UNIVERSITY OF CALIFORNIA
Santa Barbara

Three Essays in Health Economics

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Allison E. Witman

Committee in Charge:

Professor Kelly Bedard, Chair

Professor Olivier Deschênes

Professor Shelly Lundberg

Professor Heather Royer

September 2014

The Dissertation of
Allison E. Witman is approved:

Professor Olivier Deschênes

Professor Shelly Lundberg

Professor Heather Royer

Professor Kelly Bedard, Committee Chairperson

August 2014

Three Essays in Health Economics

Dedicated to my mom.

Acknowledgements

First and foremost I would like to express my deepest gratitude to my committee members Kelly Bedard, Heather Royer, Shelly Lundberg, and Olivier Deschênes. I have benefited tremendously from their mentorship and this dissertation would not have been possible without them. I am indebted to Kelly Bedard for helping me navigate each step of graduate school from advancement to candidacy through completion of the job market. I thank Kelly for giving me so much of her time to discuss my research, for her candid advice, and for her constant support in all areas of my graduate career. I am grateful to Heather Royer for her patient guidance, constant encouragement, high standards, and for reading countless drafts of my work. Heather taught me how to complete the research process - from finding a worthwhile project to polishing a finished paper. I am grateful to Shelly Lundberg for inspiring many of my research ideas. Shelly's commitment to excellence, attention to detail, and shared expertise improved my research considerably. I am thankful to Olivier Deschênes for teaching me the skill set of an empirical economist, for hiring me as a research assistant early in my graduate career, and for excellent advice in positioning my work. Olivier's advising was pragmatic and always useful, frequently pushing me forward when I felt stuck.

I would also like to thank other faculty and many fellow graduate students who took the time to discuss my research and read drafts of my papers. Among others, this list includes Peter Kuhn, Dick Startz, Ted Frech, Katherine Grooms, Wei Sun, Rish Singhania, Kevin Schnepel, Miguel Delgado Hellester, Jenna Stearns, Stefanie Fischer, and Zach Bethune. My research also benefitted from comments made by participants of the Economics Department's Human Capital Working Group and Labor Lunch Group.

I would like to thank my husband for his encouragement, patience, and support while I pursued my dream. Lastly, I would not be here without the love and support of my family, especially my mother.

Curriculum Vitæ

Allison E. Witman

Education

Ph.D., Economics, University of California Santa Barbara, 2014

M.A. Economics, University of California Santa Barbara, 2009

B.S. Business Administration with an Emphasis in Finance, Westminster College, 2005

Research Fields

Public Health Policy, Health Insurance, Aging, Human Capital

Committee Members

Kelly Bedard (Chair), Olivier Deschênes, Shelly Lundberg, Heather Royer

Honors and Fellowships

Economics Department Teaching Assistant of the Year, 2012-2013

University of California Doctoral Student Travel Grant, 2013

Graduate Opportunity Fellowship, University of California Santa Barbara, 2011-2012

Andron Fellowship, University of California Santa Barbara, 2008-2009

Teaching Experience

Instructor: Intermediate Microeconomics

Teaching Assistant: Principles of Microeconomics, Principles of Macroeconomics, Intermediate Macroeconomics, Development Economics

Conferences and Seminar Presentations

2014: Colby College, RTI International, Marquette University, Wake Forest University, University of Colorado - Denver, Indiana University School of Public and Environmental Affairs, Simon Fraser University, Substance Abuse and Mental Health Services Administration, University of Maryland - Baltimore County, Mathematica Policy Research, American Society of Health Economists 5th Biennial Conference, Western Economic Association 89th Annual Conference

2013: Western Economic Association 88th Annual Conference, Labor Lunch at the University of California Santa Barbara, All California Labor Economics Conference Poster Session

2012: Labor Lunch at the University of California Santa Barbara, All California Labor Economics Conference Poster Session

2011: Labor Lunch at the University of California Santa Barbara

Abstract

Three Essays in Health Economics

Allison E. Witman

This dissertation consists of three essays in health economics. The first two essays investigate how the benefit structure of the United States' two largest public insurance programs – Medicare and Medicaid – affects beneficiaries and their families. The first essay examines the impact of an older spouse's Medicare eligibility at age 65 on the insurance coverage of a younger, Medicare-ineligible spouse. I find that Medicare eligibility of an older spouse can crowd-out the health insurance coverage of a younger spouse, reducing coverage on the extensive margin as well as the generosity of coverage. Medicare eligibility of an older wife increases the likelihood that a Medicare-ineligible husband is uninsured. After an older husband turns 65, younger wives are less likely to be covered through an employer-based insurance plan and more likely to have non-group coverage.

The second essay investigates the effect of Medicaid coverage of smoking cessation therapies on smoking behavior. Since 1994, most state Medicaid programs have introduced coverage for smoking cessation therapies such as the nicotine patch, nicotine gum, prescription medication, and counseling. I show that lowering the cost of these cigarette substitutes through Medicaid coverage reduces smoking among low-income parents who have ever smoked and are likely to be eligible for Medicaid. Importantly, the effect is concentrated among women with infants, suggesting that these policies potentially reduce children's secondhand smoke exposure.

The third essay provides evidence that family structure is an important factor influencing attention deficit/hyperactivity disorder (ADHD) diagnosis, especially for boys. First, we document that a non-traditional family structure is positively correlated with ADHD diagnosis. Next, we compare the gender gap in ADHD diagnosis across traditional, single parent, and blended families, finding that the negative impact of a non-traditional family structure is much larger for boys. The male-female gap in ADHD is approximately twice as large in non-traditional families. This excess gender gap in ADHD diagnosis in non-traditional families is pervasive across child age groups, family income levels, and family size. Our findings demonstrate that family structure itself is a key factor affecting ADHD diagnosis and that boys in non-traditional families are especially vulnerable.

Professor Kelly Bedard
Dissertation Committee Chair

Chapter 1

The Medicare Eligibility Gap

1.1 Introduction

An estimated 10,000 people per day turn 65 and become eligible for Medicare, a program that provides insurance coverage for 50 million people and comprises 21 percent of national health care spending (Kaiser Family Foundation, 2012).[1] Given its size and role as the primary health insurance provider to elderly Americans, Medicare's effects have been widely studied by economists interested in the program's impact on beneficiaries. Medicare beneficiaries experience sudden changes in health insurance and health care use at age 65, increasing the likelihood of insurance coverage, the rate of multiple coverage, the use of preventative services, hospitalization, and prescription medications (Card, Dobkin, and Maestas, 2008, 2009; Decker and Rapaport, 2002; Duggan and Morton, 2010; Finkelstein and McKnight, 2008; Lichtenberg, 2002; McWilliams, Zaslavsky, Meara, and Ayanian, 2003; McWilliams, Meara, Zaslavsky, and Ayanian, 2007). Despite the

[1] In addition to being at least 65, age-based qualification for Medicare requires at least 10 years of Medicare-covered employment by one's self or spouse. Individuals under age 65 with certain disabilities also qualify for the program.

breadth of research investigating the effects of Medicare, the program's spillovers to Medicare-ineligible individuals have been largely overlooked.

Medicare is unlike the private health insurance plans that cover most Americans under age 65 in that it has no coverage provision for family members or other dependents—Medicare only covers the eligible individual. The age-based eligibility structure of Medicare means that households with an age difference between spouses will inevitably encounter a period of time in which the older spouse is eligible for the program and the younger spouse is not, creating a Medicare-eligibility gap between spouses.[2] Medicare eligibility of an older spouse creates the potential for spillovers to a younger spouse, caused by an interaction between the individual-based nature of Medicare and the household-based nature of private insurance. When an older spouse turns 65 the household will have to decide whether the older spouse will take up Medicare coverage, in which case the younger spouse will need to have their own coverage or go uninsured.

In this paper, I use data from the National Health Interview Survey (NHIS) and a regression discontinuity design to examine the impact of an older spouse's Medicare eligibility on the insurance coverage of a younger, Medicare-ineligible spouse. I find that Medicare eligibility of an older spouse can crowd-out the health insurance coverage of a younger spouse, reducing coverage on the extensive margin and the generosity of coverage. In households with an older wife and a younger husband, Medicare-ineligible husbands are 3.49 percentage points more likely to be uninsured just after a wife turns 65. This is a 44 percent increase in the fraction of married men in this age range without insurance coverage. I also provide evidence

[2]Assuming the younger spouse does not qualify based on disability status.

that the men who are going uninsured are less educated, working, and relatively healthy. Second, Medicare-ineligible wives experience large changes in the source of private coverage when a husband becomes eligible for Medicare. Ineligible wives move out of private plans in their husband's name (10.43 percentage point fall) and into private plans in their own name (9.10 percentage point increase), with a shift towards coverage that can be characterized as less generous. Additionally, I find that healthier women are more likely to be uninsured just after a husband turns 65.

These findings add to existing knowledge on the effects of the Medicare program as well as identify Medicare's age-based eligibility structure as a new source of crowd-out. Crowd-out is a reduction in private health insurance coverage caused by eligibility for public health insurance and has exclusively been studied in the context of Medicaid and Veteran's Insurance. Newly-eligible individuals may drop private coverage in favor of public insurance (Blumberg, Dubay, and Norton, 2000; Boyle and Lahey, 2010; Busch and Duchovny, 2005; Card and Shore-Sheppard, 2004; Dubay and Kenney, 1996, 1997; Lo Sasso and Buchmueller, 2004; Yazici and Kaestner, 2000; Shore-Sheppard, Buchmueller, and Jensen, 2000); however, declines in private coverage may not be limited to those who become eligible for public insurance. Crowd-out can spill over to the family members of public insurance eligibles as documented by Cutler and Gruber (1996) and Gruber and Simon (2008), who report that men whose family members become eligible for Medicaid reduce employer insurance coverage. Similar to this paper, Boyle and Lahey (2012) exploit disparate spousal eligibility for public health insurance. The authors show that wives increased labor supply after Veterans Insurance expansions granted coverage to their husbands. One explanation for this result is that wives increased labor supply in order to provide health insurance for themselves. In contrast to previous studies, the crowd-out generated by Medicare results from a perfectly anticipated increase in access to public coverage. Although the crowd-out experienced by younger spouses is temporary because they will eventually age into Medicare themselves, continuous and adequate insurance coverage is important for the near-elderly because they are high users of health care and at a higher risk for health shocks due to their age.

The regression discontinuity design has previously only been used once in the crowd-out literature in Card and Shore-Sheppard (2004) to study Medicaid-generated crowd-out. In contrast, the research design has been used extensively in the Medicare literature to estimate the causal impact of eligibility on the insurance coverage, health outcomes, and labor market participation of Medicare-eligible individuals (Card, Dobkin, and Maestas, 2008, 2009; Decker, 2005; Fairlie, Kapur, and Gates, 2012). Regression discontinuity has the advantage of relying on relatively weak identifying assumptions that approach a randomized experiment; therefore providing credible evidence that Medicare eligibility of older spouses reduces the health insurance coverage of younger spouses.

The younger spouses of Medicare-eligible individuals are a group to watch as the Patient Protection and Affordable Care Act (ACA) is implemented. The insurance coverage mandate combined with new options for younger spouses (e.g. health insurance exchanges and Medicaid expansions) will likely reduce the number of younger spouses going uninsured. Given that relatively healthy younger spouses are forgoing coverage, the addition of these people to the risk pool will potentially reduce average costs in this age range. Additionally, new coverage options for younger spouses that are not tied to employment will reduce the incentive for older spouses to remain in the workforce in order to provide health insurance to the household. Post-ACA, older spouses may take up Medicare at a higher rate and transitions in coverage for younger spouses could increase when an older spouse turns 65.

As the baby boom generation ages into Medicare eligibility, policymakers will undoubtedly propose changes to the benefit structure of the program in an effort to reduce costs while providing coverage to aging Americans. These results demonstrate that changes to the Medicare program will not only affect eligible individuals, but may also impact their family members. Analyses of proposed modifications to the program should include assessments of the impact on beneficiaries as well as potential spillovers to the spouses of Medicare beneficiaries.

The next section provides an introduction to the Medicare program with a discussion of how eligibility of one spouse may impact an ineligible spouse. Section 3 presents the data, Section 4 presents the econometric specification and identification assumptions. Section 5 presents results and Section 6 concludes.

1.2 Background

Medicare is government-subsidized insurance available to American citizens ages 65 years and older.[3] Eligible individuals have access to the four components of Medicare, each covering a specific type of service. Part A covers hospital-related

[3]Some individuals under age 65 who are disabled or have certain diseases also qualify for Medicare.

expenses and is free for most enrollees. Part B covers doctor visits, outpatient care, and other general services at a cost between $96 and $115 per month.[4] Medicare Parts A and B have relatively high cost sharing requirements and do not cover certain benefits including dental and long term care. As a result, most beneficiaries have some form of supplemental insurance (e.g. employer retiree coverage, a Medigap plan, or Medicaid) to fill in holes in the benefit package and reduce Medicare's cost sharing burden (Kaiser Family Foundation, 2010). An alternative to purchasing supplemental coverage is Medicare Part C, also known as Medicare Advantage. Medicare Part C is comprised of government subsidized, privately-administered plans that offer more comprehensive benefits than Parts A and B alone. In 2006, a prescription drug insurance plan was introduced as Medicare Part D.

An older spouse deciding to take up Medicare coverage represents a trade-off for families between individual-based and household-based coverage. Using the example of a Medicare-eligible husband with a Medicare-ineligible wife, let us consider several cases. First, a wife who provided her own health insurance prior to her husband's Medicare eligibility will experience no required change in coverage when her husband turns 65. Second, if the Medicare-eligible husband is the primary provider of health insurance to the family, then he can continue to provide health insurance for the ineligible wife, the wife can purchase insurance on her own, or she could go uninsured. Options for obtaining health insurance for the ineligible wife include enrolling in a sponsored plan from her own employer,

[4]Enrollment in Medicare Parts A and B at age 65 is automatic for individuals receiving Social Security benefits. Individuals not receiving Social Security benefits at age 65 must contact the Social Security Administration in order to enroll in the program. Those automatically enrolled due to receipt of Social Security benefits have the right to refuse Part B coverage.

purchasing directly from an insurance company in the non-group market, and qualifying for means-tested government insurance programs.[5]

Medicare eligibility is both an income and a price shock to the household. While Medicare is relatively low cost for the older spouse, the cost of insurance coverage for the younger spouse could increase if the household moves from group to individual coverage. An individual-based, private plan for the younger spouse may cost more on a per-person basis than previously held group coverage for both spouses. This increase in cost for a younger spouse can result in a reduction or elimination of health insurance coverage.

The welfare implications of an older spouse's Medicare eligibility vary depending on the choice of household model.[6] Under a unitary framework in which couples maximize a single household utility function, revealed preference dictates that a household choosing to put the older spouse on Medicare will be better off even in the case of the younger spouse losing coverage. However, household bargaining models generate ambiguous predictions for the utility of the younger spouse. While the income effect experienced by the older spouse has the potential to make both spouses better off, the increase in the older spouse's bargaining power could result in an equilibrium with lower utility for the younger partner. The possibility that Medicare's age-based eligibility structure is leaving younger spouses worse off merits a discussion of whether or not policy interventions are

[5]Beginning on October 1, 2013, individuals could apply for coverage using the health insurance marketplaces established by the Affordable Care Act.

[6]For a survey of theories of the family see Bergstrom (1995). Bargaining models are generally more accepted than unitary models of household behavior. Seminal papers in the household bargaining literature include Manser and Brown (1980); McElroy and Horney (1981); Woolley (1988); Lundberg and Pollak (1991).

warranted, beginning with an analysis of the ACA's impact on younger spouses in the Medicare eligibility gap.

Households can perfectly anticipate Medicare eligibility, meaning that the younger spouse could adjust their insurance coverage prior to the older spouse turning 65. For younger spouses who can obtain employer coverage, anticipatory adjustments would most likely be made during the employer's annual open enrollment period. Medicare eligibility of a spouse is a qualifying event that allows a younger spouse to reduce coverage or cancel a group health insurance plan any time of year; however, increases in coverage due to spousal Medicare eligibility are not permitted outside of the open enrollment period.[7] If a younger wife provides health insurance to the couple from her employer plan, she can remove her husband from the plan immediately when he turns 65 and maintain her own coverage. Alternatively, if the older husband provides insurance coverage through his employer, the younger wife would need to sign up for her own employer's coverage during the open enrollment period preceding eligibility of her husband to avoid a lapse in coverage. I investigate this possibility later in the paper and find some evidence that households are making anticipatory adjustments in coverage.

1.3 Data and Methodology

1.3.1 Data

I use data from the National Health Interview Survey (NHIS) for years 1993 to 2011. The NHIS is a cross-sectional, nationally representative household survey

[7] Internal Revenue Service Regulation 1.125-4(e).

of insurance coverage and health. The first year in the analysis is 1993 because several key insurance variables enter the survey in the that year.

The sample contains married households with an older spouse within 10 years of Medicare eligibility (i.e. between 55 and 75 years old). I construct the sample by first selecting married households. Next, I choose couples with an older spouse that is between the ages of 55 and 75. Finally, I exclude couples that were born in the same quarter.[8] Same-aged couples are excluded from the sample because they effectively age into Medicare at the same time and the identification strategy rests on one spouse aging into Medicare first. There are two types of households in the sample: older husband, younger wife couples and older wife, younger husband couples. I focus on the outcomes of the younger spouse in each of these household types, but will control for characteristics of both spouses in the regressions. The final sample includes 84,081 younger spouses, comprised of 67,554 younger wives and 16,527 younger husbands.

Table 1.1 presents selected summary statistics by gender for younger spouses. The first column includes demographic and insurance characteristics for women who are younger than their husband and the second column includes the same information for men who are younger than their wife. Row 1 shows that 80 percent of households in the sample are comprised of older husband, younger wife couples and 20 percent of households are comprised of older wife, younger husband households. The average age for younger wives and husband is 58.81 years and 59.78 years, respectively.[9] The age gap between spouses is larger for

[8]Age is measured in quarters in the NHIS.

[9]No restrictions are made on the age of the younger spouse. The age of younger spouses ranges from 19 to 74.75 years old. Appendix Figure A.1 plots the age cumulative distribution function, demonstrating that the majority of younger spouses are above 50 years old.

older husband, younger wife couples than for older wife, younger husband couples. On average, a younger wife will have 5 years after her husband turns 65 until she is Medicare-eligible while the average Medicare eligibility gap for a husband that is younger than his wife is over 3 years. The mean age difference is driven up by a small fraction of households with a large age gap between spouses; the median age difference for each group is smaller at 3.75 and 2 years, respectively.

Panel B of Table 1.1 limits the sample to households with both spouses under age 65 to show insurance coverage of younger spouses prior to Medicare eligibility of an older spouse.[10] Insurance variables are point-in-time measures of coverage at the time of the NHIS interview. Among younger spouses, 91 percent report being insured. Insurance coverage can be obtained through a government program such as Medicare, Medicaid, or Veteran's Insurance or through a private health insurance plan. Private coverage can be purchased through work or non-work sources and can be in an individual's own name or under a spouse's name and is categorized into four sources: (1) "Self (Work)" is an insurance plan from an individual's own employer, (2) "Spouse (Work)" is a plan from a spouse's employer, (3) "Spouse (Non-Work)" is a plan obtained from a non-work source under a spouse's name, and (4) "Self (Non-Work)" is a non-work plan an individual's own name. Non-work insurance is primarily comprised non-group coverage.[11,12] The

[10]Categories of insurance coverage in Table 1.1 are not mutually exclusive because some individuals report multiple forms of coverage.

[11]Private coverage from non-employment sources includes plans purchased in the non-group market, school plans, and plans obtained through local government or community programs. Approximately 90 percent of private, non-work coverage for Medicare-ineligible individuals in the sample are non-group plans.

[12]The NHIS questionnaire asks whether a specific plan is in a person's own name or a family member's name. It is not possible to determine if the family member is a spouse. It is reasonable to assume that for the majority of married households in this age range, coverage by a family member is spousal coverage.

husband's employer is the primary source of coverage for the majority of households regardless of whether the male is the older or younger spouse. Younger wives are most frequently covered via a spouse's work plan (48 percent), followed by a plan in the woman's own name from work (34 percent). Conversely, men are most often covered via their own work plan (58 percent) followed by a wife's work plan (21 percent). The fraction of younger spouses with non-work coverage is low.

1.3.2 Methodology

In order to test whether Medicare eligibility of an older spouse impacts the health insurance coverage of a Medicare-ineligible spouse, I compare younger spouses with an older spouse on either side of the age 65 Medicare eligibility threshold. If individuals are similar on either side of the threshold, the difference in outcomes can be interpreted as the causal impact of spousal Medicare eligibility. The empirical analysis is completed using a reduced-form regression discontinuity design:

$$Y_{ij} = \beta_0 + \beta_1 Spouse65_i + \beta_2 Self65_i + \beta_3 X_{ij} + h(Age_i, Age_j) + \varepsilon_{ij} \tag{1.1}$$

where Y_{ij} is a point-in-time measure of the insurance coverage of younger spouse i with older spouse j. Y_{ij} is a dummy variable indicating whether or not i has a particular type of insurance coverage. $Spouse65_i$ is a dummy variable for Medicare eligibility of i's spouse, set to 1 if i's spouse is 65 or older and 0 otherwise.

$Self65_i$ is a dummy for Medicare eligibility of the younger spouse i, set to 1 if i is 65 or older and 0 otherwise.[13] X_{ij} includes controls for the younger spouse's education, race, and an early Social Security eligibility dummy for both the older and younger spouse.[14] The specification includes a quadratic in both spouses' ages ($h(Age_i, Age_j)$) that is fully interacted with post-65 age dummies (one for the older spouse and one for the younger spouse) to allow the functional form to vary on either side of the age 65 cutoff. Survey year and region fixed effects are included. Lastly, ε_{ij} is an error term that accounts for the impact of unobserved characteristics on the outcome of interest and standard errors are clustered by age of the older spouse. Equation (1.1) will be estimated separately for men and women because spousal Medicare eligibility has heterogeneous effects by gender.

The coefficient β_1 is the effect of interest, measuring the impact of an older spouse turning 65 on the younger spouse's insurance coverage.[15] β_1 compares the insurance of younger spouses with a partner that has recently turned 65 to the insurance coverage of younger spouses with a partner that is just below age 65. Thus, β_1 measures the effect of turning 65 relative to a pre-65 control group that knows with certainty when they will enter eligibility for Medicare. In contrast to regression discontinuity designs that compare treated and untreated groups, age-

[13]The coefficient β_2 on $Self65_i$ gives the impact of a younger spouse's own Medicare eligibility on their own insurance coverage. This is the effect measured in Card, Dobkin, and Maestas (2008, 2009) and is not the focus of this paper. These coefficients are presented in Appendix Table A.3.

[14]Individuals have the option of taking Social Security benefits as early as age 62. The Social Security eligibility dummy equals 1 if the individual is greater than 62 and 0 otherwise.

[15]β_1 captures the reduced-form effect of spousal Medicare *eligibility* rather than take up. Figure A2 shows the first-stage graph and estimate of 0.64 (i.e., the effect of an older spouse turning 65 on take up of Medicare). Instrumental variables estimates of spousal Medicare take up are $\hat{\beta}_1/0.64$.

based treatment makes a comparison between those who are treated and those who will soon be treated.[16]

1.3.3 Identification

The regression discontinuity research design is compelling because it overcomes the omitted variable bias problem given a modest set of assumptions. Moreover, some of the assumptions are partially testable. Interpretation of the effects of Medicare eligibility on outcomes as causal requires two assumptions (Lee and Lemieux, 2009). First, the conditional expectation functions of the potential outcomes must be continuous with respect to age across the Medicare eligibility threshold, which is analogous to saying that in the absence of treatment at age 65 outcomes would trend smoothly. There are two standard test for violation of the continuity assumption. First, there should be no changes in other variables across the threshold if this assumption holds. I test for discontinuities in education, race, labor market participation, health status, and Social Security receipt and present the results in Figure A3 and Table A2. These estimates are all statistically insignificant except for a decline in the fraction of the sample that is white, which is likely due to sampling error given that none of the other background characteristics change at the threshold. Second, I plot the density function of the running variable (spousal age) and test for a discontinuity at the age-65 threshold

[16] Age-based treatment is common in regression discontinuity settings. Other examples include the minimum legal drinking age, age notches in the calculation of public benefits, the age 19 limit on parental insurance coverage, and other papers using the age 65 Medicare eligibility threshold (Decker and Rapaport, 2002; Card and Shore-Sheppard, 2004; Card, Dobkin, and Maestas, 2008; Lemieux and Milligan, 2008; Carpenter and Dobkin, 2009; Card, Dobkin, and Maestas, 2009; Yoruk and Yoruk, 2011; Shigeoka, forthcoming).

of Medicare eligibility per McCrary (2008) in Figure A4. I find no evidence of violation of the continuity assumption with this second test.

Secondly, the monotonicity assumption requires that crossing the age 65 threshold cannot cause some people to take up Medicare coverage and others to reject it. The monotonicity assumption would be violated if the older spouse j had Medicare coverage before turning 65 but dropped it upon reaching the 65 threshold. Although I cannot test whether this assumption holds given the cross-sectional nature of the data, it is unlikely that a person who qualified for Medicare prior to age 65 due to disability or illness would drop coverage specifically because they turned 65.

1.4 Results

1.4.1 Main Findings

I begin with a graphical depiction of the insurance coverage of the younger spouse as a function of the older spouse's Medicare eligibility in Figure 1.1. Panels (a) and (b) plot the average rate of insurance coverage and private coverage for younger wives. Panels (c) and (d) plot the average rate of insurance coverage and private coverage for younger husbands. The horizontal axis is the older spouse's age in quarters and each graph contains a vertical line at the spousal age of 65 to indicate Medicare eligibility. Solid curves show the quadratic fit of the raw means on either side of the Medicare eligibility cutoff. A dashed line indicates the fraction of younger spouses that are age-eligible for Medicare, corresponding to the right axis of each graph.

There is no evidence of crowd-out among Medicare-ineligible wives in panels (a) and (b) of Figure 1.1, with no clear discontinuity in insurance coverage or private coverage at the spousal age of 65. Table 1.2 presents estimates of discontinuities in insurance coverage upon spousal Medicare eligibility corresponding to Figure 1.1 using equation (1.1). The top row of the table lists the dependent variable for each regression. The column labeled "Mean" presents the fraction of younger spouses with the given coverage in the two years prior to the older spouse's Medicare eligibility. The estimated discontinuities and standard errors are presented under the column labeled "RD." The results for women are presented in Panel A. The fraction of women with insurance coverage falls by 1.24 percentage points just after a husband turns 65, but the point estimate does not reach statistical significance. Husband Medicare eligibility causes no changes in the fraction of women with government coverage, private coverage, or multiple sources of coverage. On the surface, husband Medicare eligibility does not appear to cause a reduction in the fraction of women with health insurance, which is reassuring given that women are more likely to be insured via their husband and are less likely to have an alternate source of coverage through their own employer.

Medicare-ineligible men, on the other hand, experience reductions in coverage when their wife turns 65. In panels (c) and (d) of Figure 1, the fraction of men reporting any insurance coverage and private coverage falls discontinuously to the right of the spousal age 65 threshold. Panel B of Table 1.2 presents the estimated discontinuities for younger husbands. The fraction of men who are insured falls by 3.49 percentage points and the fraction of men with private coverage falls 4.73 percentage points when an older wife turns 65. This is a 44 percent increase in the number of men who are uninsured and a 6 percent decrease in private coverage. The approximately 2 percentage point difference between the fall in private coverage and any coverage is comprised of a fall in multiple forms of coverage for younger husbands.

The asymmetry of findings for men and women is striking and possible explanations will be explored at the end of this section. First, I investigate private coverage more closely by focusing on the source of private health insurance.

Figure 1.2 plots the sources of private insurance coverage for younger spouses with corresponding estimates presented in Table 1.3. For women, spousal Medicare eligibility is associated with a movement out of coverage under a husband's name and into coverage in the wife's own name. Panels (a) and (b) of Figure 1.2 show insurance coverage of younger wives in a husband's name and in a wife's own name, respectively. Both work and non-work coverage from an older husband fall discontinuously when a husband turns 65. As reported in Panel A of Table 1.3, the largest decline in coverage is from a husband's employer with an estimated reduction of 8.04 percentage points compared to a 2.39 percentage point reduction in spousal non-work coverage.

Wives offset the decline in private coverage from a husband by increasing coverage in their own name, as shown in panel (b) of Figure 2. The estimated increase in coverage from a wife's own employer is 4.62 percentage points and the increase non-work coverage in their own name is 4.48 percentage points as shown in Table 1.3. Thus, women take up insurance from both their employer and non-work sources approximately equally when an older husband reaches Medicare eligibility. As a result of this movement, the composition of private coverage for Medicare-ineligible women is different on either side of the husband Medicare eligibility threshold. Husband Medicare eligibility causes net movement out of employer-provided plans and net movement into non-work (usually non-group) plans for coverage. Historically, non-group coverage has been considered less generous than employer coverage, covering fewer benefits and requiring higher out-of-pocket costs.

Panels (c) and (d) of Figure 1.2 plot the fraction of men with private coverage in their wife's name and own name with corresponding estimates presented in Panel B of Table 1.3. The fraction of husbands covered via a wife's employer falls by 6.98 percentage points when an older wife turns 65 and can be seen in Panel (a) of Figure 1.2. Unlike younger wives, younger husbands do not offset this fall in spousal coverage by taking up coverage in their own name. There are no changes in coverage in a husband's own name form either work or non-work sources.

In summary, when an older spouse turns 65 younger spouses experience a decline in coverage from the older parter. Younger wives offset this fall in spousal coverage by taking up plans in their own name from work and non-work sources. Younger husbands do not offset the fall in spousal coverage and as a result, the fraction of men without insurance increases.

There are several possible explanations for the higher propensity of males to go uninsured. First, varying attitudes towards risk could explain some component of men's willingness to forgo coverage. Evidence from experimental economics demonstrates that men are less risk averse than women (Eckel and Grossman, 2008; Croson and Gneezy, 2009; Charness and Gneezy, 2012). Younger husbands' increased tolerance for risk is consistent with the results in Cutler, Finkelstein, and

McGarry (2008), who find that individuals who have a higher risk tolerance are more willing to go uninsured. Second, the available coverage options for younger husbands may be different than for younger wives. The decline in coverage for men is driven by a reduction in an older wife's work plan. The men who lose coverage from their wife may not have access to an employer plan because if they did, they likely would have already been the provider of health insurance to the family. Additionally, gender asymmetries in access and cost in the non-group market may explain the heterogeneous results. Additionally, coverage in the non-group market for men over 60 was also more expensive than for women prior to the Affordable Care Act. In addition to differential preferences for coverage across men and women, forces in the non-group market may contribute to men's higher propensity to lose coverage in the Medicare eligibility gap.

1.4.2 Heterogeneity

I now examine heterogeneity of effects across three margins: completed education, labor force participation, and health status.[17] While each of these categories is smooth across the spousal age 65 threshold, both labor market participation and health are declining functions of spousal (and own) age.[18] As a consequence, the bandwidth in a regression discontinuity design would ideally be smaller than the bandwidth used in this paper. However, given the sample size required for adequate power I estimate equation (1.1) with the full bandwidth. The results

[17]Estimates by race are available upon request. The relatively small sample size of non-white respondents makes identifying effects by race infeasible.

[18]Appendix Table A.2 presents estimated discontinuities in education, labor force participation, and health status at spousal Medicare eligibility. Accompanying graphs are in Appendix Figures A.3 and A.4.

provide interesting evidence that certain groups are more affected by the Medicare eligibility gap, but should be interpreted with caution.

Table 1.4 presents coefficients from a separate regression for the group listed in the first column of the table.[19] Panel A shows results by education level. For younger wives, there is no differential effect on insurance coverage or private coverage by education level when a husband turns 65. However, education level does play a role for men. Younger husbands with a high school or less education are 5.31 percentage points less likely to have insurance coverage after a wife turns 65. This result is statistically different from the insignificant point estimate for husbands with at least some college. Panel B presents results by labor market participation status, which is not a source of notable heterogeneity for younger wives. The fall in insurance coverage for men who are working is 4.05 percentage points, which is a larger estimated effect than the 2.46 percentage point fall in coverage for non-working men, although not statistically different. Lastly, Panel C includes coefficients from estimates by health status. Healthy wives are 1.10 percentage points less likely to have insurance coverage and healthy husbands are 5.42 percentage points less likely to have insurance coverage after an older spouse turns 65. Results for insurance coverage of younger spouses from Table 1.4 are presented graphically in Figure 1.3.

A new result emerges from this analysis showing that a higher fraction of healthy men and women are uninsured after a spouse turns 65. The propensity for healthier individuals to go uninsured is evidence of adverse selection in the health insurance market, which is a standard empirical finding summarized in Cutler

[19] Regressions are run separately for each group. Results are similar when the groups are pooled and the $Spouse65$ variable is interacted with group categories.

and Zeckhauser (2000) and recently revisited by Einav, Finkelstein, and Cullen (2010). Consequently, healthy individuals may be making an optimal choice to go uninsured if they do not forgo necessary care or experience a health shock during the Medicare eligibility gap. However, the men who are becoming uninsured also appear to be working and have less than a high school education. This group of men may have jobs that do not offer health insurance coverage, may find the cost of non-group coverage prohibitively high, and may not be able to afford to pay for treatment out of pocket after a health shock. The Affordable Care Act's insurance mandate may bring these relatively healthy individuals into the health insurance market, improving the health of individuals in the risk pool and potentially driving down average costs for this age group.

1.4.3 Robustness Checks

In Table 1.5, I present several robustness checks of the main findings. The main identifying assumption in a regression discontinuity design is that the treatment and control group are comparable; therefore, removing demographic controls from the regression should not affect the estimates. The first row of Table 1.5 presents the main estimates from Tables 1.2 and 1.3 using a second order polynomial and controlling for background characteristics. The next row, labeled "Second Order Polynomial, No Controls" presents results from regressions without background characteristics, including only a quadratic polynomial in the older spouse's age that differs on either side of the eligibility threshold, a dummy for the older spouse's eligibility, a dummy for the younger spouse's eligibility, year fixed effects, and region fixed effects. The point estimates are very similar to the main specifications that include demographic controls. One exception is that the point estimate on government coverage for younger wives becomes statistically significant. There is no reason to believe that government coverage should fall discontinuously and this result is likely due to sampling error.

Additionally, estimates can vary with the choice of polynomial. The main specification in this paper uses a second order polynomial, which is standard in papers using the NHIS and a regression discontinuity design. Nevertheless, the third row of Table 1.5 presents coefficients from regressions in which the age of the older and younger spouse is with a third degree polynomial. On the whole, varying the degree of polynomial produces similar results as the main specification with few exceptions.

The regression discontinuity framework identifies discrete changes in coverage at the age 65 cutoff of spousal Medicare eligibility; however, households anticipating Medicare eligibility of an older spouse may adjust the coverage of a younger spouse ahead of time. Anticipatory adjustments will not be embodied in the estimated discontinuities in coverage, potentially biasing coefficients towards zero and underestimating the impact of spousal Medicare eligibility. The "donut" regression discontinuity design removes observations near the cutoff, generating estimates that embody changes at and around the discontinuity (Barreca, Lindo, and Waddell, 2011).[20] In the fourth row of Panels A and B in Table 1.5, I re-estimate equation (1.1) excluding couples with an older spouse within 6 months of Medicare eligibility, leaving a 1 year donut in the data. These estimates in-

[20]The donut design is most frequently cited as a method to account for heaping in the data, but can also be used to address changes in behavior due to anticipation of treatment as in Barcellos and Jacobson (2014).

clude changes in insurance coverage that not only occur right at age 65, but also 6 months before and after an older spouse is 65. This exercise yields a statistically significant 2.88 and 4.52 percentage point reduction in the fraction of younger wives and husbands with insurance coverage. Overall, the point estimates from this specification are slightly larger in absolute value than the main estimates for both younger husbands and wives, indicating that some adjustments in coverage are made before and after the older spouse 65.

Lastly, I address the concern that the results could be confounded by couples close in age because the younger spouse ages into Medicare just after the older spouse. In the fifth row of Table 1.5, I limit the sample to couples with at least a one year age gap between the older and younger spouse. Although the standard errors increase slightly, the point estimates are very similar to those presented in Tables 1.2 and 1.3. On the whole, results do not appear to be driven by couples that are very close in age.

1.5 Discussion

As the baby boom generation begins to reach the age of Medicare eligibility, an increasing number of married households will face a tradeoff between household-based coverage and individual-based coverage, or may even consider forgoing coverage for a Medicare-ineligible spouse. In this paper, I find that Medicare eligibility of an older spouse can crowd-out the insurance coverage of a younger spouse. Younger husbands who are relatively healthy, working, and have less than a high school education are less likely to have insurance just after a wife turns 65. Relatively healthy women are more likely to be uninsured after a husband turns 65; but the biggest change in coverage for women occurs on the intensive margin. Private coverage in a husband's name falls and coverage in a wife's own name increases with an increase in the fraction of women insured via plans that can be considered less generous.

Younger spouses of Medicare-eligible individuals will be one group impacted by the changes in the insurance market after the Patient Protection and Affordable Care Act (ACA). The health insurance exchanges are a new source of coverage for younger spouses and may be an attractive option given the projected decline in premiums in the over-60 non-group market (O'Connor, 2013) combined with the premium subsidies available for households between 138 and 400 percent of the poverty line. The evidence of adverse selection in the under-65 market generated by Medicare eligibility of older spouses presented in this paper suggests that some new entrants to the insurance market in this age range will be relatively healthy. Importantly, the availability of an alternative source of coverage for younger spouses means that older spouses will be more likely to take up Medicare and will have less incentive to remain in the workforce to provide health insurance for a Medicare-ineligible spouse.

Medicare will undoubtedly remain a focal point of policymakers trying to balance providing adequate insurance coverage for the growing number of elderly Americans with the need to curb rapidly increasing health care costs. Because most Americans have household-level coverage prior to Medicare eligibility, proposals such as raising the age of eligibility to 67 or changing the benefit structure of the program will not only affect newly eligible individuals, but also their family members. Analyses of proposed changes to the program should include assessments of the impact on beneficiaries as well as potential spillovers to the spouses of Medicare beneficiaries.

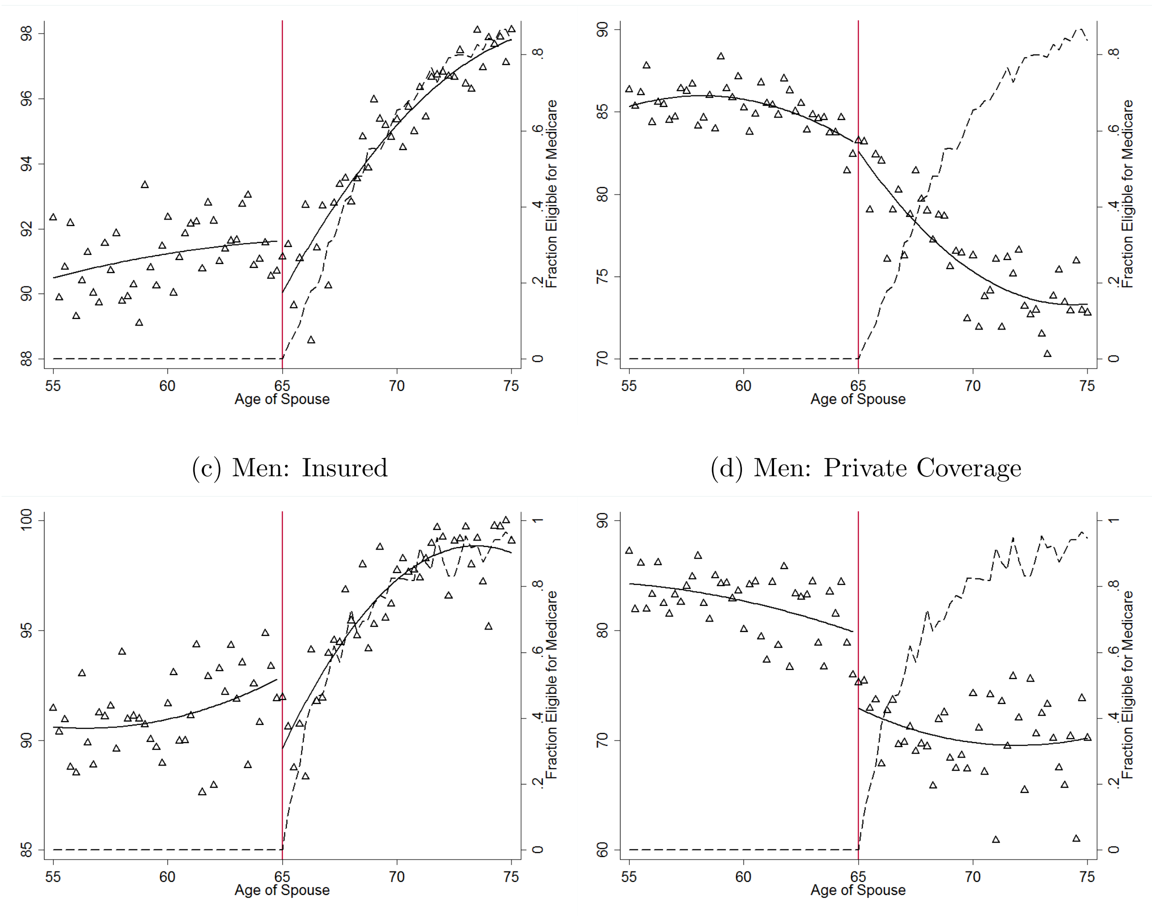
Figure 1.1: Health Insurance Coverage of Younger Spouses

(a) Women: Insured

(b) Women: Private Coverage

(c) Men: Insured

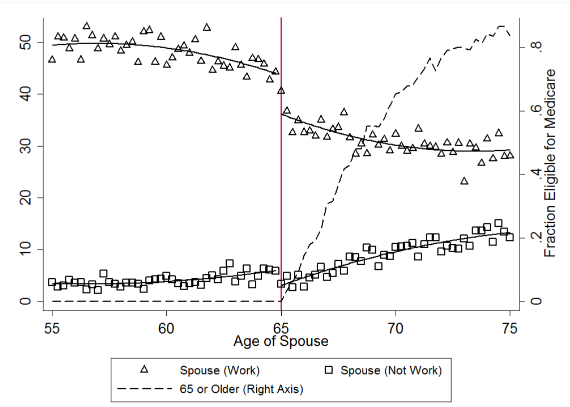
(d) Men: Private Coverage



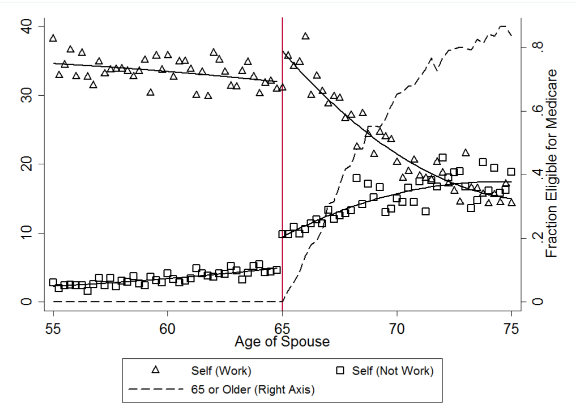
Note: Graphs show the reduced form effect of spousal Medicare eligibility on the health insurance coverage of the younger spouse. Scatterplots are means of the raw data and solid lines are quadratic polynomial fits. The dashed line shows the fraction younger spouses eligible for Medicare using the right axis.

Figure 1.2: Sources of Private Coverage of Younger Spouses

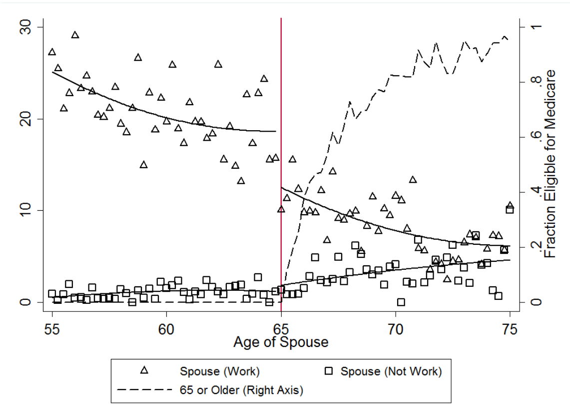
(a) Women: Coverage by Spouse



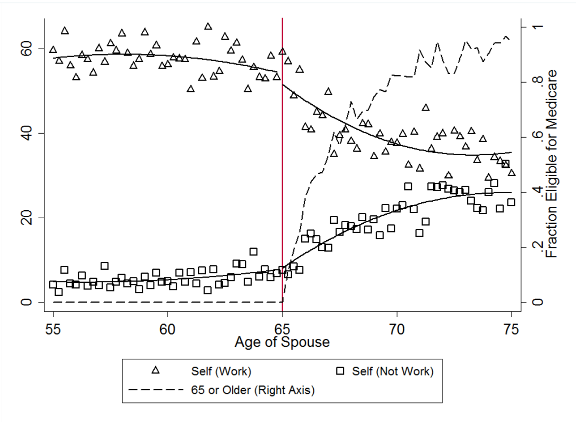
(b) Women: Coverage by Self



(c) Men: Coverage by Spouse



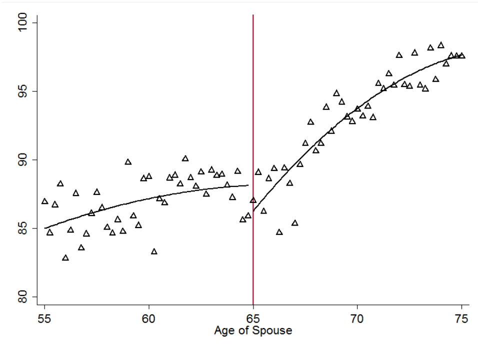
(d) Men: Coverage by Self



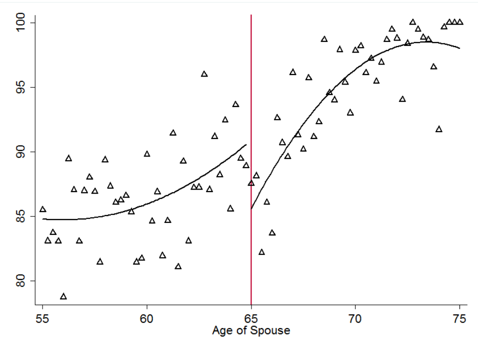
Note: Graphs show the reduced form effect of spousal Medicare eligibility on the source of private health insurance for the younger spouse. Scatterplots are means of the raw data and solid lines are quadratic polynomial fits. The dashed line shows the fraction younger spouses eligible for Medicare using the right axis.

Figure 1.3: Fraction of Younger Spouses with Insurance Coverage by Subpopulation

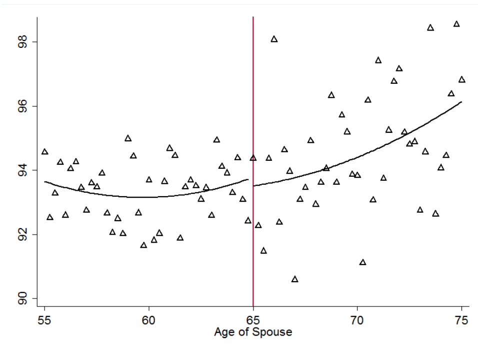
(a) Women: High School or Less



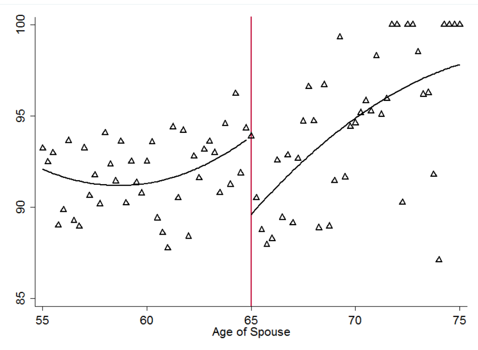
(b) Men: High School or Less



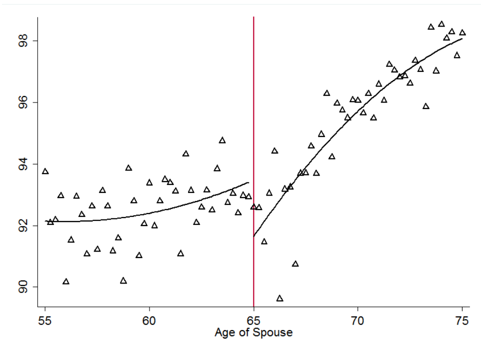
(c) Women: Working



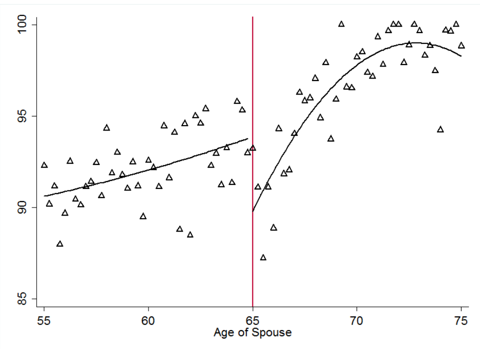
(d) Men: Working



(e) Women: Healthy



(f) Men: Healthy



Note: Graphs show the reduced form effect of spousal Medicare eligibility on insurance of the younger spouse for different subpopulations. Scatterplots are means of the raw data and solid lines are quadratic polynomial fits.

Table 1.1: Selected Summary Statistics of Younger Spouses

Panel A: Demographic Characteristics		
	Women	Men
% of Sample	80.15	19.85
Age	58.81	59.78
Age Gap Between Spouses	5.00	3.40
Education		
% Less than High School	14.91	18.17
% High School	37.88	30.06
% Some College	24.69	23.55
% More than College	22.52	28.22
Race		
% White	83.41	82.37
% Black	6.32	6.93
% Hispanic	3.86	3.03
% Other	6.41	7.67
N	67,554	16,527

Panel B: Insurance Characteristics Prior to Spousal Medicare Eligibility		
	Women	Men
% Insured	91.16	91.08
% Government Coverage	8.66	12.32
% Private Coverage	85.32	82.72
% 2+ Sources of Coverage	8.75	9.06
Source of Private Coverage		
% Self (Work)	33.52	57.71
% Self (Non-Work)	3.34	5.44
% Spouse (Work)	48.33	21.19
% Spouse (Non-Work)	4.05	1.04

Note: Summary statistics are from pooled 1993 to 2011 NHIS data. Panel A presents demographic characteristics of younger husbands and wives whose older spouse is within ten years of Medicare eligibility (between 55 and 75 years old). Panel B restricts the sample to households with both a husband and a wife that are below age 65.

Table 1.2: The Impact of Spousal Medicare Eligibility on Insurance Coverage of the Younger Spouse

Panel A: Women								
	Insured		Government		Private		2+ Plans	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Spouse65	91.54	-1.24	11.32	-0.69	83.77	-0.41	8.75	-0.08
		(0.80)		(0.67)		(1.14)		(0.66)

Panel B: Men								
	Insured		Government		Private		2+ Plans	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Spouse65	92.10	-3.49*	17.63	0.52	80.50	-4.73*	9.69	-1.98
		(1.47)		(2.01)		(2.12)		(1.74)

Note: Table presents reduced form estimates of spousal Medicare eligibility on the insurance coverage of a younger spouse using NHIS data from 1993 to 2011. The dependent variable in each regression is listed above the columns labeled 'Mean' and 'RD.' Entries in the 'Mean' column are the fraction of younger spouses with the given type of coverage in the two years prior to an older spouse's Medicare eligibility. Regressions include controls for race and education of the younger spouse, quadratics in the age of both spouses separately interacted with dummy variables for Medicare eligibility of the younger and older spouse at age 65, dummy variables for both spouses' Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Table 1.3: The Impact of Spousal Medicare Eligibility on the Source of Private Insurance Coverage of the Younger Spouse

Panel A: Women								
	Spouse (Work)		Spouse (Non-Work)		Self (Work)		Self (Non-Work)	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Spouse65	45.53	-8.04***	5.18	-2.39***	32.18	4.62**	4.46	4.48***
		(1.66)		(0.63)		(1.54)		(0.43)

Panel B: Men								
	Spouse (Work)		Spouse (Non-Work)		Self (Work)		Self (Non-Work)	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Spouse65	18.54	-6.98**	1.21	0.49	55.13	0.45	7.51	0.69
		(2.26)		(0.73)		(2.73)		(1.36)

Note: Table presents reduced form estimates of spousal Medicare eligibility on the insurance coverage of a younger spouse using NHIS data from 1993 to 2011. The dependent variable in each regression is listed above the columns labeled 'Mean' and 'RD.' Entries in the 'Mean' column are the fraction of younger spouses with the given type of coverage in the two years prior to an older spouse's Medicare eligibility. Regressions include controls for race and education of the younger spouse, quadratics in the age of both spouses separately interacted with dummy variables for Medicare eligibility of the younger and older spouse at age 65, dummy variables for both spouses' Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Table 1.4: The Impact of Spousal Medicare Eligibility on Insurance Coverage of the Younger Spouse, by Selected Characteristics of the Younger Spouse

	Women		*Men*	
	Insured	Private	Insured	Private
High School or Less	-1.25	-0.17	-5.31*	-4.00
	(1.26)	(1.88)	(2.56)	(3.05)
Some College Plus	-1.15	-0.81	-1.39	-5.12
	(0.81)	(1.28)	(1.45)	(2.62)
Panel B: Working & Not Working				
	Women		*Men*	
	Insured	Private	Insured	Private
Working	0.28	0.41	-4.05*	-4.03
	(1.01)	(1.27)	(1.87)	(2.34)
Not Working	-2.07	-0.27	-2.46	-3.23
	(1.11)	(1.61)	(2.17)	(3.73)
Panel C: Health Status Poor/Fair & Good/Very Good/Excellent				
	Women		*Men*	
	Insured	Private	Insured	Private
Poor/Fair	1.30	4.88	0.90	-2.94
	(2.30)	(3.34)	(2.44)	(6.43)
Good/VeryGood/Excellent	-1.10*	-1.10	-5.42**	-7.98**
	(0.54)	(0.80)	(1.61)	(2.49)

Note: Table presents reduced form estimates of spousal Medicare eligibility on the insurance coverage of a younger spouse using NHIS data from 1993 to 2011. Each coefficient is from a separate regression for the group listed in the leftmost column of the table. Regressions include quadratics in the age of both spouses separately interacted with dummy variables for Medicare eligibility of the younger and older spouse at age 65, dummy variables for both spouses' Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Table 1.5: Robustness Checks

	Insured	Gov	Private	2+ Plans	Spouse (Work)	Spouse (Non-Work)	Self (Work)	Self (Non-Work)
Panel A: Women								
Second Order Polynomial (Orignial Estimates)								
Spouse65	-1.24	-0.69	-0.41	-0.08	-8.04***	-2.39***	4.62**	4.48***
	(0.80)	(0.67)	(1.14)	(0.66)	(1.66)	(0.63)	(1.54)	(0.43)
Second Order Polynomial, No Controls								
Spouse65	-1.34	-1.33*	-0.42	-0.90	-7.21***	-2.89***	3.99**	4.51***
	(0.72)	(0.58)	(1.02)	(0.61)	(1.50)	(0.64)	(1.50)	(0.42)
Third Order Polynomial								
Spouse65	0.40	-0.54	1.01	-0.09	-7.35***	-2.59***	5.12**	4.83***
	(0.64)	(0.73)	(1.18)	(0.67)	(2.00)	(0.75)	(1.81)	(0.49)
Donut RD								
Spouse65	-2.88*	0.20	-2.18	0.86	-10.80***	-2.19*	6.51**	3.78***
	(1.09)	(1.11)	(1.35)	(1.04)	(1.58)	(1.03)	(1.95)	(0.72)
Age Gap>1 Year								
Spouse65	-0.84	-0.65	-0.37	-0.24	-7.60***	-2.38**	4.28*	4.54***
	(0.87)	(0.73)	(1.25)	(0.66)	(1.76)	(0.74)	(1.81)	(0.55)
Panel B: Men								
	Insured	Gov	Private	2+ Plans	Spouse (Work)	Spouse (Non-Work)	Self (Work)	Self (Non-Work)
Second Order Polynomial (Orignial Estimates)								
Spouse65	-3.49*	0.52	-4.73*	-1.98	-6.98**	0.49	0.45	0.69
	(1.47)	(2.01)	(2.12)	(1.74)	(2.26)	(0.73)	(2.73)	(1.36)
Second Order Polynomial, No Controls								
Spouse65	-4.61**	-1.36	-5.91**	-3.88*	-6.74**	0.28	0.19	-0.81
	(1.39)	(2.10)	(1.94)	(1.66)	(2.19)	(0.68)	(2.53)	(1.31)
Third Order Polynomial								
Spouse65	-3.15	-0.68	-2.20	0.26	-6.56*	0.15	4.58	0.58
	(1.65)	(2.43)	(2.32)	(1.89)	(2.79)	(0.72)	(2.49)	(1.41)
Donut RD								
Spouse65	-4.52*	2.88	-7.21*	-1.66	-9.38***	1.17	-2.25	1.38
	(2.19)	(2.65)	(3.15)	(2.69)	(2.61)	(1.29)	(4.22)	(2.42)
Age Gap>1 Year								
Spouse65	-2.40	-0.22	-4.12	-3.96*	-7.58**	1.08	0.22	0.18
	(2.09)	(2.48)	(2.55)	(1.72)	(2.79)	(0.83)	(3.34)	(1.28)

Note: Table presents reduced form estimates of spousal Medicare eligibility on the insurance coverage of a younger spouse using NHIS data from 1993 to 2011. Each coefficient is from a separate regression using the specification described in the leftmost column of the table. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Chapter 2

Medicaid Coverage of Smoking Cessation Treatment and Smoking

2.1 Introduction

Despite reductions in smoking rates over time, tobacco use remains the leading cause of preventable mortality in the United States. Smoking imposes substantial costs to society as a whole, both in terms of lives lost and dollars spent. Nearly 450,000 Americans die from smoking-related diseases annually while an estimated $193 billion in direct medical costs and productivity losses are incurred each year (Adhikari, Kahende, Malarcher, Pechacek, and Tong, 2008). Still, 19 percent of American adults smoke and continuing to lower the smoking rate is a primary goal of public health policy. The Affordable Care Act (ACA) addresses smoking directly by mandating that insurers cover smoking cessation treatments (SCT) such as the nicotine patch, nicotine gum, and prescription medications beginning in 2010 for pregnant women and 2014 for all individuals. This mandate, in combination with the ACA's expansion of Medicaid eligibility to adults up to 138 percent of the federal poverty line will greatly increase access to quitting aids for this group whose health care costs are largely borne by taxpayers.

By requiring that insurers cover smoking cessation therapies, the ACA effectively reduces the cost of cigarette substitutes to insured smokers. This paper estimates a causal relationship between a reduction in the price of cigarette substitutes and smoking behavior using state variation in the timing of Medicaid coverage for nicotine dependence treatment as a natural experiment. I estimate a linear probability model of smoking behavior using repeated cross-sectional data from the Current Population Survey Tobacco Use Supplements (CPS-TUS) between 1998 and 2007. Medicaid coverage of smoking cessation therapies reduces smoking by 4.33 percentage points among the sample of low-income parents who are current or former smokers and are likely to be eligible for Medicaid. The smoking rate for this group is 71 percent, translating to a 6 percent reduction in smoking. This effect is concentrated among women with very young children, suggesting that these policies have the additional benefit of reducing secondhand smoke exposure among children.

I also employ Medicaid prescription drug utilization data to document significant heterogeneity in take-up of the benefit across states. Among a subsample of states that introduced the benefit, the number of doses of SCTs prescribed ranged from nearly 14 thousand in Illinois to 10 in South Dakota 4 years after the benefit initiated. Increasing take-up of the benefit among smokers should be a because Medicaid beneficiaries are 53 percent more likely to smoke than the general adult population (Armour and Fiebelkorn, 2009). As a result, this group whose health care expenditures are publicly funded suffer disproportionately from smoking-related health problems. Armour and Fiebelkorn (2009) estimate that 11 percent of Medicaid expenditures are attributable to smoking, totaling 22 billion dollars in 2004.

Other policy interventions to reduce smoking such as cigarette excise taxes, indoor smoking bans, advertising restrictions, and public health information campaigns have focused on raising the cost to smoke or changing preferences for smoking. These policies have been widely studied by economists, especially cigarette excise taxes and indoor smoking bans.[1] Cigarette taxes are largely agreed upon as an effective means to reduce smoking (Chaloupka and Warner, 2000). However, smokers may engage in compensating behavior in response to cigarette tax increases by inhaling more deeply and switching to cigarettes with higher nicotine content, suggesting that estimates of the public health benefit resulting from higher cigarette taxes are overstated (Evans and Farrelly, 1998; Farrelly, Bray, Pechacek, and Woollery, 2001; Adda and Cornaglia, 2006; Abrevaya and Puzzello, 2012). Clean indoor air laws that prohibit smoking in workplaces, bars, restaurants, etc. are primarily aimed at reducing secondhand smoke exposure by prohibiting smoking inside buildings, but also have the effect of reducing smoking in general (Chaloupka and Warner, 2000; Carpenter, 2009; Bitler, Carpenter, and Zavodny, 2010; Carpenter, Postolek, and Warman, 2011).

[1] The economic literature on smoking is very large. I refer readers to the extensive review of the smoking literature prior to 2000 in Chaloupka and Warner (2000). Selected recent papers include DeCicca, Kenkel, and Mathios (2002); Tauras and Chaloupka (2003); Chaloupka and Tauras (2004); Saffer, Wakefield, and Terry-McElrath (2007); DeCicca and McLeod (2008); Carpenter (2009); Adda and Cornaglia (2010); Bitler, Carpenter, and Zavodny (2010); Anger, Kvasnicka, and Siedler (2011); Carpenter, Postolek, and Warman (2011); Abrevaya and Puzzello (2012); Callison and Kaestner (2013).

Insurance coverage of smoking cessation treatment differs from cigarette taxes and smoking bans in two ways. First, taxes and bans raise the monetary and time cost of smoking while insurance coverage of smoking cessation therapies lowers the cost of cigarette substitutes. In this manner, SCT coverage is more similar to interventions that provide incentives to quit smoking (Volpp, Gurmankin Levy, Asch, Berlin, Murphy, Gomez, Sox, Zhu, and Lerman, 2006; Volpp, Troxel, Pauly, Glick, Puig, Asch, Galvin, Zhu, Wan, DeGuzman, Corbett, Weiner, and Audrain-McGovern, 2009; Gin, Karlan, and Zinman, 2010). Second, cigarette taxes and smoking bans reduce smoking along two possible margins — by preventing initiation of smoking among non-smokers and by reducing smoking among current smokers. Insurance coverage of SCTs reduces smoking along the second margin only, by helping current smokers quit. While preventing initiation of smoking circumvents its health consequences altogether, quitting smoking can reverse many of its negative health effects. Smokers who quit experience reductions in the health costs of smoking including lower risk of cancer, coronary heart disease, and stroke and benefit from more years of life (Novello, 1990; Ostbye, Taylor, and Jung, 2002; Ostbye and Taylor, 2004).

The paper proceeds as follows. Section 2.2 provides background information about Medicaid coverage of smoking cessation therapies and take-up of the benefit. Section 2.3 describes the data used for the empirical analysis and includes descriptive statistics for the sample. Section 2.4 explains the econometric strategy, followed by the estimation results in Section 2.5. Placebo checks are included in Section 2.6 and Section 2.7 concludes.

2.2 Background

2.2.1 Medicaid Coverage of Smoking Cessation Treatments

Medicaid is government-subsidized health insurance for over 62 million low-income children, pregnant women, low-income adults, and disabled adults. Children comprise 49 percent of Medicaid's beneficiaries, 25 percent are non-disabled adults, and the remainder are disabled adults and elderly Medicare-Medicaid dual eligibles. Enrollment is projected to increase by nearly 26 million people by 2020, 80 percent of whom will be adults that are eligible under the new ACA rules (Office of the Actuary, 2011).

Medicaid programs are state-administered, resulting in significant heterogeneity in both the timing of benefit adoption and the generosity of benefits across states.[2] Table 2.1 describes variation in Medicaid coverage of smoking cessation treatment across Medicaid programs. For each state that has implemented any form of coverage, the table lists the year coverage began, the type of therapies initially covered, the number of therapies initially covered, and the number of therapies covered in 2007.[3] Prior to 1996, only Rhode Island's Medicaid program offered any coverage for nicotine dependence treatment. In 1996, the Agency for Health Care Policy and Research's (AHCPR) published evidence-based guidelines advising clinicians and health care administrators to identify smokers and conduct interventions to reduce smoking. The Agency recommended that insurance purchasers (e.g. Medicaid, Medicare, employers) require insurers to cover counseling

[2]The District of Columbia also has a Medicaid program.

[3]The last year included in the analysis in this paper is 2007. For a description of how the sample years were chosen, refer to Section 2.3.

and other treatments for nicotine addiction. That same year, 18 Medicaid programs initiated coverage for nicotine dependence treatment. Between 1996 at 2007, an additional 26 Medicaid programs began some form of coverage.

Although most states offered some form of coverage prior to the ACA, Table 2.1 shows that the number of treatments covered varies significantly across states. Smoking cessation treatments can be categorized into three types: nicotine replacement therapies, pharmacotherapies, and counseling. Nicotine replacement therapies include the nicotine patch, gum, lozenge, nasal spray, and inhaler. Versions of the patch, gum, and lozenge are available over-the-counter, while nasal spray and inhalers are available by prescription only. Pharmacotherapies include bupropion and varenicline, marketed under the names Zyban and Chantix.[4] These prescription medications reduce nicotine cravings and nicotine withdrawal symptoms. Lastly, counseling includes group, individual, and telephone counseling.

Until 1996, most states only covered nicotine replacement therapies. Once Zyban entered the market in 1997, nearly every state that offered a nicotine replacement therapy also covered Zyban. Over time, states have increased the number of covered therapies — the average program initiated with 4.8 therapies and has expanded to cover 6.5 therapies. Medicaid most commonly covers the nicotine patch, nicotine gum, and Zyban, while counseling is the least likely treatment to be covered.

This is the first economics paper to investigate the effect of Medicaid coverage of smoking cessation therapies on smoking behavior; however, a handful of

[4]Zyban was approved by the FDA for smoking cessation therapy in 1997; however, the same active ingredient is included in some antidepressant medications and was prescribed for smoking cessation prior to 1997. Chantix entered the market in 2006.

studies have been completed in the field of public health. These papers employ a variety of statistical methods on different samples, resulting in a range of estimates from very large reductions in smoking to no effect. Petersen, Garrett, Melvin, and Hartmann (2006) uses Pregnancy Risk Assessment Monitoring System (PRAMS) data to compare the quitting rates during pregnancy of women in states with Medicaid coverage of smoking cessation to the quitting rates of pregnant women in states without coverage. Although women in states with coverage are 1.6 times more likely to quit than women in states without coverage, this difference could be due to state characteristics that are correlated with coverage of SCTs by Medicaid. Land, Warner, Paskowsky, Cammaerts, Wetherell, Kaufmann, Zhang, Malarcher, Pechacek, and Keithly (2010) use data from the Behavioral Risk Factor Surveillance System to examine Massachusetts' implementation of SCT coverage in 2006, finding that the smoking rate fell by 26 percent among Medicaid smokers after the reform. Because the timing of SCT coverage coincided with the state's health care reform, it is not possible to separate the effect of SCT coverage from the other effects of health reform. The authors also describe advertising campaigns, a cigarette tax increase, and a large increase in the number of Medicaid enrollees that occurred just after the policy change and acknowledge that their estimates embody the effects of these concurrent events. Liu (2009, 2010) uses the CPS-TUS to investigate quitting behavior; however, the sample is conditioned on being a current smoker, which could be affected by the policy itself. Most recently, Adams, Markowitz, Dietz, and Tong (2013) find no impact of Medicaid SCT coverage on smoking during pregnancy or after delivery for Medicaid mothers using PRAMS data; however, the authors split the treatment into three separate variables, making it difficult to identify an effect.

Despite inconclusive evidence on the efficacy of Medicaid coverage for nicotine dependence treatment, randomized-control trials and quasi-experimental research suggests that use of smoking cessation therapies is effective at reducing smoking. Clinical trials show that smokers who use nicotine replacement therapies are 50 to 100 percent more likely to quit than individuals given a placebo, with similar results for pharmacotherapy (Cummings and Hyland, 2005; Wu, Wilson, Dimoulas, and Mills, 2006; Stead, Perera, Bullen, Mand, Hartmann-Boyce, Cahill, and Lancaster, 2012). Increased availability of nicotine replacement therapies (e.g. lower price or over-the-counter availability) has been found to reduce demand for cigarettes in economic studies (Keeler, Hu, Keith, Manning, Marciniak, Ong, and Sung, 2002; Tauras and Chaloupka, 2003; Chaloupka and Tauras, 2004). If smoking cessation therapies are effective at helping smokers quit, yet there is inconclusive evidence that insurance coverage of these therapies lowers the smoking rate among Medicaid patients, it is possible that Medicaid patients are not using the benefit. The next section explores this possibility.

2.2.2 Use of Smoking Cessation Therapies by Medicaid Beneficiaries

Despite the availability of Medicaid smoking cessation benefits in most states and the relative effectiveness of these therapies at helping smokers quit, take-up of the benefit is not universally high. Land, Warner, Paskowsky, Cammaerts, Wetherell, Kaufmann, Zhang, Malarcher, Pechacek, and Keithly (2010) report that 37 percent of Massachusetts Medicaid smokers used the benefit within two years, while only 2 to 4 percent of Medicaid smokers in Arkansas and Wisconsin used some form of SCT after coverage was implemented (Burns and Fiore, 2001; Li and Dresler, 2012). One possible explanation for low take-up is that awareness of the benefit is low. In a survey of Medicaid physicians and patients in two states that offered coverage for smoking cessation treatment, only 60 percent of doctors and 36 percent of patients were aware that any coverage was offered (McMenamin, Halpin, Ibrahim, and Orleans, 2004). A secondary explanation is that smokers who are trying to quit rarely use smoking cessation therapies. Among individuals who have unsuccessfully tried to quit smoking during the previous 12 months, only 16 percent used some form of quitting aid.[5]

Given the low SCT take-up rate in the Arkansas and Wisconsin Medicaid programs, it is important to demonstrate that Medicaid coverage increases the use of smoking cessation therapies before moving on to estimating an effect on smoking behavior. In order to determine if patients are receiving treatment, I complete an event study analysis of the use of smoking cessation therapies in 9 states that initiated coverage during the time period of this study using Medicaid state drug utilization Data.[6] The states included in the analysis are Illinois, Kentucky, Mississippi, Nebraska, Pennsylvania, South Dakota, Utah, Washington, and West Virginia.[7] This analysis reveals that Medicaid patients are using smoking cessa-

[5]Source: Author's calculation from the 2003 CPS-TUS, which included a set of questions about quitting attempts.

[6]State drug utilization data are available online from the Center for Medicaid and Medicaid Services at http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Benefits/Prescription-Drugs/Medicaid-Drug-Programs-Data-and-Resources.html.

[7]In future iterations of the paper, I plan to extend the analysis to all states that offer coverage.

tion therapies after the benefit begins. Panel (a) of Figure 1 plots the number of prescriptions and doses prescribed annually for 2 years before and 4 years after initiation of Medicaid coverage of smoking cessation therapies. The total number of prescriptions for these states increases rapidly after coverage is initiated, growing from approximately 20 thousand in the first year of coverage to over 60 thousand after 4 years. The number of doses increases similarly, growing from 800 thousand to 2.3 million during the same time period. Panel (b) plots the number of prescriptions and doses per adult Medicaid beneficiary, resulting in 0.40 prescriptions and 13 doses per beneficiary after 4 years. Since initiation of the benefit caused prescriptions for smoking cessation therapies to increase among Medicaid patients, it is worthwhile to proceed to estimating the relationship between SCT coverage and smoking.

2.3 Data

I use data from several sources to estimate the relationship between SCT coverage and smoking behavior. The primary data are the Current Population Survey Tobacco Use Supplements, which contain information on smoking behavior from a large, nationally-representative sample of households. These data are combined with information about Medicaid coverage of smoking cessation therapies published in the Center for Disease Control (CDC) Morbidity and Mortality Weekly Reports. These data, along with additional information on smoking policies, Medicaid thresholds, and unemployment rates are described in detail below.

The time period for the analysis is limited to the years 1998 to 2007. Pre-1998 data are not included in the analysis because the Personal Responsibility and Work Opportunity Act (PRWORA) of 1996 was implemented in July 1997, significantly altering government benefit eligibility for low-income individuals. Using data from prior to 1998 could confound the effects of PRWORA with the effects of Medicaid coverage of smoking cessation treatment. The last year included in the analysis is 2007, which is dictated by availability of data on parental Medicaid thresholds.

2.3.1 Medicaid Coverage of Smoking Cessation Therapies

Information about Medicaid coverage of smoking cessation therapies is obtained from surveys of state Medicaid programs conducted by the Center for Health and Public Policy Studies at the University of California at Berkeley and reported in CDC Morbidity and Mortality Weekly Reports (Halpin, McMenamin, Orleans, and Husten, 2004; Halpin, McMenamin, Cella, Husten, and Rosenthal, 2006; Halpin, McMenamin, Cella, Bellows, and Husten, 2008; McMenamin, Halpin, Bellows, Husten, and Rosenthal, 2009). The surveys include questions about when any coverage began within a state, which therapies are included, as well as which populations are covered. By combining results from these surveys, I construct a data set containing information on which treatments are covered each state and year. A summary of these data is provided in Table 2.1.

2.3.2 Smoking Behavior

Information on smoking behavior is from the Current Population Survey Tobacco Use Supplements (CPS-TUS) for years 1998 to 2003 and 2006 to 2007.[8] The Current Population Survey is a nationally representative, monthly household survey of labor force participation. The monthly survey often includes sets of supplemental questions on particular topic such as health, schooling, fertility, and immigration. Periodically, respondents are asked a series of questions about smoking and other tobacco-related behaviors as part of the Tobacco Use Supplement, which is sponsored by the National Cancer Institute and the Centers for Disease Control. The CPS-TUS is a repeated cross section of individuals useful for describing smoking behavior of Americans over time. Individuals who have smoked at least 100 cigarettes in their entire life are identified as current or former smokers and are asked a series of follow-up questions about smoking behavior. The smoking measures used in this paper are self and proxy reports of smoking at least some days and smoking every day.

2.3.3 Additional Policy Controls

Both smoking policies and state Medicaid programs were evolving during the time period of this study, necessitating data to control for changes in these policy areas over time. To account for more aggressive tobacco-control policies in states, I use data on cigarette excise taxes and indoor smoking restrictions from the CDC's State Tobacco Activities Tracking and Evaluation System. Smoking has a pro-

[8]The Tobacco Use Supplement was not included in the 2004 or 2005 CPS, hence a two-year gap in the smoking data.

cyclical component (Ruhm, 2005); therefore, unemployment rates obtained from The Bureau of Labor Statistics are used to control for state economic conditions. Lastly, during this time period state Medicaid programs were expanding benefits to more children and parents. I control for the increase in the number of adults on the program with parental Medicaid income eligibility thresholds provided by Sarah Hamersma and Matthew Kim.[9]

2.3.4 Estimation Sample

The estimation sample includes parents with a family income below 200 percent of the poverty line who have ever been a smoker. Insurance coverage for smoking cessation therapy is relevant to individuals who smoke; therefore, I first limit the sample to current and former smokers defined as having smoked at least 100 cigarettes during their lifetime. Next, I keep respondents who are likely to be eligible for Medicaid by selecting low-income adults who have children.[10] By choosing the sample in this way, I am focusing the analysis on individuals are likely to be affected by changes in Medicaid coverage for smoking cessation therapy.

Table 2.2 reports summary statistics for the sample, which includes 37,281 individuals. The average respondent is 35 years old, the sample is 54 percent female, 77 percent are married or cohabiting, and the average respondent has 2 children. As a result of sampling low-income individuals, the average family

[9]For more information about the parental eligibility thresholds used in this paper, see Hamersma and Kim (2009, 2013).

[10]I limit the sample to parents with 1 to 5 children because I am only able to match parental Medicaid thresholds to these individuals.

income is \$19,006 per year and most individuals have a high school education or less.

The last two rows of Table 2.2 report information on the two measures of smoking behavior used in the paper. Seventy-one percent of the sample reports currently being a smoker; this variable takes a value of 1 if the respondent reports smoking on at least some days and zero otherwise. Thus, 29 percent of the sample is comprised of individuals who are former smokers. Fifty-eight percent of respondents smoke every day; this variable takes a value of 1 if the respondent reports smoking every day and zero otherwise.

2.4 Estimation Strategy

I use the roll-out of Medicaid smoking cessation coverage across states over time as a natural experiment to test the effectiveness of coverage at reducing smoking. When estimating the relationship between a policy variable and an outcome of interest, the econometrician's concern is that an omitted variable affecting both the policy variable and the outcome will bias the estimates. In order to account for the possibility of omitted variables bias, I control for both time-varying and time-invariant factors using the following linear probability model:[11]

$$Smoke_{ist} = \beta_0 + \beta_1 Covered_{st} + X_i\alpha + W_{st}\gamma + L_{st}\psi + \delta_s + \lambda_t + \pi_{rt} + \varepsilon_{ist}$$

[11] I have also estimated the equation using a probit model, and the results are similar to the linear probability model. Linear probability model results in Tables 2.3, 2.4, and 2.5 are replicated in Tables B.2, B.3, and B.4 using a probit specification.

where $Smoke_{ist}$ is a measure of smoking behavior of individual i living in state s in year t. $Covered_{st}$ is an indicator variable that is 1 in year t if state s's Medicaid program covers smoking cessation treatment and zero otherwise. The coefficient of interest is β_1, which captures the effect of initiating Medicaid smoking cessation coverage on smoking behavior. X_i is a vector of individual characteristics including age, race, education, marital/cohabitation status, family income, and number of children. Age is controlled for using dummy variables for the 7 year age category of 18 to 24 years old and 5 year age categories for ages between 25 and 64 years old. Race, education, marital/cohabitation status, and income categories are also entered as dummy variables to allow as much flexibility as possible in the estimating equation. The elements of X_i control for differences in smoking behavior across demographic subgroups.

The vector W_{st} includes state and time-specific characteristics including the state parental Medicaid threshold, the tax per pack of cigarettes, the number of indoor smoking restrictions, and the state unemployment rate. During this time period, most state Medicaid programs repeatedly increased the eligibility thresholds for parents, expanding coverage to more parents over time. It is important to include Medicaid thresholds in the regression because expanding Medicaid eligibility could have an independent effect on smoking behavior by changing the composition of the Medicaid population. Parental Medicaid thresholds are merged to each individual based on state, month, and family size. Thus, I control for the individual-specific Medicaid threshold within a state and month. Cigarette taxes and indoor smoking restrictions (e.g. schools, workplaces, restaurants, bars, multi-unit housing, etc.) also changed greatly during the period of this study and not controlling for these policies could lead to biased estimates of β_1. The final component of W_{st} is the unemployment rate, which controls for the general economic climate.

Lastly, state fixed effects (δ_s) absorb time-invariant state features and year fixed effects (λ_t) control for changes in the smoking rate at a national level over time. State-specific time trends (L_{st}) model state trajectories in smoking behavior and census region-year fixed effects (π_{rt}) capture regional time trends as flexibly as possible. Standard errors are clustered at the state level to account for correlation in the error term across individuals living in the same state.

2.5 Results

2.5.1 Main Estimates

To examine the relationship between Medicaid coverage of smoking cessation therapies and smoking behavior, I begin with an event study analysis of the dynamics of smoking before and after Medicaid coverage of SCTs. Figure 2.2 presents the smoking rate before and after coverage, relative to the level of smoking in the year coverage began. The level of smoking in a given year is the coefficient from a regression of a dichotomous smoking indicator on dummy variables for the four years before and the 6 years after coverage began in a state, with the year coverage began as the omitted category in the regression. The regression includes all controls included in columns (3) and (6) of Table 2.3, discussed below.[12] In

[12]Although a balanced panel of states is ideal for an event study, analysis, the two-year gap in the CPS-TUS during 2004 and 2005 makes it impossible to create a balanced panel of states

Figure 2.2, the solid line represents the point estimate on smoking and the dashed lines indicate the 95 percent confidence interval of the smoking estimate. The point estimates for the years prior to Medicaid coverage of smoking cessation treatment bounce above and below zero, and are all indistinguishable from zero. This is reassuring because it suggests that the regression specification adequately controls for the time trend in smoking prior to the policy change. Immediately after coverage begins, the smoking rate falls by approximately 2.5 percentage points. The reduction in smoking is constant during the first 4 years after the program initiates, suggesting that on average, Medicaid coverage of SCTs has an immediate effect on smoking behavior rather than taking several years to reduce smoking.

Table 2.3 presents results from regressions on two measures of smoking behavior: smoke and smoke every day. These regressions are estimated using the equation in Section 2.4 and I include three specifications for each dependent variable. The coefficient shown in columns (1) and (4) is from a regression that includes state fixed effects, year fixed effects, region by year fixed effects, and state linear time trends. This specification assumes that Medicaid coverage of smoking cessation therapy is exogenous once time-invariant state characteristics, a national trend in smoking, shocks specific to a region and year, and state-specific trends in smoking over time are accounted for. Columns (2) and (5) add controls for individual characteristics in order to account for variation in smoking behavior across demographic characteristics. Individual controls include age, age squared, race, education, marital/cohabitation status, family income, and number of children.

with at least 2 pre-period years and more than 3 post-period years. Therefore, the results shown in Figure 2.2 are from an unbalanced panel of states.

Lastly, columns (3) and (6) add state-specific, time-varying controls. These controls include the parental Medicaid threshold, the cigarette excise tax, the number of indoor smoking restrictions, and the unemployment rate.

The first three columns of Table 2.3 present estimates of the introduction of Medicaid coverage on smoking at least some days. The estimate in column (1) is interpreted as Medicaid coverage of SCT causing a 5.22 percentage point reduction in smoking. The magnitude attenuates slightly to 4.68 percentage points when person-specific controls are added in column (2). The estimate is unchanged after adding state-specific controls in column (3), implying that coverage reduces smoking by 4.33 percentage points among low-income parents who are current or former smokers. The mean smoking rate is 71 percent for this group, resulting in more than a 6 percent reduction in the smoking rate.

Columns (4) to (6) show the coefficients from regressions of smoking every day, which reveals the effects of SCT coverage on intense smokers. Everyday smokers comprise 58 percent of the overall sample and 82 percent of the smokers in the sample. Smoking every day falls by over 3 percentage points in columns (4) and (5); however, adding time-varying state controls roughly halves the estimate and removes its significance in column (6). This less robust finding for everyday smokers suggests that the decline in smoking is only partially driven by everyday smokers and a portion of the decline in smoking is due to individuals who previously smoked only some days.

In summary, there is clear evidence that introduction of insurance coverage for smoking cessation therapies reduces smoking on the extensive margin, but the effect on everyday smokers is less robust. An event study analysis demonstrates that on average the reduction in smoking occurs immediately after policy introduction, rather than taking a few years to become effective. The remainder of the paper presents estimates using the preferred specification in columns (3) and (6) of Table 2.3 because it controls for the gamut of individual and state features.

2.5.2 Heterogeneity of Effects

Effectively designing policy requires knowledge of which groups of people respond to a particular intervention. Therefore, I re-estimate the model for several subgroups of interest in Table 2.4. For each subgroup listed in the leftmost column of the table, I present the change in smoking and smoking every day following initiation of Medicaid coverage of smoking cessation therapies. Each coefficient is from a separate regression, standard errors are given in parenthesis, and the mean of the dependent variable for each subgroup is given in brackets.

This exercise reveals that the groups who are responsive to the policy change are those that are most likely to be on Medicaid insurance. I first estimate the regression equation separately by gender, finding that Medicaid coverage of SCTs results in women reducing smoking by 5.96 percentage points. On a mean smoking rate of 72 percent, this is a 8 percent reduction in smoking among sample females. Men, on the other hand, do not reduce smoking in response to Medicaid coverage of smoking cessation therapies. The lack of an effect for men can reflect two possibilities; either the policy intervention is indeed ineffective for men, or most men in the sample are not eligible for Medicaid. Without knowing the Medicaid status of individuals in the sample, it is not possible to discern which explanation is correct.[13] Expansion of Medicaid coverage that includes smoking cessation treatment to adults without children as part of the ACA creates an opportunity to evaluate the policy's effect on men using publicly-available data. For both men and women, there is no statistically significant effect on smoking everyday.

Moving down the table, the policy has the largest effect on individuals with the lowest education level. Again, individuals in this group are most likely to be eligible for Medicaid. Among those with less than a high school education, Medicaid coverage of smoking cessation therapies reduces smoking by 13.4 percentage points. This is a very large 17 percent reduction in the extensive margin of smoking behavior. Smoking every day falls by 10.5 percentage points, which is also a 17 percent reduction for everyday smokers. The results for the largest education category - high school education - are puzzling. The coefficients on smoking and smoking everyday are both positive, and the latter is statistically significant.[14] Among the sample of low-income parents at risk for smoking with at least some college, the policy reduces smoking by 7.81 percentage points. The point estimate is similar for smoking every day, but does not quite reach statistical significance.

Lastly, Medicaid coverage of smoking cessation therapies is effective at reducing smoking for individuals below 100 percent of the federal poverty line. This

[13] Medicaid coverage during the previous year is asked in the March interview of the CPS. None of the Tobacco Use Supplements are conducted in March, meaning that individuals would have to be matched across months in order to obtain Medicaid status, causing a reduction in the sample size. A matched sample from the CPS-TUS would not be suitable for analysis because of the smaller number of observations and because the November 2001 and 2003 supplements would be dropped since the individuals in those supplements are not interviewed in March.

[14] This perverse effect may be related to the high smoking rate of GED holders, whom I cannot differentiate from high school graduates in the sample. The smoking rates for high school dropouts, GED holders, and high school graduates are approximately 25 percent, 45 percent, and 23 percent respectively.

finding is also consistent with the poorest individuals being more likely to have Medicaid coverage.

Next, I investigate heterogeneity in smoking reduction by the age of the children in the household. Naturally, reducing smoking in households with children is a priority because of the health effects of secondhand smoke and the intergenerational correlation in smoking behavior. Children exposed to secondhand smoke may suffer from additional health problems such as increased risk of illness, more frequent and severe asthma attacks, and more ear infections (Surgeon General, 2006). Children who are young when a parent quits smoking benefit from more years without secondhand smoke exposure. Moreover, smoking during pregnancy increases health risk for both the infant and the mother in the form of complications such as miscarriage, membrane ruptures, birth defects, and still-birth (Tong, Jones, Dietz, D'Angelo, and Bombard, 2009). Women who smoke during pregnancy have lower birth weight babies on average and are at a greater risk for having an infant classified as low birth weight (Sexton and Hebel, 1984; Almond, Chay, and Lee, 2005; Lien and Evans, 2005).

Table 2.5 presents estimates from a regression specification that allows for separate effects of Medicaid coverage of smoking cessation therapy by age of the youngest child in the household. This regression interacts the indicator variable for Medicaid coverage of SCTs with a dummy variable for the age category of the youngest child in the household. Youngest children are categorized into three age groups: 0 to 1 years old, 2 to 5 years old, and 6 to 17 years old. The first row of Table 2.5 shows that Medicaid coverage of smoking cessation therapy reduces smoking by 5.07 percentage points and reduces smoking every day by 5.65

percentage points for parents whose youngest child is an infant. The magnitude of the effect is much smaller and insignificant for parents of young children between the ages of 2 and 5 years old at -1.21 and -2.15 percentage points for smoking and smoking every day, respectively. For parents of older children, the effect on both measures of smoking behavior is zero.[15]

2.5.3 Generosity of Coverage

As shown in Table 2.1, there is diversity in number of smoking cessation treatments covered by Medicaid across states. This heterogeneity, combined with the expansion of coverage to more therapies over time within many states creates an opportunity to test whether or not increasing the number of therapies covered improves outcomes. This exercise is useful because advocacy groups are calling for more explicit language requiring coverage of all smoking cessation therapies in the Affordable Care Act.

Under the ACA, drugs used to promote smoking cessation are non-excludable from coverage by insurers. However, the American Lung Association, the American Cancer Society Cancer Action Network, and the Partnership for Prevention have issued a white paper stating that "simply requiring health plans to cover 'tobacco cessation' is not enough...[we] urge the department of Health and Human Services to include a comprehensive cessation benefit" in the ACA (Cancer Action Network, American Lung Association, and Partnership for Prevention, 2011). This request for comprehensive coverage of all available treatments is based on

[15] In results not shown, heterogeneous effects by number of children in the household are estimated. The effect does not vary by the number of children in a household, rather, the age of the most recent child appears to be more relevant to quitting smoking.

the idea that offering a variety of options for smokers will increase the probability of successfully quit smoking.

Table 2.6 presents results from a regression specification that includes an indicator variable for any SCT coverage and a second indicator variable for coverage of 7 or more therapies in a given year. Since 1998, the average program initiated coverage with 4.7 therapies covered and expands coverage by almost 2 therapies over time. The regression is specified to differentiate between the average program offering somewhere between 4 and 6 treatments and a generous program offering at least 7 therapies. For the 7 states that initiate coverage with at least 7 therapies, both dummy variables will turn on when the program begins. For the 8 states that initiate coverage with less than 7 therapies and expand coverage to include more than 7, only the first dummy will turn on initially. Once coverage is expanded to more than 7 therapies, the second dummy will also turn on to capture the additional effect on smoking behavior from expanding generosity. The first row of the table gives the effect of having any SCT coverage and the coefficient in the second row gives the effect of having 7 or more therapies available.

Column (1) presents the results on the extensive margin of smoking and shows that adding more therapies does increase the likelihood that an individual quits. Initiating any smoking cessation coverage causes a 3.78 percentage point reduction in smoking. Expanding coverage to 7 or more therapies adds a marginal reduction of 2.57 percentage points. No statistically significant effects for smoking every day are detectable. This finding is evidence supporting the notion that more treatment options increase the efficacy of insurance coverage for smoking cessation treatment.

2.6 Placebo Checks

A negative relationship between Medicaid SCT coverage and smoking could be observed if the econometric model does not adequately control for the downward trend in smoking. If the decline in smoking is fully captured in the model, then estimating the regression equation for individuals who are not affected by Medicaid SCT coverage should produce no effect of SCT coverage on smoking.

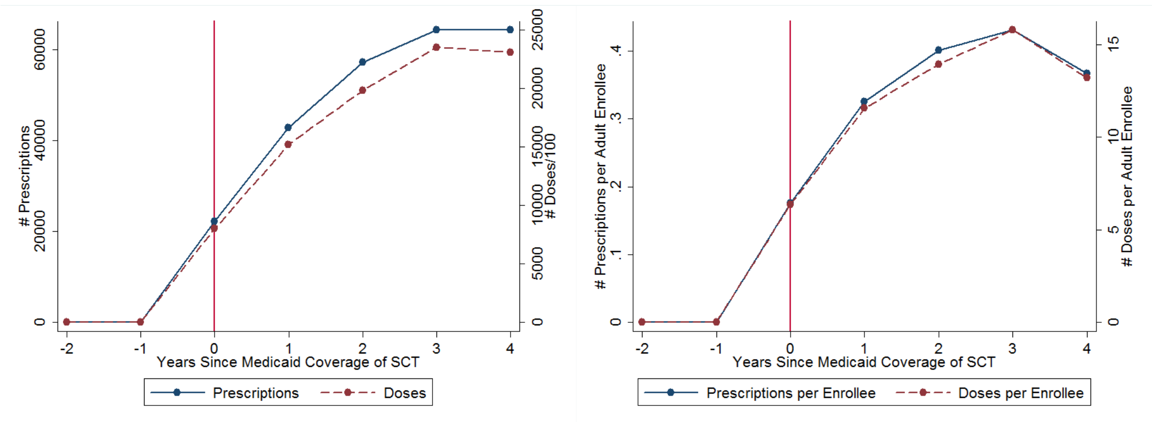
Table 2.7 presents results from re-estimating the regressions for groups whose smoking behavior should be unaffected by the policy changes because they are ineligible for Medicaid. In Panel A of Table 7, I estimate the equation on a sample of adults with no children. The coefficients are precise zeros. In Panel B, the estimation sample includes parents with annual family incomes above 200 percent of the federal poverty level. Again, these estimates are zeros. This zero effect on individuals that are unlikely to be affected by the policy suggests that the effect of Medicaid SCT coverage is identified in the model, reinforcing the paper's main conclusion that Medicaid coverage of smoking cessation treatment is an effective means for reducing smoking among the Medicaid population.

2.7 Discussion

Reducing smoking remains a primary goal of public health policy, as evidenced in the Affordable Care Act's mandate that health insurers cover smoking cessation treatment. Using variation in the timing of introduction of Medicaid coverage for smoking cessation therapies, this paper demonstrates that reducing the cost of cigarette substitutes by offering insurance coverage of smoking cessation therapies is effective at curbing smoking. Medicaid coverage reduces smoking by 6 percent among a sample of low-income parents who are current or former smokers, an effect that translates to a 21 percent reduction in smoking among Medicaid-eligible smokers. This effect is concentrated on mothers with small children, not only improving the health of the mother but also potentially reducing secondhand smoke exposure of her children. Using a unique dataset of Medicaid claims for smoking cessation therapies, I also document significant heterogeneity in use of the benefit across states. These results suggest that while insurance coverage of smoking cessation treatment under the ACA will likely improve the smoking rate, smokers may need to be encouraged to utilize smoking cessation therapies to maximize the impact of the policy.

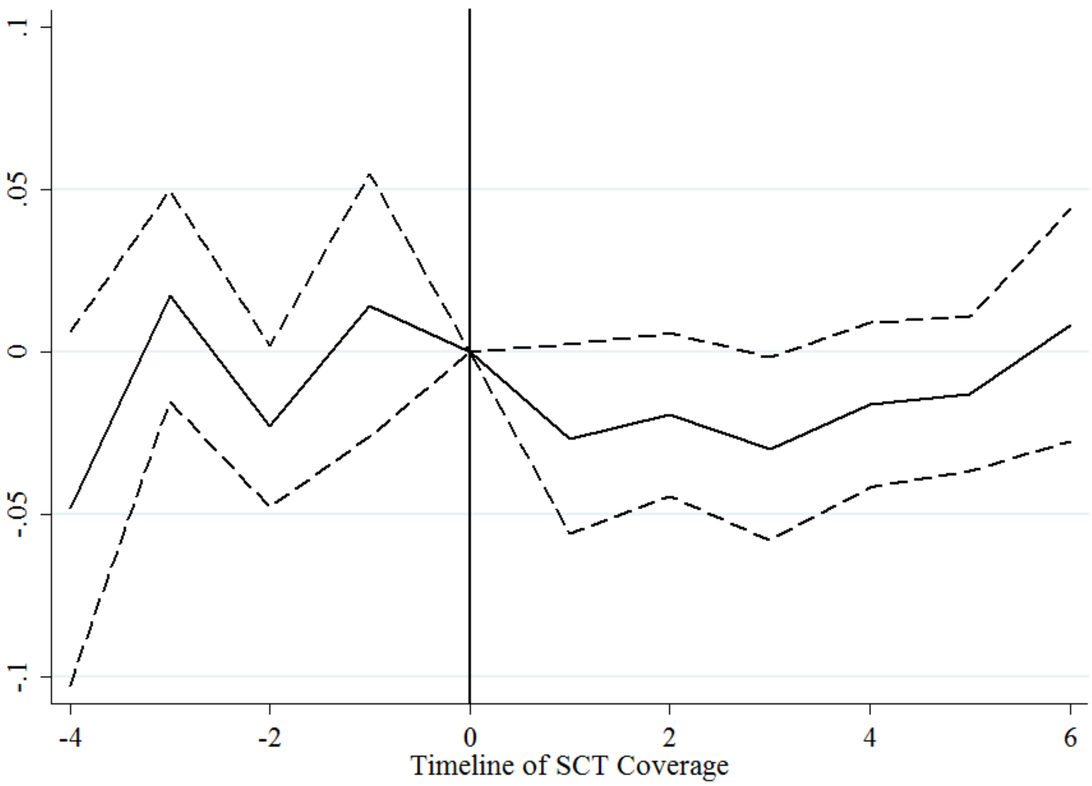
Figure 2.1: Medicaid Claims for Smoking Cessation Therapies

(a) Total Prescriptions and Doses (b) Prescriptions and Doses per Adult Beneficiary



Note: Graphs use Medicaid claims data to plot the number of prescriptions and doses of smoking cessation therapies dispensed for 9 states for two years before and four years after Medicaid coverage of nicotine dependence treatment. The solid line indicates the number of prescriptions and the dashed line indicates the number of doses. Panel (a) presents the total number of prescriptions and doses. Panel (b) presents the number of prescriptions and doses per adult Medicaid beneficiary. The nine states included in the data are Illinois, Kentucky, Mississippi, Nebraska, Pennsylvania, South Dakota, Utah, Washington, and West Virginia.

Figure 2.2: Event Study of Smoking Rates Before and After Coverage Initiates



Note: Graph shows the results of an event study analysis using CPS-TUS data. The solid line indicates the point estimate of the smoking rate relative to the rate in year 0, when Medicaid coverage of smoking cessation treatment begins. The dashed lines indicate the 95 percent confidence interval of the estimate.

Table 2.1: Medicaid Coverage of Smoking Cessation Therapies

State	Year Any Coverage Began	Number of Therapies Initially Covered				Number of Therapies Covered in 2007
		Nicotine Replacement[1]	Pharmacotherapy[2]	Counseling[3]	Total	Total
Rhode Island	1994	0	0	2	2	7
California	1996	3	0	0	3	7
Colorado	1996	3	0	0	3	9
Delaware	1996	3	0	0	3	7
District of Columbia	1996	1	0	0	1	6
Louisiana	1996	1	0	0	1	6
Maine	1996	4	0	0	4	8
Maryland	1996	3	0	0	3	6
Minnesota	1996	1	0	2	3	9
Montana	1996	2	0	0	2	7
Nevada	1996	3	0	0	3	7
New Hampshire	1996	3	0	0	3	9
New Jersey	1996	0	1	0	1	10
New Mexico	1996	3	0	0	3	9
North Carolina	1996	1	0	0	1	7
North Dakota	1996	2	0	0	2	5
Texas	1996	3	0	0	3	6
Virginia	1996	3	0	0	3	9
Wisconsin	1996	2	0	0	2	6
Florida	1997	0	0	2	2	6
Michigan	1997	2	1	0	3	6
Ohio	1998	3	1	0	4	7
Oregon	1998	4	1	3	8	10
Arkansas	1999	0	1	0	1	5
Hawaii	1999	2	1	0	3	7
Indiana	1999	4	1	2	7	9
Kansas	1999	1	1	2	4	5
New York	1999	2	1	0	3	8
Oklahoma	1999	2	1	0	3	8
Vermont	1999	4	1	0	5	7
Illinois	2000	4	1	0	5	7
West Virginia	2000	4	1	2	7	7
Kentucky	2001	0	0	2	2	3
Mississippi	2001	4	1	0	5	9
South Dakota	2001	0	1	0	1	2
Utah	2001	5	2	3	10	10
Nebraska	2002	0	0	1	1	1
Pennsylvania	2002	4	1	2	7	9
Washington	2002	0	0	1	1	2
South Carolina	2004	5	1	0	6	7
Alaska	2006	5	2	1	8	8
Massachusetts	2006	5	2	2	9	9
Idaho	2007	5	1	0	6	6
Iowa	2007	2	1	0	3	3
Wyoming	2007	3	2	2	7	7

Program start dates and therapies covered are from CDC Mortality and Morbidity Weekly Reports.

[1]Nicotine replacement therapies include the nicotine patch, gum, inhaler, lozenge, and nasal spray.

[2]Pharmacotherapy include Zyban and Chantix. Zyban became available in 1997 and Chantix was released in 2006.

[3]Counseling includes group, individual, and telephone counseling.

Table 2.2: Descriptive Statistics for Low-Income Parents Who Have Smoked at Least 100 Cigarettes

	Mean	SD
Age	35.40	(9.17)
Female	0.54	(0.50)
Married	0.60	(0.49)
Cohabiting	0.17	(0.37)
Single	0.23	(0.42)
# Children	1.94	(0.91)
Family Income ($)	19,006	(9863)
Education		
Less than High School	0.28	(0.45)
High School	0.43	(0.50)
Some College	0.24	(0.43)
College or More	0.05	(0.21)
Race		
White	0.65	(0.48)
Black	0.14	(0.35)
Hispanic	0.16	(0.37)
Asian/Pacific Islander	0.02	(0.14)
Other	0.02	(0.14)
State Controls		
Tax Per Pack ($)	0.59	(0.46)
Number of Indoor Smoking Restrictions	3.65	(2.46)
Unemployment Rate	4.86	(1.08)
Parental Medicaid Threshold[1]	0.74	(0.43)
Outcome Variables		
Smoke	0.71	(0.46)
Smoke Every Day	0.58	(0.49)
N	37,281	

Note: Data are the Current Population Survey Tobacco Use Supplement (CPS-TUS) for years 1998 to 2003, and 2006 to 2007. Sample includes individuals who have smoked at least 100 cigarettes in the past, have between 1 and 5 children, and have annual family income below 200% of the poverty line. Arizona is excluded from the sample due to lack of information about the state's Medicaid smoking cessation treatment coverage.

[1]Parental Medicaid thresholds are reported as a percentage of the federal poverty line.

Table 2.3: Effect of Medicaid Smoking Cessation Therapy Coverage on Smoking Behavior

	(1) Smoke	(2) Smoke	(3) Smoke	(4) Smoke Every Day	(5) Smoke Every Day	(6) Smoke Every Day
Smoking Cessation Covered	-0.0522***	-0.0468***	-0.0433***	-0.0378***	-0.0336**	-0.0195
	(0.0163)	(0.0146)	(0.0155)	(0.0130)	(0.0130)	(0.0143)
Mean of Dependent Variable	0.706	0.706	0.706	0.583	0.583	0.583
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
RegionxYear FE	YES	YES	YES	YES	YES	YES
State Linear Trends	YES	YES	YES	YES	YES	YES
Individual Controls	NO	YES	YES	NO	YES	YES
State Controls	NO	NO	YES	NO	NO	YES
Observations	37,281	37,281	37,281	37,281	37,281	37,281

Note: The table shows coefficients from linear regressions of smoking behavior on a dummy variable for Medicaid coverage of smoking cessation therapies using the CPS-TUS. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Effect of Medicaid Smoking Cessation Therapy Coverage on Smoking Behavior by Demographic Characteristics

	(1) Smoke	(2) Smoke Every Day
Gender		
Female	-0.0596***	-0.0252
[n=21,078]	(0.0150)	(0.0177)
	[0.719]	[0.598]
Male	-0.0194	-0.0104
[n=16,203]	(0.0264)	(0.0256)
	[0.692]	[0.566]
Education		
Less than High School Education	-0.134***	-0.105***
[n=9,688]	(0.0282)	(0.0310)
	[0.756]	[0.624]
High School Education	0.0360	0.0551**
[n=16,317]	(0.0228)	(0.0230)
	[0.730]	[0.613]
Some College or More	-0.0781**	-0.0579
[n=11,276]	(0.0356)	(0.0378)
	[0.621]	[0.499]
Income		
Income <100% FPL	-0.0780***	-0.0520
[n=14,638]	(0.0283)	(0.0312)
	[0.763]	[0.624]
Income Ó100% FPL	-0.0155	0.00187
[n=22,643]	(0.0237)	(0.0213)
	[0.669]	[0.557]
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES

Note: The table shows coefficients from linear regressions of smoking behavior on a dummy variable for Medicaid coverage of smoking cessation therapies using the CPS-TUS. Each cell includes the coefficient of interest from a separate regression. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gende, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses and the mean of the dependent variable is in brackets.

*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Effect of Medicaid Smoking Cessation Therapy Coverage by Age of Youngest Child

	(1) Smoke	(2) Smoke Every Day
Smoking Cessation Covered*Youngest Child 0 to 1	-0.0507***	-0.0565***
	(0.0122)	(0.0110)
Smoking Cessation Covered*Youngest Child 2 to 5	-0.0121	-0.0215
	(0.0119)	(0.0155)
Smoking Cessation Covered*Youngest Child 6 to 17	-0.00362	0.00277
	(0.0108)	(0.00896)
Mean of Dependent Variable	0.706	0.583
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES
Observations	37,281	37,281

Note: The table shows coefficients from linear regressions of smoking behavior on a dummy variable set equal to 1 if Medicad covers smoking cessation therapy interacted with a dummy variables for the age of the youngest child in the household. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Effect of Number of Smoking Cessation Therapies Covered by Medicaid on Smoking Behavior

	(1)	(2)
	Smoke	Smoke Every Day
Smoking Cessation Coverage	-0.0378**	-0.0199
	(0.0165)	(0.0144)
Number of Therapies Ó7	-0.0257*	0.00201
	(0.0149)	(0.0163)
Mean of Dependent Variable	0.706	0.583
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES
Observations	37,281	37,281

Note: The table shows coefficients from linear regressions of smoking behavior on a dummy variable set equal to 1 if Medicad covers smoking cessation therapy and a second variable containing the number of therapies covered. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Effect of Number of Smoking Cessation Therapies Covered by Medicaid on Smoking Behavior

	(1) Smoke	(2) Smoke Every Day
Panel A: Adults with No Children		
Smoking Cessation Covered	-0.00142	0.000382
	(0.00980)	(0.0106)
Panel B: Parents with Family Income >200% of Federal Poverty Line		
Smoking Cessation Covered	-0.00868	-0.00944
	(0.0193)	(0.0201)
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES

Note: The table shows coefficients from linear regressions of smoking behavior on a dummy variable for Medicaid coverage of smoking cessation therapies using the CPS-TUS. The sample in Panel A includes adults age 18 to 64 with no children. The sample in Panel B includes parents with family income above 200 percent of the federal poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Chapter 3

Family Structure and the Gender Gap in ADHD Diagnosis

3.1 Introduction

Attention deficit/hyperactivity disorder (ADHD) is the most common neurobehavioral disorder among America's youth (Feldman and Reiff, 2014), imposing significant short and long-run costs on sufferers.[1] Children with symptoms of ADHD have lower grades, higher special education enrollment, higher incidence of learning disabilities, higher delinquency, and lower completed education(Mayes, Calhoun, and Crowell, 2000; Currie and Stabile, 2006; Fletcher and Wolfe, 2008, 2009). In adulthood, individuals who have ever been diagnosed with ADHD have lower levels of employment, earn less, and are more likely to receive social assis-

[1]ADHD is a developmental disorder characterized by inability to focus, hyperactivity, impulsivity, and difficulty paying attention (National Institute of Mental Health 2012). The American Psychiatric Associations diagnostic criteria for ADHD requires that a child present at least six symptoms of hyperactivity or inattention. Several symptoms must be present before age 12, symptoms must be present in two or more settings (e.g. home and school), and must interfere with social, academic, or occupational functioning. Appendix A includes the American Psychiatric Associations criteria for ADHD diagnosis including the list of possible symptoms that must be displayed.

tance (Fletcher, 2014). The number of children diagnosed with ADHD increased by 42 percent between 2003 and 2011, by which time 11 percent of children had been diagnosed with the disorder (VIsser, Danielson, Bitsko, Holbrook, Kogan, Ghandour, Perou, and Blumberg, 2014).

Rates of ADHD vary dramatically by geography, race, income, and gender, suggesting that diagnosis is influenced by factors other than just the underlying prevalence of the disorder. For example, nearly 19 percent of children in Kentucky have received an ADHD diagnosis compared to only 6 percent in Nevada, low income children have higher rates of diagnosis, and boys are twice as likely as girls to have ADHD (Akinbami, Liu, Pator, and Reuben, 2011). Since diagnosis of ADHD in childhood relies on parent and teacher reports of behavior and is inherently subjective, researchers have attempted to identify factors related to over- and/or under-diagnosis of the disorder. For example, Elder and Lubotsky (2009), Elder (2010), and Evans, Morrill, and Parente (2010) show that children who are young for their grade are more likely to be diagnosed with ADHD than children who are very similarly aged but missed the entry cutoff. Fulton, Hinshaw, Levine, Stone, Brown, and Modrek (2009) show that physician supply is correlated with the prevalence of ADHD, but find no relationship between a states educational policies and ADHD prevalence. While these large gaps across demographic and socioeconomic groups seem unlikely to arise entirely from differences in the true underlying prevalence, their origins remain largely unexplained.

We provide evidence that family structure is an important factor influencing ADHD diagnosis, especially for boys. Using data from the National Health Interview Survey from 1998 to 2012, we show that children in non-traditional families are more likely to be diagnosed with ADHD. We compare the gender gap in ADHD diagnosis across traditional, single parent, and blended families, finding that the negative impact of a non-traditional family structure is much larger for boys.[2] The male-female gap in ADHD is approximately twice as large in non-traditional families. Boys in traditional families are 5.5 percentage points more likely to be diagnosed with ADHD than girls in traditional families. This gap is 9.0 percentage points in single parent households and 11.2 percentage points in blended households. The existence of a gender gap in ADHD diagnosis across all family types is consistent with a higher prevalence among boys; however, the much larger gap in non-traditional families suggests that boys diagnosis is especially impacted by the type of household they live in.

These results are consistent with the recent findings of Bertrand and Pan (2013). They show that family structure is an important determinant of the gender gap in disruptive behavior. They find that the male-female gap in externalizing behavior is nearly twice as large in single mother households compared to traditional households, which is similar to the magnitude of the ADHD gap estimated in this paper. Our results demonstrate that these externalizing gender gaps are not simply behavioral, but also extend to diagnosis of a psychological disorder.

Our findings are part of a growing literature exploring male vulnerability during childhood and whether this might be part of the reason that disadvantaged

[2]Interpretation of our findings as causal relies on the assumption that child gender is essentially random within family structure; however, a small relationship does exist between child gender and family structure. The magnitude of the excess gap in ADHD diagnosis is too large to be explained by selection into family structure by child gender. We discuss the literature relating family structure to child gender in Section 2.

boys fare poorly educationally and in the labor market. Since ADHD adversely effects cognitive and non-cognitive development, excess male-female gaps in ADHD rates for non-traditional families are consistent with worse adult outcomes for boys from disadvantaged backgrounds.[3] But from what does the gap arise? Lundberg, Pabilonia, and Ward-Batts (2007) and Bertrand and Pan (2013) show that single mothers spend less time with male children, while boys in two-parent households receive the same or more parental time investment than girls. However, Bertrand and Pan (2013) find that differences in parental time investment explain only a small portion of the gender gap in externalizing behavior. Alternatively, Gershon and Gershon (2002) show that girls with ADHD more frequently have internalizing symptoms, and manifest fewer symptoms overall, while boys more often have hyperactive and externalizing symptoms. It is certainly possible that non-traditional families are less able to cope with boys ADHD symptoms, which are more likely to be disruptive due to their externalizing nature, and are therefore more likely to seek help and obtain a diagnosis. While there is still a lot to learn about why boys fare relatively worse than girls in non-traditional families, ADHD is known to affect short and long-run outcomes and the results in this paper clearly document huge excess male-female gaps in ADHD in non-traditional families.

[3] See Heckman and Rubinstein (2001), Jacob (2002), Heckman, Stixrud, and Urzua (2006), Becker, Hubbard, and Murphy (2010), and Chetty, Friedman, Saez, Whitmore Schanzenbach, and Yagan (2011)

3.2 Data

We use data from the 1998 to 2012 National Health Interview Survey (NHIS). The NHIS is a cross-sectional, annual household survey that collects information on health conditions, health care use, and detailed demographic characteristics from a nationally representative sample. We draw on parental reports of child health for one child in the household from the Sample Child Supplement. Our main outcome variable is a parental report of whether the sample child has ever been diagnosed with ADHD. In addition to ADHD diagnosis, we also use parental reports of child behavior including whether the child has a good attention span, is worried, is unhappy, or has difficulties with emotions, concentration, behavior, or getting along with others.[4] Lastly, we use diagnoses of cognitive and physical health including whether the child has learning or developmental disabilities, hearing problems, ear infections, asthma, and food allergies.

The sample includes 99,148 children aged 5 to 16 who live with at least one biological or adoptive parent. Children are classified as belonging to a traditional family if they live with both biological parents or two adoptive parents, a single parent family if there is only one parent in the household (either biological or adoptive), and a blended family if the household contains one biological/adoptive parent who is cohabiting with a non-biological parent in the household. For ex-

[4]The NHIS records parental reports of good attention span, child worry, and child unhappiness on a three point scale of not true, somewhat true, and certainly true. We recode these variables to 1 if the parent answers somewhat or certainly true and zero otherwise. The variable for difficulties in emotions, concentration, behavior, or being able to get along with others is coded as 0 if there are no difficulties or minor difficulties and 1 if the difficulties are definite or severe.

ample, a child living in a household with a biological mother and a step-father or adoptive father would be classified as living in a blended family.[5]

Our primary interest is comparing the gender gap in ADHD diagnosis across traditional, single parent, and blended families. This analysis is complicated by the fact that family structure is not randomly assigned. Of particular concern is the possibility that child gender influences family structure. In fact, previous research shows that having a male child slightly increases the probability that unwed parents marry and that married parents remain married (Katzev, Warner, and Acock, 1994; Mott, 1994; Lundberg and Rose, 2003; Bedard and Deschenes, 2005; Dahl and Moretti, 2008). However, Morgan and Pollard (2003) show that the correlation between child gender and subsequent divorce is gone by 1994 in Current Population Survey data. And, Lundberg, McLanahan, and Rose (2007) find that the association between child gender and parental living arrangements disappears by the time the child is one year old using a sample of low-income parents from the Fragile Families and Child Wellbeing Study. Overall, the evidence suggests that by the 2000s (the time period of our data), the impact of child gender on family structure is likely at most very small. As will be discussed further in Section 4, this slight selection effect into family structure by child gender is far too small to explain the 3.5-5.5 percentage point excess ADHD gender gaps we estimate for non-traditional family structures.

The demographic and socioeconomic summary statistics by child gender and family structure presented in 3.1 are also consistent with there being very limited

[5] In the NHIS, family structure is a snapshot of the household at the time of the interview. The ADHD variable is measured as ever having been diagnosed. No information is collected about the timing of an ADHD diagnosis, marriages, separations, or divorces, making it impossible to determine whether the diagnosis was made before or after a change in family structure.

selection into family structures related to child gender. 3.1 shows that there are very few differences in child or parental characteristics by gender within or across family structures, and that the few differences that exist are extremely small. The only male-female gap that is statistically different across family structures (difference-in-difference) is number of children. The male-female gap is 0.06 lower in single parent families and 0.05 lower in blended families compared to traditional families. This is consistent with an extremely small difference in family composition. In all other cases observables are balanced. In other words, child gender appears to be nearly randomly assigned across family structures; boys and girls are effectively equally likely to be observed in traditional, single, and blended families.

In contrast to observable characteristics, which are essentially equal across child gender within and across family structures, 3.2 shows that most health and behavioral outcomes differ across gender within family structures. For example, boys are more likely to have learning disabilities, developmental disabilities, emotional difficulties, and asthma, and are less likely to have a good attention span across all family structures. And at the top of the list of worse outcomes for boys across all family structures is the probability of ADHD. The magnitude of the gender gap between boys and girls in ADHD diagnosis is striking at 9 percent, 11 percent, and 5 percent for single parent, blended, and traditional families respectively.

Difference-in-difference calculations that compare the gaps between boys and girls across family structures are presented in the last two columns of 3.2. These results provide preliminary evidence that boys in non-traditional families are doing especially poorly. The gap between boys and girls in ADHD diagnosis is 3 percentage points larger in single parent families than in traditional families. Likewise, the ADHD diagnosis gap 6 percentage points larger in blended than traditional families. Similar gaps emerge in attention span and learning disabilities.

3.3 Empirical Specification

In order to test whether family structure affects the gender gap in ADHD diagnosis, we use a linear probability framework that compares boys and girls in traditional, single parent, and blended families:

$$ADHD_{irt} = \beta_0 + \beta_1 M_{irt} + \beta_2 S_{irt} + \beta_3 M_{irt} * S_{irt} + \beta_4 B_{irt} + \beta_5 M_{irt} * B_{irt} + X_{irt}\theta + \gamma_r + \delta_s + \varepsilon_{irt}$$

$ADHD_{irt}$ is an indicator for whether or not child i living in region r interviewed in year t has ever been diagnosed with ADHD. The variables M, S, and B indicate that the child is male, living in a single parent household, or living in a blended family household.[6] The omitted group in the regression is girls in traditional families. Unless otherwise stated, all regressions contain a vector of background characteristics (X) that includes indicator variables for the number of children in the family, race, and age, as well as birth weight, the age of the youngest parent in the household, the education level of the most educated parent in the household, and a 5th order polynomial in household income. Region and year fixed effects absorb regional variation and control for a national time trend in ADHD diagnosis.

[6] Bertrand and Pan (2013) use the same identification strategy.

The coefficient β_1 is the male-female ADHD gap for traditional families. Similarly, $(\beta_1 + \beta_3)$ and $(\beta_1 + \beta_5)$ are the male-female ADHD gaps for single parent and blended families. The difference-in-difference estimate of the excess male-female gap for single parent families relative to traditional families is then β_3, and the equivalent excess gap for blended families is β_5.

As there is certainly non-random selection into family structure that is a function of parental characteristics, the coefficients β_2 and β_4 should not be interpreted as the causal effect of single parenthood and blended family structure on ADHD diagnosis. Although these coefficients are best thought about as simple correlations, to the best of our knowledge the relationship between family structure and ADHD has not been documented. For this reason we briefly discuss these findings in 3.4.1.

In contrast, under the assumption that child gender is not an important determinant of family structure, the male-female gap differences across family structures (β_3 and β_5) have a causal interpretation. While the balance we see across observable characteristics is largely consistent with this view, one should nonetheless interpret cautiously. That being said, for selection to account for the very large excess gender gaps we will report in 3.4.1, child gender based family structure selection would have to be much larger than the previous literature suggests.

3.4 Results

3.4.1 Family Structure and Gender Gaps in ADHD Diagnosis

3.3 presents regression estimates of the male-female gap in ADHD diagnosis across family structures. Column 1 includes the entire sample of children between the ages of 5 and 16, column 2 restricts the sample to children between the ages of 5 and 10, and column 3 restricts the sample to children aged 11 to 16.

Two new findings emerge from the first column of 3.3. First, children in non-traditional families have higher rates of ADHD than children in traditional families. Girls in single parent (blended) families are 1.2 (2.4) percentage points more likely to have an ADHD diagnosis than girls in traditional families. Boys in single parent (blended) families are 4.7 (8.1) percentage points more likely to be diagnosed than boys in traditional families. Perhaps surprisingly, the rate of ADHD is higher in blended families than single parent families.[7] Although the increased incidence of ADHD among children in single parent and blended families may be partially due to unobserved household characteristics correlated with family structure, the results are nevertheless interesting and previously undocumented.

[7] There is a large literature relating family structure to child outcomes; however, there is no consensus on whether estimated relationships are causal or merely correlations. In general, children in blended and single parent families fare similarly, but worse than children in traditional families. However, differences in outcomes are not always found between children raised in traditional and non-traditional families. See, for example, Ermisch and Francesconi (2001), Painter and Levine (2000), Case, Lin, and McLanahan (1999), Case, Lin, and McLanahan (2001), Evenhouse and Reilly (2004), Ginther and Pollak (2004), Gennetian (2005), Antecol and Bedard (2007).

The second new finding in the first column of 3.3 is that the male-female gap in ADHD diagnosis is much larger in non-traditional families. While boys in traditional households are 5.5 percentage points more likely to have been diagnosed with ADHD than girls, this gap is 3.5 percentage points larger in single parent families and 5.7 percentage points larger in blended families. In both cases the excess male-female gap (β_3 and β_5) is statistically significant at the 1% level.

The second and third columns of 3.3 show that the magnitude of the excess gender gap in non-traditional families is similar for children ages 5-10 and 11-16. That is, most of the gap emerges during early ages and does not widen substantially as children enter pre-teen and teen years. The excess male-female gap for single parent (blended) families is 3.5 (5.2) and 3.3 (5.6) percentage points for ages 5-10 and 11-16, respectively. Because the gender gaps are essentially identical across age ranges, the remainder of the paper uses the entire 5-16 age range.

While the specification used in 3.3 controls for household income, number of children in the household, and the age of the youngest parent in the household, it is reasonable to wonder if the results are driven by certain income groups, family sizes, or teen mothers. The first three columns of 3.4 report the results for 3.3 for each third of the income distribution. While a priori one might expect the excess male-female gaps to be largest at low income levels, the estimates in Table 4 reveal that the excess gaps for single parent and blended families exist, and are similar in size, across the entire income distribution. The point estimates do fluctuate somewhat across income levels, but the majority have overlapping confidence intervals. Although income may play a role in ADHD diagnosis, it does not appear to be a mechanism influencing differential gender gaps in diagnosis across family structure.

The next three columns of 3.4 run 3.3 separately by number of children in the household (family size). Again, the excess male-female gaps for single parent and blended families are remarkably consistent across sub-sample. The point estimates for the excess single parent male-female gap ranges from 3.3 to 4.0, and similarly from 4.7 to 6.9 for blended families.

The last two columns of 3.4 run 3.3 separately by mothers age at first birth for the subsample of children who live with their biological mother.[8] The first column includes children whose mother was a teenager when she had her first child and the second column includes children whose mother was at least 20 years old at her first birth. In single mother households, the excess gender gap is substantially larger for children of teen moms - 5.6 compared to 3.2 percentage points. This difference is statistically significant at conventional levels. That being said, the excess gender gap among children of non-teen single mothers is still large at 3.2 percentage points. In contrast, in blended family households, maternal age at first birth does not substantially affect the gender gap in ADHD diagnosis. But again, the excess gender gap is large - 4.8 percentage points for children of teen moms and 5.7 percentage points for children of non-teen moms.

Overall, we find large excess male-female ADHD gaps for single parent and blended families compared to traditional families for all age, income, family size, and age of mother at first birth groups. The magnitude of the gap and the ubiquity of its presence is, perhaps surprising, and certainly cause for concern.

[8] The age of the mother is only known if the mother resides in the household.

3.4.2 Family Structure and Gender Gaps in Other Cognitive Outcomes

The size of the excess male-female ADHD gap for non-traditional families suggests that we may see excess gaps in other cognitive outcomes related to, or resulting from, ADHD. Table 5 uses 3.3 to estimate the excess gaps in non-traditional families for outcomes that one might think would be associated with ADHD: good attention span, learning disability, developmental disability, emotional difficulties, worried, and unhappy. The emotional difficulties variable includes difficulties in emotions, concentration, behavior, or getting along with others. To the degree that treatment of ADHD alleviates its symptoms, gaps in these outcomes will be smaller than the gap in ADHD diagnosis.

The most striking result in 3.5 is the consistent male-female gap in cognitive outcomes. Parents consistently report that boys have worse attention spans, are more likely to have learning and developmental disabilities as well as emotional difficulties, but are less worried and happier than girls. In both single parent and blended households, an excess gender gap emerges for attention span, learning disability, and emotional difficulties.[9] One result does emerge that is not consistent with the rest of our findings. In blended families, the sign on the coefficient for the excess gap in developmental disabilities is negative, indicating that the male-female gap in developmental disabilities is smaller in blended than traditional families.

[9]Learning disabilities are frequently associated with ADHD. In a sample of 119 children, Mayes, Calhoun, and Crowell (2000) find that 70 percent of children with ADHD also had a learning disability.

Notably, there is no excess gender gap in worry or unhappiness in non-traditional families despite anxiety and depression being associated with ADHD. One reason the excess gender gap in ADHD may not translate to an excess gender gap in worry or unhappiness is boys lower likelihood of having internalizing symptoms, which are more associated with anxiety and depression. In their meta-analysis of gender differences in ADHD, Gershon and Gershon (2002) note that "females were rated as higher on internalizing problems than males, suggesting that comorbid conditions such as depression and anxiety may be more problematic for ADHD females."

3.4.3 Family Structure and Gender Gaps in Physical Health

3.6 presents results from regressions of gender and family type on physical health using 3.3. In some sense, the results from 3.6 can be viewed as a falsification test because diagnosis of physical health problems is inherently less subjective than mental health diagnoses. Thus, we would not expect the gender gap in hearing problems, ear infections, asthma, and food allergies to vary by family structure as long as our regressions adequately control for other factors affecting these diagnoses. The coefficients on the interaction terms in 3.6 show that there is no meaningfully large or consistent variation in physical health gender gaps by family structure. With the exception of a small excess gender gap in hearing problems in single parent households, the male-female gaps in ear infections, asthma, and food allergies are the same in traditional and non-traditional families.

3.5 Discussion

ADHD is the most common neurobehavioral disorder in childhood, yet seemingly unusual patterns in diagnosis remain largely unexplained and imply that the disorder is frequently under- and/or over-diagnosed. In this paper, we show that family structure is an important factor affecting diagnosis of ADHD and that family structure is particularly influential in the diagnosis of boys. First, we document that a non-traditional family structure is positively correlated with ADHD diagnosis for both boys and girls. Second, comparisons across family types show a large excess male-female gap in ADHD diagnosis in non-traditional families. The male-female gap in traditional, single parent, and blended families is 5.5, 9.0, and 11.2 percentage points, respectively. This excess gap in non-traditional families is pronounced across child ages as well as maternal age at first birth and exists across all levels of income and family size. The sheer magnitude of the excess male-female gap suggests that it could have substantial long-term consequences for boys in non-traditional families since ADHD and its symptoms are associated with lower completed education, earnings, and labor market participation.

Table 3.1: Child Demographics By Gender and Family Structure

	Single Parent Family			Blended Family			Traditional Family			Difference-in-Difference	
	Boys	Girls	Difference	Boys	Girls	Difference	Boys	Girls	Difference	Single-Traditional [(1)-(2)] -[(5)-(6)]	Blended-Traditional [(3)-(4)] -[(5)-(6)]
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)		
Parent Age	38.22	38.25	-0.03	35.27	35.38	-0.11	39.34	39.40	-0.06	0.03	-0.05
	(7.93)	(7.85)		(6.82)	(6.99)		(6.65)	(6.64)			
# Children in Family	1.88	1.92	**-0.04**	2.09	2.12	-0.03	2.21	2.19	**0.02**	**-0.06**	**-0.05**
	(0.97)	(1.01)		(1.08)	(1.10)		(0.99)	(0.97)			
Child Age	10.82	10.90	-0.07	11.22	11.23	-0.01	10.55	10.51	0.04	-0.11	-0.05
	(3.50)	(3.52)		(3.39)	(3.37)		(3.53)	(3.52)			
Birth Weight (grams)	2,855	2,759	**96**	2,897	2,803	**95**	2,948	2,879	**70**	26	25
	(1,287)	(1,240)		(1,280)	(1,226)		(1,287)	(1,219)			
Race											
White	0.49	0.48	0.00	0.65	0.64	0.01	0.70	0.69	0.01	0.00	0.00
	(0.50)	(0.50)		(0.48)	(0.48)		(0.46)	(0.46)			
Black	0.28	0.28	-0.01	0.13	0.14	-0.01	0.07	0.07	0.00	0.00	-0.01
	(0.45)	(0.45)		(0.34)	(0.35)		(0.25)	(0.26)			
American Native	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	(0.10)	(0.09)		(0.09)	(0.10)		(0.07)	(0.07)			
Asian	0.01	0.01	0.00	0.01	0.02	**-0.01**	0.04	0.05	0.00	0.00	0.00
	(0.12)	(0.12)		(0.12)	(0.14)		(0.21)	(0.21)			
Hispanic	0.16	0.16	0.00	0.14	0.14	0.00	0.15	0.15	0.00	0.00	0.00
	(0.36)	(0.36)		(0.35)	(0.35)		(0.35)	(0.35)			
Other Race	0.05	0.04	0.00	0.04	0.04	0.00	0.03	0.03	0.00	0.00	0.00
	(0.21)	(0.20)		(0.20)	(0.20)		(0.18)	(0.18)			
Multiple Race	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00
	(0.09)	(0.09)		(0.09)	(0.09)		(0.07)	(0.08)			
Highest Education Level of Parent(s)											
Less than High School	0.17	0.17	0.00	0.11	0.11	0.00	0.08	0.08	0.00	0.00	0.00
	(0.37)	(0.37)		(0.31)	(0.31)		(0.27)	(0.27)			
High School Diploma or GED	0.3	0.29	0.01	0.28	0.28	0.00	0.19	0.18	0.00	0.00	0.00
	(0.46)	(0.45)		(0.45)	(0.45)		(0.39)	(0.39)			
Some College	0.36	0.37	-0.01	0.39	0.39	0.01	0.3	0.3	0.00	-0.01	0.00
	(0.48)	(0.48)		(0.49)	(0.49)		(0.46)	(0.46)			
Bachelors Degree	0.12	0.12	0.00	0.15	0.15	0.00	0.25	0.25	0.00	0.00	0.00
	(0.33)	(0.33)		(0.36)	(0.36)		(0.43)	(0.43)			
Masters or More	0.05	0.05	0.00	0.06	0.07	-0.01	0.18	0.19	-0.01	0.01	0.00
	(0.22)	(0.22)		(0.25)	(0.26)		(0.39)	(0.39)			
Household Income	30,079	29,911	167	52,760	52,462	299	71,036	71,094	-58	226	357
	(24,055)	(23,868)		(35,155)	(35,309)		(34,664)	(34,786)			
N	13,679	13,135		6,519	6,316		30,794	28,705			

Note: Summary statistics are from the 1998 to 2012 National Health Interview Survey. Traditional families include both a biological mother and father. Single parent families include a single (unmarried and not cohabiting) biological parent. Blended families include a biological parent married or cohabiting with a non-biological parent of the sample child. The sample includes children between the ages of 5 and 16. Standard deviations are in parenthesis. Bolded cells indicate that the difference is statistically significant at the 5% level.

Table 3.2: Child Outcomes by Gender and Family Structure

	Single Parent Family			Blended Family			Traditional Family			Difference-in-Difference	
	Boys	Girls	Difference	Boys	Girls	Difference	Boys	Girls	Difference	Single-Traditional [(1)-(2)] -[(5)-(6)]	Blended-Traditional [(3)-(4)] -[(5)-(6)]
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)		
ADHD	0.15	0.06	**0.09**	0.19	0.08	**0.11**	0.09	0.03	**0.05**	**0.03**	**0.06**
	(0.36)	(0.24)		(0.39)	(0.26)		(0.29)	(0.18)			
Good Attention Span	0.82	0.89	**-0.07**	0.79	0.88	**-0.09**	0.9	0.94	**-0.04**	**-0.04**	**-0.05**
	(0.38)	(0.31)		(0.41)	(0.33)		(0.30)	(0.24)			
Learning Disability	0.14	0.08	**0.06**	0.14	0.08	**0.06**	0.09	0.05	**0.04**	**0.02**	**0.02**
	(0.34)	(0.26)		(0.34)	(0.27)		(0.28)	(0.21)			
Developmental Disability	0.06	0.03	**0.03**	0.05	0.04	**0.01**	0.04	0.02	**0.02**	0.00	**-0.01**
	(0.24)	(0.18)		(0.22)	(0.19)		(0.21)	(0.15)			
Emotional Difficulties	0.31	0.21	**0.10**	0.33	0.26	**0.07**	0.19	0.13	**0.06**	**0.04**	0.01
	(0.46)	(0.41)		(0.47)	(0.44)		(0.39)	(0.33)			
Worried	0.3	0.3	-0.01	0.3	0.32	-0.02	0.22	0.24	**-0.02**	0.01	0.00
	(0.46)	(0.46)		(0.46)	(0.47)		(0.42)	(0.43)			
Unhappy	0.15	0.17	-0.01	0.16	0.17	-0.01	0.08	0.09	**-0.01**	0.00	0.00
	(0.36)	(0.37)		(0.36)	(0.37)		(0.27)	(0.29)			
Hearing Problem	0.04	0.03	**0.01**	0.04	0.04	0.01	0.03	0.02	**0.00**	**0.01**	0.00
	(0.21)	(0.18)		(0.20)	(0.19)		(0.16)	(0.16)			
3+ Ear Infections in 12 Months	0.05	0.05	0.00	0.04	0.05	0.00	0.04	0.04	0.00	0.00	0.00
	(0.21)	(0.22)		(0.20)	(0.21)		(0.20)	(0.20)			
Asthma	0.22	0.16	**0.06**	0.19	0.15	**0.04**	0.16	0.11	**0.05**	0.01	0.00
	(0.41)	(0.37)		(0.40)	(0.36)		(0.36)	(0.31)			
Food Allergy	0.05	0.05	0.00	0.04	0.04	-0.01	0.04	0.04	0.00	0.00	0.00
	(0.21)	(0.21)		(0.19)	(0.21)		(0.20)	(0.20)			
N	13,679	13,135		6,519	6,316		30,794	28,705			

Note: Summary statistics are from the 1998 to 2012 National Health Interview Survey. Traditional families include both a biological mother and father. Single parent families include a single (unmarried and not cohabiting) biological parent. Blended families include a biological parent married or cohabiting with a non-biological parent of the sample child. The sample includes children between the ages of 5 and 16. Standard deviations are in parenthesis. Bolded cells indicate that the difference is statistically significant at the 5% level.

Table 3.3: Child Gender, Family Structure, and ADHD Diagnosis

	ADHD		
	5 - 16 Years Old	5 - 10 Years Old	11 - 16 Years Old
Male	0.055***	0.042***	0.069***
	(0.002)	(0.003)	(0.004)
Single Parent	0.012***	0.006	0.017***
	(0.003)	(0.004)	(0.005)
Male*Single Parent	0.035***	0.035***	0.033***
	(0.005)	(0.006)	(0.007)
Blended	0.024***	0.017***	0.031***
	(0.004)	(0.006)	(0.006)
Male*Blended	0.057***	0.052***	0.056***
	(0.007)	(0.010)	(0.010)
Mean of Dep. Var	0.0832	0.0636	0.101
Observations	99,148	48,044	51,104
R-squared	0.049	0.046	0.047

Note: Table presents estimates of child gender and family structure on ADHD diagnosis using NHIS data from 1998 to 2012. The sample includes children ages 5 to 16 years old. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: Child Gender, Family Structure, and ADHD Diagnosis by Income, Family Size, and Mother's Age at First Birth

	Income			Number of Children			Mother's Age at First Birth	
	Bottom Third	Middle Third	Top Third	1	2	3+	≤19	>20
Male	0.064***	0.052***	0.063***	0.055***	0.061***	0.047***	0.051***	0.055***
	(0.007)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.007)	(0.002)
Single Parent	0.012**	0.004	0.007	0.006	0.011**	0.021***	0.007	0.017***
	(0.006)	(0.006)	(0.010)	(0.006)	(0.005)	(0.006)	(0.008)	(0.004)
Male*Single Parent	0.023**	0.045***	0.039**	0.035***	0.033***	0.040***	0.056***	0.032***
	(0.010)	(0.010)	(0.019)	(0.009)	(0.008)	(0.009)	(0.012)	(0.006)
Blended	0.015*	0.028***	0.034***	0.011	0.030***	0.031***	0.021**	0.029***
	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.005)
Male*Blended	0.048***	0.070***	0.035**	0.069***	0.047***	0.054***	0.048***	0.057***
	(0.015)	(0.013)	(0.014)	(0.013)	(0.011)	(0.012)	(0.016)	(0.009)
Mean of Dep. Var	0.111	0.0865	0.0734	0.0981	0.0811	0.0711	0.0926	0.0779
Observations	26,416	26,538	26,505	27,752	41,582	29,814	15,020	78,863
R-squared	0.055	0.055	0.042	0.050	0.049	0.047	0.058	0.047

Note: Table presents estimates of child gender and family structure on ADHD diagnosis using NHIS data from 1998 to 2012. The sample includes children ages 5 to 16 years old. Households with a missing value for income are excluded from regressions by income group. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Child Gender, Family Structure, and Cognitive Outcomes

	Good Attention Span	Learning Disability	Developmental Disability	Emotional Difficulties	Worried	Unhappy
Male	-0.036***	0.041***	0.025***	0.019***	-0.019***	-0.014***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)
Single Parent	-0.012**	-0.003	0.000	0.008**	0.053***	0.051***
	(0.006)	(0.003)	(0.002)	(0.004)	(0.009)	(0.007)
Male*Single Parent	-0.037***	0.023***	0.005	0.021***	0.013	0.000
	(0.008)	(0.005)	(0.003)	(0.005)	(0.011)	(0.008)
Blended	-0.035***	0.017***	0.013***	0.031***	0.061***	0.058***
	(0.008)	(0.004)	(0.003)	(0.005)	(0.011)	(0.009)
Male*Blended	-0.051***	0.017**	-0.010**	0.017**	-0.000	0.003
	(0.012)	(0.007)	(0.004)	(0.008)	(0.015)	(0.012)
Mean of Dep. Var	0.892	0.0828	0.0380	0.0513	0.260	0.115
Observations	44,120	99,139	99,139	55,259	44,120	44,120
R-squared	0.031	0.031	0.015	0.025	0.036	0.029

Note: Table presents estimates of child gender and family structure on developmental outcomes using NHIS data from 1998 to 2012. The sample includes children ages 5 to 16 years old. Learning disability and developmental disability are included in the 1998 to 2012 surveys and difficulties is included in the 2004 to 2012 surveys. Worried, unhappy, and good attention span are included in the 2004 to 2007 and 2010 to 2012 surveys. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Child Gender, Family Structure, and Physical Health

	Hearing Problem	3+ Ear Infections in 12 Months	Asthma	Food Allergy
Male	0.003**	-0.002	0.049***	-0.002
	(0.001)	(0.002)	(0.003)	(0.002)
Single Parent	-0.001	0.001	0.025***	-0.001
	(0.002)	(0.003)	(0.005)	(0.003)
Male*Single Parent	0.008**	-0.002	0.009	0.001
	(0.003)	(0.003)	(0.006)	(0.003)
Blended	0.005	0.003	0.023***	0.003
	(0.003)	(0.003)	(0.006)	(0.003)
Male*Blended	0.003	-0.003	-0.003	-0.004
	(0.004)	(0.004)	(0.008)	(0.004)
Mean of Dep. Var	0.0314	0.0432	0.154	0.0437
Observations	99,139	99,139	99,139	99,139
R-squared	0.008	0.018	0.019	0.005

Note: Table presents estimates of child gender and family structure on health outcomes using NHIS data from 1998 to 2012. The sample includes children ages 5 to 16 years old. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Bibliography

ABREVAYA, J., AND L. PUZZELLO (2012): "Taxes, Cigarette Consumption, and Smoking Intensity: Comment," *The American Economic Review*, 102(4), 1751–1763.

ADAMS, E. K., S. MARKOWITZ, P. M. DIETZ, AND V. T. TONG (2013): "Expansion of Medicaid Covered Smoking Cessation Services: Maternal Smoking and Birth Outcomes," *Medicare & Medicaid Research Review*, 3(3), E1 – E23.

ADDA, J., AND F. CORNAGLIA (2006): "Taxes, Cigarette Consumption, and Smoking Intensity," *The American Economic Review*, 96(4), pp. 1013–1028.

ADDA, J., AND F. CORNAGLIA (2010): "The Effect of Bans and Taxes on Passive Smoking," *American Economic Journal: Applied Economics*, 2(1), 1–32.

ADHIKARI, B., J. KAHENDE, A. MALARCHER, T. PECHACEK, AND V. TONG (2008): "Smoking-Attributable Mortality, Years of Potential Life Lost, and Productivity Losses — United States, 2000–2004," Morbitity and Mortality Weekly Report 57, Centers for Disease Control.

Akinbami, L. J., X. Liu, P. N. Pator, and C. Reuben (2011): "Attention Deficit Hyperactivity Disorder Among Children Aged 5-17 Years in the United States, 1998-2009," NCHS Data Brief 70, National Center for Health Statistics.

Almond, D., K. Y. Chay, and D. S. Lee (2005): "The Costs of Low Birth Weight," *The Quarterly Journal of Economics*, 120(3), 1031–1083.

Anger, S., M. Kvasnicka, and T. Siedler (2011): "One last puff? Public smoking bans and smoking behavior," *Journal of Health Economics*, 30, 591–601.

Antecol, H., and K. Bedard (2007): "Does Single Parenthood Increase the Probability of Teenage Promiscuity, Substance Abuse, and Crime?," *Journal of Population Economics*, 20, 55–71.

Armour, B. S., and E. A. F. I. C. Fiebelkorn (2009): "State-Level Medicaid Expenditures Attributable to Smoking," *Preventing Chronic Disease*, 6(3), A84.

Barcellos, S. H., and M. Jacobson (2014): "The Effects of Medicare on Medical Expenditure Risk and Financial Strain," Working Paper 19954, National Bureau of Economic Research.

Barreca, A. I., J. M. Lindo, and G. R. Waddell (2011): "Heaping-Induced Bias in Regression-Discontinuity Designs," *NBER Working Paper*, (17408).

Becker, G. S., W. H. J. Hubbard, and K. M. Murphy (2010): "Explaining the Worldwide Boom in Higher Education of Women," *Journal of Human Capital*, 43(3), 203–241.

Bedard, K., and O. Deschenes (2005): "Sex Preferences, Marital Dissolution and the Economic Status of Women," *Journal of Human Resou*, 40(2), 411–434.

Bergstrom, T. (1995): "A Survey of Theories of the Family," in *Handbook of Population and Family Economics*, ed. by M. Rosenzweig, and O. Stark, pp. 21–59. Elsevier.

Bertrand, M., and J. Pan (2013): "The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior," *American Economic Journal: Applied Economics*, 5(1), 32–64.

Bitler, M. P., C. S. Carpenter, and M. Zavodny (2010): "Effects of venue-specific state clean indoor air laws on smoking-related outcomes," *Health Economics*, 19(12), 1425–1440.

Blumberg, L. J., L. Dubay, and S. A. Norton (2000): "Did the Medicaid expansions for children displace private insurance? An analysis using the SIPP," *Journal of Health Economics*, 19(1), 33 – 60.

Boyle, M. A., and J. N. Lahey (2010): "Health Insurance and the Labor Supply Decisions of Older Workers: Evidence from U.S. Department of Veterans Affairs Expansion," *Journal of Public Economics*, 94, 467–478.

Boyle, M. A., and J. N. Lahey (2012): "Spousal Labor Market Effects from Government Health Insurance: Evidence from a Veterans Affairs Expansion," Working Paper, Center for Retirement Research at Boston College wp2012-16, Center for Retirement Research.

Burns, M. E., and M. C. Fiore (2001): "Under-use of Tobacco Dependence Treatment Among Wisconsin's Fee-for-service Medicaid Recipients," *Wisconsin Medical Journal*, 100(3), 54–58.

Busch, S. H., and N. Duchovny (2005): "Family coverage expansions: Impact on insurance coverage and health care utilization of parents," *Journal of Health Economics*, 24(5), 876–890.

Callison, K., and R. Kaestner (2013): "Do higher tobacco taxes reduce adult smoking? New evidence of the effect of recent cigarette tax increases on adult smoking," *Economic Inquiry*.

Cancer Action Network, American Lung Association, and Partnership for Prevention (2011): "The Need for Tobacco Cessation Treatment in the Essential Health Benefits Package," Online.

Card, D., C. Dobkin, and N. Maestas (2008): "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare," *The American Economic Review*, 98(5), pp. 2242–2258.

——— (2009): "Does Medicare Save Lives?," *The Quarterly Journal of Economics*, 124(2), 597–636.

Card, D., and L. D. Shore-Sheppard (2004): "Using Discontinuous Eligibility Rules to Identify the Effects of the Federal Medicaid Expansions on Low-Income Children," *The Review of Economics and Statistics*, 86(3), pp. 752–766.

Carpenter, C., and C. Dobkin (2009): "The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age," *American Economic Journal: Applied Economics*, 1(1), pp. 164–182.

Carpenter, C., S. Postolek, and C. Warman (2011): "Public Place Smoking Laws and Exposure to Environmental Tobacco Smoke (ETS)," *American Economic Journal: Economic Policy*, 3(3), 35–61.

Carpenter, C. S. (2009): "The Effects of Local Workplace Smoking Laws on Smoking Restrictions and Exposure to Smoke at Work," *Journal of Human Resources*, 44(4).

Case, A., I.-F. Lin, and S. McLanahan (1999): "Household Resource Allocation in Stepfamilies: Darwin Reflects on the Plight of Cinderella," *American Economic Review*, 89(2), 234–238.

——— (2001): "Educational Attainment of Siblings in Stepfamilies," *Evolution and Human Behavior*, 22(4), 269–289.

Chaloupka, F. J., and J. A. Tauras (2004): "The Impact of Nicotine Replacement Therapies on Cigarette Demand," *Journal of Economics and Finance*, 28(3), 395–403.

Chaloupka, F. J., and K. E. Warner (2000): "Chapter 29 The economics of smoking," in *Handbook of Health Economics*, ed. by A. J. Culyer, and J. P. Newhouse, vol. 1, Part B of *Handbook of Health Economics*, pp. 1539 – 1627. Elsevier.

Charness, G., and U. Gneezy (2012): "Strong Evidence for Gender Differences in Risk Taking," *Journal of Economic Behavior & Organization*, 83(1), 50 – 58.

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

Croson, R., and U. Gneezy (2009): "Gender Differences in Preferences," *Journal of Economic Literature*, 47(2), 448–74.

Cubanski, J., J. Huang, A. Damico, G. Jacobson, and T. Neuman (2010): "Medicare Chartbook," Fourth edition, Kaiser Family Foundation.

Cummings, K. M., and A. Hyland (2005): "Impact of Nicotine Replacement Therapy on Smoking Behavior," *Annual Review of Public Health*, 26(1), 583–599, PMID: 15760302.

Currie, J., and M. Stabile (2006): "Child Mental Health and Human Capital Accumulation: The Case of ADHD," *Journal of Health Economics*, 25(25), 1094–1118.

Cutler, D. M., A. Finkelstein, and K. McGarry (2008): "Preference Heterogeneity and Insurance Markets: Explaining a Puzzle of Insurance," *American Economic Review*, 98(2), 157–62.

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

Cutler, D. M., and R. J. Zeckhauser (2000): "Chapter 11: The anatomy of health insurance," in *Handbook of Health Economics*, ed. by A. J. Culyer, and J. P. Newhouse, vol. 1, Part A, pp. 563 – 643. Elsevier.

Dahl, G., and E. Moretti (2008): "The Demand for Sons," *The Review of Economic Studies*, 75(4), 1084–1120.

DeCicca, P., D. Kenkel, and A. Mathios (2002): "Putting Out the Fires: Will Higher Taxes Reduce the Onset of Youth Smoking?," *Journal of Political Economy*, 110(1), pp. 144–169.

DeCicca, P., and L. McLeod (2008): "Cigarette taxes and older adult smoking: Evidence from recent large tax increases," *Journal of Health Economics*, 27(4), 918 – 929.

Decker, S., and C. Rapaport (2002): "Medicare and Disparities in Women's Health," Working Paper 8761, National Bureau of Economic Research.

Decker, S. L. (2005): "Medicare and the Health of Women with Breast Cancer," *Journal of Human Resources*, XL(4), 948–968.

Dubay, L. C., and G. M. Kenney (1996): "The Effects of Medicaid Expansions on Insurance Coverage of Children," *The Future of Children*, 6(1), pp. 152–161.

——— (1997): "Did Medicaid Expansions for Pregnant Women Crowd-Out Private Insurance?," *Health Affairs*, 16(1), 185–193.

DUGGAN, M., AND F. S. MORTON (2010): "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization," *American Economic Review*, 100(1), 590–607.

ECKEL, C. C., AND P. J. GROSSMAN (2008): "Men, Women and Risk Aversion: Experimental Evidence," in *Handbook of Experimental Economic Results*, ed. by C. R. Plott, and V. L. Smith, vol. 1, Part 7, chap. 113, pp. 1061–1073. Elsevier, 1 edn.

EINAV, L., A. FINKELSTEIN, AND M. R. CULLEN (2010): "Estimating Welfare in Insurance Markets Using Variation in Prices," *The Quarterly Journal of Economics*, 125(3), 877–921.

ELDER, T. E. (2010): "The importance of relative standards in ADHD diagnoses: Evidence based on exact birth dates," *Journal of Health Economics*, 29(5), 641 – 656.

ELDER, T. E., AND D. H. LUBOTSKY (2009): "Kindergarten Entrance Age and Childrens Achievement: Impacts of State Policies, Family Background, and Peers," *The Journal of Human Resources*, 44(3), 641–683.

ERMISCH, J. F., AND M. FRANCESCONI (2001): "Family structure and children's achievements," *Journal of Population Economics*, 14(2), 249–270.

EVANS, W. N., AND M. C. FARRELLY (1998): "The Compensating Behavior of Smokers: Taxes, Tar, and Nicotine," *The RAND Journal of Economics*, 29(3), pp. 578–595.

Evans, W. S., M. S. Morrill, and S. T. Parente (2010): "Measuring Inappropriate Medical Diagnosis and Treatment in Survey Data: The Case of ADHD Among School-Age Children," *Journal of Health Economics*, 29(5), 657–673.

Evenhouse, E., and S. Reilly (2004): "A Sibling Study of Stepchild Well-being," *Journal of Human Resources*, 39(1), 248–276.

Fairlie, R. W., K. Kapur, and S. Gates (2012): "Job Lock: Evidence from a Regression Discontinuity Design," Working Papers 201215, School Of Economics, University College Dublin.

Farrelly, M. C., J. W. Bray, T. Pechacek, and T. Woollery (2001): "Response by Adults to Increases in Cigarette Prices by Sociodemographic Characteristics," *Southern Economic Journal*, 68(1), pp. 156–165.

Feldman, H. M., and M. I. Reiff (2014): "Attention DeficitHyperactivity Disorder in Children and Adolescents," *New England Journal of Medicine*, 370(9), 838–846, PMID: 24571756.

Finkelstein, A., and R. McKnight (2008): "What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending," *Journal of Public Economics*, 92(7), 1644 – 1668.

Fletcher, J., and B. Wolfe (2008): "Child mental health and human capital accumulation: The case of {ADHD} revisited," *Journal of Health Economics*, 27(3), 794 – 800.

——— (2009): "Long-term consequences of childhood ADHD on criminal activities," *Journal of Mental Health Policy and Economics*, 12(3), 119–138.

Fletcher, J. M. (2014): "The Effects of Childhood ADHD on Adult Labor Market Outcomes," *Health Economics*, 23(2), 159–181.

Fulton, B. D. R. M. S., S. P. Hinshaw, P. Levine, S. Stone, T. T. Brown, and S. Modrek (2009): "National Variation of ADHD Diagnostic Prevalence and Medication Use: Health Care Providers and Education Policies," *Psychiatric Services*, 60(8), 1075–1083.

Gennetian, L. (2005): "One or two parents? Half or step siblings? The effect of family structure on young children's achievement," *Journal of Population Economics*, 18(3), 415–436.

Gershon, J., and J. Gershon (2002): "A Meta-Analytic Review of Gender Differences in ADHD," *Journal of Attention Disorders*, 5(3), 143–154.

Gin, X., D. Karlan, and J. Zinman (2010): "Put Your Money Where Your Butt Is: A Commitment Contract for Smoking Cessation," *American Economic Journal: Applied Economics*, 2(4), pp. 213–235.

Ginther, D., and R. Pollak (2004): "Family structure and childrens educational outcomes: Blended families, stylized facts, and descriptive regressions," *Demography*, 41(4), 671–696.

Gruber, J., and K. Simon (2008): "Crowd-out 10 years later: Have recent public insurance expansions crowded out private health insurance?," *Journal of Health Economics*, 27(2), 201 – 217.

Halpin, H., S. McMenamin, C. Cella, N. Bellows, and C. Husten (2008): "State Medicaid Coverage for Tobacco-Dependence Treatments — United States, 2006," Morbidity and Mortality Weekly Report 57, Centers for Disease Control.

Halpin, H., S. McMenamin, C. Cella, C. Husten, and A. Rosenthal (2006): "State Medicaid Coverage for Tobacco-Dependence Treatments — United States, 2005," Morbidity and Mortality Weekly Report 55, Centers for Disease Control.

Halpin, H., S. McMenamin, C. Orleans, and C. Husten (2004): "State Medicaid Coverage for Tobacco-Dependence Treatments — United States, 1994–2002," Morbidity and Mortality Weekly Report 53, Centers for Disease Control.

Hamersma, S., and M. Kim (2009): "The effect of parental Medicaid expansions on job mobility," *Journal of Health Economics*, 28(4), 761 – 770.

——— (2013): "Participation and crowd out: Assessing the effects of parental Medicaid expansions," *Journal of Health Economics*, 32(1), 160 – 171.

Heckman, J. J., and Y. Rubinstein (2001): "The Importance of Noncognitive Skills: Lessons from the GED Testing Program," *American Economic Review*, 91(2), 145–149.

Heckman, J. J., J. Stixrud, and S. Urzua (2006): "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24(3), pp. 411–482.

Jacob, B. A. (2002): "Where the boys aren't: non-cognitive skills, returns to school and the gender gap in higher education," *Economics of Education Review*, 21(6), 589 – 598.

Kaiser Family Foundation (2012): "Medicare at a Glance," Number 1066-15.

Katzev, A. R., R. L. Warner, and A. C. Acock (1994): "Girls or Boys? Relationship of Child Gender to Marital Instability," *Journal of Marriage and the Family*, 56, 89–100.

Keeler, T. E., T.-w. Hu, A. Keith, R. Manning, M. D. Marciniak, M. Ong, and H.-Y. Sung (2002): "The benefits of switching smoking cessation drugs to over-the-counter status," *Health Economics*, 11(5), 389–402.

Land, T., D. Warner, M. Paskowsky, A. Cammaerts, L. Wetherell, R. Kaufmann, L. Zhang, A. Malarcher, T. Pechacek, and L. Keithly (2010): "Medicaid Coverage for Tobacco Dependence Treatments in Massachusetts and Associated Decreases in Smoking Prevalence," *PLoS ONE*, 5(3), e9770.

Lee, D. S., and T. Lemieux (2009): "Regression Discontinuity Designs in Economics," Working Paper 14723, National Bureau of Economic Research.

Lemieux, T., and K. Milligan (2008): "Incentive effects of social assistance: A regression discontinuity approach," *Journal of Econometrics*, 142(2), 807 – 828, The regression discontinuity design: Theory and applications.

Li, C., and C. M. Dresler (2012): "Medicaid Coverage and Utilization of Covered Tobacco-Cessation Treatments: The Arkansas Experience," *American Journal of Preventive Medicine*, 42(6), 588 – 595.

Lichtenberg, F. R. (2002): "The Effects of Medicare on Health Care Utilization and Outcomes," *Forum for Health Economics & Policy*, 5 (Frontiers in Health Policy Research), Article 3.

Lien, D. S., and W. N. Evans (2005): "Estimating the Impact of Large Cigarette Tax Hikes: The Case of Maternal Smoking and Infant Birth Weight," *The Journal of Human Resources*, 40(2), pp. 373–392.

Liu, F. (2009): "Effect of Medicaid Coverage of Tobacco-Dependence Treatments on Smoking Cessation," *International Journal of Environmental Research and Public Health*, 6, 3143–3155.

——— (2010): "Quit attempts and intention to quit cigarette smoking among Medicaid recipients in the USA," *Public Health*, 124, 553 – 558.

Lo Sasso, A. T., and T. C. Buchmueller (2004): "The effect of the state childrens health insurance program on health insurance coverage," *Journal of Health Economics*, 23(5), 1059 – 1082.

Lundberg, S., S. McLanahan, and E. Rose (2007): "Child Gender and Father Involvement in Fragile Families," *Demography*, 44(1), 79–92.

Lundberg, S., S. Pabilonia, and J. Ward-Batts (2007): "Time Allocation of Parents and Investments in Sons and Daughters," *Working Paper, University of Washington*.

Lundberg, S., and R. Pollak (1991): "Separate Spheres Bargaining and the Marriage Market," Discussion Papers in Economics at the University of Washington 91-08, Department of Economics at the University of Washington.

Lundberg, S., and E. Rose (2003): "Child Gender and the Transition to Marriage," *Demography*, 40(2), 333–350.

Manser, M., and M. Brown (1980): "Marriage and Household Decision-Making: A Bargaining Analy," *International Eco*, 21, 21–34.

Mayes, S. D., S. L. Calhoun, and E. W. Crowell (2000): "Learning Disabilities and ADHD: Overlapping Spectrum Disorders," *Journal of Learning Disabilities*, 43(5), 417–424.

McCrary, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, 142(2), 698 – 714.

McElroy, M. B., and M. J. Horney (1981): "Nash-Bargained Household Decisions: Toward a Generalization of the Theory of Demand," *International Econom*, 22, 333–349.

McMenamin, S., H. Halpin, N. Bellows, C. Husten, and A. Rosenthal (2009): "State Medicaid Coverage for Tobacco-Dependence Treatments — United States, 2007," Morbidity and Mortality Weekly Report 58, Centers for Disease Control.

McMenamin, S. B., H. A. Halpin, J. K. Ibrahim, and C. Orleans (2004): "Physician and enrollee knowledge of Medicaid coverage for tobacco dependence treatments," *American Journal of Preventive Medicine*, 26(2), 99 – 104.

McWilliams, J. M., E. Meara, A. M. Zaslavsky, and J. Z. Ayanian (2007): "Use of Health Services by Previously Uninsured Medicare Beneficiaries," *New England Journal of Medicine*, 357(2), 143–153.

McWilliams, M. J., A. Zaslavsky, E. Meara, and J. Ayanian (2003): "Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults," *Journal of the American Medical Association*, 290(6), 757–764.

Morgan, S. P., and M. S. Pollard (2003): "Do Parents of Girls Really Have a Higher Risk of Divorce?," *Working Paper*.

Mott, F. L. (1994): "Sons, Daughters and Fathers Absence: Differentials in Father-Leaving Probabilities and in Home Environments," *Journal of Family Issues*, 15(1), 97–128.

National Center for Health Statistics (2010): "Data File Documentation, National Health Interview Survey, [Machine-readable data file and documentation]," National Center for Health Statistics, Centers for Disease Control and Prevention, Hyattsville, Maryland.

Novello, A. C. (1990): "Surgeon General's Report on the Health Benefits of Smoking Cessation," Public Health Report 105, Department of Health and Human Services.

O'Connor, J. T. (2013): "Comprehensive Assessment of ACA Factors that will Affect Individual Market Premiums in 2014," Discussion paper, Miliman.

Office of the Actuary (2011): "2011 Actuarial Report on the Financial Outlook for Medicaid," Discussion paper, Centers for Medicare & Medicaid Services.

Ostbye, T., and D. H. Taylor (2004): "The Effect of Smoking on Years of Healthy Life (YHL) Lost among Middle-Aged and Older Americans," *Health Services Research*, 39(3), 531–552.

Ostbye, T., D. H. Taylor, and S.-H. Jung (2002): "A Longitudinal Study of the Effects of Tobacco Smoking and Other Modifiable Risk Factors on Ill Health in Middle-Aged and Old Americans: Results from the Health and Retirement Study and Asset and Health Dynamics among the Oldest Old Survey," *Preventive Medicine*, 34(3), 334 – 345.

Painter, G., and D. I. Levine (2000): "Family Structure and Youths Outcomes: Which Correlations are Causal," *The Journal of Human Resources*, 35(3), 524–549.

Petersen, R., J. M. Garrett, C. L. Melvin, and K. E. Hartmann (2006): "Medicaid reimbursement for prenatal smoking intervention influences quitting and cessation," *Tobacco Control*, 15(1), 30–34.

Ruhm, C. J. (2005): "Healthy living in hard times," *Journal of Health Economics*, 24(2), 341 – 363.

Saffer, H., M. Wakefield, and Y. Terry-McElrath (2007): "The Effect of Nicotine Replacement Therapy Advertising on Youth Smoking," Working Paper 12964, National Bureau of Economic Research.

Sexton, M., and J. R. Hebel (1984): "A clinical trial of change in maternal smoking and its effect on birth weight," *JAMA*, 251(7), 911–915.

Shigeoka, H. (forthcoming): "The Effect of Patient Cost Sharing on Utilization, Health, and Risk Protection," *American Economic Review*.

Shore-Sheppard, L., T. C. Buchmueller, and G. A. Jensen (2000): "Medicaid and crowding out of private insurance: a re-examination using firm level data," *Journal of Health Economics*, 19(1), 61 – 91.

Stead, L., R. Perera, C. Bullen, D. Mand, J. Hartmann-Boyce, K. Cahill, and T. Lancaster (2012): "Nicotine replacementtherapyfor smoking cessation (Review)," Discussion paper, The Cochrane Collaboration.

Tauras, J. A., and F. J. Chaloupka (2003): "The demand for nicotine replacement therapies," *Nicotine & Tobacco Research*, 5(2), 237–243.

Tong, V. T., J. R. Jones, P. M. Dietz, D. D'Angelo, and J. M. Bombard (2009): "Trends in Smoking Before, During, and After Pregnancy — Pregnancy Risk Assessment Monitoring System (PRAMS), United States, 31 Sites, 2000 - 2005," MMWR 58, Centers for Disease Control and Prevention.

VIsser, S. N., M. L. Danielson, R. H. Bitsko, J. R. Holbrook, M. D. Kogan, R. M. Ghandour, R. Perou, and S. J. Blumberg (2014):

"Trends in the Parent-Report of Health Care Provider-Diagnosed and Medicated Attention-Deficit/Hyperactivity Disorder: United States, 2003-2011," *Journal of the American Academy of Child & Adolescent Psychiatry*, 53(1), 34–46.

Volpp, K. G., A. Gurmankin Levy, D. A. Asch, J. A. Berlin, J. J. Murphy, A. Gomez, H. Sox, J. Zhu, and C. Lerman (2006): "A Randomized Controlled Trial of Financial Incentives for Smoking Cessation," *Cancer Epidemiology Biomarkers & Prevention*, 15(1), 12–18.

Volpp, K. G., A. B. Troxel, M. V. Pauly, H. A. Glick, A. Puig, D. A. Asch, R. Galvin, J. Zhu, F. Wan, J. DeGuzman, E. Corbett, J. Weiner, and J. Audrain-McGovern (2009): "A Randomized, Controlled Trial of Financial Incentives for Smoking Cessation," *New England Journal of Medicine*, 360(7), 699–709, PMID: 19213683.

Woolley, F. (1988): "A Non-Cooperative Model of Family Decision Making," *Working Paper*, TIDI/125 (London School of Economics).

Wu, P., K. Wilson, P. Dimoulas, and E. Mills (2006): "Effectiveness of smoking cessation therapies: a systematic review and meta-analysis," *BMC Public Health*, 6(1), 300.

Yazici, E., and R. Kaestner (2000): "Medicaid Expansions and the Crowding Out of Private Health Insurance Among Children," *Inquiry*, 37(1), 23–32.

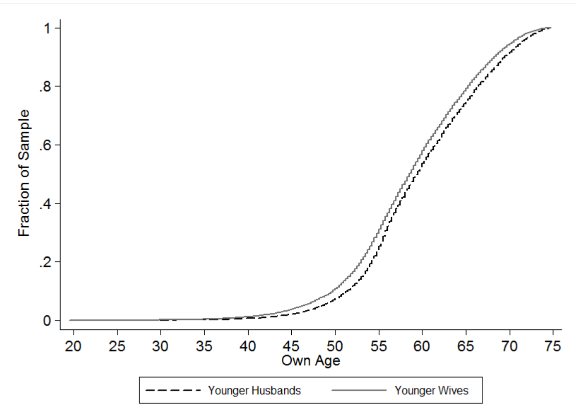
Yoruk, B. K., and C. E. Yoruk (2011): "The impact of minimum legal drinking age laws on alcohol consumption, smoking, and marijuana use: Evidence from a regression discontinuity design using exact date of birth," *Journal of Health Economics*, 30(4), 740 – 752.

Appendices

Appendix A

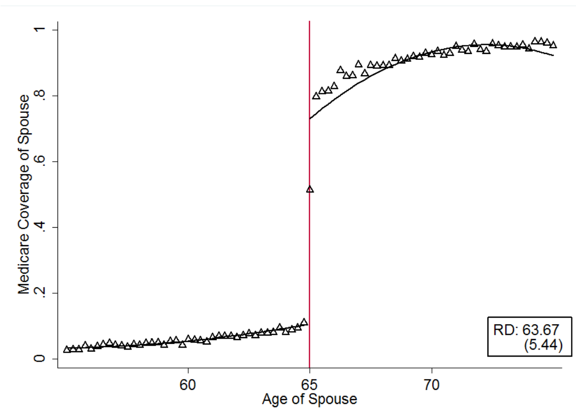
The Medicare Eligibility Gap

Figure A.1: Age Distribution of Younger Spouse Sample



Note: Graph shows the cumulative distribution function of younger spouses' age by gender.

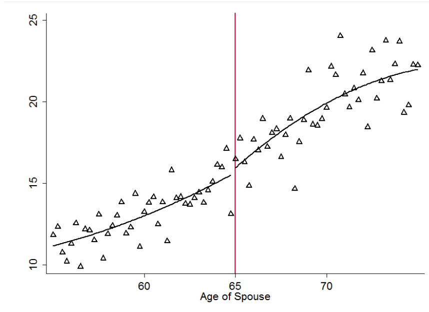
Figure A.2: First Stage Estimate



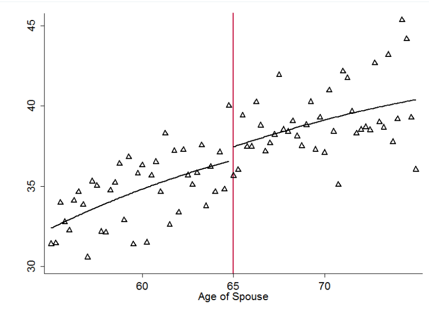
Note: The graph shows the fraction of older spouses that report having Medicare coverage as a function of the age of the older spouse. The scatterplot is the raw data and the curves are quadratic polynomial fits estimated separately on each side of the age-65 threshold. The first-stage estimate of the take up of Medicare at age 65 among older spouses is 63.67 percent.

Figure A.3: Education and Race of Younger Spouses

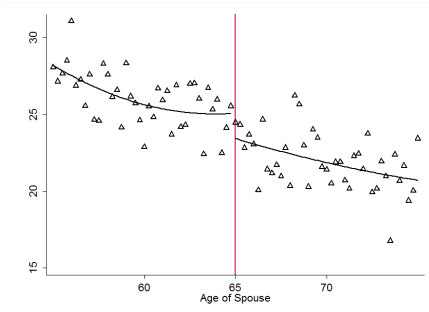
(a) Less than High School



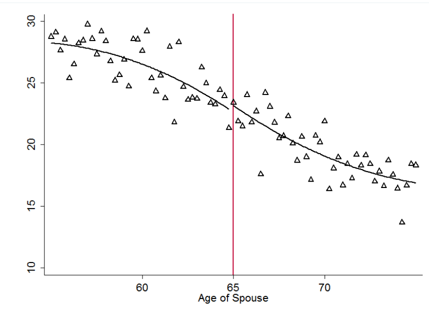
(b) High School



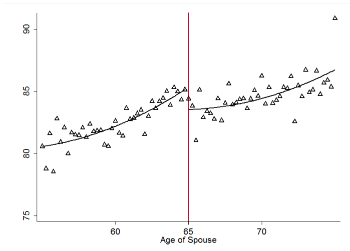
(c) Some College



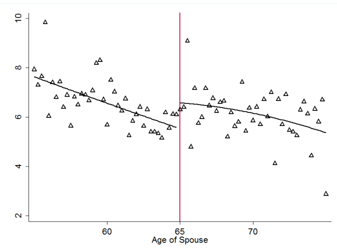
(d) College Plus



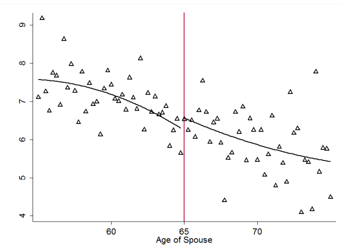
(e) White



(f) Black



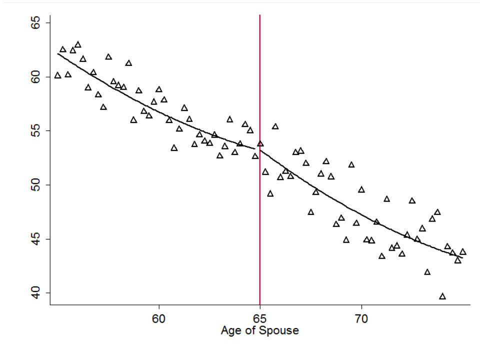
(g) Hispanic



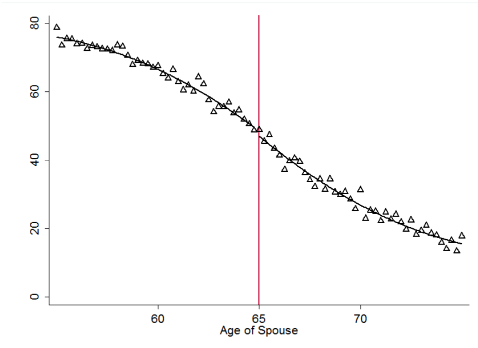
Note: Graphs show the fraction of younger spouses with each education level and race plotted against the age of the older spouse. Scatterplots are means of the raw data and solid lines are quadratic polynomial fits.

Figure A.4: Labor Force Participation and Health Status of Younger Spouses

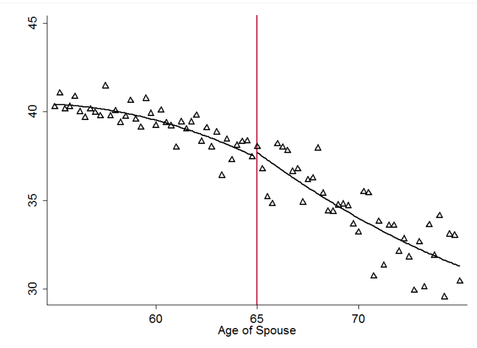
(a) Health Excellent/Very Good



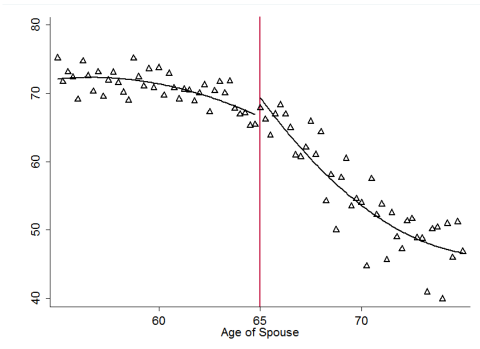
(b) Working



(c) Hours Worked



(d) Health Insurance Offered at Work



Note: Graphs show the fraction of younger spouses with a given labor force participation status and health status plotted against the age of the older spouse. Scatterplots are means of the raw data and solid lines are quadratic polynomial fits.

Table A.1: Comparison of Bandwidth and Polynomial Choices in Regressions of Insurance Coverage on Spousal and Own Medicare Eligibility

Panel A: Women			
Degree of Polynomial	Bandwidth		
First Order	24 Quarters	32 Quarters	40 Quarters
Spouse65	-1.14	-1.73**	-1.65**
	(0.68)	(0.59)	(0.53)
Self65	6.79***	7.37***	7.64***
	(0.53)	(0.49)	(0.46)
Second Order			
Spouse65	-0.15	-0.47	-1.24
	(0.71)	(0.71)	(0.80)
Self65	6.10***	6.88***	7.33***
	(0.72)	(0.62)	(0.56)
Third Order			
Spouse65	1.78**	0.65	0.40
	(0.65)	(0.65)	(0.64)
Self65	5.52***	6.47***	6.83***
	(0.80)	(0.74)	(0.67)
Fourth Order			
Spouse65	1.59*	1.64*	0.92
	(0.72)	(0.67)	(0.68)
Self65	5.54***	6.18***	6.54***
	(0.98)	(0.90)	(0.85)

Panel B: Men			
Degree of Polynomial	Bandwidth		
First Order	24 Quarters	32 Quarters	40 Quarters
Spouse65	-3.84**	-3.23**	-3.24**
	(1.31)	(1.14)	(1.06)
Self65	6.98***	7.07***	7.31***
	(1.41)	(1.18)	(1.07)
Second Order			
Spouse65	-3.25	-3.79*	-3.49*
	(1.63)	(1.54)	(1.47)
Self65	6.14**	6.63***	6.53***
	(1.91)	(1.60)	(1.44)
Third Order			
Spouse65	-2.57	-2.92	-3.15
	(1.76)	(1.68)	(1.65)
Self65	6.28*	5.93**	6.24**
	(2.57)	(2.14)	(1.91)
Fourth Order			
Spouse65	-2.29	-1.68	-2.92
	(2.03)	(1.89)	(1.77)
Self65	5.28	4.85	5.18*
	(3.14)	(2.68)	(2.44)

Note: Table presents reduced form regression discontinuity estimates of spousal and own-Medicare eligibility on a dummy variable for own insurance coverage. Columns report estimates using a bandwidth of 24, 32, and 40 quarters around the age of 65. Estimates are presented for first, second, third, and fourth order polynomials in spousal and own age. Regressions include and age polynomial interacted with dummy variables for own and spousal Medicare eligibility at age 65, own race and education controls, dummy variables for own and spousal Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Table A.2: Estimates of Discontinuities in Education, Race, Health Status, Labor Force Participation, and Social Security Benefits of Younger Spouses

	Less than High School	High School	Some College	College or More
Spouse65	-0.27	0.74	-1.39	0.91
	(1.11)	(1.41)	(0.95)	(0.97)

	White	Black	Hispanic	Good/Very Good/Excellent Health
Spouse65	-1.72*	0.89	0.59	0.01
	(0.82)	(0.65)	(0.34)	(1.20)

	Working	Hours Worked[À]	Health Insurance Offered at Work[À‡]	Receive Social Security Income[ÿ]
Spouse65	-0.38	-0.19	1.62	-0.28
	(1.05)	(0.63)	(1.24)	(1.12)

Note: Table presents estimates of discontinuities upon an older spouse reaching Medicare eligibility at age 65. All dependent variables are point-in-time except for receipt of Social Security income, which is during the previous calendar year. Regressions include quadratics in age interacted with dummy variables for own and spousal Medicare eligibility at age 65, dummy variables for own and spousal Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.

*p<0.05, **p<0.01, ***p<0.001

[À]Conditional on working.

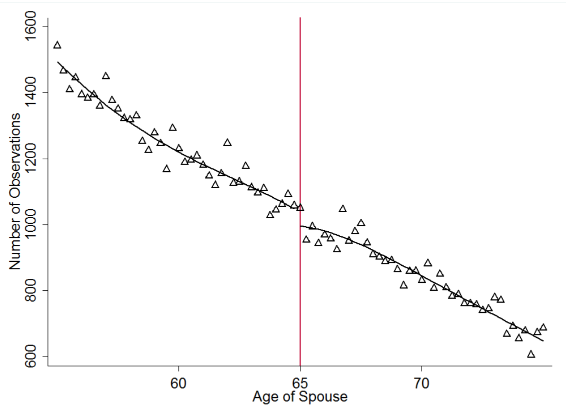
[ÿ]Regression includes years 1997 - 2011.

Table A.3: The Impact of Medicare Eligibility of the Younger Spouse on Insurance Coverage of the Younger Spouse

Panel A: Women								
	Insured		Government		Private		2+ Plans	
	Mean	RD	Mean	RD	Mean	RD		
Self65	91.36	7.33***	15.60	67.34***	82.78	-8.10***	10.74	49.18***
		(0.56)		(0.88)		(0.91)		(1.00)
	Spouse (Work)		Spouse (Non-Work)		Self (Work)		Self (Non-Work)	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Self65	36.98	-3.93**	4.65	5.44***	30.31	-11.62***	12.87	1.31
		(1.29)		(0.73)		(0.96)		(0.81)
Panel B: Men								
	Insured		Government		Private		2+ Plans	
	Mean	RD	Mean	RD	Mean	RD		
Self65	91.81	6.53***	22.60	58.23***	78.19	-10.00***	12.48	38.93***
		(1.44)		(2.14)		(2.28)		(2.35)
	Spouse (Work)		Spouse (Non-Work)		Self (Work)		Self (Non-Work)	
	Mean	RD	Mean	RD	Mean	RD	Mean	RD
Self65	14.43	-0.04	1.11	1.12	53.06	-17.27***	10.84	5.96**
		(1.59)		(0.76)		(2.43)		(2.01)

Note: Table presents reduced form estimates of spousal Medicare eligibility and own Medicare eligibility on own insurance coverage using NHIS data from 1993 to 2011. Entries in the 'Mean' column are means of own insurance coverage for the two years prior to spousal Medicare eligibility (first row of each panel) or own Medicare eligibility (second row of each panel). Regressions include quadratics in age interacted with dummy variables for own and spousal Medicare eligibility at age 65, own race and education controls, dummy variables for own and spousal Social Security eligibility at age 62, region, and year fixed effects. Standard errors are clustered by spouse age and are presented in parentheses.
*p<0.05, **p<0.01, ***p<0.001

Figure A.5: Density of Spousal Age



Note: The graph plots the number of older spouses in the sample at each age to test for violation of the continuity assumption. The curves are quadratic polynomial fits estimated separately on each side of the age-65 threshold. The estimated discontinuity at age 65 is not statistically significant.

Appendix B

Medicaid Coverage of Smoking Cessation Treatment and Smoking

Table B.1: Use of Nicotine Replacement Therapies and Pharmacotherapies

State	Year Any Coverage Began	Years Since Coverage Began				
		0	1	2	3	4
Panel A: Number of Doses Prescribed (100's)						
Illinois	2000	2283	5890	11055	14451	14982
West Virginia	2000	1381	2232	2633	2459	2505
Kentucky[1]	2001	0	0	0	0	0
South Dakota	2001	17	25	76	67	10
Utah	2001	78	335	450	507	502
Mississippi	2001	1855	1874	1304	1989	1447
Nebraska[1]	2002	0	0	0	0	0
Pennsylvania	2002	2377	4824	4303	4042	3625
Washington[1]	2002	14	18	7	3	0
Panel B: Number of Doses Prescribed Per Adult Beneficiary (100's)						
Illinois	2000	0.76	1.92	3.34	4.57	4.42
West Virginia	2000	2.65	4.17	4.78	4.47	4.56
Kentucky[1]	2001	0.00	0.00	0.00	0.00	0.00
South Dakota	2001	0.10	0.14	0.39	0.33	0.05
Utah	2001	0.16	0.63	0.63	0.65	0.65
Mississippi	2001	2.69	2.35	1.56	2.11	1.46
Nebraska[1]	2002	0.00	0.00	0.00	0.00	0.00
Pennsylvania	2002	0.92	1.78	1.43	1.20	0.94
Washington[1]	2002	0.01	0.01	0.00	0.00	0.00

Note: This table displays the number of units of nicotine replacement and pharmacotherpy prescribed per adult Medicaid beneficiary for the year coverage initiated in the state and the following 4 years. Data is Medicaid State Drug Utilization data available online from Medicaid.gov.

[1]State only covered counseling.

Table B.2: Probit Regressions

	(1) Smoke	(2) Smoke	(3) Smoke	(4) Smoke Every Day	(5) Smoke Every Day	(6) Smoke Every Day
Smoking Cessation Covered	-0.0623***	-0.0530***	-0.0493***	-0.0468***	-0.0380***	-0.0347***
	(0.0155)	(0.0170)	(0.0152)	(0.0161)	(0.0133)	(0.0133)
Mean of Dependent Variable	0.706	0.706	0.706	0.583	0.583	0.583
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
RegionxYear FE	YES	YES	YES	YES	YES	YES
State Linear Trends	YES	YES	YES	YES	YES	YES
Individual Controls	NO	YES	YES	NO	YES	YES
State Controls	NO	NO	YES	NO	NO	YES
Observations	37,281	37,281	37,281	37,281	37,281	37,281

Note: The table shows marginal effects from probit regressions of smoking behavior on a dummy variable for Medicaid coverage of smoking cessation therapies using the CPS-TUS. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table B.3: Probit Regressions by Demographic Characteristics

	(1)	(2)
	Smoke	Smoke Every Day
Gender		
Female	-0.0633***	-0.0264
[n=21,078]	(0.0153)	(0.0181)
	[0.719]	[0.598]
Male	-0.0227	-0.0110
[n=16,203]	(0.0278)	(0.0258)
	[0.692]	[0.566]
Education		
Less than High School Education	-0.144***	-0.109***
[n=9,688]	(0.0316)	(0.0330)
	[0.756]	[0.624]
High School Education	0.0328	0.0550**
[n=16,317]	(0.0237)	(0.0237)
	[0.730]	[0.613]
Some College or More	-0.0778**	-0.0586
[n=11,276]	(0.0356)	(0.0377)
	[0.621]	[0.499]
Income		
Income <100% FPL	-0.0884***	-0.0533*
[n=14,638]	(0.0301)	(0.0315)
	[0.763]	[0.624]
Income Ó100% FPL	-0.0161	0.00102
[n=22,643]	(0.0244)	(0.0214)
	[0.669]	[0.557]
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES

Note: The table shows marginal effects from probit regressions of smoking behavior on a dummy variable for Medicaid coverage of smoking cessation therapies using the CPS-TUS. Each cell includes the coefficient of interest from a separate regression. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age categories, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses and the mean of the dependent variable is in brackets.

*** p<0.01, ** p<0.05, * p<0.1

Table B.4: Probit Regressions by Age of Youngest Child

	(1) Smoke	(2) Smoke Every Day
Smoking Cessation Covered*Youngest Child 0 to 1	-0.0517***	-0.0558***
	(0.0111)	(0.0109)
Smoking Cessation Covered*Youngest Child 2 to 5	-0.0124	-0.0217
	(0.0116)	(0.0155)
Smoking Cessation Covered*Youngest Child 6 to 17	-0.00406	0.00241
	(0.0104)	(0.00893)
Mean of Dependent Variable	0.706	0.583
State FE	YES	YES
Year FE	YES	YES
RegionxYear FE	YES	YES
State Linear Trends	YES	YES
Individual Controls	YES	YES
State Controls	YES	YES
Observations	37,281	37,281

Note: The table shows marginal effects from probit regressions of smoking behavior on a dummy variable set equal to 1 if Medicad covers smoking cessation therapy interacted with a dummy variables for the age of the youngest child in the household. The sample includes parents with 1 to 5 children and family income below 200% of the poverty line. Individual controls include gender, age, age squared, education dummies, family income dummies, an indicator variable for married/cohabiting, and the number of children. State controls include the parental Medicaid threshold as a percentage of the poverty line, the unemployment rate, the cigarette tax per pack, and the number of indoor smoking restrictions. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1