Teen Birth, Redlining, and Upward Mobility: Evidence from Within and Across Austin

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May 2026†

1 Introduction

In 2025, Governor Greg Abbott declared that Texas was the "land of freedom and opportunity" (Office of the Texas Governor 2025). Was he right? And why? This paper proposes and investigates teen birth rates and Home Owners' Loan Corporation redlining scores as two potentially causal hypotheses for Austin, Texas' upward mobility. In particular, we form our hypotheses by using three methods to find variables that explain both variation in upward mobility between Austin and other regions and variation within Austin: a coefficient sensitivity test, a marginal R^2 analysis, and a Random Forest machine learning model. After identifying teen birth and redlining scores as candidate hypotheses, we test for key covariates to examine our hypotheses and identify potential causal mechanisms. Ultimately we find that the negative association between teen birth and upward mobility is reasonably robust to key covariates, lockbox data, and ZIP vs. census tract analysis. In particular, given that the relationship between teen birth and upward mobility differs by sex, we discuss a labor-market-driven causal mechanism based on gendered childcare expectations. Secondly, we find that many variables such as college share, teen birth, incarceration, and employment account for HOLC's negative association with upward mobility. Turning toward qualitative map data, we use the case study of Eastview Austin Community College to discuss college attainment as a potential mechanism behind redlining's historical influence. Because this analysis is purely descriptive, we outline two quasi-experimental methods to better verify our causal hypotheses using Roe vs. Wade and the formation of Eastview Austin Community College as exogenous shocks. Finally, we conclude with a discussion of limitations and policy implications.

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†I am so sorry for how long this paper seems. At the end of this paper, I've attached a screenshot of an email from Greg that says as long as the main text is within the 12-17 page limit, I can include graphics, tables, and robustness checks in the Appendix. I appreciate you taking the time to read this.

2 Data

We use Opportunity Insight's Opportunity Atlas and Social Capital Atlas (Chetty et al. 2018; Opportunity Insights n.d.). Because the Opportunity Atlas is census tract data while the Social Capital Atlas is ZIP code data, we group Opportunity Atlas data by ZIP code, weighted by census tract population. Because this lowers the sample size dramatically, when greater certainty is required, we use census tract-level data (flagged in tables and figures).

2.1 Sample and Variable Definitions

All upward mobility values are determined from the 1978-83 birth cohort while incarceration and teen birth data is measured in 2010. As such, when possible, control variables or causal variables under consideration are measured in 2010. See detailed breakdown of variable definitions either using the Opportunity Atlas or here (Chetty et al. 2018). For a more detailed understanding of the demographic differences in upward mobility, we use pooled measures of upward mobility across all groups; pooled measures for white, black, Asian, Hispanic, male, and female groups; and all possible permutations of racial / ethnic identity and gender (ex: Asian woman, Black male, etc.). Upward mobility by race is estimated using household income while upward mobility by gender is estimated using individual income. Native American upward mobility is omitted in this analysis due to sparse data.

Control Variables. Our control variables are racial share (2010), urban share (2010), and poverty share (2010).

Variables of Interest. Our variables under consideration include college share (2010), HOLC ratings (1930s), economic connectedness (late 2010s), single parent share (2010), total number of jobs in a 5 mile radius (2015), fraction of high-paying jobs (2015), average annual job growth (2004-2013), employment rate (2000), job density (2013), concentration of atmospheric fine matter (2010), incarceration rates (2010), teen birth rates (2010) and average 3rd grade standardized test scores (2013). Because we have demographic breakdowns of incarceration by gender and race / ethnicity and teen birth by gender, we match upward mobility's gender and race / ethnicity with the gender and race / ethnicity measures of incarceration and teen birth's. For example, the outcome pooled black upward mobility corresponds to pooled black incarceration and the teen birth rate for black women.

Lockbox Data. For robustness, we replicate portions of our analysis using lockbox data upward mobility and incarceration data from the 1984-89 birth cohort.

2.2 Summary Statistics

As shown in **Table 1**, Austin's pooled upward mobility is broadly reflective of national trends while Austin's female pooled mobility is slightly higher than both state and national averages. Austin's pooled male upward mobility is lower than state averages but similar to national averages. Standard deviations across the board are roughly similar. Some demographic differences in upward mobility in Austin are lower values for black men (∼1.5-2pp lower than national and state averages), higher values for white women (∼4pp higher than national average) in Austin, and higher values for Asians (∼4pp higher than national average).

3 Methods

To avoid confirmation bias and find robust causal hypotheses, we first narrow the list of potentially causal variables by observing variables that explain between variation between Austin and other regions and explain variation within Austin. From there, we test against key covariates to assess plausibility and determine specific causal mechanisms.

3.1 Between Austin Variation

To understand which variables explain Austin's "opportunity premium" or "discount" compared to other regions, we use the following base model for zip code z.

$$Y_z = \beta_0 + \beta_1 \text{texas}_z + \beta_2 \text{austin}_z + \gamma_1 W_z + \epsilon$$

Y_z represents upward mobility of a ZIP code. texas_z is a binary variable indicating whether a ZIP code is in Texas. austin_z is a numeric, "pseudo-binary" variable indicating whether a ZIP code is in Austin. Because some ZIP codes span census tracts that are both inside and outside of Austin, austin_z represents a weighted proportion of census tract populations within a ZIP code that are in Austin. Finally, W_z represents the list of control variables. To explore how different variables explain the difference (or lack thereof) in average upward mobility in Austin compared to other regions, we run the following model for each candidate variable. Note that no two candidate variables are added at the same time.

$$Y_z = \beta_0 + \beta_1 \text{texas}_z + \beta_2 \text{austin}_z + \gamma_1 W_z + \gamma_2 X_z + \epsilon$$

X_z represents the causal variable under consideration. The goal of this analysis is to observe the difference in $\hat{\beta}_1$ between the base model and the above. For example, if we find that the original base model had a high Austin premium (a statistically significant positive $\hat{\beta}_1$) but the addition of college share renders $\hat{\beta}_1$ statistically indistinguishable from zero, this provides small evidence that college share may explain Austin's greater-than-national-average upward mobility.

3.2 Within Austin Variation

To explore what explains variation within Austin, we use a Marginal ΔR^2 analysis and a Random Forest analysis.

3.2.1 Marginal ΔR^2 Analysis

Filtering the data to Austin only, for each candidate causal variable, X_z, we calculate the ΔR^2 by subtracting the R^2 of a marginal model that includes this additional predictor from the R^2 of a base model with only controls.

$$\Delta R^2 = R^2(\underbrace{Y_z = \beta_0 + \gamma_1 W_z + \gamma_2 X_z + \epsilon}_{\text{Marginal Model}}) - R^2(\underbrace{Y_z = \beta_0 + \gamma_1 W_z + \epsilon}_{\text{Base Model}})$$

3.2.2 Random Forest Machine Learning

Because the Marginal ΔR^2 analysis is only able to capture additional linear predictive ability, we use a Random Forest model to capture nonlinear predictive ability. We estimate the model for each identity group's upward mobility and order the variables based on the percentage increase in mean squared error when removing from the model. We use 10-fold cross validation to determine the number of variables randomly sampled at each split. Unfortunately because Austin lacks sufficient ZIP code sample size, we turn toward the census tract data, requiring us to drop Economic Connectedness as a variable of interest. Additionally, HOLC is removed because of a lack of valid data. Otherwise, the list of considered variables is identical to that in **Section 3.1** and **Section 3.2.1**.

3.3 Causal Hypothesis & Mechanisms

After conducting the above tests, we pick causal hypotheses that explain both between Austin and within Austin variation. To test these hypotheses and uncover a causal mechanism, we run the following regression and observe the changes in $\hat{\beta}_1$, the variable of interest's coefficient, for each and all covariates δ_z.

$$Y_z = \beta_0 + \beta_1 X_z + \gamma_1 W_z + \gamma_2 \delta_z + \epsilon$$

We replicate this process with lockbox data, merging atlas data by tract for missing lockbox values.

4 Results

4.1 Between Austin Variation

Table 2 shows whether Austin's upward mobility statistically significantly differs from national or state-level averages after adjusting for a base set of controls. While Austin's overall mobility is not statistically distinguishable from Texas', decomposing mobility by sex reveals that men in Austin face lower mobility than Texas broadly while women have greater mobility compared to Texas. However, the raw average value for upward mobility for men remains larger than that for women, but any "Texas premium" in upward mobility for men in Texas is offset by an "Austin discount" while the "Texas discount" in upward mobility for women in Texas is offset by an "Austin premium". Further decomposition by race is illuminating: the "Austin premium" for women is largely driven by white women while the "Austin discount" is driven by black, white, and especially Hispanic men. These demographic trends are robust when looking at either ZIP or tract-level data with the exception of tract-level analysis finding a minor ”Austin discount” for overall upward mobility. As such, what explains upward mobility in Austin may differ by racial, ethnic, and gender identity group.

Table 3 summarizes how the Austin coefficient changes as variables are added to the base model. The variables of interest are those that cause the sign of the Austin coefficient to change. For instance, overall mobility in Austin is statistically indistinguishable from zero but when holding college share, economic connectedness, or teen birth constant, Austin has statistically significantly lower upward mobility compared to Texas at the 5% level. On the other hand, other variables of interest such as employment, share of high paying jobs, and single parent share do not change the original coefficient on Austin at the 5% level. This process is visually illustrated in **Figures 3, 4, and 5.** Replicating this analysis for all groups identifies the following variables of interest:

	Pooled	Female	Male
Pooled	College Share Econ. Conn. Teen Birth Rate	College Share Econ. Conn. Employment Rate Teen Birth Rate	HOLC
Asian	None	College Share Econ. Conn.	None
Black	HOLC Incarceration Rate	None	HOLC
White	College Share Teen Birth Rate	College Share Econ. Conn. Teen Birth Rate	HOLC
Hispanic	HOLC	Incarceration Rate Teen Birth Rate	HOLC

There appears to be a gendered effect of HOLC evidenced by HOLC changing the Austin coefficient only for men but not women. On the other hand, college share, economic connectedness, and teen birth appear to explain the ”Austin premium” for women. Additionally, certain variables are only relevant for certain racial groups: college share only for white and Asian individuals and incarceration rate for black and Hispanic individuals. This makes causal identification more nuanced since we must ask not only if a variable is causal but also for whom it is causal.

4.2 Within Austin Variation

In this section, we examine if the same variables as in **Section 4.1** also explain the variation within Austin through a Marginal R^2 analysis and a Random Forest.

4.2.1 Marginal R^2 Analysis

Table 4 shows the change in R^2 after adding a variable of interest to the base model. **Figures 6, 7, and 8** visually represent the marginal changes in R^2 at the Austin, Texas, and United States level to give a relative scale of predictive importance. A summary of the top 4 marginally predictive variables is shown below:

	Pooled	Female	Male
Pooled	Teen Birth (0.0923) Single Parent (0.0779) Employment (0.0682) HOLC (0.0433)	Teen Birth (0.1666) HOLC (0.1390) College (0.0592) Single Parent (0.0292)	Single Parent (0.0835) Employment (0.0779) # of Jobs (0.0639) High Paying Jobs (0.0422)
Asian	Incarceration (0.2824) Teen Birth (0.0590) Econ. Conn. (0.0539) College (0.0508)	Test Scores (0.3247) College (0.2183) High Paying Jobs (0.1665) Econ. Conn. (0.1163)	PM Concentration (0.1075) Employment (0.0850) Econ. Conn. (0.0709) Job Density (0.0442)
Black	HOLC (0.2846) College (0.1068) Job Growth (0.0627) Employment (0.0590)	Teen Birth (0.0907) Incarceration (0.0487) Econ. Conn. (0.0406) College (0.0263)	Job Growth (0.1773) Test Scores (0.0886) PM Concentration (0.0761) High Paying Jobs (0.0725)
White	Employment (0.1111) High Paying Jobs (0.0845) Test Scores (0.0467) Single Parent (0.0383)	Job Growth (0.0748) College (0.0592) Teen Birth (0.0568) Employment (0.0476)	Employment (0.1055) High Paying Jobs (0.0726) Test Scores (0.0561) HOLC (0.0435)
Hispanic	HOLC (0.2632) Incarceration (0.2196) Job Density (0.0087) Test Scores (0.0053)	HOLC (0.1514) Econ. Conn. (0.0850) Job Density (0.0707) College (0.0566)	Incarceration (0.0838) Teen Birth (0.0520) PM Concentration (0.0456) College Share (0.0338)

Similar to **Section 3.1**, HOLC is a relevant variable in black and Hispanic upward mobility, and teen birth rate, college share, incarceration, economic connectedness continue to be relevant. HOLC appears especially compelling since R^2 jumps by around 26-28pp with its inclusion for pooled black and Hispanic upward mobility. Interestingly, unlike the analysis in **Section 3.1**, HOLC does not appear as predictive for men within Austin. In fact, HOLC increased R^2 by 0.1390 and 0.1514 for pooled and Hispanic women respectively while only 0.0435 for white men. Additionally, college appears slightly predictive for women's upward mobility even when decomposed by race (especially for Asian women) but not as predictive of men's upward mobility since college is only a top 4 predictor for Hispanic men. Finally, while no variables changed the Austin coefficient for Asian groups, the Marginal R^2 analysis indicates that certain variables such as incarceration, test scores, and college are highly predictive for within-Austin variation, implying that for Asians in Austin, what drives outcomes may differ between Austin and other cities and within Austin. Regardless, overlap in variables between the results above and those in **Section 3.1** is encouraging because it indicates that one variable can explain upward mobility both within and between Austin and other regions.

4.2.2 Random Forest Machine Learning

The top four predictors (omitting controls) and the increase in mean squared error when removing the predictor is summarized below.

Teen birth, incarceration, and college remain highly predictive but the Random Forest model appears to weigh economic variables such as the number of jobs, fraction of high paying jobs, and employment highly as well. Note

	Pooled	Female	Male
Pooled	Teen Birth (26.554) Incarceration (16.179) # of Jobs (15.110) College (13.213)	Teen Birth (18.372) College (16.080) # of Jobs (6.638) Test Scores (6.009)	# of Jobs (11.219) Incarceration (10.831) Teen Birth (10.683) High-Paying Jobs (7.939)
Asian	PM Concentration (2.398) Test Scores (1.786) College (1.740) Single Parent (1.252)	Test Scores (3.165) College (3.137) # of Jobs (1.571) Teen Birth (1.083)	Incarceration (4.357) Job Growth (2.558) PM Concentration (2.133) # of Jobs (2.050)
Black	Employment (10.217) Test Scores (8.902) # of Jobs (7.602) Single Parent (4.812)	College (6.581) Employment (5.780) PM Concentration (3.378) Teen Birth (3.185)	Employment (7.807) Test Scores (7.099) PM Concentration (4.090) College (3.482)
White	College (15.053) PM Concentration (12.436) Employment (9.959) Incarceration (7.287)	College (13.054) Teen Birth (11.334) PM Concentration (7.897) # of Jobs (7.027)	PM Concentration (10.718) Incarceration (7.862) College (7.195) Employment (6.886)
Hispanic	# of Jobs (9.056) Teen Birth (8.401) PM Concentration (5.445) College (4.571)	# of Jobs (7.751) College (6.629) Employment (5.436) Single Parent (4.337)	Teen Birth (10.256) # of Jobs (10.136) College (7.418) Incarceration (5.742)

that HOLC and Economic Connectedness were dropped from the Random Forest model due to lack of sample size.

4.3 Causal Hypothesis & Mechanisms

We believe the ability of teen birth and HOLC to explain both variation between Austin and other cities and within Austin variation robustly throughout the analysis above provides evidence of a potential causal story. However, we imagine that these variables have multiple causal mechanisms that impact upward mobility. For instance, underinvestment due to HOLC scores may influence education, teen births, employment, or incarceration which all may causally influence upward mobility. Additionally, teen birth can impact both educational and labor market outcomes through preventing college attainment or "high-skill" jobs. We summarize our attempt to test our hypotheses and isolate the specific causal mechanisms behind the two variables below:

Teen Birth. **Table 6** demonstrates how robustly stable and negative the teen birth rate coefficient remains even when holding college share, economic connectedness, incarceration, single-parent share, particulate matter, employment, high paying job share, and job growth constant across upward mobility for all genders. In particular, **Figure 9** shows the strength of the negative linear relationship between teen birth and upward mobility across demographics. Interestingly, the teen birth coefficient for women is nearly twice as negative compared to that of men. However, when decomposing this relationship into racial subgroups in **Table 7** the relationship is only statistically significantly negative for white individuals. Note that Asians are dropped from the racial decomposition due to lack of Asian teen birth data in Austin. When we conduct a similar analysis using tract-level data in **Table 8**, the teen birth coefficient remains stable and negative for pooled upward mobility and female upward mobility even when adding covariates but not statistically distinguishable from zero for men even with no covariates. Racial decomposition using tract-level data in **Table 9** shows statistically significant negative relationships for black individuals even with covariates but not for white or Hispanic individuals.

We replicate this analysis using lockbox data in **Table 10** and find similar stability in the pooled sample but not for Hispanic and white individuals. In fact, for Black Americans, the coefficient on teen birth actually flips statistically significantly positive. However, when using tract-level lockbox data in **Table 11**, teen birth continues to be negatively correlated with upward mobility after covariates in the pooled and Hispanic sample but not for the black sample. Strangely, white individuals see a statistically significant positive relationship with teen birth and upward mobility. These minor inconsistencies with the lockbox data and the horse race nature of the regressions lead us to believe these results should be interpreted carefully.

However, while the racial decomposition is uncertain, we believe the above analysis gives a strong case that teen birth may matter causally and not all of teen birth's effect on upward mobility is through mechanisms such as economic connectedness or college. Instead, we hypothesize a causal pathway inspired by Claudia Goldin's work on women's careers (Goldin 2021). When a teen birth occurs, pregnancy and raising a child often requires immediate financial capital for medical fees, food, and care. As such, these teens are likely forced to enter the job market, which not only trades off against college attainment, but also forces them to take low-skill labor that has limited upside for future wage growth. In particular, we imagine this is far worse for women compared to men because as Claudia Goldin notes, women are forced to take jobs that afford them the flexibility of childcare (which often pay less than "greedy jobs") or outright exit the labor market entirely (Goldin 2021). This may potentially explain why the coefficient of teen birth is much more negative for female upward mobility than male upward mobility at both the ZIP and tract-level because, due to dominant gender and childcare norms, men can stay in the labor force, albeit by accepting low skill labor.

Redlining.[1] We also investigate how the HOLC coefficient for pooled upward mobility changes when adding additional variables in **Table 12** and find that college share, teen birth, fine particulate matter, and employment make the coefficient statistically indistinguishable from zero. Using tract-level data in **Table 13**, we find that college share, teen birth, and single parent share reduce all score factors of HOLC scores so that they are statistically indistinguishable from zero. Using the ZIP code level lockbox data in **Table 14**, college share, fine particulate matter, single parent share, and employment reduce the HOLC coefficient to be statistically indistinguishable from zero. In the tract-level lockbox data, college share, teen birth, fine particulate matter, single parent share, and employment caused all factors of HOLC's coefficient to be statistically indistinguishable from zero (**Table 15**). Census-level analysis may be more appropriate since there are only 10 ZIP codes with valid HOLC data.

While there is no definitive quantitative answer to the specific mechanism, redlining clearly matters for Austin's upward mobility. In particular, **Figure 1** shows the extent of redlining in downtown Austin through the stark divide

[1] Due to limited overlapping controls, we limited controls to poverty share (2010) and share of black individuals (2010).

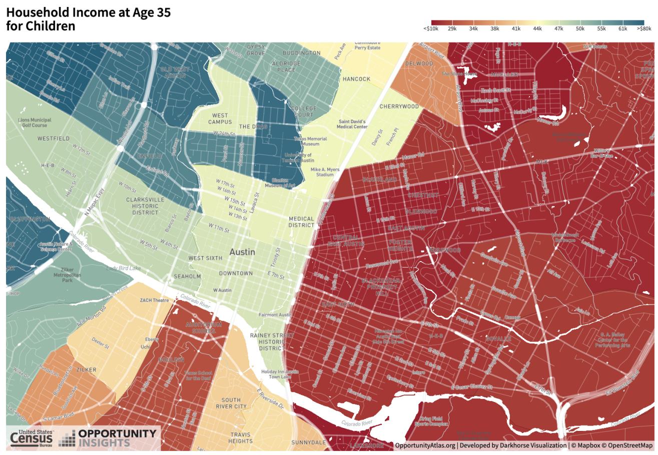

Figure 1: Downtown vs. East Austin (Pooled, Pooled)

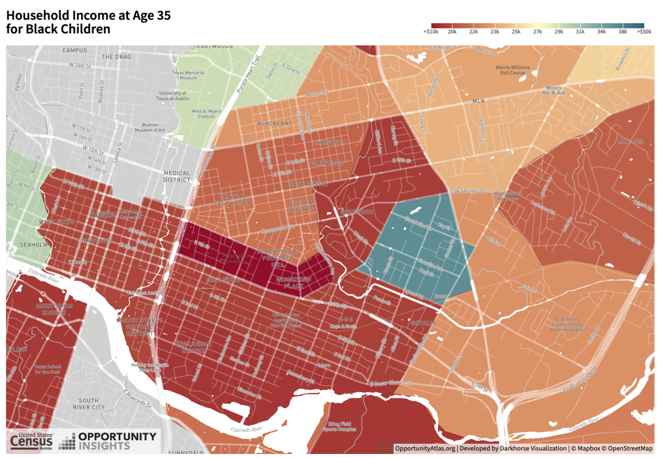

Figure 2: Downtown vs. East Austin (Pooled, Black)

in outcomes along the I-35 highway. This stark divide is explained by Austin's segregated past: in 1928, using zoning laws and eminent domain, Austin's city plan enforced residential segregation with an explicit racist agenda to force all black families to move to East Austin. In the 1930s, the Home Owners' Loan Corporation (HOLC) labeled these areas as hazardous, causing local investment to dry up (University of Richmond, Digital Scholarship Lab 2023; Reconnect Austin n.d.). In fact, even until 1977, only 0.2% of real estate investment from banks and loan associations in Austin went toward East Austin properties (University of Richmond, Digital Scholarship Lab 2023).

However, there is an interesting exception to the East Austin pattern. **Figure 2** shows a small patch of high upward mobility in an otherwise red East Austin. Our initial hypothesis was that because this patch directly corresponds to Austin Community College's Eastview Campus and because college share robustly reduces the HOLC coefficient, greater college attainment may explain this outlier. However, fascinatingly, this patch does not exist for Hispanic, Asian, or white individuals - only black citizens. This is surprising because if college or educational attainment truly explains this tract's upward mobility, why does it only influence black upward mobility? One clue is that this campus was created in 1999 (meaning it aligns with the cohort in question) and not only focused on workforce training but also had a particular emphasis on diversity and African American cultural belonging. As such, there may be a qualitative and quantitative case for college share as the specific mechanism through how HOLC underinvestment influenced upward mobility. Fully understanding this tract's success may be key in understanding how the historical legacy of redlining can be overcome.

5 Limitations

We note the following limitations:

1. None of the analyses conducted here strongly establish causality due to major concerns about omitted variable bias and reverse causality. In particular, the R^2 analysis may be misleading if a marginal predictor is highly correlated with other predictors causing a high increase in R^2 even if that marginal predictor is not very related to the outcome. Additionally, machine learning models are only about prediction, not causation.

2. Because we run multiple regressions in **Section 3.1**, there is a concern about multiple hypothesis testing, especially since we did not do a Bonferroni correction for simplicity. As such, there is a risk that by chance a variable makes the Austin coefficient statistically significant (or vice versa) due to the sheer number of statistical tests.

3. For some demographic groups, particularly Asian groups, the sample size falls dramatically, making results unreliable, especially for the random forest. In particular, when doing HOLC analysis, we drop the Asian share in our controls due to the lack of overlapping data. While using tract-analysis may address this concern, we are unable to use both economic connectedness and tract-level analysis.

4. Holding covariates constant and observing coefficient changes does not uncover causal mechanisms by itself and only provides suggestive evidence for them. In fact, controlling for too many covariates can block causal pathways.

5. Due to only having cross-sectional data, we are unable to observe relationships over time. While we may expect variables like incarceration or teen birth to be relatively stable over time, ideally we could regress these values over the 1980s to capture changes in childhood conditions.

6 Quasi-Experimental Proposals

One quasi-experimental design is presented for each causal hypothesis: teen birth and HOLC redlining scores.

6.1 Teen Birth - Difference-in-Differences IV Study

Using Roe vs. Wade, decided on January 22, 1973, as an exogenous shock to teen birth rates in Austin, a difference-in-differences design can exploit how some regions in the United States had already legalized abortion and thus, Roe vs. Wade likely had little impact on abortion access and teen births in those cities. On the other hand, abortion was completely illegal pre-Roe, and as such, a control and treatment group emerge.

Data. Teen birth and age 35 upward mobility, labor force participation, and wage data for women in Austin and a control city for birth cohorts 1949-1978 (the 1954 birth cohort is 19 during Roe and we want 5 years before to see parallel trends. Including birth cohorts through 1978 creates a 5 year period post Roe).

Methodology. The first stage regression observes if the change in average teen birth rates between pre-1973 and post-1973 in Austin is statistically different from that of a control city using the following regression for woman i.

$$\text{Teen Birth}_{ic} = \alpha_0 + \gamma_c + \alpha_1 \text{Roe Exposure}_c + \alpha_2 \text{Austin}_i + \alpha_3(\text{Roe Exposure}_c \times \text{Austin}_i) + \epsilon_{ic} \tag{1}$$

Austin_i represents a binary indicator of whether woman i grew up in Austin. γ_c represents cohort fixed effects. The Roe Exposure_c variable is the post-period variable and is calculated as $\frac{\text{\# of teen years (ages 15–19) after 1973}}{5}$ within the bounds of [0, 1] because teen birth does not have a sharp definition and abortion access likely has exposure-related effects based on how old one is. Overall, the α_3 coefficient represents the first stage estimate. Using the same structural equation as above, the second stage observes whether Roe changed upward mobility, labor force participation, or wages in Austin relative to the same control city.

$$\text{Y}_{ic} = \pi_0 + \gamma_c + \pi_1 \text{Roe Exposure}_c + \pi_2 \text{Austin}_i + \pi_3(\text{Roe Exposure}_c \times \text{Austin}_i) + \epsilon_{ic} \tag{2}$$

π_3 represents the reduced form coefficient of interest. The overall effect of teen birth on the outcome variable is found by $\frac{\hat{\pi}_3}{\hat{\alpha}_3}$. Observing the effects on labor force participation and wage data may provide suggestive evidence of our labor market driven causal mechanism of teen birth.

Identifying Assumptions. Because this quasi-experimental methodology is a fusion of instrumental variables with a difference-in-differences, it must meet the following identifying assumptions:

- Relevance: Roe Exposure must have a strong effect on teen birth, otherwise the 2SLS estimator breaks down due to high standard errors and non-normal sampling in the estimates. We report the F-statistic to verify.

- Exclusion: Roe Exposure can only influence upward mobility through teen births, and Roe Exposure is not correlated with other determinants of upward mobility. This a large assumption. Firstly, it's possible that Roe vs. Wade generally changed adult pregnancy rates, education uptake, and labor force participation which directly influence upward mobility. Secondly, cities in conservative states may differ meaningfully from liberal states, thereby making other determinants of upward mobility like educational attainment or gender norms potentially correlated with Roe Exposure. Balance tables can help address these concerns.

- Parallel Trends: The control group is an accurate reflection of Austin's counterfactual teen birth and upward mobility growth absent the Roe vs. Wade decision. If a control group is difficult to find, we may use the synthetic control methodology outlined in class. Balance tables can also help address this concern.

- The 2SLS estimator is only a local average treatment effect, the effect of teen birth on women whose fertility decisions are affected by Roe vs. Wade. We suspect that this LATE is broadly representative, although looking at abortion migration data and abortion rate data may help determine how many individuals are "always-takers" or "never-takers."

6.2 HOLC Redlining - Exposure Based Difference-in-Differences Study

Because historical data are sparse and isolating random variation in 1930s racist redlining is difficult (everything becomes endogenous or reverse-causal), we change the scope of the question to ask what causally increases upward mobility within redlined neighborhoods. In particular, we are interested in investigating the cause of high black upward mobility in tract 48453000801 in **Figure 2**. We hypothesized earlier that the creation of the Eastview Austin Community College in 1999 may have led to greater upward mobility. To test this, we use a difference-in-differences design that treats the creation of the Eastview Austin Community College as exogenous.

Data. Birth year, household location, and upward mobility data for birth cohorts 1974 to 1984 (the birth cohort 1974 is 25 years old when Eastview ACC was created, and birth cohort 1984 is 15 years old when Eastview ACC was created). Eastview ACC acceptance data can help isolate the causal mechanism of college attendance.

Methodology. We implement a cohort-by-distance difference-in-differences design, where distance to Eastview ACC captures continuous treatment intensity and variation across birth cohorts captures differential exposure to the college at key ages. This mimics the design of an event study but uses birth cohorts instead of continuous years due to the lack of time series data. Mathematically, we run the below regression for individual i in birth cohort k who grew up in tract c to the East of I-35.

$$Y_{ick} = \alpha + \sum_{k \neq 1974} \beta_k (\text{Distance}_{ic} \times 1[\text{Cohort} = k]) + \gamma_c + \delta_k + \epsilon_{ick}$$

Y_{ick} represents upward mobility or college share. γ_c represents census tract fixed effects. δ_k represents birth cohort fixed effects. Distance_{ic} represents distance in miles from Eastview Austin Community College to one's home as an exposure treatment effect. $1[\text{Cohort} = k]$ is an indicator variable if individual i's cohort matches k. We chose 1974 as the baseline cohort since these individuals will be 25 when the Community College opens and likely deep in the labor market. The coefficient of interest is β_k which for each cohort, measures the gap between the difference between "close" and "far" areas and the baseline 1974 difference. We expect that, as birth cohorts reach 1986-1984, Eastview ACC's creation will align with high-school graduating years, and these individuals will better be able to take advantage of ACC's benefits, generating a negative β_k (closer proximity means less distance). Observing the significance of β_k for college share can suggest evidence of college attendance as a potential causal mechanism of Eastview's causal impact on East Austin.

Identifying Assumptions: see below.

- Parallel trends. In the absence of Eastview's development, the relationship between distance to the ACC location and outcomes are the same across birth cohorts. A potential violations is that areas near Eastview were already improving faster before 1999. We can test for this by examining whether coefficients for pre-exposure cohorts are statistically distinguishable from zero.

- Eastview ACC location is quasi-random. If Eastview's construction location was due to pre-existing conditions being worse or better than surrounding areas, there is potential selection bias in the Distance_{ic} term.

- There are no additional East Austin shocks that affect younger birth cohorts near Eastview differently than birth cohorts farther from Eastview In other words, no other treatment effect near 1999 except Eastview's development. This assumption may be suspect because many gentrification projects spawned near Eastview within this time period.

- No large self-selection / migration. After the construction is announced, families may move closer to ACC, creating endogeneity in upward mobility and the Distance_{ic} term. Observing migration panel data between census tracts will be helpful.

- Correct functional form. The effect of distance on college uptake or upward mobility may not be linear.

7 Implications

Overall, our results provide suggestive evidence that teen pregnancy and HOLC redlining scores are relevant factors in explaining Austin's upward mobility. Firstly, we find that teen pregnancy and HOLC redlining scores explain both variation in upward mobility between Austin and other regions and variation within Austin. Teen pregnancy's negative relationship with upward mobility is surprisingly robust across multiple measures of upward mobility, across ZIP-level vs. census-tract-level data, even when adding many demographic and economic covariates and controls, and even when using the lockbox data. We hypothesize that labor market outcomes unmeasured in this paper for teen mothers and fathers may explain the coefficient's persistent strength. In particular, teen families may be forced to enter the low-skilled labor market, stunting future upward mobility, particularity along gendered lines due to dominant norms surrounding childcare. Secondly, while, qualitatively and quantitatively, HOLC redlining scores appear to reduce upward mobility through underinvestment, adjusting for certain variables such as college share, teen birth, etc. dramatically weaken the coefficient. Case study evidence from Eastview Austin Community College may provide suggestive evidence that college share may be the particular causal mechanism through which redlining's influence can be overcome. This has powerful implications for a policymaker: it may imply (but does not prove) that the historical forces of redlining are surmountable through modern-day educational and cultural reinvestment in these communities. Identifying the specific causal mechanism is beyond the scope of this paper but we conclude with two ways to test our two causal hypotheses and mechanisms using a difference-in-differences design. Regardless, both hypotheses point toward early-teen focused interventions warranting greater study and attention for upward mobility.

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Table 1: Upward Mobility Summary Statistics by Race/Ethnicity x Gender by Region

	(1) Pooled			**(2) Black**			**(3) White**			**(4) Hispanic**			**(5) Asian**		
Statistic	US	TX	AUS	US	TX	AUS	US	TX	AUS	US	TX	AUS	US	TX	AUS
Panel A: Pooled															
Mean	44.18	44.38	44.45	34.07	34.88	34.14	46.84	48.37	48.59	43.23	44.95	43.19	57.46	59.81	61.11
SD	6.63	4.76	5.99	5.62	5.09	4.78	6.15	5.32	6.08	7.52	5.27	8.79	10.22	9.43	10.65
Q1	39.77	41.38	40.68	30.66	31.92	31.42	42.46	45.02	45.34	39.04	41.59	39.60	51.23	54.54	56.21
Median	43.67	44.21	44.43	33.25	34.42	32.95	46.09	48.04	48.62	43.03	44.47	42.53	57.69	60.00	59.51
Q3	48.26	47.11	47.81	36.59	37.23	36.24	50.62	51.45	52.76	47.18	47.77	46.81	63.53	65.28	67.21
N	30996	1931	75	11236	1140	55	30667	1888	75	11850	1787	74	5037	389	30
Panel B: Female															
Mean	40.55	40.00	43.04	41.37	41.84	42.86	40.86	40.83	44.46	42.06	40.51	43.02	56.43	57.95	54.65
SD	5.70	4.25	4.22	5.69	5.21	5.80	6.34	5.46	5.13	7.04	5.25	5.11	9.99	8.10	10.92
Q1	36.55	37.35	39.50	38.05	38.81	39.55	36.42	37.25	41.12	37.75	37.44	39.15	50.74	52.82	48.99
Median	39.76	39.51	41.96	40.80	41.40	41.81	40.09	40.36	43.95	41.77	40.38	42.61	56.82	57.98	52.81
Q3	44.04	42.13	46.34	44.16	44.64	45.55	44.68	43.99	48.25	46.01	43.43	45.54	62.08	62.64	59.28
N	30880	1925	74	8905	931	40	30299	1837	74	7429	1583	73	2643	209	13
Panel C: Male															
Mean	48.13	50.22	48.36	40.15	41.33	38.43	50.25	52.95	50.84	49.53	52.27	48.14	58.57	58.94	58.49
SD	6.20	5.41	5.26	6.11	6.01	5.05	6.31	5.98	6.34	7.27	6.56	5.43	10.08	9.25	11.82
Q1	43.96	46.63	45.09	36.43	37.69	36.04	45.94	48.94	46.84	45.43	47.98	44.56	53.17	53.23	50.94
Median	47.78	49.69	48.16	39.75	41.21	37.84	49.82	52.57	50.36	49.29	51.69	47.23	58.38	60.08	57.29
Q3	52.03	53.38	52.00	43.52	44.65	41.39	54.11	56.44	53.96	53.27	56.03	51.54	64.06	64.51	68.31
N	30899	1929	75	8875	909	37	30338	1852	75	7241	1589	73	2794	214	15

Table 2: Upward Mobility by Race/Ethnicity

	ZIP-Level					Tract-level				
	(1) Pooled	(2) Asian	(3) Black	(4) White	(5) Hisp	(1) Pooled	(2) Asian	(3) Black	(4) White	(5) Hisp
Panel A: Pooled										
(Intercept)	49.365***	54.191***	35.972***	50.675***	44.822***	46.535***	54.086***	35.214***	48.637***	44.292***
	(0.079)	(0.926)	(0.130)	(0.084)	(0.166)	(0.058)	(1.627)	(0.107)	(0.064)	(0.178)
Texas	1.519***	3.815***	0.980***	2.128***	2.203***	2.036***	4.589***	0.926***	2.639***	2.263***
	(0.096)	(0.502)	(0.165)	(0.122)	(0.138)	(0.068)	(0.317)	(0.119)	(0.095)	(0.104)
Austin	-0.711	-0.249	-1.498*	-0.032	-3.122**	-1.091**	-0.629	-0.997*	-0.444	-2.415***
	(0.736)	(1.681)	(0.654)	(0.753)	(1.116)	(0.363)	(1.647)	(0.478)	(0.427)	(0.510)
N	32554	5426	12329	32244	13617	70961	15438	33506	67406	37477
Panel B: Male										
(Intercept)	52.587***	56.846***	42.811***	53.678***	51.666***	50.075***	56.404***	42.971***	51.724***	50.905***
	(0.078)	(1.918)	(0.171)	(0.086)	(0.241)	(0.062)	(2.747)	(0.164)	(0.072)	(0.280)
Texas	2.484***	1.480*	1.506***	2.768***	2.716***	2.516***	2.713***	1.622***	2.876***	2.554***
	(0.120)	(0.639)	(0.216)	(0.146)	(0.189)	(0.083)	(0.471)	(0.164)	(0.125)	(0.133)
Austin	-2.397***	-1.942	-2.616**	-2.412***	-4.981***	-2.270***	-4.352	-1.640*	-2.119***	-4.125***
	(0.718)	(2.912)	(0.847)	(0.715)	(0.692)	(0.376)	(3.223)	(0.678)	(0.492)	(0.518)
N	32498	3008	9742	31916	8818	70718	8087	24506	65043	25298
Panel C: Female										
(Intercept)	42.539***	49.778***	41.705***	43.140***	40.431***	40.501***	47.196***	40.708***	41.407***	39.398***
	(0.071)	(1.661)	(0.143)	(0.085)	(0.199)	(0.056)	(2.557)	(0.127)	(0.067)	(0.232)
Texas	-0.469***	2.622***	0.321	-0.039	-0.720***	0.092	2.919***	0.163	0.433***	-0.334**
	(0.099)	(0.590)	(0.184)	(0.143)	(0.150)	(0.076)	(0.445)	(0.143)	(0.114)	(0.112)
Austin	1.508**	-4.825	0.141	2.350***	1.086	1.068**	-2.044	0.131	1.490**	0.666
	(0.472)	(2.942)	(0.909)	(0.643)	(0.587)	(0.335)	(2.484)	(0.627)	(0.468)	(0.445)
N	32472	2852	9795	31869	8999	70675	7732	24784	64746	25775
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Austin Coefficient Sensitivity by Marginal Variable (ZIP-Level)

	Pooled					Female					Male				
Variable	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic
Base Model	-0.711	-0.249	-1.498*	-0.032	-3.122**	1.508**	-4.825	0.141	2.350***	1.086†	-2.397***	-1.942	-2.616**	-2.412***	-4.981***
	(0.736)	(1.681)	(0.654)	(0.753)	(1.116)	(0.472)	(2.942)	(0.909)	(0.643)	(0.587)	(0.718)	(2.912)	(0.847)	(0.715)	(0.692)
College Share (2010)	-1.815**	-1.976	-2.184**	-1.792**	-4.214***	-0.294	-5.958*	-0.742	0.137	-0.301	-3.123***	-3.143	-3.005***	-3.616***	-5.619***
	(0.658)	(1.687)	(0.683)	(0.673)	(1.079)	(0.401)	(3.032)	(0.954)	(0.611)	(0.517)	(0.668)	(2.837)	(0.850)	(0.696)	(0.663)
HOLC Grade	4.169	10.241†	-0.926	5.038†	2.034	3.463*	—	0.279	5.375***	2.102	2.972	—	-0.656	0.301	-2.578
	(3.151)	(5.466)	(1.422)	(2.848)	(1.967)	(1.479)		(0.746)	(1.523)	(1.642)	(2.869)		(1.673)	(1.190)	(2.112)
Economic Connectedness	-1.889**	-0.932	-2.036**	-1.179†	-3.550**	0.272	-5.652*	-0.631	1.118†	0.234	-3.105***	-2.524	-3.080***	-3.248***	-5.183***
	(0.610)	(1.651)	(0.692)	(0.684)	(1.155)	(0.462)	(2.884)	(0.932)	(0.646)	(0.557)	(0.590)	(2.873)	(0.862)	(0.698)	(0.691)
Single Parent Share	-0.857	-0.027	-1.504*	-0.177	-3.089**	1.505**	-4.620	0.169	2.345***	1.123†	-2.515***	-1.642	-2.502**	-2.528***	-4.886***
	(0.615)	(1.637)	(0.648)	(0.681)	(1.112)	(0.464)	(2.997)	(0.907)	(0.640)	(0.583)	(0.619)	(2.919)	(0.836)	(0.683)	(0.698)
# of Primary Jobs (2015)	-0.753	-0.252	-1.505*	-0.157	-3.156**	1.412**	-4.826	0.122	2.196***	0.998†	-2.435***	-1.944	-2.616**	-2.519***	-5.022***
	(0.731)	(1.681)	(0.655)	(0.750)	(1.116)	(0.459)	(2.937)	(0.913)	(0.622)	(0.587)	(0.712)	(2.906)	(0.847)	(0.717)	(0.694)
High-Pay Jobs Share (2015)	-1.119	-0.759	-1.679*	-0.493	-3.419**	1.145*	-5.712†	-0.188	1.963**	0.728	-2.843***	-2.736	-2.769**	-2.913***	-5.444***
	(0.727)	(1.700)	(0.655)	(0.763)	(1.116)	(0.459)	(2.991)	(0.912)	(0.635)	(0.578)	(0.712)	(2.900)	(0.856)	(0.741)	(0.702)
Job Growth (2004–13)	-0.675	-0.220	-1.473*	0.002	-3.167**	1.591***	-4.700	0.174	2.434***	1.094†	-2.367**	-1.810	-2.596**	-2.378***	-4.981***
	(0.740)	(1.685)	(0.651)	(0.759)	(1.114)	(0.474)	(2.938)	(0.909)	(0.643)	(0.587)	(0.720)	(2.919)	(0.842)	(0.719)	(0.692)
Employment Rate	-1.412†	-0.872	-1.630*	-0.714	-3.169**	0.622	-4.979†	-0.327	1.394*	0.970	-2.839***	-2.400	-2.460**	-2.770***	-4.992***
	(0.743)	(1.706)	(0.651)	(0.773)	(1.118)	(0.478)	(2.947)	(0.901)	(0.671)	(0.588)	(0.723)	(2.927)	(0.854)	(0.732)	(0.694)
Job Density (2013)	-0.718	-0.263	-1.497*	-0.026	-3.122**	1.506**	-4.821	0.138	2.355***	1.081†	-2.403***	-1.940	-2.624**	-2.405***	-4.989***
	(0.731)	(1.680)	(0.652)	(0.753)	(1.117)	(0.473)	(2.943)	(0.908)	(0.641)	(0.589)	(0.715)	(2.913)	(0.846)	(0.715)	(0.690)
Fine Particulate Matter	-0.647	-0.186	-1.423*	0.059	-3.141**	1.511**	-4.794	0.169	2.405***	1.056†	-2.304***	-1.934	-2.574**	-2.241**	-4.998***
	(0.701)	(1.674)	(0.653)	(0.734)	(1.111)	(0.475)	(2.943)	(0.908)	(0.656)	(0.586)	(0.694)	(2.916)	(0.846)	(0.704)	(0.689)
3rd Grade Math Scores	-1.179†	-0.448	-1.734**	-0.394	-3.251**	1.136*	-4.961†	-0.073	1.925**	0.921	-2.744***	-2.227	-2.667**	-2.663***	-5.118***
	(0.705)	(1.681)	(0.649)	(0.753)	(1.116)	(0.455)	(2.921)	(0.907)	(0.640)	(0.584)	(0.699)	(2.919)	(0.846)	(0.724)	(0.693)
Incarceration Rate	-0.426	1.176	-1.187†	-0.030	-3.056**	1.392**	-4.654	0.495	2.306***	1.174*	-2.119**	0.450	-2.892***	-2.154**	-4.882***
	(0.715)	(1.779)	(0.679)	(0.750)	(1.081)	(0.468)	(2.935)	(0.742)	(0.646)	(0.594)	(0.653)	(2.713)	(0.800)	(0.693)	(0.659)
Teen Birth Rate	-2.112***	-0.076	-1.610**	-1.521*	-2.955**	0.662†	-4.991†	-0.073	1.114†	1.300*	-3.531***	-1.478	-3.016***	-3.407***	-4.878***
	(0.373)	(1.764)	(0.526)	(0.602)	(1.115)	(0.354)	(2.972)	(0.846)	(0.619)	(0.553)	(0.438)	(2.993)	(0.790)	(0.687)	(0.672)

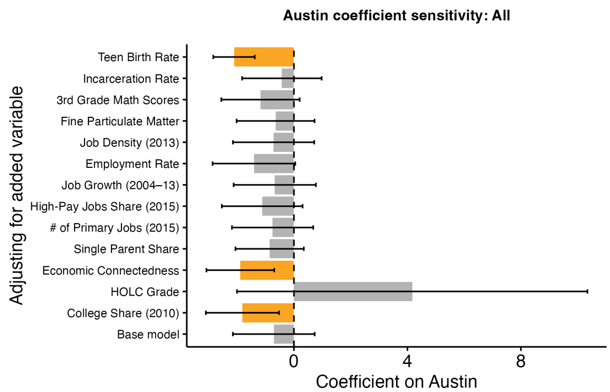
Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

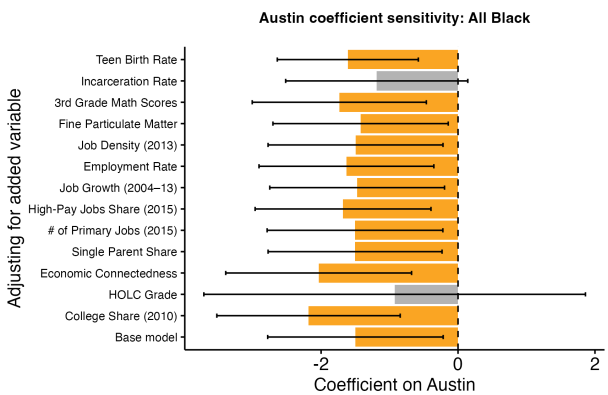
Note: This table does not show the coefficient of the given variable, but the coefficient on the $austin_i$ dummy in the second regression of **Section 3.1**.

HOLC grade is dropped for Asian outcomes due to lack of Asian upward mobility data where HOLC grades are valid.

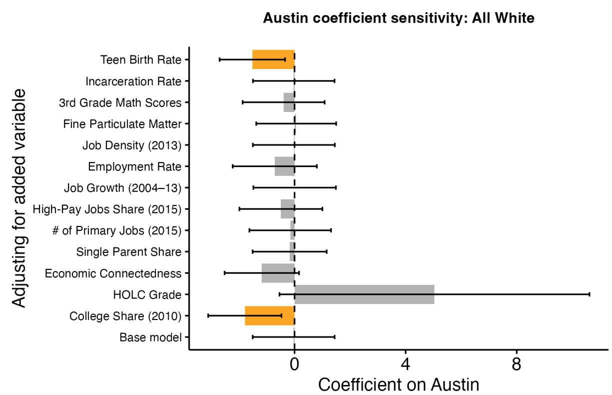
Figure 3: Austin Coefficient Sensitivity by Pooled Racial/Ethnic Group



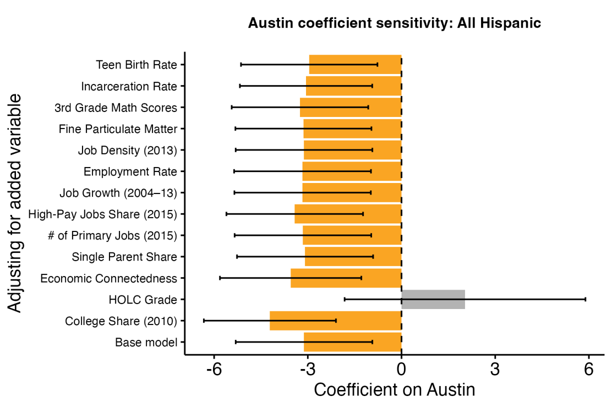
(a) Pooled



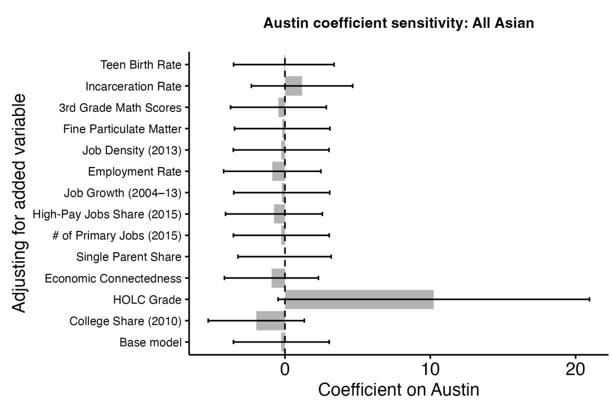
(b) Black



(c) White

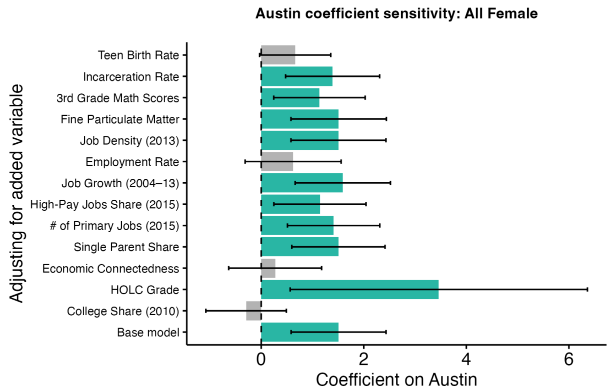


(d) Hispanic

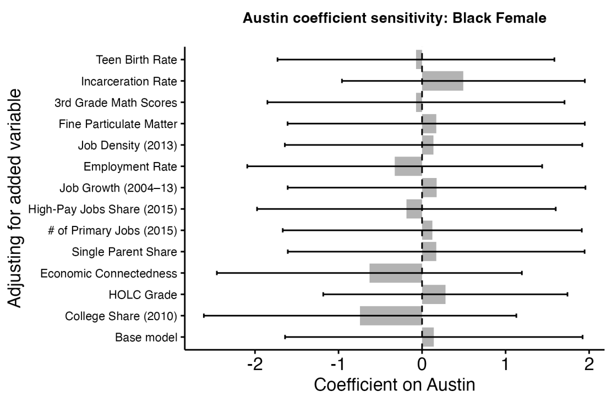


(e) Asian

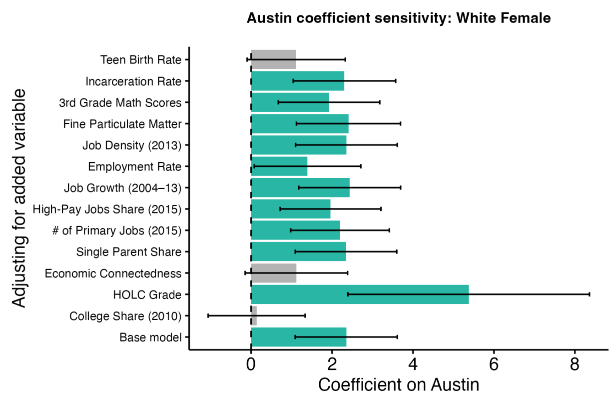
Figure 4: Austin Coefficient Sensitivity by Female Racial/Ethnic Group



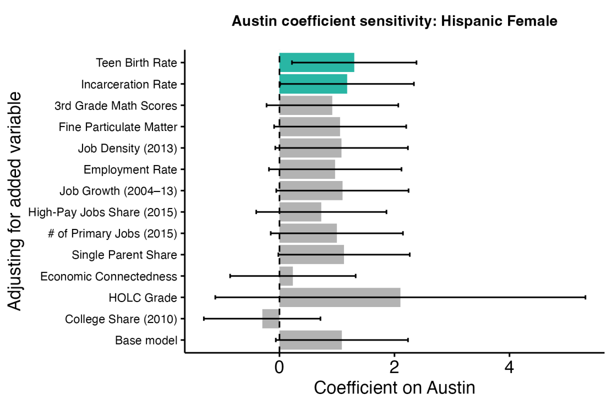
(a) Pooled Female



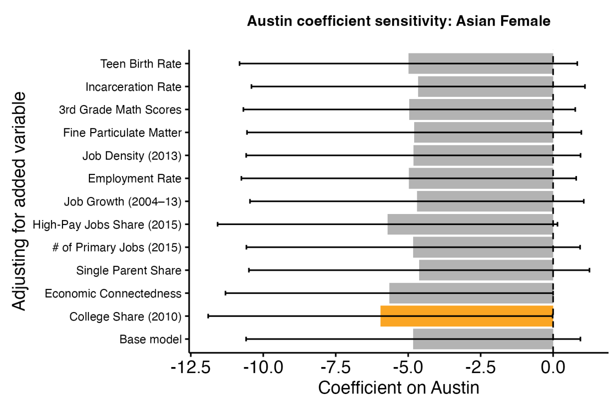
(b) Black Female



(c) White Female

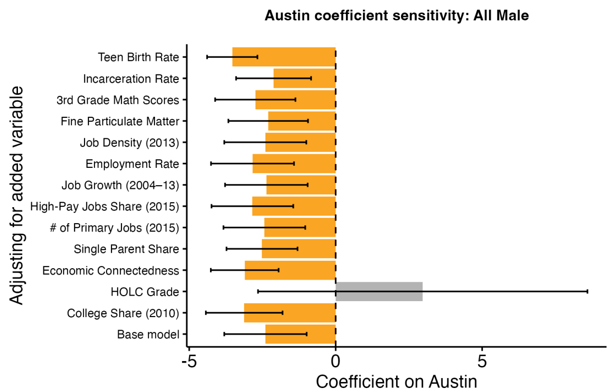


(d) Hispanic Female

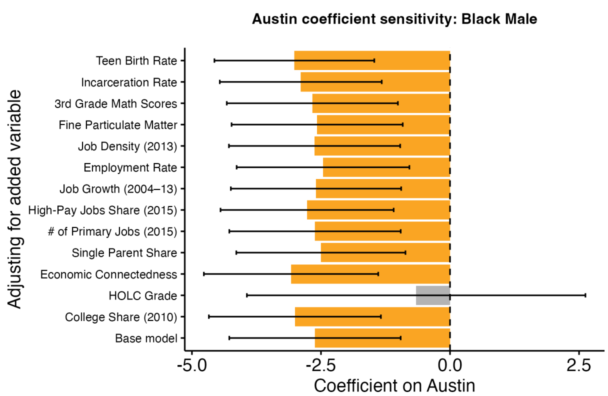


(e) Asian Female

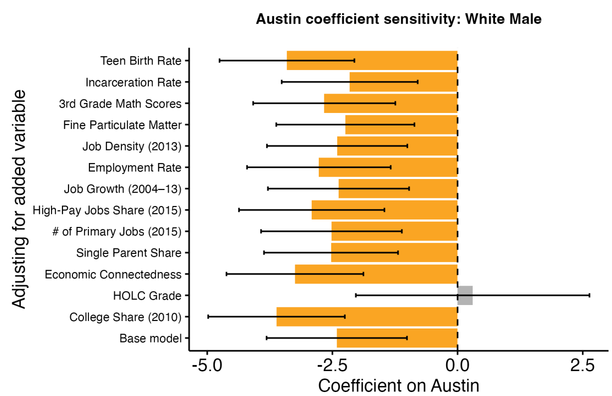
Figure 5: Austin Coefficient Sensitivity by Male Racial/Ethnic Group



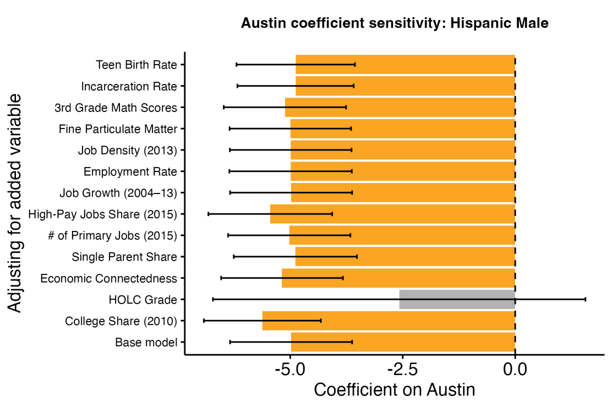
(a) **Pooled Male**



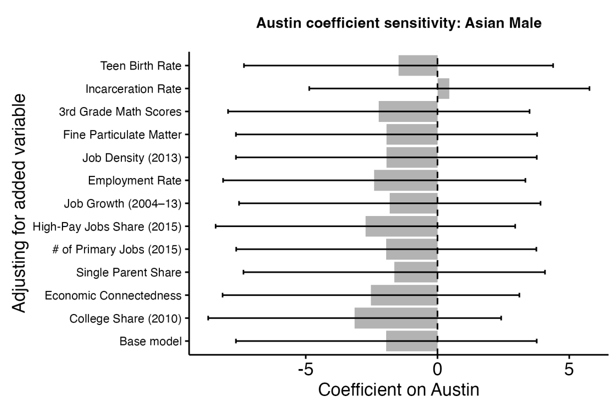
(b) **Black Male**



(c) **White Male**



(d) **Hispanic Male**



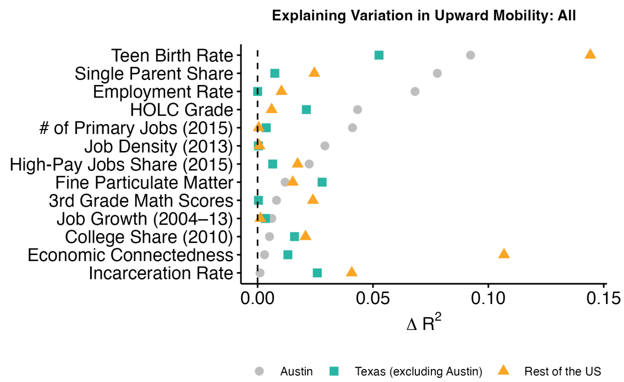
(e) **Asian Male**

Table 4: Marginal R^2 Estimates for Austin

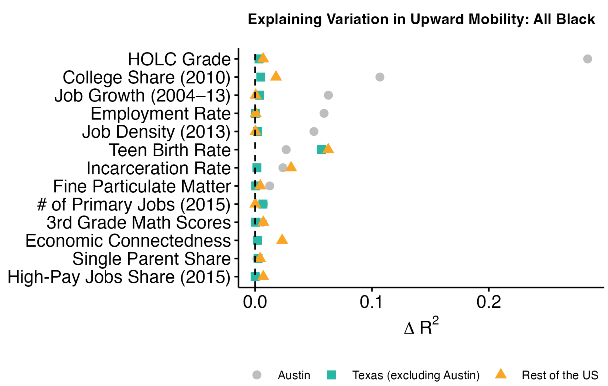
	Pooled					Female					Male				
Variable	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic
College Share (2010)	0.0052	0.0508	0.1068	0.0072	0.0042	0.0592	0.2183	0.0263	0.0655	0.0566	0.0305	0.0112	0.0226	0.0420	0.0338
HOLC Grade	0.0433	—	0.2846	0.0029	0.2632	0.1390	—	—	0.0003	0.1514	0.0340	—	—	0.0435	0.0266
Economic Connectedness	0.0030	0.0539	0.0020	0.0004	0.0014	0.0001	0.1163	0.0406	0.0003	0.0850	0.0060	0.0709	0.0016	0.0000	0.0296
Single Parent Share	0.0779	0.0417	0.0015	0.0383	0.0021	0.0292	0.0923	0.0202	0.0183	0.0056	0.0835	0.0095	0.0224	0.0417	0.0051
# of Primary Jobs (2015)	0.0411	0.0003	0.0074	0.0166	0.0005	0.0040	0.0737	0.0002	0.0189	0.0001	0.0639	0.0065	0.0562	0.0161	0.0255
High-Pay Jobs Share (2015)	0.0224	0.0096	0.0011	0.0845	0.0031	0.0060	0.1665	0.0155	0.0000	0.0510	0.0422	0.0130	0.0725	0.0726	0.0071
Job Growth (2004–13)	0.0062	0.0501	0.0627	0.0022	0.0013	0.0045	0.0112	0.0002	0.0748	0.0000	0.0172	0.0047	0.1773	0.0079	0.0319
Employment Rate	0.0682	0.0039	0.0590	0.1111	0.0027	0.0018	0.0612	0.0249	0.0476	0.0073	0.0779	0.0850	0.0029	0.1055	0.0002
Job Density (2013)	0.0292	0.0209	0.0503	0.0083	0.0087	0.0142	0.0117	0.0037	0.0213	0.0707	0.0126	0.0442	0.0001	0.0021	0.0191
Fine Particulate Matter	0.0119	0.0298	0.0125	0.0019	0.0024	0.0014	0.0002	0.0000	0.0377	0.0278	0.0064	0.1075	0.0761	0.0105	0.0456
3rd Grade Math Scores	0.0082	0.0400	0.0064	0.0467	0.0053	0.0042	0.3247	0.0057	0.0070	0.0096	0.0324	0.0047	0.0886	0.0561	0.0051
Incarceration Rate	0.0011	0.2824	0.0238	0.0149	0.2196	0.0153	0.0119	0.0487	0.0072	0.0236	0.0005	0.0183	0.0003	0.0047	0.0838
Teen Birth Rate	0.0923	0.0590	0.0266	0.0278	0.0002	0.1666	0.0024	0.0907	0.0568	0.0122	0.0255	0.0151	0.0173	0.0000	0.0520

Note: HOLC grade is unavailable for some Asian and Black subsamples due to limited sample size and multicollinearity, so those cells are shown as dashes. Because no Asians lived where HOLC data is available, Asian share is dropped as a control when estimating HOLC R^2.

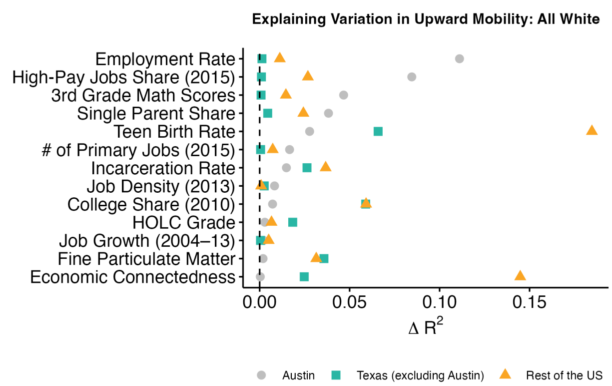
Figure 6: Marginal Change in R^2 of Pooled Race / Ethnicity Upward Mobility



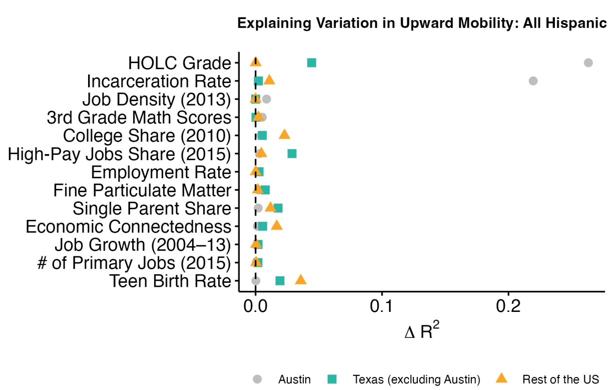
(a) Pooled



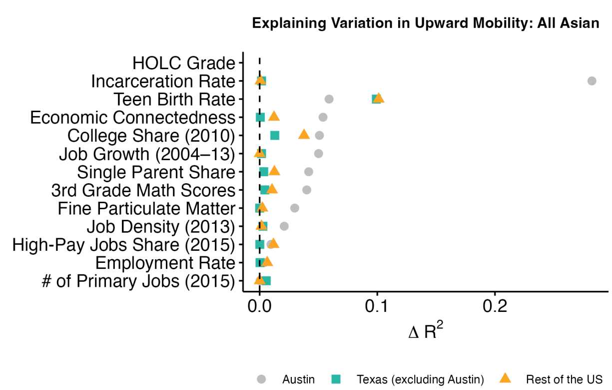
(b) Black



(c) White

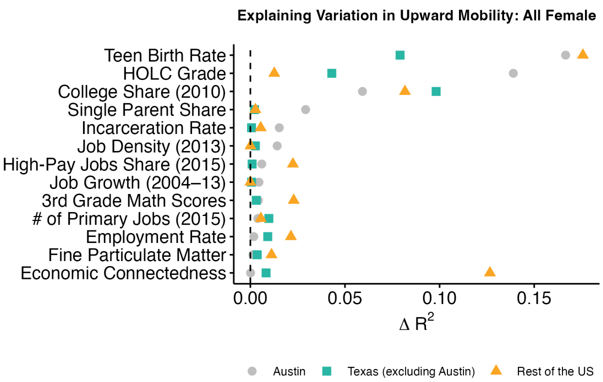


(d) Hispanic

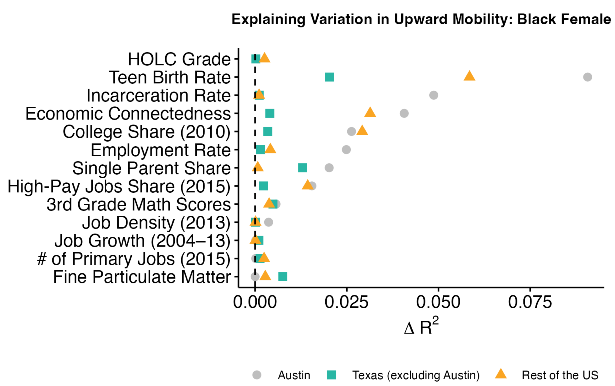


(e) Asian

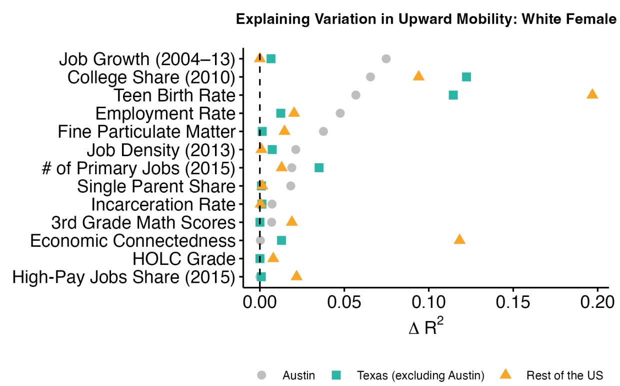
Figure 7: Marginal Change in R^2 of Female Race / Ethnicity Upward Mobility



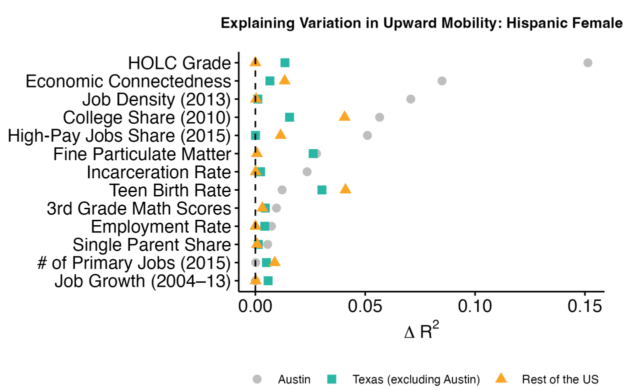
(a) **Pooled Female**



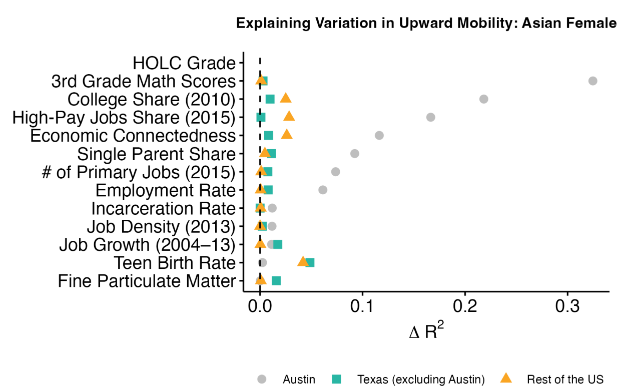
(b) **Black Female**



(c) **White Female**

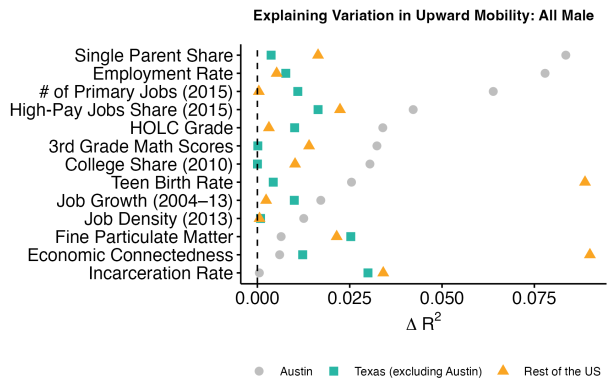


(d) **Hispanic Female**

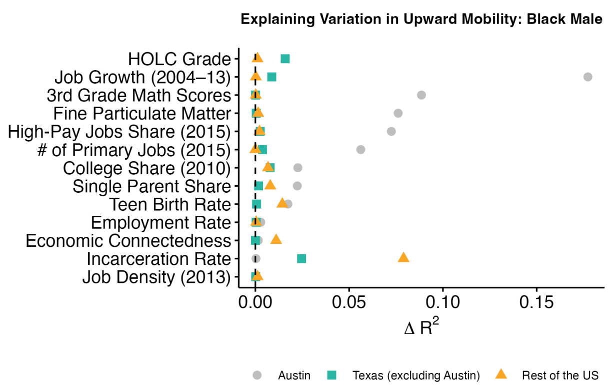


(e) **Asian Female**

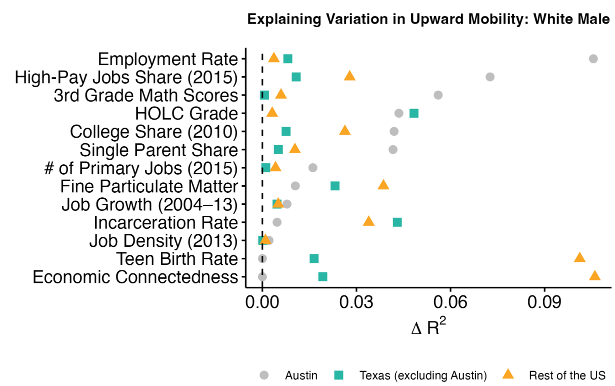
Figure 8: Marginal Change in R^2 of Male Race / Ethnicity Upward Mobility



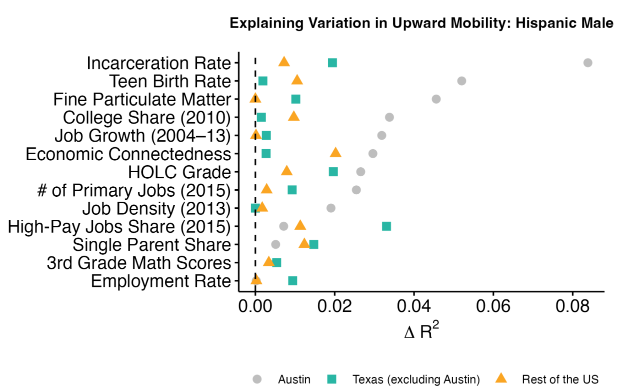
(a) Pooled Male



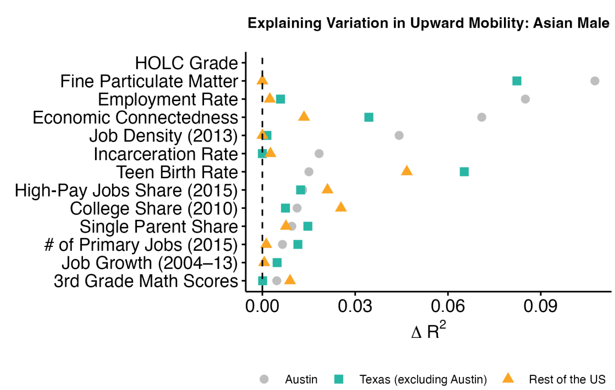
(b) Black Male



(c) White Male



(d) Hispanic Male



(e) Asian Male

Table 5: Percentage Increase in MSE by Marginal Variable Removal in Random Forest

	Pooled					Female					Male				
Variable	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic	Pooled	Asian	Black	White	Hispanic
Teen Birth Rate	26.554	0.576	3.500	3.007	8.401	18.372	1.083	3.185	11.334	4.226	10.683	-0.746	-0.723	3.986	10.256
	(1)	(8)	(7)	(14)	(2)	(1)	(6)	(7)	(3)	(8)	(5)	(11)	(16)	(12)	(1)
Hispanic Share (2010)	18.194	2.116	0.360	29.476	5.654	12.848	1.506	4.331	13.253	6.996	13.297	-0.514	2.659	11.605	8.083
	(2)	(3)	(12)	(1)	(5)	(3)	(5)	(4)	(1)	(2)	(1)	(10)	(10)	(2)	(3)
# of Primary Jobs (2015)	15.110	0.370	7.602	7.087	9.056	6.638	1.571	1.311	7.027	7.751	11.219	2.050	1.495	6.344	10.136
	(4)	(11)	(4)	(7)	(1)	(7)	(4)	(13)	(6)	(1)	(3)	(5)	(13)	(7)	(2)
Incarceration Rate	16.179	-0.065	0.851	7.287	4.479	0.035	-0.727	-0.819	0.263	0.897	10.831	4.357	1.671	7.862	5.742
	(3)	(13)	(10)	(6)	(9)	(15)	(12)	(16)	(16)	(15)	(4)	(1)	(12)	(4)	(5)
Poverty Share (2010)	14.794	4.513	11.759	6.668	6.554	7.442	0.632	5.056	7.093	4.035	12.818	1.792	9.624	13.855	3.772
	(5)	(1)	(1)	(8)	(4)	(6)	(8)	(3)	(5)	(9)	(2)	(6)	(1)	(1)	(9)
College Share (2010)	13.213	1.740	1.607	15.053	4.571	16.080	3.137	6.581	13.054	6.629	7.053	1.210	3.482	7.195	7.418
	(6)	(5)	(8)	(2)	(7)	(2)	(3)	(1)	(2)	(3)	(9)	(8)	(6)	(5)	(4)
Fine Particulate Matter	10.869	2.398	-0.588	12.436	5.445	5.503	-0.060	3.378	7.897	3.681	7.787	2.133	4.090	10.718	2.370
	(7)	(2)	(14)	(3)	(6)	(9)	(10)	(6)	(4)	(10)	(8)	(4)	(5)	(3)	(10)
Asian Share (2010)	9.258	1.121	5.935	4.821	7.043	9.373	4.728	2.818	3.597	5.706	6.654	-2.116	6.467	5.984	1.147
	(8)	(7)	(5)	(10)	(3)	(4)	(1)	(8)	(13)	(4)	(10)	(15)	(4)	(8)	(12)
Black Share (2010)	9.083	-0.753	-0.330	8.152	4.264	7.945	0.486	2.264	6.061	4.428	7.794	0.302	3.123	4.755	0.924
	(9)	(15)	(13)	(5)	(10)	(5)	(9)	(10)	(9)	(6)	(7)	(9)	(8)	(10)	(13)
Fraction of High-Paying Jobs	7.839	-0.129	0.434	5.925	2.674	3.572	-0.668	2.758	4.305	2.857	7.939	-1.011	3.272	4.677	-0.530
	(10)	(14)	(11)	(9)	(13)	(11)	(11)	(9)	(11)	(11)	(6)	(12)	(7)	(11)	(16)
Employment Rate	7.753	0.170	10.217	9.959	4.553	3.436	-2.037	5.780	3.181	5.436	5.126	1.394	7.807	6.886	5.356
	(11)	(12)	(2)	(4)	(8)	(12)	(15)	(2)	(14)	(5)	(12)	(7)	(2)	(6)	(6)
Job Density (2013)	4.665	-2.994	1.411	0.252	1.388	1.818	-1.911	1.922	5.158	1.113	3.152	-2.781	0.780	-0.102	0.717
	(12)	(16)	(9)	(16)	(15)	(14)	(14)	(11)	(10)	(14)	(16)	(16)	(14)	(16)	(14)
3rd Grade Math Scores	2.701	1.786	8.902	4.719	3.384	6.009	3.165	0.333	3.829	2.838	4.962	-1.111	7.099	5.959	2.127
	(15)	(4)	(3)	(11)	(12)	(8)	(2)	(14)	(12)	(12)	(14)	(14)	(3)	(9)	(11)
Single Parent Share	4.246	1.252	4.812	4.108	4.206	4.069	0.685	1.634	6.886	4.337	6.605	-1.012	2.990	3.694	0.089
	(13)	(6)	(6)	(12)	(11)	(10)	(7)	(12)	(7)	(7)	(11)	(13)	(9)	(13)	(15)
Urban Share (2010)	1.052	0.410	-0.730	2.763	1.654	2.400	-3.304	3.579	6.794	2.012	5.016	2.699	0.696	2.271	4.212
	(16)	(10)	(15)	(15)	(14)	(13)	(16)	(5)	(8)	(13)	(13)	(2)	(15)	(14)	(7)
Job Growth (2004–13)	2.832	0.452	-1.003	3.946	-0.992	-0.339	-0.793	-0.287	2.313	-2.850	3.473	2.558	2.169	2.113	4.012
	(14)	(9)	(16)	(13)	(16)	(16)	(13)	(15)	(15)	(16)	(15)	(3)	(11)	(15)	(8)
N	295	22	118	278	242	293	19	102	275	232	293	19	95	274	220

Entries are % increase in MSE; ranks are shown in parentheses.

Table 6: Teen Birth Rate Coefficient Sensitivity by Gender (Atlas - ZIP)

	Pooled			Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	55.721*** (1.721)	61.045*** (4.582)	67.008*** (4.709)	49.265*** (1.813)	45.518*** (3.332)	45.754*** (4.732)	55.849*** (2.606)	56.785*** (6.123)	64.590*** (7.553)
Teen Birth Rate	-36.212*** (6.446)	-44.715*** (7.201)	-45.709*** (6.388)	-35.882*** (6.806)	-34.020*** (9.437)	-33.756*** (9.589)	-16.522* (7.905)	-21.215* (9.961)	-24.691** (9.019)
College	—	-10.225** (3.599)	-8.635* (3.532)	—	6.372 (5.217)	6.912 (4.712)	—	-12.811* (5.520)	-12.019* (5.147)
Economic Connectedness	—	-1.490 (2.637)	-1.592 (2.424)	—	-2.949 (2.153)	-2.806 (2.106)	—	1.937 (3.909)	1.241 (3.394)
Incarceration Rate	—	67.885 (65.039)	47.819 (49.020)	—	21.985 (24.814)	21.411 (27.169)	—	-16.137 (21.474)	-4.044 (18.955)
Single-Parent Share	—	-6.801 (5.040)	-4.523 (4.642)	—	-7.246 (4.782)	-7.587 (5.321)	—	-12.991† (6.745)	-7.553 (6.825)
PM2.5	—	0.197 (0.473)	0.803* (0.396)	—	0.781 (0.524)	0.622 (0.531)	—	0.612 (0.699)	1.272† (0.682)
Employment (2000)	—	—	-13.049* (4.987)	—	—	2.677 (5.474)	—	—	-17.613* (7.641)
High Pay Share	—	—	-9.658* (4.359)	—	—	-1.183 (7.628)	—	—	-8.351 (6.852)
Job Growth	—	—	22.669* (11.055)	—	—	-10.782 (9.954)	—	—	32.092* (13.441)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	74	70	70	74	70	70	74	70	70

Heteroskedastic standard errors in parentheses.
† p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7: Teen Birth Rate Coefficient Sensitivity by Race (Atlas - ZIP)

	Black			Hispanic			White		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	32.065*** (2.064)	25.077** (8.302)	29.138* (10.447)	41.976*** (6.017)	31.991*** (7.918)	38.769** (11.773)	55.966*** (2.007)	56.311*** (8.466)	78.165*** (10.155)
Teen Birth Rate	-6.720 (4.507)	-7.765 (6.299)	-7.899 (6.138)	1.372 (13.962)	10.378 (11.143)	12.951 (12.195)	-18.756* (7.887)	-13.257 (13.159)	-24.014* (10.612)
College	—	-14.943 (10.155)	-8.808 (9.124)	—	-5.987 (14.471)	2.950 (9.466)	—	-4.795 (7.680)	-2.368 (5.539)
Economic Connectedness	—	8.970 (5.763)	9.106† (5.010)	—	8.730 (6.042)	8.165 (5.733)	—	-1.194 (5.971)	-0.016 (5.142)
Incarceration Rate	—	7.321 (14.558)	9.963 (15.129)	—	-159.656*** (42.168)	-165.316*** (47.187)	—	-23.367 (32.075)	-25.051 (23.410)
Single-Parent Share	—	5.571 (10.346)	3.860 (10.723)	—	-5.484 (16.221)	-1.628 (19.663)	—	-10.385 (8.703)	-1.569 (6.363)
PM2.5	—	0.562 (0.997)	0.581 (0.879)	—	0.073 (0.686)	-0.179 (0.706)	—	0.435 (0.818)	0.973 (0.839)
Employment (2000)	—	—	6.572 (10.638)	—	—	8.919 (8.557)	—	—	-28.860** (10.710)
High Pay Share	—	—	-26.709* (10.854)	—	—	-34.563 (32.091)	—	—	-20.896* (8.774)
Job Growth	—	—	-14.890 (17.861)	—	—	-30.733 (28.317)	—	—	-2.820 (15.700)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	40	39	39	73	69	69	74	70	70

Heteroskedastic standard errors in parentheses.
† p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 8: Teen Birth Rate Coefficient Sensitivity by Gender (Atlas - Census Tract)

	Pooled			Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	52.662***	56.376***	61.539***	47.180***	40.872***	41.529***	52.705***	58.103***	63.086***
	(1.292)	(2.473)	(3.538)	(1.399)	(3.025)	(4.440)	(1.744)	(2.749)	(4.334)
Teen Birth Rate	-21.168***	-15.864***	-15.830***	-21.844***	-17.939***	-17.932***	-6.901	-4.457	-4.133
	(4.057)	(4.152)	(3.928)	(4.159)	(4.678)	(4.711)	(6.283)	(6.825)	(6.846)
College	—	$4.448^{\dagger}$	$4.751^{\dagger}$	—	11.598***	11.388**	—	-0.570	0.553
		(2.642)	(2.639)		(3.394)	(3.508)		(3.552)	(3.654)
Incarceration Rate	—	-59.172***	-62.378***	—	-0.672	-0.933	—	-20.414	-20.262
		(14.697)	(15.383)		(14.233)	(14.681)		(15.207)	(15.111)
Single-Parent Share	—	-0.655	-0.146	—	-1.343	-1.314	—	-1.319	-1.034
		(1.872)	(1.855)		(2.474)	(2.494)		(2.057)	(2.048)
PM2.5	—	-0.848*	-0.535	—	0.117	0.110	—	$-0.734^{\dagger}$	-0.680
		(0.349)	(0.345)		(0.415)	(0.407)		(0.374)	(0.413)
Employment (2000)	—	—	-5.915	—	—	-0.867	—	—	-1.593
			(3.670)			(3.983)			(4.452)
High Pay Share	—	—	-8.880*	—	—	0.359	—	—	$-10.562^{\dagger}$
			(4.151)			(5.288)			(6.021)
Job Growth	—	—	-0.627	—	—	-1.034	—	—	-8.544*
			(3.305)			(4.213)			(3.335)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	297	295	295	297	293	293	296	293	293

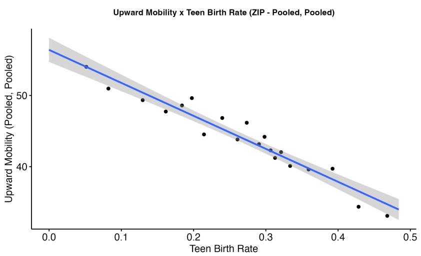
Heteroskedastic standard errors in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Teen Birth Rate Coefficient Sensitivity by Race (Atlas - Census Tract)

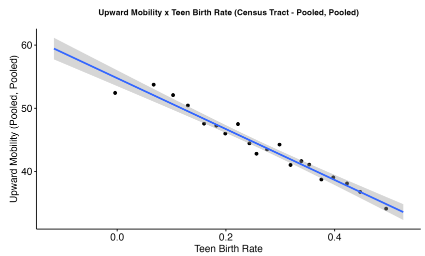
	Black			Hispanic			White		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Intercept)	37.415***	46.052***	41.410***	46.269***	51.971***	49.841***	52.371***	50.410***	57.248***
	(4.999)	(6.219)	(10.203)	(2.003)	(3.470)	(4.606)	(1.254)	(3.175)	(4.816)
Teen Birth Rate	-12.079**	-12.427**	-12.003**	-9.168**	-5.913	-4.835	-0.271	2.866	2.330
	(4.141)	(4.198)	(4.205)	(3.403)	(3.642)	(3.592)	(3.864)	(3.827)	(3.759)
College	—	-6.485	-6.738	—	5.269	7.573	—	9.825**	11.477**
		(6.617)	(6.539)		(5.386)	(5.247)		(3.443)	(3.491)
Incarceration Rate	—	-6.156	-5.099	—	-55.268**	-56.543**	—	$-21.310^{\dagger}$	$-23.070^{\dagger}$
		(11.646)	(11.654)		(19.540)	(19.709)		(12.060)	(12.248)
Single-Parent Share	—	0.771	-0.200	—	-1.964	-1.735	—	-2.860	-2.124
		(3.191)	(3.592)		(2.677)	(2.792)		(2.635)	(2.644)
PM2.5	—	-0.978	-1.111	—	-1.166*	-1.010*	—	-0.353	-0.106
		(0.704)	(0.724)		(0.503)	(0.500)		(0.446)	(0.465)
Employment (2000)	—	—	2.215	—	—	6.431	—	—	-3.906
			(5.258)			(4.790)			(4.536)
High Pay Share	—	—	8.610	—	—	$-12.445^{\dagger}$	—	—	-15.543*
			(12.012)			(6.521)			(6.463)
Job Growth	—	—	-2.150	—	—	2.687	—	—	-6.014
			(6.068)			(5.601)			(4.137)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	118	118	118	242	242	242	279	278	278

Heteroskedastic standard errors in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

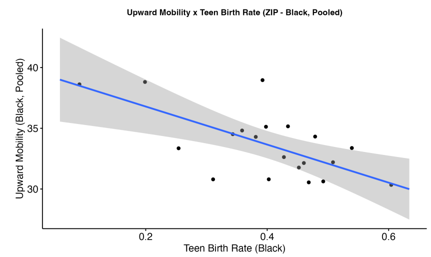
Figure 9: Teen Birth x Upward Mobility Scatterplots



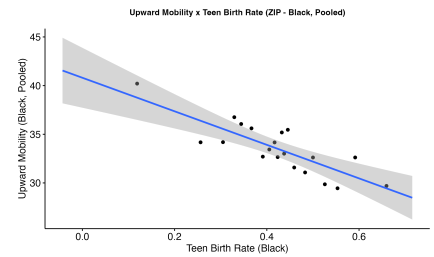
(a) Pooled (ZIP)



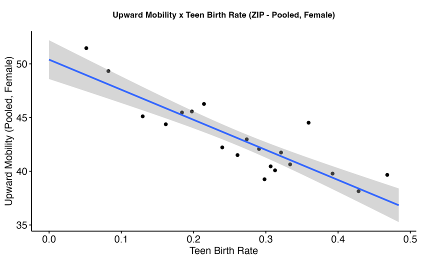
(b) Pooled (Tract)



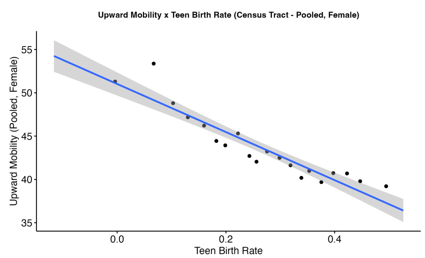
(c) Black (ZIP)



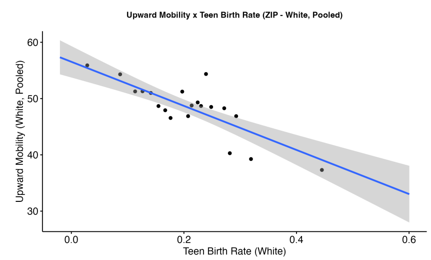
(d) Black (Tract)



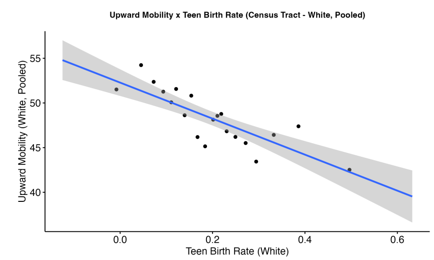
(e) Female (ZIP)



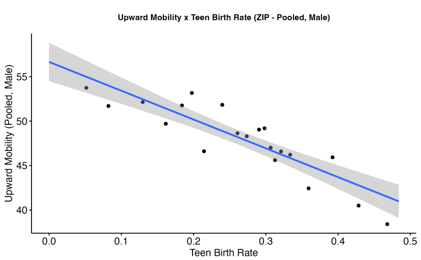
(f) Female (Tract)



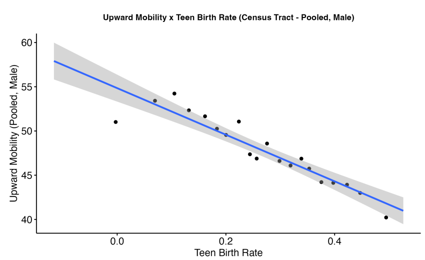
(g) White (ZIP)



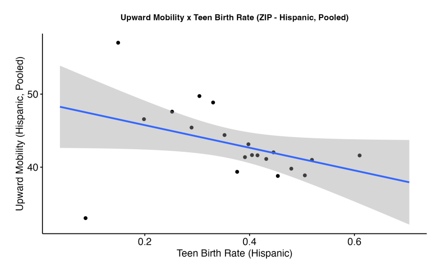
(h) White (Tract)



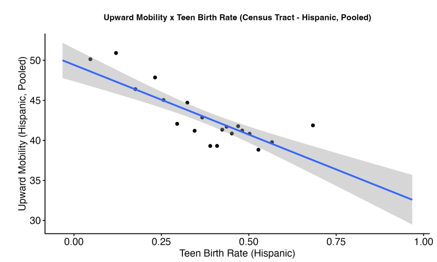
(i) Male (ZIP)



(j) Male (Tract)



(k) Hispanic (ZIP)



(l) Hispanic (Tract)

Table 10: **Teen Birth Rate Coefficient Sensitivity (Lockbox - ZIP)**

	Pooled		Black		Hispanic		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	51.405*** (1.116)	57.611*** (3.756)	31.096*** (2.048)	14.557 (9.074)	51.139*** (2.014)	48.137*** (6.330)	49.915*** (1.481)	58.948*** (7.153)
Teen Birth Rate	-12.005* (4.844)	-13.929* (5.360)	-1.587 (3.153)	6.109* (2.807)	-8.736† (4.785)	-3.803 (4.752)	7.994 (7.444)	-0.939 (9.775)
College	—	-7.211† (3.757)	—	0.101 (7.651)	—	-1.388 (6.334)	—	-7.586 (5.652)
Economic Connectedness	—	5.548** (2.060)	—	13.509** (4.216)	—	5.275 (4.981)	—	7.489* (2.865)
Incarceration Rate	—	-8.169 (21.192)	—	-23.006 (16.147)	—	48.669* (23.883)	—	-32.033 (22.237)
Single-Parent Share	—	-5.295 (3.878)	—	-9.735† (5.267)	—	-0.657 (8.806)	—	-2.878 (7.358)
PM2.5	—	-0.458 (0.317)	—	-1.423 (0.986)	—	-0.645 (0.744)	—	0.222 (0.510)
Employment (2000)	—	-0.564 (4.667)	—	32.123** (11.159)	—	2.840 (8.314)	—	-10.328 (7.986)
High Pay Share	—	-11.590** (3.928)	—	-15.023 (13.297)	—	-3.354 (12.491)	—	-17.873** (5.866)
Job Growth	—	-14.411* (6.700)	—	-16.575 (11.472)	—	-21.000 (14.978)	—	-11.252 (9.671)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	74	70	40	39	73	69	74	70

Heteroskedastic standard errors in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: **Teen Birth Rate Coefficient Sensitivity (Lockbox - Census Tract)**

	Pooled		Black		Hispanic		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	51.068*** (0.881)	59.520*** (2.830)	35.601*** (5.104)	33.019*** (7.187)	50.095*** (1.469)	51.799*** (4.016)	49.159*** (1.083)	58.517*** (3.478)
Teen Birth Rate	-11.864*** (3.415)	-8.703** (3.216)	-8.025* (3.112)	-4.548 (2.956)	-5.671* (2.277)	-5.089* (2.175)	7.935* (3.484)	8.997** (3.426)
College	—	-0.721 (2.694)	—	3.311 (4.217)	—	-1.013 (3.694)	—	-0.271 (3.525)
Incarceration Rate	—	-17.646 (17.337)	—	-20.208* (8.912)	—	-22.365 (18.165)	—	-24.565* (9.838)
Single-Parent Share	—	0.244 (2.212)	—	-3.470 (2.265)	—	-2.454 (2.373)	—	-0.279 (2.961)
PM2.5	—	-0.801** (0.308)	—	-1.251* (0.523)	—	-1.087* (0.441)	—	-0.296 (0.402)
Employment (2000)	—	1.906 (2.977)	—	4.505 (4.319)	—	3.677 (4.055)	—	-1.143 (3.994)
High Pay Share	—	-10.233* (4.037)	—	9.767 (9.356)	—	11.330† (6.140)	—	-15.110** (4.909)
Job Growth	—	-5.160† (2.710)	—	-2.631 (3.436)	—	-9.442* (4.103)	—	-5.141 (3.732)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	297	295	118	118	242	242	279	278

Heteroskedastic standard errors in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: HOLC Coefficient Sensitivity (Atlas - ZIP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HOLC Grade	-8.411*	-6.963†	-8.072*	-1.064	-6.373†	-3.697	-5.123*	-7.323†	-10.560*	-8.425*
	(2.413)	(3.242)	(3.023)	(0.716)	(2.875)	(2.010)	(1.672)	(3.150)	(3.867)	(2.475)
College Share (2010)	—	12.903	—	—	—	—	—	—	—	—
		(14.755)								
Economic Connectedness	—	—	5.551	—	—	—	—	—	—	—
			(13.156)							
Teen Birth Rate	—	—	—	-60.045***	—	—	—	—	—	—
				(5.759)						
Incarceration Rate	—	—	—	—	-184.662	—	—	—	—	—
					(93.685)					
Fine Particulate Matter	—	—	—	—	—	-19.034	—	—	—	—
						(9.573)				
Single Parent Share	—	—	—	—	—	—	-22.315*	—	—	—
							(6.866)			
Employment (2000)	—	—	—	—	—	—	—	-20.995	—	—
								(34.098)		
High-Pay Share	—	—	—	—	—	—	—	—	198.580	—
									(295.099)	
Job Growth	—	—	—	—	—	—	—	—	—	50.480
										(47.441)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10	10	10	9	10	10	10	10	10	10

Heteroskedastic standard errors in parentheses. Intercept omitted for clarity
Due to limited overlapping controls and low sample size, we limit controls to poverty share (2010) and black share (2010) and drop the horse race.
HOLC grade is a coefficient since ZIPs have weighted HOLC grades.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: HOLC Coefficient Sensitivity (Atlas - Census Tract)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HOLC Grade 2	-7.507*	-7.128†	-3.387	-7.270*	-5.367	-5.837	-4.914	-7.718*	-7.772*	-1.212
	(3.479)	(3.455)	(5.104)	(3.496)	(3.726)	(3.978)	(4.169)	(3.371)	(3.319)	(3.028)
HOLC Grade 3	-13.376**	-8.489†	-5.687	-12.149*	-8.149	-9.109	-17.464***	-12.468*	-13.805**	1.430
	(4.184)	(4.823)	(6.487)	(4.415)	(5.165)	(5.536)	(4.508)	(5.412)	(3.794)	(6.715)
HOLC Grade 4	-11.956*	-8.063	-5.201	-10.442*	-10.971**	-8.474†	-9.187	-10.623	-11.433*	-1.391
	(4.289)	(4.939)	(6.185)	(4.663)	(3.826)	(4.813)	(6.042)	(6.670)	(4.823)	(4.917)
College Share (2010)	—	17.460*	—	—	—	—	—	—	—	10.800
		(8.327)								(8.487)
Teen Birth Rate	—	—	-27.244†	—	—	—	—	—	—	-3.821
			(15.066)							(8.904)
Incarceration Rate	—	—	—	-91.305*	—	—	—	—	—	-110.374*
				(42.036)						(42.657)
Fine Particulate Matter	—	—	—	—	-11.314†	—	—	—	—	-12.251†
					(6.406)					(6.592)
Single Parent Share	—	—	—	—	—	-9.326†	—	—	—	-2.805
						(5.174)				(5.571)
Employment (2000)	—	—	—	—	—	—	-31.417	—	—	-2.692
							(23.289)			(20.339)
High-Pay Share	—	—	—	—	—	—	—	-88.914	—	-93.232
								(246.928)		(145.922)
Job Growth	—	—	—	—	—	—	—	—	-12.692	3.323
									(17.572)	(12.957)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30	30	29	30	30	29	30	30	30	28

Heteroskedastic standard errors in parentheses. Intercept omitted for clarity
HOLC grade is a factor since a Census Tracts get a categorical score.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: **HOLC Coefficient Sensitivity (Lockbox - ZIP)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HOLC Grade	-2.880** (0.762)	-2.049 (1.558)	-2.870* (1.048)	-3.140* (0.884)	-2.839* (0.913)	-2.102 (1.374)	-2.317† (1.039)	-1.396† (0.622)	-4.505* (1.361)	-2.867* (0.983)
College Share (2010)	—	7.408 (11.852)	—	—	—	—	—	—	—	—
Economic Connectedness	—	—	0.173 (10.026)	—	—	—	—	—	—	—
Teen Birth Rate	—	—	—	3.110 (9.682)	—	—	—	—	—	—
Incarceration Rate	—	—	—	—	-3.790 (55.197)	—	—	—	—	—
Fine Particulate Matter	—	—	—	—	—	-3.142 (6.752)	—	—	—	—
Single Parent Share	—	—	—	—	—	—	-3.827 (8.744)	—	—	—
Employment (2000)	—	—	—	—	—	—	—	-28.645** (6.516)	—	—
High-Pay Share	—	—	—	—	—	—	—	—	150.059 (82.411)	—
Job Growth	—	—	—	—	—	—	—	—	—	-48.854 (31.123)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10	10	10	9	10	10	10	10	10	10

Heteroskedastic standard errors in parentheses. Intercept omitted for clarity
Due to limited overlapping controls and low sample size, we limit controls to poverty share (2010) and share black (2010) and drop the horse race.
HOLC grade is a coefficient since ZIPs have weighted HOLC grades.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: **HOLC Coefficient Sensitivity (Lockbox - Census Tracts)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HOLC Grade 2	-3.403 (4.244)	-3.037 (4.230)	0.995 (3.995)	-3.886 (4.142)	-2.786 (4.780)	-3.526 (5.526)	-0.347 (4.433)	-3.121 (4.559)	3.623 (5.769)
HOLC Grade 3	-7.572† (3.872)	-4.600 (4.068)	1.042 (3.862)	-6.573† (3.653)	-6.051 (5.436)	-6.375 (5.281)	-12.925* (4.747)	-8.759* (3.760)	-6.590 (6.376)
HOLC Grade 4	-7.835* (3.361)	-5.509 (3.759)	-0.261 (3.780)	-6.372* (3.068)	-7.547† (3.678)	-6.964 (4.462)	-4.140 (4.817)	-9.580** (3.281)	4.758 (5.936)
College Share (2010)	—	10.589 (10.600)	—	—	—	—	—	—	24.337† (12.997)
Teen Birth Rate	—	—	-30.278** (8.737)	—	—	—	—	—	-16.601 (21.350)
Incarceration Rate	—	—	—	-77.567† (43.539)	—	—	—	—	-13.543 (70.424)
Fine Particulate Matter	—	—	—	—	-3.293 (4.939)	—	—	—	7.639 (8.636)
Single Parent Share	—	—	—	—	—	-3.690 (5.758)	—	—	-4.834 (6.055)
Employment (2000)	—	—	—	—	—	—	-40.977† (20.588)	—	-52.443† (26.277)
High-Pay Share	—	—	—	—	—	—	—	116.281 (257.665)	229.124 (237.455)
Job Growth	—	—	—	—	—	—	—	—	-9.382 (23.720)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	31	31	29	30	31	30	31	31	28

Heteroskedastic standard errors in parentheses. Intercept omitted for clarity
HOLC grade is a factor since a CZ gets a categorical score.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Gregory Bruich via gmail.com   Apr 30, 2026, 12:15 PM (1 day ago)

to me

Hi Brian,

Thanks for checking. Please keep the main text to 17 pages maximum.

If you want to include an appendix with extra results, that would be fine. I think that is the best place for additional robustness checks, alternative geographic definitions like ZIP vs. CZ, and more detailed descriptive breakdowns.

Best,
Greg