

Public Health Insurance and Near-Elderly Mortality* †

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November 24, 2021

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(This draft is preliminary and will be updated frequently)

Abstract

Despite being at the forefront of policy debates, credibly estimating whether health insurance reduces mortality remains empirically elusive. The key challenge is creating research designs that have the statistical power to reliably detect the effects of health insurance on mortality. This paper presents new, population-level estimates of the impact of Medicare and Medicaid on near-elderly mortality. We link complete, administrative death records to individual survey responses for nearly 30% of the US population using restricted-access Census data. To understand the effects of Medicare on mortality, we use a regression discontinuity design, comparing the mortality of individuals just above and below the age-65 eligibility threshold. We also consider whether the impact of Medicare on mortality differs by demographics, previous health insurance status, and income. Somewhat in contrast to recent policy discussions and research findings, we find no statistically significant effects of Medicare on mortality for previously uninsured or low-income individuals. For Medicaid, we study the effects of the ACA Medicaid Expansion on near-elderly mortality using a differences-in-differences design with states that expanded Medicaid as the treatment group and states that did not as the control group. Certain results are currently awaiting Census disclosure.

*We thank Marika Cabral, Mike Geruso, Rich Murphy, Seth Neller, Gerald Oettinger, Dean Spears, Bob Town, as well as seminar attendees at the University of Texas at Austin for helpful comments and suggestions. We also thank Karin Johnson for her guidance, and Leticia Esther Fernandez and James Noon for their support with the Census Dissertation Mentorship Program.

†**Disclaimer.** Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2603. (CBDRB-FY21-P2603-R9240)

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Introduction

Public health insurance consumes over \$1.4 trillion each year, much of which is purported to prolong life (NHE, 2021). The US National Institutes of Health, for example, alone invest more than \$40 billion annually in order to “enhance health, lengthen life, and reduce illness and disability” (NIH, 2021). Whether health insurance reduces mortality nonetheless remains uncertain.¹ Goldin et al. (2021) summarize the state of the literature:

The relationship between health insurance and mortality is a central question in the field of health economics and lies at the core of contemporary policy debates. Despite numerous studies, the issue remains hotly debated, at least in part because the causal effect of health insurance is difficult to credibly estimate.

The key empirical challenge in determining the impact of health insurance on mortality involves statistical power. Mortality is a rare event, and the treatment effect of health insurance on mortality need not be large. Therefore, it is difficult to construct research designs, either experimental or quasi-experimental, that can be expected to detect treatment effects even when they exist. Because health insurance is expensive, the costs of randomizing health insurance access to a large number of people is infeasible, so experimental designs suffer from small sample sizes. For instance, the Oregon Health Insurance Experiment, which randomized Medicaid access by lottery to low-income adults, estimated a nonsignificant -16% mortality change with a confidence interval of [-82%, +50%], making it difficult to draw conclusions about the mortality effects of insurance.

While quasi-experimental studies offer larger sample sizes, they introduce other empirical hurdles. Specifically, the assumptions required for identifying causal effects are much stronger. Additionally, data are often available only at the aggregate level, making it difficult to distinguish treated from untreated groups (Black et al., 2019). For example, the ACA expanded Medicaid to 2 percentage points of the US population, primarily low-income adults (Black et al., 2019). Publicly available mortality data, however, generally do not include income measures which would indicate Medicaid eligibility, making it difficult to identify individuals who receive coverage. An additional concern with both experimental and non-experimental designs is that, even if low-powered designs find statistically significant effects of health insurance on mortality, it is difficult for researchers and policymakers to make conclusions regarding the size of estimates.²

¹ Black et al. (2017), Black et al. (2019), Sommers et al. (2017), Levy and Meltzer (2008), and Gaudette et al. (2018) provide literature reviews of the effects of health insurance on mortality. See Jason Abaluck’s Theader, <https://threadreaderapp.com/thread/1454293779804876802.html> for a graphical and disseminable overview.

² The reason is that statistically significant results from low-powered designs substantially overestimate the magnitudes of actual effects in the presence of selective publication. Gelman and Carlin (2014) provides an overview of research design and misleading statistically significant estimates. DellaVigna and Linos (2021) provides an empirical example of how the combination of low statistical power and selective publication result in inflated estimates. By scaling up nudging experiments previously published in academic journals, they find that estimates from the academic publications overestimate treatment effect by over six times, and 70% of this difference comes from low statistical power and selective publication.

Two recent studies offer perhaps the most compelling research designs for estimating the effects of health insurance on mortality, potentially overcoming low-power concerns of previous studies. Goldin et al. (2021) evaluates an IRS outreach program that randomized letters to millions of uninsured individuals who were already eligible for subsidized or public health insurance, inducing them to increase health insurance enrollment and lowering mortality among the near-elderly (ages 45-64) who enrolled. The cost-effective methodology allowed the researchers to send over 1 million letters to uninsured individuals ages 45-64 (larger sample size when all ages included) with about a 2%-increase in observed health insurance enrollment relative to the control group, vastly increasing the sample size over previous experimental designs. They find immediate and large reductions in mortality for those ages 45-64: one additional month of health insurance coverage reducing the mortality rate by 10% relative to the control group over two years.³ While the external validity of the experiment is unclear, as anywhere from 2% to 29% of the near-elderly could be induced to enrollment, the outreach letters were sent to adults who would likely be the target of future outreach efforts.⁴ This is relevant to large public health insurance expansions, as previous estimates suggest over half of ACA Medicaid coverage gains were due to “woodwork effects”, or enrollment by those already eligible Frean et al. (2017), i.e., an information shock. Overall, Goldin et al. (2021) provides perhaps the most convincing research design for the partial equilibrium effects of health insurance on mortality for low-income adults, increasing sample size and statistical power over previous experiments through low-cost, randomized, IRS outreach letters that induced health insurance enrollment.

The other paper is Miller et al. (2021), which improves upon previous quasi-experimental studies of the ACA Medicaid expansion by linking administrative death records with survey data containing detailed information on socioeconomic status. They conduct a differences-in-differences design with states that expanded Medicaid as the treatment states and states that did not expand Medicaid as the control states. Their restricted-access data allows them to hone in on low-income individuals likely to gain Medicaid eligibility, circumventing some of the problems with using aggregate data for differences-in-differences studies of the effects of health insurance on mortality as outlined by Black et al. (2019). Miller et al. (2021) identify 566,000 low-income (or less than a high school degree) individuals aged 55-64 across expansion and non-expansion states who would likely become eligible for Medicaid after the ACA Medicaid Expansion. In their target sample, they find that the uninsured rate decreased by 4.4 (or 5.8) percentage points and that the probability of enrollment in Medicaid increased by 12.8 percentage points following the expansions. Their first stage suggests improvements over aggregate data in identifying the target population of ACA Medicaid Expansions, potentially increasing statistical power. They find a large and immediate 9.4% decrease (appearing in the 1st year and persisting through in the mortality rate of for their low-income, ages 55-64, target sample in ACA Medicaid Expansion states relative to non-expansion states.

³ Goldin et al. (2021) note difficulties in determining effect sizes due to potential non-linearities in the relationship between coverage and mortality.

⁴ See Kaestner (2021) and McCubbin (2021) for more discussion of the external validity of the IRS outreach letter RCT and compliers.

Miller et al. (2021) and Goldin et al. (2021) provide two of the most compelling research designs to date for estimating the effects of health insurance on mortality.⁵ They achieve higher statistical power, increasing ability to detect mortality effects. Both find evidence that health insurance caused large and immediate reductions in mortality for low-income, near-elderly individuals. These findings have importance for contemporary policy debates on the value of the largest public health insurance programs - Miller et al. (2021) in particular estimate that 19,200 lives were saved from the ACA Medicaid Expansion through 2017, and that number would jump to 34,800 if all states expanded Medicaid. These papers have been noted as “the two highest quality studies to date” of the effects of health insurance on mortality (Abaluck).⁶ In addition to their estimates of large mortality effects, Goldin et al. (2021) and Miller et al. (2021) contribute to the literature with pathbreaking usage of linked datasets, and their research provides a roadmap for future researchers interested in studying the effects of health insurance on mortality with restricted data.

This paper presents new, population-level estimates of the impact of Medicare and Medicaid on mortality. We use restricted-access Census data to link complete, administrative death records to individual survey responses for nearly 30% of the US population in order to increase the statistical power of two quasi-experiments. For Medicare, we use a regression discontinuity design to study the effects of universal Medicare eligibility at age 65 on mortality, comparing the mortality of individuals just before and after the age-65 eligibility threshold. For Medicaid, we use a differences-in-differences design with states that expanded Medicaid as the treatment group and states that did not expand Medicaid as the control.

For Medicare, the large sample sizes afforded by our dataset allow us to further examine whether the impact of gaining insurance on mortality differs by previous health insurance status or by income-level. We find no statistically significant effects of Medicare on mortality for the full population, previously uninsured, or low-income individuals.⁷ We find no statistically significant effects of Medicare on mortality for the full population, previously uninsured, or low-income individuals. The regression discontinuity estimate for the effect of Medicare eligibility at age-65 on those who were previously uninsured is +1.8% change in the monthly probability of death [95% CI: -7.1%,

⁵ Abaluck et al. (2021) also provides compelling evidence of health insurance influencing mortality, but it is about variation in mortality across plans, rather than health insurance access.

⁶ The statistical merit of these analyses is debated. Kaestner (2021) claims, “I find that the two studies provide little useful information on this important research question. Both studies lack statistical power to detect reasonably sized effects. ... [Goldin et al. (2021) has virtually no external validity.” See McCubbin (2021) and Wherry (2021) for the authors’ response.

⁷ Previous studies have found Medicare reduces mortality for those hospitalized with non-deferrable conditions (Card et al., 2009) and differences in mortality rates across Medicare Advantage plans (Abaluck et al., 2021). Chetty et al. (2016) finds no change in mortality at age-65 for those at the 5th percentile of income. Card et al. (2004) finds no change in mortality at age-65 for the full population. We review these papers in more detail in the literature review section.

+10.8%].⁸ ⁹ The regression discontinuity estimate for the effect of Medicare eligibility at age-65 on low-income individuals is +1.9% change in the monthly probability of death [95% CI: -1.2%, +5.1%].¹⁰

These findings are consistent with previous research on effects of Medicare eligibility at age-65 on mortality. In contrast to previous research that examines the effects of Medicaid and subsidized private insurance on mortality, however, we do not find significant effects of Medicare on mortality for low-income or previously uninsured near-elderly individuals. There are several reasons why the effects of Medicare on mortality may differ from those of Medicaid and subsidized private insurance. First, Medicare has different cost-sharing, premiums, and networks than other forms of insurance, and this could affect mortality. Second, take-up for Medicare is near-universal at age-65 (greater than 95%), meaning almost everyone newly eligible for Medicare at age-65 actually gains coverage (Bhaskar et al., 2019). ACA Expansions were largely targeted based on income: not everyone who gained eligibility actually gained coverage, and many who gained coverage were already eligible (Frean et al., 2017). The regression discontinuity estimates of Medicare on mortality may reflect the impact of universal public health insurance to the near-elderly, as opposed to targeted interventions such as ACA Expansions, where it is unclear who are the compliers (those newly eligible who take-up or those previously eligible). While our confidence intervals rule out large reductions in mortality found by previous research on Medicaid and subsidized private insurance, we caution that our research design is powered only to detect large effects.

As a complement to our main research question about Medicare and mortality, we examine the closely related question of Medicaid's impact on mortality, using somewhat different datasets and a completely separate identification strategy. We do this because our null results of Medicare on near-elderly mortality seem at least possibly in conflict with recent findings of Medicaid's large impacts on near-elderly mortality.

For Medicaid, we consider the mortality effects of the ACA Medicaid Expansion, which provides federal funding for states to expand Medicaid eligibility to adults with incomes below 138% of the federal poverty level. We revisit the differences-in-differences design with states that expanded Medicaid as the treatment group and states that did not as the control group to study the mortality effects of the ACA Medicaid Expansion, similar to Miller et al. (2021). We first use publicly-available CDC vital stats data to see if the ACA Medicaid Expansion reduced mortality for individuals ages

⁸ We caution the reader against putting too much weight in current confidence intervals, as there are known deficiencies in inference using regression discontinuity equations with discrete bins Kolesár and Rothe (2018). Our existing estimates are limited by what has passed restricted Census disclosure process – we currently observe the monthly probability of death for three years on each side of the age-65 Medicare eligibility cutoff for various subgroups of the population. Future research aims to change the granularity of data used, bandwidth, and inferential methods in order to arrive at more reliable estimates of the effects of Medicare eligibility on mortality. Likewise, we will conduct more formal power analyses. Nevertheless, our current disclosed data provide useful visual evidence of discontinuous jumps (or lack thereof) as well as changes in slope of month mortality around the eligibility threshold.

⁹ A power analysis simulation based on the ages just before the cutoff, suggests that the probability of detecting a 15% mortality effect for $\alpha = .1$ is 80%.

¹⁰ A power analysis simulation based on the ages just before the cutoff, suggests that the probability of detecting an 8% mortality effect for $\alpha = .1$ is 80%.

55-64 without a high school degree, a group for which large mortality effects have been found using restricted-access data (Miller et al., 2021). Our event study analysis shows differential pre-trends in mortality between the expansion and non-expansion states, suggesting a violation of the parallel trends identifying assumption. As noted by Black et al. (2019) and Miller et al. (2021), there are limitations to using CDC data to study the effects of the ACA Medicaid expansion on mortality due to the difficulty of identifying eligible individuals. We therefore use restricted-access Census data linking death records to individual surveys to examine the effects of the ACA Medicaid Expansions on near-elderly mortality. We discuss the relative merits of using publicly-available CDC data versus restricted individual-level data. The results of this analysis, however, are awaiting Census disclosure.

We divide our paper into two distinct chapters, one for each quasi-experimental study that we conduct. The first chapter covers the regression discontinuity design of the effects of Medicare eligibility at age-65 on mortality. The second chapter discusses the differences-in-differences analysis of the effects of the ACA Medicaid Expansion on mortality.

1 - Medicare

This chapter examines whether Medicare eligibility at age-65 reduces mortality. We link complete, administrative death records to individual survey responses for nearly 30% of the US population using restricted-access Census data. To understand the effects of Medicare on mortality, we use a sharp regression discontinuity design, comparing the mortality of individuals just above and below the age-65 eligibility threshold. We further examine whether the impact of Medicare on mortality differs by demographics, previous health insurance status, and income. We find no statistically significant effects of Medicare on mortality for the full population, previously uninsured, or low-income individuals.

This chapter begins by describing Medicare in the United States and recent proposals to expand Medicare. We briefly summarize the existing literature on the effects of the Medicare on both non-health and health-related outcomes. We discuss why Medicare might reduce mortality, the empirical challenges in detecting any effects of Medicare on mortality for various subgroups of the population, and the strengths and weaknesses of using a regression discontinuity design to study Medicare eligibility and mortality. We then present the results of our analysis.

1.1 - Background (Medicare)

Medicare is the largest single purchaser of health care in the United States. A Federal public health insurance program, Medicare insures over 60 million individuals and spends \$900 billion annually on health care, over 4% of GDP.¹¹ Medicare provides effectively universal coverage for Americans beginning at age 65. That is, almost all Americans gain Medicare eligibility at age 65, regardless of

¹¹ Data in this section come from CMS and Kaiser Family Foundation.

income or previous health insurance status. Additionally, greater than 95% of the population enroll in Medicare after age 65 (Bhaskar et al., 2019). Notably, individuals with End-Stage Renal Disease and disabilities can enroll in Medicare before 65. Of the 62 million Americans enrolled in Medicare, 54 million are over 65 (qualify based solely on age), and 8 million gain eligibility before age 65 due to previous health conditions. Medicare covers hospitalizations, physician services, prescription drugs. There are deductibles and coinsurance for Medicare plans, and most individuals have some form of supplemental insurance coverage to cover some of these costs.

Legislation was introduced in September 2021 to reduce the Medicare eligibility age from 65 to 60, which could expand Medicare eligibility to over 20 million Americans. If enacted, this would be one of the largest public health insurance expansions since the introduction of Medicare and Medicaid in the 1960s. Representative Jayapal, a sponsor of the legislation, titled an opinion piece in favor of the expansion “Congress must lower the Medicare Age to save the lives of older Americans.” (Pramila and Shrager, 2021) In her op-ed with Dr. Shrager, Jayapal claims, “Americans aged 60-64 have the highest mortality rates compared to those in the same age range in peer countries — but once they reach 65, mortality rates drastically reduce. Why does turning 65 mark such a visible transition point in preventing illness and death? The answer is simple: Medicare.” Hence, whether and how much Medicare reduces mortality is at the forefront of discussions on the value of what could be the largest public health insurance expansion since the 1960s. We review the literature on why one might expect Medicare to reduce mortality in the next section.

1.2 - Literature Review (Medicare)

Mortality is the end result of both cumulative and acute factors involving biology, medicine, behavior, and socioeconomic status. It is not theoretically clear why or if we should expect health insurance to reduce mortality in the short-run (or even long-run). While there are a variety of non-healthcare pathways by which health insurance could improve health (such as reduction of financial stress, changes in labor force participation, aggregate effects from improved hospital finances), perhaps the most straightforward pathway for Medicare reducing mortality is as follows: 1) Individuals who gain Medicare also gain increased access to health care (whether by gaining any insurance or more generous coverage). 2) Health care treatments are effective, so increased access to health care improves health. 3) Improved health increases longevity.

Despite the seeming simplicity of this pathway, it remains hotly debated by policymakers. Then Presidential Candidate Mitt Romney, when debating the future of the Affordable Care Act, claimed, “We don’t have a setting across this country where if you don’t have insurance, we just say to you, ‘Tough luck, you’re going to die when you have your heart attack.’ No, you go to the hospital, you get treated, you get care, and it’s paid for, either by charity, the government or by the hospital.” NPR (2012). There is a safety-net of health care services and financial relief for uninsured individuals in the United States, and hospitals are required by EMTALA to provide healthcare emergency departments regardless of health insurance status (?). While EMTALA

requires provision of emergency care, hospitals often provide non-emergency care to uninsured individuals. 90 percent of hospitals reported never denying services to any uninsured individual on an IRS survey of non-profit hospitals (Hellinger, 2009). Moreover, a safety-net of clinics and charity often reduce the financial burden of health care for uninsured or low-income individuals (Finkelstein et al., 2018; Duggan et al., 2019). Even if health insurance increases health care utilization and improves health (or improves health by some other pathway), it is not clear whether such effects could be detected empirically. Health is a complex, long-term, stock measure (Grossman, 2017). If health insurance improves health, observable effects could take a long time to develop or might be small, making the effects of health insurance on mortality difficult to detect empirically. We briefly review the literature on the effects of Medicare on both non-health outcomes and mortality below, highlighting the empirical challenges.

1.2.1 - Experimental Evidence

The primary experimental studies in this area derive from the Oregon Health Insurance Experiment (OHIE), which conducted a randomized lottery for Medicaid eligibility to low-income, working-age adults (James, 2015; Baicker and Finkelstein, 2011; Baicker et al., 2013; Finkelstein et al., 2012) and the RAND Health Insurance Experiment, which varied cost-sharing among health plans (Newhouse et al., 1993). The RAND health experiment shows that cost-sharing substantially affects utilization (Newhouse et al., 1993), but the experiment was underpowered to study mortality. The OHIE finds Medicaid access increased utilization of preventative and hospital care and improved self-reported measures of health. It did not, however, improve clinical measures of health, or reduce mortality. Notably, the confidence intervals on the mortality effect were too wide to make any conclusions. The RAND Experiment and OHIE show that both access to health insurance as well as generosity of health insurance (ex. lower cost-sharing) both affect utilization, but due to small sample sizes they were underpowered to study mortality. We turn to the quasi-experimental literature below.

1.2.2 - Quasi-Experimental Evidence

Given that universal eligibility begins at age-65, the primary quasi-experimental designs used to study Medicare generally compare outcomes for individuals just on each side of the age-65 eligibility thresholds. We present a selection of the literature here, and will update this section in future drafts.

1.2.2.1 - Access to Care and Utilization

Perhaps the most straightforward pathway for health insurance to reduce mortality is through increased access to and use of health services.¹² For instance, Medicare receipt might enable individuals to purchase drugs, obtain preventative care, or increase (or prevent unnecessary) hospital care. Given the existing health safety-net for uninsured individuals, and differences in generosity

¹² An additional pathway is through reduced financial distress. Barcellos and Jacobson (2015), Goldsmith-Pinkham et al. (2021), and Finkelstein and McKnight (2008) find that Medicare improves financial health.

between private insurance and Medicare, it is theoretically ambiguous whether and how Medicare would increase access to care and utilization. The literature largely supports that Medicare increased access to health care and utilization. Card et al. (2008) finds large changes in hospital utilization just after individuals turn 65, including a 16% increase in bypasses and 23% increase in lower-body joint replacement. Several studies find improvements in preventative care. Myerson et al. (2020) find large increases in cancer detection after age 65, and Wallace et al. (2021) find increases in influenza vaccination rates. Einav et al. (2015) show that changes in cost-sharing provisions associated with Medicare Part D affect drug consumption. Moreover, evidence suggests that individuals facing higher health care prices cut back on "high-value" health care that has been shown in clinical trials to greatly reduce mortality (ex. statins). Chandra et al. (2021) show that an increase in out-of-pocket price faced by Medicare Part D users resulted in cutbacks in statins and antihypertensives. Overall, there is evidence to suggest that Medicare affects utilization, including utilization of life-saving health care.

1.2.2.2 - Health and Mortality

Clinical trials show that medical treatments are effective for a host of conditions.¹³ If the Medicare increases health care utilization, and health treatments improve health, then Medicare could improve health and reduce mortality. That said, Medicare eligibility might not immediately result in health improvements, or health improvements might be too small to be detected in the existing data.

Illustrating how changes in utilization might not affect health outcomes, Shigeoka (2014) exploit a sharp reduction in cost-sharing (60-80%) at age 70 in Japan. While utilization increases, health and mortality are unchanged. The healthcare systems in Japan and the United States differ greatly, and so their results might not generalize to the US.

Levy and Meltzer (2008) and Black et al. (2017) offer literature reviews on the effects of health insurance on mortality in the US. Early observational studies attempted to show causal effects of health insurance on mortality, but factors such as income and health status confound comparisons of the mortality rates of those with and without insurance. Later quasi-experimental studies found mixed results of health insurance on health and mortality. Finkelstein and McKnight (2008) finds no evidence of reduced mortality with the introduction of Medicare in the 1960s, but Chay et al. (2010) finds a mortality effect at that time. Dunn and Shapiro (2019) and Huh and Reif (2017) find reductions in cardiovascular level mortality associated with the introduction of Medicare Part D. Chandra et al. (2021) finds the cost-sharing provisions of Medicare prescription drug benefit program affect mortality associated with statins and antihypertensives for those with the highest risk of heart attack and stroke. Abaluck et al. (2021) finds large differences in mortality rates across Medicare Advantage plans. Card et al. (2009) use a regression discontinuity design at the age-65 eligibility cutoff to show that 1-yr mortality decreased 3% for individuals admitted to the hospital with non-deferrable conditions. Myerson et al. (2020) find reduced population-

¹³ <https://www.cochranelibrary.com/>

level cancer mortality at age 65. Card et al. (2004) use a regression discontinuity at age 65 to examine the overall population, but find no reduction. Chetty et al. (2016) find no change in mortality at age 65 for individuals at the 5th percentile of income using IRS data. Wallace et al. (2021) find improvements in self-report health at age-65, but no changes in mortality. Summarizing the literature, Levy and Meltzer (2008) claims, "...convincing evidence demonstrates that health insurance can improve health measures of some population subgroups." The literature does not find population-level estimates of Medicare reducing all-cause mortality in modern times, which we examine in our analysis below. As noted by Black et al. (2017), most studies of Medicare examine short-run effects on mortality right around the age-65 eligibility cutoff. Several studies expand the analysis beyond this cutoff by using panel data to follow uninsured near-elderly individuals and examine their health utilization, self-reported health, and mortality trajectories after turning 65.¹⁴ While the sample sizes that they study are small (usually less than 2,000), these analyses offer insights into the health and consumption profiles of uninsured individuals, a group that cannot be identified in aggregate data sources with mortality information. Polsky et al. (2009) and Black et al. (2017) find no effects of Medicare eligibility on mortality. McWilliams et al. (2009) finds an increase in healthcare utilization just after 65 for the previously uninsured. Our linked data allow us to identify mortality of uninsured and low-income individuals for large sample sizes, and we estimate how mortality changes around the Medicare eligibility age-65 cutoff for uninsured and low-income individuals in our analysis below.

1.3 - Data (Medicare)

In order to improve upon previous estimates of the effects of Medicare eligibility at age 65 on mortality, we rely on restricted Census data linking administrative death records to detailed survey data containing information on health insurance and socioeconomic status. We link complete, administrative death records to individual survey responses for nearly 30% of the US population. The large sample sizes afforded by this linkage, observation of exact dates of birth and death, and ability to target specific subsamples of the population of policy-relevance could plausibly provide an improvement in statistical power, reliability of estimates, and understanding of the effects of Medicare eligibility at age 65 on mortality. For instance, previous studies using HRS panel data to observe near-elderly mortality observe fewer than 2,000 uninsured individuals (McWilliams et al., 2004), (Black et al., 2017), and (Polsky et al., 2009). We observe just under 100,000 near-elderly uninsured individuals in our linked dataset. We detail the various datasets that we use in our analysis below, highlighting both the benefits and limitations of our data for various subgroups of interest.

¹⁴ Michael McWilliams (2009) provides a literature review on the health consequences of uninsurance.

1.3.1 - Census Numident Death Records

In all of our analysis we use the Census Numident for information on mortality. The Census Numident is a person-level file constructed by the Census Bureau from administrative data kept by the Social Security Administration (SSA). The SSA uses the Numident to record information on Social Security Number (SSN) holders. The Numident measures all-cause mortality, providing information on exact day of birth and death as well as demographic information (but not socioeconomic data) for individuals with a SSN. Given that all nearly all Americans receive a Social Security Number, the Numident file contains information on approximately 518 million individuals (both deceased and living), offering a near census of deaths of the US population in recent years.

These records are highly reliable sources of death data. Finlay and Genadek (2021) offers a comprehensive overview of the Census Numident and assesses the quality of mortality data in the Census Numident compared to vital statistics data from the CDC, noting that the death counts in the Census Numident are nearly identical with those from CDC vital statistics since the 1990s.¹⁵ Additionally, Census Numident death counts are nearly identical to those from CDC vital statistics for all age groups except infants. Overall, the Census Numident data contains all-cause mortality data on nearly everyone in the United States, with exact days and birth of death, so it is well-suited for studying small and sudden changes in mortality caused by a universal health insurance eligibility policy such as the Medicare age-65 eligibility cutoff.

We use Numident data by itself as well as the Numident linked to various Census survey products in order to study the effects of Medicare eligibility on mortality for various subgroups of the US population. The linkage between survey data and the Census Numident is performed using Protection Identification Keys (PIKs), which are created by the Census Bureau to uniquely identify people across data sources (Finlay and Genadek, 2021). The matching rate between various data sources available within the restricted Census infrastructure is often very high, exceeding 90% for many Census survey products.¹⁶ When linking Numident data to survey data, we drop observations with mismatched date of birth or demographic variables. Given that the overall quality of the PIK matching is high, and we only drop a small percentage of observations. We link the 2020 Census Numident file to American Community Surveys from 2001-2017 as well as the 2000 Census Longform. Census survey data contain important information on socioeconomic and health insurance status that is not contained in the Numident death records, which allows us to identify groups of economic and policy interest, potentially providing large sample sizes to increase statistical power and improve the reliability of estimates. We describe the datasets and linkages we use to identify these target groups below.

In the samples that we study, we generally restrict our sample to individuals born between 1940 and 1952, who would turn 65 between 2005 and 2017. Our sample thus reflects a recent time

¹⁵ This correspondence between Numident and CDC vital stats is corroborated by Chetty et al. (2016). Finlay and Genadek (2021) also provides a useful guide to for researchers considering using the Numident or restricted Census infrastructure to link to other Census surveys or administrative data.

¹⁶ Mulrow et al. (2011) provide detailed information on PIK matching rates.

period.¹⁷ We focus on mortality at ages around the Medicare eligibility age-65 cutoff. Specifically, we restrict our analysis to mortality three years on each side of the age-65 eligibility cutoff, focusing on mortality from ages 62 to 67 years old.¹⁸ Our preferred measure of mortality is probability of death by age in months. We create a monthly probability of death measure by using for the denominator the number of individuals for our analysis group who were alive at a given age in months and the numerator the number of individuals who die at that age in months. To give an example, suppose 100,000 individuals live to be 64 years and 11 months old, and 100 individuals die after turning 64 years and 11 months old but before turning 64 years and 12 months old. We then consider the monthly probability of death for 64 years and 11 months to be $100/100,000 = .1\%$.¹⁹

The monthly mortality measures that we study are not observed in public death records, as those records do not contain exact dates of birth and death.²⁰ Observing monthly mortality allows us to better observe sudden changes in mortality as well as changes in trends around the Medicare age-65 cutoff. In all of the samples that we study, monthly mortality measures are rounded to either four or three significant digits, depending on the sample size, and as per restricted Census disclosure rules. We also give approximations for the number of individuals in each sample that we study, as we cannot disclose the denominators used to calculate the monthly probability of death measures.

We begin by analyzing the Census Numident death records unlinked to any survey data. As noted above, we restrict our sample to individuals born between 1940 and 1952, and calculate monthly probability of death for 36 months on each side (72 months total) of the Medicare age-65 eligibility cutoff. The Census Numident contains information on race and gender as well as exact date of birth and death, allowing us to study the effects of Medicare eligibility at age-65 on mortality for the (i) full US population (ii) Blacks (iii) Males (iv) Females. Our approximate sample sizes are, respectively, (i) 49,850,000 (ii) 5,503,000 (iii) 25,320,000 (iv) 24,530,000.

1.3.2 - Census Survey Data

We link Numident death records to the Census' ACS 2001-2017 surveys, which contain information on individuals' health insurance and socioeconomic status. We use linked ACS surveys to focus on individuals who are (i) uninsured (ii) have any health insurance (iii) have private health insurance just before the Medicare age-65 eligibility cutoff.²¹ We restrict our sample to individuals born before 1952, and calculate monthly probability of death for 36 months on each side (72 months

¹⁷ Future versions of this paper aim to examine changes in the effects of Medicare eligibility on mortality over time and by region, highlighting whether and how effects have changed under different large changes to relevant public health insurance programs (such as before and after introduction of Medicare Part D and before and after the ACA Medicaid Expansions).

¹⁸ Because the Numident file records individuals with a SSN, in order to avoid the risk of individuals entering and exiting the dataset within our relevant age range, we drop individuals who receive a SSN after turning 62 from our analysis, which is a very small fraction of individuals in recent decades.

¹⁹ Future versions of this paper aim to change the granularity of death measures used (i.e. daily, quarterly, etc.).

²⁰ It is possible to observe mortality measures by age in years (ex. 64 and 65), but not by month, in public data.

²¹ We follow other researchers in excluding publicly insured from analysis (Kronick, 2009).

total) of the Medicare age-65 eligibility cutoff. We omit individuals who respond to the survey after their 62nd birthday, as response to the survey precludes death, and these individuals would enter into the 62-67 age range that we study. The ACS survey is a repeated cross-section, so we do not observe individuals in each year. Accordingly, in order to classify an individual based on time-varying variables such as insurance status, we restrict our sample to near-elderly survey respondents, which we consider to be 55 or older. This group is close to the Medicare age-65 cutoff, and so their survey response is more likely to reflect their health insurance status around the age-65 cutoff. Health insurance status can change between survey response and age 65. Our approach to assigning health insurance status based on survey responses of the near-elderly resembles that used in previous studies that study mortality by health insurance states. Black et al. (2017) and Polsky et al. (2009) provide useful discussions of the merits of using near-elderly survey measures of health insurance status as proxies for insurance status at later dates. There are limitations to using ACS surveys to study health insurance status, as survey respondents might misreport their health insurance status (Pascale et al., 2019) (Bhaskar, Shattuck, and Noon, Bhaskar et al.), (Bhaskar et al., 2019). Lynch et al. (2011) notes advantages of NHIS health insurance responses, and Black et al. (2017) discuss advantages of HRS surveys that contain information on health status. That said, the sample size of the ACS is extremely large relative to other surveys, which could help in improving the reliability of mortality estimates.

The restricted Census ACS surveys approximately 1.5% of the US population annually, or 4.5 million individuals.²² The health insurance variables that are of research interest to us are available since 2008, so we use 10 ACS survey years (2008-2017) to arrive at our samples. That is, we start with 45 million ACS survey respondents, or approximately 15% of the US population. After linking to the Numident death files, restricting our sample to age bins three years around the Medicare age-65 eligibility cutoff, and classifying individuals based on their health insurance status just before the age-65 cutoff, we arrive at the following sample sizes (which approximate the denominators used to calculate monthly probability of death) for our subgroups of interest: (i) uninsured – 97,500 individuals (ii) any health insurance – 874,000 (iii) private health insurance – 785,000.²³

Our sample sizes are very large compared to previous studies. Black et al. (2017) examines approximately 1,440 uninsured and 7,433 privately insured and Polsky et al. (2009) examines approximately 738 uninsured and 4,741 privately insured.²⁴ Our sample sizes are over 50x larger than many previous non-experimental studies, but these studies have several advantages in that they can observe health status and measure health insurance more accurately.²⁵ Nevertheless, we believe the large sample sizes that we examine are useful for improving our understanding of the

²² Note that the restricted data contains 4.5 million respondents as opposed to 3 million in public use data.

²³ As discussed above, the counts we give for number of individuals in each sample that we study are approximations, as we cannot disclose the denominators used to calculate the monthly probability of death measures.

²⁴ Kronick (2009) looks at over 600,000 NHIS respondents aged 18-64, but only observes follow-up mortality measures for a small fraction of these respondents near the age-65 eligibility cutoff.

²⁵ We discuss our sample and findings in the context of perhaps the most convincing experimental study, Goldin et al. (2021), which randomized IRS outreach letters to millions of potentially uninsured individuals, inducing 21,000 near-elderly individuals to gain private and Medicaid coverage, in the Background and Results sections.

effects of health insurance on mortality. While the sample sizes that we study are large compared to previous work, we give a note of caution regarding our regression estimates. The sample sizes listed above approximate denominators used to calculate monthly probability of death, but the number of deaths around the cutoff will be much lower, as about 1-2% of individuals who are alive at age 65 die that year (.07-.14% when looking at monthly probabilities).²⁶ We discuss our regression discontinuity method and results in more detail below.

We also use the 2001-2017 ACS surveys to study changes in health insurance status and potential non-mortality confounding factors such as changes in employment around the Medicare age-65 eligibility cutoff, focusing on survey respondents aged 62-67 at the time of interview. We discuss how Medicare eligibility at age-65 changes health insurance status in the Methodology and Results Sections below, and whether changes in other variables at age-65 could confound our estimates of the effects of Medicare eligibility on mortality in the Robustness section.²⁷

In order to measure income, we link Numident death records to the 2000 Census long-form, which contains income measures for 1/6 of the US population, or roughly 50 million individuals, taken from survey responses in 2000. We restrict our sample to individuals who were less than 62 years old at the time of the survey, as survey response precludes death, and we calculate monthly probability of death for 36 months on each side (72 months total) of the Medicare age-65 eligibility cutoff. We use linked Census long-form data to study the following subgroups of economic interest: (i) high-income respondents (household income over \$143,000 in 2021 dollars) (ii) low-income respondents (individuals without a high school education or below the Federal Poverty Line). Our high-income approximates individuals from the top quartile of household income.²⁸ We use no high school education in determining our low-income sample because it remains constant in later time periods.²⁹ Our low-income sample is a proxy for the low-income group who gained Medicaid eligibility with under the ACA Medicaid Expansions, providing a useful comparison of the effects of public health insurance eligibility for two different forms of health insurance coverage. We examine the effects of Medicare eligibility at age 65 on mortality for all of our target groups in the next sections.

1.4 - Methodology (Medicare)

Medicare offers near-universal health insurance eligibility for all individuals in the US at age 65. While some individuals have Medicare eligibility before age 65 (such as those with end stage renal disease or disabilities), there is a clear and sudden spike in Medicare coverage at age 65 that has been well-document in previous research Card et al. (2009). Figure 1 Panel (a) shows a greater than

²⁶ See Figure 3 and the Results Section.

²⁷ Linked data is not required to examine changes in health insurance status or non-employment outcomes around the Medicare eligibility cutoff, and previous research such as Card et al. (2009) has documented changes in these variables around the age-65 cutoff.

²⁸ Calculated using publicly available Census 2000 survey data from IPUMS USA, using \$90,000 (in 2000 dollars) household income).

²⁹ See Miller et al. (2021) for a similar approach.

60% increase in Medicare coverage at the eligibility cutoff. Given universal eligibility at age 65 and large gains in Medicare coverage at this threshold, we use a sharp regression discontinuity design to study the effects of Medicare eligibility on mortality, comparing the mortality of individuals just above and below the age-65 eligibility threshold. A sharp regression discontinuity design at age-65 has been used extensively in previous research to study the effects of universal Medicare eligibility for a variety of outcomes, including financial and health outcomes (Barcellos and Jacobson, 2015) (Card et al., 2009). We introduce our regression discontinuity estimating equation and primary identifying assumptions below.

We study how Medicare eligibility at age 65 affects mortality for several different groups, the construction of which are outlined in the Data Section. First, we study the effects of Medicare eligibility on mortality for the full US population and by demographic characteristics. For these samples, treatment effects can be thought of as a combination of effects for those who were previously uninsured as well as those previously insured. Previously insured individuals than gain Medicare coverage could experience different cost sharing, premium, and provider networks, any of which could ultimately affect mortality. We attempt to isolate the mortality effects of gaining Medicare eligibility by previous health insurance status by examining changes in mortality around age 65 for individuals who were previously insured with any health plan, privately insured, or uninsured. We also study the effects of Medicare eligibility on mortality for high-income and low-income individuals. The low-income population studied resembles those who gained *Medicaid* eligibility under the Affordable Care Act, and we compare the effects of these two forms of health insurance on mortality in the preceding sections.

We note here several limitations of using a regression discontinuity design to study the effects of Medicare eligibility on mortality. First, the regression discontinuity design is best suited for detecting effects around the cutoff. Mortality is a result of both cumulative and acute factors, and health insurance might reduce mortality only in the long-run, but not in the short-run. If Medicare eligibility affects mortality only in the long-run, regression discontinuity estimates that find no effect at the cutoff could be misleading. We observe granular data on the monthly probability of death around the age-65 cutoff, which we examine to see if there is a change in mortality trends around the age-65 cutoff, but we refrain from making inference away from the eligibility threshold. Our regression discontinuity estimates, then, should be thought of as the effects of Medicare eligibility on short-run mortality.³⁰ Our estimates also detect the effects of Medicare eligibility specifically at age 65, so we might lack the external validity to make conclusions regarding Medicare expansions to a much younger population. Given that recent proposals to change the Medicare eligibility age focus on age 60, an age close to 65, external validity issues regarding the age-specific cutoff might not warrant concern. Additionally, effects of Medicare eligibility at age 65 offer useful comparisons to several recently published papers that find large and immediate reductions in mortality for near-elderly individuals who receive health insurance coverage or eligibility (Miller et al., 2021) ; (Goldin

³⁰ Given previous estimates of immediate mortality effects in Goldin et al. (2021), Miller et al. (2021), and Abaluck et al. (2021), it is not unreasonable to expect immediate effects of health insurance on mortality.

et al., 2021), which we discuss below and throughout the Results Section.

The regression discontinuity estimate is perhaps better suited for understanding what happens when an individual who is, for example, low-income, uninsured, or who has private insurance gains Medicare eligibility at age 65, rather than what would happen to mortality for these groups if the Medicare eligibility age were reduced to 60.³¹ While this might be a limitation in understanding how large expansions of Medicare would affect mortality, it potentially offers generalizable empirical evidence as to the short-run effects on mortality of near-elderly individuals (whether low-income, uninsured, or previously insured) gaining health insurance eligibility.

We use the following estimating equation for our regression discontinuity analysis:

$$Y_{age} = \alpha + \delta \cdot Medicare_{age} + f(age) + Medicare_{age} \cdot f(age) + \varepsilon_{age} \quad (1)$$

Our regression terms are describes as follows: (i) Unit of observation (running variable), age : Age binned to the month level (ii) Outcome, Y_{age} : Logged count monthly probability of death by age in months (iii) Treatment, $Medicare_{age}$: Older than 65, and, thus, eligible for Medicare. (iv) Trend controls, $f()$: First-order polynomial (v) Discontinuity estimator, δ : Percent change in Y_{age} as a result of the Medicare eligibility at age-65.

Our data consists of monthly probability of death by age in months for three years on each side of the Medicare age-65 cutoff, so we use a three year bandwidth in our preferred specification³² Our regression discontinuity examines whether mortality changes after universal Medicare eligibility at age 65. Treatment is defined by the binary variable $Medicare_{age}$, which is equal to one if age is above the Medicare eligibility age-65 cutoff and zero otherwise.³³ The coefficient, δ gives the effect of Medicare eligibility on mortality, and represents the percent change in the monthly probability of death. We estimate our equation using rectangular weighting.³⁴ We use Equation 1 separately for the various groups described in the Data Section, examining the effects by demographics, previous health insurance status, and previous income levels.

³¹ Garthwaite (Garthwaite) offers an overview of aggregate effects associated with Medicare expansions, and Finkelstein (2007) provides empirical evidence of aggregate effects from the introduction of Medicare.

³² Our data that we use in our analysis is derived from restricted Census data. Future versions of this paper will explore robustness in bandwidth, bin selection, and addition of covariates.

³³ Medicare eligibility actually begins on the first of month individuals turn 65. We treat the 65th birthday as gaining Medicare eligibility for now, and aim to revisit earlier eligibility with more granular data in future versions of this paper.

³⁴ Kolesár and Rothe (2018) note issues with standard errors and clustering on discrete running variables (such as month) in regression discontinuity designs, and we aim to perform robustness tests with more granular data in future versions of this paper.

1.4.1 - Identifying Assumption

The key identifying assumption of the regression discontinuity equation is that unobservable factors that affect the outcome are continuous through the Medicare age-65 eligibility cutoff Lee and Lemieux (2010). There are several factors associated with mortality that could change discontinuously at age 65. For instance, employment, income, and social security could all jump at the cutoff, and these factors have been associated with mortality in previous research Fitzpatrick and Moore (2018), Sullivan and Von Wachter (2009), and Snyder and Evans (2006). The relationship between employment, income, social security, and mortality is complex, and it is unclear in which direction these factors could bias regression estimates.³⁵ Empirical evidence from Fitzpatrick and Moore (2018) and Snyder and Evans (2006) suggests that increases in retirement, income, and social security income in older ages might increase mortality, biasing our estimates upward. We note existing empirical evidence suggesting no large spikes at age 65 for these factors below.

Another possible confounder is changes in medical practices around age 65 that are unrelated to health insurance status. Card et al. (2009) briefly mention U.S. government agencies recommending different influenza shot requirements for people over and under 65, but the population that they study (those admitted to hospital with immediate health concerns) might be unlikely to be affected by such recommendations. Recent behavioral research has identified heuristics employed by health professionals such as left-digit bias based on age Coussens (2018), Dalmacy et al. (2021), Olenski et al. (2020). For instance, Coussens (2018) notes that those admitted to the hospital on who are just over 40 years old are 20% more likely to be diagnosed with ischemic heart disease than those who are 39 years old. To the extent that health professionals use similar heuristics, perhaps classifying those over 65 as elderly and giving them different medical treatment, our regression discontinuity estimates could be biased, most likely downward biased based on the assumption that increased medical treatment would reduce mortality. We leave this heuristic factor untested empirically, as it is difficult to disentangle increases in treatment due to such heuristic factors with increased utilization brought about by health insurance receipt.

Perhaps the most prominent potential confounder of our regression discontinuity employment. Sullivan and Von Wachter (2009) and Fitzpatrick and Moore (2018) suggest employment and retirement affect mortality. As noted by Card et al. (2009) and Von Wachter (2002), the phasing out of mandatory retirement rules in the 70s and 80s has drastically reduced the incidence of retirement at age 65.³⁶ Using data from the NHIS and March CPS, Card et al. (2009) note no large jumps in employment at age 65, and Barcellos and Jacobson (2015) and Goldsmith-Pinkham et al. (2021) also find smooth employment profiles around the cutoff using different datasets. Barcellos and Jacobson (2015) also finds no empirical evidence of jumps in education, family income, and geographic location around the age-65 Medicare eligibility cutoff. We use ACS survey data to see whether employment, household income, social security income, and retirement income jump at the

³⁵ See Fitzpatrick and Moore (2018) for a literature review.

³⁶ In more recent years, the incidence of retirement falls more heavily on age 62. Fitzpatrick and Moore (2018) find mortality increases at age 62, where social security claims and retirement spike.

cutoff (Figure 5). We find no jumps at the cutoff, but note that mismeasurement might not allow us to detect small effects. Fitzpatrick and Moore (2018) use Social Security administrative data to note a small increase in Social Security claims at age 65, albeit much less pronounced than the increase at age 62. To the extent that this small increase in Social Security influences mortality, our results could be biased.

Overall, the empirical evidence points to no or only small jumps in factors such as employment, Social Security, and income around the age 65 cutoff. While we cannot observe whether medical practices unrelated to health insurance change substantially at age 65, we believe the regression discontinuity design provides credible estimates of the effects of Medicare eligibility at age 65 on mortality.

1.4.2 - External Validity

We note here several limitations of using a regression discontinuity design to study the effects of Medicare eligibility on mortality. First, the regression discontinuity design is best suited for detecting effects around the cutoff. Mortality is a result of both cumulative and acute factors, and health insurance might reduce mortality only in the long-run, but not in the short-run. If Medicare eligibility affects mortality only in the long-run, regression discontinuity estimates that find no effect at the cutoff could be misleading. We observe granular data on the monthly probability of death around the age-65 cutoff, which we examine to see if there is a change in mortality trends around the age-65 cutoff, but we refrain from making inference away from the eligibility threshold. Our regression discontinuity estimates, then, should be thought of as the effects of Medicare eligibility on short-run mortality.³⁷ Our estimates also detect the effects of Medicare eligibility specifically at age 65, so we might lack the external validity to make conclusions regarding Medicare expansions to a much younger population. Given that recent proposals to change the Medicare eligibility age focus on age 60, an age close to 65, external validity issues regarding the age-specific cutoff might not warrant concern. Additionally, effects of Medicare eligibility at age 65 offer useful comparisons to several recently published papers that find large and immediate reductions in mortality for near-elderly individuals who receive health insurance coverage or eligibility (Miller et al., 2021) ; (Goldin et al., 2021), which we discuss below and throughout the Results Section.

The regression discontinuity estimate is perhaps better suited for understanding what happens when an individual who is, for example, low-income, uninsured, or who has private insurance gains Medicare eligibility at age 65, rather than what would happen to mortality for these groups if the Medicare eligibility age were reduced to 60.³⁸ While this might be a limitation in understanding how large expansions of Medicare would affect mortality, it potentially offers generalizable empirical evidence as to the short-run effects on mortality of near-elderly individuals (whether low-income, uninsured, or previously insured) gaining health insurance eligibility. We discuss the results of our

³⁷ Given previous estimates of immediate mortality effects in Goldin et al. (2021), Miller et al. (2021), and Abaluck et al. (2021), it is not unreasonable to expect immediate effects of health insurance on mortality.

³⁸ Garthwaite (Garthwaite) offers an overview of aggregate effects associated with Medicare expansions, and Finkelstein (2007) provides empirical evidence of aggregate effects from the introduction of Medicare.

analysis in the next section.

1.5 - Results (Medicare)

We use a regression discontinuity design to estimate the effects of universal Medicare eligibility at 65 on mortality for the full population, as well as by demographics, previous health insurance status, and previous income levels. As mentioned in the Methodology Section, these estimates are perhaps best thought of as the short-run effects on mortality for near-elderly individuals.

Figures 2, 3, and 4 show the monthly probability of death for three years on each side of the universal Medicare age-65 eligibility cutoff. The figures show mortality by age in months for the various populations described in the Data Section. Figure 2 shows mortality by age in months for the full population as well as for Blacks, males, and females. Figure 3 displays the results for those who had any health insurance, private insurance, or were uninsured just before the age-65 cutoff. Figure 4 shows mortality by age in months for low-income and high-income individuals. Tables 1 and 2 presents the estimates from Equation 1, the regression discontinuity that estimates the effect of Medicare eligibility at age 65 on the change in monthly probability of death. Our preferred specification is estimated based on monthly age bins three years on each side of the age-65 eligibility cutoff. Our existing estimates are limited by what has passed restricted Census disclosure process – we currently observe the monthly probability of death for three years on each side of the age-65 Medicare eligibility cutoff for various subgroups of the population. Future research will change the granularity of data used, bandwidth, and inferential methods in order to arrive at more reliable estimates of the effects of Medicare eligibility on mortality. We will also conduct more formal power analyses.³⁹ Despite its current deficiencies, our current disclosed data provide useful visual evidence of discontinuous jumps (or lack thereof) as well as changes in slope of month mortality around the eligibility threshold. We discuss our results in three subsections, one corresponding to each of Figures 2, 3, and 4 - mortality by (i) demographics (ii) previous health insurance status (iii) income.

1.5.1 - Mortality by Demographics

Figure 2 shows no large discontinuity or change in slope of monthly probability of death at the age-65 cutoff. Panels (a) – (d) show mortality for the full US population, Blacks, females, and males. The underlying samples are derived from Census Numident death records, which covers nearly every death in the United States. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 1. This estimate gives the change in the monthly probability of death around the age-65 eligibility cutoff (ex. -0.45% change in monthly probability of death for the full US population). The regression estimate for the full population is -.45% [CI: -.99% , +.10%], for Blacks is +.13% [CI: -1.28%, +1.53%], for males is

³⁹ We will also study changes in the regression discontinuity over time and after the introduction of the Affordable Care Act and Medicare Part D.

-.62% [CI: -1.22% , -.02%], for females is -.26% [CI: -1.09%, +.56%]. The estimate is statistically significant for males ($p = .044$). Given that this is the only statistically significant estimate from nine separate subsamples that we study, we caution against multiple hypothesis testing. Sample sizes for each population are approximations (in thousands), as we cannot disclose the denominators used to calculate the monthly probability of death measures. Overall, our findings echo previous studies of population-level all-cause mortality, with no large jumps or changes in the probability of death at the Medicare eligibility age-65 cutoff.

1.5.2 - Mortality by Previous Insurance Status

Figure 3 shows no large discontinuity or change in slope of monthly probability of death at the age-65 cutoff. Panels (a) – (c) show mortality for ACS respondents who were previously insured, privately insured, or uninsured. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 2. The regression estimate for those with any health insurance is -2.02% [CI: -5.75%, +1.71%] for the privately insured is +1.76% [CI: -6.07%, +2.55%], for the uninsured is +1.85% [CI: -7.08% ,+10.77%]. We find no significant effects of Medicare eligibility at age 65 on the uninsured, but our confidence intervals do not rule out socially important reductions in mortality. Moreover, a power analysis simulation based on the ages just before the cutoff, suggests that the probability of detecting a 15% mortality effect for $\alpha = .1$ is 80%, so our design is not well-powered to detect small effects.

Our results are consistent with earlier studies (Black et al., 2017) (Polsky et al., 2009) that use HRS panel data to follow uninsured near-elderly mortality trajectories after turning 65. Our results contrast with recent findings by Goldin et al. (2021), who find large and immediate changes in mortality for uninsured individuals who receive Medicaid or subsidized private insurance coverage. There are several possible reasons for this. First, we examine Medicare, which has different cost-sharing, networks, and other plan characteristics. Additionally, Medicare coverage is near-universal at age-65, so our estimate looks across the uninsured population, while they examine individuals who responded to IRS outreach letters. They use tax filings to identify the uninsured population, whereas we use survey responses. Survey responses could have misreporting, or, given that they measure insurance status at a point in time, include individuals who may only be uninsured for a small fraction of the year. While this group is still policy relevant, the effects of Medicare coverage could very well be muted for them if there is concavity in the relationship between health insurance coverage and mortality (Goldin et al., 2021). Finally, our regression discontinuity estimate reflects mortality changes right at the age-65 cutoff. While Goldin et al. (2021) finds immediate mortality changes for individuals ages 45-64, most of the effects load on individuals ages 45-54, and there could be differences in the effects of health insurance for these age groups. Overall, given the different populations studied, measures of uninsured status, and form of insurance, we caution against making cross-study comparisons.

1.5.3 - Mortality by Income

Figure 4 shows no large discontinuity or change in slope of monthly probability of death at the age-65 cutoff. Panels (a) and (b) show mortality for 2000 Census Long-form respondents who are low-income and high-income. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 2. The regression estimate for low-income individuals is +1.93% [CI: -1.22%, +5.07%] and for high-income individuals is +0.73% [CI: -3.70%, +5.16%]. We find no significant effects of Medicare eligibility at age 65 for low-income individuals (no high school degree or below the Federal Poverty Line). Moreover, a power analysis simulation based on the ages just before the cutoff, suggests that the probability of detecting an 8% mortality effect for $\alpha = .1$ is 80%.

Our results are consistent with Chetty et al. (2016), which finds no effects on mortality at age 65 for individuals at the 5th percentile of income. It is unclear whether we should expect differences in Medicare eligibility on mortality for those at the 5th percentile of income vs. those without a HS degree or below the FPL. Access to charity care, safety-net, and public health insurance could differ for these groups, as well as underlying health conditions. The low-income population that we study resembles the target group of the ACA Medicaid Expansions, and our results contrast with studies that find large and immediate reductions in mortality for the near-elderly who gain Medicaid eligibility (Miller et al., 2021). There are several possible reasons for this. The different plan characteristics of Medicare and Medicaid could affect mortality. Moreover, Medicare has nearly universal take-up, whereas the ACA Expansions were associated with large “woodwork” effects, and many individuals who were eligible did not actually enroll in Medicaid (Frean et al., 2017). Our sample includes deaths from 2005 through 2020, so many of the individuals we examine will already have Medicaid, making our effects muted. Future versions of this paper will explore changes in mortality at the Medicare age-65 cutoff before and after the ACA Medicaid Expansion as well as after the introduction of Medicare Part D. The ACA Medicaid Expansion also influenced hospital and state finances, so there could be aggregate effects associated with differences-in-differences estimates of the ACA Medicaid Expansion. We examine the effects of the ACA Medicaid Expansion on a similar low-income group in the next section.

We note an important caveat to the interpretation of our regression discontinuity estimates of the effects of Medicare on mortality at age 65. Recent legislation to lower the Medicare age to 60 has argued that expanding Medicare to lower age groups will save lives. Our regression discontinuity estimates, while they do not find reductions in mortality at the age 65 cutoff, do not necessarily conflict with this policy goal. Medicare is the largest payer for health care in the United States, so expansions of Medicare could have large aggregate effects (Finkelstein, 2007). According to Case and Deaton (2020), for a low-income earner working on half the median wage, the average family health insurance policy adds 60 percent to the cost of employing them (Gawande, 2020). The cost savings from the employer not having to pay for health insurance could be shifted to workers in the form of higher wages (Gruber, 1994). To the extent that higher income improves health, a large expansion of Medicare could reduce mortality.

1.6 - Conclusion (Medicare)

Overall, our findings are consistent with previous research on effects of Medicare eligibility at age-65 on mortality. In contrast to previous research that examines the effects of Medicaid and subsidized private insurance on mortality, we do not find significant effects of Medicare on mortality for low-income or previously uninsured near-elderly individuals. While our confidence intervals seem to rule out large reductions in mortality found by previous research on Medicaid and subsidized private insurance, we caution that our research design is powered only to detect large effects. Given the social benefits of reduced mortality, even small reductions in mortality can greatly affect the merits of public health insurance expansions. Future research should continue to look for ways to improve the statistical power of research designs in order to more reliably detect small effects of health insurance on mortality.

2 - Medicaid

This chapter examines whether Medicaid eligibility reduces mortality for near-elderly individuals. We begin by using CDC data and a differences-in-differences design to analyze whether the ACA Medicaid Expansion reduced the mortality rate for individuals aged 55-64. We do not find that the ACA Medicaid Expansion reduced mortality. We note several potentially important limitations in using CDC data for studying the effects of Medicaid on mortality. We discuss ways of circumventing these limitations by using the restricted Census infrastructure to link survey data to administrative death records.⁴⁰ Future versions of this paper aim to use restricted Census data to examine whether Medicaid reduces mortality, and we are currently awaiting Census review.

This chapter begins by describing Medicaid in the United States and the ACA Medicaid Expansions. We briefly summarize the existing literature on the effects of the ACA Medicaid Expansions on both non-health and health-related outcomes. We discuss why Medicaid might reduce mortality, the empirical challenges in detecting any effects of Medicaid on mortality, and the strengths and weaknesses of using a differences-in-differences design to study the ACA Medicaid Expansions on mortality. We then present the results of our analysis using CDC data.

2.1 - Background (Medicaid)

The largest means-tested program in the United States, Medicaid provides public health insurance to over 75 million children, low-income families, disabled individuals, and indigent seniors.⁴¹ States have flexibility in administering Medicaid, and Medicaid health insurance often offers generous premium and cost-sharing support for individuals. Given the number of Medicaid recipients and distinct populations served, there have been a tremendous number of studies of the effects of

⁴⁰ Miller et al. (2021) and Miller et al. (2021) Also use restricted Census data to examine the effects of Medicaid on mortality, and we discuss their work below.

⁴¹ Buchmueller et al. (2016) provides a thorough description of the Medicaid program. See also (Kaiser Family Foundation 2021) for state specific information.

Medicaid on a wide range of outcomes. Currie and Duque (2019) and Gaudette et al. (2018) offer excellent overviews of the literature, noting the recent explosion in research examining the effects of Medicaid on low-income, working age, non-disabled adults, which parallels a subsequent rise in the number of such individuals covered by Medicaid. Previously excluded from Medicaid participation, the primary reason for the increase in Medicaid coverage among low-income adults is the ACA Medicaid Expansion and several earlier, similar state Medicaid expansions (such as Massachusetts).

The Affordable Care Act (ACA) is the largest health care overhaul since the creation of Medicare and Medicaid in 1965. A primary goal of the ACA is to reduce the national uninsured rate by providing affordable health insurance to low-income adults. In order to achieve this goal, the ACA provides federal funding for states to expand Medicaid eligibility to adults with incomes below 138 percent of the federal poverty level (FPL).⁴² The ACA originally required states to expand Medicaid, but the Supreme Court ruled in *National Federation of Independent Business v. Sebelius* that Medicaid expansions are optional for states. Since the start of the ACA expansions in 2014, 39 states have chosen to expand Medicaid through the ACA (KFF).

The optional nature of the state ACA Medicaid expansions provides a natural experiment for researchers to examine the effects of public health insurance expansions. Using expansion states as a treatment group and non-expansion states as a control, researchers have analyzed a variety of outcomes, including insurance rates, individual financial health, access to care, and utilization, and health outcomes. The next section summarizes these findings in the context of whether health insurance reduces mortality.

2.2 - Literature Review (Medicaid)

Mortality is the end result of both cumulative and acute factors involving biology, medicine, behavior, and socioeconomic factors. It is not theoretically clear why or if we should expect health insurance to reduce mortality in the short-run (or even long-run). While there are a variety of non-healthcare pathways by which health insurance could improve health (such as reduction of financial stress, changes in labor force participation, aggregate effects from improved hospital finances), perhaps the most straightforward pathway for Medicaid reducing mortality is as follows: 1) Individuals who gain Medicaid also gain increased access to health care. 2) Health care treatments are effective, so increased access to health care improves health. 3) Improved health increases longevity.

Despite the seeming simplicity of this pathway, it remains hotly debated by policymakers. Then Presidential Candidate Mitt Romney, when debating the future of the Affordable Care Act, claimed, "We don't have a setting across this country where if you don't have insurance, we just say to you, 'Tough luck, you're going to die when you have your heart attack.' No, you go to the hospital, you get treated, you get care, and it's paid for, either by charity, the government or by the hospital." NPR (2012). There is a safety-net of health care services and financial relief

⁴² The federal government pays 100 percent of the costs to cover newly eligible enrollees through 2016, and this share gradually decreases to 90 percent of costs by 2020.

for uninsured individuals in the United States, and hospitals are required by EMTALA to provide healthcare emergency departments regardless of health insurance status. While EMTALA requires provision of emergency care, hospitals often provide non-emergency care to uninsured individuals. 90 percent of hospitals reported never denying services to any uninsured individual on an IRS survey of non-profit hospitals (Hellinger, 2009). Even if health insurance increases health care utilization and improves health (or improves health by some other pathway), it is not clear whether such effects could be detected empirically. Health is a complex, long-term, stock measure (Grossman, 2017). If health insurance improves health, observable effects could take a long time to develop or might be small, making the effects of health insurance on mortality difficult to detect empirically. We briefly review the literature on the effects of the ACA Medicaid Expansion on both non-health outcomes and mortality below, highlighting the empirical challenges faced in credibly estimating the effects of the ACA Medicaid Expansion on mortality.

2.2.1 - Experimental Evidence

Both the ACA Medicaid Expansion and earlier state Medicaid expansions have been studied extensively using observational and quasi-experimental methods. The primary experimental studies in this area derive from the Oregon Health Insurance Experiment (OHIE), which conducted a randomized lottery for Medicaid eligibility to low-income, working-age adults. James (2015), Baicker and Finkelstein (2011), Baicker et al. (2013), and Finkelstein et al. (2012) find that Medicaid eligibility greatly increased utilization of preventative and hospital care and improved self-reported measures of health. It did not, however, improve clinical measures of health, or reduce mortality. Notably, the confidence intervals on the mortality effect were too wide to make any conclusions. The OHIE's findings of improved financial health, self-reported health, and increased utilization are echoed in quasi-experimental studies on the ACA Medicaid Expansion, while there is mixed evidence on mortality effects. We outline these findings below.

2.2.2 - Quasi-Experimental Evidence

A large body of literature uses differences-in-differences analyses with states that expanded Medicaid as the treatment group and states that did not expand as the control group to study both health and non-health outcomes. Given the large volume of research produced on the ACA Medicaid Expansion, we summarize only a selection of papers in this section, and note that Antonisse et al. (2018) Mazurenko et al. (2018) Gruber and Sommers (2019) and Currie and Duque (2019) provide literature reviews of the ACA Medicaid expansions.

2.2.2.1 - Financial Health

Hu et al. (2018) and Miller et al. (2021) find that ACA Medicaid Expansions improve individual financial health, reducing unpaid debts. To the extent that individual financial health improves physical health, whether through reduced stress or ability to purchase inputs that improve their

health stock, Medicaid eligibility could reduce mortality. In addition to individual finances, there are potential aggregate effects of the ACA Medicaid Expansions on mortality. Since the ACA Medicaid Expansions are primarily federally funded, the ACA Medicaid Expansions improved the fiscal health of the states that choose to expand Medicaid, costing states that did not expand Medicaid \$43 billion dollars in 2018 (Gruber and Sommers, 2020). To the extent that states can employ the additional funds towards programs that improve health, then the ACA Medicaid Expansion could reduce mortality.

2.2.2.2 - Access to Care and Utilization

Perhaps the most straightforward pathway for health insurance to reduce mortality is through increased access to and use of health services. For instance, Medicaid receipt might enable individuals to purchase drugs, obtain preventative care, or increase (or prevent unnecessary) hospital care. Given the existing health safety-net for uninsured individuals, and the potential for the crowding-out of individuals with private insurance, it is theoretically ambiguous whether and how the ACA Medicaid Expansion would increase access to care and utilization. The literature largely supports that ACA Medicaid Expansions increased access to health care and utilization (Antonisse et al., 2018), (Miller and Wherry, 2017), (Wherry and Miller, 2016). (Miller and Wherry, 2019) finds a reduction in the uninsured rate, increased in Medicaid participation, and a smaller reduction in private insurance. They also find reductions in the proportion of individuals who were unable to afford needed medical care and delayed medical care due to costs. Simon et al. (2017) finds that the ACA Medicaid Expansions increased certain forms of preventative care. Ghosh et al. (2019) finds seven additional prescriptions per year per newly enrolled Medicaid beneficiary. Duggan et al. (2019) find that the ACA Medicaid Expansions offset locally-funded safety net programs, increased hospital utilization, and improved hospital finances.⁴³ Their findings suggest the potential for large supply-side responses to the ACA Medicaid Expansions. Using the universe of hospitalization data in 20 states from AHRQ, Garthwaite et al. (2019) find increases in hospital utilization, and heterogeneity in effects by state. They also find that the increase in hospital care comes largely from "deferrable" medical conditions, suggesting that the Medicaid expansions were well-targeted to those in need of health care access. Overall, the sizeable body of empirical evidence that the ACA Medicaid Expansion improved access to care and increased utilization provides plausibility to the theory that the ACA Medicaid Expansion could improve health, which we discuss in the section below.

2.2.2.3 - Health and Mortality

Clinical trials show that medical treatments are effective for a host of conditions.⁴⁴ If the ACA Medicaid Expansion increased health care utilization, and health treatments improve health, then the ACA Medicaid Expansion could improve health and reduce mortality. That said, the ACA

⁴³ Dunn et al. (2021) offers an overview of the effects of Medicaid expansions on hospitals.

⁴⁴ <https://www.cochranelibrary.com/>

Medicaid Expansion might not immediately result in health improvements, or health improvements might be too small to be detected in the existing data. Gruber and Sommers (2019) and Soni et al. (2020) summarize the existing literature on the effects of the ACA on health outcomes. While some studies find improvements in self-reported health, the evidence is less clear if the ACA improved clinical outcomes. Soni et al. (2020) notes that surveys with clinical data generally have small sample sizes. However, the availability of longitudinal databases of electronic health records in the future could remove empirical roadblocks. McInerney et al. (2020) uses HRS surveys to focus on the effects of the ACA Medicaid Expansion on individuals aged 50-64 and find large improvements in physical health. We outline the mixed and controversial evidence for whether Medicaid reduces mortality below, highlighting some of the empirical challenges posed by this research question.

The Oregon Health Insurance Experiment, which randomized Medicaid eligibility to low-income adults, is one of the few examples of an experiment randomizing health insurance in the United States. While the Oregon Health Insurance Experiment finds significant effects for several outcomes such as self-reported health, it is ill-suited to detect the effects of health insurance on mortality. Since mortality is a low-frequency outcome, many individuals are needed in the experiment in order to reliably detect effects. The confidence interval for the effects of Medicaid on the mortality rate is [-82% to 50%], too large to make any causal conclusions. Given the problems faced in using experiments to detect the effects of health insurance on mortality, researchers have turned to observational studies both to understand the relationship and make causal statements about the effects of Medicaid on mortality.

Black et al. (2017) provides a literature review of observational studies that look at both the short-term and long-term effects of health insurance on mortality. While observational studies offer insights into the relationship between health insurance and mortality, factors such as income and health status confound comparisons of the mortality rates of those with and without insurance.⁴⁵ Due to concerns that causal inferences from observational studies are unreliable, researchers have generally relied on quasi-experimental studies in recent years in order to understand the effects of Medicaid on mortality.

Sommers et al. (2017) summarizes the findings of several quasi-experimental studies on state Medicaid expansions in the 2000s.⁴⁶ Using differences-in-differences designs, Sommers et al. (2014), Sommers et al. (2012), and Sommers (2017) find that state Medicaid expansions almost immediately reduce mortality, with one study finding a 6% decrease in mortality even five years after the policy. Quasi-experimental evidence from the ACA Medicaid Expansion finds reductions in mortality for specific medical conditions - Swaminathan et al. (2018) find reductions in 1-year mortality for individuals with end-stage renal disease; Khatana et al. (2019) – find fewer cardiovascular-related deaths in states that expanded Medicaid versus those that did not. Borgschulte and Vogler (2020) use restricted-micro data from the CDC and find that the ACA Medicaid Expansions reduced all-

⁴⁵ It should be noted that a number of papers use survey data with detailed socioeconomic data (sometimes including health status) and attempt to control for possible confounders. Black et al. (2017) discusses the merits of observational studies for studying the effects of health insurance on mortality.

⁴⁶ See also ? ? Black et al. (2019) Miller et al. (2021)

cause mortality for those aged 20-to-64 by 3.6%. They find substantial reductions in mortality even for younger individuals, and their estimates suggest that the benefits of reduced mortality could offset the net-of-transfer costs of the ACA Medicaid expansion.

Despite the numerous findings of reduced mortality, there are still concerns regarding the validity of differences-in-differences estimates on the effects of the ACA Medicaid Expansion on mortality. Black et al. (2019) note concerns of non-parallel pretreatment trends due to rising mortality in Medicaid non-expansion states relative to those in expansion states. They also note that lack of statistical power plagues the validity of estimates of the ACA Medicaid Expansion on mortality. Because the percentage of the overall population who receive Medicaid as a result of the population is low, it is difficult to detect anything other than very large mortality effects in existing data sources such as county-level death certificate data.⁴⁷ In order to reliably detect the effects of the ACA Medicaid Expansion on mortality, Black et al. (2019) note the need for data that contains information on mortality, income, or health insurance status in order to identify subsamples with larger first stages. That is, granular data on who is targeted by the ACA Medicaid Expansions is needed.

The empirical difficulties in arriving at causal estimates of the effects of health insurance can be summarized as follows:

(i) experiments randomizing health insurance are expensive (because health insurance is expensive), so the number of individuals in a given experiment will be small. Mortality is a low-frequency outcome, so many individuals will need to be observed to detect statistically significant effects on mortality. Therefore, it is difficult to design experiments testing whether health insurance affects mortality.

(ii) quasi-experimental methods such as differences-in-differences examining the effects of state Medicaid expansions on mortality suffer from data limitations. Since state Medicaid expansions only affect a small percentage of the general population, detailed data that can identify subsamples targeted by insurance expansions is needed in order to have sufficient statistical power to reliably make causal estimates.

All in all, it is difficult to design experiments or quasi-experiments on the causal effects of health insurance on mortality that have enough statistical power to detect all but the largest effects. Two recent studies offer perhaps the most compelling research designs for estimating the effects of health insurance on mortality, potentially overcoming low-power concerns of previous studies. Goldin et al. (2021) evaluates an IRS outreach program that randomized letters to millions of uninsured individuals who were already eligible for subsidized or public health insurance, inducing them to increase health insurance enrollment and lowering mortality among the near-elderly (ages 45-64) who enrolled. They find immediate and large reductions in mortality for those ages 45-64: one additional month of health insurance coverage reducing the mortality rate by 10% relative to the control group over two years. The other paper is Miller et al. (2021), which improves upon

⁴⁷ According to Black et al. (2019), there is a roughly 1% for the general population and 4% for low-educated population aged 55-64 in the reduction in the uninsured rate as a result of the ACA.

previous quasi-experimental studies of the ACA Medicaid expansion by linking administrative death records with survey data containing detailed information on socioeconomic status. They conduct a differences-in-differences design with states that expanded Medicaid as the treatment states and states that did not expand Medicaid as the control states. They find a large and immediate 9.4% decrease (appearing in the 1st year and persisting through in the mortality rate of for their low-income, ages 55-64, target sample in ACA Medicaid Expansion states relative to non-expansion states.⁴⁸

We revisit the effects of the ACA Medicaid Expansion on mortality for near-elderly mortality in the sections below. Given our previous finding that Medicare eligibility at age 65 does not reduce mortality for low-income individuals (a group similar to those affected by the ACA Medicaid Expansions), and recent findings that ACA Medicaid Expansions greatly reduce mortality for low-income individuals of a similar age, we study the effects of the ACA Medicaid Expansion on the near-elderly in order to improve our understanding of both the effects of Medicare and Medicaid on mortality.

2.3 - Data (Medicaid)

We use CDC multiple cause of death data for 2005-2018 from CDC (2020) for our analysis. The multiple cause of death data is derived from death certificates across the United States and contains information on cause of death, age at death, race, sex, and education. We use ICD-10 UCOD 358 codes to classify cause of death into both amenable and non-amenable categories, amenable causes of death being those that can be avoided with quality health care.⁴⁹ We use 10-year age buckets, focusing on ages 55-64 in our primary specification. We also focus on individuals without a high school education, a group that is more likely to be low-income and, thus, affected by the ACA Medicaid Expansion. We aggregate our cause of death data to state level counts by age group, education level, and cause of death. In order to arrive at an annual mortality rate by group, we use publicly available ACS data from 2005-2018 for the denominators, aggregating the data to state level counts by age group and education level, collapsing ACS' detailed education variable to correspond with the categories of education response in the NVSS death records. In sum, the primary outcome that we measure is annual mortality rates for years 2005-2018 by state for those aged 55-64 without a high school education by cause of death.

There are several limitations in the data used, and we discuss how our preferred outcome overcomes these. First, cause of death could be misreported on death certificates Ruhm (2018). We examine all-cause mortality, amenable deaths, and non-amenable deaths, all very large groups in order to reduce error in cause of death measurement. A second potential limitation of using death certificate data is mismeasurement of the education variable. Sorlie and Johnson (1996) compare education response to household survey (CPS) and death certificate data, noting large discrepancies.

⁴⁸ The impact and methodology of these papers is described in more detail in the Introduction to this paper.

⁴⁹ Our classification of cause of death resembles Borgschulte and Vogler (2020), Sommers (2017), and Nolte and McKee (2004).

Individuals usually overstate their education levels on death certificate data. Because we focus on individuals with no high school education (the lowest education response available), overstating is less of a concern for our preferred group. For those deaths recorded as less than HS on the death certificate, 91% responded that they had less than a HS education on the CPS. A related concern with our data is that the numerators come from death certificates, but the denominators come from U.S. Census (ACS) survey data. If the education measures from these two disparate data sources are mismatched, our annual mortality measures by age and education level could be misclassified. Given that those without a high school education are less likely to misreport, the discrepancies between our numerator and denominator could be somewhat mitigated. However, our outcome measure of annual mortality could be improved with detailed Census survey data linked to death records.

Central to debates on the reliability of diff-in-diff estimates of the ACA Medicaid Expansion is whether the analysis is sufficiently powered. Perhaps the primary concern with death certificate data is the lack of detailed socioeconomic data that can help identify the target group for the ACA Medicaid Expansion, resulting in a lack of statistical power. Our future research aims to use restricted Census data linking federal survey data with individual socioeconomic data to administrative death records in order to better hone in on those eligible for Medicaid.⁵⁰ For now, we conduct our analysis on CDC death records aggregated to the state level, focusing on the annual mortality rate for those aged 55-64 without a high school education. We aim to discuss the reliability of the estimates using this subgroup of the aggregate death records compared to estimates using detailed individual data linked to death records in future versions of this paper.

2.4 - Methodology (Medicaid)

The ACA Medicaid expansion grants Medicaid eligibility to working age adults with income below 138% of the Federal Poverty Line. The ACA originally required states to expand Medicaid, but the Supreme Court ruled in *National Federation of Independent Business v. Sebelius* that Medicaid expansions are optional for states. Since the start of the ACA expansions in 2014, 39 states have chosen to expand Medicaid through the ACA (KFF), creating geographic variation across time that researchers have extensively used to study many different outcomes Antonisse et al. (2018).

We follow the existing literature in our empirical strategy for studying the effects of the ACA Medicaid Expansions on mortality. That is, we use a differences-in-differences regression with geographic variation across time in states' adoption of the ACA Medicaid Expansion - states that expanded Medicaid are the treatment states and states that did not expand are the controls.

Our primary specification is an event study differences-in-differences regression that compares the relative mortality rates for states that expanded Medicaid under the ACA to those that did not. Our "treatment" is whether a state expanded Medicaid:

⁵⁰ For more information on the restricted Census data, see the Data section in the Medicare chapter above or Finlay and Genadek (2021) and Miller et al. (2021).

$$Y_{st} = \alpha + \sum_{k=-T} \gamma_k \cdot (\text{Medicaid_Expansion}_{sk}) + \mu_s + \lambda_t + \epsilon_{st} \quad (2)$$

where "k" indexes time relative to the year a state expanded Medicaid. *Medicaid_Expansion_{sk}* = 1 if state *s* expanded Medicaid *k* years ago, and *T* = -6,-5,-4,-3,-2,-1,0,1,2,3,4. So, the first year after a state expands Medicaid is designated *k* = 0, and the last pre-treatment period (*k* = -1) is used as the baseline reference. γ_0 is the estimate of the effect of the ACA Medicaid Expansion the year of expansion, γ_{-1} is the estimated effect one year before expansion. Y_{st} is the state annual mortality rate. $\mu_s + \lambda_t$ are state and time fixed effects, respectively. We cluster standard errors at the state level (Bertrand et al., 2004) and use population weights.

Our assignment of states to treatment and control groups follows that used in Miller et al. (2021). We drop five states (MA, DC, VT, DE, NY) that had early Medicaid expansions (before the ACA Medicaid Expansions began in 2014) from our analysis. We consider states that expanded after January 1, 2014 to have expanded in the following years: MI (2014); NH, PA, IN (2015); AK and MT (2016); and LA (2017). Lyncurgus et al. (2021), Mann et al. (2021), and Black et al. (2019) note several different specifications used to study the effects of the ACA Medicaid Expansion on mortality. While some papers drop additional states that partially expanded Medicaid before 2014 (such as Wisconsin), and others use propensity-score weighting to account for pre-trends (Borgschulte and Vogler (2020)), we choose a specification that resembles Miller et al. (2021).

2.4.1 - Identifying Assumption

The identifying assumption for the differences-in-differences regression is parallel trends. This assumption posits that changes in the outcome variable over time would have been the same in both treatment and control groups in the absence of the state Medicaid expansion. While this assumption cannot be directly tested, Equation 2 can be used to examine whether the treatment and control groups have different pre-trends. While the ACA Medicaid Expansion has been studied extensively using a differences-in-differences design similar to ours, parallel trends could occur for one outcome but not another. Notably, there has been tremendous divergence in mortality trends across geographies and by socioeconomic status over the last decade, and such trends could confound our results (Case and Deaton, 2021), (Case and Deaton, 2020), (NASEAM, 2021). Additionally, we can examine the post-trends to see whether effects appear instantaneously, persist, or only develop over time. Given that health is a stock measure, it is not clear *a priori* whether mortality effects would appear immediately.⁵¹ Whether effects are transient or persistent is important economically, as it translates into substantially more lives saved.

2.4.1 - External Validity

It is important to discuss conceptually whether differences-in-differences regression with the ACA Medicaid Expansion provides economically and policy-relevant estimates. The ACA Medicaid Ex-

⁵¹ Previous estimates of the ACA Medicaid Expansion on mortality find immediate effects (Miller et al., 2021).

pansion could differ significantly from randomized experiments involving Medicaid due to aggregate effects. Duggan et al. (2021) and Gruber and Sommers (2020) find large improvements in both hospital and state finances, both of which could reduce mortality in the affected geographic regions. Echoing the previous literature, our differences-in-differences design focuses on the expansion of Medicaid eligibility rather than coverage due to data constraints. While this puts limitations on determining the result as to what happens when an individual receives Medicaid, understanding the aggregate effects of an extremely large expansion of Medicaid eligibility for low-income individuals is perhaps the most economically and politically relevant measure, as it reflects one of the largest policy levers for expanding health insurance.

We discuss the results of our differences-in-differences design below for our primary sample - those aged 55-64 without a high school education, as well as placebo groups that are less likely to be affected by the ACA Medicaid Expansion - those aged 65-74 and with college education. We also consider heterogeneity in treatment timing (Goodman-Bacon (2021)), migration, and other robustness below.

2.5 - Results (Medicaid)

2.5.1 - Mortality Trends

We begin by looking at the trends in all-cause mortality for those aged 55-64 without a HS education. As noted by Case and Deaton (2021) and NASEAM (2021) mortality has been rising for individuals without a HS degree, reversing decades long trends of decreasing mortality.⁵² Figure 6 Panel (a) echoes these studies, showing annual probability of death increasing from below 1.5% to over 1.65% from 2006 to 2018. Figure 6 Panels (b) and (c) breakdown the mortality trends into amenable deaths (those that could be affected with quality health care) and non-amenable deaths, showing that most of the rising mortality is due to increases in non-amenable deaths.

Figure 7 breaks down the changes in mortality by treatment and control states - that is, states that expanded Medicaid through the ACA vs. states that did not. We omit states that are not included in our differences-in-differences regression - states expanded Medicaid before the ACA (MA, NY, DE, DC, VT). We also omit here states that expanded Medicaid from 2015 to 2018, the last year of our data. Looking at all-cause mortality in Figure 7 Panel (a), there is a noticeable divergence in mortality trends between the treatment and control states. The states that did not expand Medicaid experience a large increase in mortality starting in 2011, just years before the ACA Medicaid Expansion, while the expansion states have relatively flat mortality rates.⁵³ The probability of death for those aged 55-64 without a HS education in non-expansion states increase dramatically from 2011 to 2013, rising from nearly 1.6% to 1.8%. The annual probability of death

⁵² See also Leive and Ruhm (2021) for a literature review and breakdown of how changing education status explains existing trends.

⁵³ Figure 7 Panels (b) and (c) show mortality by amenable and non-amenable causes of death, revealing a similar pattern of rising mortality in states that did not expand Medicaid in the period before the 2014 ACA Medicaid Expansion went into effect.

then flattens out for this group from 2014 to 2016. There is a slight drop in probability of death for the expansion states just after 2014, but mortality increases every year afterwards. It is not altogether clear how a large effect of the ACA Medicaid Expansion on mortality would appear in the descriptive trends. One plausible scenario is that there would be either an immediate drop after 2014 in the mortality of the expansion states or a noticeable decline in the mortality trend, but this does not appear to play out in the data. We turn to a differences-in-differences analysis in order to formally analyze whether there is a causal effect of the ACA Medicaid Expansion on mortality. Importantly for our analysis, there is a noticeable divergence in mortality trends between treatment and control states starting several years before the 2014 expansion that could call into question the identifying assumption of parallel trends.

2.5.2 - Differences-in-Differences Estimates

Figure 8 Panel (a) shows our main result - a differences-in-differences event study that examines whether the ACA Medicaid Expansion reduced mortality. The year before a state expanded Medicaid is the baseline year of "-1". The year after a state expanded Medicaid is "0". To give an example, for a state that expanded Medicaid in 2014, "-1" would be 2013 and "0" would be 2014. μ gives the average probability of death in 2013, which will be the baseline year for most expansion states. The event study shows a declining trend in the years before a state expands, with wide confidence intervals on the point estimates. While there is a drop in the probability of death in the year a state expands of approximately -.00075 (relative to a mean of .0158, this is approximately a 4.7% reduction in mortality), this drop is similar to the drop from two to one year before expansion (.00065). That is, there appear to be violations of the parallel trends assumption, which is perhaps not surprising given the diverging trends in mortality between treatment and control states that could be observed in Figure 7.⁵⁴ Given the violation of the parallel trends assumption, any causal statements regarding the effects of the ACA Medicaid Expansion on mortality should be called into question.

2.5.3 - Robustness

The differences-in-differences estimates suggest that any causal statement made regarding regression estimates is not robust to existing pre-trends. We also note several other factors that could influence the interpretation of results here. First, previous studies of the ACA Medicaid Expansion find no effects on migration, a potential driver of our result (Goodman, 2017). Additionally, given that some states enacted ACA Medicaid Expansions after 2014, there are potential concerns with heterogeneity in treatment timing (Goodman-Bacon, 2021). When we omit states that expanded after 2014 (MI, NH, PA, IN, AK, MT, and LA), our results are similar. We also examine in Figure 9 differences-in-differences estimates for various other population subgroups - (i) ages 65-75 without a HS education; (ii) - ages 45-54 without a HS education; (iii) - ages 55-64 with some college or

⁵⁴ Similar patterns emerge in Figure 8 Panels (b) and (c) when breaking down the results by amenable and non-amenable causes of death.

more, but find no apparent pattern that would call our main differences-in-differences event study interpretation into question.

2.6 - Conclusion (Medicaid)

Our differences-in-differences event study find violations of the parallel trends assumption, making it difficult to make causal statements regarding the effects of the ACA Medicaid Expansion on mortality. That said, there are potential limitations in the CDC data source that we use. As noted in the Data Section our target group of those without a HS education might not be a good proxy for the actual target group of ACA Medicaid expansions. Recent research by Miller et al. (2021) has used linked administrative death and survey data in order to better identify those likely to gain Medicaid eligibility, increasing statistical power and improving estimates. They find a 9.4% reduction in mortality for low-income individuals aged 55-64, providing some of the most compelling evidence in the literature on whether health insurance affects mortality. In future versions of this paper, we aim to use restricted Census data, and we will discuss the reliability of estimates using CDC data compared to estimates using detailed linked data. Our analysis is currently awaiting disclosure review at the Census.

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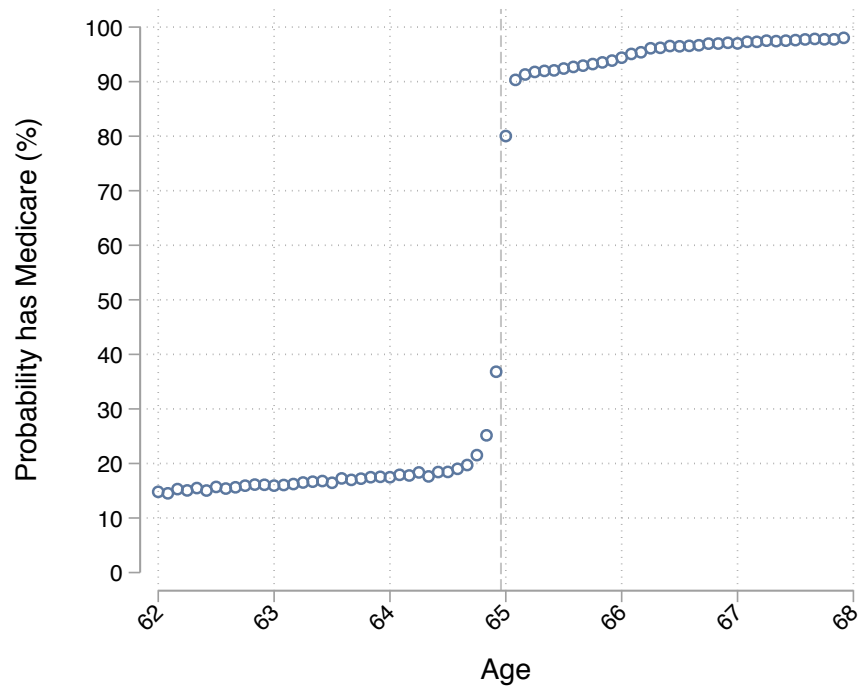
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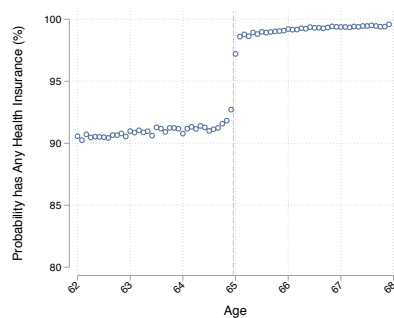
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Figures

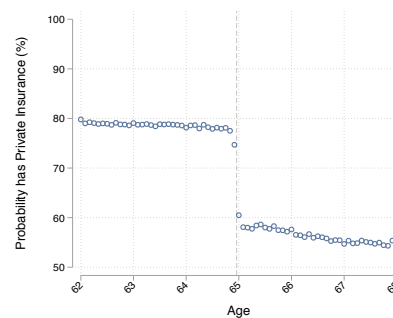
Figure 1 – Health Insurance Coverage at the Medicare Age-65 Cutoff (First Stage)



(a) Medicare



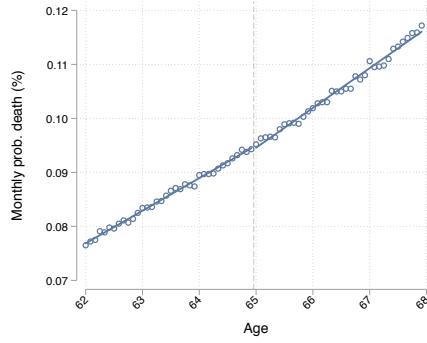
(b) Any Health Insurance



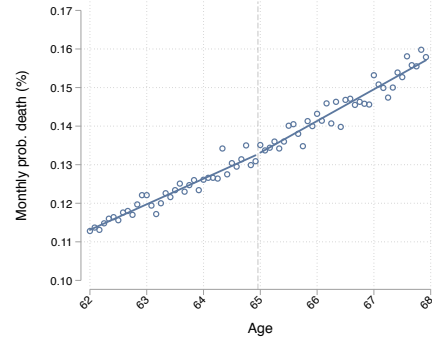
(c) Private Insurance

Notes: Panel (a) shows a large percentage of the US population enroll in Medicare immediately after becoming eligible for Medicare at age 65. Panels (b) and (c) show the change in having any health insurance coverage or private insurance. Data come from restricted Census ACS surveys (2001-2017).

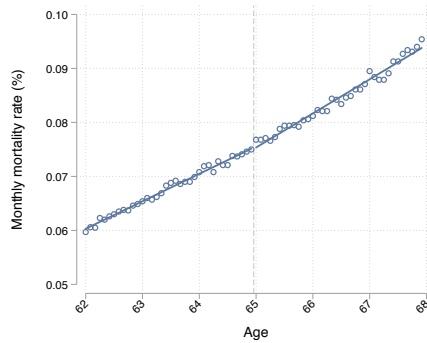
Figure 2 – Does Medicare Eligibility at Age-65 Reduce Mortality?



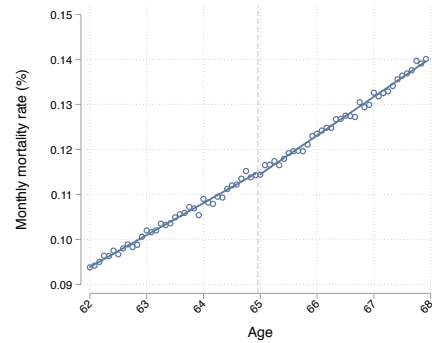
(a) Full Population



(b) Black



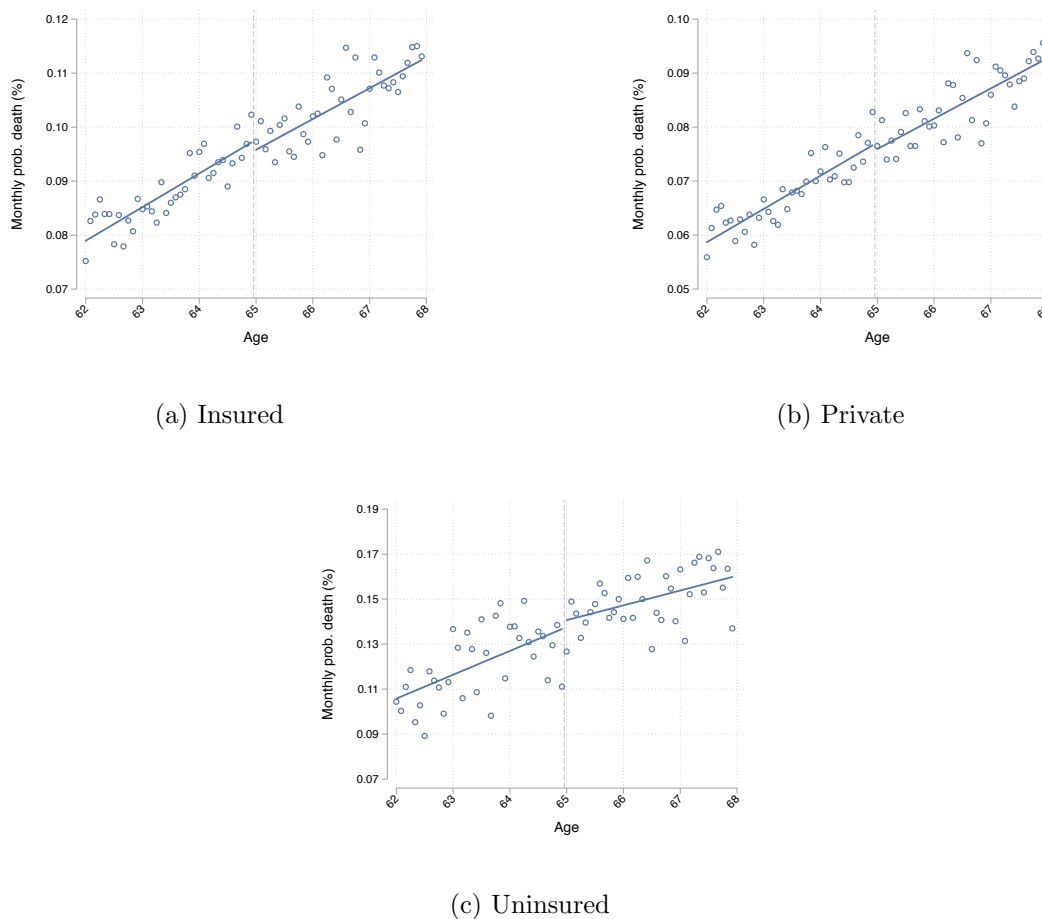
(c) Female



(d) Male

Notes: This figure shows the monthly probability of death for three years on each side of the universal Medicare age-65 eligibility cutoff. The X-axis shows age in months, and the Y-axis shows monthly probability of death. The figures show no large discontinuity or change in slope of monthly probability of death at the age-65 cutoff. Panels (a) – (d) show mortality for the full US population, Blacks, females, and males. The sample is restricted to individuals born between 1940 and 1952. Death records come from Census Numident, which covers nearly every death in the United States. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 1.

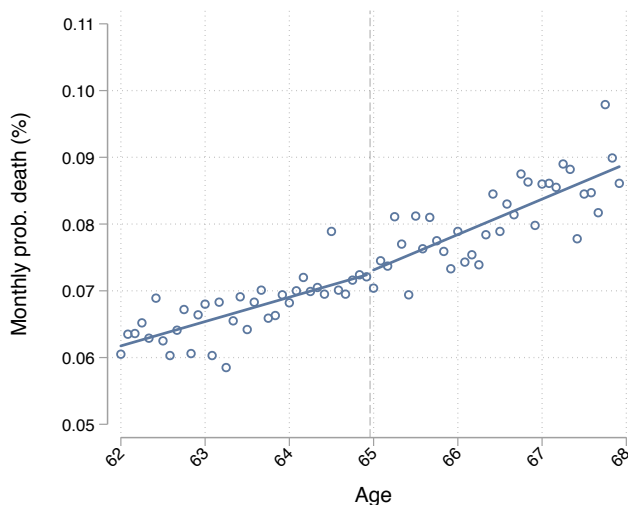
Figure 3 – Does Medicare Eligibility at Age-65 Reduce Mortality? (Heterogeneity by Insurance Status)



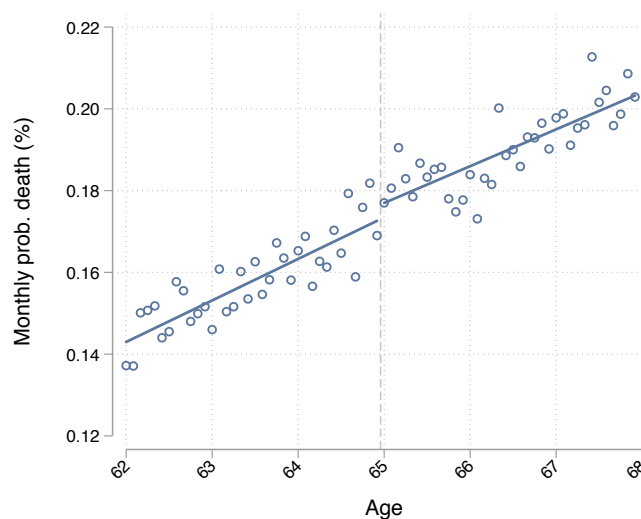
Notes: This figure shows the monthly probability of death for three years on each side of the universal Medicare age-65 eligibility cutoff. The X-axis shows age in months, and the Y-axis shows monthly probability of death. The figures show no large discontinuity or change in slope of monthly probability of death at the age-65 cutoff. Panels (a) – (c) show mortality for those with any health insurance, privately insured, or uninsured in years just before turning 65. Data come from restricted Census ACS, and insurance status is determined by respondents aged 55-62. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 2.

Figure 4 – Does Medicare Eligibility at Age-65 Reduce Mortality? (Heterogeneity by Income Level)

(a) High-Income

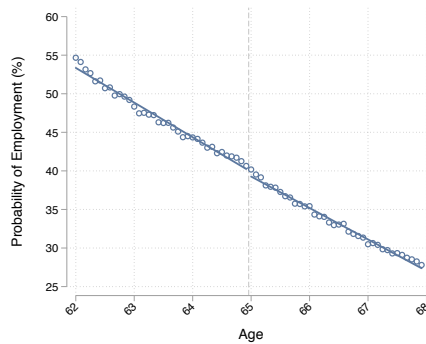


(b) Low-Income

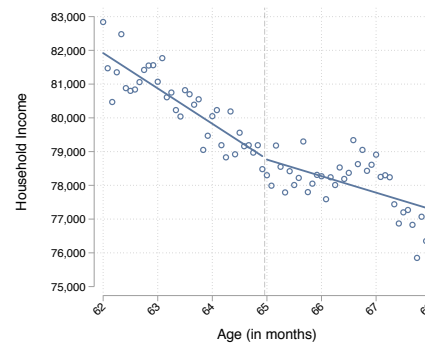


Note: This figure shows the monthly probability of death for three years on each side of the universal Medicare age-65 eligibility cutoff. The X-axis shows age in months, and the Y-axis shows monthly probability of death. Panels (a) and (b) show mortality for low-income and high income groups. Low-income individuals are those without a high school degree or below the Federal Poverty Line. High-income individuals are those in the top quartile of income. Data come from restricted Census 2000 long-form, and income status is determined by respondents aged 55-62. The corresponding regression discontinuity estimates on the effect of Medicare on mortality (Equation 1) are given in Table 2.

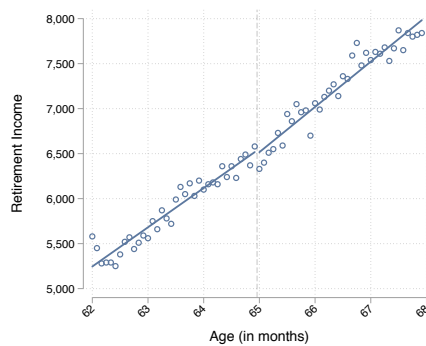
Figure 5 – Do Employment and Income Change at the Medicare Age-65 Eligibility Cutoff? (Robustness)



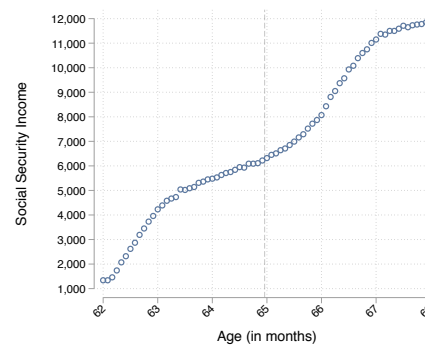
(a) Employment



(b) Household Income



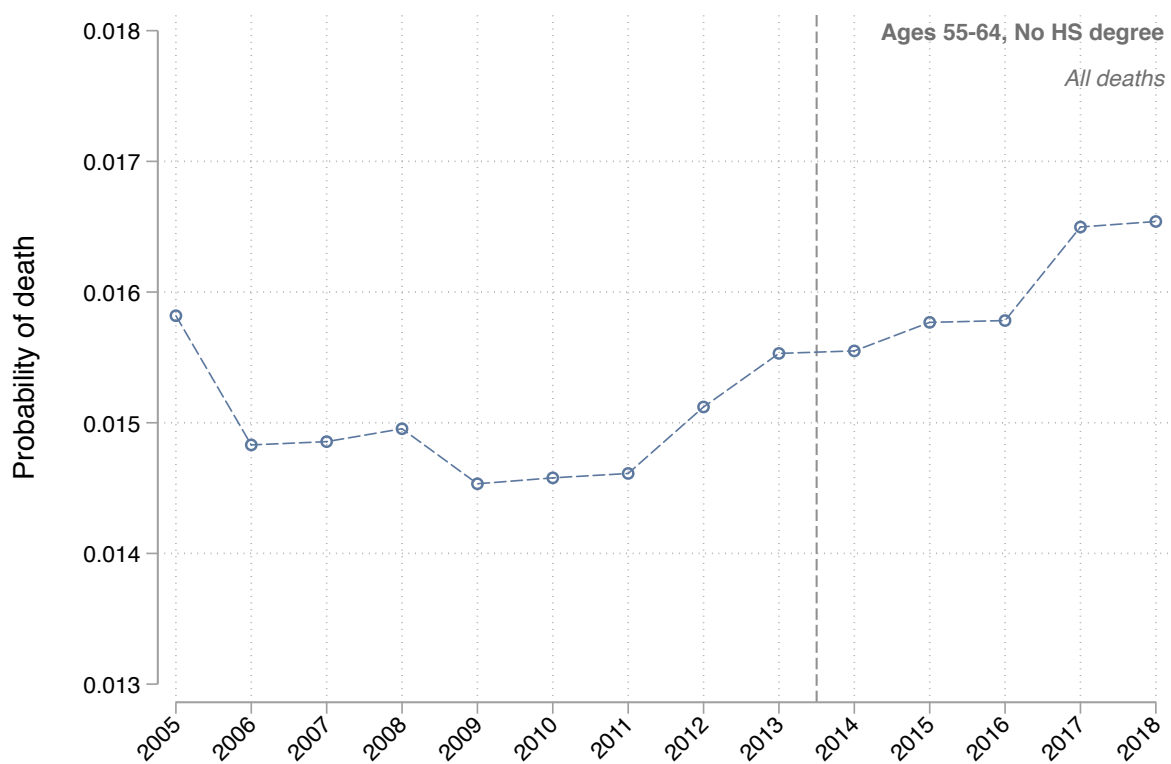
(c) Retirement Income



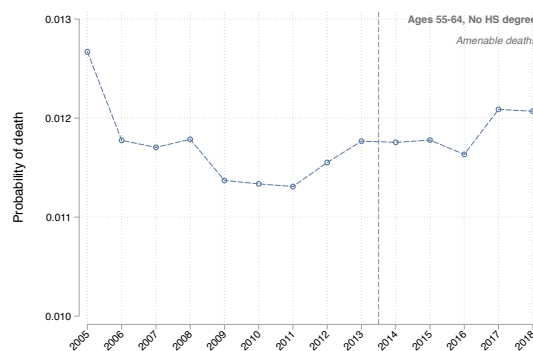
(d) Social Security Income

Notes: This figure shows whether employment, household income, social security income, and retirement income jump at the Medicare eligibility age-65 cutoff. The X-axis measures age in months, and the Y-axis show probability of employment or income. These factors are associated with mortality, and a discontinuous change in these variables at the Medicare eligibility age-65 cutoff could confound our results. We find no jumps at the cutoff. Data come from restricted Census ACS surveys (2001-2017).

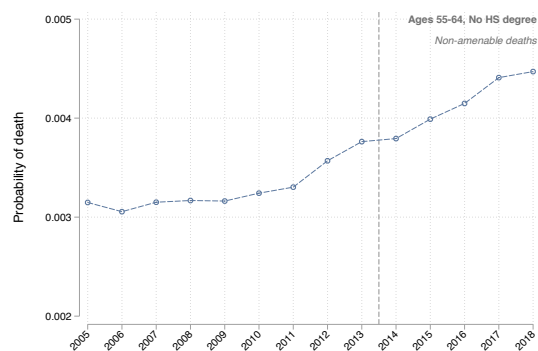
Figure 6 – Annual Mortality Trends (Ages 55-64, No HS)



(a) Total Deaths



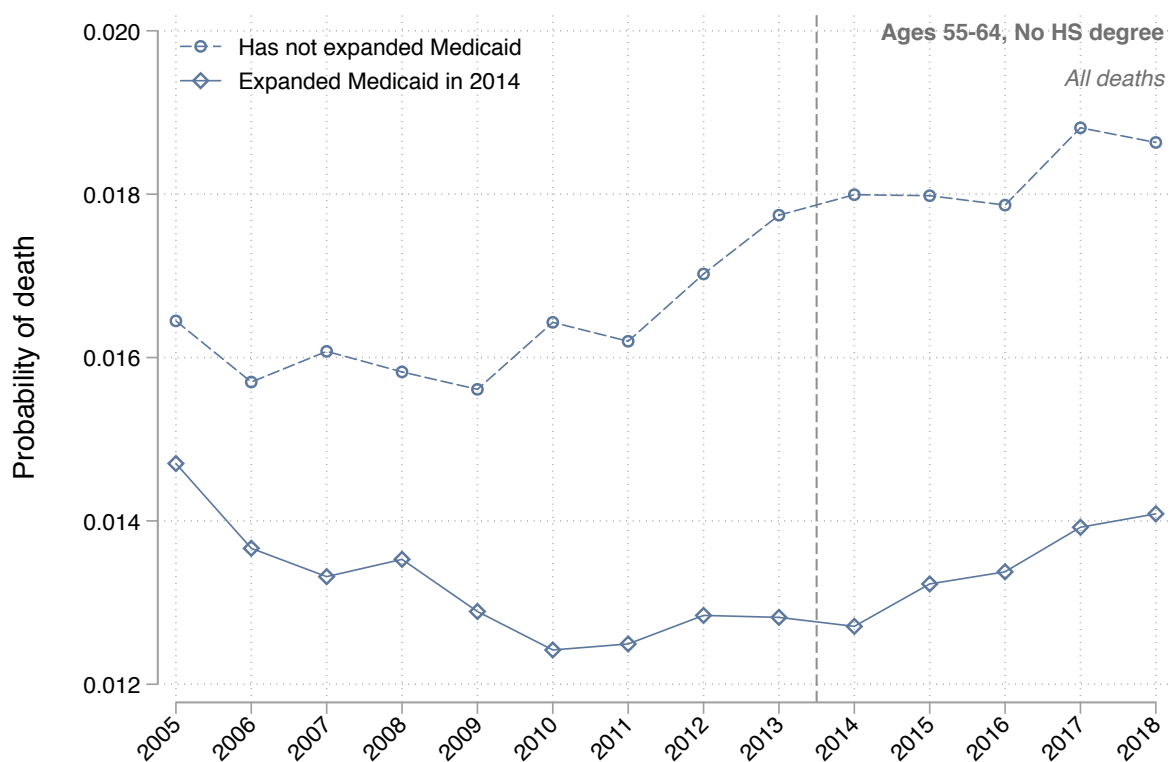
(b) Amenable Deaths



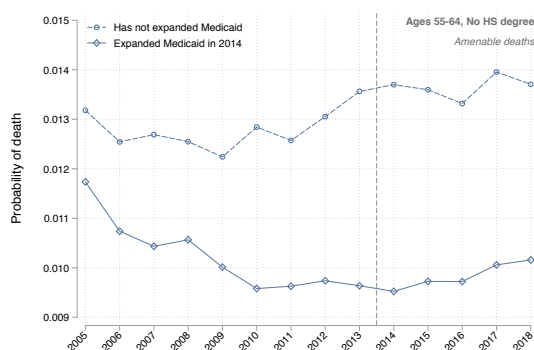
(c) Non-amenable Deaths

Notes: This figure shows trends in annual probability of death for those aged 55-64 without a HS education. Panel (a) shows all-cause mortality, and Panels (b) and (c) breakdown the mortality trends into amenable deaths (those that could be affected with quality health care) and non-amenable deaths. Data come from CDC vital stats.

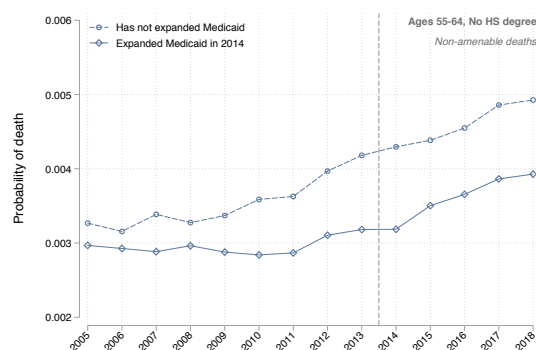
Figure 7 – Annual Mortality Trends (Ages 55-64, No HS) - ACA Medicaid Expansion vs. Non-Expansion States



(a) Total Deaths



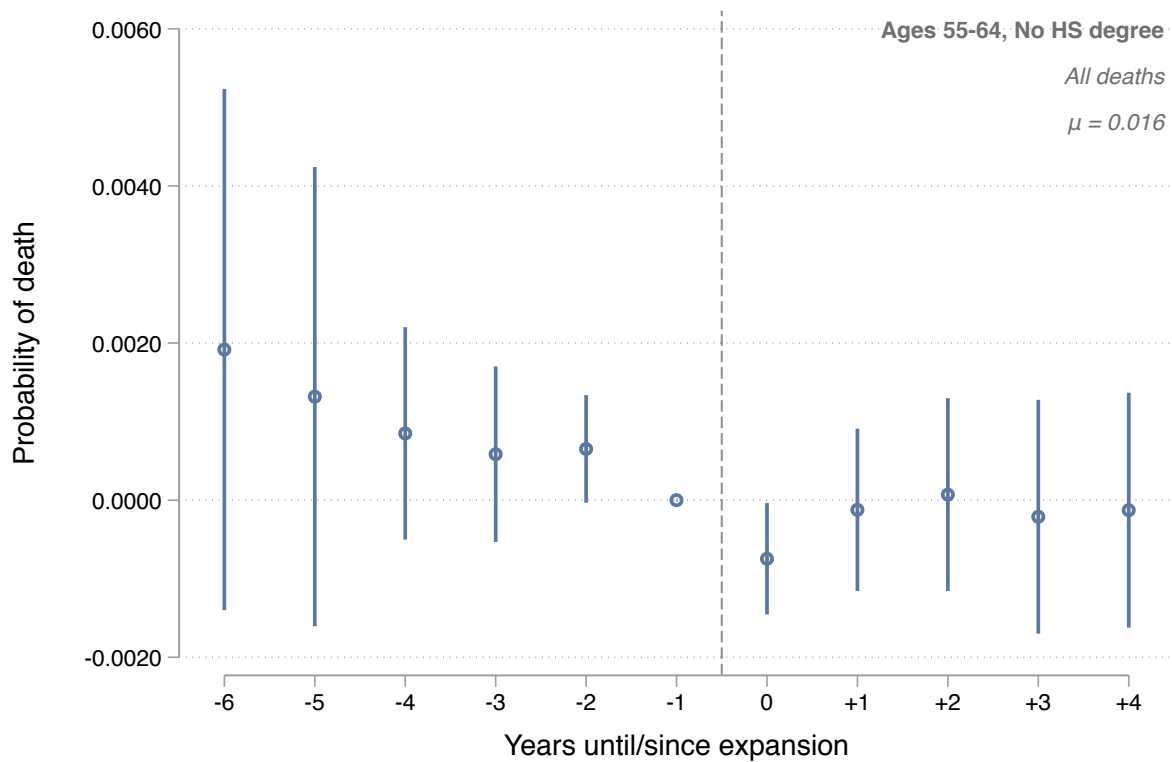
(b) Amenable Deaths



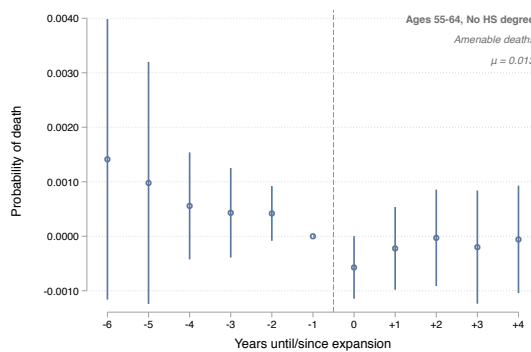
(c) Non-amenable Deaths

Notes: This figure breaks down the changes in mortality by treatment and control states - that is, states that expanded Medicaid through the ACA vs. states that did not. We omit states that are not included in our differences-in-differences regression (Equation 2) - states that expanded Medicaid before the ACA (MA, NY, DE, DC, VT). We also omit here states that expanded Medicaid from 2015 to 2018, so that only the 2014 Medicaid Expansion states are included in the expansion group. This figure shows a diverging trend in mortality between expansion and non-expansion states in the years just before the expansion. Panel (a) shows all-cause mortality, and Panels (b) and (c) breakdown the mortality trends into amenable deaths and non-amenable deaths. Data come from CDC vital stats.

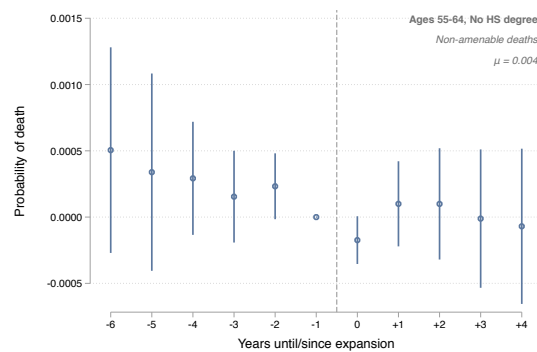
Figure 8 – Differences-in-Differences Event Study (Ages 55-64, No HS) - ACA Medicaid Expansion vs. Non-Expansion States



(a) Total Deaths



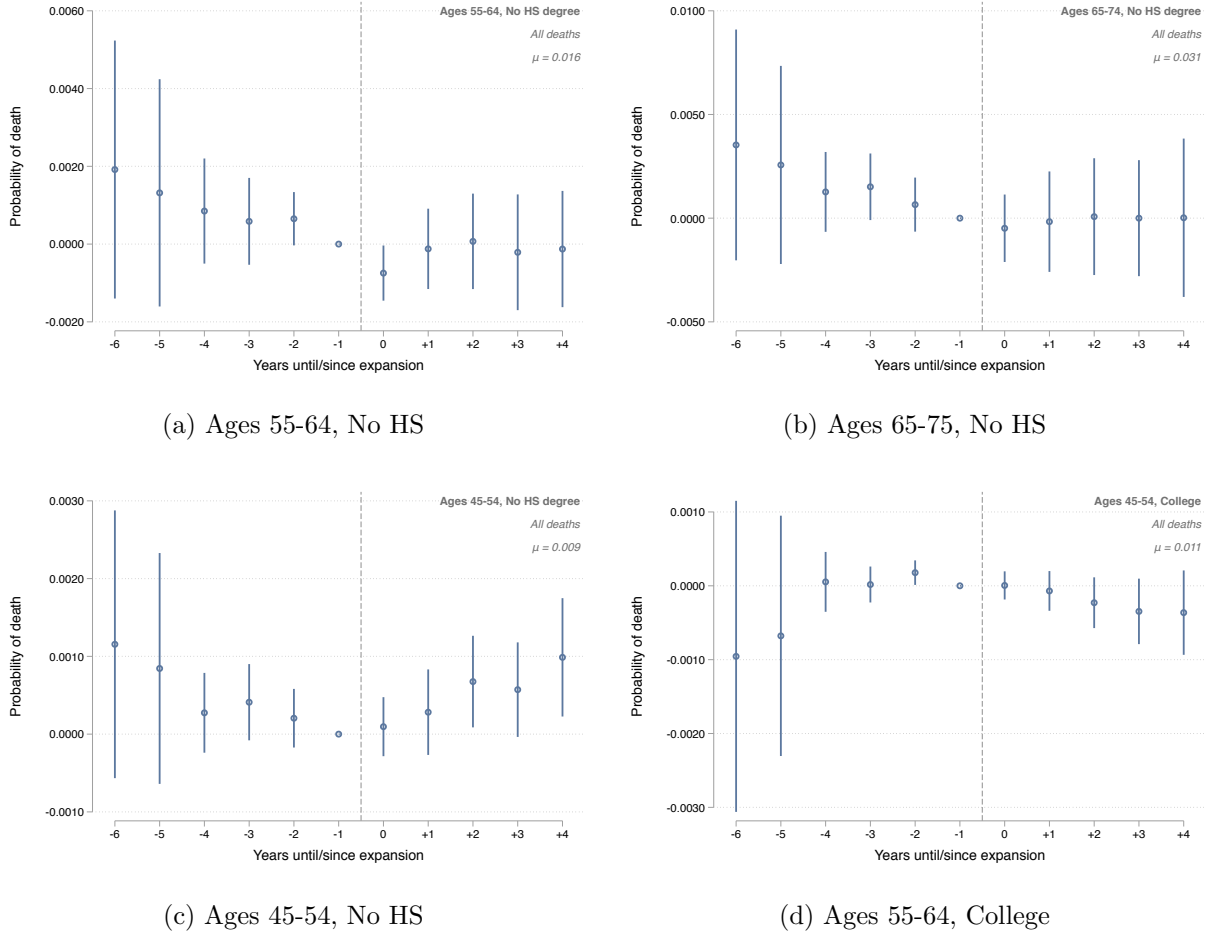
(b) Amenable Deaths



(c) Non-amenable Deaths

Notes: This figure shows the results of Equation 2, a differences-in-differences event study regression that examines whether the ACA Medicaid Expansion reduced mortality. The year before a state expanded Medicaid is the baseline year of "-1", and the X-axis shows the years before and after a state expanded Medicaid. The Y-axis shows the annual probability of death for individuals aged 55-64 without a high school degree. Panel (a) shows the results for all-cause mortality, and Panels (b) and (c) show the results for amenable and non-amenable deaths, respectively. μ gives the average probability of death in 2013, which will be the baseline year for most expansion states. The differences-in-differences estimate suggests a violation of the parallel trends assumption. Data come from CDC vital stats.

Figure 9 – Differences-in-Differences Event Study - Placebo Groups



Notes: This figure shows the results of Equation 2, a differences-in-differences event study regression that examines whether the ACA Medicaid Expansion reduced mortality. The year before a state expanded Medicaid is the baseline year of “-1”, and the X-axis shows the years before and after a state expanded Medicaid. The Y-axis shows the annual probability of death. Panels (a)-(d) differ in the age group and education attainment of the sample. Our primary sample is individuals aged 55-64, without a high school degree (Panel (a)). We examine placebo groups of different ages and education levels in Panels (b) - (d). μ gives the average probability of death in 2013, which will be the baseline year for most expansion states. The differences-in-differences estimate suggests a violation of the parallel trends assumption. Data come from CDC vital stats.

Tables

Table 1 – Does Medicare Eligibility at Age-65 Reduce Mortality?

	Demographics			
	(1) Full	(2) Black	(3) Male	(4) Female
Medicare Eligibility	−0.00445 (0.00274)	0.00127 (0.00705)	−0.00620 ** (0.00302)	−0.00262 (0.00413)
Sample Size (000s)	49.850	5.503	25.320	24.530

Notes: This table shows the regression discontinuity estimates for the effects of Medicare eligibility at age 65 on mortality. The treatment effect of Medicare eligibility on mortality, δ from Equation 1, is shown in the first line of the table, *Medicare Eligibility*. This estimate gives the change in the monthly probability of death around the age-65 eligibility cutoff (ex. -0.45% change in monthly probability of death for the full US population). Sample sizes for each population are approximations (in thousands), as we cannot disclose the denominators used to calculate the monthly probability of death measures. Data come from the Census Numident administrative death records.

Table 2 – Does Medicare Eligibility at Age-65 Reduce Mortality? (Heterogeneity by Income Level and Previous Insurance Status)

	Insurance			Income	
	(1) Insured	(2) Private	(3) Uninsured	(4) Low-income	(5) High-Income
Med. Elig.	−0.02019 (0.01871)	−0.01759 (0.02162)	0.01850 (0.04473)	0.01926 (0.01575)	0.00728 (0.02220)
Size 000s	874	785	97.5	574	588

Notes: This table shows the regression discontinuity estimates for the effects of Medicare eligibility at age 65 on mortality. The treatment effect of Medicare eligibility on mortality, δ from Equation 1, is shown in the first line of the table, *Medicare Eligibility*. This estimate gives the change in the monthly probability of death around the age-65 eligibility cutoff by (as given by survey respondents aged 55-62) previous insurance and income status. Sample sizes for each population are approximations (in thousands), as we cannot disclose the denominators used to calculate the monthly probability of death measures. Data come from the restricted Census 2008-2017 ACS and 2000 Census Longform.