NBER WORKING PAPER SERIES

MEDICAID AND MORTALITY:
NEW EVIDENCE FROM LINKED SURVEY AND ADMINISTRATIVE DATA

Sarah Miller
Norman Johnson
Laura R. Wherry

Working Paper 26081
http://www.nber.org/papers/w26081

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2019, Revised January 2021

The authors gratefully acknowledge the help of J. Clint Carter and John Sullivan in accessing restricted-use Census data. The authors would also like to thank Andrew Goodman-Bacon, Jonathan Gruber, Alex Hollingsworth, Lawrence Katz, Helen Levy, Kosali Simon, Benjamin Sommers, and four anonymous reviewers for helpful comments. The authors also thank conference and seminar participants at the American Society of Health Economics, Federal Reserve Bank of Chicago, Federal Reserve Board of Governors, Imperial College, Midwest Health Economics Conference, NBER Summer Institute Health Care, NYU Wagner, Princeton University, UC Riverside, and the University of Chicago. Laura Wherry benefited from facilities and resources provided by the California Center for Population Research at UCLA, which receives core support (R24-HD041022) from the Eunice Kennedy Shriver National Institute of Child Health and Human Development. This paper is released to inform interested parties of research and to encourage discussion. The views expressed in this manuscript are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research, and any views expressed on statistical, methodological, technical, or operational issues are those of the authors and not necessarily those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board (DRB) and Disclosure Avoidance Officers have reviewed the statistical output for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to its release. This research was performed at a Federal Statistical Research Data Center (FSRDC) under FSRDC Project Number 1743 (CBDRB-FY20-P1743-R8696, CBDRB- FY20-P1743-R8671, CBDRB-FY20-P1743-R8754). The DRB release numbers for results using the Mortality Disparities in American Communities data are CBDRB-FY19-310 and CBDRB-FY19-400.

Medicaid and Mortality: New Evidence from Linked Survey and Administrative Data
Sarah Miller, Norman Johnson, and Laura R. Wherry
NBER Working Paper No. 26081
July 2019, Revised January 2021
JEL No. I1,I13

ABSTRACT

We use large-scale federal survey data linked to administrative death records to investigate the relationship between Medicaid enrollment and mortality. Our analysis compares changes in mortality for near-elderly adults in states with and without Affordable Care Act Medicaid expansions. We identify adults most likely to benefit using survey information on socioeconomic status, citizenship status, and public program participation. We find that, prior to the ACA expansions, mortality rates across expansion and non-expansion states trended similarly, but beginning in the first year of the policy, there were significant reductions in mortality in states that opted to expand relative to non- expanders. Individuals in expansion states experienced a 0.132 percentage point decline in annual mortality, a 9.4 percent reduction over the sample mean, as a result of the Medicaid expansions. The effect is driven by a reduction in disease-related deaths and grows over time. A variety of alternative specifications, methods of inference, placebo tests, and sample definitions confirm our main result.

Sarah Miller
Ross School of Business
University of Michigan
701 Tappan Street
Ann Arbor, MI 48109
and NBER
mille@umich.edu

Norman Johnson
U.S. Bureau of the Census
norman.j.johnson@census.gov

Laura R. Wherry
Wagner Graduate School of Public Service
New York University
295 Lafayette Street
New York, NY 10012
and NBER
laura.wherry@nyu.edu

An online appendix is available at http://www.nber.org/data-appendix/w26081

I Introduction

Low-income individuals in the U.S. experience dramatically worse health than those with high incomes. For example, the annual mortality rate for older adults in families earning less than 138 percent of the Federal Poverty Level (FPL) is 1.7 percent, more than 4 times higher than the 0.4 percent rate experienced by higher-income individuals of the same age.[1] This low-income group also experiences higher risks of dying from diabetes (by 787%), cardiovascular disease (552%), and respiratory disease (813%) in a given year relative to those in higher income families, despite the existence of effective medical treatment and management for these types of chronic conditions. These higher rates of death translate to dramatic differences in life expectancy across income groups. Chetty et al. (2016) find that men at the bottom of the income distribution live on average nearly 15 years less, and women over 10 years less, than those at the top of the income distribution conditional on surviving to age 40. While data from nearly all countries show a positive correlation between income and health, this correlation is stronger in the U.S. than other high income countries (Semyonov et al., 2013).

One policy that could play an important role in reducing these disparities is the Medicaid eligibility expansion of the Affordable Care Act (ACA). The ACA brought about the largest expansion of health insurance coverage in the U.S. since the creation of Medicare and Medicaid in 1965. Over 20 million people have gained coverage since the ACA (Martinez et al., 2018), the majority of whom are low-income adults receiving coverage through the Medicaid program (Frean et al., 2017). Other research has shown that this expansion in coverage improved access to effective medical care that beneficiaries otherwise would not receive, including mortality-reducing prescription drugs (Ghosh et al., 2019), earlier detection and treatment of treatable cancers (e.g. Eguia et al., 2018; Sabik et al., 2018; Soni et al., 2018), and hospital and emergency department visits for conditions that require immediate care (Duggan et al., 2019), in addition to a variety of other types of potentially beneficial medical care (see Gruber and Sommers, 2019). However, despite the size and scope of this policy, its impact on the health of those who benefited remains uncertain.

A major challenge to understanding how the ACA affects health is the limited availability of large-scale data that links individual-level information on eligibility for expanded coverage to objective measures of health. Analyses of survey data can use information on individual characteristics to examine eligible adults, but such data are typically limited to self-reported health measures, which may not correlate with actual changes in health. Studies using these measures have offered inconsistent findings, with some indicating that the ACA expansions improved self-reported health, while others found no effect or even negative impacts of the ACA expansions (e.g. Cawley et al., 2018; Courtemanche et al., 2018b; Miller and Wherry, 2017; Sommers et al., 2017). Meanwhile, analyses of mortality data rely on death records aggregated to the state- or county-level, without information on individual-level factors that determine eligibility such as income (e.g. Borgschulte and Vogler, 2020; Chen, 2019; Khatana et al., 2019; Swaminathan et al., 2018; Yan et al., 2020). Without information on these relevant individual-level characteristics, these studies may be underpowered to reliably detect mortality effects of the ACA (Allen and Sommers, 2019), and may in fact vastly overstate magnitudes (Black et al., 2019).

[1] Authors' calculations using death rates from 2008 to 2013 derived from the publicly-available National Health Interview Survey Linked Mortality File (National Center for Health Statistics, 2019) for adults ages 55 to 64 with family incomes below 138% FPL and those with family incomes 400% FPL or greater.

In this paper, we provide new evidence of the impact of Medicaid on health by using administrative Medicaid enrollment and mortality data linked to large-scale, individual survey records. We use this novel dataset to examine the impact of the sizeable Medicaid eligibility expansion that occurred in some states under the ACA. In 2014, the ACA expanded eligibility for the Medicaid program to include all adults in families with incomes under 138 percent of the FPL. Previously only pregnant women, adults with disabilities, and very low income parents tended to qualify for Medicaid coverage. Although intended to apply to all states, a 2012 Supreme Court decision made the Medicaid eligibility expansion optional. As a result, only 29 states and the District of Columbia expanded coverage in 2014, with 7 additional states electing to expand over the next several years. Despite non-universal adoption, the ACA Medicaid expansions still represent a historic expansion in insurance coverage. Approximately 13.6 million adults gained Medicaid coverage under the ACA (Medicaid and CHIP Payment and Access Commission, 2018); for comparison, Medicare enrolled about 19 million elderly beneficiaries after its creation in 1965 (Bureau of the Census, 1969). We take advantage of variation in state adoption of this large expansion in coverage to compare changes in mortality among individuals in expansion states and non-expansion states.

In contrast to prior research that relies on death certificate data with limited information on individual characteristics, our data include detailed survey measures collected from the 2008 to 2013 years of the American Community Survey (ACS). This large-scale national survey contains approximately 4 million respondents in each year and allows us to observe information on specific characteristics that determine Medicaid eligibility such as income, citizenship status, and the receipt of other social assistance. With this information, we are able to identify individuals targeted by the ACA Medicaid expansions and, in this way, overcome the inherent limitations present in existing studies that rely only on aggregate death records. We focus on those in this group who were between the ages of 55 and 64 in 2014, who are at greater risk of mortality, although we also present results for all non-elderly adults and other age groups. We follow individuals in our sample over time to examine changes in coverage by Medicaid, by linking respondents to administrative records on Medicaid enrollment, and document sizeable changes in annual and cumulative Medicaid coverage in the Medicaid expansion states. Next, we examine whether there is an associated change in mortality by linking the sample to the Census Numident file which contains administrative records on the date of death for all individuals with Social Security Numbers (SSNs) who die in the United States. The Census Numident file allows us to observe mortality rates for our sample through 2017, four years after the initial ACA Medicaid eligibility expansions. We further examine changes in mortality by the underlying cause of death using data from the Mortality Disparities in American Communities (MDAC) project, which links the 2008 wave of the ACS to death certificate records using the National Death Index.

Our analysis shows that the ACA Medicaid expansions reduced mortality among this targeted group. Prior to the expansions, individuals in our sample residing in expansion and non-expansion states had very similar trends in both Medicaid coverage and mortality. At the time of the expansion, the trajectories of these two groups diverged significantly, with expansion state residents seeing increases in Medicaid coverage and decreases in annual mortality rates. In the first year following the coverage expansion, the probability of mortality declined by about 0.089 percentage points, or a 6.4 percent reduction over the sample mean. The estimated impact of the expansions increases over time, suggesting that exposure to Medicaid results in increasing health improvements. By the fourth year, the expansion reduced annual mortality rates by 0.208 percentage points among expansion state residents. In our supplemental analysis using the MDAC data, we find evidence that healthcare amenable and internal (disease-related) causes of death fell as a result of the expansions, but no evidence of a decline in deaths due to external causes, such as car accidents. We show these estimates are robust to a large number of alternative specifications. We also conduct several placebo tests to assess the validity of our analysis including examining the impact of the expansions on those age 65 or older in 2014 who did not gain Medicaid eligibility; examining the effect on individuals in higher income families who were less likely to be affected; and, conducting the analysis in the pre-ACA period before we would expect to see relative changes in mortality across state groups. We find no relative change in coverage or mortality across expansion and non-expansion states among the elderly or in the pre-ACA period, settings in which no Medicaid expansion occurred. Among those in higher income families, we find small but statistically significant increases in Medicaid coverage as well as small decreases in mortality, consistent with a causal impact of Medicaid on mortality.

Our analysis provides new evidence that expanded Medicaid coverage reduces mortality rates among low-income adults. If we assume that similarly sized mortality reductions would have occurred in the non-expansion states, our estimates suggest that approximately 15,600 deaths could have been averted if the ACA expansions were adopted nationwide as originally intended by the ACA. This highlights an ongoing cost to non-adoption that is relevant to both state policymakers and their constituents.

II Background

Many studies have shown that Medicaid coverage, and the ACA expansion in particular, increases access to and use of health care and reduces financial burden for low-income adults, but evidence on its health effects proves more difficult to document and is less conclusive (Gruber and Sommers, 2019; Soni et al., 2018). Studies that do examine health often rely on self-reported health measures from survey data. The evidence from these studies spans from estimated large or modest improvements in reported health associated with Medicaid expansion (Cawley et al., 2018; Lee and Porell, 2018; Simon et al., 2017; Sommers et al., 2016, 2017), to no effects (Courtemanche et al., 2018a,b; Miller and Wherry, 2019; Sommers et al., 2015; Wherry and Miller, 2016) or even small but marginally significant negative effects (Miller and Wherry, 2017). One concern with self-reported health data is that it may not accurately measure changes in physical health. For example, changes in self-reported health may reflect increasing awareness of health problems or interactions with the health care system, rather than actual changes in physical health. Increased contact with health providers could lead to, e.g., new information about a previously undiagnosed illness and, as a consequence, a worsened self-perception of health. This could bias downwards estimates of the effect of public health insurance on health.[2] Furthermore, the reliability of self-reported health measures for U.S. adults and their association with objective health measures are documented to be worse among lower socioeconomic status groups (Dowd and Zajacova, 2007, 2010; Zajacova and Dowd, 2011).

[2]This bias could also operate in the opposite direction if increased interaction with providers improves one's perception of health. See Currie and Gruber (1995) for more discussion.

The Oregon Health Insurance Experiment (OHIE) provided the first experimental evidence on the effects of Medicaid coverage on beneficiaries. The researchers did not observe significant effects of Medicaid coverage on any of the collected health measures (blood pressure, cholesterol, and blood sugar levels) (Baicker et al., 2013). Using administrative data, they also found no evidence that Medicaid coverage led to a reduction in mortality during the 16 months following coverage gain. Their estimate suggested a 16 percent reduction in mortality associated with acquiring Medicaid, but with a large confidence interval that could not rule out sizeable changes in either direction (Finkelstein et al., 2012).

As the data become available, researchers are beginning to evaluate the mortality effects of the ACA Medicaid expansions.[3] A small number of recent studies use population-level mortality data to estimate changes in adult mortality in expansion states compared to non-expansion states. These studies reach very different conclusions, either unable to detect mortality effects (Black et al., 2019) or estimating varying sized reductions in adult mortality: 3.6 percent among adults ages 20-64 (Borgschulte and Vogler, 2020) and 1.2 percent among adults ages 55-64 (Chen, 2019). Yan et al. (2020) find no reduction in all-cause mortality among adults ages 20-64, but a 2.7 percent decrease in health care amenable mortality. Khatana et al. (2019) focus on changes in cardiovascular disease-related mortality among adults ages 45-64 and document a 2.9 percent reduction over the baseline mortality rate. Finally, Swaminathan et al. (2018) find an 8.5 percent decrease in one-year mortality for patients with end stage renal disease initiating dialysis associated with the ACA Medicaid expansions.

There is also recent evidence that health insurance coverage (inclusive of Medicaid) can affect mortality. Goldin et al. (2021) provide new experimental evidence documenting such mortality effects by studying an IRS program that sent informational letters about health insurance enrollment to a randomly-selected sample of taxpayers who were subject to the ACA mandate penalty for being uninsured. The letters both significantly increased enrollment in insurance (both private exchange coverage and Medicaid) and reduced mortality among those between the ages of 45 and 64 and uninsured at the time of the intervention. The results from this experiment suggest that one additional month of insurance coverage lowered the two year mortality rate of recipients by about 0.18 percentage points, or over 10 percent. The authors found no effects of the letter on mortality for those under age 45.

One of the primary impediments to fully understanding the impact of Medicaid on mortality has been data availability. Previous studies using aggregated data rely on changes in survival for the Medicaid eligible to translate into overall mortality effects observable at the population level. Data from death certificate records contain very little socioeconomic information on the decedent; in particular, they contain no information on the decedent's income, use of public programs, whether he or she previously had health insurance coverage, or other characteristics that might affect Medicaid eligibility. Without data that links information on individual Medicaid eligibility to mortality, researchers must rely on differences in exposure over larger population groups – for example, residents of certain states or counties – which contain many individuals who are not directly affected by Medicaid policy.[4] This

[3]A separate but related literature has examined the relationship between public health insurance and child mortality using variation in exposure tied to the introduction of Medicaid and later expansions in public coverage under Medicaid and the Children's Health Insurance Program. For the most part, these studies have found significant declines in mortality associated with expanded coverage for infants and children both in the short-term (e.g. Currie and Gruber, 1996a,b; Goodman-Bacon, 2018; Howell et al., 2010) and long-term (Brown et al., 2018; Goodman-Bacon, 2016; Wherry and Meyer, 2016).

[4]Variation in exposure to the policy based on state of residence, as well as local geographic characteristics (such as

decreases the power to detect changes in mortality of a plausible magnitude, leading some researchers to conclude that "it will be extremely challenging for a study [on the ACA Medicaid expansions] to reliably detect effects of insurance coverage on mortality unless these data can be linked at the individual level to large-sample panel data" (Black et al., 2019).

In this paper, we aim to contribute to this knowledge base by providing new evidence on the mortality effects of Medicaid. We build on the accumulation of evidence from prior studies but offer three important advantages. First, we use individual characteristics to study mortality among the Medicaid-eligible population, rather than use analyses that rely on population-level data and may be underpowered to detect effects. This may be particularly salient in the case of the ACA Medicaid expansions, when insurance coverage is estimated to have increased by as little as 1 percentage point among all nonelderly adults (Black et al., 2019). Second, using administrative Medicaid enrollment information, we confirm a large change in coverage for our study population. The longitudinal enrollment data improves on the more commonly used survey measures of Medicaid coverage, which can be subject to substantial misreporting (Boudreaux et al., 2013), and also allow us to examine the total amount of coverage accumulated by residents of expansion states over the entire sample period. Documenting changes in accumulated coverage is important because studies suggest that health insurance coverage can have longer term effects that extend beyond just the coverage period (e.g. Boudreaux et al., 2016; Brown et al., 2018; Currie et al., 2008; Goodman-Bacon, 2016; Thompson, 2017; Wherry and Meyer, 2016; Wherry et al., 2017). Third, we estimate effects for this Medicaid-eligible population using much larger sample sizes than were used in the only experimental evaluation of Medicaid coverage, the Oregon Health Insurance Experiment. This larger sample is particularly important when examining mortality as an outcome since it is an extreme and infrequent health event. These advantages overcome the existing limitations in both experimental and non-experimental studies of Medicaid, allowing us to further advance the evidence on the program's mortality effects.

III Data and Outcomes

To conduct our analysis, we link individuals across three different data sources. First, we use restricted data from the 2008 to 2013 waves of the American Community Survey, which has a sample size approximately 50 percent larger than the public-use version, to identify our population of interest. We select respondents who, based on their pre-ACA characteristics, were likely to benefit from the ACA Medicaid expansions. We include only individuals who either are in families with income at or under 138 percent of the FPL or who have less than a high school degree.[5] Since we only have information on income captured at one point in time, the latter criterion is used to identify individuals who are of low socioeconomic status but might not meet the income cutoff at the time of the ACS interview. Results are similar if we include only those with less than a high school degree, or only those with incomes under 138 percent of the FPL, rather than defining the sample using the union of these two criteria; see

baseline uninsurance or poverty rates at the county level) are sources that have been used. In addition, some researchers have used information on the decedent's educational attainment as a proxy for individual income, although this information is reported by the next of kin and subject to substantial measurement error (see e.g., Rostron et al., 2010; Sorlie and Johnson, 1996).

[5]We define family income using the Census family definition of all related individuals living in the same household. Results are very similar if we follow the more restrictive definition of a family unit proposed by the State Health Access Data Assistance Center (2012) for studies of health insurance coverage.

later discussion in Section VII. We exclude non-citizens, many of whom are not eligible for Medicaid, and those receiving Supplemental Security Income (SSI), who are automatically eligible for Medicaid in most states. We restrict our primary analysis to individuals who were ages 55 to 64 in 2014. This higher age group has relatively high mortality rates, and is also consistent with the sample criteria used in Black et al. (2019). We present results for all non-elderly adults, and for a variety of different age subgroups, in additional analyses in Section VII. Finally, we exclude residents of 4 states and DC that expanded Medicaid to low-income adults prior to 2014.[6] There are approximately 566,000 respondents who meet our sample criteria.[7]

Descriptive statistics for the sample by state Medicaid expansion status are reported in Appendix Table A1 (all appendix information is included in an Online Appendix). The average age of the respondents in the two groups is similar. However, individuals in expansion states are slightly better off with higher average income (147% of the FPL vs. 140%) and educational attainment (45.3% with less than high school education vs. 46.8%), as well as lower baseline rates of uninsurance (32.6% vs. 37.3%), than individuals in non-expansion states. In addition, individuals in expansion states are more likely to be white or Hispanic, while a higher share of those in non-expansion states are Black.

Second, we link these data to the Census Numident file. The Census Numident file is derived from the Social Security Administration (SSA) Numerical Identification file, which includes information on date and county of birth and date of death (if it has occurred) for individuals with a Social Security Number (SSN).[8] These data have been used in, e.g., Brown et al. (2018); Chetty et al. (2011, 2016); Dobbie and Song (2015); Sullivan and von Wachter (2009), and other research relying on death information from tax records. Total deaths reported in the SSA file by age and year closely track the numbers reported by the National Center for Health Statistics (Chetty et al., 2016). The Census Bureau updates its Numident file each year with new information from the SSA Numerical Identification file. It formats the data so that there is a single record per individual, reflecting the most accurate and up-to-date information at that point in time. We use data from the Census Numident for deaths occurring in 2017 and earlier.

The Census Numident and ACS data are linked via the Census Bureau's Personal Identification Validation System (PVS). This system assigns individuals in each dataset a protected identification key (PIK), an anonymized identifier that allows Census to track individuals across datasets. Approximately 90 percent of all ACS respondents are successfully assigned a PIK using available information on name, address, and date of birth, with a slightly higher match rates for citizens (92 percent) (Bond et al., 2014). The assignment of a PIK allows respondents in the ACS to be matched to the Census Numident file. PIKS for the Census Numident file are assigned using social security numbers (SSNs) and date of birth (Mulrow et al., 2011). Since our analysis is restricted to older citizens, and since nearly all American citizens have SSNs assigned by the time they reach adulthood (see Bernstein et al., 2018),

[6] DE, MA, NY, and VT all expanded coverage to individuals with incomes reaching the poverty line or greater prior to the ACA; DC received approval to implement its ACA Medicaid expansion early with enrollment starting in 2011.

[7] Note that Census disclosure rules prohibit the disclosure of exact sample sizes and require rounding. All sample sizes for these data are therefore rounded according to disclosure rules.

[8] In addition to this death information from the SSA, the Census Bureau also has information on date of death from the National Death Index (NDI) for some individuals and years, which it incorporates into its date of death measure when available. The NDI collects detailed information on deaths from state vital statistics offices. Respondents to the 2008 ACS were linked to the NDI for the years 2008-2015, as part of the Mortality Disparities in American Communities project.

we expect to have nearly full coverage of deaths in the Numident file.

Once these data are linked, we observe the vital status of each individual during the year they respond to the ACS and each subsequent year. For example, we observe the vital status of an individual who responds to the 2008 ACS during each year from 2008 through 2017; for an individual who responds to the 2013 ACS, we observe his or her vital status from 2013 through 2017. We construct our outcome measure to represent mortality during each calendar year. If the individual is alive in a given year, the outcome variable takes a value of 0; if that individual died in that year it takes a value of 1. Once an individual has died, he or she is removed from the sample for subsequent years. In this way, we measure changes in the annual probability of death during a given year among individuals who were alive at the beginning of that year. The annual mortality rate is about 1.4 percent for our sample on average across all years, and approximately 1.3 percent among respondents in expansion states during the year just prior to expansion.[9]

Third, we further link our sample of ACS respondents to administrative records on Medicaid enrollment from the Centers for Medicare & Medicaid Services (CMS). We use the same PVS methods as were applied to the mortality data to link these newly available records to our sample of ACS respondents. About 93 percent of Medicaid enrollment records successfully receive a PIK assignment using SSN and date of birth information (Fernandez et al., 2015). CMS data on enrollment allows us to observe Medicaid enrollment longitudinally for our sample and to document how the probability of enrollment, and total cumulative exposure to Medicaid, changed in the expansion states relative to the non-expansion states. We use data from 2008 through 2016, the most recent data available. In our analyses of cumulative enrollment, we impute the number of days enrolled in 2017 using enrollment information from 2016, state of residence, age, gender, and race. To construct this imputation, we use information on transitions into and out of Medicaid observed in the previous year. See Appendix Section 1 for more information.[10] When examining the probability of being enrolled any time during a calendar year, we simply omit 2017 and use data on enrollment through 2016.

While our data uniquely offer the opportunity to link mortality, Medicaid enrollment, and economic variables at the individual level, there are also several important limitations. First, we observe the economic characteristics of individuals (income and educational attainment, receipt of social services, and citizenship status) at the time they respond to the ACS in the pre-period, between 2008 and 2013. These are time-varying characteristics, however, and may not accurately reflect economic characteristics at the time of the Medicaid expansions for some members of our sample. For example, an individual in a low-income family in 2008 may be in a higher-income family by 2014, at the time the expansions occurred. Similarly, individuals may migrate to different states between the time they responded to the ACS and the time the expansions occurred, resulting in our misclassification of whether that individual was exposed to the eligibility expansion.[11] In general, we expect that this type of misclassification will bias our estimates towards zero. In addition, the CMS administrative enrollment information allows us to accurately examine and characterize the amount of exposure to the policy for our analytic sample

[9] These annual averages are calculated excluding mortality rates for individuals during their year of ACS interview.

[10] There are a number of other minor data issues surrounding the CMS enrollment data, which are outlined in this Appendix section.

[11] Note, however, that individual migration decisions do not appear to be correlated with state Medicaid expansion (Goodman, 2017).

during the post period for the years the data are available.

A second limitation is that our data do not include information on the cause of death. The death information in the Census Numident is derived primarily from the Social Security Administration death records, which contain only date of death. We therefore supplement our main analysis with data from the 2008 year of the ACS, which was linked to death certificate records from 2008 to 2015 as part of the Mortality Disparities in American Communities (MDAC) project. While this drastically reduces both the sample size and follow-up period, it does allow us to conduct exploratory analyses of changes in mortality based on the underlying cause of death as reported on the death certificate.

IV Empirical Strategy

Our empirical strategy looks at changes in annual mortality in the expansion states relative to the non-expansion states before and after the implementation of the ACA Medicaid expansions. We estimate this using an event-study model that allows us to assess the evolution of relative outcomes while controlling for fixed differences across states and national trends over time. We estimate:

$$Y_{isjt} = Expansion_s \times \sum_{\substack{y=-6 \\ y \neq -1}}^{3} \beta_y I(t - t_s^* = y) + \beta_t + \beta_s + \beta_j + \gamma \mathbf{I}(j = t) + \epsilon_{isjt}. \tag{1}$$

As described earlier, our data is constructed at the individual (i) by year (t) level. Each individual responds to the ACS during a survey wave (j) and reports their state of residence (s). In our first stage analysis, Y_{isjt} measures eligibility or coverage in each year. For our analysis of mortality, the dependent variable is $Died_{isjt}$, which denotes death during each year t among individuals who were alive at the beginning of year t. We only observe mortality over a partial year during the year of the individual's ACS interview (j), since that individual had to be alive in order to respond to the survey. To account for this, we include an indicator variable that year t is the year that the individual responded to the ACS (i.e., that $j = t$).[12] In this equation, β_s denotes state fixed effects and β_j denotes fixed effects associated with each survey wave. β_t denotes calendar year fixed effects, which account for general trends in mortality for all individuals in our sample, including their gradual aging over time.

The variable $Expansion_s$ equals 1 if individual i was living in a state that opted to expand Medicaid eligibility between 2014 and 2017, and zero otherwise. Indicator variables $I(t - t_s^* = y)$ measure the time relative to the implementation year, t_s^*, of the expansion in each state, and are zero in all periods for non-expansion states.[13] While most states expanded in the beginning of 2014, some states expanded later in the year or in subsequent years. If a state expanded on or after July 1 of a given year, we code it as having expanded in the subsequent year.[14] The omitted category is $y = -1$, the year prior to the expansion. Therefore, each estimate of β_y provides the change in outcomes in expansion states relative

[12] We do not have information on the date of the ACS interview. If we drop the observations for which we observe less than a full year of mortality, our results are unchanged.

[13] We group together $y \leq -6$ into a single indicator variable interacted with expansion status since we only observe $y < -6$ for late expander states.

[14] In our analyses, states that expanded Medicaid in 2014 are AR, AZ, CA, CO, CT, HI, IL, IA, KY, MD, MI, MN, NJ, NM, NV, ND, OH, OR, RI, WA, and WV. Michigan implemented their expansion in April 2014 with the remainder of states expanding in January 2014. States that we considered to have 2015 expansions are NH (implemented August 15, 2014), PA (January 1, 2015), and IN (February 1, 2015). We consider AK (September 1, 2015) and MT (January 1, 2016) to be 2016 expansion states and LA (July 1, 2016) to be a 2017 expansion state.

to non-expansion states during year y, as measured from the year immediately prior to expansion. If mortality rates for expansion and non-expansion states were trending similarly prior to the ACA, we expect that estimated coefficients associated with event times $y = -6$ to $y = -2$ will be small and not statistically significant. We estimate equation (1) with a linear probability model and report heteroskedasticity-robust standard errors that are clustered at the state level.[15] All analyses use ACS survey weights.

In addition to the event study analyses, we also present difference-in-differences (DD) estimates as a summary of the effect across all post-expansion years. These are estimated using the same equation except that the event study indicators are replaced with a single variable denoting an expansion state during the post period ($Expansion_s \times Post_t$). This indicator turns on starting in the year of expansion for each state.

Because we have a fixed sample that ages in each period, mortality rates increase over time (i.e., our sample is oldest in the last year, 2017). In this way, our analysis tracks the mortality trajectory for a fixed cohort defined as adults ages 55 to 64 in 2014 and is representative of the outcomes over time for this group. Since mortality rates are higher during the post-period for our sample due to aging, regardless of exposure to Medicaid, comparing our estimates of the effects of the ACA Medicaid expansions to the mortality rate in the pre-ACA period as a counterfactual is incorrect. Instead, we estimate a "counterfactual" rate for those living in expansion states that depends on average mortality rates observed during the post period. We calculate this rate as the average annual mortality rate in the expansion states in the post-expansion period minus the reduced form mortality difference-in-differences estimate. This rate tells us what the mortality rate would have been in the treated states in our sample if their mortality rates had followed the same trajectory we observe in the control states. By constructing the counterfactual rate in this manner, we are able to take into account both the aging of the sample and the mortality reduction of expanded Medicaid coverage during the post-period, see discussion in Goodman-Bacon (2016).

V Results

V.A Medicaid Eligibility, Medicaid Enrollment, and Insurance Coverage

We first estimate the impact of the ACA Medicaid expansions on Medicaid eligibility and coverage for individuals in our sample. We show that, using a variety of data sources and approaches, respondents residing in the expansion states experienced significant increases in Medicaid eligibility, Medicaid enrollment, and health insurance coverage relative to those in the non-expansion states. The effects we document among our disadvantaged sample are substantially larger than those estimated in the population overall (e.g. Black et al., 2019), indicating that the individual-level characteristics we used to define our sample are successful in identifying those most likely to be affected by the eligibility expansions.

[15] In Appendix Table A2, we examine the sensitivity of our results to using both a standard logistic regression and a Cox proportional-hazards model. The difference-in-differences estimates from these nonlinear models are modestly smaller in magnitude than the linear probability model, but continue to show large and statistically significant reductions in mortality as a result of the ACA Medicaid expansions. In addition, our inference is similar if we cluster the errors at the Census division level or allow for spatial correlation of the errors using the methods proposed by Conley (1999). See discussion in Appendix Section 4 and results in Appendix Table A8.

First, we examine how eligibility for Medicaid changed in expansion relative to non-expansion states. Individuals eligible for Medicaid are "conditionally covered" by the program, in the sense that they may choose to remain uninsured and enroll only when they become ill. This concept of conditional coverage was first discussed by Cutler and Gruber (1996) in their study of historic Medicaid expansions for pregnant women and children; it may be even more relevant in our context, however, given another change under the ACA designed to make it easier for the uninsured to gain immediate access to Medicaid-funded services. For the first time, the federal government required states to allow presumptive eligibility under their Medicaid programs. Specifically, the ACA granted hospitals the ability to make presumptive eligibility determinations for Medicaid for certain groups covered in their state, including the non-elderly ACA expansion population (Caucci, 2014).[16] This means that if patients appear to have incomes low enough to qualify for Medicaid, hospitals may grant temporary Medicaid enrollment. Recipients of this temporary enrollment status may immediately receive health services and providers are guaranteed reimbursement for those services. In addition to presumptive eligibility, federal law directs states to provide retroactive coverage for new enrollees by covering medical bills incurred up to 3 months prior to their application date if they met the eligibility criteria during that time.[17] By not requiring an individual to first enroll in Medicaid prior to receiving Medicaid-funded care, these policies reinforce the notion that all eligible individuals are effectively covered by the program even if not actually enrolled.

We estimate Medicaid eligibility for our sample using information on state eligibility rules (see Appendix Section 2 for additional information) and characteristics of respondents in the 2008 to 2017 waves of the ACS who were ages 55 to 64 in 2014, and otherwise meet the same sample definition as used in our main analyses. Note that we are unable to use individual panel data for this analysis since we only observe respondent characteristics for our linked ACS-mortality sample during the year they completed the ACS survey. While repeated cross-sectional data for this cohort does not exactly mirror the individual panel data used to study mortality, it allows us to provide an estimate of the changes in eligibility likely similar to those experienced by our main sample. We rely on the same data to study changes in overall insurance coverage over time, since this information is also not captured in our panel data.

Next, we use the longitudinal administrative data on Medicaid enrollment to examine changes in Medicaid coverage in each year, and in the total number of years of Medicaid coverage experienced.[18] We use three different dependent variables to measure coverage changes. The first is equal to 1 if the individual is enrolled in Medicaid during year t and 0 otherwise, capturing changes in coverage in each year. The second variable equals the number of days enrolled by the individual in each year, including zero days for those who do not enroll. Third, we examine the total days during which the individual was enrolled up to and including year t, divided by 365; i.e., the total accumulated number of years

[16] Previously presumptive eligibility programs were optional for states and limited to pregnant women and children. States also had discretion over what types of providers could grant presumptive eligibility for these groups.

[17] A handful of states (AR, IA, IN, NH) had federal waivers to waive retroactive coverage for the expansion population, or other existing Medicaid eligibility groups, during our study period (Musumeci and Rudowitz, 2017).

[18] In this analysis, we use Medicaid enrollment data for all individuals starting with the year of their ACS interview. However, since we have complete enrollment information for each year, we exclude the $\gamma\mathbf{I}(j=t)$ term from equation (1). This term is also excluded from the other first-stage analyses described above that rely on repeated cross-sections of the ACS.

of Medicaid enrollment. This third version acknowledges that health insurance coverage may have beneficial health effects that extend even after the period of coverage is over and that health benefits may accumulate over time.[19]

Finally, we also document how overall insurance coverage evolved following the expansion. In contrast to Medicaid enrollment, we do not have administrative data on insurance coverage. Instead, we use a repeated cross-section of respondents from the 2008 to 2017 waves of the ACS to measure point-in-time insurance coverage for individuals who meet our sample criteria, as we did to determine changes in eligibility.[20] We also explore the impact of the expansion on insurance coverage using two alternative data sources. First, we examine changes in contemporaneous insurance coverage using the National Health Interview Survey (NHIS), which is considered to have the most valid coverage estimates nationally (Lynch et al., 2011). In contrast to the ACS, the NHIS uses state-specific names for Medicaid/CHIP in its coverage questions; it also includes a verification question for the uninsured. Second, we use the panel Health and Retirement Study (HRS) to examine cumulative changes in insurance coverage. We use restricted versions of both datasets that include state identifiers and construct analytic samples using the same sample criteria as our main sample.

The results are presented in Figure I and in the first five columns of Table I. We find a large increase in Medicaid eligibility associated with the ACA Medicaid expansions with gains of between 49 and 51 percentage points during each post-expansion year, as compared to the year just prior to expansion. Consistent with many other studies of this policy, we find significant increases in Medicaid coverage and decreases in uninsurance associated with the decision to expand Medicaid eligibility. We find the probability an individual is enrolled in Medicaid during the year increases by 12.8 percentage points, and that on average, individuals in expansion states experience 43 additional Medicaid enrolled days per year relative to those in non-expansion states (with those who do not enroll coded as having 0 enrolled days). We aggregate the number of days enrolled in each year to examine the cumulative number of Medicaid enrolled years. Cumulative Medicaid enrollment experienced by our sample also increases significantly, with respondents in Medicaid expansion states experiencing 0.38 additional years of Medicaid relative to those in non-expansion states on average, or about 0.67 additional years by the end of our sample period.

Using data from the ACS, we find that self-reported uninsurance decreases by 4.4 percentage points, on average, following the expansions. The estimates for years 1 and 2 are larger than those for year 3, which likely reflects the increasing share of the sample that is aging into Medicare over the study period. Note that we find somewhat larger impacts of the Medicaid expansions on coverage using the NHIS, with decreases ranging from 4.9 to 9.5 percentage points across the post-expansion years, and an average decline in the post-expansion period of 5.8 percentage points (see Appendix Figure A1 and Appendix Table A3). Estimates from both the NHIS and ACS indicate that a significant share of new Medicaid enrollees would have some form of insurance coverage in the absence of Medicaid expansion. Some of this "crowd-out" may reflect the availability of subsidized exchange coverage for individuals

[19]See, e.g., Boudreaux et al. (2016); Brown et al. (2018); Currie et al. (2008); Goodman-Bacon (2016); Thompson (2017); Wherry and Meyer (2016); Wherry et al. (2017) for evidence of such long-term effects.

[20]To assess comparability with our estimates based on administrative data, we also provide estimates of how self-reported Medicaid enrollment changed using the same data, although it is important to note that there is a well-known under-report of Medicaid enrollment in survey data (Boudreaux et al., 2015). See Appendix Figure A1 and Appendix Table A3.

with family incomes above the poverty line starting in 2014 in non-expansion states.

Finally, it is important to note that the insurance coverage changes documented in the ACS and NHIS only provide information on coverage changes in any given year. However, just as the ACA Medicaid expansions affected the accumulation of Medicaid coverage over time, they also affected the accumulation of insurance coverage. We do not have longitudinal administrative data on the total number of years of insurance coverage as we do with Medicaid enrollment. However, we are able to shed light on cumulative insurance coverage using data from the HRS.[21] Our sample in the HRS is much smaller than the ACS-mortality panel (N=1,359 vs. 566,000) but allows us to provide at least some suggestive evidence regarding cumulative insurance coverage. We find that respondents living in expansion states report having accumulated 0.39 additional years of continuous insurance coverage in the post-expansion period relative to respondents in the non-expansion states. This estimate is imprecise and only significant at the 10 percent level, albeit of a similar magnitude to the cumulative change in Medicaid coverage that we document in both the HRS (Appendix Table A3) and the administrative CMS data (Table I).

Taken together, our first stage analysis indicates that there were large and significant impacts of the ACA Medicaid expansions on eligibility, Medicaid enrollment, and insurance coverage for our target sample. In addition, individuals accumulated more years of exposure to Medicaid and insurance coverage as a result of these expansions.

V.B Mortality

The previous section established that the Medicaid expansions had a meaningful impact on eligibility, enrollment, and coverage for our sample. We now examine the impact of this expansion on mortality. Our estimates of equation (1) are presented in Figure II and in the sixth column of Table I. Prior to the ACA expansion, mortality rates trended similar across the two groups: pre-expansion event study coefficients are close to zero and not statistically significant. Starting in the first year of the expansion (year 0), we observe mortality rates decrease significantly among respondents in expansion states relative to non-expansion states. The coefficient estimated in the first year of expansion indicates that the probability of annual mortality declined by 0.089 percentage points. In years 1 and 2, we find reductions in the probability of a little over 0.1 percentage points and, in year 3, a reduction of 0.208 percentage points. All estimates are statistically significant, and our confidence intervals include meaningfully-sized effects.[22]

The immediate impact of the Medicaid expansion on mortality mirrors several analyses that find sizable changes in health care utilization during the first year of the expansions. For example, Garthwaite et al. (2017) find large changes in hospital ED usage; Wherry and Miller (2016) find increases in hospitalizations, physician visits, and diagnoses of chronic illnesses; Ghosh et al. (2019) find increases in the use of prescription drugs; and, Sommers et al. (2015) find improvements in access to medication and personal physicians all emerging within the first year of the Medicaid expansions.

In addition, we find evidence that the mortality effects of the expansions are growing over time. As discussed earlier, mortality is increasing over time for our panel as they reach older ages. However,

[21] See Appendix Section 3 for details on the HRS sample construction and analysis.

[22] For example, in year 0, we are able to rule out reductions in mortality smaller in magnitude than 0.018 percentage points; in year 1, 0.033 percentage points; in year 2, 0.021 percentage points and in year 3, 0.045 percentage points.

when we examine the coefficient estimates as compared to a counterfactual mortality rate for each event time, we find that the proportionate change in mortality is increasing in each year, from an estimated 7.0 percent reduction in year 0 to a 11.9 percent reduction in year 3.[23]

The top panel of Table I shows the difference-in-differences estimate that pools all post-expansion years together. Using this model, we estimate an average reduction in annual mortality of 0.132 percentage points. This represents a reduction in mortality of about 9.4 percent relative to the sample mean, or 8.1 percent relative to our estimated counterfactual mortality rate during the post period of 1.63 percent.[24]

We conduct additional analyses to identify the changes in death rates by the underlying cause of death using the MDAC. These analyses rely on a much smaller sample and shorter follow-up period, and so we consider this analysis to be exploratory in nature. We examine deaths due to non-disease related (i.e. "external") and disease-related (i.e. "internal") causes separately. We also examine a subset of deaths caused by internal factors that are considered to be "health care amenable" (Nolte and McKee, 2003), which have been studied in the existing literature (e.g. Sommers et al., 2014; Sommers, 2017).

These results are presented in Table II. We observe similar patterns for internal mortality and health care amenable mortality as we do in our main results, with relative decreases beginning in the first year after the expansions occur. The event study coefficients are not statistically significant for health care amenable mortality, and are significant at the $p < 0.10$ level for deaths from internal causes; however, we find a highly significant reduction in deaths related to internal causes under the difference-in-differences model. In contrast, mortality from external causes, which may be less affected by insurance coverage, does not appear to decrease after the expansions. The point estimates on the event study indicators are not statistically significant and the difference-in-differences estimate is only significant at the 10 percent level. The estimate is positive in sign, although we note that there is a slight upward pre-trend in these deaths in expansion states relative to non-expansion states.

We further probe cause of death by conducting an analysis using the ICD code groupings by body system. This exercise is meant to be exploratory with the hope that it will provide guidance for future work should better data become available. The results are reported in Appendix Table A4. For most diseases, we observe negative coefficients; the largest negative point estimates are observed for deaths related to neoplasms (cancer), endocrine and metabolic diseases (primarily diabetes), cardiovascular and circulatory system diseases, and respiratory diseases. Two of these (cardiovascular/circulatory and endocrine/metabolic) are marginally significant at the 10 percent level. The point estimates suggest that cardiovascular disease might account for approximately 38 percent of the overall reduction in internal mortality, with endocrine and metabolic diseases accounting for another 18 percent. Changes in mortality for these two body groupings are consistent with recent evidence documenting a decrease

[23] As described earlier, we estimate a counterfactual mortality rate that takes into account both that our panel is aging over time and the mortality reduction of expanded Medicaid coverage during the post-period. For each event time, it is equal to the sum of the post-expansion mortality rate in expansion states in that period and the absolute value of the corresponding event study coefficient for that period. The counterfactual rates are 1.28 percent in year 0, 1.51 percent in year 1, 1.60 percent in year 2, and 1.75 percent in year 3. We are then able to express our reduced form effects as a 7.0 percent reduction in year 0, 7.9 percent reduction in year 1, 8.2 percent reduction in year 2, and 11.9 percent reduction in year 3.

[24] The counterfactual mortality rate is calculated as the average annual mortality rate observed in the in expansion states in the post-expansion period (1.494 percent) minus the reduced form mortality difference-in-differences estimate (-0.1320pp).

in metabolic syndrome related conditions (obesity, high blood pressure, diabetes) and complications arising from these conditions among near-elderly adults under the Medicaid expansions (McInerney et al., 2020). We also see a small negative but statistically significant impact on diseases related to the skin and subcutaneous tissue, for which diabetes is an important risk factor (Ki and Rotstein, 2008).

VI Alternative Specifications and Robustness Checks

VI.A Role of Staggered Treatment Timing

Recent research demonstrates that variation in treatment effects across different "treatment cohorts," defined by their treatment timing, can make event study estimates difficult to interpret. In our context, we have four different treatment cohorts with 21 states expanding Medicaid in 2014, 3 states expanding in 2015, 2 states in 2016, and 1 state in 2017. Sun and Abraham (2020) show that, if each of these cohorts have different profiles of time-varying treatment effects, the event study estimates can be contaminated by treatment effects from other periods. We demonstrate that this variation in treatment timing is not a concern in our context by conducting additional analyses that (1) limit the expansion states to the 2014 expanders, and (2) use the alternative estimation method proposed in Sun and Abraham (2020). The event study results from these two approaches are reported in Appendix Figure A2 and are very similar to our main results. In addition, the difference-in-differences estimate when dropping the late expanding states is reported in the second row of Figure III, with the estimate from our main specification provided in the first row for comparison purposes. The estimate is very similar to our main result. Further details on these analyses may be found in Appendix Section 5.

In related work, Goodman-Bacon (2019) demonstrates that staggered treatment timing combined with the presence of time-varying treatment effects can lead to biased DD estimates. This can occur when earlier treatment cohorts function as controls for later treatment cohorts while on a differential path due to their earlier treatment. We do not expect this to be a major concern in our context given that we have so few late adopter states and a relatively short post period. However, to determine the potential influence of comparisons of states with different treatment times, we implement the Goodman-Bacon (2019) decomposition that examines the role of each 2x2 DD comparison in the two-way fixed effects DD estimate.[25] We find that only 11 percent of the DD estimate is derived from comparisons of states with different treatment times. The DD estimate that excludes this source of variation, relying solely on comparisons of treated and untreated units, is very similar, although slightly larger in magnitude than our main DD estimate (see Table A5).

VI.B Further Investigating Differential Pre-Trends

Next, we consider the potential impact of differential linear pre-trends in expansion and non-expansions states. While we do not find any evidence of differential pre-trends in the event study, we explore how well-powered this test is in our context. To do this, we first determine the size of a linear pre-trend we are powered to detect following the procedure described in Roth (2019). Our analysis suggests that we could detect with 80 percent power a fairly small negative linear trend of a magnitude of 0.03235 percentage points or greater (in absolute terms) in our event study model (i.e. a pre-trend of such size

[25]We implement this decomposition following the methods outlined in Goodman-Bacon (2019) and based on the code in Goodman-Bacon et al. (2019).

is likely to generate at least one statistically significant pre-period event study coefficient). If a trend of a size of up to -0.03235 percentage points is indeed present (although not detectable to us), we calculate that it would generate, by year 3 following the expansion, a bias of at most -0.08873 percentage points.[26] Our actual estimate in year 3 is -0.2082 percentage points, and substantially larger (2.3x) than this potential bias.

Next, we explicitly allow for differential linear trends in the model. First, we estimate an alternative version of the model that allows for differential pre-trends in expansion and non-expansion states by replacing the pre-expansion event study coefficients with a linear trend in event time for expansion states, as in, e.g. Dobkin et al. (2018) and Gross et al. (2020). The estimates of this specification are reported in Appendix Table A6 and are very similar to our main estimates. Second, we estimate a version of the model that includes state-specific linear pre-trends, following the two-step procedure proposed by Goodman-Bacon (2019). The result from this approach is presented in the third row of Figure III and is similar to our main model. Third, we estimate a model that controls for local trends in mortality among counties with different demographic and economic characteristics by interacting the 2013 county-level unemployment rate, median income, poverty rate, share Black, share Hispanic, and share female population with linear year trends. Including these trend terms does not appreciably affect our estimate, as seen in the fourth row of Figure III.[27]

VI.C Confounding Factors and Threats to Validity

Even if outcomes were evolving similarly for the two groups of states prior to expansion, the assumptions of our model would be violated if they experienced differential economic or policy shocks around the time of the expansion that drove changes in health outcomes. We explore this by introducing different sets of covariates and examining the impact of their inclusion on our estimates. The difference-in-differences estimates are presented graphically in Figure III. We also include event study versions for these alternative specifications, with our original estimates depicted in grey for comparison, in Appendix Figure A3.

We first examine sensitivity to controls for local economic conditions. In the fifth row of Figure III, we control for predicted changes in labor demand at the county level (see Appendix Section 4 for further details). Row 6 includes time-varying controls for county-level economic characteristics (unemployment rate, poverty rate, median household income). Our estimate remains unchanged with the inclusion of these variables.

We next examine whether differential exposure to the opioid crisis could be an important confounding factor. Analysis of the MDAC data shows that the change in mortality we observe is driven by a decrease in deaths due to internal, disease-related causes, which do not include drug overdoses. However, we further explore this possibility by directly controlling for state policies that have been tied to opioid overdose rates in the seventh row of Figure III. This model includes the following controls: indicators for prescription drug monitoring programs (PDMP), mandatory PDMPs that require physicians to access patients' prescription histories, state regulations for pain clinics, legalization of medical

[26] We calculate the bias following the formula presented in Roth (2019), which takes into account the additional bias introduced by passing a pre-test.

[27] We also consider the presence of non-linear differential pre-trends using methods outlined in Rambachan and Roth (2019). Our analysis suggests our results are reasonably robust to unrelated deviations in the two groups. See Appendix Section 4 for more details.

marijuana, open legal marijuana dispensaries, and interactions between an indicator that the state had a triplicate prescription program and year fixed effects.[28] We continue to find a large and statistically significant decrease in mortality with the inclusion of these controls.

Next we examine the sensitivity of our results to a control for different exposure to trade from China (i.e., the "China Shock" described in Autor et al., 2013, 2019). This previous research has connected increased trade competition with declining economic and social conditions, which may in turn affect health. We allow counties to have different time trends by interacting the commuting-zone level of exposure to Chinese imports per worker from 2000 to 2014 with year fixed effects.[29] The inclusion of this control variable does not impact our mortality estimate.

Finally, in row 9, we control for the demographic composition of our sample by adding individual covariates for race, age, and gender to our model. Once again the results are largely unchanged by the inclusion of these covariates. We also estimate a model (in row 10) that includes all of the controls described above. We continue to find a negative and statistically significant impact of the ACA Medicaid expansions on mortality rates in our sample, and cannot reject that the effect estimated in this model is significantly different than our main result.

One separate concern is that a small subset of our sample ages into Medicare during the 2015-2017 years in the post-period. If the Medicare program differs systematically across states in a manner that is correlated with Medicaid expansion, we might inadvertently be picking up differential mortality effects under the Medicare program. To rule out this concern, we re-estimate our model for the subgroup ages 55-61 in 2014, who do not qualify for Medicare during the post period. The results from this analysis may be found in Appendix Table A7 and are similar to those for our main sample.

VI.D Placebo Tests

To further assess the validity of our empirical approach, we conduct several "placebo" tests. In these tests, we investigate whether we observe effects of the Medicaid expansions in populations that were unaffected or less affected by the policy change.

Our first placebo test shifts the analysis sample back in time to the pre-ACA period. This test can assess whether any elements of our sample construction, such as drawing the ACS sample only in the pre-expansion period, might lead to spurious results. We construct the data in the same fashion as our main analysis, but use mortality data from 2004 to 2013 for ACS respondents in the 2004 to 2009 survey years (rather than mortality data from 2008 to 2017 for the 2008 to 2013 survey years). We construct a variable indicating that a state expanded that corresponds to $Expansion_s$ in equation (1), but estimate our model as if the first expansions occurred in 2010 rather than 2014, with states expanding t years after 2014 treated as if they expanded in $2010+t$. The results of this placebo test using the pre-ACA period is presented in the first row of Figure IV. As expected, we find no effects on Medicaid coverage or mortality in expansion states during this placebo pre-ACA period.

Next, we expand on this analysis by randomly assigning Medicaid expansion status to the same number of states and years as occurred under the ACA Medicaid expansions, rather than estimating

[28]We draw heavily on Alpert et al. (2019) to identify these opioid related policies, following the sources and coding outlined in their paper. See Appendix Section 4 for additional details.

[29]Note that these measures are not available for Alaska and Hawaii, so we drop these two states when estimating this specification.

placebo effects for the actual expansion states. As with the previous exercise, we conduct this placebo test using pre-ACA data, prior to when the actual expansions occurred. We repeat this exercise 10,000 times and compile the coefficient estimates and t-statistics from the difference-in-differences model. The results are presented in Appendix Figure A4, with the vertical lines indicating the 5th and 95th percentiles of this "placebo" distribution; our model estimate is depicted with a dashed line. This exercise allows us to further investigate the likelihood that we might encounter similarly sized mortality effects by chance. Our estimates for the ACA Medicaid expansions fall well below the 5th percentiles of the distributions of placebo coefficient estimates and t-statistics, further increasing our confidence that we are estimating a true policy effect.

We next examine whether we observed similar mortality effects for two population groups that were less likely to be affected by the policy. The first test uses individuals who were age 65 and older at the time of the expansions. These individuals have near universal coverage through the Medicare program and should not be directly affected by the coverage expansions.[30] We re-estimate equation (1) for this sample and the results are presented in the second panel of Figure IV. As predicted, we observe no effect of the Medicaid expansions on Medicaid coverage for this group. We also see no effect of the expansions on mortality rates for this group.[31]

We next examine individuals ages 55 to 64 in families earning 400% FPL or greater at the time of the ACS survey. This group should be less affected than our main sample of low-income or low-education respondents. However, they may still gain Medicaid coverage under the expansions due to changes in income over time, or if their income is reported with error. As seen in the third row of Figure IV, we do find small but statistically significant increases in Medicaid enrollment associated with the expansions among this group. We also see correspondingly small but, for some years, statistically significant reductions in mortality for this group. These changes are consistent with a causal effect of expanded Medicaid coverage on mortality. One interesting note is those reporting higher incomes in the survey, but who later enroll in Medicaid, exhibit very high average mortality compared to those who do not enroll in Medicaid. This indicates that individuals in the high income group who do enroll in Medicaid are highly selected (e.g. having experienced a serious health event that resulted in income loss).[32]

We also formally test for a differential effect in our main sample relative to the age 65+ and 400% FPL+ placebo groups by estimating a "triple difference" model. Details on this approach are found in Appendix Section 6. The "triple difference" estimates reported in the bottom two rows of Figure III are slightly smaller than our main DD results but remain statistically and economically significant.

VII Additional Analyses

We also conduct several additional analyses on different samples and subgroups to further characterize the impact of the Medicaid expansions. First, we examine changes in mortality for all nonelderly adults

[30]Prior work has documented some spillover effects on the health care utilization of this population under pre-ACA state Medicaid expansions, but analyses of the ACA Medicaid expansions find no evidence of such spillovers and are able to rule out very small effects (Carey et al., 2018).

[31]Results are similar if we also restrict the elderly to be in low-income families.

[32]If we scale the average mortality effect by the corresponding estimate for the change in any Medicaid coverage, the decrease for the high-income group is larger in size than for our main sample. We believe this reflects a larger role of adverse selection for the higher-income group.

and other age subgroups. Our main analysis is limited to individuals ages 55 to 64 at the time of the Medicaid expansions, a group with higher mortality rates that has been the focus of other work on this topic (e.g. Black et al., 2019). In the first row of Appendix Table A9, we also estimate the impact of Medicaid expansion on mortality for individuals who meet our sample inclusion criteria but are ages 19 to 64 in 2014. We find a significant increase in enrollment in any Medicaid coverage of 12.7 percentage points. The mortality estimate is not statistically significant but suggests a 3.9 percent decrease relative to the counterfactual rate. We next estimate the effects for other subgroups in this age range (ages 19-29, 30-39, 40-49, and 50-54). We find significant increases in Medicaid enrollment for all groups, but less evidence of corresponding mortality changes. The largest decrease in mortality is observed at ages 50-54 but is not statistically significant. We are unable, however, to rule out meaningful declines in mortality for any age group.

Next, we further probe heterogeneity by age within our main age group of interest, adults age 55 to 64 years old in 2014, and at older ages. In Appendix Figure A5 we report the percent reduction in mortality associated with the Medicaid expansions in 3-year age bins. We construct this by dividing the reduced form difference-in-differences estimate by the counterfactual mortality rate for each age group. We see that the largest mortality reductions occur at the oldest age groups, with those age 59-61 and 62-64 both experiencing statistically significant reductions in mortality. Reductions in mortality are smaller and not statistically significant for those at younger ages (53-55 and 56-58) and for those age 65 and older in 2014, who were Medicare eligible.

We next examine the effects of the expansions on different subgroups of our main analysis sample defined by race and ethnicity, gender, marital status, or other characteristics. The results of these analyses are reported in Appendix Table A10. We find evidence of larger mortality effects for white, non-Hispanic adults when compared to other racial and ethnic groups. Surprisingly, we detect no effect of the expansions on non-Hispanic Black respondents. We also find larger effects for the males in the sample. These differences are present despite sometimes smaller first stage estimates for these two groups, although their estimated mortality risk is higher (as seen by a comparison of their counterfactual mortality rates). In addition, the confidence intervals on the mortality estimates do not rule out meaningful declines in mortality for any subgroup. We did not find evidence of mortality differences by marital status. And, when we narrow the socioeconomic criteria to either less than a high school degree or less than 138 percent of the FPL, we find overall very similar first stage and mortality estimates for the two groups. Within this set of heterogeneity analyses, there does not appear to be a strong correlation between the size of the first stage and the effect of the expansion on mortality. However, we note that different groups tend to experience mortality from different causes, some of which may be more or less amenable to health interventions. Across subgroups there may also be differential barriers to seeking and receiving care. We leave further exploration of this heterogeneity for future work.

Finally, an additional analysis limits the main sample to approximately a 30 percent subset who reported being uninsured at the time of the survey. As this group is slightly younger on average,[33] the counterfactual mortality rate is a bit lower than in the overall sample, at 1.46 percent per year (vs. 1.63 percent in the sample overall). The point estimates indicate somewhat larger decreases in mortality

[33]We estimate that the average age of uninsured respondents in our sample is 59.0 in 2014, compared to an average of 59.4 years for insured respondents. This difference is statistically significant with a p-value < 0.0001.

for this group of 0.150 percentage points (or 10.3 percent of the counterfactual rate) compared to the reduction in the main sample of 0.132 percentage points (or 8.1 percent of the counterfactual rate). The fact that those who were uninsured prior to the ACA experienced larger mortality improvements as a result of the policy is in line with our expectations. Indeed, it is somewhat surprising that the differential in the reduction in mortality between those who were uninsured at the time of the ACS and the overall population of low-income older adults is not even larger, particularly because they experienced larger gains in Medicaid enrollment;[34] however, this may be due to the lower mortality rate in this group.

VIII Interpreting the Estimates and Comparisons to Past Work

VIII.A Scaling the Mortality Effects by Coverage Changes

Our results show consistent evidence of a decrease in all-cause mortality among low socioeconomic status, older adults under the ACA Medicaid expansions. In the difference-in-differences model, we estimate an average decrease in annual mortality of 0.132 percentage points during the four-year post period (top panel of Table I). We can combine this estimate with the first stage estimates to provide information on the treatment effect of Medicaid coverage on the group that actually enrolled. For such a scaling to be interpretable as the treatment effect, we must assume that the Medicaid expansions only affected individuals who enrolled in Medicaid. This assumption may be violated if the Medicaid expansions improved access to care more broadly, for example by reducing hospital closures, or improved the health of non-enrollees through other means such as increasing available resources to families that had some uninsured members prior to the expansion.

Our analysis of administrative Medicaid enrollment records indicates that our sample accumulated 0.375 additional years of Medicaid enrollment, on average, as a result of the ACA expansions (see Section V.A). Combining this estimate with the 0.132 percentage point reduction in mortality implies that one year of Medicaid enrollment decreases mortality by about 0.35 percentage points ($=\frac{0.132}{0.375}$). We also find that the probability of enrollment in Medicaid in any given year increased by 12.8 percentage points as a result of the ACA expansions. Assuming that mortality responds only to coverage in a given year, rather than the total amount of coverage experienced, this estimate suggests that contemporaneous enrollment in Medicaid reduces mortality by 1.03 percentage points ($=\frac{0.132}{0.128}$).

To better understand the magnitude of these changes, we would ideally compare them to the mortality rate for sample members who enrolled in Medicaid as a result of the expansions (i.e., the "compliers," see Imbens and Angrist, 1994) in the absence of the policy. As discussed earlier, we estimate a counterfactual mortality rate of approximately 1.63 percent for all sample members in the expansion states. However, we expect that the counterfactual mortality rate among the compliers is likely much higher if, for example, those in worse health are more likely to enroll in Medicaid. The literature indicates that such adverse selection does occur (e.g. Kenney et al., 2012; Marton and Yelowitz, 2015); this may also be exacerbated by policies designed to provide immediate coverage to

[34] Note that we are unable to estimate the change in Medicaid eligibility or contemporaneous insurance coverage for this subgroup as we did for the other subgroups, due to the lack of information on historical insurance coverage in the ACS. However, we have explored changes in contemporaneous and cumulative insurance coverage for a similar panel in the HRS (see Appendix Table A11). Due to the small sample size, the estimates are imprecisely estimated but do suggest changes in both contemporaneous and cumulative insurance coverage that are larger in size than those for our main sample.

those in need, as discussed earlier (i.e. presumptive eligibility and retroactive coverage). As further evidence of this, a recent study by Garthwaite et al. (2019) finds that individuals moving from uninsured to Medicaid status in ACA Medicaid expansion states had higher than average hospital and ED visits during the pre-ACA period.

We estimate an upper bound for this counterfactual rate for the compliers using observed mortality for actual enrollees in our sample. We first estimate average annual mortality for enrollees in the expansion states during the post-period at 2.0 percent. We consider this an upper bound because the CMS enrollment data does not identify the eligibility pathway for coverage and some of these individuals likely would have qualified for coverage even if there were no eligibility expansions (e.g. if they became disabled);[35] we therefore expect that this group likely exhibits worse health than those who are induced to enroll by the policy change.

We then take into account the mortality reduction resulting from the gain in Medicaid coverage. Our analysis suggests that a year of Medicaid coverage is associated with a reduction in annual mortality of 0.35 percentage points (as discussed above). On average, those who were not enrolled in Medicaid prior to the ACA, but did enroll in expansion states after the ACA, remain enrolled for about 2.7 years over our sample period. If compliers experienced 2.7 additional years of coverage due to the expansions, their counterfactual mortality rate would be 2.95 percent ($=2.0 + 2.7 \times 0.35$).

Given these calculations, we may therefore expect the counterfactual mortality rate for the compliers to fall somewhere above the estimate for all sample members of 1.63 percent, but below this upper bound of 2.95 percent. Combined with our estimated treatment effect of a 0.35 percentage point reduction in mortality associated with 1 year of accumulated Medicaid enrollment, these counterfactual rates suggest that one year of Medicaid coverage reduces individual mortality by between 11.9 and 21.5 percent. Meanwhile, our estimate of the treatment effect for contemporaneous Medicaid enrollment (1.03pp) indicates a resulting reduction in individual mortality of between 34.9 and 63.2 percent.

If we expect that the mortality effects of Medicaid are solely driven by changes in access to care for individuals who would otherwise be uninsured, we may prefer to scale our reduced form estimates by the change in net insurance coverage, rather than the change in Medicaid coverage. This calculation implicitly assumes that there is no difference between private insurance coverage and Medicaid that would meaningfully impact mortality risk. If coverage only affects mortality during the year in which the respondent is enrolled (i.e., no longer term effects), the change in contemporaneous insurance coverage (a 4.4 percentage point increase in overall insurance, see Table I) implies much larger treatment effects, ranging from 102 to 184 percent reductions in individual mortality.

These large estimate sizes suggest that this scaling may miss important effects for those who enrolled in Medicaid as a result of the expansions but would have otherwise enrolled in exchange or employer-based coverage. For example, there may be significant financial differences in the cost of coverage or medical care that affect health care utilization decisions and household finances, both of which may affect mortality risk.[36] There may also be differences in the types of services covered.

[35] Note that those who were disabled prior to the ACA should be excluded as our sample criteria excludes those reporting SSI receipt.

[36] Medicaid is typically free for beneficiaries with no or minimal cost-sharing for service receipt. In contrast, private insurance coverage typically requires an annual premium, as well as additional cost-sharing. A recent study estimates that, under the ACA Medicaid expansions, new Medicaid enrollees ages 50 to 64 saved approximately $3,100 in out-of-pocket expenditures each year (McInerney et al., 2020).

Unlike most private insurers, Medicaid covers many long-term home- and community-based services and supports (Rudowitz et al., 2019), which may be important for individuals with complex health needs and high mortality risk. Alternatively, this calculation may miss other spillover effects among Medicaid non-recipients, or the presence of cumulative effects of insurance coverage that are not captured in contemporaneous coverage measures.[37] Finally, it is important to note that the confidence interval on the estimated mortality effect includes much smaller reductions in mortality.

VIII.B Comparisons to Previous Estimates

In this section, we compare the treatment effects that we estimate to those published in the literature. In order to take into account differences in coverage changes and population mortality rates across the different study settings, we compare the proportional average treatment effects for new Medicaid enrollees or for the newly insured.

First, we use the public-use replication kit for the OHIE to examine the effect of Medicaid coverage on participants who were ages 55-64 at the time of the experiment to derive estimates comparable to those presented here (reported in Appendix Table A12). Among this age group, ever receiving Medicaid reduced the probability of mortality over a 16 month period by 1.65 percentage points, or a decline of 71.7 percent relative to the control mean, although this estimate is not statistically significant (associated with a p-value of 0.128).[38] This estimated proportional treatment effect is very similar to the estimate in our analysis (i.e. 63 percent) described in the last section.

We also use OHIE data to estimate the effect of insurance coverage, rather than Medicaid coverage, on mortality. We do this by examining the subsample of participants who responded to the OHIE survey and provided information on their insurance status at an initial survey (completed an average of 1 month after coverage approval), or at a survey approximately one year later (an average of 13 months after coverage approval, see Finkelstein et al., 2012). Using the gain in coverage measured in the initial survey, we find a decrease in mortality of 326 percent (p=0.071) when compared to the control group mean. Using the 12-month measure, we find a 335 percent mortality reduction (p=0.153).[39] These are both larger than our estimate of the impact of new insurance coverage under the ACA Medicaid expansions, although the confidence intervals overlap with our estimate. See Appendix Section 7 for further discussion.

Recent work by Goldin et al. (2021) also provides experimental evidence on the impact of health insurance on mortality. Taking advantage of changes in insurance status generated by randomly assigned informational letters, the authors find that each additional month of health insurance coverage reduced mortality in their sample of 45 to 64 year olds by 0.178 percentage points over a two-year period, or 10.1 percent compared to their estimated complier baseline mortality rate. Assuming the effect of coverage decays geometrically, the authors estimate that 12 months of coverage results in a reduction in mortality over the two-year period of 106 percent relative to their estimated complier

[37] When we consider cumulative exposure to insurance coverage using estimates from our HRS sample, the implied treatment effects indicate that each year enrolled in any coverage reduces mortality by between 12 and 21 percent. However, these estimates are fairly imprecise.

[38] We can also scale this effect by 12/16th to arrive an annual effect of Medicaid on mortality of 1.24 percentage points. This is comparable, but larger, than the 1.03 percentage point treatment effect of contemporaneous Medicaid enrollment estimated in our analysis.

[39] Note that baseline mortality for the control group is lower among survey respondents since participants had to be alive in order to respond to the survey.

mean, which is in the range of our estimates for the effects of contemporaneous insurance coverage.

In addition to these two experiments, there are also several quasi-experimental analyses that examine the effects of insurance coverage expansions on non-elderly adult mortality. To facilitate comparisons across these studies, we estimate the implied mortality effects for individuals either gaining Medicaid or insurance coverage as proportionate changes over a counterfactual mortality rate. Studies often vary in how they treat measurement error in survey reports of Medicaid enrollment and in the assumed counterfactual mortality rate; we therefore apply a consistent set of adjustments across these studies. We also present 95 percent confidence intervals for these estimates. Further details on the approach used to construct these scaled estimates and their confidence intervals may be found in Appendix Section 7.

The resulting estimates are reported in Appendix Table A13. It is clear from this table that our estimates are in the ballpark of those from existing work examining the mortality effects of Medicaid or insurance expansions for low-income adults. Sommers (2017) examines changes in mortality among 20 to 64 year-olds following pre-ACA Medicaid expansions in Arizona, Maine, and New York. Using a difference-in-differences design, he finds a mortality reduction of 64.5 percent among individuals gaining insurance coverage. Similarly, taking advantage of county-level variation in the impact of the Massachusetts health reform of 2006, Sommers et al. (2014) find that insurance coverage reduces mortality by 27.3 percent among 20 to 64 year olds. Using mortality records aggregated to the county level, Borgschulte and Vogler (2020) find adults age 20 to 64 experienced a 47.3 percent reduction in mortality under the ACA Medicaid expansions. In our analysis, we find that new insurance coverage reduces mortality by 50 percent among those in our sample age 19 to 64 (although this effect was not statistically significant), in line with the estimates from these other studies. Chen (2019), however, finds a much smaller and statistically insignificant effect on the order of 9 percent for adults ages 25-64 under his analysis of the ACA Medicaid expansions.

Fewer papers include estimates for the age group that we study.[40] Black et al. (2019) and Chen (2019) find smaller implied mortality effects of individual insurance coverage when compared to our study. The estimate in Black et al. (2019), however, is imprecisely estimated with a large confidence interval inclusive of our estimate.

To summarize, the existing experimental literature on the effect of health insurance on mortality shows large effects, suggesting that reductions in mortality associated with insurance well exceed the average mortality rate of the control group. Such large effects may be due to adverse selection, i.e. that those who sign up for health insurance are particularly vulnerable and would have experienced high mortality rates in the absence of insurance. Evidence from the quasi-experimental literature tends to find smaller, but still substantial (9-65 percent), reductions in mortality associated with coverage. Our estimates tend to be smaller than those documented in the experimental literature but somewhat larger than those reported in quasi-experimental studies.

IX Conclusion

Low-income adults in the United States experience dramatically worse health and reduced longevity as compared to their higher income counterparts. The ACA expansion of Medicaid eligibility to poor

[40] While some studies present subgroup analyses by age, they do not include the corresponding first stage estimates needed to estimate the implied individual treatment effect.

and near-poor adults represents a historic effort to improve access to high-quality medical care for this population. Robust evidence that Medicaid increases the use of effective medical care indicates that the ACA expansion could play a crucial role in reducing income disparities in health among U.S. adults. However, the magnitude of any health improvements experienced by beneficiaries remains largely uncertain, in part due to the limited amount of data available that contains information on both socioeconomic status and objective measures of health.

In this paper, we evaluate these expansions by leveraging data linkages across large-scale federal survey and administrative data. These data linkages allow us to overcome several empirical challenges that previous research in this area encountered, including the lack of information about individual-level characteristics that determine Medicaid eligibility and the systematic mis-reporting of Medicaid enrollment that occurs in survey data. Using these data, we show that the ACA Medicaid expansions substantially reduced mortality rates among those who stood to benefit the most.

Our estimated change in mortality for our sample translates into sizeable gains in terms of the number of lives saved under Medicaid expansion. Using the ACS, we calculate that there are about 3.7 million individuals who meet our sample criteria living in expansion states. Our results therefore indicate that approximately 4,800 fewer deaths occurred per year among this population due to Medicaid expansion, or roughly 19,200 fewer deaths over the first four years alone. This calculation relies on the assumption used throughout the paper; namely, that in the absence of the ACA expansions, mortality in expansion and non-expansion states would have trended similarly.

Our estimates also reveal some information about the potential cost of state decisions not to expand Medicaid. These calculations necessarily rely on the assumption that the effects of Medicaid expansion in the non-expansion states would be similar to those observed in the expansion states. The change in mortality in non-expansion states if they were to adopt the expansion could be larger (e.g., if the beneficiaries in the non-expansion states have worse baseline access to effective health care) or smaller (e.g., if the health system has less capacity to treat the newly insured in non-expansion states). Given these caveats, we estimate that, as there are approximately 3 million individuals meeting this sample criteria in non-expansion states, failure to expand in these states resulted in 15,600 additional deaths over this four year period that could have been avoided if the states had elected to expand coverage.

References

Allen, H. and B. D. Sommers (2019, October). Medicaid Expansion and Health: Assessing the Evidence After 5 Years. *JAMA 322*(13), 1253–1254. Publisher: American Medical Association.

Alpert, A., W. Evans, E. M. Lieber, and D. Powell (2019, November). Origins of the Opioid Crisis and Its Enduring Impacts. Technical Report w26500, National Bureau of Economic Research, Cambridge, MA.

Autor, D., D. Dorn, and G. Hanson (2019, September). When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men. *American Economic Review: Insights 1*(2), 161–178.

Autor, D. H., D. Dorn, and G. H. Hanson (2013, October). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–2168.

Baicker, K., S. L. Taubman, H. L. Allen, M. Bernstein, J. H. Gruber, J. P. Newhouse, E. C. Schneider, B. J. Wright, A. M. Zaslavsky, and A. N. Finkelstein (2013). The Oregon Experiment — Effects of Medicaid on Clinical Outcomes. *New England Journal of Medicine 368*(18), 1713–1722.

Bernstein, S., R. Diamond, T. McQuade, and B. Pousada (2018, November). The Contribution of High-Skilled Immigrants to Innovation in the United States. Working Paper, Stanford University.

Black, B., A. Hollingsworth, L. Nunes, and K. Simon (2019, February). The Effect of Health Insurance on Mortality: Power Analysis and What We Can Learn from the Affordable Care Act Coverage Expansions. Technical Report w25568, National Bureau of Economic Research, Cambridge, MA.

Bond, B., J. D. Brown, A. Luque, and A. O'Hara (2014, April). The Nature of the Bias When Studying Only Linkable Person Records: Evidence from the American Community Survey. Technical Report Working Paper #2014-08, Center for Administrative Records Research & Applications, U.S. Census Bureau.

Borgschulte, M. and J. Vogler (2020, May). Did the ACA Medicaid Expansion Save Lives? *Journal of Health Economics*, 102333.

Boudreaux, M., K. T. Call, J. Turner, B. Fried, and B. O'Hara (2013). Accuracy of Medicaid reporting in the ACS: Preliminary results from linked data. pp. 14.

Boudreaux, M. H., K. T. Call, J. Turner, B. Fried, and B. O'Hara (2015, December). Measurement Error in Public Health Insurance Reporting in the American Community Survey: Evidence from Record Linkage. *Health Services Research 50*(6), 1973–1995.

Boudreaux, M. H., E. Golberstein, and D. D. McAlpine (2016, January). The Long-Term Impacts of Medicaid Exposure in Early Childhood: Evidence from the Program's Origin. *Journal of Health Economics 45*, 161–175.

Brown, D. W., A. E. Kowalski, and I. Z. Lurie (2018). Long-Term Impacts of Childhood Medicaid Expansions on Outcomes in Adulthood. *Review of Economic Studies* (Forthcoming).

Bureau of the Census (1969, April). Estimates of the Population of States, by Age 1965 to 1987. Current Population Reports Series P-25, No. 420, U.S. Department of Commerce, Washington, DC.

Carey, C., S. Miller, and L. Wherry (2018, October). The Impact of Insurance Expansions on the Already Insured: The Affordable Care Act and Medicare. Technical Report w25153, National Bureau of Economic Research, Cambridge, MA.

Caucci, L. (2014, August). Hospital Presumptive Eligibility. Brief, Office for State, Tribal, Local and Territorial Support, Centers for Disease Control and Prevention.

Cawley, J., A. Soni, and K. Simon (2018, September). Third Year of Survey Data Shows Continuing Benefits of Medicaid Expansions for Low-Income Childless Adults in the U.S. *Journal of General Internal Medicine 33*(9), 1495–1497.

Chen, J. (2019, August). Does Medicaid Save Lives? SSRN Scholarly Paper ID 3432701, Social Science Research Network, Rochester, NY.

Chetty, R., J. N. Friedman, N. Hilger, E. Saez, D. W. Schanzenbach, and D. Yagan (2011, November). How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project Star. *The Quarterly Journal of Economics 126*(4), 1593–1660.

Chetty, R., M. Stepner, S. Abraham, S. Lin, B. Scuderi, N. Turner, A. Bergeron, and D. Cutler (2016, April). The Association Between Income and Life Expectancy in the United States, 2001-2014. *JAMA 315*(16), 1750.

Conley, T. G. (1999, September). GMM estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1–45.

Courtemanche, C., J. Marton, B. Ukert, A. Yelowitz, and D. Zapata (2018a, January). Early Effects of the Affordable Care Act on Health Care Access, Risky Health Behaviors, and Self-Assessed Health: Early Effects of the Affordable Care Act. *Southern Economic Journal 84*(3), 660–691.

Courtemanche, C., J. Marton, B. Ukert, A. Yelowitz, and D. Zapata (2018b, January). Effects of the Affordable Care Act on Health Care Access and Self-Assessed Health After 3 Years. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing 55*, 1–10.

Currie, J., S. Decker, and W. Lin (2008). Has Public Health Insurance for Older Children Reduced Disparities in Access to Care and Health Outcomes? *Journal of Health Economics 27*, 1567–1581.

Currie, J. and J. Gruber (1995, March). Health Insurance Eligibility, Utilization of Medical care, and Child Health. Working Paper 5052, National Bureau of Economic Research.

Currie, J. and J. Gruber (1996a, May). Health Insurance Eligibility, Utilization of Medical Care, and Child Health. *The Quarterly Journal of Economics 111*(2), 431–466.

Currie, J. and J. Gruber (1996b). Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women. *Journal of Political Economy*, 1263–1296.

Cutler, D. M. and J. Gruber (1996, May). Does Public Insurance Crowd Out Private Insurance. *The Quarterly Journal of Economics 111*(2), 391–430.

Dobbie, W. and J. Song (2015, March). Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection. *American Economic Review 105*(3), 1272–1311.

Dobkin, C., A. Finkelstein, R. Kluender, and M. J. Notowidigdo (2018, February). The Economic Consequences of Hospital Admissions. *American Economic Review 108*(2), 308–352.

Dowd, J. B. and A. Zajacova (2007, December). Does the Predictive Power of Self-Rated Health for Subsequent Mortality Risk Vary By Socioeconomic Status in the US? *International Journal of Epidemiology 36*(6), 1214–1221.

Dowd, J. B. and A. Zajacova (2010, October). Does Self-Rated Health Mean the Same Thing Across Socioeconomic Groups? Evidence From Biomarker Data. *Annals of Epidemiology 20*(10), 743–749.

Duggan, M., A. Gupta, and E. Jackson (2019, January). The Impact of the Affordable Care Act: Evidence from California's Hospital Sector. Working Paper 25488, National Bureau of Economic Research.

Eguia, E., A. N. Cobb, A. N. Kothari, A. Molefe, M. Afshar, G. V. Aranha, and P. C. Kuo (2018, October). Impact of the Affordable Care Act (ACA) Medicaid Expansion on Cancer Admissions and Surgeries. *Annals of Surgery 268*(4), 584–590.

Fernandez, L. E., S. Rastogi, S. R. Ennis, and J. M. Noon (2015, April). Evaluating Race and Hispanic Origin Responses of Medicaid Participants Using Census Data. *CARRA Working Paper Series Working Paper #2015-01.*

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, and K. Baicker (2012, July). The Oregon Health Insurance Experiment: Evidence from the first year. *The Quarterly Journal of Economics Advance Access.*

Frean, M., J. Gruber, and B. D. Sommers (2017, May). Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act. *Journal of Health Economics 53*, 72–86.

Garthwaite, C., J. Graves, T. Gross, Z. Karaca, V. Marone, and M. Notowidigdo (2019). All Medicaid Expansions Are Not Created Equal: The Geography and Targeting of the Affordable Care Act. BPEA Conference Drafts, Brookings Papers on Economic Activity, Cambridge, MA.

Garthwaite, C., T. Gross, M. Notowidigdo, and J. A. Graves (2017, February). Insurance Expansion and Hospital Emergency Department Access: Evidence From the Affordable Care Act. *Annals of Internal Medicine 166*(3), 172.

Ghosh, A., K. Simon, and B. D. Sommers (2019, January). The Effect of Health Insurance on Prescription Drug Use Among Low-Income Adults:Evidence from Recent Medicaid Expansions. *Journal of Health Economics 63*, 64–80.

Goldin, J., I. Z. Lurie, and J. McCubbin (2021). Health Insurance and Mortality: Experimental Evidence from Taxpayer Outreach. *The Quarterly Journal of Economics 136*(1), 1–49.

Goodman, L. (2017). The Effect of the Affordable Care Act Medicaid Expansion on Migration. *Journal of Policy Analysis and Management 36*(1), 211–238.

Goodman-Bacon, A. (2016, December). The Long-Run Effects of Childhood Insurance Coverage: Medicaid Implementation, Adult Health, and Labor Market Outcomes. Technical Report w22899, National Bureau of Economic Research, Cambridge, MA.

Goodman-Bacon, A. (2018, February). Public Insurance and Mortality: Evidence from Medicaid Implementation. *Journal of Political Economy 126*(1), 216–262.

Goodman-Bacon, A. (2019, July). Difference-in-Differences with Variation in Treatment Timing. Working Paper, Vanderbilt University, Nashville, TN.

Goodman-Bacon, A., T. Goldring, and A. Nichols (2019, September). bacondecomp: Stata module for decomposing difference-in-differences estimation with variation in treatment timing. *Statistical Software Components S458676, Boston College Department of Economics*.

Gross, T., M. J. Notowidigdo, and J. Wang (2020, April). The Marginal Propensity to Consume over the Business Cycle. *American Economic Journal: Macroeconomics 12*(2), 351–384.

Gruber, J. and B. D. Sommers (2019). The Affordable Care Act's Effects on Patients, Providers, and the Economy: What We've Learned so Far. *Journal of Policy Analysis and Management 0*(0), 1–25.

Howell, E., S. Decker, S. Hogan, A. Yemane, and J. Foster (2010, December). Declining Child Mortality and Continuing Racial Disparities in the Era of the Medicaid and SCHIP Insurance Coverage Expansions. *American Journal of Public Health 100*(12), 2500–2506.

Imbens, G. W. and J. D. Angrist (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica 62*(2), 467–475.

Kenney, G. M., V. Lynch, J. Haley, and M. Huntress (2012, August). Variation in Medicaid Eligibility and Participation among Adults: Implications for the Affordable Care Act. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing 49*(3), 231–253.

Khatana, S. A. M., A. Bhatla, A. S. Nathan, J. Giri, C. Shen, D. S. Kazi, R. W. Yeh, and P. W. Groeneveld (2019, June). Association of Medicaid Expansion With Cardiovascular Mortality. *JAMA Cardiology*.

Ki, V. and C. Rotstein (2008, March). Bacterial skin and soft tissue infections in adults: A review of their epidemiology, pathogenesis, diagnosis, treatment and site of care. *The Canadian Journal of Infectious Diseases & Medical Microbiology 19*(2), 173–184.

Lee, H. and F. W. Porell (2018, October). The Effect of the Affordable Care Act Medicaid Expansion on Disparities in Access to Care and Health Status. *Medical Care Research and Review*, 107755871880870.

Lynch, V., G. M. Kenney, J. Haley, and D. M. Resnick (2011). Improving the Validity of the Medicaid-CHIP Estimates on the ACS. Technical report, Urban Institute, Washington, DC.

Martinez, M. E., E. P. Zammitti, and R. A. Cohen (2018, November). Health Insurance Coverage: Early Release of Estimates From the National Health Interview Survey, January – June 2018. Technical report, U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics.

Marton, J. and A. Yelowitz (2015). Health insurance generosity and conditional coverage: Evidence from medicaid managed care in Kentucky. *Southern Economic Journal 82*(2), 535–555.

McInerney, M., R. Winecoff, P. Ayyagari, K. Simon, and M. K. Bundorf (2020, January). ACA Medicaid Expansion Associated With Increased Medicaid Participation and Improved Health Among Near-Elderly: Evidence From the Health and Retirement Study. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing 57*, 0046958020935229. Publisher: SAGE Publications Inc.

Medicaid and CHIP Payment and Access Commission (2018). Medicaid Enrollment Changes Following the ACA.

Miller, S. and L. R. Wherry (2017, March). Health and Access to Care during the First 2 Years of the ACA Medicaid Expansions. *New England Journal of Medicine 376*(10), 947–956.

Miller, S. and L. R. Wherry (2019, May). Four Years Later: Insurance Coverage and Access to Care Continue to Diverge Between ACA Medicaid Expansion and Non-Expansion States. *AEA Papers and Proceedings*.

Mulrow, E., A. Mushtaq, S. Pramanik, and A. Fontes (2011, March). Assessment of the U.S. Census Bureau's Person Identification Validation System. Final Report to the U.S. Census Bureau, NORC at the University of Chicago, Chicago, IL.

Musumeci, M. and R. Rudowitz (2017, November). Medicaid Retroactive Coverage Waivers: Implications for Beneficiaries, Providers, and States. Issue Brief, The Henry J. Kaiser Family Foundation, Washington, DC.

National Center for Health Statistics (2019, February). Office of Analysis and Epidemiology, Public-use Linked Mortality File, 2015. Technical report, Hyattsville, MD.

Nolte, E. and M. McKee (2003, November). Measuring the Health of Nations: Analysis of Mortality Amenable to Health Care. *BMJ : British Medical Journal 327*(7424), 1129.

Rambachan, A. and J. Roth (2019, December). An Honest Approach to Parallel Trends. *Havard University Working Paper*.

Rostron, B. L., J. L. Boies, and E. Arias (2010). *Education reporting and classification on death certificates in the United States*. Number no. (PHS) 2010-1351 in DHHS publication. Hyattsville, Md. : Washington, DC: U.S. Dept. of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics ; For sale by the U.S. G.P.O., Supt. of Docs.

Roth, J. (2019, July). Pre-test with Caution: Event-study Estimates After Testing for Parallel Trends. *Harvard University Working Paper*.

Rudowitz, R., R. Garfield, and E. Hinton (2019, March). 10 Things to Know about Medicaid: Setting the Facts Straight. Library Catalog: www.kff.org.

Sabik, L. M., W. W. Tarazi, S. Hochhalter, B. Dahman, and C. J. Bradley (2018). Medicaid Expansions and Cervical Cancer Screening for Low-Income Women. *Health Services Research 53*(S1), 2870–2891.

Semyonov, M., N. Lewin-Epstein, and D. Maskileyson (2013, March). Where Wealth Matters More for Health: The Wealth–Health Gradient in 16 Countries. *Social Science & Medicine 81*, 10–17.

Simon, K., A. Soni, and J. Cawley (2017, March). The Impact of Health Insurance on Preventive Care and Health Behaviors: Evidence from the First Two Years of the ACA Medicaid Expansions. *Journal of Policy Analysis and Management 36*(2), 390–417.

Sommers, B. D. (2017, July). State Medicaid Expansions and Mortality, Revisited: A Cost-Benefit Analysis. *American Journal of Health Economics 3*(3), 392–421.

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

Sommers, B. D., M. Z. Gunja, K. Finegold, and T. Musco (2015, July). Changes in Self-reported Insurance Coverage, Access to Care, and Health Under the Affordable Care Act. *JAMA 314*(4), 366.

Sommers, B. D., S. K. Long, and K. Baicker (2014). Changes in Mortality After Massachusetts Health Care Reform. *Annals of Internal Medicine 160*, 585–593.

Sommers, B. D., B. Maylone, R. J. Blendon, E. J. Orav, and A. M. Epstein (2017, June). Three-Year Impacts Of The Affordable Care Act: Improved Medical Care And Health Among Low-Income Adults. *Health Affairs 36*(6), 1119–1128.

Soni, A., K. Simon, J. Cawley, and L. Sabik (2018, February). Effect of Medicaid Expansions of 2014 on Overall and Early-Stage Cancer Diagnoses. *American Journal of Public Health 108*(2), 216–218.

Sorlie, P. D. and N. J. Johnson (1996). Validity of Education Information on the Death Certificate. *Epidemiology 7*(4), 437–439. Publisher: Lippincott Williams & Wilkins.

State Health Access Data Assistance Center (2012, March). Defining "Family" for Studies of Health Insurance Coverage. Technical Report Issue Brief #27, University of Minnesota, Minneapolis, MN.

Sullivan, D. and T. von Wachter (2009, August). Job Displacement and Mortality: An Analysis Using Administrative Data. *The Quarterly Journal of Economics 124*(3), 1265–1306.

Sun, L. and S. Abraham (2020, August). Estimating Dynamic Treatment Effects in Event Studies With Heterogeneous Treatment Effects. *MIT Working Paper*.

Swaminathan, S., B. D. Sommers, R. Thorsness, R. Mehrotra, Y. Lee, and A. N. Trivedi (2018, December). Association of Medicaid Expansion With 1-Year Mortality Among Patients With End-Stage Renal Disease. *JAMA 320*(21), 2242–2250.

Thompson, O. (2017, January). The Long-Term Health Impacts of Medicaid and CHIP. *Journal of Health Economics 51*, 26–40.

Wherry, L. R. and B. D. Meyer (2016, August). Saving Teens: Using a Policy Discontinuity to Estimate the Effects of Medicaid Eligibility. *Journal of Human Resources 51*(3), 556–588.

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

Wherry, L. R., S. Miller, R. Kaestner, and B. D. Meyer (2017, April). Childhood Medicaid Coverage and Later-Life Health Care Utilization. *The Review of Economics and Statistics 100*(2), 287–302.

Yan, B. W., F. A. Sloan, W. J. Boscardin, F. Guo, and R. A. Dudley (2020, May). The Opioid Epidemic Blunted the Mortality Benefit of Medicaid Expansion. *Medical Care Research and Review*, 107755872091962.

Zajacova, A. and J. B. Dowd (2011, October). Reliability of Self-rated Health in US Adults. *American Journal of Epidemiology 174*(8), 977–983.

Table I: Impact of the ACA Expansions on Coverage and Mortality: Difference-in-Differences Estimates

	Medicaid Eligibility (1)	Any Medicaid Coverage in Year (2)	Days of Medicaid in Year (3)	Cumulative Medicaid Years Experienced (4)	Uninsured (5)	Died in Year (6)
Difference-in-differences Model:						
Expansion × Post	0.498 (0.026)***	0.128 (0.020)***	42.99 (8.89)***	0.375 (0.061)***	-0.044 (0.010)***	-0.00132 (0.00050)**
Event Study Model:						
Year 3	0.493 (0.032)***	NA	NA	0.671 (0.082)***	-0.039 (0.012)***	-0.00208 (0.00083)**
Year 2	0.511 (0.026)***	0.128 (0.028)***	43.33 (9.78)***	0.472 (0.065)***	-0.050 (0.010)***	-0.00131 (0.00056)**
Year 1	0.500 (0.025)***	0.129 (0.021)***	50.79 (12.49)***	0.305 (0.047)***	-0.053 (0.011)***	-0.00119 (0.00044)***
Year 0	0.510 (0.022)***	0.115 (0.020)***	33.74 (7.27)***	0.128 (0.021)***	-0.038 (0.006)***	-0.00089 (0.00036)**
Year -1 (Omitted)	0	0	0	0	0	0
Year -2	0.010 (0.006)*	-0.008 (0.006)	-2.33 (2.05)	-0.018 (0.011)	0.002 (0.006)	0.00015 (0.00047)
Year -3	0.009 (0.010)	-0.008 (0.010)	-3.45 (3.75)	-0.029 (0.021)	0.001 (0.006)	-0.00029 (0.00053)
Year -4	0.008 (0.010)	-0.006 (0.010)	-0.49 (2.78)	-0.038 (0.030)	-0.007 (0.009)	0.00011 (0.00069)
Year -5	0.008 (0.011)	-0.004 (0.013)	0.35 (3.59)	0.053 (0.036)	0.000 (0.009)	0.00091 (0.00069)
Year -6	0.006 (0.011)	-0.015 (0.021)	-2.86 (5.58)	0.077 (0.045)*	-0.003 (0.015)	-0.00021 (0.00070)
N (Individuals x Year)	714,673	3,493,000	3,493,000	4,000,000	714,673	4,030,000
N (Individuals)	714,673	566,000	566,000	566,000	714,673	566,000

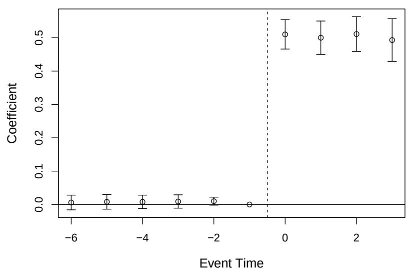
Notes: This table displays the event study coefficient estimates of equation (1), as well as the coefficient from the difference-in-differences model. The sample is defined as U.S. citizens ages 55-64 in 2014 who do not receive SSI and who have either less than a high school degree or family income below 138% FPL. For models based on restricted-use data, sample sizes are rounded following Census disclosure rules. See text for more details. Significance levels: *=10%, **=5%, ***=1%.

Table II: Impact of the ACA Expansions on Coverage and Mortality: Cause of Death

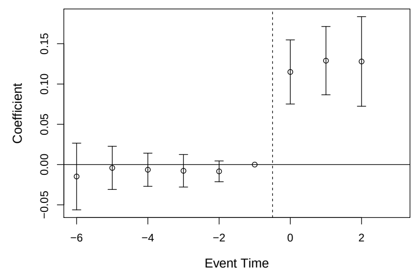
	Deaths from Internal Causes (1)	Deaths from Health Care Amenable Causes (2)	Deaths from External Causes (3)
Difference-in-Differences Model:			
Expansion × Post	-0.00235 (0.00675)***	-0.00099 (0.00050)*	0.00038 (0.00020)*
Event Study Model:			
Year 1	-0.00221 (0.00126)*	-0.00041 (0.00082)	0.00010 (0.00039)
Year 0	-0.00209 (0.00108)*	-0.00103 (0.00075)	0.00025 (0.00032)
Year -1 (Omitted)	0	0	0
Year -2	-0.00053 (0.00083)	0.00065 (0.00053)	-0.00007 (0.00034)
Year -3	0.00088 (0.00104)	0.00014 (0.00072)	-0.00007 (0.00044)
Year -4	-0.00044 (0.00112)	-0.00008 (0.00082)	-0.00032 (0.00038)
Year -5	0.00075 (0.00095)	0.00047 (0.00074)	-0.00022 (0.00037)
Year -6	0.00071 (0.00106)	0.00023 (0.00062)	-0.00060 (0.00035)
N (Individuals x Year)	683,000	683,000	683,000
N (Individuals)	88,500	88,500	88,500

Notes: This table displays the event study coefficient estimates of equation (1) using the MDAC. Sample sizes are rounded following Census disclosure rules. See text for more details. DRB Disclosure Approval #: CBDRB-FY19-310. Significance levels: *=10%, **=5%, ***=1%.

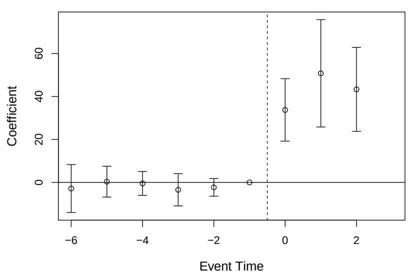
Figure I: Effect of the ACA Medicaid Expansions on Eligibility and Coverage



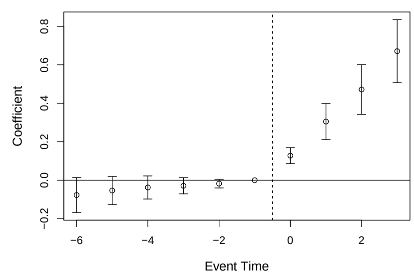
(a) Medicaid Eligibility (ACS)



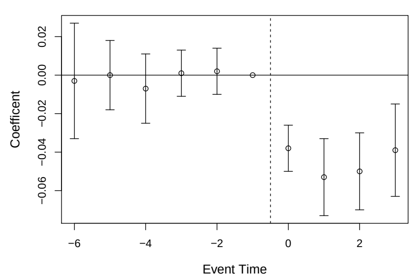
(b) Any Medicaid Enrollment in Year (CMS)



(c) # Days Medicaid Enrollment in Year (CMS)



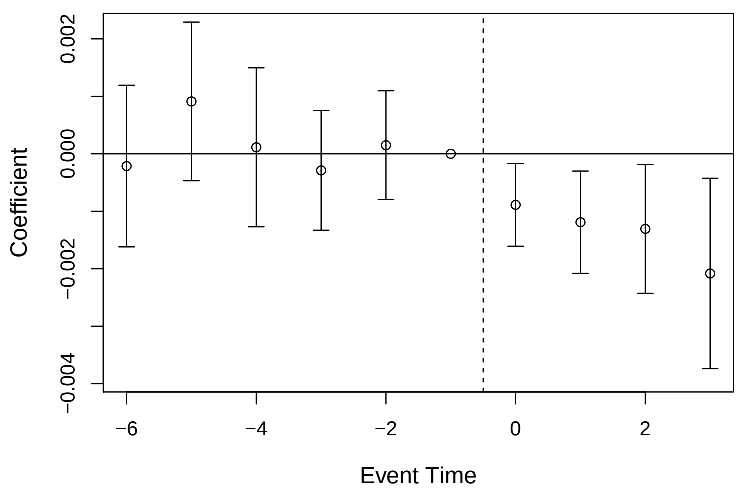
(d) Cumulative Years of Medicaid Exposure (CMS)



(e) Uninsured (ACS)

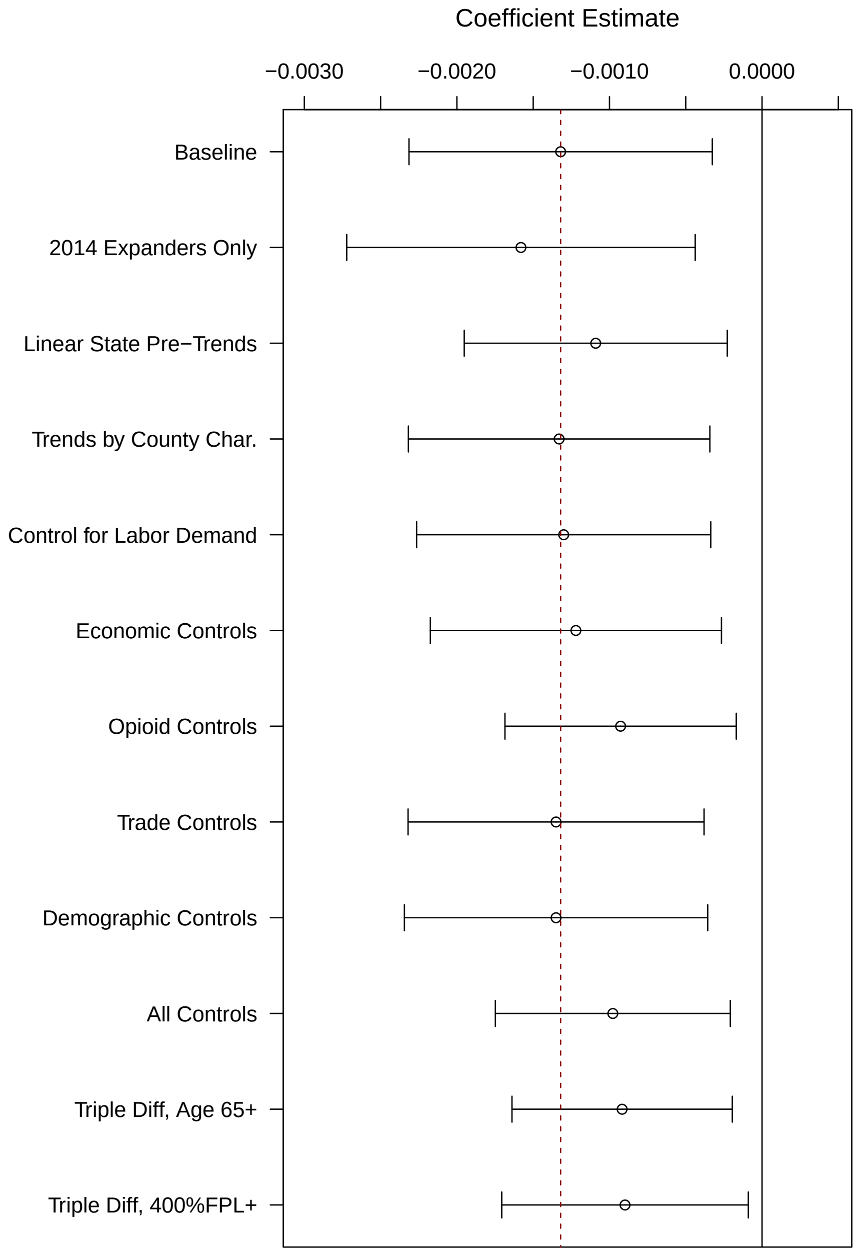
Note: These figures report coefficients from the estimation of equation (1) for the outcomes of Medicaid eligibility, Medicaid coverage, and uninsurance from the 2008-2017 American Community Survey (ACS) and 2008-2016 Centers for Medicare & Medicaid Service (CMS) administrative enrollment data. Note that scales differ across the five figures. The coefficients represent the change in outcomes for expansion states relative to non-expansion states in the six years before and four years after expansion, as compared to the year immediately prior to the expansion. The sample is defined as U.S. citizens ages 55-64 in 2014 who are not SSI recipients and who have either less than a high school degree or family income below 138% FPL. See Section V.A for additional details on the analysis and Appendix Section 2 for information on the Medicaid eligibility determination.

Figure II: Effect of the ACA Medicaid Expansions on Annual Mortality



Note: This figure reports coefficients from the estimation of Equation 1 for annual mortality. The coefficients represent the change in mortality for expansion states relative to non-expansion states in the six years before and four years after expansion, as compared to the year immediately prior to the expansion. The sample is defined as U.S. citizens ages 55-64 in 2014 observed in the 2008-2013 American Community Survey who are not SSI recipients and who have either less than a high school degree or family income below 138% FPL.

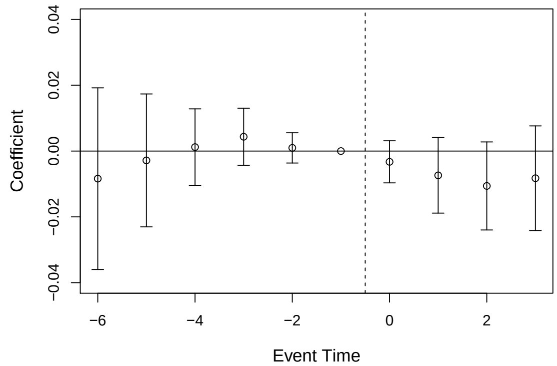
Figure III: Effect of Medicaid Expansions on Mortality: Alternative Specifications



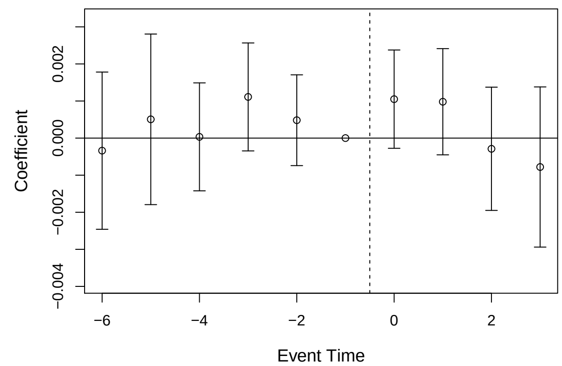
Notes: This figure plots difference-in-differences estimates for models that include only 2014 expanders, include linear state pre-trends, include different sets of covariates, or use an additional comparison group (triple difference model). The dotted line denotes our main estimate, which is also plotted with confidence intervals at the top of the figure for comparison purposes.

Figure IV: Placebo Tests

Pre-ACA Years

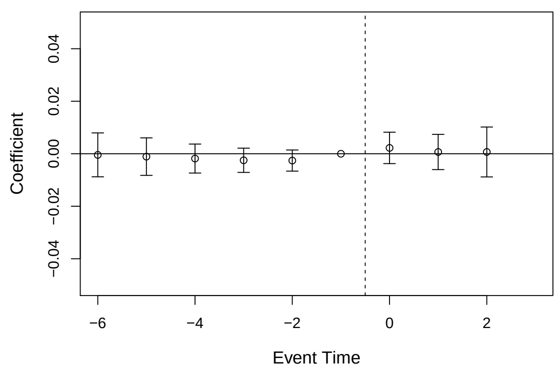


(a) Medicaid Coverage

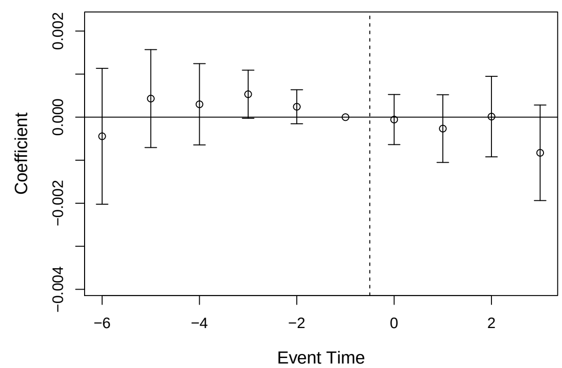


(b) Annual Mortality

Age 65+ in 2014

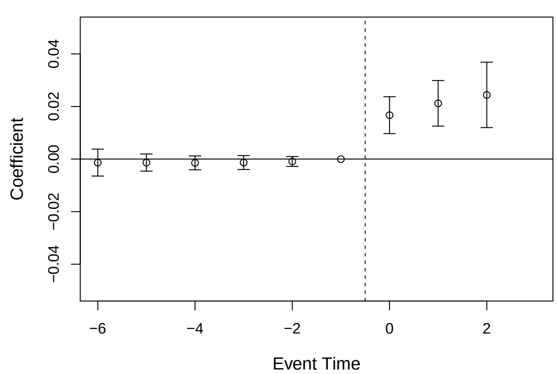


(c) Medicaid Coverage

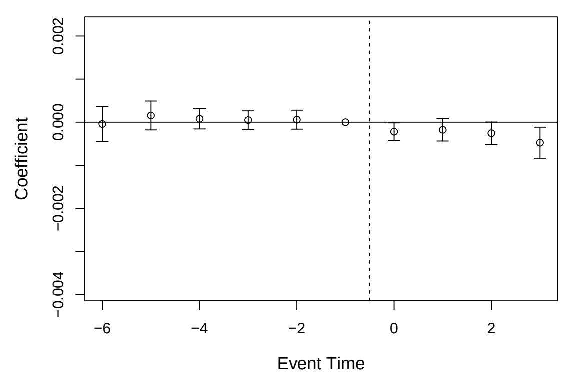


(d) Annual Mortality

Income 400%FPL +



(e) Medicaid Coverage



(f) Annual Mortality

Note: Row 1 figures plot coefficients from equation (1) using pre-ACA years of data. Row 2 presents estimates from the ACA study period for those age 65 and older in 2014 who would not have been affected by the Medicaid expansion due to their eligibility for the Medicare program. Row 3 presents estimates for individuals in higher income families who were less likely to gain Medicaid coverage. See text in Section VI.D for additional information.