

# Attendance Boundary Policy and the Segregation of Public Schools in the United States

Tomas Monarrez

UC Berkeley

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# Racial Segregation and Schools in the United States

- ▶ School desegregation is one of the most ambitious social policies in U.S. history.
- ▶ Starting with *Brown* in 1954, the government placed a mandate on local school districts to integrate.
- ▶ Decision signaled the beginning of an era of federal oversight on local desegregation efforts.
- ▶ We are now on the other side of this era, local officials have been handed the reins back. But the mandate remains.
- ▶ What is the landscape school integration policy in the modern, unsupervised status quo?

## School Attendance Boundaries (SABs)

- ▶ SABs are the country's most common form of student assignment policy, serving 95% of K-12 pupils in SY 2013-14.
- ▶ Local district officials are responsible for drawing these.
- ▶ Beyond state provisions allowing school transfers, there is no regulation on SAB policy.
- ▶ SABs adjust periodically to accommodate school construction and neighborhood aging.

## Research Questions

- ▶ How do policymakers set SABs? Do they do so to target school segregation?
- ▶ What is the distribution of modern integration policy?
- ▶ What does the integrative school district look like?
- ▶ Does integration policy matter for educational outcomes?
- ▶ Is integration policy stable to non-compliance reactions from parents?

# This Talk

- ▶ Develop a counterfactual, 'neighborhood schools', SAB policy for (almost) each large school district.
- ▶ Relative to this, I estimate a parameter measuring the rate at which actual SABs integrate.
  - ▶ Call this parameter 'district-specific integration policy'.
- ▶ I describe the distribution of integration policy and characterize integrative districts.
- ▶ How unstable is integration policy? Estimate causal effect of SAB racial composition on racial Tiebout sorting (white flight?)

## Findings

- ▶ The average district enacts SABs that are modestly integrative, reducing segregation by about 10%.
- ▶ There is substantial policy heterogeneity across districts.
  - ▶ 5% of districts oversegregate schools by more than 10%.
  - ▶ 12% reduce segregation by more than a third.
- ▶ Districts with active desegregation court orders show policy 60% stronger than the average district.
  - ▶ Notably, there are districts that never had orders, but are just as integrationist.
- ▶ The integrative district travels larger distance to school, and is smaller, better funded, less residentially segregated, and more gerrymandered. Some evidence of smaller school quality gaps.
- ▶ The effect of SAB composition on residential composition change is about 15% over a decade.

# Roadmap

1. Literature and Data
2. Empirical Framework.
3. The Distribution of Integration Policy.
4. Validation of Method.
5. Characterization of Integration Policy.
6. Integration Policy and Household Non-Compliance.

## Literature Review and Data



# Literature

- ▶ SABs and School Segregation
  - ▶ Saporito et al. (2006, 2009, 2016); Richards (2014).
- ▶ The Effects of School Segregation
  - ▶ Card and Rothstein (2007); Hanushek et al. (2009); Jackson (2009); Billings et al. (2014).
- ▶ Desegregation orders
  - ▶ Cascio et al (2008, 2010); Reber (2005, 2010, 2011); Johnson (2011); Coleman et al (1966).
- ▶ School Assignment / Choice
  - ▶ Black (1999); Rothstein (2006); Bayer et al. (2007).
  - ▶ Abdulkadiroglu, et al. (2006), Pathak (2011).
- ▶ Congressional Gerrymandering
  - ▶ Chen and Cottrel (2016)

# Data

- ▶ SABS - School Attendance Boundary Survey (SABS)
  - ▶ Coverage: 90% of LEAs, 85% of schools. 2013 SY.
  - ▶ Short Panel: SABS pilot survey, 500 large LEAs, 2009 SY.
  - ▶ Long Panel: 2000-2010 SAZs for CMS.
- ▶ 2010 Census Blocks – Population by Race by Age
  - ▶ Minorities (blacks and hispanics) and non-minorities (all others).
- ▶ Other sources:
  - ▶ 2010 Census Block Groups - Income
  - ▶ Common Core of Data (NCES)
  - ▶ Office of Civil Rights (OCR) - School Quality
  - ▶ Ed Facts - Student Proficiency Data
  - ▶ Stanford CEPA - Desegregation orders / Achievement Gaps
- ▶ **Sample Selection:**
  - ▶ Primary Schools.
  - ▶ LEAs with at least 5 primary schools with overlapping grades.
  - ▶  $N = 1,607$  LEAs, serving 11.5 million K4 students.

# SABs

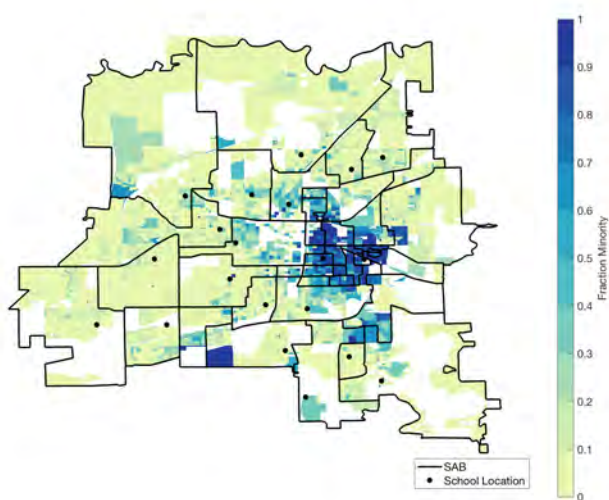


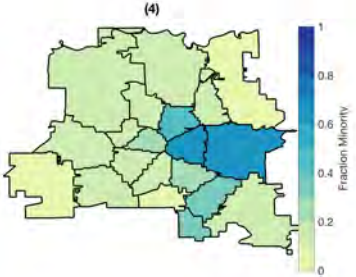
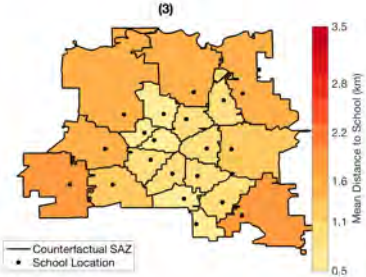
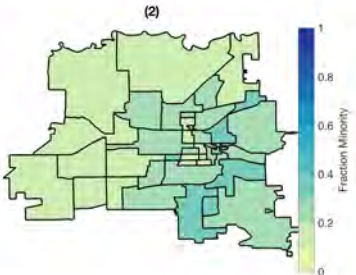
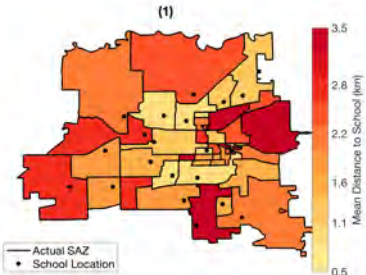
Figure: School Attendance Boundaries – Springfield Public Schools, IL.

## Empirical Framework

# Counterfactual SABs

- ▶ In order to assess extent of manipulation of boundaries, a baseline is needed for comparison.
- ▶ For the case of SABs, a natural counterfactual is boundaries that minimize student distance travelled to school (Voronoi Map) .
  - ▶ Can be motivated with an analogy to a 'neighborhood schools' scheme.
  - ▶ Call this baseline: 'Neighborhood SABs'.
- ▶ Assuming Neighborhood SABs are a low cost alternative to actual SABs:
  - ▶ Districts reveal preference when making costly departures from this baseline.

# Neighborhood SABs



# Neighborhood SABs

- ▶ Quick Aside: Euclidean Distance?
  - ▶ While quick and elegant, Euclidean distance may be an unrealistic approximation of travel time.
- ▶ One solution: Query Google Maps API
  - ▶ Pro: True travel time.
  - ▶ Con: Slow and costly. We need to compute millions of distances.
- ▶ Another Solution: Compute road network using Census road shapefiles and use Dijkstra's algorithm to find shortest path.
  - ▶ Pro: Don't need permission
  - ▶ Con: Ignores speed limits and congestion.

## Stylized Model of Integrative SAB Drawing

- ▶ Schools/Neighborhoods  $i = 1, \dots, K$ .
- ▶ Neighborhood Population  $N_i = N$ .
- ▶ Minority population  $N_i^m$ 
  - ▶ Neighborhood composition:  $r_i = N_i^m / N$ .
- ▶ At baseline, students assigned neighborhood school.
- ▶ Policymaker may assign  $a_{ij}$  students from neighborhood  $i$  to school  $j$ 
  - ▶ School composition:  $s_i = S_i^m / S_i = \sum_j a_{ij} r_j / \sum_j a_{ij}$ .
  - ▶ Baseline school comp.:  $s_i = r_i$
- ▶ Integration Policy: reassign a fraction  $p$  of pupils from neighborhood to other schools.

$$a_{ij}^p = \begin{cases} \frac{p}{K-1} N_i & \text{if } i \neq j \\ (1-p) N_i & \text{if } i = j \end{cases}$$

- ▶ School composition now:  $s_i = (1-p)r_i + p\bar{r}_{-i}$



# Integration Policy Estimation

- ▶ Consider the following statistical model for the assigned fraction of minority students,  $s$ , at a given school  $i$  ran by district  $j$ :

$$s_{ij} = \gamma_j + \beta_j r_{ij} + \nu_{ij} \quad (1)$$

where  $n_{ij}$  is the fraction minority in the school's neighborhood.

- ▶ For a given district, compute race-specific average school composition.

$$\bar{s}_j^r \approx \gamma_j + \beta_j \bar{r}_j^r$$

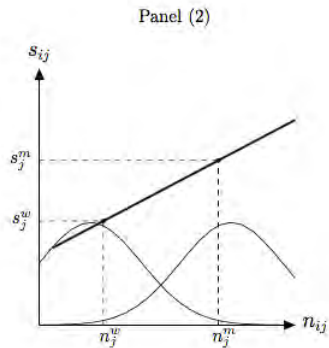
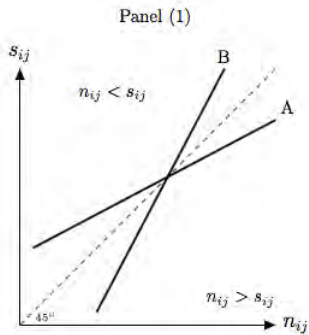
then

$$\Delta \bar{s}_j \approx \beta_j \Delta \bar{r}_j \quad (2)$$

- ▶ **Define the SAB Integration Rate (Policy)**

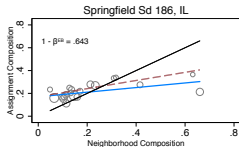
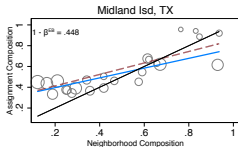
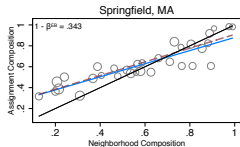
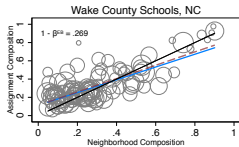
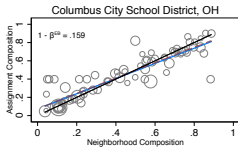
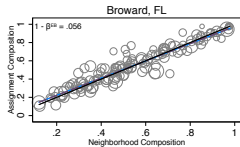
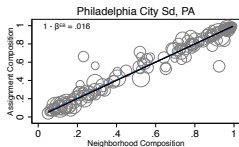
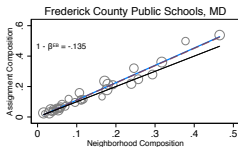
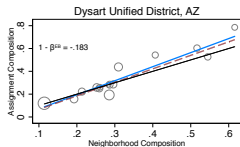
$$\rho_j = 1 - \beta_j \quad (3)$$

# Integration Policy Estimation



The Distribution of Integration Policy.

# Empirical Distribution of Integration Policy



# Empirical Distribution of Integration Policy

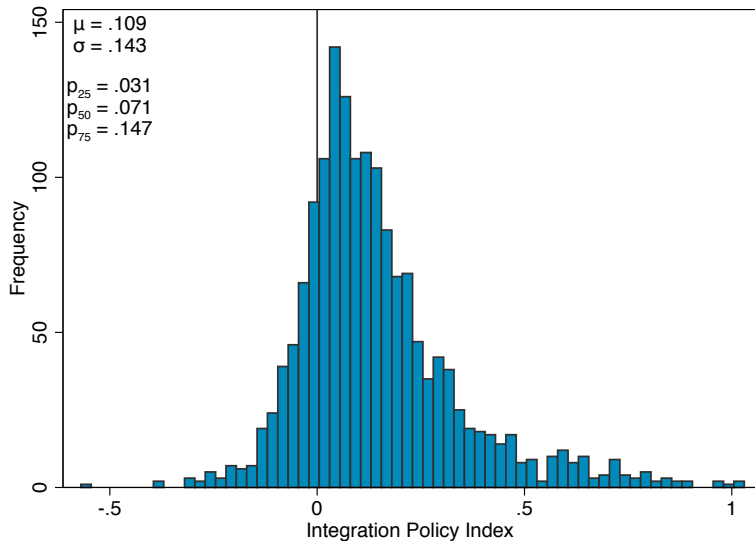


Figure: Distribution of Integration Policy Index

# Empirical Distribution of Integration Policy

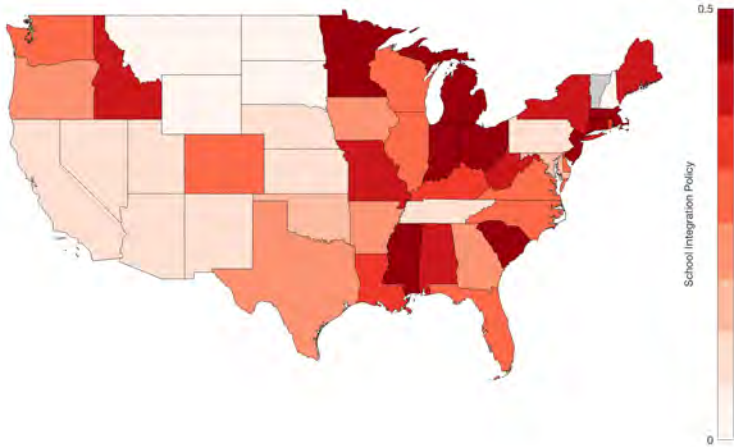


Figure: Spatial Distribution of Integration Policy

## Validation of Method

## Validation: Desegregation Orders

- ▶ In theory, desegregation court orders raise the opportunity cost of maintaining a segregated school system.
- ▶ The federal government can withhold Title I funding from districts that do not comply with the Civil Rights Act.
- ▶ Researchers have shown that districts with more funding at risk were more likely to desegregate (e.g. Cascio et al., QJE 2010).
- ▶ It is important to differentiate between districts that have been under order, versus those that have one in effect.
- ▶ All else equal, one would expect districts with effective orders to have stronger integration policy.



# Validation: Desegregation Orders

Table: OLS – Outcome: Estimated SAB Integration Rate

	(1)	(2)	(3)	(4)
Ever Under Order	0.0624*** (0.0188)	0.0410* (0.0209)		
Released from Order			0.0586*** (0.0212)	0.0305 (0.0238)
Order in Effect			0.0753*** (0.0187)	0.0653*** (0.0187)
Covariates	✓	✓	✓	✓
State Fixed Effects		✓		✓
Mean of Independent Variable	.469		.318	
N	1607	1604	1607	1604
R <sup>2</sup>	0.0568	0.195	0.0580	0.199

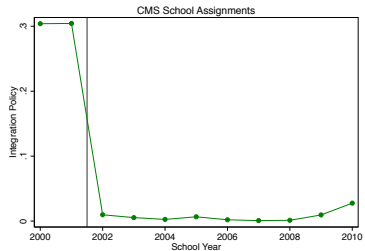
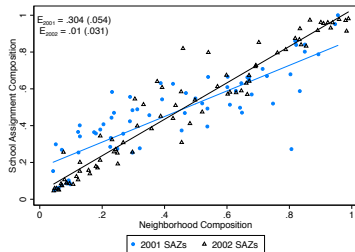
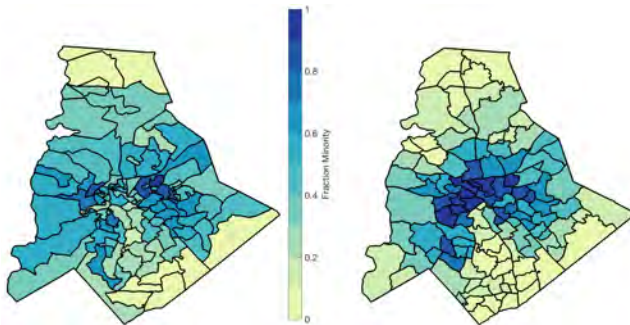
Standard errors clustered at the state level in all models.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Validation: The End of Busing in Charlotte, NC

- ▶ Charlotte Mecklenburg Schools (CMS) has an important role in the history of school desegregation.
- ▶ CMS was the defendant in the Supreme Court's 1971 *Swann* case, making desegregation busing constitutional.
- ▶ CMS implemented integration policy until a lawsuit in 1999 challenged it on the basis of equal protection.
- ▶ Starting in 2002, CMS switched to a choice plan, with default assignments based on 'neighborhood schools'.
- ▶ I have obtained SAB data from CMS elementary schools for years 2000-2010.

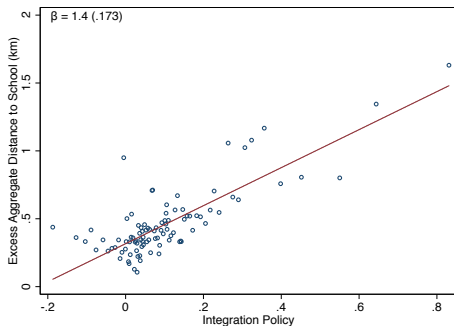
# Validation: The End of Busing in Charlotte, NC



## Validation: Distance to School

- ▶ The baseline comparison policy is based on minimum student distance travelled to school.
- ▶ By construction, actual SABs must have weakly higher distance per pupil than baseline.
  - ▶ Define: Excess Distance =  
Actual Distance Travelled by Avg. Student –  
Baseline Distance Travelled by Avg. Student
- ▶ Estimated integration policy measures attenuation in excess exposure to minorities.
- ▶ Such attenuation need not vary systematically with excess distance.
- ▶ However, integration plans typically involve busing implying large distances.

# Validation: Distance to School



	Excess Distance (km)			Ln(Marginal Distance Cost)		
	(1)	(2)	(3)	(4)	(5)	(6)
Integration Policy	1.400*** (0.173)	1.388*** (0.188)	1.218*** (0.204)	0.543 (0.403)	-0.372*** (0.102)	-0.286** (0.122)
Observations	1605	1605	1602	1327	1327	1325
$R^2$	0.256	0.277	0.438	0.008	0.645	0.669
StateFE			✓			✓
Covariates		✓	✓		✓	✓

Standard errors clustered at the state level in all models.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Validation: Gerrymandering

- ▶ SAB integration policy entails a districting problem related to congressional gerrymandering.
  - ▶ In political science, several metrics have been proposed to measure gerrymandering.
    - ▶ Many are based off a district's 'bizarreness'.
    - ▶ The idea is that in the absence of manipulation, districts would have a 'regular' shape.
    - ▶ Define  $Bizarreness = Area(SAB) / Area(ConvexHull(SAB))$
- Fig
- ▶ Caveat: The literature seems to be moving away from these metrics as they lack counterfactuals. See Chen and Cottrell (2016).

# Validation: Gerrymandering

Table: OLS – Outcome: Estimated SAB Integration Rate

	(1)	(2)	(3)	(4)	(5)
SAB Satellites (Busing)	0.202*** (0.0399)				-0.0163 (0.0883)
Average SAB Bizarreness		0.677*** (0.0928)			0.726*** (0.228)
Open Enrollment			0.0305 (0.118)		0.141 (0.102)
Multiple Assignment				0.131*** (0.0246)	0.139*** (0.0250)
Observations	1602	1602	1602	1602	1602
$R^2$	0.229	0.265	0.190	0.237	0.317
IndepVarMean	.112	.216	.019	.145	
StateFE	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓

Standard errors clustered at the state level in all models.

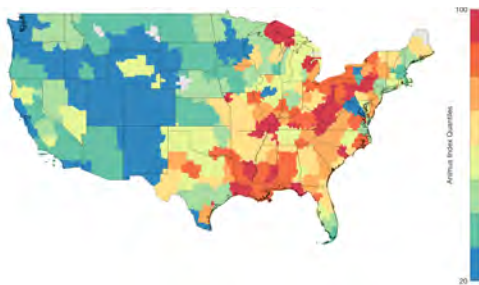
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Validation: Racial Animus

- ▶ Historically, school desegregation efforts have been met with great social unrest arguably related to racial animus.
- ▶ In the context of this project, one can posit that racial animus shifts a district's preferences for racial integration.
- ▶ Stephens-Davidowitz (2014) proposes a proxy for racial animus based on Google search queries that use racially charged language.
- ▶ Do districts with more racial animus have lower integration policy?



# Validation: Racial Animus



	(1)	(2)	(3)	(4)
Racial Animus	0.0224 (0.104)	-0.209 (0.166)	-0.155 (0.106)	-0.277** (0.112)
Covariates	✓	✓	✓	✓
No Western States		✓		✓
State Fixed Effects			✓	✓
N	1602	1156	1599	1153
R <sup>2</sup>	0.0493	0.0569	0.196	0.189

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Characterization of Integration Policy

# Characterization of Integration Policy

Now that we are (fairly) certain that the proposed metric captures integration policy, we may ask:

- ▶ What do integrative districts look like?
- ▶ Which district characteristics are most predictive of integration policy?
- ▶ Is integration policy beneficial for minority students?

# Characterization: Basic Demographics

Table: OLS – Outcome: Estimated SAB Integration Rate

	(1)	(2)	(3)	(4)	(5)
Ln(Total District Population)	-0.0221*** (0.00479)			-0.0196*** (0.00710)	-0.0124** (0.00531)
Baseline School Segregation		-0.175*** (0.0553)		-0.0257 (0.101)	-0.140** (0.0587)
District Baseline Composition			-0.0739*** (0.0228)	-0.0153 (0.0279)	0.0401* (0.0211)
Constant	0.373*** (0.0600)	0.127*** (0.0135)	0.127*** (0.0140)	0.352*** (0.0799)	
State Fixed Effects					✓
Mean of Independent Variable	12.44	.168	.395		
N	1605	1605	1605	1605	1602
R <sup>2</sup>	0.0383	0.0223	0.00929	0.0391	0.190

Standard errors clustered at the state level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Characterization: Enrollment Segregation

	Segregation of Assignments		Segregation of Enrollments	
	(1)	(2)	(3)	(4)
Integration Policy	-0.287*** (0.0387)	-0.152*** (0.0197)	-0.279*** (0.0500)	-0.150*** (0.0185)
Baseline School Segregation		0.909*** (0.0260)		0.941*** (0.0514)
Observations	1605	1602	1605	1602
DepVarMean	.158		.195	
StateFE		✓		✓
Covariates		✓		✓

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Characterization: LEA Finance

<i>Panel A: Socioeconomic Characteristics</i>	(1)	(2)	(3)	(4)	(5)
ln(Median HH income)	-0.0222 (0.0238)				0.0542 (0.0425)
ln(Median property value)		-0.0230 (0.0174)			-0.0388 (0.0233)
Fraction of pupils FRL			0.0234 (0.0424)		-0.0951 (0.0793)
Fraction of schools Title I eligible				0.104*** (0.0280)	0.163*** (0.0418)
Mean of Independent Variable	10.913	12.083	.622	.783	.783
<i>Panel B: District Finance</i>	(1)	(2)	(3)	(4)	(5)
ln(Total Revenue)	0.0925* (0.0482)				
ln(Local Revenue)		0.0340 (0.0204)			0.0566** (0.0242)
ln(State Revenue)			-0.00844 (0.0174)		0.0350* (0.0201)
ln(Federal Revenue)				-0.0188 (0.0206)	-0.0328 (0.0198)
Covariates	✓	✓	✓	✓	✓
State Fixed Effects	✓		✓	✓	✓
Mean of Independent Variable		8.45	8.496	6.95	
N	1600	1600	1600	1600	1600
R <sup>2</sup>	0.198	0.198	0.193	0.194	0.202

Note: Standard errors clustered at the census block group level in all models.

# Characterization: Racial Gaps

Definition of exposure gap in variable  $y$ :

$$\Delta y = E[y|minority] - E[y|white]$$

Teachers

	(1) Inexperienced Teachers	(2) Certified Teachers	(3) Teacher Absenteeism
Integration Policy	-2.493*** (0.646)	-0.203 (0.598)	-0.523 (0.421)
Covariates	✓	✓	✓
State FE	✓	✓	✓
Mean of Dependent Var	.867	-.378	.692
N	1600	1600	1600
R <sup>2</sup>	0.279	0.170	0.133

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Characterization: Racial Gaps

## School Quality

	(1)	(2)	(3)
	GT Program	Ability Grouping	Student Retention Rate
Integration Policy	0.118*** (0.0359)	0.568 (1.498)	-0.0309*** (0.00717)
Covariates	✓	✓	✓
State FE	✓	✓	✓
Mean of Dependent Var	-.081	-.144	.023
N	1600	1600	1600
R <sup>2</sup>	0.329	0.0705	0.325

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



# Characterization: Racial Gaps

## CEPA Achievement Gaps

	(1) ELA	(2) Math	(3) Composite
Integration Policy	0.0793 (0.0542)	0.0357 (0.0467)	0.0630 (0.0453)
Covariates	✓	✓	✓
State FE	✓	✓	✓
Mean of Dependent Var	.698	.657	.679
N	1251	1165	1312
R <sup>2</sup>	0.536	0.406	0.500

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Characterization: Racial Gaps

## Ed Facts Proficiency Gaps

	(1) ELA	(2) Math	(3) Composite
Integration Policy	0.0216 (0.0139)	0.0200 (0.0147)	0.0208 (0.0142)
Covariates	✓	✓	✓
State FE	✓	✓	✓
Mean of Dependent Var	.21	.204	.207
N	1594	1594	1594
R <sup>2</sup>	0.660	0.553	0.613

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Recap

## Contributions

- ▶ Developed counterfactual SAB policy for large sample of school districts.
- ▶ Proposed empirical framework to assess SAB integration policy relative to this baseline.
- ▶ Validated method showing that SAB integration rate is related to variables that, *a priori*, we would expect to relate to integration policy.
- ▶ Described and characterized distribution of modern integration policy.

## Question Remaining

- ▶ How unstable is integration policy, regarding household non-compliance and residential/Tiebout sorting?

## Integration Policy and Non-Compliance

# Integration Policy and Non-Compliance

- ▶ Researchers have documented that desegregation court orders led to increases in private school enrollment of whites and white flight to the suburbs (e.g Baum-Snow and Lutz (2011)).
- ▶ Are these patterns present in the current context of integration policy?

# Non-Compliance: Descriptive

Table: Integration Policy and Outside Options

	<u>ln(# Private Schools)</u>	<u>ln(Private School Enrollment)</u>			<u>Suburban Ring</u>	<u>ln(Charter Enr.)</u>
	(1)	(2)	(3)	(4)	(5)	(6)
		Total	White	Minority		
P	0.0481 (0.0804)	-0.327* (0.170)	-0.478 (0.350)	0.0331 (0.227)	0.0114 (0.0431)	-0.166 (0.603)
P × South	-0.154 (0.137)	0.212 (0.333)	0.456 (0.444)	-0.342 (0.365)	-0.0764 (0.0591)	-0.409 (0.776)
P × Midwest	0.234** (0.116)	1.118*** (0.319)	1.397*** (0.424)	0.324 (0.378)	0.121* (0.0721)	0.105 (0.961)
P × West	-0.195 (0.171)	0.304 (0.393)	0.691 (0.444)	-0.0679 (0.484)	0.0684 (0.0552)	0.274 (0.849)
Covariates	✓	✓	✓	✓	✓	✓
State Fixed Effects	✓	✓	✓	✓	✓	✓
Mean of Dep. Var.	2.953	7.773	7.273	6.139	.125	5.974
N	1600	1600	1600	1600	1598	1600
R <sup>2</sup>	0.927	0.765	0.751	0.850	0.630	0.743

Standard errors clustered at the state level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Case Study: The Effect of SAB Composition

- ▶ As mentioned above, Charlotte Mecklenburg Schools (CMS), NC, ended its school integration plan in 2002.
- ▶ CMS abruptly changed its SABs from an integration scheme in 2001 to a minimum distance scheme in 2002.
- ▶ The exact timing of this policy shock was unlikely to be predicted by households.
- ▶ This presents an opportunity to estimate the causal effect of SAB composition on the composition of residences
  - ▶ Key parameter allowing us to assess the stability of SAB integration to residential sorting

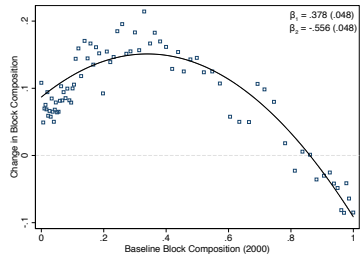
## Case Study: The Effect of SAB Composition

- ▶ I construct a longitudinal data set of Census Blocks for the years 2000 and 2010.
- ▶ I am interested in the effect of a change in SAB composition in the ten year change in block racial composition.
- ▶ Parallel analysis of effects on property prices.

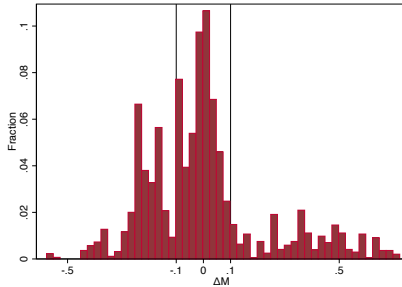
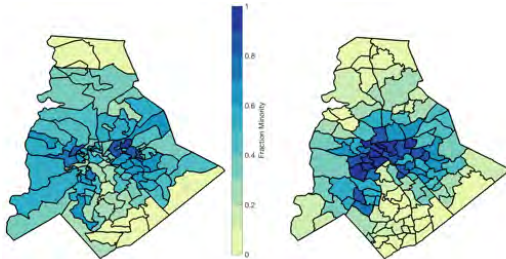
	2000		2010		Change	
	mean	sd	mean	sd	mean	sd
<i>Census Block Demographics</i>						
Block Population	141.10	220.95	175.65	331.67	34.55	210.30
Fraction Minority	0.33	0.35	0.41	0.35	0.08	0.18
<i>Census Block Real Estate</i>						
ln(Mean Property Sales Price)	11.98	0.71	11.89	0.94	-0.08	0.65
ln(Mean Property Appraisal Value)	11.92	0.70	11.84	0.73	-0.07	0.41
<i>SAB Demographics (2000 Census Constant)</i>						
SAB Population	803.52	254.08	621.20	211.71	-182.32	302.30
Fraction Minority	0.43	0.21	0.43	0.31	0.00	0.23
Observations	4393		4393		4393	



# Case Study: The Effect of SAB Composition



# Case Study: The Effect of SAB Composition



## Case Study: Empirical Strategy

- ▶ Correlated mean reversion in block composition changes implies that we must control for baseline block composition.
- ▶ Pre-period SABs were integrative, hence non-random. Variation used for estimation should come from within small geo areas for which such selection concern is minimal.
- ▶ Propose following class of regression models to estimate the causal effect of SAB composition.

$$\Delta y_{bk} = \gamma_{ks_0(b)} + \beta \Delta M_{s(b)} + g(y_{bk0}) + \epsilon_{bk} \quad (4)$$

- ▶ ID Assumption: Conditional on baseline composition, new SABs were as good as randomly drawn within small geographic areas (Old SABs and Census Tracts).

# Case Study: Results

<i>Panel A: Change in Block Composition</i>	(1)	(2)	(3)	(4)
Change in SAB Composition (2000 Census)	0.158*** (0.0334)	0.193*** (0.0283)	0.151*** (0.0474)	0.143** (0.0601)
Baseline SAB Composition	✓			
Quadratic Baseline Composition	✓	✓	✓	✓
Old SAB Fixed Effects		✓	✓	
Census Tract Fixed Effects			✓	
Old SAB-by-Census Tract Fixed Effects				✓
N	4393	4393	4393	4393
R <sup>2</sup>	0.236	0.416	0.519	0.543
<i>Panel B: Change in Mean Property Price</i>	(1)	(2)	(3)	(4)
SAB Composition Shock	0.0422 (0.0812)	-0.0174 (0.0966)	-0.0666 (0.176)	-0.0282 (0.215)
Baseline SAB Composition	✓			
Quadratic Baseline Composition	✓	✓	✓	✓
Old SAB Fixed Effects		✓	✓	
Census Tract Fixed Effects			✓	
Old SAB-by-Census Tract Fixed Effects				✓
N	3460	3460	3460	3451
R <sup>2</sup>	0.0407	0.0938	0.161	0.194

*Note:* Standard errors clustered at the census block group level in all models.

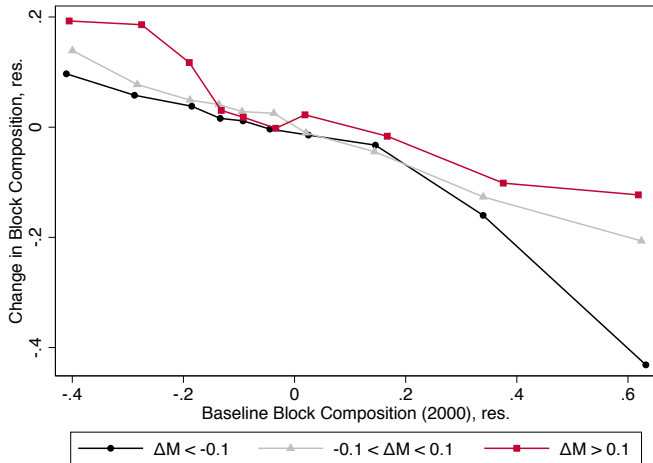
# Case Study: Results

<i>Panel A: Change in Block Composition</i>	(1)	(2)	(3)	(4)
SAB Composition Shock	0.151*** (0.0474)	0.155*** (0.0473)	0.161*** (0.0521)	0.172*** (0.0661)
New School		-0.0311** (0.0129)	-0.0309** (0.0132)	-0.0204 (0.0165)
SAB Shock × New School			-0.0117 (0.0419)	-0.0552 (0.0542)
Quadratic Baseline Composition	✓	✓	✓	✓
Old SAB Fixed Effects	✓	✓	✓	
Census Tract Fixed Effects	✓	✓	✓	
Old SAB-by-Census Tract Fixed Effects				✓
N	4393	4393	4393	4393
R <sup>2</sup>	0.519	0.521	0.521	0.544
<i>Panel B: Change in Mean Property Price</i>	(1)	(2)	(3)	(4)
SAB Composition Shock	-0.0666 (0.176)	-0.0668 (0.175)	-0.0897 (0.168)	-0.0215 (0.206)
New School		0.00142 (0.0516)	0.000682 (0.0517)	-0.0563 (0.0566)
SAB Shock × New School			0.0510 (0.177)	-0.00787 (0.216)
Quadratic Baseline Composition	✓	✓	✓	✓
Old SAB Fixed Effects	✓	✓	✓	
Census Tract Fixed Effects	✓	✓	✓	
Old SAB-by-Census Tract Fixed Effects				✓
N	3460	3460	3460	3451
R <sup>2</sup>	0.161	0.161	0.161	0.194

*Note:* Standard errors clustered at the census block group level in all models.

# Case Study: Results

## Mechanisms



## Discussion

- ▶ Shocks in SAB composition generated by the end of busing in CMS provide opportunity to estimate causal effect of SAB composition on white flight.
- ▶ I can reject the non-existence of a white flight reaction at the 1% confidence level.
- ▶ Nevertheless, white flight is relatively small, a 25 pp. increase in SAB fraction minority leads to about a 3.95 pp. increases in the fraction minority of residences over a decade.
- ▶ Find no evidence of dynamic effects on real estate values.
- ▶ Integration policy seems to be stable to Tiebout residential sorting for at least a few years.

# Conclusions

- ▶ Integration policy is still a prevalent feature of public school systems across the country.
- ▶ Some districts try harder than others. We can now quantify these differences with precision.
- ▶ Integration policy is a normal good for districts.
- ▶ Integration policy is associated with smaller racial gaps in school quality measures, but not with smaller achievement gaps.
- ▶ Tiebout sorting exists but it is gradual and relatively modest. Integration policy is stable in the short-run to medium-run.

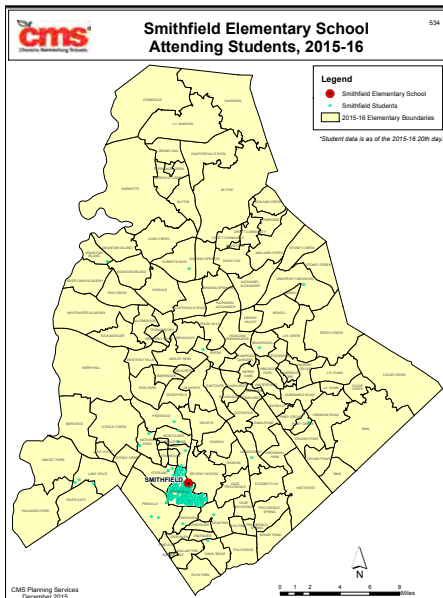


THANK YOU!

## APPENDIX

# Appendix: Students Attend Assigned School

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# Appendix: SAZs Change Periodically

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Table: SAZ Changes Summary Stats – 2009-2013 SY

	LEAs with New Schools		LEAs without New Schools	
	mean	count	mean	count
<i>All Schools</i>				
1(Any Change)	0.34	3903	0.32	4909
1('Effective' Change)	0.14	3903	0.17	4909
<i>Schools with Any SAZ changes</i>				
Intensive Change (Num. Blocks)	0.94	1327	-2.28	1553
Pct. population change	0.03	1327	-0.01	1553
<i>Schools with Effective SAZ changes</i>				
Intensive Change (Num. Blocks)	2.49	548	-3.95	845
Pct. population change	0.07	548	-0.02	845

## Appendix: Shrinking Estimates via Empirical Bayes

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We have a noisy estimate of the parameter of interest:

$$\hat{\beta}_j = \beta_j + e_j$$

then

$$\underbrace{\text{Var}(\hat{\beta}_j)}_{\text{empirical}} = \text{Var}(\beta_j) + \text{Var}(e_j)$$

But we also have estimates of the noise term:  $\hat{\sigma}^2(\hat{\beta}_j) \equiv \hat{\sigma}_j^2$ . Let  $\widehat{\text{Var}}(e_j) = \frac{1}{J} \sum_j \hat{\sigma}_j^2$ . Now, define

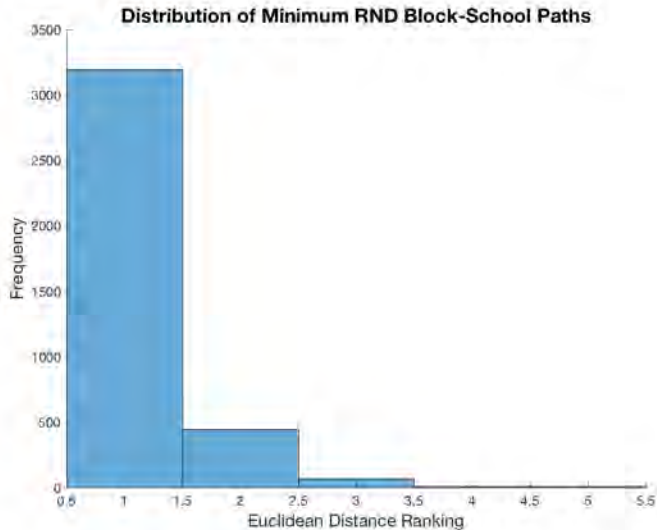
$$\hat{\sigma}_o^2 \equiv \text{Var}(\hat{\beta}_j) - \widehat{\text{Var}}(e_j)$$

Compute estimate of signal-to-noise ratio:  $\lambda_j = \frac{\hat{\sigma}_o^2}{\hat{\sigma}_o^2 + \hat{\sigma}_j^2}$ .

Finally, shrink betas toward 1:

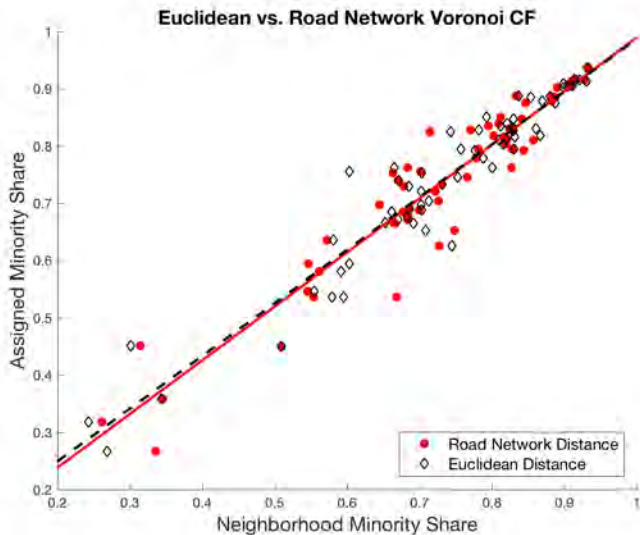
$$\hat{\beta}_j^{EB} \equiv \lambda_j \hat{\beta}_j + (1 - \lambda_j)$$

# Empirical Framework – Road Network Voronoi Zones



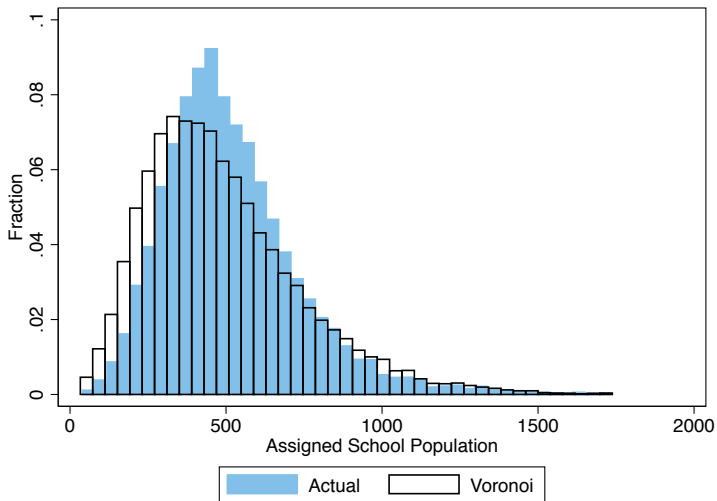
# Empirical Framework – Road Network Voronoi Zones

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# Appendix: Distribution of School Capacity

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# Appendix: SAB Bizarreness

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