there are also increases in urgent and emergency admissions. The figure shows that Medicare eligibility results in

²⁸Tables ?? and ?? present analogous statistics to Table 2 but separate the estimates to be pre-ACA versus post-ACA time periods (Table ??) or Medicaid expanding states versus non-expanding states (Table ??). Consistent with expectations, the share of individuals transitioning from no insurance to Medicare is lower post-ACA (5.7 percent versus 9.8 percent) and in Medicaid expanding states (4.5 percent versus 8.3 percent).

a persistent increase in elective admissions, well above the level we would expect based on the trajectory of people under 65.

Figure 5 plots the change in access to care and utilization outcomes and hospitalization rates by type (all, elective, urgent, and emergency) against the proportion transitioning from no insurance to Medicare. Each point in the figure represents a pair of state-by-time-period RD estimates, with the “reduced form” on the y -axis and the “first stage” on the x -axis. The approximately linear slopes suggest that relationships between gaining insurance and changes in utilization do not vary widely across states and time periods and, as discussed in Section II.D, form the basis of a falsification test of our mean independent LATEs assumption. Nevertheless, the figure does not directly test whether other channels, such as moving from private coverage to Medicare, may exert independent effects on the outcomes.²⁹

A. Multi-channel Two-Sample IV Estimates

To determine how the different types of insurance a person may have affects their access to care, we estimate the parameters in Equation (2). Table 3 reports the resulting coefficient estimates and standard errors, as well as multiplicity-adjusted p -values that control the false discovery rate (FDR).³⁰ The first three columns present the estimated effects of the three types of changes in insurance coverage on BRFSS measures of access to health care. The table reveals that going from being uninsured to being covered by Medicare results in a 53.9 percentage point decline in the probability of reporting foregoing medical care due to cost. This decline exceeds the baseline level of foregone care among uninsured 64 year olds (36.7), but the baseline level nevertheless falls within the coefficient’s confidence interval. This result suggests that Medicare fully resolves issues of ac-

²⁹Figures ?? and ?? present analogous plots against different “first-stage” estimates (the proportions transitioning from single coverage to Medicare and single coverage to Medicare plus a second payer, respectively). These figures reveal no obvious relationships between either “treatment” and the outcomes.

³⁰The false discovery rate represents the expected proportion of total rejections that are false rejections (Anderson, 2008). Controlling the FDR at 5% implies that 19 of 20 rejections should be true rejections.

cess due to cost for the previously uninsured. For people transitioning from being uninsured to Medicare, there is a 32.8 percentage point increase in the probability that they have a medical provider; this increase closes the gap between the insured and the uninsured. There are also large increases in the probability of having had a checkup in the last year for both people transitioning from no insurance to Medicare (41.2 percentage points) and people transitioning onto Medicare from another type of insurance (23.1 percentage points).³¹ These estimates are fairly robust to bandwidth choices, as can be seen in Figures ??, ??, and ?. The estimates are not driven by outliers, and the relationships between the change in insurance and the change in access to care, particularly for the transition from no insurance to Medicare, can be observed in the scatter plots in Figures ??, ??, and ?.

The last four columns of Table 3 present estimates of the effect of insurance on inpatient hospital stays. For people transitioning from not being insured to Medicare there is a statistically significant increase in the hospital admission rate of 13.2 per 100. This increase is more than double the average hospitalization rate of uninsured 64 year olds (4.9 per 100). The increase in hospital admissions is largely driven by a statistically significant 7.4 percentage point increase in elective admissions. This increase is an order of magnitude larger than the rate of elective admissions for uninsured 64 years olds (0.48 per 100). There is also some evidence of a 3.6 percentage point increase in emergency hospitalizations, implying that for every 100 people without insurance there are 3.6 emergency hospitalizations foregone per year. Given that these are typically hospitalizations for emergent conditions, not having insurance likely results in serious harm despite the care guaranteed under EMTALA. The second and third rows of the table reveal that the other two insurance transitions, and particularly the transition to two sources

³¹There is a surprising 8.8 percentage point reduction in the probability of having a checkup for people who transition from having insurance to Medicare and a 2nd payer. This could be a result of Medicare's coverage limitations or respondent confusion about what constitutes a checkup. Medicare does not cover annual physical examinations, although it began covering annual wellness visits (which exclude a physical exam) in 2011. It is also possible this perverse finding is a result of the substantial number of outcomes and treatments examined.

of insurance (Medicare plus Medigap), do not appear to increase hospitalization rates.³² Figures ??, ??, and ?? present evidence that these estimates are robust to bandwidth choices.

The estimates in Table 3 rely on the assumption of mean independent LATEs (Equation (4)). That is, while treatment effects may be heterogeneous, the heterogeneity should not be systematically related to the fractions transitioning from being uninsured to Medicare. We report the results of several robustness and falsification tests, described in Section II.D, to establish the validity of our estimates.

First, Appendix ?? demonstrates that if the mean independent LATEs assumption fails, the relationship between changes in health care utilization and changes in insurance transitions becomes nonlinear. We thus execute a falsification test that estimates a version of Equation (2) that includes quadratic terms and interactions. The fourth row of Table 3 reports F -statistics for the null hypothesis that the coefficients on the quadratic terms and interactions all equal zero. All F -statistics are statistically insignificant.³³

Second, we separately estimate our multi-channel IV model using within-state variation and between-state variation. The first approach relies primarily on pre/post ACA variation, while the second approach relies on cross-state variation. While both approaches are potentially subject to biases, there is little reason to expect that the biases should be identical across both sources of variation. Tables ?? and ?? report estimates using time-series and cross-sectional variation respectively.³⁴ Table ?? includes state fixed effects, using only within-

³²When interpreting these estimates, note that individuals are likely to self select into insurance plans that best meet their needs. The LATE that we estimate for the transition from single coverage to two sources of insurance, for example, need not represent the ATE of transitioning the entire population from single coverage to two source of insurance, as people with greater healthcare needs may choose to add a secondary payer. Nevertheless, in most scenarios individuals have a choice of insurance plans: many employers offer multiple plans; Medicare can be used in isolation or with Medigap policies; and Medicaid has a variety of health plan options in many states. Thus we expect that our LATEs may be more representative of the effects of gaining insurance than the ATE of assigning everyone to a single plan type would be.

³³The F -statistics in the first three columns, corresponding to BRFSS outcomes, are all far from significance. Two of the F -statistics for hospitalization outcomes are weakly significant, while the other two are far from significance.

³⁴Access measures, from BRFSS, are available for all 51 states, while utilization measures, from HCUP, are available for only 23 states. Thus there is generally a higher proportion of between-state variation for

state variation over time, while Table ?? uses only pre-ACA data and collapses everything to the state level, using cross-sectional variation.³⁵

Figure 6 compares the main coefficient of interest — the effect of transitioning from no insurance to Medicare — to the main specification. For six of the seven outcomes, the coefficient is similar in sign and magnitude when using either time-series or cross-sectional variation. Furthermore, in no case are the other two coefficients — the effects of transitioning from single coverage to Medicare or Medicare and another coverage — statistically different when using the two orthogonal sources of variation (Tables ??, ??, ??). For a single outcome, whether an individual had a checkup in the past year, the main coefficient of interest is negative when estimated using time-series variation and positive when estimated using cross-sectional variation. The difference is not statistically significant, but the coefficients for the effects of transitioning from single coverage to Medicare and single coverage to Medicare and another coverage are both statistically different at the 5% level when comparing Table ?? and Table ?? ($t = 2.2$ in both cases). The multi-channel estimates for this outcome are thus less robust, as they are effectively identified using cross-sectional variation only.

Third, another test of the mean independent LATEs assumption is to plot the IV coefficient for the effect of the uninsured-to-Medicare transition against the size of the uninsured-to-Medicare first stage for each state-pre/post-ACA cell. Figures ?? through ?? reveal that there are no systematic relationships between the treatment effect magnitudes and the fractions transitioning from uninsured to Medicare. We thus fail to reject the joint null hypothesis of mean independent

BRFSS outcome regressions than for HCUP outcome regressions. For the primary channel of interest, transitioning from no insurance to Medicare, 60% of the variation arises between states and 40% arises within states, in the BRFSS outcome sample. For the HCUP outcome sample, 57% of the variation arises between states and 43% arises within states. For the single-coverage-to-Medicare transition, the proportions are roughly reversed; e.g., 45% of the variation arises between states and 55% arises within states in the BRFSS sample. Finally, for the single-coverage-to-dual-coverage transition, a supermajority of the variation arises between states (e.g., 83% between and 17% within, in the BRFSS sample). This split makes it difficult to identify this channel using within-state variation alone, and also contributes to lower precision for the other channels when estimating a multiple regression using only within-state variation.

³⁵For completeness, Table ?? reports estimates using the full sample of between-state variation (pre- and post-ACA). The estimates are qualitatively similar to those in Table ??.

LATEs and a single-channel exclusion restriction.

Finally, note that the regressors in Equation (2) are themselves coefficient estimates and thus contain sampling error. In this case the sampling error is known, so Table ?? presents estimates from an errors-in-variables model that accounts for the attenuation bias caused by this measurement error in insurance transitions. The large sample size of the ACS results in fairly precise estimates of the insurance transitions, and it is not surprising that the measurement-error adjusted estimates in Table ?? are similar to the estimates in Table 3.

B. Comparing Multi-Channel and Single-Channel IV Estimates

The multi-channel IV approach is novel and requires an additional assumption beyond the typical instrumental variables assumptions. In addition, using surveys that are repeated cross-sections complicates estimating the first-stage changes in insurance. Though we make efforts to address the concerns that arise in this context, it is worth comparing the estimates from the multi-channel IV with estimates from the familiar single-channel, two-sample IV.

Table 4 presents estimates of the effect of health insurance on access to care from the standard single-channel, two-sample IV design. These estimates are consistent if the only channel that affects access to care at age 65 is the transition from not having insurance to Medicare. The estimates are directly analogous to the top row of Table 3.³⁶ The estimates for foregone care, having a medical provider, and having had a checkup in the last year are somewhat smaller than, but not statistically different from, the corresponding estimates in Table 3. Finally, the estimates of the effects of insurance on hospitalization rates from the two research designs are very close and statistically indistinguishable. This increases our confidence in the estimates from both research designs because they have different sources of potential bias.

³⁶As can be seen in Figures ?? and ??, the estimates from the single-channel, two-sample IV design are robust to bandwidth choices.

C. What Types of Hospital Admissions Are Affected by Insurance Coverage?

Table 5 presents estimates of the effect of having insurance on hospital admissions by Diagnosis Related Group (DRG) from the two-sample IV approach. These estimates are valid under the assumption that, as suggested by the three-channel estimates, only the transition from uninsured to Medicare affects the probability of being hospitalized. The table includes the 15 groups of DRGs that are most affected by insurance coverage. These 15 groups of conditions account for about 50% (6.7/13.4) of the total increase in hospitalizations. It is likely that the care people are unable to get because they don't have insurance reduces both their life expectancy and their quality of life. As can be seen in Table 5, not having health insurance results in 3.3 foregone emergency hospitalizations per 100 people. Table ?? breaks out the foregone emergency admissions by cause.³⁷ The three conditions that are largest drivers of foregone care are septicemia or severe sepsis, cardiac arrhythmia & conduction disorders, and renal failure. These are conditions where delayed or foregone treatment can be fatal (Salah et al., 2021). As can be seen in Table 5 insurance status has an even larger effect on the probability people will get an elective surgery. The elective procedure with the largest increase is major joint replacement. There is evidence from the literature that both knee and hip replacements substantially improve mobility and quality of life (Skou et al., 2015, 2018; Shan et al., 2014). Table 5 thus suggests that gaining insurance significantly improves the welfare of the previously uninsured.

IV. Conclusion

The near elderly uninsured have much lower rates of health care utilization than the privately insured despite being in substantially worse health on average. They are also much more likely to report having foregone care due to cost.

Using a novel multi-channel estimation method that accounts for the effects of the multiple transitions that occur across the population at age 65, we document

³⁷Tables ?? and ?? analogously break out foregone elective and urgent admissions by cause.

that gaining health insurance reduces the probability that the near elderly will forego care due to cost by 53.9 percentage points. Gaining insurance closes the gap between the insured and the uninsured in both the probability of having a medical provider and the probability of having a checkup in the last year. We also find that people that transition from not having insurance to Medicare see a large increase in the rate at which they get inpatient hospital care — 13.2 percentage points — with most of the increase due to a 7.4 percentage point rise in elective admissions. The fifteen-fold increase in elective inpatient treatments is driven largely by knee and hip replacements. These are documented to substantially increase quality of life and longevity. The substantial increase in admissions for treatment of emergency conditions including among other things sepsis, cardiac arrhythmia, and renal failure, likely saves lives.

While mortality and health effects are beyond the scope of this paper, we note that Goldin, Lurie and McCubbin (2021) estimates that becoming insured reduces mortality rates for middle-aged to older adults by perhaps five percent. Furthermore, Ziedan, Simon and Wing (2022) finds that cancellations of scheduled outpatient appointments results in higher mortality rates during the following year. Most of our utilization measures change between 50 and 100 percent upon transitioning from no insurance to Medicare, so combining our estimates with Goldin et. al's suggests an elasticity of mortality with respect to healthcare utilization of approximately -0.05 to -0.1 .

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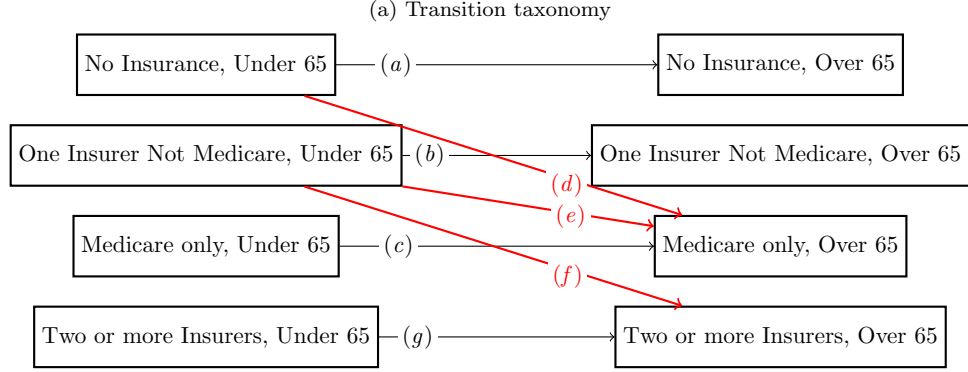
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FIGURE 1. COMMON INSURANCE TRANSITIONS AT AGE 65



Note: $p_a + p_b + p_c + p_d + p_e + p_f + p_g = 1$, where $p_j = P(\text{transition type } j)$

(b) Insurance Levels in Terms of Unobserved Transition Probabilities

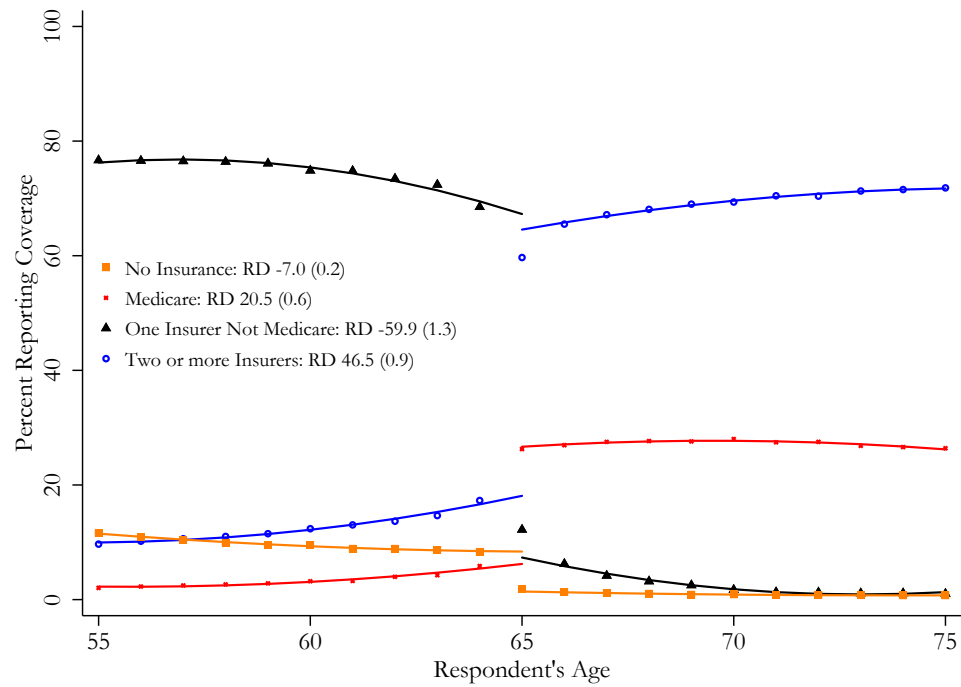
Just Under 65	Just Over 65
$\lim_{age \uparrow 65} P(\text{No Insurance} \mid \text{age}) = p_a + p_d$	$\lim_{age \downarrow 65} P(\text{No Insurance} \mid \text{age}) = p_a$
$\lim_{age \uparrow 65} P(1 \text{ Non-Mcare Insurance} \mid \text{age}) = p_b + p_e + p_f$	$\lim_{age \downarrow 65} P(1 \text{ Non-Mcare Insurance} \mid \text{age}) = p_b$
$\lim_{age \uparrow 65} P(\text{Medicare only} \mid \text{age}) = p_c$	$\lim_{age \downarrow 65} P(\text{Medicare only} \mid \text{age}) = p_d + p_c + p_e$
$\lim_{age \uparrow 65} P(2+ \text{ Insurers} \mid \text{age}) = p_g$	$\lim_{age \downarrow 65} P(2+ \text{ Insurers} \mid \text{age}) = p_f + p_g$

(c) Transition Probabilities in Terms of Observed Insurance Levels

$$\begin{aligned}
 p_a &= \lim_{age \downarrow 65} P(\text{No Insurance} \mid \text{age}) \\
 p_b &= \lim_{age \downarrow 65} P(1 \text{ Non-Medicare Insurance} \mid \text{age}) \\
 p_c &= \lim_{age \uparrow 65} P(\text{Medicare only} \mid \text{age}) \\
 p_d &= \lim_{age \uparrow 65} P(\text{No Insurance} \mid \text{age}) - \lim_{age \downarrow 65} P(\text{No Insurance} \mid \text{age}) \\
 p_e &= \lim_{age \downarrow 65} P(\text{Medicare only} \mid \text{age}) - \lim_{age \uparrow 65} P(\text{Medicare only} \mid \text{age}) \\
 &\quad + \lim_{age \downarrow 65} P(\text{No Insurance} \mid \text{age}) - \lim_{age \uparrow 65} P(\text{No Insurance} \mid \text{age}) \\
 p_f &= \lim_{age \downarrow 65} P(2+ \text{ Insurers} \mid \text{age}) - \lim_{age \uparrow 65} P(2+ \text{ Insurers} \mid \text{age}) \\
 p_g &= \lim_{age \uparrow 65} P(2+ \text{ Insurers} \mid \text{age})
 \end{aligned}$$

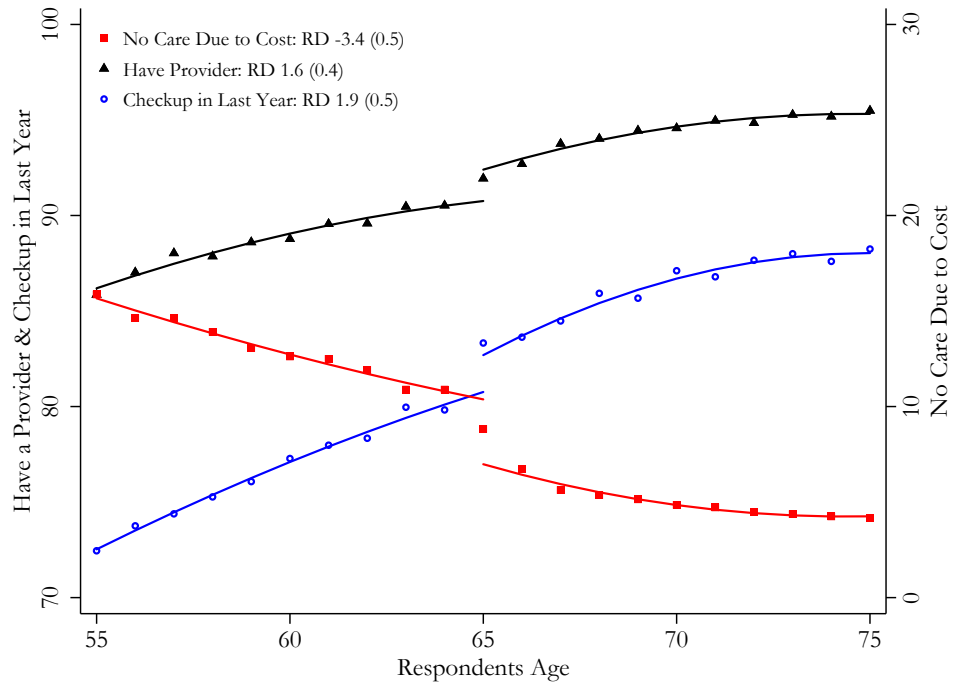
Notes: Panel (a) presents transitions in health insurance coverage that individuals are likely to experience after they turn 65. The three red diagonal lines labeled (d), (e), and (f) denote the changes in insurance coverage that Medicare eligibility is likely to cause: no insurance to Medicare, one type of insurance to Medicare, and one type of insurance to two or more types of coverage, respectively. The four horizontal lines denote people who do not change their insurance coverage when they become eligible for Medicare. Changes in insurance are estimated via regression discontinuity, and insurance transitions are computed as shown in Panels (b) and (c). Estimates are done by state and time-period as described in the text; national estimates of these transitions compared to transitions from a panel survey in Table 2.

FIGURE 2. AGE PROFILE OF INSURANCE COVERAGE



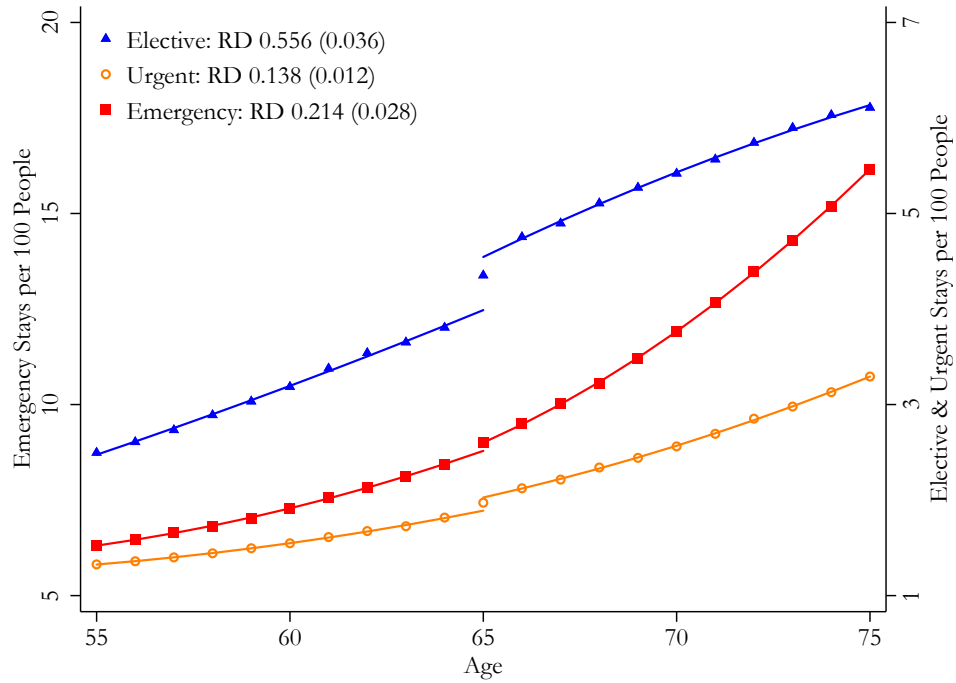
Notes: Age profile of the proportion of the population reporting different types of insurance coverage for the 2008-2017 period from the ACS. Insurance categories correspond with those in Figure 1 and the changes at 65 are estimated separately by state and time period as described in the text.

FIGURE 3. AGE PROFILE OF ACCESS TO CARE AND UTILIZATION



Notes: Age profile of access to care and utilization outcomes for the 2008-2017 period from the BRFSS 2008-2017 with a bandwidth of 10. The left y-axis corresponds to the proportion of people that report they have a regular provider and the proportion that have had a checkup in the last year, and the right y-axis corresponds to the proportion that have foregone care due to cost in the last year. Changes at 65 are estimated separately by state and time period as described in the text.

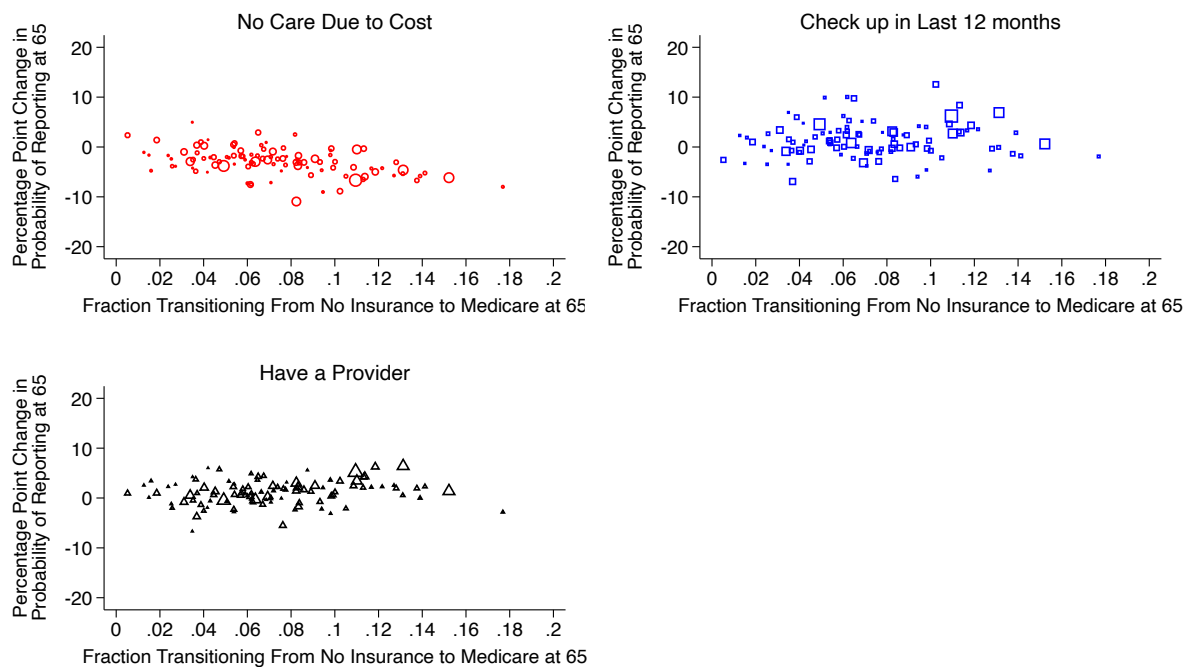
FIGURE 4. AGE PROFILE OF HOSPITALIZATION RATES



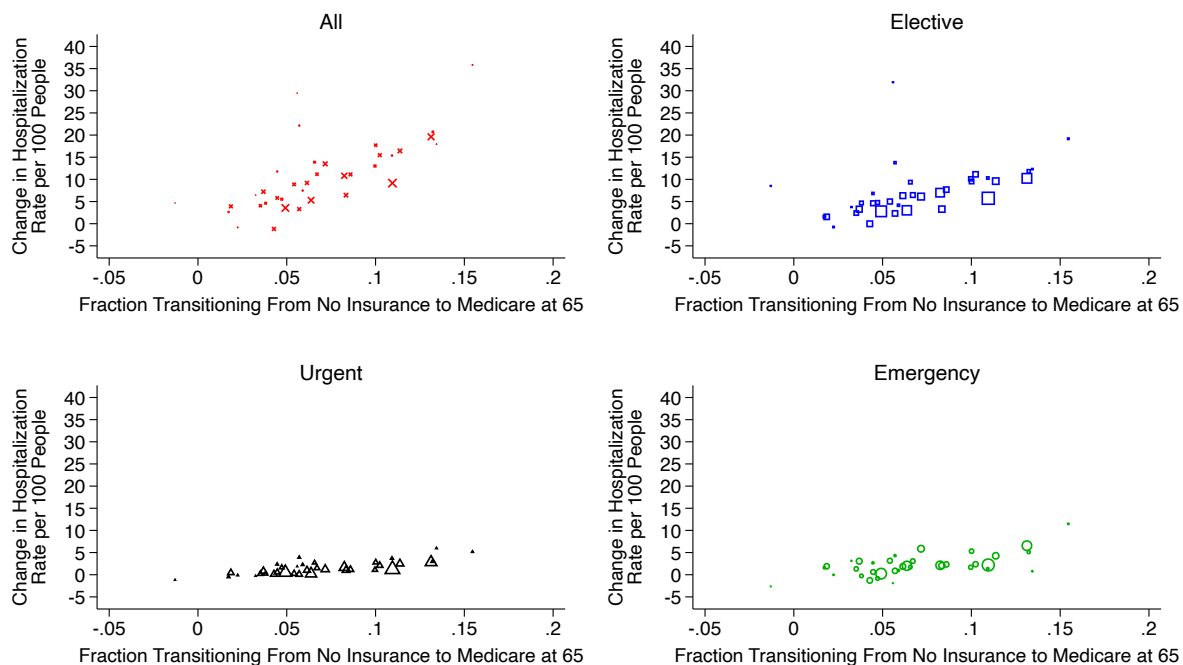
Notes: Age profile of hospitalization rates per 100 people for the 2008-2017 period from hospital admission records of select states. Denominators are derived from US Census population estimates in the state-year of the admission. The left y-axis corresponds to emergency hospital stays per 100 people, and the right y-axis corresponds to elective and urgent hospital stays per 100 people. Changes at 65 are estimated separately by state and time period as described in the text.

FIGURE 5. PROPORTION TRANSITIONING FROM NO INSURANCE TO MEDICARE AND CHANGE IN OUTCOMES

(a) Access to Care and Utilization



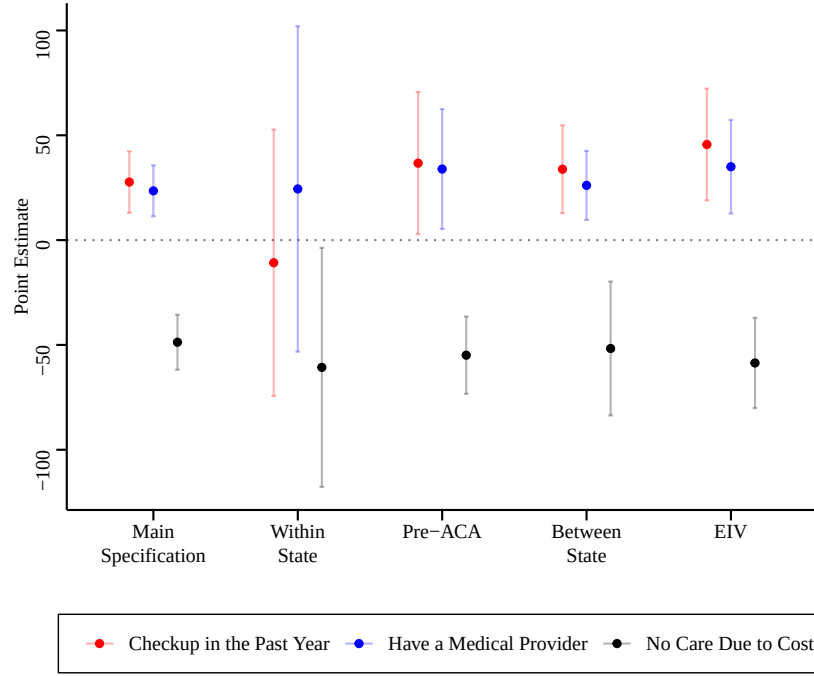
(b) Hospitalization Rates



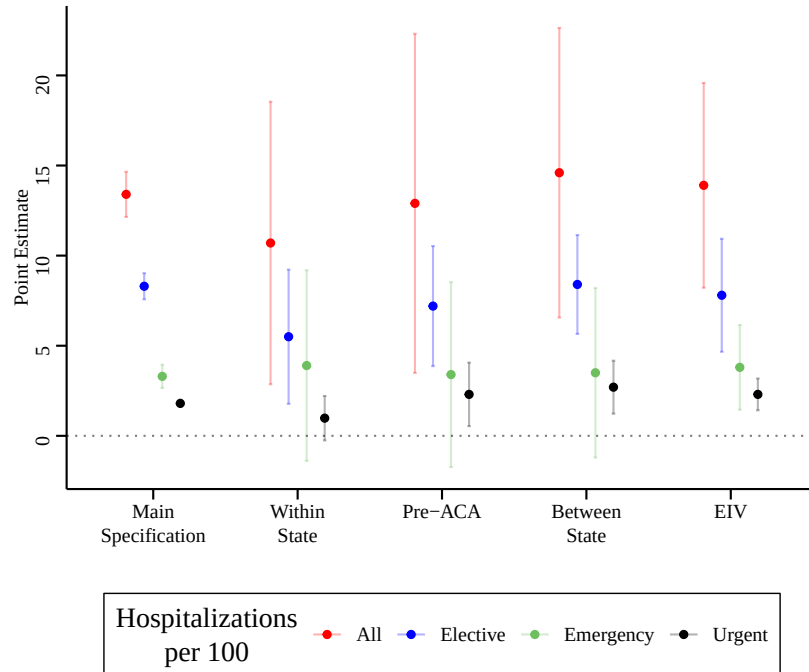
Notes: The proportion of people in a state-time period transitioning from no insurance to Medicare at age 65 plotted against the percent change in access to care and utilization rates (top) and hospitalization rate per 100 people (bottom) in that state-time period. The size of the points corresponds to population of the state.

FIGURE 6. ROBUSTNESS OF MAIN RESULTS TO DIFFERENT SPECIFICATIONS

(a) Access to Care and Utilization



(b) Hospitalization Rates



Notes: The figure plots the outcomes of the no insurance to Medicare channel from our main specification (first row of Table 4) as well as alternative specifications: using within-state variation (Tables ??), limiting the sample to before the ACA (Table ??), between-state variation (Table ??), and an error-in-variables model (Table ??).

TABLE 1—HEALTH AND UTILIZATION AMONG THE NEAR ELDERLY, BY INSURANCE STATUS

	Uninsured	Private	Medicaid	Other
Share of Aged 60-64 (%)	11.0	68.0	8.2	12.9
<i>Self-Reported Health</i>				
Self-Reported Health: Excellent	16.1	24.2	5.8	10.9
Self-Reported Health: Very Good	23.3	34.4	8.8	18.1
Self-Reported Health: Good	36.1	29.6	29.1	32.1
Self-Reported Health: Fair	18.5	9.2	34.9	25.8
Self-Reported Health: Poor	6.1	2.7	21.3	13.1
<i>Health Status</i>				
Has any functional limitation	49.1	43.3	78.7	70.5
Difficult to or can't carry 10 lb	11.0	6.9	40.6	26.2
Difficult to or cannot walk 1/4 mile	17.6	11.1	52.8	38.9
Has any activity limitation	22.4	14.0	66.9	53.8
Unable to work due to health problem	12.4	7.5	53.4	40.3
<i>Access</i>				
No care due to cost	31.5	4.0	10.1	12.1
No meds due to cost	24.5	5.1	15.4	13.5
Delayed filling meds due to cost	26.7	7.8	13.1	16.5
<i>Health care utilization</i>				
One or more office visits (last year)	63.2	90.8	93.0	92.3
Any overnight hospital stay (last year)	6.4	9.1	20.9	15.9
Number of times in hospital overnight (last year)	0.10	0.14	0.41	0.32
One or more emergency department visits (last year)	16.7	15.1	37.4	29.5

Notes: Summary statistics by insurance status among individuals aged 60-64 from the NHIS. Health care utilization variables refer to events in the last year. The “other” category of insurance is 45 percent Medicare, 36 percent Military or VA, 6 percent other government program, and the remaining unknown/refused to answer.

TABLE 2—COMPARISON OF ESTIMATED HEALTH INSURANCE TRANSITION RATES WITH MEPS

		Age 65				
		Source	None	One, Not Medicare	Medicare	Two or More
Age 64	None	ACS	1.4	0.0	7.0	0.0
		MEPS	1.1	0.1	11.8	2.9
	One, Not Medicare	ACS	0.0	7.3	13.5	46.5
		MEPS	0.3	5.7	15.7	44.7
	Medicare	ACS	0.0	0.0	6.2	0.0
		MEPS	0.0	0.0	4.7	0.9
	Two or More	ACS	0.0	0.0	0.0	18.1
		MEPS	0.0	0.1	1.6	10.3

Notes: ACS transition percentages are obtained using the estimation method described in Section II. The estimates are for all states and the District of Columbia 2008-2017. The corresponding transition percentages estimated from the Medical Expenditure Panel Survey (MEPS) are in the next row. For the MEPS, we do not include those who are unsure if insured (<1 percent of the sample).

TABLE 3—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE: MULTI-CHANNEL TWO-SAMPLE IV ESTIMATES

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-53.9 (11.3) [0.001]	32.8 (11.9) [0.015]	41.2 (14.1) [0.011]	13.2 (3.5) [0.004]	7.4 (1.6) [0.001]	2.2 (0.53) [0.001]	3.6 (1.7) [0.057]
Insured → Medicare	-20.2 (10.2) [0.063]	2.6 (5.3) [0.491]	23.1 (6.8) [0.004]	-1.2 (1.3) [0.273]	0.05 (0.67) [0.571]	-0.03 (0.19) [0.571]	-1.2 (0.50) [0.043]
Insured → Medicare + 2nd Payer	7.1 (3.7) [0.066]	-2.8 (2.3) [0.185]	-8.8 (3.1) [0.014]	0.15 (0.57) [0.571]	-0.02 (0.25) [0.571]	-0.09 (0.09) [0.273]	0.2 (0.3) [0.296]
F test (quadratics and interactions)	0.69 0.6544	0.63 0.7023	0.55 0.7716	2.06 0.0914	2.35 0.0588	1.00 0.4455	0.96 0.4726
Mean Age 64							
Uninsured	36.7	64.4	54.7	4.9	0.48	0.43	4.0
Insured	7.9	93.6	82.7	15.1	3.8	1.7	9.5
All	10.8	90.5	79.8	13.9	3.4	1.6	8.8
Observations							
State Cells	102	102	102	36	36	36	36
American Community Survey	7,125,102	7,125,102	7,125,102	3,157,108	3,157,108	3,157,108	3,157,108
BRFSS/Hospitalizations	1,803,710	1,803,226	1,790,630	41,865,902	10,253,559	4,836,319	26,571,641

Notes: Estimates on data collapsed pre and post ACA weighted by population ages 55 to 75. The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors. For context the estimated hospitalization rate at age 64 for each group is (from MEPS): None → Medicare: 7.7; Insured → Medicare: 9.0; Insured → Medicare + Second Payer: 18.0. The p-value of the F-test is presented directly below the F-Statistic.

TABLE 4—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE: SINGLE-CHANNEL TWO-SAMPLE IV ESTIMATES

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-48.7 (6.7) [0.001]	23.5 (6.2) [0.001]	27.7 (7.5) [0.001]	13.4 (0.64) [0.001]	8.3 (0.37) [0.001]	1.8 (0.10) [0.001]	3.3 (0.33) [0.001]
Mean Age 64							
Uninsured	36.7	64.4	54.7	4.9	0.48	0.43	4.0
Insured	7.9	93.6	82.7	15.1	3.8	1.7	9.5
All	10.8	90.5	79.8	13.9	3.4	1.6	8.8
Observations							
American Community Survey	7,125,102	7,125,102	7,125,102	3,157,108	3,157,108	3,157,108	3,157,108
BRFSS/Hospitalizations	1,803,710	1,803,226	1,790,630	41,865,902	10,253,559	4,836,319	26,571,641

Notes: The estimates are from a two-sample IV research design. The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors.

TABLE 5—EFFECT OF INSURANCE ON HOSPITALIZATION RATES BY DRG FAMILY WITH LARGEST GROWTH IN ADMISSIONS

DRG Description	DRGs	All	Elective	Urgent	Emergency
All DRGs (All Admissions)		13.4 [0.001]	8.3 [0.001]	1.8 [0.001]	3.3 [0.001]
Major joint replacement or reattachment of lower extremity	469-470	2.680 [0.001] 0.923	2.495 [0.001] 0.861	0.130 [0.001] 0.029	0.051 [0.001] 0.032
Major small & large bowel procedures	329-331	0.410 [0.001] 0.222	0.330 [0.001] 0.130	0.039 [0.001] 0.018	0.039 [0.002] 0.073
Perc cardiovasc proc	246-251	0.386 [0.001] 0.400	0.250 [0.001] 0.093	0.100 [0.001] 0.061	0.030 [0.040] 0.244
Psychoses	885	0.356 [0.001] 0.278	0.044 [0.001] 0.029	0.163 [0.001] 0.094	0.146 [0.001] 0.153
Major male pelvic procedures	707-708	0.346 [0.001] 0.110	0.330 [0.001] 0.105	0.013 [0.001] 0.004	0.002 [0.008] 0.001
Coronary bypass	231-236	0.302 [0.001] 0.125	0.224 [0.001] 0.065	0.061 [0.001] 0.017	0.016 [0.018] 0.042
Spinal fusion	456-460	0.301 [0.001] 0.163	0.278 [0.001] 0.149	0.023 [0.001] 0.006	0.001 [0.086] 0.008
Septicemia or severe sepsis	870-872	0.289 [0.001] 0.612	0.020 [0.001] 0.013	0.039 [0.001] 0.059	0.228 [0.001] 0.540
Cardiac arrhythmia & conduction disorders	308-310	0.271 [0.001] 0.332	0.030 [0.001] 0.023	0.042 [0.001] 0.040	0.197 [0.001] 0.268
Cervical spinal fusion	471-473	0.268 [0.001] 0.087	0.257 [0.001] 0.077	0.009 [0.001] 0.004	0.002 [0.064] 0.006
Esophagitis, gastroent & misc digest disorders	391-392	0.248 [0.001] 0.387	0.023 [0.001] 0.015	0.066 [0.001] 0.046	0.157 [0.001] 0.326
O.R. procedures for obesity	619-621	0.248 [0.001] 0.044	0.234 [0.001] 0.042	0.012 [0.001] 0.002	0.002 [0.001] 0.000
Circulatory disorders except AMI, w card cath	286-287	0.241 [0.001] 0.215	0.056 [0.001] 0.020	0.038 [0.001] 0.029	0.146 [0.001] 0.166
Other vascular procedures	252-254	0.221 [0.001] 0.140	0.185 [0.001] 0.065	0.021 [0.001] 0.020	0.010 [0.054] 0.055
Extracranial procedures	37-39	0.206 [0.001] 0.070	0.194 [0.001] 0.055	0.010 [0.001] 0.004	0.002 [0.071] 0.010

Notes: Single-channel IV estimates for the None $\rightarrow$ Medicare channel for the Diagnosis Related Groups that had the largest increases in elective admissions at age 65. The first row of each block contains the estimate of the increase in admissions per 100 people that transitioned from not having to having insurance at 65. False discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the point estimates, and the final row in each block presents the admission rate per 100 people at age 64 regardless of insurance status. The first row contains estimates for all DRGs as shown in Table 4.

Supplemental Appendix

Health Insurance and Access to Care for the Near Elderly

Michael Anderson, Carlos Dobkin, Nicole Maestas, and Liam Rose

I. Derivation of Estimating Equations

Consider a case in which an instrument Z (in our context the age-65 threshold) may affect multiple treatments (in our context insurance transitions). We first derive Equation (2). Let H be the observed change in an individual's outcome at age 65 with H_0 , H_{I1} , H_{I2} , and H_{I3} corresponding to potential changes in the outcome based on whether the individual undergoes no insurance transition or insurance transitions $I1$, $I2$, or $I3$ respectively.

We use the following assumptions and abbreviations to derive Equation (2):

A.R : Random assignment of Z

A.MO : Monotonicity

A.ER : Exclusion restriction, $E[u_{st} | I1_{st}, I2_{st}, I3_{st}] = 0$

IE : Iterated expectations

OR : Observations rule

Under the exclusion restriction the change in the outcome does not depend on the instrument Z conditional on insurance transitions Ij , so using the observations rule we may write:

$$H = H_0 + (H_{I1} - H_0)I1 + (H_{I2} - H_0)I2 + (H_{I3} - H_0)I3$$

An observed insurance transition Ij (for $j = 1, 2, 3$) is a function of potential insurance transitions Ij_1 (the transition when $Z = 1$) and Ij_0 (the transition when $Z = 0$). Again using the observations rule we may write:

$$Ij = Ij_1Z + Ij_0(1 - Z)$$

For a given state s and period t we can now derive the reduced-form estimand of the RD:

$$\begin{aligned}
& E[H \mid Z = 1] - E[H \mid Z = 0] \\
& \stackrel{OR}{=} E[H_0 + (H_{I1} - H_0)I1 + (H_{I2} - H_0)I2 + (H_{I3} - H_0)I3 \mid Z = 1] \\
& \quad - E[H_0 + (H_{I1} - H_0)I1 + (H_{I2} - H_0)I2 + (H_{I3} - H_0)I3 \mid Z = 0] \\
& \stackrel{A.R}{=} \sum_{j=1}^3 E[(H_{Ij} - H_0)Ij_1 \mid Z = 1] - E[(H_{Ij} - H_0)Ij_0 \mid Z = 0] \\
& \stackrel{A.R}{=} \sum_{j=1}^3 E[(H_{Ij} - H_0)(Ij_1 - Ij_0)] \\
& \stackrel{IE}{=} \sum_{j=1}^3 E[E[(H_{Ij} - H_0)(Ij_1 - Ij_0) \mid (Ij_1 - Ij_0)]] \\
& \stackrel{A.MO}{=} \sum_{j=1}^3 E[(H_{Ij} - H_0) \mid (Ij_1 - Ij_0) = 1] \cdot P(Ij_1 - Ij_0 = 1)
\end{aligned}$$

In this context $E[(H_{Ij} - H_0) \mid (Ij_1 - Ij_0) = 1]$ is the local average treatment effect (LATE) for compliers for insurance transition type j . For completeness note that the first-stage estimand of the RD is:

$$\begin{aligned}
& E[Ij \mid Z = 1] - E[Ij \mid Z = 0] \\
& \stackrel{OR}{=} E[Ij_1 \cdot Z + Ij_0 \cdot (1 - Z) \mid Z = 1] - E[Ij_1 \cdot Z + Ij_0 \cdot (1 - Z) \mid Z = 0] \\
& = E[Ij_1 \mid Z = 1] - E[Ij_0 \mid Z = 0] \\
& \stackrel{A.R}{=} E[Ij_1 - Ij_0] \\
& \stackrel{A.MO}{=} P(Ij_1 - Ij_0 = 1)
\end{aligned}$$

Combining the results above yields:

$$(1) \quad H_{st} = \tau_{1st}I1_{st} + \tau_{2st}I2_{st} + \tau_{3st}I3_{st} + u_{st}$$

where H_{st} is the reduced-form estimate for state s in period t , Ij_{st} are first-stage estimands for state s in period t , τ_{jst} are LATEs for state s in period t , and u_{st} is a residual reflecting estimation error in H_{st} .

Decompose the LATEs to averages and deviations from averages, $\tau_{jst} = \bar{\tau}_j + \tilde{\tau}_{jst}$. We now show that estimating Equation (1) yields the average LATEs (i.e., $\bar{\tau}_1, \bar{\tau}_2, \bar{\tau}_3$) if we make an additional assumption:

$$A.MI : \text{Mean independent LATEs, } E[\tilde{\tau}_{jst} \mid I1_{st}, I2_{st}, I3_{st}] = 0$$

The conditional expectation function (CEF) of H_{st} with respect to $I1_{st}, I2_{st}, I3_{st}$ is:

$$\begin{aligned} E[H_{st} \mid I1_{st}, I2_{st}, I3_{st}] &= E[\bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \tilde{\tau}_{1st} I1_{st} + \tilde{\tau}_{2st} I2_{st} + \tilde{\tau}_{3st} I3_{st} + u_{st} \mid I1_{st}, I2_{st}, I3_{st}] \\ &= \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} E[\tilde{\tau}_{jst} \mid I1_{st}, I2_{st}, I3_{st}] + E[u_{st} \mid I1_{st}, I2_{st}, I3_{st}] \\ &\stackrel{A.ER}{=} \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} E[\tilde{\tau}_{js} \mid I1_{st}, I2_{st}, I3_{st}] \\ &\stackrel{A.MI}{=} \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} \end{aligned}$$

For completeness we note that if the CEF is linear, then linear regression estimates the CEF. Let $E[Y|X] = X\beta$. Then:

$$\begin{aligned} &E[(X'X)^{-1}(X'Y)] \\ &\stackrel{IE}{=} E[E[(X'X)^{-1}(X'Y)]|X] \\ &= E[(X'X)^{-1}(X'E[Y|X])] \\ &= E[(X'X)^{-1}(X'X)\beta] \\ &= \beta \end{aligned}$$

In summary, estimating Equation (2) yields consistent estimates of the average

LATEs under the mean independence of LATEs assumption. Furthermore, restricting the intercept to zero can increase precision while requiring no additional assumptions.

We now consider the case in which mean independence of LATEs (*A.MI*) fails. Let *FOTE* denote a first order Taylor expansion. The CEF of the reduced form under no mean independence of LATEs becomes (approximately):

$$\begin{aligned}
& E[H_{st} \mid I1_{st}, I2_{st}, I3_{st}] \\
&= E[\bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \tilde{\tau}_{1st} I1_{st} + \tilde{\tau}_{2st} I2_{st} + \tilde{\tau}_{3st} I3_{st} + u_{st} \mid I1_{st}, I2_{st}, I3_{st}] \\
&= \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} E[\tilde{\tau}_{js} \mid I1_{st}, I2_{st}, I3_{st}] + E[u_{st} \mid I1_{st}, I2_{st}, I3_{st}] \\
&\stackrel{A.ER}{=} \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} E[\tilde{\tau}_{js} \mid I1_{st}, I2_{st}, I3_{st}] \\
&= \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} g_j(I1_{st}, I2_{st}, I3_{st}) \\
&\stackrel{FOTE}{\approx} \bar{\tau}_1 I1_{st} + \bar{\tau}_2 I2_{st} + \bar{\tau}_3 I3_{st} + \sum_{j=1}^3 Ij_{st} (\theta_j + \sum_{k=1}^3 \theta_{jk} I k_{st}) \\
&= \delta_1 I1_{st} + \delta_2 I2_{st} + \delta_3 I3_{st} + \delta_4 I1_{st}^2 + \delta_5 I2_{st}^2 + \delta_6 I3_{st}^2 \\
&\quad + \delta_7 I1_{st} I2_{st} + \delta_8 I1_{st} I3_{st} + \delta_9 I2_{st} I3_{st}
\end{aligned}$$

This result motivates a straightforward test of the mean independence assumption (*A.MI*): regress the reduced-form estimate for state s in period t on a quadratic of the first stage estimates for state s in period t , as well as the two-way interactions between the first stage estimates, and perform a joint test on the quadratic and interaction term coefficients. Formally, run the regression

$$\begin{aligned}
H_{st} = & \delta_1 I1_{st} + \delta_2 I2_{st} + \delta_3 I3_{st} + \delta_4 I1_{st}^2 + \delta_5 I2_{st}^2 + \delta_6 I3_{st}^2 \\
& + \delta_7 I1_{st} I2_{st} + \delta_8 I1_{st} I3_{st} + \delta_9 I2_{st} I3_{st} + u_{st}
\end{aligned}$$

and test the null hypothesis $\delta_4 = \delta_5 = \dots = \delta_9 = 0$.

II. Error in Variables Model

The variables $I1_{st}$, $I2_{st}$ and $I3_{st}$ are estimates of the changes in insurance coverage as described in Section II.D. In finite samples these estimated changes have the following relationship with the true changes in insurance coverage, $I1_{st}^*$, $I2_{st}^*$, and $I3_{st}^*$:

$$\begin{aligned} I1_{st} &= I1_{st}^* + \eta_{1st} \\ I2_{st} &= I2_{st}^* + \eta_{2st} \\ I3_{st} &= I3_{st}^* + \eta_{3st} \end{aligned}$$

where η_{1st} , η_{2st} and η_{3st} are mean-zero measurement error terms. These η terms represent classical measurement error and their presence attenuates parameter estimates in Equation (2).

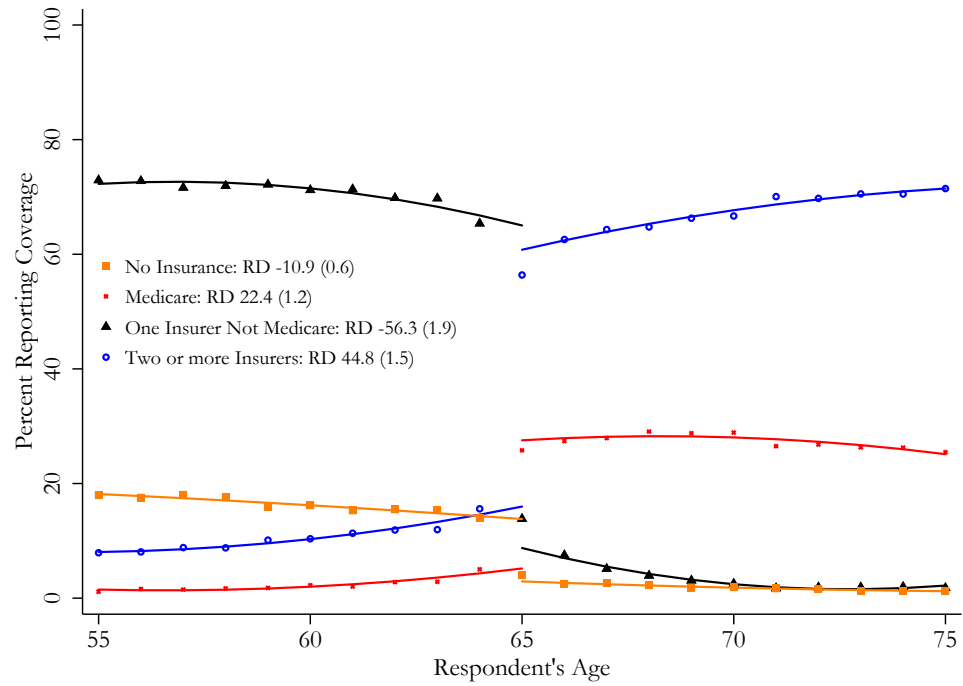
We take two steps to address the potential attenuation bias. First, since much of the time series variation in the first-stage estimates arises from the ACA, we collapse the data from state-year cells to state-pre/post-ACA cells, increasing the sample size in each cell. Second, we directly estimate the degree of measurement error and adjust for it using an error in variables (EIV) model. In a simple EIV model the η terms are uncorrelated with each other, but in our context $Cov(\eta_{jst}, \eta_{kst}) \neq 0$ because the insurance transitions apportion the population into mutually exclusive subgroups. We thus estimate the variance-covariance matrix of these errors, denoted Σ_{st} for each state and time period, via bootstrapping. (Note that the errors in the measurement of the insurance transitions (the first-stage coefficients) are uncorrelated with errors in the measurement of the health care utilization outcomes (the reduced-form coefficients) because they are estimated using different datasets.) We then estimate the effect of the three insurance transitions, denoted by the vector τ , as

$$(2) \quad \tau = \left(\sum_{st} (\mathbf{I}'_{st} \mathbf{I}_{st} - \widehat{\Sigma}_{st}) \right)^{-1} \left(\sum_{st} \mathbf{I}'_{st} H_{st} \right)$$

where $\mathbf{I}_{st} = (1, I1_{st}, I2_{st}, I3_{st})$ is a vector of the three transition probabilities plus a constant and $\hat{\Sigma}_{st}$ is the estimate of the variance-covariance matrix of the transition probability errors for state s in year t . In the simplest EIV model with zero covariances between insurance transitions, Equation (2) is equivalent to inflating the OLS coefficient on Ij_{st} by σ_j^2/σ_j^{*2} , where σ_j^2 and σ_j^{*2} represent the variances of Ij_{st} and Ij_{st}^* respectively.

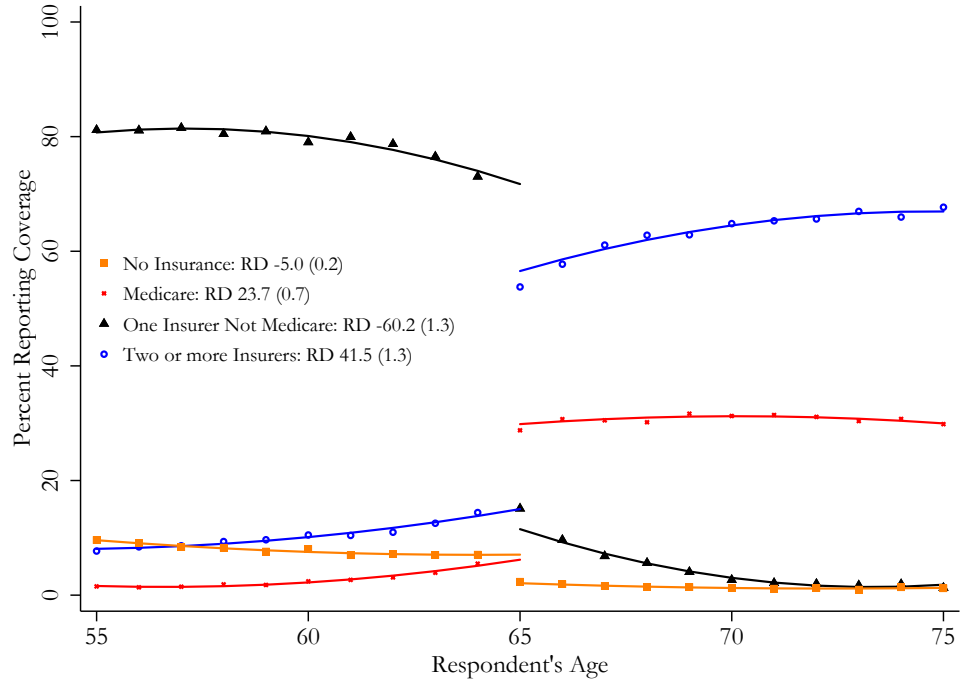
III. Additional Figures and Tables

FIGURE A1. AGE PROFILE OF INSURANCE COVERAGE FOR CALIFORNIA PRE ACA



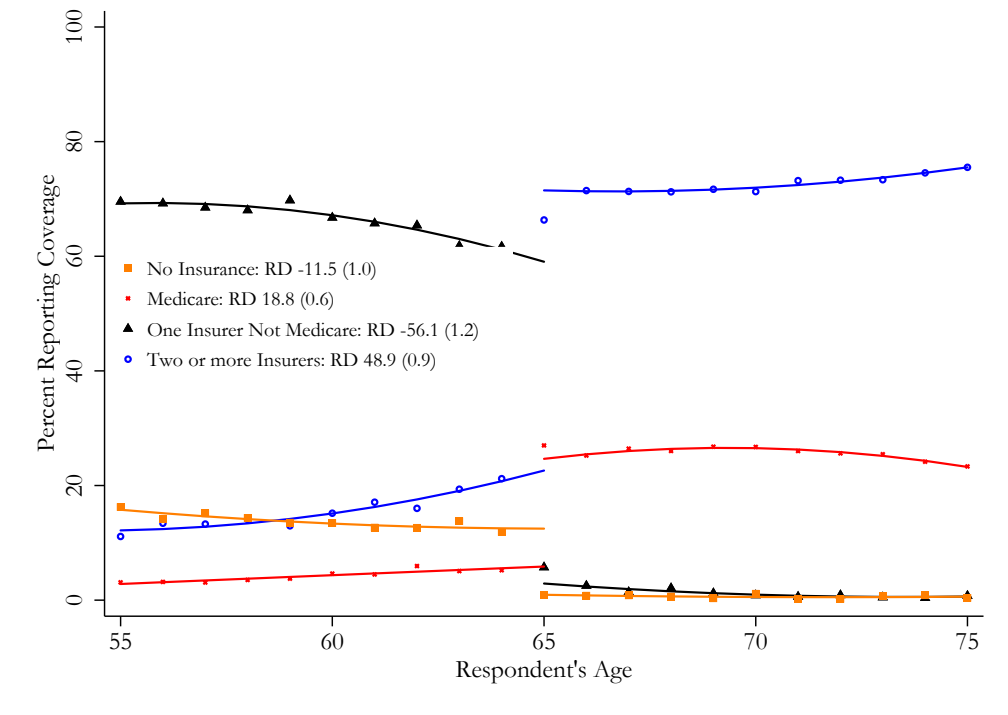
Notes: These estimates are from the American Community Survey.

FIGURE A2. AGE PROFILE OF INSURANCE COVERAGE FOR CALIFORNIA POST ACA



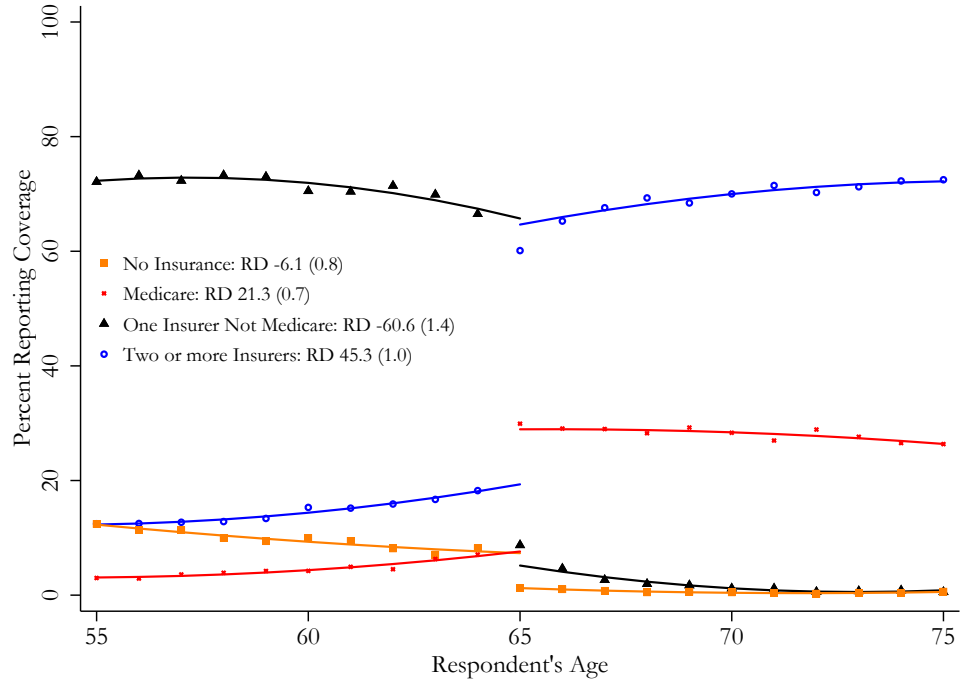
Notes: These estimates are from the American Community Survey.

FIGURE A3. AGE PROFILE OF INSURANCE COVERAGE FOR NORTH CAROLINA PRE ACA



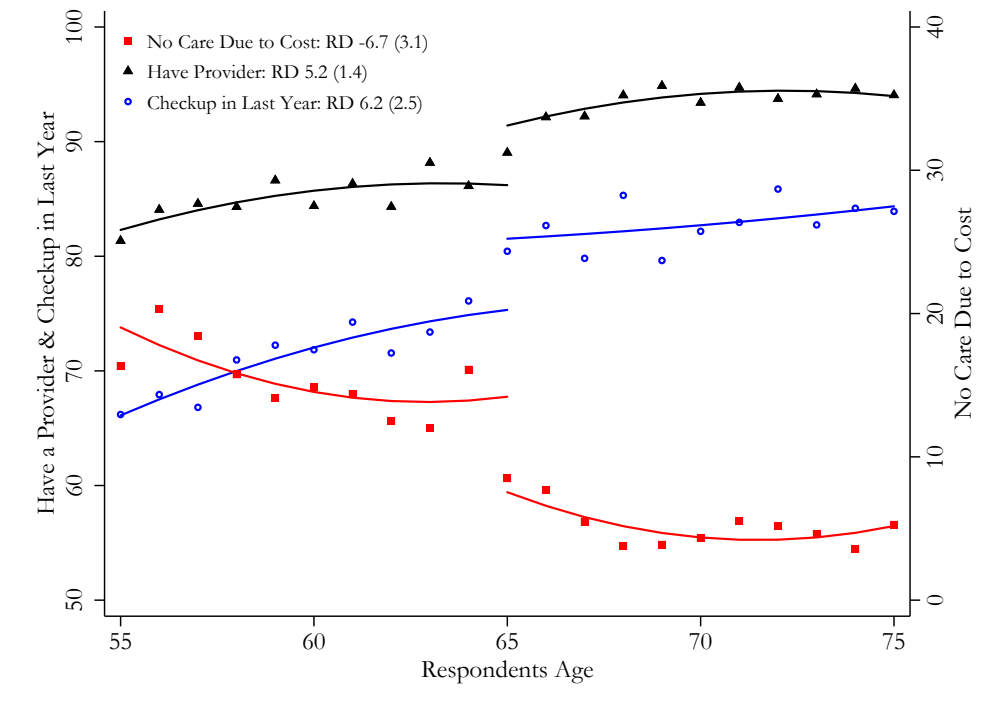
Notes: These estimates are from the American Community Survey.

FIGURE A4. AGE PROFILE OF INSURANCE COVERAGE FOR NORTH CAROLINA POST ACA



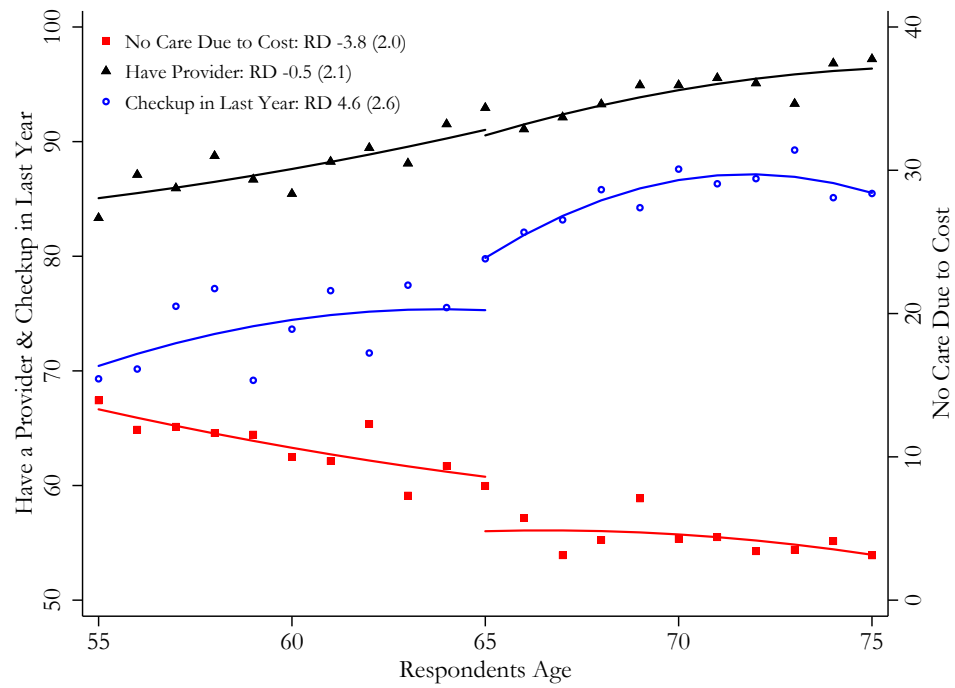
Notes: These estimates are from the American Community Survey.

FIGURE A5. AGE PROFILE OF HEALTH CARE ACCESS FOR CALIFORNIA PRE ACA



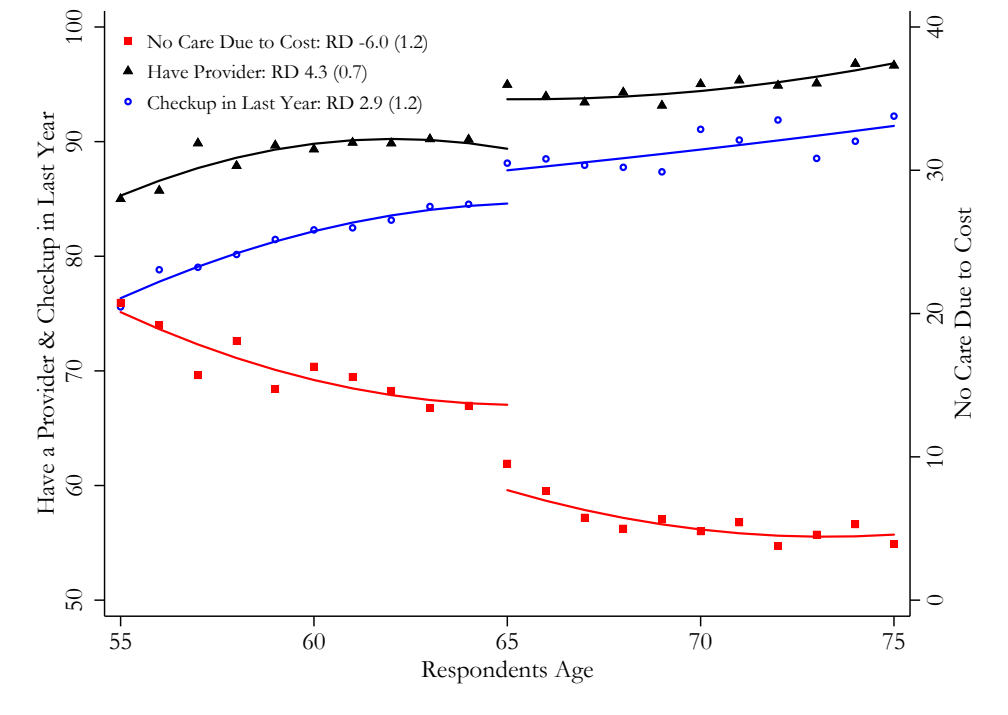
Notes: These estimates are from the Behavioral Risk Factor Surveillance System.

FIGURE A6. AGE PROFILE OF HEALTH CARE ACCESS FOR CALIFORNIA POST ACA



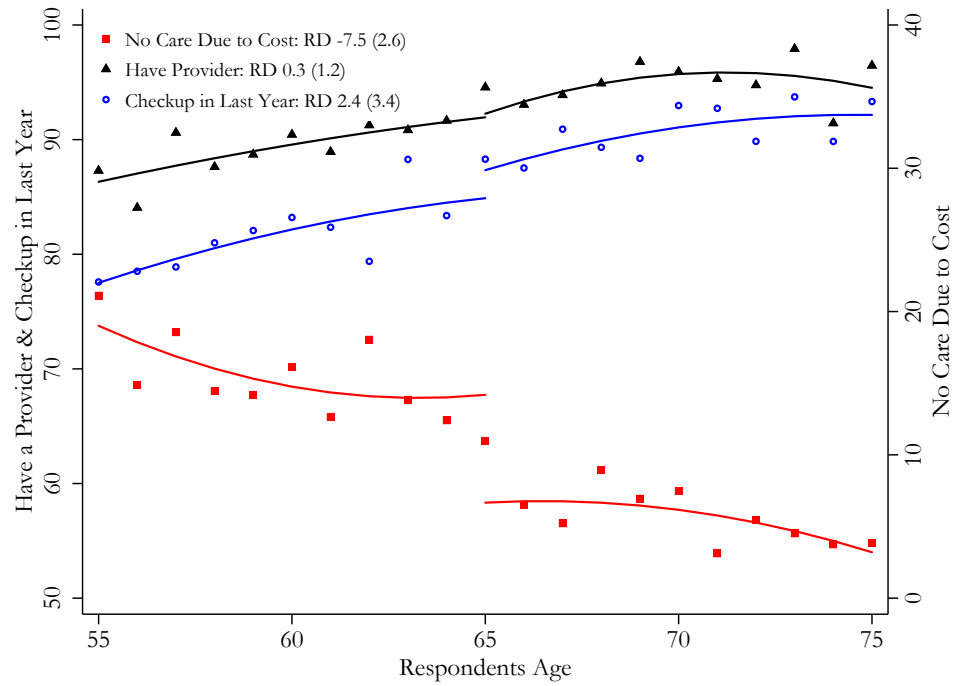
Notes: These estimates are from the Behavioral Risk Factor Surveillance System.

FIGURE A7. AGE PROFILE OF HEALTH CARE ACCESS FOR NORTH CAROLINA PRE ACA



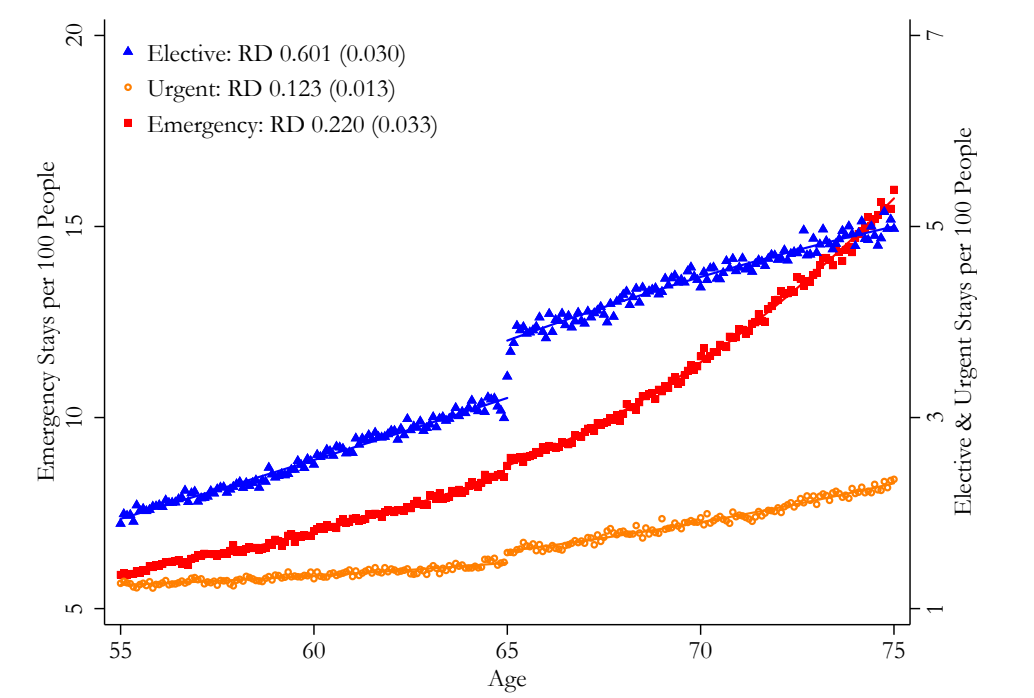
Notes: These estimates are from the Behavioral Risk Factor Surveillance System.

FIGURE A8. AGE PROFILE OF HEALTH CARE ACCESS FOR NORTH CAROLINA POST ACA



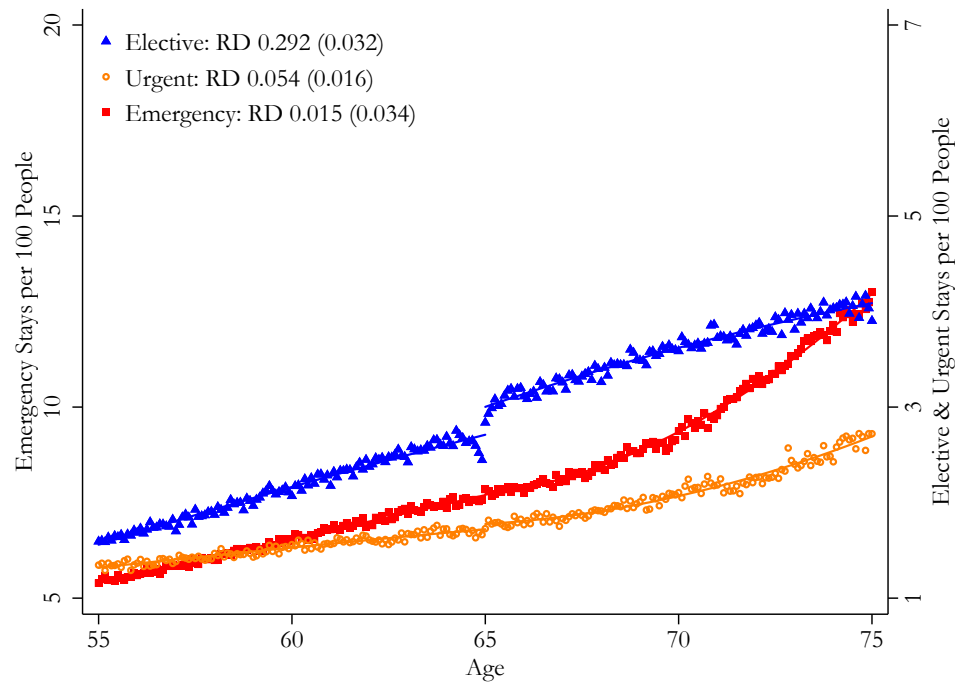
Notes: These estimates are from the Behavioral Risk Factor Surveillance System.

FIGURE A9. AGE PROFILE OF HOSPITALIZATIONS FOR CALIFORNIA PRE ACA



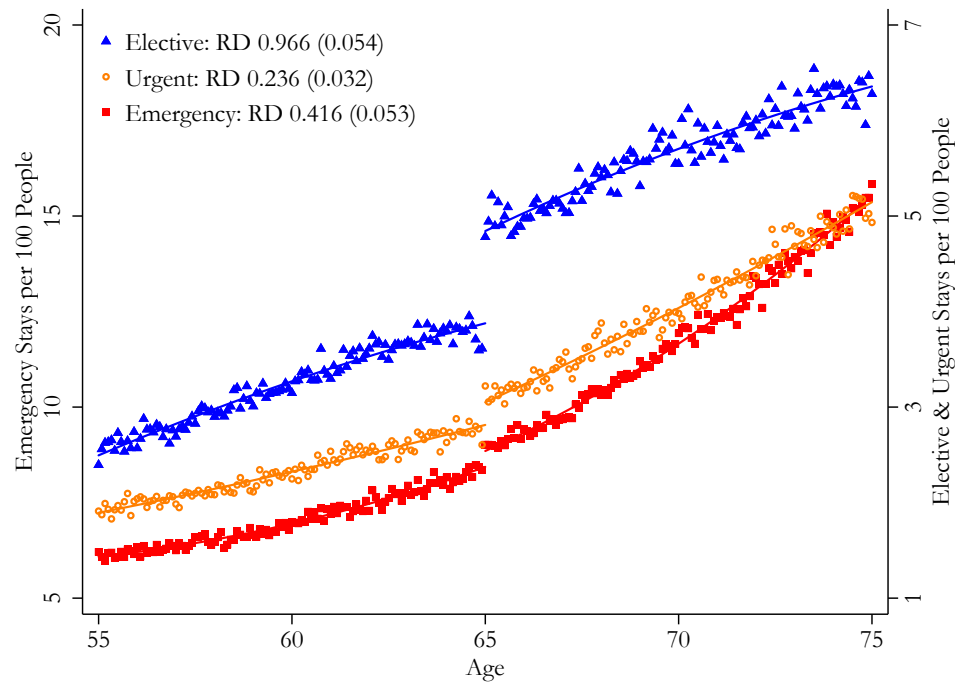
Notes: These estimates are from the HCUP.

FIGURE A10. AGE PROFILE OF HOSPITALIZATIONS FOR CALIFORNIA POST ACA



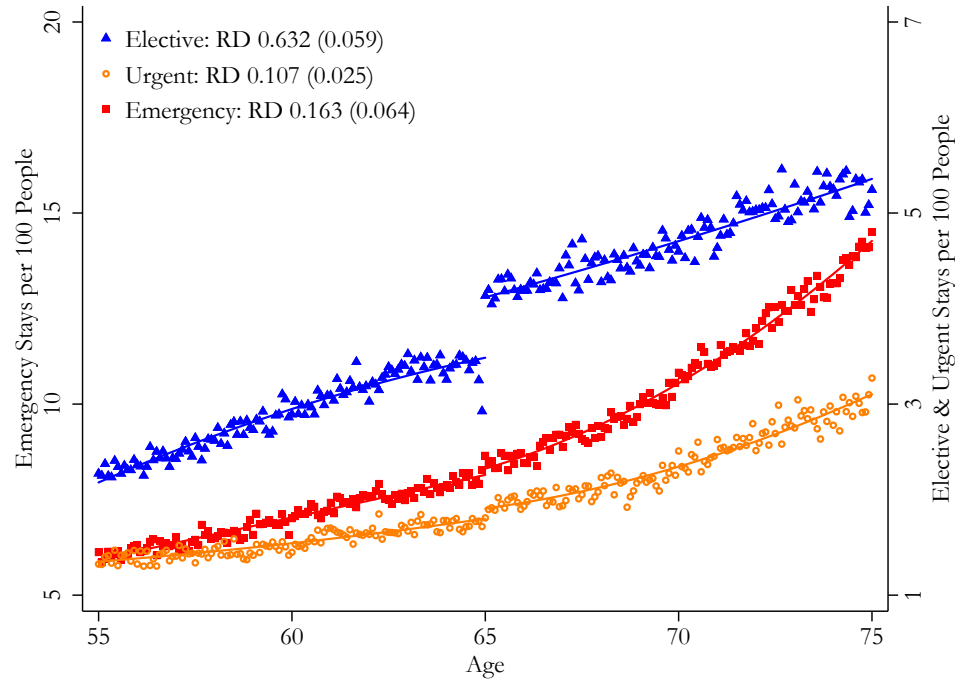
Notes: These estimates are from the HCUP.

FIGURE A11. AGE PROFILE OF HOSPITALIZATIONS FOR NORTH CAROLINA PRE ACA



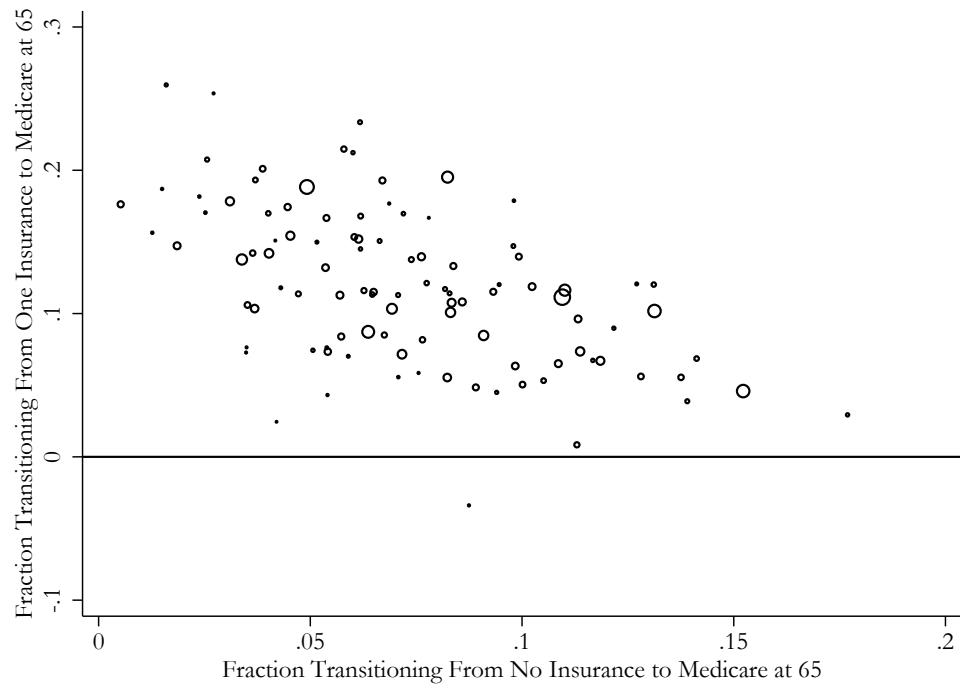
Notes: These estimates are from the HCUP.

FIGURE A12. AGE PROFILE OF HOSPITALIZATIONS FOR NORTH CAROLINA POST ACA



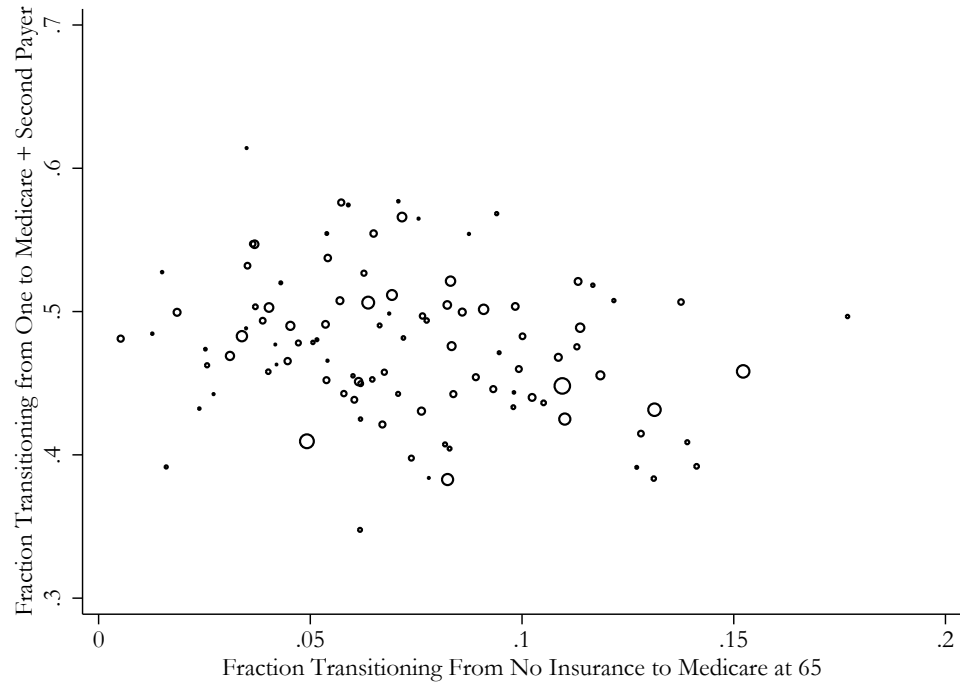
Notes: These estimates are from the HCUP.

FIGURE A13. VARIATION IN INSURANCE TRANSITIONS ACROSS STATES AND TIME PERIODS



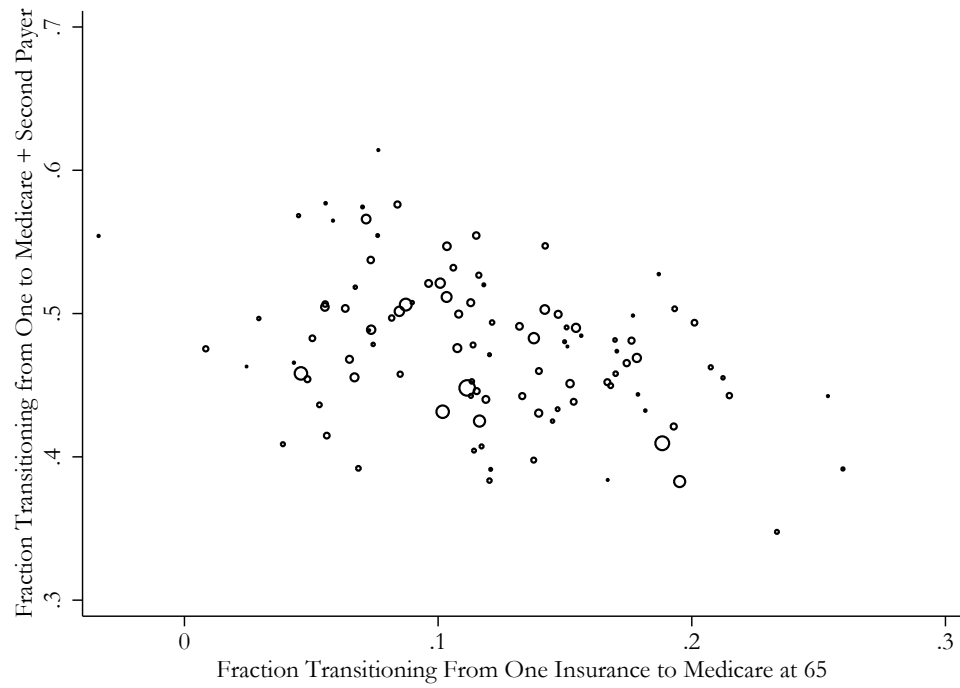
Notes: These estimates are by state and time period with the size of the circle determined by the state population.

FIGURE A14. VARIATION IN INSURANCE TRANSITIONS ACROSS STATES AND TIME PERIODS

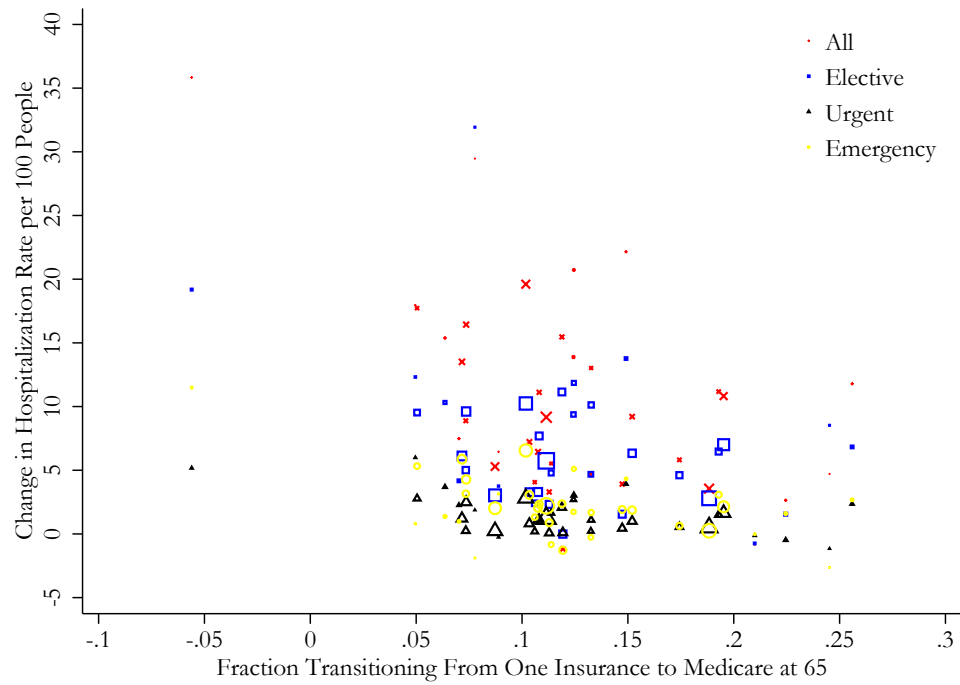


Notes: These estimates are by state and time period with the size of the circle determined by the state population.

FIGURE A15. VARIATION IN INSURANCE TRANSITIONS ACROSS STATES AND TIME PERIODS

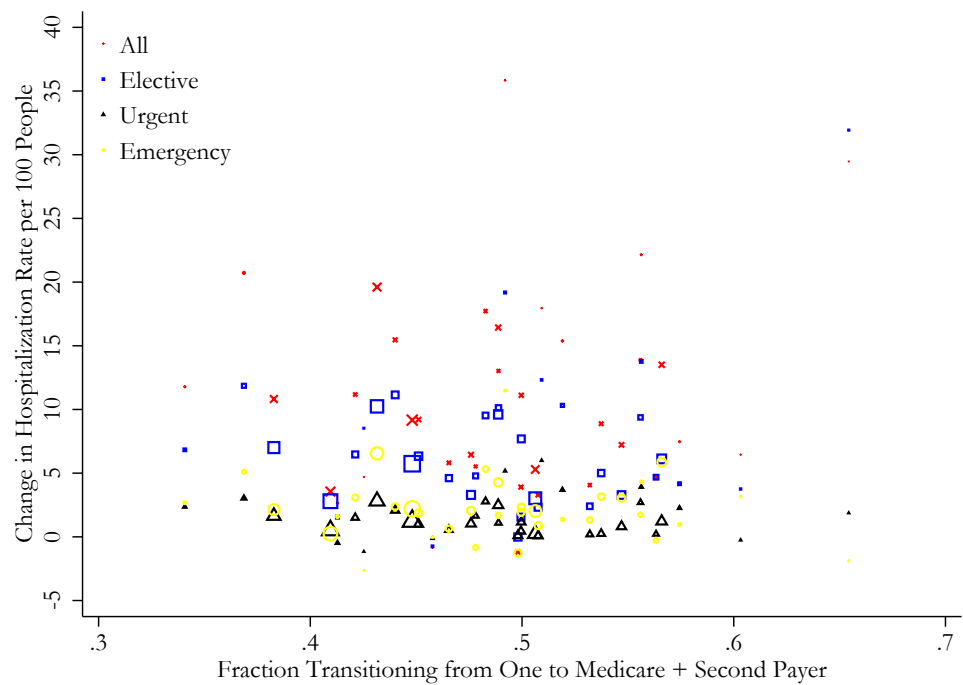


Notes: These estimates are by state and time period with the size of the circle determined by the state population.

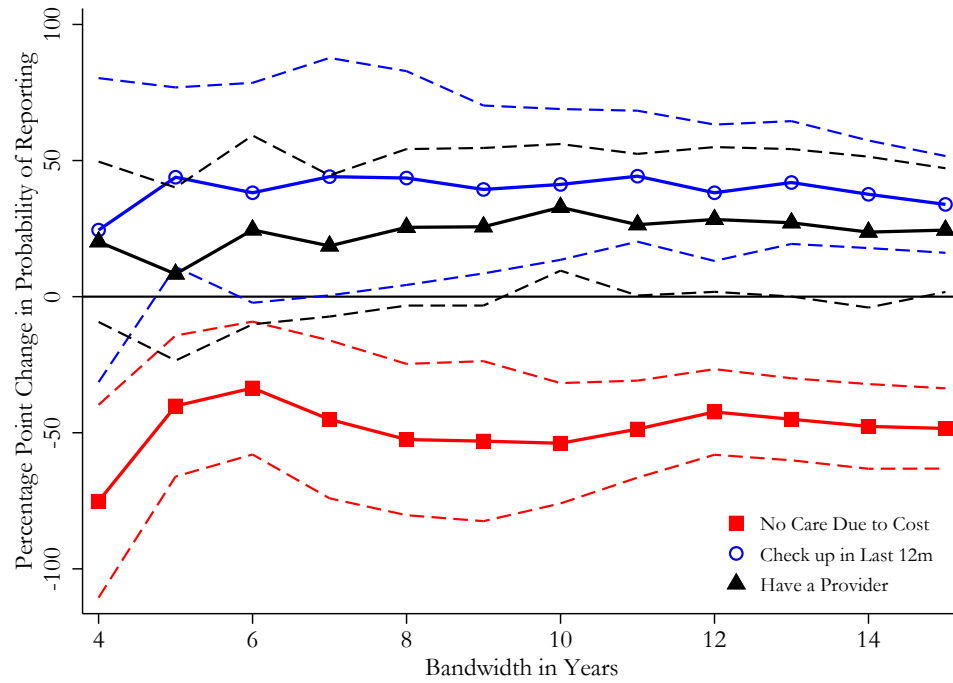
FIGURE A16. INSURANCE TRANSITION: ONE $\rightarrow$ MEDICARE

Notes: Data from ACS and HCUP.

FIGURE A17. INSURANCE TRANSITION: ONE → MEDICARE + 2ND PAYER

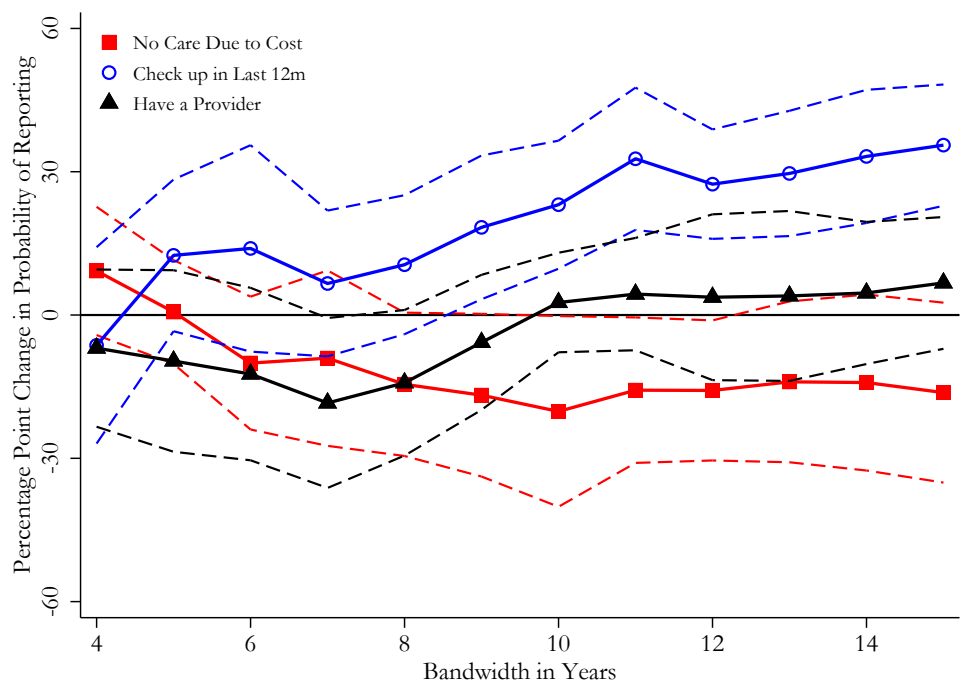


Notes: Data from ACS and HCUP.

FIGURE A18. ROBUSTNESS TO BANDWIDTH: NO INSURANCE $\rightarrow$ MEDICARE

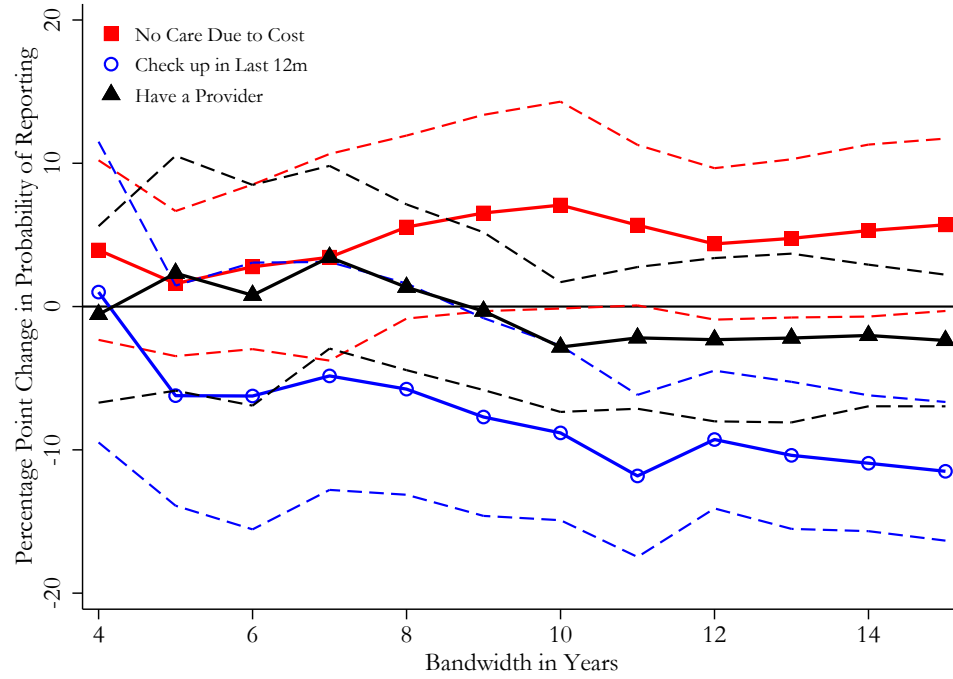
Notes: These estimates are for the no insurance to Medicare transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A19. ROBUSTNESS TO BANDWIDTH: INSURED $\rightarrow$ MEDICARE

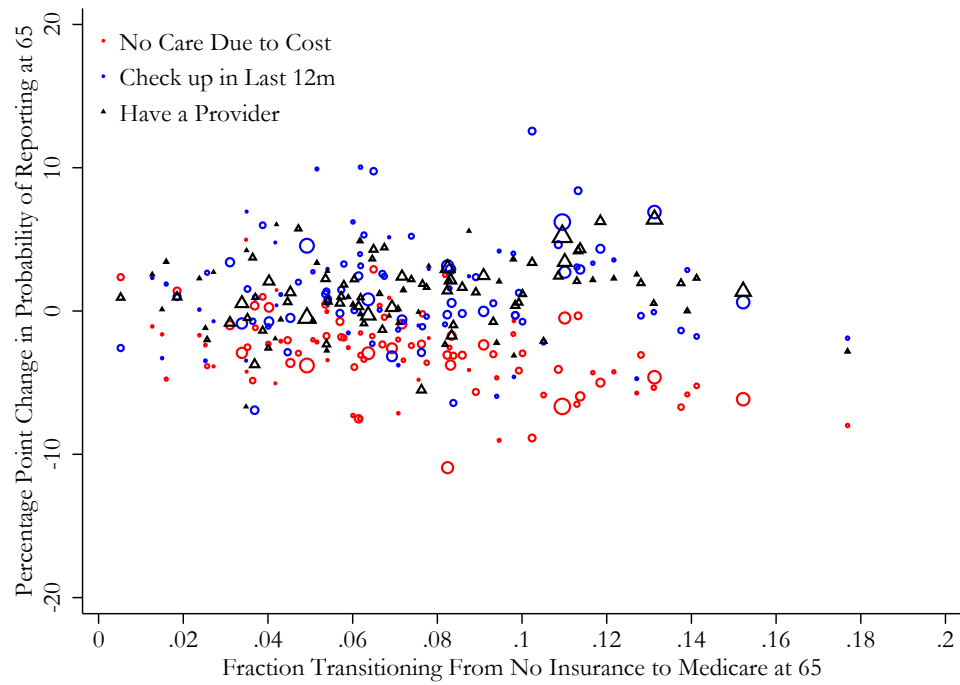


Notes: These estimates are for the insured to Medicare transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

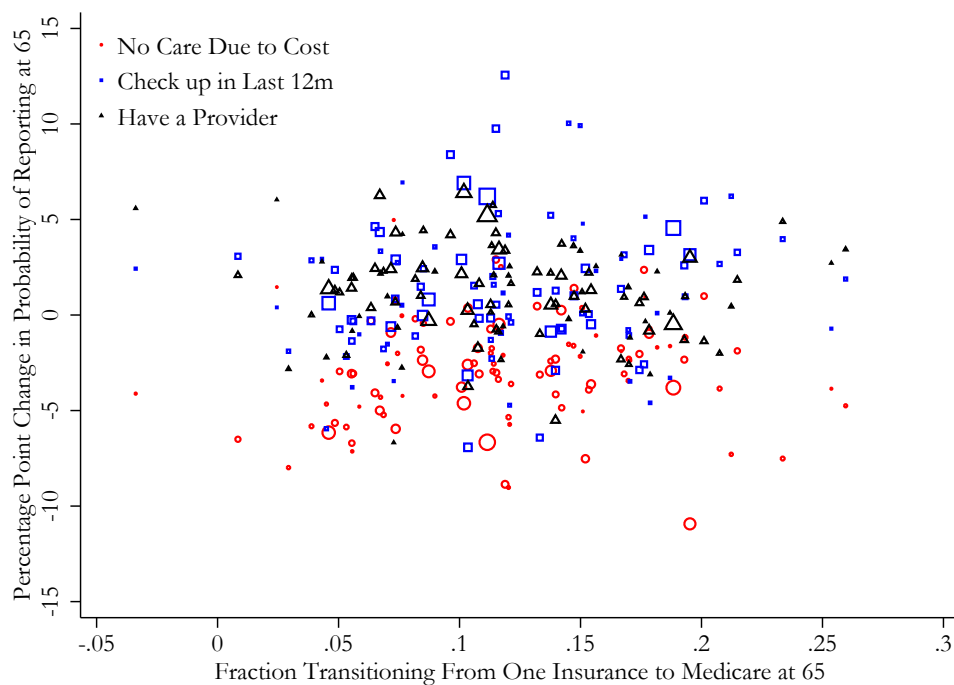
FIGURE A20. ROBUSTNESS TO BANDWIDTH: INSURED $\rightarrow$ MEDICARE AND SECOND PAYER



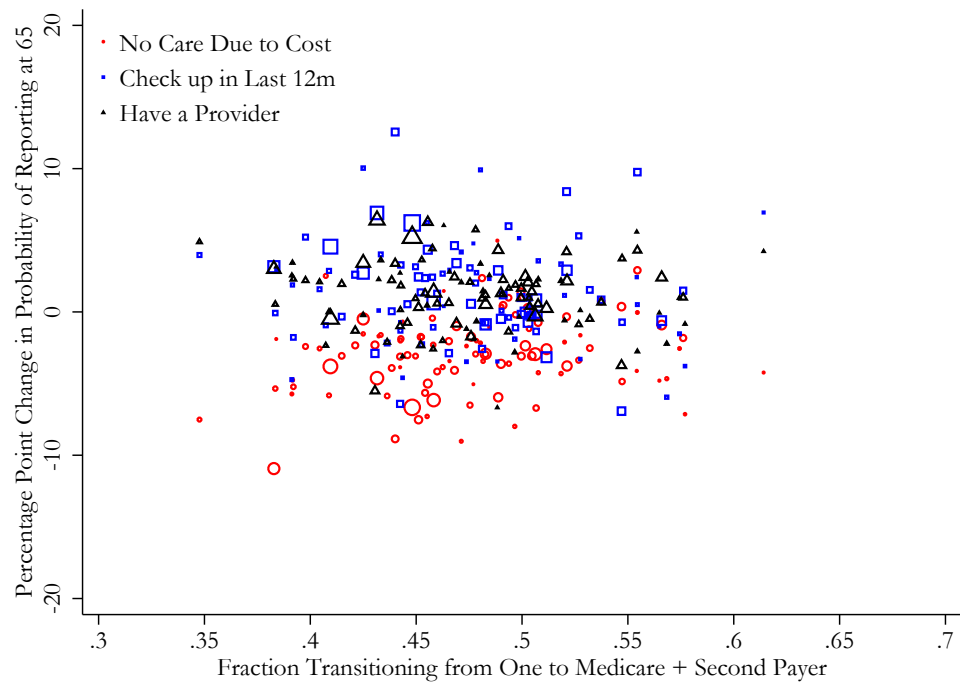
Notes: These estimates are for the insurance to Medicare and second payer transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A21. INSURANCE TRANSITION: NONE $\rightarrow$ MEDICARE

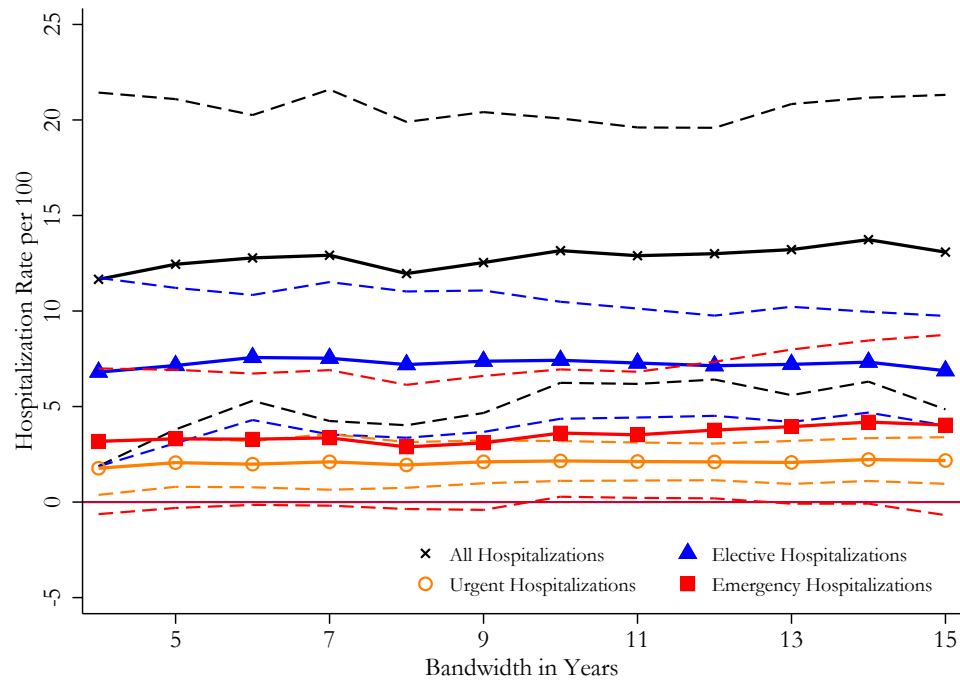
Notes: Data from ACS and BRFSS. Each marker corresponds to a state and time period and the marker size reflects the sample size for the state and time period.

FIGURE A22. INSURANCE TRANSITION: ONE $\rightarrow$ MEDICARE

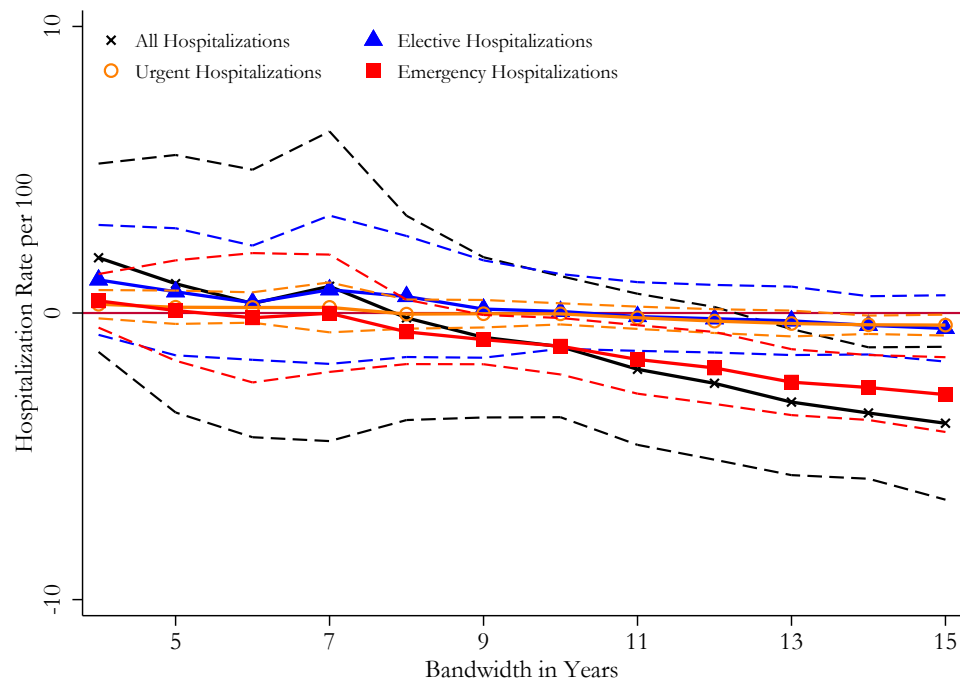
Notes: Data from ACS and BRFSS. Each marker corresponds to a state and time period and the marker size reflects the sample size for the state and time period.

FIGURE A23. INSURANCE TRANSITION: ONE $\rightarrow$ MEDICARE + 2ND PAYER

Notes: Data from ACS and BRFSS. Each marker corresponds to a state and time period and the marker size reflects the sample size for the state and time period.

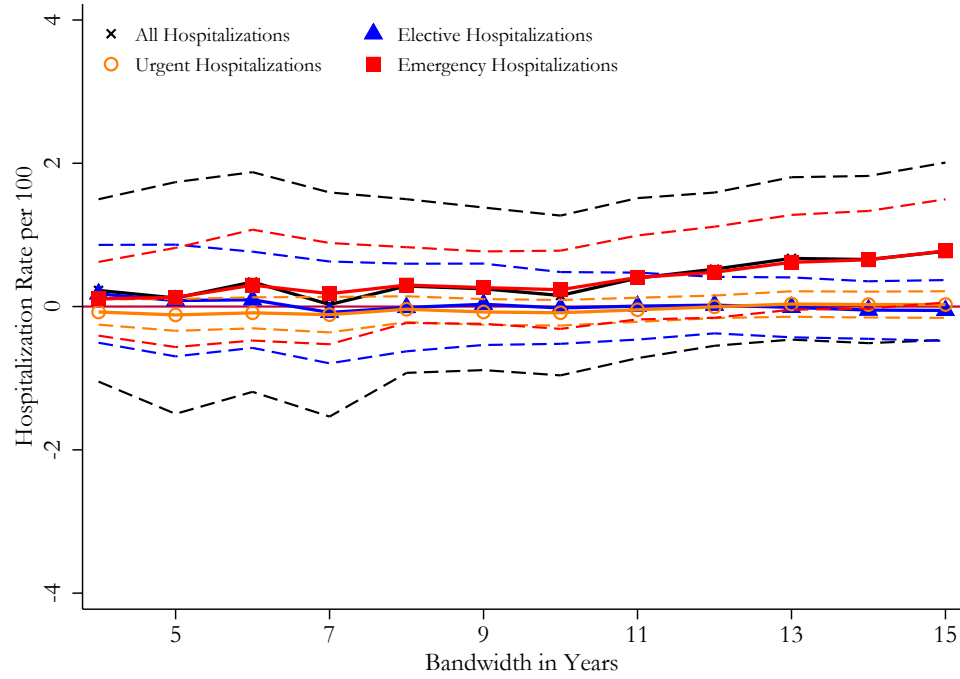
FIGURE A24. ROBUSTNESS TO BANDWIDTH: NO INSURANCE $\rightarrow$ MEDICARE

Notes: These estimates are for the no insurance to Medicare transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A25. ROBUSTNESS TO BANDWIDTH: INSURED $\rightarrow$ MEDICARE

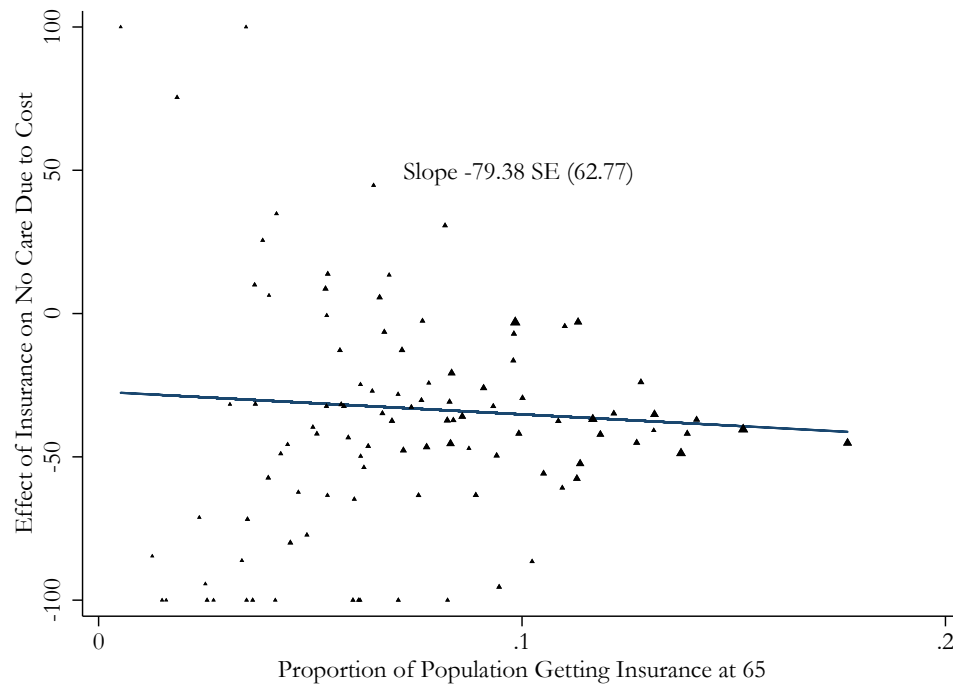
Notes: These estimates are for the insured to Medicare transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A26. ROBUSTNESS TO BANDWIDTH: INSURED $\rightarrow$ MEDICARE AND SECOND PAYER



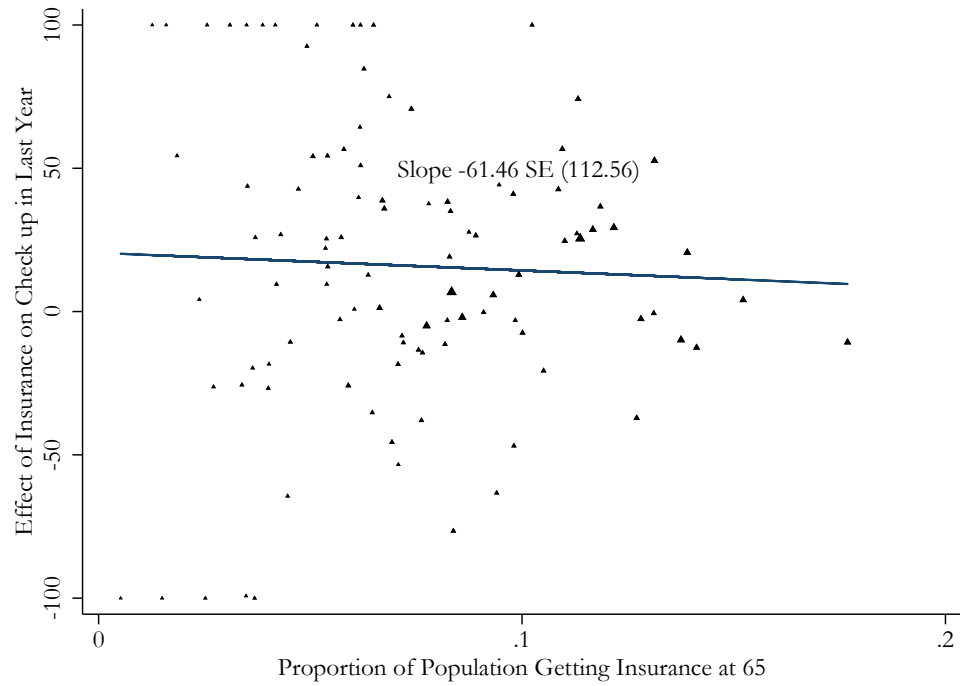
Notes: These estimates are for the insurance to Medicare and second payer transition. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A27. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



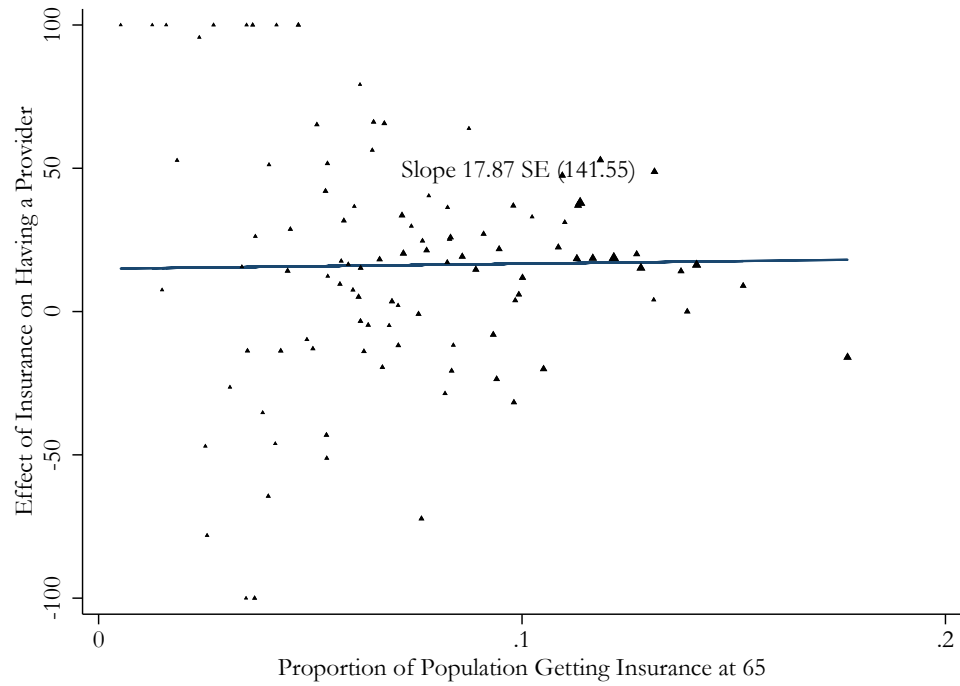
Notes: Effects greater than 100 have been set to 100 after line is fit.

FIGURE A28. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



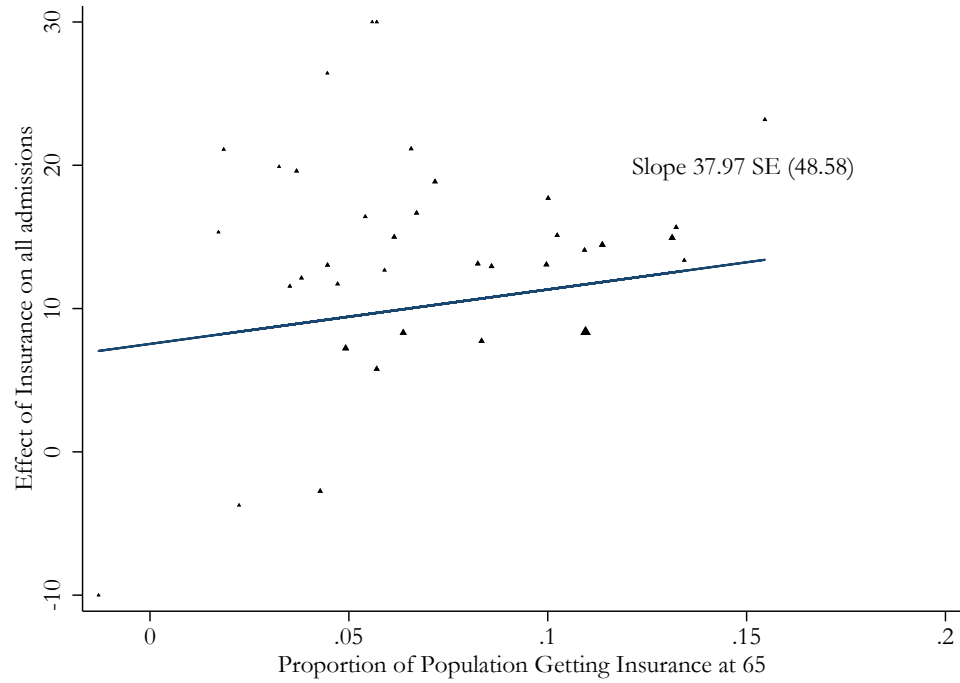
Notes: Effects greater than 100 have been set to 100 after line is fit.

FIGURE A29. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



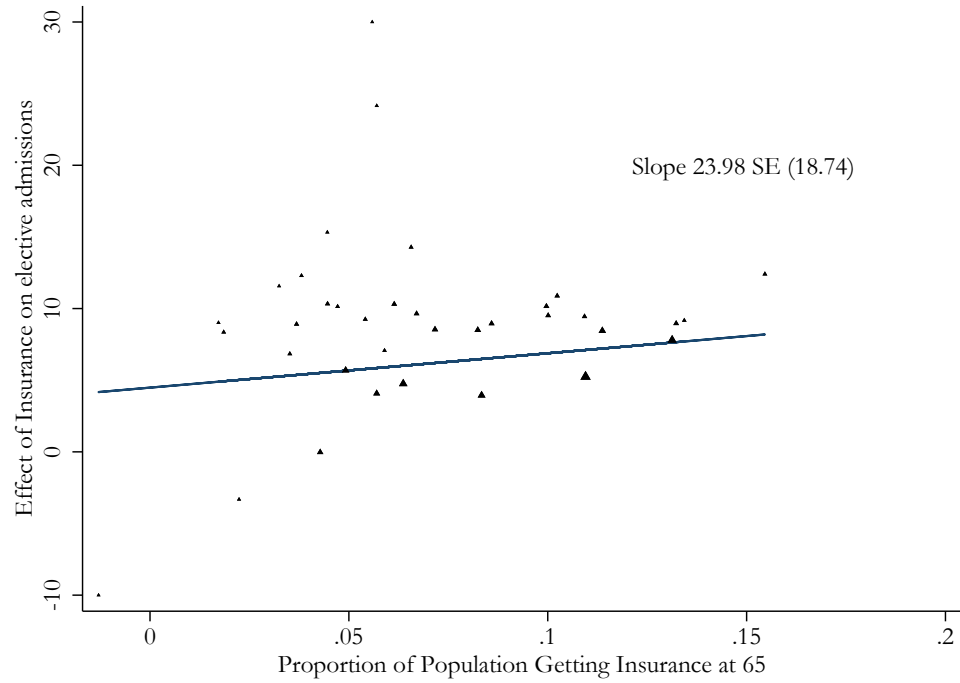
Notes: Effects greater than 100 have been set to 100 after line is fit.

FIGURE A30. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



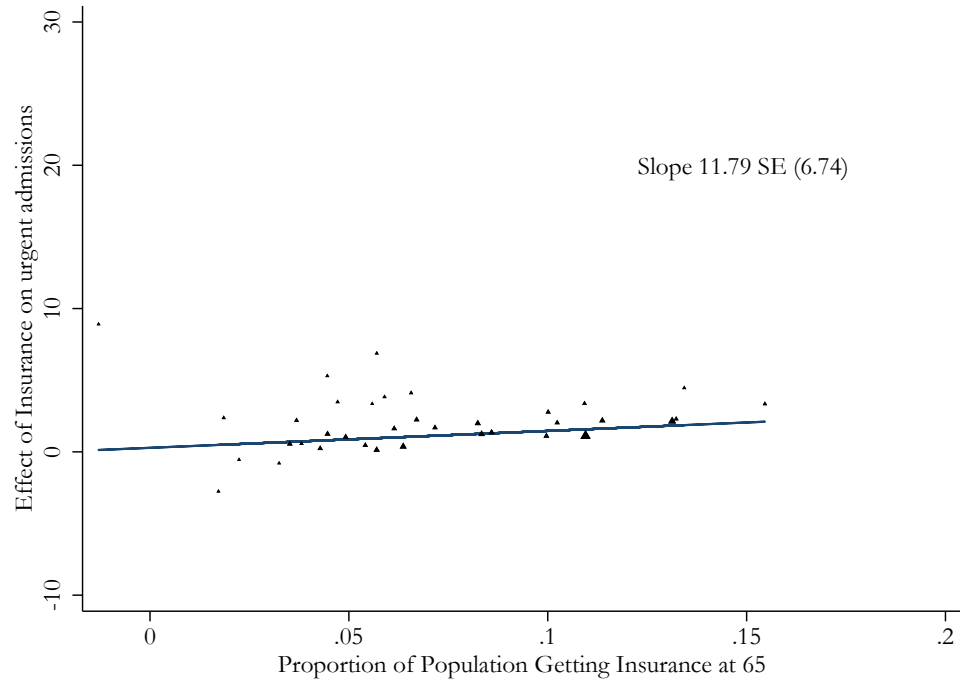
Notes: Effects greater than 30 and less than -10 have been set to 3000 and 1000 respectively after the line is fit.

FIGURE A31. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



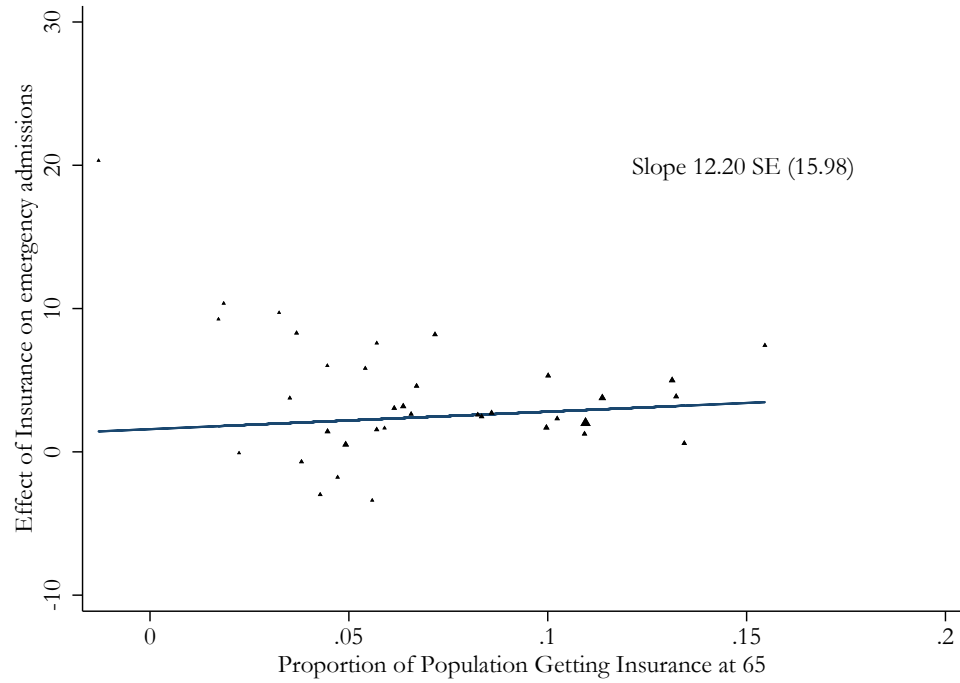
Notes: Effects greater than 30 and less than -10 have been set to 3000 and 1000 respectively after the line is fit.

FIGURE A32. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



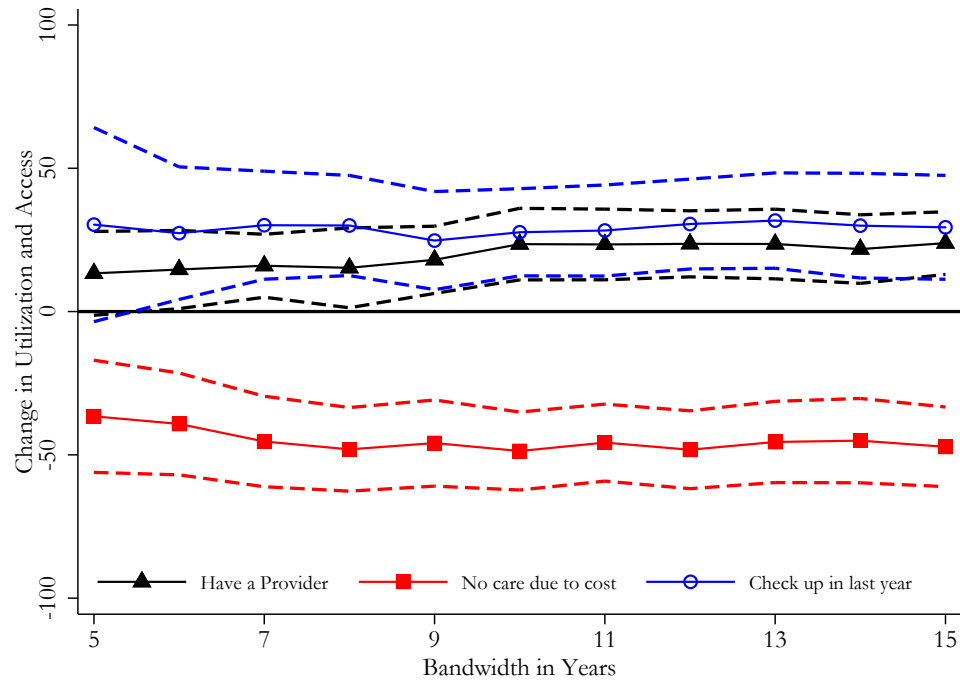
Notes: Effects greater than 30 and less than -10 have been set to 3000 and 1000 respectively after the line is fit.

FIGURE A33. VARIATION IN EFFECT OF GAINING INSURANCE BY FRACTION GAINING INSURANCE IN STATE



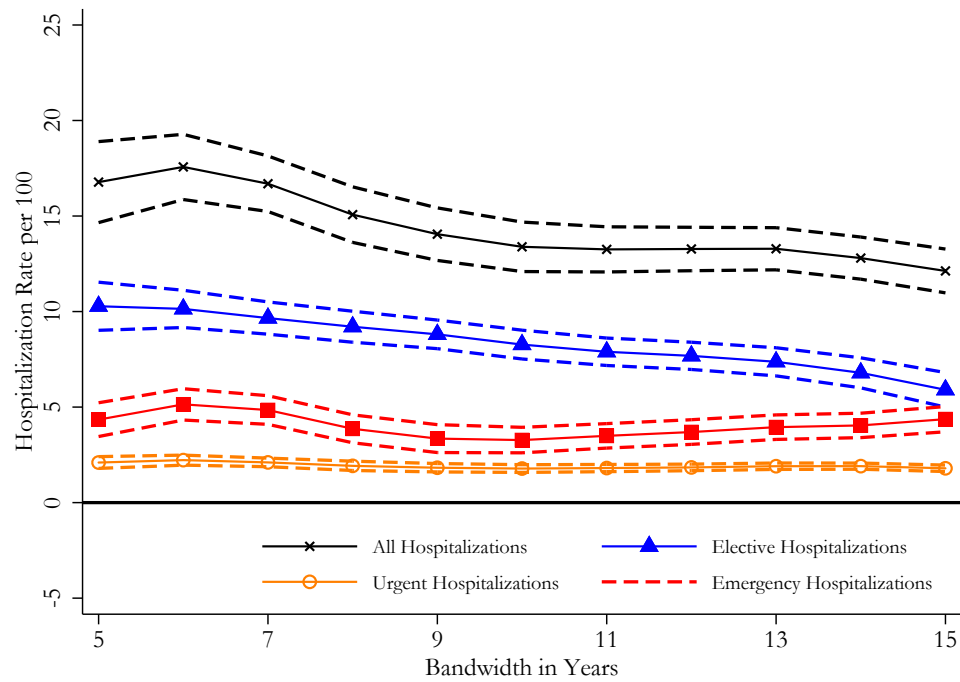
Notes: Effects greater than 30 and less than -10 have been set to 3000 and 1000 respectively after the line is fit.

FIGURE A34. ROBUSTNESS TO BANDWIDTH: EFFECT OF INSURANCE TWO SAMPLE IV



Notes: These estimates are from a two sample IV approach with the first stage change in insurance from the ACS and the access measures from the BRFSS. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

FIGURE A35. ROBUSTNESS TO BANDWIDTH: EFFECT OF INSURANCE TWO SAMPLE IV



Notes: These estimates are from a two sample IV approach with the first stage change in insurance from the ACS and the access measures from administrative hospital records. The solid lines with the markers are the point estimates and the dashed lines are the confidence intervals.

TABLE A1—ESTIMATED HEALTH INSURANCE TRANSITION RATES WITH MEPS, AGE 62-63 PLACEBO TRANSITION

		Age 63			
		None	One, Not Medicare	Medicare	Two or More
	None	12.0	2.0	0.1	0.0
Age 62	One, Not Medicare	0.9	68.7	0.1	0.9
	Medicare	0.0	0.0	4.7	0.4
	Two or More	0.0	0.2	0.5	9.6

Notes: Transition percentages estimated from the Medical Expenditure Panel Survey (MEPS) as in Table 2, but between the ages of 62 and 63.

TABLE A2—COMPARISON OF ESTIMATED HEALTH INSURANCE TRANSITION RATES PRE VS POST ACA

		Age 65				
		ACA	None	One, Not Medicare	Medicare	Two or More
Age 64	None	Pre	1.5	0.0	9.8	0.0
		Post	1.4	0.0	5.7	0.0
	One, Not Medicare	Pre	0.0	6.0	9.2	48.1
		Post	0.0	7.9	15.4	45.8
	Medicare	Pre	0.0	0.0	5.7	0.0
		Post	0.0	0.0	6.5	0.0
	Two or More	Pre	0.0	0.0	0.0	19.7
		Post	0.0	0.0	0.0	17.4

Notes: Transition percentages are obtained using the estimation method described in the Section II. The estimates are for all states and the District of Columbia 2008-2017.

TABLE A3—COMPARISON OF ESTIMATED HEALTH INSURANCE TRANSITION RATES POST ACA (EXPANDERS VS NON EXPANDERS)

			Age 65			
			None	One, Not Medicare	Medicare	Two or More
Age 64	None	Expand	1.3	0.0	4.5	0.0
		Didn't Expand	1.7	0.0	8.3	0.0
	One, Not Medicare	Expand	0.0	8.5	15.9	47.0
		Didn't Expand	0.0	6.6	14.2	43.1
	Medicare	Expand	0.0	0.0	5.9	0.0
		Didn't Expand	0.0	0.0	7.8	0.0
	Two or More	Expand	0.0	0.0	0.0	16.9
		Didn't Expand	0.0	0.0	0.0	18.4

Notes: ACS transition percentages are obtained using the estimation method described in the Section II.

TABLE A4—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE (WITHIN STATE VARIATION)

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-60.7 (29.1) [0.363]	24.4 (39.6) [0.999]	-10.8 (32.4) [0.999]	10.7 (4.0) [0.319]	5.5 (1.9) [0.319]	0.98 (0.63) [0.819]	3.9 (2.7) [0.819]
Insured → Medicare	-21.6 (27.3) [0.999]	-10.5 (17.5) [0.999]	-16.6 (20.2) [0.999]	-1.3 (2.0) [0.999]	-0.17 (0.93) [0.999]	-0.34 (0.32) [0.999]	-0.87 (1.36) [0.999]
Insured → Medicare + 2nd Payer	7.0 (9.9) [0.999]	3.8 (9.6) [0.999]	10.0 (7.8) [0.857]	1.4 (1.5) [0.999]	1.1 (0.7) [0.819]	0.34 (0.23) [0.819]	0.13 (1.01) [0.999]
F test (quadratics and interactions)	1.07 0.3979	0.28 0.9430	0.47 0.8247	1.47 0.3457	1.11 0.4647	0.12 0.9878	0.64 0.6984
Mean Age 64							
Uninsured	36.7	64.4	54.7	4.9	0.48	0.43	4.0
Insured	7.9	93.6	82.7	15.1	3.8	1.7	9.5
All	10.8	90.5	79.8	13.9	3.4	1.6	8.8
Observations							
State Cells	102	102	102	36	36	36	36
American Community Survey	7,125,102	7,125,102	7,125,102	3,157,108	3,157,108	3,157,108	3,157,108
BRFSS/Hospitalizations	1,803,710	1,803,226	1,790,630	41,865,902	10,253,559	4,836,319	26,571,641

Notes: Estimates on data collapsed pre and post ACA weighted by population ages 55 to 75. The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors. For context the estimated hospitalization rate at age 64 for each group (from MEPS) None → Medicare: 7.7; Insured → Medicare: 9.0; Insured → Medicare + Second Payer: 18.0. The p-value of the F-test is presented directly below the F-Statistic.

TABLE A5—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE (PRE ACA)

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-54.9 (9.4) [0.001]	33.9 (14.6) [0.082]	36.7 (17.3) [0.085]	12.9 (4.8) [0.074]	7.2 (1.7) [0.011]	2.3 (0.9) [0.074]	3.4 (2.62) [0.286]
Insured → Medicare	-7.9 (11.0) [0.385]	21.6 (13.4) [0.174]	42.2 (17.2) [0.074]	-4.4 (4.3) [0.315]	-1.2 (2.0) [0.421]	-0.58 (0.84) [0.385]	-2.5 (2.1) [0.315]
Insured → Medicare + 2nd Payer	4.7 (3.2) [0.206]	-6.1 (3.8) [0.174]	-10.4 (4.7) [0.082]	0.88 (1.1) [0.385]	0.27 (0.53) [0.446]	-0.002 (0.180) [0.647]	0.56 (0.53) [0.315]
F test (quadratics and interactions)	0.88 0.5167	0.49 0.8123	1.77 0.1296	2.79 0.0571	2.05 0.1302	3.47 0.0284	1.14 0.3924
Observations							
State Cells	51	51	51	22	22	22	22
American Community Survey	4,034,651	4,034,651	4,034,651	1,911,664	1,911,664	1,911,664	1,911,664
BRFSS/Hospitalizations	1053347	1,053,314	1,045,761	26,250,300	6,601,289	3,176,848	16,342,508

Notes: Estimates on data collapsed pre ACA weighted by population ages 55 to 75. The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors. For context the estimated hospitalization rate at age 64 for each group (from MEPS) None → Medicare: 7.7; Insured → Medicare: 9.0; Insured → Medicare + Second Payer: 18.0. The p-value of the F-test is presented directly below the F-Statistic.

TABLE A6—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE (BETWEEN STATE VARIATION)

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-51.7 (16.3) [0.008]	26.1 (8.4) [0.008]	33.8 (10.7) [0.008]	14.6 (4.1) [0.008]	8.4 (1.4) [0.001]	2.7 (0.75) [0.008]	3.5 (2.4) [0.132]
Insured → Medicare	-22.8 (10.0) [0.033]	15.7 (7.4) [0.046]	43.8 (12.2) [0.007]	-2.5 (3.7) [0.337]	-0.93 (1.81) [0.394]	-0.50 (0.61) [0.323]	-1.1 (1.6) [0.337]
Insured → Medicare + 2nd Payer	7.4 (2.8) [0.015]	-5.0 (2.7) [0.071]	-12.7 (3.4) [0.007]	0.31 (0.95) [0.448]	0.11 (0.46) [0.448]	-0.04 (0.14) [0.448]	0.22 (0.45) [0.394]
F test (quadratics and interactions)	0.73 0.6286	0.24 0.9591	0.86 0.5285	1.00 0.4640	1.67 0.2014	0.88 0.5361	0.64 0.6993
Mean Age 64							
Uninsured	36.7	64.4	54.7	4.9	0.48	0.43	4.0
Insured	7.9	93.6	82.7	15.1	3.8	1.7	9.5
All	10.8	90.5	79.8	13.9	3.4	1.6	8.8
Observations							
State Cells	51	51	51	23	23	23	23
American Community Survey	7,125,102	7,125,102	7,125,102	3,157,108	3,157,108	3,157,108	3,157,108
BRFSS/Hospitalizations	1,803,710	1,803,226	1,790,630	41,865,902	10,253,559	4,836,319	26,571,641

Notes: Estimates on data collapsed pre and post ACA weighted by population ages 55 to 75. The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors. For context the estimated hospitalization rate at age 64 for each group (from MEPS) None → Medicare: 7.7; Insured → Medicare: 9.0; Insured → Medicare + Second Payer: 18.0. The p-value of the F-test is presented directly below the F-Statistic.

TABLE A7—EFFECT OF CHANGE IN INSURANCE COVERAGE ON ACCESS TO CARE (EIV)

	No Care Due to Cost	Have a Medical Provider	Checkup in the Past Year	Hospitalizations per 100			
				All	Elective	Urgent	Emergency
None → Medicare	-58.6 (11.0) [0.001]	35.0 (11.4) [0.004]	45.6 (13.6) [0.003]	13.9 (2.9) [0.001]	7.8 (1.6) [0.001]	2.3 (0.45) [0.001]	3.8 (1.2) [0.004]
Insured → Medicare	-23.8 (9.9) [0.019]	2.8 (6.0) [0.514]	27.9 (8.2) [0.003]	-1.6 (1.4) [0.195]	-0.11 (0.66) [0.546]	-0.08 (0.25) [0.546]	-1.4 (0.7) [0.040]
Insured → Medicare + 2nd Payer	8.8 (3.6) [0.018]	-3.2 (2.6) [0.179]	-10.7 (3.5) [0.004]	0.15 (0.55) [0.546]	-0.04 (0.25) [0.546]	-0.09 (0.09) [0.234]	0.25 (0.26) [0.234]
Mean Age 64							
Uninsured	36.7	64.4	54.7	4.9	0.48	0.43	4.0
Insured	7.9	93.6	82.7	15.1	3.8	1.7	9.5
All	10.8	90.5	79.8	13.9	3.4	1.6	8.8
Observations							
State Cells	102	102	102	36	36	36	36
American Community Survey	7,125,102	7,125,102	7,125,102	3,157,108	3,157,108	3,157,108	3,157,108
BRFSS/Hospitalizations	1,803,710	1,803,226	1,790,630	41,865,902	10,253,559	4,836,319	26,571,641

Notes: The outcomes in the first three columns are from the BRFSS and are scaled so they can be interpreted as percentage point changes. Standard errors are in parentheses below the point estimates, and false discovery rate adjusted p-values that control FDR for the entire table are presented in square brackets below the standard errors. For context the estimated hospitalization rate at age 64 for each group (from MEPS) None → Medicare: 7.7; Insured → Medicare: 9.0; Insured → Medicare + Second Payer: 18.0.

TABLE A8—EFFECT OF INSURANCE ON HOSPITALIZATION RATES BY DRG FAMILY WITH LARGEST GROWTH IN EMERGENCY ADMISSIONS

DRG Description	DRGs	All	Elective	Urgent	Emergency
All DRGs (All Admissions)		13.4 (0.64)	8.3 (0.37)	1.8 (0.10)	3.3 (0.33)
Septicemia or severe sepsis	870-872	0.289 (0.046) 0.612	0.020 (0.007) 0.013	0.039 (0.012) 0.059	0.228 (0.041) 0.540
Cardiac arrhythmia & conduction disorders	308-310	0.271 (0.032) 0.332	0.030 (0.008) 0.023	0.042 (0.010) 0.040	0.197 (0.028) 0.268
Renal failure	682-684	0.194 (0.036) 0.290	0.009 (0.005) 0.011	0.018 (0.011) 0.034	0.167 (0.033) 0.244
Esophagitis, gastroent & misc digest disorders	391-392	0.248 (0.046) 0.387	0.023 (0.007) 0.015	0.066 (0.011) 0.046	0.157 (0.044) 0.326
Psychoses	885	0.356 (0.043) 0.278	0.044 (0.010) 0.029	0.163 (0.020) 0.094	0.146 (0.028) 0.153
Circulatory disorders except AMI, w card cath	286-287	0.241 (0.028) 0.215	0.056 (0.008) 0.020	0.038 (0.008) 0.029	0.146 (0.024) 0.166
G.I. hemorrhage	377-379	0.142 (0.031) 0.236	0.005 (0.005) 0.007	0.029 (0.008) 0.025	0.108 (0.027) 0.204
Respiratory infections & inflammations	177-179	0.107 (0.019) 0.088	0.001 (0.003) 0.004	0.007 (0.007) 0.012	0.098 (0.018) 0.072
Cholecystectomy	411-419	0.171 (0.025) 0.151	0.054 (0.011) 0.022	0.023 (0.007) 0.018	0.093 (0.019) 0.112
Chronic obstructive pulmonary disease	190-192	0.130 (0.051) 0.532	0.032 (0.008) 0.019	0.010 (0.015) 0.061	0.086 (0.044) 0.451
Simple pneumonia & pleurisy	193-195	0.112 (0.032) 0.341	0.013 (0.006) 0.013	0.022 (0.013) 0.041	0.077 (0.032) 0.287
Other digestive system diagnoses	393-395	0.088 (0.020) 0.118	0.009 (0.004) 0.007	0.008 (0.008) 0.015	0.071 (0.018) 0.096
Major gastrointestinal disorders & peritoneal infections	371-373	0.079 (0.021) 0.072	0.001 (0.003) 0.003	0.009 (0.007) 0.010	0.068 (0.017) 0.059
Complications of treatment	919-921	0.085 (0.013) 0.053	0.010 (0.004) 0.005	0.017 (0.005) 0.009	0.059 (0.010) 0.038

Notes: Single-channel IV estimates for the None → Medicare channel for the Diagnosis Related Groups that had the largest increases in elective admissions at age 65. The first row of each block contains the estimate of the increase in admissions per 100 people that transitioned from not having to having insurance at 65. The standard errors are in parenthesis below the point estimates and the final row in each block presents the admission rate per 100 people at age 64 regardless of insurance status. The first row contains estimates for all DRGs as shown in Table 4.

TABLE A9—EFFECT OF INSURANCE ON HOSPITALIZATION RATES BY DRG FAMILY WITH LARGEST GROWTH IN ELECTIVE ADMISSION

DRG Description	DRGs	All	Elective	Urgent	Emergency
All DRGs (All Admissions)		13.4 (0.64)	8.3 (0.37)	1.8 (0.10)	3.3 (0.33)
Major joint replacement or reattachment of lower extremity	469-470	2.680 (0.190) 0.923	2.495 (0.182) 0.861	0.130 (0.011) 0.029	0.051 (0.012) 0.032
Major male pelvic procedures	707-708	0.346 (0.031) 0.110	0.330 (0.030) 0.105	0.013 (0.003) 0.004	0.002 (0.001) 0.001
Major small & large bowel procedures	329-331	0.410 (0.039) 0.222	0.330 (0.033) 0.130	0.039 (0.007) 0.018	0.039 (0.014) 0.073
Spinal fusion	456-460	0.301 (0.027) 0.163	0.278 (0.027) 0.149	0.023 (0.005) 0.006	0.001 (0.005) 0.008
Cervical spinal fusion	471-473	0.268 (0.020) 0.087	0.257 (0.019) 0.077	0.009 (0.003) 0.004	0.002 (0.004) 0.006
Perc cardiovasc proc	246-251	0.386 (0.037) 0.400	0.250 (0.016) 0.093	0.100 (0.015) 0.061	0.030 (0.028) 0.244
O.R. procedures for obesity	619-621	0.248 (0.021) 0.044	0.234 (0.021) 0.042	0.012 (0.002) 0.002	0.002 (0.001) 0.000
Coronary bypass	231-236	0.302 (0.024) 0.125	0.224 (0.017) 0.065	0.061 (0.008) 0.017	0.016 (0.010) 0.042
Extracranial procedures	37-39	0.206 (0.020) 0.070	0.194 (0.018) 0.055	0.010 (0.004) 0.004	0.002 (0.005) 0.010
Other vascular procedures	252-254	0.221 (0.030) 0.140	0.185 (0.017) 0.065	0.021 (0.009) 0.020	0.010 (0.015) 0.055
Uterine & adnexa proc for non-malignancy	742-743	0.167 (0.021) 0.074	0.159 (0.020) 0.068	0.009 (0.003) 0.004	-0.001 (0.003) 0.003
Back & neck proc exc spinal fusion	490-491	0.138 (0.018) 0.076	0.145 (0.017) 0.065	0.005 (0.004) 0.004	-0.012 (0.004) 0.007
Cardiac valve & oth maj cardiothoracic proc	216-221	0.161 (0.019) 0.079	0.135 (0.017) 0.057	0.014 (0.005) 0.007	0.013 (0.008) 0.014
Rehabilitation	945-946	0.194 (0.017) 0.084	0.135 (0.014) 0.057	0.043 (0.008) 0.021	0.013 (0.004) 0.004
Bilateral or multiple major joint procs of lower extremity	461-462	0.126 (0.016) 0.029	0.119 (0.015) 0.028	0.005 (0.002) 0.001	0.002 (0.001) 0.000

Notes: Single-channel IV estimates for the None → Medicare channel for the Diagnosis Related Groups that had the largest increases in elective admissions at age 65. The first row of each block contains the estimate of the increase in admissions per 100 people that transitioned from not having to having insurance at 65. The standard errors are in parenthesis below the point estimates and the final row in each block presents the admission rate per 100 people at age 64 regardless of insurance status. The first row contains estimates for all DRGs as shown in Table 4.

TABLE A10—EFFECT OF INSURANCE ON HOSPITALIZATION RATES BY DRG FAMILY WITH LARGEST GROWTH IN URGENT ADMISSIONS

DRG Description	DRGs	All	Elective	Urgent	Emergency
All DRGs (All Admissions)		13.4 (0.64)	8.3 (0.37)	1.8 (0.10)	3.3 (0.33)
Psychoses	885	0.356 (0.043) 0.278	0.044 (0.010) 0.029	0.163 (0.020) 0.094	0.146 (0.028) 0.153
Major joint replacement or reattachment of lower extremity	469-470	2.680 (0.190) 0.923	2.495 (0.182) 0.861	0.130 (0.011) 0.029	0.051 (0.012) 0.032
Perc cardiovasc proc	246-251	0.386 (0.037) 0.400	0.250 (0.016) 0.093	0.100 (0.015) 0.061	0.030 (0.028) 0.244
Alcohol/drug abuse or dependence	894-897	0.137 (0.029) 0.131	0.062 (0.008) 0.018	0.089 (0.009) 0.022	-0.013 (0.023) 0.090
Esophagitis, gastroent & misc digest disorders	391-392	0.248 (0.046) 0.387	0.023 (0.007) 0.015	0.066 (0.011) 0.046	0.157 (0.044) 0.326
Coronary bypass	231-236	0.302 (0.024) 0.125	0.224 (0.017) 0.065	0.061 (0.008) 0.017	0.016 (0.010) 0.042
Rehabilitation	945-946	0.194 (0.017) 0.084	0.135 (0.014) 0.057	0.043 (0.008) 0.021	0.013 (0.004) 0.004
Cardiac arrhythmia & conduction disorders	308-310	0.271 (0.032) 0.332	0.030 (0.008) 0.023	0.042 (0.010) 0.040	0.197 (0.028) 0.268
Septicemia or severe sepsis	870-872	0.289 (0.046) 0.612	0.020 (0.007) 0.013	0.039 (0.012) 0.059	0.228 (0.041) 0.540
Major small & large bowel procedures	329-331	0.410 (0.039) 0.222	0.330 (0.033) 0.130	0.039 (0.007) 0.018	0.039 (0.014) 0.073
Circulatory disorders except AMI, w card cath	286-287	0.241 (0.028) 0.215	0.056 (0.008) 0.020	0.038 (0.008) 0.029	0.146 (0.024) 0.166
Heart failure & shock	291-293	0.098 (0.036) 0.439	0.012 (0.006) 0.014	0.035 (0.012) 0.046	0.048 (0.035) 0.379
G.I. hemorrhage	377-379	0.142 (0.031) 0.236	0.005 (0.005) 0.007	0.029 (0.008) 0.025	0.108 (0.027) 0.204
Major chest procedures	163-165	0.116 (0.018) 0.084	0.091 (0.016) 0.064	0.024 (0.004) 0.005	0.001 (0.006) 0.014
Postoperative & post-traumatic infections	862-863	0.076 (0.014) 0.055	0.004 (0.004) 0.006	0.023 (0.006) 0.012	0.049 (0.012) 0.038

Notes: Single-channel IV estimates for the None → Medicare channel for the Diagnosis Related Groups that had the largest increases in elective admissions at age 65. The first row of each block contains the estimate of the increase in admissions per 100 people that transitioned from not having to having insurance at 65. The standard errors are in parenthesis below the point estimates and the final row in each block presents the admission rate per 100 people at age 64 regardless of insurance status. The first row contains estimates for all DRGs as shown in Table 4.