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Abstract

Healthcare for the Elderly

by

Liam Rose

This dissertation explores health care utilization and provision for the elderly. My research aims to answer questions about the health effects of specific types of care, government and insurance policies, and major life events.

The first chapter, entitled "Retirement and Health: Evidence from England," investigates the effects of retirement on individual health. With many governments actively considering incentivizing longer working lives by raising the minimum age for pension programs, I examine the discontinuity at the State Pension Age in order to find the causal effect of retirement on health behaviors, health outcomes, health care utilization, and mortality. I focus on England due to a clearly-defined pension age and lack of confounding government programs, and use a full range of novel datasets, including census records, large nationwide surveys, and mortality records. I find that retirement substantially improves well-being, self-reported health, and decreases the proportion of people reporting long-term illnesses and disabilities. However, there is no evidence of an immediate effect on cognitive ability, health behaviors, or health care utilization. Consistent with this, I further show that there is no effect of retirement on mortality. Finally, I show that individuals' show signs of lower stress, with changes to both health markers and day-to-day activities. My estimates are generally more precise

than those found in previous literature, and this paper is the first to examine a full range of health-related outcomes with administrative and survey data in a unified context.

The second chapter investigates the effect of skilled nursing facilities. Here, I leverage a Medicare policy that induces a sharp change in the probability of being discharged to a skilled nursing facility (SNF) in order to generate causal estimates of the health effects of this type of care. Despite being a significant source of health care spending and of Medicare's annual budget, SNF care has been understudied, with systematic differences in individuals that enter into a SNF. The identification of this paper uses Medicare's requirement of a three-day stay in order to cover SNF care. Using inpatient and emergency department records, I find that those that narrowly made the cutoff experience a substantial increase in the probability of being discharged to a SNF, and a subsequent decrease in readmission probability.

The third chapter explores the long-term effects of month of birth on self-reported health and morality rates. I use data from the Census of England and Wales and death certificates from the Office of National Statistics to examine these effects, focusing on a large sample of individuals born between 1940 and 1960. I find that individuals born in fall and early winter months are less likely to report being in poor health and have better mortality rates, particularly compared to those born in late spring and summer.

To my parents, who gave unconditional support

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Part I

Retirement and Health: Evidence from England

Chapter 1

Retirement and Health: Evidence from England

1.1 Introduction

Life expectancy has jumped dramatically in the last century, with much of the change concentrated in life expectancy at birth. However, health conditional on age has also improved substantially, and life expectancy at advanced ages has seen large increases. Entitlement programs for the elderly have only recently begun to adjust to these changes. In England, the state pension age has been constant for men since 1925, while life expectancy for British citizens at age 50 has increased from 75 in 1955 to 82.6 in 2011 (Human Mortality Database). Similarly in the United States, the age for full retirement benefits under social security has increased just one year since the program's inception in 1935, while life expectancy at age 50 has increased by 8.8 years (CDC). This trend has led policymakers to consider and implement increases in the normal retirement age as governments face budget shortfalls due to an increase in the average duration of retirement.

These policy debates have spurred an increased interest in the link between retirement and health outcomes. Leaving the labor force releases many individuals from day-to-day sources of stress and greatly increases leisure time. In the cross section, however, health deteriorates with age, and acute changes to health can push individuals into retirement earlier than expected. This interdependence has made it difficult to accurately assess what effect retirement has on lifestyle and health outcomes, and the direction of this relationship is theoretically ambiguous. Providing labor is often stressful and taxing, and relieving an individual of this burden may improve the individual's health (Ekerdt, Bosse, and LoCastro 1983). Yet it may also be the case that retirement leads to a loss of well-being, as individuals often lose the social network of their coworkers and may feel less useful to society (Szinovacz, Vinick, and Ekerdt 1992). Empirical studies that adjust for observable differences have often found negative effects of retirement, but some researchers have found positive effects as well.[1] More recently, researchers have attempted to disentangle this relationship using variation in retirement probabilities induced by pension rules (Kofi Charles 2004, Gorry, Gorry, and Slavov 2016), early retirement incentives (Kuhn, Wuellrich, and Zweimüller 2010, Bloemen, Hochguertel, and Zweerink 2017, Hernaes et al. 2013, Hallberg, Johansson, and Josephson 2015), or cross-country differences (Coe and Zamarro 2011), yet results have been inconclusive,

1. Minkler (1981) gives a review of the idea that retirement harms health, including some correlational studies that show null or positive effects on health.

with some finding beneficial effects of retirement and others showing starkly detrimental effects – including on the likelihood of mortality.

I contribute to the literature by comprehensively tracing out the effect of reaching retirement age on individual's lifestyles, health care utilization, health outcomes, and chances of mortality. I focus on England due to a clearly defined age-based pension rule and a lack of any confounding programs in the same age range. In particular, retirement does not coincide with a change in access to or cost of health care. This setup lends itself to applying a regression discontinuity design around the pension age. By using a multitude of data sources – including census data, large cross-sectional and longitudinal surveys, and mortality records – I am able to provide both precise estimates and multiple estimates for the same outcomes, ensuring robustness of results. As such, I am able to provide an exhaustive view of the transition individuals face upon reaching the pension age.

I break the causal chain of retirement into four stages. The standard first stage is to verify reaching the state pension age increases the probability of retirement. Next, I examine behavioral and environmental changes that could affect an individual's health status. This includes health behaviors – such as smoking, drinking, exercising, and regular contact with friends and family – along with health care utilization, the change in environment of daily activity, and the additional income from the state pension. Following this, I investigate health outcomes, which can be split into self-reported measures and objective measures, such as scores on cognitive tests and vital signs. The final step is mortality. These classifications are useful for analyzing the mechanisms through which retirement can change an individual's health status.

Recent quasi-experimental studies provide an ambiguous picture of what effects retirement should have on health. Kofi Charles (2004) and Neuman (2008) use age-specific cutoffs as instruments for social security in the U.S., finding a positive effect on self-reported well-being, but no effect on health outcomes. Conversely, Coe and Zamarro (2011) use cross-country variation in pension rules in Europe and find a strong positive effect on health outcomes but null effects on health behaviors. Bloemen, Hochguertel, and Zweerink (2017) and Hallberg, Johansson, and Josephson (2015) use targeted retirement programs that induced early retirements, with both finding positive effects on mortality rates. In contrast, Kuhn, Wuellrich, and Zweimüller (2010) also uses exogenous access to early retirement and find *negative* effects on mortality rates, while Hernaes et al. (2013) do not find an effect in either direction. Two recent studies focusing on the social security age in the U.S. have found vastly different results. Gorry, Gorry, and Slavov (2016) use the social security eligibility age and eligibility for employer pensions as instruments to show that retirement improves both health and life satisfaction. Using the same population and age in an RD setting, Fitzpatrick and Moore (2016) find that retirement induces a sharp increase in mortality rates.

Various factors could result in these seemingly contradictory estimates, especially the application of different research designs to different populations. Further, these papers often face data limitations that impact estimation and institutional factors that impact identification. Thus, instead of focusing on a narrow set of outcomes, this paper seeks to trace out the outcomes in the causal chain of retirement and health within a unified context. Using multiple data sources for contemporaneous cohorts of retirees in the U.K., I mimic the methods utilized in previous works to generate a rich picture of the transition an individual faces when leaving the work force. To my knowledge, this paper is the first to integrate administrative records and comprehensive surveys from the same population, allowing for both a much larger sample size and robustness checks not available to other researchers.

I first find that reaching the state pension age induces a large portion of the English population to retire. This effect is somewhat larger for men than for women, with the latter able to collect the state pension at a younger age. Further, this effect is nearly twice as large for those without post-secondary education.

I show that that retirement substantially improves individuals' self-reported health. I find that retirement reduces the proportion of people that report being in poor health, and the probability that they report having a persistent health problem. This result is significant across data sets and robust to specification changes.

Next, I investigate potential sources of this abrupt improvement. I find no evidence of an immediate change in health care utilization, and limited evidence of positive effects in health behaviors such as frequent exercise, smoking, and social contact. In contrast with previous results, I find no evidence of an immediate change in cognitive and memory scores. I do, however, show that individuals show signs of lower stress in both subjective and objective measures, and that they report higher life satisfaction. I further show that they substitute their time from working into sleep and leisure. Congruent with these results, death certificate data show that there is no effect of retirement on mortality.

These results advance the understanding of the relationship between retirement and health in several important ways. The first is that individuals clearly report better health after retirement, but show little movement in key outcomes such as utilization, cognitive ability, and mortality. This confirms recent studies showing that the negative correlation between retirement and health is an artifact of the endogeneity of the retirement decision, and suggests that the effect is due to no longer providing labor rather than behavioral changes by the individual. This fits with a large neuroscience literature on long-term effects of stress on overall health.[2] Next, this paper shows that many results are sensitive to data source and research design, and my approach allows for extensive robustness checks. This indicates that studies using a specific data source should be interpreted cautiously when discussing external validity. Perhaps most importantly, the approach taken in this paper provides a clear framework to think about how retirement could affect the most salient health outcomes, such as mental health, utilization, and mortality. Without negative effects in health behaviors and health outcomes, it is difficult to conceive of a mechanism that would cause retirement to be linked to cognitive decline or increased mortality rates.

The rest of the paper proceeds as follows. Section 2 examines previous work on the link between retirement and health, and provides institutional background on the state pension. Section 3 details the data sources used and identification strategy. Section 4 gives results, and Section 5 compares results directly to previous literature and

2. See, for example, Cooper and Marshall (2013), or Sapolsky (2004) for an accessible review.

concludes.

1.2 Background

1.2.1 Retirement and Health

Early work on the relationship between retirement and health frequently stemmed from the psychology literature and broadly characterized the associations between retirement and subjective well-being. A strong majority of these studies conclude a negative relationship, with retirement associated with lower life satisfaction (Bossé et al. 1987), depression (Portnoi 1983), and lower well-being (Atchley and Robinson 1982, Grâce et al. 1994, among others). This relationship is also reported for physical ailments, such as cardiovascular disease (Moon et al. 2012). These studies describe the negative relationship when individuals retire, but lack the capacity to take the endogeneity of the decision into account. Without this, it is not possible to conclude whether this negative relationship is because of retirement, or if those in poor health are simply more likely to retire.[3]

More recently, researchers have attempted to disentangle these effects using a

3. There is an extensive literature examining the relationship between retirement and health that corrects for observable characteristics, and many of these studies find the negative relationship discussed above. However, others have found positive effects of retirement. Mein et al. (2003) examine civil servants and show that mental health worsened for those that continued working for high socioeconomic status individuals. Westerlund et al. (2009) find that retirement reduces the proportion of French gas and electric company workers that report being in poor health, although this same group did not have decreased episodes of respiratory disease, diabetes, coronary disease, or fatigue (Westerlund et al. 2010). Jokela et al. (2010) find a negative effect on mental health for those that retired due to ill health, but a positive effect for those that retired voluntarily or at the pension age. Lupton et al. (2010) find that a later retirement delays the onset of Alzheimer's disease, and Butterworth et al. (2006) that only that those retired early had significantly worse mental health. Drentea (2002) show that retirees report less anxiety and distress, but is not associated with symptoms of depression, and Midanik et al. (1995) find less reported stress for retirees.

variety of techniques. As mentioned previously, this includes long-standing retirement and pension rules, early and unexpected retirement incentives, and cross-country variation. Regardless of identification strategy, these studies tend to focus on a particular subset of health-related outcomes.

Of these, health behaviors have been given the least attention. These outcomes are often difficult to measure, and are potentially more subject to biases inherent to surveys. Insler (2014) used individuals' predicted retirement age from the Health and Retirement Survey (HRS) as an instrument to find that retirement increases exercise and decreases smoking. Using pension rules in Germany, Eibich (2015) show that retirement increases activity, sleep, and leisure time activities, and that it decreases smoking rates and BMI. Müller and Shaikh (2017) used the Survey of Health, Ageing and Retirement in Europe (SHARE) in an RD design to show that a spouse's retirement increases physical activity, but also increases cigarette and alcohol consumption. Motegi, Nishimura, and Terada (2016) also find that retirement increases exercise for Japanese retirees, but show that retirement *reduces* drinking and does not change smoking rates.

In contrast, the effect of retirement on health outcomes has been extensively studied. Within this broad category, the effect on mental health and cognitive ability have been of particular interest. Kofi Charles (2004) was the first to examine this relationship with a causal argument, using both the age of Social Security benefit eligibility and a change in laws affecting when Social Security can first be withdrawn. With this, he finds retirement has a positive effect on mental health measured with two indicators for loneliness and depression. Rohwedder and Willis (2010) investigate the observation that countries that have a larger proportion of the work force working later in life also have a smaller difference in cognitive performance between older and younger men. Using cross-country variation in eligibility ages for early and full public pension benefits, they find that retirement reduces cognitive scores by nearly 1.5 standard deviations. This finding kicked off a wave of interest in the topic. Leveraging eligibility ages as instruments, Bonsang, Adam, and Perelman (2012), Mazzonna and Peracchi (2012), and Tumino et al. (2016) find a negative effect on cognitive function, although Coe and Zamarro (2011) do not find any effect. Coe et al. (2012) also does not find an effect using exogenous offers of early retirement windows. However, Bingley and Martinello (2013) point out that cross-country differences in eligibility ages is invalid as an instrument without education controls due to being correlated with differences in years of schooling, and argue that failing to do so results in a negative bias that would explain a large portion of these results that report a negative effect of retirement.

With a persistent notion that retirement harms health, the relationship between retirement and physical health has also been examined extensively. Of course, the way in which physical health is measured varies widely, with subjective measures frequently used due to their ease of collection in surveys. Coe and Zamarro (2011) use early and full retirement ages across European countries as instruments to show substantial positive effects of retirement on self-reported health. Neuman (2008) finds similar results in the U.S., also using early and full retirement ages as instruments. Gorry, Gorry, and Slavov (2016) uses a similar set of instruments in the U.S. and also find that retirement improves self-reported health and life satisfaction. Insler (2014) instead uses individuals' expected retirement age as an instrument, again finding positive effects on self-reported health status.

Works using different identification strategies have shown similar results.[4] Using the Health Survey for England in a regression discontinuity setting, Johnston and Lee (2009) find positive effects of retirement on self-reported health and mental health.[5] Bound and Waidmann (2007) compare trends before and after the state pension age in England and find a small positive effect on physical health for men, as measured by self-reported measures and blood tests. The RD design used by Eibich (2015) also reports an improvement in self-reported health, as does Zhu (2016) evaluation of a change in the Australian pension eligibility age.[6] Behncke (2012) combines the IV model with propensity score matching using the ELSA in England, concluding that retirement increases the probability that an individual is diagnosed with a chronic condition.

As part of the effect of retirement on health outcomes, some studies have included outcomes related to the effect on healthcare utilization. This has particularly important policy implications, as changes to retirement eligibility ages could significantly impact the budgets of government healthcare programs. Eibich (2015) finds that retirement reduces the number of annual doctor visits but not the probability of a hospital admission, while Hallberg, Johansson, and Josephson (2015) does show a reduction

4. Dave, Rashad, and Spasojevic (2008) does find negative effects on mobility and daily activity as well as the number of health issues. Later studies, however, show that simply including individual-level fixed effects is not likely to account for all unobserved selection. Insler (2014), for example, directly compares a fixed effects model to the FE-IV model and shows that negative effects can be reversed or nullified with the latter approach.

5. This work is essentially replicated as a part of this paper, with consistent results.

6. This change in the eligibility age — increasing the eligibility age at a rate of six months every two years – is similar but not identical to the one implemented by the UK starting in 2011.

in the number of hospital inpatient days. However, Caroli, Lucifora, Vigani, et al. (2016) find an increase in the number of doctor's visits, and Gorry, Gorry, and Slavov (2016) find no effect on utilization.

With limited evidence that retirement affects health behaviors and mixed evidence on health outcomes, it seems unlikely that leaving the labor force could cause immediate changes to the probability of mortality without substantial contemporaneous changes to life circumstances. Nevertheless, multiple studies have founds effects in this area. Bloemen, Hochguertel, and Zweerink (2017) use an exogenous shock to retirement eligibility for a group of public employees in the Netherlands to estimate the effect of retirement on the probability of mortality within five years. They find that retirement decreased the probability of mortality by 2.5 percentage points. Hallberg, Johansson, and Josephson (2015) finds similar effects with a similar program for Swedish army officers. Conversely, Fitzpatrick and Moore (2016) use the Social Security age in the U.S. in a regression discontinuity setting to estimate an *increase* in the probability of mortality by 2 percentage points for men, and Kuhn, Wuellrich, and Zweimüller (2010) find similar effect sizes using an exogenous change to unemployment rules in Austria. Finally, Hernaes et al. (2013) finds no effect on mortality among Norwegian workers exposed earlier to a rollout of early retirement rules, and Bound and Waidmann (2007) and Coe and Lindeboom (2008) both find no effect on mortality.

1.2.2 England State Pension

The English State Pension system has been the subject of intense political discussion and action in recent years, with political parties making reform a key part of their platforms and legislation. Here, I provide context for this debate and details for how the pension applied to the population examined in this study.

The system began in 1908 with the Old Age Pensions Act, which gave a maximum of 5 schillings a week – or 7 schillings 6 pence to married couples – to qualified individuals over the age of 70.[7] The full amount was given to those that earned 21 pounds per year, and reduced for those that earned more, up to a maximum of 31 pounds and 10 schillings in earnings per year. Nearly 600,000 individuals were granted the pension upon implementation of the law, which was to be funded by younger generations. At that time, life expectancy at 70 was just under 10 years (Office for National Statistics).

In 1925, the first contributory pension system was introduced. The Widows', Orphans', and Old-Age Contributory Pensions Act was based on contributions paid by both the employer and the employee, and removed the means-test while also lowering the age of eligibility to 65. Importantly, the higher rate for married couples was only paid after both individuals reached their 65th birthdays. This was altered in 1940 by lowering the eligibility age for women to 60. The National Insurance Act 1946 made contributions to the state pension mandatory, insuring universal social security.

The next reforms to the basic state pension did not come until 1995, with

7. Individuals that did not qualify included those that received poor relief, "lunatics" in a state of asylum, ex-convicts that had been out of prison for less than 10 years, individuals convicted of drunkenness, and individuals guilty of "habitual failure to work". Further, there was a "character test", requiring recipients to be in good character.

the Pensions Act 1995. This raised the pension age for women to 65 as well, with the change happening gradually from April 2010 to April 2020 based on birth date. The pension age was further increased for both genders to 68, with the change scheduled to take place between 2024 and 2046. Finally, this law also lowered the number of years of work required for full payment for both genders to 30. With a change of government in 2010, the Conservative Party decided to increase the pace of gender equalization with the Pensions Act 2011, which pushed the date of equal pension ages to November 2018. Further, the law scheduled the increase for both genders to move from 65 to 66 from November 2018 to October 2020.

In addition to the basic state pension, the UK has had several earnings-based pension schemes sponsored by the government. The State Earnings Related Pension Scheme (SERPS) ran from 1978-2002, with employees contributing over their working lives to receive a portion of the earnings above a "lower earning limit", which was about the amount of the basic state pension. At the outset of the scheme, individuals received 25 percent of their earnings, although this was lowered to 20 percent in 1988.[8] The pension was proportional to the number of years spent contributing for those that retired before 1998. Further, employers could choose to opt out of SERPS if they had a final-salary pension scheme, and in turn would pay reduced National Insurance contributions.

SERPS was replaced in 2002 by the State Second Pension (S2P), with the goal of increasing payouts to low-income earners. S2P operates similarly to SERPS, but treat

8. Specifically, the pension was calculated by taking the total yearly earnings that fell between the "lower earning limit" and the "upper earning limit" in a tax year, then dividing this number by 4 (from 1978-1998) or 5 (from 1988-2002, although this was phased in). This amount is then divided by the number tax years that the individual made contributions.

earnings below the lower earning limit as if they were at the threshold, and redistributes the percent of total earnings – from 20 percent for all levels to 40 percent for earnings at the lower earning limit, 10 percent for those in the middle, and 20 percent for those at the upper earning limit. The reform also included individuals with long-term illnesses and disabilities who had previously only been eligible for the basic state pension. The S2P, however, is in the process of being phased out. Following the Pensions Act 2014, for those that reached the state pension age after April 6, 2016, a more generous flat-rate state pension payment of £155.65 per week.[9]

Individuals are allowed to continue working while receiving the state pension. Additionally, personal pensions registered with HM Revenue and Customs (HMRC) can be contributed to tax-free within certain limits. Contributions are tax-free if they are under 100 percent of yearly earnings, £40,000, and £1 million in an individual's lifetime. Personal pensions can be accessed without a tax penalty 10 years earlier than the state pension age.

As discussed below, this paper uses data from 1990-2011. The full pension benefit varied over this time period, but was capped at £102.15 per week in 2011. Increases occurred annually at a rate that was the highest of the average percentage growth in wages in Great Britain, the UK CPI, or 2.5 percent.

9. During a transitional period, this amount could be higher if expected S2P payments were over a certain amount. The amount can also be higher if an individual chooses to defer payment, at a rate of 5.8 percent per year increase.

1.3 Data and Methodology

1.3.1 Data Sources

I use multiple comprehensive data sources to obtain a clear picture into the transition individuals face at retirement.

First, I use data from the 2001 and 2011 England and Wales Censuses. The Census of the United Kingdom takes places on a decennial basis, and is conducted by the Office of National Statistic (ONS) in England and Wales. With mandatory participation, these data allow for nearly universal information on an individual's labor market status, as well as the populations in each month-of-birth cohort.[10] For 2011, this gives a sample population of just under 57 million. In addition to retirement information, both censuses include two questions on individuals' health, asking how their health was in general and if they have a long-term disability or illness.

Next, I use a number of large-scale surveys conducted in England and Wales. Of these, some are cross-sectional in nature and others have a panel structure. For those that are a panel, I also stack across waves when utilizing an RD framework.

The English Longitudinal Survey on Aging (ELSA) is a household survey examining the health and quality of life of the elderly. It is modeled closely after the Health and Retirement Study (HRS) that takes place in the United States, with many of the same questions asked. I use the Harmonized ELSA files that are designed to imitate the RAND HRS files, such that variable names and definitions line up closely. This allows

10. Those who do not fill out a census form face a maximum fine of £1,000 and a criminal record.

for easy comparison of results with other work in the retirement and health literature that utilize the HRS.[11] These files use waves 1-6, which were conducted from 2002 to 2013. The first wave consisted of 11,050 respondents all above the age of 50. The survey asks a comprehensive set of questions, allowing it to be used for retirement outcomes, health behaviors outcomes, and health outcomes.

The British Household Panel Survey (BHPS) was conducted from 1991-2009 by the Institute for Social and Economic Research (ISER) at the University of Essex. The survey was done annually for each adult member of a nationally representative sample of households, giving about 10,000 respondents. The enumerators also followed adult children if they split from the original household, and included all adult members of the new household as well. The questions are wide-ranging in nature and are designed to examine social and economic changes at the household and individual level. This dataset also includes more refined birth cohort measures, allowing for improved RD estimates. The BHPS asks an even more wide range of questions than the ELSA, and it can be used for retirement outcomes, health behavior outcomes, and health outcomes.

The Health Survey for England (HSE) is an annual survey put on by the Information Centre for Health and Social Care and the Department of Health. It has been ongoing since 1991, with about 8,000 adults and 2,000 children responding each year. After information is collected with an interview, a specialty nurse will visit if the participant agrees. I use data from 2000-2009, giving nearly 150,000 responses. The HSE is cross-sectional, and is used for retirement outcomes, health behavior outcomes,

11. Some examples include Bonsang, Adam, and Perelman (2012), Insler (2014), and Gorry, Gorry, and Slavov (2016).

and health outcomes.

The England labor Force Survey is a large survey on labor market conditions that is conducted quarterly. I use data from 1992-2001 for a sample population of 6.1 million. Here, the data is used for the purposes of garnering another estimate of the effect of the State Pension Age on retirement status with a question asking if the individual worked in the previous week.

Inpatient admission data come from the National Health Service (NHS) through the Hospital Episode Statistics (HES). These data include all inpatient admissions at NHS hospitals in England for a given year, and I utilize data from 1990-2010. This gives a near complete census of admission records for this time period, allowing for precise estimates of changes to health care utilization.

Finally, mortality data is provided by the Office of National Statistics (ONS). This includes counts of deaths by age, gender, and underlying cause. These data include all deaths that occurred in England between 1990 and 2011.

1.3.2 Methods

The question of interest is the effect of retirement on health, namely,

$$H_i = \beta_0 + \beta_1 R_i + \varepsilon_i$$

where R_i denotes the retirement status of individual i and H_i is the individual's health status. Retirement status could be endogenous, as a negative health shock could induce an individual to retire. To circumvent this, the primary approach in this paper is a regression discontinuity (RD) design, leveraging the threshold in eligibility for the state pension at the retirement age. This threshold allows for a clean examination of retirement, as — unlike in the United States — there are no other major benefits to reaching that age.[12] I use the following standard RD equation.

$$H_i = \alpha_0 + \alpha_1 StatePension_i + \alpha_2 Age_i + \alpha_3 Age_i * StatePension_i +$$
$$\alpha_4 Age_i^2 + \alpha_5 Age_i^2 * StatePension_i + \epsilon_i$$

where $StatePension_i$ is a dummy indicating if an individual is older than his or her age required to be eligible for the state pension. I use a bandwidth of 5 years when refined age measures are available and 10 years otherwise. Optimal bandwidth procedures (for example, Calonico, Cattaneo, and Titiunik 2014) suggest using bandwidths between 4 years and 12 years depending on the data source and outcome, with suggested bandwidths for sources with refined age measures generally around 5 years and suggested bandwidths for sources less refined measures around 8-10 years.[13] Robustness to bandwidth figures for some key results are shown in the appendix, with full robustness checks available on request.

One concern is that surveys may oversample retirees due their increased avail-

12. The only additional benefits to reaching retirement age is free local bus travel and annual winter fuel payments. Winter fuel payments are one-time tax-free payments made to eligible household in November or December and range from £100 to £300. These payments are sent automatically to those receiving the state pension.

13. As examples, the procedure developed in Calonico, Cattaneo, and Titiunik (2014) and Calonico et al. (2016) recommends a bandwidth of 9.4 years for the outcome of good self-reported health from the ELSA, 9.1 years for fair, and 9.1 years for bad; similarly, 7.6 years, 10.1 years, and 8.6 years for the same outcomes in the HSE.

ability. Figure A.3 shows that this is unlikely to be true, with age densities smooth across the state pension threshold for both genders.[14] Table A.10 further shows that demographic characteristics do not change across this threshold for either gender.

The secondary approach is nearly identical, but takes advantage of the panel structure of the longitudinal surveys. The fixed effects instrumental variables approach is the most common in recent literature, and similarly leverages a discrete change in retirement probability at an eligibility age.[15] This method includes individual fixed effects to account for time-invariant unobserved characteristics that are correlated with both retirement and health and time fixed effects to control for time-specific shocks in a given wave of a survey. However, controlling for time- and individual-level fixed effects do not account for negative health shocks that can induce retirement. The eligibility age is then used to instrument for retirement. For this to be a valid instrument, it must be correlated with retirement probability and affect health only through the act of retirement. The first assumption is easily verified with the first stage equation as follows:

$$R_{it} = \gamma_0 + \gamma_1 Z_{it} + \eta_t + \rho_i + \varepsilon_{it}$$

where R_{it} is individual i's retirement status in time t, Z_{it} is the set of instruments, η_t is a time fixed effect, and ρ_i is an individual fixed effect. The predicted values are then

14. The 2011 Census shows a spike in the density before the pension age for men and after the pension age for women, with this cohort inflated by the increase in the birthrate immediately following World War II. However, the should not affect the estimates, as outcomes are reported in proportions and the change in the birthrate did not happen discontinuously; McCrary tests report a p-value of 0.259 (McCrary 2008).

15. For example, Bonsang, Adam, and Perelman (2012), Coe et al. (2012), and Gorry, Gorry, and Slavov (2016) all use this approach.

used in the reduced form equation.

$$H_{it} = \delta_0 + \delta_1 \hat{R}_{it} + \eta_t + \rho_i + \varepsilon_{it}$$

Because discrete age thresholds should not affect health status directly, it is unlikely that this instrument can affect health outcomes through channels other than retirement. This is particularly true in England, where this age threshold is not associated with a change in health insurance coverage as it is in the U.S.

While both methods yield similar results, the advantage of the RD approach is to effectively pool survey participants by age group, allowing for more precise estimates and an abstraction away from issues with survey attrition. I can also pool across datasets when questions are sufficiently similar to further increase precision.[16] The FE-IV approach, however, does allow for multiple thresholds to be examined, such as the sharp changes in retirement probability in the United States at both ages 62 and 65.

1.4 Results

This paper comprehensively examines the changes an individual may experience upon leaving the labor force. I first establish the first stage effect of the pension age on retirement. Next, I show results on individuals' self-reported health. I explore these results by then examining the effect of retirement on health behavior, the effect of retirement on health outcomes and utilization, and the effect of the retirement on

16. Some outcomes are elicited in each of the ELSA, BHPS, and HSE. In these cases, I first standardize the outcomes within data source and then stack the data from these sources.

mortality. I then provide estimates for individuals without higher education, for whom effect sizes might be larger. Finally, I compare my results to those found in prior studies.

1.4.1 First Stage: Retirement at the Pension Age

First, I examine the proportion of workers that exit the labor force at the State Pension Age. Figures 1.1a and 1.1b give the age profiles for men and women, respectively, of retirement status centered around their respective state pension age from the 2011 England and Wales Census. Across genders there is a sharp and marked increase in the proportion of individuals retired, although the change is noticeably larger for men. Table 1.1 gives the complementary point estimates along with estimates from other data sources, with standard errors clustered by age in the RD estimates and by individual in the FE-IV regressions.[17] The proportion of men retired increases by about 20 percentage points according to the census, and increases by about 10 percentage points for women from the same data source. Because these estimates are generated from the entire population, these are the preferred estimates. Estimates from the HSE and ELSA are higher, and FE-IV estimates shown in Panel (B) give similar estimates. As expected, the state pension age strongly predicts the probability of retirement.

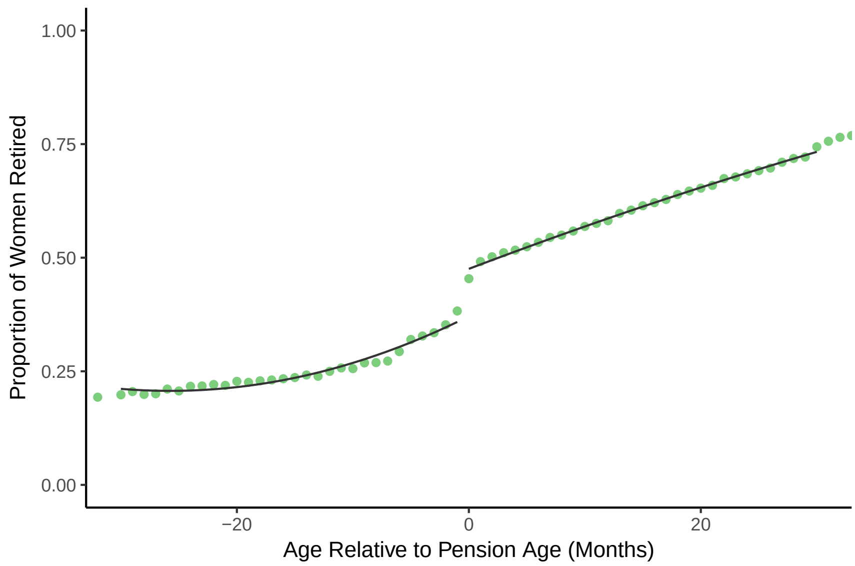
It is possible that any relationship between retirement and health may simply be an income effect. Without being supplemented by any other income source, it would be difficult to live using only the state pension payments, and retirement would mark a sharp drop in purchasing ability for individuals that attempt to do so. As such, most

17. RD figures for these estimates are shown in Figure A.1

Figure 1.1: Age Profile of Retirement Status from 2011 Census

(a)

(b)



Notes: Retirement status by age in bins by gender from the 2011 England and Wales Census. Each point is a proportion of total respondents that fall in that particular age bin (1 month for men, 2 months for women). The figure is centered around the State Pension Age, which is 65 for men varies by month-of-birth cohort for women.

Table 1.1: Effect of State Pension Age on Retirement Status

(a) Regression Discontinuity

	Retired	Retired	Retired	Working LW	Retired	Retired	Retired	Working LW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State Pension Age	0.301***	0.222***	0.199***	−0.110***	0.163***	0.199***	0.104***	−0.046***
	(0.019)	(0.016)	(0.012)	(0.009)	(0.010)	(0.021)	(0.011)	(0.007)
Constant	0.435***	0.536***	0.419***	0.284***	0.266***	0.227***	0.371***	0.351***
	(0.013)	(0.015)	(0.004)	(0.002)	(0.002)	(0.007)	(0.009)	(0.005)
Dataset	HSE	ELSA	2011 Census	labor Survey	HSE	ELSA	2011 Census	labor Survey
Gender	Men	Men	Men	Men	Women	Women	Women	Women
Observations	13,454	18,083	121	121	16,442	21,515	61	121
Adjusted R^2	0.470	0.449	0.998	0.996	0.396	0.406	0.998	0.995

(b) FE-IV

	Retired	Retired	Retired	Retired
	(1)	(2)	(3)	(4)
State Pension Age	0.310***	0.391***	0.273***	0.396***
	(0.0136)	(0.0146)	(0.0114)	(0.0115)
Dataset	ELSA	BHPS	ELSA	BHPS
Observations (n)	18,083	46,729	21,515	56,098
Individuals (i)	5,849	6,575	6,857	7,716

Notes: First stage estimates of reaching the State Pension Age on whether an individual is retired (*Retired*) or worked in the previous week (*Working LW*). Panel (A) gives regression discontinuity estimates, and Panel (B) provides FE-IV estimates from the longitudinal data sources. For the estimates from the 2011 census, the State Pension Age was in transition for women in 2011 and was set to 61.5; in the remaining columns the State Pension Age is 65 for men and 60 for women. * significant at 10%, ** significant at 5%, *** significant at 1%.

households have savings and/or private pensions as supplementary or primary income sources in the retirement years, with the state pension expected to contribute 36 percent of the average retiree's income.[18] Table A.1 shows evidence of this by providing estimates of the effect of reaching the state pension age on income and wealth. This shows that if anything, there is an increase in total income at this age on average, with this result consistent across the BHPS, ELSA, and HSE.

It is also possible that this finding is because only a subset of the population retires at the age threshold, while the vast majority begin taking a pension (see Figures A.1(a) and A.1(b)). This could mean that those that retire see a sizable change in income even when the average change in the population is negligible. Tables A.1 and A.2 shows results counter to this idea with estimates from the Wealth and Assets Survey, a longitudinal national survey focusing on household wealth. Estimate from Table A.1 show that net income decreases significantly, but pension income increases by a nearly equal amount. As a result, household wealth does not change significantly whether or not the value of pensions is included. For those that do not retire, shown in Table A.1, pension income increases significantly, and the value of household wealth decreases. But, when pension wealth is taken out of household wealth, there is no longer a statistically significant change. This suggest that this sub-population's extra income is from beginning to collect the pension while still working, and that their wealth is being decreased by the expected amount until the next survey wave. Together, this would indicate the health effects of retirement are not simply due to lost income, and cannot be compared

18. From Prudential's Class of 2015 retirement study.

to health effects of being unemployed or having a spouse lose their job.[19]

1.4.2 Self-Reported Health

Figures 1.2 and A.6 and Table 1.2 show the effects of retirement on self-reported health. Self-reported health has consistently been found to be an accurate predictor of future health outcomes and utilization (Idler and Benyamini 1997), and I am able to provide estimates of this measure with far greater precision than any previous work by using the 2001 and 2011 Censuses of England and Wales. I split the analysis of the 2001 and 2011 Censuses for two reasons. First, the wording of the question changed slightly, and the 2011 Census includes 5 possible options instead of 3.[20] Second, the threshold is at a different age for women in 2001 (age 60) than it is for women in 2011 (age 61.5).

The effect of retirement on self-reported health for men, shown in Figure 1.2 and odd numbered columns of Table 1.2, is estimated to be small but significant and concentrated among those reporting bad or very bad health. There is an 11 percent drop in the proportion of men reporting this status in the 2001 census, and a 2.5 percent drop in the 2011 census. These changes are absorbed by the "good" category in 2001, and the "fair" category in 2011. Estimates from survey data sets mirror these results, with the coefficient estimate on the proportion of men reporting bad general health negative

19. See for example Gallo et al. 2000

20. In the 2001 Census, the question was: "Over the last twelve months would you say your health on the whole has been:". The check box options are "good", "fairly good", and "not good". In the 2011 Census the question is "How is your health in general?", and the options are "very good", "good", "fair", "bad", and "very bad". I aggregate "very good" and "good" as well as "bad" and "very bad" to make estimates more comparable. While the change in possible categories does not affect the estimates of the changes at the retirement age, it does affect the levels at all ages. This is discussed thoroughly in Smith and White (2009).

and even larger than the Census-based estimates. Further, the results also present in the FE-IV estimates shown in Table A.7.

Changes to women self-reported health upon retirement is reported in Figure A.6 and even numbered columns of Table 1.2. These indicate a drop in the proportion of women with bad or very bad general health of 6 percent and 4.5 percent from the 2001 and 2011 censuses, respectively. The change is absorbed by increases to the proportion reporting good and fair in 2001, and an increase to good only in 2011. Results from survey data sets are mostly consistent, but not statistically significant, and FE-IV estimates in Table A.7 show similar drops in the proportion of individual's reporting poor health. These results are consistent with previous work showing that the strongest effects of retirement are in "perceived health" (e.g. Johnston and Lee 2009), and that objective measures of health may be difficult to measure immediately (e.g. Gorry, Gorry, and Slavov 2016).

The Census also asks individuals if they have an long-term illness or disability that limits day-to-day activities. Figure A.7 shows the age profiles of this question by gender for the 2011 and 2001 censuses, and point estimates are provided as the last set of estimates in Table 1.2. There is a significant drop in the proportion of men reporting having a long-term illness or disability in the 2001 census, and a significant drop for women in both 2001 and 2011. The effect size is largest for men in 2001 at about 7 percent, with women steady at about 2.5 percent in both decades. Results from the survey data sets are not significant although the question wordings vary. The exception is for men in the BHPS with the FE-IV specification, shown in Table A.7.

Together, these results provide strong and robust evidence that retirement improves self-reported health, with effects particularly strong for those in poor health to begin with.

Table 1.2: Effects of Retirement on Self-Reported Health

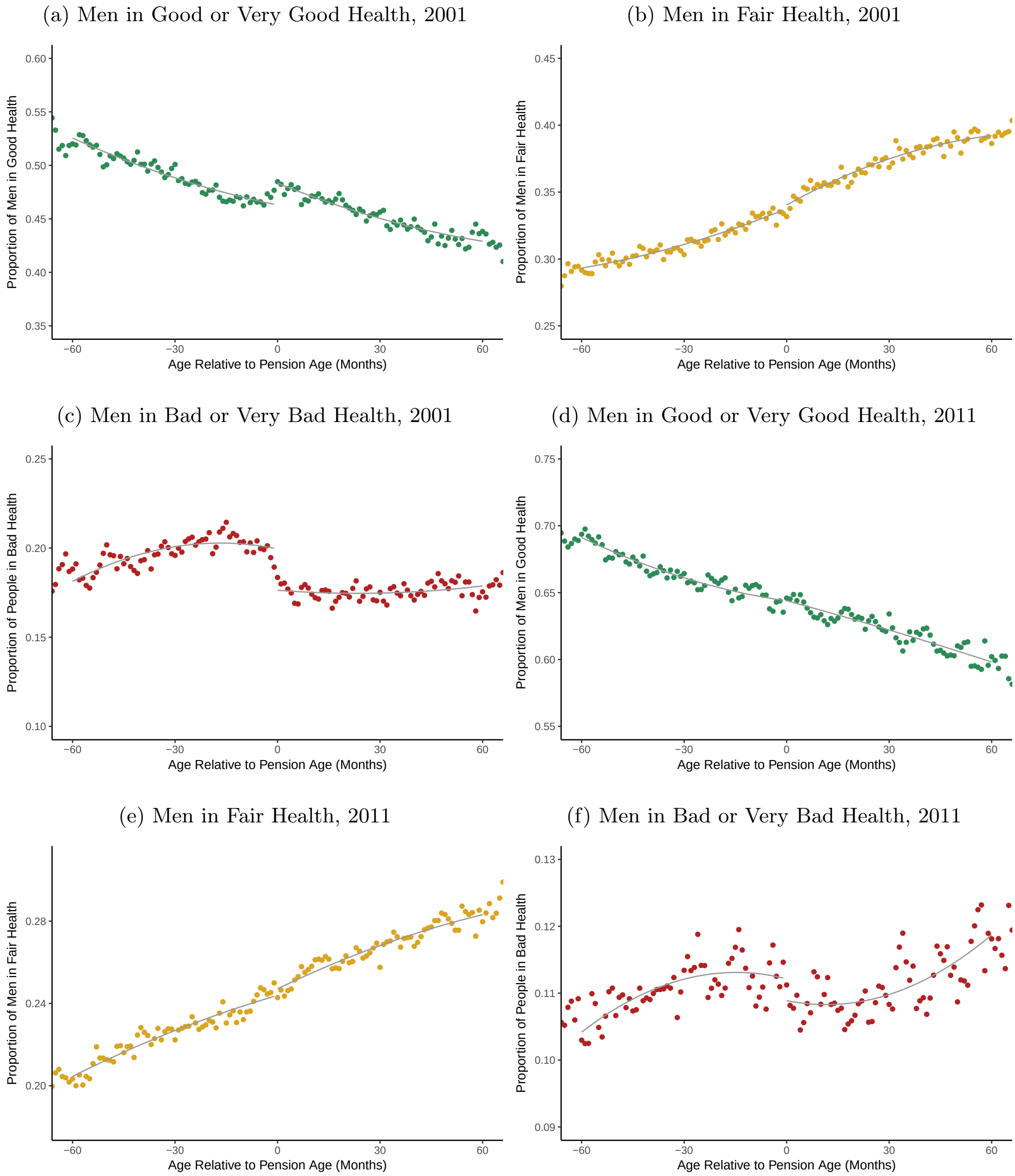
	2011 Census		2001 Census		BHPS,ELSA,HSE	
	(1)	(2)	(3)	(4)	(5)	(6)
Good	0.000	0.004	0.020***	0.006*	0.041*	0.070
	(0.003)	(0.002)	(0.003)	(0.003)	(0.023)	(0.045)
	0.644	*0.704*	*0.463*	*0.504*	*−0.179*	*−0.137*
Fair	0.003	0.000	0.003	0.004**	0.033	−0.019
	(0.002)	(0.002)	(0.003)	(0.002)	(0.042)	(0.041)
	0.244	*0.207*	*0.338*	*0.332*	*0.059*	*0.059*
Bad	−0.003**	−0.004**	−0.023***	−0.010***	−0.069**	−0.051
	(0.002)	(0.002)	(0.003)	(0.003)	(0.035)	(0.043)
	0.112	*0.088*	*0.200*	*0.164*	*0.106*	*0.089*
Long Illness/Disability	0.002	−0.007***	−0.028***	−0.008***	−0.034	−0.026
	(0.003)	(0.003)	(0.003)	(0.003)	(0.031)	(0.023)
	0.321	*0.276*	*0.414*	*0.310*	*0.255*	*0.130*
Gender	Men	Women	Men	Women	Men	Women
Observations	121	61	121	121	26,954	34,754

Notes: Regression discontinuity estimates of reaching the State Pension Age on self-reported health and long-term illnesses and disabilities. *Good*, *Fair*, and *Bad* are outcome variables split from a single question asking the individual about their general health. "Good" means the individual indicated "Very Good" or "Good", and "Bad" means the individual indicated "Bad" or "Very Bad". *Long Illness/Disability* asks the individual if they have a long-term illness or disability. For estimates from the 2011 Census, the State Pension Age is in transition for women in the 2011 and is 61.5; in the other columns the State Pension Age is 65 for men and 60 for women. Estimates just before the threshold are listed in italics just below the standard errors. * significant at 10%, ** significant at 5%, *** significant at 1%.

1.4.3 Health Outcomes

With individuals reporting substantially better health — particularly for with worse health overall — I next investigate if these effects induce changes to measurable health outcomes. Table 1.3 investigates how retirement affects mental health and cog-

Figure 1.2: Age Profiles of Self-Reported Health from the 2001 and 2011 Censuses, Men



Notes: Proportion of the male population reporting good or very good health, fair health, or bad or very bad health, respectively, from the 2001 and 2011 England/Wales censuses. Each point is a proportion of total respondents that fall in that particular age month bin. The census question is: 'How is your health in general?'

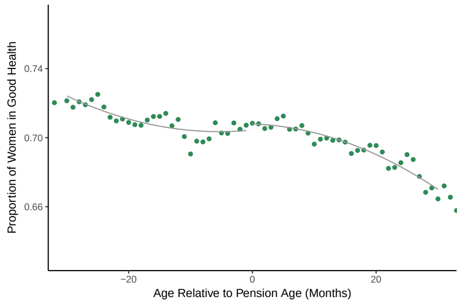
Figure 1.3: Age Profiles of Self-Reported Health from the 2001 and 2011 Censuses, Women

(a) Women in Good or Very Good Health, 2001

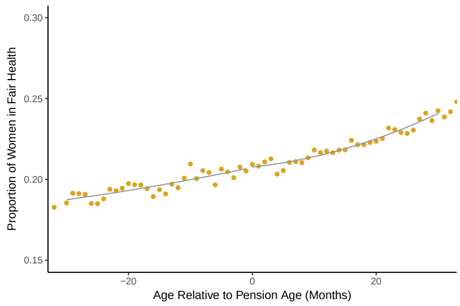
(b) Women in Fair Health, 2001

(c) Women in Bad or Very Bad Health, 2001

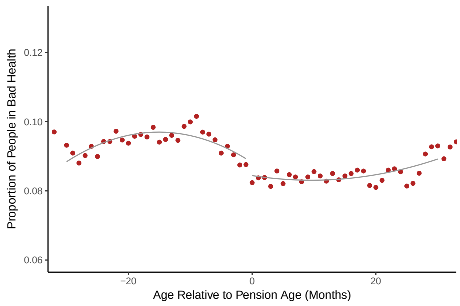
(d) Women in Good or Very Good Health, 2011



(e) Women in Fair Health, 2011



(f) Women in Bad or Very Bad Health, 2011

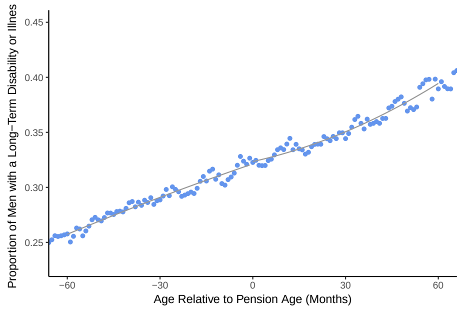


Notes: Proportion of the female population reporting good or very good health, fair health, or bad or very bad health, respectively, from the 2001 and 2011 England/Wales censuses. Each point is a proportion of total respondents that fall in that particular age bin (1 month for men in 2001 and 2011, 1 month for women in 2001, and 2 months for women in 2011). The census question is: 'How is your health in general?'

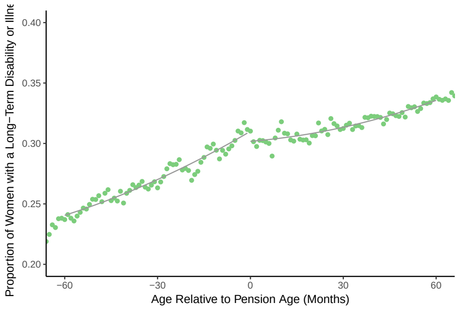
Figure 1.4: Age Profile of Long-Term Illness or Disability from 2001 and 2011 Census

(a) Men, 2001

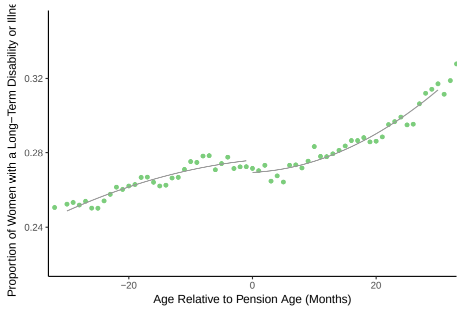
(b) Men, 2011



(c) Women, 2001



(d) Women, 2011



Notes: Self-reported long-term illness or disability status by age in bins by gender from the 2001 and 2011 England and Wales Censuses. Each point is a proportion of total respondents that fall in that particular age bin (1 month for men in 2001 and 2011, 1 month for women in 2001, and 2 months for women in 2011). The figure is centered around the State Pension Age, which is 65 for men and varies by month-of-birth cohort for women. The census question is: 'Are your day-to-day activities limited because of a health problem or disability which has lasted, or is expected to last, at least 12 months?'

Table 1.3: Effect of Retirement on Cognition and Mental Health Outcomes

(a) Men

	Orient Date	Recall Score	Memory Score	Verbal Score	Depression Score
	(1)	(2)	(3)	(4)	(5)
State Pension Age	0.026	0.009	−0.014	0.037	0.006
	(0.034)	(0.022)	(0.042)	(0.057)	(0.048)
Constant	0.006	−0.031	0.074**	0.051	−0.123***
	(0.023)	(0.020)	(0.038)	(0.053)	(0.037)
Dataset	ELSA	ELSA	ELSA	ELSA	ELSA,HSE,BHPS
Observations	17,986	18,000	14,812	14,884	23,829
Adjusted R^2	0.008	0.064	0.015	0.036	0.001

(b) Women

	Orient Date	Recall Score	Memory Score	Verbal Score	Depression Score
	(1)	(2)	(3)	(4)	(5)
State Pension Age	−0.005	0.006	−0.007	−0.033	−0.018
	(0.018)	(0.006)	(0.014)	(0.065)	(0.034)
Constant	−0.001	0.060***	3.869***	11.761***	0.073***
	(0.018)	(0.005)	(0.013)	(0.054)	(0.024)
Dataset	ELSA	ELSA	ELSA	ELSA	ELSA,HSE,BHPS
Observations	15,096	21,439	21,431	21,442	31,687
Adjusted R^2	0.000	0.000	0.003	0.026	0.003

Notes: Regression discontinuity estimates of reaching the State Pension Age on mental health outcomes. *Orient Date* indicates if the respondent was able to name the date. *Recall Score* is a sum of immediate and delayed word recall tests. *Memory Score* is a test of how well an individual can remember previously given instructions, with partial credit up to a score of 4 for performing the task as instructed. *Verbal Score* asks respondents to name as many animals as they can in one minute, with the score being the number of acceptable answers. *Depression Score* is standardized scores from the 8-item Centre of Epidemiological Studies Depression (CES-D) scale and the GHQ-12 questionnaire, where a higher value indicates a higher likelihood of minor psychiatric disorders. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.4: Effect of Retirement on Health Outcomes, Men

(a) Health Problems and Indicators

	Limits to Daily Activity	Health Prob. Index	Any Health Prob	Systolic BP	Diastolic BP	Pulse
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.026	-0.116^{*}	-0.051^{*}	-0.897	-0.135	-1.881^{***}
	(0.063)	(0.069)	(0.029)	(1.393)	(0.769)	(0.478)
Constant	-0.185^{***}	1.660^{***}	0.474^{***}	149.058^{***}	83.034^{***}	69.625^{***}
	(0.050)	(0.052)	(0.024)	(1.095)	(0.564)	(0.328)
Dataset	ELSA & BHPS	BHPS	BHPS	BHPS	HSE	HSE
Observations	19,445	12,014	12,014	3,264	3,264	3,274
Adjusted R^2	-0.000	0.006	0.006	0.013	0.005	0.001

(b) Utilization

	Hospital	GP	Dentist	Eye Exam	Blood Test	Cholesterol
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.037	-0.020	0.019	0.028	-0.017	-0.014
	(0.026)	(0.058)	(0.021)	(0.027)	(0.026)	(0.032)
Constant	0.718^{***}	2.650^{***}	0.559^{***}	0.439^{***}	0.633^{***}	0.376^{***}
	(0.019)	(0.047)	(0.018)	(0.017)	(0.021)	(0.027)
Dataset	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Observations	10,505	11,518	11,525	11,525	11,525	11,525
Adjusted R^2	0.000	0.002	0.004	-0.000	0.001	-0.000

Notes: Regression discontinuity estimates of reaching the State Pension Age on health outcomes for men. *Limits to Daily Activity* indicates if health limits daily activities such as walking and dressing. *Health Prob. Index* is an index created by simply summing the number of health issues individuals indicated, and *Any Health Prob* is a dummy variable if the individual indicated at least one health issue. Under panel (b), all variables indicate if the individual has utilized that service in the previous 12 months with the exception of *GP*, which is number of visits in the previous 12 months. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.5: Effect of Reaching the State Pension Age on Health Outcomes, Women

(a) Health Problems and Indicators

	Limits to Daily Activity	Health Prob. Index	Any Health Prob	Systolic BP	Diastolic BP	Pulse
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.026	−0.024	0.005	-3.994^{***}	−0.104	-1.487^{***}
	(0.063)	(0.071)	(0.022)	(1.028)	(0.765)	(0.421)
Constant	-0.185^{***}	1.670^{***}	0.459^{***}	146.425^{***}	76.813^{***}	72.479^{***}
	(0.050)	(0.051)	(0.017)	(0.636)	(0.449)	(0.294)
Dataset	ELSA & BHPS	BHPS	BHPS	BHPS	HSE	HSE
Observations	19,445	15,922	15,922	4,119	4,119	4,131
Adjusted R^2	−0.000	0.002	0.002	0.058	0.003	−0.000

(b) Utilization

	Hospital	GP	Dentist	Eye Exam	Blood Test	Cholesterol
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.033	-0.081^{***}	−0.001	0.013	−0.012	−0.024
	(0.065)	(0.023)	(0.020)	(0.024)	(0.022)	(0.017)
Constant	0.718^{***}	2.718^{***}	0.641^{***}	0.460^{***}	0.561^{***}	0.273^{***}
	(0.054)	(0.021)	(0.016)	(0.016)	(0.012)	(0.010)
Dataset	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Observations	13,890	15,556	15,574	15,574	15,574	15,574
Adjusted R^2	0.001	0.000	0.003	0.000	0.002	0.006

Notes: Regression discontinuity estimates of reaching the State Pension Age on health outcomes for women. *Limits to Daily Activity* indicates if health limits daily activities such as walking and dressing. *Health Prob. Index* is an index created by simply summing the number of health issues individuals indicated, and *Any Health Prob* is a dummy variable if the individual indicated at least one health issue. Under panel (b), all variables indicate if the individual has utilized that service in the previous 12 months with the exception of *GP*, which is number of visits in the previous 12 months. * significant at 10%, ** significant at 5%, *** significant at 1%.

nitive ability for men and women. Columns (1)-(4) are tests of memory and cognitive ability, administered by the survey teams. “Depression score" is derived from the CES-D scale in the ELSA and the GHQ-12 questionnaire in the BHPS and HSE, and is a standardized score from each of the tests. For both men and women, there is no significant change in any of these related outcomes. These results are perhaps expected, as it is unlikely to have immediate impacts on mental health and cognition upon retiring. In FE-IV estimates — with a lag between retirement and the time of the survey — show that men improve across all measures of mental health.

Panel (A) of Tables 1.4 and 1.5 shows estimates to changes in health problems and health indicators for men and women, respectively. Column (1) is a standardized measure of whether the respondent has health issues that affects daily activities such as dressing and bathing. *Health Prob. Index* in column (2) aggregates the number of health problems respondents list, and *Any Health Prob.* is a dummy variable indicating if the respondent lists any health problem. Blood pressure and pulse are measured by a nurse for respondents that agree to have their vital signs taken.

For men, there is some evidence that retirement decreases the number of health problems as well as the probability of having any health problems (columns (4) and (5)). Women do not see any significant changes in these outcomes. These results may be due to differences in environment after retiring, where an individual's physical capabilities may no longer be strained on a regular basis. However, objective measures provided by the HSE indicate that retirement reduces systolic blood pressure for women, and pulse for both sexes. There is evidence that hypertension and higher resting heart rates can be linked to stress.[21]

I examine the effect of retirement on healthcare utilization in Panel (B) of Tables 1.4 and 1.5. For men, there is no change in the probability of being admitted to the hospital, the number of doctor visits, going to the dentist, having an eye exam, or having a blood test. For women, there is a small but statistically significant decrease in the number of annual visits to a general practitioner. Together, this indicates that there is little evidence that retirement affects individuals' use of medical services. [22]

1.4.4 Mortality

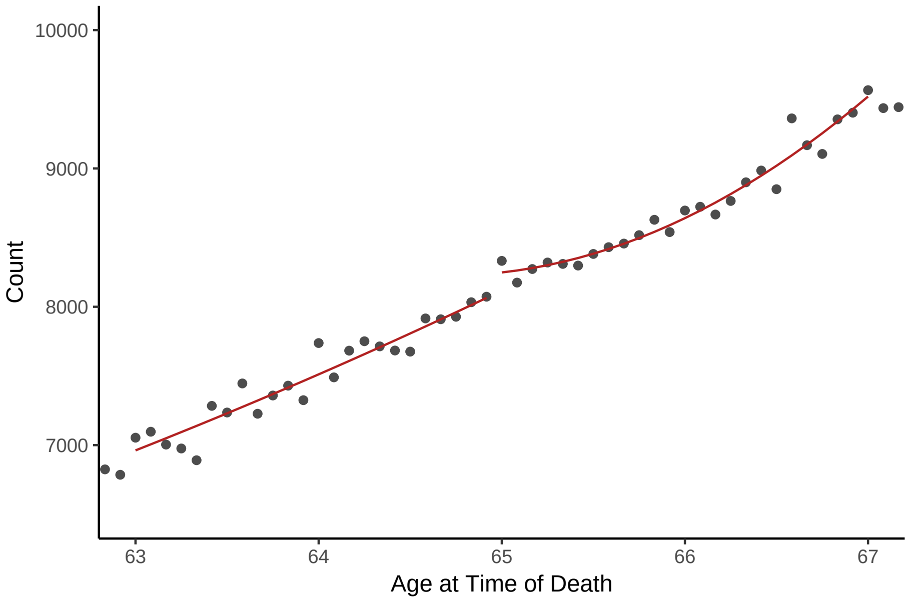
With individuals reporting better health and fewer long-term ailments, it seems unlikely that retirement could affect mortality in a negative way. Figures 1.5 and 1.6 show this to be true. Figure 1.5 shows the age profiles of mortality separately for men and women with month-of-birth cohort bins relative to the respective state pension ages. Neither sex shows a significant discontinuity at the threshold, and Figure 1.6 gives regression discontinuity estimates by bandwidth to confirm this; there is only one statistically significant estimate across sexes for any bandwidth under 5 years.[23]

Table 1.6 gives complementary point estimates as well as a heterogeneity analysis by cause of death. This includes 7 broad categories of death — categorized using ICD-9 and ICD-10 codes — as well as an "other" category that includes all other causes not specifically listed. For men, shown in Panel (a), there is a significant increase in

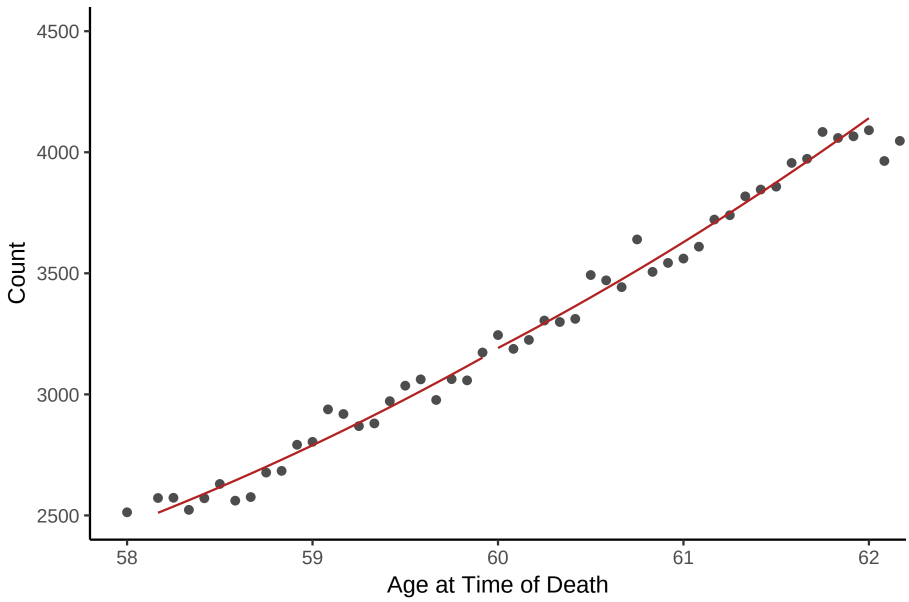
21. See Chida and Steptoe (2010) for a meta-analysis of this literature.
22. However, Table A.6 shows that the use of services does decrease for women with the FE-IV specification, specifically in the probability of a hospital admission.
23. Optimal bandwidth procedures suggest bandwidths between 2.1 and 3.8 years.

Figure 1.5: Mortality Age Profiles, England 1990-2011

(a) Men



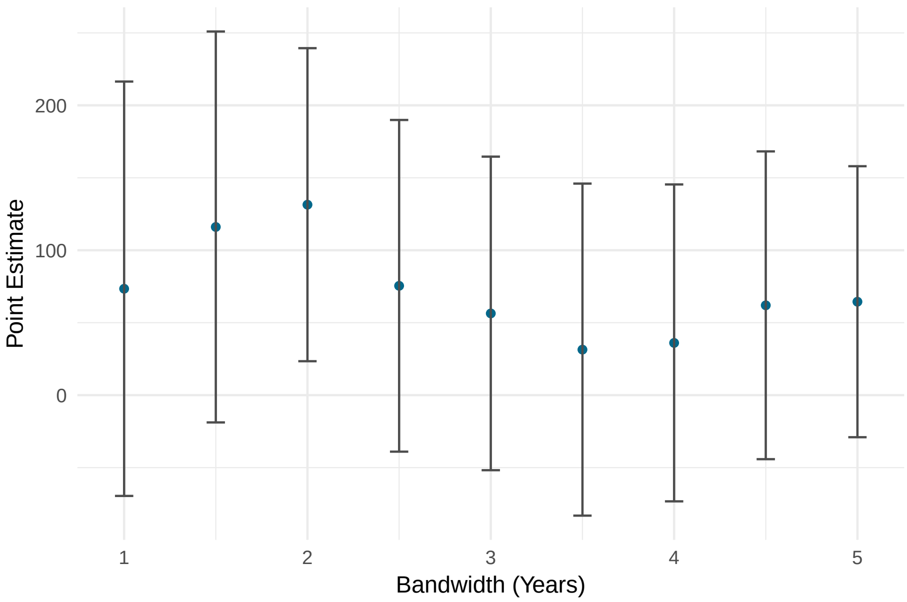
(b) Women



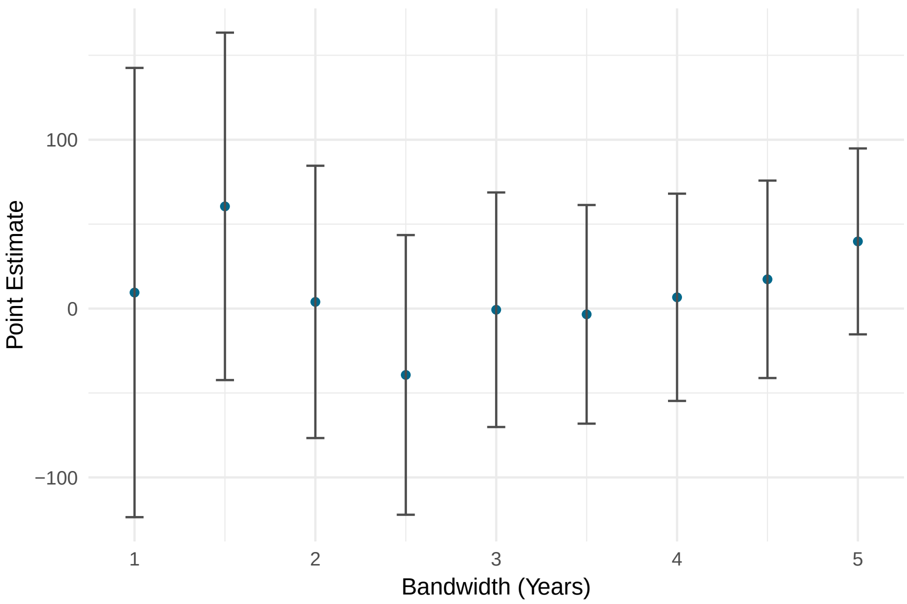
Notes: Age profiles of mortality by gender from England from 1990-2011. Each point is a count of the number of individuals in that month-of-birth cohort that died relative to the State Pension Age.

Figure 1.6: Robustness of Mortality RD Estimates, England 1990-2011

(a) Men



(b) Women



Notes: Regression discontinuity robustness of bandwidth choice for mortality by gender. Each point is a separate regression discontinuity point estimate with 95 percent confidence interval bars of the effect of reaching the State Pension Age on mortality counts.

Table 1.6: Effect of Retirement on Mortality

(a) Men

	Cause of Death								
	All Causes	Cancer	Infectious	Respiratory	Vascular	Diabetes	Mental	Injuries	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State Pension Age	131.435**	65.909*	−1.497	16.916	32.603	17.044**	0.318	−6.591	5.641
	(55.105)	(37.448)	(8.694)	(15.007)	(27.991)	(8.088)	(4.476)	(6.333)	(25.764)
Constant	8,116.768***	3,194.333***	65.729***	520.581***	3,231.244***	81.163***	20.405***	88.058***	910.193***
	(37.649)	(24.862)	(8.123)	(11.801)	(23.372)	(6.759)	(3.823)	(4.267)	(21.742)
Observations	49	49	49	49	49	49	49	49	49
Adjusted R^2	0.981	0.947	0.055	0.895	0.975	0.578	0.634	0.296	0.802

(b) Women

	Cause of Death								
	All Causes	Cancer	Infectious	Respiratory	Vascular	Diabetes	Mental	Injuries	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State Pension Age	3.955	−10.705	7.674	−23.476***	12.265	4.779	1.038	0.207	13.240
	(38.542)	(33.207)	(5.413)	(8.830)	(21.007)	(3.876)	(1.935)	(4.130)	(18.231)
Constant	3,187.412***	1,659.975***	29.819***	199.427***	742.922***	39.289***	8.129***	44.086***	457.959***
	(30.411)	(25.067)	(4.120)	(4.749)	(16.654)	(2.944)	(1.232)	(2.512)	(15.250)
Observations	49	49	49	49	49	49	49	49	49
Adjusted R^2	0.988	0.964	0.366	0.939	0.957	0.547	0.308	0.199	0.870

Notes: Regression discontinuity estimates of reaching the State Pension Age on mortality. The “other" category is a catch-all that includes all other subcauses not explicitly listed. * significant at 10%, ** significant at 5%, *** significant at 1%.

the number of diabetes-related deaths at the age of 65. For women, shown in Panel (b), there is a significant decrease in moralities caused by the respiratory system. Neither of these results remain significant for all reasonable choices of bandwidth, and are sensitive to polynomial order. These results indicate that there is no effect of retirement on mortality.

1.4.5 Health Behavior

Table 1.7: Effect of Retirement on Health Behavior, Men

(a) Self Care

	Smokes	Inside Smoke	Drinks	Exercise	# of Drinking Days/Week	Cigarette Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	−0.006	0.004	0.020	0.002	−0.072	−0.003
	(0.038)	(0.023)	(0.017)	(0.041)	(0.095)	(0.039)
Constant	-0.141^{***}	0.204^{***}	0.111^{***}	0.035	3.150^{***}	0.344^{***}
	(0.037)	(0.022)	(0.017)	(0.039)	(0.089)	(0.037)
Dataset	BHPS,HSE,ELSA	HSE	ELSA,HSE	BHPS,HSE,ELSA	ELSA	HSE
Observations	26,241	13,470	16,118	17,882	13,191	13,510
Adjusted R^2	0.002	0.008	0.001	0.000	0.002	0.011

(b) Friends and Family

	See Friends & Family Weekly	Eat Out	Meaningful Friendships	Social Satisfaction	Life Satisfaction	Age of Closest Friend
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	-0.111^{***}	0.149^{***}	−0.006	0.070	0.141^{**}	1.187
	(0.017)	(0.049)	(0.053)	(0.063)	(0.065)	(0.947)
Constant	−0.014	0.415^{***}	-0.105^{**}	0.186^{***}	0.094^{**}	56.213^{***}
	(0.010)	(0.029)	(0.051)	(0.043)	(0.040)	(0.675)
Dataset	ELSA	BHPS	HSE	BHPS	BHPS	BHPS
Observations	22,117	4,979	8,719	8,633	8,627	5,384
Adjusted R^2	0.000	0.003	0.000	0.007	0.011	0.008

	Work	Routine Housework	Other Domestic Work	Sleep	Leisure	Passive Leisure	Social Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	−29.085***	−1.163	3.873**	9.924***	16.451***	10.001***	6.450***
	(8.093)	(1.703)	(1.756)	(2.748)	(4.014)	(3.108)	(2.214)
Constant	156.290***	52.292***	123.387***	612.984***	495.043***	338.771***	156.271***
	(7.391)	(1.407)	(1.506)	(2.440)	(3.662)	(2.711)	(1.506)
Dataset	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Observations	5,406	5,406	5,406	5,406	5,406	5,406	5,406
Adjusted R^2	0.211	0.055	0.095	0.156	0.183	0.226	0.015

(c) Time Use

Notes: Regression discontinuity estimates of reaching the State Pension Age on functional outcomes for men. *Smokes* is if the individual currently smokes. *Inside Smoke* measures if anyone in the household smokes indoors. *Exercise* refers to frequent (once per week) activity. *See Friends & Family Weekly* is a standardized measure of whether respondents have weekly contact with their friends, family, or children. *Meaningful Friendships* is a standardized measure capturing if respondents report having friends that care about them and can be relied on. *Social Satisfaction* and *Life Satisfaction* are standardized scores of measures of individuals' satisfaction with their social lives and life overall, respectively. Time use outcomes are denominated in minutes, where columns (1)-(5) are mutually exclusive and exhaustive. *Social Leisure* includes leisure activities involving meeting or talking with people and *Passive Leisure* includes leisure activities usually done alone or are not usually conducive to establishing social networks. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.7: Effect of Retirement on Health Behavior, Women

(a) Self Care

	Smokes	Inside Smoke	Drinks	Exercise	# of Drinking Days/Week	Cigarette Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.039	0.011	0.009	−0.081*	−0.193***	0.006
	(0.047)	(0.014)	(0.019)	(0.047)	(0.057)	(0.033)
Constant	−0.051	0.228***	−0.007	0.039	2.340***	0.389***
	(0.040)	(0.006)	(0.010)	(0.046)	(0.052)	(0.013)
Dataset	BHPS,HSE,ELSA	HSE	ELSA,HSE	BHPS,HSE,ELSA	ELSA	HSE
Observations	32,735	16,457	20,437	23,895	15,470	16,457
Adjusted R^2	0.003	0.008	0.001	0.000	0.000	0.007

(b) Friends and Family

	See Friends & Family Weekly	Eat Out	Meaningful Friendships	Social Satisfaction	Life Satisfaction	Age of Closest Friend
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	−0.016	−0.048	0.049*	−0.002	0.025	−0.646
	(0.016)	(0.041)	(0.029)	(0.044)	(0.062)	(0.822)
Constant	−0.037**	0.527***	0.056***	0.137***	0.113***	54.173***
	(0.016)	(0.023)	(0.016)	(0.029)	(0.037)	(0.618)
Dataset	ELSA	BHPS	HSE	BHPS	BHPS	BHPS
Observations	29,686	6,909	10,681	11,988	11,985	7,606
Adjusted R^2	0.000	−0.000	0.001	0.009	0.009	0.014

With only minor changes in key health outcomes and no changes in mortality, I next investigate if the significant changes to self-reported health may be driven by health-related behaviors and changes to individuals' day-to-day environment. Panel (A) of Tables 1.7 and 1.7 shows estimates for drinking, smoking, and exercising by gender. While there is some evidence that women are less likely to exercise frequently upon retiring, there is no statistically significant change in smoking or drinking rates for men or women. This is perhaps to be expected, as these habits are unlikely to begin or cease completely in short periods of time for individuals in their 60s. Instead, columns (5) and (6) examines intensity measures; namely, number of days per week an individual consumes alcohol and a cigarette intensity measure that classifies individuals into non-smokers (0 cigarettes per day), light smokers (1-10 per day), moderate smokers (11-20 per day), or heavy smokers (20+ per day). Here, men do not show an change in either category, but women report drinking less frequently.

Panel (B) of these tables refers to changes in the frequency and quality of social interaction. Column (1) reports estimates of a standardized and combined measure of whether individuals see their friends, children, and/or relatives on a weekly basis. Men are slightly less likely to see their friends and family, while there are no changes for women. Men are also more likely to go out to eat regularly. Men see a significant increase in self-reported life satisfaction, with the question asked on a sliding scale from "completely unsatisfied" to "completely satisfied". There is no statistically significant change in any category for women. Further, neither sex shows a significant change in the average age of their closest friend. FE-IV estimates do report substantial increases

	Work	Routine Housework	Other Domestic Work	Sleep	Leisure	Passive Leisure	Social Leisure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	-17.120^{**}	1.974	2.342^{*}	4.266^{**}	8.538^{**}	4.917^{**}	3.621^{*}
	(7.313)	(1.666)	(1.258)	(2.071)	(3.783)	(2.406)	(2.148)
Constant	138.586^{***}	139.382^{***}	97.497^{***}	613.840^{***}	450.695^{***}	285.866^{***}	164.833^{***}
	(6.641)	(1.368)	(1.049)	(1.877)	(3.168)	(2.167)	(1.545)
Dataset	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Observations	7,283	7,283	7,283	7,283	7,283	7,283	7,283
Adjusted R^2	0.144	0.021	0.023	0.136	0.181	0.200	0.022

(c) Time Use

Notes: Regression discontinuity estimates of reaching the State Pension Age on functional outcomes for women. *Smokes* is if the individual currently smokes. *Inside Smoke* measures if anyone in the household smokes indoors. *Exercise* refers to frequent (once per week) activity. *See Friends & Family Weekly* is a standardized measure of whether respondents have weekly contact with their friends, family, or children. *Meaningful Friendships* is a standardized measure capturing if respondents report having friends that care about them and can be relied on. *Social Satisfaction* and *Life Satisfaction* are standardized scores of measures of individuals' satisfaction with their social lives and life overall, respectively. Time use outcomes are denominated in minutes, where columns (1)-(5) are mutually exclusive and exhaustive. *Social Leisure* includes leisure activities involving meeting or talking with people and *Passive Leisure* includes leisure activities usually done alone or are not usually conducive to establishing social networks. * significant at 10%, ** significant at 5%, *** significant at 1%.

in individuals' satisfaction with their social lives and life satisfaction for both genders (Column B6 of Tables A.3 and A.4).

Panel (C) reports changes in time use from the BHPS. Columns (1)-(4) — representing work, housework, sleeping, and leisure — are mutually exclusive, and columns (5) and (6) divides leisure into passive and social leisure, respectively. Passive leisure represents activities usually undertaken alone, while social leisure includes activities that usually involves meeting or interacting with other people.[24] As expected, there is a significant decrease in the amount of time working, with the decrease larger for men. These estimates show that the time is substituted into leisure and sleeping, with both genders showing an increase in these categories. Furthermore, the increase in leisure represents over half of the time substitution for both genders, and more of this time goes toward passive leisure.

1.4.6 Heterogeneity by Education

24. Passive leisure includes eating at home, media consumption, and computer use. Active leisure includes outings, eating and drinking out, sports, hobbies, and friend visits.

Table 1.7: Heterogeneity in the Effect of Retirement by Education for Men

(a) Retirement and Pensions

	Retired	Retired	Retired	Any Pension	Income Last Month	Income	HH Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	0.324^{***}	0.368^{***}	0.294^{***}	0.809^{***}	115.528	−0.227	−0.001
	(0.013)	(0.023)	(0.019)	(0.075)	(96.771)	(0.353)	(0.018)
Constant	0.400^{***}	0.391^{***}	0.491^{***}	0.005	$1{,}458.217^{***}$	9.751^{***}	0.183^{***}
	(0.006)	(0.017)	(0.018)	(0.004)	(63.709)	(0.326)	(0.012)
Dataset	2001 Census	HSE	ELSA	BHPS	BHPS	HSE	ELSA
Observations	121	8,293	7,139	6,799	6,799	6,553	7,138

(b) Health behavior

	Smokes	Drinks	Exercise	Days Drinking/Week	Cigarette Intensity	See Friends & Family Weekly	Social Satisfaction	Life Satisfaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State Pension Age	0.004	−0.014	0.050	−0.368	−0.003	-0.063^{**}	0.095	0.192^{*}
	(0.021)	(0.029)	(0.059)	(0.276)	(0.052)	(0.027)	(0.152)	(0.100)
Constant	-0.052^{***}	0.089^{***}	-0.106^{***}	2.935^{***}	0.426^{***}	0.066^{***}	5.272^{***}	0.055
	(0.017)	(0.016)	(0.031)	(0.235)	(0.049)	(0.024)	(0.091)	(0.067)
Dataset	BHPS,ELSA,HSE	BHPS,ELSA,HSE	BHPS,ELSA,HSE	ELSA	HSE	ELSA	BHPS	BHPS
Observations	13,177	7,286	8,098	4,984	8,352	8,421	4,670	4,663
Adjusted R^2	0.003	0.001	−0.000	0.002	0.020	0.000	0.007	0.012

	Bad	Bad	Disabled/ Long-Term Illness	Hospital	GP	Depression Score	Limit Daily Activities	Any Health Problem	Pulse
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State Pension Age	-0.026^{***}	-0.034	-0.031^{***}	0.022	0.009	-0.042	-0.006	-0.063^{*}	-2.713^{***}
	(0.003)	(0.071)	(0.003)	(0.034)	(0.042)	(0.069)	(0.126)	(0.033)	(0.729)
Constant	0.218^{***}	0.221^{***}	0.439^{***}	0.682^{***}	0.396^{***}	-0.009	-0.175^{**}	0.495^{***}	71.253^{***}
	(0.002)	(0.043)	(0.002)	(0.027)	(0.031)	(0.034)	(0.089)	(0.028)	(0.608)
Dataset	2001 Census	BHPS,ELSA,HSE	2001 Census	BHPS	BHPS, ELSA,HSE	BHPS, ELSA,HSE	ELSA,BHPS	BHPS	HSE
Observations	121	13,576	121	5,869	9,896	11,830	9,406	6,795	2,070

(c) Health Outcomes

Notes: Regression discontinuity estimates of reaching the State Pension Age for men without post-secondary education. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 1.7: Heterogeneity in the Effect of Retirement by Education for Women

(a) Retirement and Pensions

	Retired	Retired	Retired	Any Pension	Income Last Month	Income	HH Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	0.163^{***}	0.151^{***}	0.254^{***}	0.681^{***}	29.444	0.197	−0.009
	(0.008)	(0.011)	(0.020)	(0.063)	(88.274)	(0.289)	(0.014)
Constant	0.399^{***}	0.268^{***}	0.180^{***}	0.006^{**}	$1,773.389^{***}$	10.696^{***}	0.165^{***}
	(0.004)	(0.006)	(0.007)	(0.003)	(66.130)	(0.203)	(0.008)
Dataset	2001 Census	HSE	ELSA	BHPS	BHPS	HSE	ELSA
Observations	121	10,569	9,874	10,208	10,208	8,255	9,872

(b) Health behavior

	Smokes	Drinks	Exercise	Days Drinking/Week	Cigarette Intensity	See Friends & Family Weekly	Social Satisfaction	Life Satisfaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State Pension Age	−0.037	0.005	−0.026	-0.164^{**}	0.009	−0.019	0.028	0.042
	(0.053)	(0.024)	(0.055)	(0.068)	(0.058)	(0.039)	(0.094)	(0.074)
Constant	0.080^{**}	-0.099^{***}	-0.105^{***}	1.880^{***}	0.471^{***}	0.068^{**}	5.088^{***}	0.098^{***}
	(0.038)	(0.005)	(0.036)	(0.066)	(0.045)	(0.032)	(0.054)	(0.036)
Dataset	BHPS,ELSA,HSE	BHPS,ELSA,HSE	BHPS,ELSA,HSE	ELSA	HSE	ELSA	BHPS	BHPS
Observations	17,812	9,796	11,975	6,805	10,595	12,831	7,392	7,392
Adjusted R^2	0.003	0.001	−0.000	−0.000	0.012	−0.000	0.007	0.008

It might be the case that different types of workers are more sensitive to government-instituted age thresholds for public pensions. In the United States, for example, it has been shown that blue-collar workers with more demanding jobs are far more likely to claim social security early, and those with managerial or profession jobs are less likely Public Affairs (2014). With this in mind, I present estimates for individuals without any post-secondary education in Tables 1.7 and 1.7 for men and women, respectively.

Panel (a) shows first stage results for the probability of being retired and the change in income and assets. Estimates for this group are higher than the overall population, with estimates roughly 1.5 times larger for both men and women. This indicates that they are more likely to leave the labor force upon reaching the state pension age. Similar to the larger population, there is no evidence of significant change in household income.

Panel (b) gives estimates for health behavior. Men do not change their drinking, smoking, or exercise habits upon retirement, but they are less likely to see their friends and children on a weekly basis. Women do not see any changes in health behavior.

Finally, Panel (c) shows estimates for healthcare utilization and outcomes. Both men and women without higher education show no change in utilization of services, and men are less likely to report having any health problem. Similar to the main results, there is no evidence that retirement affects mental health in this population. Perhaps surprisingly, effects on self-reported health are only slightly higher than for the general population. This suggests that it is not simply the cessation of physically-demanding,

	Bad	Bad	Disabled/ Long-Term Illness	Hospital	GP	Depression Score	Limit Daily Activities	Any Health Problem	Pulse
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
State Pension Age	−0.011***	−0.046	−0.010***	0.059*	−0.032	−0.067	0.081	0.008	−1.245
	(0.003)	(0.071)	(0.003)	(0.032)	(0.034)	(0.044)	(0.107)	(0.021)	(1.351)
Constant	0.174***	0.187***	0.322***	0.671***	0.262***	0.212***	−0.244***	0.486***	72.449***
	(0.002)	(0.043)	(0.002)	(0.022)	(0.025)	(0.024)	(0.093)	(0.016)	(0.983)
Dataset	2001 Census	BHPS, ELSA,HSE	BHPS	BHPS	BHPS, ELSA,HSE	BHPS, ELSA,HSE	ELSA, BHPS	BHPS	HSE
Observations	121	19,071	121	8,753	14,154	17,317	13,918	10,203	2,680

(c) Health Outcomes

Notes: Regression discontinuity estimates of reaching the State Pension Age for women without post-secondary education. * significant at 10%, ** significant at 5%, *** significant at 1%.

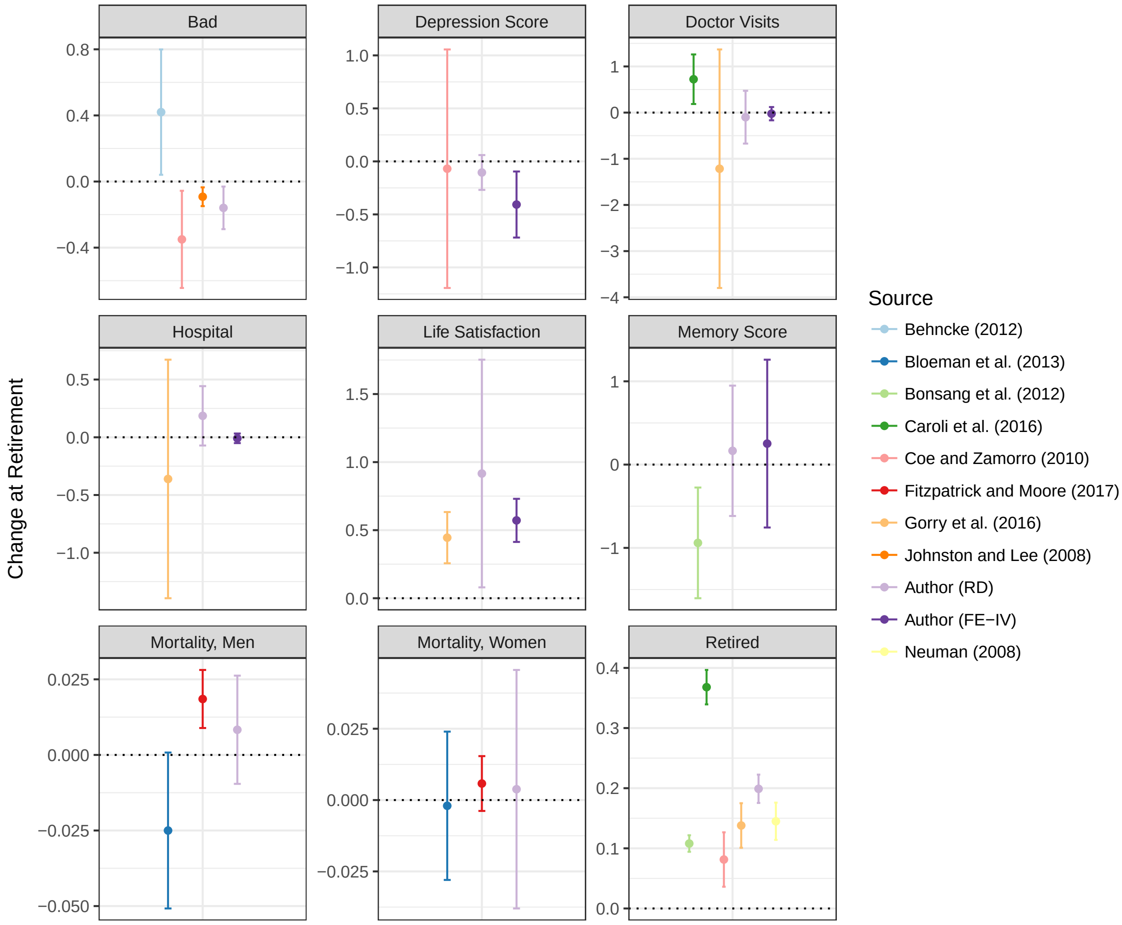
blue-collar labor that is driving the improvements in health. While this segment of the population is certainly affected strongly, combining these estimates with the larger first stage estimates would indicate that workers without higher education are somewhat less likely to experience an improvement in health upon retirement.

1.5 Conclusion

This paper discusses the link between retirement and health, which is a well-studied relationship. Unlike previous papers, however, this paper traces out the chain of possible effects of reaching the conventional retirement age on a homogeneous population. To this end, it is important to compare estimates obtained here to those in the existing literature. Figure 1.7 gives estimates and confidence intervals from multiple studies for several outcomes included in the main results of this paper. It is important to note that included authors and estimates are not a judgement of quality or importance; rather, these are outcomes that are derived from sources that are sufficiently comparable to outcomes in my data sources. This could be because the author used the same data, because the datasets are aligned — as is the case with the ELSA and the Health and Retirement Study in the U.S. — or because the question was worded in a similar manner. The weakness of this comparison, of course, is that potentially important estimates are left out if not directly comparable.

Estimates in Figure 1.7 are for men only, unless otherwise noted. I report both RD and FE-IV specifications, and the estimates are for the change at the threshold

Figure 1.7: Comparison to Previous Results



Notes: Author estimates of the effect of retirement compared to previous results from the literature. Each point is shown with a 95 percent confidence interval. The outcome variable is listed above each panel with an independent y-scale, and is for men only unless otherwise specified. Author RD estimates are rescaled by the first stage from the 2011 Census, with the standard errors computed via the delta method. *Bad* refers to individuals reporting bad or very bad overall health, and author estimates are reported as a weighted mean of estimates obtained in previous results (see Table 1.2). *Memory Score* is the sum of the immediate and delayed word recall test.

for the RD estimates and effect of being over the threshold for the FE-IV estimates. RD estimates are rescaled by the first stage from the 2011 census, with standard errors computed via the delta method. Units are specific to each panel. In the top left panel for “bad" overall health, I take a weighted average of my estimates from the 2001 and 2011 Census.

While my estimates are generally more precise than those found in previous literature, there are relatively few instances that estimates stand in opposition. The first exception is in memory score, which is the sum of an immediate and delayed word recall test, where I find a null result that contrasts with the negative effect found in Bonsang, Adam, and Perelman (2012). The other major exception is in mortality for men, with results unable to match those of Fitzpatrick and Moore (2016).

The results presented here point to several clear implications about the relationship between retirement and health. First, it is clear that the state pension age affects retirement decisions, with a significant portion of the population aligning retirement with that threshold. Second, retirement substantially improves individuals' self-reported health, especially for those on the lower end of the spectrum. Individuals are also less likely to report having long-term ailments, and men report fewer health problems while women have lower measured blood pressures. Both sexes have lower pulse rates, and sleep and take more leisure upon retirement. Sleep deprecation in particular is associated with higher blood pressure and pulse rates (Lusardi et al. (1996)), as well as increased hypertension (Gottlieb et al. (2006)). As such, results suggest retirement improves health stocks through lower stress, an interpretation supported by a substantial literature on the relationship between long-term stress and health. Third, there is little consistent evidence that retirement affects health behaviors, such as smoking, drinking, exercising, and socializing. Fourth, there is similarly limited evidence on the effect of retirement on cognition and mental health. Finally, congruent to these findings, retirement does not appear to significantly impact healthcare utilization and mortality.

Policy implications of these findings are somewhat ambiguous and subject to policymakers' priorities. Governments considering increasing the retirement age should be aware that it will impact individuals' health and well-being, but without tangible costs in healthcare utilization and mortality, the benefit to state budgets may take precedent. Of course, these results are likely not static, particularly as retirement ages creep towards the age of 70 in the decades to come. Effects on health of working longer and retiring later will require further investigation when these policies are fully implemented.

Chapter 2

The Effects of Skilled Nursing Facility Care: Regression Discontinuity Evidence from Medicare

2.1 Introduction

Nursing-care and continuing-care facilities account for about 5 percent of all health care costs in the United States, amounting to nearly $150 billion annually (CDC, 2014). A substantial portion of this spending is on post-acute care following an inpatient stay in the hospital. Among Medicare beneficiaries, 20 percent of hospitalizations result in a discharge to a SNF, and about 6 percent of Medicare's expenditures go toward SNF care (MedPac 2013). These facilities provide comprehensive, around-the-clock care in an outpatient setting, allowing patients that are unable to return to their homes to receive advanced care in a less costly manner. While in these facilities, individuals receive care to recover from surgeries and medical events that require regular skilled care and rehabilitation.

The additional care is intended to improve patient outcomes during short- to medium-term recovery from an injury or illness. Because of this, Medicare covers the majority of the initial cost of the SNF stay if the inpatient stay meets certain minimal requirements. Nevertheless, it has been established that up to 23 percent of these post-acute beneficiaries face hospital readmission within 30 days of being discharged to a SNF (Mor et al. 2010). These readmissions are costly both in terms of adverse patient outcomes — with patients at increased risk for otherwise avoidable complications — and financial burden, with the cost of the readmissions estimated at over $4 billion per year (Ouslander et al. 2010, Segal 2011). As a result, the Centers for Medicare and Medicaid Services (CMS) have floated policy proposals that would take readmission rates into account as part of payment rates to skilled nursing facilities, and are scheduled to go into effect in 2019 (Centers for Medicare and Medicaid Services 2015).[1]

Despite their integral and significant part of the health care system, evidence on the effectiveness of this type of care is limited, primarily due to selection issues among patients that utilize these services. Because of the intensity of care and high costs, patients discharged to SNFs are typically in poorer health. The decision to discharge to a SNF is associated with a number of patient-specific and region-specific characteristics; age, hip fractures, strokes, and having secondary insurance are all associated with an increase in the likelihood of a SNF discharge, while more income, more children, and

1. CMS already implemented the Hospital Readmissions Reduction Program (HRRP) in 2012, which reduces payments to hospitals with excess readmissions.

more hospital competition are all negatively associated (Picone, Mark Wilson, and Chou 2003, Bowles, Foust, and Naylor 2003). Yet it is not known how beneficial this additional care is, especially to patients on the margin when a discharge decision is made at the end of an inpatient stay. Consequently, it is unclear if this type of care is over- or under-priced by insurers and other providers. Overpriced care may prevent financially constrained individuals from receiving care, while underpricing may induce the moral hazard that has been shown to exist in other sectors of the U.S. health care market.[2] This is counteracted by many patients' desire to remain in their homes, and there is some evidence that the demand for this type of care is inelastic (Grabowski and Gruber 2007).

This paper attempts to answer the question of how being discharged to a nursing home affects patient outcomes. Medicare requires a patient spend a minimum of three days as an inpatient before subsidizing the cost of SNF care. For patients that qualify, Medicare will cover about 80 percent of all costs for an average duration stay.[3] Utilizing a regression discontinuity approach, I compare patients that qualified for SNF coverage against those that narrowly missed the necessary length of stay. This allows for the comparison of beneficiaries that differ only on the generosity of insurance coverage of post-acute care, with patients that do not go to a SNF left with either no formal care or intermittent care. Most discharges occur during the daytime when patients are awake

2. Newhouse et al. (1993), Finkelstein and McKnight (2008), Card, Dobkin, and Maestas (2009), as examples.

3. Medicare completely covers the first 20 days of a stay, then requires a coinsurance payment of $164.50 per day for the next 80 days of the stay. The average length of stay is 28 days and the average cost per day is $228.

and the hospital has more support staff available. Then, because length-of-stay days are computed based on the number of midnights in the hospital, people admitted just before or just after midnight spend a similar number of hours in the hospital, but individuals admitted just prior to midnight are more likely to qualify for Medicare coverage of the SNF stay.[4] I use administrative hospital records covering both emergency department visits and inpatient admissions from several large states, ensuring the sample sizes are large enough to precisely estimate effects for patients most affected by the Medicare restrictions.

I find that patients that are admitted just before midnight and are therefore more likely to qualify for Medicare coverage of their SNF care are 22 percent more likely to be discharged to a SNF. About two-thirds of the this change is absorbed by routine home discharges, with the remaining portion driving an increase in managed home healthcare uptake for this group. Patients that were more likely to go to a SNF upon discharge were 1.1 percentage points less likely to readmitted for any cause within the next 30 days. This suggests that for SNF care reduces the probability of 30-day readmission by 33 percent for the affected population. Furthermore, I find suggestive evidence that this group is also less likely to return for treatment to the emergency department without an inpatient admission in the same time frame.

To my knowledge, these results are the first to comprehensively document the effects of SNF care on patient outcomes using quasi-experimental methods, and suggest that this care is beneficial even for patients on the margin. My results present evidence

4. This approach is somewhat similar to that of Almond and Doyle (2011), who leverage the midnight discontinuity with mandatory stay lengths for childbirth to examine newborn health.

that not only does the additional subsidized care induce patients and providers to change discharge plans, but also that that both groups substantially benefit when restrictions on SNF care are eased. Simple calculations indicate that these benefits would be close to budget neutral for Medicare, with the reduction in readmissions offsetting the majority of the costs associated with the additional SNF care.

The paper is organized into five sections. Section 1 provides background information on Medicare rules regarding skilled nursing facility care and a review of the literature on patient readmissions. Section 2 describes the datasets used in the analysis. Section 3 outlines the estimation strategy and Section 4 provides the estimated effects of being discharged to a skilled nursing facility for a Medicare beneficiary. Section 5 concludes.

2.2 Background & Policy Significance

2.2.1 U.S. Health Insurance & Moral Hazard

The U.S. spends over 17 percent of GDP on healthcare, which is nearly twice the median value (8.6 percent) and well over the average for high-income countries (11.6 percent). Despite this, life expectancy at birth is no better than other high income countries (*World Health Statistics* 2016). One possible explanation is that the additional spending has negligible marginal return, and that there is significant overconsumption of health care services driven by moral hazard.

Assessing moral hazard in health insurance markets is confounded by adverse selection, as demand for health care services will appear higher for individuals with more insurance (Cutler and Reber 1998, Finkelstein, McGarry, et al. 2006). In unique situations, researchers were able to circumvent this by giving out health insurance experimentally. Famously, the RAND Health Insurance Experiment (HIE) produced variation in the generosity of assigned policies that revealed a price elasticity of -0.2 without differences in health outcomes, which has been taken to be evidence of moral hazard in the U.S. health care market (Newhouse and Group 1993, Baicker and Chandra 2008).[5] More recently, the state of Oregon allowed a large Medicaid expansion to be rolled out via lottery. This revealed a significant increase in hospital admissions, prescription drug use, and emergency department visits — including visits for causes that were classified as primary care treatable — for the lottery winners, without significant improvements in measured physical health (Finkelstein et al. 2012, Taubman et al. 2014, and Baicker et al. 2013).

Beyond these rare examples, researchers have exploited insurance rules to find plausibly exogenous changes in coverage generosity. These studies include policy changes in patient cost-sharing (Chandra, Gruber, and McKnight 2007), the the price elasticity of prescription drugs (Goldman et al. 2006), the advent of Medicare (Finkelstein and McKnight 2008), and the transition into Medicare at age 65 (Card, Dobkin, and Maestas 2009). These studies generally find that health care services are price sensitive, and that the benefits of the additional services are either absent or difficult to detect. Perhaps most significant to this study however, Grabowski and Gruber (2007) find no evidence

5. However, while most field experiments include a control group that does not receive the treatment at all, this was not possible in the HIE (Levy and Meltzer 2008).

of increases in nursing facility utilization when Medicaid financial means restrictions become less severe, concluding that nursing home care is inelastic with respect to coverage generosity. However, this comes entirely from the Medicaid population, who are far more likely to use nursing homes for long-term care of chronic diseases.

2.2.2 Hospital Readmissions & Medicare Coverage of Skilled Nursing Facilities

Approximately 1.4 million Americans reside in one of the country's 15,700 nursing homes at a given time, at a cost of $143 billion in 2013 (Harris-Kojetin et al. 2013). Medicare is the primary payer for 14.5 percent of these residents, as Medicare only covers SNF care for a limited amount of time and under certain conditions (Kaiser Family Foundation 2013). Further, not all nursing facilities are certified by Medicare or are willing to take Medicare patients. However, Medicare spending on nursing facility care still amounted to $31.3 billion in 2011, or about 6 percent of Medicare's total expenditure (MedPac 2013). Nursing care facility expenditures increased to $155 billion in 2014, which was strongly driven by the 4.1 percent growth in Medicare spending (National Health Expenditure Accounts, 2015).

In general, Medicare beneficiaries are discharged to a SNF when a physician decides the patient needs daily skilled care following an inpatient stay in the hospital. Medicare will only subsidize these services when the inpatient stay meets the conditions to be a "qualifying hospital stay." For this, the most stringent criteria are that the patient spend three midnights as an inpatient, which includes the day of admission but does *not* include the day of discharge.[6] Additionally, time spent as an outpatient — including time in the emergency room or time in observation services — do not count toward this three-day minimum.

Medicare does not cover long-term care for patients, and SNF coverage can only last for a maximum of 100 days per benefit period. A benefit period measures a beneficiary's use of hospital and skilled nursing services, and begins the day the patient is admitted as an inpatient. The benefit period ends when the patents has not received inpatient or SNF care for 60 consecutive days, and there is no limit to the number of benefit periods a beneficiary may receive. Following the start of a benefit period, Medicare beneficiaries pay nothing for the first 20 days in the skilled nursing facility, then pay daily coinsurance for the 80-100th day. This coinsurance amount was $133.50 in 2009, increasing to $164.50 in 2017. After that point, the patient is responsible for the full costs of the facility. Survey estimates of the median daily costs range from $225-$248 (Genworth Cost of Care Survey 2016, Lincoln Financial Group "What Care Costs" Study 2017, Metlife Market Survey of Long-Term Care Costs of 2012). However, Medicare data put this amount at $354 *after* deductible and coinsurance amounts have been deducted (Medicare SNF Fee-for-Service Claims Data, 2014).

This policy may create unnecessary costs for both Medicare and for beneficiaries, as it is possible for patients to be left without coverage for their physician's first-choice discharge plan (Lipsitz 2013). The rule was implemented in 1965, when it took about three days for a Medicare patient to be admitted, evaluated, and discharged,

6. The other criteria are simply that the physician prescribes SNF care and that skilled services are required to treat a medical condition that was also treated during the inpatient stay.

but this process has been streamlined to 1 to 2 days for many patients (Lipsitz 2013). There have been attempts to modify the rule, and the Health Care Financing Administration (now CMS) ran pilot studies that eliminated the three-midnight requirement, but decided against permanent implementation after it was deemed to have little effect on costs and the quality of patient care. The three-night stay requirement was also waived by the Medicare Catastrophic Coverage Act (MCCA) of 1988, but the act was repealed after just one year following a 243 percent increase in Medicare expenditures for SNF care in an evaluation study (Aaronson, Zinn, and Rosko 1994). Grebla et al. (2015) find that there is a small decrease in the average length of inpatient stay when the three-day restriction is relaxed for select Medicare Advantage plans, although the majority of this effect is driven by an increase in average length of stay for the control group during the study period.

With about 20 percent of Medicare patients discharged to a skilled nursing facility, the effect of this type of post-acute care has been surprisingly understudied. Because SNFs provide intensive, around-the-clock care, alternative discharge plans represent significant reductions in the amount of care provided to individuals. These patients face difficulties with follow-up appointments and tests, medications, and trips to the emergency department (Arora et al. 2010). Elderly patients often struggle with housekeeping tasks and need for more information about their discharge plan (Mistiaen et al. 1997). Shorter hospital stays often necessitate more intensive post-discharge follow-up, and home services and families are often required to act as safety nets with more comprehensive discharge planning (Naylor et al. 1999). However, it is often the case that the primary care physician is unaware of the hospitalization entirely, despite recommendations by major medical societies that the PCP be informed during all care transitions (Arora et al. 2010).

Of course, patients discharged to a SNF are generally in poorer health, and it is difficult to compare them to patients discharged to home care (Allen et al. 2011). The decision to discharge to a SNF is associated with a number of patient-specific and region-specific characteristics; age, hip fractures, strokes, and having secondary insurance are all associated with an increase in the likelihood of a SNF discharge, while more income, more children, and more hospital competition are all negatively associated (Picone, Mark Wilson, and Chou 2003, Bowles, Foust, and Naylor 2003). Policies that penalized hospitals for overly short inpatient stays gave inconsistent effects on rehospitalization rates among patients that were discharged to a SNF, with only some diagnoses groups showing improvements in rehospitalization rates (Unruh et al. 2013). It has been established that patients face substantial risk when transitioning between care settings, as communication between practice settings can be fragmented (Coleman 2003). Toward the end of an inpatient stay, hospital-based physicians often create discharge plans that detail a medication regimen, future tests and appointments for the patient to undertake, and/or pending test results to be followed up by an outpatient physician. It has been shown that many of these plans are not diligently followed, and these errors are associated with higher rates of rehospitalization (Moore et al. 2003).[7] It can be the case that

7. Doyle, Graves, and Gruber (2015) show that patients that go to hospitals that are more likely to discharge to a SNF have increased one-year mortality rates, and that these hospitals have relatively lower spending. It is unclear if this result is driven by hospital heterogeneity or the impact of SNF care, as the identification strategy has patients quasi-randomly assigned to hospitals rather than identifying

the discharge summary and the patient care referral form simply do not match up. Tjia et al. (2009) found that this resulted in medical discrepancies in medications in nearly three quarters of SNF admissions, while Wong et al. (2008) found remarkably similar figures for home discharges. Interventions to improve this have typically been targeted at long-term SNF occupants rather than those receiving the Medicare short-term rehabilitation services examined in this paper (LaMantia et al. 2010).

In this study I do not compare patients by discharge status directly, rather using time of admission for identification. This avoids the selection bias issue by leveraging variation in the probability of going to a SNF that results from Medicare coverage rules. Importantly, medical literature has established no link between time of hospital inpatient admission and medical outcomes.[8]

Finally, there is an ongoing policy debate as to which beneficiaries qualify as a "marginal" patient. While some services are regarded as "inpatient only," hospitals are given considerable discretion on the admission decision, and similar patients may be admitted for a short hospital stay at one hospital and kept for outpatient observation services at another. This decision affects both Medicare payouts to the hospital and out-of-pocket costs for beneficiaries. CMS has attempted to standardize this decision, proposing that patients should to move to inpatient care if the physician believed they should be in the hospital for at least two midnights. But the proposed "two-midnight rule" was immediately controversial when proposed and implementation was

variation in discharge plans.

8. Some studies have focused on day of admission, most often finding no association between mortality rates and weekend admission (Ensminger et al. 2004). Further, others have concluded that there is no association with off-hour admission, regardless of the day of the week (Meynaar et al. 2009).

delayed (Cassidy 2015). As such, Medicare beneficiaries face potentially far-reaching consequences based on their time of admittance as an inpatient.

2.3 Data

2.3.1 Data Description

I use data detailing individual-level hospital inpatient stays and emergency department visits to examine the impact of a slight difference in admission time on downstream medical outcomes. The Healthcare Cost and Utilization Project (HCUP) centralizes data provided voluntarily by participating states, and the databases are derived from administrative records. HCUP is a Federal-State-Industry partnership funded by the Agency for Healthcare Research and Quality (AHRQ), which is itself a branch of the U.S. Department of Health and Human Services.

The State Inpatient Databases (SID) gives information on the universe of inpatient stays for a participating state in a given year. The State Emergency Department Databases (SEDD) provide information on the universe emergency department admissions that do *not* result in an inpatient admission. These two databases include an identifier which allows me to track individuals across datasets over time. This allows the data to be longitudinal for all hospital-related encounters for a patient, even across years, with the only restriction being to this is that patients cannot be tracked across states.

HCUP gathers health care data from 47 states and the District of Columbia, which covers 97 percent of all inpatient discharges annually. Databases are standardized for comparability, such that AHRQ transforms the administrative health care data into uniform databases with common data elements. However, states are given the freedom to decide which variables they wish to provide to HCUP in both the inpatient and emergency department databases. Further, states can change what information they provide from year to year. This study uses data from states with large populations that also provide hour of admission. The sample consists of data from Florida, New York, and Washington from 2009-2013, resulting in a dataset containing 20 million inpatient admissions and more than 55 million emergency department visits. I am left with just over 15 million encounters once only Medicare beneficiaries are considered.[9] The discharge data include patient demographics, procedure and diagnosis codes, primary payer, and admission and discharge time. The data are extremely rich, and give a comprehensive picture of a patient's medical conditions and treatments received in the emergency department or as an inpatient. Summary statistics are provided in Table B.6.

For general statistics on Medicare utilization of SNF care, I use provider-level data from the Skilled Nursing Facility Utilization and Payment Public Use File. This database gives details on services and charges to Medicare beneficiaries residing in skilled nursing facilities, with all information from calendar year 2013.

9. More specifically, I use data from 2010-2013 for Florida and New York in the main analysis. Data from 2009-2011 for Washington is used only in summary statistics and in the balance check, as Washington does not submit data to the emergency department database.

2.3.2 Analysis Sample

One limitation of the hospital database records is that all admission times are reported only in hours, with the minutes imputed to zero.[10] While this does not create any bias in the estimates of the discontinuity, it is somewhat limiting in efforts to present results visually. Additionally, the lumping makes the smoothness of the density of admissions across midnight slightly harder to assess. Admissions will clearly be decreasing as the volume of patients decreases throughout the night, but some hospitals show a larger decrease at midnight. The question is whether there is a drop at midnight due to hospital shift times resulting in staffing changeovers or systematic misreporting of admission time. I drop the subset of hospitals for which there is evidence of a change in admission rates at midnight from the sample.[11] Appendix B.1 goes into detail on how hospitals were chosen to be included in the sample, and Table B.2 shows first stage estimates with all hospitals included that are nearly identical to those derived from the main analysis sample.

With the included hospitals, Figure 2.1 plots the number of admissions by hour of the day. The change at midnight is larger than the change at 1 a.m. (19 percent decrease against 11.5 percent decrease), but is smaller than changes at other areas of the distribution (up to a 32 percent increase in the morning hours).

10. Two states, New Mexico and Nebraska, actually do provide admission times in hours and minutes along with linkage variables, but the population sizes of these states prevents them from being particularly useful for this analysis given clear round-number bias in admission times.

11. A small subset of hospitals were contacted to attempt to get a better understanding of the effect of shift structure. Of these, it was more common among dropped hospitals to have shifts beginning at 11 or 12 for some personnel, although these hospitals were not able to verify that these shift structures were in place during the time period included in this analysis.

Data trimming presents an interesting econometric problem in this context. In a normal regression discontinuity setup, the primary trimming can be done by choosing the correct bandwidth, often through a packaged procedure.[12] In this setting, the maximum bandwidth is limited by the 24-hour clock. Instead, the difficulty is isolating the group that faces the Medicare 3-day rule without inducing a compositional change. There are two reasons for this. First, patients with length of stays that were very short or very long are not affected by the three-day Medicare rule. Including them in the analysis reduces the precision of the estimates by stacking individuals, who, for example, had similar admission times but had length of stays that differed by several days or even weeks. Second, the vast majority of discharges take place during daylight hours. Hence, the simplest solution of truncating by length of stay in days can increase the variance of results quite significantly.

With this in mind, the dataset is trimmed in the following ways. First, only patients that list Medicare as the primary or secondary payer are included.[13] Next, elective admissions are dropped, although this has negligible impact as these individuals are unlikely to be admitted close to midnight. I concentrate on the group most susceptible to the Medicare rule by examining patients that had inpatient stays close to the 3-day threshold. Because the day of discharge does not count toward the tally needed for SNF eligibility, I exclude patients that stayed less than 60 or more than 84 hours as an inpatient, i.e. 12 hours on either side of the 72 hour mark. Appendix B.2 gives density

12. For example, the popular optimal bandwidth procedure detailed in Imbens and Kalyanaraman (2012).

13. Florida does not provide a secondary payer, and as such I only include patients with Medicare as the primary payer. Additionally, I drop patients that were "discharged" to other sections of a hospital.

figures and first stage results after each of these trimming steps is made. While these results are clearly heavily attenuated, they do highlight that the effects are present in the larger Medicare population.

To provide evidence that this particular hour truncation is not crucial to the analysis, Figure B.7 shows the change in eligibility for SNF coverage from Medicare at midnight (shown in orange) and the change in proportion discharged to a SNF at midnight (shown in green) for a range of possible hour trimmings. Each point is a regression discontinuity estimate of the change at midnight with a 4-hour bandwidth. The change in SNF eligibility is increasing as the range of included hours becomes smaller, approaching 100 percent of patients when the range is very small. However, it is not monotonically increasing, reflecting the bunching in discharges. The change in the SNF discharge rate at midnight is relatively more constant, although again increasing in when the included range is very small. The blue points represent the ratio between these two to form the IV estimate, where the change in SNF eligibility can be seen as a first stage and actual SNF discharge as the reduced form. This ratio is relatively flat across all trimming ranges, indicating that the trimming range chosen for analysis will not be a key driver of results. Further, I show as a falsification exercise that there is no change in the SNF discharge rate for non-Medicare patients aged 60-64 in Table B.1a, and similarly show that there is no change for individuals with inpatient stays that were less than 60 hours or greater than 84 hours in Table B.1b.[14]

14. Medicare Advantage plans have the option of waiving the three-day requirement, and patients with these plans would provide another useful falsification test. However, the data do not provide the specific Medicare Advantage plan that a patient is enrolled in, and Grebla et al. (2015) found that only a small proportion of Medicare Advantage plans had actually waived the requirement. As such, Medicare

It is possible that patients and providers could manipulate length of stay on the discharge end of the stay. The extent that this occurs is likely minimal given the large costs to the hospital of an extra night of stay, as Medicare reimburses hospitals according to patient condition (prospective payment system) rather than for services received (fee for service). Conversations with several physicians and hospitalists indicated that while most would not be willing to alter stay lengths for insurance purposes, there may be some individuals willing to do so when the change is marginal and the benefit the patient substantial.[15] As such, I check this in two ways. First, figure B.10a shows a histogram of stay lengths for all non-elective Medicare admissions. If patients and providers were engaging in this manipulation, there would be a substantial increase in the number of three-day — and hence SNF-coverage eligible — stays over two-day stays for this population. Here, the number of two-day stays is nearly equal to the number of three-day stays. Second, I examine the probability that a patient is still in the hospital at 4 A.M. on the fourth day after their admission; for midnight admits, for example, this would be the probability the individual is still in the hospital 76 hours after she was admitted. This time is chosen because of the low probability of any discharges occurring at that point. Figure B.10b shows these probabilities by admission time for patients with the restrictions listed above except for the length of stay trimming. This shows a bump in the probability of staying until 4 A.M. on the fourth day for patients admitted at midnight, with the probability returning to the previous trajectory for patients admitted

Advantage patients are included in the analysis sample, with the small fraction of patients on plans that waived the requirement likely attenuating estimates.

15. This answer is difficult to elicit, as it also ties in to the proposed "two-midnight rule" with Medicare's increased scrutiny of short inpatient stays.

at other times.[16] This indicates any effects I find of SNF care are actually somewhat attenuated, as a fraction of patients admitted just after the midnight threshold — and thus less likely to be SNF eligible — are given an extra day of high-level inpatient care in the hospital.

2.4 Estimation Strategy

Consider a simple reduced-form model of the effect of being discharged to a skilled nursing facility on medical outcomes:

$$Y_i = \alpha_0 + \alpha_1 SNF_i + \varepsilon_i \tag{2.1}$$

Here, Y_i can be taken to be 30-day readmission probability for individual i, and SNF_i is a dummy variable indicating if the individual was discharged to a SNF. Then, the error term ε_i gives all other determinants of Y_i, and estimate of α_1 will give the effect of receiving nursing facility care after an inpatient stay on the probability of being readmitted to hospital within 30 days.

It is unreasonable to expect to obtain consistent estimates of α_1 because of the correlation between SNF discharge status (SNF_i) and the many unobserved factors that determine an individual's likelihood of returning to the hospital. The inpatient physician has considerable influence on the discharge decision, and will generally make this decision based on the patient's recent medical history, test results, and disposition.

16. RD estimates for this bump are estimated to be around two percentage points, but only with a local polynomial regression.

While these factors may technically be observable, it is not feasible for full medical records to be made available to researchers. Further, the patient's or patient advocate's wishes may influence the decision as well, as leaving the hospital for a temporary stay at a SNF is costly for both the provider and the patient; the provider incurs pecuniary costs of care, while the individual must cope with additional time out of their home in addition to the financial obligations.

In general, patients that are discharged to a SNF instead of to their homes are in poorer health. Table 2.1 shows differences in means between patients discharged to a SNF and those discharged under any other status code for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient. Beneficiaries with SNF discharges have more diagnoses and chronic conditions on their record, were discharged later, and were nearly nine years older.[17] Clearly, patients discharged to a SNF had different dispositions and inpatient experiences, on average.

To avoid the confounding effect of omitted variables, I rely on a sharp discontinuity in the probability being discharged to a skilled nursing facility. Let $Z_i = 1\{LOS \geq 3\}$ be a dummy variable that indicates if an individual stayed three or more calendar days as an inpatient. The length of stay is measured as the number of midnights spent in the hospital. This means that people with nearly identical amounts of time in the hospital can have a one day difference in length of stay if they are admitted right before or after midnight. Figure 2.2 plots the time of admission profile of stay lengths in both days and hours. This shows that the length of stay in hours is continuous around mid-

17. Note that interestingly, patients discharged to a SNF actually have slightly lower total charges than patients discharged elsewhere, on average.

night admission, but the length of stay in days changes discretely. While beneficiaries admitted before midnight all stayed three days or more, the probability of staying three or more days — and thus being eligible for SNF coverage from Medicare — drops to under 25 percent for those admitted after midnight.

Fundamentally, an individual admitted as an inpatient just before midnight is very similar to an individual admitted just after midnight. With the Medicare coverage rules, however, the individual admitted just before midnight has a longer length of stay and is suddenly eligible for SNF coverage. This fuzzy RD design allows for identification of α_1 assuming that no other variables change discretely at midnight, i.e. that $\mathbb{E}[\varepsilon_i|LOS_i = a]$ is continuous at admission time a equal to midnight. This assumption could be violated if, for example, patients admitted after midnight are less healthy, or are less likely to receive an operating room procedure. Column (2) of Table 2.2 gives RD estimates for these measures, along with associated p-values in column (3). The number of chronic conditions, operating room procedures, and probability of dying in the hospital do not vary significantly across the midnight threshold. This is also true for the average arrival time to the emergency department and discharge hour, as well as individuals' age and gender. The average number of procedures does increase marginally, by 3 percent, although this is not significant with either a linear or cubic polynomial, or with a larger bandwidth. There is also a slight change in the racial composition at midnight with patients about 7 percent more likely to be black, although there is not a significant change in any other race.[18] Nor shown in this table are total hospital charges,

18. It is unclear what is driving the imbalance in race, but this difference appears to be entirely driven by the state of New York with insignificant point estimates from Florida alone. Further, the point

which mechanically are \$2000 cheaper on average for those admitted after midnight, with the hospital billing based on the length of stay in days rather than hours. Thus, due to hospital billing practices, a beneficiary admitted before midnight would have a more expensive stay if Medicare did not cover these costs.[19]

I estimate the reduced form effect of being discharged to a nursing home on outcome Y_i using regressions of the form:

$$Y_i = \beta_0 + \beta_1 Midnight_i + g(AdmitTime_i) + \beta_2 X_i + \xi_i \tag{2.2}$$

where $Midnight_i$ is a dummy variable equal to 1 if the individual was admitted as an inpatient before midnight or 0 otherwise. Note that this is the reverse of a typical "left-to-right" RD notation. This is done to make estimates easier to interpret, as the group in the before midnight side of the discontinuity are the individuals more likely to be satisfy the requirements for SNF coverage. The $g(AdmitTime_i)$ term is a quadratic polynomial in time of admission, although results are robust to this choice.[20] A vector of observable characteristics X_i is included in some regressions, and includes flexible controls for age, number of procedures as an inpatient, and number of diagnoses on record.[21] I generally use a bandwidth of 8 hours, and cluster standard errors by hour

estimates are weaker if a more flexible cubic specification is used. In the interest of transparency, the time of admission profiles for race and age are presented in Appendix B.5. The figure for *proportion white* suggests some "non-elective" may be miscategorized, with a sharp uptake in the morning hours when planned admissions are often scheduled.

19. Medicare does have a deductible for inpatient stays, but it does not vary with length of stay.

20. See Table B.5 for robustness checks on key results with a linear specification and different bandwidth choices.

21. Because patients and the discharge decision could potentially vary by hospital and the day of the week of the admission, I further show robustness to including hospital fixed effects, weekend fixed effects, and hospital-by-weekend fixed effect in Table B.5.

of admission. Because this a relatively low number of clusters (Cameron, Gelbach, and Miller 2008), key results with alternative handling of standard errors is presented in Table B.8. This equation is used to estimate both the first stage — the change in the composition of discharges related to admission time — and the reduced form, which is the change in the share of people that return to the hospital in a defined period of time. The causal effect of nursing facility use on outcome Y_i is reached by combining the first stage and reduced form results. Specifically, I divide the effect of being admitted after midnight on outcome Y_i by the effect of being admitted after midnight on likelihood of being discharged to a nursing facility, SNF_i. Thus, the midnight discontinuity is used as an instrument to identify the causal effect of care at a skilled nursing facility (Hahn, Todd, and Van der Klaauw 2001).

Finally, I back out the characteristics of the compliers, i.e. those induced to going to a SNF by being admitted before midnight. These beneficiaries behave differently than the "always takers" — who go to SNF regardless of time of admissions — and "never takers", who are not discharged to a SNF regardless of admission time. While is it not possible to identify individual compliers, their characteristics can be described in order to give a sense of the types of beneficiaries that respond to the Medicare incentive. To do this, I first estimate the change at midnight for a vector of individual characteristics twice, first while restricting the sample to only patients that go to a SNF and again for only those that did not go to a SNF:

$$X_i = \alpha_0 + \alpha_1 Midnight_i + g(AdmitTime_i) + \epsilon_i \quad \text{SNF} \tag{2.3}$$

$$X_i = \delta_0 + \delta_1 Midnight_i + g(AdmitTime_i) + \epsilon_i \quad \text{non-SNF} \tag{2.4}$$

Then, the means can be estimated from both the SNF-going group and the non-SNF-going group:

$$\bar{X}_{C,\text{ SNF}} = \frac{\hat{\beta}_0}{\hat{\beta}_1}\hat{\alpha}_1 + \hat{\alpha}_0 + \hat{\alpha}_1 \tag{2.5}$$

$$\bar{X}_{C,\text{ non-SNF}} = \hat{\delta}_0 + \hat{\delta}_1 + \frac{\hat{\beta}_0 - 1}{\hat{\beta}_1}\hat{\delta}_1 \tag{2.6}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are from the first stage regression estimating the change in the SNF-going rate at midnight. (2.5) and (2.6) can then be combined — weighted by the variances of $\hat{\alpha}_1$ and $\hat{\delta}_1$ — giving estimates of the means of the complier group, $\bar{X}_C$. The means of the characteristics of the never-takers can be estimated from the group admitted just before midnight in (2.4), and the characteristics of the always-takers from the group admitted just after midnight in (2.3).

2.5 Results

2.5.1 Discharge Location

Figure 2.3 presents the time of admission profile for being discharged to a skilled nursing facility. Specifically, the plot shows the proportion of people discharged to a SNF for each hour of admission with fitted values from equation 2.2 superimposed. Midnight is centered at 0 on the x-axis.

Figure 2.3 reveals a discrete drop in the proportion of Medicare beneficiaries discharged to a nursing facility at the midnight admission hour. The estimate of this jump is shown in the first column of Table 2.3, with the estimated change given at 3.37 percentage points. In the table, standard errors — clustered by hour of admission — are listed below the point estimates, and estimates for beneficiaries admitted just before midnight are given in italics. The proportion of the sample population that is discharged to a SNF just before midnight is estimated to be 14.86 percent, meaning that there is a 22 percent increase in SNF discharges for people that were admitted before midnight and were hence more likely to have Medicare coverage for the SNF stay. Columns 2 and 3 give estimates for the proportion of people that are discharged to their homes without further care — in other words, a routine discharge — and the proportion of beneficiaries discharged to their home with the expectation of receiving organized home healthcare. This latter category indicates that the individual is being sent home, but under the care of a home health service organization in anticipation of receiving skilled care such as a home attendant or nursing aide. The final column represents all other discharge codes.[22]

These two categories are being examined here to demonstrate where post-midnight beneficiaries are going in lieu of being discharged to a nursing home. From Table 2.3, it is evident that there is an decrease in routine discharges of about 2.5 per-

22. There are over 20 patient discharge status codes; the three enumerated categories make up about 90 percent of all discharges.

centage points, with the pre-midnight estimate at 17.8 percent.[23] This means that the majority of the change in skilled nursing discharges is being absorbed by home discharges. However, organized home health care also decreases significantly at the midnight threshold, implying that some patients that would have gone to a nursing facility if Medicare coverage was provided to them were instead scheduled to have in-home visits. Medicare describes this form of post-acute care as the "Medicare home health benefit", and consists of a Medicare-approved health care professional intermittently visiting the home of the patient to provide one or more of skilled nursing care, physical therapy, speech-language pathology, or continued occupational therapy. This form of care has a lower barrier to entry than SNF care — as it is less costly to Medicare — and there is no minimum inpatient stay requirement. However, patients must only need "intermittent" skilled care, defined as care that is needed fewer than seven days each week or less than eight hours each over a period of 21 days. As such, this option much less medical care and supervision than being discharged to a SNF. Finally, the other discharges category shows an increase that is a small but statistically significant, although not with additional controls included.

It is clear the Medicare beneficiaries are responding to the reduced costs for skilled nursing care by increasing their use of these services. This is perhaps unsurprising, as the cost of SNF care (about $250 per day) is often prohibitively expensive to patients and their families. Further, the alternative choices could leave some patients needing to fill in the gaps via a caregiver ($20-$30 hour), with Medicare home health care

23. This is very close to the rate for all Medicare patients nationwide, at 18.4 percent (HCUP Statistical Brief #205, 2016).

services not providing homemaker services or personal care, such as cooking, bathing, and dressing. Consistent with this result, CMS Skilled Nursing Facility Transparency Data show that the average stay in a skilled nursing facility is just 28 days for Medicare beneficiaries, which leaves the average beneficiary with a bill of just $1288 for nearly a month of care, significantly less than the median cost of $6500 if paid out of pocket. Despite inconveniences associated with temporary SNF care, patients on the margin have a clear incentive to opt in to a more intensive level of care at a steeply discounted cost.

2.5.2 Patient Outcomes

Next, I examine the effect of a discharge to a SNF on the probability of readmission to the hospital. The Centers for Medicare and Medicaid Services has become increasingly concerned with the rate at which beneficiaries return to the hospital, and uses a 30-day risk standardized readmission measure as a key benchmark in hospital performance. More recently, CMS has made these numbers public and reduced payments to hospitals with excess readmissions. The Hospital Readmissions Reduction Program (HRRP) began in fiscal year 2013, and initially encompassed only patients with one of three diagnosis codes: acute myocardial infarction, heart failure, and pneumonia. Here, I focus first on the likelihood of patients to return to the hospital — either as an inpatient or only to the emergency department — for any cause.

Table 2.4 presents estimates on the change in readmission and revisitation rates as an inpatient for beneficiaries admitted before midnight, i.e. those that were more likely to be eligible for SNF coverage. Following Medicare's standard, readmission times are calculated from the point the patient is discharged to the next admission, rather than from the initial admission. "ED only" signals that the individual returned to the emergency department but was not readmitted, while a "revisit" indicates that the patient returned to the emergency department *or* was readmitted.

The first set of estimates reveal that the chance of being readmitted to the hospital within 30 days decreases by approximately 1.1 percentage points for this group, representing a change of about 7.5 percent. This effect is also present and statistically significant at 14 days (0.83 percentage points, 9.2 percent) and 100 days (0.96 percentage points, 3.8 percent). This indicates that the group that was more likely to go to a SNF due to having it covered by Medicare is less likely to experience readmission. All of these estimates in Table 2.4 remain significant whether or not the additional controls are included in the regressions, with the point estimates only altered slightly, if at all.[24]

The second set of estimates examine the change in the chances of returning only to the emergency department. Unlike readmittance, the group with a higher SNF-discharge rate do not have ED-only visits in lower rates after two weeks, and the coefficients on the 30-day interval are very small and only significant at the 90 percent level. The third set of estimates measures the chances of having any visit to the emergency department on return, whether or not the patient was later admitted. This is similar to revisits, but records explicitly if the patient visited the emergency department on return

24. To give a clearer picture of the timeline on returning to the emergency department or being readmitted, Figure B.11 shows the relevant portion of the CDF of hospital revisits. The distribution is nearly identical between the higher-SNF group (before midnight admits) and the lower-SNF group (after midnight admits) over the first seven days after discharge. The functions then diverge, and maintain roughly the same separation well beyond the 35 days shown.

to the hospital. Estimates show coefficients that are negative and similar in magnitude to being readmitted. This is consistent with evidence that patients without insurance or public insurance are more likely to return to the emergency department for follow-up care that could have been handled in an outpatient setting (Ladha et al. 2011). Finally, the "revisit" category shows that the the chance of returning to the ED or being readmitted within two weeks decreases by approximately 1.25 percentage points for the group more likely to go to a SNF, and the risk of returning within 30 days decreases by about 1.3 percentage points. The change is also present 100 days after discharge, but is no longer statistically significant.

Figures 2.4 and 2.5 give the complementary visual representation of these estimates, with centered time of admission plotted against readmission rate and ED-return rate for a given length of time. In Figure 2.4 there is a clear increase for both the 14- and 30-day probabilities of being readmitted, and a smaller jump for the 100-day measure. Again, this shows that for patients in the group more likely to go to a SNF, the likelihood of returning to the hospital and being readmitted is reduced. Figure 2.5 shows the change for midnight admits of returning to the ED but not being readmitted, with the group more likely to be SNF-eligible showing a general decrease but not as clear of a discrete jump.

This finding implies skilled nursing facilities are better at keeping patients from being readmitted in a relatively short period of time. The effect is strongest in the very short term — including the 30-day mark used for Medicare policymaking — and tapers off as the length of time from the initial inpatient stay increases.

Combining these estimates with those from the first stage gives an IV estimate of the change in the likelihood of returning to the hospital for those that were discharged to a SNF. For the 30-day timeframe, the estimate for being readmitted is quite large at -33.1 percent (standard error of 0.08).[25] The corresponding estimate for 30-day emergency department only is smaller and statistically significant at the 90 percent level (-7.9 percent, standard error of 0.046).

This finding leads to two obvious and related questions: Why are patients that go to a SNF upon discharge less likely to return to the hospital, and why are they less likely to be readmitted? Clearly, these questions cannot be addressed completely with this identification strategy, but I am able to provide evidence for answers to both inquiries.

I investigate the first question by examining the specific health problems of patients upon returning to the hospital. With this, I can examine if the hospital returns are concentrated in causes that are most sensitive to the quality of post-hospital discharge care. Specifically, beneficiaries in a skilled nursing facility may be less vulnerable to adverse events related to medication, follow-up care, or infections (Levenson 2014). Table 2.5 breaks down ED-return and readmission 30-day rates by diagnosis when the patient returns. Here, each dependent variable is a dummy variable indicating whether or not a patient had that diagnosis listed as their primary diagnosis when she returned to the hospital. The categories were formed from ICD-9 Codes truncated to two digits to make the categories more general. The specific 18 categories in the table were formed

25. IV standard errors calculated via the delta method.

by looking at the most common diagnoses in the analysis sample as well as categories — such as congestive heart failure, pneumonia, urinary tract infections, and chronic obstructive pulmonary disease — that should be manageable in a nursing home. Note that the categories are exhaustive, such that the variable “Other” accounts for all other diagnoses not explicitly listed.

For readmission, the probability of being readmitted with a specific diagnosis changes discretely for only one specific category: heart disease (includes heart failure and diseases of pericardium). This is a large category and significant category, with nearly two percent of individuals admitted just before midnight with this diagnosis getting readmitted within 30 days. For those that were more likely to go to a SNF, the probability of being readmitted with a heart disease primary diagnosis drops significantly by about 10 percent.

However, for returning to the emergency department without inpatient admission, there are diagnoses categories with opposing signs. When patients are in the group more likely to go to a SNF, they are more likely to return to the emergency department for heart disease, and this same group is less likely to return to the ED for general symptoms (including syncope) and intestinal disorders. Importantly, the high SNF-going group is also more likely to return to ED for complications from care.

One explanation for the results presented here would be that SNFs are more able to treat minor issues with patients, and patients avoid having their condition degrade to the point that a readmission is necessary. Some of these patients would then be treated at the SNF without going to the hospital, thus explaining the lack of congruity between emergency department visits and readmission rates. As evidence, some categories show that the patients in the group less likely to go to a SNF face a higher probability of returning to the ED, but are no more likely to be readmitted. Diagnoses that fit this description include general symptoms and intestinal disorders. These diagnoses should not associated with the quality of care, suggesting that the facilities are able to treat patients and prevent readmissions for some conditions.[26]

2.6 Conclusion

Little has been documented about the effect of skilled nursing facility care in previous literature. Difficulties in estimating effects stem from selection bias among patients, in which sicker and/or better off patients are much more likely to be discharged to a SNF. In this paper, I use Medicare's eligibility rules for skilled nursing facility care coverage in a quasi-experimental design. I document that Medicare's restrictions have a considerable effect on both the likelihood of being discharged to a SNF after an inpatient stay and on the likelihood of being readmitted to the hospital in a relatively short period of time. Medicare beneficiaries admitted just before midnight are more likely to receive SNF care after discharge than those admitted just after midnight. The majority of this change is absorbed by routine discharges to the patients' homes, but I also find decreases in managed home health care. I then find that this increase in SNF care makes these beneficiaries somewhat less likely go back to the hospital by way of the

26. Of course, it is possible that the primary diagnosis may mask lapses in care, such that the primary diagnosis remains from a previous adverse event, but was subsequently exacerbated by less than ideal care. Unfortunately, the identification strategy used here does not allow me to investigate this further.

emergency department, but substantially less likely to be readmitted to the hospital. This result holds for very short time periods (2-4 weeks), with evidence that the effect shrinks slightly as the duration from the initial inpatient stay increases.

These results have several implications for both Medicare's reimbursement rules and for skilled nursing facility care in general. First and foremost, it is clear that patients are responding to incentives by taking the Medicare-subsidized SNF care when it becomes available. Ex ante, this result may be surprising, given that many beneficiaries would prefer to return home after a hospital stay.[27] However, SNF care is very expensive for a reason, with around-the-clock care by a professional staff. Given that the next most intensive option for beneficiaries — home health care — provides significantly fewer medical and personal services, it is reasonable that some patients on the margin are induced into being discharged to a SNF. As mentioned previously, this is consistent with average length of stay in a SNF being just over a week longer than the period completely covered by Medicare. Medicare considers 30-day readmission to be a key measure of patient health, and reduces payments to hospitals with excess readmissions. Further, CMS has proposed reducing payments to SNFs with excess readmissions as well. To the extent to which this measure is an accurate measure of post-acute care, the results presented here indicate non-inelastic preferences for this type of care on the part of Medicare beneficiaries. While results from Doyle, Graves, and Gruber (2015) suggest that excessive SNF usage may be an indicator of poor hospital quality, these results give

27. The University of Michigan Health and Retirement Study (HRS) even leads the question of expected future nursing facility use with: "Of course nobody wants to go to a nursing home, but sometimes it becomes necessary."

evidence that a portion of the population can benefit substantially from SNF care.

Because the identification strategy of this study identifies a local average treatment effect, the estimated effects are for those induced to change their discharge location by being admitted after midnight. Compliers will likely differ from the general population, especially in this setting where the treatment can change the living situation of the individual. Always-takers — those who enter the nursing facility regardless of discharge time — are likely to be sicker on average, while never-takers will be more healthy on average.

Mean observable characteristics of all three groups are shown in Table 2.6. These calculations are for patients admitted at midnight — such that the treatment here is defined as *not* going to a SNF — with this group less likely to eligible for a Medicare-covered SNF stay. On average, compliers appear to be slightly more healthy, with fewer chronic conditions and procedures as an inpatient than both always takers and never takers. However, this group experiences more procedures than the never takers on average, but fewer than the always takers. The complier group is also much more likely to be female, and is younger than the always-takers but nearly seven years older than the never-takers. These calculations further reinforces that the complier group — i.e. those that do not go to the SNF because it is not covered by Medicare — are on the margins of where to be discharged, such that it is the lack of Medicare coverage.

The results presented here show that patients substantially benefit from this post-acute care. Going to a SNF helped reduce hospital readmissions by as much as 33 percent.This suggests that compared to the high costs of SNF care, the burden is offset by preventing readmissions, with the cost of readmissions for Medicare exceeding $24 billion annually (Hines et al. 2014).

Medicare cost reports indicate that CMS spends $354 per day for SNF care for beneficiaries. This is dwarfed by the average cost of a day as an inpatient at $2346 (HCUP Statistical Brief #180, 2014). As such, relaxing the 3-day rule for SNF care may be sensible from a policy standpoint despite the increased costs of SNF care. With an all-cause 30-day readmission rate of 17.2 per 100 admissions, patients with Medicare as the primary payer are the most likely to return to the hospital of any insurance type (Hines et al. 2014). The complier group in my sample — taken to be be beneficiaries with an average age of 79 and 10.5 diagnoses on record — has a slightly higher rate at 17.38 per 100 admissions. Each readmission costs Medicare, on average, $13,800 (HCUP Statistical Brief #199). From my results, the 3.3 more people per 100 going to SNFs cost an estimated $32,700, calculated by multiplying by the average SNF stay that lasts 28 days and average costs to Medicare of $354 per day.[28] The is slightly more than the savings from a reduction of 1.1 per 100 beneficiaries reduction in readmissions, calculated to be $15,732.[29] Therefore, for the complier group that has the SNF coverage made available to them, the increase to Medicare costs would be $15,000 per 100 individuals. In 2012, there were 354,637 Medicare-covered hospital stays that lasted at least three days (including time in the emergency department) but had fewer than three inpatient nights (Inspector General 2013). Given this amount, a modest relaxation of the Medicare

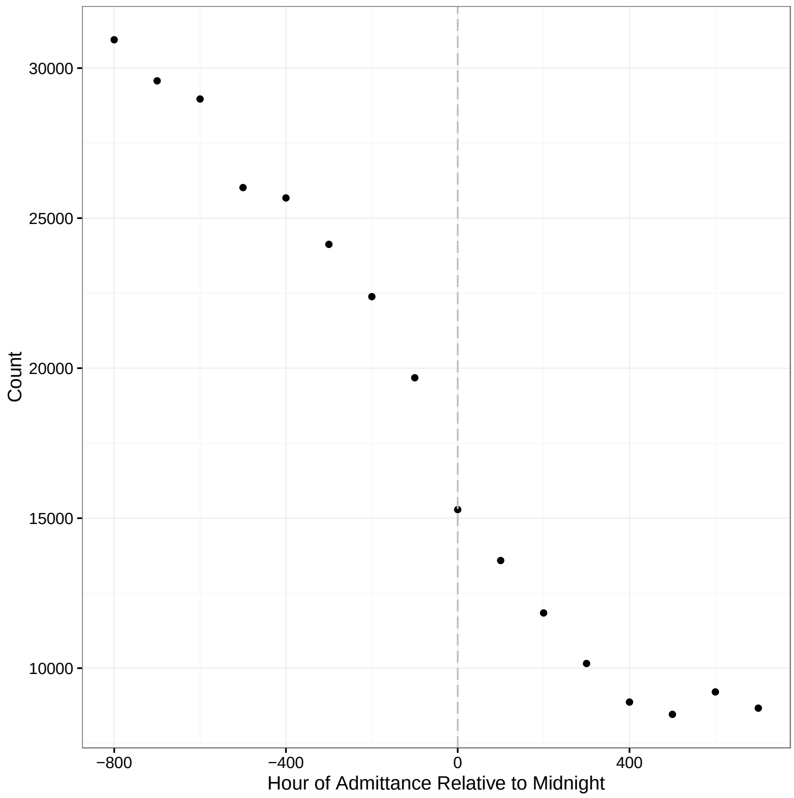
28. The average cost and length of SNF stay are calculated from the CMS Skilled Nursing Facility Transparency Data for calendar year 2013.

29. This is calculated from the point estimate in Table 2.4 of 0.014 multiplied by the average cost of a readmission to Medicare of $13,800.

three-night requirement for SNF coverage has the potential to improve health outcomes and costs just \$53 million. As such, this analysis suggests CMS would incur modest costs by removing the length-of-stay requirement on inpatient stays before providing coverage for skilled nursing facility care. However, patients are generally readmitted because of deteriorating health, and it is difficult to measure the long-term health impacts of reducing these events. Further, these calculations do not include benefits of SNF care that are difficult to capture — such as reduced expenditure on at-home care and the reduction in the burden on family caretakers — nor costs that a similarly difficult to calculate, such as increased home-to-home time for some patients.

These results suggest that the policymakers concerned about excess Medicare readmissions should consider these restrictions to care carefully, as they offer an effective way forward for further readmission reduction programs.

Figure 2.1: Frequency of Admission by Hour



Notes: Counts of inpatient admissions by hour of admission for the final sample, with data from included hospitals in New York, Washington, and Florida from 2009-2013 for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient.

Table 2.1: Differences Between Patients By Discharge Location

	Other Discharge		SNF Discharge			
	Mean (1)	SD (2)	Mean (3)	SD (4)	Difference (5)	p-value (6)
NPR	1.175	1.246	0.742	1.807	-0.433***	<0.001
NDX	10.426	4.532	11.228	4.597	0.802***	<0.001
NChronic	5.873	2.797	6.25	2.772	0.377***	<0.001
EDHour†	1315.655	530.739	1278.562	558.213	-37.093***	<0.001
Age	73.065	10.27	81.812	13.74	8.747***	<0.001
Died	0.024	0.00	0.000	0.153	-0.024***	<0.001
Discharge Hour	1486.627	278.062	1540.862	319.389	54.235***	<0.001
Female	0.542	0.475	0.657	0.498	0.115***	<0.001
Hispanic	0.133	0.266	0.077	0.339	-0.056***	<0.001
Black	0.133	0.302	0.101	0.34	-0.032***	<0.001
White	0.68	0.409	0.787	0.466	0.107***	<0.001
OR Procedure	0.074	0.282	0.088	0.261	0.014***	<0.001
Median Income	2.464	1.114	2.55	1.132	0.086***	<0.001
Total Charges	25010.063	14046.803	22602.586	17768.687	-2407.477***	<0.001

Notes: Differences in means for patient characteristics and experiences for non-elective admissions with stay lengths between 60 and 84 hours, with "SNF Discharge" means subtracted from "Other Discharge" means. All estimates come from hospital inpatient administrative records from New York and Florida from 2010-2013. Sequentially, the dependent variables are: Number of ICD-9 procedures as an inpatient, number of diagnoses on record, number of chronic conditions on record, emergency department arrival time, age at time of admission, whether the patient died, discharge hour, patient gender, patient race (Hispanic, Black, and White), an indicator for one or more major operating room procedures, median income by state for the patient's ZIP code, and total charges. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%. †Only Florida provides information on ED arrival time.

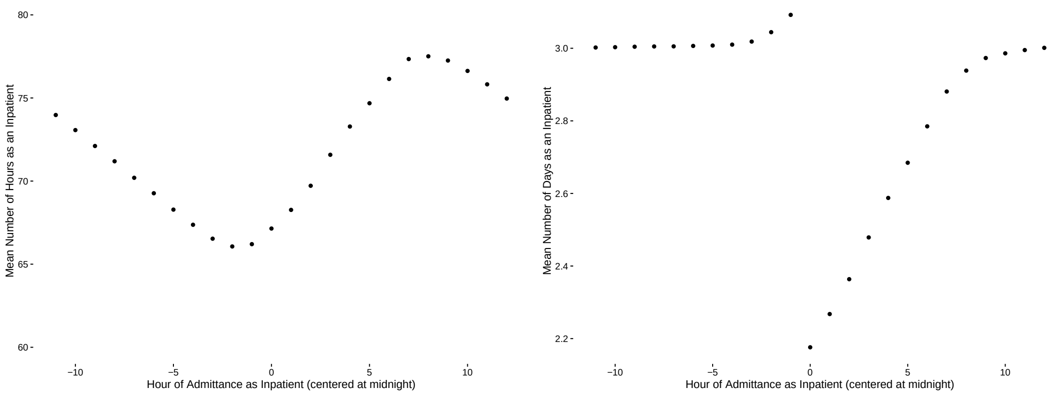
Table 2.2: Differences Between Patients Admitted Before and After Midnight

	Constant (1)	RD Estimate (2)	p-value (3)
NPR	0.9984	0.0333	0.0356**
NDX	10.4018	−0.0294	0.4961
NChronic	5.8067	0.0208	0.1805
ED Hour†	19:52	43.2	0.6668
Age	72.3929	−0.3095	0.2600
Died	0.0189	0.0018	0.6604
Discharge Hour	14:48	−6.528	0.1826
Female	0.5613	−0.0127	0.1131
Hispanic	0.1265	0.0034	0.6207
Black	0.1254	0.0094	0.0011***
White	0.7005	−0.0152	0.1072
Other Race	0.0476	0.0024	0.3486
OR Procedure	0.0689	0.0001	0.9798
Median Income	2.4129	0.0166	0.3477
DRG‡	29,914.65	399.67	0.3439

Notes: RD estimates for patient characteristics and experiences for non-elective admissions with stay lengths between 60 and 84 hours. All estimates come from hospital inpatient administrative records from New York and Florida from 2010-2013. Estimates are from collapsed data. The constant gives the estimate for each dependent variable just before midnight. Sequentially, the dependent variables are: Number of ICD-9 procedures as an inpatient, number of diagnoses on record, number of chronic conditions on record, emergency department arrival time, age at time of admission, whether the patient died, discharge hour, patient gender, patient race (Hispanic, Black, and White, or other), an indicator for one or more major operating room procedures, median income by state for the patient's ZIP code, and DRG code. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%. †Only Florida provides information on ED arrival time. ‡DRG is a numerical representation of categorical DRG codes.

Figure 2.2: Time of Admission Profile of Length of Stay in Days and Hours

(a) Length of Stay in Hours (b) Length of Stay in Days



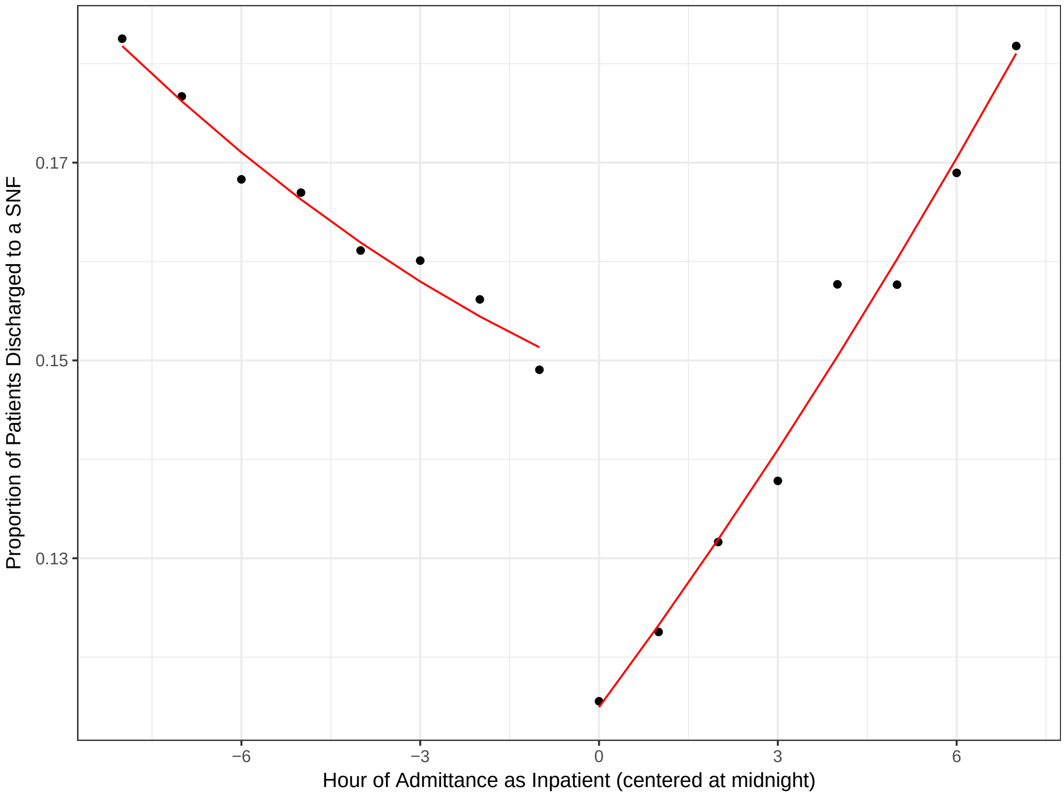
Notes: The time of admission as inpatient profile for the length of stay in hours (Panel 2.2a) and days (Panel 2.2b), with data from a near census of inpatient visits in New York, Washington, and Florida from 2009-2013 for Medicare beneficiaries that stayed between 60 and 84 hours as an inpatient.

Table 2.3: Change in Discharge Location for Midnight Admissions

	Skilled Nursing Facility		Home (Routine)		Organized Home Healthcare		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change at Midnight	0.0337***	0.0309***	−0.0254***	−0.0204***	−0.0070***	−0.0096***	−0.0025**	−0.0011
	(0.0030)	(0.0023)	(0.0036)	(0.0024)	(0.0025)	(0.0023)	(0.0013)	(0.0016)
	0.1486		*0.6134*		*0.1775*		*0.0309*	
Controls	No	Yes	No	Yes	No	Yes	No	Yes
n	257,703	257,703	257,703	257,703	257,703	257,703	257,703	257,703

Notes: Estimates from equation (2.2) with a dummy variable for discharge status as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

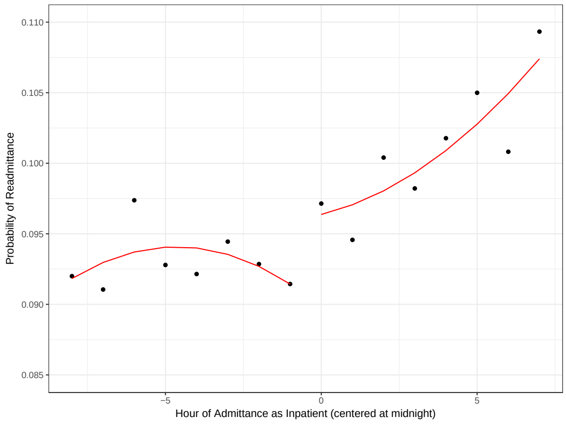
Figure 2.3: Time of Admission Profile of Likelihood of Being Discharged to a SNF



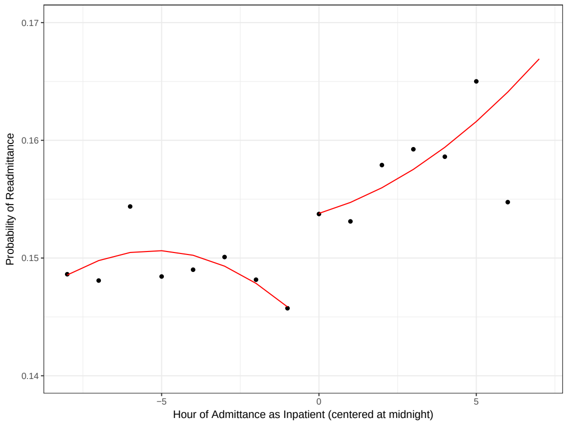
Notes: The time of admission as inpatient profile for the likelihood of being admitted to a skilled nursing facility is shown, with data from a near census of inpatient visits in New York and Florida from 2010-2013. The fitted values (red line) are from equation (2.2) with a quadratic polynomial in time of admission.

Figure 2.4: Time of Admission Profile of Likelihood of Readmission as an Inpatient

(a) 14 Days



(b) 30 Days



(c) 100 Days

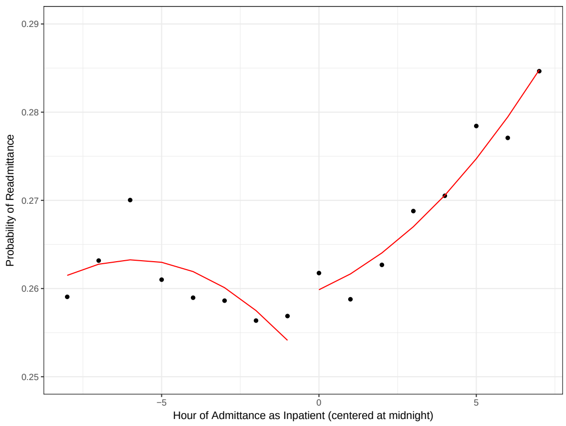
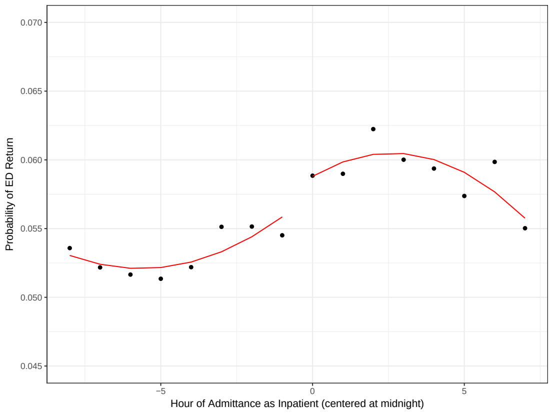
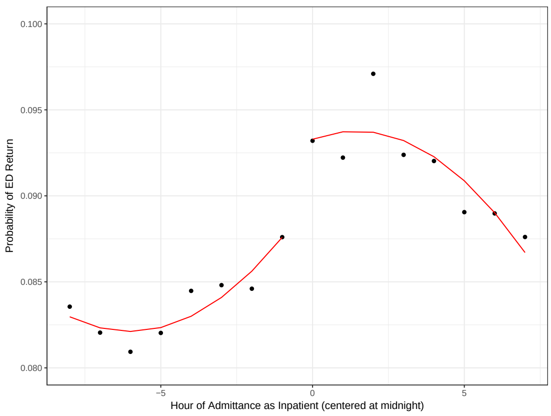


Figure 2.5: Time of Admission Profile of Likelihood of Emergency Department Revisit (Not Later Admitted)

(a) 14 Days



(b) 30 Days



(c) 100 Days

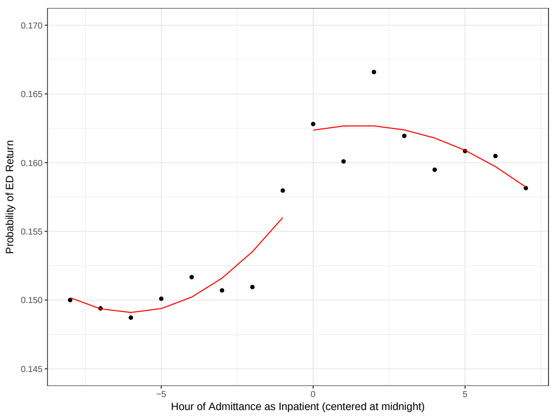


Table 2.4: Change in Revisits and Readmissions for Midnight Admissions

Timeframe:	14 Days		30 Days		100 Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Readmission	-0.0083^{***}	-0.0085^{***}	-0.0112^{***}	-0.0114^{***}	-0.0096^{***}	-0.0103^{**}
	(0.0027)	(0.0026)	(0.0025)	(0.0023)	(0.0038)	(0.0041)
	0.0898		*0.1455*		*0.2527*	
ED Visit Only	-0.0039	-0.0037	-0.0027^{*}	-0.0024^{*}	0.0009	0.0011
	(0.0028)	(0.0027)	(0.0015)	(0.0014)	(0.0027)	(0.0028)
	0.0567		*0.0913*		*0.1628*	
Any ED on Return	-0.0092^{**}	-0.0093^{**}	-0.0089^{***}	-0.0091^{***}	-0.0046	-0.0054
	(0.0045)	(0.0043)	(0.0028)	(0.0024)	(0.0049)	(0.0053)
	0.1372		*0.2158*		*0.3731*	
Revisit	-0.0122^{**}	-0.0122^{**}	-0.0138^{***}	-0.0138^{***}	-0.0087	-0.0092
	(0.0051)	(0.0049)	(0.0031)	(0.0027)	(0.0055)	(0.0059)
	0.1465		*0.2368*		*0.4156*	
Controls	No	Yes	No	Yes	No	Yes
n	257,708	257,708	257,708	257,708	257,708	257,708

Notes: Estimates from equation (2.2) with a dummy variable for returning to the hospital as the respective dependent variables. The first two dependent variables indicate if the patient was readmitted as an inpatient and if the event was an ED visit only, respectively. The next dependent variable takes on a value of 1 if the patient returned to the ED within the indicated amount of time, whether or not they were later admitted. For "revisit", a value of 1 for the dependent variable means that the patient returned to the hospital within the indicated amount of time in any capacity. The first set of estimates correspond to the plots shown in Figure 2.4 , and the second set of estimates correspond to the plots in Figure 2.5. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table 2.5: Readmission and Revisit for Specific Diagnoses for Midnight Admissions (Within 30 Days)

Next Visit:	Heart Disease (1)	General Symptoms (2)	Pneumonia & Flu (3)	COPD (4)	UTI (5)	Renal Failure (6)
Readmit	−0.0017***	−0.0008	−0.0007	0.0002	−0.0009	−0.0005
	(0.0005)	(0.0010)	(0.0005)	(0.0009)	(0.0008)	(0.0003)
	0.0172	*0.0094*	*0.0049*	*0.0081*	*0.0040*	*0.0035*
ED Only	0.0011**	−0.0037***	−0.0002	0.0008	−0.0005	0.0003
	(0.0004)	(0.0007)	(0.0002)	(0.0007)	(0.0006)	(0.0001)
	0.0037	*0.0257*	*0.0002*	*0.0037*	*0.0041*	*0.0004*
	Ischemic Heart Disease (7)	Intestinal Disorders (8)	Complications From Care (9)	Lower Body Fractures (10)	Upper Body Fractures (11)	Drugs & Poisons (12)
Readmit	0.00004	−0.0004	−0.0002	0.0001	−0.000005	−0.0002
	(0.0004)	(0.0008)	(0.0004)	(0.0002)	(0.0002)	(0.0003)
	0.0080	*0.0060*	*0.0060*	*0.0014*	*0.0005*	*0.0009*
ED Only	0.0001	−0.0012***	0.0004**	−0.0002**	0.0002	0.0001
	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
	0.0006	*0.0017*	*0.0028*	*0.0003*	*0.0006*	*0.0006*
	Skin Diseases (13)	Ear Diseases (14)	Psychoses (15)	Dorsopathies & Rheumatism (16)	Cerebro-vascular (17)	Other (18)
Readmit	0.0001	0.0003	−0.0008	0.0001	−0.00005	−0.0057***
	(0.0002)	(0.0006)	(0.0009)	(0.0001)	(0.0007)	(0.0018)
	0.0022	*0.0066*	*0.0062*	*0.0018*	*0.0045*	*0.0541*
ED Only	0.00001	−0.0001	−0.0003	−0.0004	−0.0001	0.0010
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0001)	(0.0021)
	0.0016	*0.0004*	*0.0013*	*0.0039*	*0.0004*	*0.0393*

Notes: Estimates from equation (2.2) with dependent variables above each of the 18 cells, with "Readmit" referring to a readmission for that specific cause and "ED Only" meaning an ED visit without admission for that cause. Return categories are exhaustive. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table 2.6: Mean Characteristics Compliers, Always Takers, and Never Takers

	Compliers	Bootstrap Std. Error	Always Takers	Never Takers
Age	79.36	(2.9187)	80.21	71.56
Diagnoses	10.74	(1.0339)	11.28	10.28
Procedures	0.54	(0.3411)	0.72	0.99
Chronic	5.52	(0.6501)	6.26	5.76
Median Income Quartile	2.53	(0.2502)	2.34	2.31
Female	0.73	(0.1183)	0.65	0.54
White	0.76	(0.1011)	0.74	0.68
Hispanic	0.10	(0.0710)	0.10	0.14
Black	0.11	(0.0736)	0.12	0.15

Notes: Compliers are individuals that are induced *not* to go to SNF when they are admitted after midnight. Means are calculated as described in the text.

Chapter 3

Long-Term Month-of-Birth Effects in Self-Reported Health and Mortality in England

The effect of season and month of birth has long been of interest to researchers across fields in both social and natural sciences. The timing of a child's birth has been shown to be associated with a diverse set of early and later life outcomes, and attentiveness to these effects stems from efforts to learn more about the long-run effects of early life environment.

The literature in health has examined a wide range of these seasonal relationships. Month-of-birth effects have well studied in neurodevelopmental disorders, with schizophrenia, autism, and dyslexia receiving particular attention.[1][2] While schizophrenia has been shown to have much higher incidence among children born in winter or early spring, other areas give a less clear picture, largely due to the relative infrequency of the outcomes. In developing areas, the effect of season of birth is linked to weather patterns, disease, pollution, or conflict, where a health shock due to one of these causes in the fetal period or infancy can strongly affect later life morbidity and mortality.[3] Yet, month of birth has been shown to affect life expectancy in developed countries — including the United States — across the globe, with those born in spring dying earlier than those born in the fall Doblhammer 2004.

This paper makes a contribution to this literature by documenting long-term month-of-birth effects on self-reported health and mortality in England and Wales. I examine these outcomes using the national census and mortality records to find precise estimates on both dimensions for every individual born between 1940 and 1960 that was still alive at the time of the 2001 Census. I find that those born in fall and early winter months are less likely to report being in poor health and have lower mortality rates, while those born in late spring and summer are worse off. The size of the effect is 1.5-2 percent for both outcomes, meaning that those born in summer are about 2 percent more likely to report poor health and have 2 percent higher mortality rates.

1. See Davies et al. (2003) for a review of the literature on schizophrenia. Livingston, Adam, and Bracha (1993) find effects of developmental dyslexia in summer, while Donfrancesco et al. (2010) find larger effects in Autumn, although the latter's seasonal effects are interacted with school age entry. Barak et al. (1995) and Stevens, Fein, and Waterhouse (2000) find higher instances of autism for individuals born in March with very small sample sizes ($n < 200$), but Stevens, Fein, and Waterhouse (2000) find no such effect with a larger sample in Israel.

2. See Antonsen et al. (2012) for a review of the effect on suicides.

3. See Currie and Vogl (2013) for an overview.

To my knowledge this is the first paper to document the long-run effects of timing of birth on self-reported health, which has been shown to be an important predictor of later medical services usage and mortality Miilunpalo et al. 1997. Further, it is the first to survey England and Wales, and does so with a larger sample than most papers in this literature at over 13 million individuals. Results are consistent with Doblhammer and Vaupel (2001), Doblhammer (2004), and Doblhammer, Scholz, and Maier (2005), who find similar patterns of life expectancy in the United States, Denmark, Austria, Australia, and Germany.[4]

In economics, much of the interest in this subject stems from the desire to use season or month of birth as an exogenous indicator for policies that divide individuals born in the same time period. There are a large number of papers that use quarter of birth or month of birth as an instrumental variable, and others that argue for or against the sensibility of this identification strategy.[5] Generally, these works find that individuals born in winter months are worse off, experiencing lower educational attainment and wages. Authors have tended to argue that it is compulsory schooling laws that create these differential outcomes. My results run contrary to much of this strand of the literature that purport to find improved outcomes for those born in summer months,

4. Doblhammer, Scholz, and Maier (2005) and Gavrilov and Gavrilova (2011) study the effects of month of birth on the likelihood of living to advanced ages using data from Germany and the United States, repectively. Both find increased longevity for those born September-November.

5. Notable papers in this strand of the literature include Angrist and Keueger (1991), Angrist and Krueger (1992), Angrist and Krueger (1995), Angrist and Krueger (2001), Neal and Johnson (1996), Bound, Jaeger, et al. (1996), Staiger, Stock, et al. (1997), Bound and Jaeger (2000), and Imbens and Rosenbaum (2005), among others. This paper does not wade into this debate, and as Angrist and Krueger (1992) admitted, quarter of birth was only used as an instrument due to the unavailability of more precise dates of birth. Better data have since answered their original question on compulsory schooling (see Dobkin and Ferreira (2010)).

and more recently it has been shown that family background characteristics have strong relationships with both quarter of birth and later outcomes, with these explaining nearly half of the relationship between season of birth and later outcomes such as wages and years of education Buckles and Hungerman 2013. With many of these papers focused on the U.S., it is possible that the different locale may explain some of the difference, although it may also be that these labor market outcomes are not affected by month-of-birth in the same manner as later life self-reported health and morality.

3.1 Data and Methods

The data for self-reported health and disabilities come from the 2001 Census of England and Wales. This includes all residents of these areas for a total of just over 52 million people. The census was completed in April 2001. Among other questions, respondents were asked to rate if their general health over the last twelve months has been "good", "fairly good", or "not good". They were also asked if they have any long-term illness, disability, or health problem that limits day-to-day activities of the ability to work.

Mortality data come from the Office of National Statistics (ONS) and include every death from 1990-2010. I truncate these data to April 1996-April 2006, or the five years before and after the 2001 Census. Given that the census gives a complete record of who was alive by month-of-birth in April 2001, mortality rates are calculated by finding the proportion of people in each birth cohort that survive to the following month.[6] I

6. Clearly, this sample contains some degree of mortality selection, as the unhealthiest individuals

then take an average of these survival probabilities to find the mortality rate for each birth cohort for the April 1996-April 2006 period.

I find month-of-birth effects by calculating the average deviation from a moving average trend. The specification is as follows:

$$Y_{ct} = \boldsymbol{Month} + \varepsilon_{ct} \tag{3.1}$$

Here, Y_{ct} is outcome Y for birth cohort c in time t (measured in months and years). $\boldsymbol{Month}$ indicates month of birth, with the constant suppressed. For regressions using the census, the time dimension is eliminated, as all results were recorded in April 2001. Y_c is then the deviation from the moving average of proportion of people in that birth cohort reporting that their health is "not good" reported in percentage points (multiplied by 100). For mortality, Y_{ct} is the deviation of the mortality rate for birth cohort c in month t. I multiply this number by 100,000 for ease of interpretation.

An alternative specification is to regress on the outcomes (poor health and mortality) themselves, and include a third-order polynomial along with the month dummies.[7] Results from this specification are reported in Appendix B.

The main specification examines all births between 1940 and 1960 in both data sources. This avoids the retirement age of 65 for men that is shown to significantly affect self-reported health (see the first chapter of this dissertation). Appendix A provides

will have already perished by the beginning of the sample. However, this analysis does not consider early-life outcomes, and if anything this selection should mute the effects of month of birth.

7. Specifically, the regression would take the form of $Y_c = \beta_0 + \beta_2 DoB_c + \beta_3 DoB_c^2 + \beta_4 DoB_c^3 + \boldsymbol{Month} + \epsilon_c$, where DoB is the month and year of birth.

estimates from for those born between 1945 and 1960 in order to avoid individuals born during World War II for the census sample, with results largely consistent but less precise.

3.2 Results

3.2.1 Self-Reported Health

Figure 3.1 examines the simple date-of-birth profile of the proportion of people that report being in poor health at the time of the 2001 Census. The red line overlaid is a 12-month moving average. The overall trend is clearly decreasing, as younger individuals in this window are about half as likely to report being in poor health. Even among this population, however, there is evidence of seasonal effects of month of birth.

I next examine the deviations from this moving average by month of birth in Figure 3.3. This is presented as a "Tukey" style box and whisker plot by month, with the 25th, 50th, and 75th percentiles plotted by the box, and the whiskers showing the largest values up to 1.5 times the interquartile range. Outlying points are plotted individually. From this figure, it is apparent that when an individual is born in the year affects self-reported health. Individuals born in the late spring or summer are more likely to report being in poor health, while those in fall are better off. This effect, while lessened, even extends through the winter, lasting until February. Figure C.1 shows that for the oldest individuals in this sample, being born in late spring or summer is the equivalent of being an entire year older in terms of likelihood of reporting being in poor health.

Table 3.1 gives estimates of these effects in columns (1) - (3), derived from equation (1) and reported as percentages. Effect sizes are generally small, but do show that there is an effect of when an individual is born. Those born in late fall and early winter (September - December) are about 0.2 percentage points less likely to be in poor health. In contrast, those born in June and July are roughly 0.2 percentage points more likely to report being in poor health. This translates to an effect size of 1.5-2 percent when compared to the average proportion of people reporting poor general health. There is very little difference in effects for men and women, with the notable exception of women born in August reporting worse health.

3.2.2 Mortality

Figure 3.2 shows the date-of-birth profile of average monthly mortality rates per 100,000 from 1996-2006. As with Figure 3.1, the red line represents a simple 12-month moving average. Unsurprisingly, mortality rates decrease dramatically among younger populations, and again Figure C.1 shows high seasonality for the oldest cohorts in this sample.

Deviations from this moving average by birth month are shown in Figure 3.4. Similarly to self-reported health, those born in late spring or summer have higher mortality rates, although any positive effects for individuals born in fall are muted. Columns (4) - (6) of Table 3.1 show the estimates of these effects. The largest effects by far are those born in August, who experience 0.78 more deaths per 100,000 on average. This translates to a 2 percent increase over the 34.6 per 100,000 average rate for the entire population in this sample. For reference, the effect on mortality rates of being another year older is about 1 per 100,000 for the youngest in this sample, and 5-6 per 100,000 for the oldest.

Mortality effects do show substantial difference between men and women. Women born in August exhibit higher mortality rates while men do not, and women born in February show lower mortality rates that men do not experience. June and July births are similarly worse for men than for women.

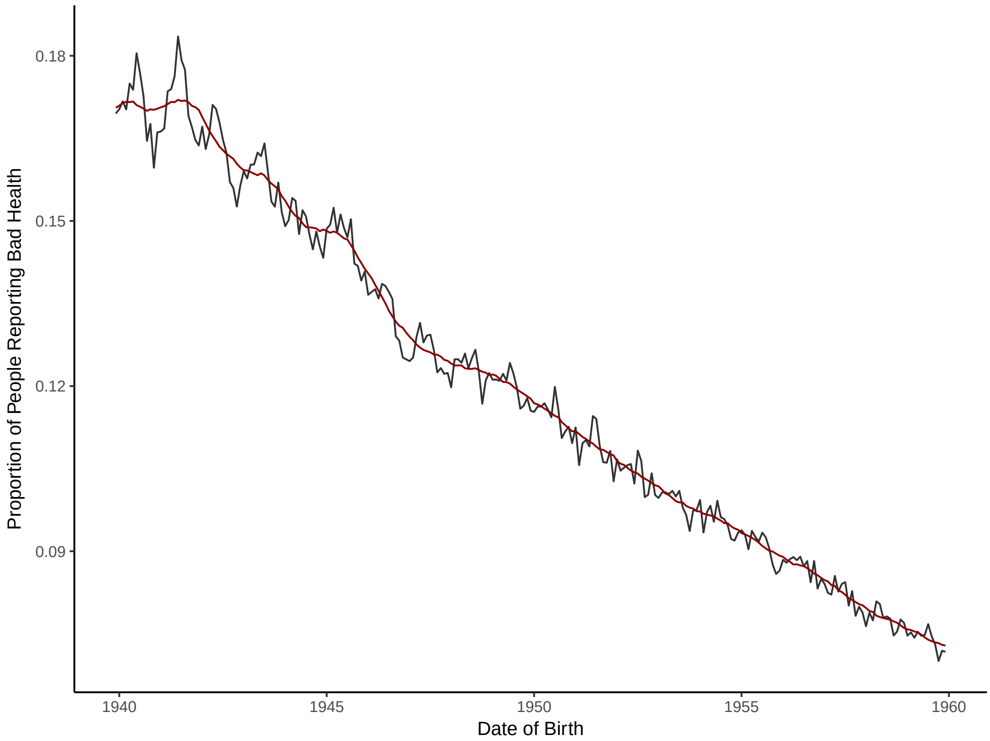
3.3 Conclusion

These results show that individuals born from 1940-1960 in England and Wales are morel likely to have lower mortality rates and better self-reported health if they are born in fall or early winter as opposed to late spring and summer. The magnitudes of these effects are about 1.5 - 2 percent for each outcome.

Figure 3.5 shows how these month-of-birth effects vary for older and younger cohorts. This plots the average percent deviation from the moving average in the raw data for each decade of birth from the 1910s to the 1970s, thus expanding the sample from the main results.[8] While the figures show the trend observed in the overall results, there are some outliers. Those born in the 1970s in late spring are better off both in terms of self-reported health and morality rates. This is similarly true for those born in the 1910s, although it is worth noting that this group contains considerable mortality

8. These figures are reported in terms of percents instead of deviations because of the large change in the levels of the outcome variables between older and younger cohorts. For example, the average mortality rate for those born before 1920 is well over 10 times higher than for those born in 1970.

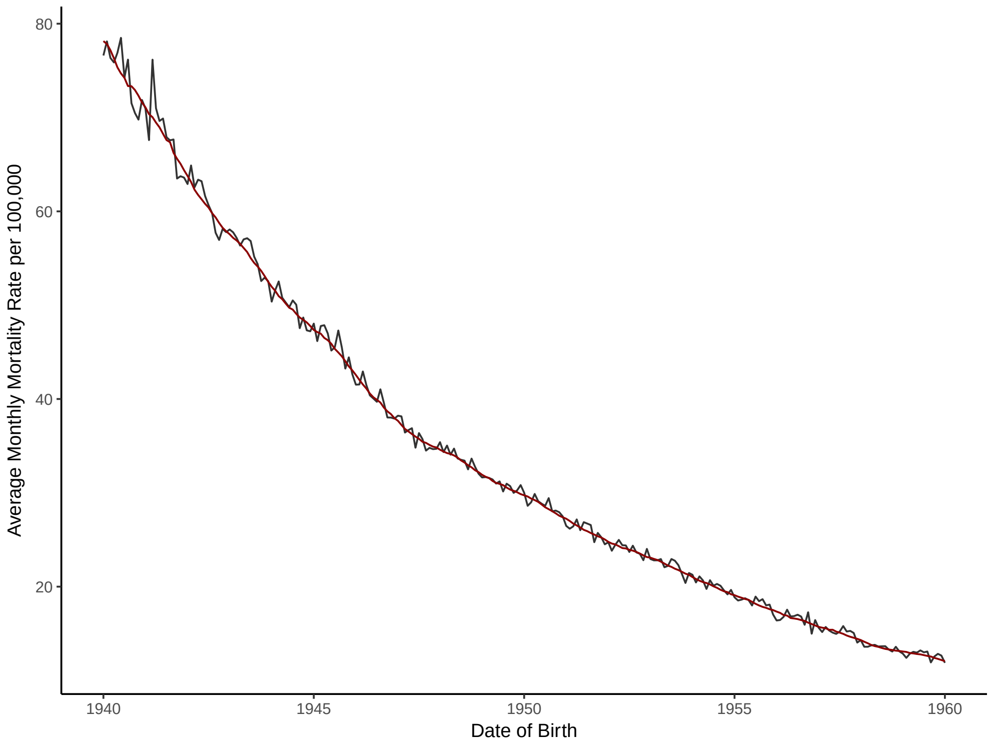
Figure 3.1: Date-of-Birth Profile of the Proportion of People Reporting Poor Health



Notes: Date-of-birth profile of the proportion of people born 1940-1960 that report that their general health is "not good" from the 2001 Census of England and Wales. The red line represents a 12-month moving average.

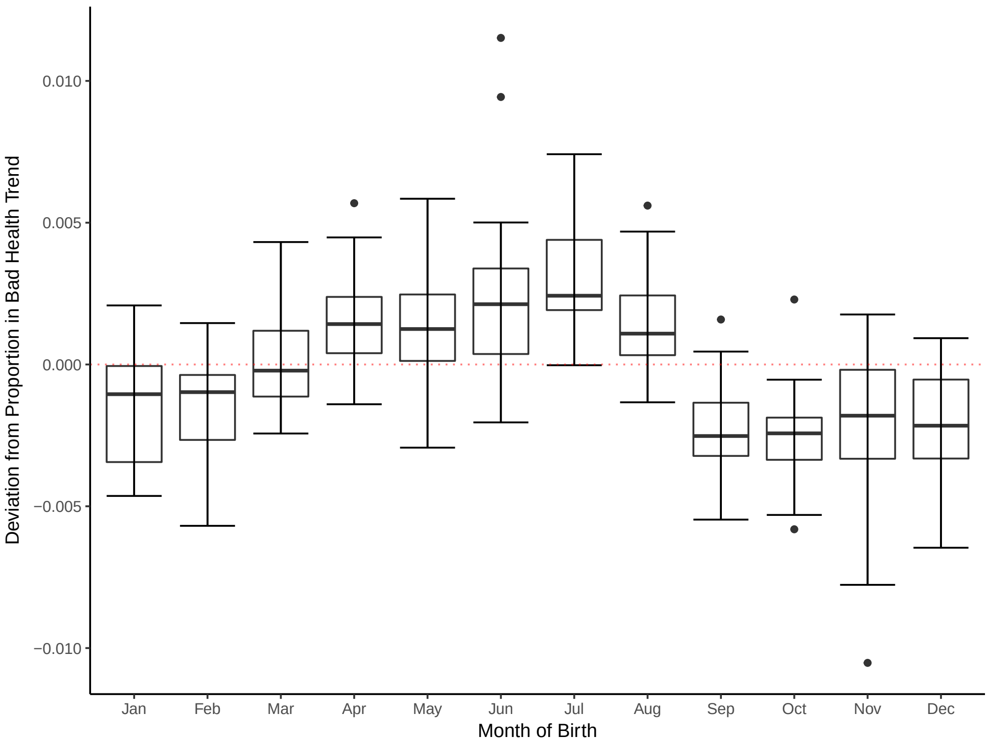
selection. For both, those born in fall seem to be better off, although these estimates are less precise. While it is clear from this work that seasonal effects do exist, it is beyond the scope of this paper to further address the causes of such effects, and efforts to do so would be purely speculative.

Figure 3.2: Date-of-Birth of Average Monthly Morality Rate by Date of Birth



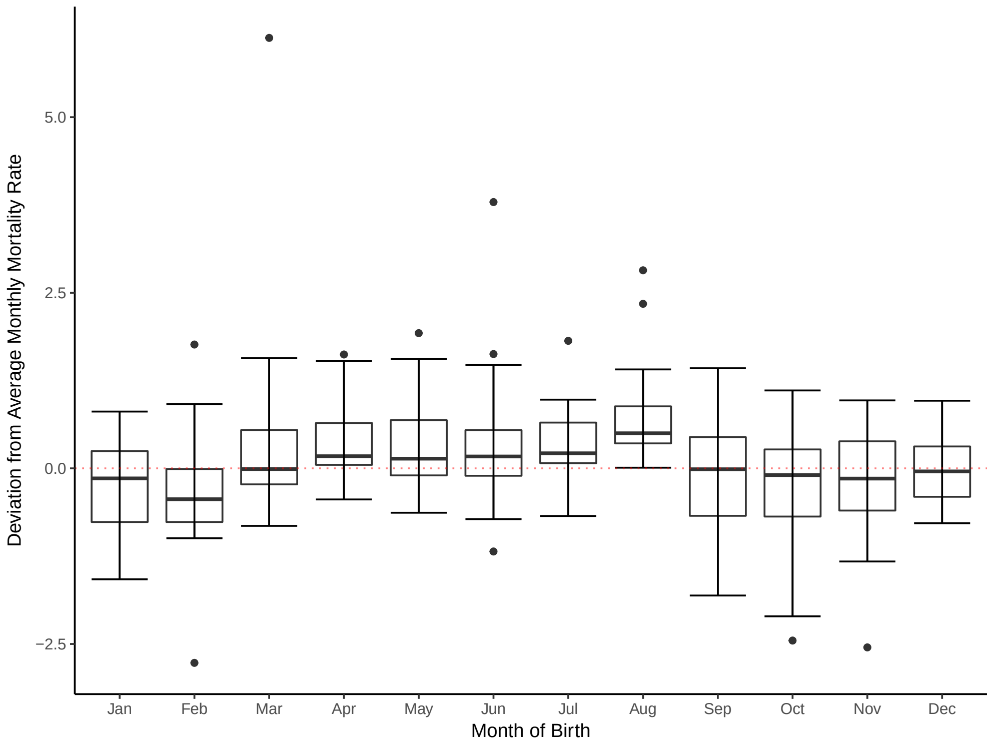
Notes: Date-of-birth profile of the average monthly mortality rate for the period from 1996-2006 for people born 1940-1960. The red line represents a 12-month moving average.

Figure 3.3: Deviations from Moving Average of Reporting Poor Health by Month of Birth



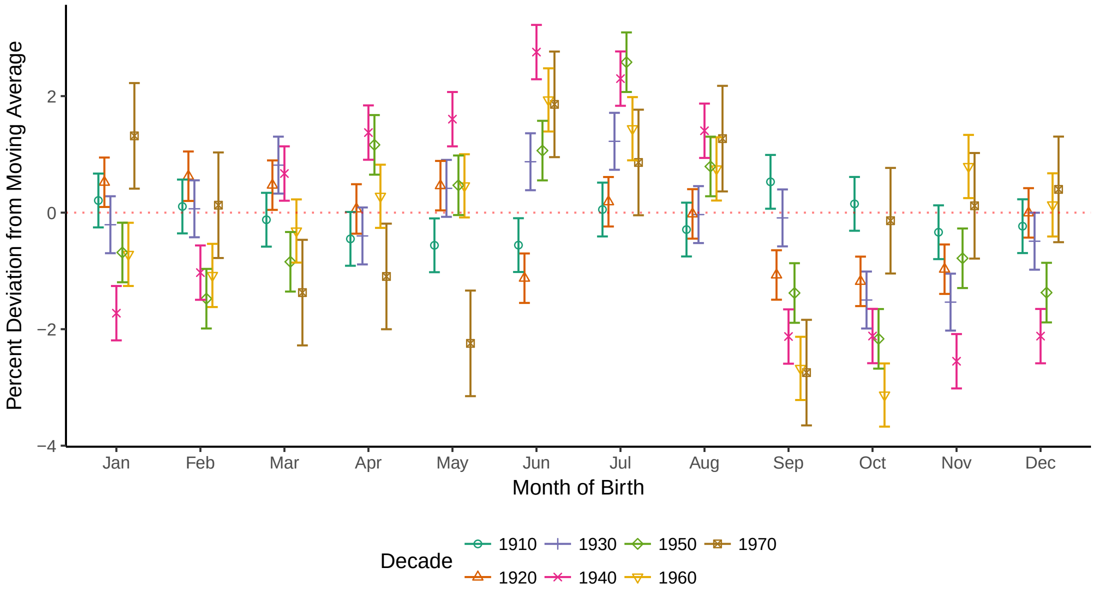
Notes: Deviations by month of birth from the moving average shown in Figure 3.1. The top, middle, and bottom of each box represent the 25th, 50th, and 75th percentiles, respectfully.

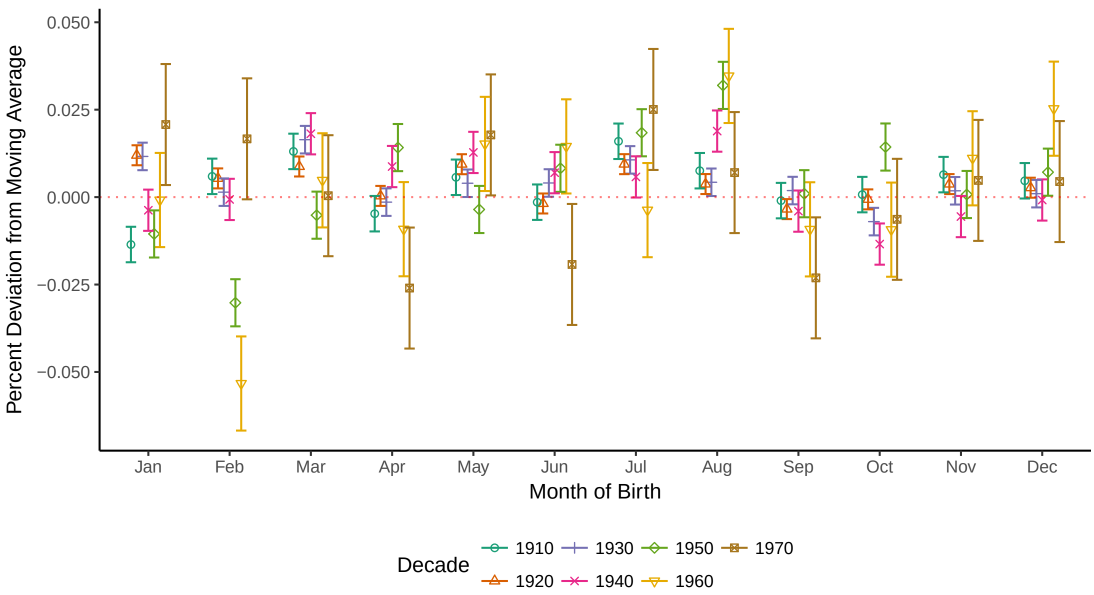
Figure 3.4: Deviations from Moving Average of Average Monthly Mortality Rate by Month of Birth



Notes: Deviations by month of birth from the moving average shown in Figure 3.2. The top, middle, and bottom of each box represent the 25th, 50th, and 75th percentiles, respectfully.

Figure 3.5: Month-of-Birth Effects by Decade





Notes: Average percent deviation by decade of birth from the moving average of proportion of people reporting poor health (top) and morality rates (bottom). 95% confidence intervals shown.

Table 3.1: Average Monthly Deviation from Moving Average

	Proportion Reporting Bad Health			Mortality Rate		
	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
January	-0.152^{***}	-0.135^{**}	-0.169^{***}	-0.238	-0.440^{*}	-0.036
	(0.045)	(0.065)	(0.058)	(0.184)	(0.265)	(0.204)
February	-0.153^{***}	-0.197^{***}	-0.109^{*}	-0.331^{*}	-0.168	-0.459^{**}
	(0.043)	(0.049)	(0.058)	(0.189)	(0.271)	(0.209)
March	0.012	-0.033	0.056	0.452^{**}	0.714^{***}	0.180
	(0.037)	(0.060)	(0.038)	(0.189)	(0.271)	(0.209)
April	0.156^{***}	0.124^{***}	0.189^{***}	0.391^{**}	0.026	0.736^{***}
	(0.037)	(0.044)	(0.049)	(0.189)	(0.271)	(0.209)
May	0.142^{***}	0.145^{***}	0.139^{**}	0.308	0.418	0.221
	(0.048)	(0.051)	(0.068)	(0.189)	(0.271)	(0.209)
June	0.263^{***}	0.347^{***}	0.178^{**}	0.382^{**}	0.814^{***}	-0.041
	(0.072)	(0.073)	(0.078)	(0.189)	(0.271)	(0.209)
July	0.299^{***}	0.267^{***}	0.331^{***}	0.342^{*}	0.469^{*}	0.214
	(0.046)	(0.057)	(0.049)	(0.189)	(0.271)	(0.209)
August	0.142^{***}	0.073	0.210^{***}	0.778^{***}	0.762^{***}	0.784^{***}
	(0.041)	(0.054)	(0.044)	(0.189)	(0.271)	(0.209)
September	-0.225^{***}	-0.166^{***}	-0.281^{***}	-0.105	-0.027	-0.183
	(0.039)	(0.041)	(0.055)	(0.189)	(0.271)	(0.209)
October	-0.250^{***}	-0.282^{***}	-0.219^{***}	-0.289	-0.453^{*}	-0.105
	(0.039)	(0.050)	(0.054)	(0.189)	(0.271)	(0.209)
November	-0.227^{***}	-0.209^{***}	-0.243^{***}	-0.227	-0.317	-0.150
	(0.071)	(0.080)	(0.080)	(0.189)	(0.271)	(0.209)
December	-0.219^{***}	-0.204^{***}	-0.235^{***}	0.017	0.074	-0.061
	(0.044)	(0.073)	(0.047)	(0.189)	(0.271)	(0.209)
Observations	241	241	241	241	241	241
Outcome Mean	12.0	11.9	12.1	34.6	42.4	27.0

Notes: Estimates by month of the average deviation from the 12-month moving average from equation (1). “Mean of Outcome” refers to the mean of the outcome variable (Proportion in poor health or average mortality rate) for the entire sample period. Proportion in poor health is reported in percentage points and mortality rates in per 100,000 terms. Morality rates are calculated by finding the proportion of people in each birth cohort that survive to the following month. Robust standard errors in parenthesis. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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Appendix A

Appendix for Chapter 1

A.1 Additional First Stage Tables and Figures

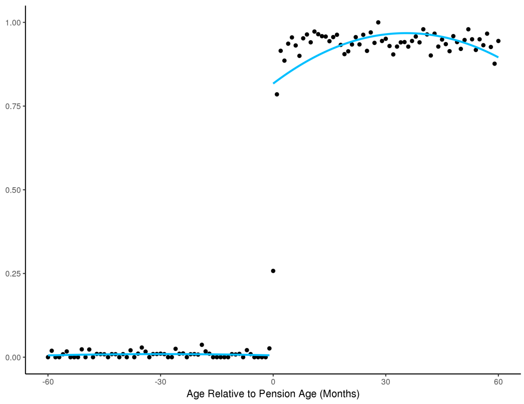
Table A.1: Effect of State Retirement Age on Wealth, Wealth and Assets Survey

	Net Income	Pension Income	HH Wealth	HH Wealth, No Pension
	(1)	(2)	(3)	(4)
State Pension Age	-10,520**	11,160***	-74,797	56,744
	(4,812)	(2,449)	(78,077)	(68,636)
Dataset	WAS	WAS	WAS	WAS
Observations (n)	4,168	4,168	42,595	42,595
Individuals (i)	2,084	2,084	18,940	18,940

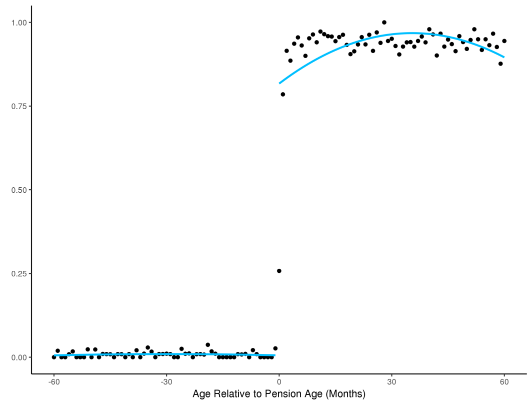
Notes: Estimates of reaching the State Pension Age by household on income and wealth from the Wealth and Assets Survey. The State Pension Age is 65 for men and 60 for women, and estimates refer to when the household primary reference member reaches that age. Household wealth measures are windorized at the 5 percent level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure A.1: Age Profiles of Reaching the State Retirement Age on Pensions and Retirement

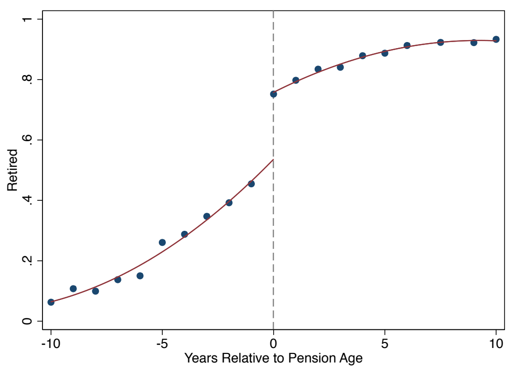
(a) Men Collecting a Pension, BHPS



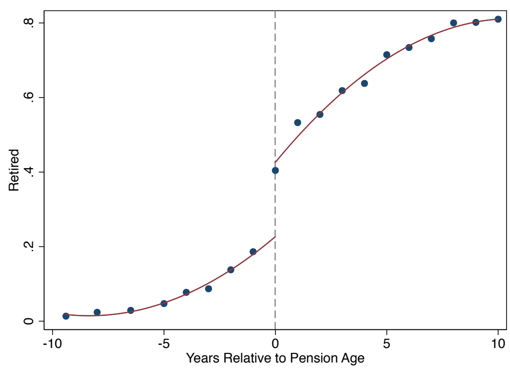
(b) Women Collecting a Pension, BHPS



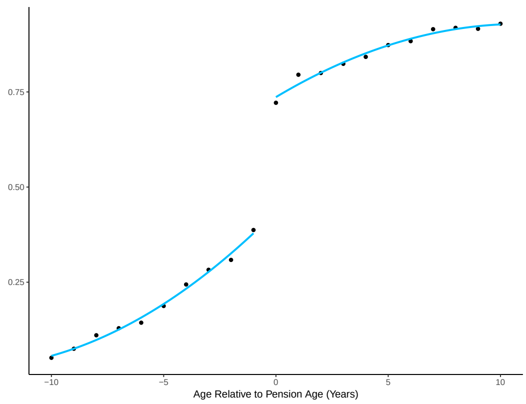
(c) Men Retired, ELSA



(d) Women Retired, ELSA



(e) Men Retired, HSE



(f) Women Retired, HSE

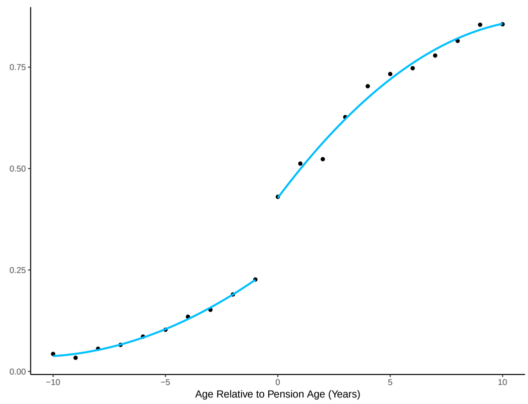
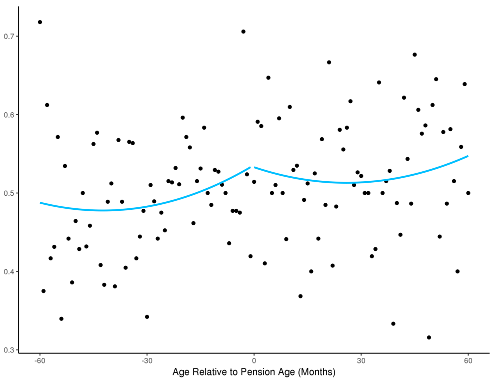
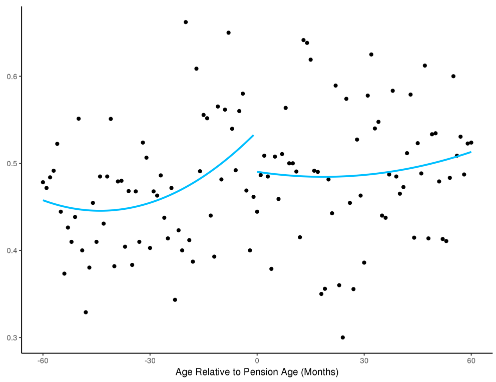


Figure A.2: Age Profiles of Health Behaviors

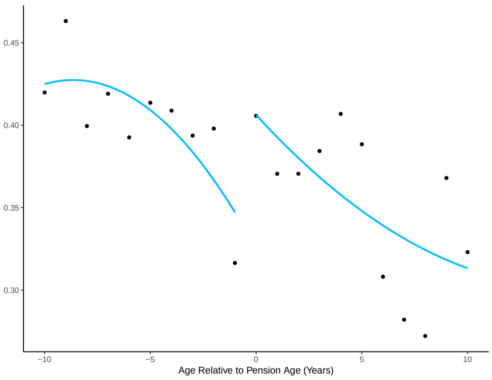
(a) Frequent Exercise for Men, BHPS



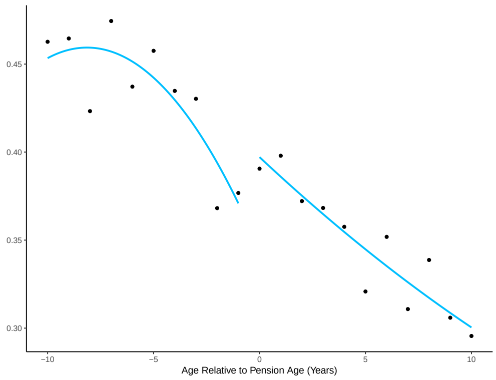
(b) Frequent Exercise for Women, BHPS



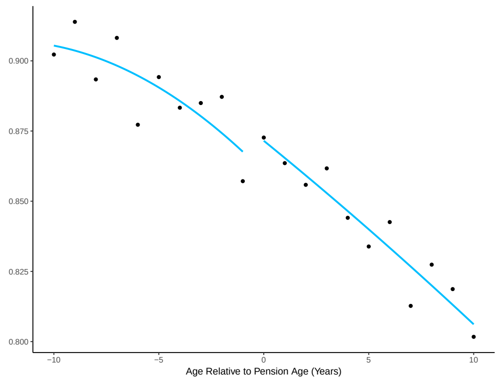
(c) Frequent Exercise for Men, HSE



(d) Frequent Exercise for Women, HSE



(e) Proportion of Men Drinking, HSE



(f) Proportion of Women Drinking, HSE

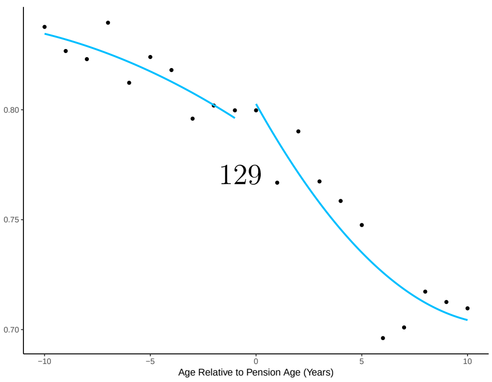


Table A.2: Effect of State Retirement Age on Wealth for Non-Retiring Individuals, Wealth and Assets Survey

	(1)	(3)	(5)	(7)
VARIABLES	Net Income	Pension Income	HH Wealth	HH Wealth, No Pension
over65	8,092	6,368***	-31,125***	-4,244
	(10,683)	(972.9)	(12,031)	(7,304)
Dataset	WAS	WAS	WAS	WAS
Observations (n)	31,837	31,837	73,658	73,658
Individuals (i)	27,899	27,899	45,255	45,255

Notes: Estimates of reaching the State Pension Age by household on income and wealth from the Wealth and Assets Survey for household whose primary member is not retired in the survey wave after reaching the State Pension Age. The State Pension Age is 65 for men and 60 for women, and estimates refer to when the household primary reference member reaches that age. Household wealth measures are winsorized at the 5 percent level. * significant at 10%, ** significant at 5%, *** significant at 1%.

A.2 Additional Tables and Figures on Health Behaviors

A.3 Additional Tables and Figures on Health Outcomes

A.4 Additional Tables on Mortality

A.5 Regression Discontinuity Balance Table and Density Figures

A.6 Regression Discontinuity Robustness Figures

Table A.3: FE-IV Estimates of the Effect of Retirement on Health Behaviors, Men

(a) Self-Care

	Smokes (1)	Smokes (2)	Drinks (3)	Exercise (4)	Exercise (5)
State Pension Age	0.00231	0.00812	0.0124	0.0790*	-0.247**
	(0.0214)	(0.0112)	(0.0188)	(0.0469)	(0.107)
Dataset	BHPS	ELSA	ELSA	BHPS	ELSA
Gender	Men	Men	Men	Men	Men
Observations (n)	40,677	16,628	14,969	18,080	16,645
Individuals (i)	5,333	4,406	4,118	4,274	4,413

(b) Friends and Family

	See Kids Weekly (1)	See Family Weekly (2)	See Friends Weekly (3)	See Friends (4)	Out to Eat (5)	Social Satisfaction (6)
State Pension Age	0.0850**	0.0704	0.0280	0.0135	0.0320	0.415***
	(0.0376)	(0.0460)	(0.0490)	(0.00831)	(0.0205)	(0.0952)
Dataset	ELSA	ELSA	ELSA	BHPS	BHPS	BHPS
Gender	Men	Men	Men	Men	Men	Men
Observations (n)	13,100	13,508	13,747	45,818	45,818	32,323
Individuals (i)	3,566	3,790	3,832	5,664	5,664	4,876

Notes: FE-IV estimates of reaching the State Pension Age on health behavior outcomes for men. *Smokes* is if the individual currently smokes in the BHPS, while the ELSA asks if they ever smoke. *Exercise* refers to frequent (once per week) activity. *Friends Care* signifies if the individual feels that is true (=2), partly true (=1), or not true (=0) that they have friends that would care for them if needed; *Rely* asks is the same scale for friends they can rely on. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.4: FE-IV Estimates of the Effect of Retirement on Health Behaviors, Women

(a) Self-Care

	Smokes (1)	Smokes (2)	Drinks (3)	Exercise (4)	Exercise (5)
State Pension Age	0.0389**	-0.00670	0.00358	0.0824**	0.00368
	(0.0154)	(0.0107)	(0.0199)	(0.0385)	(0.103)
Dataset	BHPS	ELSA	ELSA	BHPS	ELSA
Gender	Women	Women	Women	Women	Women
Observations (n)	49,878	19,643	17,888	22,055	19,645
Individuals (i)	6,480	4,995	4,726	5,204	4,996

(b) Friends and Family

	See Kids Weekly (1)	See Family Weekly (2)	See Friends Weekly (3)	See Friends (4)	Out to Eat (5)	Social Satisfaction (6)
State Pension Age	0.0651*	0.142***	0.0590	0.00190	0.00879	0.307***
	(0.0345)	(0.0423)	(0.0445)	(0.00737)	(0.0172)	(0.0821)
Dataset	ELSA	ELSA	ELSA	BHPS	BHPS	BHPS
Gender	Women	Women	Women	Women	Women	Women
Observations (n)	16,127	16,652	16,966	55,097	55,097	39,328
Individuals (i)	4,213	4,467	4,506	6,715	6,715	5,880

Notes: FE-IV estimates of reaching the State Pension Age on health behavior outcomes for women. *Smokes* is if the individual currently smokes in the BHPS, while the ELSA asks if they ever smoke. *Exercise* refers to frequent (once per week) activity. *Friends Care* signifies if the individual feels that is true (=2), partly true (=1), or not true (=0) that they have friends that would care for them if needed; *Rely* asks is the same scale for friends they can rely on. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.5: FE-IV Estimates of the Effect of Retirement on Mental Health

(a) Men

	Orient Date (1)	Recall Score (2)	Memory Score (3)	Verbal Score (4)	Life Satisfaction (5)	Depression Score (6)	Likert (7)	Caseness (8)
State Pension Age	-0.0284	0.268	0.112	0.252	0.572***	-0.407**	-1.621***	-0.870***
	(0.0401)	(0.254)	(0.0980)	(0.514)	(0.0808)	(0.159)	(0.261)	(0.152)
Dataset	ELSA	ELSA	ELSA	ELSA	BHPS	ELSA	BHPS	BHPS
Gender	Men	Men	Men	Men	Men	Men	Men	Men
Observations (n)	19,572	19,582	16,382	16,461	32,271	19,546	41,334	43,102
Individuals (i)	4,981	4,981	4,825	4,840	4,876	4,974	5,254	5,362

(b) Women

	Orient Date (1)	Recall Score (2)	Memory Score (3)	Verbal Score (4)	Life Satisfaction (5)	Depression Score (6)	Likert (7)	Caseness (8)
State Pension Age	-0.0284	0.268	0.112	0.252	0.382***	-0.407**	0.00537***	0.00219***
	(0.0401)	(0.254)	(0.0980)	(0.514)	(0.0732)	(0.159)	(0.000986)	(0.000568)
Dataset	ELSA	ELSA	ELSA	ELSA	BHPS	ELSA	BHPS	BHPS
Gender	Women	Women	Women	Women	Women	Women	Women	Women
Observations (n)	19,572	19,582	16,382	16,461	39,331	19,546	50,487	50,487
Individuals (i)	4,981	4,981	4,825	4,840	5,873	4,974	6,359	6,359

Notes: FE-IV estimates of reaching the State Pension Age on mental health outcomes. *Orient Date* indicates if the respondent was able to name the date. *Recall Score* is a sum of immediate and delayed word recall tests. *Memory Score* is a test of how well an individual can remember previously given instructions, with partial credit up to a score of 4 for performing the task as instructed. *Verbal Score* asks respondents to name as many animals as they can in one minute, with the score being the number of acceptable answers. *Depression Score* is from the 8-item Centre of Epidemiological Studies Depression (CES-D) scale. The *Likert* and *Caseness* scores are different codings of responses from the GHQ-12 questionnaire, in which a higher value indicates a higher likelihood of minor psychiatric disorders. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.6: FE-IV Estimates of the Effect of Retirement on Health Outcomes

(a) Men

	Limit Motor Ability (1)	Limit Daily (2)	Limit Daily (3)	Health Prob. Index (4)	Any Health Problem (5)	Hospital (6)	GP (7)	Dentist (8)	Eye Exam (9)	Cholesterol (10)
State Pension Age	-0.207**	-0.0847	0.102***	-0.0949	-0.0274	-0.00902	-0.0232	0.0382	0.00851	0.132***
	(0.0952)	(0.0879)	(0.0270)	(0.0705)	(0.0246)	(0.0212)	(0.0731)	(0.0269)	(0.0317)	(0.0320)
Dataset	ELSA	ELSA	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Gender	Men	Men	Men	Men	Men	Men	Men	Men	Men	Men
Observations (n)	12,600	12,600	39,287	45,145	45,818	45,807	43,102	43,132	43,132	43,132
Individuals (i)	3,729	3,729	5,556	5,621	5,664	5,663	5,362	5,362	5,362	5,362

(b) Women

	Limit Motor Ability (1)	Limit Daily (2)	Limit Daily (3)	Health Prob. Index (4)	Any Health Problem (5)	Hospital (6)	GP (7)	Desist (8)	Eye Exam (9)	Cholesterol (10)
State Pension Age	-0.227**	-0.137	0.129***	-0.116**	0.0125	-0.0434***	-0.0845	-0.217***	-0.149*	-0.494***
	(0.0955)	(0.0908)	(0.0206)	(0.0588)	(0.0220)	(0.0159)	(0.0600)	(0.0543)	(0.0779)	(0.158)
Dataset	ELSA	ELSA	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS	BHPS
Gender	Men	Men	Women	Women	Women	Women	Women	Women	Women	Women
Observations (n)	14,107	14,107	47,321	54,179	55,097	55,065	52,646	16,781	16,781	16,781
Individuals (i)	4,113	4,113	6,615	6,667	6,715	6,715	6,497	4,661	4,661	4,661

Notes: FE-IV estimates of reaching the State Pension Age on health outcomes. *Limit Motor Ability* indicates if health limits motor ability. *Limit Daily* measures if health limits daily activities. *Health Prob. Index* is an index created by simply summing the number of health issues individuals indicated, and *Any Health Prob* is a dummy variable if the individual indicated at least one health issue. Outcomes *Hospital*, *Dentist*, *Eye Exam*, and *Cholesterol* indicate if the individual has utilized that service in the previous 12 months, while *GP* is number of visits in the previous 12 months. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.7: FE-IV Effects of Retirement on Self-Reported Health

	BHPS		ELSA	
	(1)	(2)	(3)	(4)
Good	0.115***	0.112***	-0.0129	-0.0147
	(0.0293)	(0.0231)	(0.0438)	(0.0429)
Fair	-0.0474*	-0.0205	0.106**	0.0677
	(0.0273)	(0.0214)	(0.0450)	(0.0428)
Bad	-0.0933***	-0.0819***	-0.0458	-0.107***
	(0.0283)	(0.0224)	(0.0345)	(0.0330)
Long/Illness Disability	-0.0958***	-0.0383		
	(0.0327)	(0.0236)		
Gender	Men	Women	Men	Women
Observations (n)	45,818	55,097	16,648	19,654
Individuals (i)	5,664	6,715	4,414	4,996

Notes: FE-IV estimates of reaching the State Pension Age on self-reported health and long-term illnesses and disabilities. *Good*, *Fair*, and *Bad* are outcome variables split from a single question asking the individual about their general health. “Good" means the individual indicated “Very Good" or “Good", and “Bad" means the individual indicated “Bad" or “Very Bad". *Long Illness/Disability* asks the individual if they have a long-term illness or disability. The State Pension Age is 65 for men and 60 for women. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.8: Effect of Reaching the State Pension Age on Specific Causes of Mortality, Men

(a) Specific ICD9 and ICD10 Causes

	Cause of Death							
	AMI	Heart Disease	Bronchopneumonia	Acute Cerebrovascular	Lung	Chronic airway	Cancer, Unspecified	Colon
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State Pension Age	19.475	−12.089	8.038	0.093	53.555***	13.684	9.082	4.377
	(17.415)	(19.377)	(10.901)	(10.415)	(19.160)	(18.580)	(14.144)	(12.767)
Constant	1,202.175***	1,091.445***	142.555***	171.483***	934.659***	317.718***	239.192***	210.997***
	(10.282)	(14.707)	(7.722)	(8.227)	(17.147)	(15.413)	(11.252)	(10.015)
Observations	49	49	49	49	49	49	49	49
Adjusted R^2	0.931	0.886	0.642	0.826	0.892	0.869	0.627	0.605

(b) Specific ICD9 and ICD10 Causes, Continued

	Cause of Death						
	Aortic anyuerism	Heart Failure	Prostate	Dementia	Stomach	Diabetes	Stroke
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	−7.913	0.800	10.636	−1.809	−6.677	12.293**	8.308
	(9.568)	(6.379)	(12.731)	(4.856)	(9.089)	(6.230)	(6.321)
Constant	102.650***	41.512***	212.167***	16.602***	162.742***	57.798***	88.812***
	(8.478)	(4.642)	(11.758)	(4.417)	(7.878)	(3.944)	(5.408)
Observations	49	49	49	49	49	49	49
Adjusted R^2	0.787	0.560	0.808	0.531	0.724	0.416	0.746

Notes: Regression discontinuity estimates of reaching the State Pension Age on mortality for men. Each outcome variable is a specific ICD9 or ICD10 code for the primary cause of death. Robust standard errors in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A.9: Effect of Reaching the State Pension Age on Specific Causes of Mortality, Women

(a) Specific ICD9 and ICD10 Causes

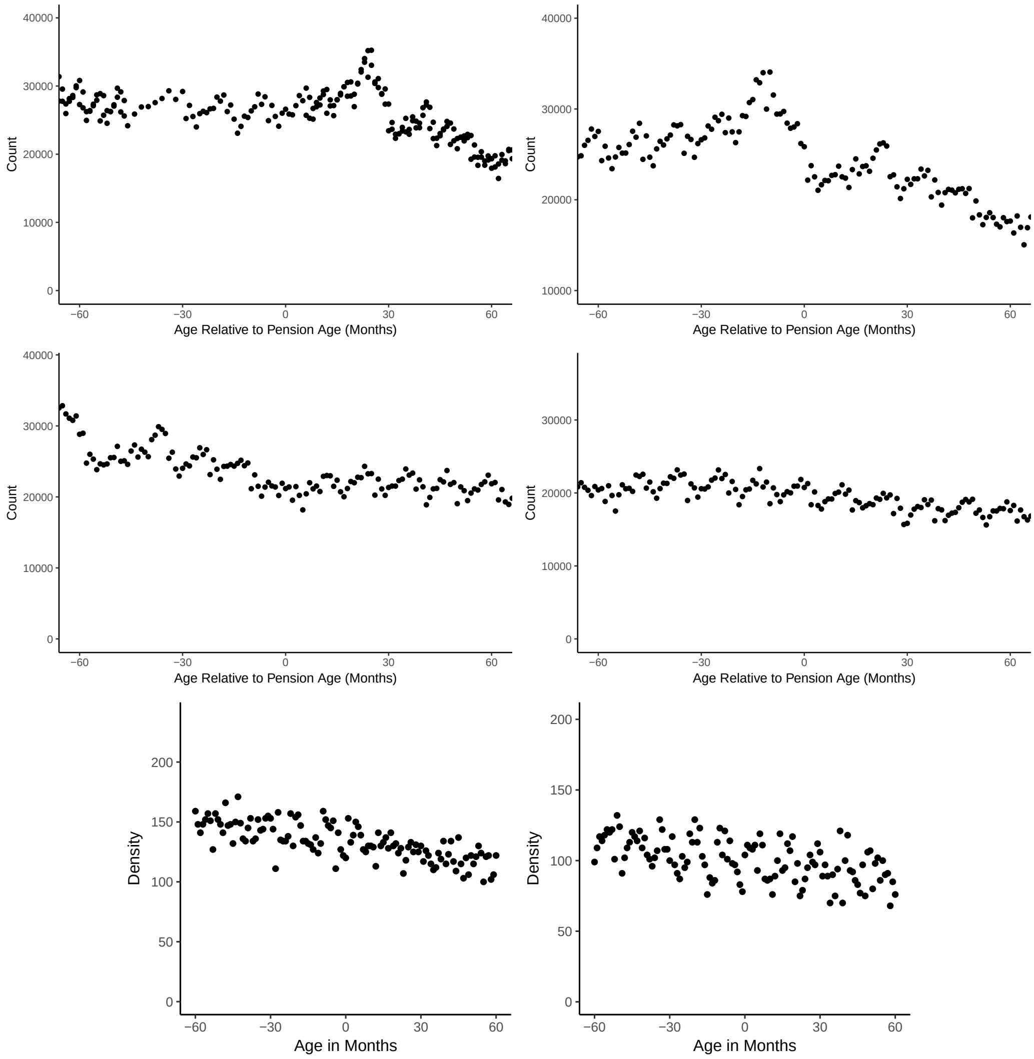
	Cause of Death							
	AMI	Heart Disease	Bronchopneumonia	Acute Cerebrovascular	Lung	Chronic airway	Cancer, Unspecified	Colon
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State Pension Age	-14.930	20.169^{***}	7.579	1.793	1.432	-17.994^{***}	-22.301^{***}	5.363
	(11.721)	(7.620)	(6.613)	(4.291)	(17.173)	(5.232)	(6.200)	(6.664)
Constant	230.428^{***}	170.750^{***}	49.917^{***}	46.704^{***}	307.607^{***}	118.557^{***}	135.386^{***}	86.993^{***}
	(8.082)	(5.380)	(3.638)	(2.937)	(15.099)	(2.969)	(4.942)	(5.273)
Observations	49	49	49	49	49	49	49	49
Adjusted R^2	0.893	0.880	0.558	0.734	0.908	0.921	0.743	0.660

(b) Specific ICD9 and ICD10 Causes, Continued

	Cause of Death						
	Aortic anyuerism	Heart Failure	Breast	Dementia	Stomach	Diabetes	Stroke
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State Pension Age	-3.393	5.264	19.467	1.352	0.244	9.201^{***}	2.214
	(2.528)	(3.436)	(21.878)	(1.976)	(5.451)	(3.258)	(5.101)
Constant	15.595^{***}	9.125^{***}	367.240^{***}	6.075^{***}	36.063^{***}	24.704^{***}	23.077^{***}
	(2.180)	(2.659)	(19.712)	(1.200)	(2.981)	(1.960)	(4.672)
Observations	49	49	49	49	49	49	49
Adjusted R^2	0.415	0.400	0.594	0.266	0.374	0.546	0.682

Notes: Regression discontinuity estimates of reaching the State Pension Age on mortality for women. Each outcome variable is a specific ICD9 or ICD10 code for the primary cause of death. Robust standard errors in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure A.3: Age Densities



Notes: Density of age in months, clockwise from top left: 2001 Census (Women), 2001 Census (Men), 2011 Census (Men), BHPS (Men), BHPS (Men), and 2011 Census (Women).

Table A.10: Regression Discontinuity Balance Estimates of Demographic Characteristics

(a) Men

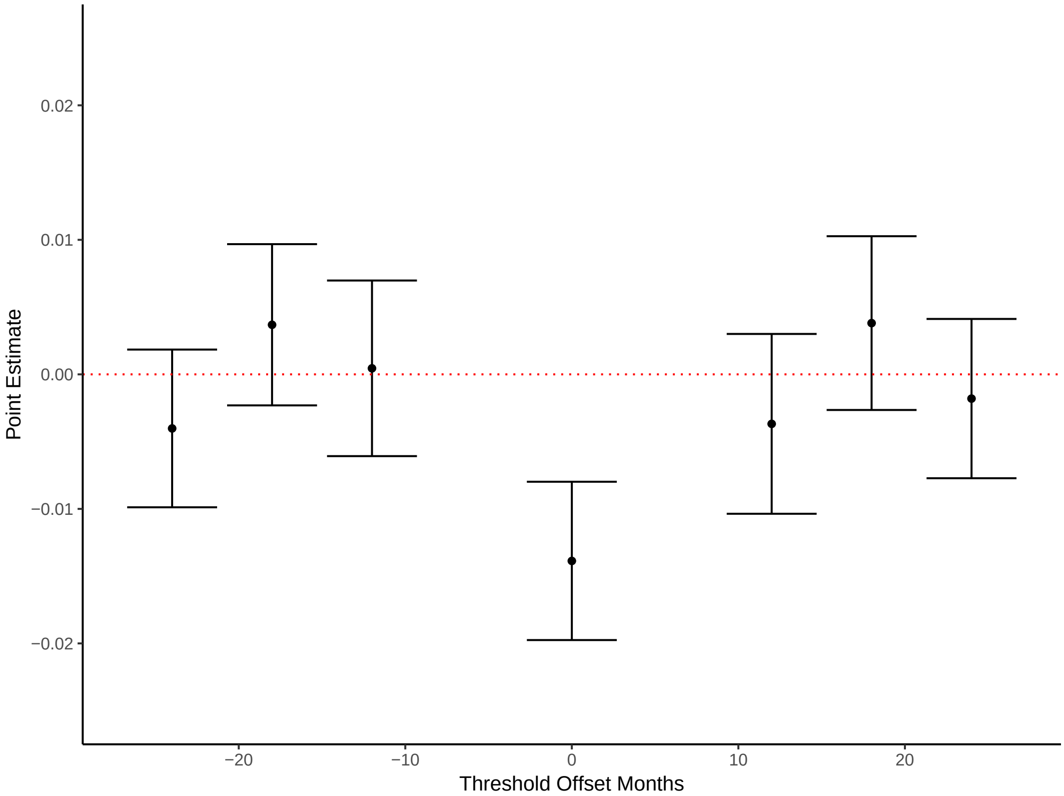
	Educated	Race	Married	Race	Married	Educated
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.038	0.133	0.012	−0.039	0.086	0.002
	(0.026)	(0.138)	(0.021)	(0.026)	(0.179)	(0.009)
Constant	0.384***	0.996***	0.768***	1.119***	2.486***	0.689***
	(0.021)	(0.083)	(0.016)	(0.013)	(0.166)	(0.006)
Dataset	BHPS	BHPS	BPHS	HSE	HSE	ELSA
Observations	11,394	680	12,186	4,757	5,813	15,611
Adjusted R^2	0.010	0.005	0.000	−0.000	0.001	0.019

(b) Women

	Educated	Race	Married	Race	Married	Educated
	(1)	(2)	(3)	(4)	(5)	(6)
State Pension Age	0.038	0.133	0.012	−0.017	−0.033	−0.001
	(0.026)	(0.138)	(0.021)	(0.045)	(0.079)	(0.014)
Constant	0.384***	0.996***	0.768***	1.110***	2.859***	0.676***
	(0.021)	(0.083)	(0.016)	(0.043)	(0.073)	(0.012)
Dataset	BHPS	BHPS	BPHS	HSE	HSE	ELSA
Observations	11,394	680	12,186	5,494	7,154	17,966
Adjusted R^2	0.010	0.005	0.000	0.002	0.007	0.027

Notes: Regression discontinuity estimates of demographic characteristics to check for balance across the pension age threshold. Robust standard errors in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1%.

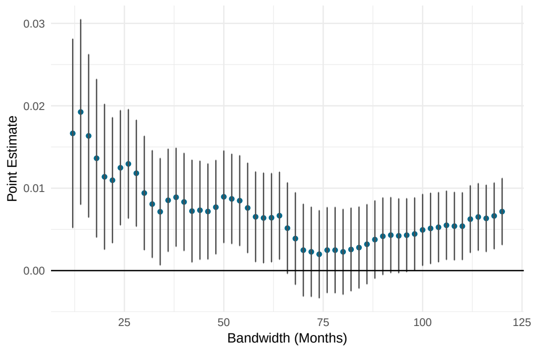
Figure A.4: Regression Discontinuity Placebo Test



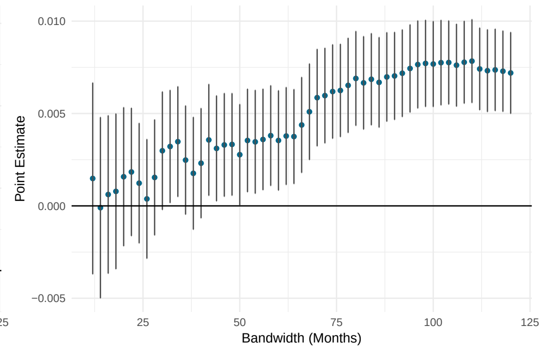
Notes: RD placebo estimates of the proportion of men reporting bad health in the 2001 Census. The y-axis shows the point estimates with 95 percent confidence intervals, and the x-axis shows age thresholds that differ from the State Pension Age by the indicated number of months. Estimates are produced using a one-year bandwidth.

Figure A.5: Bandwidth Sensitivity for Self-Reported Health from the 2001 and 2011 Censuses, Men

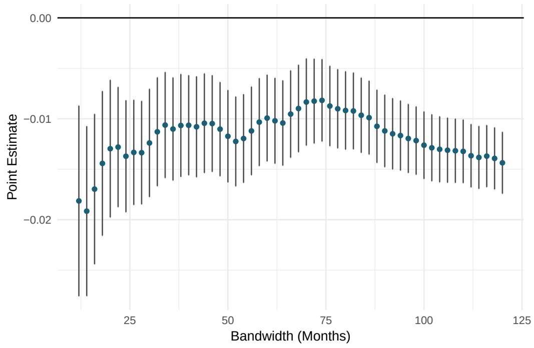
(a) Men in Good or Very Good Health, 2001



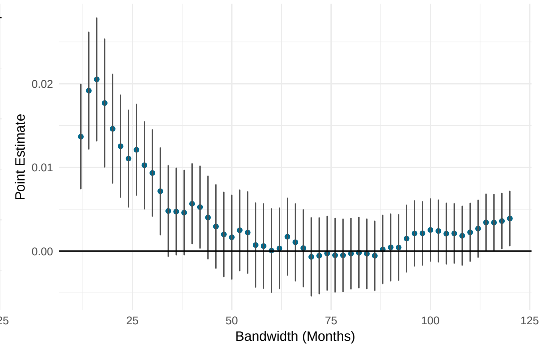
(b) Men in Fair Health, 2001



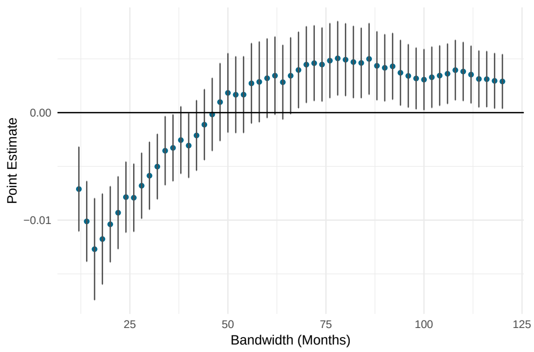
(c) Men in Bad or Very Bad Health, 2001



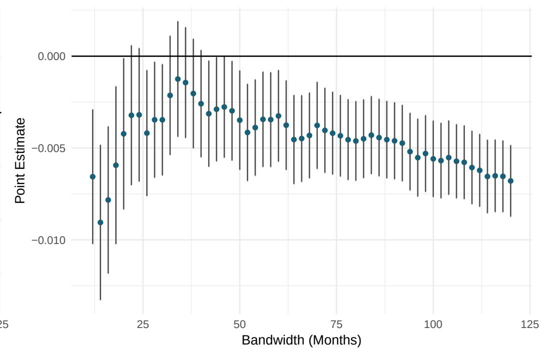
(d) Men in Good or Very Good Health, 2011



(e) Men in Fair Health, 2011



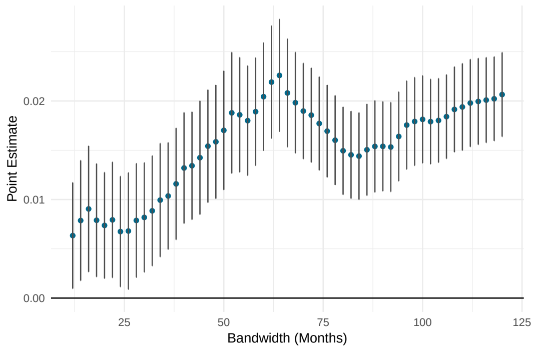
(f) Men in Bad or Very Bad Health, 2011



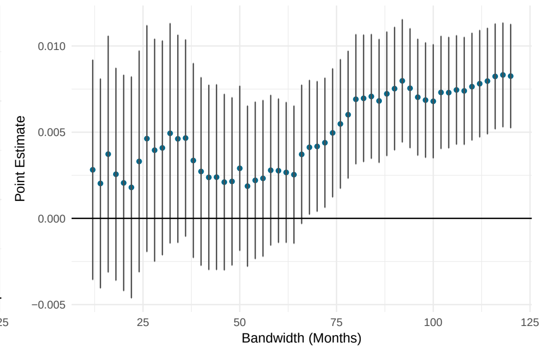
Notes: Bandwidth sensitivity figures for the proportion of the male population reporting good or very good health, fair health, or bad or very bad health, respectively, from the 2001 and 2011 England/Wales censuses. Each point is the result of a regression with the bandwidth listed on the x-axis.

Figure A.6: Bandwidth Sensitivity for Self-Reported Health from the 2001 and 2011 Censuses, Women

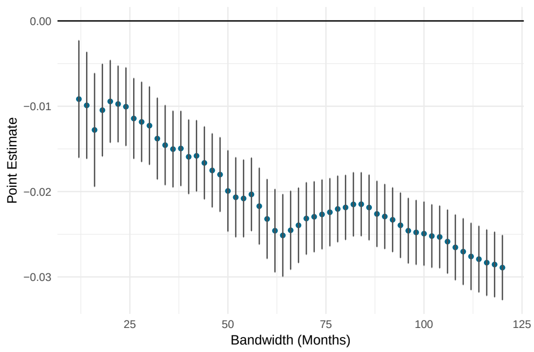
(a) Women in Good or Very Good Health, 2001



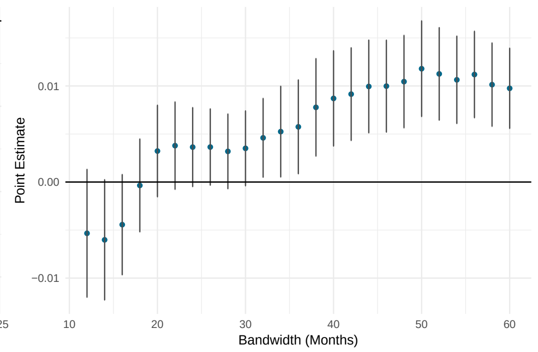
(b) Women in Fair Health, 2001



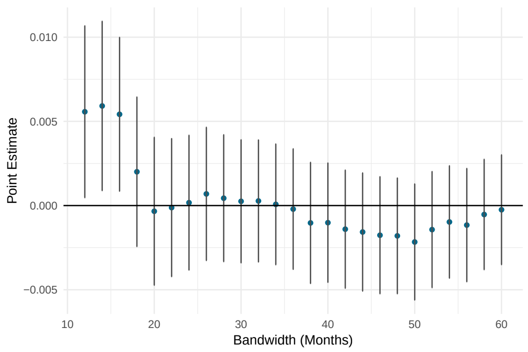
(c) Women in Bad or Very Bad Health, 2001



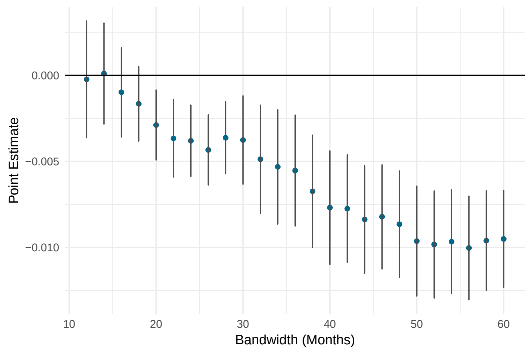
(d) Women in Good or Very Good Health, 2011



(e) Women in Fair Health, 2011

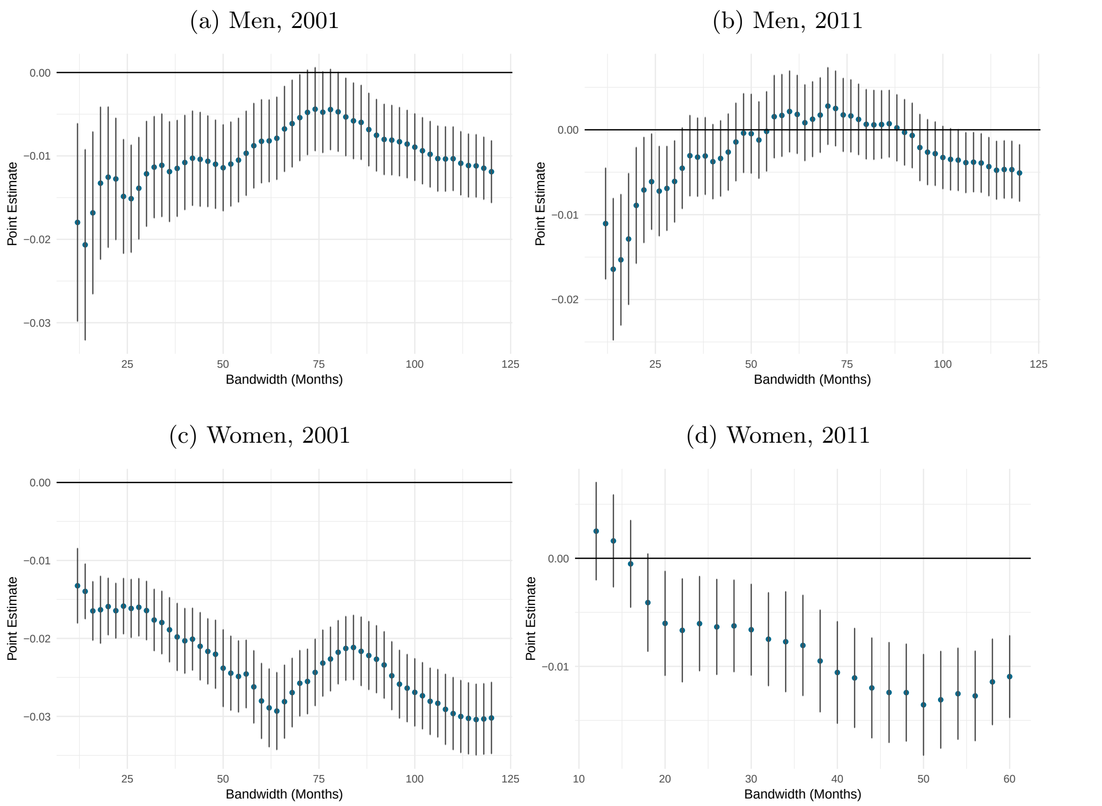


(f) Women in Bad or Very Bad Health, 2011



Notes: Bandwidth sensitivity figures for the proportion of the male population reporting good or very good health, fair health, or bad or very bad health, respectively, from the 2001 and 2011 England/Wales censuses. Each point is the result of a regression with the bandwidth listed on the x-axis.

Figure A.7: Age Profile of Long-Term Illness or Disability from 2001 and 2011 Census



(a) Men, 2001

(b) Men, 2011

(c) Women, 2001

(d) Women, 2011

Notes: Bandwidth sensitivity for self-reported long-term illness or disability status from the 2001 and 2011 Censuses. Each point is the result of a regression with the bandwidth listed on the x-axis.

Appendix B

Appendix for Chapter 2

B.1 Hospital Inclusion Criteria

Capacity and staffing normally dictate the movement of patients from the ED to inpatient wards, and some hospitals may be affected by a not uncommon shift structure that sees a shift change at 11PM. However, when an admission decision is made close to midnight, insurance and billing practices may present some hospitals with an incentive to ensure a patient is admitted before midnight. This depends on the insurance coverage of the patient as well as the length of the time the patient was in the emergency department. Many insurance plans will accept emergency room and observation charges or inpatient room and board charges on a given calendar day, but not both, with the higher cost option depending on the patient's insurance coverage as well as the amount of time and care received prior to being admitted. This consideration would not be relevant for Medicare beneficiaries without secondary coverage or Medicare Advantage, as CMS uses a prospective payment system (PPS).

While shift changes are a more plausible explanation, I cannot rule out that hospitals are sensitive to this consideration, and some in fact appear to respond to the incentive more strongly than others. More specifically, these hospitals display a sharp drop in the number of patients admitted at midnight. I restrict my sample to hospitals that do not display this phenomenon, detected by estimating the change in the volume of admissions at midnight by hospital. Specifically, I examine the density for each hospital and obtain the RD estimate with a four-hour bandwidth, then exclude any hospital with a combination of visual inspection and statistical significance of the RD estimate.

To provide evidence that some hospitals engage in more gaming than others, I first establish that the flow into inpatient wards is not discontinuous. Figure B.1 shows that emergency department arrivals do not vary discretely over time, with the natural inflow of patients increasing during the day and falling off in the early hours of the morning. Figure B.1a plots the mean time of ED arrival for patients that were later admitted as inpatients, and Figure B.1b shows the count of ED arrivals whether or not the patient was admitted, with neither of these changing dramatically at midnight. Together, these suggest that the arrival rate of patients does not decrease abruptly after midnight. Figure B.2 then plots the admission probability by ED arrival time, and again there is no significant change at midnight.[1]

These plots show no substantial difference in patient experience for included and excluded hospitals. Figure B.3, however, shows that there is a drop in inpatient

1. Note that data for Figures B.1a and B.2 come only from Florida, as other states do not disclose ED arrival time for patients that were later admitted.

admissions for excluded hospitals at midnight, while the density is much smoother for included hospitals.[2]

Figure B.4 provides insight into the largest difference between included and excluded hospitals by plotting time spent waiting in the ED by admission time, as well as the complementary figure showing ED charges by admission time.[3] This shows that for excluded hospitals there is a spike in the average time between ED arrival and inpatient admission at midnight, and that there is a corresponding spike in the billed amount for ED and observation services. One explanation for this is that these hospitals encounter some degree of backup due to a shift change at 11PM or 12AM, and patients are forced to wait longer before being transferred. However, it may also be the case that excluded hospitals have a more forceful response to the payment incentives outlined above, and as such are not included in the analysis sample.

Table B.3 shows the differences between included and excluded hospitals. There is no statistically significant difference in number of beds or discharges, and there is no clear difference in owner type. Further, there are no obvious trends among service types or urban/rural distinctions.

Table B.2 gives the first stage estimates with all hospitals included. The point estimate for the increase in the SNF discharge rate for before midnight admissions is only slightly larger than before at 3.7 percentage points, and the other categories are

2. A very small number of hospitals displayed large *increases* at midnight, and these hospitals were similarly excluded.

3. The lag between ED arrival time and inpatient admission time are underestimates, as the data do not allow me to know if this lag was greater than 24 hours. As such, all individuals are treated as if they spent less than 24 hours receiving observation services.

similarly narrowly affected.

B.2 Data Trimming Strategies & Robustness

The data used in this paper are comprehensive and include all emergency department visits and inpatient stays in a given state and year. The majority of these encounters involved patients whose conditions would not have warranted going to a SNF, regardless of coverage for that type of care. Here, I describe the steps I took to trim the data in order to focus on the patients that may have been affected by Medicare's SNF coverage policy. I also provide accompanying density figures to demonstrate that these trimming steps do not induce bias into estimated outcomes.

Starting with the entire sample, I first trim observations that come from hospitals that displayed signs of discrete change in admission policy at midnight, as previously described. The initial density and the density with these hospitals removed are presented in Figures B.5a and B.5b.

I next remove patients that did not come through the emergency department in order to exclude patients that had planned or scheduled admissions and transfers, along with patients that were transferred from other units of the same hospital. In the density for this trimming step shown in Figure B.5c, the irregular spikes in the morning hours are no longer present. Following this, I remove all patients that do not have Medicare listed as either a primary or secondary payer for their inpatient stay, and Figure B.5d shows that the density is mostly unaffected.

Finally, I trim on length of stay in hours to focus on the the three-day threshold required by Medicare. For this, my primary analysis sample includes patients that stayed between 60 and 84 hours as an inpatient, or 12 hours either side of the 72-hour mark. In order to show that this particular trimming is robust, I plot the change in SNF eligibility at midnight and the change in SNF discharge at midnight for a range of possible hour trimmings, along with the ratio of the two in Figure B.7. The change in SNF eligibility approaches 100 percent as the range of hours stayed is narrowed close to 72, with local maxima around +/- 27 hours and +/- 52 hours reflecting bunching in discharge times. The change in the SNF discharge rate shows a slight increase, going from about 0.5 percentage points to over 7 percentage points when only an extremely narrow range of hours is considered. Combining these, the ratio gives the change in SNF-going rate for the patients that were eligible for SNF discharge. This estimate is relatively constant for any trimming range, suggesting that the range used for analysis has a relatively small impact on estimates of outcomes. To further this point, Figure B.8 gives the first stage estimate, reduced form estimate, and IV estimate for different length of stay trimming lengths. The IV estimate is relatively stable, and is statistically significant for nearly all hour trimming lengths.

The main analysis sample examines Medicare beneficiaries who stayed between 60 and 84 hours as an inpatient. To provide evidence that these trimming decisions were sensible, I calculate the first stage effects for non-Medicare patients with ages 60-64 as a falsification exercise. Table B.1a shows that there is no change in the proportion of people discharged to a SNF around midnight for this population, and SNF-going rates are low overall.

Figure B.6 shows the density for the analysis sample with the length of stay trimming along with all previous steps as described. It can be seen that the density is similar to that shown in previous steps.

Table B.4 shows first stage results of the change in the SNF-going rate at midnight for each step of the trimming process. Estimates all have the same direction, with a small but discernible drop the proportion of the population going to a SNF for midnight admits. The magnitude, however, is heavily attenuated until the final step of the trimming process, when the length of stay restriction is imposed.

B.3 Summary Statistics

Summary statistics are listed in Table B.6. The first two columns come from the full sample, which is a near census of emergency department and inpatient admissions from New York, Florida, and Washington from 2009-2013. On average, patients that are admitted are older, have nearly four times as many diagnoses on record, and are more likely to have multiple procedures on their record for that stay. Once the data are limited to Medicare beneficiaries in the third column, the average patient is 70 years old, which is nearly 20 years older than the average inpatient in the full sample. Beneficiaries have more chronic conditions on their record, but actually have fewer diagnoses and procedures. Finally, the fourth column presents statistics from the trimmed sample used in the primary analysis. The average patient is nearly four years older than the average Medicare beneficiary, and has over ten diagnoses on her record.

B.4 Hospital Readmissions Reduction Program (HRRP)

I investigate whether the disparity between returning to the emergency department only and being readmitted is related to financial incentives faced by the hospitals. As mentioned previously, starting in the 2013 fiscal year hospitals faced reduced payments for excess readmissions, defined as a risk-adjusted measure compared to the national average. The Hospital Readmissions Reduction Program reduces payments at the hospital level, rather than at the patient level. However, the penalty lasts the entire fiscal year, and is between 1 and 3 percent for *all* Medicare payments. As such, hospitals have a strong incentive not to readmit Medicare beneficiaries with one of the three diagnosis codes on record.[4]

Because patients admitted just after midnight are proportionally more likely to return to the hospital in any capacity, it should be the case that this group is more likely to return to the emergency department only as well as be readmitted. If, however, hospitals are responding to the incentives of the HRRP, the expected result could be neutralized. Table B.7 presents 30-day readmission probabilities around the midnight discontinuity for two groups: those with a diagnosis that Medicare considers for the HRRP, and those with other diagnoses. This is further split into two time periods, corresponding to roughly before and after the program began. This analysis only considers

4. In subsequent years, CMS has made minor adjustments to the program by accounting for planned readmissions and expanding the list of diagnosis codes.

the primary diagnosis, and as such should be considered a lower bound.

Column (1) shows that from 2009-2012, Medicare beneficiaries with heart failure, acute myocardial infarction, or pneumonia that were initially admitted at midnight were not more likely to be readmitted within 30 days. However, column (2) shows no significant difference across midnight for patients with other diagnosis codes. Columns (3) and (4) — corresponding to calendar year 2013 — state a different effect. There is significantly positive jump of 1.3 percentage points across midnight for patients with other diagnosis codes. For patients with one of the three monitored diagnosis codes, the effect is small but significant at 0.22 percentage points. These results could indicate that hospitals are responding to the HRRP and are more reluctant to readmit patients with one of the monitored diagnoses, but not those without. Of patients that are discharged to a SNF, only 5.5 percent have one of the three diagnosis codes considered for the HRRP, compared to over 9 percent of non-SNF dischargees. With SNF patients less likely to have one of the targeted diagnosis codes, those in the high SNF-going group should be more likely to be readmitted. This suggests that the HRRP is actually attenuating the effect of post-acute SNF care, and the discontinuity in readmission rates exists in spite of hospitals responding to Medicare payment incentives and abstaining from readmitting some patients.[5]

5. This does not necessarily mean patients are not receiving health care at all. As mentioned previously, there has been a dramatic rise in both the volume and length of observation stays, in which patients are kept overnight (or longer) while the hospital continues to evaluate the patient before making an admission decision. Efforts by CMS to clarify who qualifies as an inpatient are ongoing.

B.5 Additional Tables and Figures

Table B.1: Falsification Tests

(a) Change in Discharge Location for Non-Medicare Patients

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	0.00004	0.0027	0.0019	-0.0047^{***}
	(0.0012)	(0.0037)	(0.0025)	(0.0014)
	0.0089	*0.9137*	*0.0429*	*0.0233*

Notes: Changes in discharge location for patients aged 60-64 without Medicare. Estimates from equation (2.2) with a dummy variable for discharge status as the respective dependent variables. Robust standard errors in parentheses. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

(b) Change in Discharge Location for Patients with LOS <60 Hours or >84 Hours

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	−0.0012	−0.0003	−0.0003	0.0006
	(0.0022)	(0.0026)	(0.0017)	(0.0012)
	0.2373	*0.4613*	*0.1916*	*0.0614*

Notes: Changes in discharge location for patients with length of stays less than 60 hours or more than 84 hours. All restrictions in main analysis sample remain. Estimates from equation (2.2) with a dummy variable for discharge status as the respective dependent variables. Robust standard errors in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

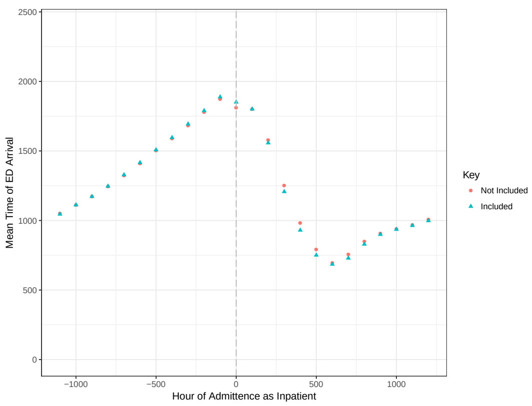
Table B.2: Change in Discharge Location with All Hospitals Included

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)
Change at Midnight	0.037***	−0.0307***	−0.0071***	−0.0003
	(0.0010)	(0.0021)	(0.0008)	(0.0010)
	0.1505	*0.5987*	*0.1792*	*0.0339*
n	691,009	691,009	691,009	691,009

Notes: Changes in discharge location with primary analysis sample but with all hospitals included. Estimates from equation (2.2) with a dummy variable for discharge status as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

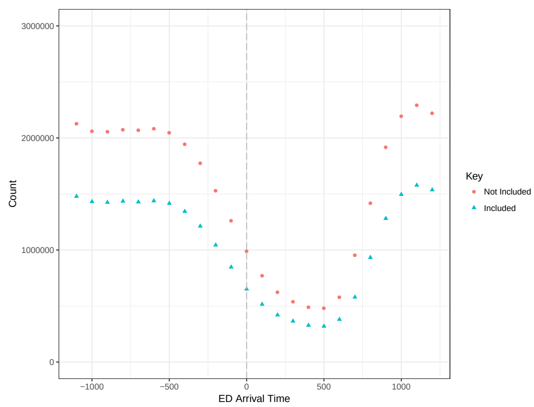
Figure B.1: Emergency Department Arrival

(a) Average ED Arrival Time for Admitted Patients



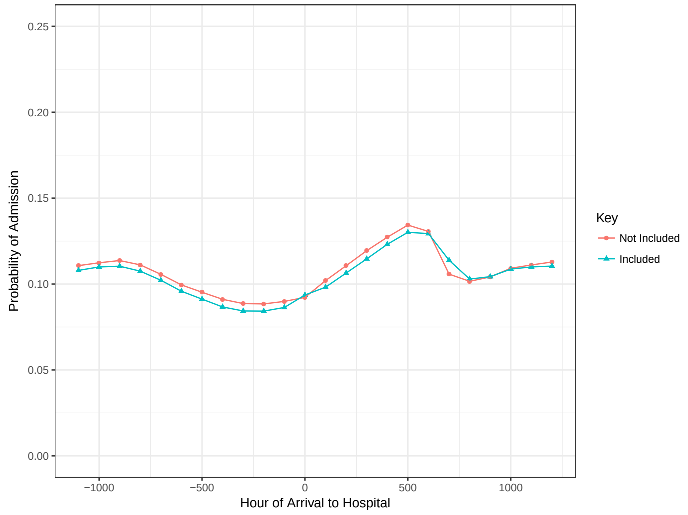
Notes: Average ED arrival time (shown on 24-hour clock) by hour of admittance as an inpatient and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

(b) Density of ED Arrival for All Patients



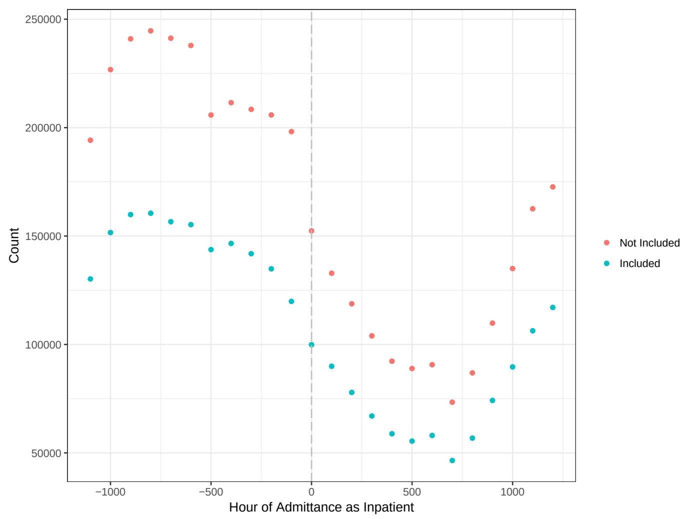
Notes: Density of ED arrival time by hour of admittance as an inpatient and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Figure B.2: Admission Probability by ED Arrival Time



Notes: Probability of inpatient admission by ED arrival time (shown relative to midnight on the x-axis) and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

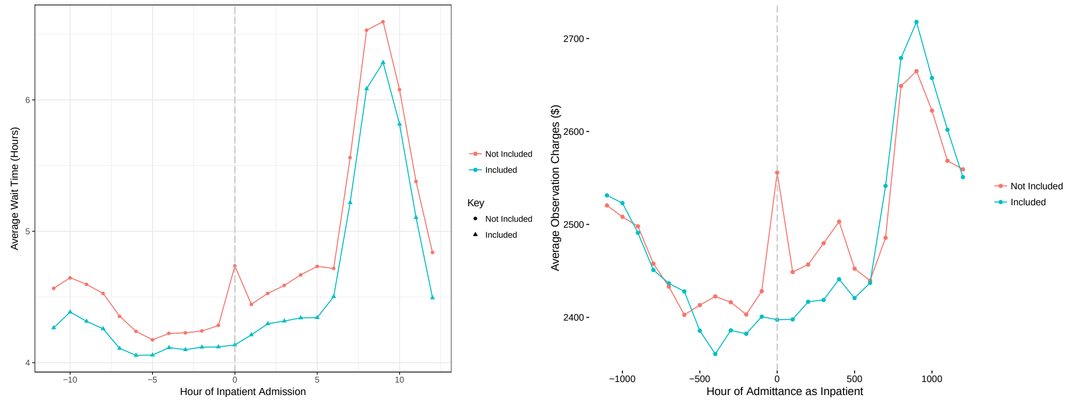
Figure B.3: Density of Inpatient Admissions by Admission Time



Notes: Density of inpatient admission by admission time and hospital inclusion. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Figure B.4: Waiting Time to Hospital Admission and ED Charges

(a) By Admission Time (b) By ED Arrival Time



Notes: (Left) Average time from arrival at the emergency room until admission plotted by time of admission as an inpatient. (Right) Observation and ED charges by time of admission as an inpatient. Included hospitals are shown in blue, while non-included hospitals are shown in red.

Table B.3: Characteristics of Hospitals Included in Analysis Sample

A. Balance

Variable	Not Included Mean	SD	Included Mean	SD	Difference	p-value
Hospital Beds	367.609	428.894	350.722	445.022	16.887	0.674
Discharges	36737.972	35971.297	41080.067	34183.027	-4342.095	0.180

B. Distribution of Characteristics

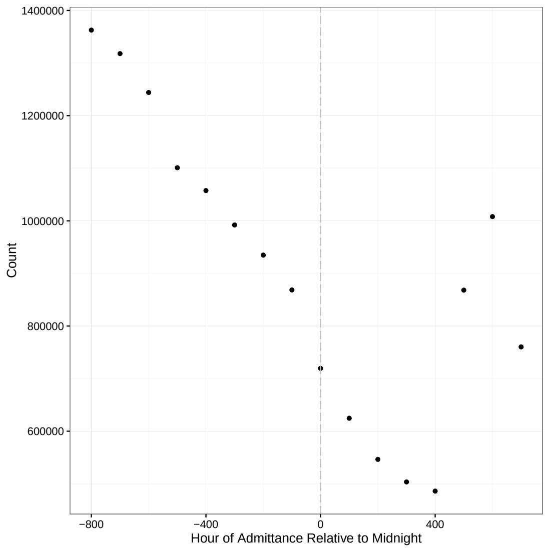
Owner Type:	Gov't, Non-Federal	Not-For-Profit	For-Profit	Gov't, Federal		
Included	22	17	119	54		
Not Included	31	21	140	66		
Service Type:	**General Med & Surgical**	**Psychiatric**	**OB/GYN**	**Rehabilitation**	**Orthopedic**	**Other**
Included	180	1	0	9	2	23
Not Included	232	10	0	8	0	13
Urban/Rural:	**Division**	**Metro**	**Micro**	**Rural**		
Included	83	94	25	13		
Not Included	90	138	21	14		

Included $n = 215$, Not Included $n = 263$

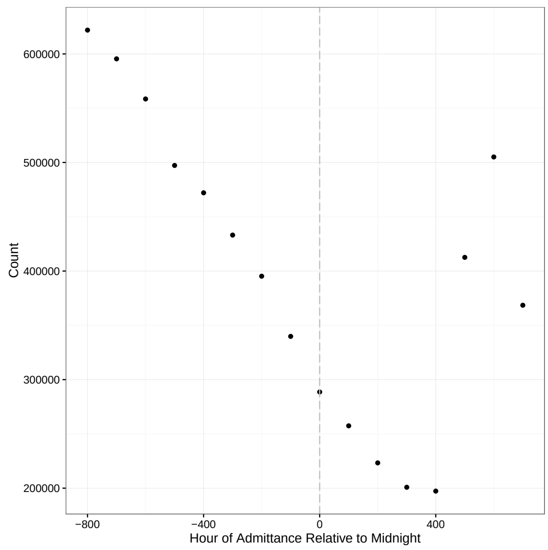
Notes: Panel A gives the differences in means for number of annual discharges and number of hospital beds between hospitals included and not included in the analysis sample. Panel B gives the distribution of owner type, service type, and urban/rural designation for these hospitals. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Figure B.5: Hospital Admission Counts by Admission Time at Each Trimming Step

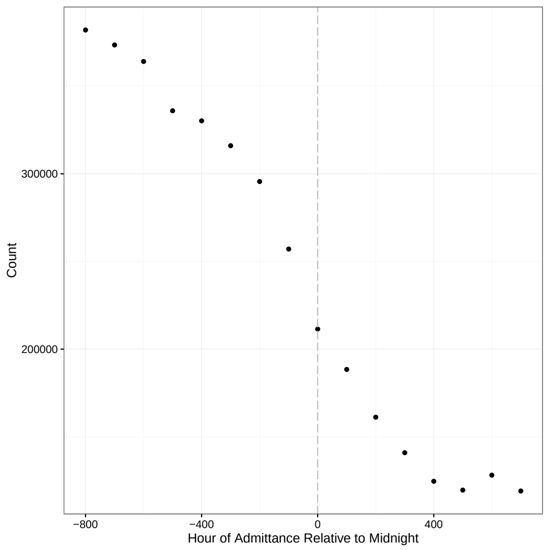
(a) Untrimmed



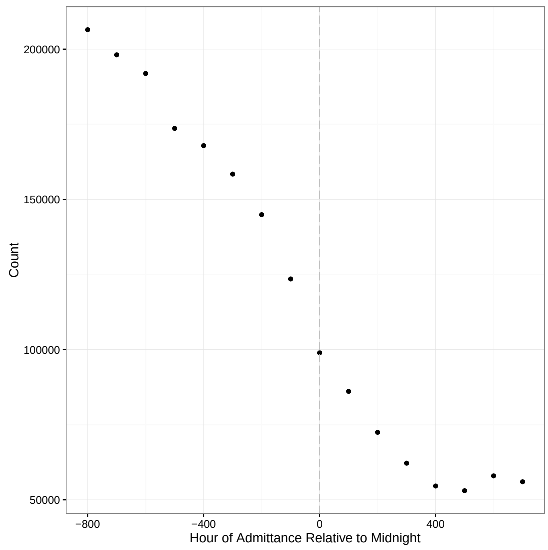
(b) With Included Hospitals



(c) With Included Hospitals and Patients from ED

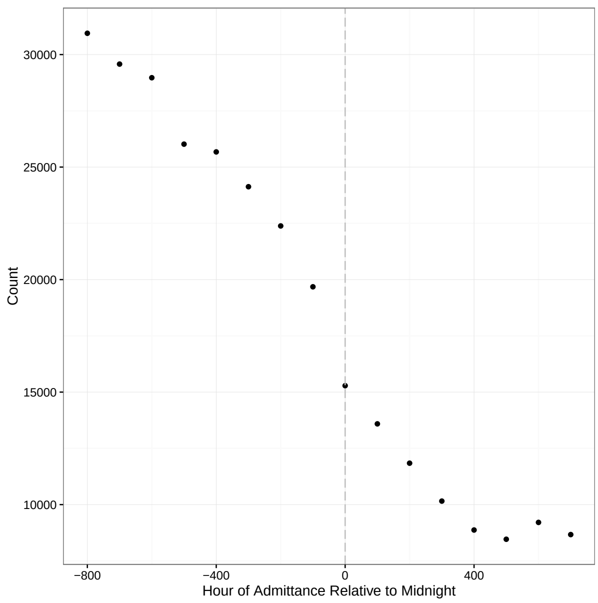


(d) With Included Hospitals, Patients from ED, and Medicare Beneficiaries



Notes: Clockwise from top left: The density of hospital admissions by hour for all patients in the untrimmed dataset, the density of hospital admissions by hour for all patients from an included hospital, the density of hospital admissions by hour for all patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital, and the density of hospital admissions by hour for all Medicare patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital.

Figure B.6: Density with Included Hospitals, Patients from ED, Medicare Beneficiaries, and Length of Stay Trimming



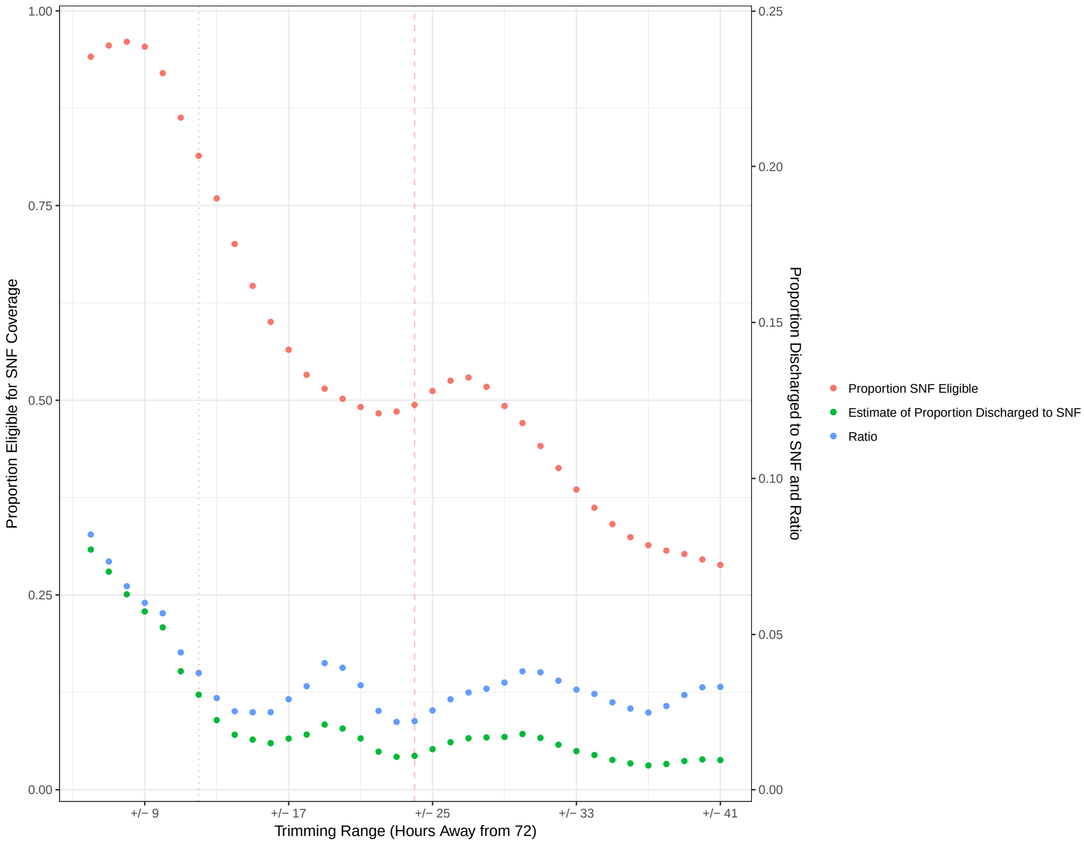
Notes: The density of hospital admissions by hour for all Medicare patients from an included hospital that went through the emergency department and were not transferred from another unit of the same hospital, and stayed between 60 and 84 hours as an inpatient.

Table B.4: Change in SNF-going Rates at Midnight by Trimming Step

	Untrimmed	Included Hospitals	From ED	Medicare	Length of Stay
Change at Midnight	−0.0068	−0.0045	−0.0022	−0.0023	−0.0340***
p-value	0.0000	0.0013	0.0438	0.1977	0.0000
Before Midnight	*0.0972*	*0.0959*	*0.1131*	*0.2148*	*0.1441*
n	23,441,389	10,680,806	6,144,715	3,144,813	477,382

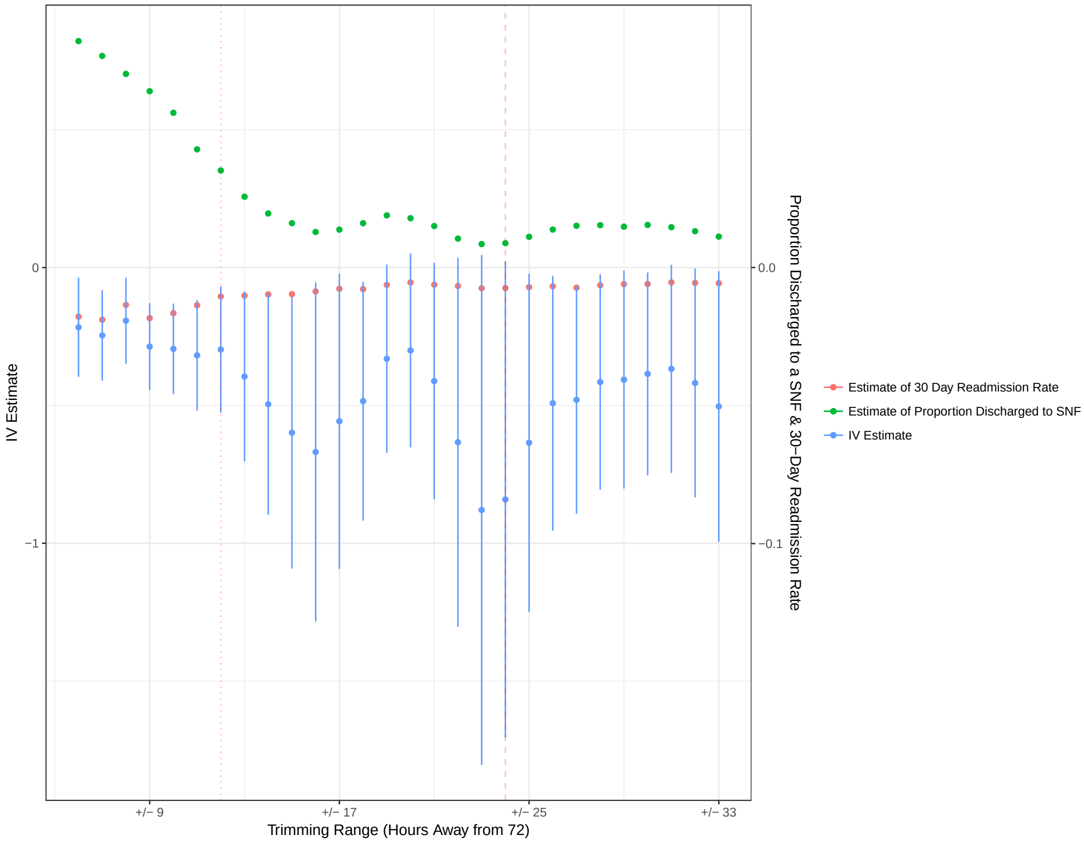
Notes: Estimates from equation (2.2) with a dummy variable for SNF discharge status as the dependent variable, with each column representing a sequential step in the trimming process. The proportion of the people admitted just before midnight with a SNF discharge status is shown in italics below the point estimates and p-values. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Figure B.7: Length of Stay Trimming Robustness, First Stage



Notes: Plot of the change in SNF eligibility at midnight (shown in orange, left axis), the change in SNF-going rate at midnight (shown in green, right axis), and the ratio between the two (shown in blue, right axis) for different trimming ranges of length of stay in hours (shown on the x-axis). Each point comes from an RD regression around midnight with 4-hour bandwidth using the data trimming as described in the text.

Figure B.8: Length of Stay Trimming Robustness, IV Estimate



Notes: Plot of the the change in SNF-going rate at midnight (shown in green), the change in the 30-day readmission rate (shown in orange), and the IV estimate formed with the previous two estimates with confidence intervals (shown in blue) for different trimming ranges of length of stay in hours (shown on the x-axis). Each point comes from an RD regression around midnight with 4-hour bandwidth using the data trimming as described in the text. The left-side axis corresponds to the IV estimate, while the right-side axis is for the first stage and reduced form.

Table B.5: Robustness to Bandwidth, Polynomial Choice, and Hospital and Weekend Fixed Effects

	Skilled Nursing Facility (1)	Home (Routine) (2)	Organized Home Healthcare (3)	Other (4)	Readmission (30 Day) (5)
			Linear Polynomial		
Change at Midnight	0.0314***	−0.0265***	−0.0025	−0.0022*	−0.0052***
	(0.0017)	(0.0037)	(0.0029)	(0.0012)	(0.0018)
	0.1139	*0.6424*	*0.1812*	*0.0341*	*0.1529*
			Bandwidth = 4 Hours		
Change at Midnight	0.0236***	−0.0112**	−0.0088**	−0.0078***	−0.0173***
	(0.0003)	(0.0048)	(0.0043)	(0.0008)	(0.0008)
	0.1153	*0.6383*	*0.1847*	*0.0338*	*0.1392*
			Bandwidth = 12 Hours		
Change at Midnight	0.0386***	−0.0311***	−0.0064**	−0.0012	−0.0079***
	(0.0053)	(0.0065)	(0.0030)	(0.0015)	(0.0026)
	0.1077	*0.6472*	*0.1830*	*0.0334*	*0.1476*
			With Weekend Fixed Effects		
Change at Midnight	0.0337***	−0.0253***	−0.0071***	−0.0025**	−0.0111***
	(0.0030)	(0.0036)	(0.0025)	(0.0013)	(0.0025)
			With Hospital Fixed Effects		
Change at Midnight	0.0330***	−0.0249***	−0.0058**	−0.0021	−0.0107***
	(0.0028)	(0.0035)	(0.0025)	(0.0013)	(0.0026)
			With Hospital x Weekend Fixed Effects		
Change at Midnight	0.0330***	−0.0251***	−0.0058**	−0.0021	−0.0106***
	(0.0029)	(0.0036)	(0.0025)	(0.0013)	(0.0026)

Notes: Estimates from equation (2.2) with a dummy variable for discharge status (columns 1-4) or 30-day readmission (column 5) as the respective dependent variables. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The proportion of the people admitted just before midnight with a given discharge status is shown in italics below the point estimates and standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Table B.6: Summary Statistics

	Full Sample			
	ED Only	Inpatient	Medicare	Trimmed
	$n = 55,010,734$	$n = 20,780,379$	$n =$10,587,472	$n = 700,934$
	(1)	(2)	(3)	(4)
Age	35.06	50.43	70.59	74.10
Discharge Hour	13:49	14:41	14:28	15:02
Diagnoses	2.50	8.47	7.892	10.583
Procedures	0.16	1.82	1.43	1.006
Chronic	-	4.11	4.08	6.03
Admission Hour	13:32	12:43	13:08	13:35
Female	0.55	0.56	0.56	0.56
Length of Stay	0.13	5.15	3.20	2.91

Notes: Summary statistics for the full sample (emergency department and inpatient separately), Medicare beneficiaries, and the trimmed sample used in the primary analysis.

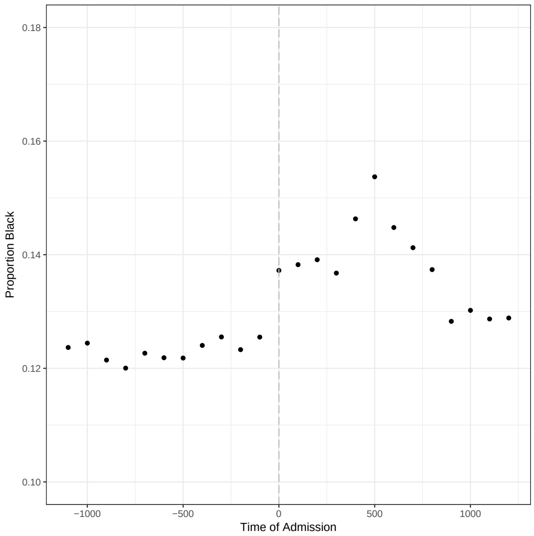
Table B.7: Change in 30-Day Readmissions for Midnight Admissions By Year and Diagnosis Group

	2010-2012		2013	
	In DRG	Not In DRG	In DRG	Not In DRG
	(1)	(2)	(3)	(4)
Readmission	0.0010	0.0086	0.0022	0.0138**
(30 Day)	(0.0009)	(0.0051)	(0.0013)	(0.0081)
	0.0151	*0.1373*	*0.0125*	*0.1123*
n	193,004		64,704	

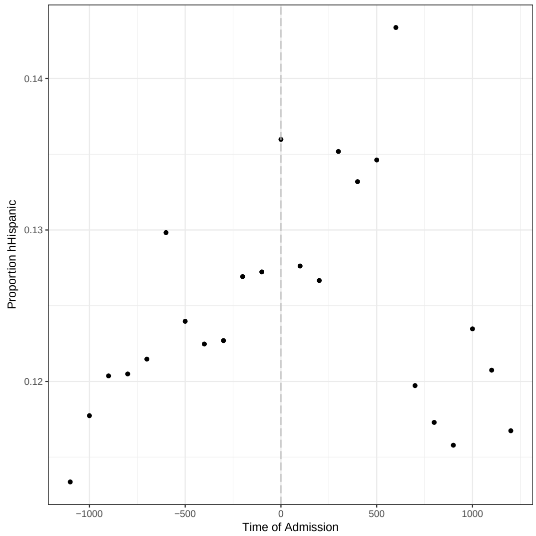
Notes: Estimates from equation (2.2), where the dependent variables are whether or not a patient was readmitted to the hospital within 30 days and whether the patient has a principal diagnosis that is one of the ICD-9 codes that Medicare considers for the Hospital Readmissions Reduction Program (HRRP). These diagnoses are acute myocardial infarction, pneumonia, and heart failure. The first two columns correspond to data pooled from the years 2010-2012, while the second two correspond to calendar year 2013. Standard errors clustered by hour of admission are shown below coefficient estimates in parenthesis. The estimates from just before midnight are listed in italics below the standard errors. Coefficients that are significantly different from zero are denoted by: *10%, **5%, and ***1%.

Figure B.9: Time of Admission Profiles of Race and Age

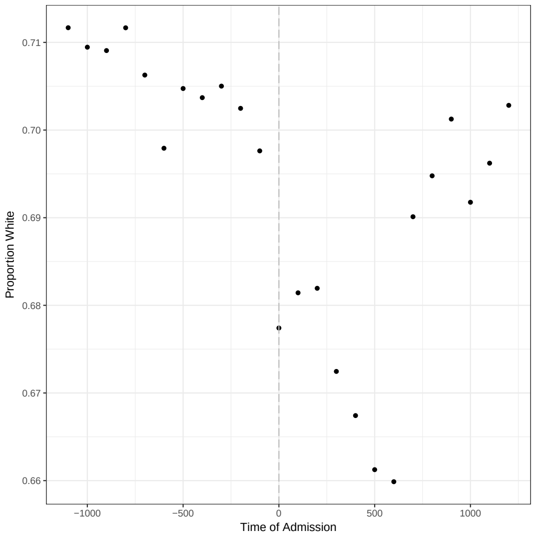
(a) Proportion Black



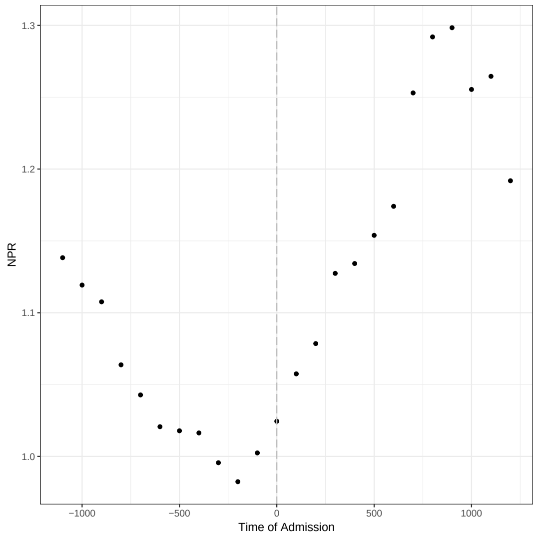
(b) Proportion Hispanic



(c) Proportion White



(d) Number of Procedures



(e) Estimates With Cubic Polynomial

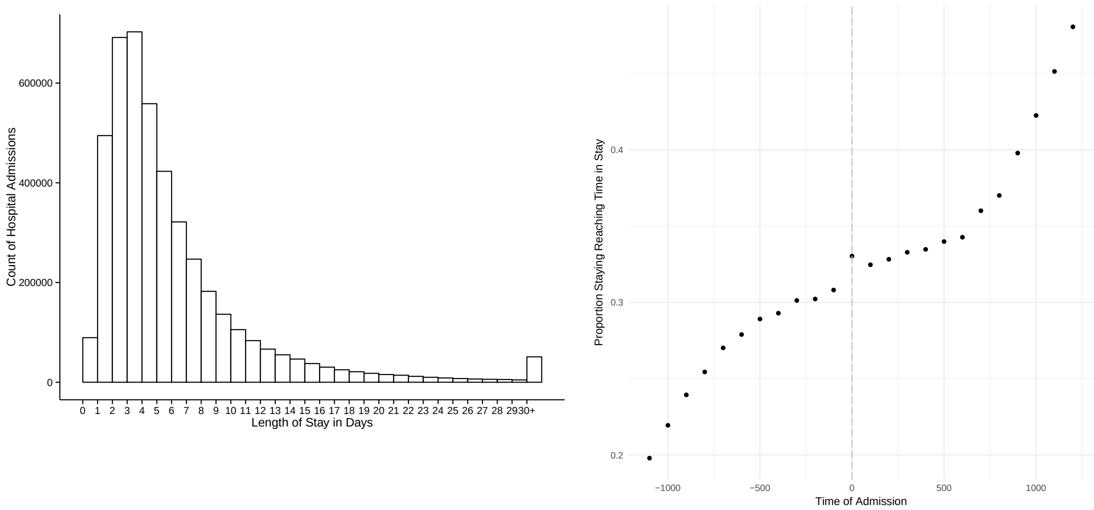
	NPR	Proportion Black	Proportion Hispanic	Proportion White
RD Estimate	0.0265	0.0094***	−0.0001	−0.0046
	(0.1700)	(0.0028)	(0.0042)	(0.0058)

Notes: Time of admission profiles by race and profile of age, as well as estimates when using a cubic polynomial.

Figure B.10: Probability of Long Hospital Stay

(a) Histogram of Stay Lengths

(b) Probability of Staying at Least Until 4 A.M. on Fourth Day of Inpatient Stay by Admission Hour



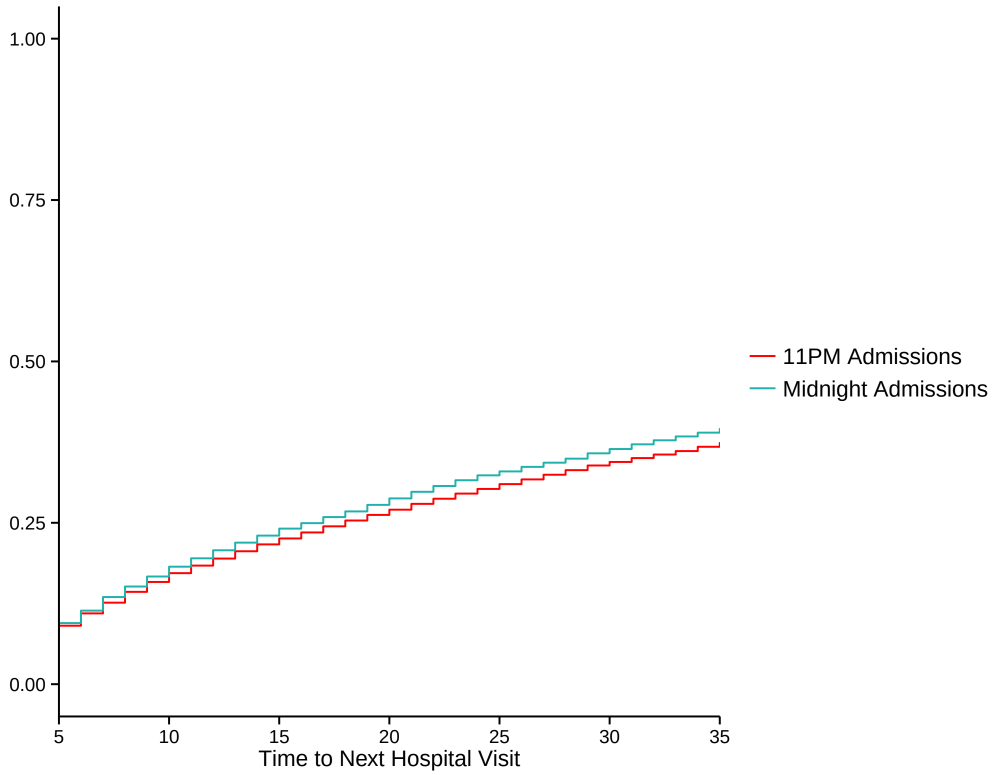
Notes: On left, the histogram of length of stay in days truncated at 30 days. Data come from all non-emergent Medicare admissions. On right, the probability that a patient admitted at a given time stays at least until 4 A.M. on the fourth day of their stay (e.g. stays at least 76 hours as an inpatient for an individual initially admitted at midnight)

Table B.8: Results with Alternative Standard Error Approaches

	Wild Bootstrap	Collapsed	Clustered
SNF-going rate	-0.033***	-0.033***	-0.033***
	(0.014)	*(0.000)*	*(0.003)*
Readmission (30 days)		0.011***	0.011***
		(0.001)	*(0.002)*

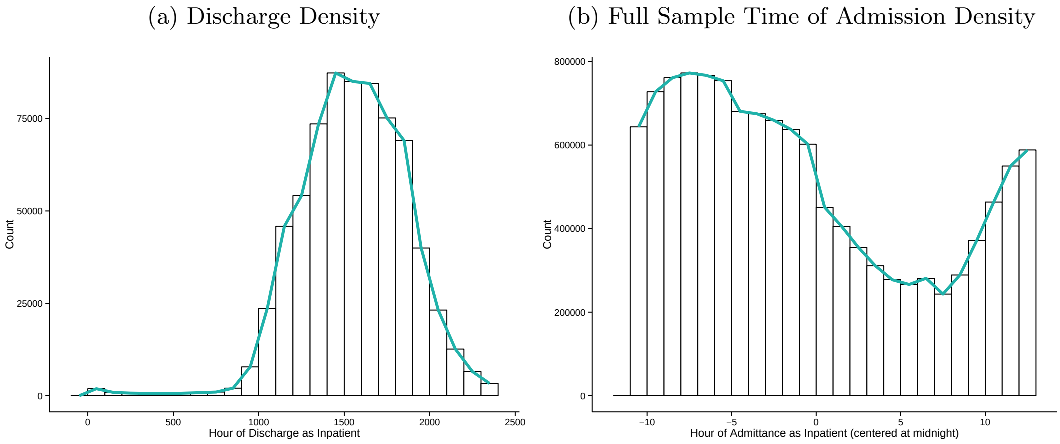
Notes: Key results with alternative approaches for handling standard errors. P-values are listed below coefficients in parentheses and italics. The first column uses wild bootstrap clustered standard errors Cameron, Gelbach, and Miller 2008. The second column estimates equation 2.2 on collapsed data, using the means at each hour of admission for each outcome. Standard errors are then standard Huber-White standard errors. The third column simply reproduces results from the main analysis for reference, using standard errors clustered by hour of admission.

Figure B.11: CDF of Hospital Revisit (5-35 Days)



Notes: CDF of return zoomed in to 5 to 35 days. "Revisit" means the patient came back to the emergency department or was readmitted. The red line is the CDF for patients admitted just before midnight, while the blue line is the CDF for patients admitted just after.

Figure B.12: Additional Densities



Notes: Histogram of the time of day patients are discharged in the analysis sample (Figure B.12a) and histogram of the time of day patients are admitted in the full sample without hospital trimming (Figure B.12b).

Appendix C

Appendix for Chapter 3

C.1 Alternate Sample Results

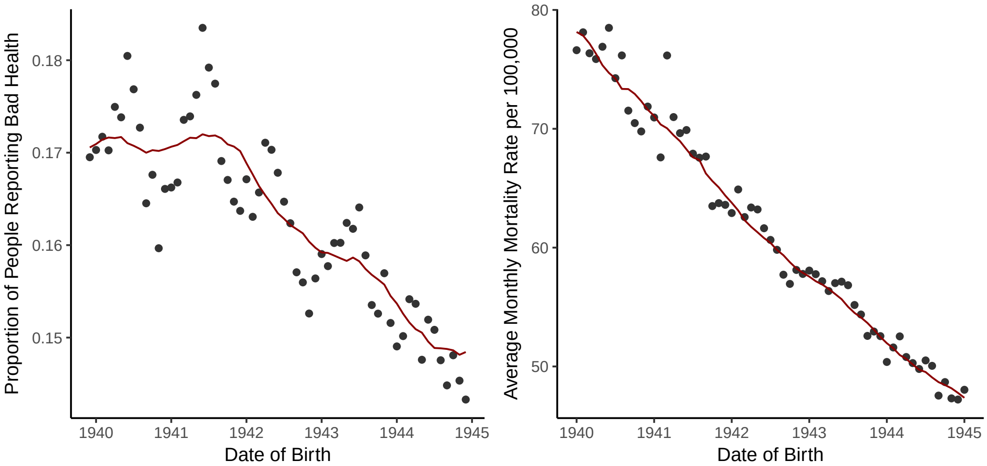
C.2 Alternative Specification Results

Table C.1: Average Monthly Deviation from Moving Average, 1945-1965 Sample

	Proportion Reporting Bad Health			Mortality Rate		
	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
April	0.086***	0.080*	0.093**	0.250**	−0.033	0.514***
	(0.031)	(0.047)	(0.042)	(0.104)	(0.168)	(0.150)
August	0.121***	0.078**	0.163***	0.657***	0.804***	0.513***
	(0.033)	(0.039)	(0.039)	(0.104)	(0.168)	(0.150)
December	−0.131***	−0.071	−0.189***	0.175*	0.147	0.204
	(0.043)	(0.065)	(0.046)	(0.104)	(0.168)	(0.150)
February	−0.119***	−0.168***	−0.071	−0.508***	−0.502***	−0.496***
	(0.039)	(0.037)	(0.059)	(0.104)	(0.168)	(0.150)
January	−0.100**	−0.078	−0.120**	−0.105	−0.072	−0.128
	(0.040)	(0.061)	(0.059)	(0.101)	(0.163)	(0.146)
July	0.203***	0.159***	0.247***	0.221**	0.347**	0.075
	(0.037)	(0.050)	(0.038)	(0.104)	(0.168)	(0.150)
June	0.133***	0.202***	0.063	−0.009	0.130	−0.145
	(0.038)	(0.049)	(0.045)	(0.104)	(0.168)	(0.150)
March	−0.009	−0.046	0.026	0.099	0.194	0.017
	(0.033)	(0.050)	(0.028)	(0.104)	(0.168)	(0.150)
May	0.083***	0.078**	0.088*	0.067	0.075	0.057
	(0.029)	(0.039)	(0.045)	(0.104)	(0.168)	(0.150)
November	−0.074	−0.075	−0.073	0.011	−0.037	0.059
	(0.048)	(0.062)	(0.059)	(0.104)	(0.168)	(0.150)
October	−0.223***	−0.213***	−0.235***	0.079	0.022	0.147
	(0.034)	(0.043)	(0.044)	(0.104)	(0.168)	(0.150)
September	−0.171***	−0.130***	−0.211***	0.037	0.071	−0.001
	(0.030)	(0.037)	(0.037)	(0.104)	(0.168)	(0.150)
Observations	241	241	241	241	241	241
Mean of Outcome	9.56	9.18	9.95	21.7	26.4	17.0

Notes: Estimates by month of the average deviation from the 12-month moving average from equation (1), with sample consisting of all individuals born 1945-1965 and alive at the time of the 2001 Census. "Mean of Outcome" refers to the mean of the outcome variable (Proportion in poor health or average mortality rate) for the entire sample period. Robust standard errors in parenthesis. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Figure C.1: Period of High Seasonality



Notes: Date-of-birth profile of the proportion of people born 1940-1945 that report that their general health is "not good" from the 2001 Census of England and Wales (left) and mortality rates (right). The red line represents a 12-month moving average. Morality rates are calculated by finding the proportion of people in each birth cohort that survive to the following month, then multiplied by 100,000.

Table C.2: Month Effects with Cubic Polynomial Trend

	Proportion Reporting Bad Health			Mortality Rate		
	All	Men	Women	All	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	27.100	−139.208***	188.069***	2,641.4	4,228.4	1,165.7
	(18.886)	(18.566)	(25.456)	(6,886.2)	(9,915.3)	(7,644.1)
August	−0.000	−0.034	0.031	0.390	0.739*	0.051
	(0.091)	(0.097)	(0.116)	(0.267)	(0.385)	(0.297)
December	−0.395***	−0.340***	−0.451***	−0.368	0.055	−0.792***
	(0.085)	(0.092)	(0.124)	(0.267)	(0.385)	(0.297)
February	−0.319***	−0.333***	−0.306**	−0.724***	−0.197	−1.196***
	(0.081)	(0.067)	(0.129)	(0.267)	(0.385)	(0.297)
January	−0.323***	−0.279***	−0.369***	−0.629**	−0.467	−0.771***
	(0.098)	(0.099)	(0.130)	(0.264)	(0.380)	(0.293)
July	0.154*	0.156*	0.151	−0.047	0.446	−0.520*
	(0.087)	(0.087)	(0.118)	(0.267)	(0.385)	(0.297)
June	0.116	0.233**	−0.005	−0.007	0.790**	−0.776***
	(0.105)	(0.102)	(0.137)	(0.267)	(0.385)	(0.297)
March	−0.149*	−0.165*	−0.137	0.060	0.687*	−0.556*
	(0.087)	(0.097)	(0.115)	(0.267)	(0.385)	(0.297)
May	−0.010	0.026	−0.048	−0.082	0.393	−0.514*
	(0.091)	(0.076)	(0.135)	(0.267)	(0.385)	(0.297)
November	−0.364***	−0.310***	−0.418***	−0.613**	−0.336	−0.881***
	(0.106)	(0.103)	(0.139)	(0.267)	(0.385)	(0.297)
October	−0.387***	−0.384***	−0.394***	−0.676**	−0.474	−0.837***
	(0.082)	(0.074)	(0.126)	(0.267)	(0.385)	(0.297)
September	−0.365***	−0.272***	−0.457***	−0.492*	−0.048	−0.915***
	(0.086)	(0.072)	(0.131)	(0.267)	(0.385)	(0.297)
Observations	241	241	241	241	241	241
Outcome Mean	12.0	11.9	12.1	34.6	42.4	27.0

Notes: Estimates by cohort of the effect of birth month. The omitted month is April. "Mean of Outcome" refers to the mean of the outcome variable (Proportion in poor health or average mortality rate) for the entire sample period. Robust standard errors in parenthesis. ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.