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

Preliminary and Incomplete – Please Do Not Circulate or Cite Yet

Mark Duggan
Stanford University and NBER
mgduggan@stanford.edu

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

Emilie Jackson
Stanford University
emilyj91@stanford.edu

September 1, 2017

Abstract

The Affordable Care Act authorized the largest expansion of public health insurance coverage in decades. While there is consensus that the law led to a substantial decline in un-insurance, effects on utilization of care and on health are not well understood. We use the universe of discharge data from non-federal hospitals and emergency rooms in California over 2008-15 to investigate the effects on health insurance coverage, health care utilization, and patient health. Our identification strategy exploits fuzzy discontinuities in Medicaid coverage at specific ages where many individuals historically became ineligible. Following implementation of the ACA, the large discontinuity in Medicaid coverage at age 21 disappears while the corresponding one at age 65 approximately doubles. We find evidence of substantial crowd-out of county insurance programs (at 21 and 65) and of private insurance (at 65 only) -- implying a large transfer from federal taxpayers to local governments and individuals. Our results demonstrate that patients choose privately owned over public hospitals once they receive coverage -- but only suggestive evidence of improvement in health outcomes such as mortality or avoidable care. Financial benefits for hospitals are more readily apparent. Hospitals previously serving a high share of un-insured patients benefit disproportionately with a 10% increase in total revenue relative to remaining hospitals.

Acknowledgements: We would like to thank Mark Shepard and several seminar participants at Stanford, UC-Berkeley, and the AEA 2017 meetings for helpful comments. We are also grateful to Betty Henderson-Sparks and Jon Teague of the California Office of Statewide Planning & Health Development for their assistance in providing the Hospital/ER discharge data. All remaining errors are our own.

I. INTRODUCTION

The Patient Protection and Affordable Care Act (ACA) was signed into law in March 2010 and authorized the largest expansion of publicly funded health insurance coverage since the introduction of Medicare and Medicaid in the mid-1960s. The main provisions of this legislation took effect on January 1, 2014, with Medicaid enrollment increasing by 18 million (30% of baseline enrollment) in the period since. In addition, enrollment in the ACA's federally subsidized private health insurance exchanges now exceeds 12 million. Recent estimates suggest the ACA-induced coverage expansions will cost the federal government $120 billion in 2017 (CBO, 2017). This substantial expansion provides a unique modern setting to study the effects of public health insurance coverage on health care utilization and health outcomes as well as the incidence on patients and health care providers.

To investigate the effects of the ACA on utilization and patient health, we use data from the state of California over the 2008-15 period that includes detailed information about all non-federal hospital discharges and emergency room (ER) visits. Our empirical approach exploits fuzzy discontinuities in public insurance coverage at ages 21 and 65 due to Medicaid eligibility rules and their interaction with the ACA mandated expansions. Pre-ACA, the age based eligibility rules caused many individuals to lose Medicaid coverage when they reached these two age thresholds.[1] The pre-ACA decline in Medicaid coverage at age 21 and age 65 among hospitalized patients is large (15 and 9 percentage points respectively). There is a large discontinuity in un-insurance at these two thresholds as well. However, while insurance coverage decreases at age 21, it increases at age 65 due to nearly universal Medicare coverage.

The ACA substantially relaxed eligibility restrictions for non-elderly individuals in California, erasing the discontinuity in Medicaid coverage at age 21 and enhancing it at age 65 since significantly more near elderly individuals could now enroll. The disparity in un-insurance between hospital patients on either side of both thresholds was nearly eliminated by the ACA. This setting therefore lends itself to a fuzzy regression discontinuity (RD) research design with age being the forcing variable that moves people in or out of public insurance for reasons that they cannot manipulate. The ACA substantially changed the size of the discontinuity at both ages and we exploit this variation in our empirical analyses.

We first focus on understanding the changes in insurance coverage following ACA implementation. The RD analysis demonstrates that the decrease in un-insurance is lower than the increase in Medicaid coverage at both age thresholds and hence there is some crowd-out of other forms of coverage. While

[1] Much of the drop in Medicaid coverage at age 65 stems from individuals switching onto Medicare. Many of these individuals remain eligible for Medicaid as "dual eligibles" with Medicare as their primary payer. The important thing for our identification strategy is that the magnitude of the change in Medicaid coverage at age 65 changes substantially after the ACA takes effect and the ACA Medicaid expansions were targeted to the non-elderly.

previous literature has focused on crowd-out of private insurance (Cutler and Gruber, 1996), we find that Medicaid has mainly crowded out coverage provided by counties to low income ("indigent") patients. Nearly half of the increase in Medicaid coverage for young adults goes toward replacing county insurance. This suggests a significant transfer of funds from the federal to local governments. Only in the case of the near-elderly do we find crowd-out of private insurance. About 35% of the increase in Medicaid coverage for near-elderly goes toward replacing private insurance with an additional 40% replacing county coverage.

Next we test if utilization of hospital care changes at these age thresholds. The effects of coverage on utilization are not obvious. A decrease in patient cost sharing and in provider reimbursement may spur greater use of health care. But improved access to preventative and outpatient care may decrease the need for hospital care. Pre-ACA, we find that the number of hospital admissions and ER visits for near-elderly individuals is 5-8% lower relative to those over 65, but only slightly lower at age 21 relative to those just younger. Post-ACA, this gap in utilization at age 65 decreases by about 70%. Hence access to insurance increases the likelihood of using hospital care – at least for the elderly -- as seen in the Oregon study (Finkelstein et al., 2012). The decrease in hospital stays is driven mainly by admissions not originating in the ER, with little or no response on admissions originating in the ER. We interpret this as evidence of elasticity of demand for medical care in situations where treatment is deferrable, but that lack of insurance was not preventing utilization in situations where treatment is non-deferrable.

Two recent studies have focused on quantifying the value of Medicaid coverage to beneficiaries by estimating the willingness to pay for Medicaid (Finkelstein et al., 2015) or the willingness to substitute from Medicaid to alternate insurers (Cabral and Cullen, 2016). An additional source of value that may not be captured by these approaches is that Medicaid may allow beneficiaries more choice among providers relative to being un-insured. We see robust evidence of this phenomenon in our setting - young (elderly) adults are 12 (34) % less likely to receive care at a public hospital (hospital stays and ER visits) when they gain insurance coverage. However, post-ACA we see this disparity essentially eliminated. In addition to moving toward privately owned hospitals, we find that patients are more likely to receive care at better quality (mortality rate) hospitals once they receive insurance coverage. Hence, the acquisition of coverage appears to lead to better quality care and is a valuable feature of insurance coverage.

With the substantial increase in health insurance coverage and greater choice of providers available to individuals, a natural question is whether these changes produce better health outcomes. An important limitation in our analysis is that we can only examine changes in health outcomes conditional on using hospital care. With this caveat, we do find suggestive evidence of reductions in in-hospital mortality and in the share of hospital stays that were potentially avoidable for patients in both age groups. Examining the share of potentially avoidable care helps infer improvements in primary care, which we do not observe directly. The estimated effects on mortality are substantial but noisy and so we cannot reject the null of no

effect. We find evidence of dynamic effects on mortality, i.e. the decrease in mortality rates for the newly insured is larger in 2015 than in 2014, particularly for the near elderly. Taken together, these results suggest that the insurance expansion is gradually affecting mortality, but the effects are not sufficiently large to estimate precisely. We also estimate large decreases in the share of potentially avoidable in-hospital care due to gain in insurance coverage.

What was the economic impact of the ACA-induced expansion in health insurance coverage on hospitals? The increase in coverage implied that most hospitals received greater average reimbursement per patient relative to what they did pre-ACA.[2] Those hospitals that served a higher proportion of un-insured patients are likely to see a greater increase in mean reimbursement per patient, provided their patient profile does not change dramatically. We find supporting evidence -- hospitals having an un-insurance share in the top one-third of all hospitals in 2008 enjoy an increase in total annual revenue relative to the remaining hospitals on the order of $100,000 per bed (or 10% of the mean across hospitals pre-ACA). This increase is entirely driven by an increase in Medicaid revenue (after accounting for decrease in County payments) of nearly a third relative to the mean in 2013. In analysis not presented here, we fail to find evidence that these hospitals are serving a greater number of patients or systematically increasing treatment intensity per patient (e.g. keeping patients longer or doing more procedures) or that they have increased capital investments. We also do not find evidence of positive spillovers of quality of care to other patient groups who were relatively unaffected by the ACA at these hospitals (e.g. infant mortality, elderly mortality).

There are four key limitations of our analysis. First, our results reflect the experience of a specific state (California) and thus may not generalize to other states (especially the 19 states that chose not to expand Medicaid since ACA passage). Second, we cannot observe health care delivered outside of the hospital or even through outpatient departments at hospitals. Because of this, we cannot directly test for improvements in access to preventative and most forms of outpatient care. Third, the RD estimates are local to individuals in the specific narrow age groups that we study (18-23 and 62-67). However, when we use an alternative approach in which we estimate the effects for adults aged 21-64 by leveraging pre-ACA variation across geographic areas in the share uninsured, we obtain similar results. Finally, we do not have information regarding the effects of the ACA on measures of economic well-being such as out-of-pocket spending, credit scores, or bankruptcy.

The rest of the paper is structured as follows. Section II briefly describes how our paper relates to the previous and current related literature on public health insurance generally and the ACA specifically. Section III describes the age based thresholds affecting public insurance coverage and the ACA mandated

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

insurance expansion in greater detail. Section IV describes the data sources and presents basic descriptive statistics. Section V presents the empirical approach. Section VI presents the main results and discusses limitations. Section VII discusses alternative robustness and falsification tests and Section VIII concludes.

II. LITERATURE (to be completed)

The effect of health insurance coverage on the demand for health care has received much attention in the economics literature. As emphasized in this previous research, it is challenging to control for unobserved differences between insured and uninsured individuals. As a result, many studies have leveraged policy-induced expansions of coverage such as the Medicaid expansions to children in the 1980s and 1990s (Currie and Gruber, 1996; Cutler and Gruber, 1996). Two of the most influential studies on this topic have deployed randomized control field experiments (Manning et al., 1987; Finkelstein et al., 2012). But these studies provide limited guidance about possible general equilibrium effects that could accompany large scale expansions such as those mandated by the ACA. Card et al. (2008) exploits a policy-induced discontinuity in coverage at age 65 to examine the impact of Medicare coverage on utilization and health outcomes while Anderson, Dobkin, and Gross (2012) investigate the effects of an age-induced change in private coverage at age 19.

On the supply side, researchers have typically exploited changes in provider reimbursement (Duggan, 2000; Dafny, 2005; Clemens and Gottlieb, 2014) to quantify provider responses on the quantity and quality of care. However, there is little evidence on the effects of or provider responses to changes in cost sharing for consumers. Finkelstein et al. (2015) argue that providers are likely the major beneficiaries of Medicaid expansions, but do not have direct supporting evidence. Garthwaite et al. (2017) examine the impact of uncompensated care on hospital finances and find that increase in the share of uninsured patients decreases hospital profits. Finally, previous evidence on public insurance expansions tends to focus on benefits to the elderly (Card et al., 2008) or children (Currie and Gruber, 1996; Dafny and Gruber, 2005). The ACA setting allows us to examine the effects on non-elderly adults, who may be more or less sensitive to the quality and quantity of health care received.

Finkelstein (2007) is perhaps closest in spirit to the hospital-level analyses in this paper since it quantifies the effects of the introduction of Medicare (a similarly large increase in public health insurance coverage) on hospital finances, employment and spending. Recent studies exploit the expansion of health coverage mandated by a 2006 reform in Massachusetts (Kolstad & Kowalski 2012, Miller 2012) that preceded the ACA. That reform was similar in structure to the ACA, however the policy-induced increase in insurance coverage was small (approximately 4%) relative to the ACA given the high rates of pre-reform health insurance coverage in Massachusetts.

Furthermore, this paper contributes to an emerging literature on the effects of the most recent insurance expansion, the ACA, on health insurance coverage, healthcare utilization and health outcomes. A growing number of papers have provided evidence that the ACA lead to widespread gains in insurance coverage (Sommers et al., 2014; Golberstein et al., 2015; Benitez and Creel, 2016; Sommers et al., 2016; Courtemanche et al., 2017*a*; Frean et al., 2017; …). Many studies thus far have used survey data, such as the American Community Survey (ACS), to measure changes across the US after the ACA (Duggan et al, 2017). Studies have exploited geographic variation in uninsurance rates prior to the ACA (Courtemanche et al., 2017*a*) and variation across time in income groups and markets (Frean, Gruber, and Sommers, 2017) to estimate the effects of the ACA. Courtemanche et al. (2017*a*) estimate coverage gains of approximately 6 percentage points in expansion states and 3 percentage points in non-expansion states and find no evidence of any crowd-out of private coverage. Frean, Gruber, and Sommers (2017) estimate that about 60% of the increase in overall coverage nationally is due to the expansion of Medicaid.

A few states opted to expand Medicaid coverage early through the ACA's early expansion option or Section 1115 waivers; however, there was significant heterogeneity in the method through which and the extent to which each state expanded its eligibility criteria.[3] Despite variation in the execution of an early expansion, the early expanders provided a nice opportunity for preliminary estimates of the ACA's effect on coverage and outcomes (Sommers et al., 2014; Golberstein et al., 2015; Sommers et al., 2015)

Evidence is limited so far on how the change in coverage from the ACA has impacted patient utilization and health outcomes. Evidence in this regard is thus far mostly limited to self-stated responses on surveys relating to individual's health and behavior but indicates that individuals have better access to care and lower out of pocket spending (Golberstein et al., 2015; Benitez and Creel, 2016; Sommers et al., 2016; Wherry and Miller, 2016; Courtemanche et al., 2017*b*). Courtemanche et al. (2017*b*) use the Behavioral Risk Factor Surveillance System and variation in treatment intensity to examine if the large increase in coverage led to any changes in risky behaviors or self-assessed health but find no statistically significant effects. They do find that patients are more 3pp more likely to have a primary care doctor and 2.4pp more likely to have a checkup. Additionally, they find some evidence that near-elderly adults experienced improvements in self-reported health, particularly in expansion states.

A couple of other studies have made use of data sources that focus on one aspect of medical care, such as emergency departments or prescriptions, to examine changes in utilization related to that specific care (Garthwaite et al., 2017; Ghosh et al., 2017). Garthwaite et al. (2017) make use of data from two large multi-state, private for-profit hospital chains to estimate outcomes such as number of emergency department (ED) visits, whether or not the visit was an emergency, and average travel time to the ED. They

[3] States that had early expansions include CA, CT, DC, MN, NJ, and WA.

find that travel time reduced almost a minute in expansion states but do not find a similar decrease in non-expansion states and thus conclude that the expansion lead patients to have more choice in hospital facilities. However, their data includes only hospitals in the two firms for which they have data and may give an incomplete picture if the ACA affected the allocation of patients across hospitals or affected private non-profit or public hospitals differently. Ghosh, Simon, and Sommers (2017) use data from a nationally representative, all-payer pharmacy database to examine the effect of having coverage on prospection drug utilization. They estimate a 19% increase in Medicaid-paid prescriptions in expansion states relative to non-expansion states and found no evidence that this increase was crowding out other forms of payments. These increases were largest in medications for diabetes, contraceptives, and cardiovascular drugs.

Additionally, there is evidence that indicates that the ACA-induced gains in health insurance coverage also positively influence individuals' financial well-being (Brevoort, 2017; Gallagher, 2017).

III. BACKGROUND

A. Affordable Care Act

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

There were two primary channels through which the ACA expanded access to health insurance, both of which became effective on January 1, 2014. First, in all states, individuals in families with incomes between 100 and 400 percent of the federal poverty level (FPL) who were not already eligible for affordable health insurance, either from an employer or from Medicaid, were now eligible for premium subsidies provided in the form of advanced tax-credits to purchase private health insurance.

Second, the ACA originally intended to expand Medicaid eligibility to all individuals below 133% of the FPL. However, legal challenges allowed states the choice to opt out of expanding Medicaid.[4] Twenty-six states chose to expand Medicaid in 2014 and since then six other states have elected to expand Medicaid. California is one of the original states to expand Medicaid. Prior to the ACA, Medicaid coverage was limited to specific low-income groups such as children, pregnant women, elderly, disabled, and some parents. Therefore, childless low-income adults are the main beneficiaries of the expansion. Duggan et al (2017) provide a more detailed summary of the ACA-induced expansions in coverage.

California is an important state to examine as the nation's most populous state and because it experienced a sizable increase in Medicaid enrollment given its large uninsured population in 2013. In

[4] The effective cutoff is 138% as there is a 5% income disregard.

California, as of March 2017, 1.4 million individuals enrolled in private plans through the state's private ACA insurance exchange. Figure XYZ displays monthly Medicaid enrollment in California during the last several years and shows that – after trending up just gradually in the 2008 through 2012 period - this increased from about 8.5 million in mid-2013 to 12.5 million by mid-2016.[5] As a result, the share of California's population enrolled in Medicaid rose from about 22% in 2013 to 32% in 2016.

To understand how the change in coverage status might affects both newly insured individuals and providers, it is important to understand how the uninsured received care prior to the expansion. Despite a lack of coverage, many previously uninsured individuals in California still obtained health services for which they frequently paid out of pocket. If they could not afford part or all of these costs, the financial burden of the uncompensated care often fell on providers and various local programs. Counties served as the insurers of last resort for many low-income individuals in California that were not otherwise covered. California spent more than 2.1 billion dollars in one pre-ACA year to care for the uninsured through programs such as the Medically Indigent Services Program (MISP), which provided care in 24 mostly urban counties, and the County Medical Services Program (CMSP), which operated in 32 predominantly rural counties (Council of Economic Advisers 2009). Consequently, the expansion of Medicaid was likely to provide a substantial financial relief to local governments in California (** more details on MISP / CMSP).

B. National Medicaid Enrollment

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

Even among states that chose to expand Medicaid, there is substantial variance in the impact on Medicaid enrollment. This is partly due to variation across states in baseline enrollment, due to states' generosity in eligibility criteria, as well as differences in the socio-economic composition of states. Figure XYZ shows the percent of the state population enrolled in Medicaid in late 2013 and the net change in

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

enrollment between late 2013 and July 2015. Compare California and New York, where almost one-third of residents in both states are now covered through Medicaid. However, this was a much larger increase in California, which saw an increase of 10 percentage points compared to an increase of 4 percentage points in New York. New York had more generous eligibility criteria that included childless adults prior to 2014 whereas childless adults were generally not covered in California. Consequently, the expansion of Medicaid had a larger impact in California.

The American Community Survey (ACS), conducted by the US Census Bureau, is the largest annual household survey sampling roughly 1% of the population. It includes information on whether an individual has health insurance coverage and the sources of coverage. An individual can select as many insurance categories as applicable including: privately purchased insurance, insurance through an employer, Medicare, Medicaid or any other government-assistance plan for disabled or low-income individuals. Figure XYZ illustrates the composition of coverage by age group pre-ACA in California using data from the ACS. As the figure shows, almost 40% of those under 21 are already covered by Medicaid while those 65 and older are covered primarily through Medicare.

IV. DATA

Our main source of data is confidential discharge data on hospital stays and emergency room (ER) visits obtained from California's Office of Statewide Health, Planning, and Development (OSHPD). We also utilize OSPHD's publicly available annual hospital-level financial data. The utilization data contain all hospitalizations and ER visits at non-federal hospitals in the state of California during the 2008 through 2015 period. The full data sets include approximately 3.8 million discharges and 11 million ER visits each year. Each observation pertains to a hospital stay or ER visit and provides information on the hospital, dates of service, patient insurance status and basic demographics, a vector of up to 25 diagnosis and procedure codes, and patient zip code. As is standard in such files, if an ER visit subsequently leads to hospitalization, then it only appears as a hospital discharge, though this data indicates whether the admission was preceded by 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. Unique patient identifiers permit us to track individuals over time, which allow the measurement of readmissions. We limit our analysis to general acute care hospitals, which account for the vast majority of discharges and ER visits in the state.[6] We exclude birth related visits and focus only on patients residing in the state of California.[7]

[6] Hospitals that would not be considered general acute care hospitals in our data consist primarily of children's hospitals, psychiatric health facilities and those specializing in long-term care.
[7] X% of the discharges in 2008 were patients with either an out of state or missing zipcode.

Table 1 provides detailed summary statistics about the data. We focus on 370 non-federal acute care hospitals of which 312 have emergency departments. Of these, 211 are private non-profit, 100 are private for-profit and 59 are government hospitals. On average, these hospitals have 230 licensed beds and total annual revenues of $181 million. In 2009-2013, 24% of non-birth related discharges among 21-64 year-old adults were insured by Medicaid while 14% were uninsured. In 2014-15, this changed to 40% and 4%, respectively.

Figure 1 Panel B presents the trend in Medicaid coverage among patients discharged from hospitals (and ERs) over 2008-15. This plot also groups individuals into the same three age groups as in Panel A. Medicaid coverage is high for individuals under 21 and rises smoothly post 2014. Coverage is low for non-elderly adults initially, but increases sharply in quarter 1 of 2014 by about 10 percentage points (or 50%) and continues to increase slowly over the remainder of the period. Medicaid coverage for the elderly is essentially unchanged after ACA implementation. Hence the discharge data suggests that increase in coverage was concentrated among adults aged 21-64. Panels A and B of Figure 2 focus attention on insurance coverage in 2014-15 over a narrow set of ages either side of the age thresholds and make the same point more forcefully.

A. Age-based discontinuities in public insurance

A common feature of public insurance programs is the use of age-based thresholds to determine eligibility. For example, individuals can enroll in Medicare when they turn 65, but not earlier -- unless they are enrolled in the Social Security Disability Insurance program or have end stage renal disease. Similarly, children enjoy relatively generous eligibility rules under Medicaid until age 18 (or 19 under some circumstances) but then often lose coverage because the eligibility criteria become more restrictive. Prior to the ACA, two such rules created large discontinuities in insurance coverage at 21 and 65 in California. Medi-Cal (as Medicaid is known in California) allowed low income childless adults aged 18-20 to enroll, but not once they were 21 or older. Once they turned 21, adults would typically be eligible only if they had children and were below the federal poverty level for their family size.[8] This created a large discontinuity in Medicaid coverage at age 21.

To shed light on the magnitude of this discontinuity, we turn to our hospital discharge data. Note that this will reflect insurance coverage conditional on using hospital care rather than the share of the population with coverage. Figure 2 Panel A presents insurance coverage for admitted patients in the age group 18-23 by different type of insurers in the period 2010-13. As the figure shows, Medicaid coverage drops by 15 percentage points (30%) at age 21 and 1 month relative to the month before turning 21. Patients

[8] Individuals receiving federal or state disability payments were automatically eligible irrespective of age and hence are the exception to this rule.

at exactly age 21 are between these two extremes. At all other ages in the interval 18-23, Medicaid coverage evolves smoothly. In our preferred specifications we will exclude patients aged exactly 21 given their partial treatment status to avoid biasing the results.

Card et al. (2008) document the large increase in insurance coverage through Medicare at age 65. When individuals enroll in Medicare, they often lose their existing insurance plan, whether private or Medicaid (though in some cases retain this other coverage and thus have double coverage). Hence, we observe a large drop in both private and Medicaid coverage at age 65. Figure 2 Panel B presents insurance coverage by type of insurer in the age group 62-67 for admitted patients in California over 2010-13. As discussed above, we find a 25(10) percentage point decrease in private (Medicaid) coverage at age 65. This drop is seamlessly compensated by an increase in Medicare coverage at 65. As with the transition at age 21, patients in the last month before turning 65 experience a partial transition and are somewhat treated. We exclude patients in this month from the preferred specifications to avoid biasing the results.

It is worth noting that our insurance coverage information includes only the primary expected payer. To the extent that an individual has coverage from multiple sources (e.g. Medicare and Medicaid), we will miss the secondary and other sources. For patients eligible for both Medicare and Medicaid, the primary expected payer is typically Medicare, with Medicaid covering deductibles and co-payments.

B. Regression discontinuity sample

We impose three restrictions to arrive at the sample used in the main analysis. 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 ACA, we exclude related hospital stays or ER visits from the analysis. Third, we exclude the years 2008-11 from the main RD analysis in order to focus on the two years just prior and two years following ACA implementation. We will present robustness checks in the appendix that relax these restrictions.

Finally, we limit the analysis sample to patients admitted within 36 months of their 21st (or 65th) birthday. This dramatically curtails the sample size and leaves us with approximately 310,000 (1.1 million) hospital stays and 3.9 million (2.7 million) ER visits over the period 2010-15. Note that while the elderly have four times as many hospital stays as the young, they have substantially fewer ER visits. Table 1 summarizes descriptive statistics on the main RD analysis sample for the young and elderly separately for hospital stays (Panel A) and ER visits (Panel B).

C. Hospital finances

To examine the effects of the insurance expansion on hospital finances we deploy annual hospital reports submitted to OSHPD and made publicly available on its website. These reports are mandated by California law and provide details on hospital finances, utilization and capacity. Table XYZ presents descriptive statistics on hospital revenue (as of 2008) and the contribution of different insurers. The mean total revenue for a hospital in California was $164 million. Medicaid accounted for less than 20% of the total revenue in 2008. Figure XYZ presents trends in hospital finances over the period 2008-16. Medicare share was relatively stable at 20% in 2013, but accelerated to 26% by 2016. This occurred in a period when total revenue per bed itself grew more rapidly. Indeed, Medicaid is the only insurer whose share of total revenue increased over this period. Both Medicare and Private insurance saw mild declines in their contribution to the total. This evidence complements the dramatic increase in Medicaid coverage of hospital patients seen in Figure 1 Panel B. In California, Medicaid is now nearly comparable to Medicare in its importance for hospital revenue.

V. EMPIRICAL STRATEGY

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

A. Regression Discontinuity design

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

$$Y = \alpha + \beta \cdot Ins + \epsilon \quad (1)$$

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

We try to solve this endogeneity problem by exploiting age-based discontinuities in public insurance eligibility at 21 and 65, as discussed in Section IV above. For example, before the ACA insurance expansion in 2014, the probability of being covered by Medicaid in California dropped nearly by half due

to eligibility restrictions when an individual turned 21. Similarly, individuals transitioned out of Medicaid at age 65 due to the onset of Medicare. This provides policy driven instruments to predict insurance coverage (the endogeneous variable Ins in equation 1). We exploit this discontinuity in eligibility rules in a regression discontinuity design by limiting the analysis sample to individuals within a narrow age range of 21 or 65. In our preferred specifications, the age bandwidth is three years above and below the threshold.

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

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

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

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

$D'_{it} = [1\ d_i\ T_t\ d_i \cdot T_t]$ is a vector of patient and time specific dummies as explained above. $\boldsymbol{\lambda}_1$ is the corresponding 4xk matrix of age coefficients whose dimensions are determined by the order k of function $G()$, a polynomial in age (a_i). In our preferred specifications we use a linear function ($k = 1$), but conduct robustness checks using higher order functions as well. Hence we impose linear changes in the outcome with age. The coefficient on d_i allows individuals one side of the threshold to have a different slope w.r.t. age. The coefficients on T_t and $d_i \cdot T_t$ allows individuals to have different slopes w.r.t. age post-2014 based on their age relative to the threshold.

The coefficients of interest in this model are θ_{11} and θ_{12} which estimate the discontinuity in insurance coverage at threshold A over 2012-13 and the change in this discontinuity post-ACA respectively. All models include a full set of HSA and year fixed effects, α_1 and γ_1 respectively. Finally, in some specifications we also include a vector of controls X_i to account for observable differences in patient characteristics, such as reason for arrival and gender.

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

Equation 3 above presents the "reduced form" model testing for a discontinuity in the outcome of interest Y_i in 2012-13 and whether there was a change in the discontinuity post-ACA. These are estimated by coefficients θ_{21} and θ_{22} respectively. The remaining coefficients and variables are exact equivalents of the elements in equation 2.

$$\mathrm{Y_{ijt}} = \alpha_{3j} + \gamma_{3t} + \beta \cdot \widehat{Ins}_{\mathrm{ijt}} + X_i \boldsymbol{\delta}_3 + \eta_{\mathrm{ijt}} \quad (4)$$

Equation 4 above presents the second stage and estimates the economic object of interest β i.e. the causal effect of health insurance coverage on outcomes like utilization of care and health, by using a predicted value of insurance coverage ($\widehat{Ins}$) obtained by estimating equation 2.

In practice, we estimate equations 2 and 4 simultaneously using linear two stage least squares (2SLS). The estimation sample excludes patients exactly at age 21 or 65 since their insurance coverage typically changes by an intermediate amount and hence they are "partially treated". In both the OLS and 2SLS procedures, we put higher weight on individuals aged within one year of the threshold in order to avoid changes away from the threshold to bias estimates.

Identification

The estimate β can be interpreted as an average causal effect under two identification assumptions (Angrist and Imbens, 1994). First, conditional independence, i.e. the age based discontinuities in public insurance coverage are un-correlated with other factors that could also affect outcomes of interest like demand for care and health. In regression discontinuity design a testable implication of this assumption is the absence of discontinuities in other important factors at the age threshold. For example, if individuals are also disproportionately likely to gain employment exactly at age 21 or leave the labor force exactly at age 65, this would potentially violate conditional independence since gaining or losing employment affects income and can directly affect health related outcomes. Card et al. (2008) present an extensive set of tests to demonstrate that there are no discontinuities in employment or income at age 65.

The second assumption is monotonicity or the absence of so-called "defiers". Under this we assume that there are no individuals who were previously un-insured and gain Medicaid (or more broadly, gain insurance) at age 21. Similarly, for the elderly sample we assume there are no individuals who are un-insured at age 64 and get Medicaid coverage at age 65. These paths would be contrary to the insurance separations produced under the age-based phasing out of Medicaid coverage. This is a maintained assumption and un-testable, but given the evidence on Medicaid coverage by age and the nature of these rules, we find it to be plausible.

B. Spatial variation

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

We deploy a differences-in-differences research design using two sources of policy driven variation. First, we use cross-sectional variation in un-insurance levels across hospital service areas before the ACA was passed (specifically, we use 2008). Since the ACA mandated expansion in Medicaid and private insurance through the exchanges, its main effect will be an increase in insurance coverage. Markets with previously higher un-insurance will see a greater decrease in un-insurance levels. Our thought experiment treats such markets as being hit by a greater "insurance shock" than others. We combine this cross-sectional variation with within-market time-series variation created by implementation of the insurance expansions.

We calculate un-insurance rates by hospital service area in 2008 as the observed proportion of hospital stays originating from a HSA ($Unins_{j08}$), that were self-insured or covered by county indigent programs. Equation $5a$ below represents the basic model to be estimated.

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

Y_{ijt} denotes an outcome of interest for patient i in HSA j in year t. T_t has the same meaning as in equations 2 - 4 above. The coefficient of interest is ξ and estimates the change in Y_j in 2014-15 vs. before the ACA (2009-13) for a market with no insurance compared with a market with full insurance. We include a full set of HSA and year fixed effects, α_j and γ_t respectively. In some specifications we also account for observable differences in patient characteristics by including a vector $\boldsymbol{X_i}$. We estimate two variants of the above model. The first imposes a linear specification as described above. The second approach is flexible and does not impose linearity, instead we interact T_t with an indicator d_{j08} for the hospital market being among the top one-third of all markets on un-insured share of patients in 2008 i.e. $d_{j08} = 1(Unins_{j08} > 0.67pct)$. The interpretation of ξ changes to being the post-pre change in outcome Y for patients in the top one-third of hospital markets by un-insurance, relative to patients in all the remaining markets.

To interpret the coefficient ξ as a causal effect of insurance expansion, we need to make two assumptions. First, outcomes in HSAs would evolve in a similar fashion in the absence of the insurance

expansions. To test the presence of possible pre-trends, we estimate models allowing effects ξ_s to vary flexibly by year from 2009 through 2015, as depicted in equation $5b$ below. This approach does not impose linearity or treat 2014 and 2015 differently than the other years.

$$Y_{ijt} = \alpha_j + \gamma_t + \sum_{s=2009}^{s=2015} \xi_s \cdot d_{j08} \cdot I(t = s) + \epsilon_{ijt} \quad (5b)$$

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

It is useful to emphasize that this analysis uses a different source of identifying variation relative to the regression discontinuity analysis, in addition to including patients aged 24-61. The estimates obtained in this analysis inform us about changes in coverage, utilization or health outcomes *relative* to patients in other hospital markets. But all patients included in the sample are potentially exposed to the insurance expansions. Hence, this approach may understate the magnitude of the effects on the outcomes of interest.

C. Variation across hospitals

An important goal in this paper is to examine the impact of the insurance expansions on hospitals. In order to do so we implement a third research design, which is a variant of the one described above. The key cross-sectional variation is now in pre-ACA un-insurance rates across hospitals rather than across hospital markets. The thought experiment is conceptually similar – hospitals with a high pre-ACA share of uninsured patients were hit by a greater insurance shock in 2014-15 relative to hospitals that mostly saw insured patients.

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

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

Equations $6a$ and $6b$ present the estimating equations that implement this approach. These are exact equivalents of the equations that exploit variation in un-insurance across hospital market areas. We have the benefit of observing hospital financials in 2016 as well and hence can deploy three years of post-ACA

data for this analysis. Since the financial data is available only at the hospital-year level, this analysis is not at the patient level.

The key assumption for identification continues to be absence of differential pre-trends in finances across hospitals. We present estimates obtained from equation $6b$ in order to examine the presence of pre-trends. Note that this analysis quantifies the effects of insurance expansions on hospital finances net of any patient sorting across hospitals that occurs due to the insurance expansion.

VI. RESULTS

A. Insurance coverage

We begin by analyzing the change in insurance coverage for patients discharged from hospitals and emergency rooms in California's non-federal general acute care hospitals over the 2012-15 period. The analysis has two goals – first, to document the change in insurance coverage around the two age thresholds before and after implementation of the expansions, and second, to test if Medicaid expansion crowded out existing forms of insurance. Throughout the paper, we consider patients covered by Medicaid, Medicare or private insurance as insured (** TriCare, etc.??). The remaining patients either pay for care themselves or are covered by the county indigent program and lack traditional health insurance coverage.

i. Insurance expansion

Figure 2 presents a scatter plot of the proportion of hospital stays over 2012-15 that are insured for the young (Panel A) and elderly (Panel B) respectively. Recall that our preferred sample includes patients whose age is within three years above or below the threshold. The figure also plots fitted values obtained by estimating equation 2 with insurance coverage as the outcome. In 2012-13, we find a 15 (7) percentage point decrease (increase) in insurance coverage at age 21 (65). Relative to a base of 73 pp (92 pp) for individuals aged 21-23 (62-64), this represents a 20% (7%) change. With the ACA insurance expansion, discontinuities at both thresholds are nearly eliminated, with only a 1 pp gap remaining.

Table 2 presents the estimated changes in insurance coverage at age 21 (Panel A) and 65 (Panel B). Each panel has two parts – on hospital and ER discharges respectively. The sample of ER discharges has been augmented to include those ER visits that result in hospital stays. We prefer to include these to avoid concerns about changes in ER admission protocols in response to the ACA. Hence we refer to this as the sample of ER arrivals throughout the paper. The patterns of changes in insurance coverage are qualitatively similar between hospital stays and ER arrivals. Hence for brevity we will discuss only the results for hospital stays. The first row presents the discontinuity pre-ACA while the second row presents the change in discontinuity post-ACA. These values correspond to coefficients θ_{11} and θ_{12} respectively in equation 2.

The values in column 4 reflect the net effect on insurance coverage and correspond exactly to those indicated by

Figure ***2***. Columns 1, 2 and 3 present the effects on specific coverage types – Medicaid, private insurance and Medicare respectively. Pre-ACA, the decrease in insurance coverage at 21 is driven mainly because of aging out of Medicaid. County indigent programs step in to cover about half of those losing Medicaid at 21. Figure A- 1 presents a detailed scatter plot and fitted values showing how coverage changes for different insurer types at age 21 in 2012-13 (Panel A) and 2014-15 (Panel B). The elderly gain insurance coverage at 65 due to the universal nature of Medicare and it mainly replaces a mix of private coverage and Medicaid (~85%), with some decrease in un-insurance. We discuss the change in coverage post-ACA in the section below on crowd-out.

ii. Crowd-out

An important policy concern associated with the expansion of public insurance programs is potential crowd-out of other forms of coverage. The RD research design is well suited to examine crowd-out since we are comparing changes in coverage for the entire group of patients in the state conditional on belonging to a specific age group.

For the young, there is suggestive evidence of a small decrease in private coverage for the treated group, but it is not robust. A prominent source of crowd-out is the replacement of county indigent programs by Medicaid post-ACA. This appears to be by design, since counties have completely withdrawn coverage in response to the expansion. In effect, more than half the increase in Medicaid coverage replaces last-resort county payments. We find crowd-out of coverage for the near-elderly as well. There is a robust decrease in private coverage, accounting for one-third of the increase in Medicaid coverage. The demise of county coverage is seen here as well and is about 40 percent as large as the expansion in Medicaid.

An important implication of the crowd-out of county and private coverage is that the decline in self-pay is much smaller in magnitude than the increase in Medicaid, both for the young and the elderly. Assuming for the moment that coverage changes translate directly to changes in spending, taxpayers spent nearly $300 on Medicaid expansion for every $100 decrease in individual payments. The remainder is a transfer from federal taxpayers to counties that previously financed hospital care for the uninsured and in case of the elderly, also to individuals (or their employers) who previously bought private insurance.

The evidence on insurance coverage thus far indicates that the setting differs for the young and elderly on three dimensions. First, young adults are much more likely to be uninsured than the near elderly before the ACA. Second, the drop in Medicaid coverage for young adults at age 21 was associated with a large increase in the share uninsured while the corresponding drop at age 65 is associated with an increase in the share on Medicare. Third and most importantly for our purposes, the magnitude and type of crowd-

out differs for the two groups. Whereas among young adults the increase largely just lowered county coverage, for the near elderly there was a substantial reduction in private coverage as well. This makes it particularly appealing to examine both groups separately.

B. Utilization of care

To study the effects of changes in health insurance coverage on utilization, we collapse the data to the age-month (denoted by s) - year level and estimate the following model with number of hospital stays or ER visits (normalized by population[9]) as outcomes.

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

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

Figure 3 presents a scatter plot of observed utilization of hospital and ER care for our young adult sample by age-month as measured by number of stays/arrivals per 1,000 California residents per year. Panels A and B present the corresponding values for 2012-13 and 2014-15, respectively. In addition, we also plot fitted values obtained by estimating equation 7. We split hospital stays based on whether the patient entered through the ER or not. This allows us to examine changes in utilization based on conditions that were emergent or not.

The figure indicates that there is little or no discontinuity in hospital stays at the threshold before and after the implementation of the ACA. There is a noticeable decrease in arrivals at the Emergency Room at age 21 and this gap appears to persist post-ACA as well. While the level of ER arrivals increases substantially with the expansion of coverage, the number of hospital stays does not change.

Figure 4 presents the corresponding plot for the elderly and offers a very different picture. There is a discontinuous increase in both hospital stays and ER arrivals at age 65. Pre-ACA, the increase in stays is noticeably larger in absolute and relative terms for stays that do not originate in the ER –presumably non-emergent. Post-ACA, there is a noticeable convergence in number of stays and ER arrivals, suggesting that the increase in insurance coverage leads to greater utilization of care by the near-elderly.

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

Table 3 presents regression coefficients on utilization of care for both the young (Panel A) and elderly (Panel B). In the case of the young, there appears to be very little price elasticity of demand for care. The IV estimates suggest that a 10% increase in insurance coverage results in 0.4 and 7 stays and ER arrivals per 1,000 person-years respectively, or approximately 2% of the mean rate of utilization. The increase among hospital stays is driven entirely by stays that do not originate in the ER, presented in column 9 with no increase among stays originating in the ER (column 7). There is a 5% increase in this segment, but they account for less than 30% of all hospital stays.

Table 3 Panel B presents estimates for the elderly sample. As indicated by Figure 4, demand for hospital care is much more price elastic for the elderly. A 10% increase in insurance coverage results in 25-30 more hospital stays and ER arrivals per 1,000 person years. Relative to the mean utilization rate, it is a much greater increase in hospital stays (20%) than in ER arrivals (8%). The growth in hospital stays is again spurred by the demand for non-emergent stays which increase thrice as much as do stays through the ER (14% vs. 5%).

Table 3 also presents estimated effects for 2014 and 2015 separately in order to examine the dynamics of change in utilization of hospital care. The pattern of coefficients suggests a gradual increase in utilization of care. This is particularly noticeable in case of the elderly, where number of stays and ER arrivals are about 50% greater in 2015 relative to 2014.

C. Choice of hospital

Having established that the Medicaid expansion led to an increase in utilization of hospital care (mainly among the near-elderly), we now examine whether there is sorting of patients across hospitals as well. We explore hospital choice on two dimensions – owner type and quality as measured by risk adjusted mortality scores. In essence, both variables are noisy measures of hospital quality, since private non-profit hospitals are often perceived as high quality hospitals in a market, whereas government owned hospitals are perceived to be at the lower end.

i. Hospital owner type

Figure 5 Panel A presents a scatter plot of observed hospital share of stays by owner type (private non-profit, for-profit and government) for young patients in 2012-13. It also presents the corresponding fitted values obtained by estimating equation 2. There is a noticeable 2 pp increase in the share of government (city, county and district) owned hospitals and corresponding decrease in share of private non-profit hospitals at the threshold. For-profit hospitals are seemingly unaffected.

Figure 5 Panel B presents the same plot for 2014-15 and indicates that the pattern has largely reversed. The discontinuity in share of government hospitals at 21 is eliminated due to a decrease for those

aged 21-23. This is balanced by a clear increase in the share of for-profit hospitals and suggestive gains for non-profits. Figure A- 2 presents the corresponding plots for the elderly with qualitatively similar patterns.

Table 4 presents regression estimates corresponding to these figures. Panel A presents estimates for the young. The average effects are well represented by the figure. The IV estimates indicate that the marginal young individual is 10% less likely to be admitted at a government hospital once she has insurance coverage. This is economically significant since it is a 40% decrease in the probability of going to a government hospital relative to an uninsured patient. Although the average effect is equally large for non-profit and for-profit hospitals, marginal patients are more likely to switch to non-profit hospitals. Consistent with evidence of dynamic increase in utilization, we find strong evidence of dynamic shifts in care towards private hospitals. The decrease in share of government owned hospitals is 25% greater in 2015 relative to 2014.

Table 4 panel B presents corresponding results for the elderly and indicates that the elderly are more likely to switch hospital type than the young. The marginal elderly patient who receives insurance coverage is 35% less likely to be admitted at a government hospital, nearly three times that for a young patient. This is a very large shift since the un-insured have only a 30% probability of being admitted at a government hospital. The pattern of an increasing shift away from government hospitals is more pronounced in case of the elderly, with the effect in 2015 nearly double that in 2014.

Our research design cannot help us disentangle mechanisms behind this shift in hospital care away from government owned hospitals. While the most intuitive explanation is that it is driven by patient preferences, it is ultimately an equilibrium outcome and one cannot rule out the role of hospital responses (such as greater targeting of recently insured individuals, or greater propensity to admit these patients at the ER) in producing this shift.

Replicating this analysis on the sample of ER arrivals may be instructive since shifts in ER arrival patterns are more likely driven by demand preferences. In fact the ER results potentially represent a lower bound on propensity to switch given that distance plays the dominant role in case of emergencies. We find similar patterns, though the effects are smaller in magnitude (IV estimates of decrease in government hospital are 7% and 30% for the young and elderly respectively. See Table A- 2 for more details). These magnitudes are similar to those found in case of hospital stays and suggest that non-patient factors are quantitatively less important.

ii. Mortality score

The above section establishes that the ACA-induced insurance coverage expansion has resulted in sorting of patients from government owned toward privately owned hospitals. Ownership type is correlated with quality or perceived quality of care (for example, academic medical centers are generally high quality

and mostly non-profit), but probably also correlates with other factors. Hence in this section we directly examine sorting on hospital quality using a standard measure – risk-adjusted 30 day mortality.

CMS calculates this measure for Medicare patients discharged from hospitals for a number of serious conditions. The raw mortality rates are adjusted for patient risk history and observed sickness at the time of admission.[10] We calculate the mean risk adjusted mortality rate for hospitals across Heart attack, Heart failure or Pneumonia, as reported by CMS in 2009. We then normalize the mortality rates such that the distribution across hospitals is standard normal. Given that the mortality scores were calculated for Medicare patients, they are likely to be more informative about quality as it pertains to care for the near elderly than for young adults. Hence we focus our discussion to results obtained on the sample of elderly patients, although we also present corresponding results for the young.

Figure 6 presents a scatter plot of our calculated normalized hospital mortality score in each age-month for hospital stays over the period 2012-15, both for the young (Panel A) and elderly (Panel B). In case of the elderly there is a noticeable drop in mortality score at age 65 in 2012-13, which narrows post 2014. This suggests that increase in insurance coverage at 65 allows patients to receive care at hospitals with lower mortality rates.

Table 5 presents the corresponding regression estimates. Panel B allows us to formally examine the magnitude of change in hospital quality at age 65. Hospital mortality score was 0.02 s.d. higher for individuals aged 62-64 in 2012-13, relative to those over 65. In 2014-15, the difference drops by 0.01 s.d. As with utilization and hospital choice, the change in hospital quality increases over time. In 2015, the difference in quality at age 65 decreases by 0.02 s.d. and is effectively eliminated. Collectively, this evidence is particularly compelling and suggests that insurance coverage enables patients to receive care at better quality hospitals.

The IV estimate suggests that gaining insurance coverage enables patients to receive care at a hospital that has 0.25 s.d. lower mortality. This is a large change in hospital quality and equivalent to moving to a hospital with 0.4 (0.25*1.63) pp lower mortality or a 3% decrease relative to the mean 30 day mortality rate.

As in the case of hospital ownership, looking at changes in hospital choice on the sample of ER arrivals could help establish a lower bound estimate of the component driven by demand preferences. Table 5 also presents equivalent results for ER arrivals. The IV estimate suggests that insurance coverage enables a patient to receive care at a hospital 0.13 s.d. lower than without coverage. This is about half the magnitude of the decrease seen for hospital stays.

[10] 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.

The results on patient sorting imply that a key benefit of expanding insurance coverage is enabling patients to choose higher quality (real or perceived) hospital care. This is a source of welfare improvement for patients irrespective of whether there are measurable improvements in health outcomes. Cost-benefit exercises that evaluate social welfare due to the insurance expansions – outside the scope of this paper -- should take this benefit into account.

D. Health Outcomes

Having examined effects of insurance coverage on utilization of care and choice of provider, we now look at the "bottom line" i.e. whether patient health outcomes have improved as a result of the expansion of insurance coverage. We choose to focus on two measures of health – in-hospital mortality and share of potentially avoidable stays/visits.

i. In-hospital mortality

Short term mortality is a commonly used measure of hospital quality and used by CMS as one of many metrics of hospital quality that affect Medicare payments. Due to data limitations, we do not observe mortality outcomes outside the hospital and hence focus on in-hospital mortality. Using other data from California, we find that deaths in the hospital accounted for 79% and 64% of 7-day and 30-day mortality respectively for patients in these age groups, over 2008-11.[11] In-hospital death is therefore the largest component of short-term mortality and a credible proxy for short-term mortality.

Figure 7 presents a scatter plot of mean in-hospital mortality rates by age-month cell in 2012-13 (Panel A) and 2014-15 (Panel B) for the sample of young patients. It also presents fitted values obtained by estimating equation 3. Not surprisingly, mortality is a rare event – the mean mortality rate in the sample is 6 per 1000 admissions. Pre-ACA, there is a noticeable increase in mortality at age 21. Mortality rates appear to converge on either side of the age threshold post-ACA due to a decrease for the newly insured group of patients. Given that mortality rates are very diffuse across the different age-month cells (coefficient of variation of 0.33) it is difficult to visually infer any change at the age threshold.

Table 6 presents the corresponding reduced form and IV estimates obtained when examining the effects of insurance expansion on in-hospital mortality. Panels A and B present the results for the young and elderly respectively. The table presents results not only for the sample of hospital stays, but also for all

[11] To examine mortality outside the hospital, we obtained confidential death-linked discharge files from OSHPD for 2008-11. This data is available through 2013 and we are working to acquire 2012-13 as well. OSHPD creates these files by linking hospital discharge files with state death records. The linkage aims to provide mortality information following the last known hospital stay in California within this time period. Hence we can compute standard mortality measures such as 7-day or 30-day mortality rates.

ER arrivals. The pattern of results is similar across hospital stays and ER arrivals and so we discuss only hospital stays here.

As suggested by Figure 7, the mortality rate is higher for 21-23 year olds pre-ACA by ~16% relative to the mean value and decreases post-ACA by similar magnitude. These estimates however, are not statistically significant. We can rule out effects larger than a third of the mean mortality rate. The IV point estimate suggests large reductions in mortality for young adults – gaining insurance coverage leads to a decrease in mortality comparable to the mean rate. This estimate is noisy (we cannot rule out an effect unless it is twice the mean mortality rate) and hence not statistically significant. Taken together, these estimated effects suggest that the expansion of insurance coverage did reduce mortality rates, however the magnitude may not be sufficiently large to be estimated with precision.

Panel B presents the results for the elderly and they are qualitatively similar as for the young. There is evidence of dynamic effects in the improvement in mortality rates for the elderly, unlike in the case of the young. Among both hospital stays and ER visits, the improvement in mortality rates in 2015 is 3-4 times larger than in 2014 and statistically significant. The IV estimate indicates a large improvement in mortality for the elderly at ~50% of the mean mortality rate.

The estimated effects on in-hospital mortality are not statistically significant. As a thought exercise, it is still useful to take the estimates and determine the implied number of lives saved in hospital deaths. If we apply a 50% improvement in mean mortality rate on the share of non-elderly (21-64) patients that gained insurance coverage due to the ACA, then we find that in its first two years after implementation the ACA insurance expansion saved about 1,100 lives annually.[12]

ii. Potentially avoidable care

A key argument used in favor of expanding insurance coverage is that beneficiaries will have access to preventative care in an outpatient setting and will not need to resort to using expensive emergency room infrastructure as default primary care. Hence a natural outcome of interest is whether the expansion did lead to a decrease in the wasteful use of hospital care. One measure used to identify such low-value care is whether the stay or visit could have been avoided with better primary care. These episodes are identified for a subset of visits[13] based on ICD 9 diagnosis codes recorded in the patient's discharge information and

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

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

have previously been used for this purpose (Kolstad and Kowalski, 2012). In our sample, approximately 20% of eligible hospital stays were identified as potentially avoidable over 2012-13.

Figure 7 presents the mean observed share of potentially avoidable hospital stays (PAH) by age-month cell for the sample of young patients in 2012-13 (Panel A) and 2014-15 (Panel B). It also plots predicted values obtained by estimating equation 3. As with mortality rates, the share of PAH also tends to fluctuate quite dramatically within this narrow age group, as seen with the pattern of fitted values. The figure suggests a slight increase in the share of PAH at age 21 pre-ACA. The share of PAH decreases post-ACA for patients both above and below the age threshold and it is unclear if the decrease is greater for patients over 21.

Table 6 formalizes intuition provided by the figure. In the case of the young, the share of PAH was ~1.4pp (7% of the mean) greater pre-ACA for those 21 and older. Post-ACA there appears to be no movement relative to those younger than 21. We should emphasize here that this estimate does not suffer from lack of precision. We can rule out a relative change in the share of PAH post-ACA of more than 2pp or 10% of the mean share. The IV estimate indicates a large causal effect of insurance coverage. Gaining coverage leads to a nearly 8pp (35%) decrease in the likelihood of a potentially avoidable stay.

The patterns are qualitatively similar for the young and elderly patients. Elderly patients benefit slightly more from insurance coverage, PAH declines by 9.5pp (nearly 50%) when a 62-64 year old patient gains health insurance in our sample.

These results are ambiguous when compared to the evidence on choice of hospital owner type, or even quality (mortality score). Pre-ACA, the group of patients with lower insurance coverage were more likely to come in for potentially avoidable reasons. However, the insurance expansion did not result in a corresponding decrease in PAH. Another conflicting factor is that the estimates obtained using the sample of ER arrivals are much smaller in magnitude and not statistically significant.

The IV estimates help us quantify the decrease in potentially avoidable hospital stays due to the insurance expansion under the ACA. Note that this is not necessarily the same as a decrease in hospital stays, only in the proportion that are possibly wasteful. Using the estimated causal effect of insurance coverage on PAH (~9% decrease) and the increase in coverage under the ACA (15% and 5% for the young and elderly respectively), we estimate that the ACA has led to about 1,200 fewer avoidable stays (3% of total PAH) for patients in these specific age groups. If we extrapolate these results to the entire non-elderly (21-64) group of patients, then the decrease will be about 6,500 stays per year or 5% of all PAH for this segment.[14]

[14] There were ~32k and ~155k eligible stays annually for the young and elderly respectively. The increase in insurance coverage affected about 4.5k and 8k patients respectively. For these patients, the share of PAH decreased by ~9% on average, which is

E. Evidence using all non-elderly adults

An important limitation of the regression discontinuity analysis in the previous section is that the estimates are local to the specific age groups 18-23 and 62-67. These are policy relevant groups, but unlikely to be representative of the non-elderly adult population. To address this limitation, we deploy an alternate research design using the sample of all non-elderly patients (21-64) as discussed in section xx above.

i. Insurance Coverage

Table 7 Panel A presents the results obtained by estimating equation $5a$ using both the linear and non-parametric specifications. Columns 1-6 presents results obtained with various insurance coverage variables as outcomes of interest. Reassuringly, the results obtained using the entire sample are qualitatively similar to those in the RD analysis. We find an increase in insurance coverage (Medicaid, Medicare or private insurance) driven primarily by the Medicaid expansion. However, a large share of the increase in coverage replaces county coverage that was previously funded through local taxes.

Across both specifications, approximately 60% of the increase in coverage derives from the Medicaid expansion, while the decrease in self-pay ranges from 50-60% of the increase in coverage. A key point where the results on the entire sample of adults diverge from the local RD estimates is the on the effects on private coverage. While the RD analysis suggests no change in private coverage (or a slight decrease), the geographical analysis suggests that markets with high share of un-insured did experience an increase in private coverage. We discuss these differences in more detail in the discussion section.

Figure 8a plots coefficients obtained by estimating the flexible non-parametric specification $5b$. There does not appear to be a pre-trend in insurance coverage or county indigent coverage, however there is a small trend of decrease in self-pay even before the expansion, particularly in 2013. This could be driven by the expansion of county indigent programs in 2013 as part of the early Medicaid expansion in California. Overall, we are reassured that there are no differential pre-trends across markets.

ii. Hospital Choice

We also present equivalent results on choice of hospital type using the full sample of non-elderly patients. As in the RD analysis, the geographical analysis also indicates that gaining insurance coverage is associated with movement of patients from government hospitals toward privately owned hospitals. Table 7 Panel A presents the corresponding estimates and figure 8b presents the non-parametric dynamic effects.

~1.2k stays annually. The entire non-elderly (21-64) group has about 650k eligible stays annually. The increase in insurance coverage affected about 70k patients annually. Applying the 9% decrease for this group gives us ~6.5k fewer stays per year.

At the mean un-insurance level of .12, the linear specification predicts a loss of approximately 1.8 pp market share from government to private hospitals post-ACA, which lies in between the equivalent estimated effects obtained for the young and elderly using the RD analysis. The figure shows a lack of pre-trends prior to 2014.

A point of inconsistency between the analysis using the specific RD sample and the entire non-elderly adult sample is the change in shares of for-profit and non-profit hospitals. The RD analysis indicates robust evidence of movement toward both types of privately owned hospitals, whereas in the geography based analysis we find that the movement is toward non-profit hospitals, with for-profit hospitals losing some share (though not statistically significant). Hence, while the pattern of patient sorting from government hospitals toward private hospitals is representative of the overall sample, movement within type of private hospitals seems to be age-specific.

F. Impact on hospitals

So far we have focused on the effects of the insurance expansion on patients' utilization of health care and on their health outcomes. However, given the unprecedented magnitude of the expansion in California, it could affect providers directly (through an increase in revenue) as well as indirectly (through provider responses to the expansion of supply). Finkelstein (2007) shows that hospitals expanded capacity and spending on technology in response to the introduction of Medicare – and this expansion was far in excess of what could be explained by the increase in utilization of care by the elderly. She argues that general equilibrium effects operating in the same direction further incentivized hospitals to ramp up spending on personnel and capital equipment.

We deploy data on hospital finances collected by OSHPD over the period 2009-16, as described in section xx above. Table 7 Panel B presents coefficients obtained by estimating equation $6a$ on hospital-year level data. Columns 1-6 present results on hospital revenue through different payers, while columns 7-9 present results on other outcomes of interest. We normalize annual revenue by each hospital's licensed bed capacity in order to account for differences in size. Further, we convert all nominal values into real 2016 dollars. We present results using both the linear and non-parametric specifications. The resulting patterns are qualitatively similar, although estimates using the linear specification are dramatically noisier.

Based on the linear specification, hospitals that had a 10% greater share of un-insured patients in 2008 experienced a relative increase of $18,000 per bed (2016 dollars) in total patient revenue over 2014-16. This increase is driven entirely by the Medicaid expansion, since all other payers have experienced a decline in revenue. This represents a 2% increase relative to the mean revenue of 1 million per bed. Note that except the increase in Medicaid revenue, none of the other revenue variables show a statistically significant increase. This analysis suffers from lack of precision in estimation. For example, to reject the

null of no change in Medicaid revenue, we need an estimate that is larger than the Medicaid revenue received by the mean hospital. The raw trends in hospital revenue (not presented) do not suggest the use of a linear specification. The trends in hospital revenue exhibit little or no change for hospitals with low levels of pre-ACA un-insurance. Much of the increase is concentrated in hospitals with highest levels of pre-ACA un-insurance. This observation motivates the use of the non-parametric approach.

The non-parametric specification offers much more precise estimates as well as larger magnitudes. Total revenue for hospitals having un-insurance rates among the top third of all hospitals in 2008 has increased by (marginally significant) $95,000 per bed -- 10% of revenue for the mean hospital -- relative to the remaining hospitals. As comparison with the linear specification, note that hospitals in the top third have an un-insurance rate about 13 pp greater than the remaining hospitals. Medicaid accounts for more than 70% of this increase, with the remainder due to increase in Medicare and Private insurance. Figure 9 presents the dynamic coefficients estimated using equation 6*b*. Reassuringly, there is no evidence of differential trends across hospitals pre-2014.

These results establish that the expansion of insurance coverage led to a disproportionate increase in revenue for hospitals that previously had high rates of un-insurance among patients. To put the magnitude of this increase in perspective, note that hospitals operate on low margins. In 2008, hospitals in California reported a mean net income of $4 million on total patient revenue of $140 million, or a margin of 3%. This margin would be lower still if we include non-patient revenue. Hence for hospitals with the highest pre-ACA un-insurance levels, this influx of money has been potentially several times their annual net income. In other results not presented here, we find no evidence of a decrease in subsidies to publicly owned hospitals (that typically had high un-insurance rates pre-ACA) as a response to the increase in payer revenue. This is in contrast to previous studies (Duggan, 2000; Baicker and Staiger, 2005) that show government hospitals being operated on a soft budget by local governments. Hence we believe this truly was an increase in hospital revenue.

What did this money do? Hospitals could potentially deploy these funds to improve quality of care generally, initiate expansions, hire more or better staff or retain as surplus. We explore this line of reasoning by examining effects on some unrelated outcomes such as mortality rates for infants (<1) and elderly (65+) patients. These patient groups are more sensitive to changes in quality of care. Table 7 Panel B presents results on these outcomes (columns 7-8). The estimates are small and statistically insignificant. In case of elderly mortality, we can rule out an effect larger than 6% of the mean value. These results suggest that the influx of revenue has not produced spillover quality improvements for non-targeted patients. Similarly, we do not find any effects on spending on capital expenditure. While it may be too early to find effects on capital spending, at least these results indicate that hospitals have not responded by upgrading facilities or equipment.

Taken together, these results suggest that the insurance expansion resulted in a transfer from taxpayers to hospitals. Finkelstein, Hendren and Luttmer (2015) suggest exactly this possibility using survey data. The lack of impact on capital spending suggests that the ACA did not spur capital investments in the manner that Medicare did – with the caveat that such decisions are taken over longer time horizons and may yet be detected with more years of data.

G. DISCUSSION

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

i. Local average treatment effects

The results from the RD analysis recover parameters that pertain to individuals close to age 21 or 65. They are likely relevant to individuals in their late twenties and fifties as well, since patterns of health and health care are relatively stable over short ranges of age. While the applicability of the estimates is limited, both groups are policy relevant. The former group has seen the greatest increase in insurance coverage under the ACA, particularly through Medicaid. The latter group could benefit further from an increase in coverage if Medicare is expanded to include the near-elderly.

Even within these age groups, the RD results reflect the experience of individuals that aged out of public insurance pre-ACA and gained coverage under the ACA. They share some common attributes such as being low-income, not having children and not having a serious disability. All of these factors precluded them from Medicaid coverage pre-ACA. These features are not particularly restrictive, especially for the young. There is a small fraction of individuals (<5%) in both groups that continues to remain un-insured. Whether the estimates will generalize to this group or not is not clear.

Finally, the estimated effects pertain to obtaining a specific form of insurance coverage – Medicaid. We could expect very different estimates if the same individuals were awarded private coverage, for example. Given that our results are qualitatively similar on several aspects to those found in a study examining the loss of private coverage at age 19 (Anderson, Dobkin & Gross, 2012), this may not be an important margin.

ii. Adverse selection or moral hazard?

The RD analysis focused on outcomes for patients and the estimates are local to two groups of patients – those in their early 20s and the near elderly (62-64). This choice was driven by the setting and research design, but it is instructive since the two groups had different insurance levels pre-ACA and experienced different changes in coverage under the ACA.

We find that the young have much lower price elasticity of utilization than the elderly. Our analysis does not allow us to determine whether or how much of this difference is driven by risk selection into the expanded Medicaid program or moral hazard response by beneficiaries, primarily since we do not observe a panel of health care use for each individual. In case of the young, the large increase in insurance coverage makes it unlikely that a particularly sick pool of beneficiaries has been brought under coverage. Instead, the lack of response on both stays and ER arrivals suggests that the marginal individual gaining Medicaid coverage is healthier than the average Medicaid patient pre-ACA.

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

iii. Patient sorting across hospitals

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

iv. Short run effects

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

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

VII. ROBUSTNESS AND FALSIFICATION CHECKS

A. Alternative specification

As discussed in section 5, our preferred specification for equations 2 and 3 uses a linear vector in patient age when predicting insurance coverage and other outcomes. This is a modeling choice that seems reasonable, but it is worth checking whether alternate ways of incorporating age affect the results and conclusions. In particular, we checked the robustness of all our results to using a quadratic function in age instead of a linear function. Due to brevity, we present equivalent results only on insurance coverage. Table 8 left panel presents equivalent results to Table 2 on hospital stays. The estimates are remarkably similar both for the young and the elderly, across the different insurer categories. The change in private coverage for the elderly post-ACA is the only aspect where the estimates differ in a noteworthy manner. The quadratic specification estimates a *greater* decrease in private coverage than the linear approach. Hence the conclusions from this analysis remain similar.

B. Alternative bandwidth

As another robustness exercise, we replicate all RD analyses using a sample defined by a narrower (2 year) age bandwidth above and below the age bandwidths of 21 and 65. We present the corresponding results obtained in Table A- 3. Due to brevity, we present estimates only on the key outcomes in insurance coverage, utilization, hospital choice and health outcomes. Across all the outcomes of interest, estimates are remarkably similar to the main estimates presented using a sample defined by a three year bandwidth. This is not very surprising since we use a weighted least squares procedure assigning higher weight to individuals of age just above and below the threshold and lower weight to individuals more than one year above or below the threshold.

The estimated decrease in private coverage for the near-elderly is substantially greater when we use a narrower bandwidth. Hence the main results could be understating the crowd-out of private coverage.

C. Placebo insurance expansion

An important concern with the results is that the estimated effects are driven not just by the insurance expansions of 2014, but are also driven by other economic trends that preceded implementation

of the ACA. This is particularly relevant in case of the estimated decrease in private coverage, which is a larger trend observed in health care data since the great recession. In order to examine whether pre-existing economic trends could be driving some of the changes in insurance coverage (our first stage) we replicate our regression discontinuity analysis over the period 2010-13 i.e. before the ACA insurance expansions were implemented.[15]

Table 8 (right panel) presents corresponding results on the sample of hospital stays by estimating equation 2 on the sample of young (Panel A) and elderly (Panel B) patients over 2010-13. As with the main results, we use a linear specification here. If our main results are not driven by some pre-existing economic trends, then the estimated discontinuity θ_{11} at the age thresholds over 2010-11 should be similar to what we find in the main results. Since there is no insurance expansion in 2012, there should no change in the discontinuity, which is captured by θ_{12} in the equation.

The pattern of estimated effects on the discontinuity in 2010-11 bears remarkable similarity to our main results presented in Table 2. None of the point estimates are more than two standard errors away than the corresponding estimates in the main table. This is reassuring because it indicates that the estimated discontinuities are stable measures of changes in insurance coverage at these age thresholds.

The evidence on change in discontinuity in 2012-13 relative to 2010-11 is somewhat mixed. We find no change in self-pay or insurance coverage, which is reassuring. However, two other results suggest that we should be more cautious about our main estimates. First, we find a small decrease in private coverage, both for the young and the elderly. It is statistically significant for the elderly and this suggests that part of the decrease we find in the corresponding main results could be driven by a pre-existing trend of declining private insurance. It is about half the magnitude of the estimated effect in 2014-15 and hence a lower bound for the crowd-out of private coverage is ~1.5 pp or 20% of the increase in Medicaid coverage under the ACA.

Second, we find small increases in Medicaid coverage, both for the young and the elderly. This is likely driven by the "early expansion" implemented by California over 2011-13. As discussed in Golberstein, Gonzales and Sommers (2015), the early expansion was rolled out in a phased manner across counties over this period and resulted in substantial increases in Medicaid coverage in those counties.

VIII. CONCLUSION

To be added….

[15] The mandate to include dependents under age 26 on parent insurance plans was implemented in 2010 itself, so it is present throughout this period and should not affect these results.

REFERENCES

Anderson, Michael, Carlos Dobkin, and Tal Gross. "The effect of health insurance coverage on the use of medical services." *American Economic Journal: Economic Policy* 4, no. 1 (2012): 1-27.

Baicker, Katherine, and Douglas Staiger (2005). "Fiscal shenanigans, targeted federal health care funds, and patient mortality." *The Quarterly Journal of Economics* 120, no. 1: 345-386.

Benitez, Joseph A., and Liza Creel (2016). "Kentucky's Medicaid expansion showing early promise on coverage and access to care." *Health Affairs* 35.3: 528-534.

Brevoort, Kenneth, Daniel Grodzicki and Martin Hackmann (2017). Medicaid and Financial Health.

Cabral, Marika and Mark R Cullen (2016). "Estimating the Value of Public Insurance Using Complementary Private Insurance," NBER working paper 22583.

Card, David, Carlos Dobkin, and Nicole Maestas. "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization and Health: Evidence from Medicare." *American Economic Review* 98, no. 5 (2008): 2242-2258.

Clemens, Jeffrey and Joshua D Gottlieb (2014). "Do physicians' financial incentives affect medical treatment and patient health?" *The American Economic Review*, *104* (4), 1320–1349.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. (2017). "Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States." *Journal of Policy Analysis and Management*, 36(1): 178-210.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. (2017b). "Early Effects of the Affordable Care Act on Health Care Access, Risky Health Behaviors, and Self-Assessed Health." NBER working paper 23269.

Currie, Janet and Jonathan Gruber (1996). "Health Insurance Eligibility, Utilization of Medical Care, and Child Health," *Quarterly Journal of Economics,* 111(2): 431-466.

Dafny, Leemore, (2005). "How do hospitals respond to price changes?" *The American Economic Review*, *95* (5), 1525–1547.

Dafny, Leemore and Jonathan Gruber, (2005). "Public insurance and child hospitalizations: access and efficiency effects," *Journal of Public Economics*, *89* (1), 109–129.

Duggan, Mark G. (2000). "Hospital Ownership and Public Medical Spending," *The Quarterly Journal of Economics*, *115* (4), 1343–1373.

Finkelstein, Amy. "The aggregate effects of health insurance: Evidence from the introduction of Medicare." *The Quarterly Journal of Economics* 122, no. 1 (2007): 1-37.

Finkelstein, Amy et al. (2012). "The Oregon Health Insurance Experiment: Evidence from the First Year," *The Quarterly Journal of Economics*, *127* (3), 1057–1106.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer (2015). "The value of medicaid: Interpreting results from the oregon health insurance experiment." No. w21308. National Bureau of Economic Research.

Frean, Molly, Jonathan Gruber, and Benjamin D. Sommers (2017). "Premium Subsidies, the Mandate, and Medicaid Expansion: Coverage Effects of the Affordable Care Act." Forthcoming, *Journal of Health Economics*.

Gallagher, Emily, Radhakrishnan Gopalan, and Michal Grinstein-Weiss (2017). "The Effect of Health Insurance on Home Payment Delinquency: Evidence from ACA Marketplace Subsidies."

Garthwaite, C., Gross, T., Notowidigdo, M., & Graves, J. A. (2017). "Insurance Expansion and Hospital Emergency Department Access: Evidence From the Affordable Care ActInsurance Expansion and Hospital Emergency Department Access." *Annals of internal medicine*, *166*(3), 172-179.

Ghosh, A., Simon, K. and Sommers, B.D., (2017). "The effect of state Medicaid expansions on prescription drug use: evidence from the Affordable Care Act*"* NBER working paper 23044.

Golberstein, Ezra, Gilbert Gonzales, and Benjamin D. Sommers (2015). "California's early ACA expansion increased coverage and reduced out-of-pocket spending for the state's low-income population." *Health Affairs* 34, no. 10: 1688-1694.

Haeder, Simon F., David L. Weimer, and Dana B. Mukamel (2015). "California hospital networks are narrower in Marketplace than in commercial plans, but access and quality are similar." *Health Affairs* 34, no. 5: 741-748.

Imbens, Guido W., and Joshua D. Angrist. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62, no. 2 (1994): 467-475.

Kolstad, Jonathan T., and Amanda E. Kowalski. "The impact of health care reform on hospital and preventive care: evidence from Massachusetts." *Journal of Public Economics* 96, no. 11 (2012): 909-929.

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., & Leibowitz, A. (1987). "Health insurance and the demand for medical care: evidence from a randomized experiment." *The American Economic Review*, 251-277.

Miller, Sarah (2012). "The Effect of Insurance on Emergency Room Visits: An Analysis of the 2006 Massachusetts Health Reform," *Journal of Public Economics,* 96 (11), pp. 893-908.

Sommers, B.D., Kenney, G.M., and Epstein, A.M. (2014). "New Evidence On The Affordable Care Act: Coverage Impacts of Early Medicaid Expansions." *Health Affairs.* 33(1):78-87.

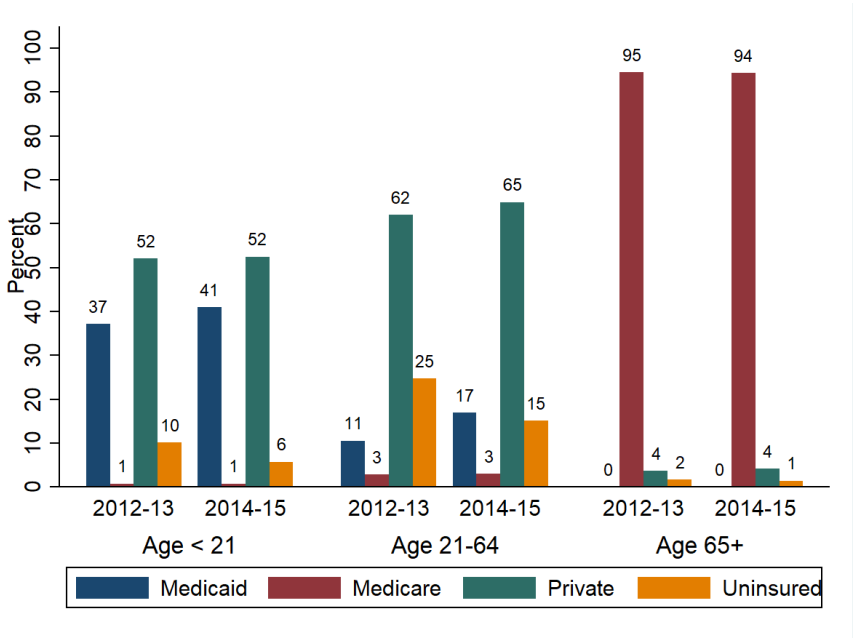
Sommers, B.D., Chua, K.P., Kenney, G.M., Long, S.K., and McMorrow, S. (2015). "California's Early Coverage Expansion under the Affordable Care Act: A County-Level Analysis." *Health Services Research*. 51(3):825-845.

Sommers, B. D., Blendon, R. J., Orav, E. J., and Epstein, A. M. (2016). "Changes in Utilization and Health Among Low-Income Adults After Medicaid Expansion or Expanded Private Insurance." *JAMA internal medicine*, *176*(10), 1501-1509.

Wherry, L. R., & Miller, S. (2016). “Early Coverage, Access, Utilization, and Health Effects Associated With the Affordable Care Act Medicaid Expansions: A Quasi-experimental Study.” *Annals of Internal Medicine*, *164*(12), 795-803.

FIGURES AND TABLES

1a: Insurance coverage in California, ACS



1b: Medicaid share of hospital stays

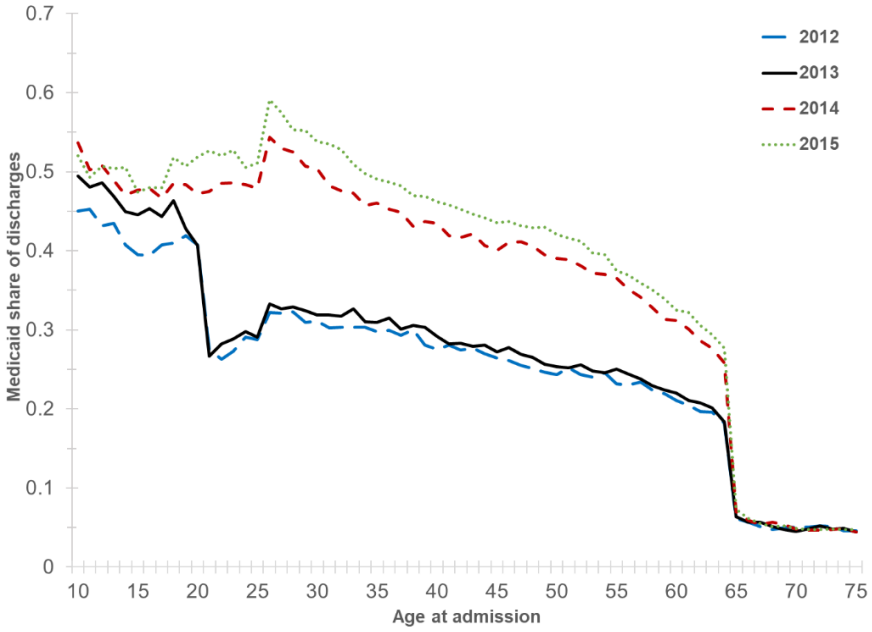


Figure 1: Insurance coverage in California

Note: This figure presents primary insurance coverage in California over 2012-15 as reported in the American Community Survey (Panel A) and Medicaid share of hospital stays for ages 10-75 as recorded in hospital discharge data (Panel B). In Panel A, if an individual reports Medicaid and Medicare, then we code Medicare as primary. Similarly, if an individual reports Private and Medicaid, then we code Medicaid as primary. This ensures coverage aggregates to 100%. The sample used in Panel B excludes cases related to pregnancy and deliveries, is limited to General Acute Care hospitals and excludes individuals residing in zip codes outside California.

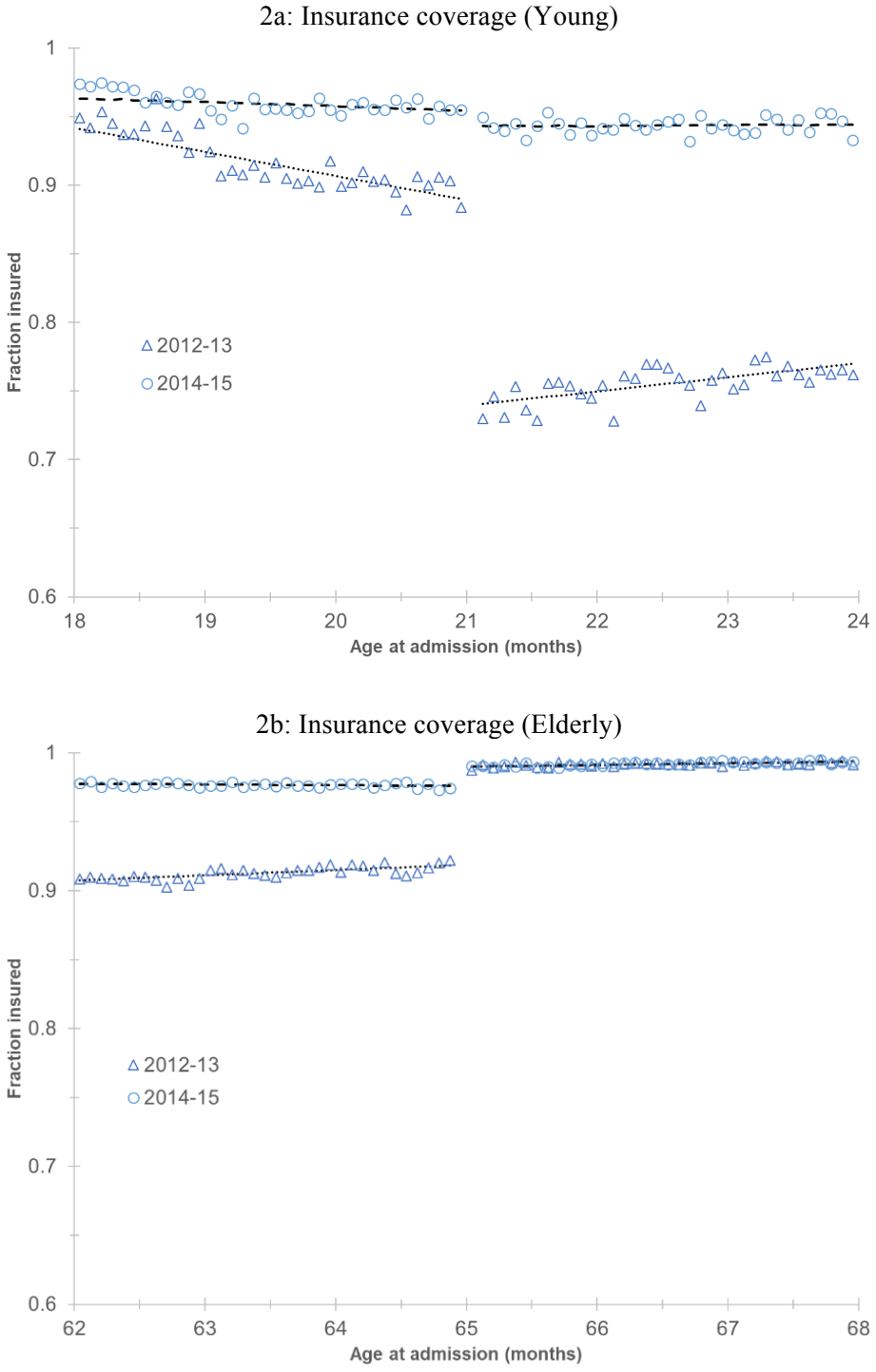


Figure 2: Insurance coverage in RD sample (hospital stays)

Note: This figure presents observed insurance coverage rates collapsed to age-month bin and corresponding fitted values (dashed line) obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) patients respectively. These plots present insurance coverage for hospital stays in the RD sample. The dependent variable is set to 1 if the individual has private insurance, Medicaid or Medicare. All models include a full set of hospital service area (HSA) and year fixed effects.

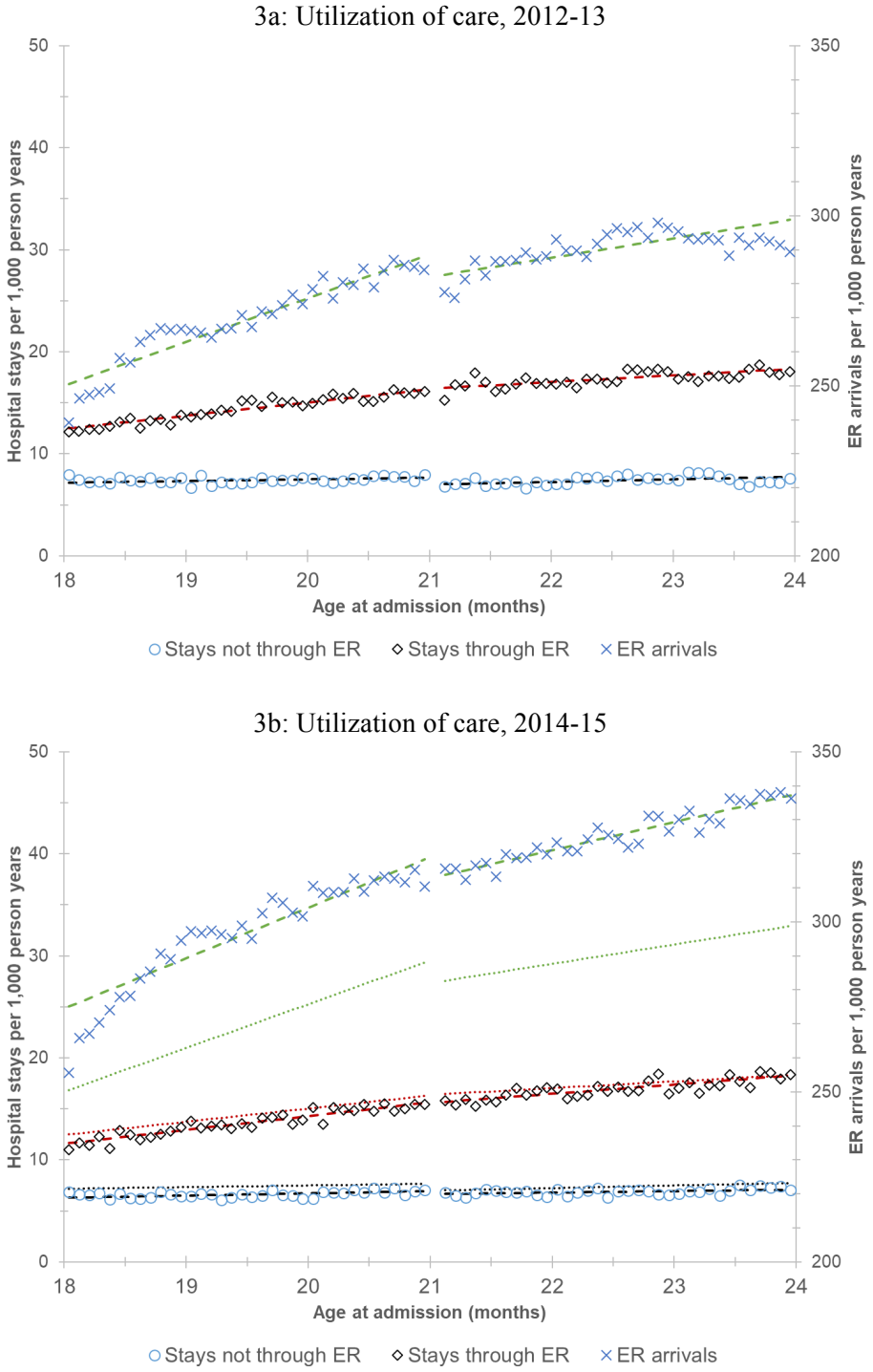


Figure 3: Utilization of hospital care (young)

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

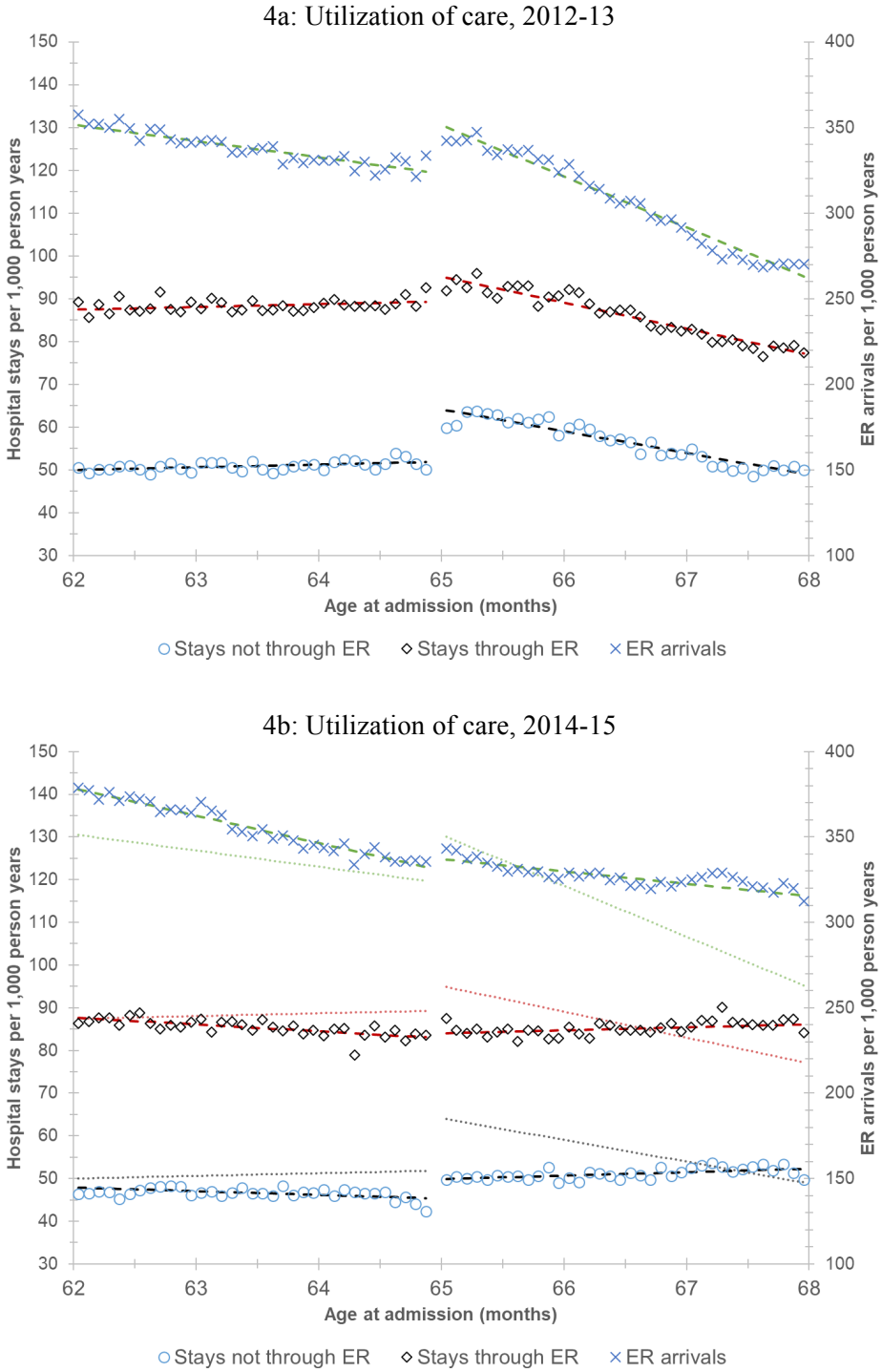
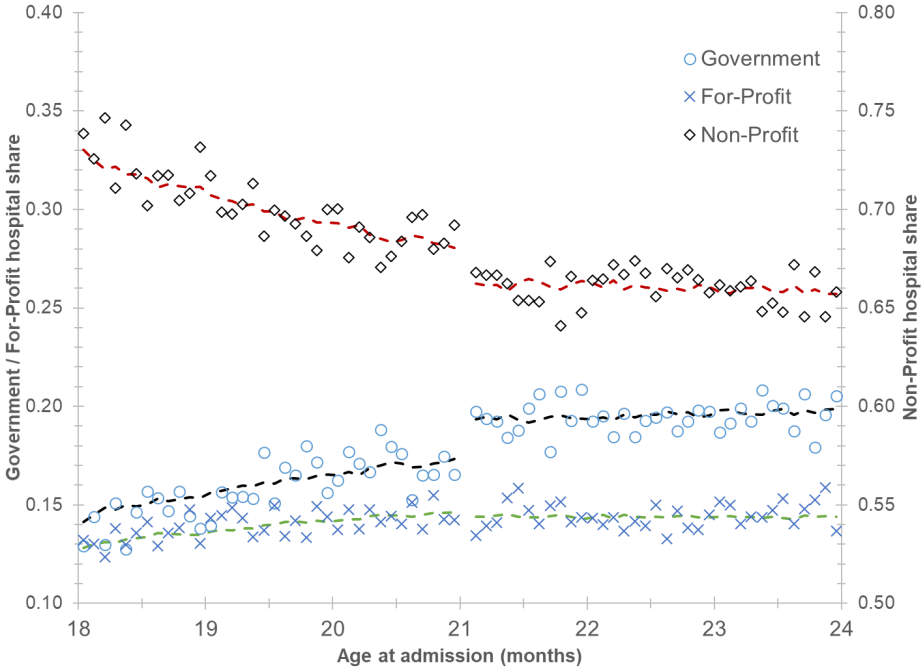


Figure 4: Utilization of hospital care (elderly)

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

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



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

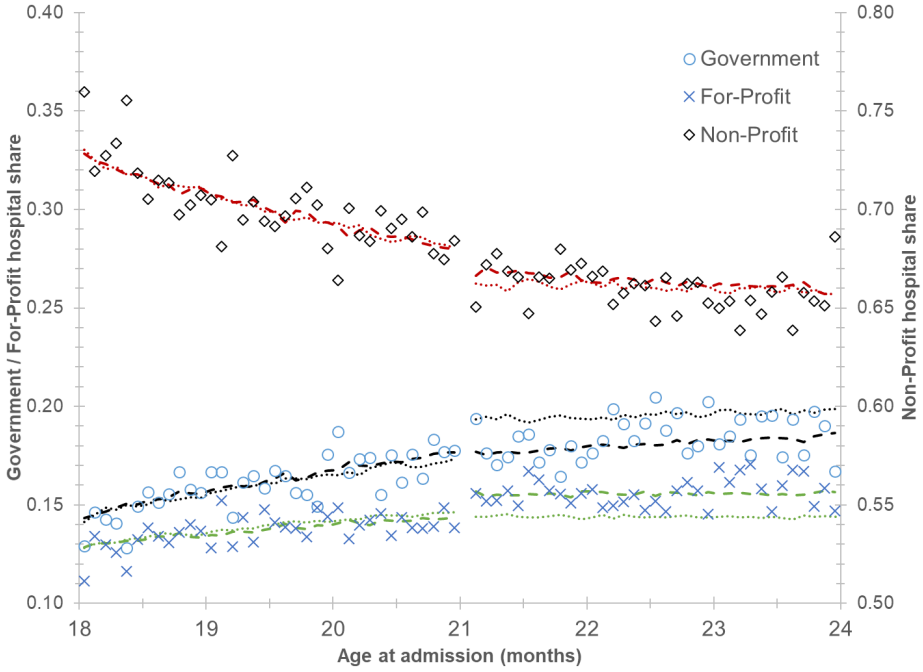
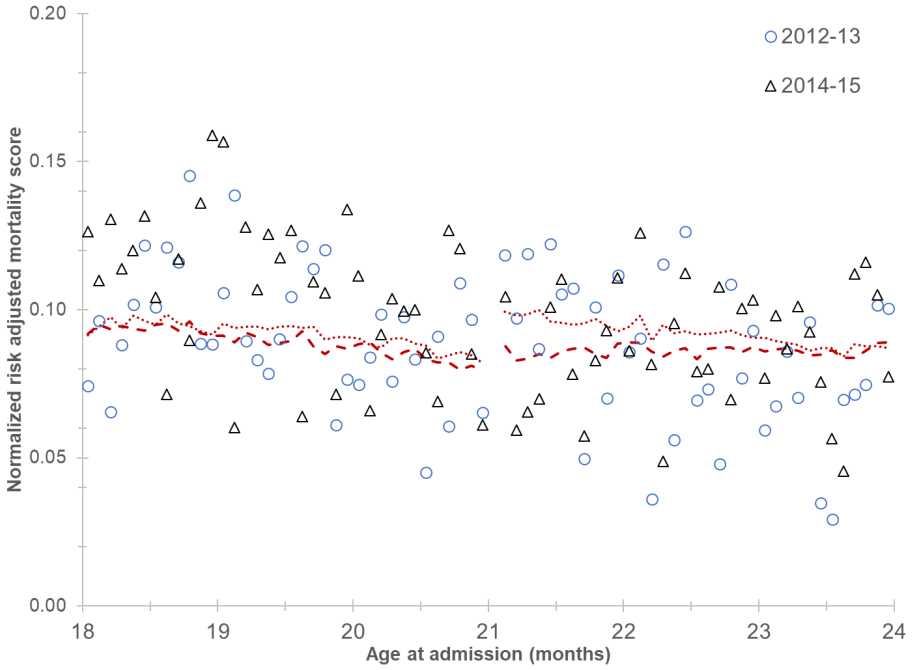


Figure 5: Hospital share by owner type (young)

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

6a: Quality of serving hospital (Young)



6b: Quality of serving hospital (Elderly)

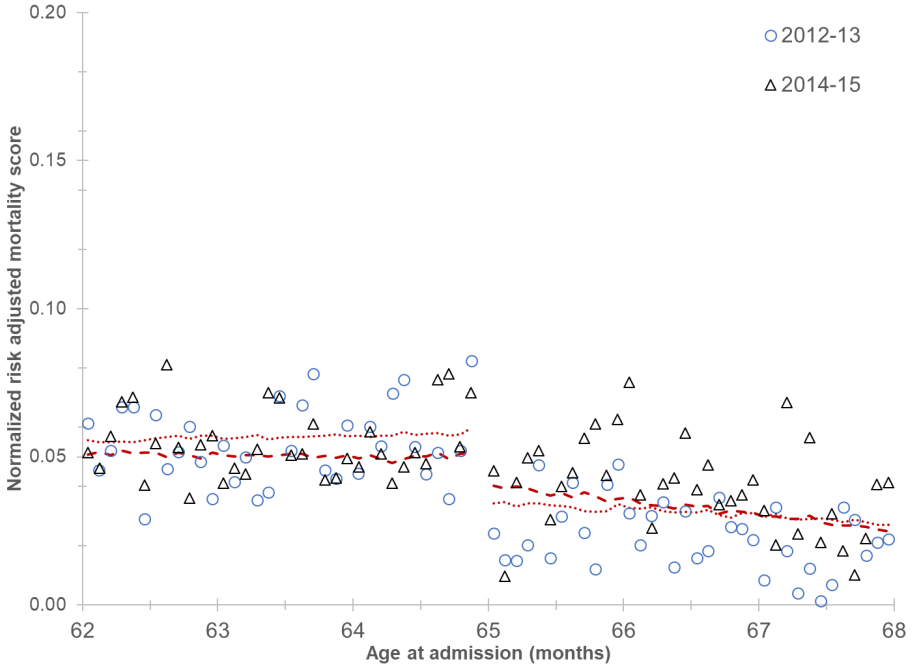
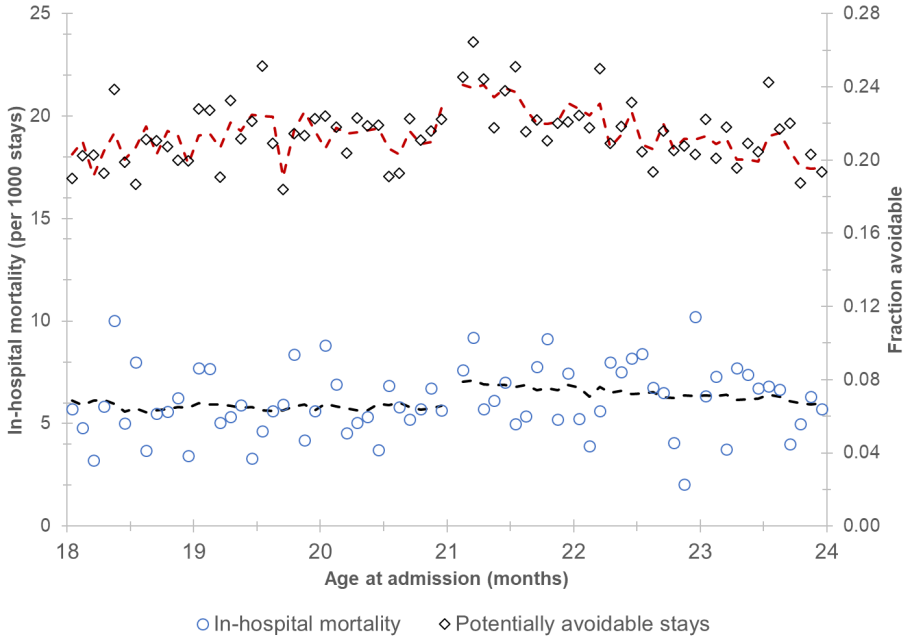


Figure 6: Quality of serving hospital (mortality score)

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

7a: Health Outcomes, 2012-13



7b: Health Outcomes, 2014-15

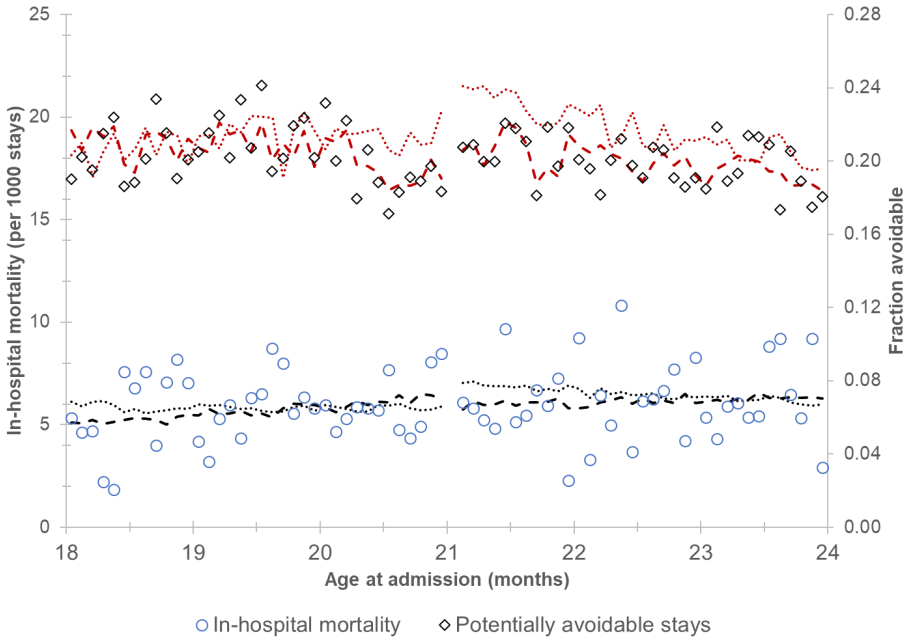
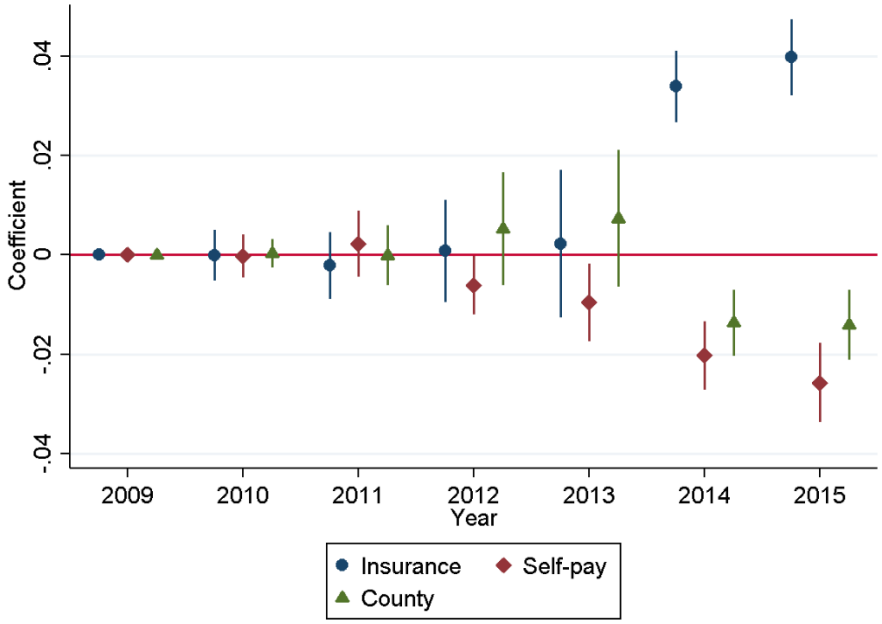


Figure 7: Health outcomes for the young

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

8a: Insurance coverage



8b: Hospital choice



Figure 8: Select evidence from sample of all non-elderly adults

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

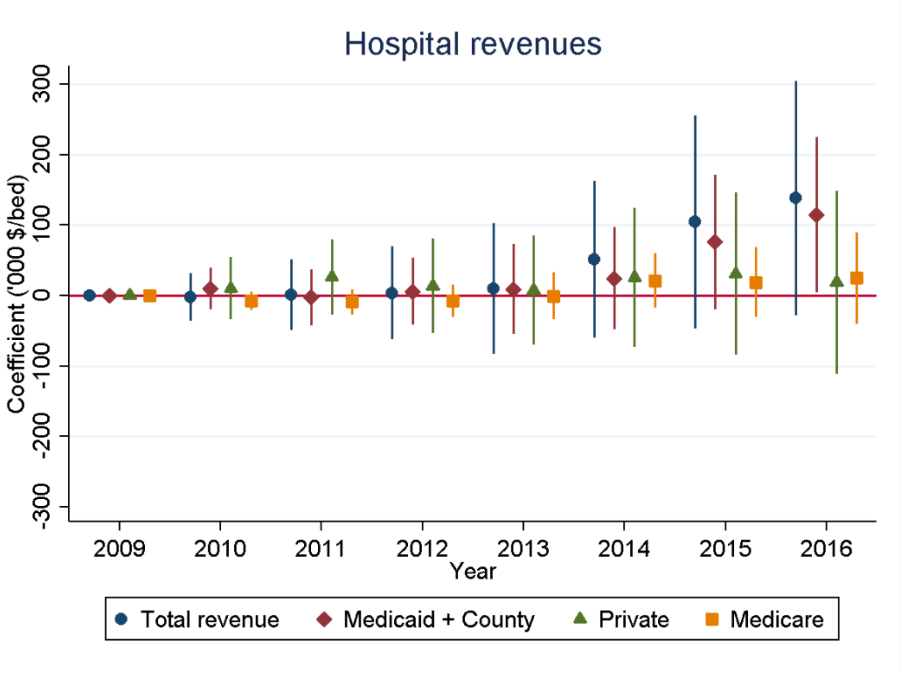


Figure 9: Hospital finances

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

Table 1: Summary Statistics

Panel A: Regression discontinuity sample

	Hospital stays				*All ER arrivals*			
	Ages 18.0 - 23.9		Ages 62.0 - 67.9		Ages 18.0 - 23.9		Ages 62.0 - 67.9	
	2012-13	2014-15	2012-13	2014-15	2012-13	2014-15	2012-13	2014-15
All observations	157,226	147,107	554,522	577,663	1,885,135	2,071,154	1,262,901	1,463,335
Admitted through ER	107,034	101,928	343,256	367,418	107,034	101,928	343,256	367,418
Medicaid	0.34	0.50	0.13	0.17	0.29	0.05	0.12	0.19
Uninsured	0.17	0.05	0.05	0.02	0.28	0.15	0.10	0.04
Utilization per 1,000 pop	23	22	141	134	280	311	322	341
Government hospital	0.18	0.17	0.11	0.11	0.17	0.16	0.15	0.15
Non-profit hospital	0.68	0.68	0.73	0.72	0.69	0.69	0.72	0.72
For-profit hospital	0.14	0.15	0.16	0.17	0.14	0.15	0.13	0.13
In-hospital mortality	0.006	0.006	0.027	0.027	0.0008	0.0006	0.0120	0.0110
Potentially avoidable	0.21	0.20	0.21	0.19	0.18	0.15	0.20	0.18

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

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

Note: This table presents descriptive statistics on the samples used in the main analyses of the paper. Panel A and B present statistics for the sample in the regression discontinuity analysis and all non-elderly (21-64) patients in the spatial variation analysis respectively. Both samples begin with the universe of all discharges and use three sample restrictions – 1) Only general acute care hospitals 2) Exclude pregnancy and delivery related cases and 3) Exclude patients with missing or out-of-CA zip codes. Fraction uninsured includes patients coded as self-pay, charity or county indigent coverage. Panel A focuses on cases pertaining to ages 18-23 (both inclusive) or 62-67. ER arrivals includes ER visits and hospital stays that originated in the ER. To calculate utilization, we normalize number of annual stays/ER arrivals by the population in relevant age group obtained from ACS 1 year estimates, hence these are measures of utilization per 1,000 person years. We obtain population estimates for each year in 2012-15 for the young (18-24) and elderly (62-69) and assume that it is uniformly distributed.

Table 2: Insurance coverage

Panel A: Ages 18.0 - 23.9	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Hospital Stays						***All ER arrivals (including those resulting in stays)***					
	Medicaid	Private	Medicare	Insured	County	Self-Pay	Medicaid	Private	Medicare	Insured	County	Self-Pay
d_i	-0.1390***	-0.0083	-0.0025	-0.1498***	0.0851***	0.0647***	-0.1259***	0.0103***	-0.0007	-0.1164***	0.0367***	0.0797***
	(0.0096)	(0.0080)	(0.0024)	(0.0069)	(0.0057)	(0.0063)	(0.0046)	(0.0030)	(0.0010)	(0.0045)	(0.0035)	(0.0043)
$d_i \cdot T_t$	0.1427***	-0.0118	0.0071*	0.1380***	-0.0835***	-0.0545***	0.1021***	-0.0130***	0.0021**	0.0912***	-0.0357***	-0.0555***
	(0.0103)	(0.0098)	(0.0040)	(0.0067)	(0.0059)	(0.0056)	(0.0046)	(0.0034)	(0.0010)	(0.0042)	(0.0034)	(0.0043)
21-23.9 Mean 2012-13	0.27	0.45	0.03	0.76	0.10	0.15	0.23	0.41	0.02	0.65	0.05	0.30
21-23.9 Mean 2014-15	0.50	0.41	0.03	0.94	0.01	0.05	0.42	0.39	0.02	0.83	0.01	0.17
Observations	304,333						3,956,289					
Panel B: Ages 62.0 - 67.9	Medicaid	Private	Medicare	Insured	County	Self-Pay	Medicaid	Private	Medicare	Insured	County	Self-Pay
d_i	0.1173***	0.2701***	-0.4586***	-0.0712***	0.0356***	0.0357***	0.1129***	0.2351***	-0.4511***	-0.1031***	0.0453***	0.0578***
	(0.0060)	(0.0087)	(0.0049)	(0.0024)	(0.0023)	(0.0016)	(0.0059)	(0.0068)	(0.0040)	(0.0038)	(0.0036)	(0.0028)
$d_i \cdot T_t$	0.0763***	-0.0265***	0.0074	0.0572***	-0.0334***	-0.0238***	0.0952***	-0.0186***	0.0053	0.0819***	-0.0416***	-0.0403***
	(0.0047)	(0.0059)	(0.0057)	(0.0025)	(0.0023)	(0.0018)	(0.0048)	(0.0044)	(0.0050)	(0.0037)	(0.0034)	(0.0029)
62-64.9 Mean 2012-13	0.20	0.46	0.25	0.91	0.04	0.05	0.19	0.43	0.22	0.85	0.05	0.10
62-64.9 Mean 2014-15	0.29	0.43	0.26	0.98	0.00	0.02	0.31	0.41	0.23	0.94	0.01	0.05
Observations	1,132,185						2,726,236					

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) patients respectively. The dependent variable is coverage by different insurers or self-pay/county indigent coverage. Private insurance includes coverage for government employees and through workers compensation. The panel on the left pertains to hospital stays while those on the right pertain to ER visits including those resulting in hospital stays. d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 3: Utilization of hospital care

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Ages 18.0 - 23.9		***Hospital stays***			***ER visits***			***Hospital stays (by admission route)***		
		All stays			All ER arrivals			Through ER		Not through ER
	Average	Dynamic	IV	Average	Dynamic	IV	Average	Dynamic	Average	Dynamic
d_s	-0.6058*	-0.6058*		-6.6522***	-6.6522***		0.0615	0.0615	-0.6674***	-0.6674***
	(0.3389)	(0.3395)		(1.6220)	(1.6250)		(0.2847)	(0.2852)	(0.1478)	(0.1481)
$d_s \cdot T_t$	0.2450			0.4303			-0.1281		0.3731*	
	(0.4422)			(2.4771)			(0.3637)		(0.2088)	
$d_s \cdot I(t = 2014)$		0.0545			-2.5874			-0.2085		0.2630
		(0.4600)			(2.6610)			(0.3829)		(0.2207)
$d_s \cdot I(t = 2015)$		0.4356			3.4481			-0.0478		0.4833**
		(0.4590)			(2.3204)			(0.3838)		(0.2172)
Ins_s			4.1814*			65.9539***				
			(2.1771)			(13.3730)				
First stage F-stat			1526.4			5081				
21-23.9 Mean 2012-13	24.7			290.3			17.3		7.4	
21-23.9 Mean 2014-15	23.8			325.6			16.9		6.9	
Panel B: Ages 62.0 - 67.9										
d_s	-18.0538***	-18.0538***		-28.1777***	-28.1777***		-5.7900***	-5.7900***	-12.2638***	-12.2638***
	(1.7540)	(1.7572)		(3.1661)	(3.1718)		(1.0289)	(1.0308)	(0.9886)	(0.9904)
$d_s \cdot T_t$	12.3164***			21.4340***			4.6454***		7.6710***	
	(1.9718)			(3.6159)			(1.2558)		(1.1542)	
$d_s \cdot I(t = 2014)$		10.4222***			16.5047***			3.8512***		6.5710***
		(1.9910)			(3.7244)			(1.3094)		(1.1637)
$d_s \cdot I(t = 2015)$		14.2106***			26.3631***			5.4395***		8.7710***
		(2.0587)			(3.6213)			(1.3274)		(1.1999)
Ins_s			258.2063***			273.4484***				
			(23.3045)			(28.4953)				
First stage F-stat			1913.9			3616.5				
62-64.9 Mean 2012-13	139.3			337.9			88.4		50.9	
62-64.9 Mean 2014-15	131.9			355.2			85.4		46.6	

Note: This table presents regression coefficients obtained by estimating equation 7 on age month-year level cells as described in Section V for the sample of young (Panel A) and elderly (Panel B) patients respectively. The dependent variable is number of stays/ER arrivals per 1,000 person years in California. d_s is an indicator that takes value one if age interval s crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. Ins_s is the share of patients in age-month s with insurance coverage. All models include a full set of year fixed effects. Robust standard errors reported. There are 284 observations in each sample.

Table 4: Hospital share by owner type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Ages 18.0 - 23.9	***Non-profit hospitals***			***For-profit hospitals***			***Government hospitals***		
	Average	Dynamic	IV	Average	Dynamic	IV	Average	Dynamic	IV
d_i	-0.0142**	-0.0142**		-0.0034	-0.0034		0.0176***	0.0176***	
	(0.0058)	(0.0058)		(0.0040)	(0.0040)		(0.0046)	(0.0046)	
$d_i \cdot T_t$	0.0102			0.0128**			-0.0230***		
	(0.0083)			(0.0055)			(0.0069)		
$d_i \cdot I(t = 2014)$		0.0051			0.0145**			-0.0196***	
		(0.0086)			(0.0062)			(0.0072)	
$d_i \cdot I(t = 2015)$		0.0153*			0.0111**			-0.0264***	
		(0.0091)			(0.0056)			(0.0075)	
Ins_i			0.0775**			0.0342			-0.1118***
			(0.0375)			(0.0286)			(0.0329)
21-23.9 Mean 2012-13	0.66			0.14			0.19		
21-23.9 Mean 2014-15	0.66			0.16			0.18		
Uninsured mean			0.59			0.12			0.29
Panel B: Ages 62.0 - 67.9									
d_i	-0.0084**	-0.0084**		-0.0123***	-0.0123***		0.0208***	0.0208***	
	(0.0033)	(0.0033)		(0.0022)	(0.0022)		(0.0033)	(0.0033)	
$d_i \cdot T_t$	-0.0011			0.0107***			-0.0095***		
	(0.0037)			(0.0034)			(0.0027)		
$d_i \cdot I(t = 2014)$		-0.0017			0.0084**			-0.0066**	
		(0.0042)			(0.0035)			(0.0026)	
$d_i \cdot I(t = 2015)$		-0.0005			0.0129***			-0.0124***	
		(0.0038)			(0.0037)			(0.0032)	
Ins_i			0.1721***			0.1679***			-0.3401***
			(0.0518)			(0.0313)			(0.0519)
62-64.9 Mean 2012-13	0.71			0.16			0.13		
62-64.9 Mean 2014-15	0.71			0.17			0.12		
Uninsured mean			0.57			0.12			0.31

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) hospital discharges respectively. The dependent variable is hospital ownership type (non-profit, for-profit or government). d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA. There are 304,333 and 1,132,185 observations in Panels A and B respectively. First stage F-statistics for IV regressions are 115.9 and 120.9 for young and elderly respectively.

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

Panel A: Ages 18.0 - 23.9	***Hospital stays***			***All ER arrivals***		
	Average effect	Dynamic effects	IV	Average effect	Dynamic effects	IV
d_i	0.0136	0.0136		0.0014	0.0014	
	(0.0087)	(0.0087)		(0.0041)	(0.0041)	
$d_i \cdot T_t$	-0.0122			-0.0045		
	(0.0143)			(0.0048)		
$d_i \cdot I(t = 2014)$		-0.0083			-0.0039	
		(0.0162)			(0.0050)	
$d_i \cdot I(t = 2015)$		-0.0162			-0.0050	
		(0.0147)			(0.0051)	
Ins_i			-0.0514			-0.0022
			(0.0595)			(0.0335)
First stage F-stat			102.8			158.6
21-23.9 Mean 2012-13	0.083			0.227		
21-23.9 Mean 2014-15	0.088			0.233		
Uninsured mean			0.181			0.198
Observations	252,918			3,325,479		
Panel B: Ages 62.0 - 67.9						
d_i	0.0208***	0.0208***		0.0140**	0.0140**	
	(0.0079)	(0.0079)		(0.0070)	(0.0070)	
$d_i \cdot T_t$	-0.0128			-0.0053		
	(0.0087)			(0.0056)		
$d_i \cdot I(t = 2014)$		-0.0057			-0.0036	
		(0.0096)			(0.0052)	
$d_i \cdot I(t = 2015)$		-0.0196**			-0.0068	
		(0.0089)			(0.0065)	
Ins_i			-0.2547***			-0.1253**
			(0.0987)			(0.0605)
First stage F-stat			113.3			71.6
62-64.9 Mean 2012-13	0.054			0.155		
62-64.9 Mean 2014-15	0.055			0.165		
Uninsured mean			0.135			0.119
Observations	933,655			2,196,516		

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) respectively. The dependent variable is standardized risk-adjusted hospital mortality score as reported by CMS in 2009. Score is based on 30-day mortality calculated for Medicare patients admitted with Heart attack, Heart Failure or Pneumonia. The panel on the left pertains to hospital stays while those on the right pertain to ER visits including those resulting in hospital stays. d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 6: Health outcomes

Panel A: Ages 18.0 - 23.9	***Hospital stays***						***All ER arrivals***					
	Mortality			Potentially Avoidable stays			Mortality			Potentially Avoidable visits		
	Average effect	Dynamic effects	IV	Average effect	Dynamic effects	IV	Average effect	Dynamic effects	IV	Average effect	Dynamic effects	IV
d_i	0.0011	0.0011		0.0143**	0.0143**		0.0001	0.0001		0.0026*	0.0026*	
	(0.0009)	(0.0009)		(0.0060)	(0.0060)		(0.0001)	(0.0001)		(0.0016)	(0.0016)	
$d_i \cdot T_t$	-0.0015			-0.0036			-0.0001			-0.0022		
	(0.0013)			(0.0087)			(0.0001)			(0.0021)		
$d_i \cdot I(t = 2014)$		-0.0017			-0.0106			-0.0001			-0.0042*	
		(0.0014)			(0.0094)			(0.0001)			(0.0023)	
$d_i \cdot I(t = 2015)$		-0.0013			0.0038			-0.0001			-0.0003	
		(0.0014)			(0.0097)			(0.0001)			(0.0023)	
Ins_i			-0.0072			-0.0766*			-0.0008			-0.0097
			(0.0062)			(0.0391)			(0.0008)			(0.0138)
First stage F-stat			115. 9			123.6			194.5			219.1
21-23.9 Mean 2012-13	0.006			0.218			0.001			0.171		
21-23.9 Mean 2014-15	0.006			0.199			0.001			0.145		
Uninsured mean			0.005			0.226			0.001			0.160
Observations	304,333			129,313			3,956,289			2,052,306		
Panel B: Ages 62.0 - 67.9												
d_i	0.0008	0.0008		0.0066**	0.0066**		0.0005	0.0005		-0.0011	-0.0011	
	(0.0008)	(0.0008)		(0.0025)	(0.0025)		(0.0004)	(0.0004)		(0.0018)	(0.0018)	
$d_i \cdot T_t$	-0.0009			-0.0044			-0.0009*			0.0012		
	(0.0011)			(0.0039)			(0.0005)			(0.0025)		
$d_i \cdot I(t = 2014)$		0.0005			-0.0062			-0.0004			0.0000	
		(0.0012)			(0.0044)			(0.0006)			(0.0028)	
$d_i \cdot I(t = 2015)$		-0.0023*			-0.0026			-0.0014***			0.0024	
		(0.0012)			(0.0041)			(0.0005)			(0.0025)	
Ins_i			-0.0124			-0.0945***			-0.0031			0.0041
			(0.0111)			(0.0290)			(0.0038)			(0.0156)
First stage F-stat			120.9			118.5			71.9			91.4
62-64.9 Mean 2012-13	0.026			0.207			0.011			0.201		
62-64.9 Mean 2014-15	0.026			0.188			0.010			0.177		
Uninsured mean			0.025			0.194			0.010			0.195
Observations	1,132,185			617,077			2,726,236			1,680,320		

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) respectively. The outcome variables are in-hospital mortality and share of potentially avoidable hospital stays/visits coded using ICD 9 diagnoses codes. The panel on the left pertains to hospital stays while those on the right pertain to ER visits including those resulting in hospital stays. d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

Table 7: Additional evidence and hospital revenue

Panel A: Non-elderly sample (aged 21-64)

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

Panel B: Hospital finances

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

Note: This table presents regression coefficients obtained by estimating equation $5a$ on case level data for the entire sample of non-elderly adults (Panel A) and equation $6a$ on hospital-level data (Panel B). All revenue variables are expressed in thousands of 2016 $. In both panels we present results obtained using linear and non-parametric specifications. $Unins_{j08}$ and $Unins_{h08}$ denote share of uninsured patients for the j^{th} HSA and hospital respectively in 2008. d_{j08} and d_{h08} are indicators that takes value one if unit j has un-insurance level in top third of the distribution. T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. Models include a full set of HSA (Panel A)/Hospital (Panel B) and year fixed effects. Standard errors are clustered by respective panel unit. Dependent variable mean values computed pre-ACA i.e. over 2009-13. Mean un-insurance share is 0.12 and 0.11 respectively across HSAs and hospitals.

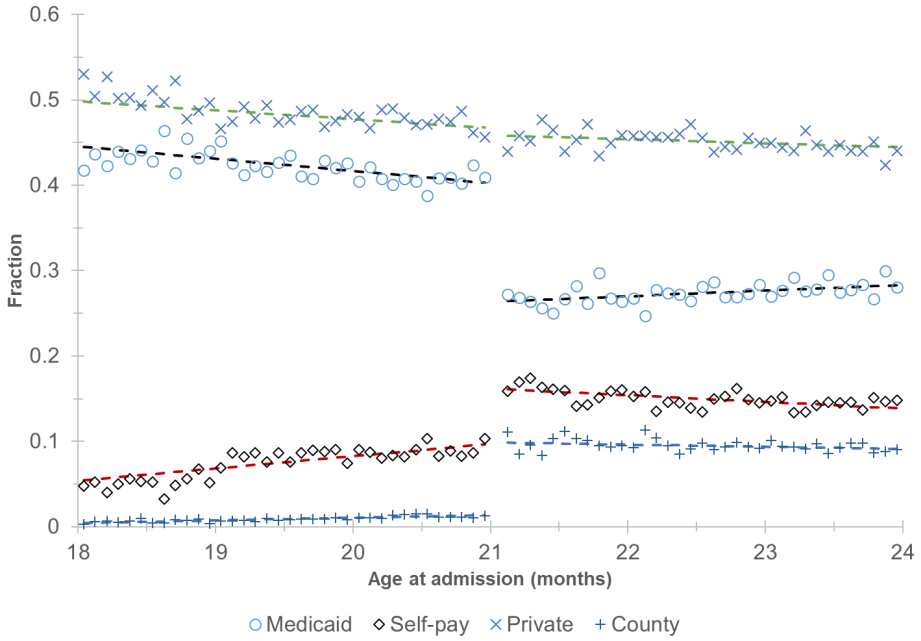
Table 8: Robustness and falsification check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quadratic specification						*2010-13 i.e. "Placebo" period*					
Panel A: Ages 18.0 - 23.9	Medicaid	Private	Medicare	Insured	County	Self-Pay	Medicaid	Private	Medicare	Insured	County	Self-Pay
d_i	-0.1423***	-0.0163	-0.0052*	-0.1638***	0.0846***	0.0792***	-0.1599***	0.0078	0.0024	-0.1497***	0.0772***	0.0725***
	(0.0109)	(0.0102)	(0.0030)	(0.0091)	(0.0067)	(0.0081)	(0.0083)	(0.0083)	(0.0028)	(0.0060)	(0.0049)	(0.0050)
$d_i \cdot T_t$	0.1498***	-0.0108	0.0094*	0.1484***	-0.0822***	-0.0662***	0.0212**	-0.0155	-0.0050	0.0007	0.0078*	-0.0085
	(0.0128)	(0.0129)	(0.0048)	(0.0087)	(0.0069)	(0.0073)	(0.0090)	(0.0098)	(0.0035)	(0.0075)	(0.0044)	(0.0070)
21-23.9 Mean Pre	0.27	0.45	0.03	0.76	0.10	0.15	0.28	0.43	0.04	0.74	0.08	0.18
21-23.9 Mean Post	0.50	0.41	0.03	0.94	0.01	0.05	0.27	0.45	0.03	0.76	0.10	0.15
Observations	304,333						318,302					
Panel B: Ages 62.0 - 67.9	Medicaid	Private	Medicare	Insured	County	Self-Pay	Medicaid	Private	Medicare	Insured	County	Self-Pay
d_i	0.1104***	0.2674***	-0.4487***	-0.0709***	0.0343***	0.0366***	0.1086***	0.2831***	-0.4545***	-0.0628***	0.0279***	0.0350***
	(0.0066)	(0.0091)	(0.0064)	(0.0029)	(0.0025)	(0.0022)	(0.0072)	(0.0116)	(0.0059)	(0.0022)	(0.0021)	(0.0015)
$d_i \cdot T_t$	0.0802***	-0.0351***	0.0112	0.0563***	-0.0322***	-0.0241***	0.0087*	-0.0133**	-0.0038	-0.0084***	0.0077***	0.0007
	(0.0070)	(0.0079)	(0.0083)	(0.0031)	(0.0026)	(0.0024)	(0.0053)	(0.0064)	(0.0061)	(0.0019)	(0.0014)	(0.0015)
62-64.9 Mean Pre	0.20	0.46	0.25	0.91	0.04	0.05	0.19	0.49	0.24	0.93	0.03	0.04
62-64.9 Mean Post	0.29	0.43	0.26	0.98	0.00	0.02	0.20	0.46	0.25	0.91	0.04	0.05
Observations	1,132,185						1,100,435					

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) patients respectively. The dependent variable is coverage by different insurers or self-pay/county coverage. Private insurance includes coverage for government employees and through workers compensation. All results pertain to the sample of hospital stays only. The panel on the left is a robustness exercise checking for mis-specification bias by using a quadratic specification instead of a linear one. The panel on the right is a falsification check by estimating effects on insurance coverage over the period 2010-13 i.e. entirely before the implementation of the insurance expansions, but using the linear specification as in Table 2. d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 (left) or 2012 (right). All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA.

APPENDIX A: FIGURES

A1a: Insurance coverage for the young (2012-13)



A1b: Insurance coverage for the young (2014-15)

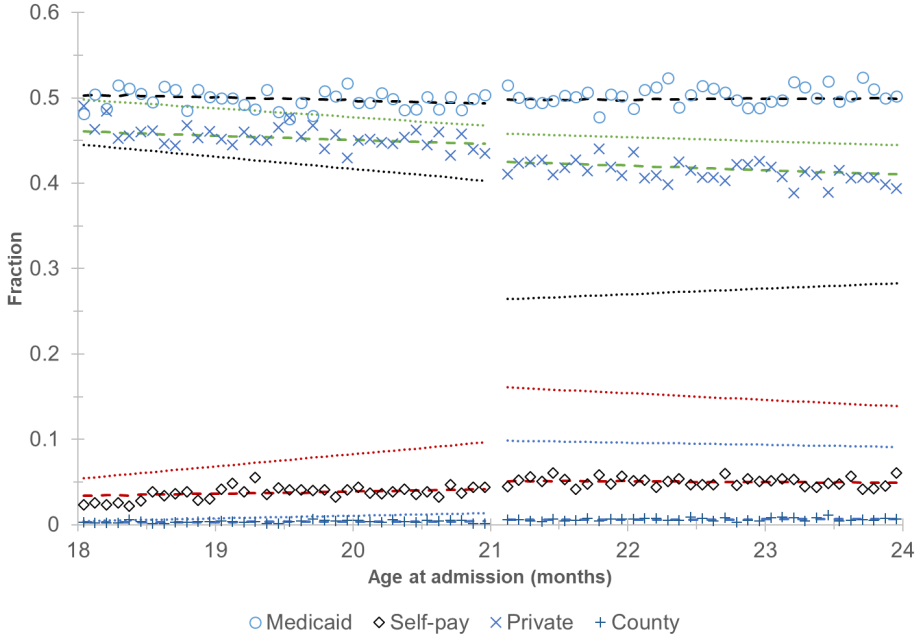


Figure A- 1: Insurance coverage for the young (details)

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

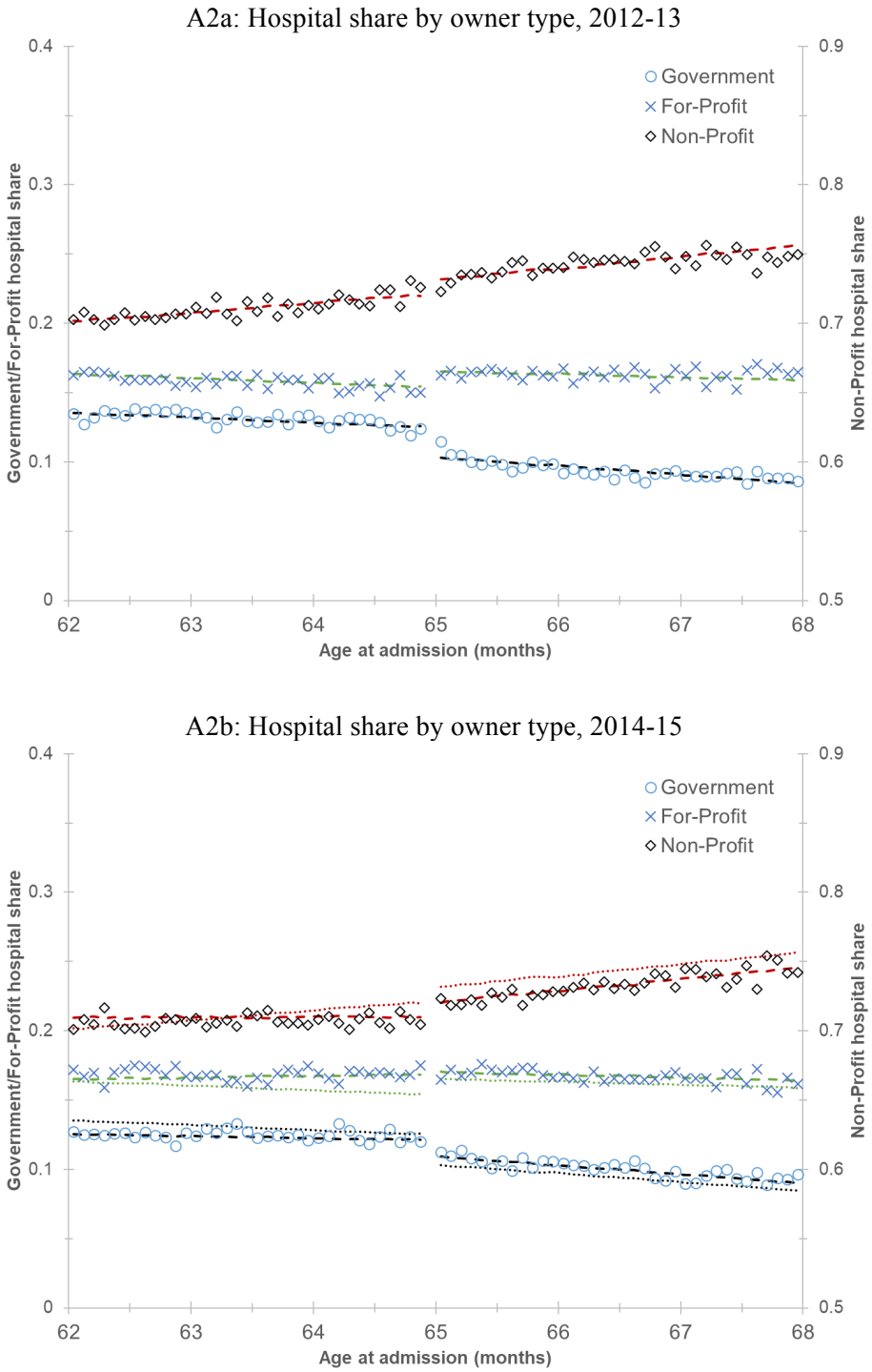
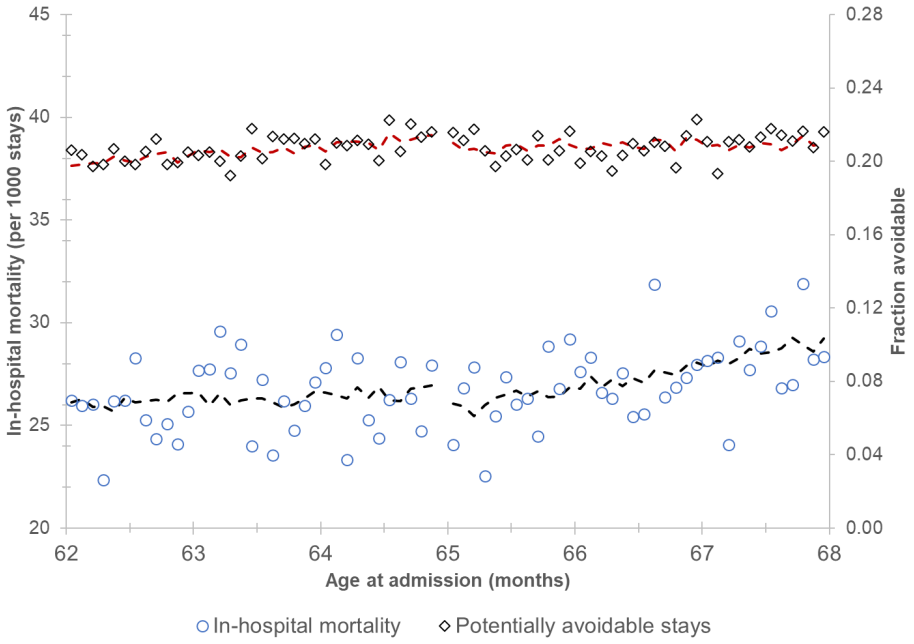


Figure A- 2: Hospital share by owner type (elderly)

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

A3a: Health outcomes, 2012-13



A3b: Health outcomes, 2014-15

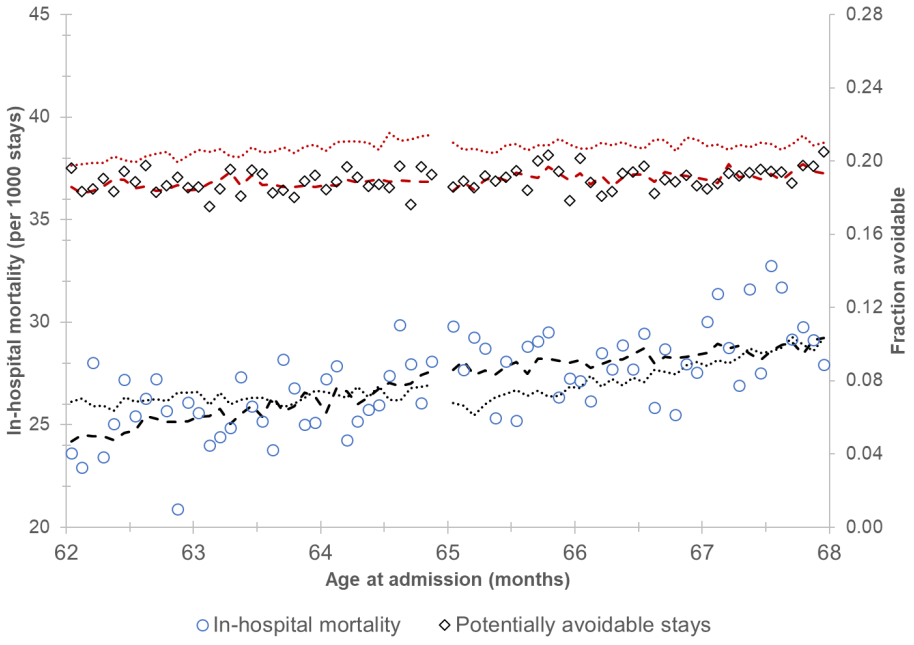


Figure A- 3: Health outcomes for the elderly

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

APPENDIX A: TABLES

Table A- 1: Number of hospital stays and ER arrivals by age

	Hospital Stays			ER arrivals		
Age at admission	**2010-11**	**2012-13**	**2014-15**	**2010-11**	**2012-13**	**2014-15**
0-4	193,509	172,122	159,230			
5-9	70,128	68,932	68,594			
10-14	71,061	68,763	68,706			
15-17	64,275	60,553	58,693			
18-20	*81,164*	*75,107*	*68,795*			
21-23	*83,149*	*85,020*	*80,904*	*868,205*	*940,006*	*1,049,616*
24-29	178,114	178,823	180,443	1,653,682	1,786,842	2,072,305
30-34	167,276	168,499	168,976	1,232,110	1,387,343	1,568,787
35-39	194,674	184,238	185,655	1,113,502	1,209,726	1,392,602
40-44	268,467	248,943	230,913	1,184,808	1,246,949	1,331,972
45-49	361,555	324,560	300,495	1,242,407	1,286,799	1,384,925
50-54	431,589	415,826	403,937	1,175,836	1,309,855	1,459,791
55-61	640,199	644,950	664,321	1,274,670	1,493,889	1,753,964
62-64	*282,797*	*279,463*	*289,121*	*431,204*	*500,248*	*591,383*
65-67	*273,018*	*285,557*	*299,041*			
68-74	609,426	608,765	622,891			
75-79	436,236	416,979	410,007			
80-85	439,070	406,646	381,712			
86-90	416,811	393,337	371,704			
Total	5,262,518	5,087,083	5,014,138	10,176,424	11,161,657	12,605,345

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Ages 18.0 - 23.9	***Non-profit hospitals***			***For-profit hospitals***			***Government hospitals***		
	Average	Dynamic	IV	Average	Dynamic	IV	Average	Dynamic	IV
d_i	-0.0059***	-0.0059***		-0.0025*	-0.0025*		0.0084***	0.0084***	
	(0.0019)	(0.0019)		(0.0014)	(0.0014)		(0.0021)	(0.0021)	
$d_i \cdot T_t$	0.0090***			0.0023			-0.0113***		
	(0.0023)			(0.0018)			(0.0023)		
$d_i \cdot I(t = 2014)$		0.0070***			0.0032*			-0.0102***	
		(0.0024)			(0.0018)			(0.0024)	
$d_i \cdot I(t = 2015)$		0.0109***			0.0014			-0.0123***	
		(0.0024)			(0.0020)			(0.0024)	
Ins_i			0.0450***			0.0268**			-0.0717***
			(0.0170)			(0.0128)			(0.0191)
21-23.9 Mean 2012-13	0.68			0.14			0.18		
21-23.9 Mean 2014-15	0.69			0.15			0.16		
Uninsured mean			0.63			0.16			0.21
Panel B: Ages 62.0 - 67.9									
d_i	-0.0215***	-0.0215***		-0.0065***	-0.0065***		0.0281***	0.0281***	
	(0.0031)	(0.0031)		(0.0019)	(0.0019)		(0.0035)	(0.0035)	
$d_i \cdot T_t$	0.0117***			0.0057***			-0.0174***		
	(0.0027)			(0.0020)			(0.0024)		
$d_i \cdot I(t = 2014)$		0.0080***			0.0050**			-0.0130***	
		(0.0028)			(0.0023)			(0.0021)	
$d_i \cdot I(t = 2015)$		0.0152***			0.0064***			-0.0216***	
		(0.0032)			(0.0020)			(0.0029)	
Ins_i			0.2375***			0.0553***			-0.2929***
			(0.0316)			(0.0179)			(0.0329)
62-64.9 Mean 2012-13	0.70			0.13			0.18		
62-64.9 Mean 2014-15	0.70			0.14			0.16		
Uninsured mean			0.54			0.14			0.32

Note: This table presents regression coefficients obtained by estimating equation 2 on case level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) ER arrivals respectively. The dependent variable is hospital ownership type (non-profit, for-profit or government). d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. All models include a full set of hospital service area (HSA) and year fixed effects. Standard errors are clustered by HSA. There are 3,956,289 and 2,726,236 observations in Panels A and B respectively. First stage F-statistics for IV regressions are 195 and 72 for young and elderly respectively.

Table A- 3: RD analysis with 2 year bandwidth (hospital stays only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Insurance coverage					***Utilization***	***Hospital choice***				***Outcomes***	
Panel A: 19.0 - 22.9	Medicaid	Private	Insured	County	Self-Pay	Stays	Govt.	Non-Profit	For-Profit	RA Mort.	Mortality	PAH
d_i	-0.1402***	-0.0128	-0.1568***	0.0851***	0.0717***	-0.8714**	0.0191***	-0.0180***	-0.0010	0.0201*	0.0011	0.0197***
	(0.0099)	(0.0087)	(0.0077)	(0.0062)	(0.0068)	(0.4195)	(0.0053)	(0.0069)	(0.0042)	(0.0105)	(0.0011)	(0.0065)
$d_i \cdot T_t$	0.1453***	-0.0110	0.1421***	-0.0831***	-0.0590***	0.5104	-0.0241***	0.0105	0.0136**	-0.0173	-0.0017	-0.0043
	(0.0112)	(0.0109)	(0.0075)	(0.0063)	(0.0061)	(0.5412)	(0.0079)	(0.0097)	(0.0060)	(0.0180)	(0.0016)	(0.0095)
Ins_i (2SLS)						5.6779**	-0.1132***	0.1135***	-0.0002	-0.1182*	-0.0067	-0.1173***
						(2.5323)	(0.0325)	(0.0430)	(0.0275)	(0.0614)	(0.0074)	(0.0382)
21-23.9 Mean 2012-13	0.27	0.45	0.75	0.10	0.15	24	0.19	0.66	0.14	0.09	0.01	0.22
21-22.9 Mean 2014-15	0.50	0.42	0.94	0.01	0.05	23	0.18	0.66	0.15	0.09	0.01	0.20
Observations	203,166					188	203,166			170,156	203,166	85,879
Panel B: 63.0 - 66.9												
d_i	0.1138***	0.2690***	-0.0718***	0.0352***	0.0366***	-17.2270***	0.0187***	-0.0052	-0.0135***	0.0220**	0.0004	0.0059*
	(0.0062)	(0.0088)	(0.0026)	(0.0024)	(0.0018)	(2.3131)	(0.0032)	(0.0036)	(0.0025)	(0.0089)	(0.0010)	(0.0031)
$d_i \cdot T_t$	0.0784***	-0.0303***	0.0578***	-0.0331***	-0.0247***	10.3404***	-0.0089***	-0.0051	0.0140***	-0.0126	-0.0008	-0.0033
	(0.0054)	(0.0065)	(0.0027)	(0.0024)	(0.0020)	(2.5293)	(0.0030)	(0.0044)	(0.0037)	(0.0104)	(0.0015)	(0.0047)
Ins_i (2SLS)						247.9842***	-0.2907***	0.1144**	0.1763***	-0.2744**	-0.0014	-0.0840**
						(30.0982)	(0.0486)	(0.0548)	(0.0341)	(0.1146)	(0.0136)	(0.0356)
63-64.9 Mean 2012-13	0.19	0.46	0.92	0.04	0.05	140	0.13	0.71	0.16	0.05	0.03	0.21
63-64.9 Mean 2014-15	0.28	0.44	0.98	0.00	0.02	131	0.13	0.71	0.17	0.05	0.03	0.19
Observations	755,040					188	755,040			622,498	755,040	411,484

Note: This table presents regression coefficients obtained by estimating equations 2,3 and 4 on case level data and equation 7 on age-month-year level data as described in Section V for the sample of young (Panel A) and elderly (Panel B) hospital stays respectively. The sample for this analysis is constructed using only a 2 year bandwidth on either side of the age thresholds. This table provides equivalent estimates to the main estimates on insurance coverage (Table 2), utilization (Table 3), hospital choice (Table 4,

Table **5**) and health outcomes (Table 6), but using a different RD bandwidth. d_i is an indicator that takes value one if patient i crosses the relevant age threshold from below (young) or above (old). T_t is an indicator that takes value one in the period post the implementation of the insurance expansion i.e. 2014 onwards. Ins_i is an indicator for the individual having insurance coverage. Case level models include a full set of hospital service area (HSA) and year fixed effects and standard errors are clustered by HSA, whereas collapsed regressions include year fixed effects only.