EFFECT OF THE AFFORDABLE CARE ACT ON UTILIZATION OF EMERGENCY AND PRIMARY CARE

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A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Health Policy and Management in the Gillings School of Global Public Health.

Chapel Hill
2019

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ABSTRACT

Paul Ronald Shafer: Effect of the Affordable Care Act
on Utilization of Emergency and Primary Care
(Under the direction of Justin Trogdon)

The Affordable Care Act (ACA) has considerably reduced the uninsured rate nationally through availability of guaranteed issue private plans (Marketplace) and Medicaid expansion. However, expanding access to health insurance coverage may not be a sufficient incentive for consumers to change their usual setting for care, reduce avoidable use of emergency departments (ED), or increase use of preventive care. One of the core arguments for expansion has been that individuals without coverage may forego preventive care, delay treatment, and subsequently overutilize the ED—leading to worse health outcomes and higher long-run health expenditures. The objective of this dissertation is to investigate the effect of the ACA on substitution between ED and primary care among the newly insured (aim 1), potential delayed effects of coverage gains on avoidable use of the ED (aim 2), and whether high deductibles serve as a barrier to the use of no-cost preventive services (aim 3).

Aim 1 uses the linkage between the 2012 National Health Interview Survey and 2013 and 2014 Medical Expenditure Panel Survey to quantify substitution between the ED and primary care settings using linear and multinomial logistic regression models. Aim 2 uses the Healthcare Cost and Utilization Project State Inpatient and Emergency Department Databases for 2008 to 2016 to identify the effect trajectory of coverage gains on avoidable ED use using county-level fixed effects and spatial regression models. Aim 3 uses insurance claims from IBM Health®

MarketScan® for 2008 through 2016 to estimate the effect of high deductible health plan enrollment on use of high-value preventive services using difference-in-differences models.

This project will provide new understanding of how consumers respond to coverage gains at both the individual and population level with a focus on emergency and primary care services—two ends of the health care spectrum that can often be substitutable, particularly for the newly insured. It will address if and when consumers substitute towards a more appropriate setting for care and also how eliminating cost sharing affects use of preventive services. These insights can be used to refine benefit design, consumer education, and expectations about the costs and health benefits of future reforms.

To my Ellie

ACKNOWLEDGEMENTS

It is hard to know where to start, there are so many people that made this dissertation and the dream of doing a PhD possible. I cannot thank my committee enough, a wonderful group of thoughtful researchers who were so giving of their expertise. They helped me refine and execute what was an ambitious dissertation project to get through in two years. Justin, thank you for being an encouraging and level-headed guide throughout this journey. You always pushed me to think about whether I was trying to do too much but never tried to talk me out of pushing my boundaries. Sally, thank you for always asking the tough questions and providing lots of wisdom and counsel about the job market. Stacie, thank you for being one of my favorite people and a model for the type of researcher, colleague, and person that I hope to be. Lindsay, thank you for sharing your time and positivity with me from afar. Two of these aims built directly upon your work, which made it so great to have you involved. Tim, thank you for the insights into life in the emergency department, both while shadowing and in framing this work.

Morris, thank you for your leadership of the PhD program and now the department, always going out of your way to help advise, promote, and just be there for us. I can still remember the excitement of seeing a campus number calling on a Sunday morning in January 2015 to let me know that I was admitted to the program, thank you for the chance to fulfill this dream. Marisa, thank you for picking up the charge of leading the PhD program and working with me both as a supervisor and guide with my teaching. Stephanie, thank you for your kindness and being a model of productivity. I have really enjoyed working with you on and off for the past few years.

To my HPM cohort, thank you so much for your friendship and support. It has been so fun to learn and grow alongside you for the past four years. To my fellow scholars in the Robert Wood Johnson Foundation Health Policy Research Scholars program, thank for your friendship and inspiration. You are all such amazing people doing important work on so many topics that matter to health and equity, it is going to be wonderful to look back later in life to see the collective impact that we have had on our world.

It is not a stretch at all to say that I would not be in this position and certainly not as well-prepared for a transition into faculty life and independent scholarship without my time at RTI. Kevin Davis, Brett Loomis, Jennifer Duke, Annice Kim, Matthew Farrelly, and others, thank you for giving me the chance to learn and grow as a researcher. You saw such potential in me and gave me so many opportunities to realize it. I never thought that I would do half of what I ended up doing in those early years of my career and I am so much better for it now. Stu Allen and Ken Snowden, thank you for taking a chance on a very motivated but high-risk applicant to UNC Greensboro nearly a decade ago. Chuck Courtemanche, thank you for showing me behind the curtain a bit of being a health economist and junior faculty member. You helped me believe that I could actually do the kind of work that I wanted to do as a career.

And of course, thank you to my parents and Jenni. We have had our ups and downs but I wouldn’t be the person I am without you, and I cannot thank you enough for your support in pursuing this dream. To my Ellie, thank you for being the smartest, kindest, and most tenacious little girl I know. You bring so much joy to my life and I will always love you so very much. I can’t wait to see where your interests and life take you.

I would also like to thank the Robert Wood Johnson Foundation for creating the Health Policy Research Scholars program, which has funded me and this work for the past three years.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACA	Patient Protection and Affordable Care Act of 2010
ACSC	ambulatory care sensitive condition
AFDC	Aid to Families with Dependent Children
AHRF	Area Health Resources Files
AHRQ	Agency for Healthcare Research and Quality
aOR	adjusted odds ratio
CBP	County Business Patterns
CHIP	Children's Health Insurance Program
CI	confidence interval
CPS	Current Population Survey
CPT	Current Procedural Terminology
DID	difference-in-differences
ED	emergency department
EDA	Emergency Department Algorithm
EPO	exclusive provider organization
FPL	federal poverty level
FQHC	federally qualified health center
HCPCS	Healthcare Common Procedure Coding System
HCUP	Healthcare Cost and Utilization Project
HDHP	high deductible health plan
HMO	health maintenance organization
HRSA	Health Resources and Services Administration

ICD-9	International Classification of Diseases, Ninth Revision
ICD-10	International Classification of Diseases, Tenth Revision
MCO	managed care organization
MEPS	Medical Expenditure Panel Survey
MSA	metropolitan statistical area
NAICS	North American Industry Classification System
NEPCT	non-emergent or emergent but primary care treatable condition
NHIS	National Health Interview Survey
NYU	New York University
OHP	Oregon Health Plan
OT	occupational therapy
PC	primary care
POS	point of service
PPO	preferred provider organization
PT	physical therapy
PQI	Prevention Quality Indicators
SAHIE	Small Area Health Insurance Estimates
SDID	semi-parametric difference-in-differences
SE	standard error
SEDD	State Emergency Department Databases
SID	State Inpatient Databases
SIPP	Survey of Income and Program Participation
VBID	value-based insurance design

CHAPTER 1: INTRODUCTION

Affordable Care Act

The Patient Protection and Affordable Care Act of 2010 was passed with the goal of expanding access to health insurance to the uninsured in the United States through an expansion of state Medicaid eligibility and subsidized individual coverage offered through state insurance exchanges. The ACA originally intended for the expansion of Medicaid coverage to be mandatory across all states, expanding coverage to all individuals and families at or below 138% of the federal poverty level regardless of meeting prior categorical eligibility requirements. However, a 2012 Supreme Court decision made the Medicaid expansion optional and 14 states have chosen not to adopt it as of February 2019 (Kaiser Family Foundation, 2019a; Supreme Court of the United States, 2012). For the first three years of Medicaid expansion under the ACA (2014 through 2016), the federal government covered 100% of the costs for newly eligible enrollees before a gradual decline to its long-term contribution of 90% in 2020 and thereafter (U.S. Department of Health and Human Services, 2011). This is in contrast to the prevailing Federal Medical Assistance Percentage, the federal contribution to Medicaid spending based on state average per capita income relative to the national average, that ranged from a minimum of a 50% up to a high of 73% (for Mississippi) in fiscal year 2014 (Kaiser Family Foundation, n.d.). As a result of the Supreme Court decision, there is an eligibility gap in those states that did not expand Medicaid in which individuals can make too much to qualify for Medicaid coverage (or never qualify regardless of income, in the case of childless adults in many states) but not enough to qualify for subsidized private coverage in the Marketplace (Kaiser Family Foundation, 2018a, 2019b), as the collection of state health insurance exchanges is commonly known. Those in the coverage gap have little hope of obtaining affordable coverage unless employer-based coverage is or becomes an option.

Under the ACA, states were given the flexibility to setup insurance exchanges in one of several forms—a state-based marketplace (fully designed and implemented by the state), state-based marketplace–federal platform or state-federal partnership marketplace (all or most functions performed by the state except for the enrollment platform), or a federally-facilitated marketplace (completely managed by the federal government). In the Marketplace, individuals between 100% and 400% of the federal poverty are eligible for subsidies in the form of advanced premium tax credits to help them purchase private insurance coverage from participating insurers in their state. Many who have qualified for subsidized individual coverage through the exchange are still in danger of delaying or refusing to seek care because of high deductibles that require enrollees to pay for the first several thousands of dollars' worth of services received each year. The in-network deductible and out-of-pocket maximum were capped at $6,350 for self-only coverage and $12,700 for family coverage for the 2014 plan year (Kaiser Family Foundation, 2015a), increasing slightly each year thereafter. These caps are doubled for out-of-network coverage, an important factor given the prevalence of so-called narrow network plans, or those plans with more restrictive provider networks that qualify for in-network cost sharing, in the Marketplace (Sen, Chen, Cox, & Epstein, 2017; Zhu, Zhang, & Polsky, 2017). Both cost sharing and provider availability have implications for how individuals will use health care after gaining coverage.

Expectations of ACA effects on health care use

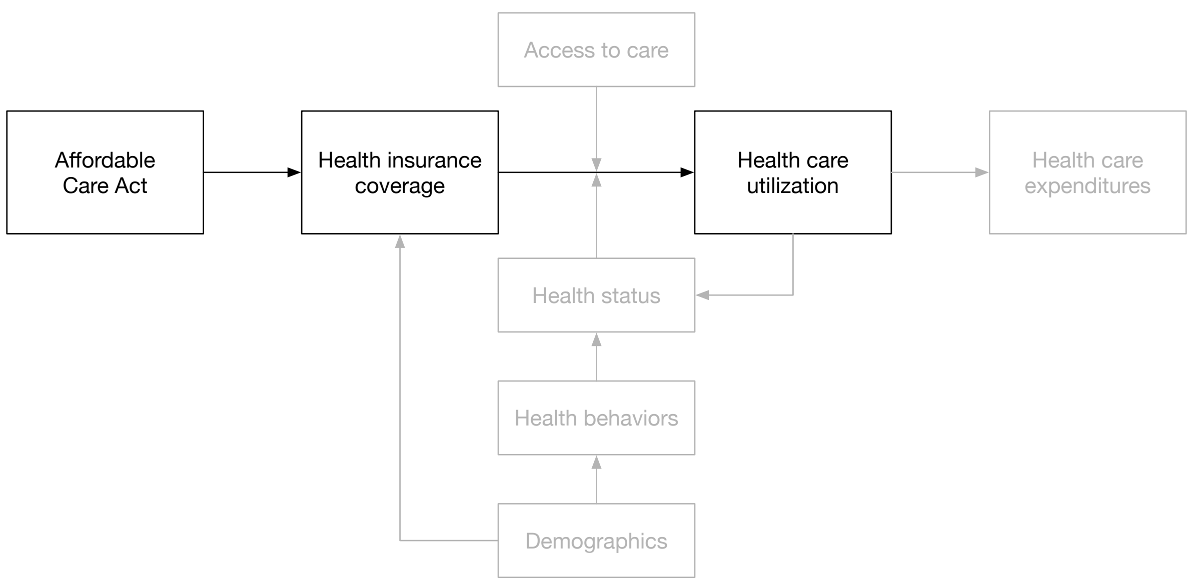
Utilization of hospital emergency departments as a safety net provider for non-emergent care by the uninsured was often cited as a problem by hospitals, providers, and public health researchers (American College of Emergency Physicians, 2004; Derlet & Richards, 2008; National

Association of Public Hospitals and Health Systems, 2013). Overutilization of the ED has implications not only for hospitals and their budgets, but for other patients as well. ED crowding has been linked to quality of care measures, including timeliness of and satisfaction with care provided, as well as health outcomes (Bernstein et al., 2009; Mullins & Pines, 2014; Stang, Crotts, Johnson, Hartling, & Guttmann, 2015). There is widespread disagreement about the size of the problem and focusing on ED use for non-emergent or preventable conditions as a problem rather than only a symptom of a larger problem (e.g., unmet social needs, lack of access) may be misplaced (Uscher-Pines, Pines, Kellermann, Gillen, & Mehrotra, 2013).

The ACA is the most fundamental national reform of the health insurance system since the passage of Medicare and Medicaid as amendments to the Social Security Act in 1965. As such, there was little empirical evidence from which to draw conclusions about the potential impact of the ACA on health care use. Prior studies have examined the impact of earlier state-based expansions of Medicaid on health care utilization for distinct services and provider types. Providers are an important component of any model of coverage expansion as physicians may respond to changes in service volume and reimbursement rates, a concept referred to as induced demand. Empirical evidence of provider induced demand exists for both the U.S. and abroad (Janet Currie & Gruber, 2001; Gosden et al., 2000; van Dijk et al., 2013). We will largely ignore the potential for induced demand as a component of the effects of coverage expansion on health care use, as the literature does, but it is an important factor to keep in mind.

The mechanism of interest in this dissertation—changes in health insurance coverage created by the passage and implementation of the Affordable Care Act—provides an opportunity to study how individuals respond to coverage gains in utilizing emergency and primary care services, including if and when substitution across these settings begins to occur. This conceptual model (Figure 1) was adapted from the Aday and Andersen framework on access to care in which "health policy" has an impact on "characteristics of population at risk", which is related to "utilization of health services" including the "type", "site", and "purpose" of medical care used (Aday & Andersen, 1974). Using that framework, insurance coverage can be considered a "mutable" (changeable) "enabling" factor for individuals that has an effect on how they consume health care. The pathway highlighted in Figure 1 is the focus for the three aims in this study with the other factors (i.e., access to care, health status, health behaviors, demographics) serving as covariates. Expenditures are not the focus of this study; however, changes in spending on preventive services will be discussed in the third aim.

Figure 1. Conceptual model



Prior evidence

Pre-ACA

We can draw on evidence from prior changes in state Medicaid eligibility criteria to develop hypotheses for how Medicaid expansion under the ACA may impact health care utilization in the states that have elected to expand Medicaid. The findings from this review will be organized around three distinct groups of patients: adults, children, and pregnant women. Generally, we would expect expansions of eligibility and/or coverage to result in increases in utilization; however, shifting between types of services is also possible. For example, we could hypothesize that newly covered adults may be more likely to visit a primary care provider instead of using the ED as a safety net. The short-term implications for utilization from this type of behavior are less clear, though obviously one could expect long-term cost savings and improvement in health outcomes from earlier diagnosis and greater use of less expensive types of providers and treatment.

Adults

For adults, we will review the findings from five studies, four of which looked at changes in eligibility or benefits in five states (Tennessee, Kentucky, Idaho, Massachusetts, and Oregon). The final study is a longer-term comparison of utilization across 10 states that expanded Medicaid in the 2000s with 14 bordering states that did not change their eligibility or benefits. Reducing eligibility and increasing cost sharing tended to result in lower utilization of services among the insured population. Increasing eligibility or benefits showed mixed results, with positive changes (reduction in preventable admissions) in some states, but null or poor findings (no changes in ED use, low uptake of wellness visits) in other states.

In 2005, Tennessee made adjustments to TennCare, its state Medicaid program, under the guise of keeping it solvent that resulted in 171,000 adult enrollees (of 1.4 million total enrollees) losing coverage. Heavrin and colleagues used state hospital administrative data on all emergency department visits from 2004 to 2006 to assess the effect of TennCare disenrollment on ED utilization (Heavrin, Fu, Han, Storrow, & Lowe, 2011). Total mean weekly ED visits statewide dropped by nearly 1,200 after disenrollment ($p<0.01$), with TennCare experiencing a 3,100 visit decline ($p<0.01$) compared to a 2,200 visit increase among the uninsured ($p<0.01$). Changes in weekly mean ED visits for private insurance, Medicare, and other coverage were either not significant and/or a change of less than 150 visits per week. Since weekly totals do not account for the relative size of each payer population, the authors also examined changes in payer composition of ED visits descriptively and using multivariate analysis. They found that proportion of visits decreased for TennCare (30.6% to 24.4%, $p<0.01$) and increased for the uninsured (12.2% to 17.5%, $p<0.01$) with both results persisting in fully adjusted models. Similarly, for visits per person-year, they found a decrease for TennCare (0.910 to 0.885, $p<0.01$) and an increase for the uninsured (0.455 to 0.587, $p<0.01$). Though overall ED volume did not markedly increase as one might hypothesize, it is clear from their findings that disenrollment was associated with an increased "role of the Tennessee ED as a safety net provider" (Heavrin et al., 2011).

Kentucky and Idaho made adjustments to their state Medicaid programs soon after the 2005 Deficit Reduction Act was signed into law in February 2006. Kentucky implemented copayments for physician visits, prescription drugs, and inpatient hospital stays and coinsurance for non-emergent use of the ED in July 2006 with increases in some reimbursement rates following in July 2007. Idaho added coverage for annual wellness exams, cancer screenings, tobacco cessation, and weight management programs in July 2006 as well as dental coverage with increased reimbursement rates through a managed care organization in September 2007. Marton and colleagues used enrollment and claims data from Kentucky and Idaho from 2004 to 2008 to examine the effects of these policy changes on utilization (Marton, Kenney, Pelletier, Talbert, & Klein, 2012). The policy changes had little effect on utilization of services in Kentucky, where the only significant findings were a slight decrease in probability of an inpatient stay during the year (18% to 17.6%, $p<0.01$) and a 4% decline in probability of taking more than one brand name prescription per month ($p<0.01$). In Idaho, only 9% of adults took advantage of the annual wellness visit newly covered under their plan during the period following the benefit change. These findings indicate that adding copayments and limitations on name-brand prescription drug use had little impact on overall utilization of services and prescriptions, with perhaps some small amount of shifting from name-brand to generic drugs. Also, providing free well-care visits did not result in significant uptake of preventive services, at least in the short term.

In 2006, Massachusetts passed what became a model for the Affordable Care Act in an effort to provide and require health insurance coverage for all residents. This was accomplished through an expansion of MassHealth, the state Medicaid program, and the creation of CommCare, through which eligible residents could obtain free or subsidized coverage in the new state health insurance exchange, referred to as the Connector. Kolstad and Kowalski used difference-in-difference models to examine the effects of the statewide coverage expansion on length of hospital stays and admissions from the emergency department (Kolstad & Kowalski, 2012). Unfortunately, their study design could not isolate the specific impact of the Medicaid expansion since the other coverage expansions were happening at the same time. They observed that health reform in Massachusetts was associated with a 36% decline in uninsurance among the inpatient hospital population, which was also associated with decreased length of stay, preventable admissions, and hospital cost growth.

In 2003, the Oregon Health Plan instituted premiums and copayments for many services under its OHP Standard plan, the state's Medicaid expansion for those between 100% and 175% FPL. Those in OHP Plus, enrolled under the federally mandated Medicaid eligibility criteria saw no change to their benefits. Lowe and colleagues examined whether the institution of a $50 copayment for ED visits impacted use, measured by number of ED visits per enrollee per year (Lowe, Fu, & Gallia, 2010). Under the federal Emergency Medical Treatment and Active Labor

Act, EDs were unable to refuse to provide service if an enrollee was unable to pay the copayment and the copayment requirement itself was ultimately reversed by a court order in June 2004. They used administrative and claims data for participants enrolled in the OHP from 2001 to 2004, excluding dual eligible, minors, and those with special eligibility from the study, providing a pre-post examination of the benefit changes. ED use by OHP Standard enrollees decreased by 16% (aOR=0.84, 95% CI=0.83, 0.86) as a result of the imposition of the copayment before recovering 9% of the decline after the copayment was reversed (aOR=1.09, 95% CI=1.06, 1.12). ED use was still approximately 8% lower after the copayment was reversed compared to before the benefit changes (aOR=0.92, 95% CI=0.89, 0.95). Their findings indicate that increases in cost sharing for Medicaid patients had a negative effect on ED utilization, even after the copayment for ED services was nullified by a court order.

An analysis of Kaiser Family Foundation data from 1999 to 2011 found that state-based Medicaid expansions in 10 states between 2000 and 2009 were not associated with a change in the percentage of enrollees with high ED utilization (≥2 emergency visits per year) when compared with enrollees in 14 bordering states that did not expand Medicaid (Ndumele, Mor, Allen, Burgess, & Trivedi, 2014). It provides evidence that expanding Medicaid eligibility was not associated with changes in high use of ED services among adults, suggesting that providing health insurance coverage may not necessarily change ED utilization habits among low-income individuals.

Children

This section describes two studies examining the effect of changes in Medicaid eligibility and benefits on utilization by children. One is a study focusing on the number of doctor visits and hospitalizations within the last year as a result of a federally-mandated eligibility expansion while the other examined effects of increased service coverage and reimbursement rate changes for medical and dental services in Kentucky and Idaho.

In the early 1980s, eligibility for Medicaid was determined by participation in Aid to Families with Dependent Children, a cash transfer (welfare) program for very low-income families. By 1992, federal Medicaid rules required states to expand coverage to groups of children in poor families with incomes higher than the AFDC limits (ages 0-5: up to 133% FPL, ages 6-19: up to 100% FPL; optional coverage for infants up to 185% FPL). Currie and Gruber exploit the variation in the timing and specific eligibility criteria employed by each state to assess the impact of Medicaid eligibility on health care utilization in children (J Currie & Gruber, 1996). Using data from the Current Population Survey, they first estimated that the takeup rate, or enrollment in Medicaid as a result of the expanded eligibility criteria between 1984 and 1992 had an upper bound of 71%, indicating that nearly 30% of those eligible were not enrolling. The CPS data were used to impute income for similar households in the National Health Interview Survey, where incomes are only reported within a range and are missing for some households. Medicaid eligibility was associated with a 9.6% drop in likelihood of not having a doctor visit in the last year, nearly halving the baseline probability, and a 4.0% increase in likelihood of hospitalization within the last year, nearly doubling the baseline probability. Their analysis indicates that Medicaid expansions, even with less than perfect uptake by those newly eligible, results in increased use of health care services by children.

Kentucky (with the exception of the Louisville area) and Idaho each used a joint delivery system for Medicaid and CHIP programs for medical and dental care for children, operating under a fee-for-service primary care case management model. Kentucky increased the number of preventive dental visits covered from one to two per year in July 2006 and increased Medicaid reimbursement rates for well-child visits by 12.5% in July 2007. Similarly, Idaho increased reimbursement rates for well-child visits by 8% to 24%, created a premium forgiveness program for those keeping up with preventive care in January 2007, and increased reimbursement rates for dental care by outsourcing to an MCO in September 2007. Kenney and colleagues used Medicaid and CHIP enrollment and claims data prior to, during, and following the policy changes to examine medical (ages 0-18) and dental visits (ages 3-18) among children in Kentucky and Idaho (Kenney, Marton, Klein, Pelletier, & Talbert, 2011). In Kentucky, there was no association between the reimbursement increase and probability of having any annual well-child visits within the last year; however, there was a 16% increase in likelihood of having any annual preventive dental visits associated with the changes in dental coverage. In Idaho, probability of receiving any annual well-child visits increased by 6% for children aged 0-5 and 19% for children aged 6-18. The reimbursement rate increase for dental services under the MCO were marginally associated with a small increase (2 percentage points) in probability of a preventive dental visit. Their findings suggest that reimbursement rate and coverage increases for Medicaid and CHIP-covered children in Kentucky and Idaho were associated with increases in medical and dental care use to varying degrees.

Pregnant women

This section describes two studies examining the effect of Medicaid expansion for pregnant women, one in California and another nationally, both from the late 1980s and early 1990s. Their findings show increases in utilization, with some seemingly beneficial (number of prenatal visits) and other less so (greater likelihood of Caesarian section deliveries for Medicaid versus uninsured).

As a result of a federal mandate to expand coverage for prenatal and maternity care, California expanded eligibility for pregnant women in Medi-Cal, the state's Medicaid program, in 1989 and again in 1990. Eligibility rose from the prior income limit of approximately 100% of the federal poverty level to 185% in July 1989 and 200% in January 1990. Braveman and colleagues conduced an analysis of birth certificates for singleton (single child) in-state births to state residents in 1990 to assess the effect of insurance status on untimely and insufficient care (Braveman, Bennett, Lewis, Egerter, & Showstack, 1993). Women on Medi-Cal were at higher risk for untimely care (aOR=3.33, 95% CI=3.26, 3.40), defined as initiation of care occurring after the first trimester, than the reference group (women with private fee-for-service insurance). Notably, this was worse than the likelihood of uninsured women receiving untimely care (aOR=2.54, 95% CI=2.47, 2.60). Compared to the reference group, women with Medi-Cal were less likely to have had insufficient prenatal care (aOR=1.63, 95% CI=1.60, 1.66), among those receiving any prenatal care, than those who were uninsured (aOR=2.49, 95% CI=2.44, 2.55). This study is limited by the lack of longitudinal data with which to look at average changes in utilization before and after these expansions or the ability to differentiate women eligible under the prior eligibility requirements versus the expanded limits. However, it does provide evidence that expanded Medicaid coverage for pregnant women is positively associated with an increased number of prenatal visits, despite seemingly having no effect on timely initiation of care.

Currie and Gruber used national birth certificate data from 1989 to 1992 to study the effect of Medicaid eligibility on childbirth treatment decisions (Janet Currie & Gruber, 2001), focusing on four procedures listed on birth certificates: 1) Cesarean section delivery, 2) use of a fetal monitor, 3) induced labor, and 4) ultrasounds. Birth certificates do not contain the mother's insurance status prior to pregnancy nor was that information available in the Detail Natality data obtained from the National Center for Health Statistics. As such, they chose to stratify the sample of childbirths by characteristics strongly correlated with availability of private insurance coverage, such as age, education, and marital status. They used this to infer which pathway a mother likely took to Medicaid coverage, either transitioning from being uninsured to gaining Medicaid coverage during pregnancy or transitioning from private insurance to Medicaid as eligibility expanded in the late 1980s for pregnant women. They estimated that a 10% increase in proportion of pregnant women eligible for Medicaid was associated with increases of 0.32% for Cesarean section delivery, 0.92% for use of a fetal monitor, 0.19% for induction of labor, and 0.55% for ultrasound among the group of women gaining coverage through Medicaid. Conversely, they found that a 10% increase in proportion eligible for Medicaid was associated with decreases of 0.79% for Cesarean section delivery, 0.53% for use of a fetal monitor, 0.30% for induction of labor, and 0.21% for ultrasound among the group of pregnant women transitioning from private insurance to Medicaid. Patterns of treatment intensity generally increased for those transitioning from being uninsured to newly Medicaid-eligible but decreased for those transitioning from private to public insurance, demonstrating that physicians may be responding to economic incentives via differences in reimbursement rates (Medicaid reimbursements were approximately half that of private insurers at the time).

Quality of included studies

For adults, this review consisted of a single multi-state analysis and four studies that included five individual states. They showed that reducing eligibility and increasing cost sharing generally resulted in lower utilization while increasing eligibility or benefits yielded mixed findings. The methods used were generally rigorous and lend support to the conclusions drawn from these studies. Ndumele *et al.* (2014) uses a difference-in-difference quasi-experimental design to examine annualized ED use between Medicaid enrollees in expansion and matched control states; however, its conclusions are limited by a small cross-sectional sample (particularly in expansion states) and lack of multivariate analysis. Heavrin *et al.* (2011) uses administrative data from all ED visits in Tennessee for two years prior to and following disenrollment of 171,000 participants from TennCare. While longer periods would be preferable, weekly data were used in their multivariate analysis so sample sizes were not an issue. This study is helped by the fact that it is not based on claims data and therefore can incorporate all patients regardless of payer. Marton *et al.* (2012) uses Medicaid enrollment and claims data from Kentucky and Idaho to examine changes in utilization at the individual level. They use logistic and linear probability models to estimate the individual likelihood of several utilization outcomes; however, this ignores possible changes in continuous utilization outcomes such as number of visits, length of inpatient stay, etc. Kolstad and Kowalski (2012) uses a nationally representative sample of hospitals with a difference-in-differences design to look at hospital utilization in Massachusetts versus the rest of the United States following Massachusetts health reform in 2006. Lowe *et al.* (2010) uses administrative data from Medicaid enrollees to conduct a comparison group analysis of ED visits over time between those enrollees subject to increased cost sharing and those not.

By virtue of a multi-state sample and expansion design similar to the ACA in Massachusetts (e.g., insurance mandate and private marketplace with subsidized coverage), Ndumele *et al.* (2014) and Kolstad and Kowalski (2012) are the most useful for projecting effects of the expansions of private insurance and Medicaid on health care utilization for adults under the ACA. The other studies were conducted in primarily smaller states outside of the South, which is where most of the population growth in the U.S. has been concentrated (Johnson, Jr. & Kasarda, 2011). Also, much of the population growth is comprised of Hispanics (Johnson, Jr. & Kasarda, 2011), who may have a higher likelihood of being uninsured (U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation, 2005), lower health literacy (Sentell & Braun, 2012), and cultural norms around health and health care that encourage delayed treatment (U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, n.d.). Therefore, the impact of coverage on utilization may not be as strongly positive or shift as much utilization to earlier and less intensive treatment as we might expect. Prior studies in states with larger Hispanic populations, like California or Texas, if they exist, may provide more useful evidence for potential effects of increased coverage for the fastest growing segment of the U.S. population.

For children, this review consisted of a national analysis and one other study conducted on two individual states (Kentucky and Idaho), which generally indicated increases in utilization as a result of eligibility expansions and increased coverage. The methods in these two studies were quite rigorous; however, there were significant issues with the data used in both studies, which casts doubt on the generalizability of their findings. Currie and Gruber (1996) uses large nationally representative surveys (CPS and NHIS) from which to draw its conclusions. It imputes Medicaid eligibility for children based on demographics and socioeconomic data in CPS and then uses the likelihood of a given child being eligible (by state, age, and year) to instrument for individual eligibility when analyzing outcomes in NHIS. While sophisticated and statistically unbiased, this approach could not truly account for the changes in coverage over time for specific individuals. Kenney *et al.* (2011) uses Medicaid enrollment and claims data from Kentucky and Idaho to examine changes in utilization at the individual level with logistic regression and hazard models. However, data on children served at rural and community health centers in Idaho were not available, which could be a significant source of bias in a largely rural state. These two studies provide limited evidence from which to project what effect the ACA may have on utilization among children, though it would seem safe to assume that increased coverage for children would be associated with increased utilization. However, youth are generally less costly (i.e. use fewer services) than other age groups (U.S. Department of Health and Human Services, n.d.-b), covered at higher rates due to pre-ACA Medicaid and CHIP availability, and mandatory immunizations for school entry in many states already serve to encourage parents to bring their children for regular wellness visits. Therefore, the impact of expanded coverage for children under the ACA may be muted.

For pregnant women, this review consisted of a national analysis and another study conducted using data from California. The findings show increases in utilization associated with greater Medicaid eligibility, with mixed judgments related to the suitability of care (more prenatal visits, higher likelihood of a Caesarian section delivery). Currie and Gruber (2001) uses national birth certificate data from which to draw their conclusions about treatment intensity; however, they are only able to relate this to general trends in eligibility for public insurance coverage as their data do not include the mother’s insurance coverage status and type. Braveman *et al.* (1993) uses a similar approach; however, California birth certificates includes sources of payment for prenatal care and expected source for the delivery that allows for directly estimating differences in prenatal care outcomes based on the mother’s insurance coverage. However, unless we can establish that the Medi-Cal population is similar to the population of low-income pregnant women nationally, it is not clear that we can project what impact Medicaid expansions under the ACA may have. Similarly, given the age of both studies, it is not clear whether these findings are generalizable to the current health care environment. However, it would be counterintuitive based on these results and economic theory to expect lower utilization as a result of expanded insurance coverage for pregnant women under the ACA. Perhaps the most important question for researchers and policymakers, based on the findings of Currie and Gruber (2001), is whether expanded insurance coverage will yield unnecessarily intensive care rather than simple increases in utilization, as prenatal care is relatively standardized in terms of recommended visit and testing schedules compared to other health conditions (American Academy of Pediatrics & American College of Obstetricians and Gynecologists, 2012).

The findings described above generally demonstrate that eligibility and benefit expansions in Medicaid are associated with increases in utilization of preventive services and decreases in utilization of more intensive care. Similarly, we find that increases in cost sharing or outright disenrollment from Medicaid coverage is associated with decreased utilization by those still insured but also have the potential unintended consequence of increases in the use of more expensive care, such as ED visits, by those newly uninsured. With the passage of the ACA in 2010, there was an expectation among policymakers and patient advocates that those newly covered, either through the Marketplace or through Medicaid expansion, would be able to more affordably access preventive services and thus shift utilization away from providers (hospitals) and services of last resort (ED visits, preventable hospital admissions). This is meant to bend the cost curve downwards over time by providing earlier treatment of disease and better management of chronic conditions, reducing long-term health care expenditures and improving health outcomes. While this review does not address health outcomes, the evidence based on past Medicaid expansions shows that at least some of the desired behavior associated with this type of policy can be expected as a result of the ACA.

As this is not a systematic review, it is possible that studies not included may have findings that directly conflict with those included and as such, the implications drawn above may be biased or incomplete. I am also limited by the fact that many studies do not address underlying factors that may also impact access and utilization of services in a given state, such as Medicaid provider participation and reimbursement rates relative to other public and private insurers. Many of the studies included are for individual states and those effects may not be generalizable to the population at-large for various reasons (e.g. health literacy, cultural beliefs, access to providers, demographics, etc.). This was largely unavoidable due to the limited number of changes to national Medicaid eligibility and benefits over the past few decades. However, each patient population studied in this review had one study that was either national or covered a large number of states.

Post-ACA

As we are now nearly a decade from the original passage of the ACA and more than five years into implementation of its two primary coverage expansions, the Marketplace and Medicaid expansion, there is some evidence of its effects on use of the ED and primary care services. The first few years after the introduction of the Marketplace and Medicaid expansion in 2014 showed substantial declines in uninsurance and evidence of improvements in self-reported health and preventive service use (Courtemanche, Marton, Ukert, Yelowitz, & Zapata, 2018; Sommers, Maylone, Blendon, Orav, & Epstein, 2017). Despite worries about primary care appointment availability with a large influx of newly insured patients, widespread issues never materialized (Rhodes et al., 2017). It is possible that although availability for new patients did not worsen, wait times and other availability barriers were enough to make primary care inconvenient and would dampen substitution away from the ED. The ACA led to improvements in individuals reporting a usual source of care (Wherry & Miller, 2016) and there are signs that the commercially insured in a single national insurer (Aetna) shifted treatment for “low-acuity” conditions away from ED settings in the last few years (Poon, Schuur, & Mehrotra, 2018).

Previous studies have estimated the effect of coverage gains on ED utilization after ACA implementation (Nikpay, Freedman, Levy, & Buchmueller, 2017; Sommers, Blendon, Orav, & Epstein, 2016; Sommers et al., 2017), yielding mixed findings. Nikpay et *al.* (2017) found that total ED use increased in Medicaid expansion states by 2.5 visits more after 2014 relative to non-expansion states (95% CI: 1.1, 3.9). Conversely, Sommers *et al.* (2016) found that Medicaid expansion was associated with a significantly decreased probability of any ED use (−6.0 percentage points, $p<0.05$) and lower use of the ED as a usual source of care (-6.1 percentage points, $p<0.01$) along with a corresponding increased use of primary care visits (0.7 per person-year, $p<0.05$). Sommers *et al.* (2017) found significant decreases in the probability of any ED use in 2015 (-5.8 percentage points, $p<0.01$) and 2016 (-6.6 percentage points, $p<0.01$) in two Medicaid expansion states (Arkansas and Kentucky) relative to a non-expansion state (Texas), but no change in average ED visits.

Specific aims

In this dissertation, I chose to focus on non-elderly adults (18 to 64 years of age) given that they had the least generous prevailing coverage environment prior to the ACA outside of employer-sponsored insurance. Each of the three populations for which I described the pre-ACA evidence above had very different eligibility profiles for Medicaid before expansion and relative costs for non-group commercial insurance. I assess the impact of the ACA on health care use among non-elderly adults through the following three aims, filling in gaps in our knowledge about its effects.

1) Is persistence of uninsurance associated with substitution between emergency department and primary care use? This aim uses longitudinal data from a linkage between two federal surveys (National Health Interview Survey and Medical Expenditure Panel Survey) to

associate insurance status with changes in person-level patterns of ED and primary care visits in 2013 and 2014. It uses the first year of the Marketplace and Medicaid expansion to provide a large set of individuals transitioning into coverage, also exploring how utilization responses vary by the differences in cost sharing burden between public and private coverage.

2) Is there a delayed effect of coverage gains under the ACA on non-emergent ED visit rates? This aim uses data on ED discharges from seven states from the Healthcare Cost and Utilization Project State Inpatient Databases and State Emergency Department Databases from 2008 through 2016. This allows for the isolation of pre-existing trends prior to large coverage gains in the years following the passage of the ACA. Two algorithms are used to identify preventable and non-emergent visits that are more likely to be substitutable to a primary care, retail clinic, and/or urgent care setting, exploring the presence of lagged effects and spatial correlation at the county level within states.

3) Do high deductibles reduce the use of 'free' preventive services under the Affordable Care Act? This aim uses commercial health insurance claims data from IBM Health® MarketScan® to identify whether high deductible plan enrollment is associated with lower use of preventive services for which the Affordable Care Act eliminated cost sharing in late 2010. It uses a cohort of adults who are continuously insured in the same plan type to assess whether there is differential response to the price shock, employing a semi-parametric difference-in-differences estimator to relax the parallel trends assumption.

Implications

Expansion of health insurance coverage to previously uninsured or underinsured (e.g., those with only catastrophic coverage, plans with high cost sharing) low-income adults allows for a potential reallocation of care from more intensive and expensive care (e.g. emergency department, untreated chronic disease) to less costly preventive care (e.g. primary care, early detection and intervention for chronic disease), reducing the rate of growth in health care expenditures in the long run. The proposed research has broad implications for pursuing the triple aim—improving health and quality of care while reducing cost. Reductions in unnecessary emergency care and preventable chronic diseases could improve health and reduce costs significantly over the life course. It is crucial to understand whether the ACA is encouraging changes in individual decision-making around the appropriate setting for care, particularly among those who were previously uninsured. If deductibles and other cost sharing continue to serve as a barrier to seeking appropriate care, then the ACA may not impact patient decision-making as expected or hoped. Even though the goal of universal health insurance coverage is one that has yet to be attained in the United States, the ACA has brought us much closer than we have ever been. As the number of uninsured individuals decreases, it will be important for public and private payers to understand the ramifications for use of different types of providers and services, as this is critical to controlling the growth of health care expenditures and improving health outcomes. If data show that expanding health insurance coverage, particularly through Medicaid expansion for those below the Marketplace subsidy eligibility threshold, is successful in reducing overall medical costs, this would provide a strong economic argument to expanding Medicaid in the remaining hold-out states as a way to encourage more efficient use of the health care system.

CHAPTER 2: IS PERSISTENCE OF UNINSURANCE ASSOCIATED WITH SUBSTITUTION BETWEEN EMERGENCY DEPARTMENT AND PRIMARY CARE USE?

Introduction

More efficient use of health care resources is often touted by policymakers, insurers, employers, and others as a goal of health insurance reforms along with improvements in access, affordability, and quality of care. Prior to the Patient Protection and Affordable Care Act of 2010, the majority of the evidence describing the effect of coverage on utilization was based on expanded eligibility for public coverage, primarily Medicaid, with the Massachusetts health reform of 2006 serving as the notable exception. These eligibility changes yielded mixed results for emergency department and/or primary care utilization (Anderson, Dobkin, & Gross, 2014; Chen, Scheffler, & Chandra, 2011; Heavrin et al., 2011; Kolstad & Kowalski, 2012; Lowe et al., 2010; Marton et al., 2012; Ndumele et al., 2014; Sommers & Simon, 2017; Taubman, Allen, Wright, Baicker, & Finkelstein, 2014). For example, the Oregon Health Insurance Experiment showed that coverage gains yielded persistently higher ED use two years after gaining coverage (Taubman et al., 2014). The state and local contexts for insurance expansion (e.g., baseline rates of coverage, health status) matter with recent work showing that these differences can explain seemingly contradictory findings in the past (Kowalski, 2018).

The ACA took a multi-pronged approach to expansion (dependent coverage up to age 26, Medicaid expansion, guaranteed issue and subsidized coverage in the Marketplace) that has covered approximately 20 million Americans (Garrett & Gangopadhyaya, 2016). The first few years after the introduction of the Marketplace and Medicaid expansion in 2014 showed substantial declines in uninsurance and evidence of improvements in self-reported health and preventive service use (Courtemanche et al., 2018; Sommers et al., 2017). Despite worries about PC appointment availability with a large influx of newly insured patients, widespread issues never materialized (Rhodes et al., 2017). However, it is possible that although availability for new patients did not worsen, wait times and other availability barriers were enough to make PC inconvenient and would depress transitions away from the ED. The ACA led to improvements in individuals reporting a usual source of care (Wherry & Miller, 2016), but research has not yet empirically addressed whether patients are actually changing their usual setting for care in response to coverage gains. Increasing length of time uninsured has been associated with lower access to care and those with insurance instability are more likely to use the ED as a primary source of care (Abdus, 2014; Schoen & DesRoches, 2000). However, to our knowledge, the relationship between changes in health care utilization and persistence of uninsurance prior to gaining coverage has not been examined in depth. Another gap is the failure to measure substitution across settings, or shifts in utilization between ED and PC after gaining coverage. Instead, studies often evaluate utilization within each setting separately. This study addresses both of these gaps by quantifying substitution between ED and PC settings within the same individuals over time and assessing whether persistence of uninsurance is associated with how patients use care once insured using a nationally representative sample.

Methods

Data

This study uses a restricted linkage between the 2012 National Health Interview Survey (NHIS) and the 2013 and 2014 Medical Expenditure Panel Survey (MEPS) as its primary data source (Agency for Healthcare Research and Quality, 2009; Centers for Disease Control and

Prevention, 2018). These years were chosen due to the implementation of the two largest ACA coverage expansions in 2014 (Medicaid expansion and Marketplace), providing a large number of individuals transitioning from uninsurance into coverage. We merged on data from the Area Health Resources File to capture county-level population characteristics and access to health care. We also used the Marketplace Public Use Files from the Centers for Medicare and Medicaid Services and data published by the Kaiser Family Foundation to create measures of Marketplace plan availability and costs in 2014, the first year in which the health insurance exchanges were in operation. This study was approved as exempt by the Non-Biomedical Institutional Review Board at the University of North Carolina at Chapel Hill (#17-0774).

Sample

We focused on nonelderly adults (18 to 64 years of age in both years) to isolate those individuals whose coverage status and health care utilization would be most affected by the introduction of the Marketplace and Medicaid expansion (n=9,605) (Figure 2). We dropped individuals who were not present in all 5 rounds of data collection (e.g., death, military service, incarceration) or were covered by Medicare in either year (e.g., dual eligible, disabled). Because of challenges attributing utilization changes for individuals who had partial coverage or multiple payers in 2014, we only included those who were continuously insured (covered for all 12 months) and who had a single payer type (i.e., private, Medicaid, TRICARE, other public) in 2014 regardless of their insurance status in 2013 and earlier. We then matched this MEPS analytic sample to the 2012 NHIS adult sample, yielding an analytic sample of 6,435 individuals or approximately 67% of the original age-restricted sample.

Measures

To assess substitution between ED and primary care, we first calculated the year-over-year change in utilization (the number of visits in 2014 minus the number of visits in 2013) within each setting separately for each individual in the analytic sample. We defined primary care visits in each year as the total number of office-based visits (as opposed to outpatient clinic visits) with a physician, physician assistant, nurse practitioner, or nurse. Visits to other types of providers (e.g., PT/OT, chiropractor, optometrist, dentist) were not included. Then, we generated a four-level categorical outcome for year-over-year substitution between settings with the following mutually exclusive and exhaustive categories: 1) increase in both ED and primary care visits (>ED, >PC); 2) same or fewer ED visits with an increase in primary care visits (≤ED, >PC); 3) increase in ED visits with the same or fewer primary care visits, (>ED, ≤PC); and 4) same or fewer of both primary care and ED visits (≤ED, ≤PC).

Persistence of uninsurance prior to 2014 was the explanatory variable of interest, defined as being continuously insured (covered for all of 2013); transiently uninsured (covered for at least one month in 2013 but not the full year); or persistently uninsured (uninsured for all of 2013) (Cannon, 2004; Short, Graefe, & Schoen, 2003). Among those categorized as persistently uninsured, over 80% (81.7%) were continuously uninsured for at least 36 months, providing a strong justification for considering this group as meaningfully different in health insurance experience than those only transiently uninsured.

We used several individual and family-level demographic characteristics in our analysis, including age, sex, race/ethnicity, education, employment status, marital status, household size, and family income as a percentage of the federal poverty level. We also derived several health and health insurance-related measures for use in our analysis. We created an indicator of self-reported health decline based on the year-over-year change (2013 to 2014) in perceived health status and an indicator for having an ambulatory care sensitive condition in 2013 (Agency for Healthcare Research and Quality, 2001; Centers for Medicare and Medicaid Services, 2015). We captured payer type in 2014 (i.e., private, public) to look for differential effects by benefit design (e.g., exposure to significant cost-sharing). Using the 2012 NHIS data, we created an indicator for having a declinable pre-existing condition for health insurance underwriting purposes using a methodology developed by the Kaiser Family Foundation (Kaiser Family Foundation, 2016b).

We included several state and county-level factors associated with access to care and health insurance along with characteristics of the socioeconomic environment in our analysis. Quartiles for the number of hospitals with an ED, number of primary care physicians, number of physician extenders, number of federally qualified health centers, and whether the county was a health professional shortage area were used to describe the availability of providers in each county (Health Resources and Services Administration, 2016). We also included unemployment rate, percentage of population non-white, in poverty, and uninsured, and whether the county was non-metro to account for the socioeconomic environment. Medicaid expansion status, number of Marketplace insurers, and average benchmark Marketplace premium for 2014 were used to describe the availability and affordability of health insurance in each state.

Statistical analysis

We used separate linear regression models to estimate the relationship between transient and persistent uninsurance on changes in emergency department visits and changes in primary care visits relative to the continuously insured group, controlling for individual-, family-, and area-level characteristics. Similarly, we used multinomial logistic regression models to estimate the association between persistence of uninsurance and substitution across settings. We estimated marginal effects of transient and persistent uninsurance on the predicted probability of being in each substitution category relative to the continuously insured group. As we are focused on individual-level changes in utilization rather than state-level policy differences (e.g., differences in Medicaid provider reimbursement rates), we include state fixed effects to account for any remaining time-invariant unobservable differences between states. We used the survey weights and design effects provided to account for the complex sampling design. All analyses were conducted in Stata® 15 for Linux (StataCorp, 2017b).

We also ran stratified versions of these analyses by presence of a declinable pre-existing condition (in 2012), having a visit for an ambulatory care sensitive condition (in 2013), and payer type (in 2014). We also performed numerous sensitivity analyses, including 1) raising the lower bound on age to 27 (as the dependent coverage provision allowed parents to include children up to the age of 26), 2) dropping those with family incomes over 400% of the federal poverty level (not eligible for advanced premium tax credits in the Marketplace), and 3) excluding those with no utilization in both years.

We are often interested in the causal effect of a policy change or change in benefit design on health or use of health care, needing to model or otherwise account for selection bias that results in different populations (i.e., demographics, socioeconomic status, health status) ending up in different pre-treatment or pre-intervention groups. A diverse set of individual-, household-, and state-level factors combine to result in an extended spell of forced or voluntary uninsurance, not easily identified with a single instrument for an instrumental variables or regression discontinuity analysis. Also, in this case, simply describing the observed experience has immense value. As additional states adopt Medicaid expansion or changes are implemented to the Affordable Care Act in the future, the ability to project changes in health care use and the associated costs will be dependent on the profile of individuals who are potentially gaining coverage, including their experience with health insurance coverage, health literacy, and potential pent-up demand for health care.

Results

The mean age in our weighted sample was 41.2 years old with the two uninsured groups being significantly younger (transiently uninsured: 36.0, persistently uninsured: 38.9) than the continuously insured group (41.6) (Table 1). The sample was 52.5% female overall with only the transiently uninsured group (61.2% female) skewed noticeably away from a near even split. The percentage of each insurance status group that is white non-Hispanic decreases as persistence of uninsurance increased, from more than two-thirds (67.3%) for the continuously insured group to about half (50.9%) for the persistently uninsured group. Educational attainment, being employed, being married, and household income were all negatively associated with persistence of uninsurance.

Across the three groups of insurance status in 2013, we do not find significant differences in number of hospitals with an ED, number of primary care physicians, or number of physician extenders by persistence of uninsurance. We do observe lower availability of federally qualified health centers (at the county-level) within the two uninsured groups. Those in the two uninsured groups were significantly more likely to live in a county with a higher percentage of its population non-white, unemployed, in poverty, and uninsured. We find no significant differences between groups by health professional shortage area status or being in a non-metro (rural) area.

ED use is generally low with an average of approximately 0.2 visits per person per year, increasing slightly with persistence of uninsurance (Figure 3). In the baseline year (2013), primary care use was higher among the continuously insured group averaging approximately one additional visit per year (3.3) than the transiently uninsured (2.2) and persistently uninsured (2.3) groups. Figure 4 shows survey weighted regression adjusted year-over-year change in ED and primary care utilization by persistence of uninsurance. We find no year-over-year change in ED use for the continuously insured and transiently uninsured groups but observe a small increase in ED use for the persistently uninsured group (0.06 visits per person, $p<0.01$). We observe small changes in year-over-year primary care utilization for the continuously insured (0.10 visit increase, $p<0.01$) and transiently uninsured (0.23 visit decrease, $p<0.05$) groups, but more than a one visit per year increase for the persistently uninsured group (1.10 visits per person, $p<0.01$). This sizable increase for the persistently uninsured group essentially catches it up with the continuously insured group once covered in 2014. These estimates of the year-over-year changes conform with the marginal effect estimates from our linear regression models of year-over-year change in ED and primary care utilization (Tables 2 and 3).

Table 4 shows the predicted probabilities for each substitution category and marginal effects by persistence of uninsurance. Nearly 60% of people across all three groups (continuously insured, transiently uninsured, persistently uninsured) are predicted to stay the same or decrease utilization in both settings with very little variation between groups. None of the marginal effects of persistence of uninsurance on substitution are significant at the 0.05 level. Coefficient estimates for the substitution models are shown in Table 5 and the sensitivity analyses described above are shown in Tables 6 through 8.

Table 9 shows the marginal effects of persistence of uninsurance on each of the three outcomes stratified by payer type, presence of a declinable pre-existing condition, and presence of an ambulatory care sensitive condition. We find that being on public insurance seems to be driving the small increase in ED use and large increase in PC use that we observed generally among the persistently uninsured. For the persistently uninsured through 2013 who transitioned to public insurance (e.g., Medicaid) in 2014, we observe a 0.24 visit increase in ED use ($p<0.01$) and a 1.94 visit increase in PC use ($p<0.10$) year-over-year. We find no changes among those who were persistently uninsured and gained private insurance or those who were transiently uninsured regardless of payer type gained in 2014. For the substitution outcome, we also observe a large negative marginal effect (-8.9 percentage points) of being persistently uninsured and gaining public insurance, relative to continuously insured, on the predicted probability of staying the same or decreasing utilization of both types of care, holding all else in the model constant, which indicates a shift towards increased utilization of one or both settings and is consistent with the other results shown. For this model only, we added state-level factors related to the ACA including Medicaid expansion status, number of Marketplace insurers, and the average benchmark premium to account for differences in plan competition and pricing across states.

We do not find any significant differential effects of persistence of uninsurance on ED or PC visits by presence of a declinable pre-existing condition (Kaiser Family Foundation, 2016b). Not having an ambulatory care sensitive condition was associated with increases in year-over-year ED utilization (transiently uninsured: 0.10, $p<0.05$; persistently uninsured: 0.09, $p<0.05$), but no significant changes for those with such a condition. However, we do observe an association between having an ambulatory care sensitive condition and PC use among the persistently uninsured. The marginal effect of being persistently uninsured, relative to continuously insured, is only a 0.42 visit increase in PC use among those without such a condition ($p<0.05$) but a 3.31 visit increase among those with an ambulatory care sensitive condition ($p<0.10$). We again observe little of significance for the substitution outcome except a 4.0 percentage point decline in the predicted probability of increases in use of both settings for the transiently uninsured with an ambulatory care sensitive condition ($p<0.05$).

Discussion

Our study finds that persistently uninsured adults respond to coverage gains by changing how much and where they use health care. We observe a large increase in primary care utilization of over one visit per year on average among patients who were persistently uninsured and gained health insurance coverage, putting their primary care use in 2014 on par with those who were continuously insured (Figure 3). These changes seem to be driven by those gaining public insurance (e.g., Medicaid) with no notable changes found for those gaining private insurance, whether on- or off-exchange. We also found a very small but significant increase in ED visits for the persistently uninsured group that was also driven by those gaining public insurance, which fits with the findings of the Oregon Health Insurance Experiment (Baicker et al., 2013; Taubman et al., 2014). Those who have been persistently uninsured may have substantial health needs and pent-up demand for health care, seeing more physicians across multiple settings to get their health under control. One year may not be long enough to bring previously uncontrolled chronic conditions under control and avoid ED visits associated with exacerbations. Similarly, a recent study also found large increases in new primary care physician visits among payer (i.e., private, Medicaid) and plan switchers in the short run that diminish over time (Barnett et al., 2017), though it only looked at continuously insured individuals. Supply of primary care settings also matters as there were significantly fewer ED visits for “minor and preventable conditions” and sizable reductions in probability of ED use for those living near an open retail clinic in New Jersey (Alexander, Currie, & Schnell, 2017). Findings for the transiently uninsured group were inconsistent and warrant further study given their implications for continuity of care, particularly as more states begin to experiment with so-called community engagement requirements (work requirements) in Medicaid that will likely increase churn.

This analysis has several limitations. Given the observational nature of this study, we are unable to make any causal claims about the relationships observed nor can we provide any qualitative understanding of the decision-making process for newly insured individuals about their use of health care. An instrumental variables analysis of the impact of payer type (e.g., cost-sharing burden differences between private and public coverage) could be possible by focusing on those between 100% and 138% of the federal poverty level using state Medicaid expansion status as an instrument; however, sample size in this data set was not sufficient to do so. It is also far from a foregone conclusion that Medicaid expansion could be considered to be a form of random assignment as these decisions are correlated with ideological and demographic composition of states (Jacobs & Callaghan, 2013; Michener, 2017; Rozier & Singer, 2016). Only having one year on each side of the coverage transition is another limitation due to potential health shocks or regression to the mean; however, we attempted to account for this by controlling for perceived changes in health year-over-year. This is also a short timeframe in which to observe behavior change, a patient would likely need long-term access to primary and specialty care before substantial shifts in ED utilization would occur. Our use of self-reported perceived health is imperfect but preferable to assessing the change in one or more diagnosis indicators that may only capture very substantial changes in health (e.g., cancer, cardiovascular disease, diabetes). Though we observe significant changes for the persistently uninsured group after gaining coverage, the utilization response during the first year covered may not reflect how they will use care in future years.

Qualitative work from the Oregon Health Insurance Experiment specifically noted that the "length of time people were insured might have been an important difference between those who reported mixed success and those who had success over time" (H. Allen, Wright, & Baicker, 2014). We find compelling evidence that expanding coverage to the long-term uninsured yields significant changes in utilization but not necessarily the desired substitution from the ED to primary care settings, at least in the short run. As policymakers at the state and federal levels consider changes to bring the remaining uninsured to gain coverage in the future (e.g., smoothing or removal of the Marketplace subsidy cliff, adoption of Medicaid expansion), it will be important to consider persistence of uninsurance as a piece of the puzzle in projecting the health care utilization and costs of those newly enrolled.

Tables and Figures

Figure 2. Sample size and inclusion criteria

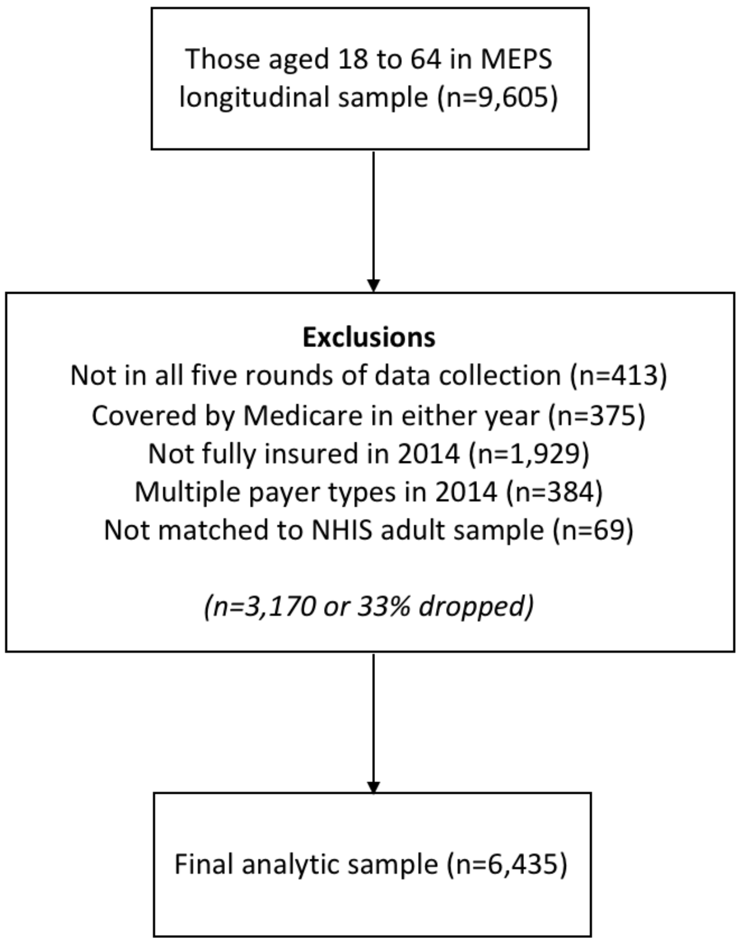


Figure 3. Weighted average emergency department and primary care visits by persistence of uninsurance prior to 2014, United States, 2013–2014

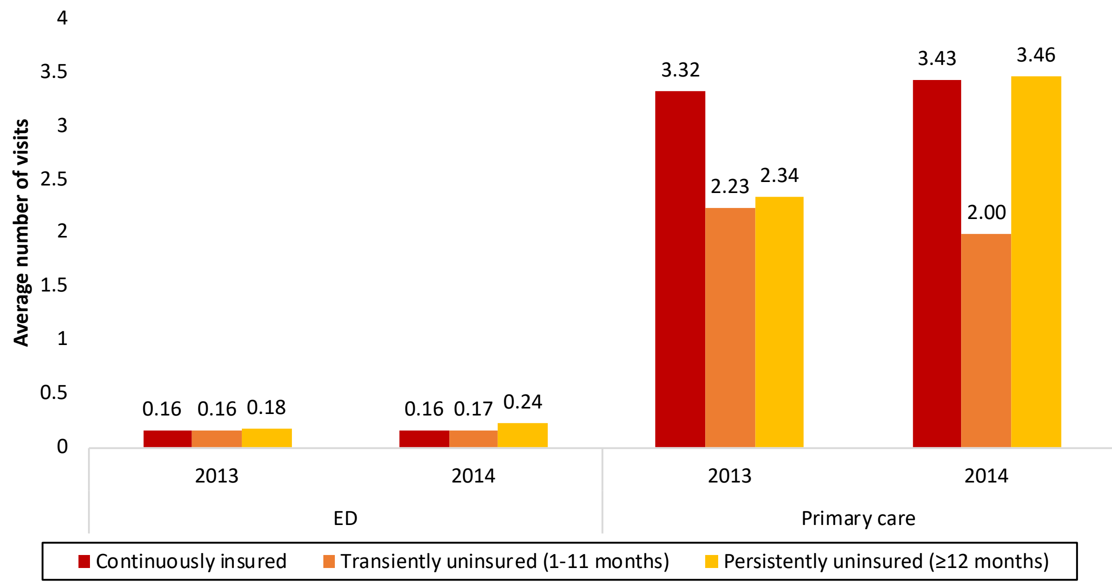
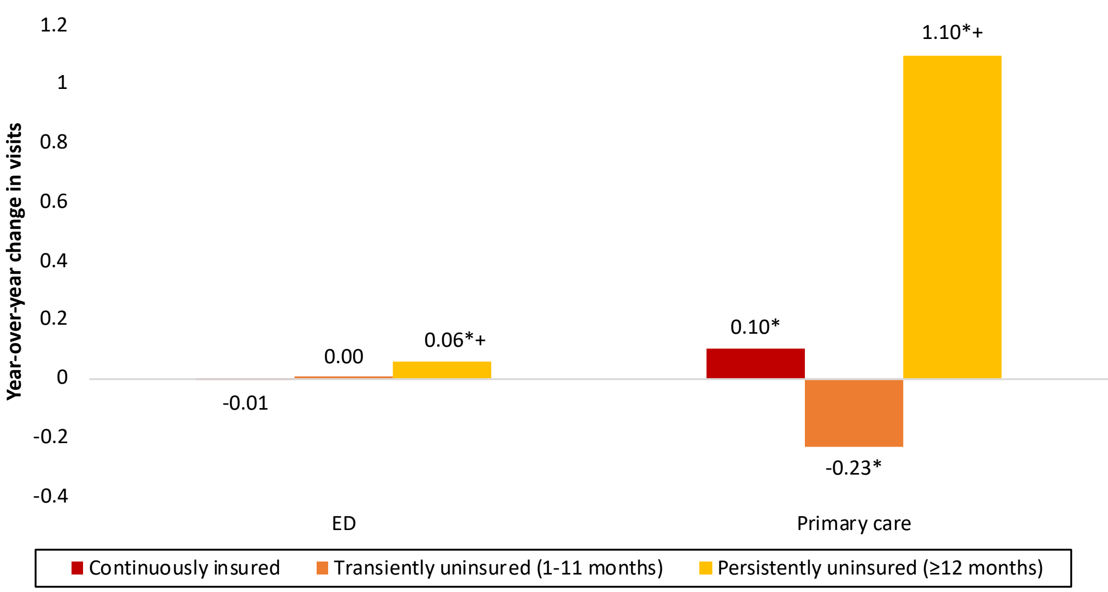


Figure 4. Weighted adjusted year-over-year change in emergency department and primary care visits by persistence of uninsurance, United States, 2013–2014



* $p<0.05$ for year-over-year change not equal to zero
+ $p<0.05$ for difference from continuously insured group

Table 1. Weighted sample characteristics by persistence of uninsurance, United States, 2013–2014

Characteristic	% or mean (standard error)			
		By persistence of uninsurance prior to 2014		
	Overall	**Continuously insured**	**Transiently uninsured** (1-11 months)	**Persistently uninsured** (≥12 months)
Number of observations	6,435	5,555	251	629
Individual-level				
Age*	41.2 (0.2)	41.6 (0.3)	36.0 (1.1)	38.9 (0.7)
Sex*				
Female	52.5%	52.4%	61.2%	49.9%
Male	47.5%	47.6%	38.8%	50.1%
Race/ethnicity*				
White, non-Hispanic	65.7%	67.3%	54.7%	50.9%
African American, non-Hispanic	11.4%	10.9%	19.2%	13.9%
Hispanic	13.7%	12.5%	18.5%	26.8%
Other, non-Hispanic	9.1%	9.3%	7.6%	8.3%
Education*				
High school or less	31.0%	29.1%	40.9%	49.1%
Some college or more	69.0%	70.9%	59.1%	50.9%
Employed*	79.2%	80.6%	68.7%	66.4%
Married*	57.6%	60.3%	35.8%	34.1%
Household size	3.0 (0.04)	3.0 (0.04)	2.8 (0.2)	2.9 (0.1)
Household income*				
0–99%	9.4%	7.7%	20.5%	24.5%
100–199%	13.7%	11.5%	23.0%	36.0%
200-400%	30.1%	30.1%	33.8%	28.0%
>400%	46.8%	50.6%	22.7%	11.6%
Perceived decline in health *(from 2013 to 2014)**	22.8%	22.0%	27.3%	30.2%
Had an ambulatory care sensitive condition *(in 2013)**	30.4%	31.1%	23.5%	24.9%

County-level				
Number of hospitals with an ED *(quartiles)*				
1 – top	41.5%	41.7%	37.1%	41.3%
2	17.6%	18.0%	16.4%	13.6%
3	22.6%	22.8%	23.3%	20.4%
4 – bottom	18.3%	17.5%	23.1%	24.7%
Number of primary care physicians *(quartiles)*				
1 – top	30.9%	30.9%	29.9%	31.6%
2	29.2%	29.5%	26.9%	26.0%
3	21.6%	21.8%	19.4%	20.0%
4 – bottom	18.4%	17.9%	23.9%	22.4%
Number of physician extenders *(quartiles)*				
1 – top	31.0%	31.0%	28.3%	31.6%
2	29.0%	29.3%	25.0%	26.7%
3	20.5%	20.4%	25.0%	19.5%
4 – bottom	19.6%	19.3%	21.8%	22.2%
Number of federally qualified health centers *(quartiles)**				
1 – top	34.8%	35.3%	29.8%	31.4%
2	26.2%	26.7%	27.2%	20.1%
3	23.4%	22.9%	22.0%	29.9%
4 – bottom	15.6%	15.2%	21.0%	18.7%
Percentage of county population non-white*	34.3%	33.9%	38.0%	36.8%
Percentage of county population unemployed*	7.3%	7.2%	7.8%	7.7%
Percentage of county population in poverty*	15.5%	15.3%	17.1%	16.8%
Percentage of county population uninsured*	19.5%	19.2%	22.3%	21.9%
Health professional shortage area	35.8%	35.3%	38.5%	40.0%
Non-metro area	13.9%	13.8%	13.0%	16.2%

* p<0.05 for differences across groups

Table 2. Weighted linear regression estimates of year-over-year change in emergency department visits, United States, 2013–2014

Change in emergency department visits	*Coefficient (standard error)*			
	(1)	(2)	(3)	(4)
Persistence of uninsurance prior to 2014				
Continuously insured	–	–	–	–
Transiently uninsured	0.009 (0.04)	0.05 (0.04)	0.05 (0.04)	0.06 (0.04)
Persistently uninsured	0.06 (0.04)	0.10** (0.04)	0.10** (0.04)	0.10* (0.04)
Controls				
Individual-level		X	X	X
County-level			X	X
State fixed effects				X
Number of observations	6,435	6,371	6,371	6,371

* p<0.05, ** p<0.01

Individual-level controls include age, sex, race/ethnicity, education, employment status, marital status, household size, household income, presence of a perceived decline in health, and presence of an ambulatory care sensitive condition. County-level controls include number of hospitals with an ED (quartiles), number of primary care physicians (quartiles), number of physician extenders (quartiles), number of federally qualified health centers (quartiles), percentage of population non-white, percentage of population unemployed, percentage of population in poverty, percentage of population uninsured, being in a health professional shortage area, and non-metro area.

Table 3. Weighted linear regression estimates of year-over-year change in primary care visits, United States, 2013–2014

Change in primary care visits	*Coefficient (standard error)*			
	(1)	(2)	(3)	(4)
Persistence of uninsurance prior to 2014				
Continuously insured	–	–	–	–
Transiently uninsured	–0.34 (0.31)	–0.15 (0.36)	–0.24 (0.36)	–0.21 (0.36)
Persistently uninsured	1.02* (0.50)	1.24* (0.60)	1.22* (0.60)	1.18 (0.61)
Controls				
Individual-level		X	X	X
County-level			X	X
State fixed effects				X
Number of observations	6,435	6,371	6,371	6,371

* p<0.05, ** p<0.01

Individual-level controls include age, sex, race/ethnicity, education, employment status, marital status, household size, household income, presence of a perceived decline in health, and presence of an ambulatory care sensitive condition. County-level controls include number of hospitals with an ED (quartiles), number of primary care physicians (quartiles), number of physician extenders (quartiles), number of federally qualified health centers (quartiles), percentage of population non-white, percentage of population unemployed, percentage of population in poverty, percentage of population uninsured, being in a health professional shortage area, and non-metro area.

Table 4. Predicted probabilities of substitution and marginal effects by persistence of uninsurance prior to 2014, United States, 2013–2014

Outcome	*Predicted probabilities*			*Average marginal effects (95% confidence interval)*	
	Continuously insured	**Transiently uninsured** (1-11 months)	**Persistently uninsured** (≥12 months)	**Transiently uninsured** (1-11 months)	**Persistently uninsured** (≥12 months)
>ED, >PC	5.0%	4.3%	6.6%	-4.4 (-3.8, 3.0)	1.2 (-1.1, 3.4)
≤ED, >PC	31.9%	28.7%	29.1%	-1.8 (-9.4, 5.8)	0.3 (-5.0, 5.7)
>ED, ≤PC	3.7%	8.1%	5.5%	3.6 (-1.0, 8.2)	0.5 (-1.9, 2.8)
≤ED, ≤PC	59.4%	58.9%	58.7%	-1.4 (-9.1, 6.4)	-2.0 (-7.7, 3.7)

ED – emergency department, PC – primary care.
Marginal effects represent a percentage point change in the predicted probability for each substitution outcome category with respect to the continuously insured group.

Table 5. Weighted multinomial logistic regression estimates of year-over-year substitution, United States, 2013–2014

Substitution	*Coefficient (standard error)*			
	(1)	(2)	(3)	(4)
Outcome categories				
>ED, >PC				
Continuously insured	–	–	–	–
Transiently uninsured	–0.14 (0.40)	–0.14 (0.40)	–0.18 (0.41)	–0.06 (0.41)
Persistently uninsured	0.30 (0.21)	0.24 (0.20)	0.25 (0.20)	0.25 (0.22)
≤ED, >PC				
Continuously insured	–	–	–	–
Transiently uninsured	–0.09 (0.18)	–0.01 (0.19)	–0.04 (0.19)	–0.04 (0.19)
Persistently uninsured	–0.06 (0.12)	0.04 (0.13)	0.03 (0.13)	0.05 (0.14)
>ED, ≤PC				
Continuously insured	–	–	–	–
Transiently uninsured	0.80* (0.34)	0.71 (0.36)	0.67 (0.37)	0.73* (0.37)
Persistently uninsured	0.39 (0.29)	0.25 (0.28)	0.22 (0.29)	0.16 (0.31)
≤ED, ≤PC *(base outcome)*	–	–	–	–
Controls				
Individual-level		X	X	X
County-level			X	X
State fixed effects				X
Number of observations	6,435	6,371	6,371	6,371

* p<0.05, ** p<0.01

Individual-level controls include age, sex, race/ethnicity, education, employment status, marital status, household size, household income, presence of a perceived decline in health, and presence of an ambulatory care sensitive condition. County-level controls include number of hospitals with an ED (quartiles), number of primary care physicians (quartiles), number of physician extenders (quartiles), number of federally qualified health centers (quartiles), percentage of population non-white, percentage of population unemployed, percentage of population in poverty, percentage of population uninsured, being in a health professional shortage area, and non-metro area.

Table 6. Sensitivity analysis of year-over-year change in emergency department visits, United States, 2013–2014

Change in emergency department visits	*Coefficient (standard error)*			
	Full analytic sample	Drop ages 18 to 26	Drop those >400% FPL	Include with >0 total visits in both years
Persistence of uninsurance prior to 2014				
Continuously insured	–	–	–	–
Transiently uninsured	0.06 (0.04)	0.10* (0.05)	0.06 (0.06)	0.03 (0.08)
Persistently uninsured	0.10* (0.04)	0.09* (0.04)	0.12** (0.04)	0.11 (0.08)
Number of observations	6,371	5,205	4,147	3,549

* $p<0.05$, ** $p<0.01$

All models are weighted and include individual- and county-level controls and state fixed effects.

Table 7. Sensitivity analysis of year-over-year change in primary care visits, United States, 2013–2014

Change in primary care visits	*Coefficient (standard error)*			
	Full analytic sample	Drop ages 18 to 26	Drop those >400% FPL	Include with >0 total visits in both years
Persistence of uninsurance prior to 2014				
Continuously insured	–	–	–	–
Transiently uninsured	–0.21 (0.36)	–0.47 (0.39)	–0.24 (0.39)	–0.67 (0.59)
Persistently uninsured	1.18 (0.61)	0.92* (0.37)	0.65* (0.32)	2.62 (1.45)
Number of observations	6,371	5,205	4,147	3,549

* $p<0.05$, ** $p<0.01$

All models are weighted and include individual- and county-level controls and state fixed effects.

Table 8. Sensitivity analysis of year-over-year substitution, United States, 2013–2014

Substitution	Coefficient (standard error)			
	Full analytic sample	Drop ages 18 to 26[a]	Drop those >400% FPL	Include with >0 total visits in both years
Outcome categories				
>ED, >PC				
Continuously insured	–	–	–	–
Transiently uninsured	–0.06 (0.41)	–0.10 (–)	–0.04 (0.52)	–0.28 (0.63)
Persistently uninsured	0.25 (0.22)	0.23 (–)	0.54* (0.24)	0.39 (0.34)
≤ED, >PC				
Continuously insured	–	–	–	–
Transiently uninsured	–0.04 (0.19)	–0.14 (–)	0.15 (0.20)	0.02 (0.23)
Persistently uninsured	0.05 (0.14)	0.06 (–)	0.11 (0.14)	0.32 (0.20)
>ED, ≤PC				
Continuously insured	–	–	–	–
Transiently uninsured	0.73* (0.37)	1.09 (–)	0.76 (0.41)	0.55 (0.40)
Persistently uninsured	0.16 (0.31)	–0.07 (–)	0.34 (0.29)	0.31 (0.37)
≤ED, ≤PC *(base outcome)*	–	–	–	–
Number of observations	6,371	5,205	4,147	3,549

[a] Weighted variance matrix was nonsymmetric, standard errors and p-values not obtained.
* p<0.05, ** p<0.01
All models are weighted and include individual- and county-level controls and state fixed effects

Table 9. Stratified marginal effects of persistence of uninsurance prior to 2014 on year-over-year utilization of emergency departments and primary care, United States, 2013–2014

Outcome	*Average marginal effect (95% confidence interval)*					
	Payer type[a] (2014)		*Declinable pre-existing condition (2012)*		*Ambulatory care sensitive condition (2013)*	
	Private	Public	No	Yes	No	Yes
ED visits (change in visits)						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	0.07 (-0.02, 0.16)	0.09 (-0.13, 0.30)	0.10 (-0.01, 0.22)	0.27 (-0.02, 0.57)	0.10* (0.01, 0.20)	-0.13 (-0.32, 0.07)
Persistently uninsured	0.03 (-0.03, 0.09)	0.24** (0.07, 0.41)	0.06 (-0.09, 0.21)	–0.11 (-0.35, 0.13)	0.09* (0.003, 0.17)	0.10 (-0.07, 0.28)
PC visits (change in visits)						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	-0.31 (-1.00, 0.38)	-0.44 (-2.42, 1.55)	-0.13 (-1.40, 1.14)	0.03 (-2.75, 2.80)	–0.11 (-0.86, 0.64)	–0.65 (-2.21, 0.92)
Persistently uninsured	0.06 (-0.34, 0.47)	1.94 (-0.26, 4.14)	2.62 (-0.82, 6.06)	0.87 (-1.43, 3.17)	0.42 (-0.01, 0.84)	3.31 (-0.64, 7.26)
Substitution (percentage point change in predicted probability)						
>ED, >PC						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	-0.5 (-4.7, 3.7)	1.0 (-8.3, 10.2)	4.1 (-4.4, 12.6)	-2.8 (-11.0, 5.3)	0.8 (-3.3, 4.9)	-4.0* (-7.9, 0.0)
Persistently uninsured	-0.7 (-3.1, 1.7)	2.9 (-1.9, 7.7)	0.8 (-2.3, 3.8)	-3.7 (-11.0, 3.7)	0.6 (-1.7, 2.9)	2.1 (-4.1, 8.4)
≤ED, >PC						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	-3.3 (-11.3, 4.8)	0.6 (-12.8, 14.0)	-8.7 (-21.1, 3.7)	-3.2 (-22.9, 16.6)	-2.5 (-11.2, 6.1)	1.7 (-13.6, 17.0)
Persistently uninsured	-1.6 (-8.0, 4.8)	2.4 (-6.1, 11.0)	1.2 (-7.1, 9.6)	3.9 (-14.4, 22.2)	1.5 (-4.2, 7.2)	-1.2 (-14.0, 11.6)
>ED, ≤PC						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	2.8 (-1.6, 7.3)	4.6 (-2.5, 11.8)	0.5 (-4.2, 5.3)	-2.7 (-7.4, 2.1)	4.6 (-0.8, 10.1)	-1.5 (-6.9, 3.8)
Persistently uninsured	-0.8 (-3.2, 1.5)	3.6 (-1.0, 8.2)	0.7 (-2.3, 3.7)	-5.3** (-7.2, -3.3)	0.3 (-1.8, 2.5)	-0.6 (-5.8, 4.7)

≤ED, ≤PC						
Continuously insured	–	–	–	–	–	–
Transiently uninsured	1.0 (-7.8, 9.7)	-6.2 (-20.1, 7.6)	4.1 (-9.2, 17.3)	8.7 (-12.2, 29.6)	-2.9 (-11.5, 5.7)	3.8 (-12.3, 19.7)
Persistently uninsured	3.1 (-4.0, 10.2)	-8.9* (-17.6, -0.2)	-2.7 (-11.6, 6.2)	5.0 (-13.2, 23.3)	-2.5 (-8.6, 3.7)	-0.3 (-13.5, 12.8)
Number of observations	6,371		2,762		6,371	

ED – emergency department, PC – primary care.

* p<0.05, ** p<0.01

[a] Payer type models also include controls for state Medicaid expansion status, number of Marketplace insurers in the state, and state average benchmark premium in 2014.

CHAPTER 3: IS THERE A DELAYED EFFECT OF COVERAGE GAINS UNDER THE AFFORDABLE CARE ACT ON AVOIDABLE ED VISIT RATES?

Introduction

Potentially avoidable visits to the emergency department are an indication of missed opportunities for the health care system and patients—for earlier intervention in disease, developing an ongoing relationship with a primary care provider and/or practice, and assessing social needs. A study of a single large commercial insurer suggests that care for “low-acuity” conditions has shifted away from ED settings (Poon et al., 2018) but it is unclear if this finding is generalizable to the wider insured population. Those findings could be driven by changes in plan generosity (e.g., increasing deductibles and copayments) or enrollment composition of the single national insurer in their study (Aetna), or reflective of an increase in the supply of non-ED care settings.

The effect of coverage expansions on ED use is a separate but related issue because of the misperception that the uninsured use the ED at substantially higher rates than the insured and less appropriately (Zhou, Baicker, Taubman, & Finkelstein, 2017). The Oregon Health Insurance Experiment showed a causal effect of gaining public coverage on greater use of the ED (Taubman et al., 2014) even though observational evidence from other pre-ACA studies focused on expansion and contraction of Medicaid eligibility provide mixed findings (Heavrin et al., 2011; Kolstad & Kowalski, 2012; Lowe, McConnell, Vogt, & Smith, 2008; Marton et al., 2012; Ndumele et al., 2014; Sommers & Simon, 2017).

The ACA expanded health insurance coverage in the non-elderly adult population through the dependent coverage provision, establishing a health insurance Marketplace with key consumer protections, and by expanding Medicaid eligibility. The dependent coverage provision took effect in September 2010, six months after the passage of the ACA, allowing young adults to remain on their parents' health insurance plan up to age 26. The Marketplace, as the collection of federally and state-run health insurance exchanges is known, provides access to guaranteed issue health insurance coverage with premium subsidies available to those between 100% and 400% of the federal poverty level, as long as employer-based coverage is not already available. Medicaid expansion, if adopted by a state, allows residents with incomes up to 138% of the federal poverty level to enroll in Medicaid regardless of failure to meet prior categorical eligibility requirements (e.g., pregnant women, parents of young children).

Previous studies have estimated the population-level effect of coverage gains on ED utilization—before the ACA (Gandhi, Grant, & Sabik, 2014), after early Medicaid expansion in California (Sabik, Cunningham, & Tehrani, 2017), and after ACA implementation (Nikpay et al., 2017; Sommers et al., 2016, 2017)—but none has examined both the longer-run trajectory of effects or focused on non-emergent ED utilization after the Marketplace and Medicaid expansion. We address both gaps in the literature by providing estimates of whether coverage gains yield reductions in avoidable ED visits over time. We use two well-known algorithms to identify different categories of potentially avoidable visits—preventable and non-emergent ED visits—exploring potential delayed effects and spatial correlation using a census of discharge records in seven states from before the passage of the ACA to up to three years after the Marketplace and Medicaid expansion took effect.

Methods

Data

Our study uses visit-level hospital discharge data from the Agency for Healthcare Research and Quality Healthcare Cost and Utilization Project from seven states over the years from 2008 to 2016 to capture ED use before and after passage of the ACA. For participating states, HCUP provides a census of discharges from inpatient, emergency department, and ambulatory settings (Agency for Healthcare Research and Quality, 2018). We obtained both the State Inpatient Databases and State Emergency Department Databases for each state-year in the analysis to ensure that we were capturing both discharges from the ED and inpatient discharges that originated in the ED. Not all states participate in HCUP (either at all, across all databases, or continuously), which means that the universe of states suitable for our analysis was limited. Non-participating states often have ED discharge data available but information included in non-HCUP discharge databases varies considerably. The advantage of HCUP is a high level of standardization of measures and coding across state-years. We chose a set of seven geographically and demographically diverse states for inclusion: Arizona, Florida, Iowa, Kentucky, Maryland, New Jersey, and North Carolina. As of August 2018, two states had data available from 2008 through 2015 (Maryland and New Jersey) with the other five through 2016 (Arizona, Florida, Iowa, Kentucky, North Carolina), which allows us to capture the first two to three years beyond the introduction of the Marketplace and Medicaid expansion in 2014 and several years beyond the dependent coverage provision that took effect in late 2010.

We focus on the non-elderly adult population (18 to 64 years of age) given the three channels of expansion in the ACA noted above. The coverage environments for children and the elderly were already significantly different due to the near-universality of Medicare for the elderly and the more generous availability of public coverage for children of lower income families through Medicaid and the Children's Health Insurance Program. We also use data from the Health Resources and Services Administration Area Health Resources Files, Census Bureau Small Area Health Insurance Estimates, and Census Bureau County Business Patterns to provide annual county-level measures of population, demographics, insurance coverage, and supply of and demand for health care (Census Bureau, n.d.-a, n.d.-b; Health Resources and Services Administration, n.d.). The Census Bureau TIGER/Line® Shapefiles were used to capture contiguity of counties (Census Bureau, 2019).

Measures

The outcome of interest in our study is the county-quarter number of ED visits per 1,000 non-elderly adults. We calculated this ED visit rate by first restricting the original discharge-level data to those aged 18 to 64 who were residents of the state represented by that database (e.g., Arizona residents in the Arizona SEDD or SID). Second, visits were aggregated to a county-quarter total. Finally, the county-quarter rate was calculated using the county-year population for this specific age group from the SAHIE.

The visit rate per 1,000 captures all ED use, which is not a measure that we would necessarily expect to be as sensitive to changes in population-level health insurance coverage rates as focusing on visits that may be avoidable. We employed two algorithms for ascertaining whether each ED visit was potentially avoidable: 1) the ambulatory care sensitive conditions criteria, defined in the AHRQ Prevention Quality Indicators Guide, and 2) having a greater than 50% probability of being either non-emergent (not needing treatment within 12 hours) or emergent (needing treatment within 12 hours) but treatable in primary care, as defined by the New York University Emergency Department Algorithm. Both algorithms have been used extensively in prior analyses of avoidable, non-emergent, and/or preventable ED use (Agency for Healthcare Research and Quality, n.d.; New York University, n.d.). Ambulatory care sensitive conditions are those "for which good outpatient care can potentially prevent the need for hospitalization, or for which early intervention can prevent complications or more severe disease" (Agency for Healthcare Research and Quality, 2001). The developers of the NYU EDA state that "the algorithm is not intended as a triage tool or a mechanism to determine whether ED use in a specific case is 'appropriate' (e.g., for reimbursement purposes)" (New York University, n.d.), rather it is a useful tool for assessing differences across groups or over time in the proportion of visits that are likely to have been preventable or better treated in a different setting.

The HCUP databases capture diagnoses associated with each ED visit using International Classification of Diseases, Ninth Revision diagnosis codes through the third quarter of 2015, switching to ICD-10 thereafter. The ambulatory care sensitive conditions criteria have been specified under both coding systems, and we used the most recent specifications for each, from 2016 for ICD-9 and 2018 for ICD-10. There was substantial variation in the number of diagnosis and procedure codes reported in each state-database-year, ranging as high as 66 diagnosis codes and 50 procedure codes. To make the identification of ED visits associated with ambulatory care sensitive conditions computationally tractable given the number of total visits included in the study (133,175,161), we used only the first 10 diagnosis and procedure codes on each discharge record. This limit also helps with consistency across states as some supplied fewer codes than others. We used a modified version of the NYU EDA guidelines under both coding systems that reduces the number of visits that cannot be probabilistically assigned to one of the four categories of emergence and preventability (Johnston, Allen, Melanson, & Pitts, 2017). Similar to the overall rate, the total number of visits identified as 1) being for ambulatory care sensitive conditions or 2) having a greater than 50% probability of being either non-emergent or emergent but treatable in primary care were summed to the county-quarter level and then converted into a rate per 1,000 using the same population noted above. This latter criterion has been used as a threshold in prior studies using the NYU EDA algorithm (Gandhi & Sabik, 2014).

We included annual percentage of total population that is not white non-Hispanic, percentage of total population in poverty, median household income, and unemployment rate to account for variation in county-level demographics over time. Median household income was adjusted for inflation using the Consumer Price Index for all Urban Consumers from the Bureau of Labor Statistics. We also included the percentage of the non-elderly adult population insured in each county-year to capture changes in population-level insurance coverage over time. The number of hospitals, number of federally qualified health centers, and number of physicians (MDs, specifically) in general or family practice per 1,000 total population at the county-year level were included to account for changes in the supply of health care facilities and providers relevant for settings that are substitutes for avoidable ED visits. We capture the prevailing health status and demand for health care services in each county-year by deriving the number of inpatient days and outpatient visits per 1,000 total population. We also account for county-quarters in which a state Medicaid expansion was in effect, which applied to five (Arizona, Iowa, Kentucky, Maryland, New Jersey) of the seven states included in our study beginning in the first quarter of 2014.

Urgent care centers and retail clinics are not yet captured in AHRF, which is a significant limitation in describing the availability of potential substitutes for the ED. However, CBP does contain the number of establishments at the county level for this segment of the care environment in NAICS code 621498 (other outpatient care centers), our best available proxy for the number of retail clinics and/or urgent care centers that is collected consistently over time and geography.

These data are only available for a subset of counties and therefore were only used in alternate analyses for a restricted set of counties.

Statistical analysis

Our identification strategy relies on using within-county variation to estimate the effect of changes in population-level health insurance coverage among non-elderly adults with rates of ED use. We began with a fixed effects estimator that incorporates the covariates described above in a stepwise manner along with county, quarter, and year fixed effects and standard errors clustered by state. This naïve approach is limited in that it assumes that the effect of any changes in county-level health insurance coverage on ED use are immediate and that there are no potential lagged effects associated with the time cost of improving health insurance literacy, identifying a primary care provider, changing health care utilization habits, or any number of potential mechanisms that would explain delayed behavior change. We build upon this model by adding one- (four quarters), two- (eight quarters), and three-year (12 quarters) lags of the insurance coverage variable to the fixed effects model. This approach allows us to identify whether prior changes in population-level insurance coverage affect ED use rates in the current quarter.

The fixed effects approach relies on within-county variation in covariates and outcomes, assuming that counties (by residence of the patient) are effectively independent from one another. However, ED use patterns and the supply of and demand for health care services in one county could be correlated with those in neighboring counties. Therefore, we also explore spatial regression models that incorporate geographic lags, allowing for the outcomes and health care supply and demand in bordering counties to factor into the effect estimation (StataCorp, 2017a). This approach allows for specification of spatial autoregressive errors but not the same lagged independent variable specification as the fixed effects models. Therefore, we do not have an exact spatial regression analogue of the fixed effects model with lagged county-level health insurance coverage for comparison. Our analyses were conducted in SAS® 9.4 for Unix, Stata® 14.1 for Unix, and Stata® 15.1 for Windows (SAS Institute Inc., 2013; StataCorp, 2015, 2017b). The maps were generated using *maptile*, a user-written package for Stata® (Stepner, 2017). This study was approved as exempt by the Non-Biomedical Institutional Review Board at the University of North Carolina at Chapel Hill (#18-1555).

Results

Our analysis uses over 130 million unique ED visits in seven states over the years 2008 through 2016. We summarize the demographic and socioeconomic variation (Table 10) and the rate of ED visits (Table 11) between the included states and over the time. In addition to summarizing the rates of ED use, we compare prevalence of visits for ambulatory care sensitive conditions and non-emergent or emergent but primary care treatable conditions before and after the ICD-10 coding transition in the fourth quarter of 2015. Overall, we find that approximately 5.1% of ED visits were for ambulatory care sensitive condition, using the AHRQ definitions, and 48.7% were for non-emergent or emergent but primary care treatable conditions, using the NYU algorithm, with variation by state and year. These classifications were not mutually exclusive with 1.3% of visits categorized as satisfying both criteria, yielding 52.6% that satisfied either. We observe an increase in ambulatory care sensitive condition prevalence and decrease in non-emergent or emergent but primary care treatable condition prevalence associated with the coding transition. This divergence in prevalence between the two algorithms may be due to changes in provider coding practices associated with the ICD-10 transition, given the large expansion and greater specificity of codes available, or with the coding algorithms themselves, despite the effort to maintain comparability with the older code set. As such, we have included an indicator for quarters using ICD-10 coding in our regression analyses and have also estimated alternate versions using only quarters with ICD-9 coding as robustness checks.

There is substantial county-level variation in both ED visit rates per 1,000 non-elderly adults and the non-elderly adult insured rate in 2008 and over our study period as the ACA took effect, which we will exploit to help identify how increased population-level insurance coverage affects ED visit rates (Figures 5 through 8). County-level variation in ED visit rates per 1,000 non-elderly adults for ambulatory care sensitive conditions and non-emergent or emergent but primary care treatable conditions in 2008 and over time are also shown (Figures 9 through 12).

Table 12 shows how the effect of population-level insurance coverage on ED visit rates changes as we add controls to our fixed effects model. For total ED visits, a one percentage point increase in county-level health insurance coverage among non-elderly adults is associated with approximately 0.6 additional ED visits per 1,000 non-elderly adults per county-quarter. For ED visits for an ambulatory care sensitive condition, the effect of a one percentage point increase in county-level health insurance coverage among non-elderly adults is consistently associated with approximately 0.1 additional ED visits per 1,000 non-elderly adults per county-quarter. For ED visits for non-emergent or emergent but primary care treatable conditions, there is no evidence of an effect of changes in population-level insurance coverage on ED visits rates. Table 13 shows our estimates when adding one- (four quarters), two- (eight quarters), and three-year lags (twelve quarters) of population-level insurance coverage to our full model (Model 4 from Table 12). For total ED visits, the contemporaneous effect estimate falls slightly to 0.44 additional ED visits per 1,000 non-elderly adults per percentage point increase in coverage (95% CI: 0.08, 0.79, $p<0.05$) with all three lagged terms having no effect. For ED visits for ambulatory care sensitive conditions, the contemporaneous effect estimate falls by approximately half to 0.07 additional ED visits per

1,000 non-elderly adults for each percentage point increase in coverage (95% CI: 0.03, 0.11, $p<0.01$) with only the two-year lag term being statistically significant ($b=0.07$, 95% CI: 0.01, 0.13, $p<0.05$). Only the one-year lag term was statistically significant for ED visits for non-emergent or emergent but primary care treatable conditions, showing a slight decline in visits ($b=-0.11$, 95% CI: -0.21, 0.00, $p<0.05$) associated with a one percentage point increase in coverage four quarters prior. Medicaid expansion was associated with significant reductions in all three ED visit rates: total ED visits ($b=-4.84$, 95% CI: -8.62, -1.06, $p<0.05$), ED visits for ambulatory care sensitive conditions ($b=-0.56$, 95% CI: -1.06, -0.06, $p<0.05$), and ED visits for non-emergent or emergent but primary care treatable conditions ($b=-2.99$, 95% CI: -5.10, -0.89, $p<0.05$).

We ran robustness checks to assess how our results were affected by the ICD-10 coding transition and inclusion of a proxy for urgent care center availability. After dropping all quarters after the ICD-10 transition in the ED discharge data (quarter 4 of 2015 and beyond), there are no significant contemporaneous or lagged effects of population-level coverage gains on any of our three ED visit rate outcomes in the fixed effects models (Table 14). Our proxy for urgent care center availability (number of "other outpatient centers" per 1,000 population) was only available for a subset of counties (306 out of 446 included in the full analysis) so the results are not directly comparable to our main findings; however, we also ran the main models on this subsample for comparison (Table 15). For total ED visits, the contemporaneous effect estimate is 0.60 additional ED visits per 1,000 non-elderly adults per percentage point increase in coverage (95% CI: 0.26, 0.94, $p<0.01$) with all three lagged terms having no effect. For ED visits for ambulatory care sensitive conditions, the contemporaneous effect estimate is 0.06 additional ED visits per 1,000 non-elderly adults for each percentage point increase in coverage (95% CI: 0.04, 0.09, $p<0.01$) and the one-year lagged effect is 0.07 additional ED visits per 1,000 non-elderly adults (95% CI: 0.01, 0.13, $p<0.05$) with the two- and three-year lags having no effect. For ED visits for non-emergent or emergent but primary care treatable conditions, the one-year lagged effect is -0.18 ED visits per 1,000 non-elderly adults (95% CI: -0.26, -0.10, $p<0.01$) with the contemporaneous term and the two- and three-year lags having no effect. As shown for comparison, inclusion of urgent care centers in the model does not meaningfully affect our effect estimates in the relevant subsample.

Table 16 contains our spatial regression results using a first-order contiguous spatial lag (neighboring counties). For lags of the dependent variable only or the dependent variable and the independent variables capturing health care supply and demand, the results are fairly consistent across our ED visit rates outcomes with approximately 0.6 to 0.7 additional ED visits per 1,000 non-elderly adults in a county-quarter for each percentage point increase in population-level health insurance coverage. However, the effect of coverage becomes negative for total ED visits (b=-0.45, 95% CI: -0.51, -0.39, $p<0.01$) and ED visits for non-emergent or emergent but primary care treatable conditions (b=-0.42, 95% CI: -0.49, -0.36, $p<0.01$) when spatial autoregressive errors are included. The effect for ED visits for ambulatory care sensitive conditions (b=0.93, 95% CI: 0.92, 0.94, $p<0.01$) remains significant and increases in magnitude. If we again drop the quarters after the ICD-10 transition, all of the effects remain significant but slightly attenuated with a similar pattern of changes when the spatial autoregressive errors are included (Table 17). We were not able to estimate our spatial regression models with our proxy for urgent care center supply given the reduced number of counties and lack of appropriate contiguity in the panel.

Discussion

Our analysis used a variety of modeling approaches to show that increases in population-level health insurance coverage are not enough on their own to yield reductions in potentially avoidable ED visits. However, Medicaid expansion was associated with reductions in both the total and potentially avoidable ED visit rates, indicating that the type of coverage gained matters. We also find that geography matters, as there is spatial correlation in ED visit rates across county lines with the supply and demand for health care in neighboring counties playing a role in ED use.

The question of what makes an ED visit inappropriate or avoidable is complex and highly controversial. Several insurers have implemented post-hoc review of ED visit claims in recent years that seemingly violate the prudent layperson standard for emergency coverage (Trueger, 2018), denying coverage based on reported diagnoses rather than presenting symptoms. The sensitivity and specificity of methods for classifying appropriateness of an ED visit is fraught with problems as the severity of the potential diagnoses underlying a single presenting compliant can be highly variable (Raven, Lowe, Maselli, & Hsia, 2013). A wide range of estimates exist for the proportion of ED use attributable to non-emergent care—ranging from as low as 8% of visits to 62% (Uscher-Pines et al., 2013; Weinick, Burns, & Mehrotra, 2010).

All health insurance coverage is not created equal. There is substantial variation in benefit design across insurance types, with Medicaid having little to no cost sharing and commercial plans through the Marketplace often having high deductibles and substantial coinsurance. Simply enrolling more people is not on its own going to change health behaviors, result in more efficient use of services and settings, or improve population health, particularly when being insured does not necessarily make using health care affordable (e.g., very high spending thresholds before reaching stated actuarial value in Marketplace plans) (Polyakova, Hua, & Bundorf, 2017). It takes time to develop a trusting relationship with a provider and gaining coverage alone does not remove all access barriers or ensure receipt of high-quality care (H. Allen et al., 2014). Coverage expansions can certainly play a large role in aligning incentives and reducing uncompensated care for health systems, but expecting substantial short-term reductions in health care use and costs may be overly optimistic.

Our study has several limitations. We are interested in understanding the impact of insurance changes on ED visits that could potentially be avoided, though there is not a single straightforward method for identifying such visits. Thus, we use two commonly used algorithms that identify different types of visits that are potentially avoidable. We found a sizable difference in the percentage of ED visits identified by the AHRQ and NYU algorithms, with the former identifying ED visits that were likely preventable with better primary care and the latter capturing the likelihood that a visit did not require treatment in the ED. For these algorithms, we observed different effects of the ICD-10 transition (percentage of visits for ambulatory care sensitive conditions going up, percentage of visits for non-emergent or emergent but primary care treatable conditions going down). Also, the length of time that we observe after the Marketplace and Medicaid expansion took effect in 2014 is limited to two or three years based on the state. However, by using a long period of time prior to 2014, we aimed to establish a strong pre-ACA trend and also capture variation in the uninsured rate introduced by the dependent coverage provision that took effect in late 2010 shortly after passage of the law. Our fixed effects models exploit within-county variation in ED visit rates and population-level insurance coverage by accounting for time-invariant differences between counties. We attempted to address changes in the underlying population characteristics and health care market within each county, but it is possible that other factors that we could not control for also play a role in this relationship. These findings may not generalize to all states and/or future coverage expansions based on the characteristics of those settings (e.g., prevailing insured rate, practice patterns, health care supply and demand) and the benefit design of the coverage gained by those newly enrolled (Sommers & Simon, 2017).

It is also unclear that expanding the supply of ED substitutes for non-emergent conditions is a solution either. Greater access to community health centers, retail clinics, and urgent care centers should allow for declines in ED visit rates over time as people learn about and use these settings, as recent studies have shown (Alexander et al., 2017; L. Allen, Cummings, & Hockenberry, 2019). However, these encouraging findings contradict other studies showing that penetration of retail clinics either does not meaningfully affect ED use for "low-acuity" conditions nor does it reduce overall health care spending (Ashwood et al., 2016; Martsolf et al., 2017). Beyond insurance coverage, policymakers may need to turn to alternative models of care or payment models combined with increased attention to social determinants of health in order to achieve appropriate use of care or lower growth in health care expenditures.

Tables and Figures

Figure 5. Average quarterly ED visits per 1,000 non-elderly adults by county for included states, 2008

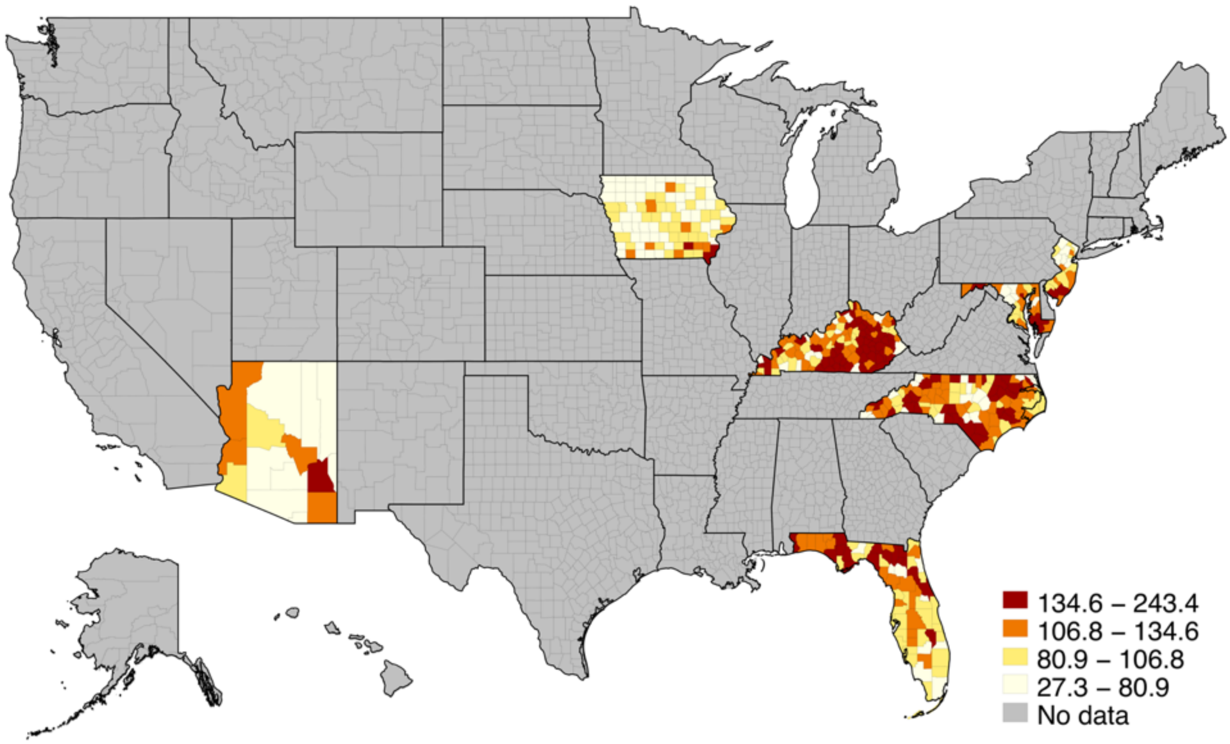


Figure 6. Annual non-elderly insured rate by county for included states, 2008

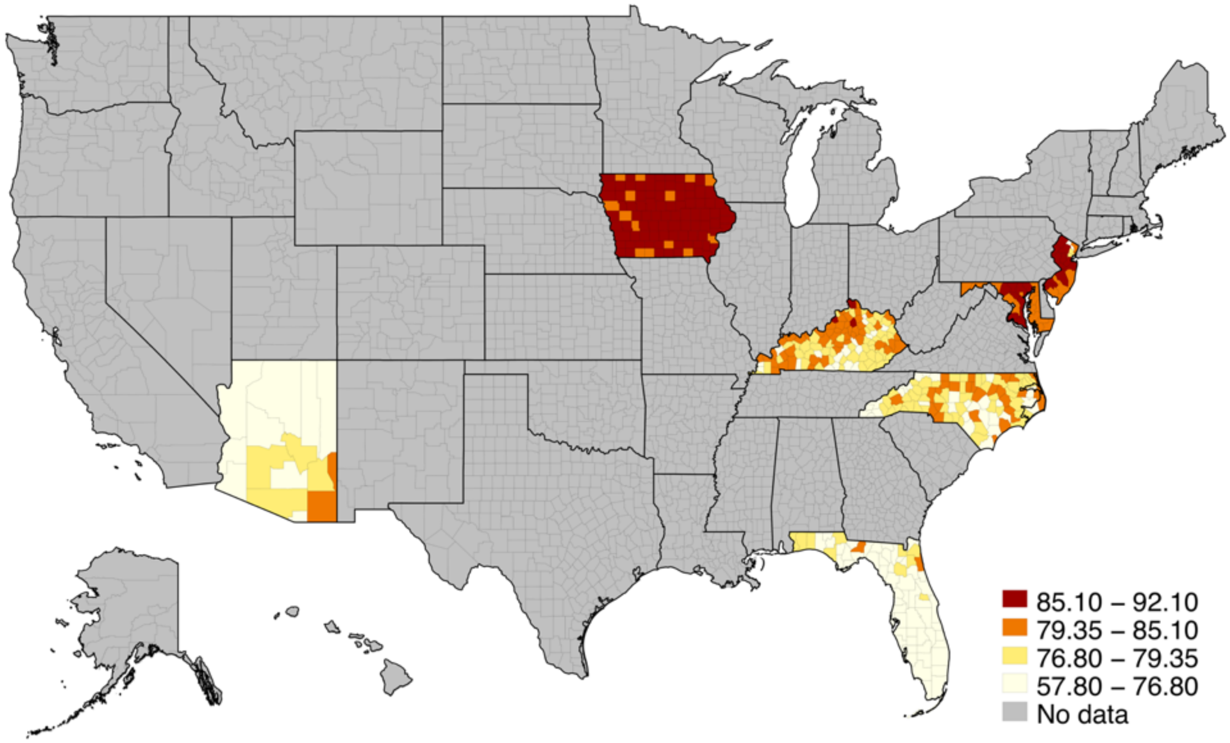
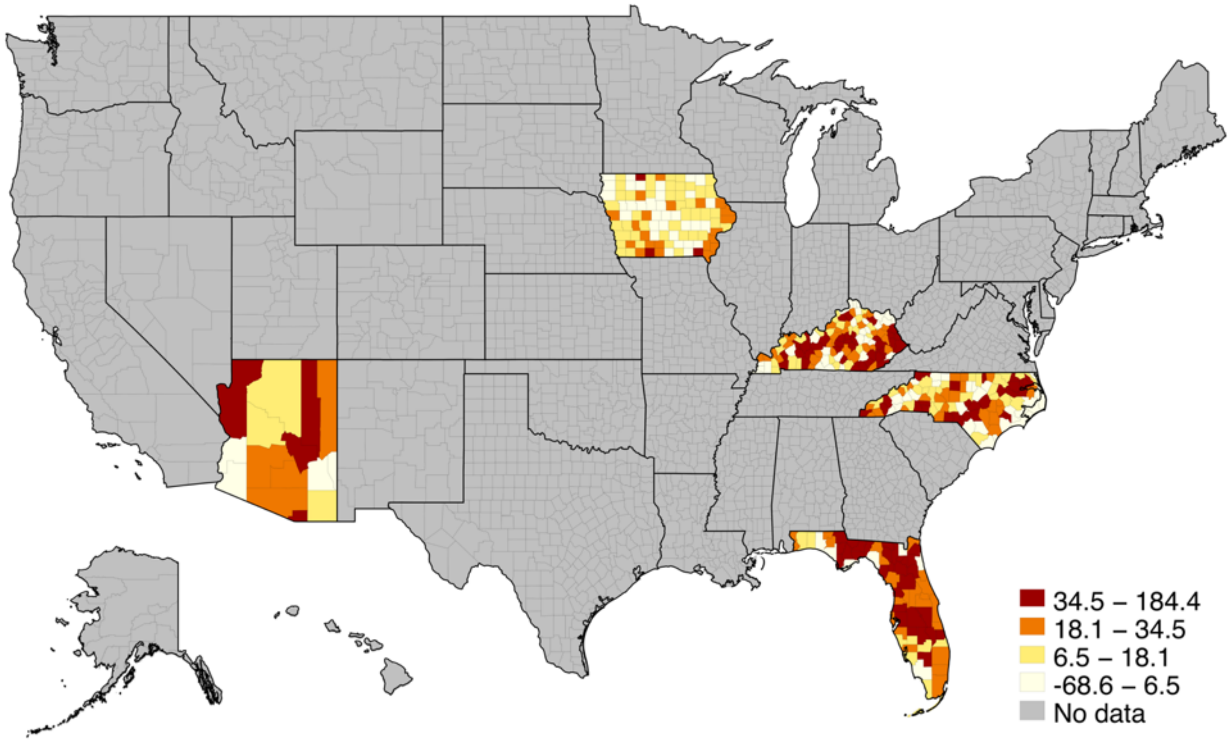


Figure 7. Change in average quarterly ED visits per 1,000 non-elderly adults by county for included states, 2008 to 2016



Note: Maryland and New Jersey are shown as missing because data for those two states were only available through 2015 as of August 2018.

Figure 8. Change in annual non-elderly adult insured rate by county for included states, 2008 to 2016

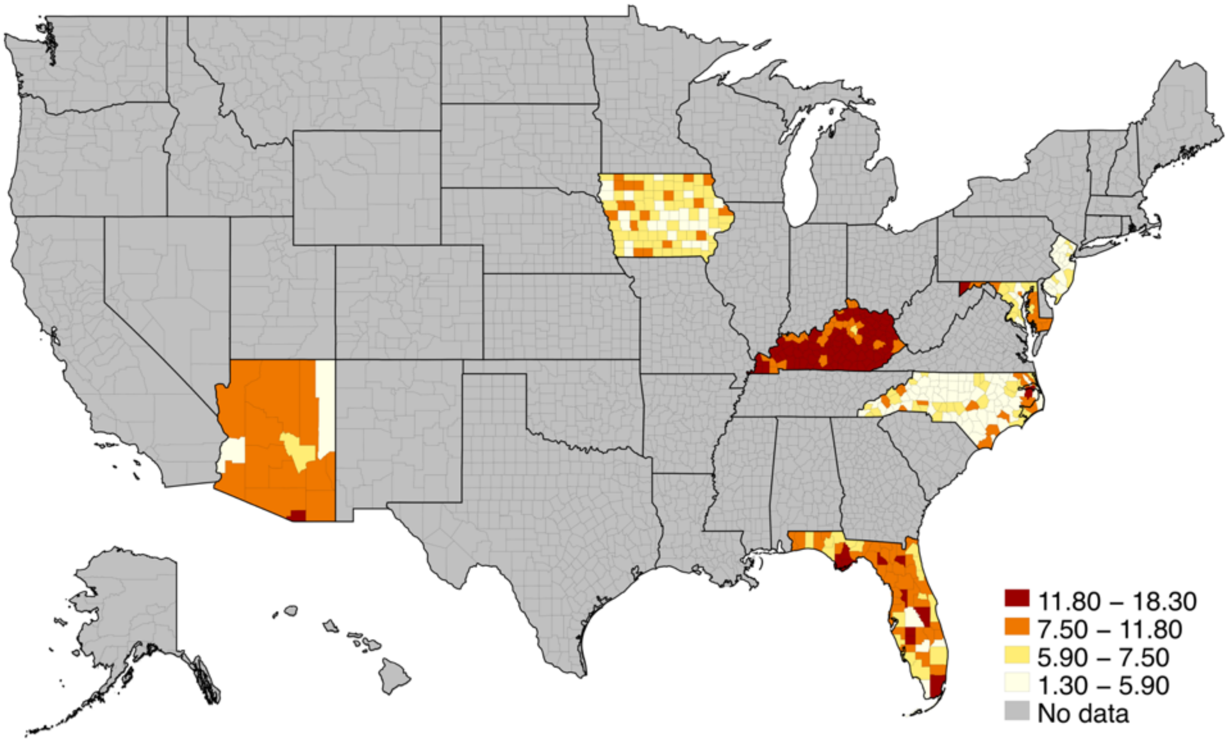


Figure 9. Average quarterly ED visits per 1,000 non-elderly adults for ambulatory care sensitive conditions by county for included states, 2008

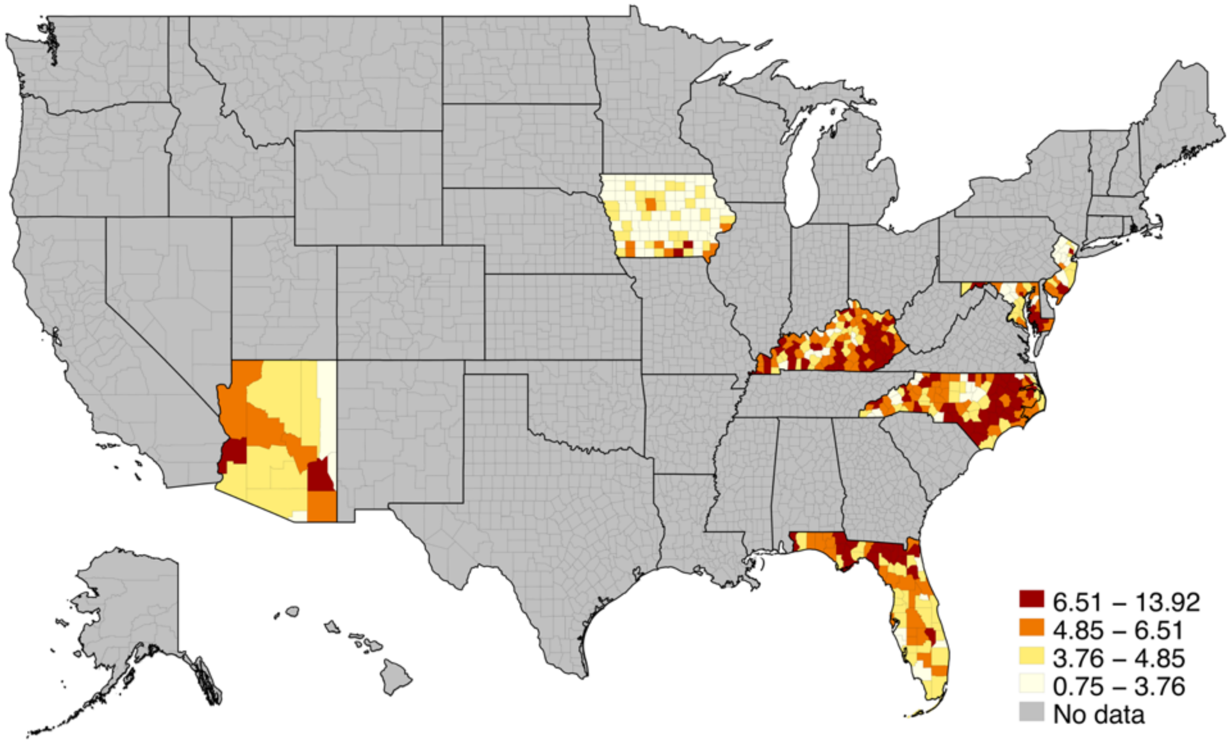


Figure 10. Average quarterly ED visits per 1,000 non-elderly adults for non-emergent or emergent but primary care treatable conditions by county for included states, 2008

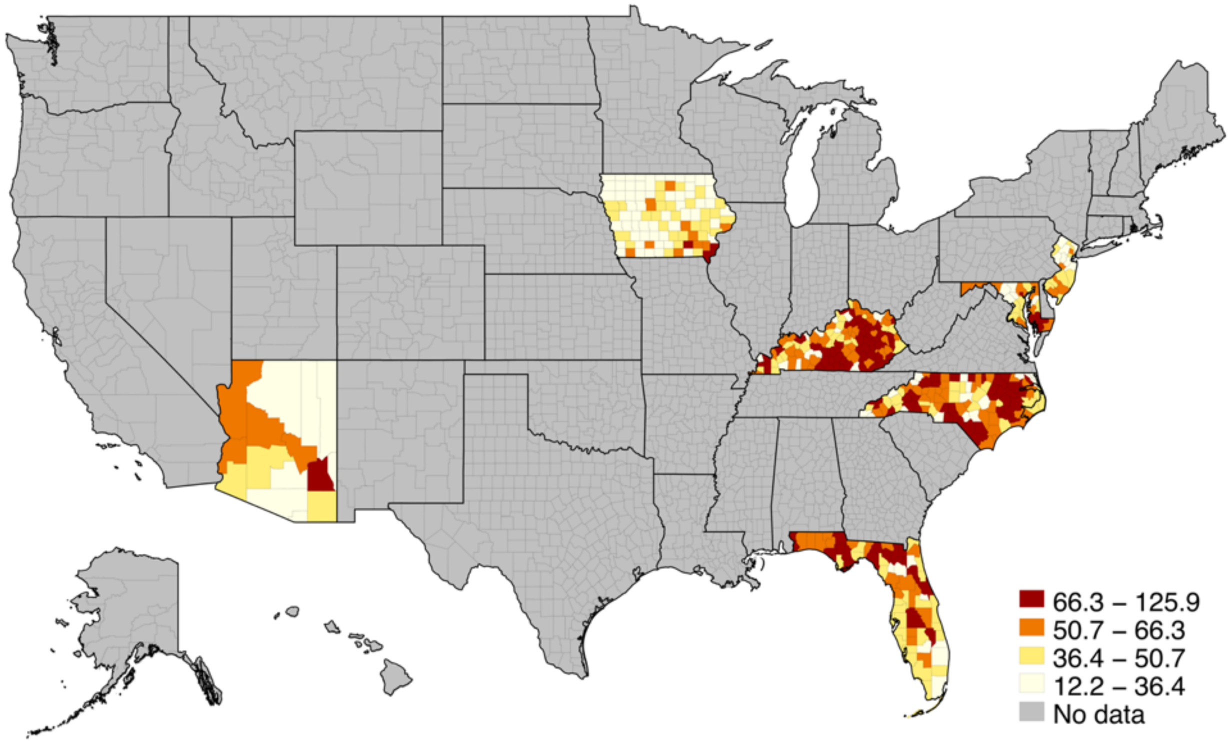
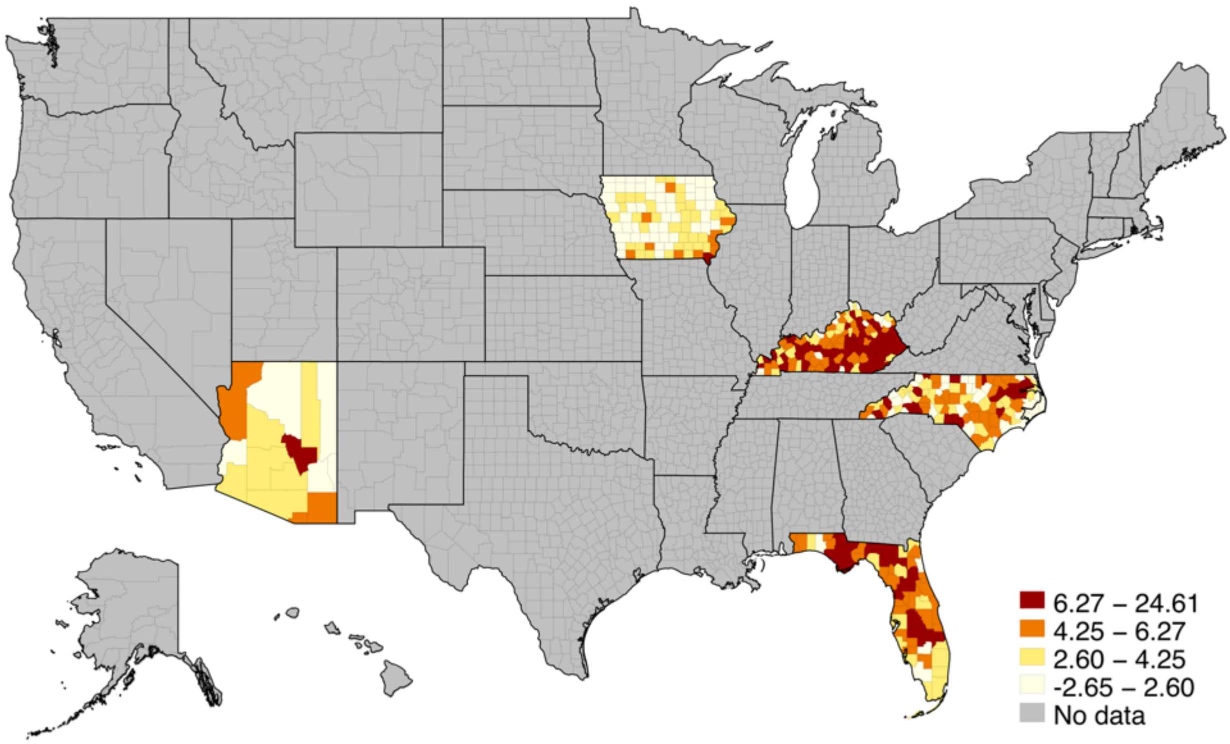
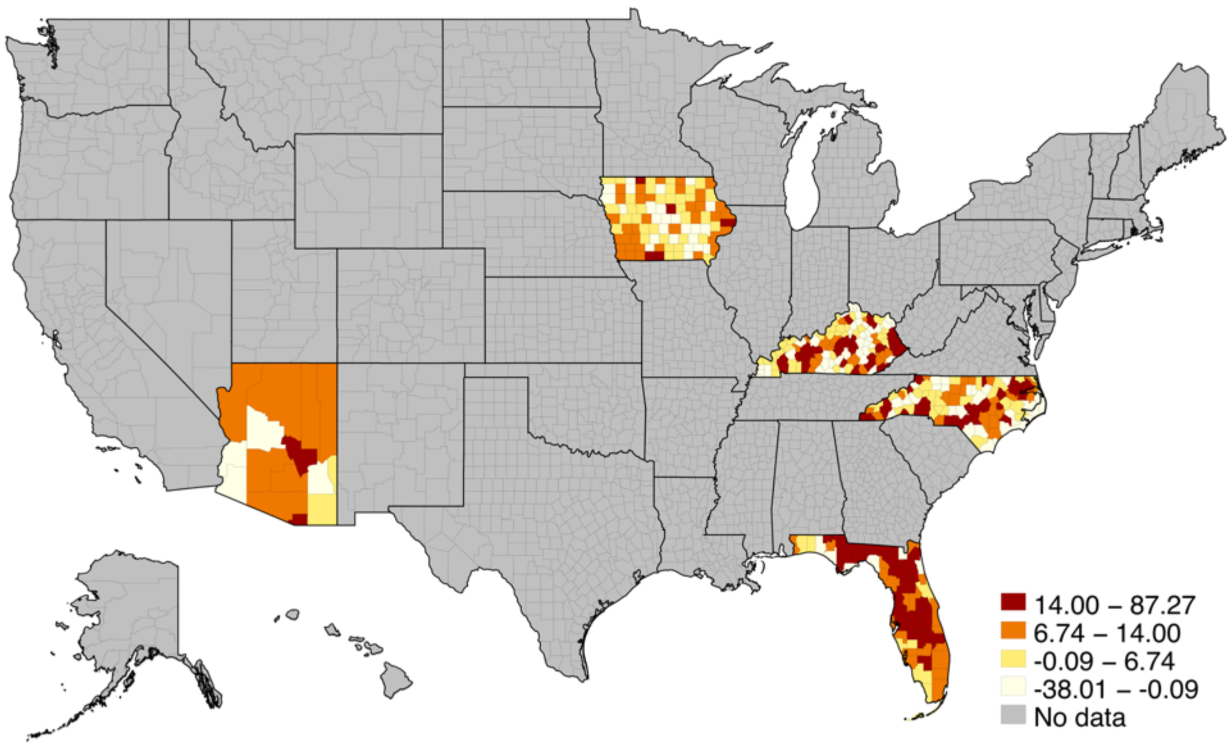


Figure 11. Change in average quarterly ED visits per 1,000 non-elderly adults for ambulatory care sensitive conditions by county for included states, 2008 to 2016



Note: Maryland and New Jersey are shown as missing because data for those two states were only available through 2015 as of August 2018.

Figure 12. Change in average quarterly ED visits per 1,000 non-elderly adults for non-emergent or emergent but primary care treatable conditions by county for included states, 2008 to 2016



Note: Maryland and New Jersey are shown as missing because data for those two states were only available through 2015 as of August 2018.

Table 10. State demographic characteristics, 2008 and 2016

State	Number of counties	Non-elderly adult population (in 1000s)		Total population (in 1000s)		% non-white and/or Hispanic		% in poverty		Unemployment rate	
		2008	*2016 (% change)*	*2008*	*2016 (% change)*	*2008*	*2016 (change)*	*2008*	*2016 (change)*	*2008*	*2016 (change)*
AZ	15	3,855	4,009 (+4.0%)	6,500	6,931 (+6.6%)	41.6%	44.5% (+2.9%)	14.7%	16.4% (+1.7%)	5.6%	5.4% (-0.2%)
FL	67	10,865	12,072 (+11.1%)	18,328	20,612 (+12.5%)	39.7%	45.1% (+5.4%)	13.3%	14.8% (+1.5%)	6.3%	4.9% (-1.4%)
IA	99	1,782	1,827 (+2.5%)	3,003	3,135 (+4.4%)	9.7%	13.8% (+4.1%)	11.4%	11.7% (+0.3%)	4.2%	3.7% (-0.5%)
KY	120	2,620	2,646 (+1.0%)	4,269	4,437 (+3.9%)	12.2%	15.0% (+2.8%)	17.3%	18.3% (+1.0%)	6.6%	5.3% (-1.3%)
MD	24	3,519	3,696 (+5.0%)	5,634	6,016 (+6.8%)	42.3%	48.5% (+6.2%)	8.2%	9.8% (+1.6%)	4.4%	4.3% (-0.1%)
NC	100	5,637	6,096 (+8.1%)	9,222	10,147 (+10.0%)	32.8%	36.5% (+5.9%)	14.6%	15.4% (+0.8%)	6.4%	5.1% (-1.3%)
NJ	21	5,384	5,478 (+1.8%)	8,683	8,944 (+3.0%)	38.3%	44.2% (+3.7%)	8.7%	10.4% (+1.7%)	5.5%	5.0% (-0.5%)

Note: These are obtained by summing or population-weighted averaging the underlying county-level data used in the analysis as appropriate.

Table 11. ED visit volumes and classification for non-elderly adults by state

State	*2008 (quarterly average) – ICD-9*			*2015 (quarterly average, quarters 1 through 3) – ICD-9*			*2015 (quarter 4) – ICD-10*			*2016 (quarterly average) – ICD-10*		
	Total	ACSC (%)	NEPCT (%)	Total	ACSC (%)	NEPCT (%)	Total	ACSC (%)	NEPCT (%)	Total	ACSC (%)	NEPCT (%)
AZ	308,384	16,161 (5.2%)	145,874 (47.3%)	397,786	20,695 (5.2%)	191,644 (48.2%)	392,734	29,303 (7.5%)	179,362 (45.7%)	411,419	30,974 (7.5%)	185,486 (45.1%)
FL	1,060,963	51,742 (4.9%)	510,842 (48.1%)	1,477,337	70,413 (4.8%)	744,399 (50.4%)	1,490,846	104,161 (7.0%)	709,245 (47.6%)	1,535,805	109,513 (7.1%)	724,273 (47.2%)
IA	154,130	6,468 (4.2%)	73,465 (47.7%)	170,388	7,757 (4.6%)	85,234 (50.0%)	163,377	10,555 (6.5%)	78,295 (47.9%)	169,310	11,057 (6.5%)	78,810 (46.5%)
KY	331,348	15,462 (4.7%)	163,187 (49.2%)	390,794	20,774 (5.3%)	188,153 (48.1%)	384,805	30,517 (7.9%)	177,301 (46.1%)	391,676	30,660 (7.8%)	173,902 (44.4%)
MD	371,150	18,471 (5.0%)	171,765 (46.3%)	399,753	19,286 (4.8%)	185,652 (46.4%)	386,985	25,689 (6.6%)	168,865 (43.6%)	–	–	–
NC	609,713	28,685 (4.7%)	304,006 (49.9%)	749,147	34,821 (4.6%)	385,604 (51.5%)	739,934	51,891 (7.0%)	253,264 (34.2%)	752,982	52,745 (7.0%)	368,670 (49.0%)
NJ	499,314	22,480 (4.5%)	226,094 (45.3%)	575,104	24,639 (4.3%)	267,948 (46.6%)	619,379	43,211 (7.0%)	363,004 (58.6%)	–	–	–

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)
Note: Maryland and New Jersey are shown as missing for 2016 because were not yet at the time of purchase (August 2018).

Table 12. Fixed effect estimates of the contemporaneous effect of changes in county-level insurance coverage on ED visit rates, 2008 to 2016

Outcome	*Coefficient (95% confidence interval)*			
	(1)	(2)	(3)	(4)
ED visits per 1,000 non-elderly adults	0.21 (-0.55, 0.98)	0.60** (0.36, 0.83)	0.56** (0.33, 0.78)	0.62** (0.36, 0.88)
ACSC ED visits per 1,000 non-elderly adults	0.12* (0.04, 0.20)	0.15** (0.08, 0.21)	0.13** (0.07, 0.20)	0.14** (0.08, 0.19)
NEPCT ED visits per 1,000 non-elderly adults	-0.22 (-0.65, 0.22)	0.02 (-0.14, 0.17)	0.01 (-0.17, 0.18)	0.04 (-0.14, 0.22)
County fixed effects and ICD-10	X	X	X	X
Quarter and year fixed effects	X	X	X	X
Medicaid expansion		X	X	X
Demographics and socioeconomic factors			X	X
Health care supply and demand				X
N (county-quarters)	15,876	15,876	15,876	15,876

* p<0.05, ** p<0.01

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)

Each cell is a separate model. Standard errors are clustered by state. Demographics and socioeconomic factors include percentage of population non-white or Hispanic, real median household income, percentage of population in poverty, and unemployment rate. Health care supply and demand includes number of hospitals per 1,000 total population, number of FQHCs per 1,000 total population, number of physicians in general or family practice per 1,000 total population, number of inpatient days per 1,000 total population, and number of outpatient visits per 1,000 total population.

Table 13. Fixed effect estimates of the lagged effect of changes in county-level insurance coverage on ED visit rates, 2008 to 2016

Covariate	*Coefficient (95% confidence interval)*		
	ED visits per 1,000 non-elderly adults	ACSC ED visits per 1,000 non-elderly adults	NEPCT ED visits per 1,000 non-elderly adults
Lag of quarterly insured rate			
0 *(current)*	0.44* (0.08, 0.79)	0.07** (0.03, 0.11)	0.08 (-0.14, 0.31)
4 *(1 year)*	0.04 (-0.24, 0.31)	0.07 (-0.01, 0.14)	-0.11* (-0.21, 0.00)
8 *(2 years)*	-0.17 (-0.63, 0.29)	0.07* (0.01, 0.13)	-0.20 (-0.48, 0.08)
12 *(3 years)*	0.33 (-0.31, 0.96)	0.02 (-0.10, 0.14)	0.23 (-0.13, 0.58)
Medicaid expansion	-4.84* (-8.62, -1.06)	-0.56* (-1.06, -0.06)	-2.99* (-5.10, -0.89)
N (county-quarters)	10,524	10,524	10,524

* $p<0.05$, ** $p<0.01$

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)

Each column is a separate model. These models include the full set of controls as shown in Model 4 of Table 12 (county, quarter, and year fixed effects, ICD-10 indicator, Medicaid expansion indicator, demographic and socioeconomic factors, and health care demand and supply). Standard errors are clustered by state.

Table 14. Fixed effect estimates of the lagged effect of changes in county-level insurance coverage on ED visit rates, 2008 to quarter 3 of 2015

Lag of quarterly insured rate	*Coefficient (95% confidence interval)*		
	ED visits per 1,000 non-elderly adults	ACSC ED visits per 1,000 non-elderly adults	NEPCT ED visits per 1,000 non-elderly adults
0 *(current)*	0.37 (-0.10, 0.84)	0.02 (-0.02, 0.06)	0.09 (-0.18, 0.36)
4 *(1 year)*	-0.10 (-0.54, 0.35)	0.01 (-0.01, 0.03)	-0.16 (-0.46, 0.14)
8 *(2 years)*	-0.22 (-0.97, 0.54)	0.03 (-0.03, 0.08)	-0.16 (-0.55, 0.22)
12 *(3 years)*	0.30 (-0.09, 0.68)	-0.001 (-0.06, 0.06)	0.21 (-0.03, 0.45)
N (county-quarters)	8,474	8,474	8,474

* $p<0.05$, ** $p<0.01$

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)

Each column is a separate model. These models include the full set of controls as shown in Model 4 of Table 12 (county, quarter, and year fixed effects, Medicaid expansion indicator, demographic and socioeconomic factors, and health care demand and supply) except for the ICD-10 indicator. Standard errors are clustered by state.

Table 15. Fixed effect estimates of the lagged effect of changes in county-level insurance coverage on ED visit rates, including urgent care centers, 2008 to 2016

Lag of quarterly insured rate	*Coefficient (95% confidence interval)*		
	ED visits per 1,000 non-elderly adults	ACSC ED visits per 1,000 non-elderly adults	NEPCT ED visits per 1,000 non-elderly adults
With urgent care centers			
0 *(current)*	0.60** (0.26, 0.94)	0.06** (0.04, 0.09)	0.21 (-0.01, 0.42)
4 *(1 year)*	-0.07 (-0.23, 0.09)	0.07* (0.01, 0.13)	-0.18** (-0.26, -0.10)
8 *(2 years)*	-0.12 (-0.56, 0.32)	0.06 (-0.005, 0.13)	-0.15 (-0.42, 0.13)
12 *(3 years)*	0.51 (-0.14, 1.17)	0.07 (-0.002, 0.15)	0.28 (-0.06, 0.63)
Same subsample but without urgent care centers			
0 *(current)*	0.60** (0.25, 0.94)	0.06** (0.04, 0.09)	0.21 (-0.01, 0.42)
4 *(1 year)*	-0.06 (-0.22, 0.10)	0.07* (0.01, 0.13)	-0.18** (-0.26, -0.09)
8 *(2 years)*	-0.11 (-0.56, 0.34)	0.06 (-0.004, 0.13)	-0.14 (-0.42, 0.13)
12 *(3 years)*	0.54 (-0.09, 1.16)	0.07* (0.004, 0.14)	0.29 (-0.03, 0.62)
N (county-quarters)	6,040	6,040	6,040

* p<0.05, ** p<0.01

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)

Each column-panel is a separate model. These models include the full set of controls as shown in Model 4 of Table 12 (county, quarter, and year fixed effects, ICD-10 indicator, Medicaid expansion indicator, demographic and socioeconomic factors, and health care demand and supply) plus the number of 'other outpatient care centers' (NAICS 621498) by county-year in the top panel. Standard errors are clustered by state.

Table 16. Spatial regression estimates of the contemporaneous effect of changes in county-level insurance coverage on ED visit rates, 2008 to 2016

Spatial lags used	*Coefficient (95% confidence interval)*		
	ED visits per 1,000 non-elderly adults	ACSC ED visits per 1,000 non-elderly adults	NEPCT ED visits per 1,000 non-elderly adults
Dependent variable only	0.70** (0.69, 0.72)	0.74** (0.72, 0.76)	0.65** (0.63, 0.67)
Dependent variable and selected independent variables (health care supply and demand)	0.67** (0.65, 0.69)	0.69** (0.67, 0.71)	0.61** (0.59, 0.63)
Dependent variable, selected independent variables (health care supply and demand), and errors	-0.45** (-0.51, -0.39)	0.93** (0.92, 0.94)	-0.42** (-0.49, -0.36)
N (county-quarters)	14,272	14,272	14,272

* p<0.05, ** p<0.01

ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)

Each cell is a separate model. These models include the full set of controls as shown in Model 4 of Table 12 (county, quarter, and year fixed effects, ICD-10 indicator, Medicaid expansion indicator, demographic and socioeconomic factors, and health care demand and supply). These estimates use a first-order spatial lag (neighboring county) weighting matrix.

Table 17. Spatial regression estimates of the contemporaneous effect of changes in county-level insurance coverage on ED visit rates, 2008 to quarter 3 of 2015

Spatial lags used	*Coefficient (95% confidence interval)*		
	ED visits per 1,000 non-elderly adults	ACSC ED visits per 1,000 non-elderly adults	NEPCT ED visits per 1,000 non-elderly adults
Dependent variable only	0.57** (0.54, 0.59)	0.44** (0.41, 0.46)	0.56** (0.54, 0.59)
Dependent variable and selected independent variables (health care supply and demand)	0.55** (0.53, 0.58)	0.42** (0.39, 0.45)	0.55** (0.52, 0.57)
Dependent variable, selected independent variables (health care supply and demand), and errors	-0.29** (-0.37, -0.20)	0.77** (0.74, 0.80)	-0.34** (-0.42, -0.26)
N (county-quarters)	13,826	13,826	13,826

* p<0.05, ** p<0.01
ACSC – ambulatory care sensitive conditions (AHRQ), NEPCT – non-emergent or emergent but primary care treatable conditions (NYU)
Each cell is a separate model. These models include the full set of controls as shown in Model 4 of Table 12 (county, quarter, and year fixed effects, Medicaid expansion indicator, demographic and socioeconomic factors, and health care demand and supply) except for the ICD-10 indicator. These estimates use a first-order spatial lag (neighboring county) weighting matrix.

CHAPTER 4: DO HIGH DEDUCTIBLES REDUCE THE USE OF 'FREE' PREVENTIVE SERVICES UNDER THE AFFORDABLE CARE ACT?

Introduction

Less than one-tenth of adults in the United States aged 35 and older are up-to-date with all recommended preventive services, falling well short of many Healthy People 2020 goals, a set of national health promotion targets (Borsky et al., 2018; Centers for Disease Control and Prevention, 2015; Healthy People 2020, n.d.). Prevention is often incentivized in alternative payment models because of its perception as a cost-effective way to improve population health. The economic benefits of providing a particular preventive service to a large population depends on its ability to reduce aggregate medical expenditures, or at least reduce their growth rate, in the long run (Carroll, 2018). This is, of course, a separate matter from the desire to reduce disease burden and improve health broadly in the population. The number needed to screen or treat to effectively reduce morbidity and mortality burden through prevention can vary widely across conditions, risk profiles, and transmission potential (Hashim, Dang, Bolotin, & Crowcroft, 2015; Kristiansen & Gyrd-Hansen, 2004; Rossignol, Labrecque, Cauchon, Breton, & Poirier, 2018; Taylor, Huffman, & Ebrahim, 2013; Tuite & Fisman, 2013).

The Patient Protection and Affordable Care Act of 2010 sought to increase use of preventive services by eliminating cost sharing to consumers, making eligible services exempt from plan deductibles, copayments, and coinsurance (Patient Protection and Affordable Care Act, 2010). Specifically, the ACA required all new and "substantially" modified commercial health insurance plans sold after September 23, 2010 (referred to as non-grandfathered plans) to cover certain high-value preventive services with no out-of-pocket cost to consumers (healthcare.gov, n.d.). Grandfathered plans, or plans originally sold before this date that did not "substantially cut benefits or increase plan costs" were not subject to this requirement, though many such plans already included, or were amended to include, first dollar coverage for some preventive services nonetheless (Kaiser Family Foundation, 2015b; UnitedHealthcare, 2018).

High deductible health plans require consumers to pay first dollar for their medical expenses up to a certain amount and we know that they tend to result in lower use of preventive services (Agarwal, Mazurenko, & Menachemi, 2017; Beeuwkes Buntin, Haviland, McDevitt, & Sood, 2011; Mazurenko, Buntin, & Menachemi, 2018). In 2010, the minimum qualifying deductible and out-of-pocket maximum per Internal Revenue Service guidelines were $1,200 and $5,950, respectively, for self-only coverage and twice that for spousal or family coverage. HDHPs have grown to make up more than one-third of the commercial health insurance market (29% of employer-sponsored and 39% of total enrollment) in 2016 (Cohen, Zammitti, & Martinez, 2018; Kaiser Family Foundation, 2016a). The majority of enrollees in the ACA exchanges are in HDHPs with large cost sharing responsibilities before their plans actually meet their stated actuarial values (Dolan, 2016; Polyakova et al., 2017).

HDHPs are generally observed to decrease utilization of both high and low value health care services and do not meet the goal of promoting more engaged consumer behavior (e.g., shopping around) (Agarwal et al., 2017; Aron-Dine, Einav, & Finkelstein, 2013; Beeuwkes Buntin et al., 2011; Brot-Goldberg, Chandra, Handel, & Kolstad, 2017; Gupta & Polsky, 2015; Kullgren et al., 2018; Manning et al., 1987; Newhouse, 2004; Sinaiko, Mehrotra, & Sood, 2016; Waters, Chang, Cecil, Kasteridis, & Mirvis, 2011). Theoretically, if consumers were able to discriminate between low- and high-value care in reducing their health care use, then HDHPs would be an effective remedy against moral hazard (Einav, Finkelstein, Ryan, Schrimpf, & Cullen, 2013). However, consumers often cannot easily assess the value of different treatment options and instead delay or forego both high and low-value care (Agarwal et al., 2017; Galbraith et al., 2012; Newhouse, 2004; Reid, Rabideau, & Sood, 2017; Wharam et al., 2018).

Though the elimination of cost sharing for preventive services affected all non-grandfathered plans, there are several reasons to believe that enrollment in an HDHP may dull the response of consumers to a more nuanced benefit such as this. First, consumer understanding of health insurance terminology and benefit design is fairly poor, so the ACA provision to increase use of preventive services by eliminating cost sharing could get lost in more salient plan features, like deductibles (Politi et al., 2014; Reed, Benedetti, Brand, Newhouse, & Hsu, 2009; Reed, Graetz, Fung, Newhouse, & Hsu, 2012), or in a lack of awareness of the benefit (Tipirneni et al., 2018). Second, even if consumers know that certain preventive services will not be subject to cost sharing, they may not correctly anticipate costs associated with the preventive service (e.g., diagnostic or treatment costs that are not exempt from cost sharing) or the benefits of knowing their risk or disease status, which are critical to making well-informed decisions (Binder & Nuscheler, 2017; Robinson & Hammitt, 2016). Further, cost constraints for patients may arise through an inability to afford the subsequent diagnostics and treatment as a result of preventive services, creating budgetary tensions between preventive services.

Prior studies have assessed how the ACA provision to eliminate cost sharing has affected preventive service use for specific services or types of services, finding mixed results (Eisenberg, Haviland, Mehrotra, Huckfeldt, & Sood, 2017; Fedewa et al., 2015; Han, Yabroff, Guy, Zheng, & Jemal, 2015; Mehta et al., 2015; Sabik & Adunlin, 2017; Wharam et al., 2016). In this study, we focus on the question of whether HDHP enrollment is associated with a differential response in the use of covered preventive services generally, another notable gap in the literature (Mazurenko, Buntin, et al., 2018). We use a quasi-experimental difference-in-differences approach to observe whether those continuously enrolled in HDHPs have a lower probability of using preventive services after the policy change than their counterparts in non-HDHPs. Our results provide insight into whether HDHPs limit the effectiveness of first-dollar coverage for preventive services in achieving the goal of increased use.

Methods

Data

This study uses a 1% random sample of commercial health insurance billing claims from the IBM® MarketScan® Commercial Database for the years 2008 through 2016. These data represent a national multi-payer set of commercially enrolled individuals, including tens of millions of covered lives in each year who are enrolled in either employer-sponsored or non-group health insurance plans (IBM Watson Health, 2017). MarketScan® data includes self-insured employers, third party administrators, and health insurers, providing one of the largest samples of privately insured individuals in the United States.

We restricted the data to enrollment and claims for non-elderly adults (18 to 64 years of age) who were enrolled for the full plan year (at least 360 days) to observe use of preventive services or the type of other coverage held (e.g., health maintenance organization, preferred provider organization, HDHP). Over 70% of age-eligible enrollees (71.2%) met this inclusion criterion during the study period. We chose not to include children as they do not make health care decisions independently and are subject to varying requirements for immunizations and other preventive services for school entry at the state and/or local levels that may attenuate any effect of the reduction in out-of-pocket costs (e.g., potential ceiling effects) (Hedden, Jessop, & Field, 2014;

Shaw et al., 2018). We also excluded the population of adults aged 65 and older as Medicare was not subject to this provision. Another inclusion criterion was consistency of plan type within the calendar year to ensure that the benefit design and other coverage characteristics (i.e., network, gatekeeping) were held constant. Nearly 95% of person-years (94.8%) meeting the age and plan days criteria maintained a consistent plan type within the plan year. In total, more than two-thirds of age-eligible person-years (67.5%) in the MarketScan® data for the years 2008 through 2016 met all of these inclusion criteria.

We created two samples from the MarketScan® annual enrollment files for use in this analysis, a cross-sectional and a cohort sample. The cross-sectional sample is used to describe trends in preventive service utilization and expenditures over the years 2008 through 2016. Each person-year meeting the inclusion criteria was retained, yielding a sample with more than 1.8 million person-years (n=1,857,172). Some individuals had multiple years of data while others may only appear for a single plan year.

The cohort sample focuses on the time period surrounding the exogenous price change, the elimination of cost sharing for certain high-value preventive services in late 2010, by requiring continuous enrollment across 2010 and 2011. The elimination of cost sharing technically took effect on September 23, 2010 though it only would have been immediately valid for new or substantially modified plans sold after that date, which would not apply to anyone in our continuously enrolled cohort sample until the 2011 plan year at the earliest. For the cohort sample, the plan consistency criterion was extended to cover both utilization years (2010 and 2011) rather than only each plan year individually. Of those age-eligible and enrolled for the full plan years in 2010 and 2011, nearly all (94.0%) had a consistent plan type across both years. We also require additional continuous enrollment for a 6-month look-back period to quantify comorbidity burden prior to observing preventive service use, yielding a sample of over ninety thousand enrollees (n=93,176) with which to estimate whether the utilization response to this policy change was affected by enrollment in a HDHP. We also created a subsample with three years of continuous enrollment (36 months total) with which to construct a 12-month comorbidity look-back period for comparison with the 6-month measure, yielding a subsample of just under ninety thousand enrollees (n=88,284).

Measures

Prior studies have tended to focus on a single or narrow set of preventive services that were subject to the elimination of cost sharing under the Affordable Care Act. Our goal was to be as inclusive as possible among eligible services relevant to the non-elderly adult population, focusing on any use and use of specific categories of preventive services. Eligible services were identified and grouped into categories similar to those defined by the Kaiser Family Foundation (Kaiser Family Foundation, 2015b), yielding five categories of preventive services use: 1) health promotion, 2) cancer, 3) chronic conditions, 4) immunizations, and 5) reproductive health and pregnancy (Tables 18 and 19). Several reproductive health services, such as contraception, breastfeeding supports, and gestational diabetes screenings, were not covered without cost sharing until August 2012 and therefore are not included in our analysis. Medications or supplements that are also available over the counter (e.g., aspirin, folic acid) were not included because they would not require a prescription and would not be observed in pharmacy claims.

Eligible preventive services were identified using the MarketScan® annual outpatient services files. Each outpatient service claim has up to four diagnosis codes and a single procedure code associated with it, all of which were used to identify relevant services. We obtained preventive service coding guidelines from UnitedHealthcare, Cigna, Kaiser Permanente (of

Washington), Blue Cross Blue Shield (of North Dakota), and the Centers for Disease Control and Prevention, which were used to identify the specific underlying preventive services using both diagnosis (ICD-9 and ICD-10) and procedure (CPT and HCPCS) codes (Blue Cross Blue Shield of North Dakota, 2014; Centers for Disease Control and Prevention, 2014; Cigna, 2015; Kaiser Permanente Washington, n.d.; UnitedHealthcare, 2018). A harmonized code set from all five sources was developed and used to identify preventive services potentially eligible for elimination of cost sharing with individual claims flagged as an enrollee having received the service if at least one applicable diagnosis and procedure code were listed (Table 20). We excluded preventive services that took place during an emergency department visit or inpatient admission as we were seeking to identify preventive services used in a primary care or outpatient clinic setting, not those incidental to an acute event where patients may not be making utilization decisions themselves. We also identified and aggregated expenditures for eligible preventive services to the person-year level, capturing out-of-pocket costs for these services, by summing across the eligible preventive service claims within a given enrollee-year.

HDHP enrollment is defined as an indicator equal to one if the plan type corresponds to either a high deductible plan without a saving option or a consumer-driven health plan, also often referred to as a consumer-directed health plan, and zero otherwise (EPO, HMO, POS, or PPO plan types). Consumer-driven health plans are high deductible plans that also include a savings option, like a health savings account (where employees and/or employers can contribute and the funds are portable) or health reimbursement arrangement (where only employers can contribute and the funds are generally not portable). Insurer-specific plan type coding is mapped to a standard set of plan types in MarketScan® with no specific threshold or criteria provided for what is considered to be a high deductible in each plan year. Those with plan types of "basic/major medical", “comprehensive”, and “POS with capitation” were excluded, comprising approximately 3% of both the person-years in the cross-sectional sample and persons in the cohort sample.

Our models include controls for demographic characteristics, including a cubic spline of age (age, age squared, and age cubed each interacted with indicators for being aged 35 to 49 and 50 to 64), sex, relationship to policy holder (self, spouse, dependent), employment status of policy holder (full-time, part-time, other or unknown), employment classification of policy holder (salary, hourly, other or unknown), and geographic location, including living in a metropolitan statistical area and state fixed effects. Those with missing state identifiers and those who moved states were excluded (less than 1% of enrollees). We accounted for prior health status by deriving several measures of comorbidity burden, using diagnoses observed in either inpatient or outpatient service claims in 2009. We calculated both Charlson (17 underlying conditions) and Elixhauser (31 underlying conditions) comorbidity indices and defined indicators for the underlying conditions within each index (Quan et al., 2005; van Walraven, Austin, Jennings, Quan, & Forster, 2009). We tested the performance of both indices and sets of condition indicators with our sample, finding that using the set of Elixhauser condition indicators provided the greatest explanatory power. We also calculated the number of inpatient admissions and number of prescriptions (unique number of generic drug names) in each person-year to capture contemporaneous changes in health status. We also control for the source of the underlying data, from either an employer or health plan.

Statistical analysis

Using the cross-sectional sample, we first described the trend in HDHP enrollment over the study period. We then compared trends in utilization of and average annual per capita expenditures (out-of-pocket and total) for eligible preventive services by plan type (HDHP or not). We inflated nominal dollar values to 2016 dollars using the Consumer Price Index for Medical

Care. Using the cohort sample, we estimated difference-in-differences models to isolate whether those enrolled in HDHPs exhibit a differential utilization response to the elimination of cost sharing for certain high-value preventive services in late 2010.

We used both parametric and semi-parametric difference-in-differences models to estimate the average treatment effect on the treated, the differential change in utilization of preventive services in 2011 among those continuously enrolled in a HDHP from 2009 through 2011. We also explored whether heterogeneous treatment effects were present by sex and tertiles of the Elixhauser comorbidity index. The full cohort sample was used to model any use of a preventive service and category-specific use, based on the five categories noted above, while the appropriate subsamples were used to estimate service-level use (as specified in Table 18). The parametric difference-in-differences model assumes parallel counterfactual trends between the treatment and control groups, which can be difficult to justify empirically and theoretically, particularly when endogenous selection into treatment occurs as it does in this setting. Those choosing to enroll in and remain in HDHPs, given the option, have varying reasons for doing so. Income plays a role, as those of higher income may be willing to bear the risk of reaching the out-of-pocket maximum and those of low income are willing (or forced by their budget constraint) to risk higher potential out-of-pocket costs in exchange for lower premiums. Health status and expected utilization also play a role, as both those who expect costs well above the out-of-pocket maximum and those who expect very low costs may be incentivized to choose the lower premiums that generally accompany HDHPs (Dowd, Feldman, Cassou, & Finch, 1991; Einav et al., 2013; Fowles, Kind, Braun, & Bertko, 2004; Parente, Feldman, & Christianson, 2004). Claims data provide few observable characteristics with which to explicitly model this selection into the treatment. We also do not observe the set of health insurance plan options available to each enrollee that could be used to identify whether an enrollee is choosing a HDHP or if it is their only option.

As such, a next best approach is to employ a semi-parametric difference-in-differences estimator, such as the one developed by Abadie, which uses a propensity score for the probability of treatment to reweight observations based on the distribution of the observable characteristics at baseline within each group (Abadie, 2005; Houngbedji, 2016a). The parametric model is identified off of the assumption that "average outcomes for treated and controls would have followed parallel paths in absence of treatment" and that selection into treatment is not dependent on "individual-transitory shocks" (Abadie, 2005), which may not be plausible when selection into endogenous treatment is occurring. The semi-parametric approach imposes the same distribution of observables across groups and thus relaxes the strong parallel trends assumption with quasi-random treatment by explicitly accounting for selection into treatment. The weights derived and used by the Abadie estimator are somewhat different from standard propensity score-based inverse probability of treatment weights and the estimation explicitly relies on the within-person change in outcome rather than treating it as a two-period cross-section or panel (Abadie, 2005; Houngbedji, 2016a). SDID also treats the propensity scores as estimated rather than assuming they are given, which can result in artificially small standard errors (Houngbedji, 2016a).

Recent work has highlighted issues with matching methods used with difference-in-difference estimators and notes that parallel pre-trends alone are not sufficient to assume success (Daw & Hatfield, 2018a, 2018b; Lindner & McConnell, 2018). However, unlike propensity score matching approaches, the Abadie estimator reweights observations rather than performing explicit matches of observations between groups. It is unclear that these critiques apply to this method as such; however, they still bear consideration. Daw and Hatfield are concerned with regression to the mean directly influencing the amount of bias introduced by matching based on 1) differences in the relative magnitude of extreme values across groups and 2) correlation between the matching variable and the post-period outcome (Daw & Hatfield, 2018a). The first is less of a concern in this context because this is essentially a modified linear probability model, a binary outcome eliminates any concerns about differences in extreme values across groups driving any effects. For completeness, we present both the DID and SDID results.

The MarketScan® annual enrollment files and inpatient, outpatient, and pharmacy claims data were processed using SAS® 9.4 for Linux and analyses were subsequently conducted in Stata® 13.0 for Linux. The Abadie semi-parametric difference-in-differences models were estimated using the user-written *absdid* package for Stata® (Houngbedji, 2016b) with the *sle* (logistic regression) option specified to force the propensity scores to be bounded between 0 and 1. We modified the program to output the propensity scores generated using our preferred specification to test for covariate balance between the reweighted treatment (HDHP) and control (non-HDHP) groups. P-values for the regression models were adjusted using a Bonferroni correction for multiple comparisons. This study was approved as exempt by the Non-Biomedical Institutional Review Board at the University of North Carolina at Chapel Hill (#18-0379).

Results

Cross-sectional sample

In our cross-sectional sample, consisting of nearly 2 million person-years (n=1,857,172), HDHP enrollment rose steadily from 2.8% in 2008 to 21.8% in 2016. Those enrolled in a HDHP were approximately one year younger on average (41.3 versus 42.2) and female representation was approximately one percentage point lower (51.7% versus 52.6%). Policy holders (60.7% versus 62.4%) were less prevalent and dependents (12.5% versus 11.1%) were more prevalent in HDHPs.

Part-time employment (of the policy holder) representation in HDHPs was low but approximately double that of non-HDHPs (1.6% versus 0.8%). Hourly paid employment (of the policy holder) was more prevalent in the HDHP group (18.8% versus 14.9%). HDHP enrollees were also more likely to live in a metropolitan statistical area (86.3% versus 84.5%).

Use of any of the preventive services that were potentially covered under the Affordable Care Act cost sharing provision increased from 2008 to 2016 (Figure 13). Those in HDHPs had lower utilization rates than those in non-HDHPs at the beginning (56.9% versus 59.0%) and end (62.2% versus 63.7%) of the study period with the difference in use between the groups narrowing somewhat from 2008 (2.1 percentage points lower) to 2016 (1.5 percentage points lower). Similarly, real average annual per capita total (Figure 14) and out-of-pocket costs (Figure 15) incurred for potentially covered preventive services also increased during this time period. HDHP enrollees incurred lower real average annual per capita total costs for potentially covered preventive services initially ($420.61 versus $511.72 in 2008) than those not in a HDHP and the difference was nearly the same by the end of the study period ($620.15 versus $707.87 in 2016). The groups incurred very similar out-of-pocket costs initially ($62.08 for HDHP and $66.53 for non-HDHP in 2008) but cost sharing grew faster for the HDHP group ($104.59 versus $80.50 in 2016). These results show that at a population level, any use of potentially covered preventive services increased during this time period with a corresponding increasing trend in total expenditures. There were no obvious changes in utilization or total expenditures coincidental with the timing of the policy change in late 2010. Our conclusions about the effect, or lack thereof, on total or out-of-pocket costs for preventive services do not qualitatively change if we condition on any use of a preventive service. However, inference is limited due to the cross-sectional design and potential changes to the composition of the MarketScan® sample over the study period.

Cohort sample

In our cohort sample, consisting of 93,176 continuously enrolled non-elderly adults during the latter half of 2009 through 2011, approximately 6% (6.4%) were enrolled in HDHPs in 2010. This is similar to the prevalence of HDHP enrollment in the cross-sectional sample during these years (7.9% in 2010 and 8.2% in 2011), but, not surprisingly, slightly lower owing to the continuous enrollment requirements that bias the sample towards non-high deductible employer sponsored coverage as a result of lower churn in group versus non-group coverage (Klein, Glied, & Ferry, 2005). Table 21 contains unweighted and weighted baseline (2010) descriptive statistics for the cohort sample by HDHP enrollment, using inverse probability of treatment weights derived from the propensity scores estimated for the SDID model. In the unweighted results, the average age and distribution of sex were not significantly different across groups. Spouses were present at a higher percentage in the HDHP group (30.5% versus 28.4%, $p<0.01$), indicating that spousal and family coverage may be slightly more prevalent in that group. Part-time employment (of the policy holder) representation in HDHPs was more than fourfold that of non-HDHPs (3.0% versus 0.7%, $p<0.01$). Hourly paid employment (of the policy holder) was slightly overrepresented in the HDHP group (17.2% versus 16.5%, $p<0.05$) with the caveat of a large other or unknown group. HDHP enrollees were less likely to live in a metropolitan statistical area (85.0% versus 86.2%, $p<0.05$). HDHP enrollees used slightly more unique prescriptions (11.5 versus 10.9, $p<0.05$) along with using slightly fewer inpatient admissions on average (0.05 versus 0.06, $p<0.01$), but had a similar Elixhauser comorbidity index. From this, we observe weakly mixed to null evidence of possible advantageous selection (better health) into HDHPs on average but also that price sensitivity on premium costs may be driving selection (i.e., higher spousal representation and part-time employment). In comparing the performance of 6- and 12-month Elixhauser comorbidity indices in the subsample with both available, we find a wider and statistically significant gap between the HDHP (0.41) and non-HDHP (0.47) groups that maintains the same rank order of the 6-month measure (0.28 for HDHP and 0.30 for non-HDHP, not significantly different), again indicating potentially weakly healthier individuals on average sorting into the HDHP group. After propensity score weighting, the differences in distributions of relationship to policy holder, employment classification of policy holder, and number of inpatient admissions were no longer significant although the differences in age, residence in an MSA, and number of unique prescriptions widened.

Examination of use of any of the included preventive services among the cohort sample shows that HDHP enrollees were slightly more likely than the non-HDHP group to use preventive services in 2010, and that gap widened in 2011 from 1.8 to 2.2 percentage points (Table 22). Any use increased significantly among the non-HDHP group from 63.0% in 2010 to 64.2% in 2011 ($p<0.01$). Although any use in the HDHP increased by a larger magnitude (from 64.8% to 66.4%), the change was not statistically significant. Real average annual per capita total costs incurred for potentially covered preventive services grew during this time period (Table 22). Real per capita total costs increased on average by \$51 for the non-HDHP group (from \$627 to \$678, $p<0.01$) and by \$62 for the HDHP group (from \$593 to \$655, not significant). HDHP enrollees had higher average real per capita out-of-pocket costs for potentially eligible preventive services in both years than the non-HDHP enrollees (Table 22). Real out-of-pocket costs increased slightly on average among non-HDHP enrollees from \$73 and \$76 ($p<0.05$). The magnitude of the change was much larger among the HDHP group (from \$91 to \$102) but, once again, the change was not significant. The increases in preventive service use incentivized by and/or incidental to the policy change as part of a secular increasing trend were not met with the promised elimination or even a reduction in average out-of-pocket costs.

Table 23 shows the difference-in-difference estimates of the average treatment effect on the treated with the DID and SDID estimators. None of the models yielded a significant differential effect of HDHP enrollment on use of any potentially covered preventive service. Nor did we find any significant heterogenous treatment effects by sex or tertiles of the Elixhauser comorbidity index. Category-specific estimates (health promotion, cancer, chronic conditions, immunizations, reproductive health and pregnancy) of the average treatment effect on the treated are shown in Table 24. There is no evidence of a significant differential effect for any of the categories of preventive services that we defined. Service-specific estimates are shown in Table 25. Similarly, we find no evidence of a differential response to the policy change by HDHP enrollment using either estimator.

We ran several alternate sets of models to confirm the robustness of our findings (not shown), including dropping all services used in the fourth quarter of either year (to wash out the time during which the policy took effect in 2010), dropping those aged 18 to 26 (those potentially eligible for the dependent coverage provision that was implemented coincident to this policy change), and using the subsample with a 12-month comorbidity look-back period (36 months of continuous enrollment rather than 30). None yielded statistically significant effect estimates after using a Bonferroni correction to adjust p-values appropriately for multiple comparisons.

Discussion

We find no evidence to suggest that HDHP enrollment resulted in a differential response to the ACA provision that sought to eliminate cost sharing for certain preventive services. Unlike prior research, which has focused on a single or smaller set of preventive services (Fedewa et al., 2015; Han et al., 2015; Mehta et al., 2015; Sabik & Adunlin, 2017; Wharam et al., 2016), we incorporate nearly all of the billable services that were subject to the late 2010 provision across several categories of health care, including health promotion, cancer, chronic conditions, immunizations, and reproductive health and pregnancy. Compared to prior studies that used a single or limited set of health system or insurer data, we used a continuously enrolled cohort of nearly one hundred thousand individuals from a national database of commercial health insurance claims, improving the generalizability of our findings to the broader population. We already know that consumers respond to higher cost sharing burdens by reducing utilization of all care, regardless of its inherent clinical value. However, our analysis shows that HDHP enrollment is not associated with a differential response to the elimination of cost sharing for certain preventive services. Of particular note, we do not find lower uptake of screening for cancer among HDHP enrollees after the policy change, similar to other studies that have found null or positive effects (Fedewa et al., 2015; Han et al., 2015; Wharam et al., 2016).

Our study has several limitations. The potential endogeneous selection into HDHPs, assuming several plan options were available, is problematic given that we do not observe income, plan choice set, and other characteristics that could be used to model plan choice in insurance claims data (Crown, 2016). Others have addressed this problem by using forced switches into a HDHP at the employer level with similar non-switching employers serving as a control group (Wharam et al., 2011, 2012, 2016, 2018). We chose a more generalizable sample with a semi-parametric approach that does not assume quasi-random group assignment, estimating an underlying propensity score for selection into treatment and using these to reweight the sample for estimation (Abadie, 2005). With only state identifiers available, we were unable to account for local differences in primary care provider availability that could play a role as a supply constraint for preventive services. However, this is primarily a concern for uninsured patients or those covered by Medicaid, particularly in the years prior to the Marketplace and Medicaid expansion taking effect. We are, however, able to isolate the utilization response conditional on the physician supply environment that each enrollee observes by using a cohort of adults continuously enrolled before and after the policy change who do not move across state lines. We are also unable to identify which plans were modified to comply with this and other ACA provisions versus those that were grandfathered for the 2011 plan year, as this information is not provided in the MarketScan® data. Grandfathered plans have largely disappeared from the individual (non-group) market, now estimated to be less than 7% of total enrollment (Altman, 2017). In the group market, there is a similar downward trend with grandfathered plan enrollment falling from a base of just over half (56%) in 2011 to just over a third (36%) just two years later (Seiler, Malcarney, Horton, & Dafflitto, 2014). As long as grandfathered plan status was not associated with whether a plan had a high deductible or not (e.g., plan modification decisions being made at the insurer-rating area level or employer level rather than systematically for specific types of individual plans), this concern is minimized for our analysis. Similarly, grandfathered plan status has implications for whether the exogenous price shock for preventive services was perceived or real.

Insurers were also responsible for creating their own preventive service coding guidelines to operationalize the ACA provision that eliminated cost sharing for certain services, with providers needing to adhere specifically in order for enrollees to be billed (or not, in this case) appropriately. Consumers and providers alike ended up being confused by this, with patients receiving surprise bills for so-called ‘free’ preventive services (Andrews, 2014; Konrad, 2011; LaMontagne, 2015). As we cannot identify specific insurers in our data, it is not possible to match the applicable coding guidelines exactly to each enrollee. We created a comprehensive list of covered diagnosis and procedure code combinations provided by the federal government and several large insurers to capture a reasonable universe of services that were targeted for the elimination of cost sharing in non-grandfathered plans.

As higher deductibles become the norm in both employer-sponsored plans and the Marketplace, placing downward pressure on the use of medical care generally, we may need more innovative approaches to benefit design to encourage utilization of high-value preventive services. Value-based insurance design, which ties cost sharing to clinical value rather than specific dollar thresholds or percentages across all and/or a class of services (e.g., reducing or eliminating cost sharing for medications to treat chronic conditions), has shown promise in limited research thus far. For example, VBID has been shown to improve medication adherence without increasing total health care expenditures though its effects on clinical outcomes are mixed (Agarwal, Gupta, & Fendrick, 2018), and considerations regarding VBID targeting certain preventive services, such as screenings, which are infrequent and targeted toward a broad population including healthy individuals, likely differ from those in the context of chronic disease management.

Plan choice and understanding the nuances of benefit design is challenging for consumers, often resulting in less than optimal choices of plans (e.g., choosing dominated plans) and utilization behavior (e.g., failing to use high-value preventive care available without cost sharing) (Bhargava, Loewenstein, & Sydnor, 2015; Sinaiko & Hirth, 2011; Sinaiko, Ross-Degnan, Soumerai, Lieu, & Galbraith, 2013), suggesting that more can be done during open enrollment and early in the plan year to support decision making (Wong et al., 2016, 2018). There are also potential mismatches between ex ante and ex post expectations of cost sharing for prevention. An extreme but fairly common example is that a patient goes in for a screening colonoscopy (not subject to cost sharing under this provision) but a polyp is found and removed causing the service to be billed as a diagnostic colonoscopy instead (subject to cost sharing). This change in cost sharing based on the outcome of the preventive service itself is far from consumer-friendly and has yielded a lot of confusion (American Cancer Society, 2018; Andrews, 2018; Colorectal Cancer Alliance, 2016).

Unfortunately, our results suggest that the provision of the ACA that eliminated cost sharing for certain preventive services was seemingly unsuccessful in reducing out-of-pocket costs for consumers, the linchpin incentive for consumers to increase use of preventive services. If use of preventive services is less than optimal and costs continue to be a barrier, then examination of coding requirements and insurer practices is needed to ensure the policy is meeting its intended goal.

Tables and Figures

Figure 13. Use of any potentially covered preventive service by HDHP enrollment, cross-sectional sample

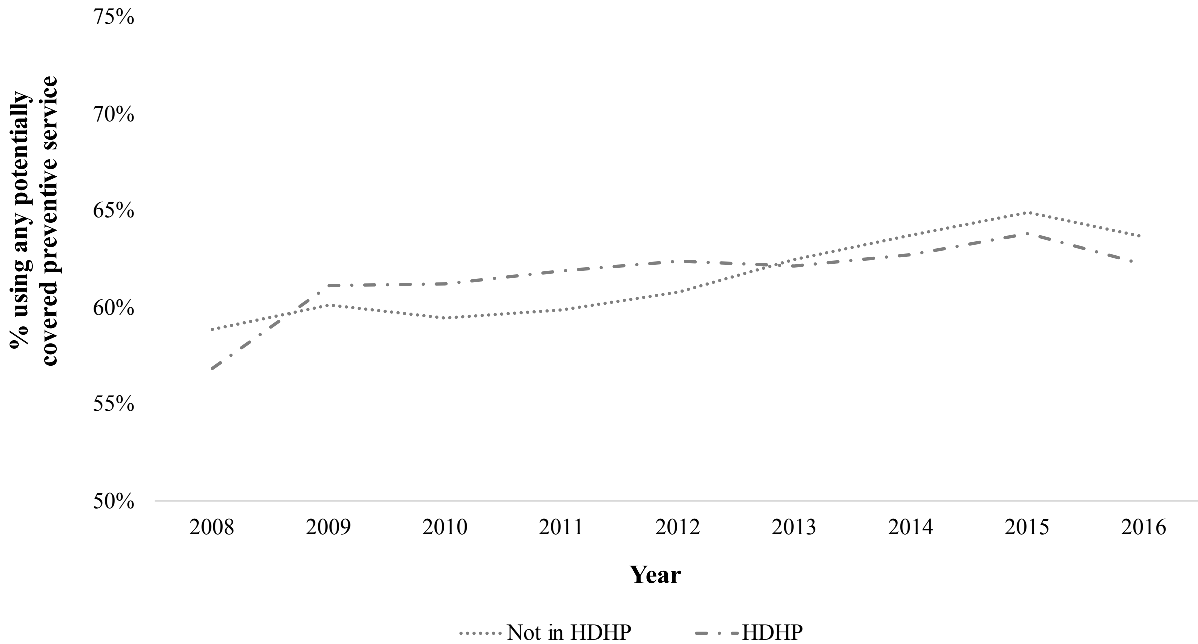


Figure 14. Real total costs for potentially covered preventive services by HDHP enrollment, cross-sectional sample

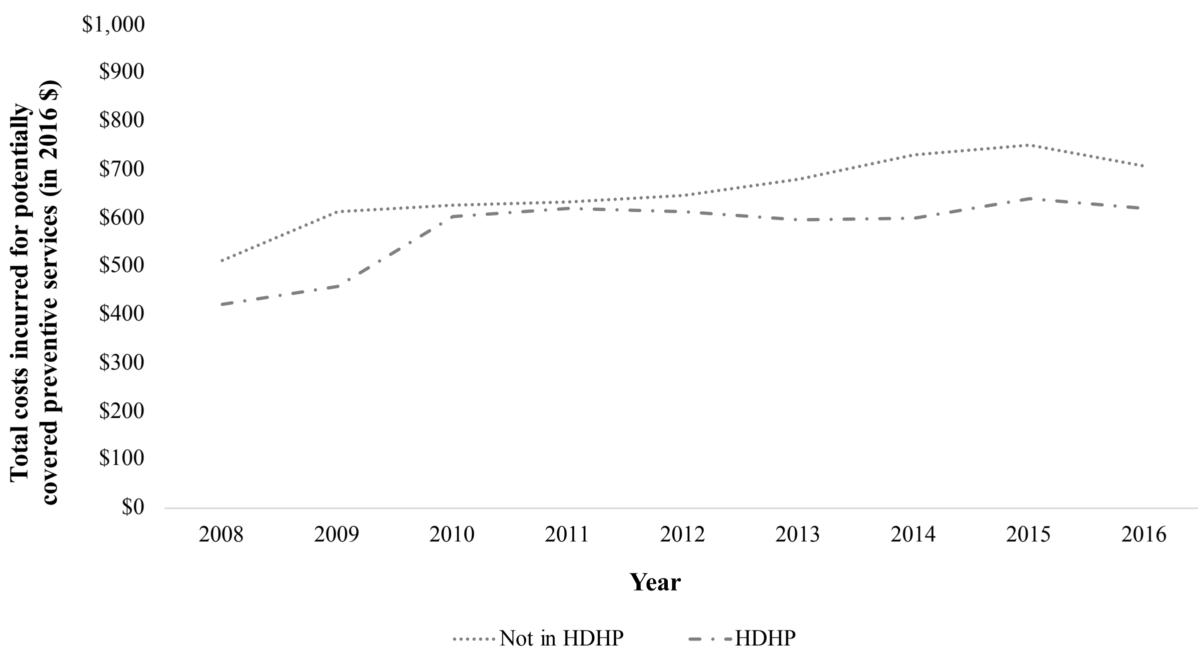


Figure 15. Real out-of-pocket costs for potentially covered preventive services by HDHP enrollment, cross-sectional sample

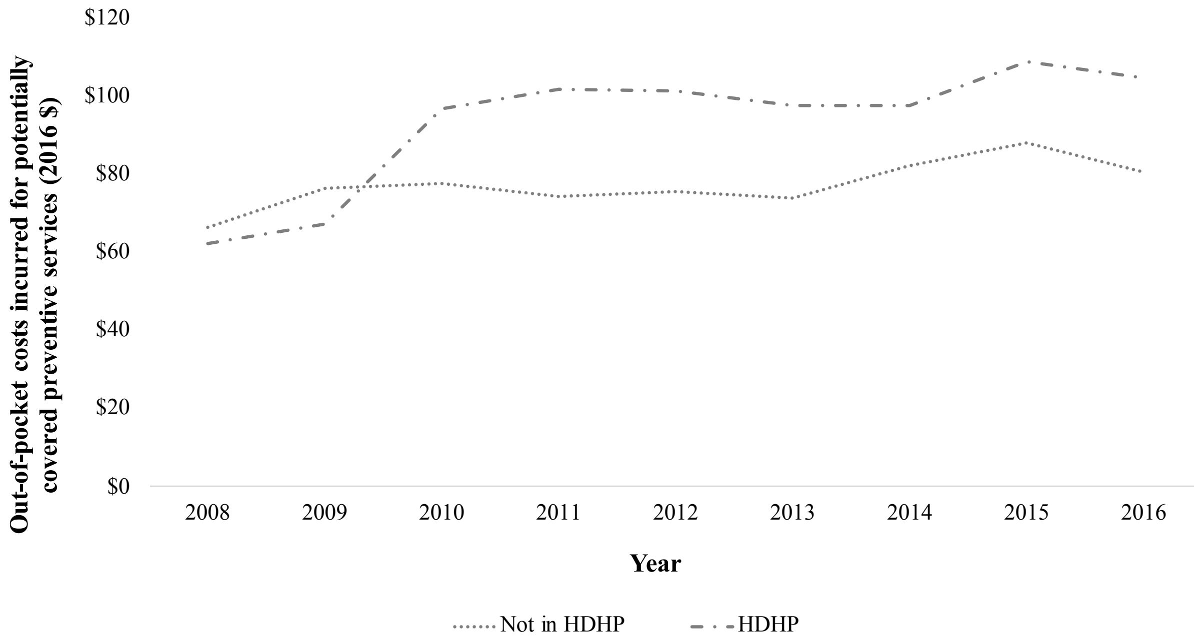


Table 18. Preventive services covered without cost sharing by non-grandfathered plans

Service	**Eligible population in analysis** *(by sex and age)*
Health promotion	
Wellness visit	All
Cancer	
Breast cancer screening	Women, 40 and older
Breast cancer genetic screening and counseling, chemoprevention	Women
Cervical cancer screening	Women, 21 and older
Colorectal cancer screening	All, 50 and older
Lung cancer screening	All, 55 and older
Chronic conditions	
Lipid disorder screening	All
Diabetes screening	All
Hepatitis B screening	All
Hepatitis C screening	All, 40 and older
Obesity screening and counseling	All
Osteoporosis screening	Women
Immunizations	
Flu	All
Other immunizations	All
Reproductive health and pregnancy	
Sexually transmitted infection (STI) screening	All
Anemia screening	Pregnant women
Bacteriurea screening	Pregnant women

Table 19. Underlying preventive services included

Service	Underlying services included
Health promotion	
Wellness visit	Initial and periodic preventive evaluation and management visits (i.e., well adult, well woman), blood pressure checks, alcohol misuse screening and counseling, intimate partner violence screening and counseling, tobacco counseling and cessation interventions, depression screening, sexual health counseling
Cancer	
Breast cancer screening	Mammography
Breast cancer genetic screening and counseling, chemoprevention	–
Cervical cancer screening	Pap test
Colorectal cancer screening	Fecal occult blood test (FOBT), fecal immunochemical test (FIT), sigmoidoscopy, colonoscopy
Lung cancer screening	Tomography
Chronic conditions	
Lipid disorder screening	–
Diabetes screening	–
Hepatitis B screening	–
Hepatitis C screening	–
Obesity screening and counseling	–
Osteoporosis screening	–
Immunizations	
Flu	–
Other immunizations	Haemophilus influenzae type b; hepatitis A; hepatitis B; human papillomavirus (HPV); meningococcal; measles, mumps, and rubella (MMR); pneumococcal; tetanus; varicella; zoster
Reproductive health and pregnancy	
Sexually transmitted infection (STI) screening	Chlamydia, gonorrhea, syphilis, human immunodeficiency virus (HIV)
Anemia screening	–
Bacteriurea screening	–

Table 20. Diagnosis and procedure codes used to identify preventive services in claims

Service	Diagnosis codes	Procedure codes
Health promotion		
Wellness visit	*ICD-9:* V692, V745, V030, V031, V032, V033, V034, V035, V036, V037, V038, V0381, V0382, V0389, V039, V040, V041, V042, V044, V044, V045, V046, V047, V048, V0481, V0482, V0489, V049, V050, V051, V052, V053, V054, V058, V059, V060, V061, V062, V063, V064, V065, V066, V068, V069, V200, V201, V202, V203, V2031, V2032, V242, V6511, V6542, V6549, V700, V708, V709, V723, V7231, V762, V7646, V7647, V790, V791, V793, V798, V799, V811, V8402, V8404, V653, V6542, V6544, V6545, 3051 *ICD-10:* Z761, Z762, Z00121, Z00129, Z00110, Z00111, Z7681, Z0000, Z0001, Z008, Z01411, Z01419, Z134, Z136, Z0130, Z0133, Z003, Z1331, Z1332, Z1389, Z713, Z717, Z7141	99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, 99215, 99381, 99382, 99383, 99384, 99385, 99386, 99387, 99388, 99389, 99390, 99391, 99392, 99393, 99394, 99395, 99396, 99397, S0610, S0612, S0613, 99420, 96110, 96127, S0302, 97802, 97803, 97804, S9470, G0442, G0443, G0444, G0446, G0447, G0451, G0473, 99401, 99402, 99403, 99404, S9443, 99406, 99407, 99408, 99409, 99410, 99411, 99412, G0101, G0334, G0402, G0436, G0437, G0438, G0439, G0445, G0396, G0397, C9801, C9802, S9075, S9453, 96150, 96152, 96153, 0403T
Cancer		
Breast cancer screening	*ICD-9:* V7610, V7611, V7612, V7619, V103, V163 *ICD-10:* Z1231, Z803, Z853	77055, 77056, 77057, 77051, 77052, 77063, 77067, G0202, G0204, G0206
Breast cancer genetic screening and counseling, chemoprevention	*ICD-9:* V700, V7231, V103, V1043, V163, V1641, V2633 *ICD-10:* Z853, Z8543, Z803, Z315, Z8041, Z8042, Z1501, Z1502	96040, S0265, S18212, S18213, S18214, S18215, S18216, S18217, 99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, 99215, 99385, 99386, 99387, 99395, 99396, 99397, 99401, 99402, 99403, 99404, 81211, 81212, 81213, 81214, 81215, 81216, 81217, 81162, G0463
Cervical cancer screening	*ICD-9:* V242, V723, V7620, V726, V7260, V7262, V7646, V7647, V8402, V8404, V762, V700, V7231, V7232, V7381 *ICD-10:* Z0000, Z0001, Z01411, Z0142, Z01419, Z1151, Z124, Z7721, Z779	88141, 88142, 88143, 88144, 88145, 88146, 88147, 88148, 88149, 88150, 88151, 88152, 88153, 88154, 88155, 88156, 88157, 88158, 88159, 88160, 88161, 88162, 88163, 88164, 88165, 88166, 88167, 88168, 88169, 88170, 88171, 88172, 88173, 88174, 88175, G0101, G0123, G0124, G0141, G0143, G0144, G0145, G0147, G0148, P3000, P3001, Q0091

Colorectal cancer screening	*ICD-9:* V160, V1851, V1859, V700, V7262, V7641, V7650, V7651, V7652, V160, V1851 *ICD-10:* Z0000, Z8379, Z1210, Z1211, Z1212, Z1213, Z800, Z8371, Z0001, Z01411, Z01419, R195, Z8379	44388, 44389, 44392, 44393, 44394, 45300, 45301, 45302, 45303, 45304, 45305, 45306, 45307, 45308, 45309, 45310, 45311, 45312, 45313, 45314, 45315, 45316, 45317, 45318, 45319, 45320, 82270, 82274, G0328, 45330, 45331, 45332, 45333, 45334, 45335, 45338, 45339, 45340, 45346, G0104, G0105, 45378, 45379, 45380, 45381, 45382, 45383, 45384, 45385, 45386, 45388, G0105, G0121, 74263, 74270, 72480, G0106, G0107, G0120, G0122, 00810, 00812, 88304, 88305, G0328, G0394, S0601, S3890, 81528, 99152, 99153, 99156, 99157, G0500, 99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, 99215, 99241, 99242, 99243, 99244, 99245, S0285
Lung cancer screening	*ICD-9:* V1582, V760 *ICD-10:* Z122, Z87891, F17210, F17211, F17213, F17218, F17219	71250, 76497, S8032, S8092, G0296, G0297
Chronic conditions		
Lipid disorder screening	*ICD-9:* V700, V7791 *or* hypertension *or* diabetes[a] *ICD-10:* Z0000, Z0001, Z13220, Z136, Z8249 *or* hypertension *or* diabetes[a]	36415, 36416, 80061, 82465, 83718, 83719, 83721, 84478
Diabetes screening	*ICD-9:* V700, V771 *or* hypertension[a] *ICD-10:* Z0000, Z131 *or* hypertension[a]	36415, 36416, 82947, 82948, 82950, 82951, 82952, 83036
Hepatitis B screening	*ICD-9:* V7262, V7389 *or* pregnancy[a] *ICD-10:* Z0000, Z0001, Z1159, Z578, Z00129 *or* pregnancy[a]	36415, 36416, 80055, 86704, 86705, 86706, 87340, 87341, G04999
Hepatitis C screening	*ICD-9:* V692, V200, V201, V202, V220, V221, V222, V230, V231, V232, V233, V234, V2341, V2342, V2349, V235, V237, V238, V2381, V2382, V2383, V2384, V2385, V2386, V2387, V2389, V239, V240, V241, V242, V700, V723, V7231, V7262, V7389 *ICD-10:* Z0000, Z00129	36415, 36416, 86803, 86804, 87522, G0472
Obesity screening and counseling	*ICD-9:* V700, 2720, 2721, 2722, 2723, 2724, 2725, 2726, 2727, 2728, 2729, V653, V778, Z713, V8530, V8531, V8532, V8533, V8534, V8535, V8536, V8537, V8538, V8539, V8541, V8542, V8543, V8544, V8545, 27800, 27801 *or* hypertension *or* diabetes[a]	97802, 97803, 97804, S9470, G0446, G0447, G0473, 99401, 99402, 99403, 99404, 99411, 99412, G0270, G0271, G0449, S9470

	ICD-10: Z6830, Z6831, Z6832, Z6833, Z6834, Z6835, Z6836, Z6837, Z6838, Z6839, Z6841, Z6842, Z6843, Z6844, Z6845, E6601, E6609, E661, E668, E669 *or* hypertension *or* diabetes[a]	
Osteoporosis screening	*ICD-9:* V8281, V1781, V4981, V700, V720, V723, V7231 *ICD-10:* Z0000, Z0001, Z13820, Z8262	76070, 76071, 76075, 76076, 76078, 76977, 77078, 77079, 77080, 77081, 77083, 78350, G0130
Immunizations		
Flu	*ICD-9:* V202, V700, V035, V036, V037, V0381, V0382, V0389, V040, V042, V043, V046, V048, V0481, V0489, V053, V054, V061, V062, V063, V064, V065, V066, V068, V069 *ICD-10:* Z00121, Z00129, Z0000, Z0001, Z23	90630, 90653, 90654, 90656, 90658, 90660, 90661, 90662, 90664, 90666, 90667, 90668, 90672, 90673, 90674, 90682, 90686, 90688, 90756, Q2033, Q2034, Q2035, Q2036, Q2037, Q2038, Q2039
Other immunizations	*ICD-9:* V202, V700, V035, V036, V037, V0381, V0382, V0389, V040, V042, V043, V046, V048, V0481, V0489, V053, V054, V061, V062, V063, V064, V065, V066, V068, V069 *ICD-10:* Z00121, Z00129, Z0000, Z0001, Z23	90460, 90461, 90465, 90466, 90467, 90468, 90470, 90471, 90472, 90473, 90474, G0008, G0009, G0010, G0377, G9141, J3530, 90620, 90621, 90631, 90632, 90633, 90634, 90635, 90636, 90637, 90638, 90639, 90640, 90641, 90642, 90643, 90644, 90645, 90646, 90647, 90648, 90649, 90650, 90651, 90659, 90669, 90670, 90671, 90683, 90684, 90697, 90698, 90699, 90701, 90703, 90704, 90705, 90706, 90707, 90708, 90709, 90710, 90711, 90712, 90713, 90714, 90715, 90716, 90718, 90719, 90720, 90721, 90722, 90732, 90733, 90734, 90736, 90739, 90740, 90741, 90742, 90745, 90746, 90747, 90748, 90750, S0195
Reproductive health and pregnancy		
Sexually transmitted infection (STI) screening	*ICD-9:* V692, V200, V201, V202, V234, V238, V240, V241, V242, V700, V723, V7231, V7262, V7388, V7389, V7398, V745, V759, V700, V745, V749, V759 *or* pregnancy[a] *ICD-10:* Z0000, Z0001, Z0189, Z118, Z224, Z7251, Z7252, Z7253, Z7721, Z779, Z226, Z228, Z229, Z113, Z114, Z1159, Z119, Z206, Z112, Z119, Z202, Z124, Z118, Z113, Z114 *or* pregnancy[a]	80055, 86780, 36415, 36416, 86631, 86632, 86689, 87110, 87270, 87320, 87490, 87491, 87492, 87801, 87810, 87850, 87590, 87591, 87592, 86701, 86702, 86703, 87389, 87390, 87391, G0432, G0433, G0435, G0450, G0475, S3645, 86592, 86593, 87534, 87535, 87806, 99401, 99402, 99403, 99404
Anemia screening	Pregnancy[a]	36415, 36416, 80055, 85004, 85013, 85014, 85018, 85025, 85027, 85041, G0306, G0307

Bacteriurea screening	Pregnancy[a]	81007, 87086, 87088

Note: Only outpatient claims from a non-emergency department facility were included. One or more diagnosis codes and a relevant procedure code must be included in the claim for it to be flagged as an eligible preventive service.

[a] Diagnosis codes for hypertension, diabetes, and/or pregnancy used can be found at https://www.cdc.gov/prevention/billingcodes.html.

Table 21. Unweighted and weighted baseline (2010) sample characteristics by HDHP enrollment, cohort sample

	Mean or % (SE)			
Characteristic	**Unweighted** *(DID)*		**Weighted** *(SDID)*	
	Not in HDHP	*HDHP*	*Not in HDHP*	*HDHP*
Age	43.6 (0.04)	43.6 (0.15)	43.6 (0.04)	42.6** (0.4)
Female	52.7% (0.2%)	52.4% (0.6%)	52.7% (0.2%)	53.1% (2.0%)
Relationship to policy holder				
Self	65.8% (0.2%)	63.6%** (0.6%)	65.7% (0.2%)	63.7% (2.0%)
Spouse	28.4% (0.2%)	30.5%** (0.6%)	28.5% (0.2%)	31.7% (2.0%)
Dependent	5.8% (0.1%)	5.9% (0.3%)	5.8% (0.1%)	4.6% (0.7%)
Employment status of policy holder				
Full-time	54.0% (0.2%)	85.8%** (0.5%)	56.0% (0.2%)	48.4%** (2.0%)
Part-time	0.7% (0.03%)	3.0%** (0.2%)	0.9% (0.03%)	1.1% (0.1%)
Other, unknown	45.3% (0.2%)	11.2%** (0.4%)	43.0% (0.2%)	50.5%** (2.0%)
Employment classification of policy holder				
Salary	18.8% (0.1%)	54.9%** (0.6%)	21.3% (0.1%)	22.5% (1.0%)
Hourly	16.5% (0.1%)	17.2%* (0.5%)	16.6% (0.1%)	18.0% (1.0%)
Other, unknown	64.7% (0.2%)	27.9%** (0.6%)	62.1% (0.2%)	59.5% (1.7%)
In MSA	86.2% (0.1%)	85.0%* (0.5%)	86.2% (0.1%)	91.7%** (0.7%)
Data from health plan *(versus employer)*	40.7% (0.2%)	2.8%** (0.2%)	38.2% (0.2%)	45.8%** (2.2%)
Number of unique prescriptions	10.9 (0.1)	11.5* (0.2)	11.0 (0.1)	8.6** (0.5)
Number of inpatient admissions	0.06 (0.001)	0.05** (0.003)	0.06 (0.001)	0.06 (0.01)
Elixhauser comorbidity index *(6 month lookback, 2009)*	0.3 (0.01)	0.3 (0.03)	0.3 (0.01)	0.3 (0.1)

* p<0.05, ** p<0.01

DID – parametric difference-in-difference (OLS), SDID – semi-parametric difference-in-differences (Abadie), HDHP – high deductible or consumer-driven health plan, MSA – metropolitan statistical area

Table 22. Any use of and unconditional real costs for potentially covered preventive services by HDHP enrollment, cohort sample

	% *(SE)*		*Mean* *(SE)*			
Outcome	***Any preventive service use***		***Real total costs***		***Real out-of-pocket costs***	
Year	2010	2011	2010	2011	2010	2011
HDHP	64.8% (0.6%)	66.4% (0.6%)	\$592.86 (\$27.37)	\$654.52 (\$30.85)	\$90.54 (\$3.72)	\$101.92 (\$4.34)
Not in HDHP	63.0% (0.2%)	64.2%** (0.2%)	\$627.42 (\$9.10)	\$678.29** (\$10.09)	\$73.25 (\$0.81)	\$75.73* (\$0.86)

* p<0.05, ** p<0.01

Table 23. Difference-in-differences estimates of the effect of HDHP enrollment on any use of potentially covered preventive services in 2011, cohort sample

Model	b (SE)			
	(1)	(2)	(3)	(4)
Any preventive service use				
DID	0.005 (0.009)	0.005 (0.008)	0.002 (0.008)	0.002 (0.008)
Adjusted R^2	0.123	0.128	0.173	0.194
SDID	0.004 (0.007)	-0.0003 (0.007)	-0.002 (0.007)	-0.002 (0.007)
Demographic controls	X	X	X	X
Geographic controls		X	X	X
# of inpatient admissions and unique prescriptions			X	X
Comorbidity indicators *(1 year lookback)*				X
N *(persons)*	93,176	93,176	93,176	93,176

* p<0.05, ** p<0.01
P-values adjusted using Bonferroni correction for multiple comparisons.
DID – parametric difference-in-difference (OLS), SDID – semi-parametric difference-in-differences (Abadie)

Table 24. Difference-in-differences estimates of the effect of HDHP enrollment on category-specific use of potentially covered preventive services in 2011, cohort sample

Category	Health promotion	Cancer	Chronic conditions	Immunizations	Reproductive health and pregnancy
Any use within category	b (SE)				
DID	-0.005 (0.009)	0.005 (0.011)	0.004 (0.008)	-0.009 (0.008)	-0.001 (0.009)
SDID	-0.012 (0.008)	-0.002 (0.010)	0.00004 (0.007)	-0.012 (0.008)	-0.008 (0.008)
N *(persons)*	93,176	65,152	93,176	93,176	93,176

* p<0.05, ** p<0.01
All models include demographic controls, geographic controls, number of inpatient admissions, number of unique prescriptions, and Elixhauser condition indicators. P-values adjusted using Bonferroni correction for multiple comparisons.
DID – parametric difference-in-difference (OLS), SDID – semi-parametric difference-in-differences (Abadie)

Table 25. Difference-in-differences estimates of the effect of HDHP enrollment on service-specific use of potentially covered preventive services, cohort sample

Service	b (SE) DID	b (SE) SDID
Health promotion		
Wellness visit	-0.005 (0.009)	-0.012 (0.008)
Cancer		
Breast cancer screening	-0.001 (0.016)	-0.015 (0.015)
Breast cancer genetic screening and counseling, chemoprevention	-0.0003 (0.013)	-0.004 (0.012)
Cervical cancer screening	-0.001 (0.013)	-0.002 (0.012)
Colorectal cancer screening	0.002 (0.014)	0.005 (0.014)
Lung cancer screening	0.0004 (0.003)	0.0004 (0.003)
Chronic conditions		
Lipid disorder screening	-0.006 (0.008)	-0.008 (0.008)
Diabetes screening	-0.005 (0.008)	-0.009 (0.008)
Hepatitis B screening	0.003 (0.003)	0.0002 (0.003)
Hepatitis C screening	0.003 (0.007)	-0.004 (0.007)
Obesity screening and counseling	-0.002 (0.008)	-0.003 (0.007)
Osteoporosis screening	0.0004 (0.013)	-0.001 (0.012)
Immunizations		
Flu	-0.009 (0.008)	-0.012 (0.008)
Other immunizations	-0.009 (0.008)	-0.012 (0.008)
Reproductive health and pregnancy		
Sexually transmitted infection (STI) screening	-0.001 (0.009)	-0.008 (0.008)
Anemia screening	0.006 (0.004)	0.001 (0.004)
Bacteriurea screening	0.006 (0.004)	0.001 (0.004)

* p<0.05, ** p<0.01

All models include demographic controls, geographic controls, number of inpatient admissions, number of unique prescriptions, and Elixhauser condition indicators. P-values adjusted using Bonferroni correction for multiple comparisons.

DID – parametric difference-in-difference (OLS), SDID – semi-parametric difference-in-differences (Abadie)

CHAPTER 5: CONCLUSION

Implications

This research has implications for our understanding of the impact of coverage expansion and increased generosity of coverage on use of the ED, primary care, and preventive services. Coverage itself plays a significant role in providing access to non-ED providers and financial risk protection from the costs of health care, but does not appear to be enough on its own to yield reductions in ED use. All coverage is not created equal and simply enrolling more people is not going to change health behaviors, patterns of health care use, or improve health, particularly when being insured does not necessarily make using care affordable or ensure receipt of high-quality care (H. Allen et al., 2014; Polyakova et al., 2017).

Based on Chapter 2, I find that the long-term uninsured significantly increase their use of primary care in the year after gaining coverage but it is not accompanied by substitution away from using the ED, at least in the short run. The more than one visit per year average increase in primary care visits among the persistently uninsured after gaining coverage was driven by those gaining public coverage (e.g., Medicaid) with no significant change among those gaining private insurance. This bodes well for increasing primary care use under proposed and potential future Medicare or Medicaid-based coverage expansions (e.g., Medicare for all, Medicare for more, Medicaid buy-ins), but less so under models where the private market drives expansion with enrollees exposed to significant cost sharing burdens. The mixed findings on the effects of coverage gains for the previously transiently uninsured are important to explore further as a more permissive stance towards state Medicaid waiver provisions under the Trump administration will allow states to experiment with work requirements that will almost certainly increase churn and decrease average enrollee time in coverage. As we explore proposals both to bring the remaining uninsured into coverage and simultaneously those that will increase churn and disenrollment, it will be important to consider the profile of persistence of uninsurance among the relevant population as a piece of the puzzle in projecting effects on health care use and the resulting costs.

One could hope that substantial health care needs and pent-up demand for primary care would eventually result in ED use trailing off as coverage gains persist over time, with earlier intervention and/or guideline concordant preventive care mitigating the factors that result in the need for many of those ED visits. However, the results from Chapter 3 indicate that population-level increases in insurance coverage do not yield lower rates of avoidable ED use several years out among non-elderly adults. The emergence of urgent care centers and retail clinics as channels to increase primary care supply and provide a lower cost setting for time-sensitive care hold promise but are not a silver bullet. Improved access to alternative settings, such as community health centers, retail clinics, and urgent care centers, should theoretically allow for declines in ED use over time but encouraging findings are offset by others that are less so, with a lack of cost savings demonstrated by greater penetration of these facilities thus far (Alexander et al., 2017; L. Allen et al., 2019; Ashwood et al., 2016; Martsolf et al., 2017).

It is encouraging that those in high deductible health plans did not exhibit a differential response to the ACA provision that eliminated cost sharing for certain preventive services, as shown in Chapter 4. However, there is little evidence to suggest that out-of-pocket costs actually declined for patients and use of many of the covered services is still well below Healthy People 2020 goals. Consumers and providers have both been confused and frustrated, likely a result of the fragmented implementation with each insurer defining their own reimbursement guidelines in order to have a preventive service claim qualify as having no cost sharing to the patient, resulting in surprise bills for what were expected to be 'free' preventive services (Andrews, 2014; Konrad, 2011; LaMontagne, 2015). As high deductible plans approach comprising half of the commercially insured market, we may need more innovative benefit designs that recognize the variation in clinical value and other barriers (e.g., multiple visits, cost of potential treatment) in order to substantially increase use of high-value preventive services.

As a nation, we are still grappling with two very different ideological points of view around what health insurance and the financing of health care should look like. We spend a greater percentage of our gross domestic product on health care than any other developed economy with middling results in terms of health and life expectancy compared to our peers. Some are pushing to abolish the existing fragmented system of health insurance coverage and replace it with a single-payer system, eliminating all or nearly all cost sharing to patients and creating significant administrative efficiencies. Others seek to roll back the protections and coverage gains made under the Affordable Care Act by providing significantly more state flexibility (and therefore, variation) in minimum coverage requirements and Medicaid eligibility and funding, reverting to a dramatically more federalist system in which the coverage environment in traditionally Democratic states will look starkly different to those in Republican strongholds. In the meantime, we continue to struggle with affordability of medical innovation even for those in generous commercial insurance plans and Medicare, with emerging therapies coming to market with eye-popping six figure list prices. There are no easy solutions regardless of the market structure. There are fundamental tradeoffs that have to be made, and are being made under the status quo, providing life-saving treatment and low-value care to many while others go without coverage.

Future Directions

Medicaid was passed along with Medicare in 1965 to provide health insurance coverage to low-income, disabled, and other vulnerable populations and has become the largest health insurance program in the United States, now covering over 65 million people (U.S. Department of Health and Human Services, 2019). As a state-federal partnership program, the federal government sets minimum eligibility criteria and benefits that states must adhere to in exchange for bearing a majority of the cost. However, states are allowed to modify those eligibility criteria and benefits through demonstration projects that "assist in promoting the objectives of the Medicaid program" (U.S. Department of Health and Human Services, n.d.-a). These demonstration projects, granted under waiver authority provided in section 1115 of the Social Security Act, have been used as a way to redesign state Medicaid programs and less so for rigorous evaluation of how to improve the program (Government Accountability Office, 2018). Medicaid expansion under the ACA has shown positive effects on health and financial well-being but as states now seek to rein in Medicaid enrollment and spending through waivers, it is important to understand how these waivers interact with the goal of "keeping America healthy" (Mazurenko, Balio, Agarwal, Carroll, & Menachemi, 2018; Miller, Hu, Kaestner, Mazumder, & Wong, 2018).

Former Secretary of Health and Human Services Tom Price encouraged states to explore work requirements, pledging to "support innovative approaches…that build on the human dignity that comes with…employment", despite evidence that "[m]ost Medicaid enrollees who can work are already working" (Kaiser Family Foundation, 2018b; U.S. Department of Health and Human Services, 2017). In Arkansas, the first state to implement a work requirements program, more than 17,000 Medicaid enrollees had been disenrolled from coverage through December 2018 (Kaiser Family Foundation, 2018c). Eleven states have submitted waiver applications to impose work requirements in their state Medicaid programs, with a range of nearly zero to 5% of Medicaid-eligible persons estimated to be subject to them but not in compliance (Silvestri, Holland, & Ross, 2018). State and federal administrative and survey data sources (e.g., Medicaid enrollment reports, NHIS, MEPS, CPS, SIPP) can be used to examine how enrollment patterns are changing with work requirements, including disparities by race, ethnicity, and disability, and their impacts on use of and foregone health care. Pharmacy claims and/or electronic prescribing data could also be used to identify changes in medication adherence for affected populations with chronic conditions, such as diabetes and hypertension, which puts patients at risk of life-threatening adverse events and health systems on the hook for expensive uncompensated emergency care.

Retroactive eligibility allows medical expenses to be covered for three months prior to the date of application for Medicaid, as long as one would have been eligible, protecting patients from financial ruin if they experience a major illness or injury. An approved 1115 waiver for Iowa in 2017 eliminated this benefit, not only in the Medicaid expansion population but nearly everyone eligible for the program without any explicit requirement to evaluate its impact (Kaiser Family Foundation, 2017). Other states have approved waivers awaiting implementation or are seeking approval for waivers that would remove retroactive eligibility from their state Medicaid programs. There has been almost no research to date quantifying the amount of care paid for using this benefit or evaluating the effects of removing retroactive eligibility on financial outcomes for Medicaid enrollees, despite several states having exemptions prior to the ACA and more seeking them now. Large federal surveys, like those noted above, and novel data sources, like credit reports and bank transactions, could be used to assess how financial burdens changed among Medicaid eligible populations after such a policy change.

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