ABSTRACT

State-Level Political Party Effects on the War on Drugs

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The United States' drug arrest rate and incarceration rates have been increasing steadily for over two decades. Additionally, there is a general perception that Republicans are "tougher on crime" than Democrats. This thesis sets out to examine whether there is, in fact, a political aspect to the war on drugs. Using an RD design with close elections, this paper examines differences in drug arrest rates, incarceration rates, and price and purity of certain drugs based on the party of the state's governor. Although public perception and anecdotal evidence may suggest that an effect does exist, this paper's results do not support that anecdotal evidence. Instead I find no significant difference between governors of different parties in regards to the the various outcomes of interest.

State-Level Political Party Effects on the War on Drugs

by

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A Thesis

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CHAPTER ONE

Introduction

During a special message to Congress in 1971, President Richard Nixon is said to have coined the phrase “The War on Drugs”(Nixon 1971). Since that time there has begun a growing trend among state and national governments to “crack-down” on drug usage within their jurisdictions. That trend is shown clearly in the fact that since 1985 drug arrests and prison populations have almost doubled. In 2013, then Attorney General Eric Holder issued a memorandum to all employees of the U.S. Department of Justice regarding prosecutions in drug cases. He wrote, “Long sentences for low-level, non-violent drug offenses do not promote public safety, deterrence, and rehabilitation.”(Holder 2013) However, in late 2016 Donald J. Trump was elected President of the United States and appointed Senator Jeff Sessions to serve as his Attorney General. In May 10, 2017 Attorney General Sessions issued a memorandum that called for prosecutors to, “charge and pursue the most serious, readily provable offense.”(Sessions 2017) Furthermore he stated that, “Any inconsistent previous policy of the Department of Justice relating to these matters is rescinded.”(Sessions 2017) This clear distinction in drug policy between Democratic and Republican Attorneys General showcases a commonly held perception: that Republicans are tougher on crime, especially in regard to drug policy.

While it appears that this trend may be supported by anecdotal evidence, this paper sets out to determine whether empirical data supports this assertion. In order to do so this paper will look at the state level in order to determine whether there is an observable difference in drug arrests and incarcerations between Republican and Democratic governors. In addition, drug prices and purity levels are also compared based on the political party of the governor.

CHAPTER TWO

Historical Background

The first step in examining the war on drugs is to look at criminal justice in the United States as a whole. As a country the United States "incarcerates its residents at a rate that is greater than every other country in the world."(Raphael and Stoll 2009) Additionally, the nationwide incarceration rate has been growing at a substantial rate since the 1970's. To get a better idea of the exact trends, I examined the trends in prison population and drug arrests from 1985-2008. These trends can be seen in Figures 2.1 and 2.2.

As shown by the data, in 1985 the total state prison population in the United States was 451,812 persons incarcerated by states. By 2008, this number had more than doubled to 1,149,664 persons. If we examine this on a per capita basis the trend still exists. Over that same time span the per 100,000 prison population rose from approximately 190 in 1985 to 378 in 2008. This represents an increase of 98.9% from 1985-2008.

The same general trends can also be seen in drug arrests. In 1985 state law enforcement agencies made a combined total of 760,018 drug related arrests. In 2008, this same number was 1,379,493 arrests. The holds for the per 100,00 amounts. This rose from 319 per 100,000 to 453 per 100,000. This represents an increase of 42% over that time period.

While these are national numbers they are all based on state level data only. The prison populations data only includes individuals that are incarcerated in state facilities for state crimes and the same is true of drug arrests. As such the increase in incarceration and arrests can be seen at the state-level.

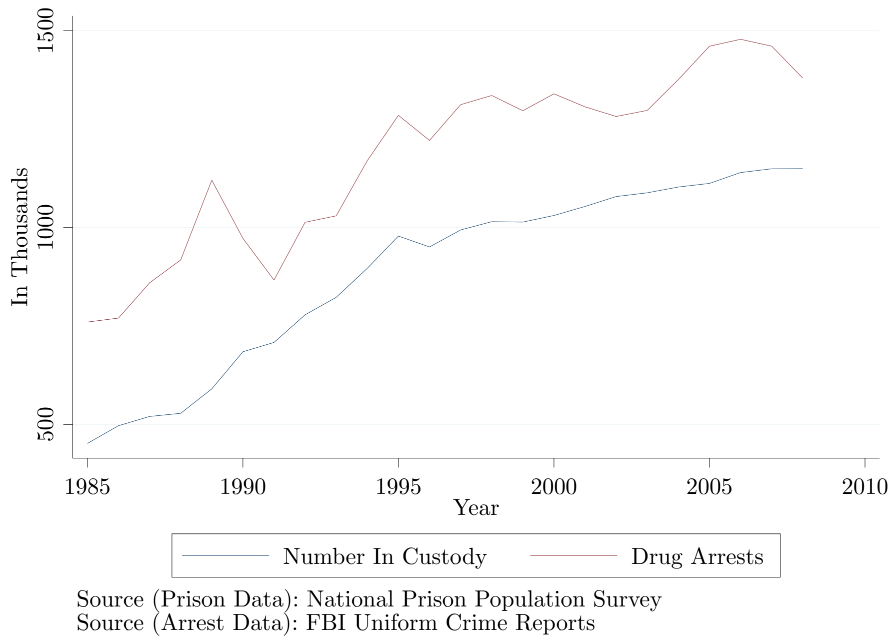

Figure 2.1. Drug arrest and prison trends (1985-2013)

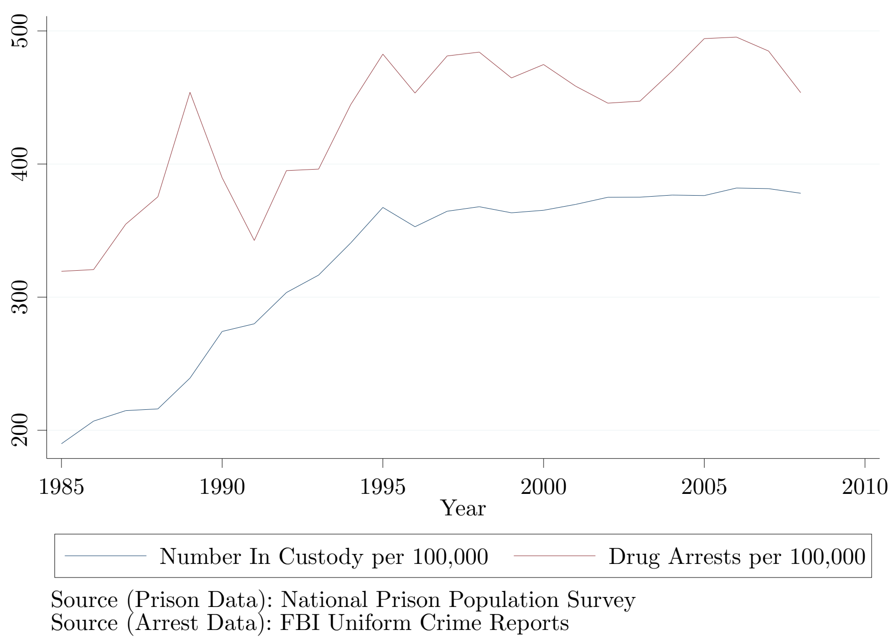

Figure 2.2. Drug arrest and prison trends per 100,000 (1985-2013)

In their 2009 book, Steven Raphael and Michael A. Stoll spend an entire chapter examining the increasing incarceration rate in the United States. They find that a major part of the reason for the increase in incarceration is changing policy at the state and national levels. Even more shocking is their statistic that, “these changes in who goes to prison [...] and for how long [...] explain 80 to 85 percent of prison expansion.”(Raphael and Stoll 2009) While they did study both the state and federal levels, data has shown that federal incarceration accounts for only 6% of total incarceration in the United States. As such, their data is compelling evidence that policy decisions at the state level do affect incarceration rates.

The empirical evidence regarding the War on Drugs highlight the need for a greater understanding of what drives these changes. The anecdotal evidence would tend to suggest that political party affiliations drive the change and the question of whether this is consistent with empirical evidence is what this paper explores.

CHAPTER THREE

Simple OLS

The historical background suggests that the increase in incarcerations and arrest rates is a state-level phenomena. As a starting point, I examine a simple OLS regression using arrest rate, incarceration rate, and drug price outcomes to determine if effects appear. I regress Governor party onto the outcomes both with and without covariates. The results of these regressions are reported in Tables 3.1-3.2.

Table 3.1. OLS regressions

VARIABLES	Price of Meth	Price of Cocaine	Price of Heroin	Incarceration Rate	Drug Arrest Rate
Governor Party	0.0295	-0.000181	0.0774	1.665	5.122
	(0.0815)	(0.0460)	(0.0966)	(8.259)	(9.138)
Constant	3.111***	3.172***	1.251***	326.7***	119.7***
	(0.215)	(0.0802)	(0.349)	(12.76)	(13.84)
Observations	784	1,064	762	1,109	1,109
R^2	0.443	0.258	0.378	0.912	0.762

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Drug Market Dependent Variables are Natural Logs

Table 3.2. OLS regressions with covariates

VARIABLES	Price of Meth	Price of Cocaine	Price of Heroin	Incarceration Rate	Drug Arrest Rate
Governor Party	0.0194	-0.0121	0.0608	0.683	1.432
	(0.0752)	(0.0403)	(0.0833)	(7.757)	(7.181)
Constant	3.901	0.658	2.880	851.4***	594.4
	(3.464)	(1.156)	(3.261)	(183.8)	(331.5)
Observations	765	1,030	754	1,072	1,072
R^2	0.466	0.322	0.484	0.919	0.782

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Drug Market Dependent Variables are Natural Logs

These regressions do not appear to show effects from Governor party. However, elections are highly endogenous and we therefore need a more stringent empirical strategy to address those issues. The remainder of this thesis discusses and implements the more stringent empirical strategy.

CHAPTER FOUR

Literature Review

In order to properly review the literature for this thesis it is necessary to break down the various aspects of the paper. First is a discussion of the general principles of a Regression Discontinuity Design and its usefulness as a causal tool. Second is a discussion of how RDD is appropriate for party effects and the identification strategy that allows that analysis. Finally, this review concludes with a brief overview of papers that have researched drug policy and proliferation throughout the U.S.

Regression Discontinuity Design

The basic idea behind RDD is that it is used to estimate the effects of being assigned a certain treatment when that treatment occurs at a specific point. In other words the probability of the treatment 'jumps' when the individual, or *state* $\times$ *year* pair, reaches a certain value for some variable. The intuition behind the usefulness of RDD is that the groups just before and just after the value will be close comparisons for each other and therefore can be used to estimate causal effects. There are several papers that showcase the usefulness of RDD and its empirical significance. In their 2007 paper Imbens and Lemieux discuss in detail the various types of an RD design as well as its potential flaws. They discuss how RD designs are used to estimate causal effects of binary treatments by using observations on either side of a discontinuity to estimate the effect of the treatment. (Imbens and Lemieux 2008) An even more detailed discussion of the RD design can be seen in Lee and Lemieux's 2010 paper. In their 2010 paper they discuss in great detail the history of the RD design as well as its many applications. One of their more notable observations is that RD designs can be treated like randomized experiments for the purpose of testing and analysis. (Lee and Lemieux 2010) As randomized experiments are considered the gold standard for causal estimation RD designs are able to achieve randomization interpretation for non-random outcomes.

One specific paper that is noteworthy in the RD field is McCrary's 2008 paper. In his paper he lays out a test to identify manipulation of the running variable. In his paper he shows that his test is implemented through a Wald test that tests against the null hypothesis that there is no discontinuity in the running variable itself. To examine the test he uses data from the U.S. House of Representatives. He first examines elections to the house where manipulation by a single individual would be nearly impossible. His density test shows no discontinuity as would be expected. He then examine votes in the House where manipulation by a single individual is not only expected but likely. Again his test supports the theory in that he finds manipulation of the running variable. (McCrary 2008)

Party Effects

Among the more difficult areas of study is the effect political parties can have on policy. The issue with the area of research is that election outcomes are highly endogenous. Two authors have papers that show how an RD design is an effective way to combat the endogeneity of election outcomes of empirical research. The first is Lee, Moretti, and Butler's 2004 paper that examines election in the U.S. House of Representatives. They use close elections, defined as within 2 points, to create a quasi-random experiment to examine how exogenous changes in political power in the U.S. House changed policies. (Lee, Moretti, and Butler 2004) The second is when Lee repeats this strategy in 2008 and shows further evidence that the RD design can have analysis that is as credible as those from a random experiment. (Lee 2008)

At the national level Lee's papers provide a good background for why RD designs are credible ways to estimate political effects. At the state-level however, two papers from Beland show that RDD is still an appropriate method for examining those effects. Both papers follow the same strategy to estimate the effect of governor party on state-level effects. In one paper Beland examines party effects on pollution and in the other he examine labor-market outcomes. He uses close elections for the Governor in order to examine whether the party of the Governor affects policy decisions at the state level. In both paper he find statistically significant effects when using close elections at either the 5% or 10% level. (Beland and Boucher 2015) (Beland 2015)

The War on Drugs/Crime

In order to see whether certain policies regarding drug enforcement are effective several papers have studied drug markets to see how changes in enforcement affect both price and consumption. Affecting drug markets is a key aspect to enforcement of drug policy. When incarceration of drug offenders is increased research has shown that prices for drugs will also increase.(Kuziemko and Levitt 2004). As result of these price increases demand for the drugs, and therefore consumption has decreased (Caulkins and Reuter 1998) (Desimone and Farrelly 2003) The combination of these two areas of research show that an increase to arrest rate can cause a decrease in the demand for drugs. (Desimone and Farrelly 2003)

To further bolster the findings that drug markets are affected by enforcement policy a separate paper compared drug prices in legal and illegal markets. The results show that the relationship between drug prohibition and drug prices is strong and that drug prohibition has a positive relationship with the price of drugs in a given market. (Miron 2003)

One final study of interest regards hardcore drug users. Theory states that for hardcore addicts the elasticity of demand with respect to price for illegal drugs would be highly inelastic. As such, the expectation would be that increased prices have little to no effect on demand. Research has found that this is not the case and that even among hardcore addicts increased drug prices negatively affect drug usage. (Dave 2008)

CHAPTER FIVE

Data

My data comes from a combination of multiple sources including IMPUS CPS data, DEA STRIDE Data, FBI Uniform Crime Reports, National Prisoner Population Survey, and election data. The data and its sources are described in more detail in this chapter.

Drug Arrests

Data on drug arrests comes from the Federal Bureau of Investigation's Uniform Crime Reports. In order to better see any results, the data is transformed by combining all drug arrests in a $state \times year$ and then dividing by the $state \times year$ population to get the per capita drug arrest rate. That rate is then multiplied by 100,000 as is custom when examining data at population adjusted levels.

Drug Price and Purity Data

Information on drug prices and purities came from the Drug Enforcement Agency's (DEA's) System to Retrieve Information from Drug Evidence (STRIDE) database. The database includes information that the DEA has obtained since the late 1970's regarding the purchase of drugs made by federal, state, and local law enforcement officials. It includes various information on the purchases. Of interest to this paper were: location, year, price, and purity of the drug. While there has been debate over the usefulness of using STRIDE data, Arkes et. al., 2008 write, "STRIDE is useful for estimating trends in the price of illicit drugs."(Arkes, Pacula, Paddock, Caulkins, and Reuter 2008) As this paper is concerned with such trends, STRIDE is an appropriate data source. The STRIDE data regarding prices are adjusted for inflation using the CPI and are transformed using a natural log.

Incarceration

Incarceration data is obtained from the National Prisoner Population Survey. The survey is administered by the U.S. Census Bureau and then published by the Department of Justice's Bureau of Justice Statistics. The data contains a wide-ranging set of information on prisoners. This includes: race, sex, type of facility, and health statistics among other data. For my research the only relevant information was the total number incarcerated which was obtained by aggregating male and female incarceration statistics at the *state* $\times$ *year* level. I again transform this data to be per 100,000 individuals.

Covariates

Data for covariates was obtained from IMPUS CPS data (Flood, King, Ruggles, and Warren 2017). The covariates fell into five different categories. The first was a set of dummy variables for income brackets in the CPS. Because of data collection changes throughout the span of the data income brackets were in ranges of $25,000 and the final bracket included all incomes above $75,000. The next was for marital status which was either married or not married. The third set of covariates examined the education level of individuals and included education levels ranging from no education at all to a bachelors degree or above[1]. The fourth set of variables was a set of age brackets. The first bracket was minors, the second was 18 to 65 year-olds and the third was all individuals over 65. The final set covariates were a set of race-gender covariates. Three race categories were created: white, black, and other race and these were then split by gender to create those covariates. Finally, all of the different variables were population adjusted to be per 100,000 individuals.

[1]CPS did not ask about degrees above a bachelors for the duration of the data in this paper.

Running Variable

The running variables, in this case margin of victory, is taken from a 2013 paper by Thomas Beland. In his paper Beland lays out the exact process by which he obtained the data:

> "For gubernatorial elections, two main data sources are used. For elections data prior to 1990, I use the ICPSR 7757 (1995) files called 'Candidate and Constituency Statistics of Elections in the United States, 1788-1990.' Data post-1990 comes from the Atlas of US Presidential Elections (2011). Only elections where either a Democrat or a Republican won are included. All states are included. Variables of interests taken from these sources are the party of the winner and the margin of victory."(Beland 2015)[2]

Margin of victory is defined as the percentage of the vote won by the Democratic candidate minus the vote won by the Republican candidate.

Legislative Power

Legislative power is also part of the data set. The legislative power data comes from data from The Council of State Governments(The Council of State Governments 2013). It includes both a variable for the percent of the state legislature that is controlled by Democrats as well as a variable that take the minimum of two values: party of governor and percent controlled by Democrats. Therefore, this variable takes one of two values: zero if the governor is Republican or the percent of the legislature controlled by Democrats if the governor is a Democrat.

Summary and Descriptive Statistics

Of the 1109 $state \times year$ pairs that are in the dataset, a Democrat was the governor 557 times and a Republican was the governor 552 times. Beland defines "close" elections as ones where the margin of victory is within either 5 or 10 percentage

[2]Beland notes that when possible he confirmed election results by checking official government data. Additionally some instances involved governors that were replaced mid-term. If the replacement was of the same party they were left in the data; however, if they were not of the same party that observation is dropped from the data because the relevant margin of victory variable is no longer present.

points. Using that definition there are 498 elections that would qualify as close at the 10% level and 262 at the 5% level. At the 10% level Democrats won 236 times and Republicans won 262 times. For the 5% level the number of times are 118 and 144 respectively. In Table 5.1 the following variables are shown for states that fall within the definition of a close election: the proportion blacks in the population; the proportion of the population that is less than 18 years old; the proportion of the population that is greater than 65 years old; the proportion of the population between the ages of 18 and 65; the proportion of the population with a High School Diploma or less; the proportion of the population with a College Education; and the natural logarithm of the population of the state. As can be seen in the table, states where a Republican Governor barely won are similar to states where a Democratic Governor barely won, a key assumption of RDD.

Table 5.2 reports the summary statistics for all covariates. Most covariates have a sample size of 1113 which is equal to the number of $state \times year$ pairs for which data is available on drug arrest rates. With the race variables some do not have sample sizes of 1113 which I attribute to changes in the question and coding of race variables in the CPS over time.

Table 5.1. Descriptive statistics for states close to discontinuity

(a) Republican states (5%)

Variable	Obs	Mean	Sd
Black	138	.116	.101
Age < 18	144	.259	.031
Age > 65	144	.121	.015
Age 18 to 64	144	.602	.022
No High School	144	.064	.025
Some HS, HS, Some College	144	.567	.055
Bachelors or more	144	.138	.071
ln(population)	144	15.223	.92

(b) Democratic states (5%)

Black	116	.093	.104
Age < 18	118	.258	.031
Age > 65	118	.114	.025
Age 18 to 64	118	.606	.021
No High School	118	.054	.023
Some HS, HS, Some College	118	.574	.041
Bachelors or more	118	.137	.052
ln(population)	118	14.953	1.009

(c) Republican states (10%)

Black	250	.106	.099
Age < 18	262	.262	.031
Age > 65	262	.119	.018
Age 18 to 64	262	.601	.022
No High School	262	.067	.03
Some HS, HS, Some College	262	.57	.05
Bachelors or more	262	.13	.064
ln(population)	262	15.119	.941

(d) Democratic states (10%)

Black	233	.106	.106
Age < 18	236	.255	.03
Age > 65	236	.116	.022
Age 18 to 64	236	.606	.018
No High School	236	.059	.028
Some HS, HS, Some College	236	.574	.043
Bachelors or more	236	.135	.057
ln(population)	236	15.033	.94

Table 5.2. Summary Statistics for Covariates

Variable	Mean	Std. Dev.	N
Income < 25k	0.322	0.132	1113
Income between 25k and 50k	0.286	0.054	1113
Income between 50k and 75k	0.143	0.045	1113
Income > 75k	0.13	0.089	1113
Not Married	0.334	0.03	1113
Married	0.433	0.027	1113
No High School	0.064	0.03	1113
Some HS, HS, Some College	0.573	0.047	1113
Bachelors or more	0.131	0.061	1113
Age < 18	0.259	0.029	1113
Age 18 to 64	0.604	0.02	1113
Age > 65	0.117	0.019	1113
White Males	0.403	0.064	1113
White Females	0.419	0.067	1113
Black Males	0.048	0.044	1094
Black Females	0.055	0.052	1087
Other Race Males	0.027	0.05	1112
Other Race Females	0.029	0.052	1109

Table 5.3. Summary Statistics for Outcomes

Variable	Mean	Std. Dev.	N
Log of Price of Meth	2.954	0.979	785
Log of Purity of Meth	3.461	0.597	934
Log of Price of Cocaine	3.479	0.444	1068
Log of Purity of Cocaine	4.074	0.21	1104
Log of Price of Heroin	3.965	1.019	764
Log of Purity of Heroin	3.564	0.569	919
Incarceration Rate	307.984	139.322	1113
Drug Arrest Rate	314.604	154.23	1113

CHAPTER SIX

Methodology

The identification strategy for this research is an RDD model. As discussed in the literature review RDD accounts for the endogeneity of election outcomes as elections can be influenced by many factors both observable and unobservable that can impact who wins an election. By using close elections the winner is a quasi-random result.(Lee 2008) Because RDD creates quasi-randomization it allows for the estimation of local average treatment effects. Therefore, any results are not only statistically significant but show causality. In this research the discontinuity exists when the margin of victory is 0%.

RDD Model

I estimate several different models for each of my outcome variables. The first estimate model is a non-parametric model of the equation:

$$Y_{st} = \beta_0 + \beta_1 D_{st} + \beta_2 MV_{st} + \beta_3 D_{st} \times MV_{st} + \beta_C C_{st} + \beta_Z Z_{st} + \varepsilon_{st} \tag{1}$$

Where Y_{st} represents the outcome of interest in state s for year t. The following outcomes are estimated: Drug Arrest Rate and Incarceration Rate. I also look at the price and purity of the following drugs: methamphetamine, heroin, and cocaine. D_{st} is the dummy variable for the governor's party with value 1 if the governor is a Democrat and value 0 if the governor is a Republican. β_1 is the coefficient of interest. If there is a political effect I expect β_1 to be significant. MV_{st} is the margin of victory in the most recent gubernatorial election for state s in year t. C_{st} represents all of the covariates for the various *state* $\times$ *year* pairs. Z_{st} includes state and year fixed effects. β_C and β_Z represent vectors of coefficients for the vectors C_{st} and Z_{st}. In order to remove any potential serial correlation, all standard errors are clustered at the state level.

The second model estimated is a parametric model of the second order and has the equation:

$$\begin{aligned} Y_{st} = \beta_0 + \beta_1 D_{st} + \beta_2 MV_{st} + \beta_3 {MV_{st}}^2 + \beta_4 D_{st} \times MV_{st} \\ + \beta_5 D_{st} \times MV_{st}^2 + \beta_C C_{st} + \beta_Z Z_{st} + \varepsilon_{st} \end{aligned} \tag{2}$$

This model adds a squared margin of victory interacted with the governor's party to better estimate the slopes on either side of the discontinuity.

The next two models follow the same form as equation (2) except they are limited in the number of states or *state* × *year* pairs that are included in the model. The third model estimate only includes states that are not from the south[1] and the fourth model only includes *state* × *year* pairs where the proportion of the legislature controlled by Democrats is greater than one-half.[2]

Identifying Assumptions

In order to use a regression discontinuity design certain identifying assumptions must be made. As mentioned earlier the discontinuity exists when the margin of victory is equal to 0. Figure 6.1 shows the distribution of the running variable. As shown in the distribution there are not any unusual jumps around the cutoff. In Figure 6.2 the McCrary Density test shows the same. The lack of unusual jumps around the discontinuity helps to solidify the appropriateness of the RDD design.

Continuity Assumptions

Outside of examining the running variable it is also important to test the covariates. If the covariates also jump at the discontinuity, this would challenge

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[1]Southern states include: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia. This resulted in 848 *state* × *year* pairs.

[2]This included 669 *state* × *year* pairs

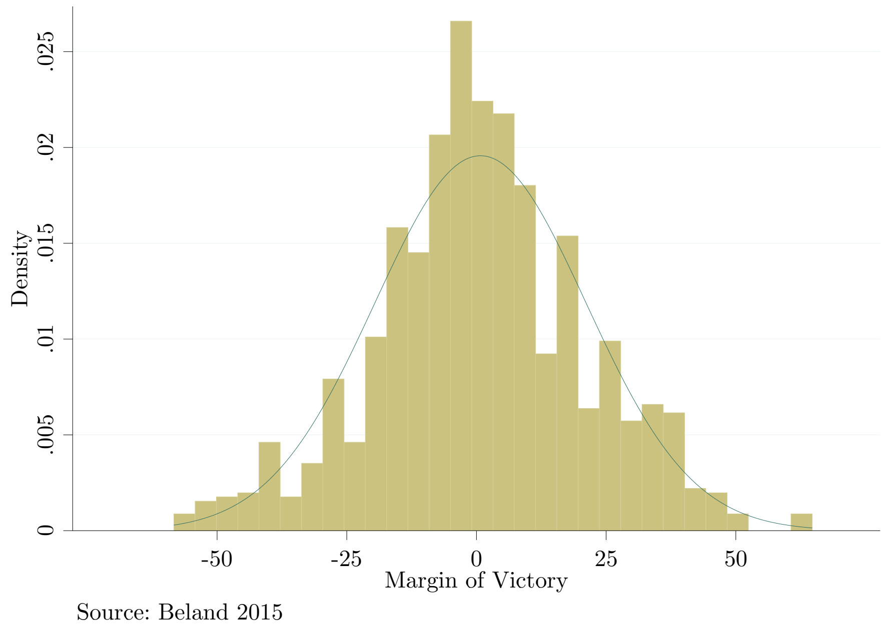


Figure 6.1. Distribution of margin of victory

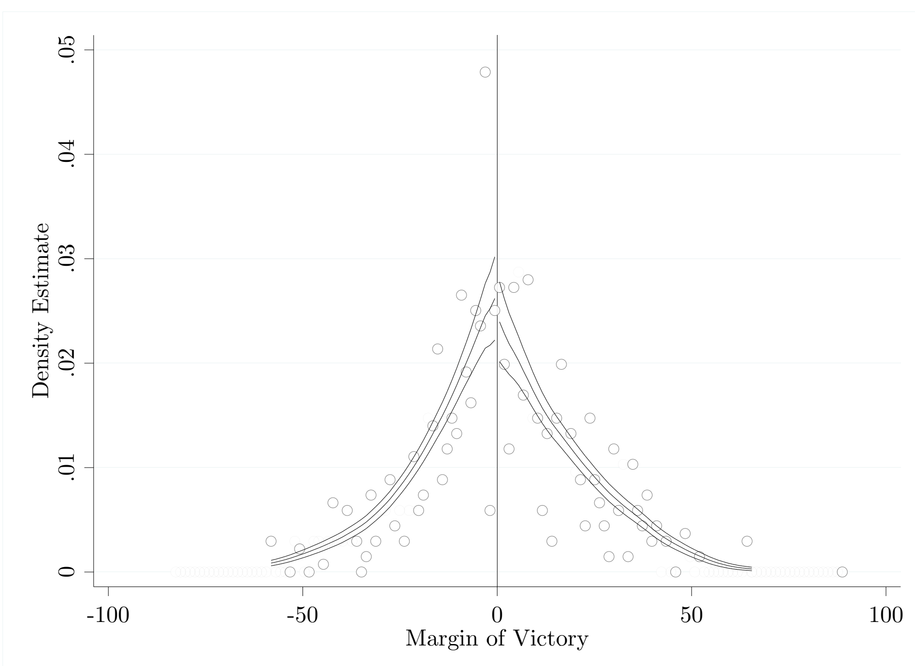
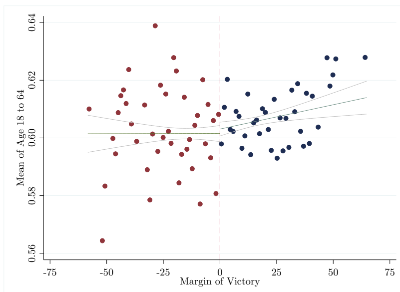
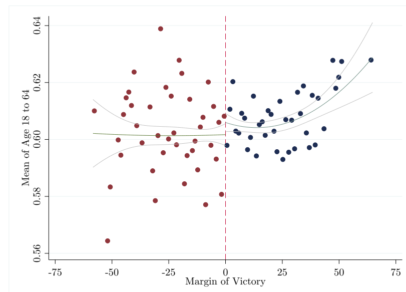


Figure 6.2. McCrary density test

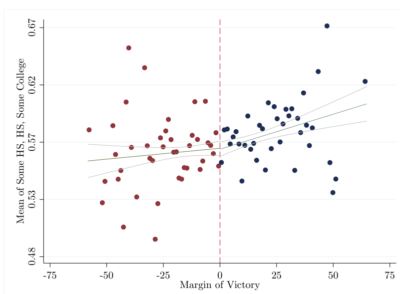
the appropriateness of the RDD design. Figure 6.3 provides a panel of some of the covariates [3]. The dotted vertical line represents the discontinuity. The green lines are regression results with the gray lines showing a 95% confidence interval for the results. As shown by Figure 6.3 (and further in the appendix) the covariates are unaffected by the discontinuity.[4]



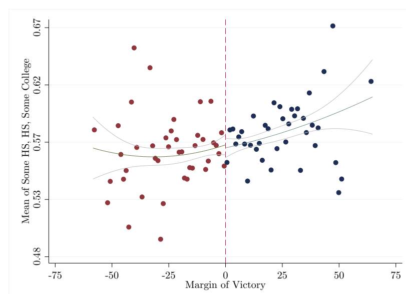
(a) Age 18 to 64 (linear)



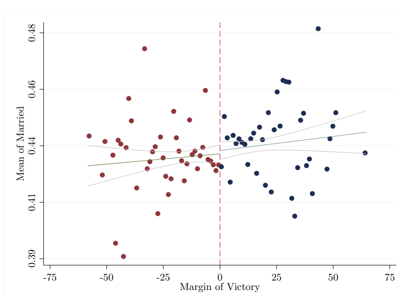
(b) Age 18 to 64 (quadratic)



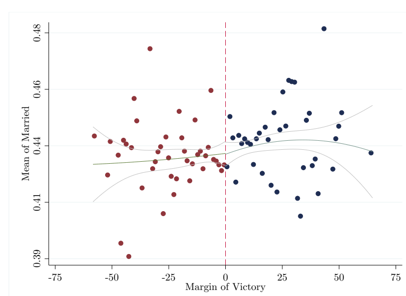
(c) Some School (linear)



(d) Some School (quadratic)



(e) Married (linear)



(f) Married (Quadratic)

Figure 6.3. Continuity graphs for covariates

[3] All covariate continuity graphs can be seen in the appendix

[4] For further discussion see Appendix B

CHAPTER SEVEN

Results

The results for all of the regressions are reported in Tables 7.1 through 7.12. Starting with the most basic regression, the linear model in equation (1). The results from the linear models are reported in Tables 7.1, 7.2, and 7.3. In none of the linear regression is Democratic Governor a statistically significant variable. This is further supported by the graphs which show the residuals from a linear regression of the outcomes on the running variable with and without covariates. These graphs can be seen in Appendix A in Figures A.1-A.4. The results show by the graphs in Figures A.1-A.4 line up closely with the results in Tables 7.1-7.3. There are no statistically significant "jumps" in the data at the discontinuity.

Table 7.1. Drug price regressions

Variables	Price of Meth	Price of Cocaine	Price of Heroin
Democratic Governor	0.0781	0.0244	0.228
	(0.117)	(0.0591)	(0.115)
Margin of Victory	0.00288	0.000319	-0.00346
	(0.00421)	(0.00144)	(0.00325)
Constant	3.797	0.592	3.118
	(3.507)	(1.159)	(3.247)
Observations	765	1,030	754
R^2	0.470	0.324	0.489

Robust standard errors in parentheses

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

All Dependent Variables are Natural Logs

Table 7.2. Drug purity regressions

Variables	Purity of Meth	Purity of Cocaine	Purity of Heroin
Democratic Governor	-0.00650	0.00165	-0.0234
	(0.0593)	(0.0242)	(0.0638)
Margin of Victory	-0.000180	-0.000104	-0.00129
	(0.00192)	(0.000604)	(0.00151)
Constant	1.810	2.827***	3.846*
	(2.409)	(0.388)	(1.508)
Observations	909	1,063	901
R^2	0.446	0.498	0.359

Robust standard errors in parentheses

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

All Dependent Variables are Natural Logs

Table 7.3. Arrest and incarceration regressions

Variables	Incarceration Rate	Drug Arrest Rate
Democratic Governor	-4.321	12.09
	(6.591)	(10.66)
Margin of Victory	0.258	0.265
	(0.255)	(0.413)
Constant	852.4***	574.4
	(184.2)	(333.2)
Observations	1,072	1,072
R^2	0.919	0.785

Robust standard errors in parentheses

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

After examining the results of the linear regressions, the next set of results to examine are those that are formed from equation (2). These are the quadratic regressions. The results in Tables 7.4-7.6 report the regression coefficients for each of the outcomes of interest. Not a single outcome has statistical significance. This result is further confirmed by the quadratic graphs which are shown in Figures A.5-A.8.

Table 7.4. Quadratic drug price regressions

Variables	Price of Meth	Price of Cocaine	Price of Heroin
Democratic Governor	0.169	0.0555	0.341
	(0.154)	(0.0765)	(0.199)
Margin of Victory	-0.00946	-0.00482	-0.0172
	(0.0144)	(0.00432)	(0.0117)
Constant	3.621	0.508	3.113
	(3.558)	(1.182)	(3.222)
Observations	765	1,030	754
R^2	0.471	0.325	0.490

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Dependent Variables are Natural Logs

Table 7.5. Quadratic drug purity regressions

Variables	Purity of Meth	Purity of Cocaine	Purity of Heroin
Democratic Governor	0.0848	-0.0146	-0.0483
	(0.0748)	(0.0310)	(0.0721)
Margin of Victory	-0.0112	0.000661	0.00355
	(0.00591)	(0.00197)	(0.00568)
Constant	1.659	2.824***	3.928*
	(2.454)	(0.393)	(1.501)
Observations	909	1,063	901
R^2	0.449	0.499	0.359

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Dependent Variables are Natural Logs

Table 7.6. Quadratic arrest and incarceration regressions

Variables	Incarceration Rate	Drug Arrest Rate
Democratic Governor	-3.499	15.32
	(7.279)	(15.88)
Margin of Victory	0.395	-0.325
	(0.738)	(1.487)
Constant	857.0***	564.3
	(186.4)	(339.0)
Observations	1,072	1,072
R^2	0.919	0.785

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

As mentioned earlier, I performed two robustness checks for the results. The first involved only using non-southern states. Prior research has argued that Southern Democrats are more conservative and as a result would act closer to their Republican counterparts than non-southern governors.(Alt and Lowry 2000) The expectation is therefore that in non-southern states, any effects would be of a greater magnitude compared to the magnitude looking at all states. As seen in Tables 7.7-7.9 the results are the same as when southern states are included, no outcome shows statistical significance.

Table 7.7. Quadratic non-southern drug purity regressions

Variables	Price of Meth	Price of Cocaine	Price of Heroin
Democratic Governor	0.305	0.0681	0.180
	(0.172)	(0.0872)	(0.220)
Margin of Victory	0.00206	-0.00420	-0.0147
	(0.0151)	(0.00493)	(0.0108)
Constant	2.930	1.375	5.004
	(3.646)	(1.090)	(3.886)
Observations	553	768	594
R^2	0.515	0.377	0.504

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Dependent Variables are Natural Logs

Table 7.8. Quadratic non-southern drug purity regressions

Variables	Purity of Meth	Purity of Cocaine	Purity of Heroin
Democratic Governor	0.155	0.000606	-0.126
	(0.0890)	(0.0392)	(0.0823)
Margin of Victory	-0.0100	-0.000505	-0.000812
	(0.00664)	(0.00215)	(0.00551)
Constant	0.728	2.820***	3.860*
	(2.676)	(0.354)	(1.637)
Observations	668	801	684
R^2	0.467	0.477	0.419

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05
All Dependent Variables are Natural Logs

Table 7.9. Quadratic non-southern arrest and incarceration regressions

Variables	Incarceration Rate	Drug Arrest Rate
Margin of Victory	0.594	0.212
	(0.885)	(1.786)
Democratic Governor	4.810	21.45
	(8.281)	(19.72)
Constant	845.8***	462.3
	(193.5)	(371.4)
Observations	810	810
R^2	0.930	0.808

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The final robustness check involves examining cases where Democrats have "Legislative Power". The theory with this robustness check is that Democrats would only be able to fully implement their policy when they have both a Democratic governor and a majority presence within the legislature. This robustness check accounts for that theory by only including *state* $\times$ *year* pairs in which Democrats controlled a majority of the state legislature. The results are reported in Tables 7.10-7.12. The results again show a lack of any statistically significant result for most of the outcome variables. One outcome does show statistical significance, the price of methamphetamine appears to decrease as the margin of victory increases. One possible interpretation of this result is that as the state becomes more democratic the price of methamphetamine would decrease. That interpretation alone would be cause to question the result as it does not appear to make sense. Therefore, in order to further investigate this result, I created a graph similar to those in Figures A.1-A.8 but which only includes the observations from Table 7.10. This graph is shown as Figure 7.1 and shows that in reality there appears to be no significant effect. In fact the graph seems to suggest the opposite, that the price of methamphetamine increases slightly as the state becomes more Democratic.

Table 7.10. Quadratic drug price regressions with Leg. Power

Variables	Price of Meth	Price of Cocaine	Price of Heroin
Democratic Governor	0.390	0.0655	0.437
	(0.195)	(0.104)	(0.265)
Margin of Victory	-0.0528*	-0.0139	-0.0390
	(0.0219)	(0.00705)	(0.0258)
Constant	-0.481	0.0900	8.092*
	(3.737)	(1.745)	(3.837)
Observations	448	655	487
R^2	0.536	0.348	0.556

Robust standard errors in parentheses

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

All Dependent Variables are Natural Logs

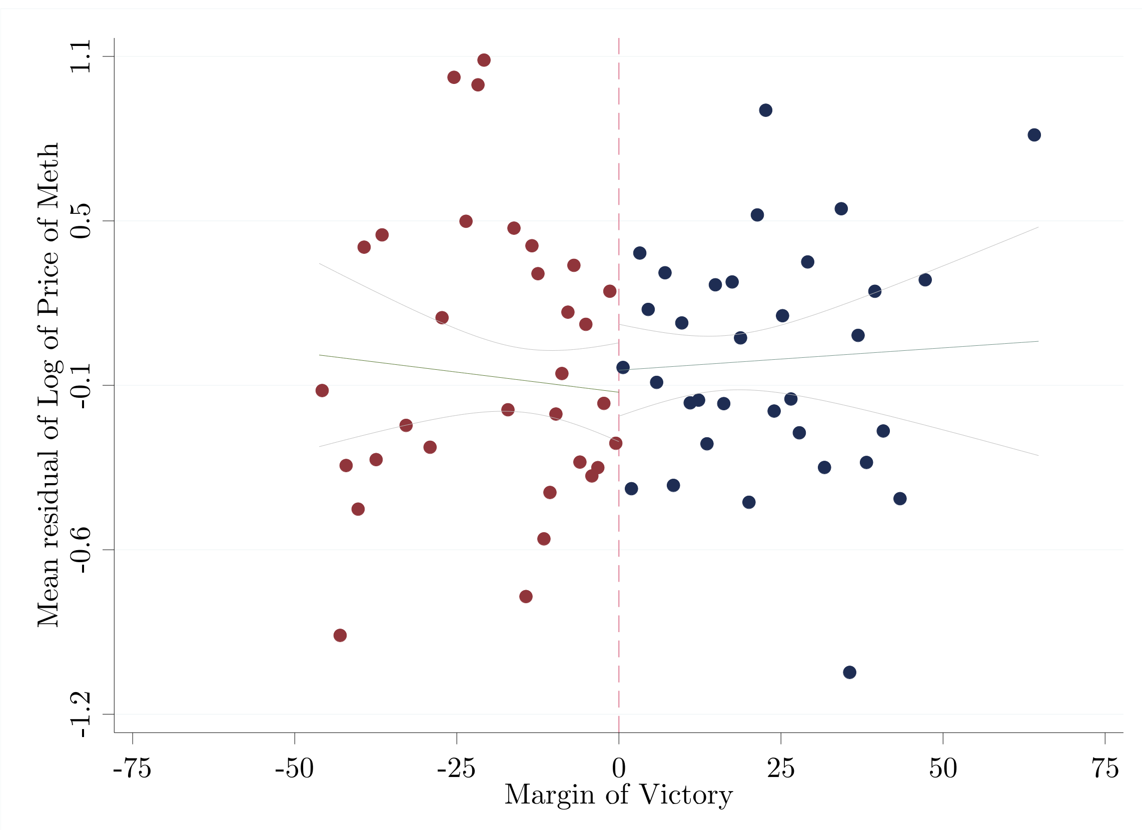


Figure 7.1. Robust methamphetamine price regression residual graph

Table 7.11. Quadratic drug purity regressions with legislative power

Variables	Purity of Meth	Purity of Cocaine	Purity of Heroin
Democratic Governor	0.0894	-0.0182	-0.0612
	(0.104)	(0.0329)	(0.103)
Margin of Victory	-0.0151	-0.000879	0.0162
	(0.0107)	(0.00340)	(0.0110)
Constant	-0.0499	3.211***	4.331*
	(2.917)	(0.327)	(1.795)
Observations	536	658	576
R^2	0.480	0.622	0.404

Robust standard errors in parentheses

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

All Dependent Variables are Natural Logs

Table 7.12. Quadratic arrest and incarceration regressions with legislative power

Variables	Incarceration Rate	Drug Arrest Rate
Democratic Governor	-8.027	13.08
	(15.28)	(21.96)
Margin of Victory	1.020	-0.104
	(1.337)	(2.757)
Constant	794.0***	760.0
	(209.1)	(381.7)
Observations	658	658
R^2	0.909	0.792

Robust standard errors in parentheses

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

CHAPTER EIGHT

Conclusion

This paper set out with the goal of examining whether there is a political aspect to the increase in drug arrests and incarceration rates in the United States. Additionally, I examined whether drug price, as a proxy for demand, and to a lesser extent drug purity, are affected by the political climate of a state. The increase in arrest rate and incarceration rate are very real as shown in the history section yet have failed to be adequately explained at the state level. The expectation going into the paper was that I would find statistically significant results for at least drug arrests if nothing else as drug arrests are a wholly executive function. A governor needs no permission from the legislature to direct state and local law enforcement agencies to seek out drug offenses at a higher level. If Republican Governors truly are tougher on crime than their Democratic counterparts we should see statistically significant increases in drug arrests under Republican Governors. As shown in the data, this is not the case. Looking at the Democratic side: if Democrats are actually focused on reducing incarceration (by substituting treatment for imprisonment) and are weaker on crime in general, there should be a significant decrease in arrests and incarceration under Democrats. Again, as can be seen in the data this is not the case. As crime in general becomes more of a legislative function, the robustness check with legislative power should show effects for Democrats when they control both the legislative and executive branches of state government. Again, the effects do not show up in the data. Even though politicians from both sides of the aisle say they will be "tough on crime," the general consensus has been the Republicans will actually be tougher, especially when it comes to drug crime. My results show that this appears to be more political posturing than a true cause and effect.

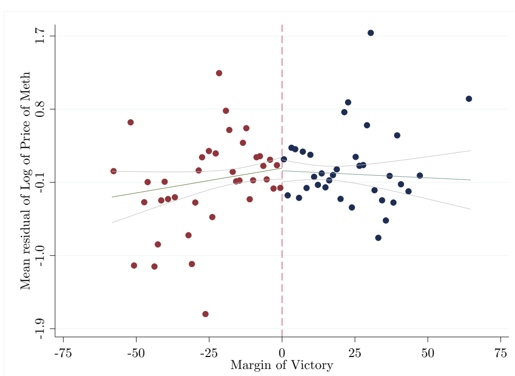
Yet the question about why the trends exist remains important. These results appear to eliminate two valid theories: increased executive enforcement of drug policing and shifting drug policy as the result of executive influence on legislative actions. Further research can hopefully begin to unravel the question of why the trends exist but for now that question remains unanswered.

APPENDICES

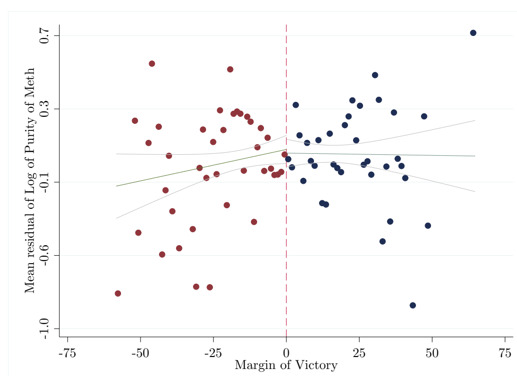
APPENDIX A

Outcome Graphs

The following are a set of outcome graphs. These were generated by running regressions of the form regress outcome on the covariates and then plotting the residuals over the margin of victory. The green line represents the line of the best fit on either side of the discontinuity and the gray lines represent the 95% confidence interval for that line of best fit. Two sets of graphs are presented. The first are the set of graphs which show a linear line of best fit (Figures A.1-A.4), the second shows a quadratic line of best fit Figures A.5-A.8). For all drug graphs the y-axis is the mean residual of a natural log of either the price or purity of the drug for a set of bins based on margin of victory. For the arrest and incarceration graphs the y-axis is the mean residual either the incarceration or drug arrest rate for a set of bins based on margin of victory. Multiple bins were tested for each graph and the results are robust to the various bin selection methods.

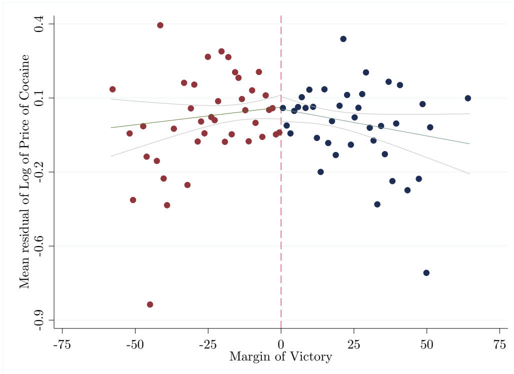


(a) Meth Price

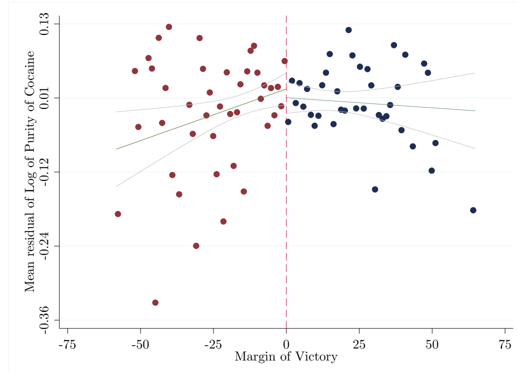


(b) Meth Purity

Figure A.1. Linear meth regression residual graphs

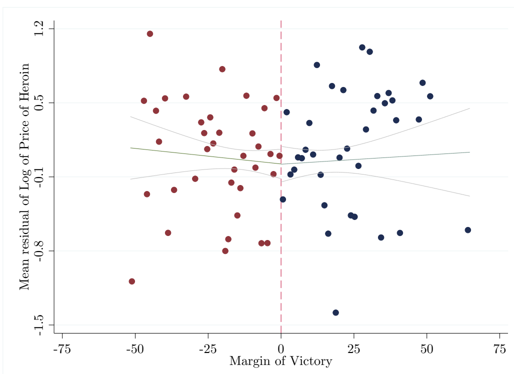


(a) Cocaine Price



(b) Cocaine Purity

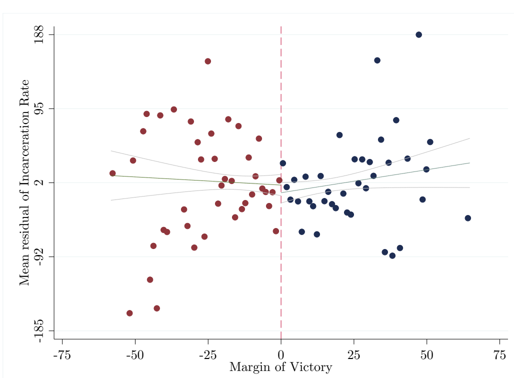
Figure A.2. Linear cocaine regression residual graphs



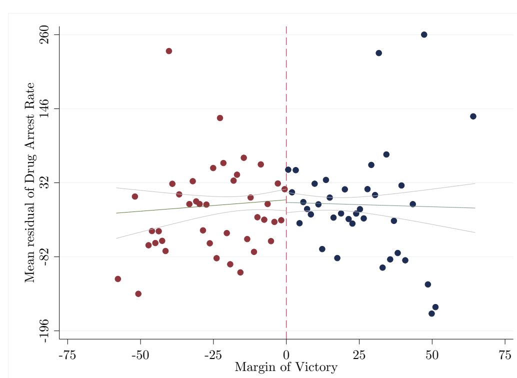
(a) Heroin Price

(b) Heroin Purity

Figure A.3. Linear heroin regression residual graphs

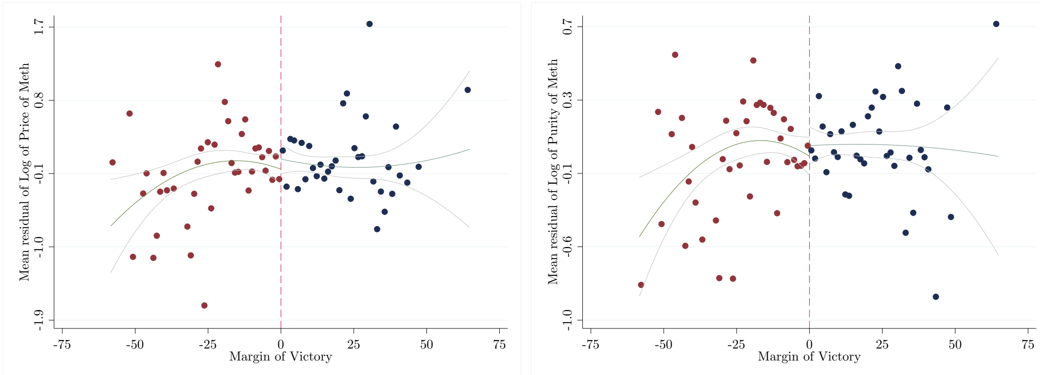


(a) Incarceration Rate



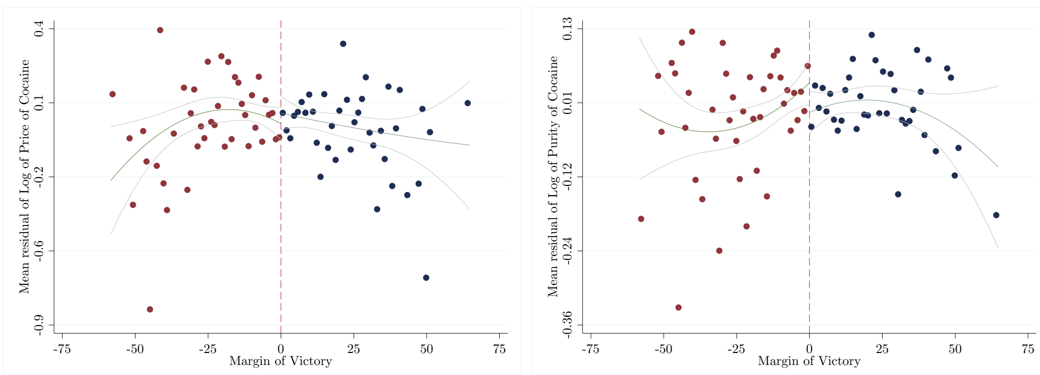
(b) Drug Arrest Rate

Figure A.4. Linear arrest and incarceration regression residual graphs



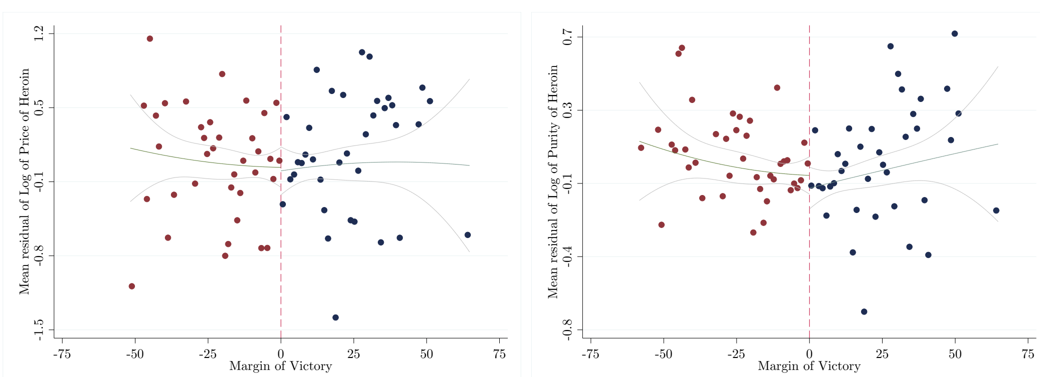
(a) Meth Price (b) Meth Purity

Figure A.5. Quadratic meth regression residual graphs



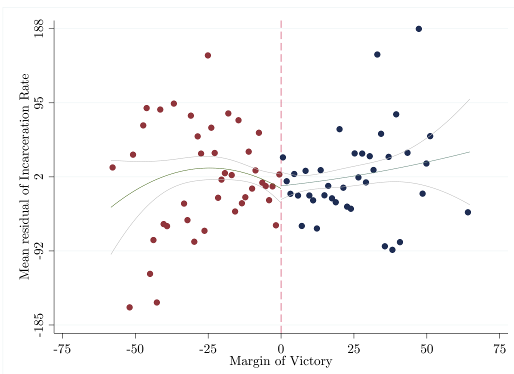
(a) Cocaine Price (b) Cocaine Purity

Figure A.6. Quadratic cocaine regression residual graphs

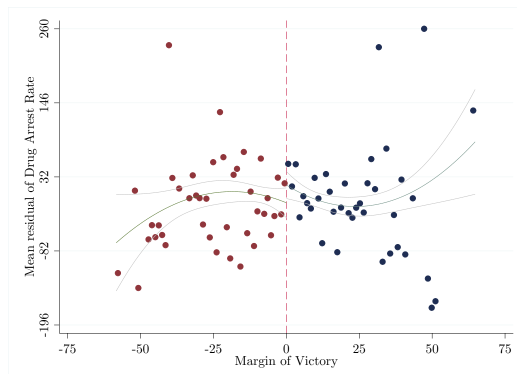


(a) Heroin Price (b) Heroin Purity

Figure A.7. Quadratic heroin regression residual graphs



(a) Incarceration Rate



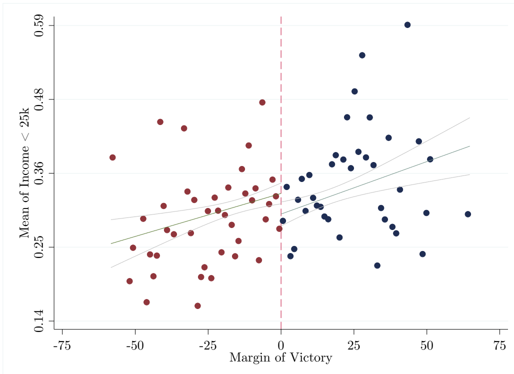
(b) Drug Arrest Rate

Figure A.8. Quadratic arrest and incarceration regression residual graphs

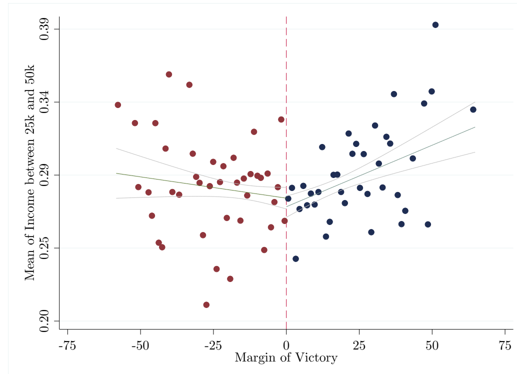
APPENDIX B

Continuity Graphs

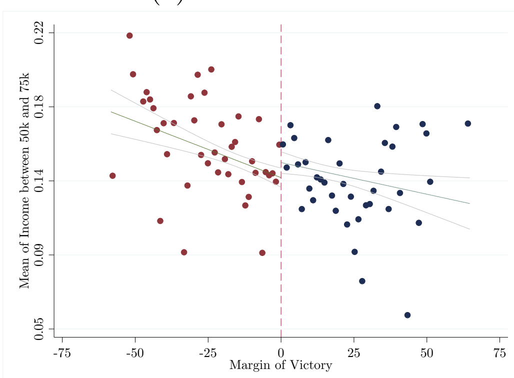
The following represent a set of continuity graphs. These graphs were made by taking the mean of the covariate within a certain range of margin of victory. These means were plotted on either side of the discontinuity to see if the covariate was jumping as a result of a change of governor. The green line represents the line of the best fit on either side of the discontinuity and the gray lines represent the 95% confidence interval for that line of best fit. Two sets of graphs are presented. The first are the set of graphs which show a linear line of best fit (Figures B.1-B.3), the second shows a quadratic line of best fit (Figure B.4-B.6).



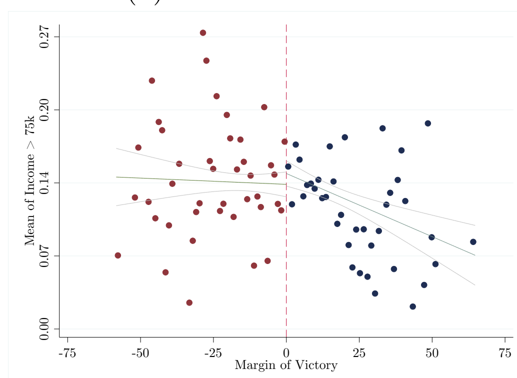
(a) Income < 25k



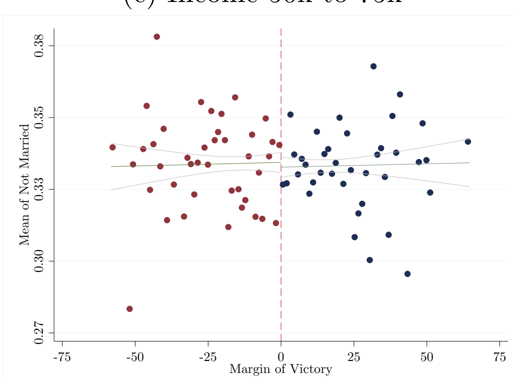
(b) Income 25k to 50k



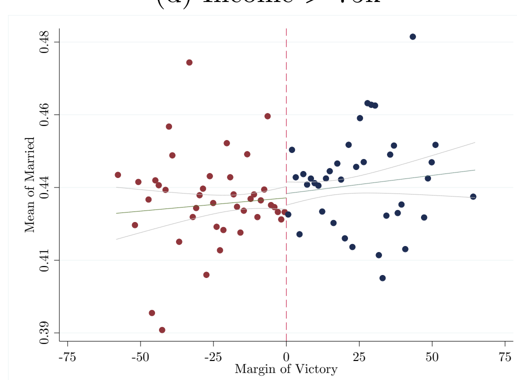
(c) Income 50k to 75k



(d) Income > 75k

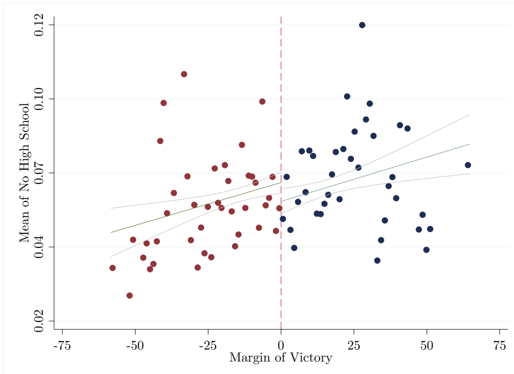


(e) Not Married

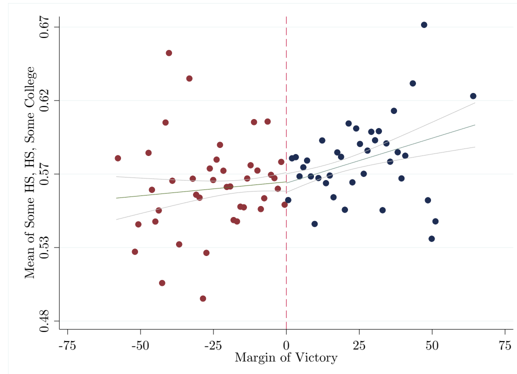


(f) Married

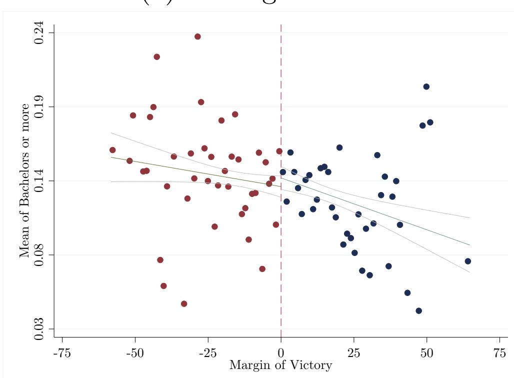
Figure B.1. Linear continuity graphs



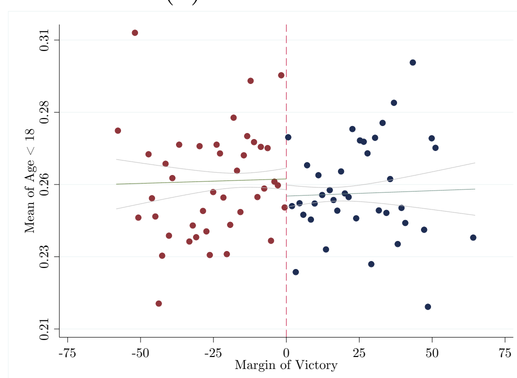
(a) No High School



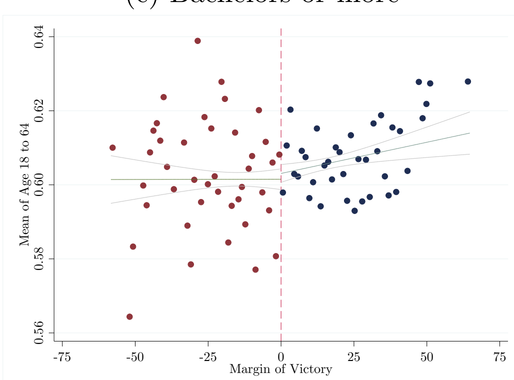
(b) Some School



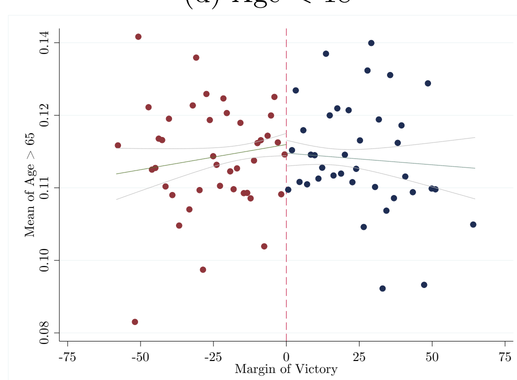
(c) Bachelors or more



(d) Age < 18

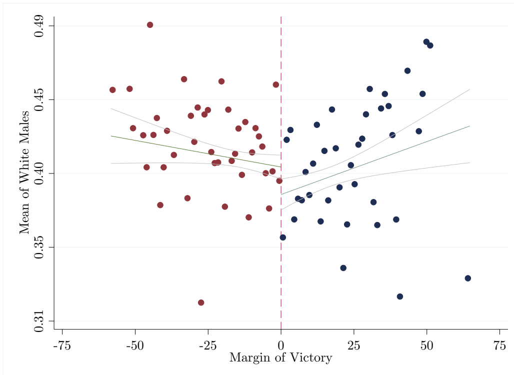


(e) Age 18 to 64

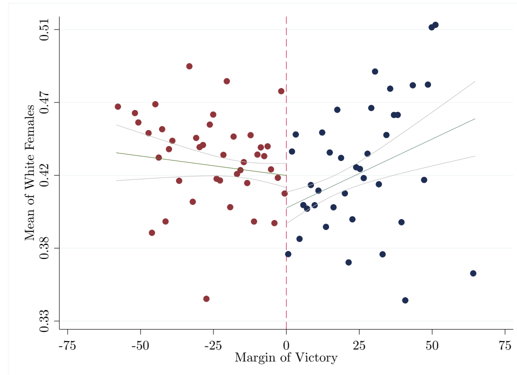


(f) Age > 65

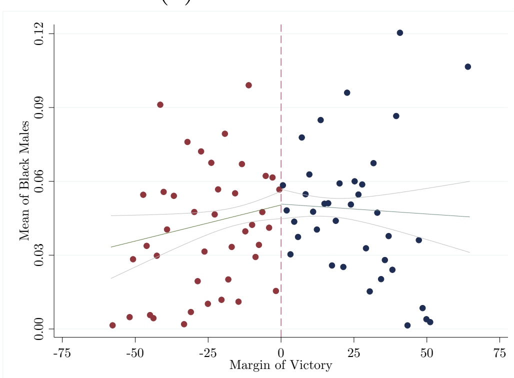
Figure B.2. Linear continuity graphs (cont.)



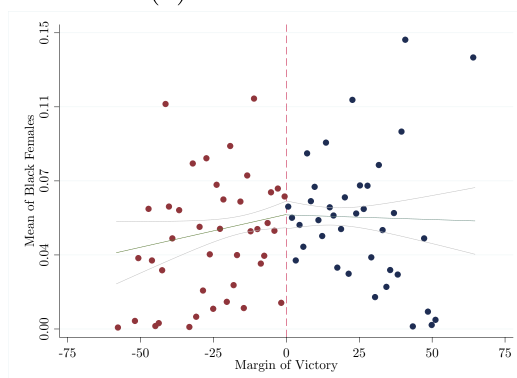
(a) White Males



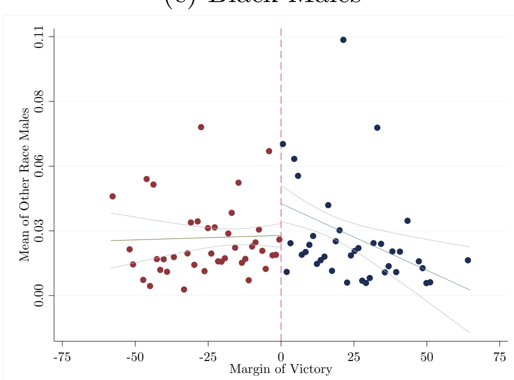
(b) White Females



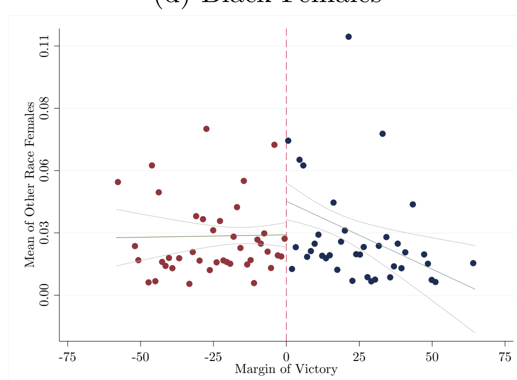
(c) Black Males



(d) Black Females

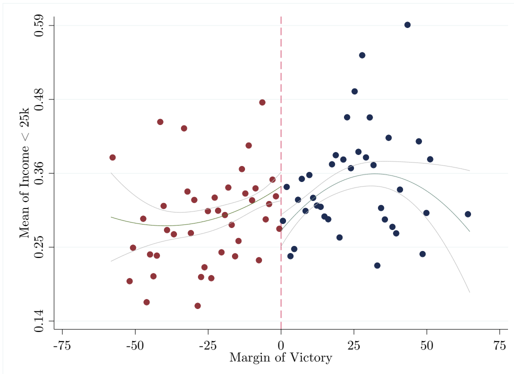


(e) Other Race Males

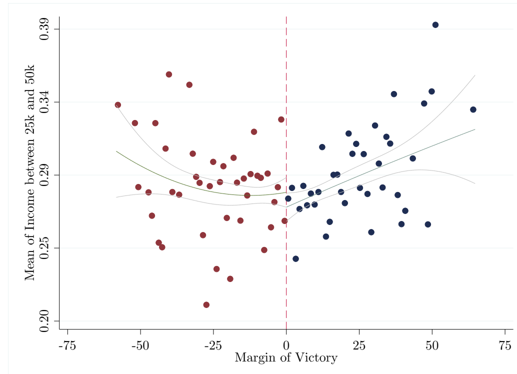


(f) Other Race Females

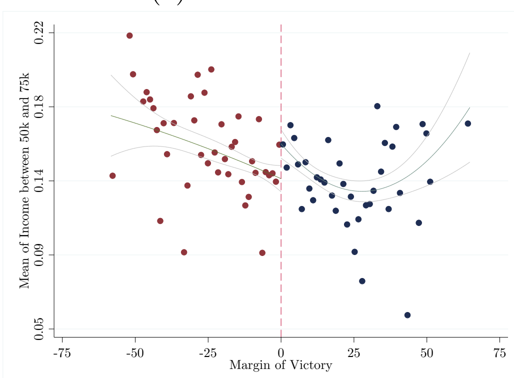
Figure B.3. Linear continuity graphs (cont.)



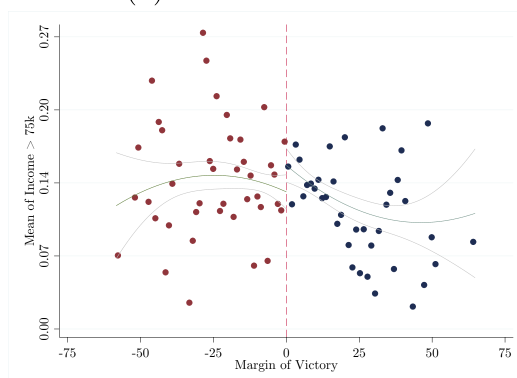
(a) Income < 25k



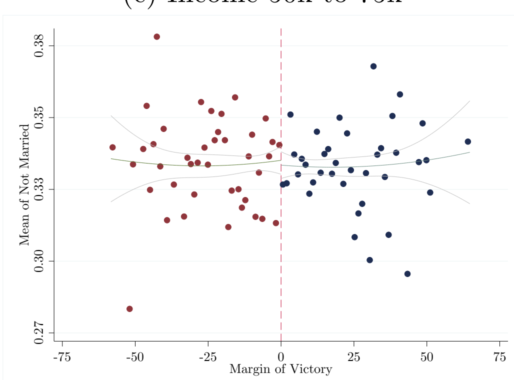
(b) Income 25k to 50k



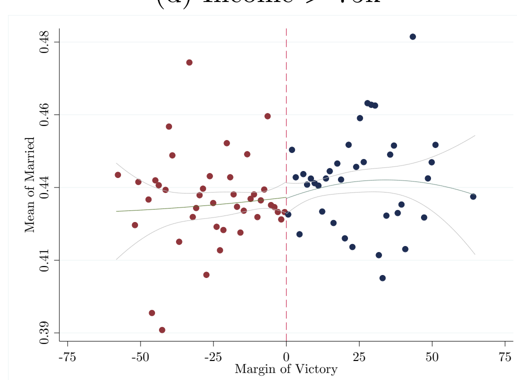
(c) Income 50k to 75k



(d) Income > 75k

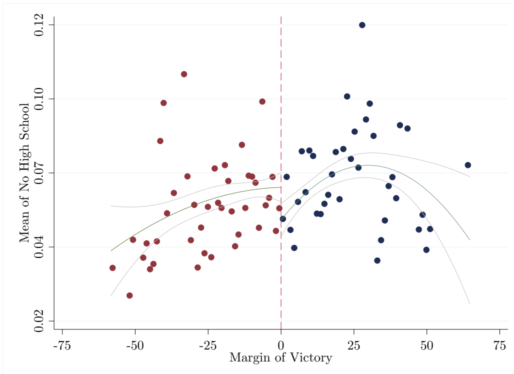


(e) Not Married

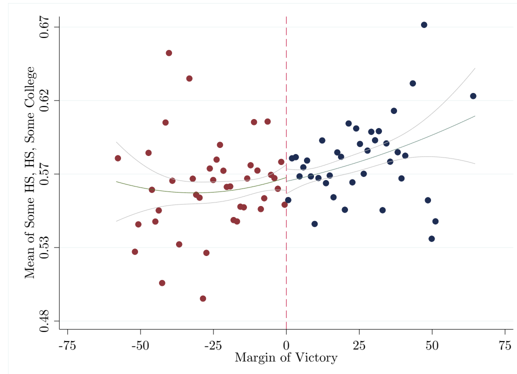


(f) Married

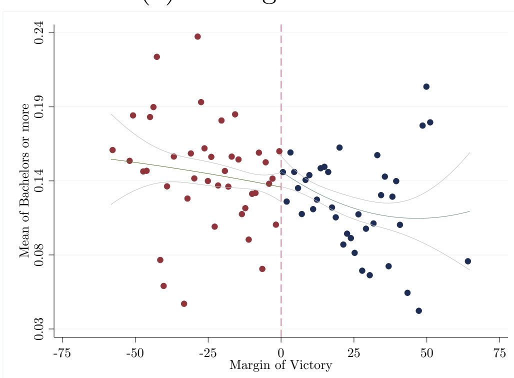
Figure B.4. Quadratic continuity graphs



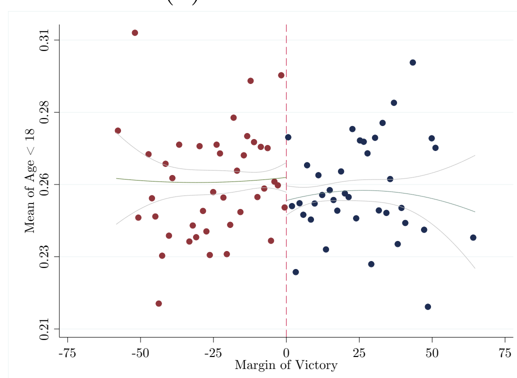
(a) No High School



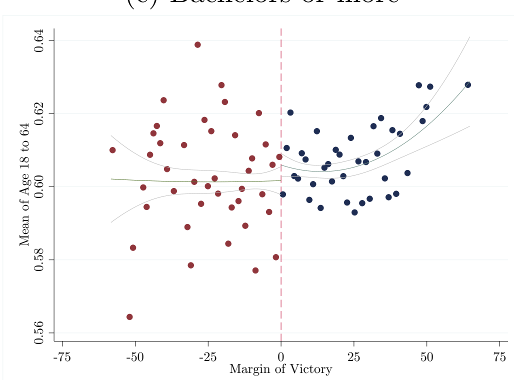
(b) Some School



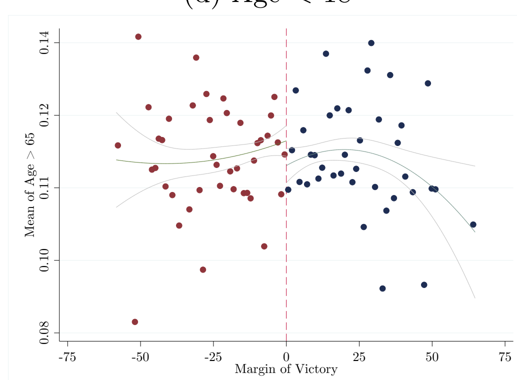
(c) Bachelors or more



(d) Age < 18

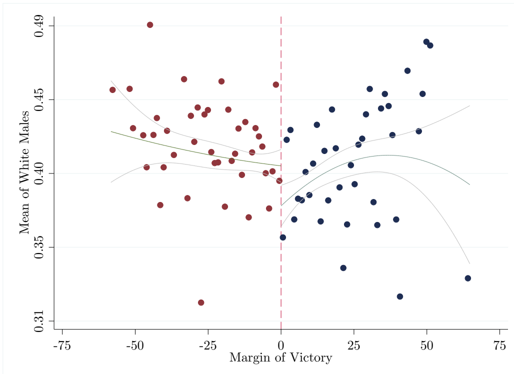


(e) Age 18 to 64

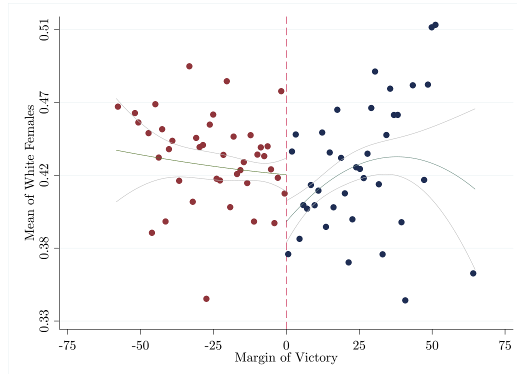


(f) Age > 65

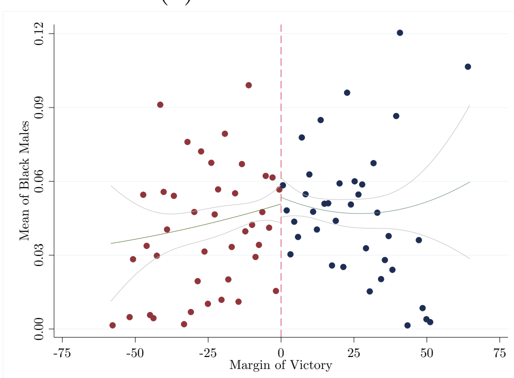
Figure B.5. Quadratic continuity graphs (cont.)



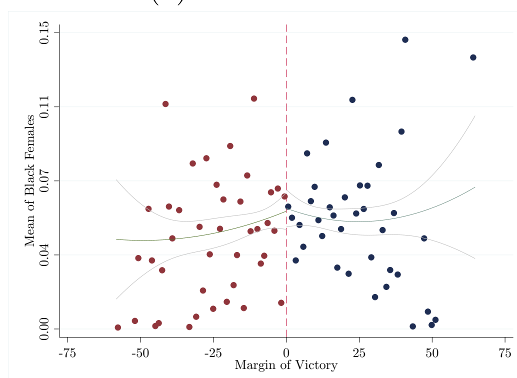
(a) White Males



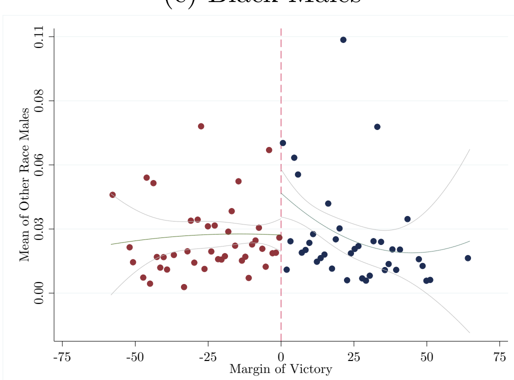
(b) White Females



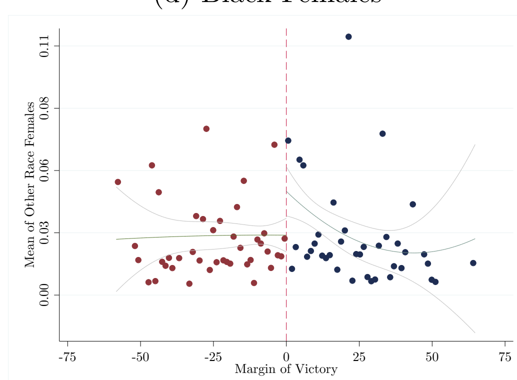
(c) Black Males



(d) Black Females



(e) Other Race Males



(f) Other Race Females

Figure B.6. Quadratic continuity graphs (cont.)

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