ABSTRACT

Does Medicare Increase Opioid Drug Usage?
A Regression Discontinuity Study

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Recently, the overuse of opioid medications in the United States has garnered national attention, spurring many leaders to declare it a national epidemic. Medicare Part D provides prescription drug coverage for various medications including opioid drugs. The problem of moral hazard in insurance predicts that services insurance covers will be overused because of the covered risk and financial burden. With Medicare, I find no statistically significant increase in opioid usage from the age threshold for Medicare eligibility. Because insurance choice is endogeneous, I use age as the running variable for a sharp regression discontinuity design, where a dummy variable for the eligibility threshold is used to indicate Medicare eligibility. Any statistically significant results from various combinations of covariates disappear when the age bandwidths are narrowed, and similarly, there is no effect with individual drug dosage.

Does Medicare Increase Opioid Drug Usage? A Regression Discontinuity Study

by

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A Thesis

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CHAPTER ONE

Introduction

Medicare Eligibility

In 1965, Congress enacted Medicare and Medicaid as a part of the Social Security Act.[1] Medicare was designed to provide health insurance to elderly citizens aged 65 or order, regardless of preexisting conditions or ability to pay. It was subsequently expanded in 1972 to cover individuals under age 65 who have qualifying disabilities or End Stage Renal Disease.[2] Prior to the implementation of Medicare, over 40 percent of citizens over age 65 did not have health insurance for hospital and other health services.[3] Because Medicaid coverage is income based, citizens and permanent residents can be eligible for coverage under both programs.

2003 saw the enactment of further expansion of Medicare via the Medicare Modernization Act, with Medicare Part D for outpatient prescription drugs as one of the major provisions.[4] The Part D plan of Medicare went into effect on January 1, 2006, allowing for enrollees of Part A or Part B to elect to pay for the additional coverage. Additional subsidies for lower-income beneficiaries cover all or part of the premiums, deductibles, and co-payments. While there are several drugs and classes of drugs that are specifically excluded from Part D coverage, opiates are not one of them. One concern with

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[1] §§1395-1395ccc, subchapter XVIII, chapter 7, Title 42

[2] U.S. Dept. HHS, *Who is eligible for Medicare?* 2015

[3] Robin Cohen et. al, "Health Insurance Coverage Trends, 1959-2007: Estimates from the NHIS"

[4] Medicare Prescription Drug, Improvement, and Modernization Act of 2003

generous insurance coverage is moral hazard, where the existence of coverage leads to overutilization of medical care.[5] While there is some debate about whether moral hazard is truly inefficient, the overuse of some medical care could prove both financially expensive and even medically dangerous.[6]

Opioid Crisis

Opioid drugs such as morphine have been utilized in medicine for centuries, with poppy derivatives like heroin developed at early as 1898.[7] The addictive properties of these drugs were such a concern that President Gerald Ford in the 1970s established a task force to address this growing problem. However, a prominent letter published in the New England Journal of Medicine in 1980 reported that only four patients out of 11,882 treated with narcotics developed addiction that was well documented and without prior history of dependence.[8] They concluded that addiction is a rare development for patients, but now Dr. Jick regrets publishing the letter due to the outsized role it had in the development of the opioid crisis, and the lack of "value to health and medicine" that the study contributed.[9] A bibliometric analysis of the effect that this letter had found 608 citations, with a significant increase after the release of OxyContin in 1995. Furthermore, over 80% of the citations did not mention the relevant details of the treated patients from the study, with

[5] Arrow Kenneth, "Uncertainty and the Welfare Economics of Medical Care", 1963

[6] John Nyman, "Is Moral Hazard Inefficient? The Policy Implications of a New Theory", 2004

[7] Sonia Moghe, "Opioid History: From 'wonder drug' to abuse epidemic" (CNN), 2016

[8] Jane Porter and Hershel Jack, "Addition Rare in Patients Treated with Narcotics" (NEJM), 1980

[9] Taylor Haney and Andrea HSU, "Doctor Who Wrote 1980 Letter on Painkillers Regrets that it Fed the Opioid Crisis" (NPR) 2017

some authors “grossly misrepresenting the conclusions” of the study.[10] The study of pain grew significantly in this same timeframe, with Dr. John Bonica founding the research journal *Pain* and the International Association for the Study of Pain in 1973.[11] In 1995, the American Pain Society published quality improvement guidelines for the treatment of both acute and chronic pain that attempted to prevent undertreatment of pain in patients, with standards such as “responsive analgesic care” and convenient access to information about these drugs.[12] The Joint Commission, soon followed, introducing in 2001 new standards for patient pain treatment, consistent with the positions of the American Pain Society and their stance on Pain as the fifth vital sign.[13]

Currently, over a hundred Americans die every day from opioid overdose.[14] With tens of thousands of Americans dying each year from overdosing on opiate drugs, and millions estimated to suffer from prescription opioid analgesic substance abuse, the opioid epidemic has been declared a national public health emergency by President Trump as increasing media and government attention has focused on the crisis.[15] In 2015, the United States consumed just over 30 percent of globally distributed opioids by weight, and 38 percent more defined daily doses than Canada’s 34,444.[16] Thus, while the United States is not the largest country by population, it is are by far the leader in opioid consumption via

[10] Pamela Leung et al, “A 1980 Letter on the Risk of Opioid Addiction” (NEJM), 2017

[11] Marcia Meldrum, “A Capsule History of Pain Management” (JAMA), 2003

[12] Michell Max et al, “Quality Improvement Guidelines for the Treatment of Acute Pain and Cancer Pain” (JAMA), 1995

[13] David Baker, “The Joint Commission’s Pain Standards: Origin and Evolution”, 2017

[14] National Institute on Drug Abuse, “Opioid Overdose Crisis”, 2018

[15] Julie Davis, “Trump Declares Opioid Crisis a ‘Health Emergency but Requests no Funds”, 2017

[16] International Narcotics Control Board, 2018

multiple metrics. This is concerning, because the rapidly rising usage of narcotic analgesics has risen commensurately with the overdose death rates from 1999 to 2008, and the continued trend will lead to many more deaths should opioid use continue without appropriate discretion.[17] As of 2012, U.S. physicians wrote enough opioid prescriptions annually (259 million) to provide a bottle of pills to every adult citizen.[18]

Purpose of Study

Because insurance suffers from the problem of moral hazard, the potentially lethal outcomes from opioid painkiller overuse is particularly concerning. With the use of narcotic analgesics rising exponentially, understanding what role insurance may play with opioid usage is certainly pertinent to addressing the larger problem at hand. By exploring the effects of insurance generosity – specifically, that of Medicare Part D plans, some insights into the impact insurance coverage has on opioid usage can be examined. While there may be health benefits derived from overuse of health services due to insurance, the overuse of opiate drugs would have a detrimental effect on health. Additionally, for publicly-funded programs like Medicare to potentially lead to higher overdose death rates would be quite disconcerting ethically, especially since taxpayers would be indirectly helping contribute to the problem.

Initial Findings

Naïve simple regression suggests that Medicare eligibility is associated with an over 6% positive effect on opioid usage. However, when the regression discontinuity

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[17] Leonard Paulozzi et al. "Vital Signs: Overdoses of Prescription Opioid Pain Relievers", 2011

[18] Centers for Disease Control and Prevention, "Vital Signs: Opioid Painkiller Prescribing", 2014

design is implemented, with age as the running variable and the threshold set at age 65, this effect disappears entirely. There were also no relevant statistically significant effects with individual opioid drugs as well as total aggregate dosage (in morphine equivalents), and no observable changes in underlying medical conditions such as back pain (spondylosis) or cancer. Based on additional regression results, it seems unlikely that Medicaid is a causal confounder.

CHAPTER TWO

Literature Review

Card Papers

At the age 65 threshold, an abrupt change occurs: the population becomes relatively homogenous in insurance coverage, with less than 1 percent uninsured.[1] Utilizing National Health Interview Survey data and a sharp regression discontinuity design, where monthly age is the running variable and presence of Medicare insurance is the treatment, they find significant increases in healthcare access at age 65. Using hospital discharge records pooled from California, Florida, and New York, they found relative large positive effects at age 65 for admissions at private for-profit and not-for-profit hospitals, little effect at Kaiser Permanente (a large California based HMO), and a large decrease at county hospitals. These results imply that supply-side reactions to the change in insurance status at age 65 contribute to the change in healthcare utilization, with both an increase in overall hospital admissions and a redistribution of where admissions are occurring. Utilization increases varied by medical condition, with larger increases for elective treatments such as hip and knee replacements, and very small increases in hospitalization rates for conditions primarily treated by drugs, such as heart failure.[2]

They also utilize a regression discontinuity design in a different study to determine the health impact of Medicare via the change in mortality rates for severely-ill patients

[1] Card et. al, "The Impact of Nearly Universal Insurance Coverage on Healthcare Utilization: Evidence from Medicare" (American Economic Review), 2008

[2] Card et. al, 2008

admitted to the emergency department. While there are some people who are eligible for Medicare before the age 65 threshold due to disability status or presence of End Stage Renal Disease, there is still a significant jump in insurance coverage at age 65, from 12% to just under 80%.[3] Utilizing similar regression discontinuity models, they find a modest but statistically significant increase in the intensity of treatment, and considerable decreases in mortality for patients.

The Role of Insurance

Dr. Schatman finds that cost-containment strategies of insurers have contributed significantly to the opioid crisis, refusing interdisciplinary pain treatment programs in favor of cheaper opiate drugs such as methadone.[4] The priority for pain treatment was driven primarily by cost, with methadone designated the first-line drug for chronic pain by both public and private insurers. From 1999 to 2010, methadone was responsible for approximately one third of prescription opioid overdose deaths, despite representing less than 10% of prescribed opioids in this same timeframe. Insurers are reluctant to cover the more expensive but safer temper-resistant/abuse-deterrent formulations (TR/ADFs) of opioids, despite the fact that abuse of opioids medication leads to significant increases in healthcare use and spending. Many times these insurers ignore evidence based best practices, authorize treatments with little proven medical efficacy, and delay payments for treatment.[5]

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[3] Card et. al, "Does Medicare Save Lives?" (Quarterly Journal of Economics), 2009

[4] Michael Schatman and Lynn Webster, "The health insurance industry: perpetuating the opioid crisis through policies of cost-containment and profitability", 2015

[5] Michael Schatman, "The Role of the Health Insurance Industry in Perpetuating Suboptimal Pain Management" (Pain Medicine), 2011

Additionally, Jeff Biddle finds that the rate of claims made by beneficiaries decreases as insurance carries increase their denial rates.[6] They found this to be particularly significant for claims rates for back injuries with worker's compensation plans. Considering the huge role that insurance has in paying for healthcare treatment in the United States, the ability for insurers to shift patient treatment preferences is particularly relevant. If increased stinginess leads to lower insurance claim rates and substitution towards cheaper medications, then increased generosity should lead to increased utilization of healthcare services, such as prescription opioid medications. Additionally, increased availability of medical insurance also increases the demand for medical care.[7] In the case of Medicare, the government provides health insurance to all individuals that are at least 65 years old, and previous studies utilizing sharp regression discontinuity designs support the assertion that Medicare insurance leads to generally increased medical treatment, with the magnitude varying by the condition.[8] For private insurance, opioid dependence claims have risen 3203% from 2007 to 2014, while claims for opioid misuse rose 317% in this same timeframe.[9] However, only 1% of opioid misuse claims were for individuals over 65, whereas 6% of claims were for those aged 56-65.

[6] Jeff Biddle, "Do High Claim-Denial Rates Discourage Claiming? Evidence from Workers Compensation Insurance" (Journal of Risk and Insurance), 2001

[7] Arrow Kenneth, "Uncertainty and the Welfare Economics of Medical Care", 1963

[8] Card et al, "The Impact of Nearly Universal Insurance Coverage on Healthcare Utilization: Evidence from Medicare" (American Economic Review), 2008

[9] Michael McCarthy, "Insurance claims related to opioid dependence have risen by 3200%, US study finds" (BMJ), 2016

CHAPTER THREE

Economic Model

Theoretical Model

In the naïve model (simple linear regression), we specify that prescription opiate painkillers usage (O_i) has a direct linear relationship with eligibility for Medicare coverage (M_i) and a matrix of demographic covariates (X_i), including race, gender, marital status, and education level.

$$O_i = \hat{\beta}_0 + \hat{\beta}_1 M_i + \hat{\beta}_s X_i + \varepsilon_i \quad (1)$$

However, insurance selection is endogeneous, with Medicare coverage depending on a variety of factors, such as age, disability status, and presence of End Stage Renal Disease. Fortunately, at age 65 all U.S. citizens and permanent residents become eligible for Medicare, so it is expected that nearly full coverage will occur at the threshold. Because age is not a variable that can be credibly manipulated by the individual, the use of age as the running variable for the regression discontinuity design is ideal. The forcing variable, in this case age, determines the treatment assignment, wholly or partially, on either side of the fixed age 65 threshold. If Medicare has more generous opioid prescription drug coverage than other healthcare plans such as Medicaid or private insurance, then there should be a significant positive effect on opioid prescription drug usage due to the change in Medicare eligibility status. This positive effect would be further strengthened from uninsured individuals enrolling in Medicare once eligible. The age variable, z_i, needs to be centered at the age 65 threshold, z_c. Additionally, a dummy variable D_i, valued at 1 when age is greater than or equal to 65, and 0 otherwise is required. This variable is used to estimate the magnitude of the Local Average Treatment Effect (LATE) of Medicare.

Thus, before age 65, the function for opioid usage is as follows:

$$O_i^0 = \hat{\beta}_0 + \hat{\beta}_2(z_i - z_c) + \hat{\beta}_s X_i + \varepsilon_i \quad (2)$$

Whereas, after the age 65, the function for opioid usage is:

$$O_i^1 = \hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2(z_i - z_c) + \hat{\beta}_s X_i + \varepsilon_i \quad (3)$$

Therefore, the linear functional form for the model with the dummy variable applied can be represented as:

$$O_i = \hat{\beta}_0 + \hat{\beta}_1 D_i + \hat{\beta}_2(z_i - z_c) + \hat{\beta}_s X_i + \varepsilon_i \quad (4)$$

However, one key problem in regression discontinuity designs are nonlinear relationships. If the true functional form of the relationship is a higher-order polynomial, when fitted with two linear regressions each side of the cutoff, appears to have a discontinuity that is not actually present. Additionally, there may also be interaction effects between the running variable and the dummy, as well as with higher order effects of the running variable. Thus, to represent this relationship and get closer to the true functional form to better determine the causal LATE of the threshold, the following function form is used:

$$O_i = \hat{\beta}_0 + \hat{\beta}_1 D_i + \hat{\beta}_2(z_i - z_c) + \hat{\beta}_3(z_i - z_c)^2 + \hat{\beta}_4 D_i(z_i - z_c) + \hat{\beta}_5 D_i(z_i - z_c)^2 + \hat{\beta}_s + \varepsilon_i \quad (5)$$

Equation (5) is applicable to a sharp regression-discontinuity design, which has several identifying assumptions. The key identifying assumption is that all other unknown determinants of the outcome variable are continuously related to the running variable. In this case, that means that if there were another variable that also had a discontinuity at the threshold, and has an economically relevant impact on prescription opioid usage, then there is a causal confounder and the regression discontinuity design is ineffective. Regression discontinuity assumes that the selection process into the treatment is completely known, but that one cannot manipulate or defect into or out of the treatment. Furthermore, only the functional form near the threshold is relevant, but there is a bias-efficiency tradeoff as the bandwidth is narrowed around the threshold to improve efficiency. Obviously, by the very nature of the design, there must be a discontinuous probability of treatment at the threshold, and for sharp regression discontinuity designs there must be few cross-overs or misallocations at the threshold. The validity of the continuity assumption is verifiable, such as via the McCrary density test. If there was a spike in the number of individuals reporting they are age 65, then it would be suspicious and regression discontinuity would not be a valid design for the sample. However, while manipulating the age that the government has on file would be exceedingly difficult, there are some individuals that are eligible for Medicare if they have End Stage Renal Disease or have received 24 months of Social Security Disability Insurance. These conditions would be independent of the age threshold, but could potentially add bias to the sharp regression discontinuity estimates, since any effect that Medicare has would already be experienced by these individuals.

CHAPTER FOUR

Data Description

Reliability of MEPS Data

In a recent study funded by the U.S. Census Bureau, Medicaid was implied to have an estimated undercount of 17.5%, with higher levels of survey response error at higher income levels and younger adults. Discussion of other papers and publications from government and academic researchers.[1] However, while there are some concerns about underreporting of Medicare Part D expenditures in the Medical Expenditure Panel Survey, other studies have shown good concordance between MEPS estimates and sample estimates for volume of drug use.[2] Thus, while there may be some concerns about possibly biased estimates involving Medicaid, the use of prescription drug data should be representative of the general United States population.

Data Construction

The primary source of demographic data was the Integrated Public Use Microdata Series Medical Expenditure Panel Survey (IPUMS-MEPS). MEPS data is collected over a 2-year span with any given participating household surveyed five times. IPUMS harmonizes data from the MEPS, allowing for consistent and replicable analysis to be performed from the data extracts. However, it does not include all of the data collected by the Agency for Healthcare Research and Quality (AHRQ) for the MEPS. Notable

[1] Michel Boudreaux et. al, “Accuracy of Medicaid reporting in the ACS”, 2013

[2] Steven Hill et. al, “Implications of the Accuracy of MEPS Prescription Drug Data for Health Services Research”, 2011

omissions include the Medical Conditions files from the Household Component Full-Year files, and the Prescribed Medicines files for the Household Component Event files. Thus, because these parts of the survey contained key information required for the analysis, these were appended to the IPUMS-MEPS data based on the uniquely identifying flags. While there may appear to be duplicate entries in the Prescribed Medicine Files, according to the AHRQ, "each record represents a unique prescribed medicine event".[3] This is not a concern for the binary outcomes of whether a patient uses opiates, but this could be a source of measurement error for total opioid dosage. Thus, the MEPS inverse probability weights were utilized in all regressions, which thus excluded any observations with a zero weight. Individuals that were missing age data were also excluded, as they could not be applied to the regression without the running variable. Additional dummies were created to pool categorical demographic data together, such as race and education data, the latter of which was not available before the 2000.

Descriptive Statistics

Overall, approximately 9 percent of individuals in the survey are on prescription opioid medication. This varying by age, with older individuals more likely to have opioid prescriptions. Table 4.1 is based off the unweighted statistics, whereas all regressions apply the appropriate inverse probability weights. There is an increase in overall opiate usage after the implementation of Medicare Part D, and this change is more pronounced among those over age 55. However, this change does not necessarily represent the effect of subscribing to Medicare, but could indicate the possibility that opiate usage increased after the implementation of Medicare Part D.

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[3] See Prescribed Medicine Files details at Meps.Ahrq.gov

Table 4.1. Summary Statistics

Vars	Excl. Ed.	Ed. 2000+	MC Pt D	Before Pt. D	Over Age 55	55+ 2006+	Age 55+ Pre-2006	Opiates Only
Opiate	0.0926	0.0977	0.104	0.0884	0.154	0.172	0.122	1
	(0.290)	(0.297)	(0.305)	(0.284)	(0.361)	(0.378)	(0.327)	(0)
Medicare	0.132	0.131	0.132	0.130	0.562	0.548	0.585	0.242
	(0.339)	(0.338)	(0.338)	(0.336)	(0.496)	(0.498)	(0.493)	(0.428)
Age	34.28	34.36	34.63	33.94	67.09	66.80	67.59	45.27
	(22.36)	(22.38)	(22.42)	(22.32)	(9.116)	(9.048)	(9.209)	(19.22)
Gender	0.523	0.523	0.522	0.524	0.560	0.555	0.567	0.603
	(0.499)	(0.499)	(0.499)	(0.499)	(0.496)	(0.497)	(0.496)	(0.489)
Hispanic	0.273	0.281	0.294	0.262	0.152	0.161	0.138	0.171
	(0.446)	(0.450)	(0.456)	(0.439)	(0.359)	(0.367)	(0.345)	(0.376)
Af. Am.	0.188	0.195	0.215	0.164	0.171	0.193	0.133	0.201
	(0.391)	(0.396)	(0.411)	(0.370)	(0.376)	(0.395)	(0.339)	(0.400)
White	0.755	0.746	0.717	0.791	0.768	0.733	0.829	0.764
	(0.430)	(0.435)	(0.450)	(0.407)	(0.422)	(0.442)	(0.377)	(0.424)
Asian	0.0561	0.0607	0.0732	0.0411	0.0569	0.0707	0.0332	0.0298
	(0.230)	(0.239)	(0.260)	(0.198)	(0.232)	(0.256)	(0.179)	(0.170)
Single	0.377	0.371	0.359	0.390	0.574	0.568	0.585	0.466
	(0.485)	(0.483)	(0.480)	(0.488)	(0.494)	(0.495)	(0.493)	(0.499)
Bachelor’s	-	0.176	0.177	0.176	0.250	0.256	0.239	0.206
		(0.381)	(0.381)	(0.381)	(0.433)	(0.436)	(0.426)	(0.404)
H.S. Dip.	-	0.333	0.326	0.343	0.448	0.440	0.462	0.478
		(0.471)	(0.469)	(0.475)	(0.497)	(0.496)	(0.499)	(0.500)
Spondylitis	0.0754	0.0756	0.0736	0.0787	0.135	0.134	0.138	0.234
	(0.264)	(0.264)	(0.261)	(0.269)	(0.342)	(0.341)	(0.345)	(0.423)
Thyroid Disease	0.0382	0.0398	0.0417	0.0369	0.112	0.114	0.108	0.0783
	(0.192)	(0.196)	(0.200)	(0.189)	(0.315)	(0.318)	(0.310)	(0.269)
Cancer	0.0364	0.0370	0.0391	0.0339	0.123	0.129	0.111	0.0935
	(0.187)	(0.189)	(0.194)	(0.181)	(0.328)	(0.336)	(0.314)	(0.291)
Diabetes Mellitus	0.0624	0.0664	0.0743	0.0541	0.206	0.224	0.175	0.137
	(0.242)	(0.249)	(0.262)	(0.226)	(0.404)	(0.417)	(0.380)	(0.344)
Obs	614,790	510,473	311,738	198,735	106,629	67,422	39,207	49,868

Interestingly, there is a higher expectation that a random opioid user is covered by Medicare. Opioid users also appear to have a higher incidence rate of various chronic medical conditions such as spondylosis. Also notable is that Medicare is not completely deterministic by age; rather the proportions of people covered by Medicare for a given age group reverse after the threshold. It is not unexpected that there is a declining number of respondents as age rises due to increased expected mortality. However, this does mean that the relevant sample for the regression discontinuity will be smaller than if the threshold were at a much earlier age.

For dosage data, in addition to dosages for individual opiate classes, a single unified dose was determined based upon medically based equivalent morphine doses. An additional variable for daily doses was also generated, and from there, a dummy variable representing the at-risk dose for overdose and addiction (90mg/day).

CHAPTER FIVE

Results

Naïve Regresssion

A simple linear observation approach (naïve regression), regressing of opioid usage directly onto Medicare seems to be promising, but there is selection bias for insurance choice, with people on Medicare having radically different characteristics than those who are not on Medicare. Because of these endogeneity problems with insurance, a regression discontinuity design to introduce exogeneous variation via a dummy variable for the threshold age is necessary. Additionally, while there appears to be a statistically significant effect on opioid usage by Medicare of at least a 6 percent increase, this is picking up additional variation such as that due to aging. As seen in Table 5.1, when additional controls are implemented, the impact of Medicare seems to decrease.

Table 5.1. Simple Linear Regression Results

Preliminary Regression	Simple Regression	Demographic Covariates	Education (Year>2000)	All Controls (Year>2000)
Medicare	0.0715***	0.0616***	0.0636***	0.0621***
	(0.00165)	(0.00166)	(0.00192)	(0.00191)
Controls	None	No Education	All	Yearly FE
Func. Form	Linear	Linear	Linear	Linear
Medicare ($\bar{x}$)	0.149	0.149	0.152	0.152
	(0.356)	(0.356)	(0.359)	(0.359)
Opiate ($\bar{y}$)	0.102	0.102	0.110	0.110
	(0.303)	(0.303)	(0.313)	(0.313)
Observations	590,233	590,233	489,508	489,508
R-squared	0.007	0.016	0.025	0.027

Insurance

As expected, there is a significant increase in the number and proportion of individuals covered by Medicare after reaching age 65, which is quite visually apparent in Figure 5.1. However, more than 20 percent of the population is already on Medicare before the threshold, and over 10 percent of the population is not on Medicare after the threshold. This could prove problematic for a sharp regression discontinuity design, as the estimates could be biased from those that are already on Medicare due to End Stage Renal Disease or Social Security Disability Insurance beneficiaries, and from those who choose not to enroll in Medicare after become eligible at age 65.

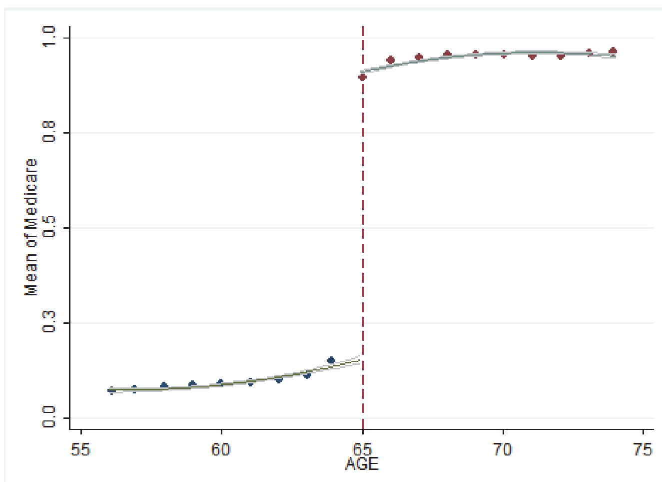

Figure 5.1. Medicare Conditional Means Graph at Age Threshold

At all bandwidths and with varying controls Medicare has a strongly positive statistically significant at the ($p < 0.01$) relationship with the dummy variable (whether the person is above age 65, inclusively), with around 80 percent of the variation explained by this relationship. Table 5.2 and all subsequent tables utilize education, gender, marital status, and racial demographics as covariates for all regressions unless otherwise specified.

Regressions were also run without the education covariates so that all years of data could be included, but this does not change the significance of the results in any of the regressions. The strength of the relationship between the age dummy and Medicare status indicates that the dummy is a good instrument for a fuzzy design, and hopefully for a sharp design as well. The increase of 78.3 percent at the ±5 bandwidth is an absolute change, not proportional. Likewise, with all other regressions where any variable is a proportion, the coefficients represent absolute changes, not percentage changes.

Table 5.2. Medicare Regression on Age

Medicare	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.783***	0.814***	0.828***	0.797***	0.807***	0.820***
	(0.0131)	(0.00722)	(0.00538)	(0.0162)	(0.00902)	(0.00684)
Medicare ($\bar{y}$)	0.513	0.441	0.390	0.508	0.436	0.385
	(0.500)	(0.497)	(0.488)	(0.500)	(0.496)	(0.487)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.778	0.806	0.819	0.764	0.792	0.804

Surprisingly, contrary to nationally reported statistics, Medicaid has a small but statistically significant jump of 3 percent at the threshold age. From the tabulation of Medicaid beneficiaries, it is evident that after a modest absolute increase in number of reported patients on Medicaid occurs, the near constant absolute number of patients in each age group results in a higher proportion of patients on Medicaid as the total number of people in each age group declines. A 3 percent change is quite considerable given the magnitude of the proportion of people that are on Medicaid near age 65. Figure 5.2 may visually distort the apparent magnitude of the change, but it does illustrate quite effectively an example of a strong discontinuity at the threshold. However, such as change could be due to a multitude of unrelated factors that lead to an increased enrollment in Medicaid after reaching 65. One possibility is that Medicaid enrollment could be partially correlated to Medicare enrollment, where the individual enrolls in both at the same time.

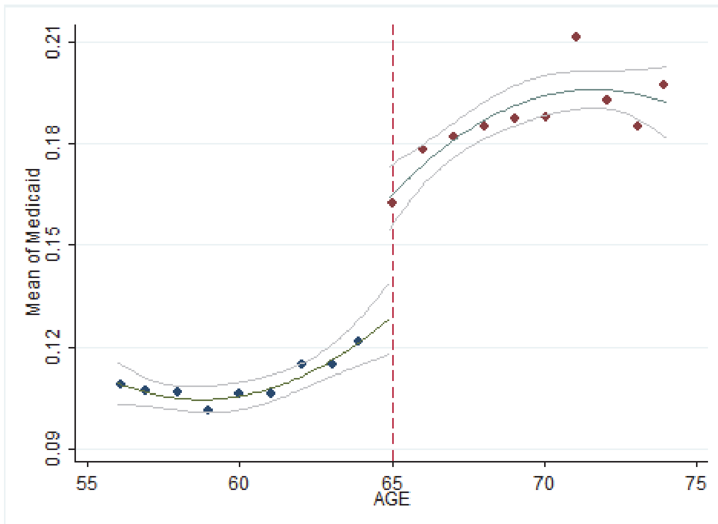

Figure 5.2. Medicaid Conditional Mean Graph at Age Threshold

Note that Medicaid nonetheless does not hold a statistically significant relationship with the age dummy at lower age bandwidths, and that any effect at the larger bandwidths is still rather small, and inconsistent in sign. Table 5.3 shows how the sign sometimes changes as the bandwidth is narrowed, while standard errors remain larger than the coefficient. As the proportion of patients covered by Medicaid varies rather dramatically each year, it would seem that even with the weights applied, that there may be some selection biases in the Medicaid portion of the sample. Nevertheless, the age dummy's lack of a statistical significance age with Medicaid is not surprising, since Medicaid declines slightly as age goes up. Thus, it seems unlikely for Medicaid to be a causal confound.

Table 5.3. Medicaid Regression on Age

Medicaid	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.00150	-0.00402	0.00187	-0.00117	-0.0103	-0.00794
	(0.00969)	(0.00588)	(0.00470)	(0.0118)	(0.00719)	(0.00579)
Medicaid ($\bar{y}$)	0.0832	0.0834	0.0834	0.0834	0.0846	0.0858
	(0.276)	(0.276)	(0.276)	(0.277)	(0.278)	(0.280)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.113	0.109	0.105	0.119	0.110	0.104

As might be expected, with workers retiring and substituting into Medicare, private insurance has a statistically significant drop after workers reach age 65. The magnitude of the effect is such that it is unlikely that this is due to a cubic functional form, and the magnitude of this drop is still less than the magnitude of the increase in Medicare coverage. Because it is possible to supplement Medicare coverage, such as with the Part D plan or with privately offered Medigap plans, this is probably in part why there was not a commensurate drop in private insurance beneficiaries as Americans started enrolling in Medicare.

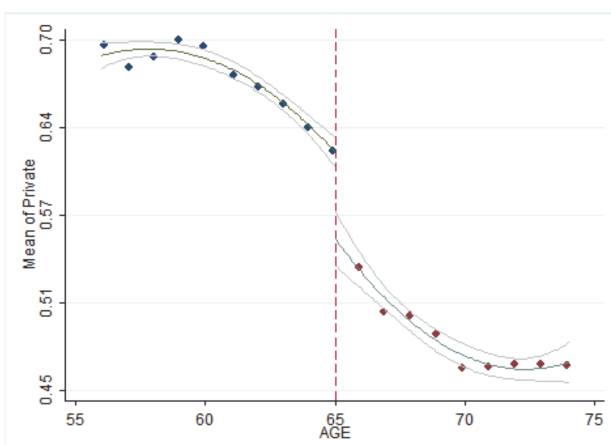

Figure 5.3. Private Insurance Conditional Mean Graph at Age Threshold

Strangely, the magnitude of the effect appears to be weaker and less statistically significant at the lower age bandwidth levels, but this is likely to be in part because of the bias-efficiency tradeoff with bandwidth selection. All of the estimates were negative and statistically significant, indicating that it is indeed likely that some patients are substituting private insurance for other coverage such as Medicare. Table 5.4 also demonstrates that this effect is apparently stronger after the implantation of Medicare Part D, but this could be due to other expansions in Medicare that reduce the need for supplemental insurance. This could also be an increase in Medicare enrollment exclusive to private insurance enrollment, if the benefits are generous enough that the demand for private insurance is nearly eliminated.

Table 5.4. Private Insurance Regression on Age

Private Insurance	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	-0.0302*	-0.0319***	-0.0628***	-0.0401*	-0.0414***	-0.0715***
	(0.0173)	(0.0107)	(0.00865)	(0.0216)	(0.0134)	(0.0109)
Priv. Ins ($\bar{y}$)	0.672	0.679	0.685	0.657	0.664	0.669
	(0.470)	(0.467)	(0.465)	(0.475)	(0.472)	(0.471)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Obs	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.161	0.173	0.177	0.167	0.179	0.181

The McCrary Density test (Figure 5.4) yields a smoothly continuous plot of the running variable, age, indicating that there is no significant drop off or rise on either side of the threshold, and thus is does not seem likely that there is manipulation in the running variable for official reporting of age to the government and medical professionals. Thus, the continuity assumption of the running variable is satisfied due to no discernable breaks.

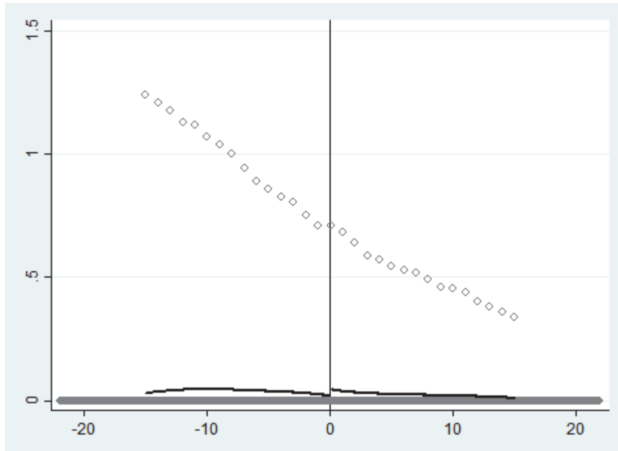

Figure 5.4. McCrary Density Test for Centered Age Variable

General Opiate Usage

While Figure 5.5 appears indicate an increase in opiate usage, the results are not statistically significant. The trend does seem to be weakly negative at narrower bandwidths after reaching the threshold, but it is likely that this is simply due to a nonlinear relationship between opioid usage and age.

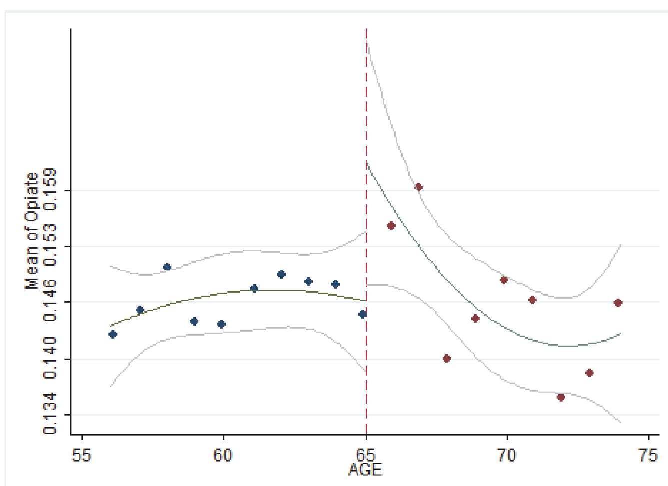

Figure 5.5. Conditional Mean Graph of Use of any Opiate on Age

As shown in the regression, none of the coefficients are statistically significant with the nonlinear functional form, regardless of bandwidth. The sign of the coefficients also varies as the bandwidth narrows and standard errors increase. Table 5.5 seems to show a larger magnitude after Medicare Part D, but these lack statistical significance.

Table 5.5. Presence of Opiates Regressed on Age

Any Opiates	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.00459 (0.0167)	-0.00113 (0.0100)	0.00196 (0.00794)	0.0176 (0.0218)	-0.00392 (0.0132)	0.00200 (0.0105)
Opiate ($\bar{y}$)	0.163 (0.370)	0.161 (0.368)	0.159 (0.366)	0.186 (0.389)	0.182 (0.386)	0.179 (0.383)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.007	0.007	0.008	0.010	0.010	0.011

In the Medicare Part D timeframe, there is a higher overall proportion of people that are on opiates, which is supported by national statistics that indicate a higher number and proportion of elderly are taking opioid prescriptions over time. Elderly are actually one of the groups with the fastest growth in use of these drugs. For the regressions, various combinations of covariates with years and bandwidths were tested, without any relevant statistically significant results before or after Medicare Part D. While there visually appears to be some increase in each conditional mean graph, such as in Figure 5.6, the confidence bands indicate that the supposed increase is not statistically significant. Furthermore, if there were a statistically significant change at the age threshold, the apparent reversal of previous trends would still be quite strange if this effect were attributed to Medicare enrollment. Thus, it seems likely that other factors are influence the change of the trend.

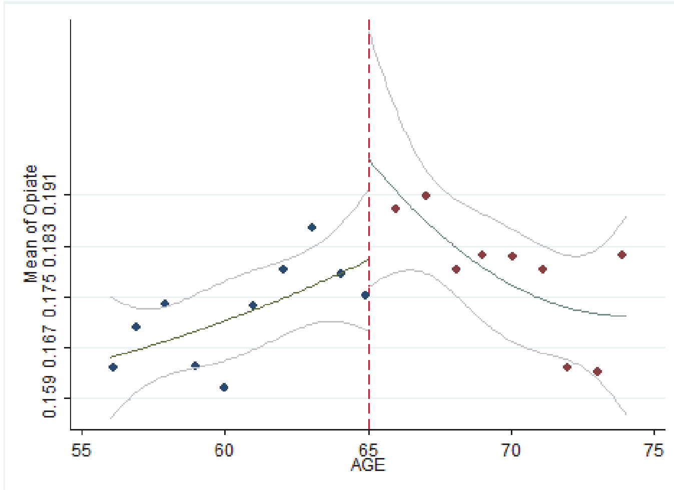

Figure 5.6. Conditional Mean Graph of Opiate use on Age after Medicare Part D

Furthermore, the graph for opiates before the implementation of Part D also indicates an apparent lack of a relationship between opiates and the age threshold before the implantation of Medicare Part D. At larger bandwidths (±25), the overall trend appears to be slightly negative, with increased variance as age increases. Thus, when this increased variance is reflected in the narrower bandwidths, confidence intervals are considerably larger than the apparent change at the threshold.

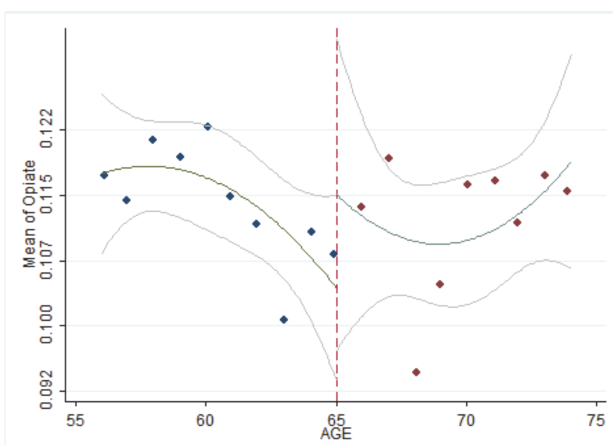

Figure 5.7. Conditional Mean Graph of Opioid Use on Age before Medicare Part D

Prescription Expenditures

At larger bandwidths, the relationship between total expenditures on all prescriptions was a smooth relationship that started to taper slightly after the threshold, with dramatic drop-offs after age 85. Figure 5.8 demonstrates that this relationship is still very smooth at smaller bandwidths, with the only noticeable effect being a slightly decline in the rate of expenditure growth.

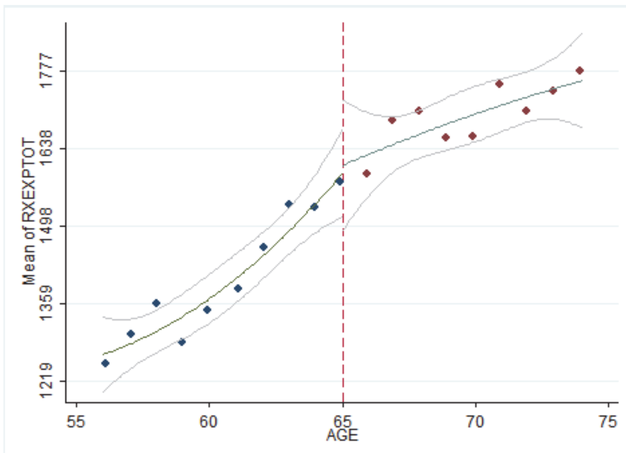

Figure 5.8. Conditional Mean Graph of All Prescription Expenditures at Age Threshold

The statistically insignificant results from the regression also fail to demonstrate a relationship between the age dummy and script spending, in contrast to the increased utilization in many services found in the Card paper. Curiously, in Table 5.6 the coefficients appear to be negative at the threshold. Additional regressions and conditional mean graphs for just opioid spending and other drug spending based on just the Prescribed Medicine Files (since IPUMS-MEPS does not breakup by drug type) also fail to demonstrate a statistically significant relationship. It is possible that opioid spending may not be a large enough proportion of many patient's prescription drug spending to be noticeable if the change is relatively small. Additionally, when it becomes unaffordable to continue buying prescription opiates, many individuals may substitute to black market alternatives such as Heroin, which would not be measurable in the MEPS data.

Table 5.6. Prescription Drug Expenditures Regressed on Age

All Drug Expenditures	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	-203.4 (203.7)	-82.19 (105.9)	-40.25 (78.15)	-234.1 (292.0)	-41.18 (151.1)	-8.244 (110.8)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.005	0.008	0.010	0.005	0.008	0.009

Medical Conditions

If there were a statistically significant change in prescription opioid usage at the age threshold when patients suddenly become eligible for Medicare, part of the effect could be explained due to an increased reporting rate of various medical conditions. This could happen if patients that are underinsured or uninsured choose to delay treatment for their medical conditions until they are eligible for Medicare, and the severity of their conditions is such that opioid drugs are necessary to treat the pain. This would likely be due to chronic conditions, since acute conditions would require immediate treatment, whereas chronic conditions that may not be treatable or curable may also be more tolerable for delaying treatment. If Medicare is sufficiently generous, such as via their Part D plan, then patients could potentially over-utilize care or fake symptoms, resulting in higher opioid drug usage. Thus, in order to determine if such as change may be occurring, the significant chronic conditions from the MEPS Medical Conditions Files were regressed on the age dummy and covariates. The following are the notable conditions among those tested.

Spondylosis is a chronic form of back pain due to age-related wear to the spinal disks. This condition is incurable and lasts for a lifetime, so it seems like a good candidate as a possible cause of increased opioid use. The distribution of the data indicates a possible nonlinear relationship between age and spondylosis, as seen in Figure 5.9.

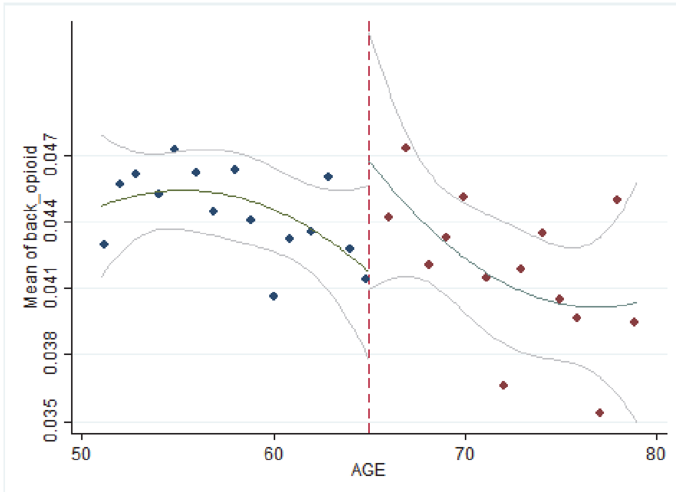

Figure 5.9. Conditional Mean Graph of Spondylosis at Age Threshold

As in previous regressions, there was no statistically significant effect, and signs of the coefficients changed as bandwidths narrowed, as shown in Table 5.7.

Table 5.7. Spondylosis Regressed on Age

Spondylosis	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.0105 (0.00945)	-0.000897 (0.00584)	0.00631 (0.00472)	0.0142 (0.0125)	-0.00501 (0.00772)	0.00807 (0.00629)
Spondylosis ($\bar{y}$)	0.0496 (0.217)	0.0495 (0.217)	0.0492 (0.216)	0.0574 (0.233)	0.0561 (0.230)	0.0557 (0.229)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.003	0.003	0.004	0.005	0.004	0.005

Thyroid disease is caused by an abnormal function in the thyroid glands, so as the body wears down, it is feasible that this may be more likely to occur. However, despite what appears to be a visible effect in Figure 5.10, this is not statistically significant effect.

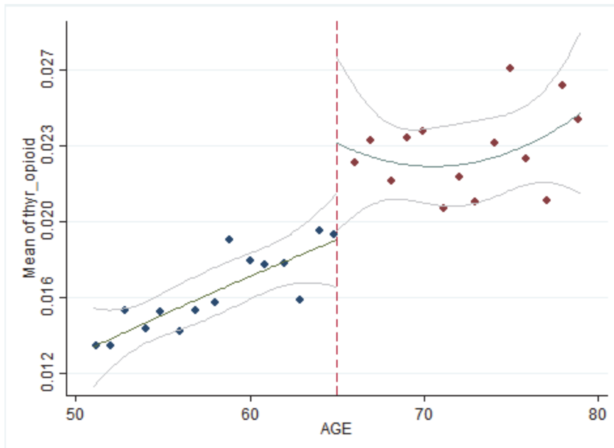

Figure 5.10. Conditional Mean Graph of Thyroid Disease at Age Threshold

The regression results in Table 5.8 also confirm the lack of effect with considerably large standard errors compared to the coefficients, and no statistical significance at any of the age bandwidths.

Table 5.8. Thyroid Disease Regressed on Age

Thyroid Disease	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.00217 (0.00668)	0.00218 (0.00406)	0.000904 (0.00326)	0.00389 (0.00901)	-0.00175 (0.00550)	-0.00155 (0.00445)
Thyroid Disease ($\bar{y}$)	0.0236 (0.152)	0.0225 (0.148)	0.0216 (0.145)	0.0278 (0.164)	0.0259 (0.159)	0.0251 (0.156)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.009	0.010	0.010	0.012	0.012	0.012

Later stage cancer patients may resort to opioid medications due to the chronic pain, but the Figure 5.11 shows a nonlinear relationship with age, with no statistically significant jump at the age threshold.

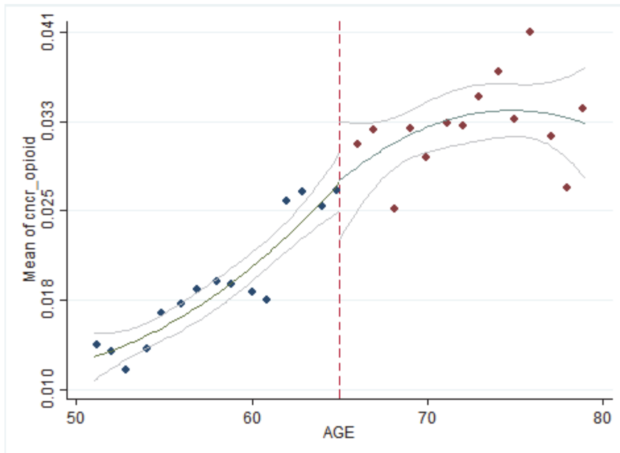

Figure 5.11. Conditional Mean Graph of All Cancer Diseases at Age Threshold

Similarly, in Table 5.9, none of the regressions at the various age bandwidths have a statistically significant result, although the running variable (not shown) does have a strongly statistically significant relationship at all but the most narrow bandwidths, indicating that cancer is indeed rising with age like what Figure 5.11 shows.

Table 5.9. Cancer Regressed on Age

Cancer	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.00181	-0.00391	-0.00262	0.00581	-0.00188	-0.00307
	(0.00863)	(0.00523)	(0.00413)	(0.0115)	(0.00708)	(0.00562)
Cancer ($\bar{y}$)	0.0332	0.0309	0.0280	0.0385	0.0352	0.0318
	(0.179)	(0.173)	(0.165)	(0.192)	(0.184)	(0.175)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.003	0.005	0.006	0.005	0.006	0.008

The trend in Figure 5.12 is completely reversed after the age threshold is reached, with a declining rate of diabetes as age rises past 65. However, there is not any apparent jump in the proportion of patients with diabetes.

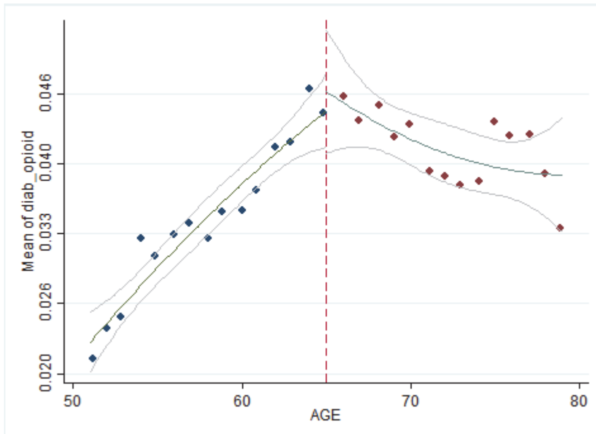

Figure 5.12. Conditional Mean Graph of Diabetes Mellitus at Age Threshold

All of the regression results in Table 5.10 indicate a negative relationship, but even this is too weak to be statistically significant.

Table 5.10. Diabetes Mellitus Regressed on Age

Diabetes	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	-0.00607 (0.00931)	-0.00284 (0.00551)	-0.00160 (0.00433)	-0.00399 (0.0125)	-0.00548 (0.00748)	-0.00289 (0.00593)
Diabetes ($\bar{y}$)	0.0441 (0.205)	0.0397 (0.195)	0.0360 (0.186)	0.0531 (0.224)	0.0476 (0.213)	0.0434 (0.204)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.005	0.006	0.007	0.007	0.007	0.009

Measured Dosages

In Figure 5.13, there appears to be the potential for a statistically significant outcome with total opioid dosage. At wider bandwidths, such as in Figure 5.14, there also is a random spike near age 55 caused by oxycodone and hydrocodone use. There is significant variance in usage, particularly after age 65. All units are in milligrams, with the dosages of each drug converted to their morphine equivalent.

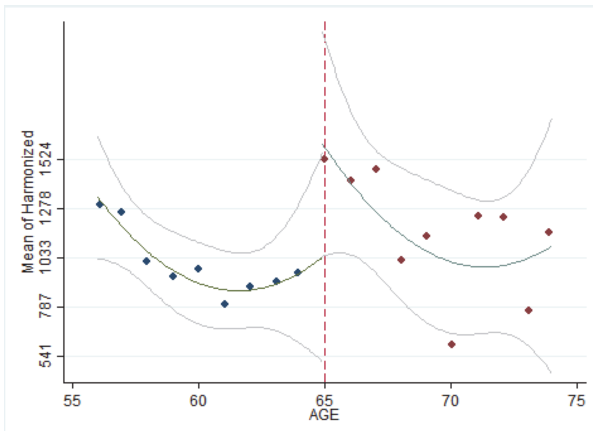

Figure 5.13. Conditional Mean Graph of All Opiates in Uniform Dose at Age Threshold

In Table 5.11, only wide bandwidths have any statistical significance, with an estimated positive increase in annual dosage of over 1000mg/yr at the ±15 age bandwidth.

Table 5.11. Converted Annual Dosage Regressed on Age

Uniform Dose	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15	BW ±25
Age65	610.0	-123.6	1,051**	-69.56	-1,167	468.9	372.2*
	(568.4)	(754.6)	(481.3)	(492.7)	(974.2)	(539.2)	(220.6)
Annual Dose ($\bar{y}$)	1,129	1,281	1,281	1,045	1,361	1,364	1,221
	(20,277)	(35,018)	(30,205)	(12,438)	(39,820)	(33,768)	(27,882)
Years	2000+	2000+	2000+	2006+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720	124,401
R-squared	0.001	0.000	0.000	0.001	0.000	0.000	0.000

The statistical significance ($p < 0.05$) at the ±15 age bandwidth disappears when looking only at the years when Medicare Part D was in place. At the ±25 age bandwidth, there is statistical significance at 10 percent ($p < 0.10$) level, with a third of the magnitude from the sample that includes years before Medicare Part D. Optimistically, 1051 mg seems like a lot, but this represents just 2.88 mg/day, which is less than a tenth of a single dose of a prescription opiate (30mg). This does equate to nearly 3 extra doses or pills per month (2.92 doses/mo), but the change in sign and lack of significance as the bandwidths narrow indicates that it would be spurious to attribute much value to these results. Similarly, the lower dosage increase after Medicare Part D is not only unintuitive, but also represents only a single extra dose a month, or 1.02 mg/day. If there was an effect due to increased Medicare enrollment on prescription opioid use, then there logically would be a stronger effect from enrollment in Medicare Part D. These results thus indicate a lack of a strong relationship of either program on overall opioid use, but there could be some noise in the data from outliers. Figure 5.14 demonstrates these potential outliers that are observable at larger age bandwidths.

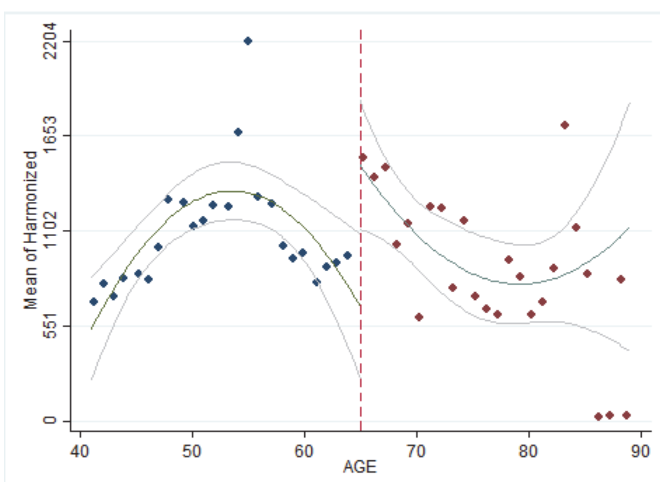

Figure 5.14. Conditional Mean Graph of Opiate Dose at Age Threshold, ±25 Bandwidth

What is more relevant to the opioid crisis are overdoses, since there may be many patients that are using their prescriptions at safe dosage levels. Thus, based on federal guidelines, 90 mg/day (morphine equivalent) was used as the metric for increased overdose and addiction risk. The dummy for whether the person exceeded this dosage threshold to hold a nonlinear relationship with age, with no discernable visual effect at the age threshold in Figure 5.15. There is significant variance in the data, particularly after the age threshold, so even if there was an actual causal effect, it is masked by the inconsistent proportions of adults exceeding the dosage threshold for increased risk.

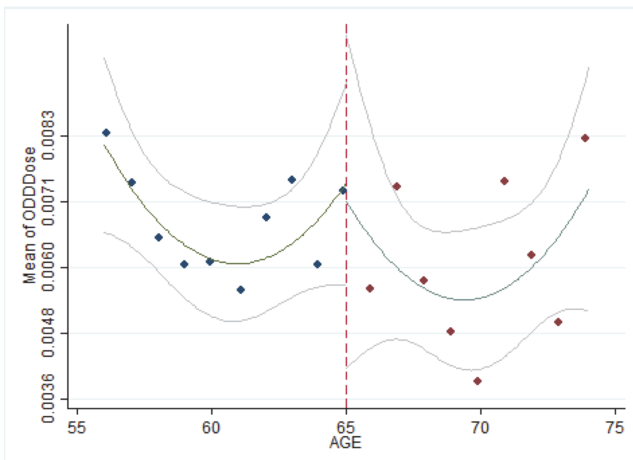

Figure 5.15. Conditional Mean Graph of Overdose Risk at Age Threshold

Like previous regression results, in Table 5.12 none of the coefficients are statistically significant, and the signs change as the age bandwidth is narrowed. If there are a significant number of patients on hospice care or other end of life treatments, then they would likely be exceeding the dose threshold for increased risk. As just 5 percent of opioid users in the sample exceed this threshold, then if a significant number of those exceeding the threshold are also on hospice, then this would confound the results.

Table 5.12. Threshold Dose for increased Addiction & Overdose Risk Regressed on Age

Overdose Risk	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	0.000598 (0.00299)	-0.00173 (0.00209)	0.000142 (0.00171)	-0.00214 (0.00408)	-0.00452 (0.00284)	-0.00121 (0.00229)
Threshold Dose ($\bar{y}$)	0.00662 (0.0811)	0.00738 (0.0856)	0.00790 (0.0885)	0.00709 (0.0839)	0.00808 (0.0895)	0.00873 (0.0930)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.002	0.001	0.001	0.002	0.001	0.001

Specific Opiates

However, just because there may not be an effect for overall opioid use does not mean that individual classes of opiates may not have increased usage. If one opioid were to go up in usage while others go down due to various factors, then the effects would be masked when these are aggregated into a single variable. Thus, each opioid drug was tested, using their original units. Overall, none of the opiates stands out as being particularly interesting at the ±5 years bandwidth with all demographic controls applied.

Table 5.13. Specific Opiates Regressed on Age, ±5 Bandwidth

Opiate	Oxy-codone	Hydro-morphone	Tramadol	Codeine	Fentanyl (mcg)	Morphine	Meth-adone	Hydro-codone
Age65	67.92 (104.4)	5.053 (6.015)	79.29 (364.8)	-42.97 (42.72)	-33.07 (79.53)	94.36 (79.05)	-18.03 (22.30)	-136.0 (375.7)
Opiate ($\bar{y}$)	188.3 (5,016)	3.329 (170.9)	677.6 (6,499)	32.70 (1,100)	21.72 (918.6)	77.56 (1,663)	9.511 (347.4)	509.0 (8,968)
Years	2006+	2006+	2006+	2006+	2006+	2006+	2006+	2006+
Obs.	27,218	27,218	27,218	27,218	27,218	27,218	27,218	27,218
R-squared	0.001	0.000	0.002	0.001	0.001	0.001	0.001	0.001

However, Oxycodone, one of the most popular and abused opiates in America, appears to have some change at the threshold. However, Figure 5.16 shows a very large variance, thus the results are not statistically significant.

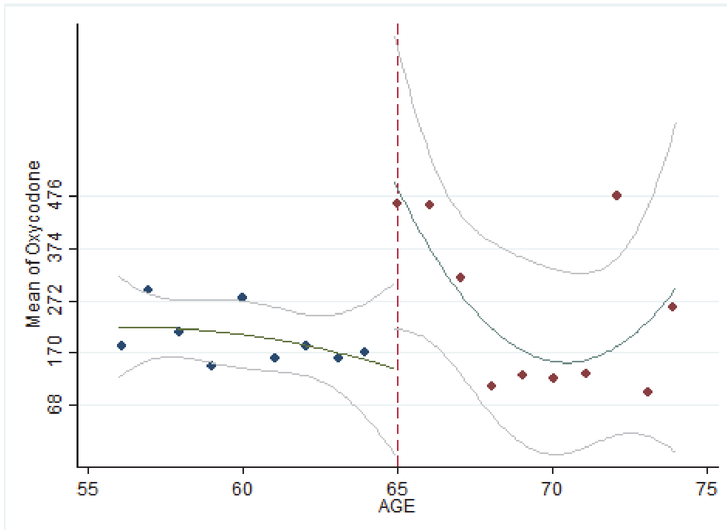

Figure 5.16. Conditional Mean Graph of Annual Oxycodone use at Age Threshold

This is supported by the regression results in Table 5.14, with only the ±15 age bandwidth holding any statistical significance ($p < 0.10$), and this effect disappears at narrower age bandwidths and after Medicare Part D implementation.

Table 5.14. Oxycodone Annual Dosage Regressed on Age

Oxycodone	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15
Age65	347.7 (285.7)	-102.6 (474.5)	506.0* (291.5)	67.92 (104.4)	-673.7 (622.0)	309.1 (329.2)
Oxycodone ($\bar{y}$)	250.4 (10,231)	330.4 (21,792)	300.7 (17,973)	188.3 (5,016)	353.7 (25,530)	324.4 (21,177)
Years	2000+	2000+	2000+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720
R-squared	0.001	0.000	0.000	0.001	0.000	0.000

Likewise, Hydrocodone, the other commonly use narcotic analgesic in America, has a very high variance after the age threshold, as seem in Figure 5.17.

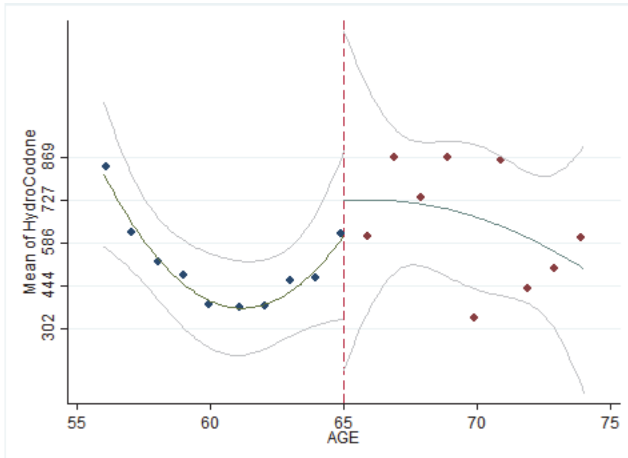

Figure 5.17. Conditional Mean Graph of Annual Hydrocodone use at Age Threshold

However, only at wider bandwidths is there a positive relationship between the age threshold and the use of hydrocodone, so there could quite possibly be a nonlinear relationship of hydrocodone use with age. As seen in Table 5.15, any relationship that is statistically significant at the ±15 age bandwidth disappears in the sample after Medicare Part D implementation, and is much weaker at the wider bandwidth for the Part D sample.

Table 5.15. Hydrocodone Annual Dosage Regressed on Age

Hydrocodone	BW ±5	BW ±10	BW ±15	BW ±5	BW ±10	BW ±15	BW ±25
Age65	117.3	84.32	371.6**	-136.0	-94.80	124.2	251.0*
	(307.6)	(214.7)	(174.4)	(375.7)	(230.3)	(181.6)	(151.7)
Hydrocodone ($\bar{y}$)	561.4	579.9	601.0	509.0	559.2	595.6	554.3
	(12,569)	(11,705)	(12,403)	(8,968)	(9,691)	(10,187)	(9,618)
Years	2000+	2000+	2000+	2006+	2006+	2006+	2006+
Observations	41,784	81,792	123,439	27,218	52,229	77,720	124,401
R-squared	0.001	0.000	0.000	0.001	0.000	0.000	0.000

Thus, like with the overall aggregate dosages regression, there does not appear to be any relationship that can be reliably attributed to the age threshold. Figure 5.18 demonstrates how much greater the variance is after the threshold, and the significant outliers before the threshold as well. Coincidentally, there is a spike near age 55 in hydrocodone use, which combined with the spike in oxycodone use at this age, likely drove the outlier found in figure 5.14.

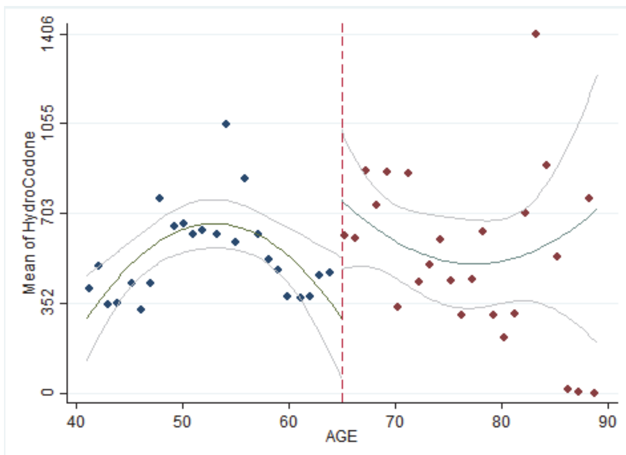

Figure 5.18. Conditional Mean Graph of Annual Hydrocodone use, ±25 Bandwidth

Medicaid

In Table 5.16, several regressions are shown adjacently for quick comparison. First, simple linear regressions of opioid usage directly on Medicaid coverage, without and with covariates. Like with Medicare, these seem to be statistically significant, but are biased. Notably, they are also a smaller magnitude than the simple linear regression with Medicare coverage. The regressions of opioid usage with age are identical to those from Table 5.5. However, the regression of Medicaid onto the age threshold indicates no statistically significant relationship with the age threshold. Thus, it seems unlikely that Medicaid coverage would confound any effects that Medicare may have, since Medicaid coverage has no statistically significant relationship with the age threshold. This is good for the regression discontinuity design, and further evidence that there does not seem to be any relationship between prescription opioid medication usage and Medicare coverage.

Table 5.16. Comparison of Medicaid Relationship with Opioid Usage at Threshold

Medicaid Comps	Simple Reg	Simple Reg	Opiate Eff BW±5	Opiate Eff BW±15	Medicaid Relat BW±5	Medicaid Relat BW±15
Medicaid	0.0148*** (0.00128)	0.0511*** (0.00155)	n/a	n/a	n/a	n/a
Age65	n/a	n/a	0.00459 (0.0167)	0.00196 (0.00794)	0.00150 (0.00969)	0.00187 (0.00470)
Opiate	0.102 (0.303)	0.110 (0.313)	0.163 (0.370)	0.159 (0.366)	n/a	n/a
Medicaid	0.159 (0.365)	0.166 (0.372)	n/a	n/a	0.0832 (0.276)	0.0834 (0.276)
Years	2000+	2000+	2000+	2000+	2000+	2000+
Obs	590,233	489,508	41,784	123,439	41,784	123,439
R-sq	0.000	0.022	0.007	0.008	0.113	0.105

CHAPTER SIX

Discussion and Conclusion

Overall, there were no relevant statistically significant results with any of the individual opioid drugs, medical conditions, and other possible measures of opioid use with the age threshold. While Medicaid's visual discontinuity in the conditional means output was initially concerning, the weighted regression found no statistically significant relationship. Additionally, neither including Medicaid as a covariate nor conditioning the regression on Medicaid status affected the statistical significance of the regression discontinuity results. Despite the lack of statistically significant results, a possible extension of the research design would be to implement a fuzzy regression discontinuity approach with a two stage least squares instrumental variables regression since Medicare coverage was not a complete binary shift, but the probability of coverage did significantly increase. One limitation to this is that disability would ideally be one of the instruments used in the first stage regression, but the Medical Expenditure Panel Survey does not measure any variables that include disability. Additionally, a very small number of individuals reported End Stage Renal Disease (<300), which would be useful as an additional instrument for the first stage regression for the fuzzy regression discontinuity design. Another possible concern with the MEPS data is possible bias in Medicaid reporting or surveying frequency, as prior studies indicated significant underreporting in NHIS and MEPS data.

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