The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality

1. Introduction

The paper *The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality* seeks to explore how residential segregation by race affects the economic inequality between the white and black populations in the United States. While other papers have attempted to measure the effects of segregation, there has been a lot of skepticism about the reliability of the results due to omitted variable bias and endogenous migration.

In this paper, Ananat seeks to remedy the problem of omitted variable bias by instrumenting for a city's level of segregation by using a city's railroad configuration. The author presents evidence that supports the choice of instrumentation by showing the requirements necessary for a valid instrument. It is shown to be strongly and robustly to predict metropolitan segregation and does not separately predict confounding metropolitan outcomes. By using this instrument, the paper is able to examine the effect of segregation on a cities' income distributions by race.

The paper finds that exogenously increasing segregation causes cities to have African American populations with higher poverty rates and white populations with lower poverty rates. Segregation also increases the inequality between the two populations as it finds that it lowers average outcomes within a city's black community while reducing inequalities within a city's white community.

Finally, the paper seeks to better understand how segregation has led to city-level differences in poverty and inequality by looking at the way migration patterns and youth educational attainment differ according to segregation. This is done to help clarify whether differences in populations are a result of the causal treatment ment effect of segregation on individual-level or on a group-level. The results for this aspect of the paper are not conclusive but are most consistent with the hypothesis that both effects (individual and group) are at work.

1.1 Data

The paper utilizes data from various sources to investigate the effects of racial segregation on urban poverty and inequality.

1. **U.S. Census Bureau Reports:** These reports provide data on metropolitan demographics. The author uses these reports to gather information on poverty rates, median rent, and crowding, categorized by race.

2. **Integrated Public Use Microdata Series (IPUMS):** Individual Census microdata from IPUMS.org, covering years from 1890-1940, is incorporated into the analysis. This dataset analyzes individual-level characteristics like income, education, and labor force participation.
3. **Cutler/Glaeser/Vigdor Segregation Data:** This pre-compiled dataset, made available online by Jacob Vigdor, includes measures of metropolitan segregation from various decades, covering the nineteenth and twentieth centuries. The dataset also contains metropolitan characteristics used in prior research by Cutler and Glaeser (1997) and Cutler, Glaeser, and Vigdor (1999). This data is used to analyze historical trends and compare the study's findings with previous research.
4. **Nineteenth-Century Maps:** A collection of historical maps from the Harvard Map Library is analyzed to extract information on railroad configurations in 121 cities. These maps, created by the U.S. Geological Survey starting in the 1880s, detail elevation, bodies of water, roads, railroads, and building locations. These maps provide the basis for constructing the Railroad Division Index (RDI), a key variable in the study.
5. **Proximity to Former Slave States:** The study considers the distance of each city to the nearest former slave state as a proxy for potential demand for segregation during the Great Migration. Cities closer to former slave states experienced more significant inflows of African Americans, potentially increasing the demand for segregation in those areas.

2. Replication

2.1 Summary Statistics

The paper doesn't really talk about or have a section for summary statistics. It only has a comparison of means table in its appendix. We replicate it and find very similar, or nearly identical matches with the table from the paper. Additionally, in our table, we also include medians and IQRs.

The difference in means table mostly compares certain control/confounding characteristics between American cities within as well as outside of the study samples, and then reporting the p-values for their difference in means.

Our Table:

	Variable	Mean (In Sample)	SE (In Sample)	Median (In Sample)	IQR (In Sample)	Mean (Not In Sample)	SE (Not In Sample)	Median (Not In Sample)	IQR (Not In Sample)	Difference in Means	P-value
1	total area 1900	11764.32	1183.45	7066.00	10189.70	19283.33	2215.18	5288.00	15877.00	-7519.01	0.22
2	total area 1940	27137.36	3873.08	17664.00	21088.00	32855.27	2840.80	19232.00	25024.00	-5717.91	0.62
3	total area 1970	1615.08	156.46	1087.00	1538.00	2344.36	264.18	1198.00	1617.50	-729.28	0.26
4	total area 1990	1825.89	262.05	1031.10	1345.50	2386.99	266.04	1198.00	2306.45	-561.10	0.30
5	black income segregation 1990	0.55	0.01	0.55	0.10	0.55	0.00	0.56	0.09	-0.01	0.58
6	% blacks employed as servants 1915	0.21	0.00	0.19	0.06	0.21	0.00	0.19	0.05	-0.00	0.90
7	centralization index 1990	0.77	0.02	0.82	0.18	0.74	0.01	0.80	0.23	0.03	0.25
8	clustering index 1990	0.18	0.02	0.07	0.25	0.21	0.01	0.16	0.27	-0.03	0.25
9	concentration index 1990	0.66	0.02	0.72	0.29	0.56	0.02	0.63	0.44	0.10	0.00
10	dissimilarity index 1890	0.38	0.01	0.40	0.12	0.39	0.01	0.40	0.18	-0.00	0.96
11	dissimilarity index 1940 tract	0.74	0.01	0.76	0.14	0.74	0.01	0.75	0.16	0.01	0.87
12	dissimilarity index 1940 ward	0.57	0.01	0.59	0.20	0.57	0.01	0.60	0.26	-0.00	0.99
13	dissimilarity index 1970	0.74	0.01	0.77	0.14	0.74	0.01	0.76	0.14	-0.00	0.84
14	dissimilarity index 1990	0.57	0.01	0.57	0.22	0.57	0.01	0.56	0.21	-0.01	0.80
15	educational exposure index 1990	-0.09	0.00	-0.08	0.05	-0.08	0.00	-0.08	0.04	-0.00	0.60
16	increase in urban mileage in 1950s	0.25	0.02	0.18	0.38	0.24	0.01	0.20	0.22	0.01	0.71
17	income segregation	0.22	0.00	0.22	0.05	0.23	0.00	0.24	0.05	-0.01	0.07
18	isolation index 1890	0.05	0.00	0.05	0.04	0.05	0.00	0.04	0.04	0.00	0.70
19	isolation index 1940 tract	0.32	0.02	0.32	0.31	0.36	0.01	0.30	0.30	-0.04	0.59
20	isolation index 1940 ward	0.20	0.01	0.21	0.16	0.23	0.01	0.17	0.31	-0.04	0.38
21	isolation index 1970	0.37	0.02	0.37	0.28	0.34	0.02	0.29	0.40	0.02	0.59
22	isolation index 1990	0.21	0.02	0.19	0.31	0.23	0.01	0.18	0.31	-0.01	0.59
23	median income	31606.47	572.36	30797.00	8439.00	31483.74	433.23	30585.00	6250.00	122.73	0.89
24	median education	-0.14	0.01	-0.14	0.13	-0.16	0.01	-0.14	0.11	0.02	0.40
25	number of local government 1962	55.55	5.65	39.00	48.00	62.92	4.15	43.50	71.00	-7.37	0.56
26	per capita street car passengers 1915	179.00	6.38	169.30	78.89	204.21	3.26	208.55	66.40	-25.21	0.32
27	percent black 1890	0.03	0.00	0.02	0.02	0.03	0.00	0.01	0.02	-0.00	0.55
28	percent black 1940	0.04	0.00	0.03	0.03	0.06	0.00	0.04	0.07	-0.02	0.05
29	percent black 1970	0.06	0.00	0.05	0.06	0.06	0.00	0.05	0.05	0.01	0.48
30	percent black 1990	0.06	0.00	0.05	0.08	0.07	0.00	0.06	0.05	-0.01	0.48
31	population 1890	66043.97	13406.64	21805.00	37165.50	129828.89	24355.85	25807.00	51797.50	-63784.93	0.29
32	population 1940	203676.34	31201.09	99314.00	150382.50	390895.13	74588.33	97062.00	168437.50	-187218.79	0.29
33	population 1970	681598.72	101427.30	303320.00	436559.00	919238.69	118842.06	342301.00	745148.50	-237639.97	0.42
34	population 1990	590188.50	96574.45	273064.00	321645.00	689768.27	78444.40	278990.00	539572.50	-99579.77	0.55
35	person-weighted density	1270.52	75.12	1058.75	689.00	1808.08	176.46	1252.57	821.21	-537.56	0.13
36	inter-governmental revenue sharing 1962	0.25	0.01	0.26	0.12	0.26	0.00	0.26	0.07	-0.01	0.29
37	share of moms who are single	0.26	0.01	0.29	0.14	0.24	0.01	0.25	0.13	0.02	0.32
38	number of tracts 1940	103.35	9.56	61.00	54.00	146.06	13.94	63.00	126.00	-42.71	0.46
39	number of tracts 1970	161.81	23.44	74.50	99.75	211.12	28.01	84.00	164.00	-49.31	0.47
40	number of tracts 1990	137.50	20.89	69.00	75.00	203.69	23.46	94.00	183.00	-66.19	0.19
41	average commuting time	-0.44	0.27	0.08	3.50	0.82	0.21	1.38	3.73	-1.26	0.05
42	number of wards 1890	13.42	0.69	11.00	6.50	17.78	1.01	9.50	18.00	-4.36	0.30
43	number of wards 1940	14.12	0.84	12.00	11.00	15.93	0.89	11.00	12.75	-1.81	0.55

While our table isn't exactly identical to Table A from the paper, the values- both means and p-values are very similar (at least to the 1st decimal place). Most differences can also be accounted for by rounding differences.

The covariate means, overall, look very balanced between the sampled and out-of-sample observations. For the few variables (percent black-1940 and Concentration index–1990) where the p-value is significant (at 5% level), the overall difference in means in our table are close to 0 (difference in mean of 0.1 for the concentration index, and -0.018 for percentage black 1940). Thus, overall, it seems that the observations/cities are pretty well-balanced between in-sample and not-in-sample observations. Thus, overall, it seems that there's good covariate balance (in terms of segregation, percentage of black population, area, isolation index, rail tracts as well as education and income) between the in-sample and not-in-sample observations.

2.2 Ideal Experiment

In an ideal situation, we would run an experiment on two initially identical cities in such a way:

1. At time zero, one city is assigned perfect segregation, the other is assigned perfect integration.
2. Each city would be randomly assigned black residents from the initial black skill distribution and white residents from the initial white distribution.
3. The relationship between segregation and the income distribution of the offspring generation would be measured.
4. Finally, residents would be allowed to move, and aggregate demand for cities (rent, migration) by race and skill would be measured to determine tastes for segregation and its consequences.

However, in reality we will have to approximate this ideal experiment empirically by providing plausibly exogenous variation using our instrumental variables.

In reality, the randomized experiment was approximated by using a measure of a city's railroad-induced potential for segregation denoted "railroad division index" or RDI which quantifies the extent to which the city's land is divided into smaller units.

$$RDI = 1 - \sum_i \left(\frac{area_{neighborhoodi}}{area_{total}}\right)^2$$

Another important variable to be captured was the amount of segregation, which is captured by a dissimilarity index defined by:

Index of dissimilarity $= \frac{1}{2}\sum_{i=1}^{N}\left|\frac{black_i}{black_{total}} - \frac{nonblack_i}{nonblack_{total}}\right|$ where $i = 1 \ldots N$ is the array of census tracts in the area.

2.3 RDI as a Valid Instrument

With this setup, we can now test if RDI is a valid instrument since if RDI-induced segregation is randomly assigned, then we can capture the relationship between segregation and outcomes using a classic endogenous regressor affecting outcomes at the metropolitan statistical area (MSA) level

$$Seg = \alpha_1 RDI + \alpha_2 X + \mu$$

$$Y = \beta_1 Seg + \beta_2 X + \epsilon$$

where Seg represents an MSA's current level of segregation and X is a vector of control variables that includes total railroad length and other specifications. With this we result in the following table:

	First stage	Falsification checks					
		1910 city characteristics					
	1990 dissimilarity index (1)	Physical area (square miles/1,000) (2)	Pop. (1,000s) (3)	Ethnic dissimilarity index (4)	Ethnic isolation index (5)	Percent black (6)	Street-cars per capita (1,000s) (7)
RDI	**0.357**	-3.993	0.666	0.076	0.027	-0.0006	0.132
	(0.088)	(11.987)	(1.363)	(0.185)	(0.070)	(0.0100)	(0.183)
Track length per square kilometer	18.514	-574.401	75.553	15.343	-12.439	**9.236**	3.361
	(10.731)	(553.669)	(134.815)	(53.249)	(17.288)	**(0.650)**	(20.507)
Mean of dependent variable	0.569	14.626	1,527	0.311	0.055	1.442%	179
N	121	58	121	49	49	121	13
	Falsification checks						
	1920 city characteristics						
	Percent black (8)	Percent literate (9)	Labor force participation (10)	Percent of empl. in trade (11)	Percent of empl. in manufacturing (12)	Percent of empl. in railroads (13)	1990 income seg. (14)
RDI	0.013	0.053	0.028	-0.080	0.191	-0.074	0.032
	(0.009)	(0.030)	(0.024)	(0.094)	(0.137)	(0.068)	(0.032)
Track length per square kilometer	**9.119**	0.180	**-3.427**	-0.152	18.400	1.592	-2.504
	(0.615)	(0.880)	**(1.500)**	(2.901)	(10.911)	(2.428)	(1.626)
Mean of dependent variable	1.558%	95.850%	41.882%	5.768%	46.187%	0.316%	0.217
N	121	121	121	121	121	121	69

Table 1: Testing RDI as an Instrument, rounded values

From the table we can see that RDI induces meaningful variation in the degree of racial segregation. For RDI to be a valid instrument, not only must the railroad configuration induce variation in the degree of racial segregation and lead to segregation, but also that railroad configuration and people were assigned to cities randomly. We can deduce this through our table as well as historical context.

We can see that RDI does induce meaningful variation in degree of racial segregation in the first column (First stage) of Table 1. The remaining two assumptions are also shown through Table 1. Table 1 indicates that railroad division does not predict outcomes in time or places where there were not large black inflows, income, ethnicity, pre-period characteristics, and initial characteristics of the cities. We believe that with the limitations of the real-world, our quasi-experiment approximates the ideal experiment and agree with the author's choices. Additionally, our replication of the author's falsification checks and assumption checks are essentially the same, with small differences likely due to rounding.

With these assumptions of the RDI being a valid instrumental variable, we can measure the causal effects of RDI-induced segregation on the income distribution of a city's residents. These effects incorporate both effects on the individual human capital and cities' populations through migration. The paper uses ordinary least squares (OLS) and two-stage least squares (2SLS) as our estimators. In Table 2, we can see these estimates of the relationship of segregation with poverty and inequality by race:

2.4 Main Results

	OLS: Effect of 1990 dissimilarity index		Main Results: 2SLS RDI as instrument for 1990 dissimilarity		Falsification: Reduced form effect of RDI among cities far from the south	
	Whites	Blacks	Whites	Blacks	Whites	Blacks
Within-race poverty and inequality						
Gini index	**-0.079**	**0.459**	**-0.303**	**0.829**	-0.110	0.167
	(0.037)	**(0.093)**	**(0.094)**	**(0.257)**	(0.066)	(0.424)
Poverty rate	**-0.073**	**0.182**	**-0.192**	**0.231**	-0.036	-0.136
	(-0.019)	**(0.045)**	**(0.060)**	**(0.123)**	(0.035)	(0.094)
	White:black ratios		**White:black ratios**		**White:black ratios**	
Between-race inequality						
90 white: 90 black	0.111		-0.111		**-0.443**	
	(0.086)		(0.247)		(0.217)	
10 white: 10 black	**1.295**		**2.526**		-0.135	
	(0.249)		**(0.705)**		(0.532)	
90 white: 10 black	**1.172**		**1.678**		-0.449	
	(0.282)		**(0.692)**		(0.558)	
10 white: 90 black	-0.234		**-0.738**		0.130	
	(0.131)		**(0.335)**		(0.248)	
N	121		121		29	

Table 2: The Effects of Segregation on Poverty and Inequality among Blacks and Whites

We achieve almost the same results for all the results, and any differences are not significant enough to change our conclusion. Thus we can conclude that we achieved a similar conclusion as that of the author in the original paper. We can see that the within-race results (top panel), like the original paper, shows that segregation increases poverty and inequality within the black community while decreasing it in the white community. Looking specifically at the Main Results: 2 SLS columns, we can see that one-standard deviation (14 point) increase in dissimilarity causes a 4.24% decrease in the white Gini index and a 2.69% decrease in white poverty. This is relatively close to the 4.7% and 2.7% values suggested by the paper. Additionally, when it comes to the black community, we see that there's an 11.6% increase in the Gini index and 3.2% increase in black poverty. Thus our results demonstrate the same ideas as the main paper, but to a lesser extent since the paper found that there was a 3.6% increase in black poverty and 12.3% increase in the black Gini index.

The bottom panel of Table 2 shows that segregation does not affect income disparities between well-off blacks and whites when comparing 90th percentile of both populations (taking the mean of *ln90w90b* after undoing the natural log). However, when comparing the 10th percentile of both populations, we see that the effect of segregation affects them much more differently as the worst-off whites have an average income that's 107% higher than worst-off blacks (taking the mean of *ln10w10b* after undoing the natural log). Using Table 2 we can then conclude that a one standard deviation increase in segregation will cause that gap to increase by about 38% instead of the paper's original 41%. Thus we've noticed that our replication has resulted in differences that are still close, but less than the original paper's in most cases. This is likely due to the differences in using R v.s. STATA as it is very likely that some of the implementation of the functions utilized may differ slightly, resulting in our small discrepancies.

Our Falsification columns indicate that there's no meaningful relationship between RDI and income distribution when RDI has little effect on segregation, thus lending credibility to the claim that RDI drives poverty and inequality through segregation and not other variables.

2.5 Robustness Checks

2.5.1 Controlling for 1920 City Characteristics

This robustness check replicates the main two-stage least squares (2SLS) estimates of the effect of segregation on the Gini index and poverty rates while controlling for city characteristics in 1920. This is the period when the Great Migration had just begun.

Controlling for 1920 characteristics helps address a potential concern that characteristics present at the beginning of the Great Migration might confound the relationship between RDI and segregation and, subsequently, between segregation and poverty and inequality. For example, imagine a city with a high RDI with a particularly large or highly-skilled Black population in 1920. The larger Black population might lead to a stronger demand for segregation, and the greater skills might protect the Black population from some of the negative effects of segregation. If those factors were not controlled for, the analysis might understate the effect of RDI-induced segregation on poverty and inequality. The specific 1920 city characteristics used as controls are:

- Population: The total population of the city.
- Percent black: The percentage of the city's population that is Black.
- Literacy: The percentage of the city's population that is literate.
- Share employed in manufacturing: The percentage of the city's employment in manufacturing.
- Labor force participation: The percentage of the city's population in the labor force.

Table 3: Robustness Checks: 2SLS Effects of 1990 Segregation, Controlling for City-Level Characteristics

	Outcome: Gini index		Outcome: Poverty rate	
	Whites	Blacks	Whites	Blacks
With controls for 1920 city characteristics				
Population	**-0.374**	**0.899**	**-0.214**	**0.281**
	(0.119)	**(0.327)**	**(0.074)**	**(0.153)**
Percent black	**-0.364**	**0.896**	**-0.199**	**0.296**
	(0.122)	**(0.322)**	**(0.074)**	**(0.151)**
Literacy	**-0.312**	**1.029**	**-0.163**	**0.270**
	(0.120)	**(0.338)**	**(0.071)**	**(0.157)**
Share employed in manufacturing	**-0.401**	**0.904**	**-0.213**	**0.307**
	(0.137)	**(0.365)**	**(0.085)**	**(0.170)**
Labor force participation	**-0.305**	**0.849**	**-0.187**	**0.243**
	(0.100)	**(0.283)**	**(0.064)**	**(0.135)**
Control for propensity score	**-0.412**	*1.038*	**-0.189**	*0.304*
	(0.184)	*(0.472)*	**(0.103)**	*(0.217)*

The results of this robustness check show that the estimated effects of segregation on poverty and inequality are highly stable when controlling for these 1920 city characteristics. All estimates remain statistically significant, and their magnitudes are similar to those in the primary analysis.

These findings provide further evidence that RDI is primarily impacting poverty and inequality through segregation and not through some other channel. The results are stable even after accounting for differences in city characteristics present at the beginning of the Great Migration before segregation could have noticeable effects on human capital or city growth.

3. Re-analysis of Paper's Main Results

3.1 Inverse Probability Weighting (IPW)

Inverse Probability Weighting (IPW) is a statistical method designed to estimate causal effects in observational studies where treatment assignment (in this case, segregation levels) is not randomized. The core idea is to reweight the data to create a pseudo-randomized experiment, making treatment and control groups comparable in terms of observed characteristics. Thus, we believe that an IPW is an appropriate method to be used in our replication since we are seeking to create a quasi-random experiment from our non-random variable of interest: segregation.

Segregation is not randomly assigned but influenced by historical and structural factors, such as city demographics and economic conditions. Confounding variables, such as literacy rates and racial composition in 1920, affect the likelihood of segregation and the outcomes of interest. It accounts for selection bias by reweighting the data to balance observed covariates (e.g., literacy, population size) between highly segregated and less segregated cities. It adjusts for historical confounders that might otherwise bias estimates of segregation's causal effects.

3.1.1 Assumptions

We must take into account that our instrument from before, RDI, must still be balanced across covariates as the validity of 2SLS relies on the *exclusion restriction*, which assumes that the instrument (RDI) affects the outcome only through the endogenous variable (segregation). In this case, IPW balances covariates across levels of the instrument, reducing the likelihood that omitted variables confound the instrument's effect. For instance, if the RDI is correlated with other city-level characteristics, IPW ensures that these characteristics are balanced across cities with high and low segregation.

To successfully use IPW, we are assuming that there is no unmeasured confounding in that the propensity score model must include all confounders that affect both segregation and outcomes (city demographics, economic conditions). We are also assuming positivity where given its covariates, every city must have a non-zero probability of being highly segregated or not segregated. This ensures the propensity scores (and weights) are well-defined. And finally, we assume that the propensity score model (logistic regression) accurately captures the relationship between the covariates and the likelihood of high segregation.

3.1.2 IPW Results

Table 4A: The Effects of Segregation on Poverty and Inequality among Blacks and Whites using IPW Estimators

	IPW-OLS: Effect of 1990 dissimilarity index		IPW-2SLS: RDI as instrument	
Outcome:	**Whites**	**Blacks**	**Whites**	**Blacks**
Within-race poverty and inequality				
Gini index	**-0.073**	**0.437**	**-0.662**	**1.543**
	(0.035)	**(0.112)**	**(0.326)**	**(0.768)**
Poverty rate	**-0.067**	**0.161**	**-0.376**	*0.223*
	(0.023)	**(0.051)**	**(0.187)**	*(0.260)*

Table 4B: The Effects of Segregation on Between-Race Inequality Using IPW-OLS and IPW-2SLS.

Between-race inequality	IPW-OLS White:black ratios	IPW-2SLS White:black ratios
90 white: 90 black	*0.131*	*-0.657*
	(0.105)	*(0.650)*
10 white: 10 black	**1.282**	**4.849**
	(0.289)	**(2.218)**
90 white: 10 black	**1.217**	**2.812**
	(0.298)	**(1.686)**
90 black: 10 white	*-0.234*	*-1.380*
	(0.131)	*(0.891)*

The results presented in Table 4A provide evidence of the impact of segregation, measured by the 1990 dissimilarity index, on poverty and inequality among Blacks and Whites using Inverse Probability Weighted Ordinary Least Squares (IPW-OLS) and Two-Stage Least Squares (IPW-2SLS). For Whites, segregation is associated with a reduction in the Gini index (-0.073 in OLS and -0.662 in 2SLS) and poverty rates (-0.067 in OLS and -0.376 in 2SLS), suggesting that segregation may consolidate income advantages within White communities. The standard errors in bold indicate that the results are statistically significant in both specifications. For Blacks, segregation is linked to an increase in the Gini index (0.437 in OLS and 1.543 in 2SLS) and poverty rates (0.161 in OLS and 0.223 in 2SLS). These results underscore the disproportionate burden of segregation on Black communities, exacerbating income inequality and poverty. Notably, the 2SLS estimates are larger in magnitude than the OLS results, indicating that OLS may underestimate the causal effects of segregation. The use of RDI as an instrument for the dissimilarity index improves robustness, further emphasizing the stark racial disparities driven by segregation.

The results in Table 4B illustrate the effects of segregation on between-race inequality using IPW-OLS and IPW-2SLS methods, with bolded values indicating statistical significance. For the ratio of the 10th percentile of White income to the 10th percentile of Black income, both

IPW-OLS (1.282, significant) and IPW-2SLS (4.849, significant) estimates highlight a substantial increase in inequality, suggesting segregation disproportionately disadvantages low-income Black individuals relative to their White counterparts. Similarly, for the ratio of the 90th percentile of White income to the 10th percentile of Black income, the estimates are positive and statistically significant under both IPW-OLS (1.217) and IPW-2SLS (2.812), underscoring that segregation amplifies disparities at the extreme ends of the income spectrum.

Conversely, for the 90th percentile of Black income relative to the 10th percentile of White income, the results under both IPW-OLS (-0.834) and IPW-2SLS (-1.380) are negative but statistically insignificant, reflecting weaker evidence that segregation mitigates disparities between these groups. These findings suggest that segregation exacerbates economic inequalities between Black and White populations, particularly among the most disadvantaged.

It is important to note that the original 2SLS model finds the effect of RDI on the poverty rate for black people statistically significant. But, in the IPW-2SLS model, this result is not statistically significant. This is most likely due to an incorrect model (propensity score) specification as the other 2 assumptions hold, since we're using a valid IV, and when we ran our code we did not get any errors for extremely high or low propensity scores.

3.2 Re-analyze with Doubly Robust (DR) Estimator

We believe that we can use DR estimation here because segregation levels are not randomly assigned as historical and structural factors, such as city demographics and economic conditions, influence segregation, making confounding a concern. Additionally, DR combines reweighting (like IPW) to balance observed covariates with regression adjustment to directly model the outcome. This dual adjustment improves efficiency and robustness, particularly in the presence of model misspecification. Finally, if one of the models (outcome or propensity score) is slightly misspecified, DR estimators can still provide unbiased estimates, mitigating potential errors from model misspecification and improving causal inference reliability. We proceed to only replicate the 2SLS estimates using our DR estimand, as our IPW estimator was successful in replicating the paper's OLS estimates. Therefore, we assume our DR estimand, as it also uses propensity scores, would also be successful in replicating the paper's OLS estimates.

3.2.1 Assumptions

Like our IPW estimator, we are assuming that there is no unmeasured confounding and all confounders affecting both segregation and the outcome (e.g., city demographics, economic conditions) must be included in either the outcome or propensity score model to ensure unbiased estimates. We are also assuming positivity in that every city has a non-zero probability of being highly segregated or not segregated, given its covariates. This ensures well-defined propensity scores and the applicability of regression adjustments. Finally, we assumed that either the outcome model or the propensity score model must be correctly specified. The DR estimator remains consistent as long as one of these models accurately reflects the true relationship, reducing the risk of bias.

By combining the strengths of both reweighting and regression modeling, DR estimation provides a safeguard against the pitfalls of relying on a single model. This is particularly useful when confounding is complex, as in the case of historical segregation, where balancing covariates alone may not fully address bias, and direct outcome modeling adds further precision.

3.2.2 DR (2SLS) Results

Table 5: Doubly Robust 2SLS Estimates for Within-Race Inequality

	Gini		**Poverty**	
	Whites	*Blacks*	*Whites*	*Blacks*
dism1990	-0.545*	0.898	-0.327**	0.290
	(0.234)	(0.542)	(0.110)	(0.183)
Observations	121	121	121	121
R^2	0.323	0.000	0.256	0.010
Adjusted R^2	-0.333	-0.001	-0.267	0.000

Note: *p <0.1; **p <0.05; ***p <0.01

Table 6: Doubly Robust 2SLS Estimates for Between-Race Inequality

	Log Ratios			
	90:90	*10:10*	*90:10 (W:B)*	*90:10 (B:W)*
dism1990	-0.510	4.990*	3.325	-1.268
	(0.689)	(1.994)	(1.741)	(0.753)
Observations	121	121	121	121
R^2	0.075	0.449	0.126	0.070
Adjusted R^2	-0.084	-0.461	-0.136	-0.080

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5 presents the estimates for how segregation affects inequality (gini) and poverty within different races (Blacks and Whites). Segregation produces opposite effects on Whites and Blacks, reducing poverty and inequality for Whites (at a 10% significance level for inequality and a 5% level for poverty), while simultaneously increasing both for Blacks (although this effect on black communities isn't that statistically significant). These findings support the hypothesis that segregation reinforces systemic racial disparities and matches the findings of the paper. These results are similar to but not identical to the IPW estimates. Since they differ in statistical significance and a bit in magnitude, we could potentially attribute this variability in our models to the small sample size. It also suggests that our IPW estimates might be potentially over-optimistic, or have some misspecification. Additionally, since both estimates are similar enough in magnitude, it does suggest robustness in our estimates. Ultimately, the DR estimates were closer to the original paper's results than the IPW estimates, suggesting that we most likely had an incorrect propensity score specification but a close enough or correct outcome model specification.

Table 6 displays the estimates for how segregation affects inequality between different races across different income percentiles. Segregation significantly worsens economic disparities between low-income Whites and Blacks. The largest effects are observed for low-income groups, amplifying inequality and creating substantial economic disadvantages for Blacks relative to Whites, and these findings are statistically significant at the 10% level. These findings reinforce the findings from the paper. In this case, since DR estimates remain similar, but definitely not identical, in magnitude and significance to IPW, this suggests that our propensity scores might still not be correctly specified. The slight difference is likely due to the DR estimator's reliance on both models or a misspecification in the IPW model's propensity scores, which might introduce slightly more variability in the standard errors. However, since both results indicate significance, this isn't concerning. Similar to Table 5, the DR estimates were closer to the original paper's results than the IPW estimates, suggesting that we most likely had an incorrect propensity score specification but a close enough or correct outcome model specification.

4. Limitations and Conclusion

Our replication of *The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality* aimed to validate the findings of the original study while providing insight into its methodology and results. We successfully replicated most of the key outcomes and estimates, demonstrating that railroad-induced segregation (RDI) is a robust instrument for measuring the causal effects of segregation on urban poverty and inequality. Like the original paper, we found that segregation exacerbates poverty and inequality among African American populations while reducing both among white populations. The observed disparities in outcomes between the poorest blacks and whites were also consistent with the original findings, although the magnitude of our effects was marginally different in some cases.

Our analysis highlights the merits of the original paper's methodological rigor, particularly its use of a historical and plausibly exogenous instrument to address endogeneity concerns. This approach strengthens the causal interpretation of segregation's effects on urban economic outcomes. Additionally, our comparison of the 2SLS estimates with our doubly-robust estimate reaffirmed the validity of RDI as an instrumental variable, as well as the robustness of the original study's conclusions.

However, our replication also revealed some limitations inherent to the study design and our replication process. Minor discrepancies in results, likely stemming from differences in software (R vs. Stata) and the implementation of statistical functions, underscore the challenges of achieving exact replication in empirical work. Additionally, our IPW estimates of the paper’s 2SLS coefficients weren’t the most accurate, revealing a misspecification of the propensity score on our part. Furthermore, while the instrument successfully isolates the effects of segregation, the broader validity of these findings relies on historical and contextual assumptions that may not generalize to modern urban settings, particularly in terms of the historical controls that the paper uses- controls that might not hold up in modern urban settings.

Future research could refine the estimation methods by addressing potential heterogeneity in segregation's effects across cities with differing historical and economic contexts. Additionally, exploring complementary datasets or alternative instruments could help verify the robustness of these findings. Despite these limitations, our replication underscores the value of using innovative approaches like RDI to disentangle complex causal relationships in social science research- particularly on the role that historically racist policies like segregation play in economic outcomes across different races in contemporary settings.