Does Schooling Create Democratic Voters? Turnout and Partisan Consequences of Additional Education

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This paper

- What is the impact of education on voter preferences and participation?
  - Turnout
  - Partisanship

Views on the Political Impacts of Education

- "As people do better, they start voting like Republicans - unless they have too much education and vote Democratic, which proves there can be too much of a good thing."
  Karl Rove

Prior Work: John Marshall

- US (AJPS, 2017):
  - Dif-n-dif IV across cohorts across states as states change (highly non-monotonic) legal school dropout ages
  - Uses survey data (CPS, NAES – Anenberg)
    - Measurement error because they only have age in years
  - **15** percentage point reduction in support for Democrats from HS completion
  - Age range: 25+

- UK (JOP, 2016):
  - Uses inter-cohort analysis from post WWII expansion of education requirements (1947 reform)
  - Uses survey data (British Election Survey)
  - **12** percentage point increase in voting for Tories per additional year of education

- What we do:
  - Data: Use exact date of birth from administrative data
    - 2000 Census for first stage
    - 2021 Registration
      - Impacts are estimated 20-40 years after graduation!
  - Methods:
    - Use Two Sample RD-IV
    - Show heterogeneity by age of effects

Innovations

- Estimate precise, well-identified effects of education on political outcomes in the short and long run using an exact birthdate RD
- Point out that the date of birth IV for educational attainment is the amalgam of two LATEs:
  - Potential High School Dropout Compliers
  - Those currently attending college
- Derive methods to disentangle quality and quantity effects of education using a more formal visual IV

- Summary of Findings:
  - Turnout: Increase in turnout per year of additional educ: 3%
    - Similar for <HS, College
    - Can interpret as a quantity effect
  - Partisanship:
    - HS: +3% "per year of educ" for independents (long run)
      - Negative but not significant impact on Dem and Rep
    - College: Short run impact
      - Positive on Democrat, Independent
      - Negative on Republican
    - College Long Run Impact – Cannot estimate

- Data: A Tale of Three Data Sets
  - Data on state early entry cutoffs
    - Annual cutoffs by state: 1964-2005 from Bedard and Dhuey (2012, JHR)
  - Census Data
    - Exact date of birth
    - Sex, Race, Living in group quarters, Education
    - Sent to 1/6 of households
  - L2 Voter Registration Data
    - Sex, Race, Exact Birth Date
    - Voter turnout data: 2008 (for some states) - 2020
    - Partisan registration data: most recent registration
      - Modeled, Non-modeled states
    - Full cross-section drawn in April 30, 2021

- Data Cleaning

1. Drop people in state-years with cutoffs between Oct. 15 and Nov. 17
   - Get rid of mobilization effects correlated with birth across the cutoff

2. Drop those born on the first of the month
   - Administrative measurement error: too many recorded births on the 1st

3. Drop people born within 1 day before/after cutoff date
   - Larger imperfect compliance

Estimation Equation

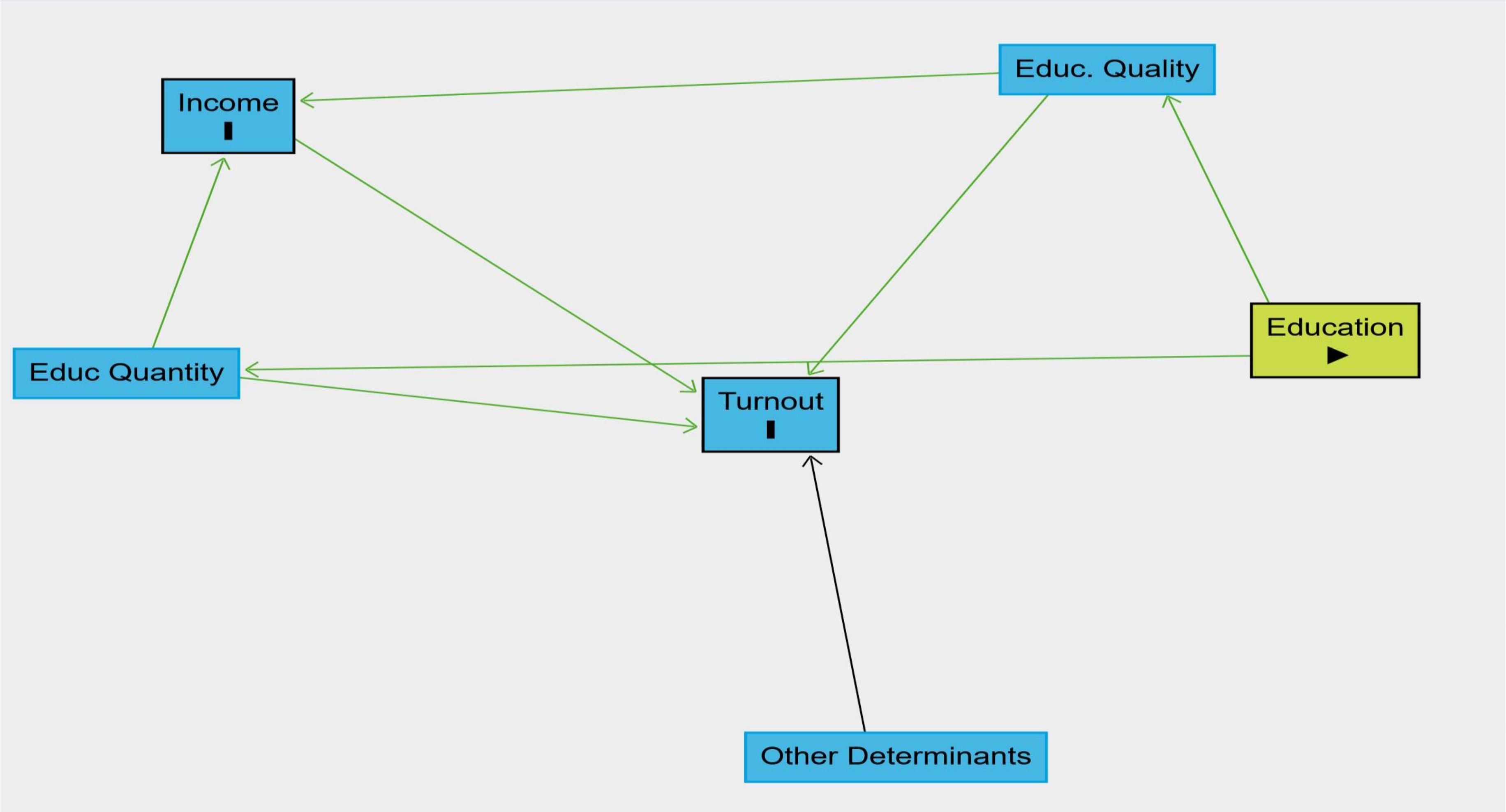
$$O_{d,s,y} = \alpha + \beta T_{d,s,y} + f(d) + T_{d,s,y} g(d) + \epsilon_{d,s,y}$$

- Outcome Variable (Turnout, Partisanship): $O_{d,s,y}$
- Treatment Variable (Birth After Cutoff): $T_{d,s,y}$
- Local Polynomial Running Variable Controls: $f(d), \quad g(d)$

- Note on Two Sample IV (TSIV)

  - Usually: Two Sample IV is biased towards zero rather than OLS
    - Obs. used to estimate the first stage don't also appear in the second stage.

  - We have two samples because we are not allowed to match Census and Voter Registration data. However, most of the individuals are the same.
    - Thus: OLS bias remains.
    - Sample size very large and asymptotics valid.
    - NB: Samples separated by 20 years (2000 Census and 2021 VR data). We consider those in the census 19-40. Most are likely still alive in the voter registration files from 2021.



Causal Channels
(Direct Acyclic Graph)

RD Specification

- Local Polynomials
  - Uniform Kernel
- Main Bandwidth: 90 day

First Stage

Effects on Education

and Income

Table 2: Covariate Balance - Census

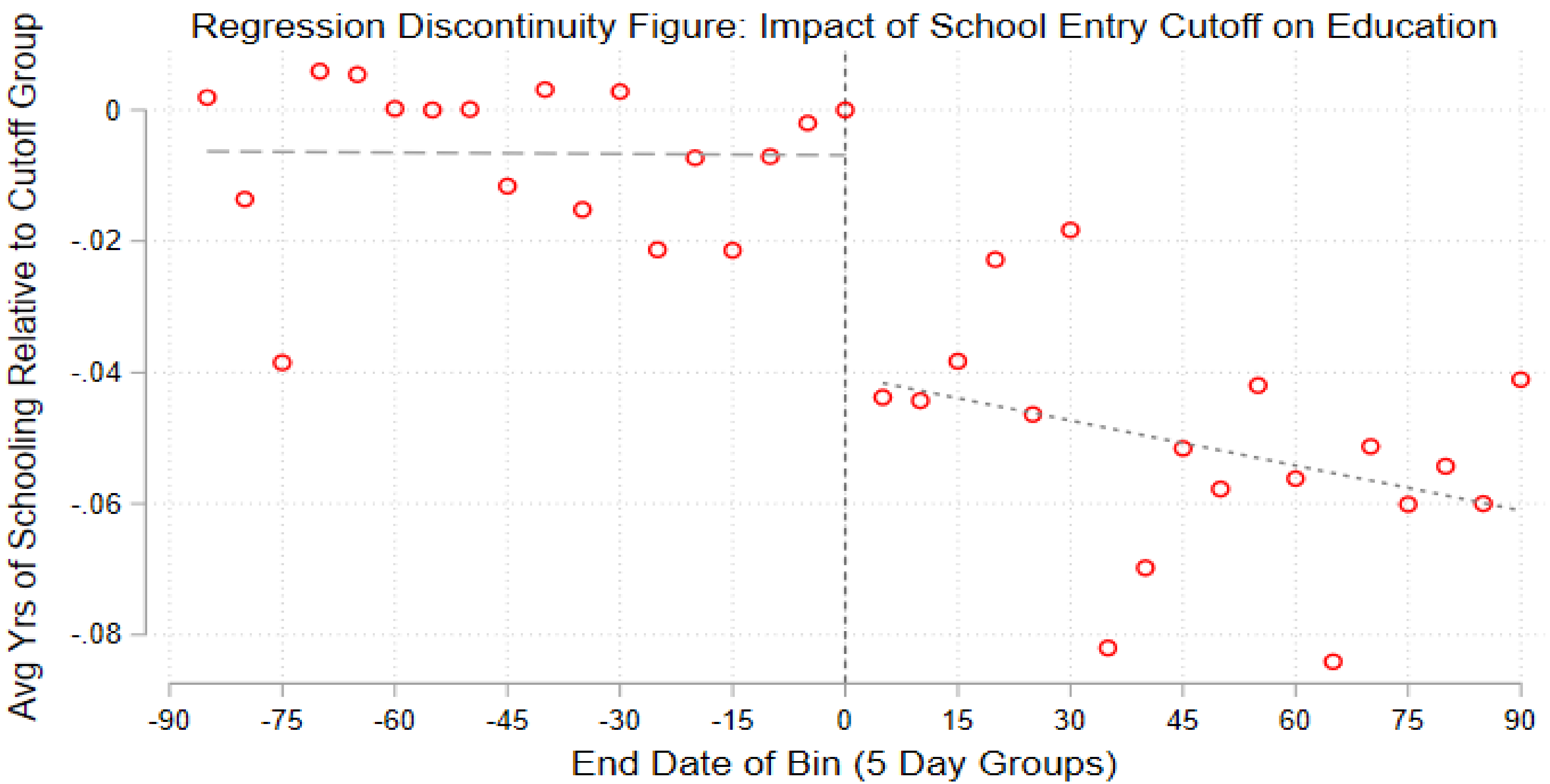
	(1) Female	(2) White	(3) Black	(4) Hispanic	(5) Asian	(6) Other Race
Born After Cutoff	-0.0008	-0.0008	-0.0002	0.0011	0.0002	0.0000
	(0.0011)	(0.0009)	(0.0007)	(0.0007)	(0.0004)	(0.0002)
Constant	0.5121***	0.6861***	0.1101***	0.1536***	0.04503***	0.0106***
	(0.0007)	(0.0006)	(0.0000)	(0.0005)	(0.0003)	(0.0001)
Number of Obs (Rounded)	4,049,000	4,049,000	4,049,000	4,049,000	4,049,000	4,049,000
R-Squared	0.0005	0.1323	0.0550	0.1561	0.0604	0.0288

Notes: Covariate balance for selected variables from the US 2000 Census. Results from estimating equation 1 for each variable. Running variable is equal to 0 for the school entry day. Data from L2 for states with registered partisanship and states with modelled partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. We also drop individuals with date of birth January 1st from the sample. *** p<0.01, ** p<0.05, * p<0.1

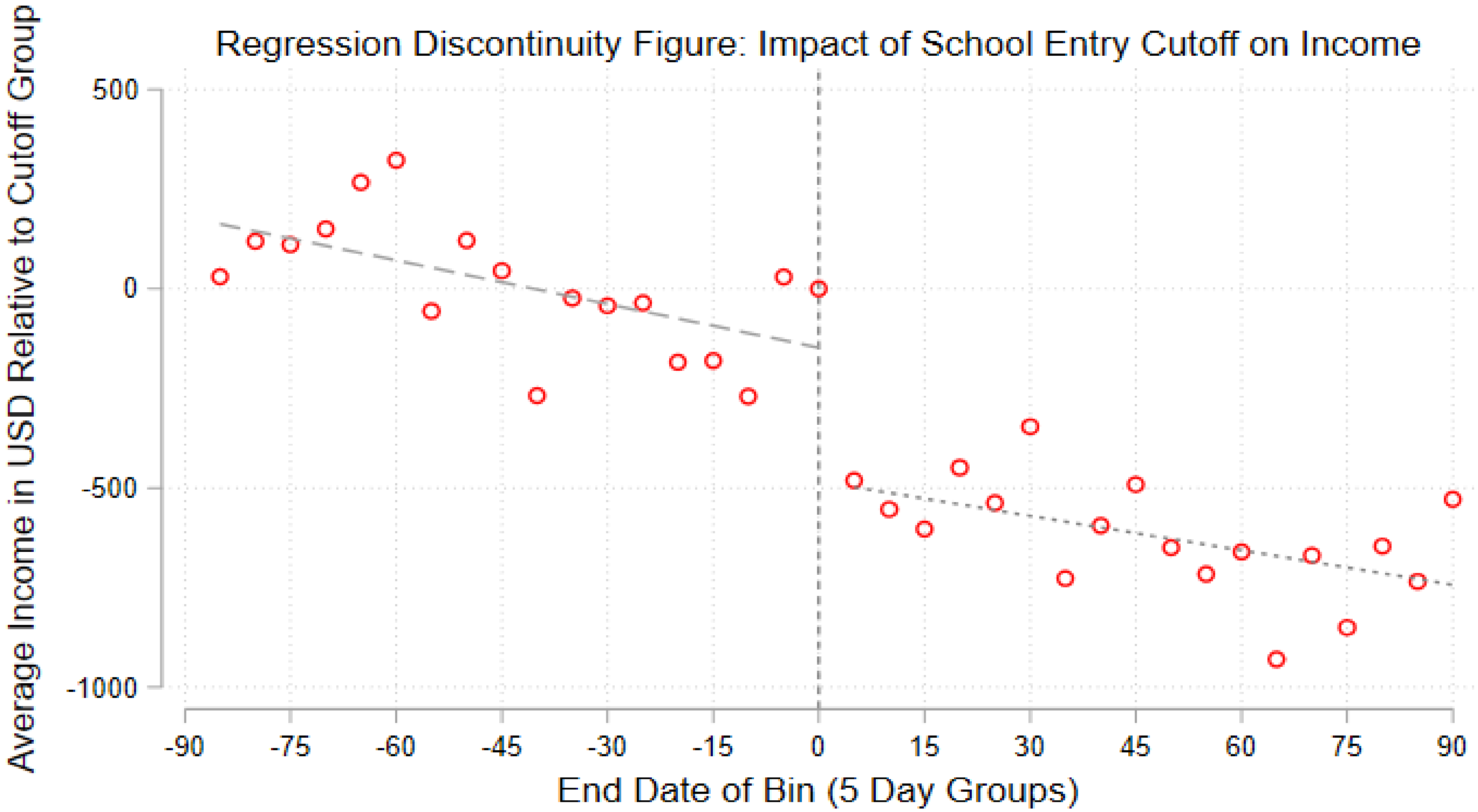
Table 3: McCrary Density Test for Change in Density at the Threshold

BW: Type	BW: Left	BW: Right	P-Value	# Obs (Rounded)	Kernel
Optimal	23	23	0.1957	1,097,000	Triangular
User-Chosen	90	90	0.2518	4,049,000	Uniform

Notes: Results from performing the density test for manipulation of the running variable as described in McCrary (2008). Running variable is equal to 0 for the school entry day. Data from L2 for states with registered partisanship and states with modelled partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. We also drop individuals with date of birth January 1st from the sample. *** $p<0.01$, ** $p<0.05$, * $p<0.1$



Note: Education of zero on the figure corresponds to 13.17 years of education. Data from the 2000 Census long form.

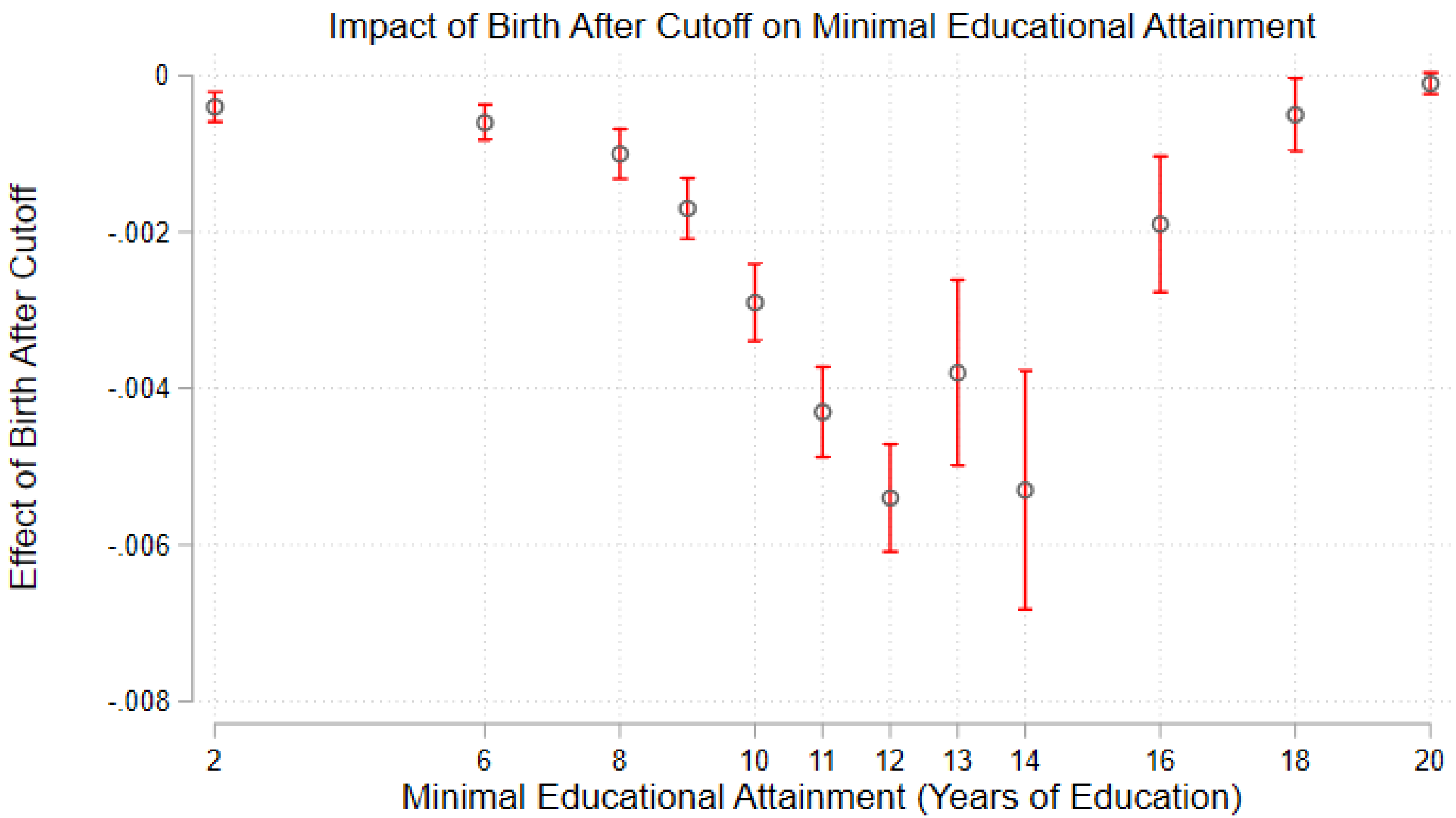


Note: Income of zero on the figure corresponds to $24,250. Data from the 2000 Census long form.

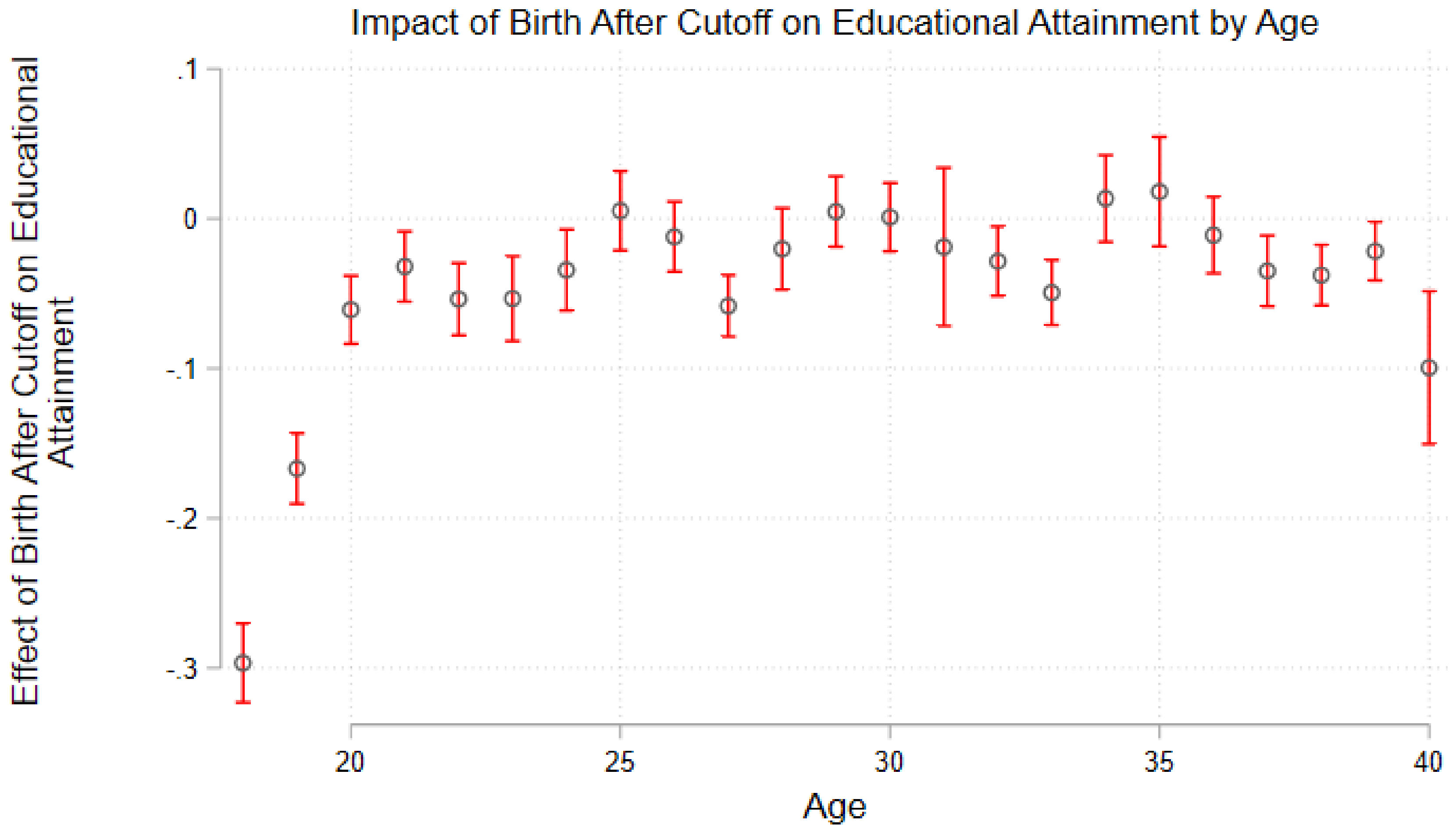
Table 1: Effects of Birth After Cutoff on Education and Income

	(1) Years of Schooling	(2) Total Income
Born After Cutoff	-0.0335***	-325.90***
	(0.0061)	(67.69)
Constant	13.17***	24080***
	(.003935)	(42.81)
Number of Obs (Rounded)	4,049,000	4,049,000
R-Squared	0.03015	0.07086

Notes: Results from estimating equation 1 for years of schooling in column (1) and total income in US dollars (2) in column 2. Running variable is equal to 0 for the school entry day. Data from L2 for states with registered partisanship and states with modelled partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. We also drop individuals with date of birth January 1st from the sample. *** p<0.01, ** p<0.05, * p<0.1



Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for states with registered partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. Data from the 2000 Census long form.



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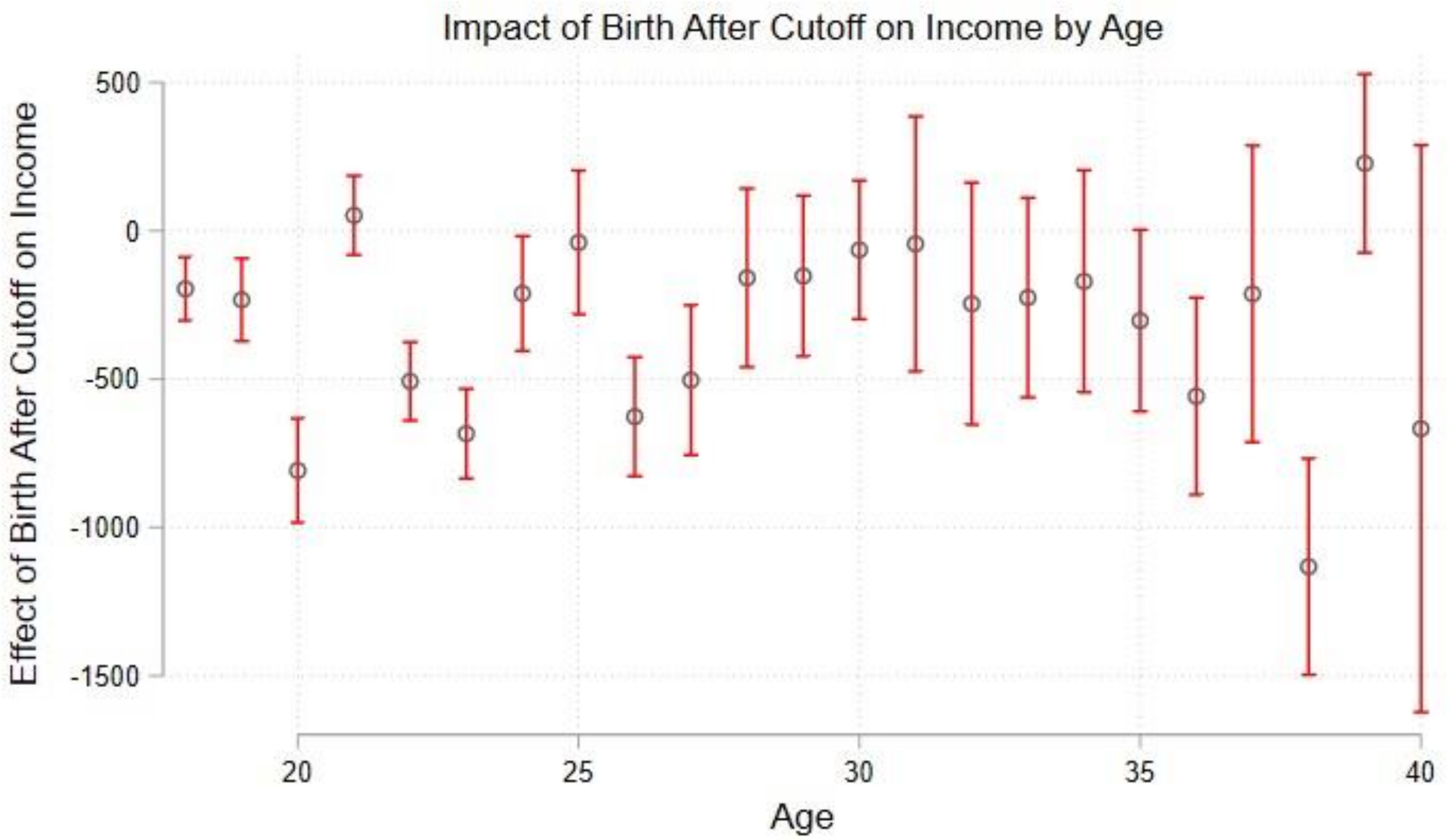


Note: Fuzzy Regression Discontinuity results from estimating equation 1. We drop all individuals with state-year cutoffs between October 15th and November 17th. Data from the 2000 Census long form.

Who is Impacted?

- Two groups
  1) Lower Education individuals who start earlier complete more schooling because they are not allowed to drop out until later (Angrist and Krueger, QJE, 1991)
     - Sometimes they are induced to complete high school
  2) Those born earlier have more education while in college
     - Only for those in late teens and early 20s

Education vs. Income

- Income: not much heterogeneity of effect
  - Not much impact for those in college so main effect is from those who drop out of high school early due to a later start
  - Two potential channels for in-college sample
    - Don't work much
    - Not much income gradient while in college (more important)

- Education: larger impact for young
  - Combination of early drop out effect for all ages and earlier start of college effect for younger in sample
  - Early start to college effect dies off as
    a) Students graduate
    b) Students take off time or delay college while of college years (attenuation of treatmenet)

Quantity vs. Quality

- Earlier birth increases the quantity of educational attainment
- Increases average income
- But….

Table 4: Effect of Birth After Cutoff on Incarceration Probability

	Incarcerated	Incarcerated	Incarcerated	Incarcerated	Incarcerated	Incarcerated	Incarcerated	Incarcerated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth After Cutoff	-0.0207%***	-0.0072%	-0.0076%	-0.0174%	-0.0222%***	-0.0022%	0.0016%	-0.0144%
	(0.0077)	(0.0068)	(0.0130)	(0.0235)	(0.0055)	(0.0048)	(0.0088)	(0.0165)
Birth After X Minority		-0.0458%**	-0.0915%**	-0.0898%		-0.0743%***	-0.1376%***	-0.1616%***
		(0.0192)	(0.0366)	(0.0606)		(0.0136)	(0.0258)	(0.0447)
Constant		0.8496%***	1.48%***	1.632%***		0.8499%	1.482%	1.644%
		(0.0168)	(0.0335)	(0.0587)		(0.0162)	(0.0324)	(0.0570)
Males Only			X	X			X	X
Under 30				X				X
Bandwidth	90	90	90	90	180	180	180	180
Number Observations	45,480,000	45,480,000	22,550,000	8,646,000	90,100,000	90,100,000	44,720,000	17,180,000
R-Squared	0.0021	0.0073	0.0149	0.0156	0.0020	0.0073	0.0148	0.0158

Notes: Results from estimating equation 1 for incarceration probability. Regressions restricted to males only in columns (3) and (7). Regressions further restricted to individuals under 30 in columns (4) and (8). Running variable is equal to 0 for the school entry day. Data from L2 for states with registered partisanship and states with modelled partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. We also drop individuals with date of birth January 1st from the sample. *** p<0.01, ** p<0.05, * p<0.1

Interpretation

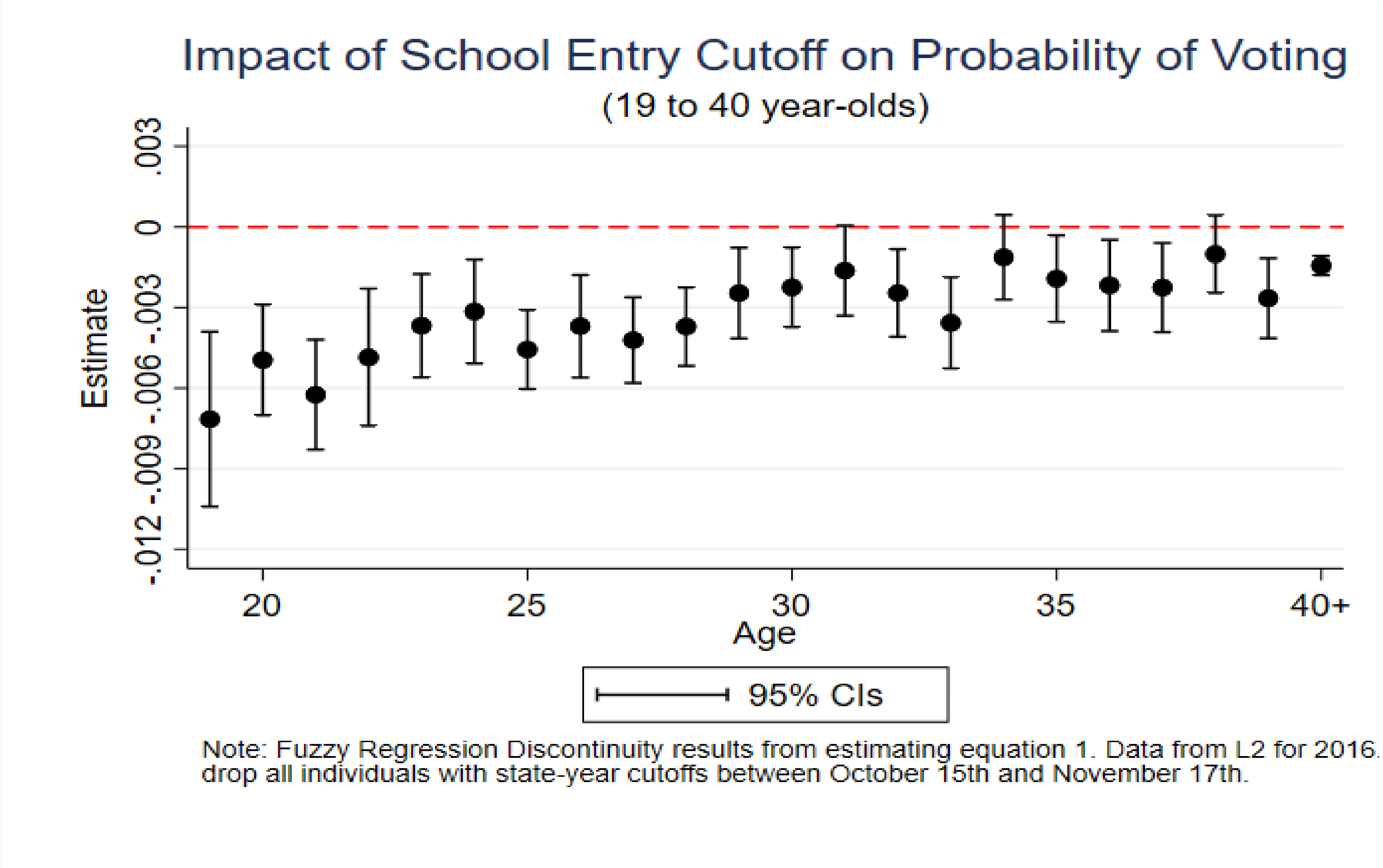
- Early start to education raises mean educational attainment and income
- Increases the probability of incarceration, particularly for minorities (minorities defined as Black + Latino)
- Reconciliation? Two effects!
  1) Quantity effect (positive)
  2) Quality effect (negative) – youngest in class
- We will revisit later when we suggest an econometric technique to extract the pure quantity effect

Reduced Form Impact

On Politcs: Turnout and Partisanship

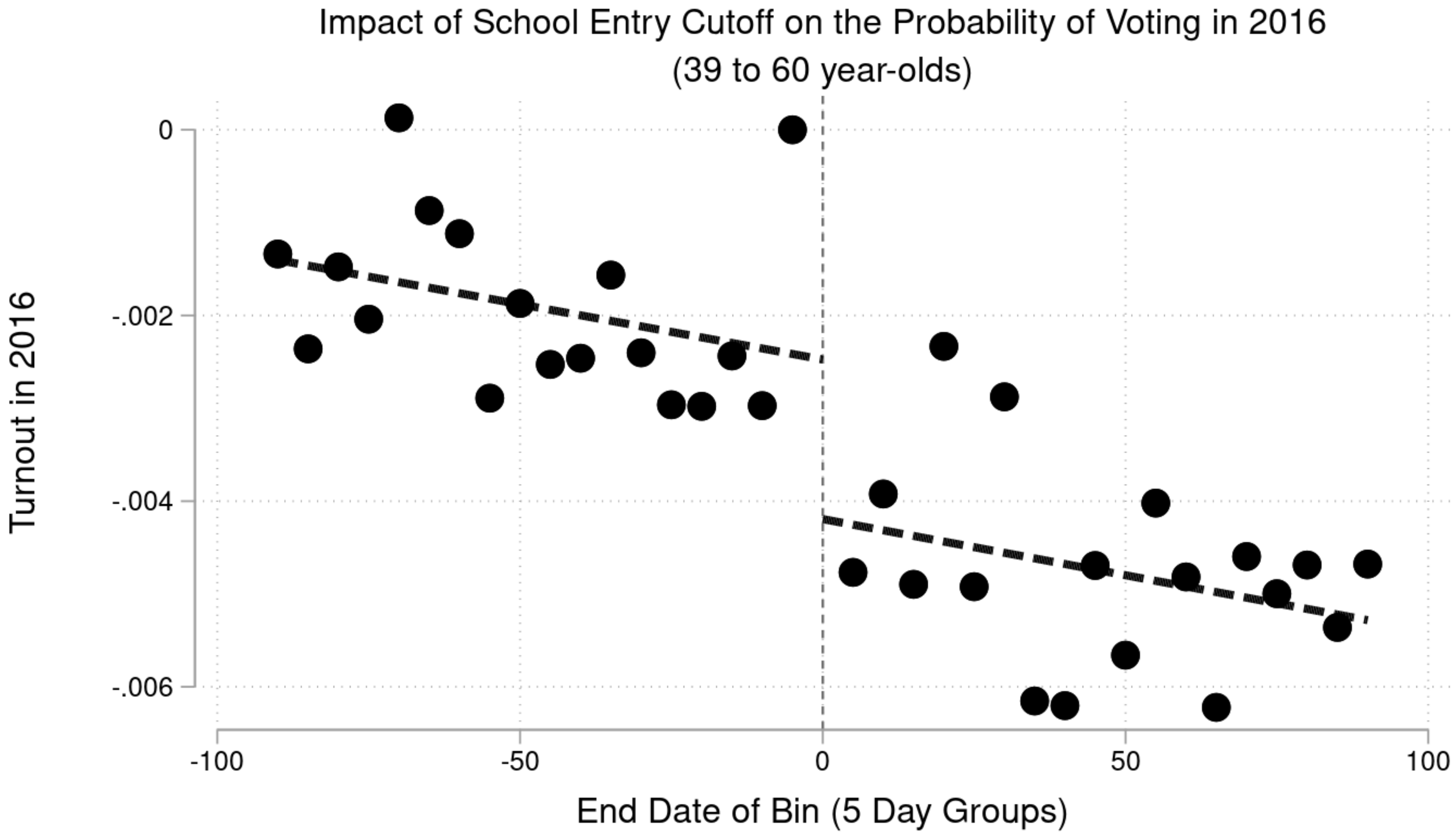
Effect on Turnout

19-40 Year Olds


Impact of School Entry Cutoff on Probability of Voting
(19 to 40 year-olds)
Estimate
.003
0
-.003
-.006
-.009
-.012
20
25
30
35
40+
Age
95% CIs
Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for 2016.
drop all individuals with state-year cutoffs between October 15th and November 17th.

Effect on Turnout: 2016

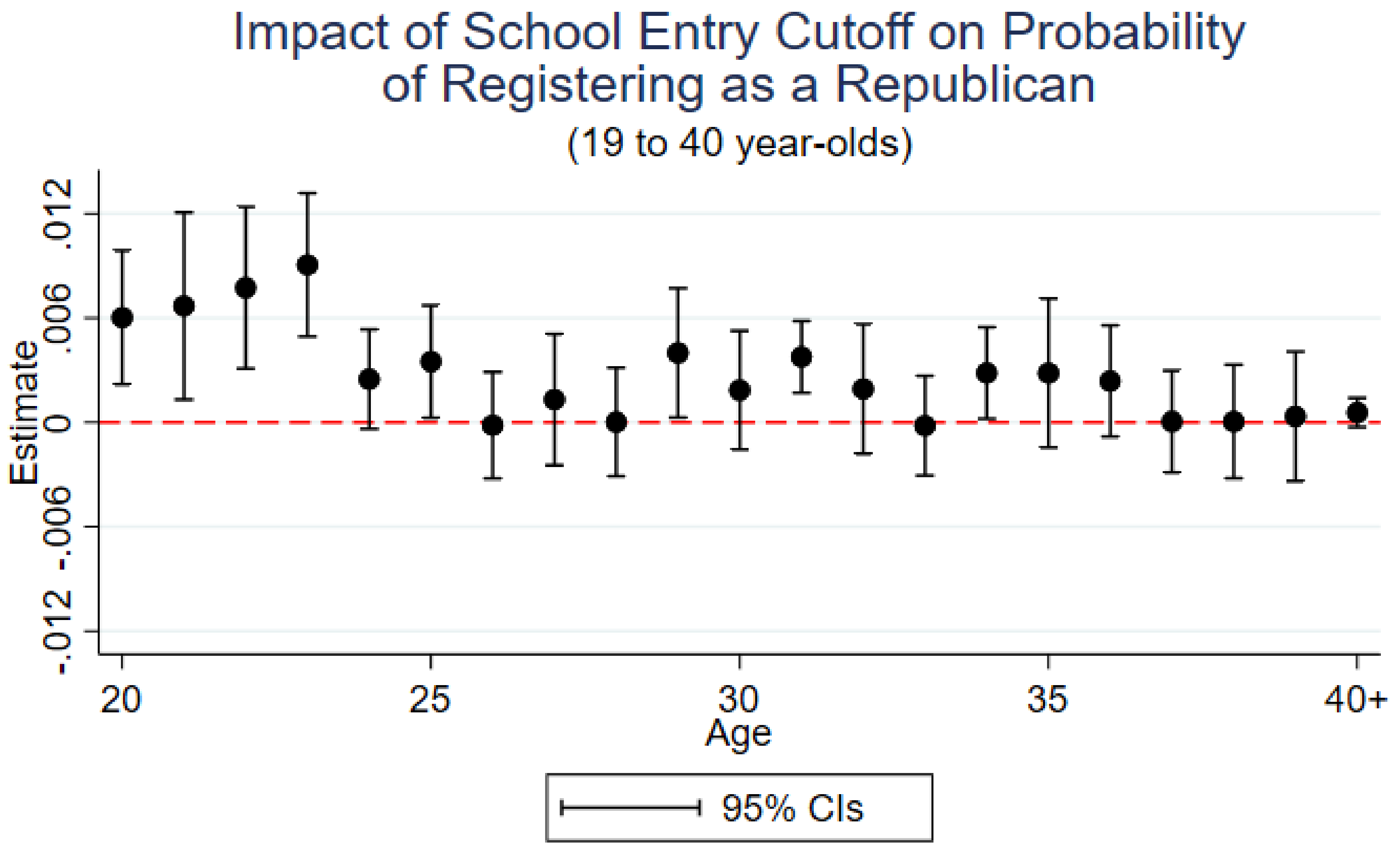
39-60 Year Olds



Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for states with registered partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th.

Effect on Registration as a Republican

19-40 Year Olds



Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for 2016. We drop all individuals with state-year cutoffs between October 15th and November 17th.

Interpretation

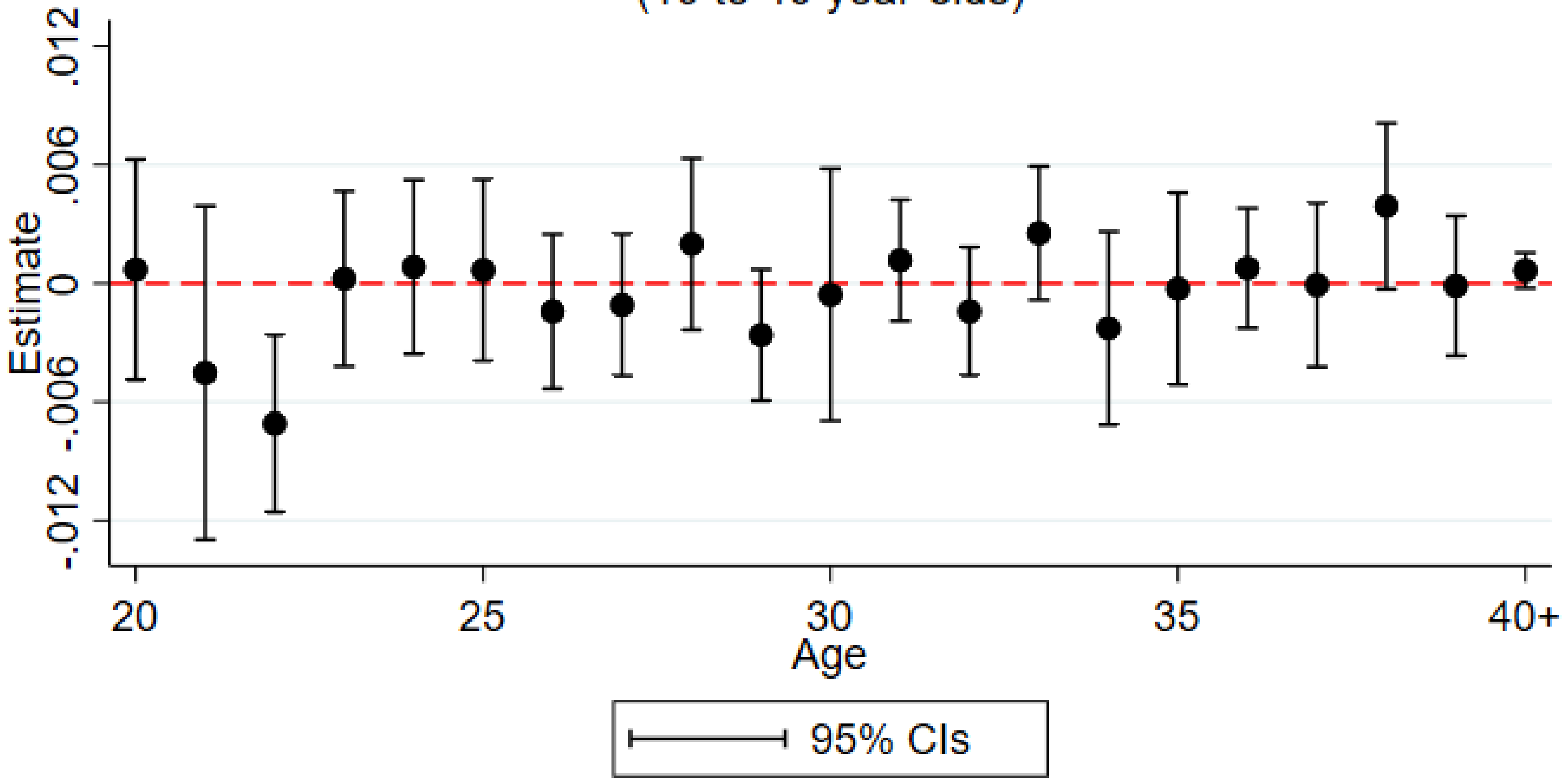
- Short Run:
  - Sizable negative impact on the young
  - Likely impact of college education (Karl Rove!)
- Long Run:
  - No differential impact on college attainment
  - Impossible to assess persistence of college effect

Effect on Registration as a Democrat

19-40 Year Olds

Impact of School Entry Cutoff on Probability of Registering as a Democrat

(19 to 40 year-olds)



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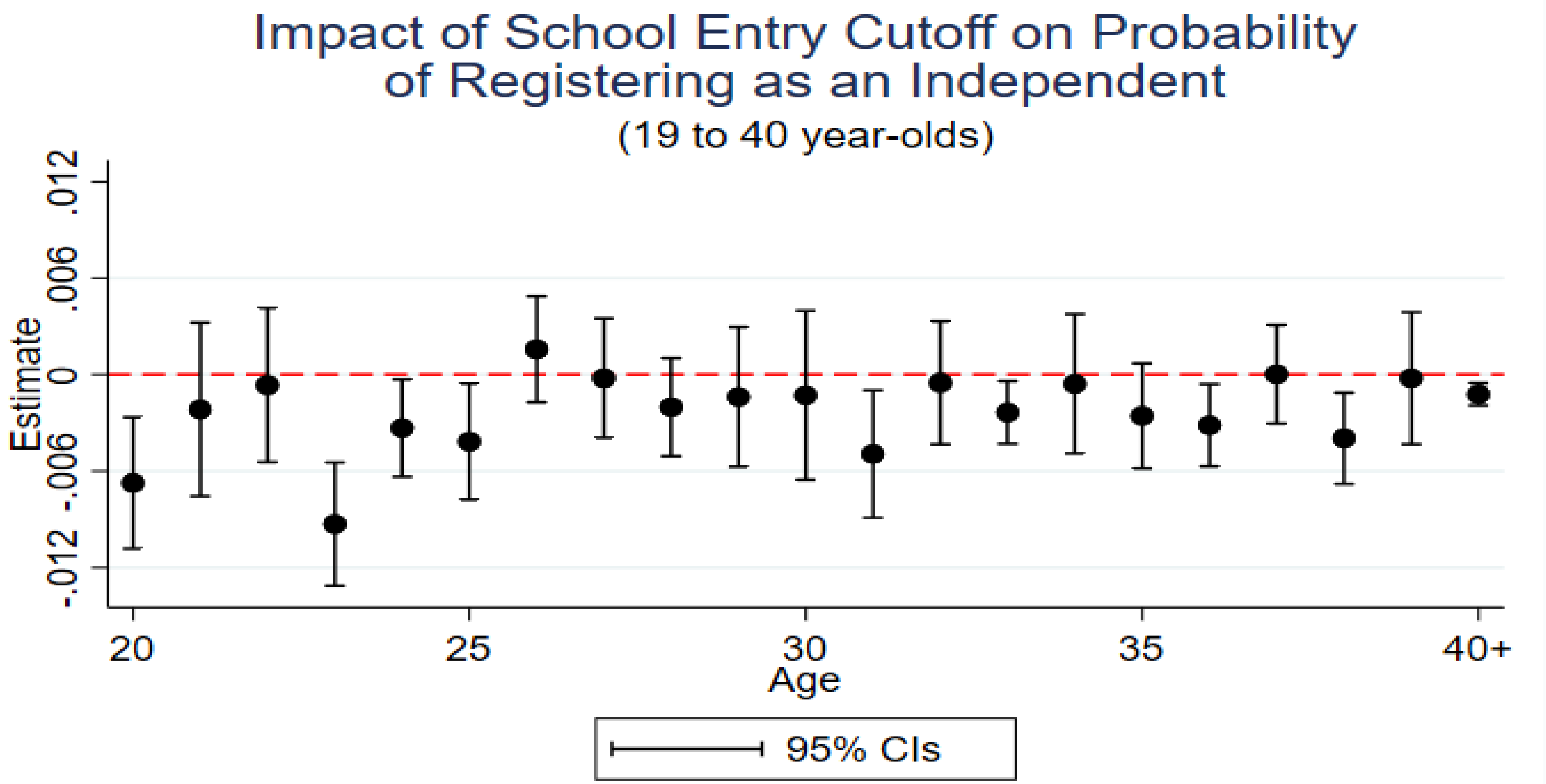

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Heterogeneity over time

TURNOUT

- Very stable effects on turnout over time
  - Midterms
  - Presidential
  - Estimate by Year, by Election Type

PARTISANSHIP

- No way to compare over time
- Only most recent partisanship data

Computing Quantity Effects

OVERVIEW OF QUANTITY EFFECT STRATEGY

- Could combine quantity and quality effects
- Assume quality effects not time varying
- Quantity effects time varying for the young
  - Shown in First Stage Results
- Use the age gradient for the young (RF vs. FS)

IMPORTANT ASSUMPTIONS

- Assume
  1) Effects are linear in quantity
     - Cannot use for isolating quantity effect on partisanship
  2) Constant in Quality

Quantity vs. Quality Effects

$$\beta(c)_s = \alpha(c)_s + \gamma(c)_s$$

- Decompose overall effect of early entry into school into quantity and quality effects. Assume quantity effects are linear (consistent with the data).

- We denote the time invariant quality effect as:

$$\alpha(c)_s$$

- And the time-varying quantity effect (per year) as:

$$\gamma(c)_s$$

Prior Work: John Marshall

- US (AJPS, 2017):
  - Dif-n-dif IV across cohorts across states as states change (highly non-monotonic) legal school dropout ages
  - Uses survey data (CPS, NAES – Anenberg)
    - Measurement error because they only have age in years
  - **15** percentage point reduction in support for Democrats from HS completion
  - Age range: 25+

- UK (JOP, 2016):
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  - **12** percentage point increase in voting for Tories per additional year of education

Isolating the Quantity Effect

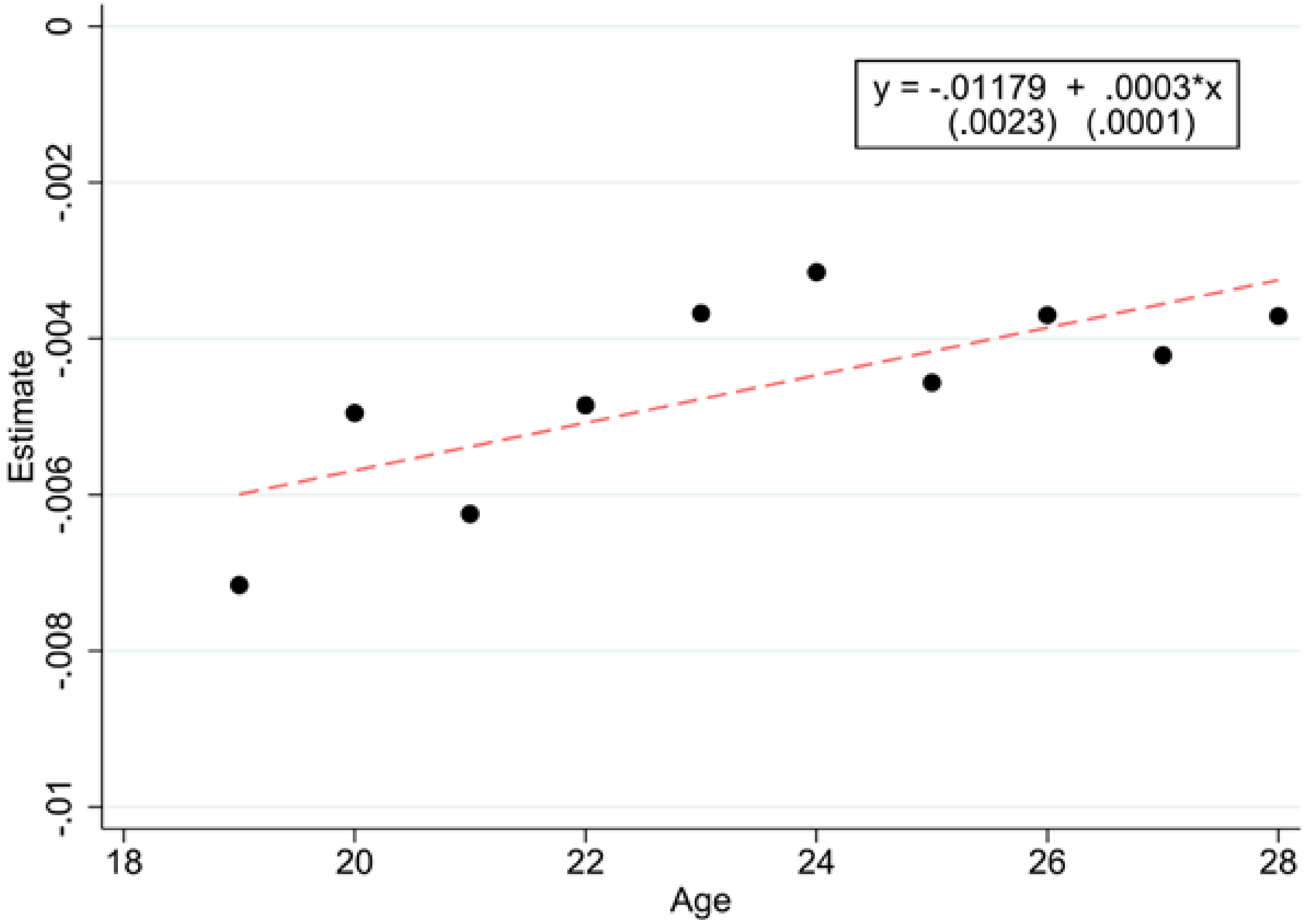
- Then, by differencing the ratio of the trend in the reduced form to the trend in the first stage, we get:

$$\frac{\Delta\beta_{rf}}{\Delta\beta_{fs}} = \frac{\alpha_{rf} + \gamma(c+t)_{rf} - \alpha_{rf} - \gamma(c)_{rf}}{\alpha_{fs} + \gamma(c+t)_{fs} - \alpha_{fs} - \gamma(c)_{fs}} = \frac{\gamma(c+t)_{rf} - \gamma(c)_{rf}}{\gamma(c+t)_{fs} - \gamma(c)_{fs}}$$

- The ratio of the difference first stage to the differenced reduced form is thus equal to the IV for the pure quantity effect:

$$\frac{(1-t)\gamma(c)_{rf}}{(1-t)\gamma(c)_{fs}} = \frac{\gamma(c)_{rf}}{\gamma(c)_{fs}}$$

Linear Estimates: Turnout


y = -.01179 + .0003*x
(.0023) (.0001)
Estimate
0
-.002
-.004
-.006
-.008
-.01
18
20
22
24
26
28
Age

Turnout Quantity Effect Computation

Isolating the Quantity Effect: Turnout

Description	Coeff.
Time Varying Component (RF)	0.0003
Time Varying Component (FS)	0.0099
Pure Quantity Effect	0.0303
IV Reduced Form	-0.0015
IV First Stage	-0.0335
IV Estimate	0.0448
Ratio of Quantity to Total IV	0.6768

Interpretation

- Cannot claim IV is the quantity of education effect
- If only reflects quantity, impact is +3% per year of education on probability of registering independent
- Independents drawn from both Republicans and Democrats but neither effect is significant

- Conclusion:
  - Turnout: Increase in turnout per year of additional educ: 3%
    - Similar for <HS, College
  - Partisanship:
    - HS: +3% "per year of educ" for independents (long run)
      - Negative but not significant impact on Dem and Rep
    - College: Short run impact
      - Positive on Dem, Independent
      - Negative on Rep
    - College Long Run Impact – Cannot estimate

- Note: Cannot differentiate between "pure" education effect and effect of education through income

Extra Slides

Prior Work: John Marshall

- US (AJPS, 2017):
  - Dif-n-dif IV across cohorts across states as states change (highly non-monotonic) legal school dropout ages
  - Uses survey data (CPS, NAES – Anenberg)
    - Measurement error because they only have age in years
  - **15** percentage point reduction in support for Democrats from HS completion
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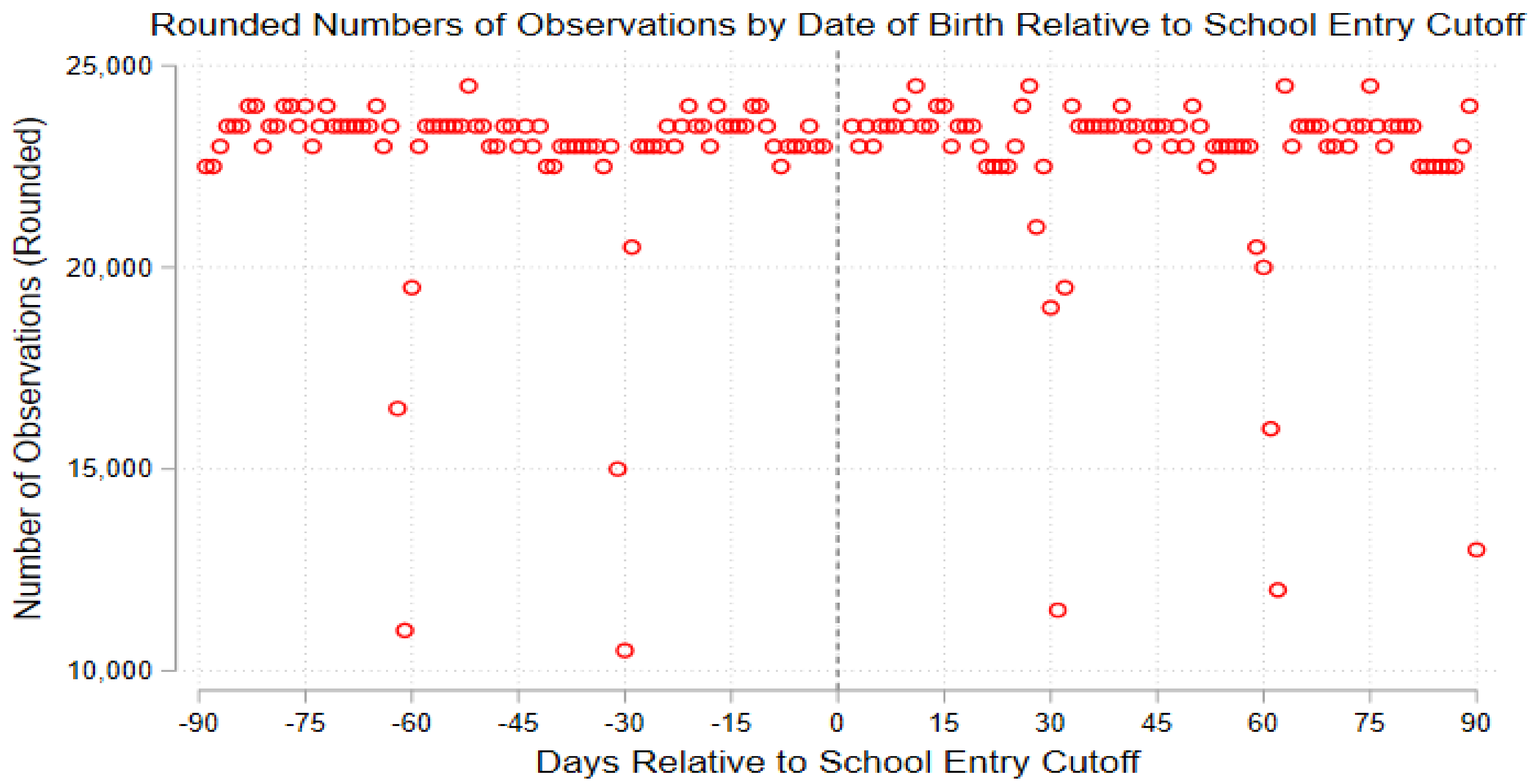


Note: Data from the 2000 Census long form.

Reason for Lower Observations on 30, 60, 90 day intervals.

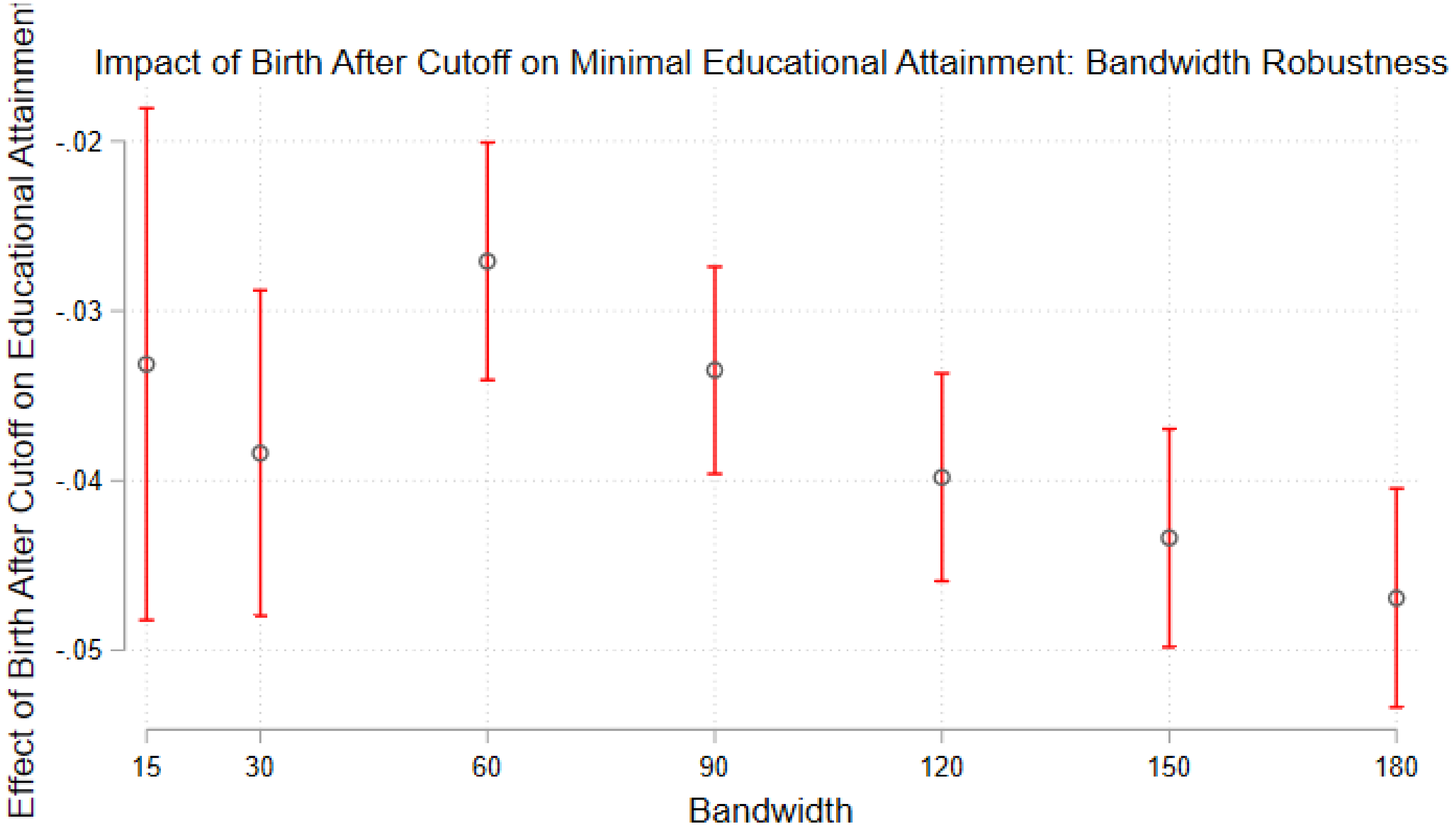
- Removal of observations on first of the month
  - Note: lower observations not exactly all 30, 60 or 90 days apart due to variation in number of days in months

Implicit Rate of Return to Education

- Rate of return to education = $\frac{\beta_{Inc}}{\beta_{Educ}} = \frac{-\$325.9}{-0.0335} = \$9728$ per year
- Note: these are far years (HS completion) which may have a higher than mean impact on wages.

Comparison to Literature

- Our estimates of the effects on income are larger than Dobkin & Ferreira (EER, 2010)
  - Driven by Texas; California estimates are similar
- Our estimates of the effects on education are near identical
  - Dobkin & Ferreira consider only CA and TX, use a quadratic, pool effects over those 30-79 and put in a number of controls



Note: Fuzzy Regression Discontinuity results from estimating equation 1. We drop all individuals with state-year cutoffs between October 15th and November 17th. Data from the 2000 Census long form.

Cohort, Time, and Heterogeneity

- Hard to separate cohort effects from age effects but:
  - Very consistent with age effects since heterogeneity in timing of schooling effects is exactly during usual college-going years

- We compute using State X Year effects, not State & Year effects.
  - Now "standard" TWFE problems not applicable to our estimation strategy
  - Also appears no trends in timing of schooling effects over time on either education (above comment) or income

Table 4: Effects of Birth After Cutoff on Education by Gender

	Years of School	Income
Birth After Cutoff	-0.0288***	-359.9***
	(0.0082)	(110.9)
Birth After X Female	-0.0087	47.6
	(0.0107)	(135.4)
Constant	13.01***	30370***
	(0.0069)	(212.9)
Number of Observations	4049000	4049000
R-Squared	0.0332	0.1038

Table A1: Bandwidth and Functional From Robustness - Effect on Education

	Schooling (Years)	Schooling (Years)	Schooling (Years)	Schooling (Years)	Schooling (Years)	Schooling (Years)
Effect of Birth After Cutoff	-0.0464***	-0.0541**	-0.0255**	-0.0514**	-0.0177**	-0.0365***
	(0.0175)	(0.0247)	(0.0107)	(0.0155)	(0.0083)	(0.0118)
Constant	13.17***	13.19***	13.17***	13.18***	13.16***	13.17***
	(0.0117)	(0.0171)	(0.0072)	(0.0103)	(0.0057)	(0.0079)
Bandwidth	30	30	60	60	90	90
Polynomial Degree	2	3	2	3	2	3
Number Obs (Rounded)	1331000	1331000	2695000	2695000	4049000	4049000
R-Squared	0.0308	0.0308	0.0304	0.0304	0.0302	0.0302

Table A2: Bandwidth and Functional From Robustness - Effect on Income

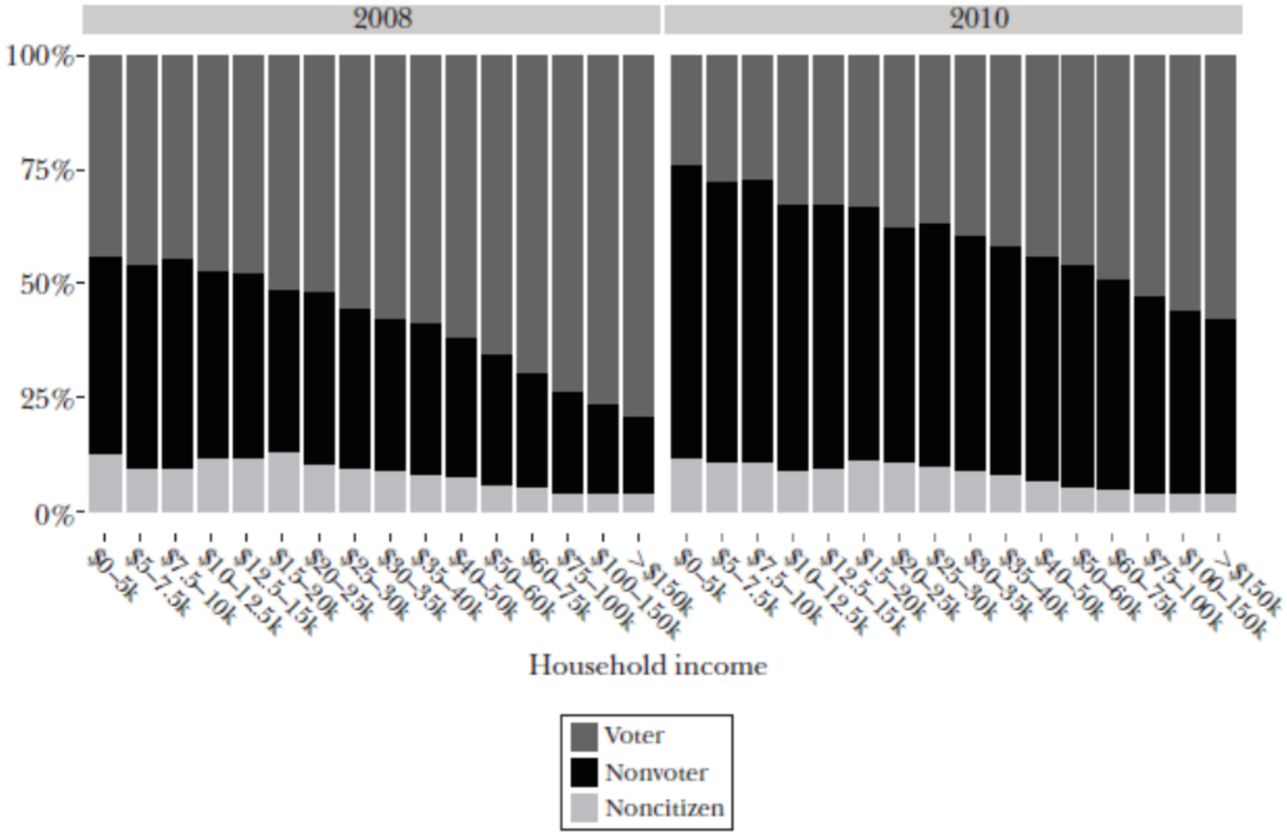
	Income	Income	Income	Income	Income	Income
Effect of Birth After Cutoff	-543.6**	-366.5	-464.6***	-528.8***	-258.1**	-671.3***
	(209.8)	(319.6)	(130.9)	(175.7)	(108.9)	(141.8)
Constant	24280***	24210***	24170***	24250***	24090***	24320***
	(154.2)	(233.5)	(97.52)	(137)	(80.99)	(111.9)
Bandwidth	30	30	60	60	90	90
Polynomial Degree	2	3	2	3	2	3
Number Obs (Rounded)	1331000	1331000	2695000	2695000	4049000	4049000
R-Squared	0.0709	0.0709	0.0713	0.0713	0.0709	0.0709

Table 7: Linear Trend Estimates of Effects by Age: Income

Model Description	Total Income	Total Income	Total Income
Linear Estimate	16.64	7.783	37.05
	(13.38)	(22.99)	(35.56)
Constant Coefficient	-738.9**	-554.8	-1162
	(334.4)	(521.8)	(769.4)
Number Observ.	3132000	1759000	1239000
R-Squared	0.05544	-0.1177	-0.1276
Age Range	19-35	19-28	19-25

Figure 4

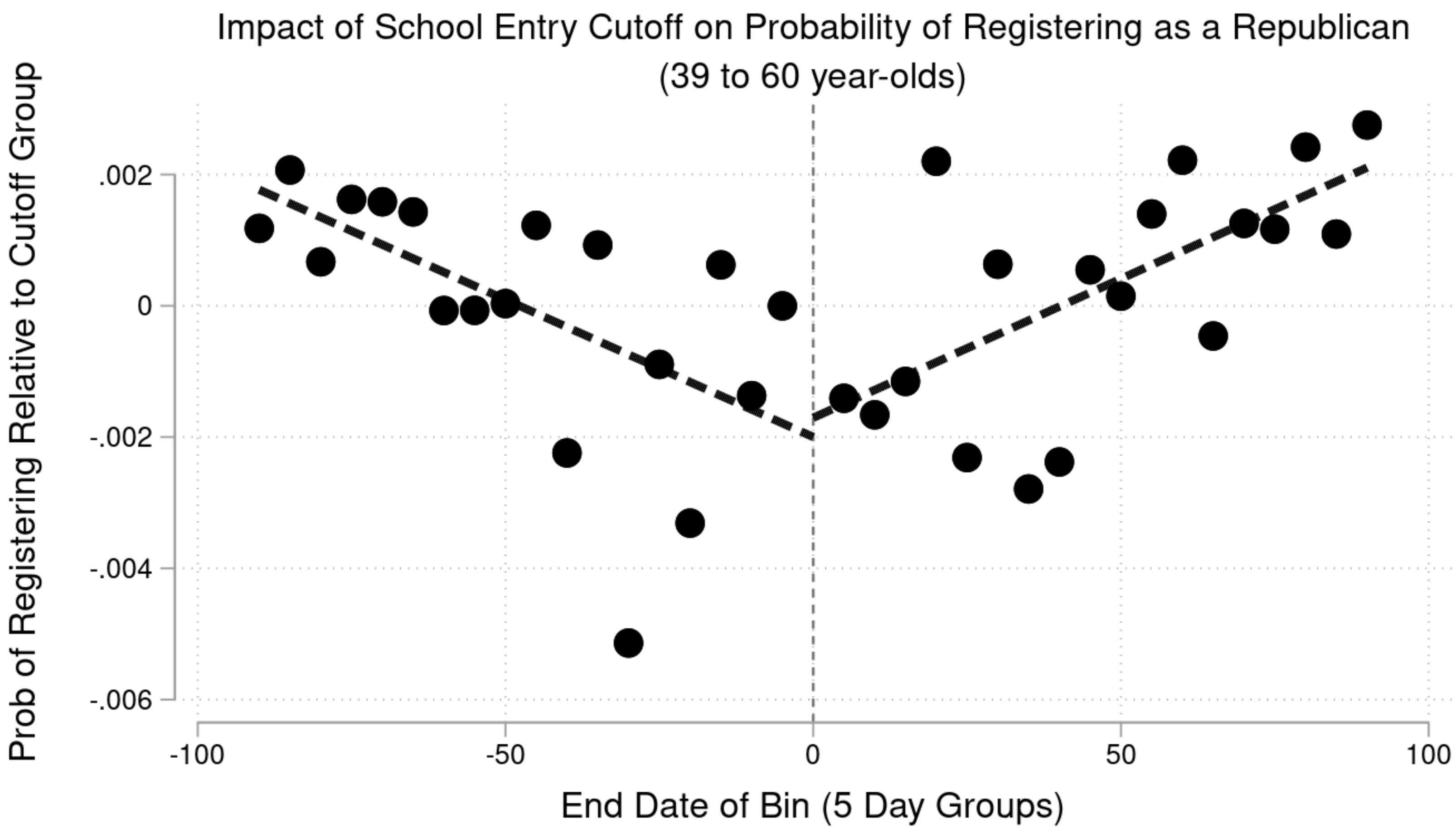
Voter Turnout by Household Income and Citizenship, 2008 and 2010



Source: Current Population Survey (2008: N=80,443; 2010: N=101,338).
Note: Figure 4 shows the relationship between voter turnout and voter household income and citizenship for the 2008 presidential and 2010 midterm elections.

Effect on Registration as a Republican

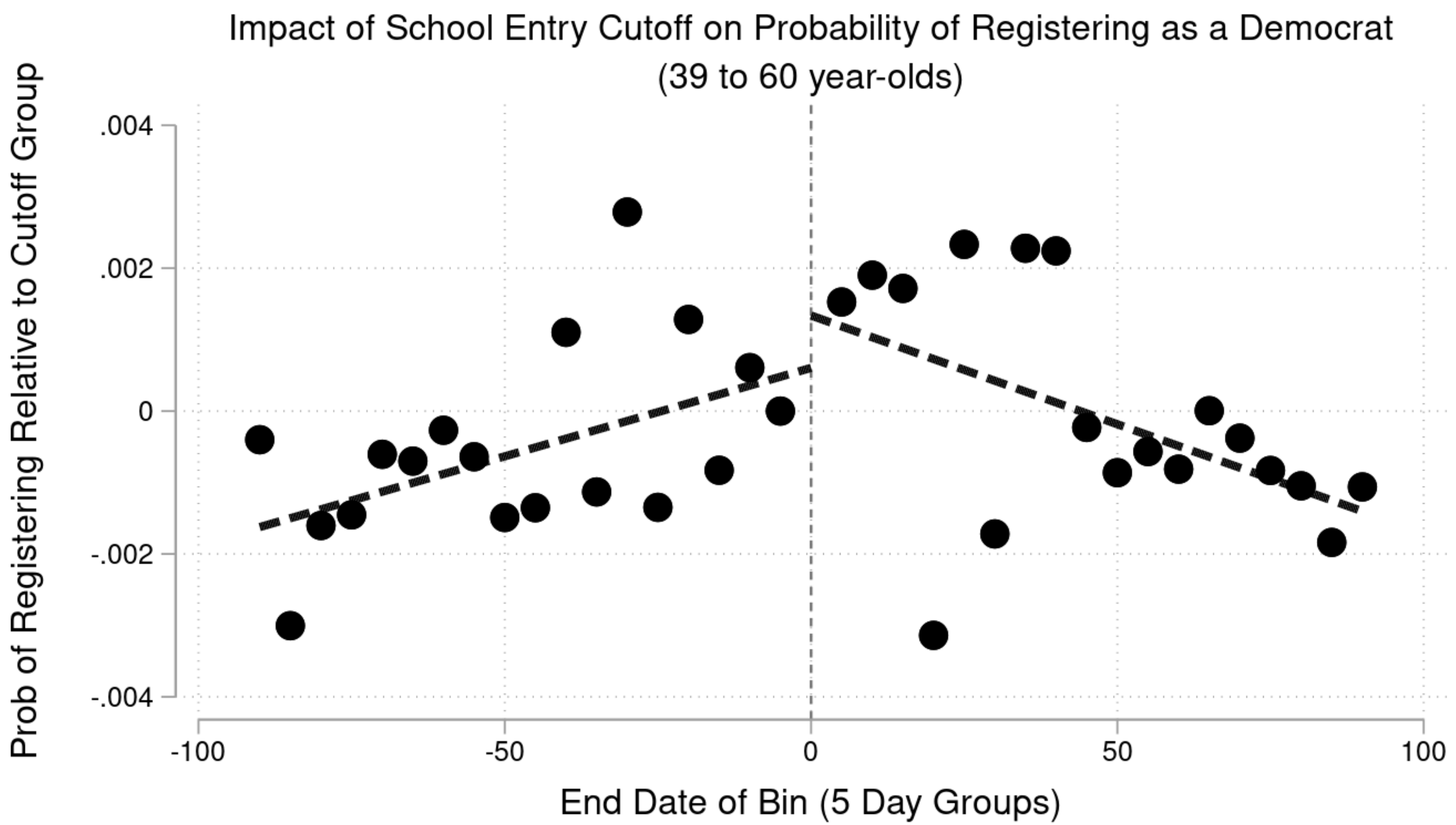
39-60 Year Olds



Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for states with registered partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th.

Effect on Registration as a Democrat

39-60 Year Olds



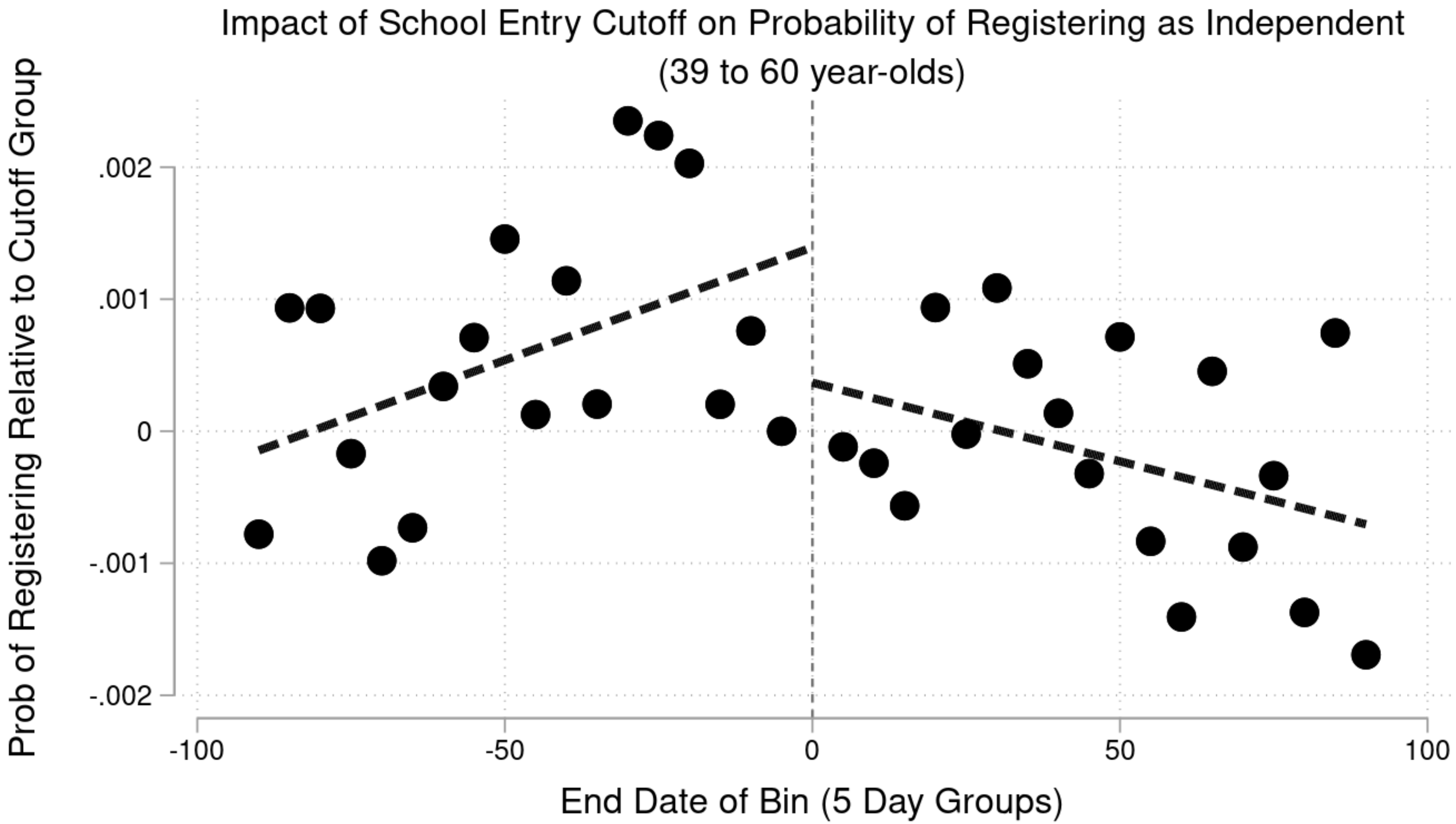
Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for states with registered partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th.

Effect on Registration as an Independent

19-40 Year Olds

Effect on Registration as an Independent

39-60 Year Olds



Note: Fuzzy Regression Discontinuity results from estimating equation 1. Data from L2 for states with registered partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th.

Robustness

FUNCTIONAL FORM AND BANDWIDTH

- Degrees 1 and 2 polynomials
- 30, 60, 90 day bandwidths

WITH/WITHOUT STATEXYEAR FE

- Lack of Robustness only with 30 day bandwidth, no StateXYear (Age Cohort) FE, and degree 2 polynomial.
- Everything else robust

Table 5: Linear Trend Estimates of Effects by Age: Education

Model Description	Education	Education	Education
Linear Estimate	0.0055***	0.0099***	0.0196***
	(0.0011)	(0.0024)	(0.0040)
Constant Coefficient	-0.1814***	-0.2815***	-0.4872***
	(0.0288)	(0.0552)	(0.0868)
Number Observ.	3132000	1759000	1239000
R-Squared	0.3759	0.3348	0.5515
Age Range	19-35	19-28	19-25

Running variable is equal to 0 for the school entry day. Data from L2 for states with registered partisanship and states with modelled partisanship. We drop all individuals with state-year cutoffs between October 15th and November 17th. We also drop individuals with date of birth January 1st from the sample. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Next Steps

1) Compute IV using Two Sample 2SLS
   - TS2SLS not equal to TSIV even though they are equivalent in the one sample variants
   - TS2SLS more efficient – not that important for us
2) Estimate standard errors for IV and quantity effect IV
   - Not clear what standard errors mean in our context
3) Work on isolating quantity effect for partisanship
4) Separate age and cohort effects by estimating effects by age from different elections over time
5) Estimate effects on partisanship in 2014 (pre-Trump)

Quantity Effects on Partisanship

- Age gradient not plausible and linear
- Cannot use new technique for partisanship
  - i.e. Republican effect grows in age through college years as education effect gets smaller
  - Suggestive of non-constant (or cumulative) impact of college education on partisanship

IV ESTIMATES OF EDUCATIONAL IMPACT ON PARTISANSHIP

PARTY	REDUCED FORM	FIRST STAGE	INSTRUMENTAL VARIABLES
Democrat	0.0007	-0.0335***	-0.0209
Republican	0.0003	-0.0335***	-0.0090
Other	-0.0010**	-0.0335***	0.0299