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THE IMPACT OF THE AFFORDABLE CARE ACT: EVIDENCE FROM CALIFORNIA'S HOSPITAL SECTOR

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ABSTRACT

The Affordable Care Act (ACA) authorized the largest expansion of public health insurance in the U.S. since the mid-1960s. We exploit ACA-induced changes in the discontinuity in coverage at age 65 using a regression discontinuity based design to examine effects of the expansion on health insurance coverage, hospital use, and patient health. We then link these changes to effects on hospital finances. We show that a substantial share of the federally-funded Medicaid expansion substituted for existing locally-funded safety net programs. Despite this offset, the expansion produced a substantial increase in hospital revenue and profitability, with larger gains for government hospitals. On the benefits side, we do not detect significant improvements in patient health, although the expansion led to substantially greater hospital and emergency room use, and a reallocation of care from public to private and better-quality hospitals.

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I. INTRODUCTION

The 2010 Patient Protection and Affordable Care Act (ACA) led to the largest expansion of publicly funded health insurance coverage since the introduction of Medicare and Medicaid more than fifty years ago. The main provisions of this legislation took effect in January 2014. In states that elected to expand their Medicaid programs as allowed for by the ACA, individuals with family incomes at or below 138 percent of the federal poverty line and without another source of coverage could enroll in the means-tested Medicaid program. Those with incomes above this threshold and without another source of coverage could sign up for private health insurance coverage in ACA exchanges. Exchange enrollees could qualify for federal subsidies to purchase health insurance if their family incomes were below 400 percent of the federal poverty line. From 2010 to 2017, the number of Medicaid recipients nationally rose from 54 million to 72 million while the number with coverage in the ACA exchanges increased from 0 to 12 million (CMS, 2018).

This intervention offers a unique opportunity to examine the effects of a large expansion of public health insurance in a modern setting. We focus on the state of California, which was one of 25 states that elected to expand Medicaid in January 2014.[1] We analyze the effects of the ACA-induced expansion in health insurance coverage through the lens of the hospital sector in California, using data on the universe of hospital stays and emergency room (ER) visits in the state as well as detailed data on hospital finances from 2008 through 2016. During this period, Medicaid enrollment in the state increased from approximately 8 million to more than 13 million while Medicaid spending more than doubled from $40 billion to $100 billion (Taylor, 2017). Additionally, nearly 1.4 million Californians obtained their health insurance through the state's ACA health insurance exchange (known as Covered California) in 2016, the final year of our study period.

We use a novel empirical approach that exploits the pre-existing discontinuity in health insurance coverage at age 65 due to the discrete onset of eligibility for Medicare.[2] This phenomenon has been used by other studies as a quasi-random insurance coverage experiment to examine the effects of Medicare (Card et al. 2008; 2009). The ACA substantially expanded the Medicaid eligibility criteria for non-elderly individuals in California, leading to a large increase in Medicaid coverage for those under the age of 65, as shown in Figure 1a, which plots the fraction of individuals at each age with Medicaid coverage in each year from 2011 through 2016. Because Medicaid eligibility criteria were already fairly broad for those under age 21, the effect on Medicaid coverage was greatest for those aged 21 to 64.

[1] 25 states, including Washington, D.C., expanded their Medicaid programs in January 2014. In the five years since January 2014, an additional 12 states have expanded or are in the process of expanding Medicaid as called for in the ACA. Many of the remaining 14 states are actively considering an expansion.

[2] A small share of individuals who are eligible for Medicaid at age 64 retain Medicaid coverage post-65 because they are eligible for both Medicaid and Medicare. Medicare is the primary insurer in these cases.

The Medicaid expansion, together with the introduction of publicly subsidized private insurance through the ACA exchanges, caused a sharp decrease in the discontinuity at age 65, as Figure 1b demonstrates. Our estimation approach compares the pre-post change in outcomes of interest for patients aged 64 (or younger) who experienced an increase in coverage, relative to those 65 and older whose insurance coverage remained unchanged through this entire period. This regression discontinuity differences-in-differences (RD-DD) approach estimates local average treatment effects most relevant for near-elderly individuals. Hence, we also present a companion set of results using the sample of all patients aged 21 to 64, in which we exploit pre-ACA variation in the share potentially eligible for Medicaid across geographic markets. Also, to address potential concerns about spurious trends, we present results from a falsification exercise assuming a placebo expansion in 2010, as well as from event studies for all outcomes of interest. Reassuringly, these results indicate no pre-existing trends that would bias our results.

We begin by examining the changes in health insurance coverage. First, we find no evidence of a net increase in private coverage among eligible hospitalized patients, which implies that most obtaining health insurance through the ACA exchanges would have had coverage through another source. We estimate an increase of 4-6 percentage points in any form of health insurance, which is driven entirely by the Medicaid expansion. In fact, our RD-DD results indicate minor crowd out of private coverage among patients in their early 60s. Second, we find that about half of the Medicaid expansion replaced county safety-net programs that previously would pay for hospital care for eligible uninsured low-income patients. Since the Medicaid expansion was financed almost entirely by the federal government, this represented a shift in financing responsibility from local taxpayers to federal taxpayers. Results from the analysis leveraging variation across geographic areas for all adults aged 21 to 64 are strikingly similar to those for 64- and 65-year-old patients, indicating that these are robustly estimated and capture the effects for younger adults as well. Taken together, our results imply that for every 10 individuals newly enrolling in Medicaid as a result of the ACA, the number with health insurance increased by approximately 8.

To estimate the effect of these coverage changes on hospital finances, we utilize annual, hospital-level financial data. Our results reveal that Medicaid reimbursed hospitals at approximately twice the level as the pre-existing county safety net programs. Hence, the replacement of county programs with Medicaid coverage benefited both local taxpayers as well as hospitals providing this care. Since government owned hospitals disproportionately bore the burden of caring for uninsured low-income patients, they were also the primary beneficiaries of this transfer from federal taxpayers. We estimate that the average government hospital received nearly a 20% increase in total revenue per bed due to the Medicaid expansion, while the corresponding estimate for private hospitals was 8%. This increase was driven entirely by higher average reimbursements rather than by additional volume. In fact, government hospitals actually lost some of their patient volume to private hospitals, which moderated the increase in their total revenues. Hospitals also reported greater profitability – an average gain of 4 percentage points in their operating margins. Our estimates imply that this increase in operating margin – when converted to dollars – is about 70% as large as the estimated increase in Medicaid revenue. Hospitals do not seem to be deploying this income toward greater capital spending or expanding bed capacity, at least in the short run.

This largely federally-financed windfall for hospitals and other health care providers represents the cost of the Medicaid expansion.[3] To understand the benefits to consumers, we explore changes in utilization of care and in patient health outcomes. A decrease in patient cost sharing may spur greater use of health care (moral hazard) 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, with a net increase of 4-6% in hospital stays and arrivals at ERs on average. In contrast to evidence from the Massachusetts reform (Kolstad and Kowalski, 2012; Miller, 2012) – and contradicting a key argument for the insurance expansion – we find a robust, statistically significant increase in ER volume. Our reduced form estimate of the resulting increase in hospital stays implies a marginal effect three times as large as corresponding estimates from the Oregon experiment (Finkelstein et al., 2012).[4] This highlights the potentially large magnitude of general equilibrium effects even in the short term, likely through supply side responses by hospitals and physicians to the Medicaid expansion and higher reimbursement.

Notwithstanding the above increase in hospital care, we fail to reject the null of no effect on patient health. Our primary metric of health is in-hospital mortality, and we focus on the subset of patients discharged with acute, emergent conditions such as Heart attack and Pneumonia to circumvent selection concerns. The point estimates indicate that in-hospital mortality has declined meaningfully post-ACA, however they are imprecisely estimated. A likely channel for improved health is reallocation of patient care to privately-owned and better-quality hospitals. Pre-ACA, 65-year-olds were significantly more likely than 64-year-olds to receive care at privately-owned and better-quality hospitals. But this gap declined by 60% on both dimensions post-ACA. We interpret this shift to be demand-driven, since we find a similar magnitude of switching in ER use, which is less likely to be influenced by insurer networks.

Our analysis has three key limitations. First, our results reflect the experience of a specific state that expanded Medicaid, and more liberally than on average. Second, we cannot observe health care delivered outside of the hospital. This precludes testing for improvements in access to preventative and

[3] The ACA did influence hospital reimbursement on other dimensions. For example, the ACA reduced the growth rate of Medicare reimbursement rates and intended to reduce the disproportionate share (DSH) program which differentially aided hospitals serving many low-income patients. However, Congress repeatedly delayed the cuts to DSH spending. The DSH cuts are currently set to begin in fiscal year 2020. More details available at https://cbcny.org/research/dsh-cuts-delayed.

[4] The Oregon experiment was negligibly small compared to the Medicaid expansion in California under the ACA (10,000 vs. ~5 million new enrollees). We interpret their IV results as estimating partial equilibrium effects on individual consumption of care upon gaining Medicaid coverage, while our reduced form results capture general equilibrium effects of the Medicaid expansion in California.

(non-ER) outpatient care, though we examine trends in potentially avoidable stays and find no change. Third, these results estimate only the short-term effects of the ACA and we acknowledge that the long-term effects, particularly on patient health, may be different.

This paper makes three primary contributions to the existing literature. First, we highlight the locally-funded safety net program in California and use a novel empirical approach to quantify its substitution by Medicaid under the expansion. This aspect has received little attention in previous assessments of insurance coverage changes following the ACA (Sommers et al., 2014; Sommers et al., 2016; Courtemanche et al., 2017*a;* Frean et al., 2017 and many others), perhaps because administrative surveys do not record safety net payers since those benefiting would not typically report being insured. These results also provide empirical evidence to confirm speculation by recent studies (Finkelstein et al., 2015; Finkelstein et al., 2017) that Medicaid beneficiaries value the program substantially below cost since it often replaces other parts of the safety net.

Second, we extend existing work on supply side effects of the ACA (Blavin, 2016; Lindrooth et al., 2018) by linking the Medicaid expansion to changes in hospital finances, particularly government owned hospitals. The Medicaid expansion resulted in a substantial transfer from federal taxpayers, split between hospitals and local taxpayers in California. It remains unclear how this additional revenue was deployed by hospitals other than increasing operating margins. This also relates to recent evidence on hospital sensitivity to insurance coverage changes (Garthwaite et al., 2016).

Third, examining the universe of hospital stays and ER visits allows us to quantify a large increase in hospital use, relative to the increase in insurance coverage. We interpret the large magnitude as being partially driven by supply side responses that encouraged hospital use. Intuitively, our estimates are about half as large as comparable estimates of the long-term effects of Medicare (Finkelstein, 2007). We fail to reject the null of no change in patient mortality, although the point estimates indicate some reduction. A likely mechanism for improved health is reallocation of patients from government to privately-owned – and better-quality – hospitals. This channel has previously received little attention as studies typically valued Medicaid on the basis of improved health or reduced financial risk (Currie and Gruber 1996b; Goodman-Bacon, 2016; Brevoort et al., 2017; Gallagher et al., 2017). Our results also extend previous work that has focused on specific categories of care, such as ER use (Barakat et al., 2017; Garthwaite et al., 2017 and Nikpay et al. 2017), drug prescriptions (Ghosh et. al., 2017), patients with specific diseases (Anderson et al., 2016) or used survey data (Courtemanche et al., 2017b).

Our results take on additional significance when one considers state decision-making regarding the Medicaid expansion, which as a result of a 2012 Supreme Court decision was left up to the states rather than mandated by the federal government. Half the states expanded Medicaid as early as possible in January 2014. But an additional 12 states have since elected to expand Medicaid, with 4 of these decisions occurring in 2018. As the remaining 14 states consider whether or not to expand their Medicaid programs, evidence regarding the effects of this expansion on insurance coverage, quality of care, and hospital finances along with state and local spending on health care can be helpful in assessing whether to proceed.

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 describes the empirical strategy for the regression discontinuity approach and presents results. Section V presents a companion set of results using geographic variation in poverty across hospital markets. Section VI presents results on changes in hospital finances. Section VII discusses some limitations in interpreting the results and section VIII 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. The pre-ACA uninsurance rate among non-elderly adults aged 21-64 was three times that of the remaining population (25% vs. 8%). The elderly benefited from nearly universal coverage provided by Medicare, while children were generously covered by Medicaid (nearly 40%).

Surveys like the ACS may overstate uninsurance rates for two reasons. First, the under-reporting of Medicaid due to its association with welfare is well documented (Klerman et al., 2005; Meyer et al., 2009). Second, surveys typically do not record local safety net programs. These programs fund medical care for a subset of low-income individuals who are not eligible for Medicaid but cannot afford to buy private health insurance. These are not considered traditional insurance since they often pay for care ex-post and hence do not provide risk protection. 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 2008. This is particularly important in our setting since California counties are legally bound to provide such safety net care. In California, safety net programs were funded primarily through a mix of state (sales tax, vehicle license fee, tobacco settlement funds) and county general funds. Federal funding through disproportionate share (DSH) funds played a small role (Taylor, 2013).

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). Prior to passage of the ACA, California spent approximately 2 billion dollars annually to care for the uninsured through 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 at least partially covered by county programs. Note that the provision of informal health care insurance to low income individuals through counties or other state financed mechanisms extended beyond California. Several other states – including those that did not expand Medicaid – offered variants of such programs. Examples include Colorado, Florida, Idaho, Indiana, Massachusetts, Michigan, New Jersey, Texas, New Mexico, Pennsylvania and Louisiana.[5] Across states, these programs vary in financing and service coverage, but share the feature that they reimbursed hospitals for services provided to low-income individuals ineligible for Medicaid.

B. The Affordable Care Act

The ACA was signed into law in March 2010 with several key objectives: increasing access to health care, introducing new consumer protections, and lowering cost and improving quality of health care. 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 without another source of coverage with family incomes below 133% of the FPL. However, legal challenges and a June 2012 Supreme Court decision allowed states the choice to opt out of expanding Medicaid. California is one of the original twenty-five states (including DC) that chose to expand Medicaid at the beginning of 2014. A dozen additional states have since elected to expand Medicaid. Duggan et al. (2017) provides a more detailed summary of ACA-mandated expansions in health insurance. The Congressional Budget Office estimates that the ACA insurance expansions directly cost the federal government $120 billion in 2017 (CBO, 2017).

Several surveys estimate the number of uninsured in the United States at the quarterly or annual level. Gallup and Sharecare surveys show that the percent of adults without health insurance was trending

[5] Louisiana offered free health care for low income individuals not on Medicaid at state owned safety-net hospitals. See https://www.kff.org/health-reform/fact-sheet/the-louisiana-health-care-landscape/. More information on Pennsylvania: http://www.dhs.pa.gov/cs/groups/webcontent/documents/document/c_259012.pdf. More information on the Colorado state program at https://www.colorado.gov/pacific/hcpf/colorado-indigent-care-program. Some other states have indigent care programs that are mainly funded through disproportionate share payments, e. g. Georgia and New York. See https://www.communitycatalyst.org/initiatives-and-issues/initiatives/hospital-accountability-project/free-care/states for an exhaustive description of indigent coverage for hospital care.

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 ACA coverage initiatives, with the Medicaid expansion being nearly twice as large as the exchanges.

Even among states that chose to expand Medicaid, there is substantial variation in the impact on Medicaid enrollment. This is driven by variation across states in baseline enrollment, due to states' initial generosity in eligibility criteria, as well as differences in the socio-economic composition of states. Appendix 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 were covered through Medicaid in late 2016. However, there was a much greater increase in California, which saw an increase of 10 percentage points compared to an increase of just 4 percentage points in New York. New York eligibility criteria included childless adults prior to 2014 whereas childless adults were generally not covered in California. Consequently, the expansion of Medicaid had a much larger enrollment impact in California. Figure A. 2 displays monthly Medicaid enrollment in California over 2010-16 and highlights the magnitude of Medicaid's expansion and how it dwarfs exchange enrollment. Medicaid enrollment increased from about 8.5 million in mid-2013 to 13.5 million by mid-2016.[6] However, enrollment on the newly established ACA individual insurance exchange plateaued at 1.4 million, or about a quarter of the increase in Medicaid. Figure 1c highlights how the dramatic increase in Medicaid translated into changes in payment for hospital care. The figure plots the share of hospital stays by patients aged 21 to 64 between 2008 and 2016 covered by different insurers. At the beginning of the sample period, Medicaid covered 23% patients, about half as much as private payers. Over the next few years there was a steady upward drift in Medicaid, but even in 2013 it covered only 26% of stays. There was a substantial jump in Medicaid coverage in 2014 due to the expansion, and by the end of the period, Medicaid was the largest payer of hospital care – covering 43% of stays, while private payers covered about 35%.

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

[6] The small jump in enrollment in 2013 is primarily due to the transition of children from the Healthy Families Program to Medicaid. However, California also started to expand coverage slightly even before the primary ACA implementation launched in January 2014 through the low-income health program, which provided coverage to about 500 thousand California residents in 2012-13 (California Budget Project, 2013). This represented only about 10 percent of the eventual increase in Medicaid enrollment.

rules created discontinuities in insurance coverage at 21 and 65 in California. Appendix Figure A. 3 presents an extract of California Medicaid eligibility requirements in the pre-ACA period. 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 to 64 were generally ineligible except in case of 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, acknowledging that this reflects insurance coverage conditional on using hospital care. Figure 1a presents Medicaid's percent of hospital stays for patients aged 10 to 75 discharged from hospitals during 2011-16. In the pre-ACA period (2011-13), Medicaid coverage is high for children aged 10 (45-50%) and gradually declines until age 21 when it falls precipitously by about 15 percentage points. It then varies smoothly again until age 65 when there is another discontinuous drop of about 12 percentage points. Note that in 2013 there was an increase in coverage for children due to the formal transfer of CHIP (Children's health insurance program) beneficiaries to Medicaid. In the post-ACA period (2014-16), the discontinuity at age 21 is eliminated, while at age 65 it is enhanced since more 64-year-olds become eligible for Medicaid.

Figure 1b presents the corresponding plot (note the expanded scale) of the percent of patients that were coded as self-pay, charity care or county indigent. Throughout the paper we collectively refer to these categories as uninsured patients. Pre-ACA, there was a striking increase of 15 pp in uninsurance at age 21, suggesting that the Medicaid eligibility restrictions were important. At age 65 there was an increase in insurance coverage due to the onset of Medicare which more than compensated for the decline in Medicaid. Post-ACA, the discontinuities in uninsurance at 21 and 65 disappear, indicating that the ACA expansions were effective in increasing coverage for the targeted groups. Note that there is no change in Medicaid or uninsurance at age 65 and above through this period, suggesting that this group was insulated from the ACA insurance coverage changes, presumably due to their nearly universal Medicare coverage.

The substantial discontinuities in Medicaid and health insurance 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 the ACA 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 2016, obtained from California's Office of Statewide Health, Planning, and Development (OSHPD). These confidential data include approximately 3.8 million hospital 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 of residence. 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 data restrictions for our analysis sample 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 pregnancy-related ER visits from the analysis. Third, we exclude patients residing outside of California or with missing zip codes of residence.[7]

We organize recorded insurance coverage into five categories – Medicaid, Private, Miscellaneous, Self-pay, and County. Miscellaneous is primarily composed of Medicare, but also includes workers' compensation and government employee plans. Self-pay includes charity cases and those who pay for their care themselves. County refers to those covered by the county indigent program discussed above.

A. Specific age thresholds

In order to construct the RD-DD sample for our preferred specifications we impose two further sample restrictions. First, we exclude the years 2008-2010 from our main analysis, reserving them for the falsification exercise and to establish baseline statistics. Our main sample therefore spans 2011-16 – three years before and three years after the ACA expansion. Second, we limit the sample to patients admitted within 12 months of their 65th (or 21st) birthday. In order to minimize measurement error we exclude individuals who arrived at the hospital within 15 days of turning 65 (or 21). In robustness checks we explore the sensitivity of our results to using larger age bandwidths. Focusing on specific age groups dramatically curtails the sample size, leaving approximately 560,000 (150,000) hospital stays and 1.3 million (1.9 million) ER arrivals over the period 2011-16 for the elderly and young 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 ER admission decisions that could change *in response* to the ACA.

Table 1 Panel A summarizes descriptive statistics on the main RD-DD analysis sample of hospital stays and ER arrivals separately for the young and elderly. The table highlights the sharp increase in

[7] Approximately 1.5% of the discharge records in 2008 were for patients having either an out of state or missing zip code.

Medicaid's share of discharges 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 people per year using California population estimates by single year of age.[8] The cohort that turned 64 in 2014 is coincidentally also one of the earlier baby boomer cohorts and is substantially larger than the cohort one year older in age. Hence normalizing by population helps eliminate a spurious increase in hospital volume for 64-year-olds in the first year of the ACA. We use in-hospital mortality as our metric of patient health. When examining effects on mortality we prefer to restrict the sample to patients discharged with a non-deferrable emergent condition such as heart attack, pneumonia, etc. to circumvent concerns related to selection and shifts in composition.[9] The emergent group intuitively has a greater mortality rate than do other patients.

B. All non-elderly adults

We supplement the RD-DD results using a larger sample of all non-elderly adults (ages 21-64) and exploit baseline variation in poverty across geographic markets. We use Hospital Service Areas (HSAs) as our unit of analysis; this is similar to the approach used in other studies that leverage geographic variation in baseline rates of coverage (Finkelstein, 2007; Courtemanche et al., 2017; Duggan et al., 2017; Frean et al., 2017).[10] HSAs are defined as "collections of contiguous zip codes whose residents receive most of their hospitalizations from hospitals in that area". There are 210 HSAs in California, and on average an HSA is smaller than a county but much larger than a zip code. Table 1 Panel B presents summary statistics on this sample. To be consistent with the RD-DD analysis, we exclude the 2008-2010 period. The resulting analysis sample has 7.5 million and 40.3 million hospital stays and ER arrivals respectively.

C. Hospital finances

OSHPD collects and publishes annual financial data on all hospitals in California. These reports are mandated by California law and provide details on hospital finances, utilization and capital investments. We use files covering 2011-16 in order to examine the effects of the insurance expansions on hospital finances. The financial data is available for a smaller number of hospitals (about 320 instead of 370) since Kaiser Permanente hospitals do not report their finances individually.[11] We make two transformations to

[8] We obtained California population estimates for 2011-16 from National Cancer Institute/NIH. They generated these estimates from population data provided by the National Center for Health Statistics (NCHS). More information available at https://seer.cancer.gov/popdata/singleages.html.

[9] We follow Doyle et al. (2015) to define these conditions and create the sample. They list the 29 conditions used to define this group in their Appendix table A1. We exclude Septicemia since there was a dramatic increase in patient volume under this diagnosis during our sample period, with a near halving of mortality, suggesting that there was a change in how patients were coded under Septicemia over this period.

[10] HSAs were defined by the Dartmouth Atlas Project. There are roughly 210 HSAs in California, of which 79 and 34 are in the LA and San Francisco metropolitan regions respectively. As comparison, there are 58 counties and approximately 1,800 zip codes.

[11] 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:

the data in preparation for our analysis. First, we convert all nominal values into real 2016 dollar values using the consumer price index for urban (CPI-U) consumers. Second, we normalize revenue, capital spending and discharges by the hospital's average number of licensed beds between 2008 and 2010 to eliminate variation purely due to hospital size.

IV. EFFECTS ON INSURANCE, UTILIZATION AND HEALTH

A. Empirical strategy

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

$$Y_i = \alpha + \beta \cdot Ins_i + \epsilon_i \tag{1}$$

Y_i denotes an outcome of interest (including utilization of care) for individual i and Ins_i is an indicator set to 1 if the individual has health insurance coverage and 0 otherwise. ϵ_i 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 at least partly on private information about their health risk as well as their appetite for risk.[12] Appendix Table A. 1 illustrates this self-selection problem by presenting key attributes for insured and uninsured individuals at age 21 (Panel A) and 65 (Panel B) using 2004-09 data from the National Health Interview Survey (NHIS). For example, insured young adults are much more likely to be in school and less likely to be married, employed or smokers. Insured elderly are more likely to be married or employed, but less likely to be smokers. The differences (Column 3) are both statistically significant and economically meaningful. These individuals are likely to differ on important unobservable characteristics as well, implying that the required condition $\mathbb{E}(\epsilon_i \, | Ins_i) = 0$ will not be not satisfied.

Recent studies (Card et al., 2008; 2009; Anderson et al., 2012; 2014) have overcome this endogeneity concern by exploiting the presence of age-based insurance eligibility restrictions and discontinuities in coverage by using a fuzzy regression discontinuity framework. For example, in our setting we can exploit the discontinuous change in insurance coverage that existed pre-ACA at age 65 to determine the causal effect of insurance coverage using equations of the type shown below.

$$\mathrm{Ins_i} = \alpha_{10} + \theta_1 d_i + \lambda_{11}(a_i - 65) + \lambda_{12} d_i (a_i - 65) + [\boldsymbol{X}_i' \psi_1 +] \, \epsilon_{1i} \tag{2a}$$

$$\mathrm{Y_i} = \alpha_{20} + \theta_2 d_i + \lambda_{12}(a_i - 65) + \lambda_{22} d_i (a_i - 65) + [\boldsymbol{X}_i' \psi_2 +] \, \epsilon_{2i} \tag{2b}$$

https://share.kaiserpermanente.org/article/fast-facts-about-kaiser-permanente/.

[12] Other factors would surely influence this as well, including the price and quality of health insurance.

Equation 2a models insurance status for patient i as a function of her age at arrival, a_i and whether she is younger than 65 ($d_i = 1$). Insurance status is assumed to vary linearly with age (through λ_{11}), allowing for a different slope for individuals under the threshold (through λ_{12}). Equation 3b presents the corresponding reduced form relationship between outcomes of interest (Y_i) such as utilization and age status d_i. In both cases we may include additional patient controls X_i as needed. These equations would be estimated using data from the pre-ACA period on patients aged close to 65. The fuzzy regression discontinuity estimator of the causal effect of insurance coverage on outcome Y is then given by $\gamma_{RD} = \theta_2/\theta_1$, and is equivalent to a local average treatment effect (LATE) estimator (Hahn et al., 2001).

However, the primary goal of this paper is to quantify insurance coverage changes *caused by the ACA* as well as resulting effects on utilization of care and patient health. To do so, we build on the above framework by exploiting the fact that the Medicaid expansion and introduction of the insurance exchange led to dramatic changes in discontinuities in insurance coverage at ages 21 and 65. This setting therefore lends itself to an RD differences-in-differences research design. Accordingly, we adapt the above estimating equation as below:

$$\mathrm{Ins_{it}} = \alpha_{10} + \delta_{1t} + \theta_{11} d_i + \theta_{12} d_i \cdot T_t + \mathrm{D_i'} \Lambda_1 \mathrm{G}(a_i) + [\boldsymbol{X_i'}\psi_1 +]\, \epsilon_{1it} \qquad (3a')$$

Equation 3a' represents the modified first stage equation. We now define d_i more generally in order to accommodate both age thresholds of interest. In the case of the young it denotes those aged 21 or older, while in the case of the elderly it denotes those aged 64 or younger.

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

The indicator $T_t = 1(t \geq 2014)$ denotes whether the ACA has been implemented. The equation allows insurance coverage to be modeled as a flexible function of age, using D_i and Λ_1. $D_i' = [1\ d_i\ ]$ is a 1x2 vector indicating patient-specific treatment status. Λ_1 is a corresponding 2xk matrix of age coefficients to be estimated, where k is the order of the age polynomial, G. In our main results we use a linear polynomial in age, i.e. $k = 1$ so that the first stage and reduced form equations reduce to the following simple form.

$$\mathrm{Ins_{it}} = \alpha_{10} + \delta_{1t} + \theta_{11} d_i + \theta_{12} d_i \cdot T_t + \lambda_{11} \bar{a}_{\boldsymbol{i}} + \lambda_{12} \bar{a}_{\boldsymbol{i}} \cdot d_i + [\boldsymbol{X_i'}\psi_1 +]\, \epsilon_{1it} \qquad (3a)$$

$$\mathrm{Y_{it}} = \alpha_{20} + \delta_{2t} + \theta_{21} d_i + \theta_{22} d_i \cdot T_t + \lambda_{21} \bar{a}_{\boldsymbol{i}} + \lambda_{22} \bar{a}_{\boldsymbol{i}} \cdot d_i + [\boldsymbol{X_i'}\psi_2 +]\, \epsilon_{2it} \qquad (3b)$$

We de-mean patient age relative to the benchmark (aged 21 or 65), which we denote $\bar{a}_i$, and include a full set of year fixed effects δ_t. For some outcomes we also include a vector of patient controls X_i to account for observable differences in patient sickness, such as arrival diagnosis category and gender. We cluster standard errors by day-of-age cells (e.g. 65 and 2 days, 65 and 3 days and so on) to account for possible correlated error terms among patients of the same day-of-age.

The coefficients of interest in this model are θ_{12} and θ_{22} and they estimate the average change in the discontinuity at the threshold due to the ACA (i.e. post vs. pre). The causal effect of insurance on Y_i i.e. the RD-DD estimator, is given by $\gamma_{RD,DD} = \theta_{22}/\theta_{12}$ (Persson, 2017) and its identification relies on stronger assumptions.

This strategy can be used to recover two types of estimators. The first estimator is the reduced form change in insurance coverage, utilization or health caused by the ACA – quantified by θ_{12} and θ_{22} above. Since these are similar to differences-in-differences estimators, the identification assumption is that in absence of the ACA insurance expansions there would be no change to the discontinuity that existed pre-ACA, i.e. $\theta_{12} = 0$ and $\theta_{22} = 0$. We present supporting evidence through a falsification exercise assuming a placebo insurance expansion in 2010. We find little or no change on any outcome of interest between 2008-09 and 2010-11, providing reassuring evidence in support of this assumption.

To the extent that insurance coverage also changes for the control groups (ages 20 and 65) as a result of the ACA, it is differenced out as a secular trend. Hence this approach will underestimate the aggregate effects of the ACA. This is a pertinent concern in the case of young adults since Medicaid coverage also increased substantially for 20-year-olds (see Figure 1a). For this reason, we focus our discussion of results on the elderly group of patients.[13]

The second estimator, $\gamma_{RD,DD}$ is a derivative of the RD estimator, γ_{RD}. As discussed in Lee and Lemieux (2010), three assumptions enable a causal interpretation. First, relevant observable and unobservable factors that could affect the outcomes of interest should vary smoothly at the age threshold. For example, if individuals are disproportionately likely to graduate from college or enter employment exactly at age 21 or exit the labor force exactly at age 65, this would violate the above assumption. Table A. 1 column 5 presents population weighted estimates from the NHIS on discontinuities in school enrollment, marital status, employment and a number of other factors at ages 21 (Panel A) and 65 (Panel B). Column 4 presents mean values at the thresholds to serve as comparison. The evidence reassuringly indicates there is no statistically significant jump in these factors – with the exception of alcohol

[13] The ACA also implemented minor cuts to growth in Medicare payment rates and introduced performance pay incentives for hospitals; hence, 65-year-old patients are not perfect ‘controls’. But these changes are minor relative to the Medicaid expansion in California.

consumption which jumps at age 21. This may bias the RD estimator for young patients, a second reason to focus on the elderly patient group.

The other two assumptions are common to all LATE estimators – exclusion of the instrument from the outcome equation, and monotonicity (Angrist and Imbens, 1994). Together, they imply that the estimated changes in utilization and health are only due to change in behavior by 'compliers', i.e. those gaining insurance due to the ACA. Given the large-scale nature of changes wrought by the ACA, supply side factors (i.e. changes in treatment or outreach by hospitals and physicians) or spillover effects on infra-marginal individuals (e. g. individuals already eligible for Medicaid) may contribute substantially to the observed changes in outcomes. Exclusion restrictions are generally strong, and in this setting they may be untenable given the substantial changes in the health insurance landscape. Hence we focus our presentation of results to the reduced form estimates.

B. Insurance coverage

We begin by analyzing changes in insurance coverage for patients discharged from hospitals in California's hospitals using data from 2011 through 2016, acknowledging that changes in insurance may have caused a change in utilization of care and who gets hospitalized. We explore that possibility in section IV.C.

i. Changes in insurance post-ACA

Figure 2 plots observed and predicted changes in insurance coverage in 2014-16 relative to 2011-13 (circles, solid lines) for the elderly (Panel A) and young (Panel B) respectively. The predicted values were obtained by estimating equation 3a on case level data, although for presentation clarity we collapse the data to month-of-age.[14] In both patient groups, insurance coverage increases differentially for the treated patient sample (i.e. 64- and 21-year-olds) post-ACA. The differential increase is much larger among the young (~14 percentage points) as compared to the elderly (6 pp). One approach to interpret the magnitude of this change in coverage is to compare it in magnitude to the pre-ACA gap in coverage between the treated and 'control' patient groups, since 21- and 64-year-olds have historically been at an insurance disadvantage relative to their counterparts aged 20 and 65, respectively. The pre-ACA gap was 15 pp and 7 pp respectively for the young and elderly (not presented in the figure). Hence the ACA nearly eliminated the disparity in health insurance coverage at these two age thresholds (also suggested by the patterns in Figure 1b).

[14] We use regression coefficients from equation 3a to predict the probability of insurance coverage for each patient. We then collapse these predicted probabilities by taking the mean across all patients admitted with the same month-of-age. For both predicted and observed values, we calculate differences between the pre-ACA and post-ACA period in each month-of-age cell. The figures plot these aggregated predicted – and corresponding observed – values.

Figure 2 also presents – as a falsification exercise – the corresponding observed and predicted changes in insurance coverage over 2010-11 relative to 2008-09 (squares, dashed lines). The estimated magnitude is an order of magnitude smaller, and of the opposite sign: -0.6 pp. In addition to being minor, this estimate implies a differential pre-trend of *decreasing* insurance coverage among those aged 64, which would work against our finding an increase in insurance coverage post-ACA. There is a similar pattern in the case of the younger patients.

Since 20-year-olds experienced a substantial increase in coverage of about 6 pp, they are not an ideal control group. Our research design recovers the incremental effects of the ACA for 21-year-olds and will understate the aggregate effect. In contrast, there was no change in insurance coverage for 65-year-olds. Hence, for the remainder of the RD analysis we will focus on results for our sample of elderly (i.e. aged 64-65) patients, while results on the younger patients (aged 20-21) are mostly relegated to the appendix.

Appendix Figure A. 4 presents a disaggregated version of Figure 2 by plotting corresponding changes for different insurer types – Medicaid, Private, Self-pay and County indigent care. We do not present the change in Medicare and miscellaneous coverage types since there is essentially none. The appendix figure indicates that Medicaid expansion drove the increase in insurance since Medicaid is the *only* source of increase in coverage for elderly patients. This figure also suggests that the increase in Medicaid may be at least partially offset by a decrease in other existing types of health insurance coverage. We discuss these changes and implications for crowd-out next.

ii. Crowd-out

An important policy concern associated with the expansion of publicly funded insurance is the potential crowd-out of existing payers. Our research design allows us to identify crowd-out of existing insurers among hospitalized individuals in California. Table 2 presents formal estimates of changes in insurance coverage at the two age thresholds for patients discharged from hospital stays, obtained by estimating equation 3a on case level data. Panels A and B present results for the elderly and young respectively. Within each panel, the top row presents the average change in coverage post-ACA for 64-year-olds relative to 65-year-olds (θ_{12}), while the remaining rows present flexibly estimated effects for each post-ACA year. Columns 1-3 present results on Medicaid, Private and Miscellaneous insurance types. Column 4 presents results on aggregate coverage, while columns 5 and 6 present results on self-pay and the county indigent program.

Table 2 Panel A has two key implications. First, overall coverage for the elderly increased less than the increase in Medicaid (5.9 pp vs. 8.7 pp). This is mainly due to a 2.6 pp decrease in private coverage. Second, the decline in self-pay is about 30 percent the size of the increase in Medicaid (2.6 pp vs. 8.7 pp). In fact, there is a larger decline in the county indigent program (3.3 pp or 40% of the Medicaid expansion) than in self-pay. Post-ACA, the county indigent program shrinks to nearly zero. The remaining 30% of the Medicaid expansion is offset by the decline in private insurance. The dynamic results indicate that insurance coverage increased gradually between 2014 and 2016, with about 85% of the average gain (7.4 vs. 8.7) obtained in the first year. Hence these results may understate the long-term effects of the expansion.

The results above permit two observations. First, the Medicaid expansion drove the increase in health insurance coverage. The ACA exchange enrollments apparently did not lead to a net increase of private coverage among elderly hospitalized patients.[15] When we discuss the effects on utilization and health, we will interpret them as primarily occurring due to the Medicaid expansion.

Second, the near demise of local safety net programs implies that a substantial share of the Medicaid expansion replaced existing state and county spending on health care. Extrapolating directly from our estimate above (40% of increase in Medicaid replaced county coverage) implies that for every $100 increase in Medicaid hospital spending, about $40 replaced safety net spending. This naïve interpretation ignores differences in patient severity and reimbursement rates between Medicaid and the safety net program. However, the reimbursement rates were in fact quite different. Financial data reported by hospitals to California indicates that in 2011-13 hospitals were reimbursed at half the rate for county indigent patients as for Medicaid patients ($1,240 vs. $2,400 per day).[16] Hence the $40 transfer from federal tax payers that fully funded the Medicaid expansion is about equally split between hospitals that now receive greater reimbursement rates, and California and county governments that largely funded the local safety net. There are distributional implications as well – if we ignore differences in the costs of raising taxes at different levels of government, this transfer was borne by federal taxpayers outside California, including those residing in states that chose to not expand Medicaid. We return to implications for hospitals in section VI when we examine effects on hospital finances.

C. Utilization of care

i. Volume

Since our data is conditional on discharge from a hospital, we cannot study the rate of hospital use at the individual level (since for example many individuals are not hospitalized during our study period). We use hospital stays or ER arrivals per 1,000 people per year (i.e. the utilization rate) as our preferred measure. We collapse the data to day-of-age at admission (denoted by s) - year cells and estimate the following model.

[15] The data does not allow us to differentiate between exchange and non-exchange plans. It is possible that exchange plans did cause an increase in private insurance coverage. If true, this was apparently more than offset by a crowd-out of other type of private coverage.

[16] In 2016 dollars. A caveat is that these numbers are for patients of all ages and include maternity stays. Both Medicaid and the county indigent programs require small or no co-payment so the effective price on the demand side is not different for the two programs.

$$y_{st} \quad = \quad \gamma_{3\mathrm{t}} + \theta_{31} d_s + \theta_{32} d_s \cdot T_t + \lambda_{31} \bar{a}_{st} + \lambda_{32} \bar{a}_{st} \cdot d_s + \epsilon_{\mathrm{st}} \qquad (4)$$

This is an exact analog of equation 3b, which was estimated on case level data. y_{st} and $\bar{a}_{st}$ denote the mean utilization rate and de-meaned age of patients in the day-of-age - year cell s, t. d_s is the corresponding indicator obtained by collapsing d_i within each day-of-age cell. The coefficient of interest is θ_{32} – the estimated change in the discontinuity in the rate of utilizing hospital care post-ACA for the treated group relative to the control.

Figure 3 presents the observed change in the rate of utilization post-ACA of hospital stays (Panel A) and ER arrivals (Panel B) for elderly patients, by month of age. In addition, we plot fitted values obtained by estimating equation 4. Panel A shows that there has been a decline in the rate of hospitalization for both 64- and 65-year-old patients, with a smaller decline for the treated group, and a noticeable drop exactly at age 65. Panel B shows on the other hand that there has been an increase in the rate of ER use for both groups, with a greater increase for 64-year-olds.

Table 3 presents estimated effects on utilization of care for elderly patients, obtained using equation 4. Table 3 column 1 presents results for all hospital stays. Columns 2 and 3 examine effects separately for hospital stays that originated through the ER and those that did not since they may respond differently to changes in insurance coverage. Similarly, columns 4 and 5 present results separately for deferrable and non-deferrable hospital stays. The table presents both average post-ACA effects (top row) and dynamic effects for each year 2014-16. We find a differential increase among 64-year-olds of 6% of the mean (8 stays per 1,000 people per year), which eliminates 40% of the pre-ACA gap in hospital stays between 64- and 65-year-olds. The estimates indicate that much of the increase is driven by stays for elective or non-emergent reasons. For example, 85% of the increase is driven by more stays for deferrable conditions, and 60% by stays that did not originate in the ER. Table 3 columns 6 and 7 present corresponding results on ER use. We present results on all patients arriving at the ER (column 6), as well as those that were discharged from the ER (column 7). The pattern of increase in ER use is similar to that of hospital stays, whether benchmarking it as a percentage of the mean level or against the pre-ACA gap between 64- and 65-year-olds. Across hospital stays and ER arrivals, the ACA resulted in an increase in utilization rate that bridged about 35-40% of the pre-ACA gap in volume between 64- and 65-year-olds.[17]

[17] Our reduced form estimates are similar in magnitude to those reported by Card et al. (2008). They examined the effects of the onset of Medicare coverage at age 65 on utilization of care and insurance 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 6% increase post-ACA. They estimated an increase of 5% and 14% in stays originating in ER vs. not, while our corresponding estimates are 3% and 10% respectively. We also estimated alternative specifications 1) using log of utilization rate as outcome, and 2) in the spirit of a regression kink i.e. allowing the effect to increase with exposure to the ACA (based on age and time since 2014). These results are qualitatively similar and are available on request.

The hospitalization rate for 64-year-olds pre-ACA was about 0.13 stays per individual per year. Our estimate implies this rate increased by 6% (~0.008) post-ACA. If it is driven entirely by the 6 percent who acquired coverage due to the ACA then it implies an increase of 0.13 (0.008/0.06) stays i.e. a doubling of utilization for marginal individuals. This effect is three times the comparable estimate from the Oregon experiment (Finkelstein et al., 2012). They report a LATE estimate of a 30% increase (Table A.26) for near-elderly individuals (aged 50-63) due to Medicaid coverage. It is possible that the newly insured individuals are sicker than existing Medicaid patients and hence need to consume more hospital care. Perhaps more importantly, our estimated increase may be driven by general equilibrium effects. For example, hospitals and physicians may have responded to the much publicized Medicaid expansion and increased reimbursement rate by expanding access to and increasing treatment intensity for low-income non-elderly patients.

ii. Choice of hospital

In addition to increasing hospital care, patients may also be receiving care at different types of hospitals after the Medicaid expansion. We explore hospital choice on two dimensions – ownership type (e.g. public, private non-profit, and private for-profit) and quality (as measured by risk adjusted mortality and readmission scores). A key benefit of expanding insurance could be enabling patients to choose higher quality care providers or providers that patients prefer for other reasons (e.g. proximity).

a. Hospital owner type

Figure 4a presents the change in the observed share of stays at government hospitals for elderly patients post ACA. It also presents the corresponding fitted values obtained by estimating equation 3b on case level data. Figure 4a indicates that patient volume shifted away marginally from government owned hospitals (~1.1 pp) post-ACA. The discontinuity in the share of government owned hospitals is more diffuse than those in insurance coverage and volume, but the patterns for 64- and 65-year-olds are clearly different, with a larger reduction in government share among 64-year-olds, whose coverage differentially increased.

Table 4 columns 1-3 present estimated effects on hospital share by owner type for elderly patients. Panel A presents results for hospital stays, while Panel B presents results on ER arrivals. The table confirms the trends shown by the plot, and suggests that for-profit hospitals gained about 70% of this shift in volume, although by 2016 both non-profits and for-profits benefit about equally. Note that 64-year-olds were more likely to receive care at government owned hospitals in the pre-ACA period. This shift from public to private hospitals among 64-year-olds after the ACA narrows the pre-ACA gap between 64- and 65-year-olds by 60%, but does not eliminate it.

Our research design cannot help us disentangle the mechanisms – specifically supply vs. demand side channels – behind this shift in hospital care toward private hospitals. Assuming Medicare patients are unconstrained in their hospital choices, the lower share of government hospitals among 65-year-olds indicates patient preference for private hospitals. Hence, the most intuitive explanation for narrowing this gap post-ACA is that it is demand driven. However, we cannot rule out the possibility that private hospitals proactively courted ACA beneficiaries (such as exchange enrollees and Medicaid beneficiaries). To inform our interpretation, we replicate the analysis on the sample of ER arrivals (Table 4b). ER arrival patterns are more likely to reflect patient preferences since they are presumably for emergencies and hence there is less scope for physician influence.[18] We find a similar pattern of movement away from government owned hospitals among ER arrivals. In fact, the shift is greater in percentage terms (11% vs. 7% for hospital stays) among ER users. Taken together, these results suggest that the differential drop in the utilization of care in public hospitals among 64-year-olds reflects the greater choice afforded by formal health insurance coverage.

b. Hospital quality

Hospital ownership is correlated with quality or with perceived quality of care (for example, academic medical centers are generally high quality and non-profit), but not perfectly so. To examine if the above sorting across hospitals is motivated by quality, we use two commonly accepted quality measures – risk-adjusted 30-day mortality and readmission rates – as indicators of hospital quality. We test if patient volume has shifted toward hospitals that were publicly certified by CMS in 2009 as having better quality outcomes.

CMS calculates these measures for Medicare patients discharged from hospitals for a number of serious conditions. The raw mortality and readmission rates are adjusted for patient risk history and observed sickness at the time of admission.[19] We start with the risk-adjusted rates for hospitals, as reported by CMS in 2009, on three conditions: heart attack, heart failure and pneumonia. We then compute the mean rate for each hospital and normalize it such that the distribution across hospitals is standard normal with a mean of 0 and standard deviation of 100.

Figure 4b presents the observed mean normalized mortality scores and corresponding fitted values obtained by estimating equation 3b on the Y-axis, against patient month-of-age on the X-axis. The plot is admittedly diffuse, without a clear discontinuity at age 65. The fitted values indicate that mean hospital mortality score increased for 65-year-old patients, while it held relatively constant for 64-year-olds, resulting in a relative improvement of about 2 pp. We do not present the corresponding plot for mean readmission scores since the estimated change is not statistically significant – although the point estimate is negative – and the plot is even more diffuse.

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[18] We also directly examined if 64-year-old patients are receiving care at hospitals located closer to them, however we did not find any consistent patterns. We used distance between the patient's and hospital's zip codes, provided by NBER. These results are available on request.

[19] 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.

Table 4 columns 4 and 5 present the formal estimated effects on mean mortality and readmission scores respectively. Panels A and B present the results for hospital stays and ER arrivals respectively. The results are similar across both panels and indicate that patient volume among 64-year-olds has shifted toward marginally better-quality hospitals. In the pre-ACA period, 64-year-olds received care at lower quality hospitals (0.04 s. d. higher mortality rate) relative to 65-year-olds. The estimated effects for hospital stays indicate that the pre-ACA disparity between 64- and 65-year-olds decreased by about half. As an additional test, we also obtained alternative estimates where the specification controls for hospital owner type. The coefficients drop in magnitude by about half but remain statistically significant in the case of mortality. We interpret this to mean patients are sorting toward better-quality hospitals even *within* the same hospital owner type, and this contributes 50% of the observed improvement in hospital quality.

To interpret the magnitude of this change we use revealed preference estimates of the additional distance patients are willing to travel to receive care at better hospitals. There is a large literature on hospital choice which has developed approaches to estimate these parameters and a full review is outside of the scope of this paper, but the most relevant reference is Tay (2003) who examines Medicare data from California, Oregon and Washington. She finds 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. Our results imply that 64-year-olds are now receiving care at hospitals with a 0.03 pp (0.02 s. d. i.e. 2% of 1.6 pp, not reported here) lower mortality rate, or approximately 0.3% of the mean 30-day mortality rate for heart attack patients (~10 pp). Crudely applying the 8-mile benchmark suggests that the average 64-year-old hospital patient is benefitting by the equivalent of a ~1 mile (0.3/3*8) reduction in travel distance.

D. Health Outcomes

Well-designed field experiments have indicated no tangible benefits of insurance coverage on patient health (Manning et al., 1987; Finkelstein et al., 2012). However, some studies on the effects of Medicaid have found mortality benefits, albeit among children (Currie & Gruber, 1996a; Bailey & Goodman-Bacon, 2015; Goodman-Bacon, 2018). Similarly, evidence from the recent Massachusetts insurance reform indicates substantial mortality benefits of expanding coverage for low income individuals (Sommers, Long and Baicker, 2014). The ACA was designed to explicitly extend insurance coverage for non-elderly adults – a group that has historically received less attention. In this section we test the effects of the ACA on patient mortality, specifically in-hospital mortality – the largest component of 30-day mortality.[20]

[20] Due to data limitations, we do not observe 30-day mortality post ACA. We obtained death-linked hospital discharge files over 2008-11 from California OSHPD to examine the link between in-hospital mortality standard metrics of mortality. 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

Appendix Table A. 2 columns 1 and 2 present regression estimates on in-hospital mortality for elderly patients obtained by estimating equation 3b. Panels A and B present results for hospital stays and ER arrivals respectively. Due to the increase in hospital use, there is a concern that unobserved decrease in patient severity may lead to spuriously estimating a decrease in mortality. Prior studies (Card et al., 2009; Doyle et al., 2015) have circumvented this concern by focusing on the subset of patients discharged with emergent non-deferrable conditions such as Heart Attack and Pneumonia, where outpatient treatment is not possible. We follow the same approach and these results are presented in column 2. The point estimate of the effect on in-hospital mortality is a statistically insignificant -0.29 pp, about 7% of the mean mortality rate in the sample. Prior to the ACA, 64-year-old patients had a higher in-hospital mortality rate (a statistically insignificant 0.35 pp difference), and this result suggests that this gap has been almost entirely eliminated. Though the estimate is noisy, we can rule out an effect greater than 10% of the pre-ACA mean mortality rate. We therefore interpret the suggestive evidence on mortality with caution and refrain from a formal cost-benefit computation.

A key argument used in favor of expanding insurance coverage was that greater immediate access to preventative care would 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 hospital care. Potentially avoidable episodes are identified for a subset of visits 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).[21] Table A. 2 column 4 presents corresponding estimated effects on the share of stays that were potentially avoidable. The coefficients are very small and statistically insignificant, suggesting there is no change. This is consistent with prior evidence from Tennessee showing that a contraction of Medicaid did not increase the share of uninsured stays for avoidable reasons (Ghosh and Simon, 2015).

E. Robustness and falsification checks

i. Alternate specification

Our preferred specification allows the slope with respect to age to differ for treatment and control groups but constrains the slopes to remain unchanged in the post-period. In this sub-section we test robustness to relaxing this constraint. Appendix Table A. 3 presents corresponding results on all key outcomes – changes in insurance coverage (columns 1-5), utilization (cols. 6-7), hospital choice (cols. 8-9)

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.

[21] 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 55% of the total sample of elderly patients in 2011-16 respectively.

and patient health (cols. 10-11). To facilitate comparison, Panel A repeats our main results. Panel B presents results using a fully flexible specification that also allows the slopes with respect to age to change in the post period, holding the bandwidth at 1-year around the benchmark age of 65. We present coefficients on the relative change in the pre-ACA gap between 64- and 65-year-olds post-ACA, as in our main results.

The results exhibit qualitatively similar patterns and most have only minor differences in point estimates. The exceptions are a substantially larger estimated increase in ER arrivals in column (7) and smaller magnitude estimates on hospital choice in columns (8) and (9). Additionally, we performed another specification check modeling outcomes as quadratic functions of age and found similar point estimates.

ii. Alternate bandwidth

We prefer one year as the narrowest feasible bandwidth to implement the RD-DD design. However, we test robustness to other choices by replicating results using a larger bandwidth of two years instead. Appendix Table A. 3 presents corresponding results of this robustness check for all key outcomes. In Panel C, we continue to use our main specification, but with a 2-year bandwidth. Panel D presents results in which we use both the flexible specification and a 2-year bandwidth.[22] The results indicate minor differences in point estimates, but qualitatively similar patterns. Taken together, the results are reassuringly robust regardless of specification or bandwidth.

iii. Falsification

A valid identification concern is that the results may be partially or fully driven by pre-existing economic trends that may differentially affect 64-year-old patients. 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. To investigate this possibility, we replicated our regression discontinuity analysis over the period 2008-11 i.e. before the ACA insurance expansions were implemented. Ideally, if our pre-ACA coefficient (2011-13) estimates a stable discontinuity in coverage, then we should find similar estimates in the 2008-09 period as well, i.e. $\theta_{11}^{08-11} = \theta_{11}^{11-16}$. If the post-ACA coefficient captures changes only due to the ACA, then we would find a zero (or very small) effect in the placebo analysis, i.e. $\theta_{12}^{08-11} \approx 0$.

Table 5 presents results from the placebo analysis on insurance coverage, utilization, hospital choice and patient health for hospital stays. It summarizes effects on key outcomes from Table 2, Table 3, and Table 4. The top row presents the estimated difference between 64- and 65-year-olds over 2008-09 i.e. θ_{11}^{08-11} from equation 3a/3b while the second row presents the change in this gap post 2010, i.e. θ_{12}^{08-11}. The placebo coefficients for post 2010 change are not significantly different from zero or are very small in magnitude. Overall, the pattern of results does not mimic the post-ACA results. For example, we find an increase in self-pay, no change in the rate of hospitalizations or the share of government hospitals. There is

[22] Again, the use of a quadratic specification does not affect coefficients with a 2-year bandwidth and these results are virtually identical to those in Panel C. Results using quadratic specification are available upon request.

a small increase in Medicaid of 0.75 pp, and a decrease in private coverage of similar magnitude, which may be due to the 'early' Medicaid expansion implemented in California in 2011 (Golberstein et al., 2015; Sommers et al., 2015; Wherry and Miller, 2016). Nevertheless, these coefficients are very small relative to the effects obtained after the full expansion took effect in January 2014.

V. ALL NON-ELDERLY ADULTS

A. Empirical strategy

We consider the RD-DD design our preferred approach, but its external validity is limited. The RD-DD estimates are mainly representative of effects for individuals just below age 65 relative to those at age 65. Additionally, patients aged 64-65 are less than 10% of the size of the non-elderly patient sample. We therefore supplement the RD-DD analysis above using an alternative approach that takes advantage of the entire non-elderly (21-64) sample and relies on variation across hospital service areas (HSAs), a commonly used hospital market definition discussed in section III.B.

The ACA was *designed* to increase insurance coverage among lower income families and individuals. In 2012, the uninsurance rate among California adults aged 19-64 with income below the 138% of the federal poverty level was 36%, in contrast to 15% for those above (Charles et al., 2017). Markets with lower average income levels therefore had higher rates of uninsurance prior to the ACA and would experience greater decrease in uninsurance due to the ACA. Our thought experiment predicts that such HSAs would experience a greater "insurance expansion shock" than markets with lower poverty.

We deploy a differences-in-differences research design exploiting cross-sectional variation in poverty rates (the share of the population below 125% of the federal poverty level) across HSAs in 2007-11. We use data from the ACS 2007-11 5-year estimates to calculate the poverty variation just prior to the ACA. Figure 5 presents a histogram of the estimated poverty rates among non-elderly adults across HSAs. There is substantial variation in poverty – the difference in poverty between the top and bottom quintile markets was 18%, coincidentally similar to the mean poverty level. In addition, we leverage within-HSA time-series variation created due to the implementation of the ACA in 2014. We estimate econometric models at the HSA-year level, presented in equation 5a.

$$Y_{jt} \; = \; \alpha_j \; + \; \gamma_t + \xi \cdot Poverty\, rate_j \cdot T_t \; + [\boldsymbol{X'_{jt}}\psi +]\; \epsilon_{ijt} \qquad (5a)$$

Y_{jt} is the mean outcome value for HSA j in year t. T_t is an indicator for years 2014 and later. The coefficient of interest is ξ which estimates the change in outcome Y post-ACA (2014-16) versus pre-ACA (2011-13) for a market with baseline poverty rate of one compared to a market with no poverty. We maintain the sample period 2011-16 in order to be consistent with the RD-DD analysis. 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 (age group, gender, and category of principal diagnosis) by including vector $\boldsymbol{X_{jt}}$. To mitigate the influence of small outlier units, we weight each HSA by pre-ACA non-elderly population estimates obtained from the same source as the poverty shares.

Identification of the causal effect of the ACA relies on the standard parallel trends assumption, i.e. outcomes for HSA markets at different poverty levels would evolve along similar paths in absence of the ACA. To test the presence of possible differential pre-trends across markets, we estimate and present results from models allowing effects ξ_s to vary flexibly by year from 2011 through 2016, omitting 2013 as the reference year, as depicted in equation 5b.

$$\mathrm{Y}_{jt} = \alpha_\mathrm{j} + \gamma_\mathrm{t} + \sum_{\substack{s=2011, \\ \neq 2013}}^{s=2016} \xi_s \cdot \text{Poverty rate}_\mathrm{j} \cdot \mathrm{I}(\mathrm{t}=\mathrm{s}) + \epsilon_{jt} \qquad (5b)$$

Note that this approach uses a different source of identifying variation relative to the regression discontinuity analysis. Estimates from the geographic analysis inform us about changes for patients residing in high poverty areas *relative* to changes for patients in affluent markets. To the extent that affluent markets also experienced changes, these will be differenced out. For example, Medicaid coverage for patients in the most affluent quintile of HSAs nearly doubled from 13% to 25% (a 12 pp increase) post-ACA. However, Medicaid coverage for the least affluent quintile increased by an even larger margin – 18 pp. This research design is designed to model only the net widening of the gap (by 6 pp) between the two groups of markets. As with the RD-DD analysis, this approach may therefore understate the aggregate effects of the ACA.

In the interest of brevity, we summarize regression results obtained using this approach into two tables. Table 6 presents the results on insurance coverage and volume of care, while Table 7 presents corresponding results on hospital choice and patient health. In both tables panel A presents the average post-ACA effect, while Panel B presents flexibly estimated effects for each year from 2011 through 2016 relative to 2013.

B. Insurance coverage

Table 6 columns 1-6 present results on changes in insurance coverage. These results lead to similar conclusions as in the RD-DD approach. First, there was a large increase in insurance coverage, driven primarily by Medicaid. The mean poverty rate in the pre-ACA period was 18%, hence the coefficient of 29 implies an average increase in Medicaid coverage of 5.2 percentage points (29*0.18). Correspondingly, the results imply an average increase of 4.8 pp in insurance coverage (26.4*0.18), which would entirely eliminate the pre-ACA disparity in coverage between the least and most affluent market quintiles (-4.7 pp). In contrast, we estimate a small and statistically insignificant increase in private coverage, implying an increase of 0.6 percentage points (3.4*0.18) on average. In fact, we can rule out an increase of greater than 1.5 pp (8*0.18) in private coverage, which would make a negligible difference to the 30 pp gap in private coverage between the least and most affluent market quintiles. Nevertheless, this result moderates the takeaway from the RD-DD results that the Medicaid expansion crowded out private payers.[23]

Second, the decline in self-pay is less than half the increase in Medicaid coverage (~2.5 pp). It is still sufficient to eliminate the disparity in self pay between the least and most affluent markets (~2 pp). About 40% of the increase in Medicaid offsets the decline of county indigent programs, strikingly similar to the estimate in the RD-DD approach. Figure 6a presents the event study plot of changes in insurance coverage, using estimates from equation 5b. It clearly shows that the increase in Medicaid coverage is about twice as large as the corresponding decrease in self-pay status, and also there were no differential pre-trends across markets.

C. Utilization (volume and hospital choice)

Table 6 columns 7-10 present the estimated effects on hospital volume (in logs). Unlike in the RD-DD analysis, we are unable to normalize the raw discharges by HSA-year population estimates since we do not have annual estimates of population by HSA. However the concern of spurious results due to the baby boom is diminished in this case since the annual variation in age profile across markets is likely very small relative to the variation in baseline poverty across markets. The estimates in Panel A imply that hospital utilization by non-elderly patients increased by ~4% across hospital stays (Col. 7) and ER arrivals (Col. 10) on average (0.2*0.18, 0.25*0.18). Columns 8 and 9 present results separately for deferrable and non-deferrable stays and intuitively show that the increase in stays is driven mainly by patients who came in with deferrable conditions. This is qualitatively similar to the estimates from the RD-DD approach and suggest that 64-year-olds experienced an increase in utilization that was only slightly greater than that for all non-elderly adults (6% vs. 4%). Figure 6b presents the corresponding event study plot and indicates a sharp increase in volume in 2014, followed by further increases in subsequent years. The plot suggests no differential trends in utilization across markets prior to the ACA.

The implied increase in hospital volume of 4-6% across both our age-based RD-DD and geographic-based empirical approaches agrees well with observed changes in utilization for non-elderly adults over this period. Appendix Figure A. 5 presents the time series of hospital stays and ER arrivals

[23] It is possible that crowd-out was greater among 64-year-olds than among all 21-64-year-olds since their average health care costs are much greater and so there would be more for employers (and possibly employees if any savings were passed on through wages) to gain from dropping coverage for this group than for their much younger counterparts.

(right axis) for patients aged 21-64. The period spans 2011-16, our analysis period. Raw discharges have been normalized by estimated population in this age group by year, so the plot presents utilization rate per 1,000 individuals per year. Consider the case of hospital stays – simply extrapolating the 2011-13 values using a linear trend would predict about 50 stays per 1,000 people in 2016. The observed rate exceeds this prediction by about 3.5 stays per 1,000 people, or 6% of the mean rate over 2011-13 (56.3). If we use the raw discharge volume changes instead, we obtain an observed increase of 5.5%. Similar analysis holds for the ER arrivals.

Table 7 columns 1-3 present corresponding results on changes in hospital shares post-ACA. We examine the change in share by hospital owner type (columns 1-2) and mean risk adjusted mortality score (Col. 3). Although the point estimates are qualitatively in the same direction as the results from the RD-DD analysis, they are smaller in magnitude (e.g. implied decrease in government hospital share is 0.6 pp relative to 1 pp in Table 4 column 1 Panel A) and we cannot rule out effects in either direction. Figure 6c presents the corresponding event study plot on share of hospital stays at private hospitals. It shows a slight increase post-ACA, with an increasing trend. The estimated effect on hospital quality (Col. 3) is particularly noisy. Overall, these results indicate heterogeneity across patients in different age groups, where the sharply estimated effects for 64-year-olds may not be representative of the trend for the entire non-elderly sample.

D. Health

Table 7 columns 4 and 5 present estimated effects on in-hospital mortality for the non-elderly patient group. Again, we primarily focus on effects for the subset of patients discharged with a non-deferrable condition (Col. 5). The results are suggestive of mortality gains, though the point estimate is not statistically significant, as in the RD-DD analysis. The estimate implies an average decrease in mortality of 0.14 pp (0.77*0.18), sufficient to eliminate a quarter of the pre-ACA mortality gap between the poorest and most affluent market quintiles (0.48 pp).

VI. HOSPITAL FINANCES

In this section, we have three goals. First, we document changes in hospital revenue due to the ACA and discuss heterogeneity in effects across hospitals based on their baseline patient mix. Government owned hospitals disproportionately served safety net and self-pay patients pre-ACA, and so the expansion would have a greater impact on them. Second, we quantify the proportion of the revenue increase that can be linked directly to increases in patient volume versus increases in prices. Medicaid reimbursed hospitals for inpatient stays and outpatient visits at about twice the rate that they received from self-paying patients and county indigent programs.[24] Hence, a substitution to Medicaid from these other sources of coverage theoretically should lead to an increase in average reimbursement rates. Our results on hospital volume in the previous two sections indicated a 4-6% increase in volume of hospital care on average. However, it may vary when we examine at the hospital level, since there was some reallocation of patients away from government hospitals. Third, we test if the influx of public insurer funds spurred capital investment and expansion by hospitals.

A. Empirical strategy

We implement a differences-in-differences research design which uses cross-sectional variation in pre-ACA uninsurance rates across hospitals. The thought experiment is conceptually similar to that used in the geographic analysis where hospitals with a high pre-ACA share of uninsured patients would experience a greater insurance shock relative to hospitals that largely served insured patients. Figure 7 illustrates the magnitude of this variation across hospitals before and after the ACA. Panel A presents a histogram of hospital uninsurance shares pre-ACA, 2008-10, calculated using hospital discharge data. Most hospitals ranged between zero to approximately 30%. Hospitals in the top quintile by uninsurance had 20 percentage point greater baseline uninsurance than hospitals in the bottom quintile. Panel B presents the distribution after the implementation of the ACA, 2014-16. The range noticeably shrank, with most hospitals now below 15%.

Equation 6a presents the estimating equation for this approach. We deploy annual data on hospital finances collected by OSHPD over the period 2011 to 2016, as described in section III.C, and correspondingly perform this analysis at the hospital-year level. To mitigate the influence of small outlier units, we weight each hospital observation by the number of pre-ACA discharges in 2008-10.

$$Y_{ht} = \alpha_h + \gamma_t + \chi \cdot \text{Uninsured}_{h-0810} \cdot T_t + \epsilon_{ht} \tag{6a}$$

The key identification assumption is the absence of differential pre-trends in finances across hospitals at different levels of baseline patient uninsurance shares. In order to test for the presence of pre-trends, we also estimate the flexible dynamic specification 6b. Note that this analysis quantifies effects of the ACA insurance expansion net of patient sorting across hospitals.

[24] Surprisingly, hospitals received similar reimbursement from self-pay customers, as from those covered by county indigent programs. This is consistent with the finding by Gruber and Rodriguez (2007) that providers are able to recover similar or more revenue from self-paying patients.

$$\mathrm{Y}_{ht} = \alpha_\mathrm{h} + \gamma_\mathrm{t} + \sum_{\substack{s=2011 \\ \neq 2013}}^{s=2016} \chi_s \cdot \mathrm{Uninsured}_{h-0810} \cdot \mathrm{I(t = s)} + \epsilon_{ht} \qquad (6b)$$

To estimate differences across hospital types we also estimate a differences-in-differences-in-differences model in equation 6c where we interact an indicator for being a government hospital, $Govt_h$, with $\mathrm{Uninsured}_{h-0810} \cdot T_t$ and the year fixed effects γ_t. The latter flexibly allows government hospitals to evolve along a different trend. We discuss results from this model wherever noteworthy. [25]

$$\begin{aligned} Y_{ht} \ = \ \alpha_h \ + \gamma_{1t} + \gamma_{2t} \cdot Govt_h + \chi_1 \cdot \mathrm{Uninsured}_{h-0810} \cdot T_t \\ + \chi_2 \cdot \mathrm{Uninsured}_{h-0810} \cdot T_t \cdot Govt_h \ + \epsilon_{ht} \end{aligned} \qquad (6c)$$

B. Hospital revenue

Table 8 Columns 1-6 present results on revenue, expressed in thousands of dollars per bed from estimating these equations. We present results on total revenue as well as from different payers (Medicaid – including managed care, Private, and all others) and types of services (inpatient vs. outpatient). All revenue variables are deflated to be in 2016 dollars (in thousands) using the CPI-U and normalized by the hospital's average number of licensed beds in the baseline period.[26] Panel A presents results from estimating equation 6a for the entire sample, while Panel B presents triple difference results to examine differences between government and privately-owned hospitals.

The key takeaway on hospital revenue is the large differential increase in Medicaid revenue for hospitals with a higher baseline share of uninsured patients. The average hospital generated an increase of about $55,000 (508*0.11) in annual Medicaid revenue per bed, which is 27% of the pre-ACA mean level. This estimate implies an incremental $4.1 billion of Medicaid payment to California hospitals each year over 2014 to 2016[27]. The estimated effect on total revenue for the average hospital is similar in magnitude, ~$50,000 increase per bed (471*.11), with a small increase from private payers being nullified by decreases elsewhere. Since total revenue was about five times as large as Medicaid alone, this increase represents only 5% of the pre-ACA mean. However, it eliminates more than 10% of the pre-ACA gap of -

[25] The results by hospital type tend to be noisy and the estimates for government and private hospitals are typically not statistically indistinguishable due to the imprecision. However, there are a few instances in which the estimates for government hospitals are statistically significant but are statistically indistinguishable from privately-owned hospitals, which are not statistically significant. Since this is not discernible in the table, we will highlight these results whenever noteworthy.

[26] To account for outliers in the financial data, we winsorize the top 1% of revenues, volume measures (stays and visits), and expansion variables (capital expenditures and license beds). For operating margin, we also winsorize outliers in the bottom 1% of values since some hospitals reported extremely negative margins. We winsorize by year, hospital type (government and privately-owned), and when applicable by payer type (e.g. Medicaid, Private, etc.) and type of service (inpatient vs. outpatient). We compute total revenue as the sum of the winsorized components rather than winsorizing it independently so that the coefficients add up across columns. Furthermore, by winsorizing values by hospital type, we eliminate the possibility that outliers of one hospital type drive our results in Panel B.

[27] Multiplying 55,000 increase in Medicaid revenue per bed per year for the average hospital with 235 beds per hospital and 320 general acute care hospitals in the sample = $4.1 billion.

$385,000 between top and bottom quintile hospitals by baseline uninsurance. Figure 8a presents event study plots obtained by estimating equation 6b. The flexibly estimated annual estimates are consistent with the average point estimates discussed above. Hospitals with greater baseline uninsurance appear to have a decreasing trend of Medicaid revenue in the pre-ACA period, but it reverses sharply after 2013. This suggests that our point estimates may even understate the magnitude of the increase in Medicaid revenue due to the ACA.

Government-owned hospitals disproportionately served county indigent patients in the pre-ACA period – 15% of their patients versus 3% at privately-owned hospitals, as well as more self-pay patients (14% vs. 8%). Hence as a group, government hospitals had much more to gain from the insurance expansions. The results by owner type in Table 8b confirm that government hospitals gained more from the expansion. The average government hospital experienced a ~$200,000 increase in revenue per bed (663*0.29), about 25% of the mean pre-ACA level for government hospitals. In contrast, the average private hospital experienced a ~$90,000 increase in revenue per bed (793*0.11), representing an 9% increase relative to their pre-ACA mean.

Previous studies argue that public hospitals have soft budget constraints (Duggan, 2000; Baicker and Staiger, 2005) and hence the increased revenue due to Medicaid would be offset by an equivalent reduction in public subsidies. Our results appear to contradict these previous studies, however future reductions in DSH payments may mitigate the revenue gains for public hospitals.

C. Price vs. Volume and profitability

Table 8 columns 7-10 examine effects on volume and average 'price' (mean revenue per discharge) components to help explain their role in the revenue effects described above. The nature of the data makes it necessary to examine quantity and price separately by inpatient and outpatient services. Column 11 presents the results on total *reported* operating margin, computed by dividing the difference between operating revenue and costs by operating revenue.[28] Examining price and volume separately helps clarify that the aggregate increase in revenue is driven entirely by price, consistent with Medicaid replacing uncompensated care. A hospital with 10% greater uninsurance share now receives $1,000 more per inpatient stay, sufficient to eliminate 12% of the pre-ACA disparity between top and bottom quintile hospitals by uninsurance (-$8,600).

Hospitals with greater baseline uninsurance *lost* patient volume relative to those previously serving a lower share of uninsured patients. Since baseline uninsurance was much lower for private hospitals (by 18 pp), this further corroborates previous results indicating a shift in patient volume from government to

[28] Operating revenue is largely composed of patient revenue (90%+), but also includes non-patient revenue due to food and merchandise sales. It does not include investment income. Operating costs are opaque since we do not observe its components.

private hospitals. The coefficient of -5.8 implies that the average government hospital has a decrease of 1.1 stays per bed (-5.8*0.18) relative to the average private hospital, about 3% (1.1/44) of the mean volume. This is strikingly similar to the estimated loss in government hospital share (-3.5*0.18/16 = ~4%) in the geographical analysis, reported in Table 7. Figure 8b presents event study plots illustrating the contrast in patterns for price and volume. Reassuringly there is no evidence of differential trends prior to the expansion.

Driven by the increased average reimbursement per discharge, hospitals with greater baseline uninsurance received a large boost in profitability. The average hospital gained about 4 pp in operating margin (35*0.11). Back of the envelope calculations imply that this translates to a gain of ~$9 million for the average acute care hospital.[29] If we aggregate this across the 320 hospitals in our sample, it implies a collective increase of $2.8 billion in hospital operating profit due to the ACA, or about 70% of the estimated increase in Medicaid revenue.

The increase in price and profitability discussed above is clearly driven by government hospitals. The average government hospital experienced an increase of ~$5,000 in reimbursement per inpatient stay (16*0.28) and 12 percentage points in operating margin (40*0.28) due to the Medicaid expansion, both of these estimates are statistically significant at the 1% level. All these results account for any reductions in government DSH support and hence imply a large windfall for government hospitals due to the ACA. In contrast, the estimated effects for private hospitals are much smaller and statistically insignificant. Figure 8c presents the corresponding event study plot of effects on operating margin by hospital type.

Overall, the results on hospital revenue and profitability are consistent with lobbying by hospital, physician and nursing industry associations to prevent repeal of the Medicaid expansion as well as to continue delays in cutting federal DSH support.[30]

D. Hospital expansion

The increase in revenue and profitability does not seem to encourage expansion; we find no evidence of differential increase in capital investments (column 12) or bed capacity (column 13). This is not entirely surprising as only a three year follow-up period may preclude finding effects on long-term investment decisions.

[29] Gain in operating profit is obtained by using increases in operating margin on the base revenue and factoring in number of beds, all for the average hospital: 0.35 coefficient * 0.11 mean uninsurance * $968,000 mean revenue per bed * 235 beds = $8.8 million. The mean operating profit in the pre-ACA period was 0.023*968,000*235 = $5.2 million. These underlying mean values are reported in Table 8 and notes. The pre-ACA mean operating margin for hospitals with non-negative values was 8%.

[30] 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. Hospital, physician and nursing industry bodies donated disproportionately more to Democrats in the 2018 midterm election. https://www.modernhealthcare.com/article/20181106/NEWS/181109952.

VII. DISCUSSION

We note three caveats related to our data and research designs that impose the following limitations when interpreting our results. First, the RD-DD results are estimates of local average treatment effects and most relevant to individuals close to age 65. The near elderly group of patients is policy relevant since it may be the next group to benefit from an expansion of Medicare.[31] However, they may not represent the average effect for the entire non-elderly group. Reassuringly, the results using geographic variation in poverty for all adults aged 21-64 corroborate key findings from the RD-DD analysis.

Second, we cannot identify the mechanisms causing patient sorting toward privately-owned hospitals. Our interpretation of the result – bolstered by corroborating evidence from ER arrivals – is that it is driven by patient preference for better care, but an alternative possible explanation is that managed care plans (which account for the majority of Medicaid enrollees) are more likely to include (exclude) private (government) hospitals from their provider networks. The evidence on systematic exclusion is weak, at least for exchange plans. 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 but do not correlate with hospital ownership or quality. Thus, it seems unlikely that narrow networks are the primary reason.

Third, our results estimate short-run effects of the insurance expansion since our data spans only three years post-ACA. The flexibly estimated annual coefficients may provide helpful guidance on how long-term effects may differ. Notably, the trends of increase in volume of care and patient sorting toward privately-owned hospitals strengthened between 2014 and 2016. This may represent an ongoing process of newly insured individuals learning how to choose providers and obtain care. This process implies continuation of volume growth and patient sorting over the next few years and therefore greater long-run effects, including on patient health.

VIII. CONCLUSION

The ACA authorized the largest expansion of publicly funded insurance since the introduction of Medicare and Medicaid in the 1960s. This intervention offers a unique opportunity to quantify the effects of public insurance expansions on providers and patients in a modern setting. In this paper we focused on the hospital sector. Using the universe of all hospital stays and ER visits, as well as data on hospital finances over 2008-16, we apply several complementary research designs to quantify costs and benefits of the ACA in the most populous state in the U.S.

[31] 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.

We find that the Medicaid expansion almost completely replaced existing county run safety-net programs in California. This was a transfer from federal taxpayers to local taxpayers (mostly counties) that previously bore these costs. Further, since Medicaid reimbursed hospitals at twice the rate that the safety net programs did, this was also a large transfer from taxpayers to hospitals. Hospitals increased revenue and profitability, with government hospitals receiving larger gains, even though they lost some patient share to privately-owned hospitals post-ACA. Understanding how the additional revenue was and will be deployed by hospitals remains an important question for future research.

We fail to find robust improvements in patient health, even though volume of hospital care has increased substantially and patients are more likely to receive care at privately-owned and better-quality hospitals. We argue that this reallocation of patient volume is demand driven, though our research design cannot distinguish supply and demand mechanisms and we leave this exercise for future work. The increase in stays and ER visits is about three times what we would predict based on partial equilibrium insurance experiments, suggesting that general equilibrium effects are large. We speculate that supply side responses are responsible, though the channels need to be investigated in future research.

The effects that we estimate for patients and hospitals were driven primarily by the expansion of Medicaid. These results take on additional significance when one considers that more than a dozen states have recently followed California's (and 24 other states) lead in 2014 and elected to expand their Medicaid programs. An additional 14 states have, as of this date, not expanded their Medicaid programs. The variation across states in decisions likely partially reflects uncertainty about the effects. We help fill this evidence gap as more states consider whether to expand public health insurance in the years ahead.

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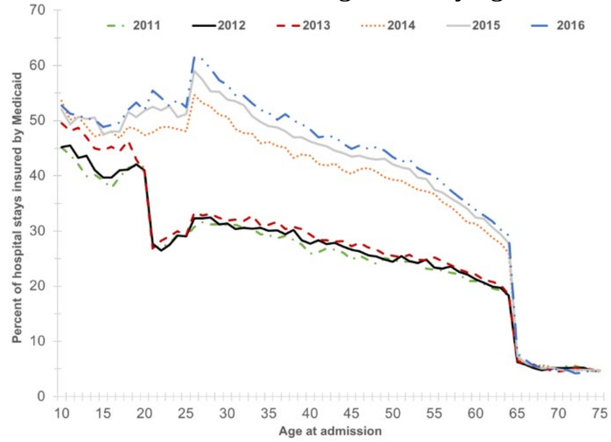
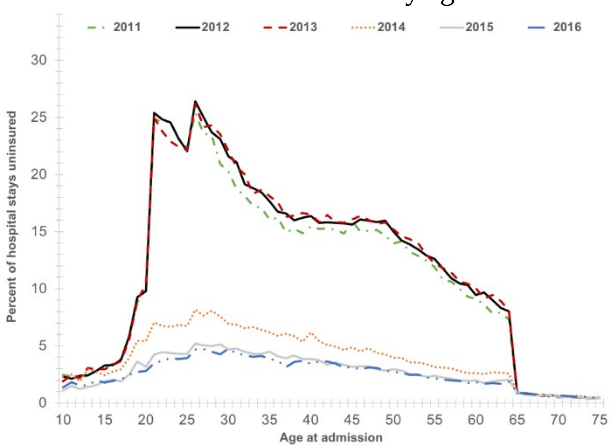
FIGURES AND TABLES

1a: Medicaid coverage trend by age



1b: Uninsured trend by age



1c: Insurance coverage trend for patients aged 21-64

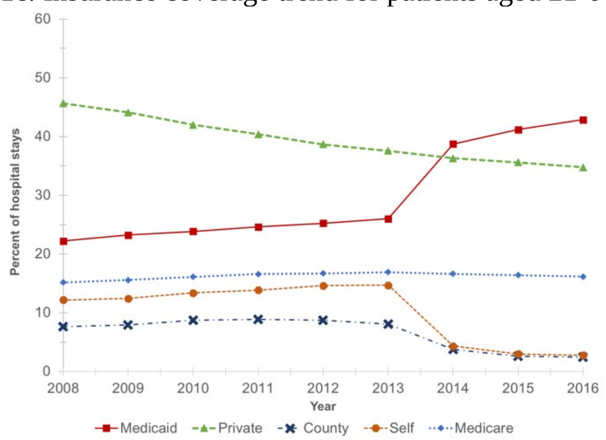
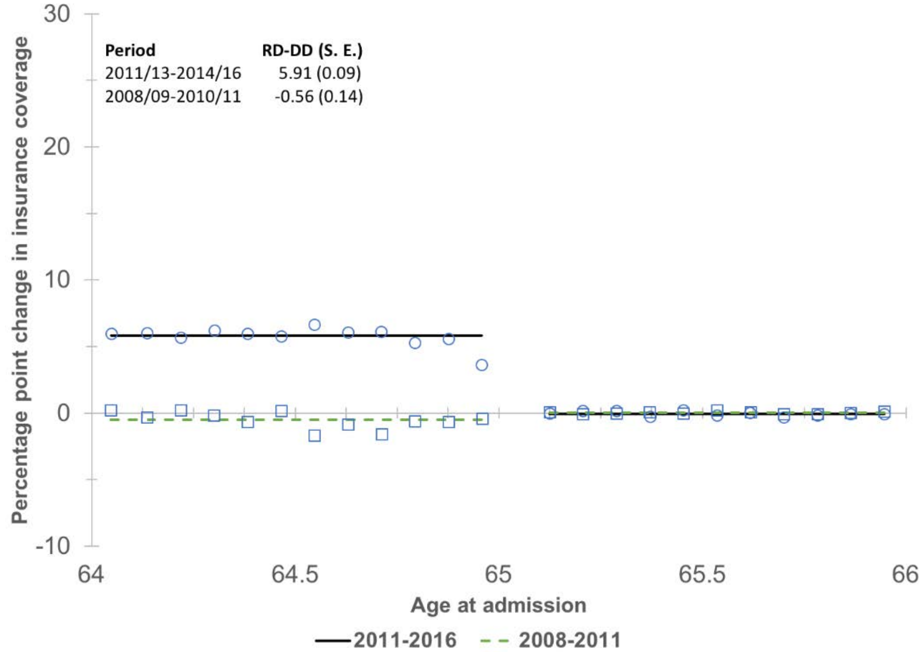


Figure 1: Insurance coverage for hospitalized patients

Note: This figure presents trends in primary insurance coverage among hospitalized patients in California as recorded in hospital discharge data. Panels A and B present the percentage of hospital stays covered by Medicaid and uninsured (i.e. self-pay, county indigent or charity care), respectively, by year between 2010-16 and single year of age for ages 10-75. Panel C presents shares of different primary payers between 2008-16 for patients aged 21-64, the group primarily affected by the ACA. The sample excludes cases related to pregnancy and deliveries, is limited to General Acute Care hospitals and excludes individuals residing in zip codes outside California.

2a: Elderly patients



2b: Young patients

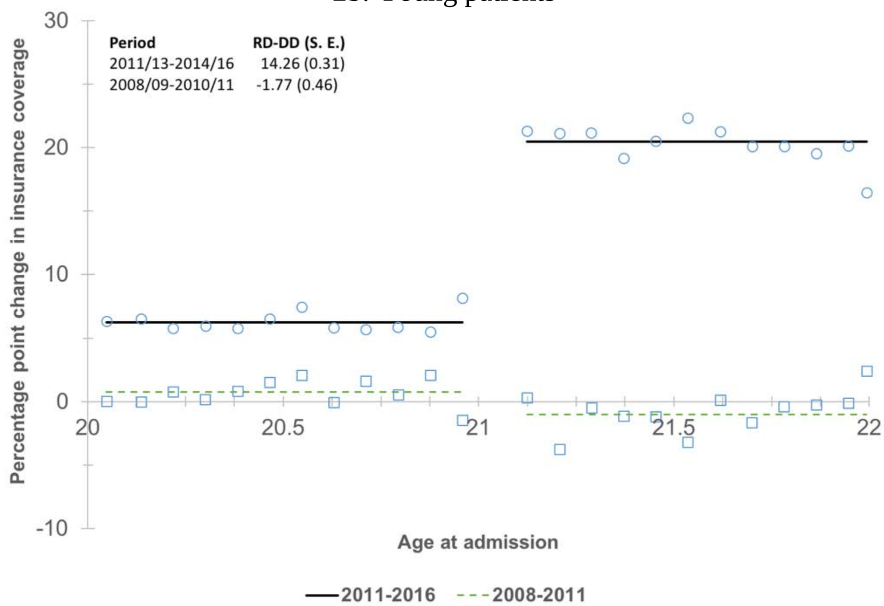


Figure 2: Insurance coverage

Note: This figure presents the percentage point change in insurance coverage among hospital patients and corresponding fitted values by month-of-age. These were obtained by estimating equation 3a on discharge level data as described in Section IV.A for the sample of elderly (Panel A) and young (Panel B) patients, respectively. The treated groups are those aged 21 (young) and 64 (elderly). Both panels present results for 2011-16 (circles, solid line), and results from 2008-11 (squares, dashed line), which serves as a falsification exercise. The dependent variable – insurance coverage – is defined by the patient not being self-pay, on charity or county indigent care and values are either 0 or 100. All models control linearly for age and include year fixed effects. To improve presentation, we collapse the data to month-of-age cells. We also note the estimated change in discontinuity, which is the coefficient on $d_i.T_t$ in Equation 3a. Standard errors are clustered by day-of-age cell. Figure A. 4 presents a more detailed version showing changes in shares of specific payers.

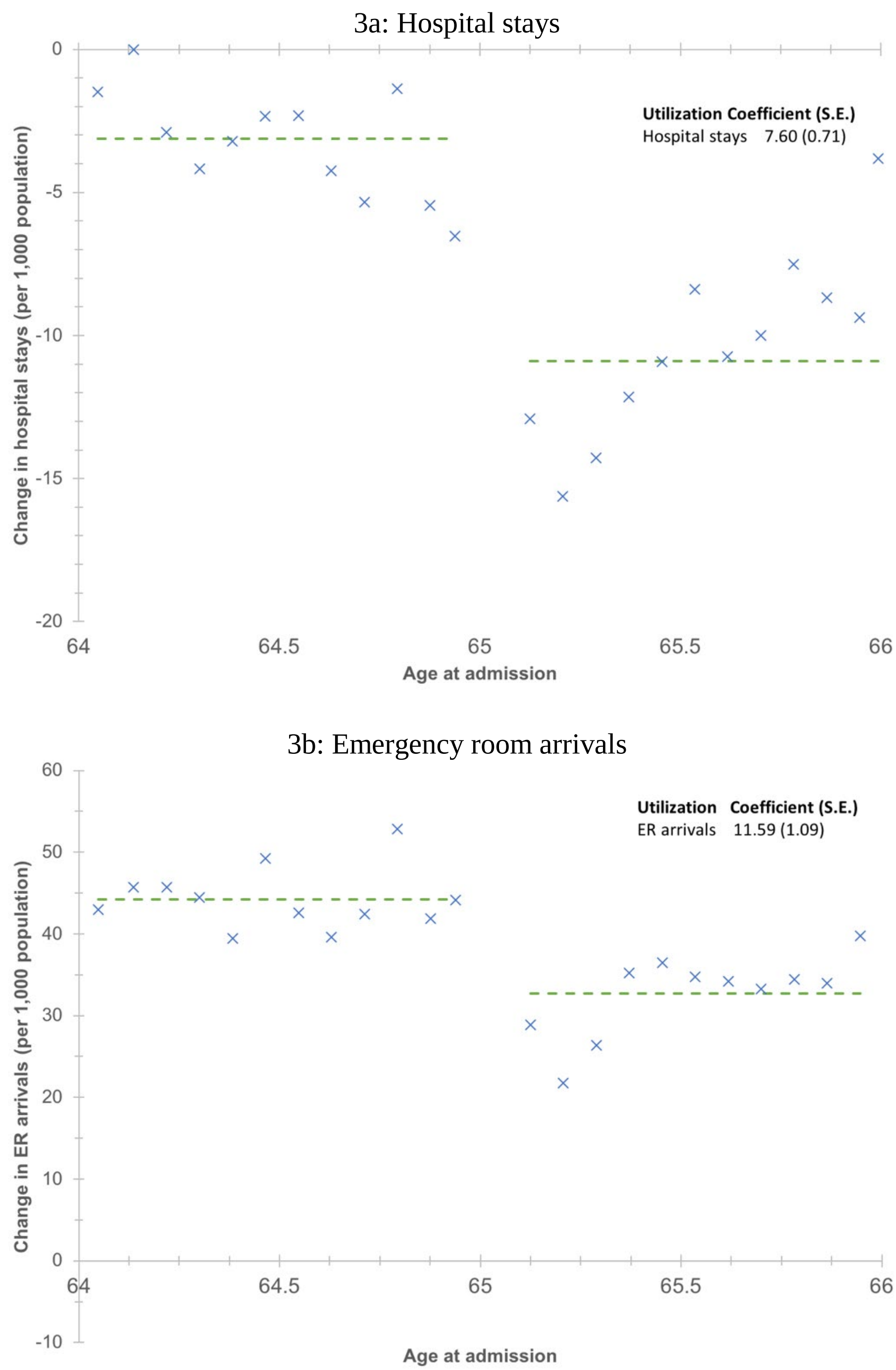
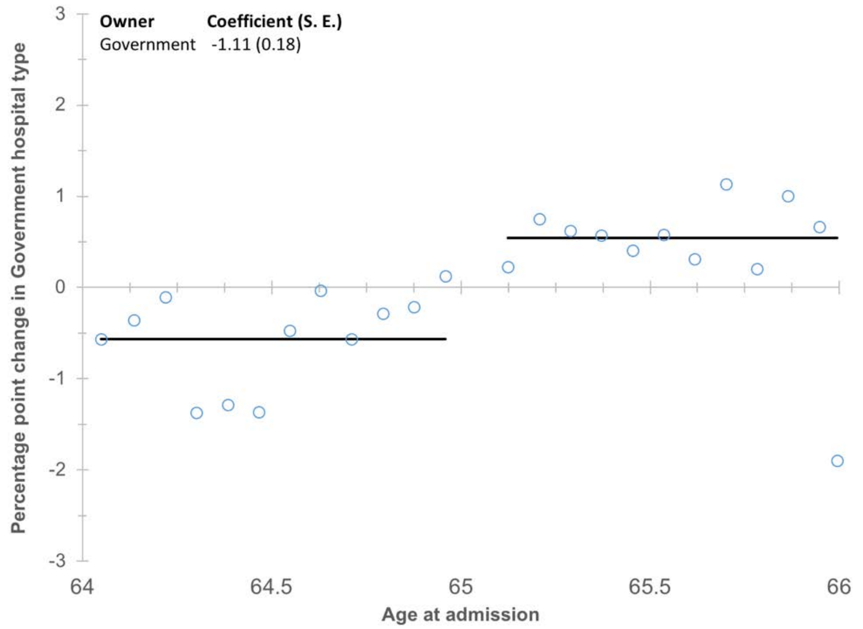


Figure 3: Utilization rate (per 1,000 people per year)

Note: This figure presents the mean post-ACA change in number of hospital stays (Panel A) and ER arrivals (Panel B), i.e. including those patients who were eventually admitted as inpatients, per 1,000 CA residents in each month-of-age cell. Raw discharges were converted to utilization rates using California population estimates, obtained from the National Cancer Institute. The regressions were estimated on data at day-of-age - year level, but for presentation clarity we collapse data to month-of-age level. Patients aged 64 constitute the treated group. We also plot corresponding fitted values (dashed lines) obtained by estimating Equation 4, as described in Section IV.C. All models control linearly for age and include a full set of year fixed effects. We also note the estimated change in discontinuity, which is the coefficient on $d_i.T_t$ in equation 4. Standard errors are clustered by day-of-age cell. Figure A. 5 presents corresponding plots for young patients.

4a: Owner type



4b: Standardized mortality score

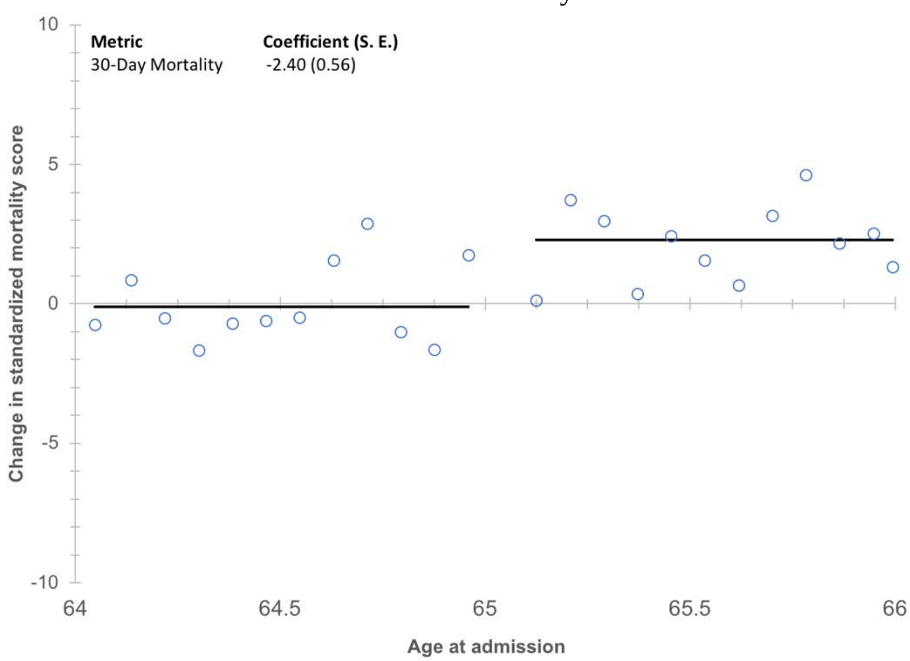


Figure 4: Hospital choice: Owner type and quality

Note: This figure presents post-ACA percentage point change in the percent of hospital stays at government hospitals (Panel A) and in mean standardized mortality score for patients, a variable with mean 0 and SD of 100 (Panel B). We also plot fitted values obtained by estimating equation 3b on case level data as described in Section IV.A. Patients aged 64 constitute the treated group. Regressions were estimated at the day-of-age - year level but for presentation clarity the data is collapsed to month-of-age level. Regressions control linearly for age and include year fixed effects. The estimated change in discontinuity, which is the coefficient on $d_i.T_t$ in equation 3b, is also presented. Standard errors are clustered by day-of-age cell. Figure A. 7 presents the corresponding plots for young patients.

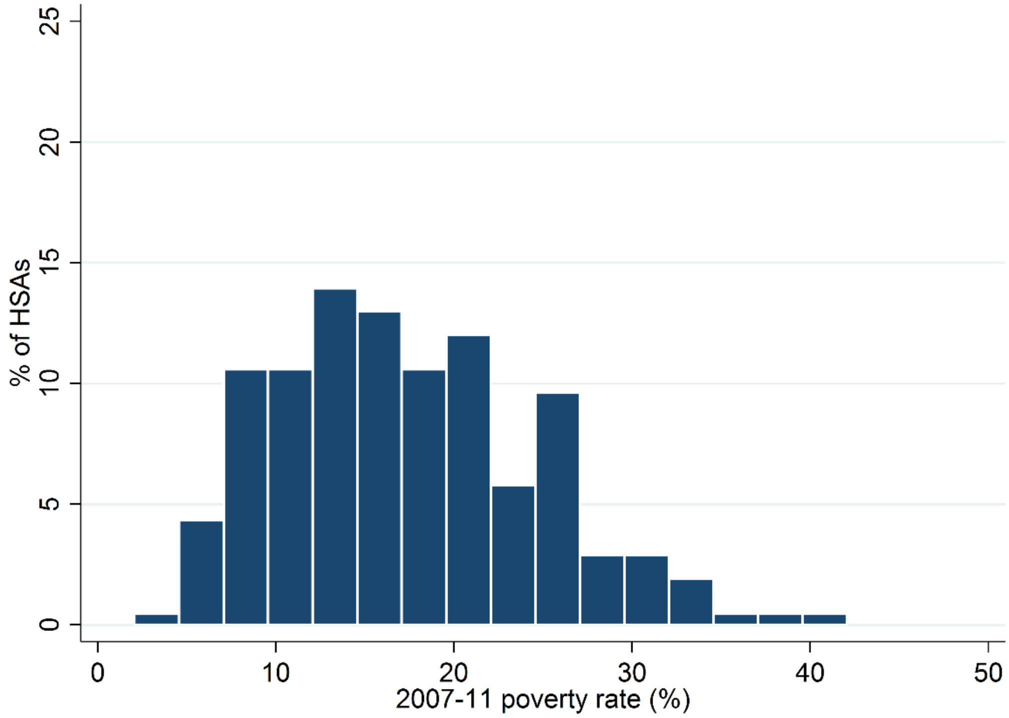


Figure 5*:* Distribution of poverty rates across Hospital Service Areas

Note: This figure presents a histogram of poverty percentage across Hospital Service Areas (HSAs). Poverty share is defined as the share of population < 125% of federal poverty level, as estimated by the 2007-11 five-year American Community Survey. There are 210 HSAs in California and they are defined to approximate local markets for hospital care and typically contain only one hospital. For more details on HSAs refer to http://www.dartmouthatlas.org/tools/faq/researchmethods.aspx. The San Francisco bay area has a disproportionate concentration of low poverty markets, for example – San Ramon (2%), Pleasanton (5%), Walnut Creek (6%), Burlingame, San Mateo and Fremont (7%), Mountain View and Livermore (8%). High poverty markets are distributed across the state with some concentration in central California along interstate 5 – Lindsay (41%), Delano (38%), Corcoran (35%), Lake Isabella (33%), Dinuba, Porterville (31%), and Merced (27%). The difference in poverty rates across HSAs was 18.3 between the least and most affluent quintiles and coincidentally the mean across markets was also 18.4. We exploit this variation in poverty across markets to identify the effects of the ACA on non-elderly adult hospital use.

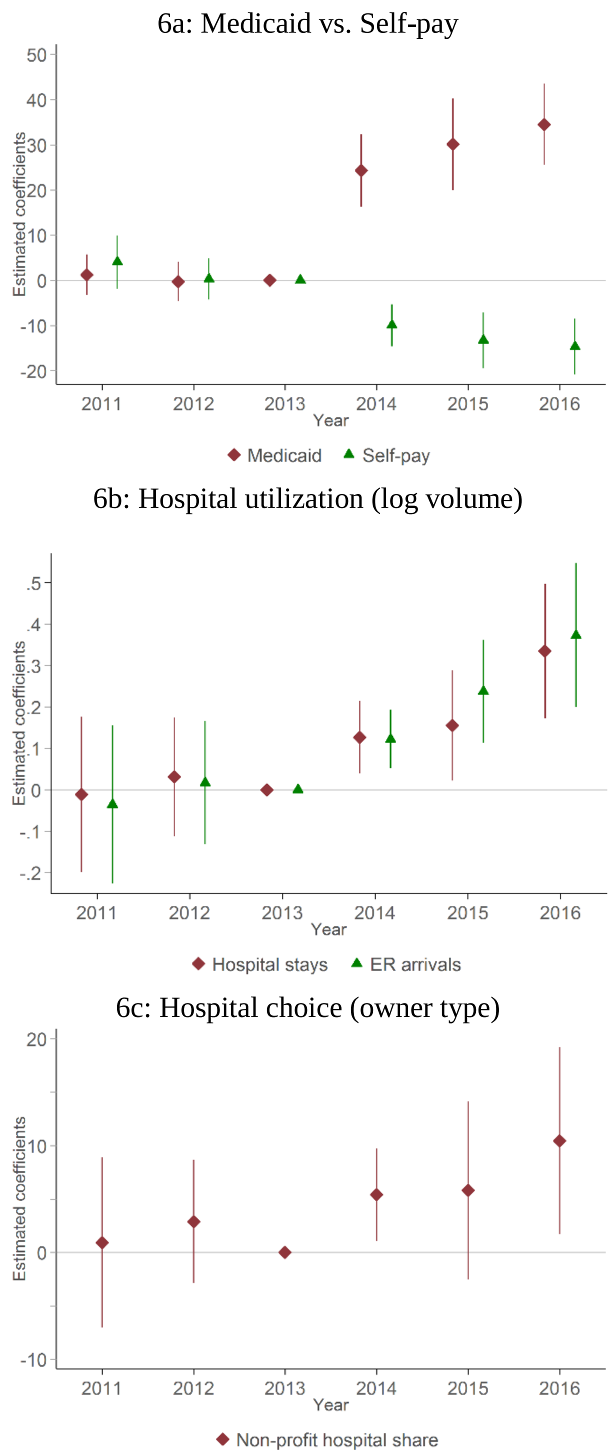
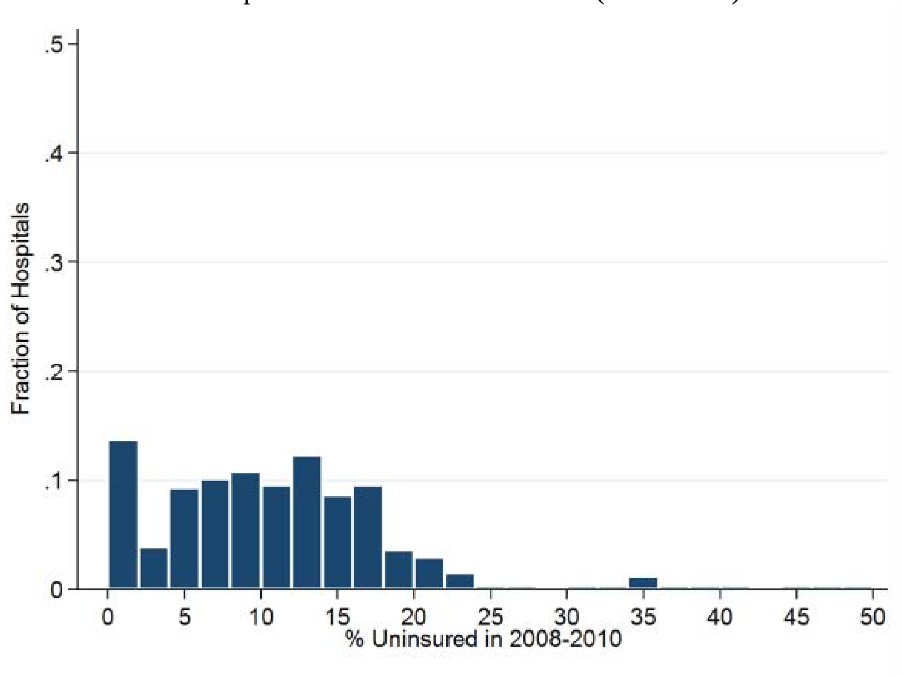


Figure 6: Results using poverty variation

<u>Note:</u> This figure presents event studies from the geographic analysis. Each panel plots coefficients on the interaction of Pov_j and indicator for each year s from 2011-16 (relative to 2013), obtained by estimating equation 5b with Medicaid or self-pay status (Panel A), log of stays or ER arrivals (Panel B), and share of stays at non-profit hospitals (Panel C) as outcome variables. Bars indicate confidence intervals at the 95% level. Pov_j is the estimated share of people in HSA j with income below 125% of the federal poverty level as reported by the ACS 2007-11 5-year estimates. These models are estimated using data from the sample of all patients aged 21-64 over 2011-16, about 7.5 million stays and 40.3 million ER arrivals. All models are estimated with data collapsed to the HSA-year level and include HSA and year fixed effects. HSAs are weighted by pre-ACA non-elderly population. Mean poverty rate was 0.183.

7a: Hospital uninsurance distribution (2008-2010)



7b: Hospital uninsurance distribution (2014-2016)

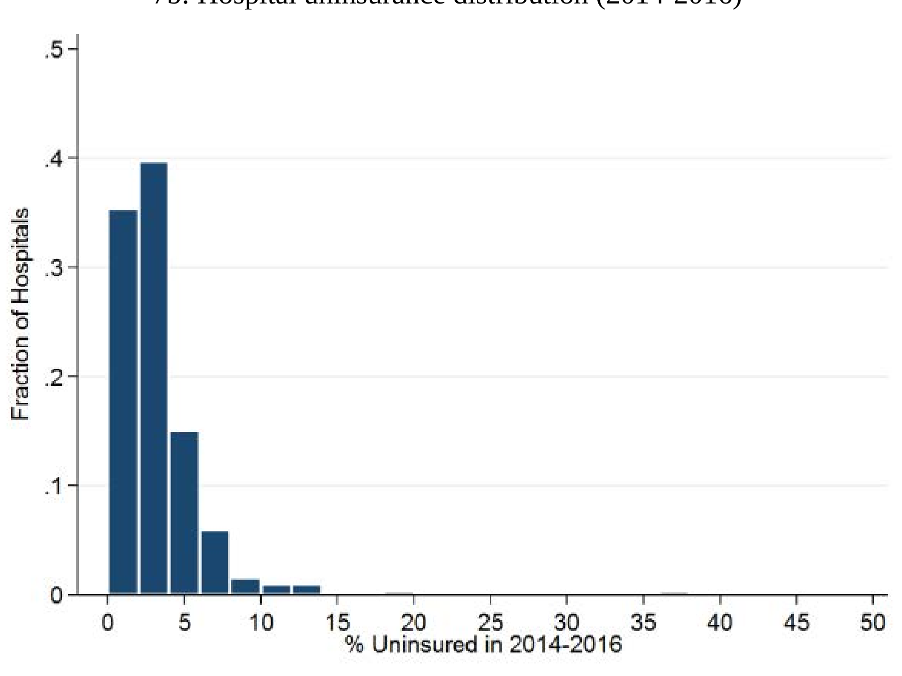


Figure 7: Hospital uninsurance distribution

Note: This figure presents histograms (by hospital) of the percentage of patients that did not have insurance coverage, in 2008-10 (Panel A, pre-ACA) and 2014-16 (Panel B, post-ACA), respectively. Uninsured patients are those coded as self-pay, county indigent or charity care. These histograms were computed using the discharge data on hospital stays and make use of the same sample restrictions as in our main analysis – limit to non-elderly adults (aged 21-64) in general acute care hospitals, exclude childbirth related cases, and exclude cases for individuals with zip codes missing or located outside California. The percent uninsured is top coded at 50% (one hospital in 2008-10). We use this variation in uninsurance across hospitals to identify effects of the ACA on hospital finances.

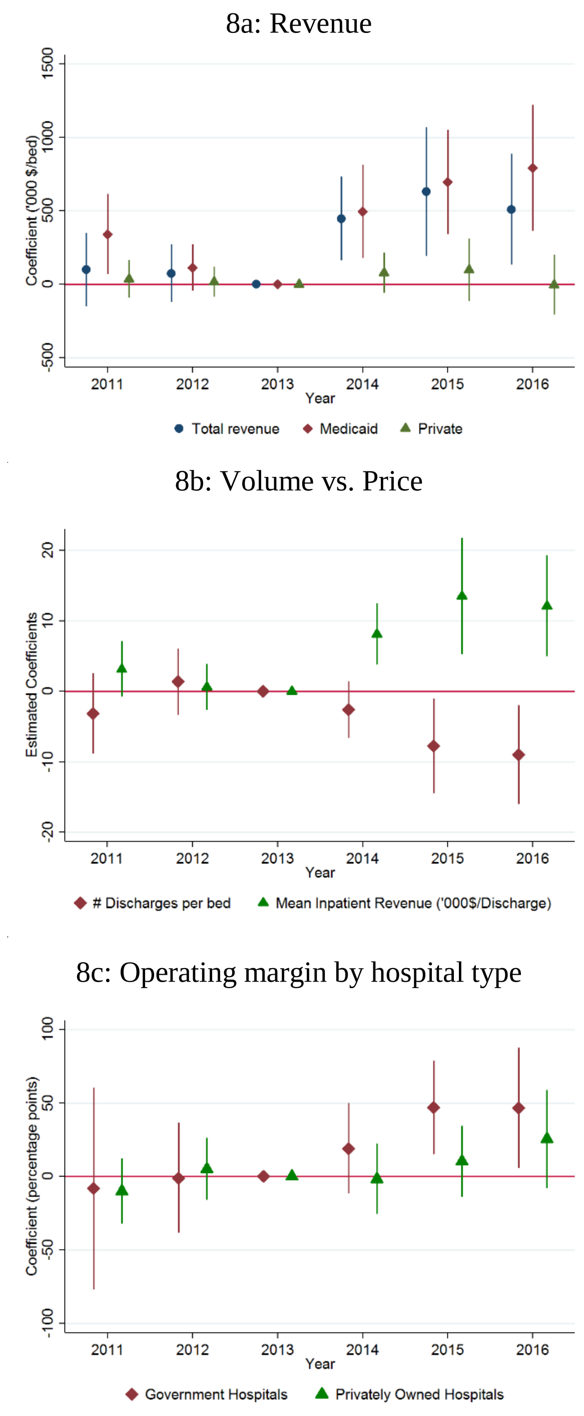


Figure 8: Effects on hospital finances

Note: This figure presents event study results using hospital-year finances data from OSHPD. We plot coefficients on the interaction of $\text{Uninsured}_{h-0810}$ with indicators for each year s from 2011-16, omitting 2013 as the reference year, obtained by estimating equation 6b with various outcome variables. Bars indicate confidence intervals at the 95% level. $\text{Uninsured}_{h-0810}$ is the share of hospital h patients coded self-pay, charity or county indigent over 2008-10. In Panel A the revenue values have been deflated to be in thousands of 2016 dollars. Panel B presents patterns for number of inpatient stays per bed (volume) and mean revenue per discharge in thousands of 2016 dollars (price). Panel C presents results on operating margin obtained by estimating models separately on the sample of government and private hospitals. Prices here refer to mean reimbursement per hospital stay. All models include hospital and year fixed effects. Hospital observations are weighted by their number of discharges in 2008-10.

Table 1: Summary Statistics

	Hospital stays				ER arrivals			
Panel A: Regression discontinuity sample	Ages 20.0 - 21.9		Ages 64.0 - 65.9		Ages 20.0 - 21.9		Ages 64.0 - 65.9	
	2011-13	2014-16	2011-13	2014-16	2011-13	2014-16	2011-13	2014-16
All observations	78,317	71,713	276,657	280,467	927,661	1,039,974	605,900	731,062
Admitted through ER	53,935	49,907	169,462	179,898	N/A	N/A	N/A	N/A
Medicaid	34.0	51.1	12.4	17.6	28.0	46.4	12.1	19.4
Private	39.8	37.3	29.8	27.3	35.8	33.5	29.2	26.9
Uninsured	17.7	4.4	4.4	1.5	30.1	14.8	9.5	4.3
County	5.1	0.4	1.8	0.2	2.9	0.7	2.7	0.5
Self-pay	12.6	4.0	2.6	1.4	27.2	14.1	6.8	3.8
Utilization per 1,000 pop.	24	23	134	127	281	334	293	332
Government hospital	18.5	17.2	11.3	11.3	17.1	15.6	15.5	14.9
In-hospital mortality	0.6	0.6	2.6	2.7	0.1	0.1	1.2	1.0
In-hospital mortality (non-deferrable)	1.1	0.8	4.1	3.3	0.1	0.1	1.8	1.2

Panel B: Non-elderly sample (21-64)	Hospital stays 2011-13	Hospital stays 2014-16	ER arrivals 2011-13	ER arrivals 2014-16
Discharges	3,791,199	3,737,040	18,578,973	21,731,937
Non-deferrable only	530,205	502,265	2,037,006	2,413,387
Medicaid	25.3	40.9	24.4	43.2
Private	38.9	35.6	34.6	32.4
Uninsured	14.4	3.3	26.6	11.3
County	5.8	0.4	5.4	0.9
Self-pay	8.6	2.9	21.2	10.4
Government hospital	15.8	14.8	18.7	16.7
Mortality (full sample)	1.60	1.64	0.35	0.30
Mortality (non-deferrable)	2.84	2.32	0.66	0.44

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 geographic 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 20-21 (both inclusive) or 64-65, and all ages are at time of admission. 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-year cell obtained from the National Cancer Institute, hence these are measures of utilization per 1,000 people per year. Government hospitals include city, county and district but not federally owned hospitals. We present in-hospital mortality for the full sample as well as the sample of patients discharged with non-deferrable conditions (i.e. conditions like Heart attack, Pneumonia, Stroke, etc.), for which patients need urgent hospital care and hence are less susceptible to selection concerns.

Table 2: Insurance coverage (hospital stays)

Panel A: Ages 64 - 65	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid	Private	Misc.	Insured	County	Self-Pay
Age 64 * Post	8.65	-2.56	-0.18	5.91	-3.27	-2.64
	(0.19)	(0.24)	(0.23)	(0.09)	(0.06)	(0.08)
Dynamic Effects						
Age 64 * 2014	7.36	-1.78	-0.11	5.47	-3.18	-2.29
	(0.28)	(0.34)	(0.33)	(0.12)	(0.06)	(0.10)
Age 64 * 2015	8.72	-2.33	-0.32	6.07	-3.31	-2.76
	(0.28)	(0.32)	(0.33)	(0.11)	(0.06)	(0.10)
Age 64 * 2016	9.80	-3.52	-0.12	6.17	-3.32	-2.85
	(0.27)	(0.32)	(0.32)	(0.11)	(0.06)	(0.09)
2011-13 mean (age 64)	18.68	42.77	30.52	91.97	3.50	4.52
Observations	557,124					
Panel B: Ages 20 - 21						
Age 21 * Post	15.78	-0.02	-1.50	14.26	-7.93	-6.33
	(0.50)	(0.50)	(0.28)	(0.31)	(0.16)	(0.28)
Dynamic Effects						
Age 21 * 2014	14.62	-0.33	-0.50	13.79	-7.89	-5.90
	(0.74)	(0.72)	(0.40)	(0.41)	(0.18)	(0.38)
Age 21 * 2015	15.00	0.99	-1.66	14.33	-7.91	-6.42
	(0.72)	(0.70)	(0.39)	(0.36)	(0.16)	(0.33)
Age 21 * 2016	17.81	-0.74	-2.37	14.69	-7.99	-6.70
	(0.74)	(0.69)	(0.38)	(0.34)	(0.17)	(0.32)
2011-13 mean (age 21)	26.95	39.75	7.89	74.59	9.15	16.27
Observations	150,030					

Note: This table presents regression results on changes in insurance coverage using the RD-DD analysis. Coefficients presented are on the interaction of indicator for being in the treated group (age 21 or 64) and post-ACA period in equation 3a. Regressions were estimated on the sample of elderly (Panel A) and young (Panel B) patients respectively, as described in section IV.A. The dependent variable is coverage by specific payer type. Miscellaneous includes Medicare, Government employees and workers' compensation. In each column and panel, the top row presents the average effect, while the dynamic effects present coefficients for each post-ACA year. This table pertains to hospital stays only. All models control linearly for age and include a full set of year fixed effects. Standard errors are clustered by day-of-age cell.

Table 3: Patient volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Hospital stays			**ER data**	
	All	Through ER	Not through ER	Deferrable	Non-Deferrable	All arrivals	ER visits
Age 64 * Post	7.78	3.09	4.69	6.47	1.31	11.51	8.42
	(0.71)	(0.55)	(0.46)	(0.64)	(0.29)	(1.12)	(0.95)
Dynamic Effect							
Age 64 * 2014	3.48	0.59	2.89	3.06	0.42	0.03	-0.57
	(0.99)	(0.77)	(0.63)	(0.87)	(0.44)	(1.57)	(1.34)
Age 64 * 2015	10.66	4.63	6.02	8.77	1.88	20.27	15.64
	(0.98)	(0.77)	(0.61)	(0.89)	(0.40)	(1.55)	(1.34)
Age 64 * 2016	9.19	4.05	5.14	7.56	1.64	14.22	10.17
	(0.98)	(0.77)	(0.60)	(0.89)	(0.40)	(1.72)	(1.46)
2011-13 mean (age 64)	127	80	47	103	24	286	207
Observations	4,198						

Note: This table presents regression results on changes in volume of hospital care using the RD-DD analysis. Coefficients presented are on the interaction of indicator for being aged 64 and post-ACA period in equation 4. Regressions were estimated on the sample of elderly patients, as described in section IV.C. The dependent variable is rate of hospital stays or ER arrivals per 1,000 people per year. To generate these utilization rates, we normalize raw discharges by population estimates for each age-year cell obtained from the National Cancer Institute. Column 1 presents the results for all hospital stays. Columns 2 and 3 present results separately based on stays that originated through and not through ERs respectively. Columns 4 and 5 present results on stays for deferrable and non-deferrable conditions respectively. Non-deferrable refers to about 15 conditions such as Heart Attack, Pneumonia, Stroke, etc. that are emergent and require immediate hospital care. Column 6 presents results for all ER arrivals, while column 7 presents results only on ER visits i.e. where the patient was discharged from the ER. All models control linearly for age and include a full set of year fixed effects. Standard errors are clustered by day-of-age cell. Appendix Table A. 4 presents results for young patients.

Table 4: Hospital choice

	(1)	(2)	(3)	(4)	(5)
	Owner type			**Quality score**	
	Non-profit	For-profit	Govt.	Mortality	Readmission
Panel A: Hospital Stays					
Age 64 * Post	0.38	0.72	-1.11	-2.40	-0.80
	(0.25)	(0.20)	(0.18)	(0.56)	(0.56)
Dynamic Effect					
Age 64 * 2014	0.48	0.30	-0.78	-1.46	-1.46
	(0.35)	(0.29)	(0.25)	(0.82)	(0.81)
Age 64 * 2015	-0.20	1.13	-0.93	-2.09	-1.56
	(0.35)	(0.29)	(0.24)	(0.80)	(0.80)
Age 64 * 2016	0.86	0.72	-1.59	-3.59	0.56
	(0.33)	(0.29)	(0.24)	(0.84)	(0.76)
2011-13 mean (age 64)	71.74	15.57	12.69	5.35	-2.02
Observations	557,124	557,124	557,124	461,070	467,106
Panel B: ER Arrivals					
Age 64 * Post	1.42	0.71	-2.12	-1.80	-0.90
	(0.16)	(0.12)	(0.12)	(0.36)	(0.37)
Dynamic Effect					
Age 64 * 2014	0.98	0.61	-1.59	-1.47	-0.66
	(0.22)	(0.17)	(0.18)	(0.52)	(0.52)
Age 64 * 2015	1.40	0.82	-2.21	-0.72	-2.21
	(0.22)	(0.17)	(0.17)	(0.48)	(0.51)
Age 64 * 2016	1.81	0.70	-2.51	-3.10	0.13
	(0.21)	(0.16)	(0.17)	(0.51)	(0.49)
2011-13 mean (age 64)	69.90	12.76	17.34	15.55	0.13
Observations	1,336,962	1,336,962	1,336,962	1,081,170	1,092,758

Note: This table presents regression results on changes in hospital share using the RD-DD analysis. We explore changes on two dimensions – hospital owner type and quality scores. Coefficients presented are on the interaction of indicator for being aged 64 and post-ACA period in equation 3b. Regressions were estimated on the sample of elderly patients, as described in section IV.A. Panels A and B present results for the hospital stays and ER arrivals respectively. The sample for hospital owner type contains ~560,000 discharges while in case of quality scores the sample is smaller (~460,000) since some hospitals are not rated by CMS. The corresponding sample sizes in case of ER arrivals are 1.3 mn and 1.1 mn respectively. The dependent variables are indicators for non-profit, for-profit or government ownership (Columns 1-3) and standardized 30-day mortality and readmission scores reported by CMS in 2009 (Columns 4-5). All models control linearly for age and include year fixed effects. Standard errors are clustered by day-of-age cell. We also estimated a version of column 4 controlling for hospital ownership. Estimates were -1.6 (0.5) and -0.7 (0.4) for hospital stays and ER arrivals respectively. Appendix Table A. 5 presents corresponding estimates for the young patients.

Table 5: Falsification exercise

	(1)	(2)	(3)	(4)	(5)	(6)	(6)	(7)	(8)	(9)	(10)	(11)
	Insurance coverage						***Utilization***		***Hospital choice***		***Health***	
	Medicaid	Private	Misc	Insured	County	Self-Pay	Stays	ER arrivals	Govt.	RA Mort.	Mortality	Mort (ND)
Age 64	9.16	24.87	-39.65	-5.62	2.38	3.24	-21.00	-31.42	1.81	-0.008	0.05	0.19
	(0.32)	(0.50)	(0.69)	(0.18)	(0.10)	(0.15)	(1.25)	(1.66)	(0.25)	(0.010)	(0.13)	(0.42)
Age 64 * Post	0.75	-0.83	-0.48	-0.56	0.22	0.34	-0.82	0.66	0.12	-0.028	0.20	0.20
	(0.22)	(0.31)	(0.30)	(0.14)	(0.08)	(0.11)	(1.07)	(1.56)	(0.20)	(0.022)	(0.11)	(0.33)
2008-09 mean (age 64)	18.00	46.84	28.35	93.20	2.72	4.09	141.06	269.93	12.33	3.71	2.86	4.85
Observations			335,644				2,798		335,644	280,544	280,544	64,039

Note: This table presents results of a falsification exercise for the RD-DD analysis using data from 2008-11 (pre-ACA) imagining a placebo ACA in 2010. Coefficients presented are on the interaction of indicator for being aged 64 and post-2010 in equations 3a, 3b and 4. This exercise provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4) and health (Table A. 2) outcomes. All models control linearly for age and include year fixed effects. When examining effects on volume, we collapse the data to the day of age-year level. When examining effects on patient health, models control for patient gender and condition category. Standard errors are clustered by day-of-age cell.

Table 6: Geographic variation in poverty (I)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Insurance coverage						Volume (log)			
	Medicaid	Private	Misc.	Insured	Self	County	All stays	Deferrable	Non-deferrable	ER arrivals
Panel A: Average effect										
Pov. rate * Post	29.34	3.39	-6.35	26.38	-14.07	-12.32	0.199	0.217	0.081	0.249
	(4.21)	(3.88)	(4.31)	(4.81)	(2.19)	(4.46)	(0.06)	(0.06)	(0.08)	(0.08)
Panel B: Dynamic effects										
Pov. rate * 2011	1.21	-2.60	1.84	0.46	4.04	-4.49	-0.011	-0.032	0.132	-0.035
	(2.30)	(4.73)	(2.27)	(3.63)	(3.01)	(2.36)	(0.10)	(0.09)	(0.13)	(0.10)
Pov. rate * 2012	-0.29	2.40	0.76	2.87	0.27	-3.14	0.032	0.011	0.167	0.017
	(2.20)	(2.77)	(1.74)	(2.62)	(2.35)	(1.28)	(0.07)	(0.07)	(0.10)	(0.08)
Pov. rate * 2013	REF	REF	REF	REF	REF	REF	REF	REF	REF	REF
Pov. rate * 2014	24.28	5.92	-4.82	25.39	-9.93	-15.46	0.126	0.113	0.220	0.122
	(4.08)	(1.89)	(3.70)	(5.87)	(2.37)	(5.02)	(0.04)	(0.05)	(0.06)	(0.04)
Pov. rate * 2015	30.12	3.66	-5.90	27.88	-13.26	-14.62	0.155	0.164	0.104	0.238
	(5.16)	(2.84)	(4.39)	(6.71)	(3.14)	(5.25)	(0.07)	(0.07)	(0.10)	(0.06)
Pov. rate * 2016	34.52	0.38	-5.74	29.16	-14.71	-14.46	0.335	0.353	0.216	0.374
	(4.59)	(3.23)	(4.87)	(6.49)	(3.15)	(5.08)	(0.08)	(0.08)	(0.18)	(0.09)
Observations	1,254									
Mean value (2011-13)	24.03	40.74	21.04	85.82	8.43	5.75	6,047	5,201	846	29,632

Note: This table presents results from the geographic analysis exploiting variation in poverty rate across hospital service markets (HSAs), as described in Section V.A. This table provides estimates on insurance coverage and volume of care. In the interest of brevity we do not report effects for the full set of outcome variables, but these are available on request. Panel A presents the DD coefficient on interaction of $poverty\ rate \cdot T_t$ from Equation 5a, where poverty rate is the share of non-elderly population below 125% of federal poverty level as reported by 2007-11 ACS 5-year estimates. Panel B presents coefficients from equation 5b flexibly estimated for each year over 2011-16 with 2013 as the reference year. There are approximately 7.5 million stays and 40.3 million ER arrivals, collapsed to the HSA-year level (209 HSAs x 6 years). The volume regressions use log of discharges as the outcome. Non-deferrable refers to the subset of approximately 1 million cases that were for non-deferrable or emergent conditions such as Heart attacks, Pneumonia, etc. All models include a full set of HSA and year fixed effects. HSAs are weighted by pre-ACA non-elderly population. Standard errors are clustered by HSA. The bottom row presents the pre-ACA mean values for outcomes. The mean values for volume are in levels, not logs. The difference in poverty rates between top and bottom quintile HSAs was 0.183 and coincidentally the mean was 0.184.

Table 7: Geographic variation in poverty (II)

	(1)	(2)	(3)	(4)	(5)
		Hospital choice		Health (Mortality)	
	Govt.	Non-profit	Mort. Score	All patients	Non-def
Panel A: Average effect					
Pov. rate * Post	-3.54	5.961	-0.60	-0.29	-0.77
	(3.12)	(4.30)	(6.86)	(0.20)	(0.66)
Panel B: Dynamic effects					
Pov. rate * 2011	4.58	0.934	-4.65	-0.46	-0.67
	(2.59)	(4.06)	(8.65)	(0.25)	(1.03)
Pov. rate * 2012	1.12	2.894	-7.60	-0.12	0.26
	(1.77)	(2.95)	(7.34)	(0.26)	(0.91)
Pov. rate * 2013	REF	REF	REF	REF	REF
Pov. rate * 2014	-3.39	5.412	-3.079	-0.36	-0.31
	(1.83)	(2.22)	(4.31)	(0.25)	(1.11)
Pov. rate * 2015	-1.30	5.809	-6.347	-0.56	-1.99
	(3.75)	(4.24)	(5.96)	(0.29)	(0.93)
Pov. rate * 2016	-0.25	10.463	-4.504	-0.52	-0.34
	(3.40)	(4.48)	(6.05)	(0.30)	(0.93)
Observations	1,254				
Mean value (2011-13)	15.7	68.0	1.6	1.60	2.83

Note: This table presents results from the geographic analysis exploiting variation in poverty rate across hospital service markets (HSAs), as described in Section V.A. This table provides estimates on utilization (choice of hospital type and quality) and patient health (in-hospital mortality). In the interest of brevity we do not report effects for the full set of outcome variables, but these are available on request. Panel A presents the DD coefficient on interaction of $poverty\ rate \cdot T_t$ from Equation 5a, where poverty rate is the share of non-elderly population below 125% of federal poverty level as reported by 2007-11 ACS 5-year estimates. Panel B presents coefficients from equation 5b flexibly estimated for each year over 2011-16 with 2013 as the reference year. There are approximately 7.5 million stays collapsed to the HSA-year level (209 HSAs x 6 years). Models for mortality are also estimated at the HSA-year level, on the entire sample (Col. 4) and sample of non-deferrable cases (Col. 5) respectively. Non-deferrable refers to the subset of approximately 1 million stays that were admitted for non-deferrable or emergent conditions such as Heart attacks, Pneumonia, etc. All models include a full set of HSA and year fixed effects. When examining effects on patient health, models also control for differences in patient gender and condition category. HSAs are weighted by pre-ACA non-elderly population. Standard errors are clustered by HSA. The bottom row presents the pre-ACA mean values for outcomes. The difference in poverty rates between top and bottom quintile HSAs was 0.183 and coincidentally the mean was 0.184.

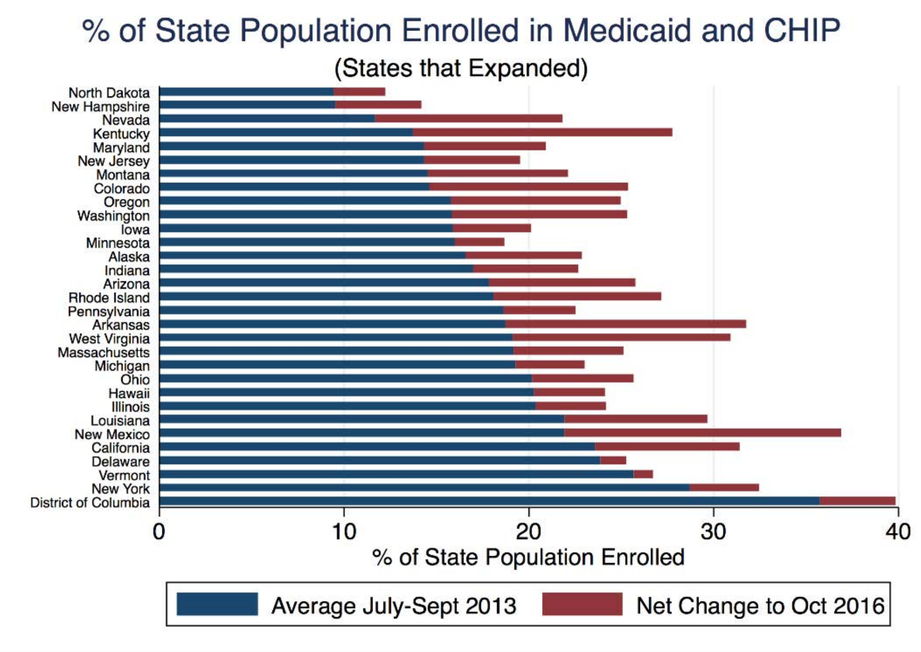
Table 8: Hospital finances and expansion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Total revenue (per bed)						**Volume (per bed)**		**Avg. price / profitability**			**Expansion**	
	Total rev. per bed ('000 $)	Medicaid per bed ('000 $)	Private per bed ('000 $)	All Other per bed ('000 $)	Inpatient per bed ('000 $)	Outpatient per bed ('000 $)	Inpatient Discharges per bed	Outpatient Visits per bed	Mean IP rev. per discharge ('000 $)	Mean OP rev. per visit ('000 $)	Operating Margin (%)	Capital exp. per bed ('000 $)	Number of Beds
Panel A: Average Effects													
Uninsured * Post	471.3	508.3	39.9	-77.0	310.3	161.0	-5.8	-58.2	10.0	0.07	35.1	29.3	-26.0
	(198.0)	(147.8)	(89.1)	(104.8)	(118.9)	(95.4)	(3.6)	(132.8)	(3.4)	(0.2)	(11.1)	(68.6)	(40.2)
Panel B: Triple Difference													
Uninsured * Post	793.5	418.5	217.0	157.9	437.6	355.9	1.6	319.2	5.3	-0.0	12.8	120.0	15.1
	(354.4)	(138.9)	(206.0)	(162.0)	(230.3)	(185.5)	(7.0)	(186.3)	(4.8)	(0.3)	(8.6)	(166.6)	(85.1)
Uninsured * Post * Govt Hospital	-130.1	81.8	-9.2	-202.7	27.8	-157.8	-12.3	-480.3	10.6	0.2	27.7	-41.1	-67.8
	(441.8)	(284.7)	(240.1)	(222.5)	(277.9)	(221.4)	(10.1)	(241.4)	(6.8)	(0.4)	(17.8)	(190.2)	(105.2)
Observations	1,923	1,923	1,923	1,923	1,923	1,923	1,923	1,923	1,923	1,845	1,923	1,923	1,923
Dep. Var. mean (11-13)													
for all hospitals	968	192	411	365	587	380	36	645	18.7	0.8	2.3	82	234
for government hospitals	803	262	255	286	400	402	28	924	15.7	0.5	-10.3	82	211
for private hospitals	1003	177	444	382	627	376	38	585	19.3	0.9	5.0	83	239

Note: This table presents regression results examining effects on hospital finances and expansion by exploiting baseline (2008-10) variation in hospitals' uninsured patient shares, as discussed in section VI.A. Coefficients presented are for the interaction of baseline uninsurance and an indicator for the post-ACA period in equation 6a. All revenue variables are expressed in thousands of dollars deflated to 2016 using the CPI-U. We winsorize values for revenue, volume, and expansion variables at the 99th percentile, and operating margin at the 1st and 99th percentile (more details in footnote 26). Operating margin is reported by hospitals to California as a percentage and is calculated as the ratio of the difference between operating revenue and costs over operating revenue. Panel A presents average effects across all hospitals. Panel B presents results from estimating a triple difference version of equation 6a where Uninsured * Post provides estimates for privately-owned hospitals and the sum of Uninsured * Post + Uninsured * Post * Govt Hospital provides estimates for government hospitals. The bottom rows present the number of observations (e.g. ~320 hospitals x 6 years) and mean value of each dependent variable pre-ACA, i.e. 2011-13 overall and by hospital type. 78 hospitals have no outpatient visits or revenue and hence drop out when examining mean revenue per outpatient visit. All models include a full set of hospital and year fixed effects. Hospital observations are weighted by their number of discharges in 2008-10. Standard errors are clustered by hospital. The mean baseline share of uninsured patients across all hospitals was 0.11. It was 0.288 and 0.108 for government and private hospitals respectively.

A. APPENDIX: FOR ONLINE PUBLICATION

A.1a: Medicaid share in expansion states



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

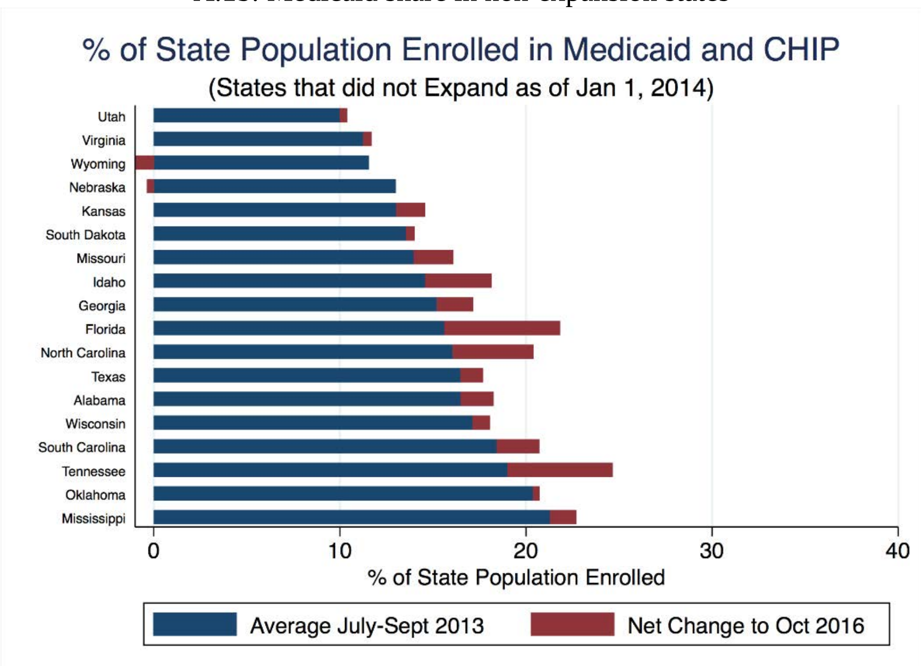


Figure A. 1: Medicaid share in expansion and non-expansion states

Note: This figure presents the Medicaid enrollment as a share of a state's population for states that expanded Medicaid under the ACA, as of January 1, 2014, (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 by Medicaid's share of population as in 2013. Comparable baseline data was not available for Connecticut (expanded) and Maine (did not expand).

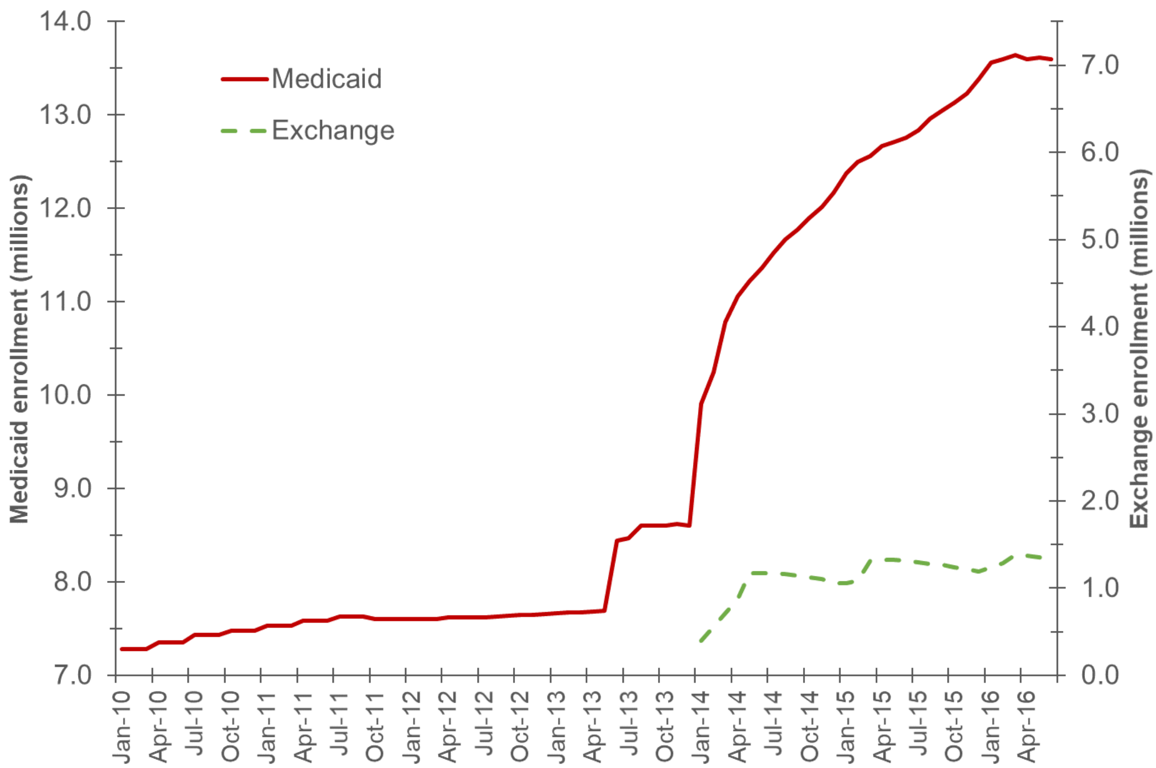


Figure A. 2: Medicaid and exchange enrollment in California

<u>Note:</u> This figure presents monthly enrollment in Medicaid and on the ACA exchange in California (right axis) over 2010-16. Enrollment data was obtained from CA Department of Health Care Services (Medicaid) and Covered California (Exchange) respectively.

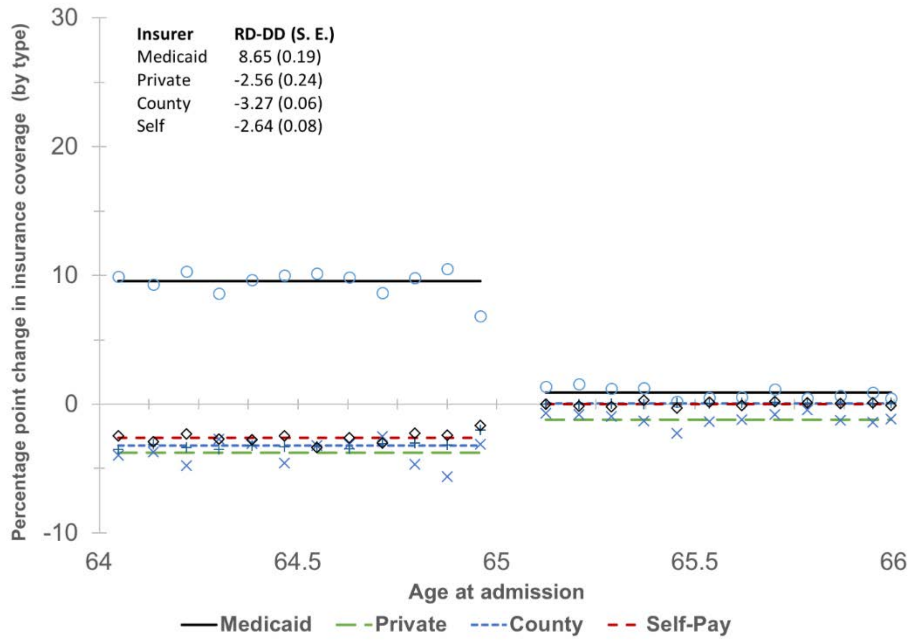
SUMMARY MEDI-CAL ELIGIBILITY*

	Public Assistance Recipient**	Medically Needy Beneficiary***	Medically Indigent Person or Family
Description of Eligible Person	SSI/SSP Aged Blind Disabled Deprivation	1. Linked to public assistance program but not eligible or does not want cash grant. 2. Aged, blind, or disabled.	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.
	CalWORKs California Work Opportunities and Responsibility to Kids	SSI/SSP–MN 1931(b)	
Age Limits	SSI/SSP Aged 65 or older Blind No age limit Disabled No age limit	SSI/SSP–MN Aged 65 or older Blind No age limit Disabled No age limit	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.
	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.	1931(b) Same as CalWORKs	
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	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	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
	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.	Community spouse resource allowance when one spouse enters long-term care on or after 11/1/90 and applies in 2007 is: $101,640.	
Motor Vehicle Limits	SSI/SSP Aged, Blind, Disabled One car if used for transportation is exempt regardless of value.	1 car exempt—no maximum value.	
	CalWORKs Exempt if total net market value is under $4,650 for applicant.		
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.	*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.	
	CalWORKs See comments under Personal Property Limit, above.	*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. 3: California Medicaid eligibility requirements

<u>Note:</u> 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.4*a*: Insurance change for the elderly



A.4b: Insurance change for the young

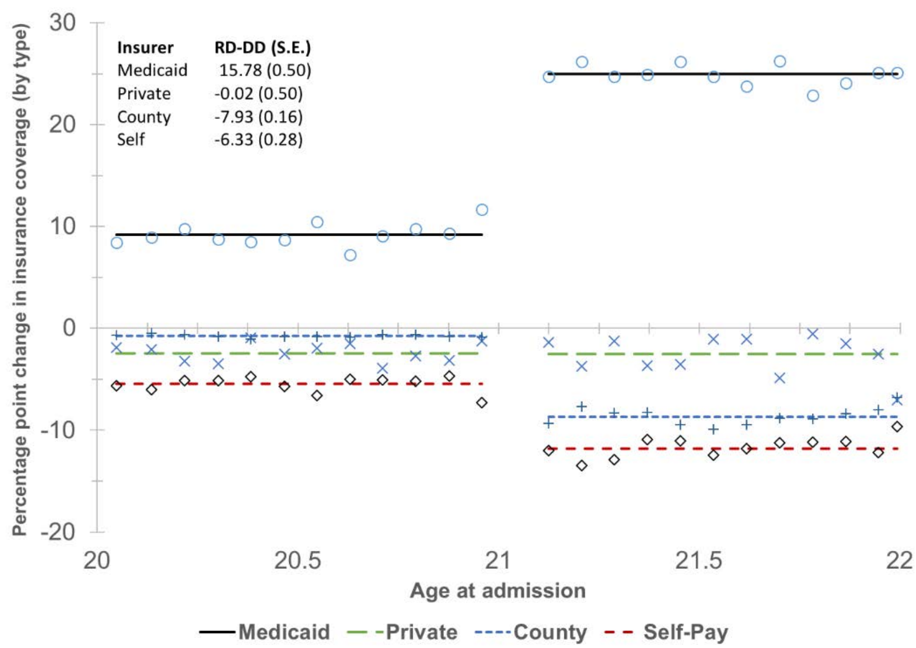


Figure A. 4: Insurance coverage changes (details)

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 3a on discharge level data as described in Section IV.A. It is a more detailed version of Figure 2. Self-pay includes charity care. The figure pertains to hospital stays in the RD sample for elderly (Panel A) and young (Panel B) patients respectively. All models control linearly for age and include year fixed effects. We also note the estimated change in discontinuity, which is the coefficient on $d_i . T_t$ in Equation 3a. Standard errors are clustered by day-of-age cells.

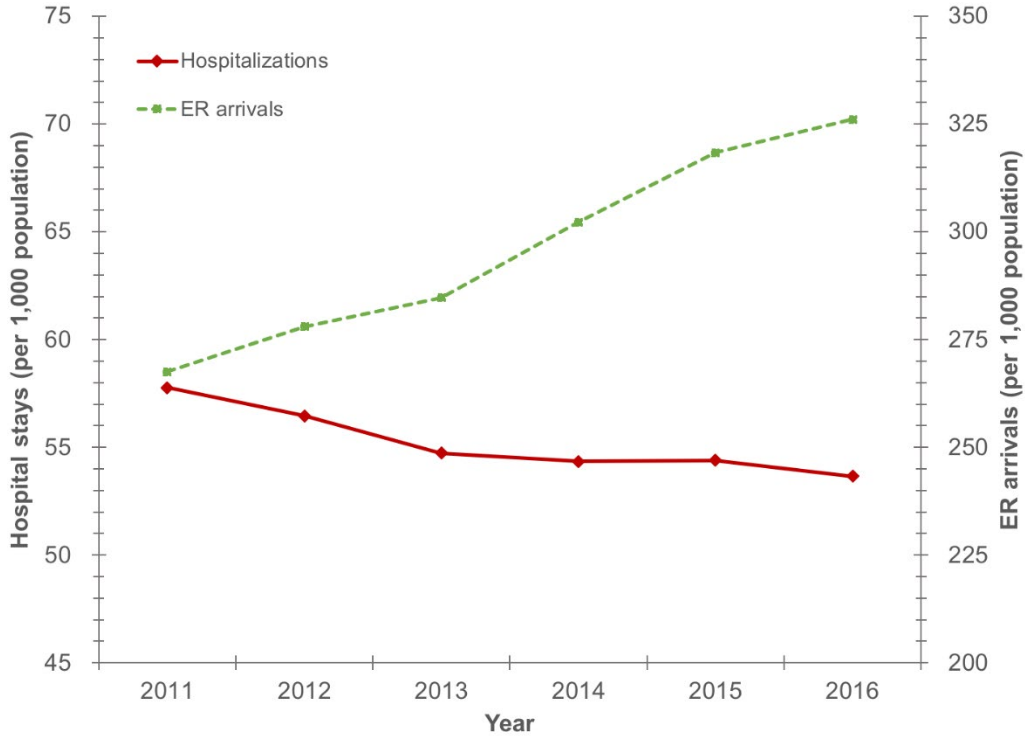
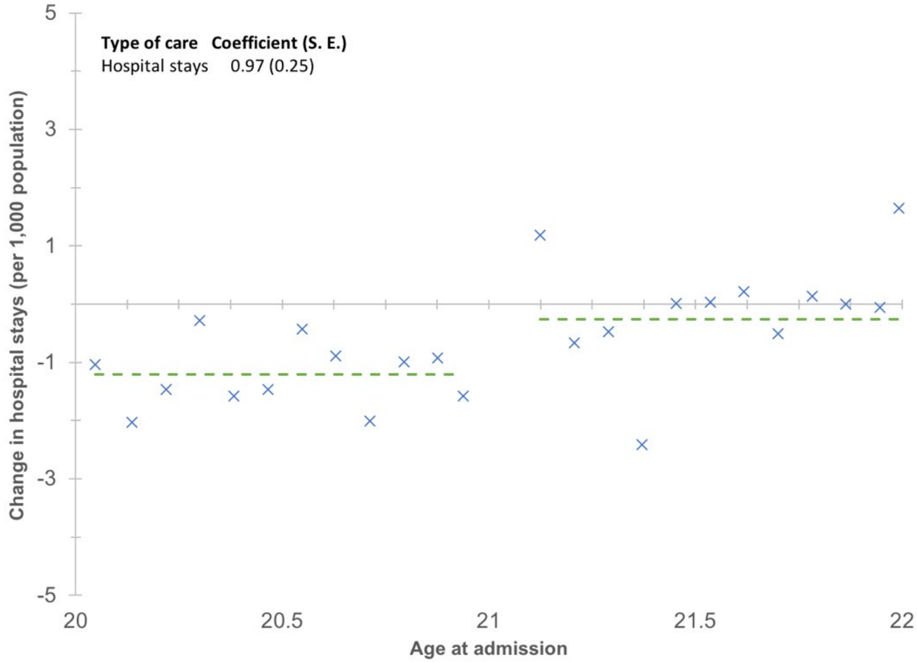


Figure A. 5: Hospital utilization by patients aged 21-64 (per 1,000 people)

Note: This figure presents the number of hospital stays (Panel A) and arrivals at Emergency rooms (Panel B) by patients aged 21-64 in California over 2011-16. The sample contains about 7.5 million discharges. ER arrivals include ER visits and those who were subsequently discharged as inpatients and the sample contains about 40.3 million observations. The raw discharges are normalized by population estimates from the National Cancer Institute for each age-year cell. These population estimates were also used in the RD-DD analysis for the same purpose. The figure makes use of the same sample restrictions as in our main analysis – limit to general acute care hospitals, exclude childbirth related cases, and exclude cases for individuals with zip codes missing or located outside California.

A.6a: Hospital stays



A.6b: Emergency room arrivals

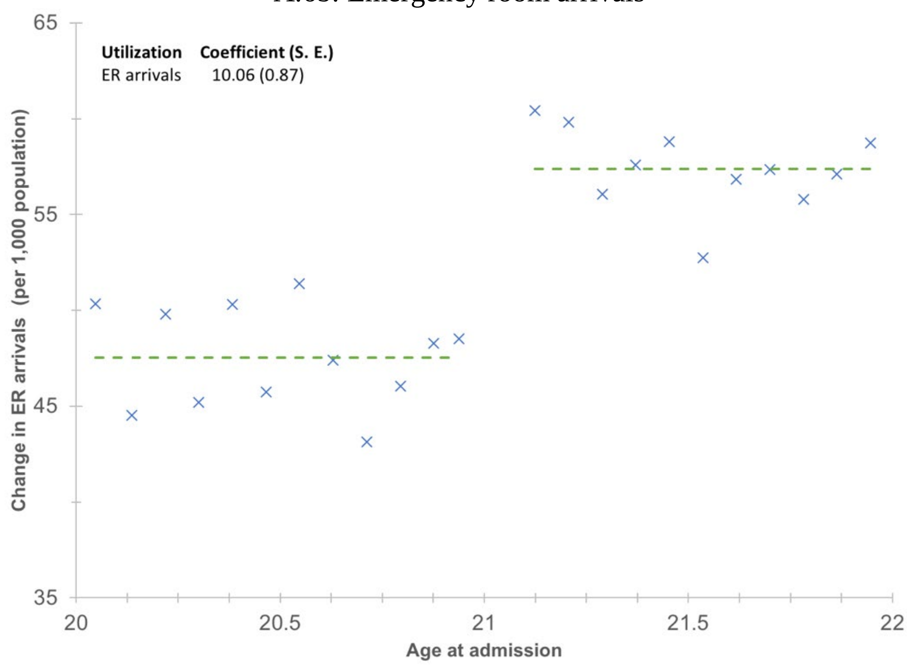
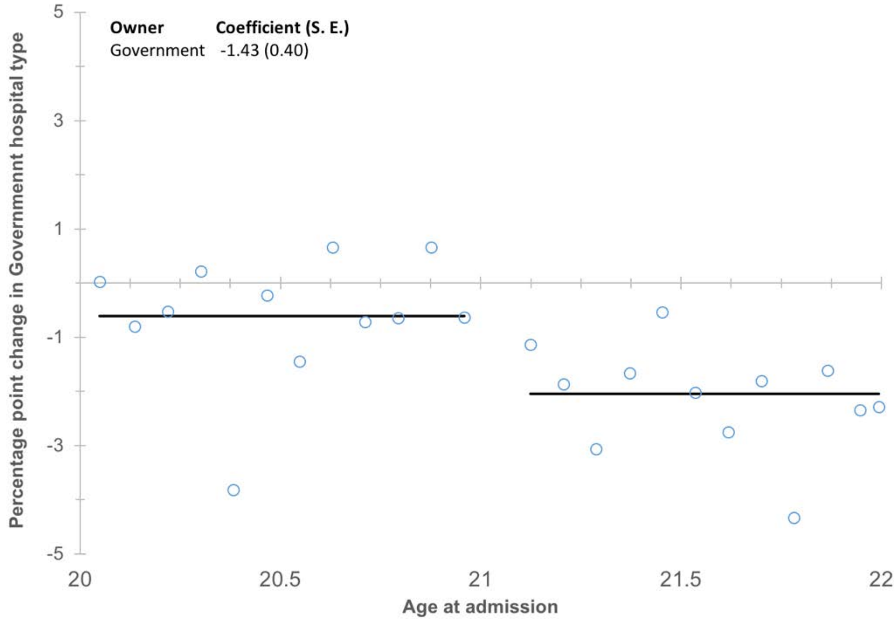


Figure A. 6: Rate of utilization for young patients

Note: This figure presents the mean post-ACA change in number of hospital stays (Panel A) and ER arrivals (Panel B), i.e. including those patients who were eventually admitted as inpatients, per 1,000 CA residents in each month-of-age cell. Raw discharges were converted to utilization rates using California population estimates, obtained from the National Cancer Institute. The regressions were estimated on data at day-of-age - year level, but for presentation clarity we collapse data to month-of-age level. Patients aged 21 constitute the treated group. We also plot corresponding fitted values (dashed lines) obtained by estimating Equation 4, as described in Section IV.C. All models control linearly for age and include a full set of year fixed effects. We also note the estimated change in discontinuity, which is the coefficient on $d_i.T_t$ in equation 4. Standard errors are clustered by day-of-age cell. Figure 3 presents corresponding results for elderly patients.

A.7a: Hospital owner type



A.7b: Hospital quality

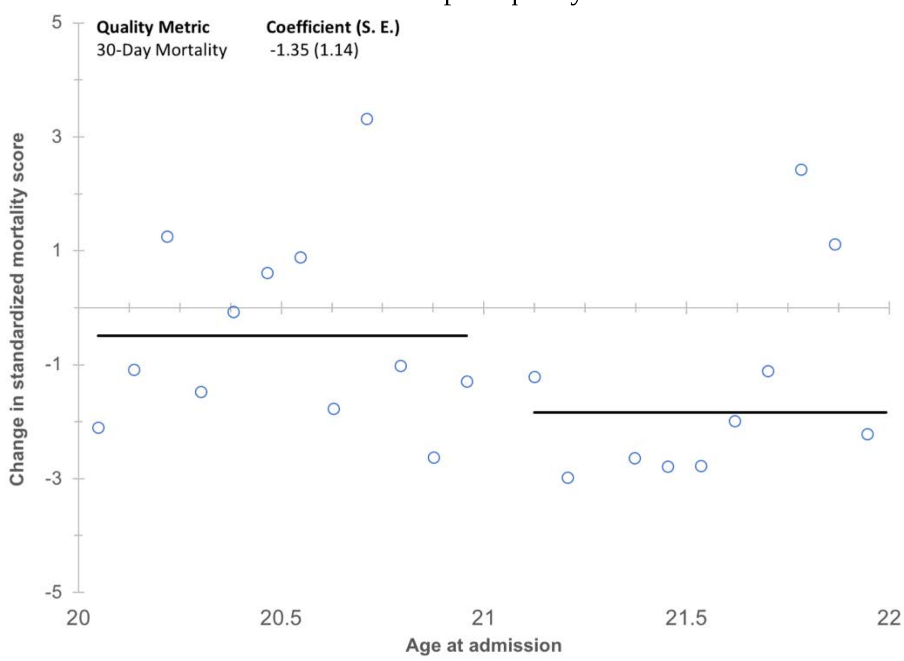


Figure A. 7: Hospital choice: Owner type and quality (Young patients)

Note: This figure presents post-ACA percentage point change in the percent of hospital stays at government hospitals (Panel A) and in mean standardized mortality score for patients, a variable with mean 0 and SD of 100 (Panel B). We also plot fitted values obtained by estimating equation 3b on case level data as described in Section IV.A. Patients aged 21 constitute the treated group. Regressions were estimated at the day-of-age - year level but for presentation clarity the data is collapsed to month-of-age level. Regressions control linearly for age and include year fixed effects. The estimated change in discontinuity, which is the coefficient on $d_i.T_t$ in equation 3b, is also presented. Standard errors are clustered by day-of-age cell. Figure 4 presents corresponding results for elderly patients.

Table A. 1: Population attributes at age thresholds (National Health Interview Survey)

	(1) Insured mean	(2) Uninsured mean	(3) Difference	(4) Mean value at threshold	(5) RD estimate at threshold
Panel A: Ages 20-21					
Married	0.08	0.13	0.044	0.07	-0.003
			(0.008)		(0.013)
Employed	0.61	0.66	0.047	0.60	0.004
			(0.012)		(0.023)
In school	0.23	0.07	-0.160	0.21	-0.028
			(0.010)		(0.019)
Percent days alcohol	0.12	0.11	-0.010	0.09	0.033
			(0.008)		(0.015)
Smoker	0.21	0.36	0.148	0.23	0.059
			(0.021)		(0.041)
Flu shot past 12 months	0.14	0.09	-0.056	0.13	0.015
			(0.014)		(0.026)
No insurance coverage	-	-	-	0.29	0.056
					(0.022)
Panel B: Ages 64-65					
Married	0.69	0.50	-0.1908	0.67	0.010
			(0.025)		(0.027)
Employed	0.37	0.35	-0.0205	0.34	-0.007
			(0.026)		(0.029)
In school	0.00	0.00	-0.0005	0.00	0.002
			(0.000)		(0.002)
Percent days alcohol	0.16	0.09	-0.0662	0.15	-0.015
			(0.020)		(0.025)
Smoker	0.17	0.30	0.1343	0.17	0.012
			(0.036)		(0.031)
Flu shot past 12 months	0.51	0.25	-0.2672	0.51	-0.066
			(0.032)		(0.042)
No insurance coverage	-	-	-	0.03	0.062
					(0.016)

Note: This table presents population weighted descriptive statistics and regression discontinuity estimates at ages 21 and 65 using data from the National Health Interview Survey (NHIS) person and sample adult files from 2004-2009. Data is limited to individuals within 12 months of their 21st and 65th birth month, excluding individuals interviewed in their month of birth. There are 11,321 and 6,883 such individuals in the person files. The outcomes percent days alcohol in past 12 months, smoking status and flu shot in past 12 months are taken from the sample adult files which have 4,375 and 3,587 individuals respectively. Standard errors (in brackets) are adjusted to account for sampling stratification as recommended by NHIS documentation. Mean value at threshold pertains to the mean value for individuals aged 20 and 65 respectively. RD estimate indicates difference in mean for individuals aged 21 and 64 (the treatment group) respectively. RD estimate obtained using OLS including linear polynomial in age and year fixed effects.

Table A. 2: Health outcomes (elderly)

	(1)	(2)	(3)	(4)
	Mortality		**Potentially Avoidable Hospitalization**	
	All stays	Non-deferrable	All stays	Non-deferrable
Panel A: Hospital Stays				
Age 64 * Post	-0.12	-0.29	-0.16	0.32
	(0.09)	(0.23)	(0.34)	(0.19)
Observations	557,124	100,541	241,715	67,777
2011-13 mean (age 64)	2.65	4.21	20.87	6.36
Panel B: ER Arrivals				
Age 64 * Post	-0.07	-0.13	0.06	-0.02
	(0.04)	(0.10)	(0.15)	(0.22)
Observations	1,336,962	218,699	629,439	141,030
2011-13 mean (age 64)	1.19	1.83	20.45	14.90

Note: This table presents estimated effects on two health outcomes – in-hospital mortality and share of stays/visits that were potentially avoidable – for elderly patients. Panels A and B present results for hospital stays and ER arrivals respectively. The dependent variables are indicators for in-hospital death (Columns 1 and 2) and potentially avoidable episode (Columns 3 and 4). Columns 1 and 3 use the entire sample, while columns 2 and 4 use only the sample of patients discharged with a non-deferrable condition. Estimated change in discontinuity post-ACA is the coefficient on $d_i \cdot T_t$ in equation 3b. All models control linearly for patient age, year fixed effects and observable differences in patient sickness, i.e. diagnosis category and gender. Standard errors are clustered by day-of-age cell. Table A. 6 presents corresponding results for young patients.

Table A. 3: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Insurance coverage					***Utilization***		***Hospital choice***		***Outcomes***	
	Medicaid	Private	Insured	County	Self-Pay	Stays	ER Arrivals	Govt.	RA Mort.	Mortality	Mort (ND)
Panel A: Main spec, BW=1											
Age 64 * Post	8.65	-2.56	5.91	-3.27	-2.64	7.78	11.51	-1.11	-2.40	-0.12	-0.29
	(0.19)	(0.24)	(0.09)	(0.06)	(0.08)	(0.71)	(1.12)	(0.18)	(0.56)	(0.09)	(0.23)
2011-13 mean (Age 64)	18.68	42.77	91.97	3.50	4.52	127	286	12.69	5.35	2.65	4.21
Observations			557,124			4,198		557,124	461,070	557,124	100,541
Panel B: Flexible spec, BW=1											
Age 64 * Post	7.91	-2.77	5.31	-2.90	-2.41	9.37	19.03	-0.65	-1.35	-0.26	-0.52
	(0.41)	(0.49)	(0.21)	(0.12)	(0.17)	(1.42)	(2.26)	(0.37)	(1.15)	(0.17)	(0.50)
Panel C: Main spec, BW=2											
Age 64 * Post	8.84	-2.31	6.08	-3.40	-2.68	9.27	15.08	-1.48	-1.62	-0.15	-0.12
	(0.13)	(0.16)	(0.07)	(0.04)	(0.05)	(0.50)	(0.82)	(0.12)	(0.41)	(0.06)	(0.16)
2011-13 mean (Age 63-64.9)	19.21	42.59	91.80	3.64	4.56	124	286	12.93	5.19	2.65	4.13
Observations			1,132,278			8,581		1,132,278	937,583	1,132,278	204,590
Panel D: Flexible spec, BW=2											
Age 64 * Post	8.21	-2.61	5.68	-3.12	-2.56	8.85	12.02	-0.96	-3.30	-0.08	-0.32
	(0.28)	(0.34)	(0.14)	(0.08)	(0.11)	(1.00)	(1.64)	(0.25)	(0.83)	(0.12)	(0.34)

Note: This table presents robustness checks of the main RD-DD results presented earlier. In the interest of brevity, we present results for key outcomes only. Columns 1-5 present results on changes in insurance coverage (Table 2), columns 6-7 present results on volume of care (Table 3), column 8 present results on hospital choice (Table 4), and columns 10-11 present results on patient mortality (Table A. 2). The main results (Panel A) use a 1-year bandwidth and the specification constrains slopes w.r.t. age to remain unchanged pre and post-ACA. Panel B presents results using a flexible specification keeping a 1-year bandwidth but allowing slopes w.r.t age to change post-ACA. Panels B and C use a sample with 2-year bandwidth, and linear I and linear-flexible (D) specifications respectively. Estimated change in the discontinuity post-ACA is the coefficient on $d_s \cdot T_t$ in equation 3b**.** All models also include a full set of year fixed effects. Columns 10-11 also include controls for observable differences in patient sickness, i.e. diagnosis category and gender. Standard errors are clustered by day-of-age cell. The number of observations and pre-ACA means for Panels A and B are noted at the end of Panel A, and those for Panels C and D are noted at the end of Panel C.

Table A. 4: Patient Volume (Young)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hospital stays					**ER data**	
	All	Through ER	Not through ER	Deferrable	Non-Deferrable	All arrivals	ER visits
Age 21 * Post	0.95	0.43	0.52	0.82	0.12	9.86	9.43
	(0.25)	(0.21)	(0.14)	(0.25)	(0.08)	(0.88)	(0.86)
Dynamic Effect							
Age 21 * 2014	0.75	0.42	0.33	0.57	0.18	5.26	4.84
	(0.35)	(0.29)	(0.19)	(0.33)	(0.11)	(1.24)	(1.21)
Age 21 * 2015	1.36	0.80	0.55	1.17	0.19	12.69	11.88
	(0.36)	(0.29)	(0.20)	(0.34)	(0.11)	(1.27)	(1.25)
Age 21 * 2016	0.74	0.05	0.69	0.74	0.00	11.62	11.57
	(0.34)	(0.28)	(0.19)	(0.32)	(0.11)	(1.44)	(1.41)
2011-13 mean (age 21)	24	16	7	21	2	277	261
Observations	4,198						

Note: This table presents regression results on changes in volume of hospital care using the RD-DD analysis. Coefficients presented are on the interaction of indicator for being aged 21 and post-ACA period in equation 4. Regressions were estimated on the sample of young patients, as described in section IV.C. The dependent variable is rate of hospital stays or ER arrivals per 1,000 people per year. To generate these utilization rates, we normalize raw discharges by population estimates for each age-year cell obtained from the National Cancer Institute. Column 1 presents the results for all hospital stays. Columns 2 and 3 present results separately based on stays that originated through and not through ERs respectively. Columns 4 and 5 present results on stays for deferrable and non-deferrable conditions respectively. Non-deferrable refers to about 15 conditions such as Heart Attack, Pneumonia, Stroke, etc. that are emergent and require immediate hospital care. Column 6 presents results for all ER arrivals, while column 7 presents results only on ER visits i.e. where the patient was discharged from the ER. All models control linearly for age and include a full set of year fixed effects. Standard errors are clustered by day-of-age cell. Table 3 presents corresponding results for elderly patients.

Table A. 5: Hospital choice (Young)

	(1)	(2)	(3)	(4)	(5)
	Owner type			**Quality score**	
	Non-profit	For-profit	Govt.	Mortality	Readmission
Panel A: Hospital Stays					
Age 21 * Post	-0.21	1.66	-1.43	-1.35	1.71
	(0.48)	(0.38)	(0.40)	(1.14)	(1.07)
Dynamic Effect					
Age 21 * 2014	0.17	1.81	-1.98	-0.70	0.80
	(0.68)	(0.52)	(0.57)	(1.63)	(1.52)
Age 21 * 2015	0.72	1.34	-2.05	-1.28	0.79
	(0.67)	(0.52)	(0.55)	(1.59)	(1.57)
Age 21 * 2016	-1.58	1.85	-0.19	-2.11	3.65
	(0.70)	(0.55)	(0.57)	(1.63)	(1.56)
2011-13 mean (age 21)	65.95	14.33	19.72	9.40	7.83
Observations	150,030	150,030	150,030	125,996	126,587
Panel B: ER Arrivals					
Age 21 * Post	0.75	0.33	-1.08	-0.52	0.16
	(0.13)	(0.10)	(0.11)	(0.30)	(0.29)
Dynamic Effect					
Age 21 * 2014	0.87	0.38	-1.25	-0.36	-0.02
	(0.18)	(0.14)	(0.15)	(0.43)	(0.41)
Age 21 * 2015	0.95	0.03	-0.98	-0.20	0.10
	(0.17)	(0.14)	(0.14)	(0.42)	(0.40)
Age 21 * 2016	0.44	0.59	-1.02	-1.00	0.38
	(0.17)	(0.15)	(0.14)	(0.41)	(0.39)
2011-13 mean (age 21)	67.91	14.34	17.76	22.9029	5.683
Observations	1,967,635	1,967,635	1,967,635	1,662,680	1,672,327

Note: This table presents regression results on changes in hospital share using the RD-DD analysis. We explore changes on two dimensions – hospital owner type and quality scores. Coefficients presented are on the interaction of indicator for being aged 21 and post-ACA period in equation 3b. Regressions were estimated on the sample of young patients, as described in section IV.A. Panels A and B present results for the hospital stays and ER arrivals respectively. The sample for hospital owner type contains ~150,000 discharges while in case of quality scores the sample is smaller (~125,000) since some hospitals are not rated. The corresponding sample sizes in case of ER arrivals are 2 mn and 1.7 mn respectively. The dependent variables are indicators for government, non-profit or for-profit ownership (Columns 1-3) and standardized 30-day mortality and readmission scores reported by CMS in 2009 (Columns 4-5). All models control linearly for age and include a full set of year fixed effects. Standard errors are clustered by day-of-age cell. We also estimated a version of column 4 controlling for hospital ownership. Estimates were -0.54 (1.1) and -0.07 (0.3) for hospital stays and ER arrivals respectively. Table 4 presents corresponding estimates for elderly patients.

Table A. 6: Health outcomes (Young)

	(1)	(2)	(3)	(4)
	Mortality		**Potentially Avoidable Hospitalization**	
	All stays	Non-deferrable	All stays	Non-deferrable
Panel A: Hospital Stays				
Age 21 * Post	-0.01	0.36	0.51	-1.11
	(0.08)	(0.31)	(0.62)	(1.08)
Observations	150,030	14,965	51,618	6,638
2011-13 mean (age 21)	0.65	1.00	22.40	15.66
Panel B: ER Arrivals				
Age 21 * Post	-0.01	0.03	-0.09	-0.40
	(0.01)	(0.03)	(0.12)	(0.29)
Observations	1,967,635	207,946	785,999	116,310
2011-13 mean (age 21)	0.08	0.09	17.76	39.25

Note: This table presents estimated effects on two health outcomes – in-hospital mortality and share of stays/visits that were potentially avoidable – for young patients. Panels A and B present results for hospital stays and ER arrivals respectively. The dependent variables are indicators for in-hospital death (Columns 1 and 2) and potentially avoidable episode (Columns 3 and 4). Columns 1 and 3 use the entire sample, while columns 2 and 4 use only the sample of patients discharged with a non-deferrable condition. Estimated change in discontinuity post-ACA is the coefficient on $d_i \cdot T_t$ in equation 3b. All models control linearly for patient age, year fixed effects, and observable differences in patient sickness, i.e. diagnosis category and gender. Standard errors are clustered by day-of-age cell. Table A. 2 presents corresponding results for elderly patients.