The Impact of the Affordable Care Act: Evidence from California's Hospital Sector

Preliminary and Incomplete

Mark Duggan
Stanford University and NBER
mgduggan@stanford.edu

Atul Gupta
University of Pennsylvania, The Wharton School
atulgup@wharton.upenn.edu

Emilie Jackson
Stanford University
emilyj91@stanford.edu

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Abstract

The Affordable Care Act (ACA) authorized the largest expansion of public health insurance coverage in decades. Evidence on the effects of the ACA on utilization of medical care, patient health and on health care providers is still emerging. We deploy administrative data from hospitals and emergency rooms in California over 2008-15 and present new empirical evidence on these outcomes. Our identification strategy exploits sharp discontinuities in Medicaid coverage at ages 21 and 65, where a large share of individuals historically became ineligible for the program. These discontinuities were significantly affected by the implementation of the ACA, creating additional exogenous variation in Medicaid eligibility. We find evidence of substantial crowd-out of county insurance programs – implying a large transfer from federal taxpayers to local governments. We estimate a large increase in the rate of hospital and ER use due to insurance coverage among the near-elderly – at least two times greater than that predicted by individual Medicaid access changes. Insurance coverage leads to patient sorting toward privately owned and better quality hospitals, creating a gain in utility equivalent to cutting travel distance by 4 miles. However, we find only suggestive improvements in patient health. Financial benefits for hospitals are more readily apparent. Hospitals previously serving a high share of uninsured patients benefit disproportionately with a 10% increase in total revenue relative to remaining hospitals.

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I. INTRODUCTION

The Patient Protection and Affordable Care Act (ACA) was signed into law in March 2010 and authorized the largest expansion of publicly funded health insurance coverage since the introduction of Medicare and Medicaid in the 1960s. The main provisions of this legislation took effect on January 1, 2014, with Medicaid enrollment increasing by 18 million since then, about thirty percent of enrollment in 2013. Enrollment in federally subsidized private health insurance exchanges now exceeds 12 million.[1] The Congressional Budget Office estimates that ACA-mandated subsidies will cost the federal government $120 billion in 2017 (CBO, 2017). This is a unique modern setting to quantify the causal effects of public insurance coverage on health care utilization and patient health as well as examine general equilibrium effects of such a large intervention on the health care sector.

We use data on the universe of hospital stays and ER visits in California from 2008 through 2015. Our primary empirical approach exploits sharp discontinuities in public insurance coverage at ages 21 and 65 (see figure 1a) which occur due to Medicaid eligibility rules. Pre-ACA, eligibility restrictions caused a large share of beneficiaries to lose Medicaid coverage when they reached either of these age thresholds.[2] For the young, the drop in Medicaid coverage led to an increase in uninsurance, while the near-elderly gained insurance coverage due to the onset of nearly universal Medicare. The pre-ACA period itself offers a standalone quasi-experimental setting to examine the effects of gaining Medicare (at 65) and losing Medicaid (at 21) using a regression discontinuity (RD) approach, similar to previous studies (Card et al., 2008; 2009; Dobkin et al., 2012; 2014).

The ACA substantially relaxed Medicaid eligibility restrictions for all non-elderly individuals in California, leading to large increases in Medicaid coverage for both the young and near-elderly introducing further variation in eligibility that we exploit as an additional source of identification. This offers a second quasi-experiment – where individuals aged 21-64 experienced a greater change in Medicaid coverage due to the ACA, relative to individuals under 21 or 65 and older – allowing us to quantify the effects of gaining Medicaid *specifically*. We estimate these effects using an RD differences-in-differences (RD-DD) research design. Estimates from the two experiments typically reinforce each other, making the evidence on the effects of insurance coverage more compelling. Finally, we use these age thresholds and their interaction with ACA implementation as instruments to predict coverage in an instrumental variable approach to

[1] Medicaid enrollment obtained from Centers for Medicare and Medicaid Services (CMS), available at https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights/total-enrollment/index.html. ACA marketplace enrollment obtained from Kaiser Family Foundation (KFF).

[2] A small share of individuals retain Medicaid coverage post-65 because they are eligible for both Medicaid and Medicare. Medicare is the primary insurer in these cases.

estimate the causal effects of gaining insurance coverage. By examining the young and near-elderly independently, we are able to shed light on the heterogeneous effects of the insurance expansions.

First, we focus on understanding the changes in insurance coverage following the implementation of the ACA. RD estimates indicate that the decrease in uninsurance is lower than the increase in Medicaid coverage at both age thresholds, implying there is some crowd-out of other forms of coverage. We find that Medicaid has mainly crowded out coverage provided by counties to low income patients. About 40-50% of the increase in Medicaid coverage for the young and the near-elderly replaces existing county programs, implying that much of the incremental spending by Medicaid on hospital care was a transfer from federal taxpayers to local and state taxpayers in California. In the case of the near-elderly we also find a sizeable crowd-out of private insurance. Overall, back-of-the-envelope calculations suggest that only about one-third of spending on the expansion financed a decrease in hospital care costs for the uninsured.

Next, we test if utilization of hospital care changes for patients in these age groups. The net effects of coverage on utilization are not obvious ex-ante. A decrease in patient cost sharing may spur greater use of health care while improved access to preventative and outpatient care may decrease the need for hospital care. This has been referred to as the access vs. efficiency tradeoff (Dafny and Gruber, 2005). We find that the access effect dominates for the near-elderly – our IV estimates imply that a 10% increase in insurance coverage causes nearly a 10-15% increase in the rate of hospital care. In contrast, we find little or no utilization effects for young adults. Our RD estimates for the near-elderly closely match those of Card et al. (2008) who examined the effects of universal Medicare coverage at age 65. However, our results indicate a much greater increase in demand for hospital care in response to Medicaid, relative to partial equilibrium studies such as Finkelstein et al. (2012), who find an increase that is about one-third as large.[3]

In addition to a change in the quantity of hospital care, we find robust evidence that insurance coverage causes a switch in the type and quality of hospital at which patients receive care. The IV estimates imply that young (near-elderly) adults are 10 (30) % less likely to receive care at a government hospital when they gain insurance coverage. We interpret this to be mostly demand driven since we find similar magnitude of switching in ER use, which is less likely to be driven by physician counsel or insurer constraints. Furthermore, we find that patients are more likely to receive care at better quality (in terms of risk adjusted mortality rate) hospitals once they receive insurance coverage. This is particularly striking for the near-elderly who switch to a hospital with at least a 0.15 s.d. better mortality score on average. Based on estimates from previous studies, this is equivalent to the utility gain associated with moving 4 miles (25%) closer to the serving hospital (Tay, 2003). Traditionally, Medicaid has been valued based on its effects on mortality (Currie and Gruber 1996b; Card et al., 2009; Goodman-Bacon, 2016) or its

[3] Their appendix table A.26 reports that utilization for elderly aged 50-64 increased by 3% (for a 10% increase in insurance) due to Medicaid coverage. In comparison, we find a 10-15% increase in hospital care due to a 10% increase in coverage.

effectiveness in decreasing financial risk for beneficiaries (Finkelstein et al. 2015). However, Medicaid coverage also appears to enable switching to better quality providers, which may not be captured in mortality effects, and thus is an additional source of value that should be considered when considering the net benefit of the program.

We also examine patients' health directly and find suggestive evidence of improvements due to the insurance expansion. We use two metrics of health – in-hospital mortality and whether or not a hospital stay or ER visit was potentially avoidable with appropriate primary care. The latter helps indirectly infer improvements in access to appropriate primary care, which we do not observe – and which improves efficiency of health care delivery. The estimated effects on mortality are substantial but noisy and we cannot reject large effects in either direction. However, we do find evidence of dynamic improvement in mortality for the near-elderly, i.e. the relative decrease in mortality rates for 62-64 year olds is larger in 2015 than in 2014. The evidence on avoidable stays and ER visits also suffers from some contradictions although the IV estimates consistently suggest large decreases in the share of potentially avoidable in-hospital care.

Finally, we explore the economic impact of the insurance expansions on hospitals. The increase in coverage implied that most hospitals received greater average reimbursement per patient relative to what they did pre-ACA.[4] Those hospitals that served a higher proportion of uninsured patients are likely to see a greater increase in mean reimbursement per patient, provided their patient profile does not change dramatically. We find supporting evidence – hospitals having uninsurance share in the top one-third of all hospitals in 2008 enjoyed a relative increase in total revenue on the order of $100,000 per bed (10% of baseline pre-ACA). This increase is entirely driven by an increase in Medicaid revenue of nearly fifty percent relative to the mean in 2013. We fail to find evidence on where the additional revenue is being deployed. For example, we find no increase in spending per patient (e.g. keeping patients longer or doing more procedures). We also do not find evidence of positive spillovers of quality of care to infra-marginal patients at these hospitals (e.g. infant mortality, elderly mortality). Of course, if the hospitals plan to use the additional revenue for capital investments and longer term improvement projects, we would not see the effects of this spending yet in the short post period that we examine.

We perform a series of robustness checks of the key assumptions we make in sample construction and model specifications, as well as a falsification check based on a placebo insurance expansion. Our core results remain valid under these tests. We also conduct a supplementary exercise using the sample of all non-elderly adults, exploiting geographic variation in pre-ACA uninsurance rates – and obtain qualitatively similar results. Nevertheless, there are four key limitations of our analyses. First, our results reflect the

[4] The ACA did influence hospital reimbursement on other dimensions as well. For example, the ACA reduced the growth rate of Medicare reimbursement rates and also funding through the DSH program (which differentially aided hospitals serving many low-income patients). So it is possible that average reimbursement did decline for some hospitals.

experience of a specific state and thus may not generalize to other states (especially the 19 states that chose not to expand Medicaid). Second, we cannot observe health care delivered outside of the hospital. Because of this, we cannot directly test for improvements in access to preventative and most forms of outpatient care. Third, the RD estimates are local to individuals in the specific narrow age groups that we study (18-23 and 62-67). Finally, we do not have information regarding the effects of the ACA on measures of economic well-being such as out-of-pocket spending, credit scores, or bankruptcy.

This paper makes three contributions. To our knowledge, we are the first to deploy administrative data on utilization of medical care to examine the effects of the ACA on utilization and health. Previous studies have mostly used survey data and find that individuals have better access to care and lower out of pocket spending (Golberstein et al., 2015; Benitez, 2016; Sommers et al., 2016*a*; Sommers et al., 2016*b*; Wherry and Miller, 2016; Courtemanche et al., 2017*b*).[5] In addition, we find evidence of crowd-out due to the Medicaid expansion. This aspect has either not received much attention or has not been detected using survey data and differences-in-differences based designs (Courtemanche et al., 2017*a;* Frean et al., 2017).

Second, we provide new quasi-experimental evidence on the effects of insurance coverage on demand for medical care in the presence of general equilibrium effects. Current baseline estimates are derived from randomized controlled field experiments (Manning et al., 1987; Finkelstein et al., 2012), but were obtained in a partial equilibrium setting. Some recent studies have exploited the health care reform in Massachusetts (Kolstad and Kowalski, 2012; Miller, 2012). This reform was on a much smaller scale than the ACA (4% increase in coverage vs. 10% increase in Medicaid alone in California). We find strong evidence that beneficiaries switch to better hospitals once they gain insurance, an aspect that has been shown to be valuable and has not been discussed in previous studies on the health benefits of Medicaid (Currie and Gruber 1996b; Goodman-Bacon, 2016). Our work is closest to Card et al. (2008; 2009) and Anderson et al. (2012; 2014) who also exploit sharp discontinuities in coverage at specific age thresholds. We build on their approach but benefit from the presence of multiple natural experiments – that produce reinforcing patterns.

Third, we focus on the supply side effects of the insurance expansion and provide new empirical evidence consistent with some previous research that providers are the primary beneficiaries of a Medicaid expansion (Finkelstein et al., 2015) as well as link to older evidence on the supply side effects of insurance expansions (Finkelstein, 2007).

[5] Studies that have used administrative data have so far focused on one aspect of medical care, such as emergency departments (Garthwaite et al., 2017) or drug prescriptions (Ghosh et. al., 2017). These studies suffer from some limitations, such as having data from specific providers (former) or pertaining to a much smaller sector of health care (hospitals account for a third of all spending on medical care, while prescription drugs contribute 10-15%). Literature showing effects of the ACA on insurance coverage is already too voluminous to summarize here (Sommers et al., 2014; Golberstein et al., 2015; Benitez and Creel, 2016; Sommers et al., 2016; Courtemanche et al., 2017*a*; Frean et al., 2017).

The rest of the paper is structured as follows. Section II provides background on insurance coverage in California and the insurance provisions of the ACA. Section III describes the data and presents descriptive statistics. Section IV presents the empirical approach. Section V presents the main results and discusses limitations. Section VI presents robustness and falsification tests and Section VII concludes.

II. BACKGROUND

A. Insurance coverage pre-ACA

The health insurance landscape prior to 2014 was characterized by relatively high uninsurance rates among specific sub-groups. According to data gathered by the American Community Survey (ACS), about 18% of the California population was uninsured in 2012-13. While this indicates a high aggregate level of uninsurance, it masks wide variation in insurance coverage across different age groups. Figure 1 Panel B presents the share of different insurer categories in California, as reported to the ACS, pre-ACA (2012-13) and post-ACA (2014-15) periods for three age groups – children (under 21), non-elderly adults (21-64) and the elderly (65 and above). Pre-ACA uninsurance rates among non-elderly adults (25%) were more than three times that of the remaining population (8%). The elderly benefited from universal coverage provided by Medicare, while children were generously covered by Medicaid (nearly 40%).

Surveys like the ACS may overstate true uninsurance rates since they do not recognize last-resort county insurance programs for the medically indigent. These programs fund medical care for a subset of low-income individuals who are not eligible for Medicaid but cannot afford to buy insurance. They are not considered equivalent to insurance since they often require individuals to provide proof of medical need or have a chronic condition. Hadley et al. (2008) estimates that about 20% of total spending on the uninsured, or about $11 billion dollars, was covered by such local programs.

In California, each county designs its indigent services program and thus there is substantial variation in eligibility requirements (e.g. income, assets, residence, age, medical need and immigration status) and services covered (California Health Care Foundation, 2009). California spent more than 2.1 billion dollars in one pre-ACA year to care for the uninsured through programs such as the Medically Indigent Services Program (MISP), which provided care in 24 mostly urban counties, and the County Medical Services Program (CMSP), which operated in 32 predominantly rural counties (Council of Economic Advisers 2009). With the exception of some MISP counties, these services were available only to non-elderly adults. Hence, a substantial fraction of non-elderly adults counted among the uninsured pre-ACA were covered by county programs.

B. The Affordable Care Act

The ACA was signed into law on March 23, 2010 with several key objectives: increasing access to health care, introducing new consumer protections, and lowering the cost and improving the quality of health care. This paper investigates the effect on health insurance coverage and the corresponding effect on health care utilization and health outcomes.

There were two primary channels through which the ACA expanded access to health insurance, both of which became effective on January 1, 2014. First, in all states, individuals in families with incomes between 100 and 400 percent of the federal poverty level (FPL) who were not already eligible for affordable health insurance, either from an employer or from Medicaid, were now eligible for premium subsidies provided in the form of advanced tax-credits to purchase private health insurance. Second, the ACA originally intended to expand Medicaid eligibility to all individuals below 133% of the FPL. However, legal challenges allowed states the choice to opt out of expanding Medicaid. California is one of the original twenty-six states (including DC) that chose to expand Medicaid in 2014. Six other states have since elected to expand Medicaid. Duggan et al (2017) provide a more detailed summary of ACA-mandated expansions in health insurance.

Several surveys estimate the number of uninsured in the United States at the quarterly or annual level. Gallup and Sharecare interview 500 Americans over the age of 18 daily and ask if the individual has health insurance coverage. Their well-being index shows that the percent of adults without health insurance was trending steadily upward prior to 2014, peaked around 18% in late 2013 and then sharply dropped to 11% by the beginning of 2016. The increase in health insurance coverage is largely attributable to both key health insurance initiatives, the Medicaid Expansion and subsidized insurance through exchanges. Although nationally there is a substantial decrease in uninsured rates, there is substantial heterogeneity in the magnitude of the reduction at the state level. States that elected to expand Medicaid tended to have substantially larger increases in insurance coverage since 2013.

Even among states that chose to expand Medicaid, there is substantial variance in the impact on Medicaid enrollment. This is driven by variation across states in baseline enrollment, due to states' generosity in eligibility criteria, as well as differences in the socio-economic composition of states. Figure A. 1 shows the percent of the state population enrolled in Medicaid in late 2013 and the net change in enrollment between late 2013 and October 2016. Compare California and New York, where almost one-third of residents in both states are now covered through Medicaid. However, this was a much larger increase in California, which saw an increase of 10 percentage points compared to an increase of 4 percentage points in New York. New York had more generous eligibility criteria that included childless adults prior to 2014 whereas childless adults were generally not covered in California. Consequently, the expansion of Medicaid had a larger impact in California. Figure 1 Panel C displays monthly Medicaid enrollment in California over 2011-16 and directly illustrates the scale of the expansion. It shows that –

after trending up very slightly from 2011 through 2012 – enrollment increased from about 8.5 million in mid-2013 to 13.5 million by mid-2016.[6] The figure also plots enrollment on the newly established ACA individual insurance exchange and shows that it plateaued at 1.3 million, or about a fourth of the increase in Medicaid. Hence, the ACA primarily expanded insurance coverage in California through Medicaid.

Returning to Figure 1 Panel B, notice that the elderly experience virtually no changes in insurer shares between 2012-13 and 2014-15. Uninsurance rates decline by 4 percentage points among children, driven entirely by a corresponding increase in Medicaid coverage. There is a ten percentage point decrease in uninsurance among non-elderly adults, driven mainly by the Medicaid expansion and increase in private coverage. Excluding the elderly since they were unaffected by design, this survey evidence suggests that the decrease in uninsurance (~8 pp) is entirely explained by Medicaid expansion (5.5 pp) and increase in private coverage (~2.5 pp), with little or no crowd out of other insurers by Medicaid.

Survey evidence has three important limitations. First, individuals typically under-report welfare coverage in surveys by 20 percent or more (Klerman et al., 2005; Meyer et al., 2009) and hence this evidence likely under-states both the initial share of Medicaid as well as its increase. Second, county indigent coverage is not recorded at all and hence potential crowd out under the ACA cannot be determined. Third, survey data on coverage cannot guide us on utilization and spending effects if Medicaid beneficiaries are more likely to use care than the average individual.

C. Age based discontinuities in public insurance

Public insurance programs commonly use age-based thresholds to determine eligibility. For example, individuals can enroll in Medicare when they turn 65, but not earlier, unless they are enrolled in the Social Security Disability Insurance program or have end stage renal disease. Similarly, children enjoy relatively generous eligibility rules under Medicaid until age 18 (or 19 under some circumstances) but then often lose coverage because the eligibility criteria become more restrictive. Prior to the ACA, two such rules created discontinuities in insurance coverage at 21 and 65 in California. Appendix Figure A. 2 presents an extract of California Medicaid eligibility requirements as of September 2007. Welfare recipients and disabled individuals were relatively generously covered. However, to enroll based on low income status ("medically indigent person or family"), individuals had to be under 21. Adults aged 21-64 were generally ineligible except under very specific circumstances such as pregnancies, nursing home residence, or enrollment in the federal Supplemental Security Income program.

To examine the magnitude of this discontinuity, we turn to administrative hospital discharge data. Note that this will reflect insurance coverage conditional on using hospital care rather than share of coverage

[6] The small jump in enrollment in 2013 is due to the transition of children from the Healthy Families Program to Medicaid.

in the population. Figure 1 Panel A presents Medicaid's share of hospital stays for patients aged 10-75 discharged from hospitals during 2012-15. In 2012, Medicaid coverage is high for children aged 10 (~45%) and gradually declines until age 21 when it falls precipitously by 15 percentage points exactly at that age. It then varies smoothly again until age 65 when there is another discontinuous drop of about 12 percentage points. The discontinuities at both age thresholds are large and account for 35-40% of the mean coverage for individuals just below the threshold. The pattern is similar in 2013, except for a mechanical increase in coverage for children due to the movement of CHIP beneficiaries into Medicaid.

The ACA makes three key changes -- as seen in the 2014 and 2015 trend lines. First, it eliminates the discontinuity at age 21. Second, it accentuates the discontinuity at age 65 since non-elderly adults are now more likely to receive Medicaid coverage. Third, there is a small increase in the share of Medicaid for children as well. Elderly adults are unaffected, by design. The large discontinuities in Medicaid coverage at the two age thresholds and their interaction with the ACA motivates our use of a regression discontinuity research design to examine the effects of gaining insurance coverage on a variety of outcomes.

III. DATA

Our main source of data contains the universe of hospital stays and emergency room (ER) visits at non-federal hospitals in the state of California for the period 2008 through 2015, obtained from California's Office of Statewide Health, Planning, and Development (OSHPD). These confidential data include approximately 3.8 million discharges and 11 million ER visits each year. Each observation pertains to a hospital stay or ER visit and provides information on the hospital, dates of service, patients' primary insurer type and basic demographics, a vector of up to 25 diagnoses and procedure codes, and patient zip code. As is standard in such files, if an ER visit subsequently leads to hospitalization, then it only appears as a hospital discharge, though the record indicates whether the stay originated as an ER visit. Crucially, we observe both a patient's birth date and admission date and hence we can precisely calculate a patient's age at admission.

We impose three restrictions to arrive at the master sample used in analyses involving the discharge data. First, we focus our attention on short-term general acute care hospitals to decrease the likelihood of small and specific hospitals (for example, rehabilitation or long-term care) driving the results. This restriction decreases the number of hospitals from 450 to 370, but retains 95% of hospital stays and nearly all ER visits. Second, since California Medicaid eligibility rules were already generous regarding pregnancy and delivery cases before the implementation of the ACA, we exclude pregnancy-related hospital stays or

ER visits from the analysis. Third, we exclude patients residing outside California or with missing zip codes of residence.[7]

We organize the insurer categories under five heads – Medicare, Medicaid, Private, County and Self. The first two include both traditional and managed care sub-segments. Private includes miscellaneous smaller insurers such as government employees and workers' compensation. Self is essentially uninsurance and includes so-called charity cases and those who pay for their care out-of-pocket. Throughout the paper, we measure uninsurance share as the sum of county and self.

A. Specific age thresholds

In order to construct the RD sample for our preferred specifications we impose two further sample restrictions. First, we exclude the years 2008-11 in order to focus on the two years just prior to and following ACA implementation. In a falsification check, we use data from 2008 through 2011, all of which precede the Medicaid expansion. Second, we limit the sample to patients admitted within 36 months of their 21st (or 65th) birthday. We also exclude individuals who arrived at the hospital within thirty days of turning 21 or less than thirty days before turning 65. These two groups of patients exhibit a partial change in insurance status and hence their inclusion amplifies measurement error. In robustness checks we explore the sensitivity of our results to using a narrower age range of two years. Focusing on specific age groups dramatically curtails the sample size, leaving approximately 310,000 (1.1 million) hospital stays and 3.9 million (2.7 million) ER arrivals over the period 2012-15 for the young and near-elderly respectively. ER arrivals include both ER visits and hospital stays that originated in the ER. Throughout the paper we prefer to analyze the sample of ER arrivals since it enables analysis without conditioning on hospital admission decisions that could change *in response* to the ACA while recognizing that the composition of ER arrivals may change after ACA implementation as well.

Table 1 Panel A summarizes descriptive statistics on the main RD analysis sample of hospital stays and ER arrivals separately for the young and elderly. The table highlights the sharp increase in the share insured by Medicaid and the corresponding decrease in uninsurance for patients in these age groups. We compute utilization rates as hospital stays and ER arrivals per 1,000 person-years using California population estimates for these years obtained from the ACS.[8] The normalization is particularly helpful in the case of elderly adults where this period coincides with the transition of baby boomers into Medicare

[7] 1-2% of the discharge records in 2008 were of patients having either an out of state or missing zip code.

[8] We obtained California population estimates for 2012-15 using 1-year ACS survey data available through www.socialexplorer.com. Although population figures are available for specific ages like 20 and 21 separately, we pool the population for the young (18-24) and elderly (62-69) separately and assume they are uniformly distributed in these groups. Hence, the population is allowed to vary over time (i.e. more 65 years olds in 2015 relative to 2012) but not across ages in any given year. This introduces measurement error but ensures there are no false positive jumps in utilization because of a large change in the denominator.

and hence large increases in the underlying population. The elderly and young use emergency rooms at about the same rate, but the elderly are six times more likely to be hospitalized.

B. All non-elderly adults

An important limitation of the RD results is that the estimates are local to the specific age groups represented. Therefore we supplement these results using a larger sample of all non-elderly adults (ages 21-64) and exploit geographic variation in uninsurance rates across Hospital Service Areas (HSAs)[9]; this is similar to the approach used in other studies (Finkelstein, 2007; Courtemanche et al., 2017; Duggan et al., 2017; Frean et al., 2017). HSAs are defined as "collections of contiguous zip codes whose residents receive most of their hospitalizations from hospitals in that area". There are roughly 220 HSAs in California, and on average an HSA is smaller than a county but much larger than a zip code. One can think of these as similar in concept to Commuting Zones which are often used to analyze shocks that affect labor markets. We use them as the unit of analysis to examine an insurance shock to hospital markets. We discuss the research design in more detail in section IV.B. Table 1 Panel B presents summary statistics on this sample. We exclude 2008 as the baseline year and the resulting data has 8.8 million hospital stays. Reassuringly, the mean values for several important variables are similar to a plausible weighted average of the mean values in the RD sample. For example, Medicaid has a 24% share of stays in the non-elderly sample in 2009-13, while it is 34% and 13% for the young and elderly respectively in the RD sample in 2012-13.

C. Hospital finances

OSHPD collects financial data on all hospitals in California and makes it publicly available on its website. These reports are mandated by California law and provide details on hospital finances, utilization and capital investments. We use files covering 2009-16 in order to examine the effects of the insurance expansions on hospital finances. The financial data is available for a smaller number of hospitals (335-340 instead of 370) since Kaiser Permanente[10] hospitals (approximately 30) do not report finances individually. We make two transformations to the revenue data in preparation to use it in our analysis. First we convert all nominal values into real 2016 dollar values using the consumer price index for urban consumers. Second, we normalize aggregate revenues for each hospital by its licensed number of beds.

Table 1 Panel C presents descriptive statistics on hospital revenue and the contributions of different types of insurers. Hospitals received about 1 million dollars per bed in revenue over the 2009-13 period. Of

[9] HSAs were defined by the Dartmouth Atlas Project. There are roughly 220 HSAs in California, of which 79 and 34 are in the LA and San Francisco metropolitan regions respectively.

[10] Kaiser Permanente is the largest health maintenance organization (HMO) in the US and owns all its medical care facilities – primary care, hospitals and post-acute care. Kaiser plan members are supposed to receive all medical care within this network. Individual medical centers do not report financial results publicly. More details available at: https://share.kaiserpermanente.org/article/fast-facts-about-kaiser-permanente/.

this, 21% was contributed by Medicaid. This share increased dramatically post-ACA to 28%. Nearly 90% of the increase in Medicaid revenue was due to the rapid growth in managed care, where all newly insured beneficiaries were placed. In contrast, revenue from county governments under indigent programs fell precipitously post-ACA. In the new regime, Medicaid is comparable to Medicare in magnitude of revenue.

IV. EMPIRICAL STRATEGY

We use three complementary research designs to investigate different questions related to the effects of the insurance expansions. These exploit different sources of variation – all driven by the nature of the insurance expansion itself – and different methodologies, as we discuss below in detail.

A. Regression Discontinuity design

Consider a conceptual reduced form model of the effect of health insurance coverage on outcome Y as below:

$$Y = \alpha + \beta \cdot Ins + \epsilon \tag{1}$$

Y denotes an outcome of interest (including utilization of care) for an individual and Ins is an indicator set to 1 if the individual has health insurance coverage and 0 otherwise. ϵ represents all unobserved factors that affect outcome Y. The key challenge in obtaining an unbiased estimate of the causal effect β is that individuals choose to purchase or enroll in health insurance coverage based on private information about their health risk as well as their appetite for risk. Hence, even if we observe some individual risk factors X_i and control for them, it is possible that the required condition $\mathbb{E}(\epsilon \mid Ins) = 0$ will not be not satisfied.

We try to solve this endogeneity problem by exploiting age-based discontinuities in public insurance eligibility at 21 and 65, as discussed in Section II.C above. For example, before the ACA insurance expansion in 2014, the probability of a hospital patient in California being covered by Medicaid dropped nearly by half exactly at age 21. Similarly, individuals transitioned out of Medicaid exactly at age 65 due to the onset of Medicare. This provides policy driven instruments exogenous to the individual that predict insurance coverage (the endogenous variable Ins in equation 1) for individuals just below or above the age thresholds. We exploit this discontinuity in eligibility rules in a fuzzy regression discontinuity framework by limiting the analysis sample to individuals within a narrow age range of the age thresholds. In our preferred specifications, the age bandwidth is three years above and below the threshold. We use the following estimating equations.

$$\mathrm{Ins}_{\mathrm{ijt}} = \alpha_{1\mathrm{j}} + \gamma_{1\mathrm{t}} + \mathrm{D}'_{\mathrm{it}}\boldsymbol{\lambda}_1 \mathrm{G}(a_i) + \theta_{11} d_i + \theta_{12} d_i \cdot T_t + X_i \boldsymbol{\delta}_1 + \epsilon_{1\mathrm{ijt}} \tag{2}$$

Equation 2 presents the "first stage" equation where insurance coverage (Ins_{ijt}) for individual patient i in HSA j at time t can be predicted by whether her age at arrival to the hospital (a_i) is above or below the relevant age threshold (A) and whether the ACA insurance expansions have been implemented. For brevity we express equation 2 using vector notation.

$$d_i = \begin{cases} 1(a_i \geq 21) & \text{if young} \\ 1(a_i < 65) & \text{if old} \end{cases}$$

The indicator d_i denotes the group of individuals just above or below the age threshold where Medicaid coverage changed discontinuously due to age restrictions. The indicator $T_t = 1(t \geq 2014)$ denotes whether the ACA has been implemented.

We model insurance coverage to vary flexibly with age, allowing a different slope for individuals based on whether they are above or below the age threshold as well as interacting it with whether the ACA was implemented or not. $D'_{it} = [1\ d_i\ T_t\ d_i \cdot T_t]$ is a vector of patient and time specific dummies. $\boldsymbol{\lambda}_1$ is the corresponding 4xk matrix of age coefficients to be estimated, where k is the number of columns in row vector G and the order of the polynomial in age (a_i). Our preferred specifications use a linear function in age ($k = 1$), but we test sensitivity of the estimates to using a quadratic function as well.

The coefficients of interest in this model are θ_{11} and θ_{12} and they estimate two different objects. The former estimates the discontinuous change in insurance coverage for 21(64) year olds relative to 20(65) year old patients, only in the pre-ACA period. The latter is a RD-DD estimator and captures the change in insurance coverage due to the ACA (i.e. post vs. pre) for 21(64) year olds relative to 20(65) year old patients. All models include a full set of HSA and year fixed effects, α_{1j} and γ_{1t} respectively. In some specifications we also include a vector of controls $\boldsymbol{X_i}$ to account for observable differences in patient characteristics, such as reason for arrival and gender.

$$\mathrm{Y_{ijt}} = \alpha_{2j} + \gamma_{2t} + \mathrm{D}'_{it}\boldsymbol{\lambda}_2\mathrm{G}(a_i) + \theta_{21}d_i + \theta_{22}d_i \cdot T_t + X_i\boldsymbol{\delta}_2 + \epsilon_{2ijt} \tag{3}$$

Equation 3 presents the "reduced form" model testing for direct effects of the eligibility restrictions on outcome of interest, Y. The coefficients θ_{21} and θ_{22} correspond exactly to θ_{11} and θ_{12} in equation 2 above. Similarly, the remaining coefficients and variables also correspond to equivalent elements in equation 2. We also estimate variants of this equation, where instead of obtaining the average change in discontinuity post-ACA we obtain the change in 2014 and 2015 separately. Note that the estimators in equation 3 quantify the magnitude of the discontinuous change in various outcomes at ages 21 and 65. These estimates are not the causal effect of insurance, our main goal. To calculate this, we return to estimating equation 1 using the predicted value of insurance coverage obtained from equation 2.

$$\mathrm{Y_{ijt}} = \alpha_{3j} + \gamma_{3t} + \mathrm{D}'_{it}\boldsymbol{\lambda}_3 \mathrm{G}(a_i) + \beta \cdot \widehat{Ins}_{\mathrm{ijt}} + X_i\boldsymbol{\delta}_3 + \eta_{\mathrm{ijt}} \tag{4}$$

Equation 4 above presents the "second" stage and estimates the economic object of interest β i.e. the causal effect of health insurance coverage on outcomes like utilization of care and health. In practice, we estimate equations 2 and 4 simultaneously using linear two stage least squares (2SLS). In both the OLS and 2SLS procedures, we put higher weight on individuals aged within one year of the threshold in order to avoid changes for individuals distant from the threshold to bias estimates. We cluster standard errors by HSA to allow for correlated errors among individuals residing in the same hospital markets.

Identification

We obtain three different types of estimators in the empirical strategy outlined above. The pre-ACA estimates of changes in insurance coverage (θ_{11}) and related outcomes (θ_{21}) at the age thresholds estimate the magnitude of discontinuity (if any) and do not link them causally to insurance. The RD-DD estimators (θ_{12}, θ_{22}) quantify the *changes* in pre-ACA discontinuities due to the implementation of the ACA. Note that these do not quantify post-ACA versions of the pre-ACA estimates. In order to interpret these as causal effects of the ACA, the identification assumption is that in absence of the ACA, there would be no change to the pre-ACA discontinuity. We do not need insurance coverage for 20 (65) year old patients to remain constant for these estimates to be valid, although that would make the setting cleaner. In fact, Medicaid coverage expanded for 20-year-old individuals as well. The absence of pre-existing differential trends is sufficient to support the identifying assumption. We use a placebo insurance expansion in 2010 to present supporting evidence. There is an inherent assumption that the nature of Medicare, Medicaid and private insurance does not change over this period of time, which is not completely satisfied.[11]

The IV estimator (β) is equivalent to a fuzzy RD estimate (Hahn et al., 2001) and quantifies the causal effect of insurance coverage on outcomes of interest for a subset of individuals in these age groups. As discussed in Lee and Lemieux (2010), we need three assumptions to attribute causality. First, all related observable and unobservable factors that could affect both insurance coverage and health should be continuous at the age thresholds. For example, if individuals are also disproportionately likely to graduate college or get a job at age 21 or leave the labor force exactly at age 65, this would be a violation. Since we

[11] Medicare prices were adjusted under the ACA and generally decreased (both directly due to price cuts and indirectly through performance pay penalties). In response, hospitals may have decreased supply of care to seniors.

measure age in monthly intervals, these factors need to shift discontinuously within thirty days of turning 21 (65), which is somewhat implausible. For example, a non-trivial share of college students may graduate at age 21 but since graduations typically occur in the summer and births are distributed relatively uniformly through the year, enrollment status is unlikely to change close to the 21st birthday. Further, data from the National Longitudinal Survey of Youth (NLSY) indicate that about 33% more college students graduate at age 22 than at age 21 (BLS, 2009; 2010). However, there is no corresponding discontinuity in insurance coverage at 22. Hence college graduation per se does not lead to a decline in insurance. Similar arguments also apply to entering the labor force at 21. In the case of the elderly, Card et al. (2008) present extensive tests to demonstrate that there are no discontinuities in employment or income at age 65. It is an un-testable and maintained assumption that unobservable factors also vary continuously at these ages.

The remaining two assumptions are common to all Local Average Treatment Effect (LATE) estimators (Angrist and Imbens, 1994). The instruments (age thresholds pre- and post-ACA) must satisfy the exclusion restriction i.e. they do not affect the outcomes of interest other than through their effect on insurance coverage. This assumption is more credible due to the evidence that age does not affect employment or income which could be alternative pathways affecting health. Finally, we need to assume the absence of individuals who 'defy' their predicted insurance transition, per the instruments. In our setting, that implies there are no individuals pre-ACA who were not on Medicaid at age 20 (64), but enrolled at age 21 (65). Post-ACA, this implies there are no individuals who move from Medicaid to uninsurance. These are reasonable assumptions since such transitions were very unlikely pre-ACA under the prevailing rules, as well as post-ACA with the contraction of county indigent programs.

B. Spatial variation

The RD design yields our main set of results, but it trades off representativeness for identification appeal. Identification assumptions in RD analyses are more relaxed relative to other designs (such as differences-in-differences) and are testable to some extent. However, the RD estimates are local to young adults and near-elderly individuals. While these age groups are important targets of health policy, they are not representative of all non-elderly adults. In order to address this limitation, we supplement the RD analysis using another research design and corroborate some of the RD results.

We deploy a differences-in-differences research design using two sources of policy driven variation. First, we use cross-sectional variation in uninsurance levels across Hospital Service Areas in 2008 (much before the ACA was passed). Regardless of other potential effects, the ACA was designed to increase insurance coverage among lower income families and individuals. In 2013, the uninsurance rate among California adults aged 19-64 with income below the federal poverty level was 36%, while only about 18%

of adults above the poverty level were uninsured.[12] Lower income neighborhoods had higher rates of uninsurance prior to the ACA and would experience greater decreases in uninsurance due to the ACA. Our thought experiment treats such HSAs as being hit by a more intense "insurance shock" than others. Second, we leverage within-HSA time-series variation created due to the introduction of the ACA in 2014. The DD estimator will quantify the impact of the ACA as the change in outcome of interest for HSAs with high pre-ACA uninsurance relative to HSAs with low pre-ACA uninsurance.

We calculate uninsurance rates for each hospital service area in 2008 ($Unins_{j08}$) as the observed proportion of hospital stays among patients residing in an HSA that were self-insured or covered by county indigent programs. Equation 5a represents the basic model to be estimated.

$$Y_{ijt} = \alpha_j + \gamma_t + \xi \cdot Unins_{j08} \cdot T_t + \epsilon_{ijt} \qquad (5a)$$

Y_{ijt} is an outcome of interest for patient i in HSA j in year t. T_t is defined as in equations 2 - 4 above. The coefficient of interest is ξ which estimates the change in outcome Y in post-ACA (2014-15) versus pre-ACA (2009-13) for a market with no insured stays compared with a market where all stays were insured. We include a full set of HSA and year fixed effects, α_j and γ_t respectively. Some specifications account for observable differences in patient characteristics by including a vector $\boldsymbol{X_i}$.

$$Y_{ijt} = \alpha_j + \gamma_t + \xi \cdot d_{j08} \cdot T_t + \epsilon_{ijt} \qquad (5b)$$

We also estimate an alternative version of equation 5a that does not impose linearity. Instead, we interact T_t with an indicator d_{j08} for the HSA being among the top one-third of all markets in terms of uninsured share of patients in 2008 i.e. $d_{j08} = 1(Unins_{j08} > 0.67pct)$. The interpretation of ξ changes to being the post-pre change in outcome Y for patients in the top one-third of hospital markets by uninsurance, relative to patients in all remaining markets.

To interpret the coefficient ξ as a causal effect of insurance expansion, we need to make two identification assumptions. First, outcomes in HSAs would evolve in a similar fashion in the absence of the insurance expansions. To test the presence of possible pre-trends, we estimate and present results from models allowing effects ξ_s to vary flexibly by year from 2009 through 2015, as depicted in equation 5c below. This approach does not impose linearity or treat 2014 and 2015 differently than the other years.

[12] Reported by the Kaiser Family Foundation based on Current Population Survey (CPS) 2014 data.

$$\mathrm{Y}_{ijt} = \alpha_\mathrm{j} + \gamma_\mathrm{t} + \sum_{s=2009}^{s=2015} \xi_s \cdot d_{\mathrm{j}08} \cdot \mathrm{I}(\mathrm{t} = \mathrm{s}) + \epsilon_{ijt} \qquad (5c)$$

Second, this analysis relies on the assumption that individuals do not switch their HSA of residence *in response* to the insurance expansions. In evidence not presented here, we analyze trends in share of hospital stays for hospital markets and find no evidence of differential trends before or after 2014.

Note that this analysis uses a different source of identifying variation relative to the regression discontinuity analysis, in addition to using a different patient sample. The estimates obtained in this analysis inform us about changes in coverage, utilization or health outcomes for patients in high uninsurance areas *relative* to patients in other markets. Though all patients included in the sample are potentially exposed to the insurance expansions, this approach will not inform us on changes in the mean across all hospital markets and it may understate true effects of the insurance expansions.

C. Variation across hospitals

An important goal in this paper is to examine the financial impact of the insurance expansions on hospitals. In order to do so we implement a third research design, which uses cross-sectional variation in pre-ACA uninsurance rates across hospitals rather than across hospital markets. The thought experiment is conceptually similar to our previous design – hospitals with a high pre-ACA share of uninsured patients would be hit by a greater insurance shock in 2014-15 relative to hospitals that mostly saw insured patients. Figure 2 illustrates this natural experiment. Panel A presents a histogram of hospital uninsurance shares as of 2008, calculated using hospital discharge data. Uninsurance ranges from nearly zero to about 50%. Panel B presents the distribution in 2014 after the expansion of Medicaid. The range has noticeably shrunk to about 30%, with most hospitals below 15%.

This analysis is performed at the hospital-year level, rather than at the patient level, since we use hospital-level data on finances.

$$Y_{ht} = \alpha_h + \gamma_t + \chi \cdot Unins_{h08} \cdot T_t + \epsilon_{ht} \qquad (6a)$$

$$Y_{ht} = \alpha_h + \gamma_t + \chi \cdot d_{h08} \cdot T_t + \epsilon_{ht} \qquad (6b)$$

Equations 6a and 6b present the estimating equations that implement this approach. These correspond exactly to the equations that exploit variation in uninsurance across hospital service areas. We have the benefit of observing hospital financials in 2016 as well and hence can deploy three years of post-ACA data for this analysis. The key assumption for identification continues to be absence of differential pre-trends in finances across hospitals. We present estimates obtained from equation 6c in order to examine the presence of pre-trends. Note that this analysis quantifies the effects of insurance expansions on hospital finances, which would incorporate the effects of any patient sorting across hospitals that occurs due to the insurance expansion.

$$Y_{ht} = \alpha_h + \gamma_t + \sum_{s=2009}^{s=2016} \chi_s \cdot d_{h08} \cdot I(t = s) + \epsilon_{ht} \qquad (6c)$$

V. RESULTS

A. Insurance coverage

We begin by analyzing the change in insurance coverage for patients discharged from hospitals and emergency rooms in California's hospitals over the 2012-15 period. We describe the changes in insurance coverage pre and post-ACA as well as any crowd-out of other insurers due to the Medicaid expansion.

i. Changes in insurance pre-ACA

Figure 3 presents a scatter plot of the proportion of hospitalized patients with insurance between 2012-15, for the young (Panel A) and elderly (Panel B) respectively. Recall that our preferred sample includes patients whose age is within three years above or below the threshold. The figure also plots fitted values obtained by estimating equation 2 with insurance coverage as the outcome. In 2012-13, we find a 15 (7) percentage point decrease (increase) in insurance coverage at age 21 (65). Relative to a base of 73 pp (92 pp) for individuals aged 21-23 (62-64), this represents a 20% (7%) change. The young are affected much more in absolute and relative terms. Appendix Figure A. 3 and Figure A. 4 present alternative versions of Figure 3 showing the change separately for each insurer type, for the young and elderly respectively. Panels A and B present insurance coverage in 2012-13 and 2014-15 respectively. Focusing on Panel A of each of these figures we see that for the young, private insurance is remarkably smooth through the threshold, while Medicaid plummets. In the case of the elderly, both private and Medicaid coverage decrease dramatically at the threshold, but the large increase in Medicare ensures that insurance coverage increases at 65.

Table 2 presents corresponding regression estimates for the changes in insurance coverage at age 21 (Panel A) and 65 (Panel B) for hospital stays. Appendix Table A. 1 presents corresponding estimates on the sample of all ER arrivals. The estimates are quantitatively similar across hospital stays and ER arrivals and so for brevity we focus on hospital stays. Within each panel, the first row presents estimates of the discontinuity in insurance share pre-ACA (θ_{11}) while the second row presents the change in this discontinuity post-ACA (θ_{12}), as discussed in Section IV.A.

Columns 1, 2 and 3 present the discontinuity in specific coverage types – Medicaid, private insurance and Medicare respectively. The values in column 4 reflect the net change in insurance coverage and correspond exactly to those indicated by Figure 3 and discussed above. Pre-ACA, the decrease in insurance coverage at 21 is driven mainly because of mandatory aging out of Medicaid. County indigent programs cover a number equivalent to about half of those losing Medicaid at age 21. In contrast, the elderly gain insurance coverage at 65 due to the universal nature of Medicare. It mainly replaces a mix of private coverage and Medicaid (~85%), with a 7 pp decrease in uninsurance.

ii. Changes in insurance post-ACA

Figure 3 indicates that post-ACA, discontinuities in insurance at both thresholds are nearly eliminated. The appendix figures (Panel B of Figure A. 3 and Figure A. 4) indicate that Medicaid expansion is the primary driver of this phenomenon since Medicaid is the only source of increase in coverage for 21-23 and 62-64 (`treated') patients. In fact, counties seem to have completely withdrawn coverage for these patient groups in response to the expansion. An important policy concern associated with the expansion of public insurance -- especially means-tested programs like Medicaid -- is potential crowd-out of other insurers that previously served these beneficiaries. The RD research design is well suited to examine crowd-out since we are comparing changes in insurer shares for all patients in the state in these age groups.

Table 2 Panel A corroborates the sharp increase in Medicaid coverage indicated by the figure. The estimate of ~14pp is to be interpreted as follows - Medicaid coverage increased in 2014-15 relative to 2012-13 for 21-23 year olds by 14 pp *more* than it did for 18-20 year olds in the *same time period*. The table also reports that there is a small decrease in private coverage for 21-23 year olds, but it is not statistically significant. A prominent source of crowd-out is the replacement of county indigent programs by Medicaid post-ACA. About half of the increase in Medicaid coverage replaces last-resort county payments (8pp vs. 14 pp).

Similarly, Table 2 Panel B indicates crowd-out among the near-elderly as well. There is a statistically and economically significant decrease in private coverage, accounting for one-third of the increase in Medicaid coverage (2.5pp vs. 7.5 pp). The demise of county coverage is seen among the near-elderly as well and is about 40 percent as large as the expansion in Medicaid.

An important implication of the crowd-out of county and private coverage is that the decline in self-pay is much smaller in magnitude than the increase in Medicaid – the key goal of the ACA. Assuming for the moment that coverage changes in hospital care are equivalent to changes in spending on hospital care, federal taxpayers incurred \$300 more in Medicaid spending to decrease the burden of hospital care for the uninsured by $100.[13] The remainder is a transfer to local governments and the state of California that previously financed county indigent programs (two-third) and also to near-elderly individuals or their employers who would otherwise purchase private insurance (one-third). There are distributional implications as well. If we ignore differences in the costs of raising taxes at different levels of government, this transfer was essentially borne by federal taxpayers including those residing in states that did not expand Medicaid under the ACA.

B. Utilization of care

Since our data is conditional on the person using hospital care, we cannot study rate of use at the individual level. Our preferred metric of utilization is rate of hospitalization or ER arrival per 1,000 person years, which we compute as described in Section III.A. We collapse the data to the age-month (denoted by s) - year level and estimate the following model.

$$\mathrm{Y_{st}} = \gamma_{3\mathrm{t}} + \mathrm{D}'_{\mathrm{st}}\boldsymbol{\lambda}_3\mathrm{G}(\overline{a_{st}}) + \theta_{31}d_s + \theta_{32}d_s \cdot T_t + \epsilon_{3\mathrm{st}} \tag{7}$$

The above equation is an exact analog of equation 3, which was estimated at the case level. $\overline{a_{st}}$ is the mean age of all patients observed in the cell s, t. d_s is the corresponding indicator obtained by collapsing d_i within each age-month bin. The coefficients of interest continue to be θ_{31} and θ_{32}. Similarly, we estimate analogs of equation 2 (first stage effect on insurance coverage) and equation 4 (IV 2SLS) to generate the full set of results on utilization of care.

The results are very different for the young and the near-elderly hence we discuss them separately. Figure 4 presents a scatter plot of mean observed utilization of hospital and ER care for the young by age-month. The primary vertical axis plots the mean rate of hospitalization per 1,000 individuals, while the secondary vertical axis plots corresponding rate of ER arrivals (note that the scales are very different). Panels A and B present the figures for 2012-13 and 2014-15, respectively. In addition, we also plot fitted values obtained by estimating equation 7. We split hospital stays based on whether the patient entered through the ER or not. This allows us to examine changes in utilization based on whether or not the conditions were emergent.

Figure 4 indicates that there is little or no discontinuity in hospital stays at age 21 before or after the implementation of the ACA. However, there is a noticeable drop in arrivals at the ER at age 21 pre-

[13] We find 50% and 75% crowd-out for ages 21-23 and 62-64 respectively. Appendix Table A. 3 shows that hospital stays are nearly equal in number in 2012-13 for patients aged 21-49 and 50-64 respectively. If we extrapolate the above estimates to apply to these larger age groups, then a weighted average estimate of crowd out is about two-third.

ACA and this gap persists post-ACA as well. The level of ER arrivals increases substantially in 2014-15 on both sides of the threshold, while the aggregate number of hospital stays virtually does not change.

Table 3 presents regression coefficients on utilization of care for both the young (odd numbered columns) and elderly (even numbered columns). Columns 1-2 present results on hospital stays, columns 3-4 on ER arrivals and columns 5-8 present results for hospital stays depending on whether they originated in the ER or not. The first four rows present various types of estimates of the discontinuity at the respective age thresholds. The first row presents the pre-ACA estimated discontinuity, the second row presents the change in this discontinuity post-ACA i.e. over 2014-15, the third row presents the change in discontinuity as at the end of 2014, and the fourth row presents the change when comparing 2015 only to the pre-ACA period. The last two estimates examine dynamics of the change in discontinuity and whether there is an accelerating trend. These two estimates are obtained from a companion set of specifications that also include the pre-ACA estimated discontinuity. The fifth row presents the LATE estimate on the causal effect of insurance change on utilization. This format is shared by many of the other result tables as well.

The overarching takeaway in the case of the young is that pre-ACA there was very little impact on utilization upon turning 21 and similarly little effect post-ACA due to Medicaid expansion. The IV estimates suggest that a 10% increase in insurance coverage results in an increase of 0.4 stays and 7 ER arrivals per 1,000 person-years, or approximately 2% of the mean rate of utilization. Relative to the large increase in insurance coverage at age 21, there is only a small change in utilization of hospital care. This suggests that there was not substantial pent-up demand for care among the young – uncompensated care was largely fulfilling demand from uninsured individuals.

Figure 5 presents the corresponding plot for the elderly and it offers a very different picture. Pre-ACA (Panel A), there was a discontinuous jump in the rate of hospitalizations and ER arrivals at age 65. The jump is noticeably larger in absolute and relative terms for hospital stays that did not originate in the ER – presumably non-emergent. Post-ACA (Panel B), there is a noticeable convergence in rate of utilization between 64- and 65-year-old patients. The figures clearly indicate that the near-elderly have increased utilization of care once they have obtained greater coverage.

Estimates in Table 3, for the elderly sample, confirm the intuition provided by Figure 5. The rate of hospital stays increases 12% at age 65 pre-ACA and this difference between 64- and 65-year-olds declines by 9% post-ACA. There are two possibilities why the gap does not entirely disappear. First, the pre-ACA natural experiment involves a greater increase in insurance coverage (see Table 2 Panel B) and hence it is likely to produce a greater jump. Second, the two experiments involve different types of coverage. Pre-ACA the transition is to Medicare, while post-ACA it is to Medicaid. The former offers more generous prices to providers and a less constrained network. Hence, it is intuitive that utilization effects are smaller for Medicaid. The LATE estimate indicates that a 10% increase in insurance coverage results in

25-30 more stays and ER arrivals per 1,000 person years. Relative to the mean utilization rate, this is a large increase in hospital stays (18%) and ER arrivals (8%). The growth in hospital stays is spurred by the demand for non-emergent stays which increase by three times as much as do stays through the ER.

Coefficients for 2014 and 2015 suggest a pattern of accelerating utilization of care (for the near-elderly only) – the increase in the rate of stays and ER arrivals is about 50% greater in 2015 relative to 2014. This implies that the increase in utilization for the near-elderly is not due to pent-up demand for care that was unleashed in 2014. A related concern is that the near-elderly may have delayed obtaining medical care prior to 2014 in anticipation of Medicaid expansion. Raw trends in utilization of care for 62-64-year-olds do not indicate such a possibility. In any case, the estimated effects on ER arrivals and stays that originated in the ER are unlikely to be biased by such anticipatory effects and provide a lower bound (8-10%) on the increase in utilization.

Our estimated effects on utilization for the young are lower than those reported by Anderson et al. (2012) who examine the effects of losing private coverage at age 20. While there are several possible explanations, we believe the primary reason is the difference in generosity (prices) and access to care between private insurance and Medicaid. The estimated effects on utilization for the near-elderly match those reported by Card et al. (2008) who used an RD approach to examine the effects of the onset of Medicare coverage.[14] In section VI.A we test the robustness of these estimates to using a different functional form to model the role of age. Using a quadratic vector in age decreases the estimated effects on utilization for the near-elderly. Hence we defer further discussion on the utilization estimates until then.

C. Choice of hospital

We now examine whether patients receive care at different hospitals once they receive insurance coverage. We explore hospital choice on two dimensions – owner type and quality as measured by risk adjusted mortality scores. A key benefit of expanding insurance could be enabling patients to choose higher quality (real or perceived) care providers. If so, this is a source of welfare improvement for patients irrespective of whether there are measurable improvements in patient health, and has received little attention in previous studies quantifying the benefits of Medicaid.

i. Hospital owner type

Figure 6 Panel A presents a scatter plot of observed share of stays by hospital owner type (private non-profit, for-profit and government) for young patients in 2012-13. The share of government and for-

[14] Card et al. (2008) examined the effects of the onset of Medicare coverage using data from California, Florida and New York. They find an 8 percent increase in the rate of hospitalization at age 65, while we find a 9% increase post-ACA. The estimated effects on hospital stays by admission route are also similar (5% vs. 3% for stays originating in ER and 14% vs. 12% for stays not through ER). They do not provide IV estimates.

profit hospitals is plotted on the primary vertical axis while that for non-profits is on the secondary vertical axis. It also presents the corresponding fitted values obtained by estimating equation 3, in this case including observable patient risk factors such as gender and reason for arrival. There is a noticeable 2 pp increase in the share of government (city, county and district) owned hospitals at age 21 and corresponding decrease in share of private non-profit hospitals. For-profit hospitals are seemingly unaffected. Table 4 presents formal regression estimates on the share of hospitals by ownership type for the young (odd numbered columns) and the elderly (even numbered columns). Pre-ACA estimates of the discontinuity at age 21 (first row) confirm the intuition provided by the figure.

Figure 6 Panel B replicates the same plot over 2014-15 and indicates that the pattern has largely reversed. The discontinuity in share of government hospitals at 21 is eliminated due to a decrease for those aged 21-23. This is balanced by a clear increase in the share of for-profit hospitals and suggestive gains for non-profits. The second row of Table 4 indicates that government hospitals have lost share nearly equally to for-profit and non-profit hospitals, although only the estimate for the former is statistically significant.

The LATE estimates indicate that the marginal young individual is 10% less likely to be admitted at a government hospital once she has insurance coverage. This is economically significant since it is a 40% decrease in the probability of receiving care at a government hospital for an uninsured patient. Marginal patients are also more likely to switch to non-profit rather than for-profit hospitals. Although we do not find evidence of dynamic changes in utilization (quantity) of care among the young, we do find evidence of a dynamic shift in volume toward private hospitals. The decrease in the share of stays at government owned hospitals is 25% greater in 2015 than in 2014.

Figure A. 5 presents the corresponding plots for the near-elderly and suggests qualitatively similar patterns. Table 4 presents corresponding regression coefficients for the near-elderly. The sorting of near-elderly toward private hospitals accelerates in 2015 and estimated effects are nearly double those in 2014. Based on the LATE estimate, the marginal near-elderly patient who receives insurance coverage is 35% less likely to be admitted at a government hospital, nearly three times that for a young patient. This is a very large shift since the uninsured near-elderly have only a 30% probability of being admitted at a government hospital.

Our research design cannot help us disentangle mechanisms behind this shift in hospital care away from government owned hospitals and toward private facilities. While the most intuitive explanation is that it is driven by patient preferences, it is ultimately an equilibrium outcome and one cannot rule out the role of hospital responses (such as greater targeting of recently insured individuals, or greater propensity to admit these patients at the ER) in producing this shift. We replicate this analysis on the sample of ER arrivals to learn more (See appendix Table A. 2). ER arrival patterns are more likely to reflect patient preferences, but they potentially represent a lower bound on the propensity to switch given that distance is the dominant factor during emergencies. Reassuringly, we find quantitatively similar estimates using ER data (LATE estimates of switching away from government hospital are 7% and 30% for the young and elderly respectively). These estimates suggest that non-patient factors are quantitatively less important.

ii. Mortality score

Hospital ownership type is correlated with quality or perceived quality of care (for example, academic medical centers are generally high quality and mostly non-profit), but probably also correlates with non-quality factors. To examine if the sorting across hospitals is motivated by quality we use a commonly accepted measure – risk-adjusted 30-day mortality – as our outcome of interest.

CMS calculates this measure for Medicare patients discharged from hospitals for a number of serious conditions. The raw mortality rates are adjusted for patient risk history and observed sickness at the time of admission.[15] We start with risk-adjusted mortality rates for hospitals, as reported by CMS in 2009, on three conditions: heart attack, heart failure and pneumonia. We then compute the mean mortality rate for each hospital and normalize it such that the distribution across hospitals is standard normal. Given that mortality rates were calculated for Medicare patients, they are likely to be more relevant and informative about care for the near-elderly than for young adults. Hence, we focus our discussion on results obtained on the sample of near-elderly patients, although we also present corresponding results for the young.

Figure 7 presents a scatter plot of mean normalized mortality rate on the Y-axis, against patient age-month on the X-axis. This figure uses data on hospital stays over 2012-15 and presents results for both the young (Panel A) and elderly (Panel B). In the case of the near-elderly there is a noticeable drop in mean hospital mortality at age 65 in 2012-13, implying that patients receive care at better quality hospitals when they switch to Medicare. Table 5 presents corresponding regression estimates for the young (columns 1 and 3) and the elderly (columns 2 and 4). The first row of column 2 confirms that hospital mortality was 0.02 standard deviation greater for individuals aged 62-64 in 2012-13, relative to those over 65.

Figure 7 also suggests that the gap in hospital quality at age 65 narrows post 2014, implying that 64 year olds are now at a lesser disadvantage relative to Medicare beneficiaries. The second row of Table 5 column 2 confirms that the pre-ACA discontinuity (0.02) drops by half post-ACA. There is strong evidence of dynamic effects in sorting on quality by the near-elderly. In 2015, the discontinuity at age 65 is effectively eliminated.

The LATE estimate suggests that gaining insurance coverage at 65 enables patients to receive care at a hospital with 0.25 s.d. lower mortality. This is a large improvement and equivalent to moving to a

[15] More details on the methodology are available at https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/OutcomeMeasures.html. The mortality measures are available at https://data.medicare.gov/data/hospital-compare.

hospital with 0.4 (0.25*1.63) pp lower mortality or a 3% decrease relative to the mean 30-day mortality rate for AMI, heart failure and Pneumonia. As in the case of hospital ownership, looking at changes in hospital choice on the sample of ER arrivals could help establish a lower bound estimate of the component driven by demand preferences. Table 5 columns 3 and 4 present equivalent results for ER arrivals. The LATE estimate suggests that insurance coverage enables a patient to receive care at a hospital with a mortality rate that is 0.13 s.d. lower than without coverage. This is about half the magnitude of the decrease seen for hospital stays.

We use revealed preference estimates of the additional distance patients are willing to travel to receive care at better hospitals in order to quantify the value of this effect of insurance coverage. There is a large literature on hospital choice which has developed approaches to estimate these objects and a full review is out of scope, but the closest reference is Tay (2003) which examines Medicare data from California, Oregon and Washington. It estimates that younger, white male heart attack patients are willing to travel up to 8 miles further to receive care at a hospital with a 3% lower mortality rate. In our setting, patients now receive care at a hospital with 0.2-0.4pp (2-3%) lower mortality rate (depending on hospital stays or ER visits) on average. Therefore, insurance coverage is equivalent to moving patients 4-8 miles closer to their hospital, 25-50% relative to the mean distance in our sample.

D. Health Outcomes

Policymakers typically consider measures of patient health and provider quality interchangeably. For example, CMS rates hospitals and Medicare sets payments for hospitals based on risk adjusted mortality, readmissions, hospital acquired infections and a host of other measures of patient health. Previous studies of provider quality and patient health have also focused largely on mortality. We follow the literature and use mortality as a key measure of patient health, specifically in-hospital mortality - a closely related[16] metric to standard measures such as 30-day mortality. Since mortality is relatively rare for the young[17], we limit our discussion on patient health to the near-elderly, although we present results for the young as well.

A key argument used in favor of expanding insurance coverage is that greater immediate access to preventative care will circumvent later wasteful use of expensive ER/hospital care. Hence, a natural second outcome of interest to measure patient health is whether the ACA led to a decrease in the wasteful use of

[16] Due to data limitations, we do not observe mortality outside the hospital. We obtained death-linked hospital discharge files over 2008-11 from California OSHPD to examine the link between in-hospital mortality and outcomes later. OSHPD creates these files by linking hospital discharge records with the state death register. Hence, we can observe standard short-term mortality outcomes like 7-day and 30-day mortality through November 2011. We find that in-hospital deaths accounted for 79% and 64% of 7-day and 30-day mortality respectively for patients in these age groups. In-hospital death is also highly predictive of 30-day mortality across hospitals, with an R-squared of over 0.9. Therefore, we believe in-hospital mortality is a reasonable proxy for 30-day mortality.

[17] The mean mortality rate for the young in our sample is 6 per 1,000 hospital stays and also tends to be noisy across different age-month cells (coefficient of variation is 0.33). Therefore, it is difficult to visually infer a change at any specific age.

hospital care. Potentially avoidable episodes are identified for a subset of visits[18] based on ICD-9 diagnosis codes recorded in a patient's discharge data and have previously been used for this purpose (Kolstad and Kowalski, 2012).

i. In-hospital mortality

Figure 8 presents a scatter plot of mean in-hospital mortality rates on the primary vertical axis against mean age-month of patients on the horizontal axis. It also presents fitted values obtained by estimating equation 3, where the regression co-variates include patient characteristics. Panels A and B present the figures for 2012-13 and 2014-15 respectively for elderly patients. Pre-ACA there is a suggestive drop in mortality at age 65 (Panel A), and this discontinuity seems to be eliminated post-ACA (Panel B).

Table 6 presents corresponding regression estimates for the young (odd numbered columns) and elderly (even numbered columns) respectively. Columns 1-4 present estimated effects on in-hospital mortality, while columns 5-8 present corresponding effects on the share of potentially avoidable stays/ER visits. The pattern of results is similar across hospital stays and ER arrivals and so for brevity we discuss only hospital stays. The estimated discontinuity at age 65 pre-ACA is small and not statistically significant. Post-ACA it appears to be completely eliminated, as indicated by the figure. There is evidence of dynamic improvement in mortality rates for the elderly. Among both hospital stays and ER visits, the improvement in mortality rates in 2015 is three times larger than in 2014, and is statistically significant. The LATE estimate is negative and large, but very noisy – we cannot rule out effects comparable to the mean level in either direction.

Although the estimated effects on in-hospital mortality are not statistically significant, it is useful to determine the implied number of lives saved in hospital deaths in California. Our most conservative causal effect is a 50% decrease in in-hospital mortality due to insurance coverage. If we apply this decrease on the share of non-elderly (21-64) patients that gained insurance coverage due to the ACA, then we find that in its first two years after implementation the ACA insurance expansion avoided about 1,100 hospital deaths annually.[19]

ii. Potentially avoidable care

[18] Potentially avoidable care hospitalization is defined only for hospital care where the primary diagnosis code pertains to a condition of the endocrine, nervous, circulatory, respiratory, digestive or ill-defined systems. These categories account for about 40% and 55% of the total sample of young and elderly patients in 2012-15 respectively.

[19] Table A. 3 presents the number of hospital stays and ER arrivals by age group. There were approximately 1.25 million hospital stays by patients aged 21-64 annually pre-ACA. The mean mortality rate for this group was 1.6 percentage points. About 140,000 individuals would gain insurance post-ACA (11%). Applying the estimated decrease in mortality to this group gives us 1,100 avoided deaths.

Figure 8 also presents the mean observed share of potentially avoidable hospital stays (PAH) on the secondary vertical axis against age-month on the horizontal axis for the sample of elderly patients. In our sample, approximately 20% of eligible hospital stays were identified as potentially avoidable over 2012-13. The figure also plots predicted values obtained by estimating equation 3, as with the other outcomes. The figure does not indicate a noticeable shift in PAH at age 65 pre-ACA, however Table 6 column 6 indicates that the share of PAH was ~0.7pp (3% of the mean) greater pre-ACA for patients aged 62-64.

The figure suggests that the share of PAH decreases post-ACA for patients both above and below 65 and it is unclear if the decrease is greater for patients on any particular side. The second row of Table 6 column 6 confirms that the change in discontinuity post-ACA is small and not statistically significant. Note that this estimate does not suffer from lack of precision. We can rule out a relative change in either direction post-ACA of more than 1pp or 5% of the mean PAH share. The coefficients for specific years do not indicate any particular pattern. The LATE estimate indicates a large causal effect of insurance coverage. Gaining coverage leads to a 9pp (40%) decrease in the likelihood of a potentially avoidable stay.

The evidence on the effects of Medicaid expansion on PAH is less convincing than corresponding results on in-hospital mortality for two reasons. First, although we find that PAH stays are greater for the 'treated' group of patients pre-ACA, there is no statistically significant decrease in PAH post-ACA. Hence, the two patterns do not reinforce each other. This could be a limitation of examining evidence just 2 years post-ACA or the difference between gaining Medicare vs. gaining Medicaid. Second, the evidence on ER arrivals is completely contradictory and suggests there is no link between insurance coverage and share of avoidable care, before or after the ACA. Hence, we use the LATE estimate with caution.

The LATE estimate helps us quantify the decrease in potentially avoidable hospital stays due to the insurance expansion under the ACA. Note that this is not an absolute decrease in hospital stays, only in the proportion that are wasteful. Using the estimated causal effect of insurance coverage on PAH (~9% decrease) and the increase in coverage under the ACA (15% and 5% for the young and elderly respectively), we estimate that the ACA has led to about 1,200 fewer avoidable stays (3% of total PAH) for patients in these specific age groups. If we extrapolate these results to the entire non-elderly (21-64) group of patients, then the decrease will be about 6,500 stays per year or 5% of all PAH for this segment.[20]

Overall, we interpret the evidence on improvements in both mortality and PAH with caution. The estimated effects are not robust and suffer from some contradictions (as discussed above), hence we shy away from translating the implied lives saved and avoided stays into dollars in a more concrete cost-benefit computation.

[20] There were ~32k and ~155k eligible stays annually for the young and elderly respectively. The increase in insurance coverage affected about 4.5k and 8k patients respectively. For these patients, the share of PAH decreased by ~9% on average, which is ~1.2k stays annually. The entire non-elderly (21-64) group has about 650k eligible stays annually. The increase in insurance coverage affected about 70k patients annually. Applying the 9% decrease for this group gives us ~6.5k fewer stays per year.

E. Evidence using all non-elderly adults

We consider the RD results as our primary results using the discharge data. However, since the estimates are local to patients in specific age groups, we complement them through an alternative research design using the sample of all non-elderly patients (21-64) as discussed in section IV.B. Below we present results on two key outcomes – changes in insurance coverage and patient sorting across hospitals.

i. Insurance coverage

Figure 9 Panel A plots coefficients obtained by estimating the flexible non-parametric specification 5c on key insurance type indicators for the sample of non-elderly (21-64) adults. There does not appear to be a pre-trend in insurance coverage or county indigent coverage, however there is a small trend of decrease in self-pay even before the expansion, particularly in 2013. This could be driven by the expansion of county indigent programs in 2013 as part of the early Medicaid expansion in California. Overall, we are reassured that there are no differential pre-trends across markets, which is the key identification assumption in this research design.

Table 7 Panel A presents the results obtained by estimating equations 5a (linear) and 5b (non-parametric) in the first and second rows respectively. Columns 1-6 present results obtained with various insurance categories as outcomes of interest. Reassuringly, the results obtained using the entire sample are qualitatively similar to those in the RD sample. We find an increase in insurance coverage (Medicaid, Medicare or private insurance) driven primarily by the Medicaid expansion. However, a large share of the increase in coverage replaces county indigent programs.

Across both specifications, approximately 80% of the net increase in coverage derives from the Medicaid expansion, while the decrease in self-pay is about 50-60% of the increase in coverage. These results diverge from the RD estimates on the effects on private coverage. While the RD analysis suggests no change in private coverage (or a slight decrease), the spatial analysis suggests that markets with a high share of uninsured pre-ACA did experience a *relative* increase in private coverage. Note that overall there was a decrease in private coverage in this sample from 41% over 2009-13 to 36% over 2014-15.

ii. Hospital choice

Figure 9 Panel B plots coefficients obtained by estimating equation 5c with shares of hospital ownership types as the outcome variables. The figure indicates there were no differential trends across hospital markets prior to 2014, supporting the identification assumption. Table 7 Panel A columns 7-9 present regression coefficients obtained by estimating equations 5a (linear) and 5b (non-parametric) in the first and second rows respectively. These results also indicate that gaining insurance coverage is associated with movement of patients from government hospitals toward privately owned hospitals. At the mean uninsurance level of 0.12, the linear specification predicts a loss of approximately 1.8 pp market share from government to private hospitals post-ACA, which lies in between the equivalent estimated effects obtained for the young and near-elderly in the RD analysis.

The RD and spatial approaches differ slightly on the details of which type of private hospital experiences an increase in patient share post-ACA. Post-ACA, the share of for-profit hospitals at both age thresholds tends to jump more than for non-profit hospitals. The IV estimates indicate that marginal patients are switching more toward non-profit hospitals, though for-profits also benefit. The spatial analysis suggests that patient movement is entirely toward non-profit hospitals, with for-profit hospitals losing some share (though not statistically significant).

F. Impact on hospital financials

We now turn our attention to effects of the insurance expansion on hospitals. Given the unprecedented magnitude of the insurance expansion in California, hospitals could be affected directly (through an increase in average prices and quantity) as well as indirectly (through expansion of supply in response). Finkelstein (2007) shows that hospital spending in response to the introduction of Medicare was far in excess of the increase in utilization of care predicted on the basis of a consumer demand response alone. She argues that hospitals expanded supply in response to the insurance expansion by investing in capacity additions and new technologies.

We deploy data on hospital finances collected by OSHPD over the period 2009-16, as described in section III.C. Figure 10 presents coefficients estimated using the flexible non-parametric specification 6c. Reassuringly, there is no evidence of differential trends in revenue across hospitals pre-2014, supporting our key identification assumption. Table ***7*** Panel B presents coefficients obtained by estimating equations 6a (linear) and 6b (flexible) on hospital-year level data. Columns 1-6 present results on hospital revenue (expressed in thousands of 2016$) contributed by different payers. The resulting patterns are qualitatively similar, although estimates using the linear specification are dramatically noisier.

Based on the linear specification, hospitals that had a 10% greater share of uninsured patients in 2008 experienced a relative increase of $18,000 (177,000*0.1) per bed in total patient revenue over 2014-16. This increase is driven entirely by the Medicaid expansion, since revenue from all other payers declined. This represents a 2% increase relative to the mean revenue of 1 million per bed. These estimates suffer from lack of precision. For example, to reject the null of no change in Medicaid revenue, we need an estimate that is larger than the revenue received from Medicaid by the mean hospital. Use of a linear specification is not supported by trends in hospital revenue (not presented here). Hospitals with low levels of pre-ACA uninsurance exhibit little or no change in trends while hospitals with the highest levels of pre-ACA uninsurance experience a dramatic increase in revenue which further motivates the use of a more flexible specification.

The non-parametric specification offers much more precise estimates as well as larger magnitudes. Total revenue for hospitals having uninsurance rates among the top third of all hospitals in 2008 has increased by (marginally significant) $95,000 per bed -- 10% of revenue for the mean hospital -- relative to the remaining hospitals. To compare with the estimate from the linear specification, note that hospitals in the top third have an uninsurance rate about 13 pp greater than the remaining hospitals. Medicaid accounts for more than 70% of this increase, with the remainder due to increase in Medicare and Private insurance.

These results strongly suggest that the expansion of insurance coverage led to a disproportionate increase in revenue for hospitals that previously had high rates of uninsurance among patients. In other results not presented here, we find no evidence of a statistically significant decrease in subsidies to publicly owned hospitals (that typically had high uninsurance rates pre-ACA) post-ACA. This is in contrast to previous studies (Duggan, 2000; Baicker and Staiger, 2005) that show government hospitals being operated on a soft budget by local governments. Therefore, we believe this truly was an increase in revenue for hospitals, including government hospitals. In addition, we do not find evidence of a disproportionate increase in the total number of non-elderly patients served at hospitals with the greatest pre-ACA uninsurance share. Hence, the increase in revenue seems to be driven mostly by an increase in revenue per patient.

To put the magnitude of this increase in perspective, note that hospitals operate on low margins. In 2008, hospitals in California reported a mean net income of $4 million out of a total patient revenue of $140 million, or a margin of 3%. This margin would be lower still if we include non-patient revenue in the topline. Thus, for hospitals with the highest pre-ACA uninsurance levels, the influx of money has been potentially several times their annual net income. These results are consistent with the strong position taken by hospital industry associations to prevent repeal of the ACA Medicaid expansion.[21]

Hospitals could potentially deploy the additional revenue to improve general quality of care, initiate expansions, hire more or better staff or retain as surplus. We explore this line of reasoning by examining effects on some unrelated outcomes such as mortality rates for infra-marginal patient groups (infants and seniors) and capital investments. These two patient groups are more sensitive to changes in quality of care than non-elderly adults or older children. Table 7 Panel B presents results on these outcomes (columns 7-8). The estimates are small and statistically insignificant. In the case of elderly mortality, we can rule out an effect larger than 6% of the mean value. This suggests that the additional revenue has not generated

[21] See for example a letter by the President of the American Hospital Association (AHA) to US Congress opposing the American Health Care Act that repealed the ACA (available at http://www.aha.org/presscenter/pressrel/2017/030817-pr-acha.shtml). More details of its lobbying against ACA repeal discussed at http://www.modernhealthcare.com/article/20170317/NEWS/170319906.

substantial spillover quality improvements for non-targeted patients. Similarly, we do not find any effects on spending on capital expenditure, acknowledging that two years may be too short a time horizon to detect investment responses.

Finkelstein, Hendren and Luttmer (2015) suggest that hospitals and physicians receive substantial value from Medicaid expansions since it mainly replaces uncompensated care that was already being provided. Their conclusion was based on patient survey data and they lacked direct evidence from hospital financial reports. Our results on hospital finances are consistent with their findings.

G. DISCUSSION

We conclude this section by making a few observations about the results and discussing some limitations in interpreting them.

i. Local average treatment effects

The results from the RD analysis recover parameters that pertain to individuals close to age 21 or 65. They are likely relevant to individuals in their late twenties and fifties as well, since patterns of health and health care use are relatively stable over short ranges of age. Both groups of beneficiaries are very policy relevant. The former group has seen the greatest increase in insurance coverage under the Medicaid expansion, as evident from appendix Figure A. 7. The figure presents the share of 21-64-year-olds covered by Medicaid and uninsured among different age groups. Panel A presents data from the ACS, while Panel B presents corresponding data from hospital stays. Young adults, in their twenties, experienced the greatest increase in Medicaid and decrease in uninsurance both in the population, as well as among individuals discharged from hospitals. The latter group could benefit further from an increase in public insurance if Medicare is expanded to include the near-elderly.[22]

The IV estimates are applicable only to compliers, i.e. individuals that aged out of Medicaid pre-ACA and gained coverage under the ACA – hence, they are applicable to a subset even within this age group. Compliers share some common attributes such as being low-income, not having children and not having a disability or serious sickness. All of these factors precluded them from Medicaid coverage pre-ACA. These features are not particularly restrictive, especially for the young.

Finally, the IV estimates pertain to obtaining public insurance. We may expect very different estimates if the same individuals were awarded private coverage, for example. Anderson, Gross and Dobkin (2012) find the likelihood of ER use decreases by 40% when individuals lose private insurance coverage at

[22] Since the 1990s several unsuccessful legislative proposals have been floated to expand Medicare to cover near-elderly individuals aged 55-64. The latest one (still on-going) was introduced in August 2017 in the US Senate. See https://www.stabenow.senate.gov/news/senator-stabenow-announces-medicare-at-55-act for more details.

age 19. This is much greater than our estimated effect on utilization for the young and could be driven by the differences between private insurance and Medicaid, differences in the sample population, and the age threshold being studied.

ii. Adverse selection

Our research design and data do not allow us to quantify whether the newly insured Medicaid beneficiaries are adversely or advantageously selected. We cannot distinguish between adverse selection and moral hazard, both of which will result in an increase in utilization of care upon gaining insurance. In the case of the young, the nature of Medicaid eligibility restrictions pre-ACA and the large increase in coverage make it likely that the newly insured beneficiaries are healthier than existing Medicaid recipients. The lack of increase in stays and ER arrivals among the young strengthens this argument.

In the case of the near-elderly, two factors suggest that the high elasticity could be driven by infusion of high risk beneficiaries into Medicaid. First, a very small proportion of the near-elderly lacked insurance pre-ACA. These could have been individuals priced out of individual insurance plans but not eligible for Medicaid. Second, marginal near-elderly patients gaining insurance experience a large increase not only in ER arrivals, but also in stays admitted through the ER, suggesting that this was a particularly sick patient group.

iii. Patient sorting across hospitals

The evidence on sorting of patients toward privately owned hospitals and hospitals with better mortality scores is robust with economically significant estimates. This pattern is particularly compelling because it is also found in the ER arrivals data. We cannot quantify the role of different mechanisms causing this sorting. The evidence indicates it is primarily driven by patient preferences for better (real or perceived) hospital care. Another factor that could contribute to this sorting pattern is narrow provider networks imposed on newly insured Medicaid and exchange patients that force them to obtain care at specific hospitals and exclude certain hospitals. Haeder, Weimer and Mukamel (2015) examine the breadth, access and quality of insurer networks offered on California’s ACA exchanges relative to commercial health plans. They find that exchange plan networks are narrower and cover care at about 80% of the hospitals relative to commercial plans. However, this reduction in network breadth does not correlate with hospital ownership or quality and does not result in lower geographic access (in terms of distance). Thus, it seems unlikely that this factor can drive the sorting pattern.

iv. Short run effects

Our sample covers only two years of data after the insurance expansion (2014-15) on hospital care and three years in the case of hospital finances. We find robust evidence of change in some aspects of utilization of care and hospital choice, but not on patient health or spillover effects on quality. These results should be seen as estimates of short-run effects of insurance expansion.

Depending on the importance of dynamics in generating changes in hospital care (e.g. newly insured beneficiaries learn how to use preventative care or choose hospitals, or hospitals learn how to better serve such patients), the long-run effects could be very different. Robust evidence of larger effects on utilization of care and sorting across hospitals in 2015 relative to 2014 suggest that long-run effects may be larger in magnitude.

VI. ROBUSTNESS AND FALSIFICATION CHECKS

A. Quadratic vector in age

As discussed in section IV.A, our preferred specification for equations 2 and 3 uses a linear vector in patient age to model the role of age. This modeling choice seems reasonable since labor market inputs like education, income and employment (that affect insurance coverage) as well as health should vary smoothly with age. In this section we test whether alternative ways of modeling the role of age affect the conclusions. In particular, we check the robustness of our main results to using a quadratic polynomial in age instead of a linear function. Table 8 presents equivalent results to Table 2 (insurance coverage), Table 3 (utilization), Table 4 and Table 5 (hospital choice) and Table 6 (patient health) on the sample of hospital stays. Panels A and B present results for the young and elderly respectively.

On changes in insurance coverage, sorting across hospitals and patient health, the estimates are remarkably similar to the main results, both for the young and the elderly. Within these outcomes, the only estimate that differs meaningfully from the main results is the change in discontinuity in private coverage at age 65 for the near-elderly post-ACA. The quadratic specification estimates a *greater* decrease in private coverage post-ACA than the linear specification, implying that the main result may be understating crowd-out.

However, using a quadratic vector to model age noticeably affects the estimates on utilization of care for the near-elderly. The estimated discontinuity pre-ACA is of similar magnitude, but the increase in utilization rate post-ACA drops by half, to about 5% of the mean level. The LATE estimate also decreases, implying a 10% increase in insurance coverage leads to a 15% (instead of 18%) increase in utilization. We prefer to focus on these estimates in order to be conservative, and use the quadratic specification when examining robustness of utilization effects. Even these effects are much greater than those obtained in a partial equilibrium setting, such as the Oregon Medicaid experiment (Finkelstein et al., 2012). Their LATE estimate for a much younger sample indicates that Medicaid coverage causes a 20% increase in likelihood of hospitalization. They do find 50% greater effects on the near-elderly (50-63) individuals in their sample (Table A.26). While some of the disparity in estimates is due to differences in the setting, sample and methodology – we believe a key reason is the difference between partial and general equilibrium effects. Two factors seem plausible, though there could be others. First, the large increase in insurance coverage accompanied by a temporary increase in Medicaid reimbursements may have induced supplier responses. For example, more hospitals and physicians may have started accepting Medicaid patients in light of the increase in reimbursement. Second, extensive media coverage and government outreach accompanied the Medicaid expansion that may have amplified demand for hospital care.

B. Placebo insurance expansion

An important identification concern in attributing changes post 2014 to the ACA is that the effects may not be driven by the insurance expansions of 2014, but by other economic trends that preceded implementation of the ACA. This is particularly relevant in the case of the estimated decrease in private coverage, which is a larger trend observed in health care data since the great recession. In order to examine whether pre-existing economic trends could be driving some of the changes in insurance coverage (our first stage) we replicate our regression discontinuity analysis over the period 2008-11 i.e. before the ACA insurance expansions were implemented.

Ideally, if our pre-ACA coefficient (2012-13) estimates a stable discontinuity in coverage under the previous equilibrium, then we should find similar estimates in the 2008-09 period as well, i.e. $\theta_{11}^{08-09} = \theta_{11}^{12-13}$. If the post-ACA coefficient captures changes only due to the ACA, then we would find a zero effect in a placebo test, i.e. $\theta_{12}^{08-09} = 0$.

Table 9 presents corresponding results on insurance coverage, utilization, hospital choice and patient health for the sample of hospital stays corresponding to the period 2008-11. It has the same format as Table 8 discussed above. The first row in both panels estimates the discontinuity in outcome over 2008-09 at ages 21 and 65 respectively. All estimated effects pre-2010 for both the young and elderly are qualitatively similar to the corresponding main results presented in previous tables. The estimated effects on hospital shares and patient health are not statistically significant in the case of the young, but are of similar magnitude and sign as the main results.

The second row in both panels presents the estimated change in discontinuity in 2010-11 relative to 2008-09. Several coefficients are not statistically significant different than zero or are close to zero. Overall the pattern of results does not foreshadow the post-ACA results. For example, we find an increase in self-insurance both among the young and the elderly and no decrease in share of government hospitals. Taken together, these estimates further reinforce the interpretation that losing insurance coverage causes sorting of patients towards government hospitals, and vice versa. Specifically, we do not find a statistically significant decrease in private coverage for the near-elderly post 2010, allaying a key concern with the crowd-out interpretation. Overall this exercise does not present evidence to challenge conclusions drawn from the main results.

C. Alternative (age) bandwidth

We replicate all RD analyses using a sample defined by a narrower (2-year) age bandwidth above and below the age bandwidths of 21 and 65, i.e. 19-22.9 and 63-66.9 respectively. We present the corresponding results on insurance coverage, utilization, hospital choice and patient health in Table A. 4, which has an identical format as Table 8. Across all outcomes of interest, estimates are remarkably similar to the main estimates presented using a sample defined by a three-year bandwidth. This is not very surprising since we use a weighted least squares procedure assigning higher weight to individuals aged one year above and below the threshold and lower weight to individuals more than one year away from the threshold.

Two coefficients for the near-elderly merit mentioning. The estimated decrease in private coverage for the near-elderly is substantially greater when we use a narrower bandwidth. Therefore, the main results could be understating the crowd-out of private coverage among the near-elderly. The estimated increase in utilization rate post-ACA is smaller in magnitude and not statistically significant when we use a two-year bandwidth, but less than 2 standard errors away from the main estimate.

VII. CONCLUSION

The Affordable Care Act (ACA) authorized the largest expansion of public insurance since the passage of Medicare and Medicaid in the 1960s. This massive intervention in the health care system offers an unprecedented opportunity to quantify the effects of public insurance coverage in a general equilibrium setting on beneficiaries and hospitals alike. We exploit the presence of sharp discontinuities in public insurance coverage at ages 21 and 65 in a regression discontinuity based research design to examine several possible effects of insurance coverage in the context of the ACA. We conduct our analysis for the state of California using the universe of all hospital stays and ER visits over 2008-15 and some supplementary data files on hospital financials. To our knowledge, this is the first examination of the effects of the ACA using administrative data on hospital care and financial reports.

We have five main findings. First, we find that Medicaid expansion crowded out existing county indigent service programs in California for patients in both age groups, as well as private insurance in the case of near-elderly patients. The crowd-out is large – our estimates imply that only about a third of incremental Medicaid spending on hospital care provided relief to uninsured individuals. The remainder was transfer from federal taxpayers to entities (mostly counties) that would previously bear these costs.

Second, we find heterogeneous effects on utilization of care. For the young, there is virtually no change in rate of arrival at the ER or hospitalization. The elderly are much more price elastic, with a 10% increase in insurance leading to a 10-15% increase in hospital care. These estimates are at least 2x larger than corresponding partial equilibrium estimates reported by Finkelstein et al. (2012) and illustrate the quantitative importance of possible general equilibrium effects. Third, insurance coverage enables patients to switch hospitals in favor of private non-profit hospitals and better quality hospitals. These effects are economically significant and suggest an important source of utility for beneficiaries that has typically been overlooked in previous cost-benefit exercises on Medicaid. Fourth, we find suggestive evidence that patient health and quality of care has improved, but the effects are not robust and often inconsistent. Fifth, we find robust evidence that the insurance expansion has resulted in a 10% relative increase in revenue for hospitals that previously had a high uninsured patient mix. We do not find corresponding evidence on spillover quality effects of this increased revenue flow, or investment responses. In addition to the main results, we provide supporting evidence using a variety of robustness checks and supplementary analyses.

Our results have important limitations. The estimates are specific to California and local to individuals in these specific age groups. Since our main data source is hospital discharge data, we do not observe health care effects outside hospitals and any non-health care effects. For example, we cannot comment on changes in access to care, quality of primary care or alleviation in consumer finances post-ACA. We do not observe hospital responses on important dimensions such as technology adoption and staffing. Exploring these aspects and linking them together in a comprehensive evaluation of this landmark reform of US health care are important directions for future research.

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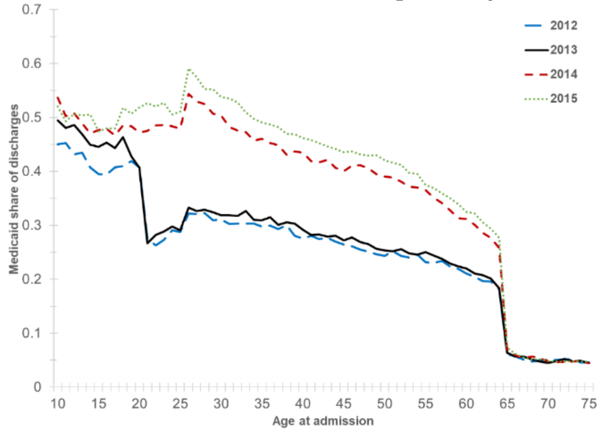
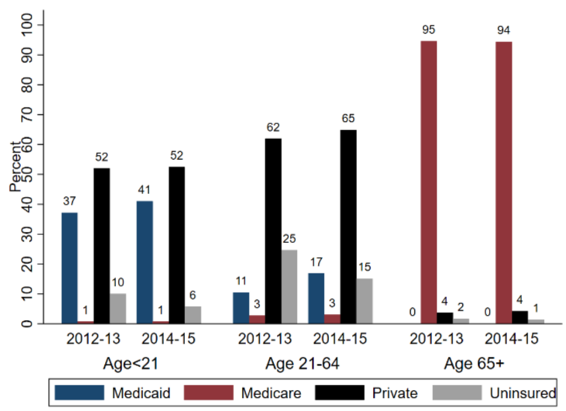
FIGURES AND TABLES

1a: Medicaid share of hospital stays



1b: Insurance coverage in California, ACS



1c: Medicaid and Exchange enrollment in California

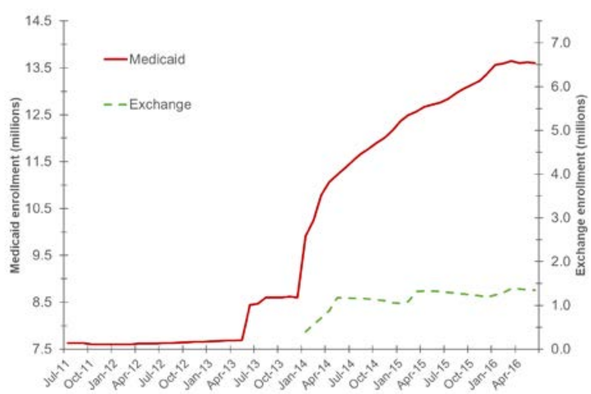
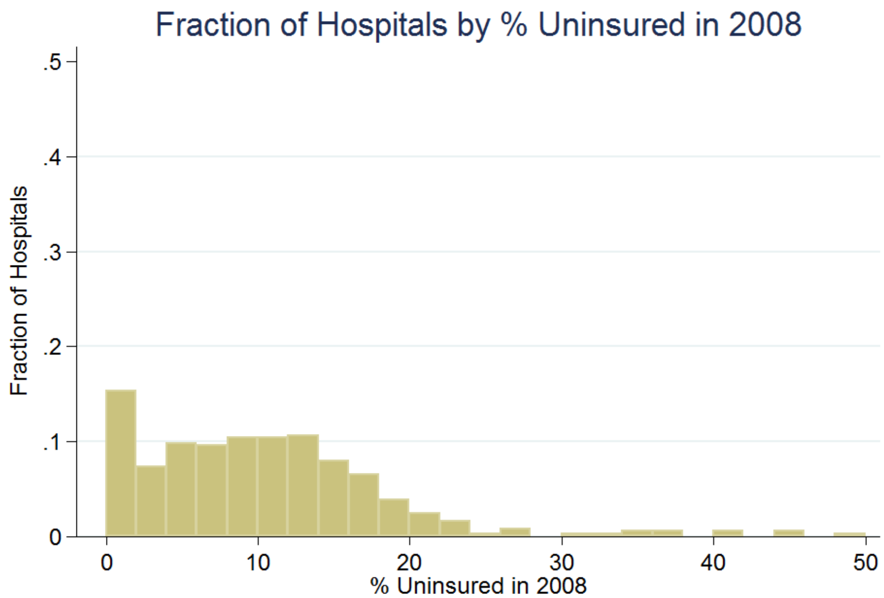


Figure 1: Insurance coverage in California

Note: This figure presents primary insurance coverage in California over 2012-15 as reported in Medicaid share of hospital stays for ages 10-75 as recorded in hospital discharge data (Panel A), the American Community Survey (Panel B), and monthly enrollment in Medicaid and ACA exchange (Panel C). The sample used in Panel A excludes cases related to pregnancy and deliveries, is limited to General Acute Care hospitals and excludes individuals residing in zip codes outside California. In Panel B, if an individual reports Medicaid and Medicare, then we code Medicare as primary. Similarly, if an individual reports Private and Medicaid, then we code Medicaid as primary. This ensures coverage aggregates to 100%. Respondents are divided as approximately 21%, 59% and 12% in the three age groups respectively. Enrollment data obtained from CA Department of Health Care Services (Medicaid) and Covered California (Exchange) respectively.

2a: Hospital uninsurance distribution (2008)



2b: Hospital uninsurance distribution (2014)

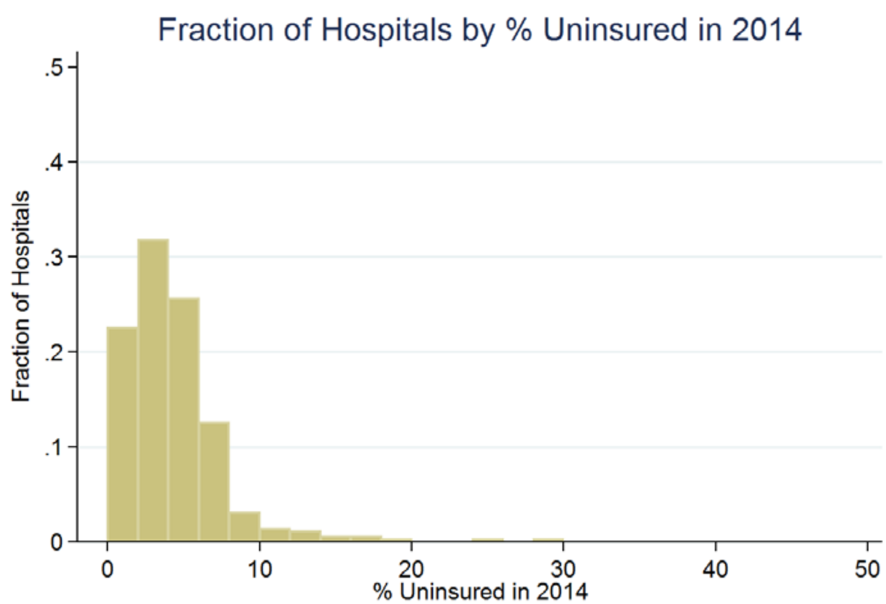
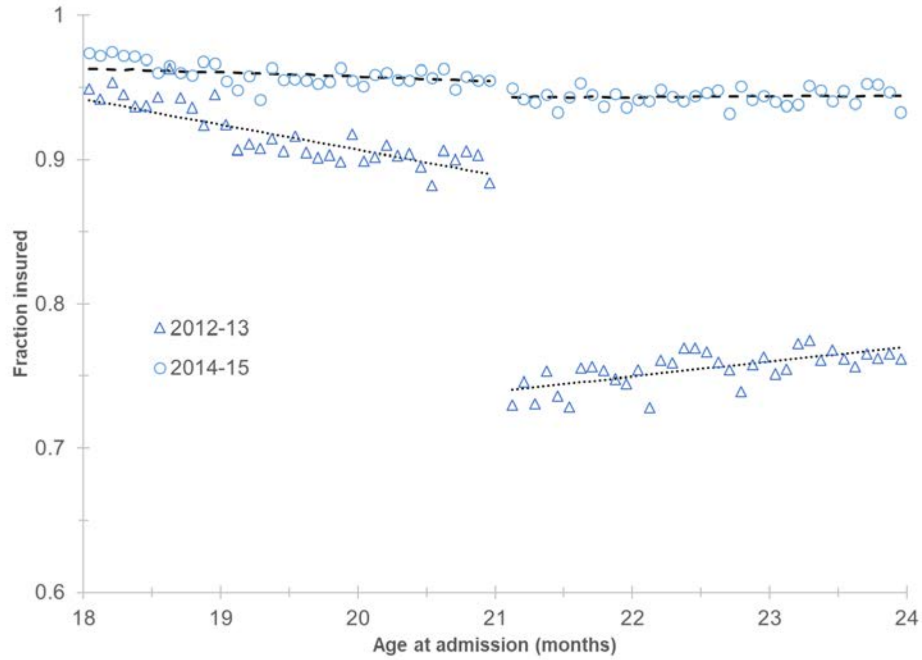


Figure 2: Hospital uninsurance distribution

Note: This figure presents histograms of hospital share of patients that did not have insurance coverage, in 2008 (Panel A, pre-ACA) and 2014 (Panel B, post-ACA) respectively. These histograms were computed using the discharge data on hospital stays. It is based on the sample of non-elderly adults (aged 21-64) and excludes cases related to pregnancy or child birth. Only general acute care hospitals are included. Uninsurance share is top coded at 50% (one hospital in 2008).

3a: Insurance coverage (Young)



3b: Insurance coverage (Elderly)

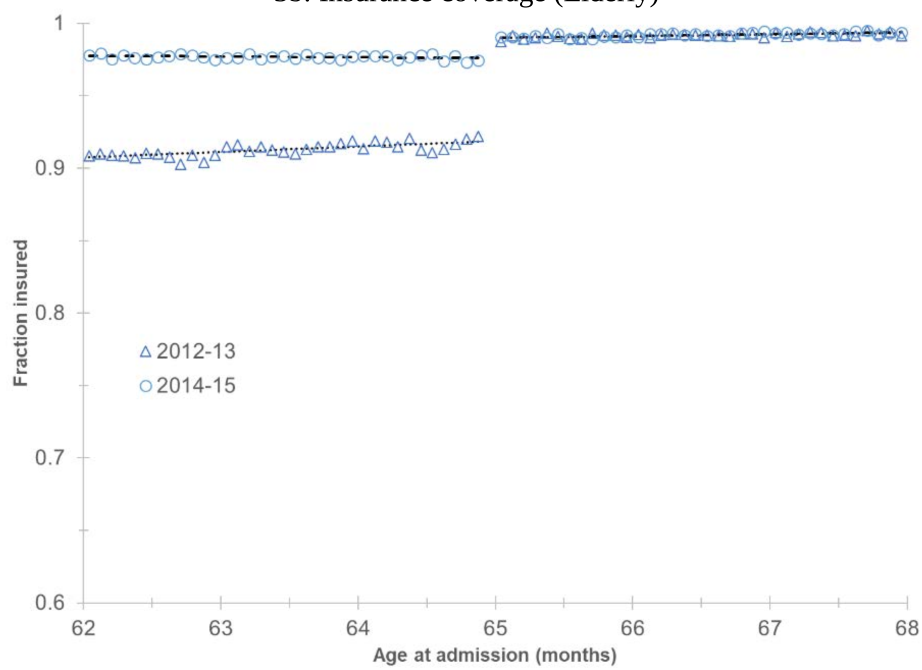
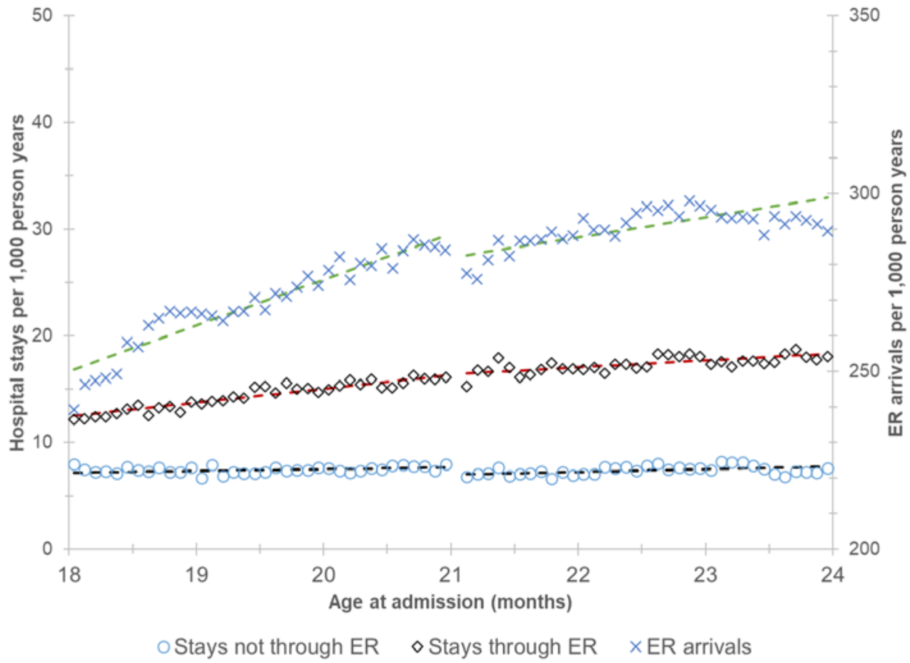


Figure 3: Insurance coverage in RD sample (hospital stays)

Note: This figure presents observed insurance coverage rates collapsed to age-month bin and corresponding fitted values (dashed lines) obtained by estimating equation 2 on case level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) patients respectively. These plots present insurance coverage for hospital stays in the RD sample. The dependent variable is set to 1 if the individual is not self-insured, on charity or county indigent. All models include a full set of hospital service area (HSA) and year fixed effects.

4a: Utilization of care, 2012-13



4b: Utilization of care, 2014-15

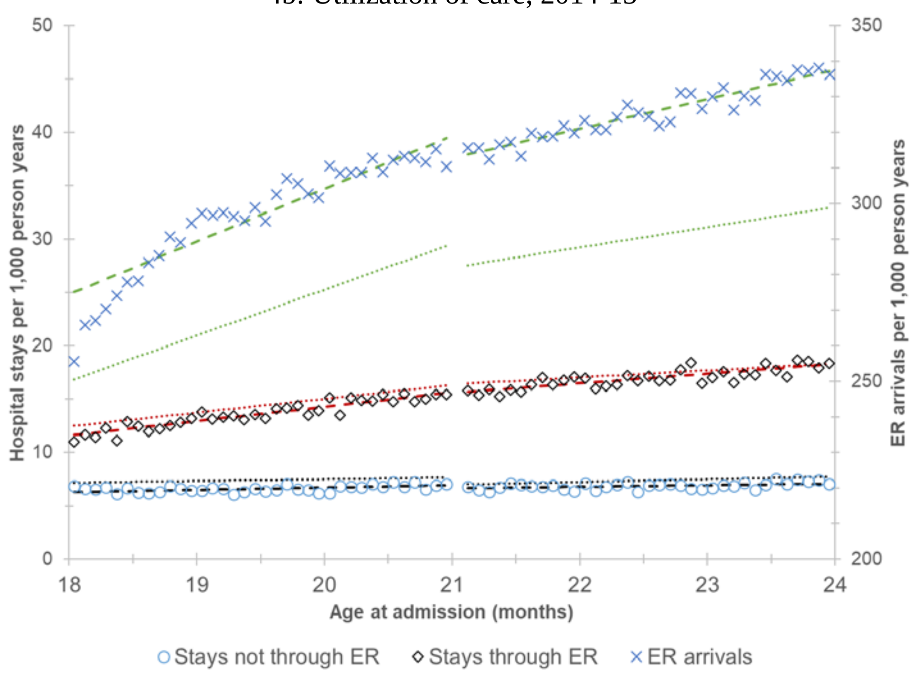
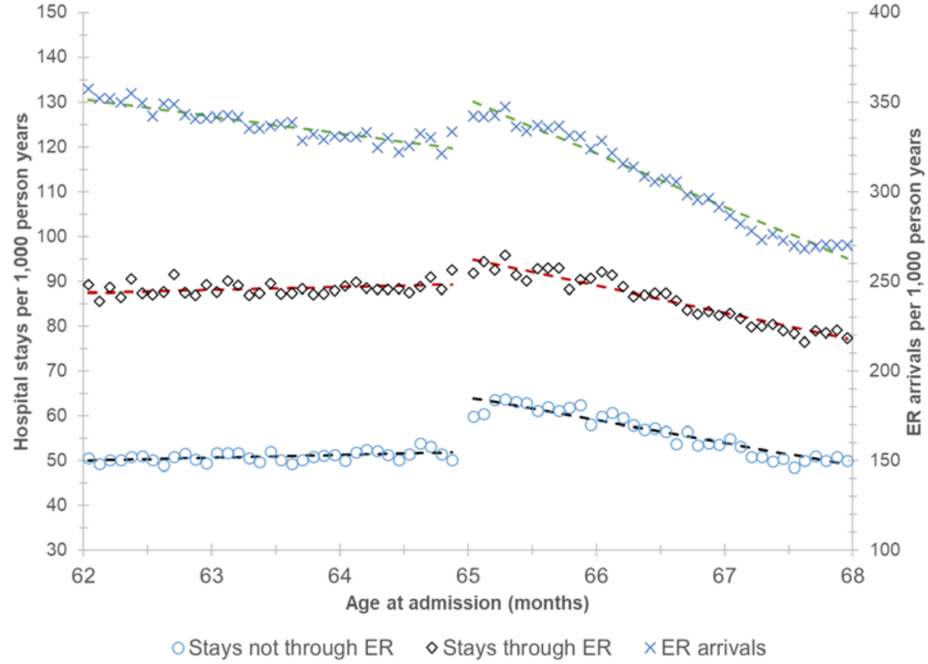


Figure 4: Utilization of hospital care (young)

Note: This figure presents observed number of annual hospital stays and ER arrivals per 1,000 CA residents in each age-month bin. It also plots corresponding fitted values (dashed lines) obtained by estimating equation 7 on age month-year level data as described in Section IV for the sample of young patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. California population estimates obtained for 2012-15 from ACS 1-year survey data. All models include a full set of year fixed effects.

5a: Utilization of care, 2012-13



5b: Utilization of care, 2014-15

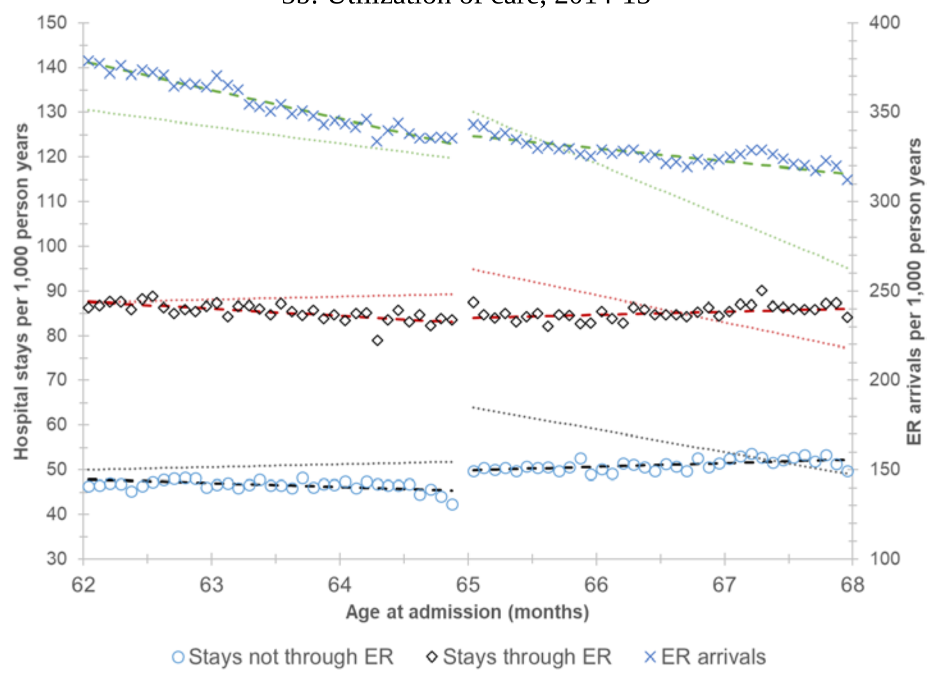
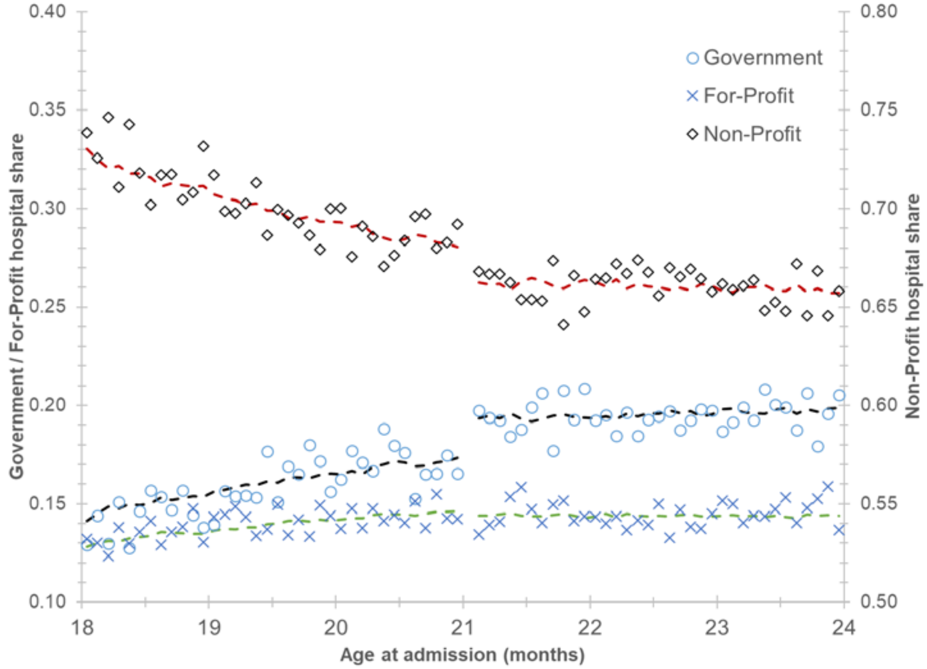


Figure 5: Utilization of hospital care (elderly)

Note: This figure presents observed number of annual hospital stays and ER arrivals per 1,000 CA residents in each age-month bin. It also plots corresponding fitted values (dashed lines) obtained by estimating equation 7 on age month-year level data as described in Section IV for the sample of elderly patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. California population estimates obtained for 2012-15 from ACS 1-year survey data. All models include a full set of year fixed effects.

6a: Hospital share by owner type, 2012-13



6b: Hospital share by owner type, 2014-15

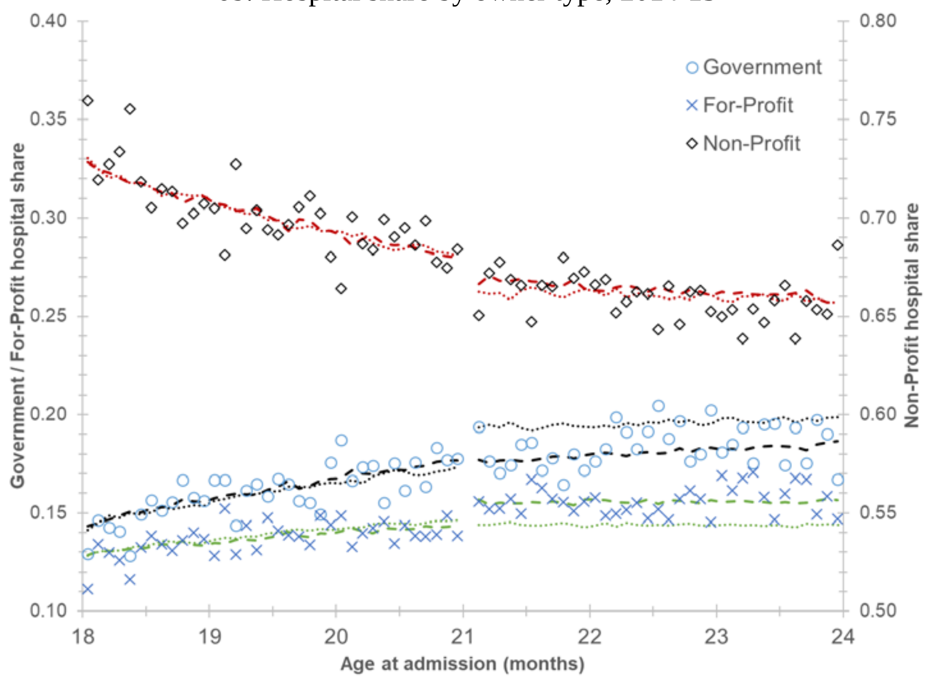
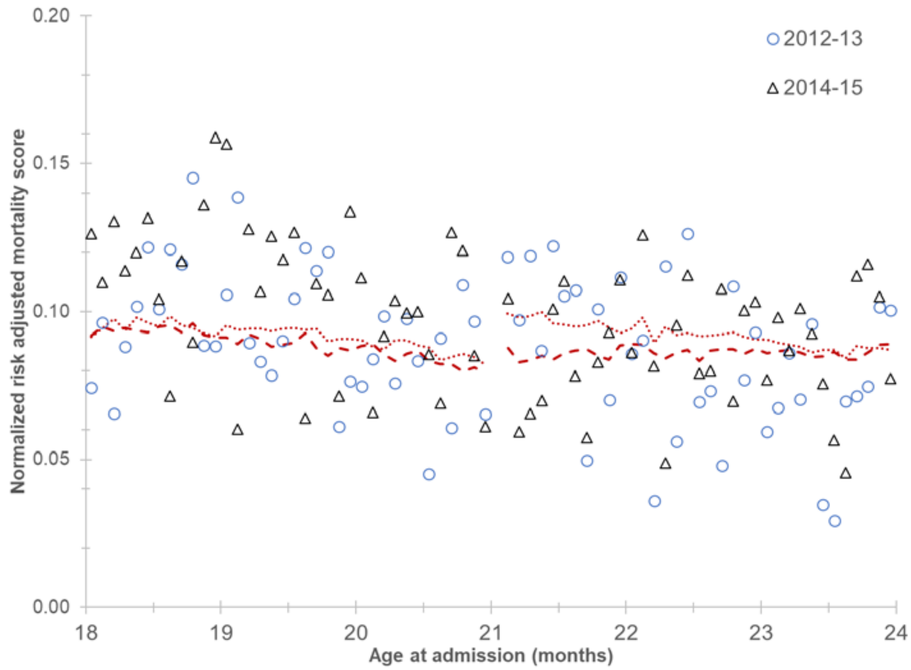


Figure 6: Hospital share by owner type (young)

Note: This figure presents observed share of hospital stays by owner type (Non-profit, For-profit or Government) collapsed to age-month bins. It also plots fitted values (dashed lines) obtained by estimating equation 2 on case level data as described in Section IV for the sample of young patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. The regression co-variates include patient characteristics such as gender and reason for arrival in addition to age. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects.

7a: Quality of serving hospital (Young)



7b: Quality of serving hospital (Elderly)

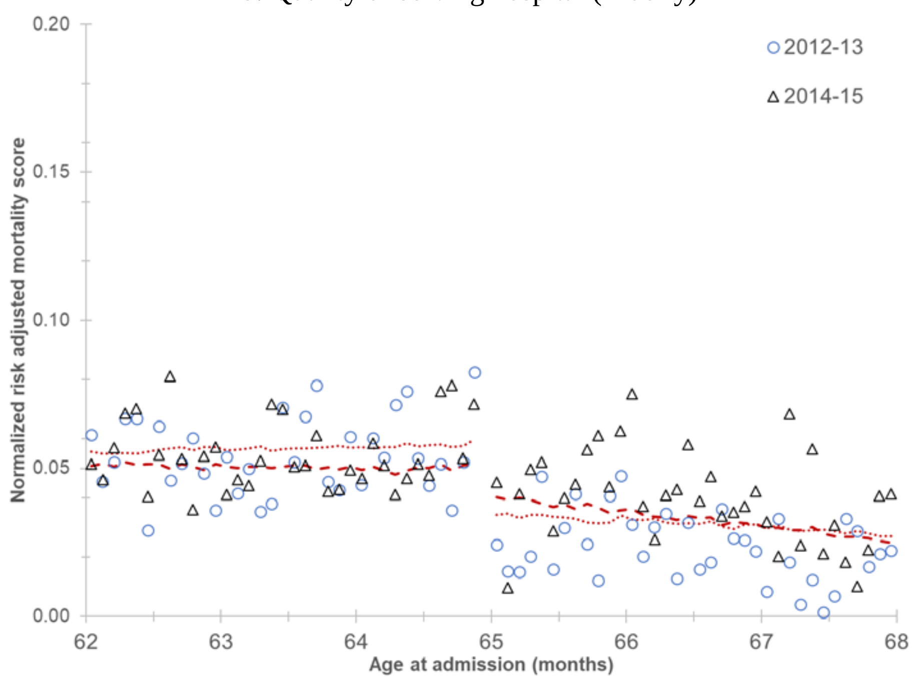
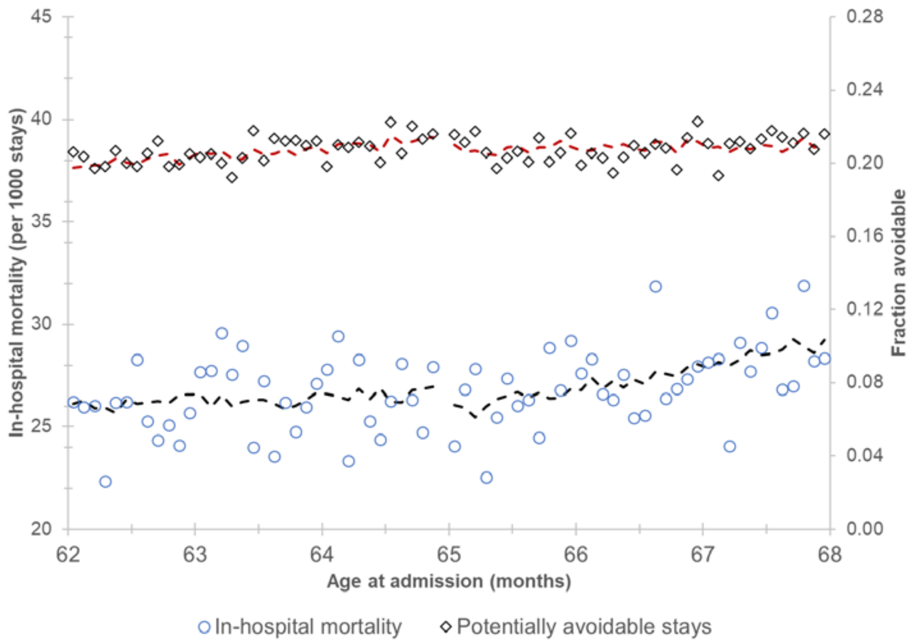


Figure 7: Quality of serving hospital (mortality score)

Note: This figure presents observed standardized risk adjusted mortality score (available at CMS Hospital Compare, corresponding to 2009) for hospital stays, collapsed to age-month bins. It also plots corresponding fitted values (dashed lines) obtained by estimating equation 2 on case level data as described in Section IV for the sample of young (Panel A) and elderly patients (Panel B) respectively. The regression co-variates include patient characteristics such as gender and reason for arrival in addition to age. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects.

8a: Health outcomes (elderly), 2012-13



8b: Health outcomes (elderly), 2014-15

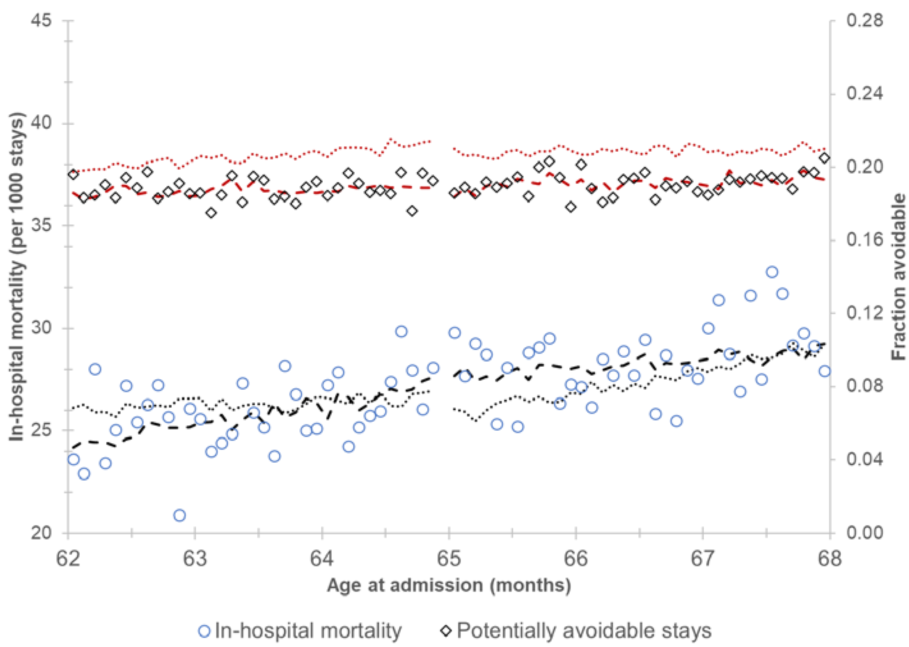


Figure 8: Health outcomes for the elderly

Note: This figure presents observed in-hospital mortality and share of potentially avoidable stays collapsed to age-month bins. It also plots corresponding fitted values (dashed lines) obtained by estimating equation 2 on case level data as described in Section IV for the sample of elderly patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. The regression co-variates include patient characteristics such as gender and reason for arrival in addition to age. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects. Potentially avoidable stays are coded based on presence of specific ICD-9 diagnoses codes for select conditions.

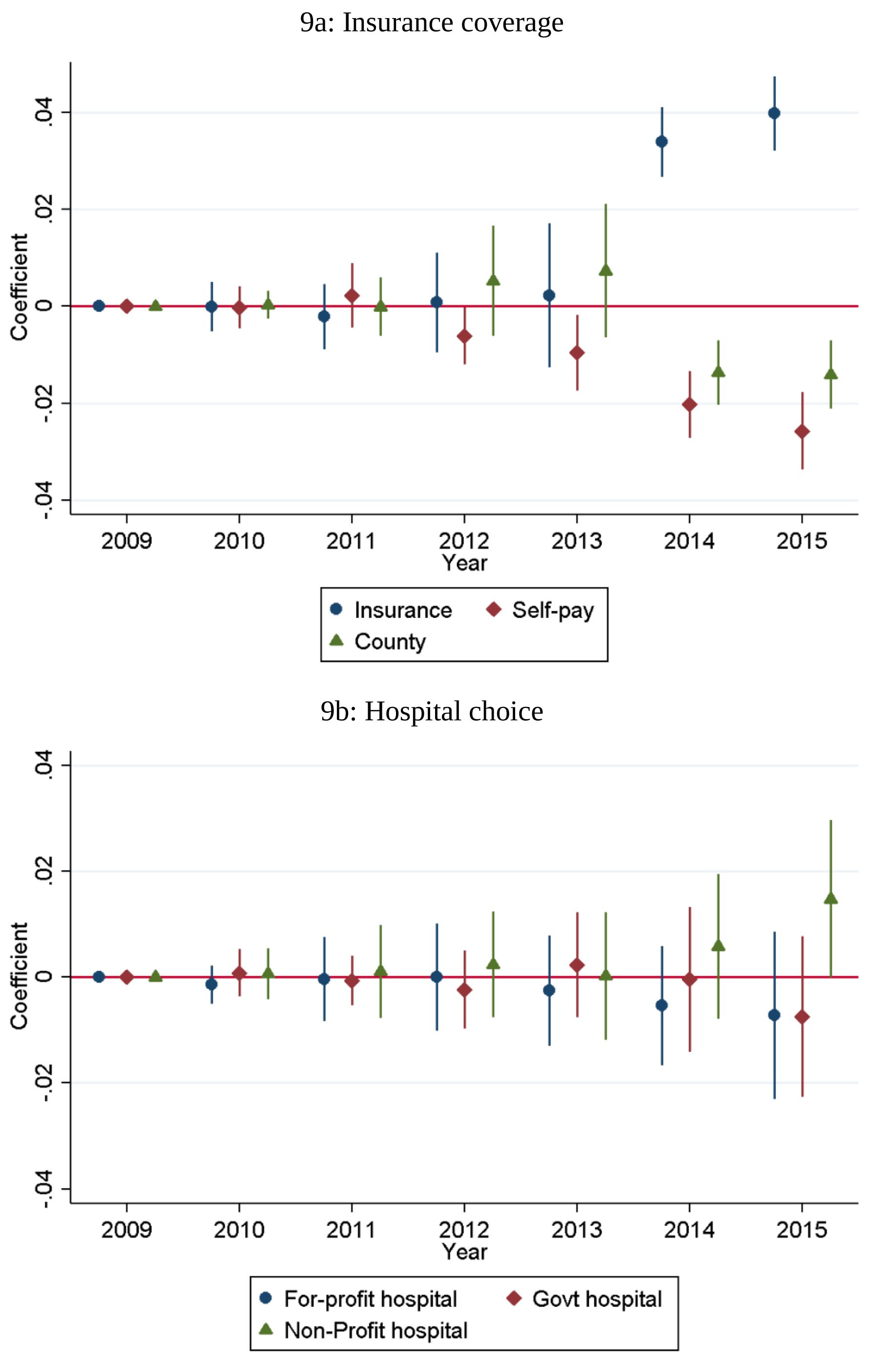


Figure 9: Select evidence from sample of all non-elderly adults

Note: This figure presents coefficients ξ_s on the interaction of d_{j08} and indicator for each year s from 2009-15, obtained by estimating equation 5c with insurance coverage (Panel A) and hospital choice (Panel B) variables as outcomes. d_{j08} is an indicator set to one if HSA j had uninsurance share of patients in the top 1/3rd markets in 2008. This model is estimated using case level data from the sample of all non-elderly adults over 2009-15, about 9 million observations and includes HSA and year fixed effects.

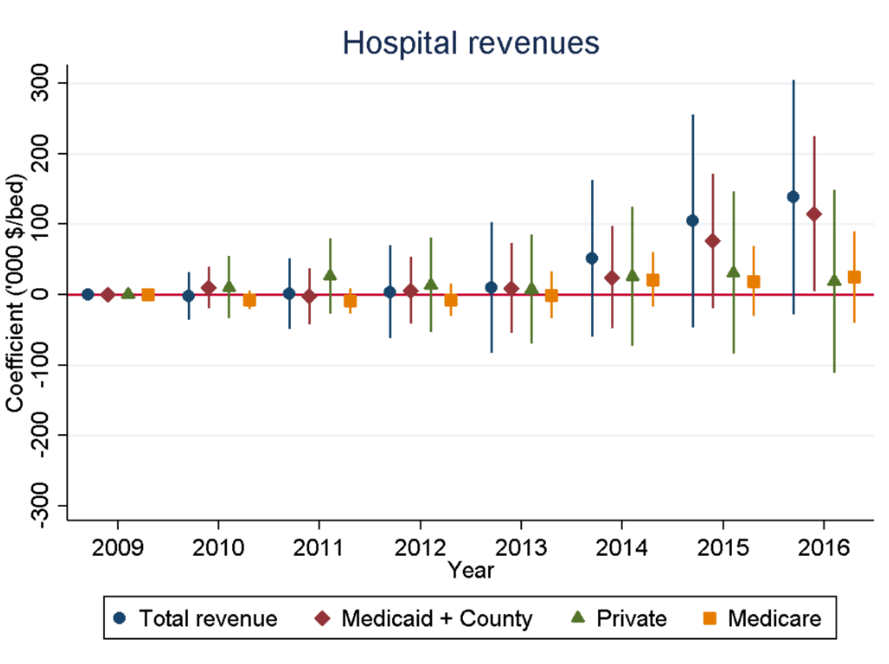


Figure 10: Hospital finances

Note: This figure presents coefficients χ_s on the interaction of d_{h08} and indicator for each year s from 2009-16, obtained by estimating equation 6b with various hospital revenue variables as outcomes. d_{h08} is an indicator set to one if hospital h had uninsurance share of patients among the top 1/3rd hospitals in 2008. All revenue values have been deflated to be in 2016 dollars. This model is estimated using hospital-year level finances data made available by OSHPD over 2009-16 and includes hospital and year fixed effects.

Table 1: Summary Statistics

Panel A: Regression discontinuity sample

	Hospital stays				*All ER arrivals*			
	Ages 18.0 - 23.9		Ages 62.0 - 67.9		Ages 18.0 - 23.9		Ages 62.0 - 67.9	
	2012-13	2014-15	2012-13	2014-15	2012-13	2014-15	2012-13	2014-15
All observations	157,226	147,107	554,522	577,663	1,885,135	2,071,154	1,262,901	1,463,335
Admitted through ER	107,034	101,928	343,256	367,418	107,034	101,928	343,256	367,418
Medicaid	0.34	0.50	0.13	0.17	0.29	0.45	0.12	0.19
Uninsured	0.17	0.05	0.05	0.02	0.28	0.15	0.10	0.04
Utilization rate	23	22	141	134	280	311	322	341
Government hospital	0.18	0.17	0.11	0.11	0.17	0.16	0.15	0.15
Non-profit hospital	0.68	0.68	0.73	0.72	0.69	0.69	0.72	0.72
For-profit hospital	0.14	0.15	0.16	0.17	0.14	0.15	0.13	0.13
In-hospital mortality	0.006	0.006	0.027	0.027	0.0008	0.0006	0.0120	0.0110
Potentially avoidable	0.21	0.20	0.21	0.19	0.18	0.15	0.20	0.18

Panel B: Non-elderly sample (21-64)

	Hospital Stays	
	2009-13	2014-15
Observations	6,403,985	2,494,122
Medicaid	0.24	0.40
Uninsured	0.14	0.04
Government hospital	0.16	0.15
Non-profit hospital	0.68	0.68
For-profit hospital	0.16	0.17

Panel C: Hospital revenue per bed (2016$ '000s)

	2009-13	2014-16
Total revenue	1,054	1,245
Medicaid	225	345
Traditional	160	173
Managed Care	64	170
Medicare	319	357
Private	464	517
County Indigent	15	5
Others	22	14
Number of hospitals	339	335

Note: This table presents descriptive statistics from the samples used in the main analyses of the paper. Panels A and B present statistics for the samples in the regression discontinuity analysis and all non-elderly (21-64) patients in the spatial variation analysis respectively. Both samples begin with the universe of all discharges and use three sample restrictions – 1) only general acute care hospitals 2) exclude pregnancy and delivery related cases and 3) exclude patients with missing or out-of-CA zip codes. Fraction uninsured includes patients coded as self-pay, charity or county indigent coverage. Panel A focuses on cases pertaining to ages 18-23 (both inclusive) or 62-67. ER arrivals include ER visits and hospital stays that originated in the ER. To calculate utilization, we normalize number of annual stays/ER arrivals by the population in relevant age group obtained from ACS 1-year estimates, hence these are measures of utilization per 1,000 person years. We obtain population estimates for each year in 2012-15 for the young (18-24) and elderly (62-69) and assume that it is uniformly distributed. Panel C presents mean values of key variables in the hospital finances data, primarily hospital revenue per licensed bed pre (2009-13) and post (2014-16) implementation of the Medicaid expansion. Revenue values are expressed in thousands of 2016 dollars. Finances data is only gathered for so-called "comparable" hospitals that excludes state-owned, Kaiser and Shriner group of hospitals. Hence the number of hospitals covered in financial analysis is about 40 lower than in the discharge data.

Table 2: Insurance coverage (hospital stays)

Panel A: Ages 18.0 - 23.9	(1)	(2)	(3)	(4)	(5)	(6)
Estimated discontinuity	Medicaid	Private	Medicare	Insured	County	Self-Pay
Pre-ACA	-0.1390***	-0.0083	-0.0025	-0.1498***	0.0851***	0.0647***
	(0.0096)	(0.0080)	(0.0024)	(0.0069)	(0.0057)	(0.0063)
Change post-ACA	0.1427***	-0.0118	0.0071*	0.1380***	-0.0835***	-0.0545***
	(0.0103)	(0.0098)	(0.0040)	(0.0067)	(0.0059)	(0.0056)
21-23.9 Mean 2012-13	0.27	0.45	0.03	0.76	0.10	0.15
21-23.9 Mean 2014-15	0.50	0.41	0.03	0.94	0.01	0.05
Observations	304,333					

Panel B: Ages 62.0 - 67.9						
	Medicaid	Private	Medicare	Insured	County	Self-Pay
Pre-ACA	0.1173***	0.2701***	-0.4586***	-0.0712***	0.0356***	0.0357***
	(0.0060)	(0.0087)	(0.0049)	(0.0024)	(0.0023)	(0.0016)
Change post-ACA	0.0763***	-0.0265***	0.0074	0.0572***	-0.0334***	-0.0238***
	(0.0047)	(0.0059)	(0.0057)	(0.0025)	(0.0023)	(0.0018)
62-64.9 Mean 2012-13	0.20	0.46	0.25	0.91	0.04	0.05
62-64.9 Mean 2014-15	0.29	0.43	0.26	0.98	0.00	0.02
Observations	1,132,185					

Note: This table presents regression coefficients obtained using case level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) patients respectively. The dependent variable is coverage by different insurers or self-pay/county indigent coverage. Private insurance includes coverage for government employees and workers' compensation. This table pertains to hospital stays. Appendix Table A. 1 pertains to ER visits including those resulting in hospital stays. Estimated discontinuity pre-ACA is the coefficient on d_i in equation 2. Estimated change in the discontinuity post-ACA is the coefficient on $d_i \cdot T_t$ in equation 2. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 3: Utilization of hospital care

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Hospital stays		***All ER arrivals***		***Hospital stays (by admission route)***			
	All stays				Through ER		Not through ER	
	Young	Elderly	Young	Elderly	Young	Elderly	Young	Elderly
Estimated discontinuity								
Pre-ACA	-0.6058*	-18.0538***	-6.6522***	-28.1777***	0.0615	-5.7900***	-0.6674***	-12.2638***
	(0.3389)	(1.7540)	(1.6220)	(3.1661)	(0.2847)	(1.0308)	(0.1478)	(0.9904)
Change post-ACA	0.2450	12.3164***	0.4303	21.4340***	-0.1281	4.6454***	0.3731*	7.6710***
	(0.4422)	(1.9718)	(2.4771)	(3.6159)	(0.3637)	(1.2558)	(0.2088)	(1.1542)
Change in 2014	0.0545	10.4222***	-2.5874	16.5047***	-0.2085	3.8512***	0.2630	6.5710***
	(0.4600)	(1.9910)	(2.6610)	(3.7244)	(0.3829)	(1.3094)	(0.2207)	(1.1637)
Change in 2015	0.4356	14.2106***	3.4481	26.3631***	-0.0478	5.4395***	0.4833**	8.7710***
	(0.4590)	(2.0587)	(2.3204)	(3.6213)	(0.3838)	(1.3274)	(0.2172)	(1.1999)
LATE	4.1814*	258.2063***	65.9539***	273.4484***	-0.3718	80.9610***	4.5531***	177.2452***
	(2.1771)	(23.3045)	(13.3730)	(28.4953)	(1.8500)	(13.4825)	(0.9440)	(13.6597)
First stage F-stat	1526.4	1913.9	5081	3616.5				
Mean utilization								
2012-13 "treated"group	24.7	139.3	290.3	337.9	17.3	88.4	7.4	50.9
2014-15 "treated" group	23.8	131.9	325.6	355.2	16.9	85.4	6.9	46.6
2012-13 uninsured	23.2	145.0						

Note: This table presents regression coefficients obtained using age month-year level data as described in Section IV. The dependent variable is mean number of hospital stays/ER arrivals per 1,000 person years at any age-month. Pre-ACA estimated discontinuity is the coefficient on d_s in equation 7. Estimated change in the discontinuity post-ACA is the coefficient on $d_s \cdot T_t$ in equation 7. Coefficients on interaction of d_s with dummies for specific years estimate the corresponding change in discontinuity in that year relative to 2012-13. The coefficient on Ins_s in equation 4 estimates the LATE. The first stage F-stats in the hospital sample are the same irrespective of outcome being investigated. All models include a full set of year fixed effects. Robust standard errors reported. There are 284 observations in each sample. Treated groups are patients aged 21-23.9 and 62-64.9 for the young and elderly respectively.

Table 4: Hospital share by owner type

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-profit hospitals		***For-profit hospitals***		***Government hospitals***	
	Young	Elderly	Young	Elderly	Young	Elderly
Estimated discontinuity						
Pre ACA	-0.0142**	-0.0084**	-0.0034	-0.0123***	0.0176***	0.0208***
	(0.0058)	(0.0033)	(0.0040)	(0.0022)	(0.0046)	(0.0033)
Change post ACA	0.0102	-0.0011	0.0128**	0.0107***	-0.0230***	-0.0095***
	(0.0083)	(0.0037)	(0.0055)	(0.0034)	(0.0069)	(0.0027)
Change in 2014	0.0051	-0.0017	0.0145**	0.0084**	-0.0196***	-0.0066**
	(0.0086)	(0.0042)	(0.0062)	(0.0035)	(0.0072)	(0.0026)
Change in 2015	0.0153*	-0.0005	0.0111**	0.0129***	-0.0264***	-0.0124***
	(0.0091)	(0.0038)	(0.0056)	(0.0037)	(0.0075)	(0.0032)
LATE	0.0775**	0.1721***	0.0342	0.1679***	-0.1118***	-0.3401***
	(0.0375)	(0.0518)	(0.0286)	(0.0313)	(0.0329)	(0.0519)
First stage F-stat	116	121				
Mean values:						
2012-13 "treated"group	0.66	0.71	0.14	0.16	0.19	0.13
2014-15 "treated" group	0.66	0.71	0.16	0.17	0.18	0.12
2012-13 uninsured	0.59	0.57	0.12	0.12	0.29	0.31
Observations	304,333	1,132,185				

Note: This table presents regression coefficients obtained using case level hospital stays data. The dependent variable is hospital ownership type (non-profit, for-profit or government). Estimated discontinuity pre ACA is the coefficient on d_i in equation 3. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in equation 3. Coefficients on interaction of d_i with dummies for specific years estimate the corresponding change in discontinuity in that year relative to 2012-13. LATE is the coefficient on Ins_i in equation 4. The first stage F-stats are the same irrespective of outcome being investigated. Columns 1, 3 and 5 present results for the young, while columns 2, 4 and 6 present results for the elderly. Treated groups are patients aged 21-23.9 and 62-64.9 for the young and elderly respectively. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 5: Quality of serving hospital (risk-adjusted mortality)

	(1)	(2)	(3)	(4)
	Hospital stays		***All ER arrivals***	
	Young	Elderly	Young	Elderly
Estimated discontinuity				
Pre ACA	0.0136	0.0208***	0.0014	0.0140**
	(0.0087)	(0.0079)	(0.0041)	(0.0070)
Change post ACA	-0.0122	-0.0128	-0.0045	-0.0053
	(0.0143)	(0.0087)	(0.0048)	(0.0056)
Change in 2014	-0.0083	-0.0057	-0.0039	-0.0036
	(0.0162)	(0.0096)	(0.0050)	(0.0052)
Change in 2015	-0.0162	-0.0196**	-0.0050	-0.0068
	(0.0147)	(0.0089)	(0.0051)	(0.0065)
LATE	-0.0514	-0.2547***	-0.0022	-0.1253**
	(0.0595)	(0.0987)	(0.0335)	(0.0605)
First stage F-stat	102.8	113.3	158.6	71.6
Mean values:				
2012-13 "treated"group	0.083	0.054	0.227	0.155
2014-15 "treated" group	0.088	0.055	0.233	0.165
2012-13 uninsured	0.181	0.135	0.198	0.119
Observations	252,918	933,655	3,325,479	2,196,516

Note: This table presents regression coefficients obtained on case level hospital stays/ER data. The dependent variable is standardized risk-adjusted hospital mortality score as reported by CMS in 2009. Score is based on 30-day mortality calculated for Medicare patients admitted with Heart attack, Heart Failure or Pneumonia. The first two columns pertain to hospital stays while columns 3 and 4 pertain to all ER arrivals. Estimated discontinuity pre ACA is the coefficient on d_i in equation 3. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in equation 3. Coefficients on interaction of d_i with dummies for specific years estimate the corresponding change in discontinuity in that year relative to 2012-13. LATE is the coefficient on Ins_i in equation 4. Treated groups are patients aged 21-23.9 and 62-64.9 for the young and elderly respectively. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 6: Health outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	In-hospital mortality				***Potentially Avoidable visits***			
	Hospital stays		All ER arrivals		Hospital stays		All ER arrivals	
	Young	Elderly	Young	Elderly	Young	Elderly	Young	Elderly
Estimated discontinuity								
Pre ACA	0.0011	0.0008	0.0001	0.0005	0.0143**	0.0066**	0.0026*	-0.0011
	(0.0009)	(0.0008)	(0.0001)	(0.0004)	(0.0060)	(0.0025)	(0.0016)	(0.0018)
Change post ACA	-0.0015	-0.0009	-0.0001	-0.0009*	-0.0036	-0.0044	-0.0022	0.0012
	(0.0013)	(0.0011)	(0.0001)	(0.0005)	(0.0087)	(0.0039)	(0.0021)	(0.0025)
Change in 2014	-0.0017	0.0005	-0.0001	-0.0004	-0.0106	-0.0062	-0.0042*	0.0000
	(0.0014)	(0.0012)	(0.0001)	(0.0006)	(0.0094)	(0.0044)	(0.0023)	(0.0028)
Change in 2015	-0.0013	-0.0023*	-0.0001	-0.0014***	0.0038	-0.0026	-0.0003	0.0024
	(0.0014)	(0.0012)	(0.0001)	(0.0005)	(0.0097)	(0.0041)	(0.0023)	(0.0025)
LATE	-0.0072	-0.0124	-0.0008	-0.0031	-0.0766*	-0.0945***	-0.0097	0.0041
	(0.0062)	(0.0111)	(0.0008)	(0.0038)	(0.0391)	(0.0290)	(0.0138)	(0.0156)
First stage F-stat	115. 9	120.9	194.5	71.9	123.6	118.5	219.1	91.4
Mean values:								
2012-13 "treated"group	0.006	0.026	0.001	0.011	0.218	0.207	0.171	0.201
2014-15 "treated" group	0.006	0.026	0.001	0.010	0.199	0.188	0.145	0.177
2012-13 uninsured	0.005	0.025	0.001	0.010	0.226	0.194	0.160	0.195
Observations	304,333	1,132,185	3,956,289	2,726,236	129,313	617,077	2,052,306	1,680,320

Note: This table presents regression coefficients obtained using case level hospital stays/ER data. The outcome variables are in-hospital mortality and share of potentially avoidable hospital stays/visits coded using ICD 9 diagnoses codes. Estimated discontinuity pre ACA is the coefficient on d_i in equation 3. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in equation 3. Coefficients on interaction of d_i with dummies for specific years estimate the corresponding change in discontinuity in that year relative to 2012-13. LATE is the coefficient on Ins_i in equation 4. Columns 1, 3, 5 and 7 present results for the young, while columns 2, 4, 6 and 8 present results for the elderly. Treated groups are patients aged 21-23.9 and 62-64.9 for the young and elderly respectively. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 7: Additional evidence and hospital revenue

Panel A: Non-elderly sample (aged 21-64)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Medicaid	Private	Medicare	Insured	Self-Pay	County	Hospital choice		
							Non-profit	For-Profit	Government
A1: Linear									
$Unins_{j08} \cdot T_t$	0.5672***	0.3059***	-0.1171***	0.7560***	-0.3874***	-0.3687***	0.2072***	-0.0529	-0.1542*
	(0.0990)	(0.0554)	(0.0388)	(0.0680)	(0.0459)	(0.0783)	(0.0702)	(0.0713)	(0.0859)
A2: Non-parametric									
$d_{j08} \cdot T_t$	0.0292***	0.0150***	-0.0075***	0.0367***	-0.0203***	-0.0164***	0.0094*	-0.0054	-0.0040
	(0.0056)	(0.0040)	(0.0026)	(0.0049)	(0.0039)	(0.0057)	(0.0056)	(0.0049)	(0.0059)
Observations	8,898,107								
Dep. Var. mean	0.29	0.44	0.16	0.89	0.07	0.04	0.68	0.17	0.16

Panel B: Hospital finances	Hospital revenue						Other outcomes		
	Total rev per bed ('000 \$)	Medicaid per bed ('000 \$)	County per bed ('000 \$)	(Mdcd+Cty) per bed ('000 \$)	Private per bed ('000 \$)	Medicare per bed ('000 \$)	Infant mortality per 1k deliv.	Elderly mortality per 1k stays	Capital exp. per bed ('000 \$)
B1: Linear									
$Unins_{h08} \cdot T_t$	177.5459	380.3411**	-99.9523	280.3887	-82.1245	-2.2596	2.0695	-14.9464	-2.0750
	(278.3836)	(191.5389)	(71.2740)	(209.9127)	(179.2109)	(76.7391)	(3.0496)	(9.4779)	(94.7181)
B2: Non-parametric									
$d_{h08} \cdot T_t$	95.3289*	91.1282***	-23.8210**	67.3072*	13.6364	26.6425	0.0633	-2.3945	2.1121
	(54.0044)	(34.8591)	(9.9376)	(36.1986)	(36.9489)	(19.5349)	(0.4758)	(1.4879)	(21.7148)
Observations	2,562						1,577	2,202	2,579
Dep. Var. mean	978	189	13	202	416	326	3.5	52.9	83

Note: This table presents regression coefficients obtained by estimating equation 6a on case level data for the entire sample of non-elderly adults (Panel A) and equation 6b on hospital-level data (Panel B). All revenue variables are expressed in thousands of 2016 \$. In both panels we present results obtained using linear and non-parametric specifications. $Unins_{j08}$ and $Unins_{h08}$ denote share of uninsured patients for the j^{th} HSA and hospital respectively in 2008. d_{j08} and d_{h08} are indicators that takes value one if unit j has uninsurance level in top third of the distribution. T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. Models include a full set of HSA (Panel A)/Hospital (Panel B) and year fixed effects. Standard errors are clustered by respective panel unit. Dependent variable mean values computed pre-ACA i.e. over 2009-13. Mean uninsurance share is 0.12 and 0.11 respectively across HSAs and hospitals.

Table 8: Robustness (alternative specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Insurance coverage					***Utilization***	***Hospital choice***				***Health***	
Panel A: 18.0 - 23.9	Medicaid	Private	Insured	County	Self-Pay	Stays	Govt.	Non-Profit	For-Profit	RA Mort.	Mortality	PAH
Estimated discontinuity												
Pre ACA	-0.1423***	-0.0163	-0.1638***	0.0846***	0.0792***	-0.9384*	0.0221***	-0.0215***	-0.0006	0.0235*	0.0012	0.0249***
	(0.0109)	(0.0102)	(0.0091)	(0.0067)	(0.0081)	(0.5630)	(0.0063)	(0.0083)	(0.0052)	(0.0137)	(0.0015)	(0.0082)
Change post ACA	0.1498***	-0.0108	0.1484***	-0.0822***	-0.0662***	0.5322	-0.0249**	0.0116	0.0133*	-0.0173	-0.0015	-0.0072
	(0.0128)	(0.0129)	(0.0087)	(0.0069)	(0.0073)	(0.7158)	(0.0099)	(0.0125)	(0.0073)	(0.0232)	(0.0020)	(0.0117)
LATE						5.8866*	-0.1190***	0.1301***	-0.0112	-0.1485*	-0.0062	-0.1289***
						(3.2631)	(0.0371)	(0.0489)	(0.0332)	(0.0759)	(0.0091)	(0.0436)
21-23.9 Mean 2012-13	0.27	0.45	0.76	0.10	0.15	25	0.19	0.66	0.14	0.08	0.006	0.22
21-22.9 Mean 2014-15	0.50	0.41	0.94	0.01	0.05	24	0.18	0.66	0.16	0.09	0.006	0.20
Observations	304,333									252,918		129,313
Panel B: 62.0 - 67.9												
Estimated discontinuity												
Pre ACA	0.1104***	0.2674***	-0.0709***	0.0343***	0.0366***	-14.9925***	0.0144***	0.0006	-0.0150***	0.0235**	0.0007	0.0034
	(0.0066)	(0.0091)	(0.0029)	(0.0025)	(0.0022)	(2.9450)	(0.0032)	(0.0040)	(0.0030)	(0.0098)	(0.0013)	(0.0039)
Change post ACA	0.0802***	-0.0351***	0.0563***	-0.0322***	-0.0241***	6.6372**	-0.0049	-0.0127**	0.0176***	-0.0097	-0.0014	-0.0009
	(0.0070)	(0.0079)	(0.0031)	(0.0026)	(0.0024)	(3.1544)	(0.0037)	(0.0051)	(0.0041)	(0.0125)	(0.0020)	(0.0059)
LATE						225.1548***	-0.2348***	0.0518	0.1831***	-0.3012**	-0.0073	-0.0542
						(38.8010)	(0.0469)	(0.0574)	(0.0409)	(0.1294)	(0.0178)	(0.0457)
63-64.9 Mean 2012-13	0.20	0.46	0.91	0.04	0.05	139	0.13	0.71	0.16	0.05	0.026	0.21
63-64.9 Mean 2014-15	0.29	0.43	0.98	0.00	0.02	132	0.12	0.71	0.17	0.05	0.026	0.19
Observations	1,132,185									933,655		617,077

Note: This table presents regression coefficients obtained by estimating equations 2,3 and 4 on case level data and equation 7 on age-month-year level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) hospital stays respectively. All specifications use a quadratic vector to model the role of age instead of a linear vector. This table provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4, Table 5) and health outcomes (Table 6). Estimated discontinuity pre ACA is the coefficient on d_i in equations 2,3 and 7. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in the same equations. LATE is the coefficient on Ins_i in equation 4. Case level models include a full set of hospital service area (HSA) and year fixed effects and standard errors are clustered by HSA, whereas collapsed regressions include year fixed effects only.

Table 9: Robustness (falsification check)

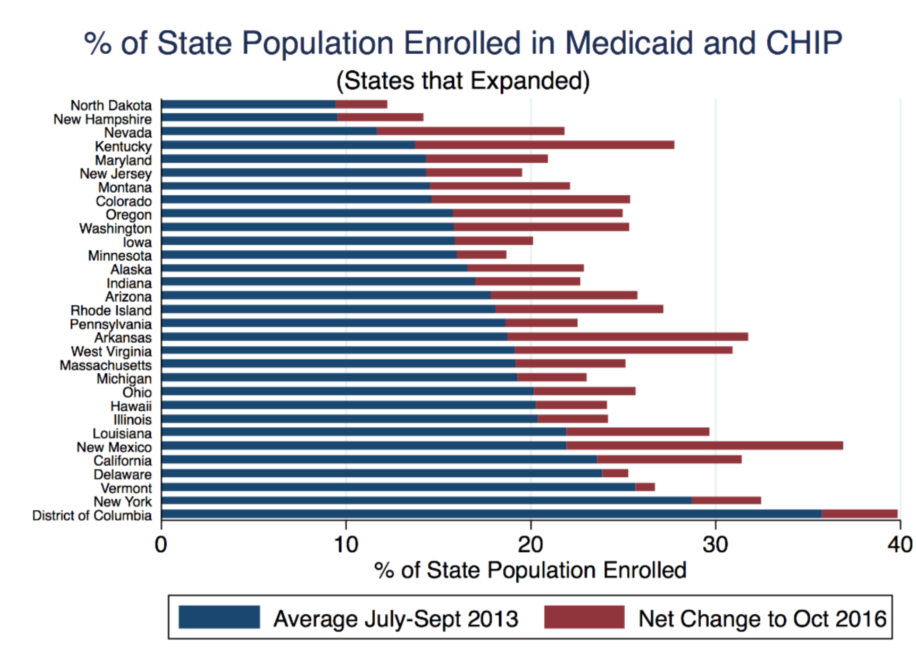
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Insurance coverage					*Utilization* †	*Hospital choice*				*Health*	
Panel A: 18.0 - 23.9	Medicaid	Private	Insured	County	Self-Pay	Stays	Govt.	Non-Profit	For-Profit	RA Mort.	Mortality	PAH
Estimated discontinuity												
Pre 2010	-0.1441***	0.0078	-0.1310***	0.0723***	0.0587***	-0.3218	0.0065	-0.0025	-0.0040	0.0141	0.0005	0.0015
	(0.0085)	(0.0084)	(0.0065)	(0.0049)	(0.0056)	(0.4056)	(0.0048)	(0.0053)	(0.0039)	(0.0105)	(0.0007)	(0.0060)
Change post 2010	-0.0161*	0.0005	-0.0186***	0.0049	0.0136***	-1.0128*	0.0123*	-0.0071	-0.0052	-0.0225*	0.0003	0.0025
	(0.0093)	(0.0095)	(0.0068)	(0.0046)	(0.0052)	(0.5817)	(0.0068)	(0.0071)	(0.0057)	(0.0128)	(0.0012)	(0.0087)
21-23.9 Mean 2008-09	0.28	0.44	0.75	0.08	0.17	24	0.21	0.64	0.14	0.06	0.007	0.19
21-22.9 Mean 2010-11	0.28	0.43	0.74	0.08	0.18	24	0.21	0.65	0.14	0.08	0.006	0.21
Observations	317,856									266,174		142,798
Panel B: 62.0 - 67.9												
Estimated discontinuity												
Pre 2010	0.1017***	0.2853***	-0.0578***	0.0263***	0.0316***	-11.0527***	0.0212***	-0.0089***	-0.0123***	0.0116*	0.0007	0.0076**
	(0.0077)	(0.0115)	(0.0020)	(0.0018)	(0.0013)	(2.4995)	(0.0028)	(0.0033)	(0.0023)	(0.0069)	(0.0009)	(0.0033)
Change post 2010	0.0070*	-0.0027	-0.0050***	0.0016	0.0034**	1.5815	-0.0004	-0.0047	0.0052	-0.0016	0.0010	-0.0017
	(0.0042)	(0.0046)	(0.0018)	(0.0012)	(0.0014)	(5.1498)	(0.0027)	(0.0039)	(0.0033)	(0.0079)	(0.0015)	(0.0044)
63-64.9 Mean 2008-09	0.18	0.52	0.93	0.03	0.04	158	0.12	0.72	0.15	0.03	0.027	0.20
63-64.9 Mean 2010-11	0.19	0.49	0.93	0.03	0.04	155	0.13	0.72	0.15	0.04	0.026	0.20
Observations	1,051,955									872,037		619,978

Note: This table presents regression coefficients obtained by estimating equations 2 and 3 on case level data and equation 7 on age-month-year level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) hospital stays respectively. Instead of using data from 2012-15, the sample discharge data are from 2008-11 – entirely before the ACA was implemented. This table provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4, Table 5) and health outcomes (Table 6). Estimated discontinuity pre 2010 is the coefficient on d_i in equations 2,3 and 7. Estimated change in discontinuity post 2010 is the coefficient on $d_i \cdot T_t$ in the same equations. Case level models include a full set of hospital service area (HSA) and year fixed effects and standard errors are clustered by HSA, whereas collapsed regressions include year fixed effects only.

† To be conservative and consistent with our discussion of main results, we present utilization estimates obtained using specifications that model age using a quadratic vector. In the case of the near-elderly, corresponding estimates from a linear specification are -21.2 (1.9) and 22.9 (3.7) respectively.

APPENDIX A: FIGURES

A.1a: Medicaid share in expansion states



A.1b: Medicaid share in non-expansion states

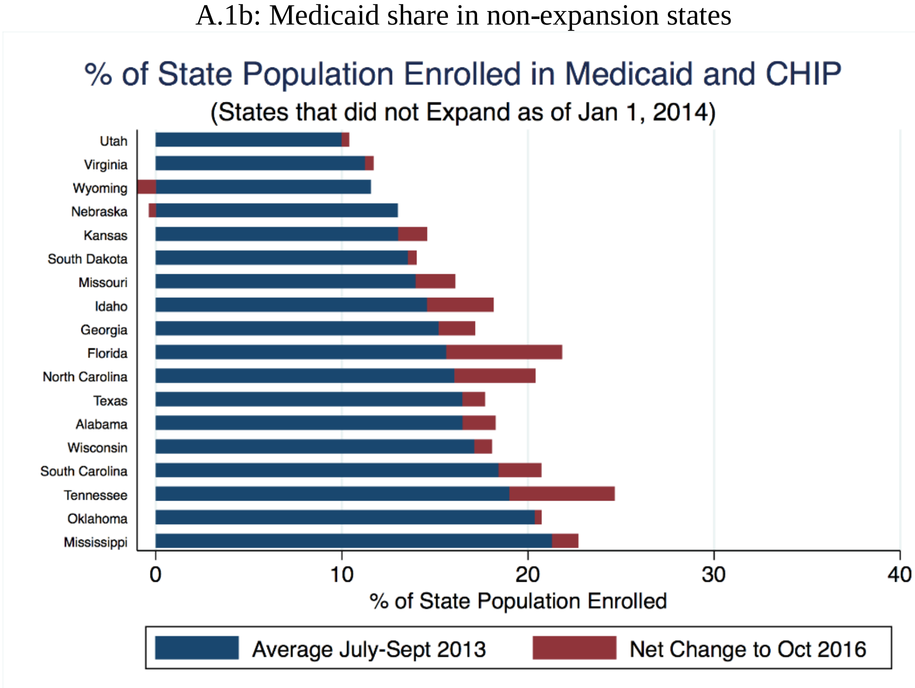


Figure A. 1: Medicaid share in expansion and non-expansion states

Note: This figure presents Medicaid share of state population for states that expanded Medicaid under the ACA (Panel A) and those that did not (Panel B). Medicaid share as of July-Sept 2013 (i.e. pre-ACA) is depicted in blue and the change through October 2016 is plotted in red. In both figures, states are sorted in ascending order of share of population in 2013. Comparable baseline data was not available for Connecticut (expanded) and Maine (did not expand).

State of California—Health and Human Services Agency Department of Health Care Services

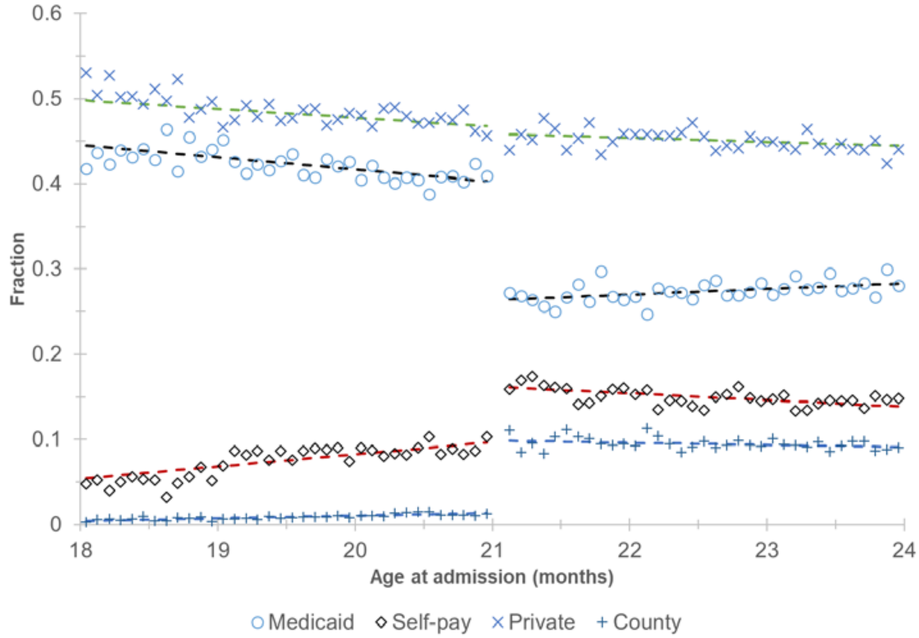
SUMMARY MEDI-CAL ELIGIBILITY*

	Public Assistance Recipient**	Medically Needy Beneficiary***	Medically Indigent Person or Family
Description of Eligible Person	SSI/SSP Aged Blind Disabled Deprivation CalWORKs California Work Opportunities and Responsibility to Kids	1. Linked to public assistance program but not eligible or does not want cash grant. 2. Aged, blind, or disabled. SSI/SSP–MN 1931(b)	Not linked to a public assistance program but who otherwise qualifies as (1) person under 21, (2) adults under 65 in either a skilled nursing facility or intermediate care facility, (3) women with a verified pregnancy, (4) nonlinked refugees/entrants in first 8 months of U.S. residency.
Age Limits	SSI/SSP Aged 65 or older Blind No age limit Disabled No age limit CalWORKs Child under 18 and/or 19 if full-time student in high school or in a vocational program which can be completed before age 19 or an 18-year-old not expected to graduate before 19 due to disabilities. No age limit for parent.	SSI/SSP–MN Aged 65 or older Blind No age limit Disabled No age limit 1931(b) Same as CalWORKs	Under 21. Adult under 65 residing in either a skilled nursing facility or an intermediate care facility, pregnant woman with a verified pregnancy, and refugee entrants in the U.S. less than 18 months.
Residence and Citizenship	California Residence. Documentation is required for both citizens and aliens, in USA lawfully or under the color of law.	California Residence. Documentation is required for both citizens and aliens, in USA lawfully or under the color of law.	
Personal Property Limits (This does not include Business Property)	SSI/SSP Aged Blind $2,000 1 person Disabled $3,000 couple CalWORKs The value of personal and real property including resources not excluded elsewhere by regulations, owned by a CalWORKs family shall not exceed $3,000 for an assistance unit with at least one member aged 60 or older or disabled, and $2,000 for all other assistance units.	Number of Persons Whose Property is Considered — Property Limit 1931(b) 1 person .... $3,000 1 person .... $2,000 2 persons .... 3,000 3 persons .... 3,150 4 persons .... 3,300 5 persons .... 3,450 Community spouse resource allowance when one spouse enters long-term care on or after 11/1/90 and applies in 2007 is: $101,640.	Number of Persons Whose Property is Considered — Property Limit 6 persons .... 3,600 7 persons .... 3,750 8 persons .... 3,900 9 persons .... 4,050 10 persons 4,200
Motor Vehicle Limits	SSI/SSP Aged, Blind, Disabled One car if used for transportation is exempt regardless of value. CalWORKs Exempt if total net market value is under $4,650 for applicant.	1 car exempt—no maximum value.	
Real Property Limits	SSI/SSP Aged, Blind, Disabled Home exempt. Other real property with net market value of $6,000 or less providing property is producing income consistent with its value. CalWORKs See comments under Personal Property Limit, above.	*Principal residence (PR),* including any appertaining buildings and land used as a home, is exempt if applicant/beneficiary lives there, temporarily absent, or if he/she is in long-term care (LTC) and his/her sibling or adult child lived there for at least one year prior to LTC entry and still lives there, if there is a bona fide effort to sell PR, or if there are legal obstacles to its sale. If beneficiary is in LTC and the former home is not otherwise exempt, it will remain exempt if it is listed for sale. It also will be exempt if the beneficiary has the intent to return and declares this in writing. *Other Nonbusiness Real Property* with a net market value of $6,000 or less is exempt if utilization requirements are met.	
Relative Responsibility	Spouse for spouse. Parent for child.	Spouse for spouse Parent for child under 21 living in the home except child with verified need for medical services which do not require parental authorization.	

Figure A. 2: California Medicaid eligibility requirements

Note: This figure presents an extract from an official notice on California Medicaid (Medi-Cal) eligibility requirements. This is available at http://www.dhcs.ca.gov/formsandpubs/forms/Forms/MCED/Info_Notice/MC002_ENG_0907.pdf and pertains to 2007. The top right portion discusses age thresholds for a person to be eligible for Medicaid under the "indigent" category, i.e. not disability or welfare recipient. Childless adults were usually ruled out unless they had special circumstances such as pregnancy (in the case of women) or were in a nursing home.

A.3a: Insurance coverage for the young (2012-13)



A.3b: Insurance coverage for the young (2014-15)

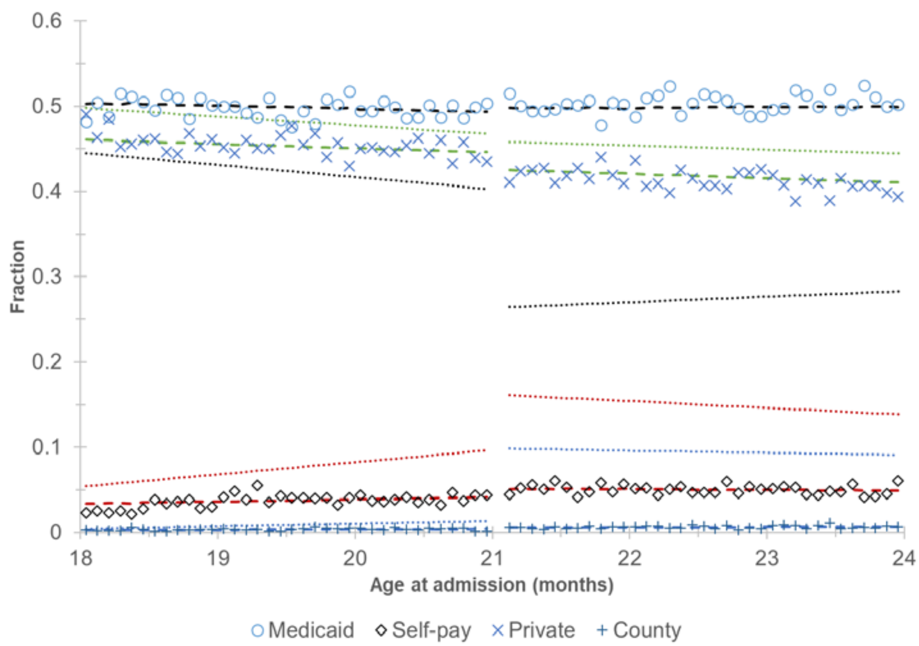
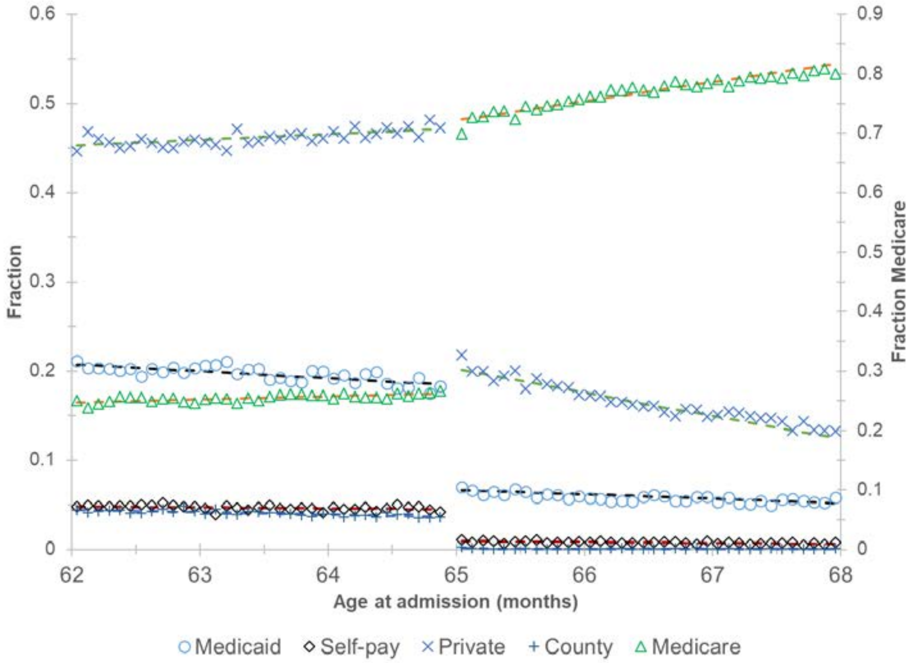


Figure A. 3: Insurance coverage for the young (details)

Note: This figure presents observed coverage rates for different insurers, collapsed to age-month bin and corresponding fitted values (dashed line) obtained by estimating equation 2 on case level data as described in Section IV. It is a more detailed version of Figure 3 Panel A. Self-pay includes charity care. Private coverage includes government employee plans and workers' compensation. The figure pertains to hospital stays in the RD sample for young patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. Panel B retains pre-ACA fitted values (dotted line) to serve as comparison All models include a full set of hospital service area (HSA) and year fixed effects.

A.4a: Insurance coverage for the elderly (2012-13)



A.4b: Insurance coverage for the elderly (2014-15)

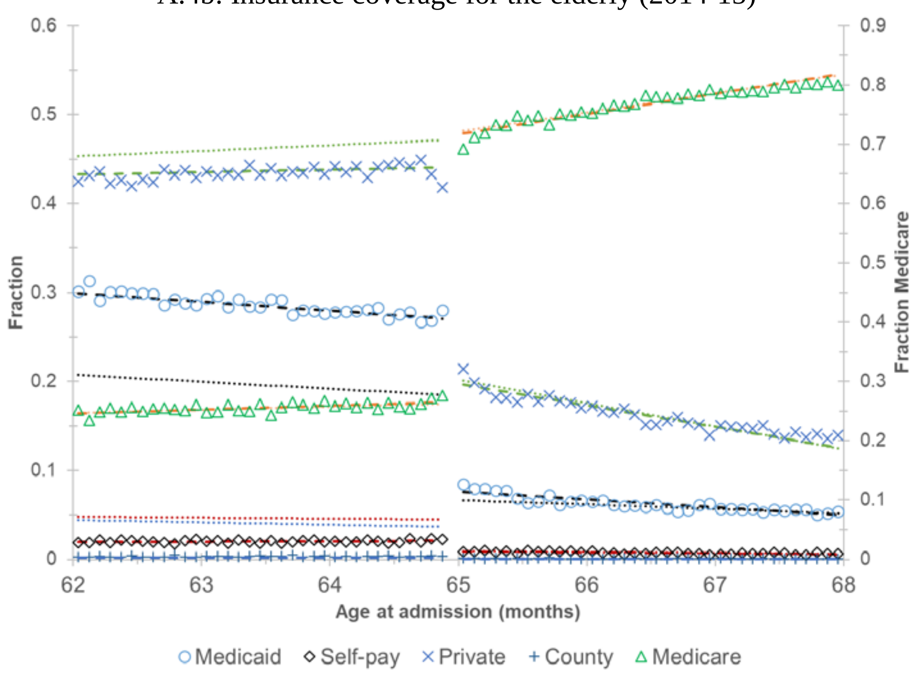
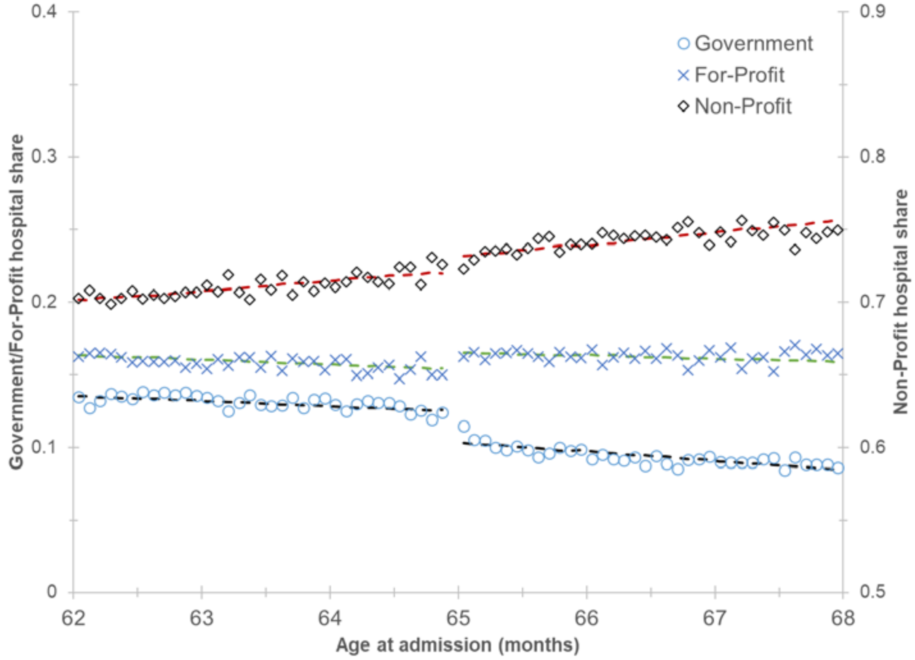


Figure A. 4: Insurance coverage for the elderly (details)

Note: This figure presents observed coverage rates for different insurers, collapsed to age-month bin and corresponding fitted values (dashed line) obtained by estimating equation 2 on case level data as described in Section IV. It is a more detailed version of Figure 3 Panel B. Note that Medicare fraction is plotted on the right vertical axis. Self-pay includes charity care. Private coverage includes government employee plans and worker's compensation. The figure pertains to hospital stays in the RD sample for elderly patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. Panel B retains pre-ACA fitted values (dotted line) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects.

A.5a: Hospital share by owner type, 2012-13



A.5b: Hospital share by owner type, 2014-15

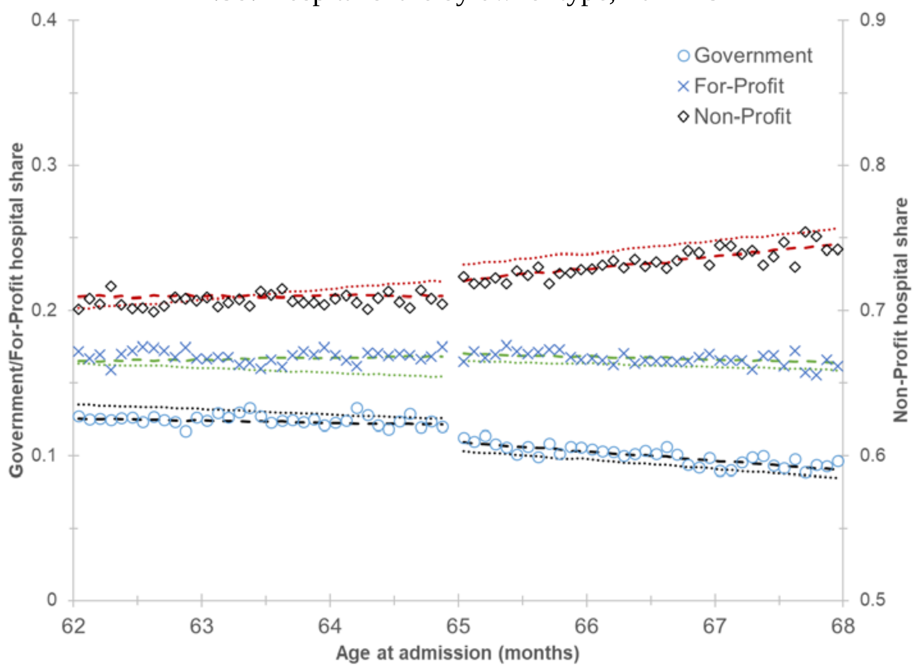
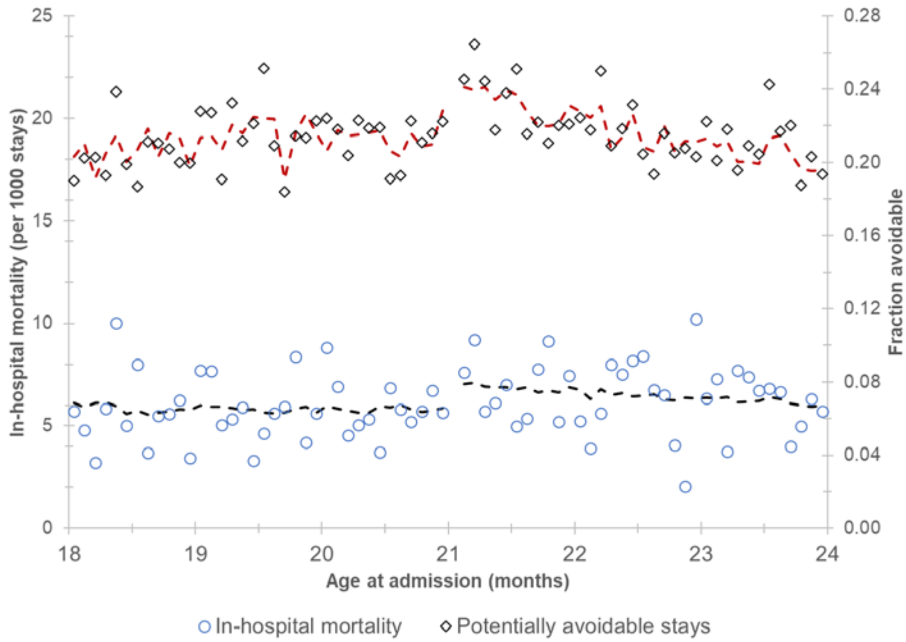


Figure A. 5: Hospital share by owner type (elderly)

Note: This figure presents observed hospital share by owner type (Non-profit, For-profit or Government) of hospital stays, by age-month cell and fitted values obtained by estimating equation 2 on case level data as described in Section IV for the sample of elderly patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. Panel B retains pre-ACA fitted values (dotted line) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects.

A.6a: Health Outcomes (young), 2012-13



A.6b: Health Outcomes (young), 2014-15

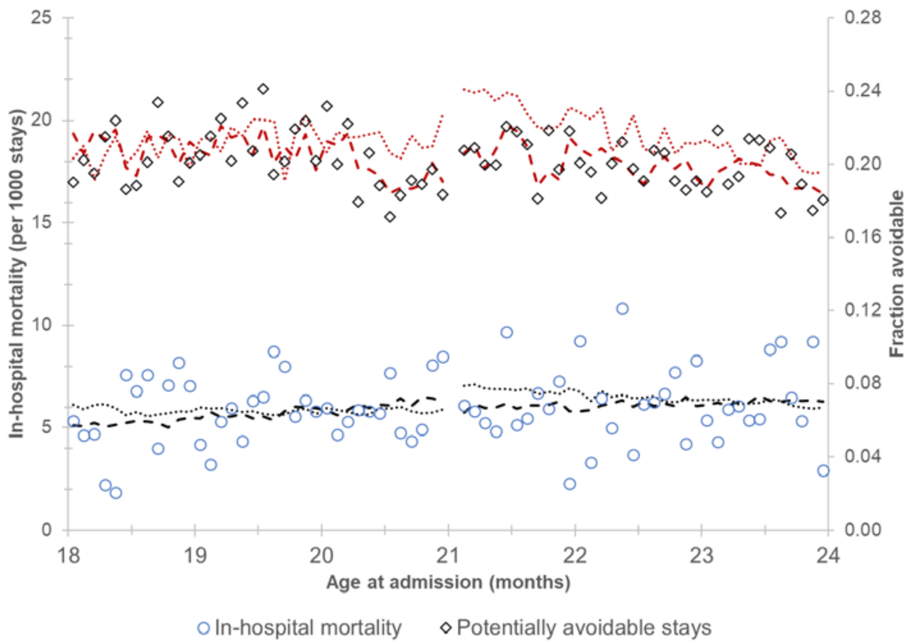
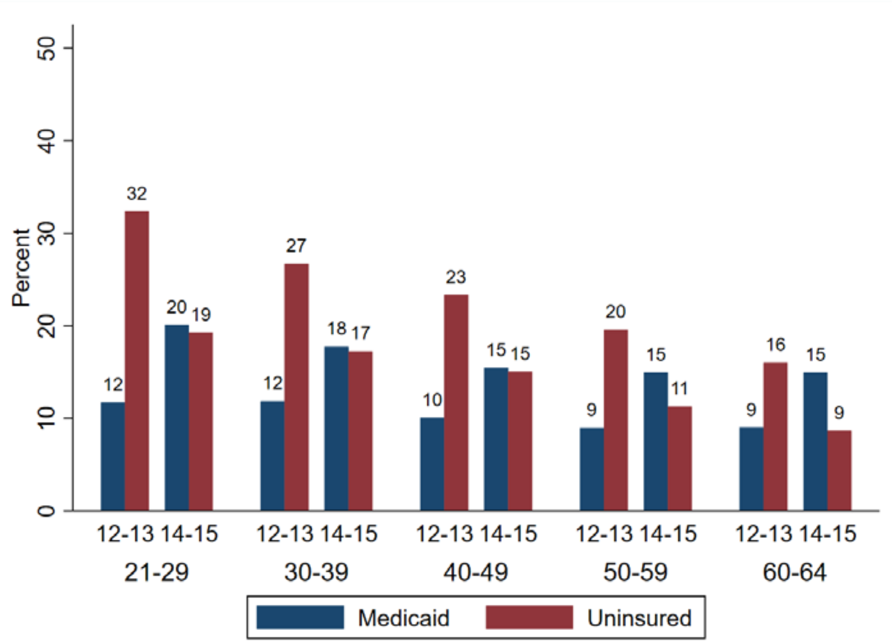


Figure A. 6: Health outcomes for the young

Note: This figure presents observed in-hospital mortality and share of potentially avoidable stays collapsed to age-month bins. It also plots corresponding fitted values (dashed lines) obtained by estimating equation 2 on case level data as described in Section IV for the sample of young patients in 2012-13 (Panel A) and 2014-15 (Panel B) respectively. The regression co-variates include patient characteristics such as gender and reason for arrival in addition to age. Panel B retains pre-ACA fitted values (dotted lines) to serve as comparison. All models include a full set of hospital service area (HSA) and year fixed effects. Potentially avoidable stays are coded based on presence of specific ICD-9 diagnoses codes for select conditions.

A.7a: ACS survey data, California



A.7b: Hospital discharge data

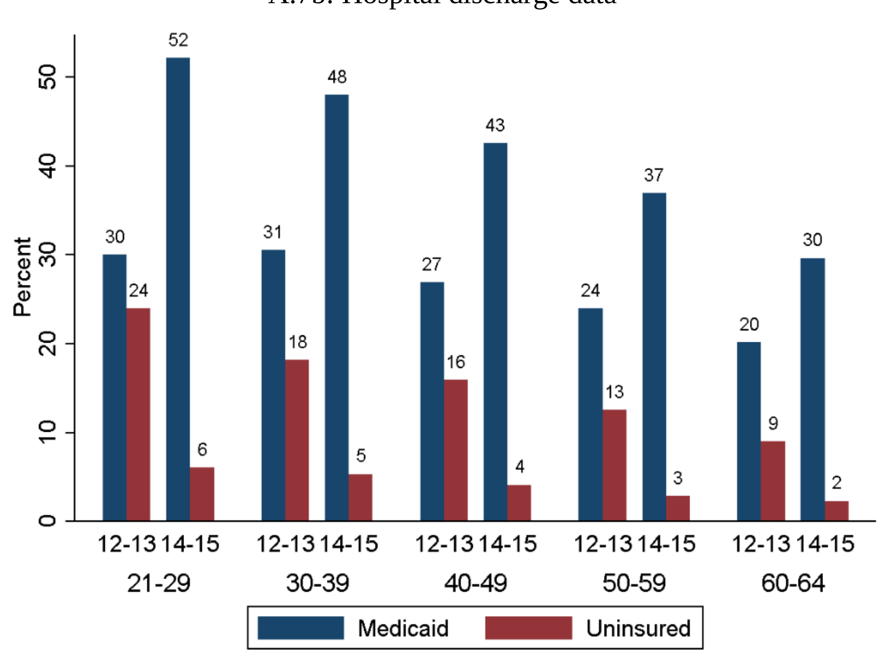


Figure A. 7: Medicaid and uninsurance by age group, California

Note: This figure uses two different data sources from California to examine the increase in share of Medicaid and decrease in uninsurance among individuals aged 21-64. Panel A presents the share of Medicaid and uninsurance as reported by the American Community Survey (ACS). Note that these are weighted averages and represent population share. Panel B presents an identical plot, but using data on hospital discharges. Panel B is therefore conditional on use.

APPENDIX A: TABLES

Table A. 1: Insurance coverage (ER arrivals)

Panel A: Ages 18.0 - 23.9	(1)	(2)	(3)	(4)	(5)	(6)
Estimated discontinuity	Medicaid	Private	Medicare	Insured	County	Self-Pay
Pre-ACA	-0.1259***	0.0103***	-0.0007	-0.1164***	0.0367***	0.0797***
	(0.0046)	(0.0030)	(0.0010)	(0.0045)	(0.0035)	(0.0043)
Change post-ACA	0.1021***	-0.0130***	0.0021**	0.0912***	-0.0357***	-0.0555***
	(0.0046)	(0.0034)	(0.0010)	(0.0042)	(0.0034)	(0.0043)
21-23.9 Mean 2012-13	0.23	0.41	0.02	0.65	0.05	0.30
21-23.9 Mean 2014-15	0.42	0.39	0.02	0.83	0.01	0.17
Observations	3,956,289					

Panel B: Ages 62.0 - 67.9						
	Medicaid	Private	Medicare	Insured	County	Self-Pay
Pre-ACA	0.1129***	0.2351***	-0.4511***	-0.1031***	0.0453***	0.0578***
	(0.0059)	(0.0068)	(0.0040)	(0.0038)	(0.0036)	(0.0028)
Change post-ACA	0.0952***	-0.0186***	0.0053	0.0819***	-0.0416***	-0.0403***
	(0.0048)	(0.0044)	(0.0050)	(0.0037)	(0.0034)	(0.0029)
62-64.9 Mean 2012-13	0.19	0.43	0.22	0.85	0.05	0.10
62-64.9 Mean 2014-15	0.31	0.41	0.23	0.94	0.01	0.05
Observations	2,726,236					

Note: This table presents regression coefficients obtained using case level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) patients respectively. The dependent variable is coverage by different insurers or self-pay/county indigent coverage. Private insurance includes coverage for government employees and worker's compensation. This table pertains to ER arrivals. Table 2 pertains to hospital stays. Estimated discontinuity pre-ACA is the coefficient on d_i in equation 2. Estimated change in the discontinuity post-ACA is the coefficient on $d_i \cdot T_t$ in equation 2. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table A. 2: Hospital share by owner type (ER arrivals)

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-profit hospitals		***For-profit hospitals***		***Government hospitals***	
	Young	Elderly	Young	Elderly	Young	Elderly
Estimated discontinuity						
Pre ACA	-0.0059***	-0.0215***	-0.0025*	-0.0065***	0.0084***	0.0281***
	(0.0019)	(0.0031)	(0.0014)	(0.0019)	(0.0021)	(0.0035)
Change post ACA	0.0090***	0.0117***	0.0023	0.0057***	-0.0113***	-0.0174***
	(0.0023)	(0.0027)	(0.0018)	(0.0020)	(0.0023)	(0.0024)
Change in 2014	0.0070***	0.0080***	0.0032*	0.0050**	-0.0102***	-0.0130***
	(0.0024)	(0.0028)	(0.0018)	(0.0023)	(0.0024)	(0.0021)
Change in 2015	0.0109***	0.0152***	0.0014	0.0064***	-0.0123***	-0.0216***
	(0.0024)	(0.0032)	(0.0020)	(0.0020)	(0.0024)	(0.0029)
LATE	0.0450***	0.2375***	0.0268**	0.0553***	-0.0717***	-0.2929***
	(0.0170)	(0.0316)	(0.0128)	(0.0179)	(0.0191)	(0.0329)
First stage F-stat	194.6	71.8				
Mean values:						
2012-13 "treated"group	0.68	0.70	0.14	0.13	0.18	0.18
2014-15 "treated" group	0.69	0.70	0.15	0.14	0.16	0.16
2012-13 uninsured	0.63	0.54	0.16	0.14	0.21	0.32
Observations	3,956,289	2,726,236				

Note: This table presents regression coefficients obtained using case level ER arrivals data. The dependent variable is hospital ownership type (non-profit, for-profit or government). Estimated discontinuity pre ACA is the coefficient on d_i in equation 3. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in equation 3. Coefficients on interaction of d_i with dummies for specific years estimate the corresponding change in discontinuity in that year relative to 2012-13. LATE is the coefficient on Ins_i in equation 4. The first stage F-stats are the same irrespective of outcome being investigated. Columns 1, 3 and 5 present results for the young, while columns 2, 4 and 6 present results for the elderly. Treated groups are patients aged 21-23.9 and 62-64.9 for the young and elderly respectively. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table A. 3: Discharge records by age and year

	Hospital Stays			All ER arrivals		
Age at admission	**2010-11**	**2012-13**	**2014-15**	**2010-11**	**2012-13**	**2014-15**
0-4	193,509	172,122	159,230	2,536,691	2,525,177	2,598,756
5-9	70,128	68,932	68,594	1,054,114	1,174,867	1,328,809
10-14	71,061	68,763	68,706	891,320	944,282	1,057,023
15-17	64,275	60,553	58,693	737,602	750,155	807,325
18-20	*81,164*	*75,107*	*68,795*	*928,143*	*928,035*	*1,008,334*
21-23	*83,149*	*85,020*	*80,904*	*926,353*	*999,630*	*1,107,149*
24-29	178,114	178,823	180,443	1,775,885	1,912,621	2,201,981
30-34	167,276	168,499	168,976	1,342,541	1,502,243	1,687,523
35-39	194,674	184,238	185,655	1,236,095	1,330,798	1,519,107
40-44	268,467	248,943	230,913	1,352,207	1,408,115	1,486,697
45-49	361,555	324,560	300,495	1,468,252	1,497,807	1,586,650
50-54	431,589	415,826	403,937	1,448,396	1,582,252	1,731,409
55-61	640,199	644,950	664,321	1,673,130	1,908,584	2,193,338
62-64	*282,797*	*279,463*	*289,121*	*603,784*	*677,534*	*778,602*
65-67	*273,018*	*285,557*	*299,041*	*513,303*	*613,711*	*716,606*
68-74	609,426	608,765	622,891	1,060,299	1,197,847	1,358,408
75-79	436,236	416,979	410,007	726,558	783,214	850,939
80-85	439,070	406,646	381,712	733,496	768,144	796,834
86-90	416,811	393,337	371,704	706,884	748,409	774,619
Total	5,262,518	5,087,083	5,014,138	21,715,053	23,253,425	25,590,109

Note: This table presents the number of hospital stays and ER arrivals (i.e. ER visits and hospital stays originating in the ER) by age group over different two-year periods from 2010-15. The RD analysis focuses on patients aged 18-23 and 62-67 (italicized). The non-elderly sample used in the geographical analysis focuses on patients aged 21-64. The RD sample and non-elderly sample cover about 15% and 50% of the total hospital stays respectively. In the case of ER arrivals, the analysis samples cover 14% and 55% of all available records.

Table A. 4: Robustness (alternative age bandwidth)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Insurance coverage					*Utilization* †	*Hospital choice*				*Outcomes*	
Panel A: 19.0 - 22.9	Medicaid	Private	Insured	County	Self-Pay	Stays	Govt.	Non-Profit	For-Profit	RA Mort.	Mortality	PAH
Pre ACA	-0.1402***	-0.0128	-0.1568***	0.0851***	0.0717***	-0.8714**	0.0191***	-0.0180***	-0.0010	0.0201*	0.0011	0.0197***
	(0.0099)	(0.0087)	(0.0077)	(0.0062)	(0.0068)	(0.4195)	(0.0053)	(0.0069)	(0.0042)	(0.0105)	(0.0011)	(0.0065)
Change post ACA	0.1453***	-0.0110	0.1421***	-0.0831***	-0.0590***	0.5104	-0.0241***	0.0105	0.0136**	-0.0173	-0.0017	-0.0043
	(0.0112)	(0.0109)	(0.0075)	(0.0063)	(0.0061)	(0.5412)	(0.0079)	(0.0097)	(0.0060)	(0.0180)	(0.0016)	(0.0095)
LATE						5.6779**	-0.1132***	0.1135***	-0.0002	-0.1182*	-0.0067	-0.1173***
						(2.5323)	(0.0325)	(0.0430)	(0.0275)	(0.0614)	(0.0074)	(0.0382)
21-23.9 Mean 2012-13	0.27	0.45	0.75	0.10	0.15	24	0.19	0.66	0.14	0.09	0.01	0.22
21-22.9 Mean 2014-15	0.50	0.42	0.94	0.01	0.05	23	0.18	0.66	0.15	0.09	0.01	0.20
Observations	203,166					188	203,166			170,156		85,879
Panel B: 63.0 - 66.9												
Pre ACA	0.1138***	0.2690***	-0.0718***	0.0352***	0.0366***	-11.5024***	0.0187***	-0.0052	-0.0135***	0.0220**	0.0004	0.0059*
	(0.0062)	(0.0088)	(0.0026)	(0.0024)	(0.0018)	(3.4549)	(0.0032)	(0.0036)	(0.0025)	(0.0089)	(0.0010)	(0.0031)
Change post ACA	0.0784***	-0.0303***	0.0578***	-0.0331***	-0.0247***	1.9313	-0.0089***	-0.0051	0.0140***	-0.0126	-0.0008	-0.0033
	(0.0054)	(0.0065)	(0.0027)	(0.0024)	(0.0020)	(3.6530)	(0.0030)	(0.0044)	(0.0037)	(0.0104)	(0.0015)	(0.0047)
LATE						186.5740***	-0.2907***	0.1144**	0.1763***	-0.2744**	-0.0014	-0.0840**
						(45.5061)	(0.0486)	(0.0548)	(0.0341)	(0.1146)	(0.0136)	(0.0356)
63-64.9 Mean 2012-13	0.19	0.46	0.92	0.04	0.05	140	0.13	0.71	0.16	0.05	0.03	0.21
63-64.9 Mean 2014-15	0.28	0.44	0.98	0.00	0.02	131	0.13	0.71	0.17	0.05	0.03	0.19
Observations	755,040					188	755,040			622,498		411,484

Note: This table presents regression coefficients obtained by estimating equations 2,3 and 4 on case level data and equation 7 on age-month-year level data as described in Section IV for the sample of young (Panel A) and elderly (Panel B) hospital stays respectively. The sample for this analysis is constructed using only a 2-year bandwidth on either side of the age thresholds. This table provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4, Table 5) and health outcomes (Table 6). Estimated discontinuity pre ACA is the coefficient on d_i in equations 2,3 and 7. Estimated change in discontinuity post ACA is the coefficient on $d_i \cdot T_t$ in the same equations. LATE is the coefficient on Ins_i in equation 4. Case level models include a full set of hospital service area (HSA) and year fixed effects and standard errors are clustered by HSA, whereas collapsed regressions include year fixed effects only.
† To be conservative, and consistent with our discussion of the main results, we present utilization estimates obtained using specifications that model age using a quadratic vector. In the case of the near-elderly, corresponding estimates using a linear specification are -17.2 (2.3), 10.3 (2.5) and 248 (30.1) respectively.