An Analysis of the Relationship Between Eviction Rates and Upward Mobility

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Abstract

Rising costs of living have been fueled by a generational shift in tastes and preferences, as cities have once again become fashionable for middle- to higher-income, well-educated professionals. What has followed has been gentrification and urban displacement, as those who can afford to live in these urban cores move in and those who cannot afford to do so anymore are priced out. Curious about the impact this might have on upward economic mobility, I combine Economist Raj Chetty's dataset on intergenerational mobility with Sociologist Matthew Desmond's dataset on eviction rates in America to quantify the relationship between eviction rates and economic mobility on a census-tract level. I find a statistically significant negative relationship between these two variables across a variety of different regression models aimed to control for potentially omitted variables. Furthermore, I document the heterogeneity in this relationship on a commuting zone-level basis as well as a race-by-race basis using data on economic mobility provided for White, Black, and Hispanic males.

1 Introduction

A massive return to the city is currently underway. Whereas just a generation ago, city planners lamented the decay of the city as white flight left once-thriving urban cores destitute, today these same urban cores once again enjoy vibrant economies as trends like urban renewal come to life. In his book, *The Great Inversion and the Future of the American City*, writer Alan Ehrenhalt describes this return to the city as a "demographic inversion," explaining that a "rearrangement of living patterns across entire metropolitan area[s]" is currently underway. "The poor and new comers," he writes, are now "living on the outskirts. The people who live near the center are those, some of them black or Hispanic but most of them white, who can afford to do so."

Many have thought about this shift largely in terms of "pull" factors that attract younger, wealthier people to city centers everywhere. One study by the Brookings Institute finds that there was only one metropolitan area—Birmingham, AL—that saw a decline in the share of young adults (18-35 age bracket) between 2010 and 2015, suggesting that younger millennials exhibit a greater appetite for urban amenities than their older counterparts. The types of specific amenities sought by these typically more-educated cohorts are outlined in Couture and Handbury (2017), who note that "initial levels of non-tradable service amenities like restaurants, bars, gyms and beauty salons have the most power to explain the recent urbanization of young professionals." Job growth has also been a standard explanation for this demographic "inversion." A widely-cited 2015 study by City Observatory, a think-tank in Portland, OR, found that "downtown employment centers of the nation's largest metropolitan areas are recording faster job growth than areas located further from the city center," a stark contrast from the decades of job growth that was concentrated in suburban office parks. The same study notes that this is driven partially by "the relatively stronger performance of urban-centered industries (business and professional services, software) relative to decentralized industries (construction, manufacturing)"; in other words, the types of industries that are dominated by a younger, more educated workforce.

But there is a key insight missing from these explanations of intra-city demographic shifts. While "pull" factors such as those described certainly bring these newcomers to the core, "push" factors are simultaneously pricing out those who have settled in the places that, in the past fifty years or so, were largely reserved for the poorest cohorts. Rising rents have led to a new kind of housing crisis as the housing supply in cities across the United States has failed to keep up with rapid job growth. According to Gaffary, for every 4.5 new jobs created in the San Francisco Bay Area, only one new home is created; as a result, the average rent for a 1-bedroom apartment there has risen to about $3,450 in March 2019, up from $2,175 in January 2011 according to data collected by Rent Jungle[1]. This mechanism effectively kicks out those who are less educated and wealthy, and it is further associated with the trends in gentrification and eviction that unfortunately characterize many our cities today.

Sociologist Matthew Desmond of Princeton University believes that this is not something that occurs by accident. Indeed, in Desmond and Wilmers (2019), he argues that the poorest populations in cities not only face the pressure of being priced out from greater socioeconomic changes, but also face this pressure directly from landlords who explicitly overcharge poor renters relative to the market value of their home. Desmond further explains how this increased rent burden among low-income families "directly contributes to their economic scarcity and hardship and is a source of residential insecurity, eviction, and homelessness." This is the unfortunate reality for an estimated 2.3 million people living through what Matthew Leger from the Harvard Kennedy School's Ash Center for Democratic Governance and Innovation calls an "eviction epidemic." "Far more work is to be done nationwide," he writes, "if we truly want to prevent millions of families from losing their homes, a life event that has already thrust countless families into cyclical and multi-generational poverty."

This leads to the question I am to explore in my research: How can we measure the relationship between eviction rates and this "multi-generational poverty" Leger implies is a causal impact of being evicted in America? A first indicator of the form this multi-generational process might take on may be pieced together from Economist Raj Chetty's work on intergenerational mobility. In his study, "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States" (2014), Chetty et al. map out the heterogeneous nature of upward mobility in the United States. On a national level, they show that the probability of upward mobility is more likely in the Midwestern regions of the United States, and less-so in the American South. Though they mention some of the factors that are correlated with this heterogeneity—including segregation, income inequality, and school expenditures—any discussion of evictions or urban displacement is left out completely.

The goal of this paper is to quantify the relationship between intergenerational mobility and

[1]Data from RentJungle: https://www.rentjungle.com/average-rent-in-san-francisco-rent-trends/

eviction rates in America, serving primarily as an extension to Chetty et al.'s work as another key variable in determining how our "land of opportunity" is distributed across the country. Section 2 outlines the source of this data, while Section 3 details the econometric tools I use to answer this question. In Section 4, I present my results on three different dimensions: First, I present these results across the entire United States as a whole; next, on a city-by-city level, showing where this relationship is stronger and where this relationship is weaker; and finally, I show how this impact differs across different racial groups. Section 5 of this paper concludes the research with a discussion on how I believe one should best interpret these relationships.

My results show that there is a statistically significant relationship between evictions and absolute upward mobility. When no controls are considered, a 10 percentage point increase in the eviction rate of a census tract is associated with an 8.2 income percentile rank decrease for children who were born at the 25th percentile of the income distribution. The relationship is still statistically significant even when considering controls and entity-fixed effects. Table 2 and Figure 1 in Section 4.1 summarize these key findings.

2 Data Sources

As mentioned, a key goal of this paper is to serve as an extension to Chetty et al.'s "Where Is the Land of Opportunity?" (2014) to assess the relationship between eviction rates and intergenerational mobility. Their research is completed using administrative data; that is, they use tax records provided by the Internal Revenue Service to record the incomes of more than 40 million children and their parents and assess how these outcomes compare to one another across time. (Details on this assessment is discussed in Section 3 below.) Given that this data is not publicly available, however, we are not able to asses the relationship between eviction rates and intergenerational mobility on an individual level. Instead, we take data provided by the Opportunity Insights website[2] which shows rates of intergenerational mobility on a census-tract level, which is publically available as it reduces the extent to which this information might be personally identifiable.

The Opportunity Insights group is a team of researchers and policy analysts based at Harvard University and led by Raj Chetty. From their website, we use the dataset on Household Income and Incarceration for Children from Low-Income Households by Census Tract, Race,

[2] Data from the Opportunity Insights webpage can be found on this link: https://opportunityinsights.org/data/

and Gender. The dataset contains more than 73,000 observations and includes 66 variables showing in fine detail the different rates of intergenerational mobility broken down by race, as well as incarceration rates. As they have shown in their research, this is a key correlate with intergenerational mobility, especially when considering within-city heterogeneity.

To obtain my data on eviction rates, moreover, we use Matthew Desmond's dataset compiled by his firm, The Eviction Lab, based at Princeton University.[3] The team has compiled this data using more than 80 million different records related to eviction. Only 12 states keep centralized court records of evictions. For the rest of the states, they used a variety of different sources, but primarily used two companies who maintain comprehensive datasets of public eviction records: LexisNexis Risk Solutions and American Information Research Services, Inc. The Eviction Lab has (in a similar fashion to Opportunity Insights) released data on the nature of evictions on a census tract level. In a somewhat different fashion, however, they have released this data on their website as a panel dataset, showing these variables by census tract as well as by year. Details on how this discrepancy in the types of datasets is accounted for is detailed in Section 3.2. The dataset contains variables on characteristics such as the actual number of evictions that take place, as well as the number of eviction filings that are completed per census tract per year.

3 Model

3.1 Definitions

To begin explaining how I quantify the relationship between "eviction" and "mobility," a brief discussion of how these terms are mathematically defined is warranted.

In Chetty et al. (2014), the researchers describe a variety different ways to measure economic mobility. They mention, for instance, a measure of intergenerational income elasticity defined as

$$IGE = \rho_{XY} \frac{SD(logY_i)}{SD(logX_1)} \tag{1}$$

which is equivalent to the coefficient value β_c when one regresses log-child income ($logY_i$) on log-parent income ($logX_i$). Though this is relatively simple to interpret as a measure of relative

[3] This research uses data from The Eviction Lab at Princeton University, a project directed by Matthew Desmond and designed by Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. The Eviction Lab is funded by the JPB, Gates, and Ford Foundations as well as the Chan Zuckerberg Initiative. More information is found at evictionlab.org.

mobility measured in income, it fails to consider how they fare *within their respective income distributions*, which leads to their definition of calculating *rank-rank slope* as a better way to interpret relative outcomes. This measure is defined as

$$\rho_{PR} = Corr(P_i, R_i) \tag{2}$$

where P_i is a parent i's percentile rank in the income distribution of parents and R_i is the same definition for a child i. Using this idea of "percentile rank" as a better measure, they then consider calculating absolute mobility, which they explain as the answer to the question when someone asks, "What are the outcomes of children from families of a given income level in absolute terms?" The answer to this question (in percentile rank terms) could best be described as

$$E[rank_k|rank_p] = \alpha + \beta * rank_p \tag{3}$$

which yields the expected child outcome conditional on their parents' income rank.

Similar to how Chetty et al. (2014) focus the majority of their analysis in their paper, for my purposes we will use the same definition of mobility they drive most of their attention to, which they define as "absolute upward mobility." This measure is equivalent to Equation (3), except that, as Chetty et al. (2014) do, we hold p constant at 25. Therefore, we will define "upward mobility" as the mean household income rank for children whose parents were at the 25th percentile of the income distribution. As mentioned earlier, these means are calculated on a census tract level; this will be the dependent variable in my regressions outlined in Section 3.3.

Furthermore, in order to account for the variation in gender for outcomes of upward mobility, I restrict my analysis of this data to males in the dataset. My focus on heterogeneity in this paper is not on gender, but on regions within the United States, different cities, and different races, as outlined in my results in Section 4.

Moreover, I use two levels to conceptualize how evictions across America are handled in Desmond's dataset. The first level is the actual eviction rate per census tract, which is defined as the "ratio of the number of renter-occupied households in an area that received an eviction judgment in which renters were ordered to leave." The second level is the eviction filing rate per census tract, which is defined as the "ratio of the number of evictions filed in an area over the number of renter-occupied homes in that area." Each of these are simple calculations defined as

$$eviction\_rate_i = \frac{\#ofevictionjudgments_i}{\#ofrenteroccupiedhouseholds_i} \tag{4}$$

$$eviction\_filing\_rate_i = \frac{\#ofevictionfilings_i}{ofrenteroccupiedhouseholds_i} \tag{5}$$

for each census tract i in my dataset.

The reason why I include these two levels is because they each have the potential to conceptualize the level of incomes for a certain census tract in different ways. For instance, a census tract with a high level of eviction filings but a much lower level of actual eviction rates might still be assumed to be a relatively low-income census tract. It would be beneficial, therefore, to understand how upward mobility is related to eviction filings as well as actual evictions, and to understand how these relationships are themselves related to one another.

3.2 Time and Space

Raj Chetty's dataset on intergenerational mobility and Matthew Desmond's dataset on eviction rates take on different formats. Specifically, Desmond's dataset is a panel dataset, including columns for each census tract as well as for each year between 2000-2016, while Chetty's has no time vector and simply includes the tract-level absolute upward mobility outcomes.

The only way possible to account for this discrepancy, then, is to filter the years in the Desmond's dataset for which child outcomes are measured in Chetty's dataset. According to the "Methods" section in the Opportunity Atlas[4], absolute upward mobility for children whose parents are at the $p = 25$ percentile of the income distribution is calculated for children born between 1978 and 1983, and their incomes are calculated for the years 2014–2015, when these children are between the ages of 31 and 37. Moreover, the "Methods" section of the Opportunity Insights website states that the census tracts individuals are assigned to are those that they lived in through age 23, i.e., in the years between 2001-2006. Therefore, in order to keep the time dimension of this data fixed, the eviction rate and eviction filing rates used are calculated as the average rates between 2001–2006.

The "Methods" section further explains how their outcome variables account for children who move across census tracts. According to the website, they "assign children to tracts in

[4] "Methods" section not from the Opportunity Insights webpage, but the Opportunity Atlas itself. Link: https://opportunityinsights.org/wp-content/uploads/2018/10/Atlas_methods.pdf

proportion to the amount of time they spent there during childhood. For instance, if a child spent half of their childhood and half in another, their outcomes would count half as much for each tract as the outcomes of a child who spent their entire life in either tract." This further reduces any discrepancies that may come up when considering how children often move across census tracts as they grow up.

3.3 Regression Analysis

I conduct multiple regressions to quantify the relationship between eviction rates and intergenerational mobility. Let Y_i = the mean absolute upward mobility for male children in census tract i as defined in Equation (3), and X_i = the average rate of evictions/eviction filings per census tract i in the years between 2001–2006. Using this notation, we estimate β_1 with the following regression

$$Y_i = \beta_0 + \beta_1 X_i + \phi_i + \epsilon_i \tag{6}$$

In Equation (6), ϕ is a set of census-tract level controls (race, median household income, median property value, rent burden, and incarceration rate) that are also calculated as the average between 2001–2006 (except for incarceration rate, which is taken from the Chetty dataset and defined as the "fraction of children born in 1978-1983 birth cohorts with parents at the 25th percentile of the national income distribution who were incarcerated on April 1st, 2010"). The ϵ_i is a standard error term for every census-tract i.

It should be expressed that, as the data is heteroskedastic, the standard errors reported in Section 4 are all robust standard errors. I could have fixed this before running my regressions by using a log-log transformation, but ultimately decided against it for sake of interpretation. Both a log-log regression as well as a level-level regression yield statistically significant estimates of β_1 anyways.

Moreover, to conduct a more robust analysis of the relationship between eviction rates and intergenerational mobility, we might want to account for potentially omitted variables that may further bias our estimate of β_1. We can attempt to control for this by using a fixed-effects regression model. As we have already held time constant, we only need to include entity-fixed effects. This model takes the form of

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \phi_i + \epsilon_i \tag{7}$$

where Z_i are unobserved heterogeneities across the entities we attempt to control for. In Section 4.1, I use two different kinds of entity-fixed effects: State-fixed effects and commuting zone-fixed effects. Standard errors reported are therefore clustered by each of these entities for their respective columns in Table 3 in Section 4.1.

At this point, it is important to remind the reader that the dependent variable for intergenerational mobility in Section 4.1 and 4.2 is a pooled calculation of all races for male children in my dataset. A race-by-race analysis in Section 4.3 will use each of the variables for racial intergenerational mobility outcomes in Chetty's dataset as the dependent variable.

A summary statistics table for each of the variables I use in my analysis of this data is produced below.

Table 1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
kfr_pooled_male_p25	62,880	0.412	0.076	−0.248	0.363	0.459	0.971
jail_pooled_male_p25	62,686	0.041	0.046	−0.566	0.013	0.062	1.129
kfr_black_male_p25	21,843	0.310	0.065	−0.305	0.269	0.344	0.822
jail_black_male_p25	18,862	0.111	0.078	−0.445	0.059	0.153	0.708
kfr_white_male_p25	57,117	0.449	0.078	−0.795	0.398	0.495	1.097
jail_white_male_p25	56,257	0.029	0.051	−1.044	0.004	0.049	1.212
kfr_hisp_male_p25	23,420	0.425	0.075	−0.266	0.381	0.464	1.017
jail_hisp_male_p25	20,856	0.031	0.051	−1.271	0.005	0.052	0.841
eviction.rate	62,880	0.028	0.031	0.000	0.008	0.036	0.427
eviction.filing.rate	62,880	0.061	0.082	0.000	0.015	0.071	0.981
pct.white	62,880	0.674	0.300	0.000	0.495	0.920	0.997
pct.af.am	62,880	0.127	0.222	0.000	0.008	0.122	0.996
pct.hispanic	62,880	0.135	0.202	0.000	0.016	0.151	0.994
pct.am.ind	62,880	0.007	0.041	0.000	0.001	0.005	0.986
pct.asian	62,880	0.037	0.071	0.000	0.003	0.036	0.912
pct.nh.pi	62,880	0.001	0.005	0	0	0.001	0
pct.multiple	62,880	0.016	0.014	0.000	0.007	0.021	0.673
pct.other	62,880	0.002	0.005	0.000	0.0003	0.002	0.332
median.household.income	62,880	48,020.460	21,797.780	0.000	33,361.480	57,879.330	216,667.700
median.property.value	62,880	171,025.700	129,123.000	0	87,600	214,266.7	1,000,001
rent.burden	62,880	0.269	0.054	0.000	0.236	0.298	0.501

4 Results

4.1 Overall

This section focuses on overall results. After removing outliers, removing NA values, and joining Desmond's dataset with Chetty's dataset, the analysis in this section uses about 63,000 census tracts that are left over from the roughly 73,000 that I started with.

Before detailing the quantitative relationship between eviction rates and absolute upward mobility, it would first help to see a visual summary of these results. Figure 1 summarizes this relationship with a bin scatter plot, showing how eviction rates are closely tied to mean income percentile outcomes for males born in the 25th percentile of the income distribution.

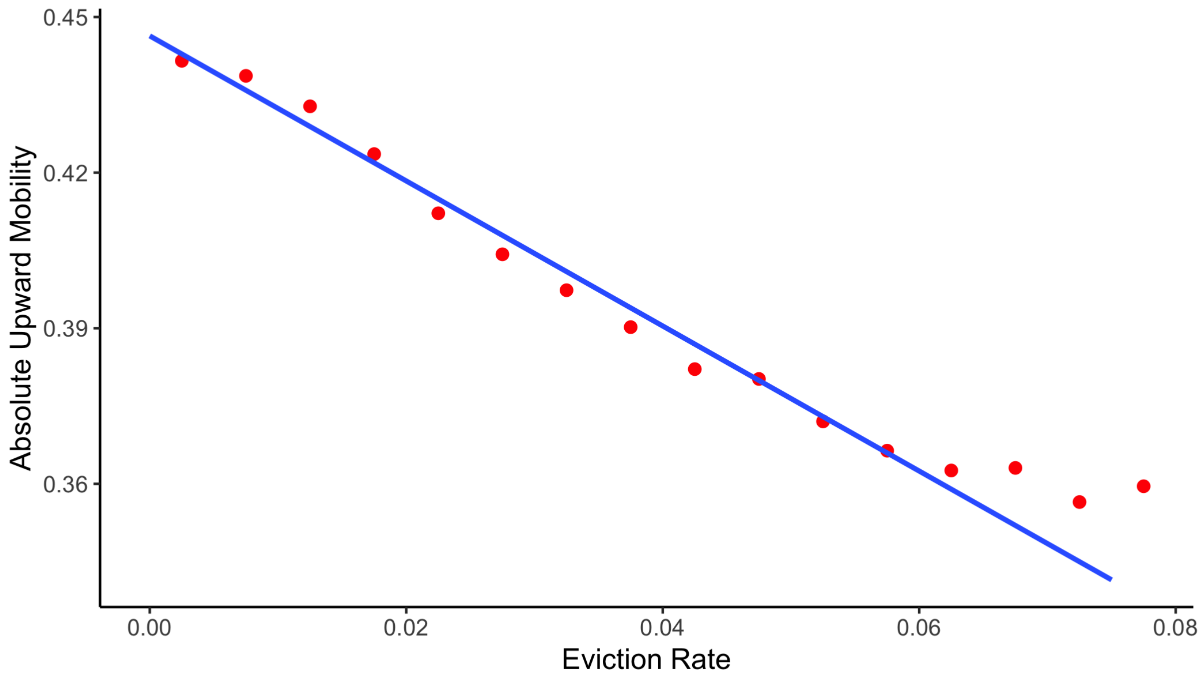

Figure 1: Bin scatterplot visualizing statistically significant negative relationship between eviction rate and absolute upward mobility per census tract

Moreover, Figure 2 on page 10 shows the relationship between eviction filing rates and absolute upward mobility. Compared to Figure 1, it should be noted that the slope is not as steep, though the output in Table 2 on page 12 suggests that the relationship is still statistically significant.

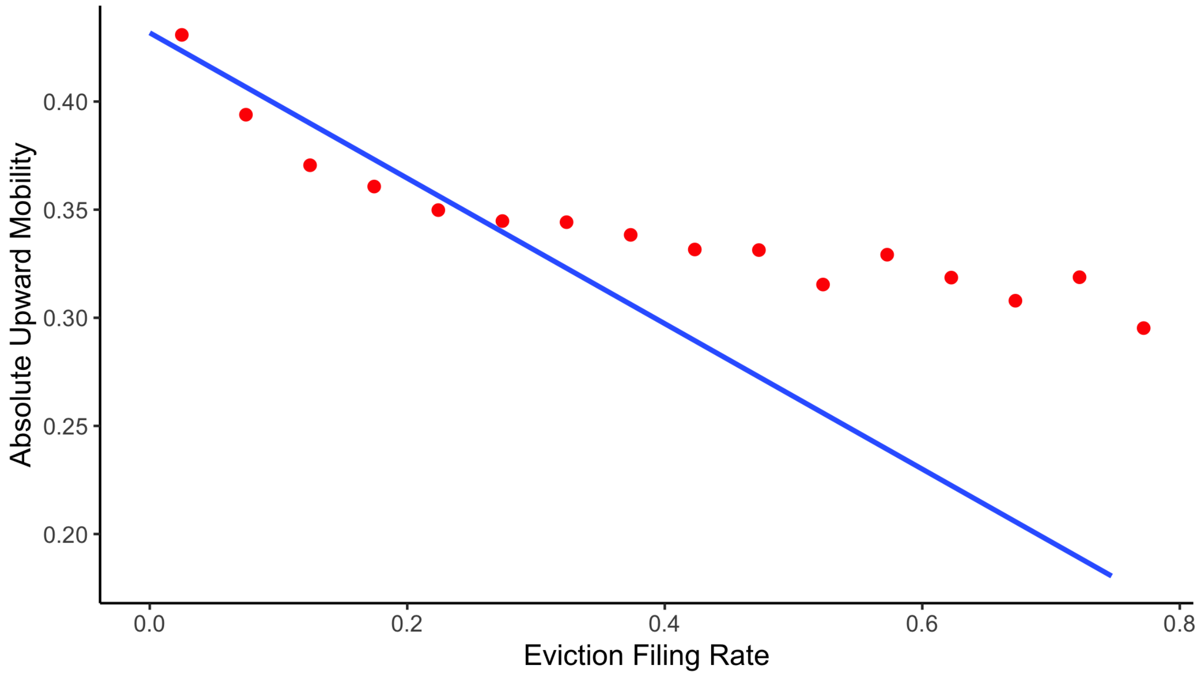

Figure 2: Negative relationship between eviction filing rate and absolute upward mobility per census tract

Echoing Figures 1 and 2 displayed above, Table 2 on page 12 suggests a statistically significant relationship between eviction rates and absolute upward mobility. Columns 1 and 2 show these results without any controls for eviction rates and eviction filing rates, respectively. Column 1 suggests that, on average, for every 10 percentage point increase in the eviction rate per census tract, the mean percentile income rank of male children who are born at the 25th percentile of the income distribution goes down by about 8 percentiles. Moreover, Column 2 suggests that, on average, the relationship between eviction filing rates and upward absolute mobility is somewhat weaker, with a 3 percentile decrease for every 10 percentage point increase in eviction filing rates. Columns 3 and 4 show that these results are still statistically significant even after controlling for variables such as race, property values, rent burdens, and incarceration rates. At this point, the reader should be reminded that the reported standard errors are robust to the heteroskedastic noise present in the data.

Note the relationship between eviction rates and eviction filing rates in Table 2. Intuitively, it might make sense that it would be the case that eviction rates have a stronger relationship to upward mobility as opposed to eviction filing rates. Echoing Leger's point in Section 1, this might be true given that the process of actually being evicted and removed from your home is an extremely disruptive life event.

Table 2: OLS and Multivariable Regression Output

	Dependent variable: kfr_pooled_male_p25			
	(1)	(2)	(3)	(4)
eviction.rate	−0.826***		−0.304***	
	(0.012)		(0.007)	
eviction.filing.rate		−0.318***		−0.087***
		(0.004)		(0.003)
pct.white			−0.042**	−0.039**
			(0.018)	(0.017)
pct.af.am			−0.164***	−0.157***
			(0.018)	(0.017)
pct.hispanic			−0.065***	−0.063***
			(0.018)	(0.017)
pct.am.ind			−0.156***	−0.149***
			(0.018)	(0.018)
pct.asian			0.094***	0.102***
			(0.018)	(0.018)
pct.nh.pi			−0.245***	−0.202***
			(0.051)	(0.053)
pct.multiple			−0.333***	−0.392***
			(0.025)	(0.025)
pct.other			0.199***	0.259***
			(0.047)	(0.050)
median.household.income			0.00000***	0.00000***
			(0.00000)	(0.00000)
median.property.value			−0.00000***	−0.000***
			(0.000)	(0.000)
rent.burden			−0.034***	−0.045***
			(0.005)	(0.006)
jail_pooled_male_p25			−0.301***	−0.317***
			(0.008)	(0.008)
Constant	0.435***	0.431***	0.461***	0.457***
	(0.0004)	(0.0004)	(0.018)	(0.017)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Using the entity-fixed effects model outlined in Equation (7), I further add entity-fixed effects to the controls used in Columns 3 and 4. Table 3 is a summary of these results, with columns 1 and 2 using eviction rate as the independent variable and columns 3 and 4 using eviction filing rate as the independent variable.

Perhaps somewhat intuitively, the coefficient values for eviction rates and eviction filing rates go down when controlling for state- and commuting-zone fixed-effects, though they are still deemed to be statistically significant. This suggests that, even when controlling for other factors that may be potentially omitted from my analysis, a very strong relationship between evictions and absolute upward mobility is still present. For every 10 percentage point increase in the eviction rate by census tract, the mean percentile rank goes down by about 2.3 percentiles in the state-fixed effects model, and by about 1.8 percentiles in the commuting zone-fixed effects model for children born at the 25th percentile of the income distribution. Similar to the results in Table 2, the relationship between the eviction filing rate and absolute upward mobility is weaker than the relationship between the actual eviction rate and absolute upward mobility.

When considering the coefficients in these fixed-effects regression models, it is important to remember that fixed-effects regression analyses are not the be-all-end-all for controlling for omitted variables. Though this is the best econometric tool I can employ to reduce the potential of ommitted variable bias, one may still reasonably suspect that more omitted variables that vary over time are present and still cause biased estimates of β_1. Nonetheless, the evidence presented in tables 2 and 3 suggests a highly significant relationship between eviction rates and upward economic mobility.

Table 3: State- and Commuting Zone-Fixed Effects Models

	Dependent variable: kfr_pooled_male_p25			
	(1)	(2)	(3)	(4)
	State-fixed	CZ-fixed	State-fixed	CZ-fixed
eviction.rate	−0.233***	−0.180***		
	(0.032)	(0.021)		
eviction.filing.rate			−0.070***	−0.057***
			(0.015)	(0.008)
pct.white	−0.047***	−0.044***	−0.046***	−0.044**
	(0.012)	(0.017)	(0.013)	(0.017)
pct.af.am	−0.165***	−0.173***	−0.163***	−0.171***
	(0.012)	(0.015)	(0.012)	(0.016)
pct.hispanic	−0.083***	−0.099***	−0.083***	−0.099***
	(0.015)	(0.021)	(0.016)	(0.021)
pct.am.ind	−0.184***	−0.205***	−0.179***	−0.204***
	(0.012)	(0.018)	(0.013)	(0.018)
pct.asian	0.088***	0.087***	0.090***	0.087***
	(0.020)	(0.016)	(0.020)	(0.017)
pct.nh.pi	−0.182	−0.134	−0.184	−0.135
	(0.131)	(0.094)	(0.140)	(0.097)
pct.multiple	−0.539***	−0.516***	−0.579***	−0.549***
	(0.109)	(0.068)	(0.120)	(0.072)
pct.other	0.099	0.011	0.097	0.009
	(0.079)	(0.066)	(0.085)	(0.068)
median.household.income	0.00000***	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
median.property.value	−0.000	−0.00000***	−0.000	−0.00000***
	(0.000)	(0.000)	(0.000)	(0.000)
rent.burden	−0.014	0.002	−0.021	−0.004
	(0.013)	(0.006)	(0.014)	(0.006)
jail_pooled_male_p25	−0.298***	−0.266***	−0.306***	−0.271***
	(0.014)	(0.012)	(0.015)	(0.012)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.2 City-by-City Analysis

My goal in this section is to lay out the heterogeneity in β_1 that exists in the relationship between eviction rates and absolute upward mobility across the United States. In the spirit of Chetty et al. (2014), here I describe the commuting zones where this relationship is strongest as well as commuting zones where this relationship is weakest. This heterogeneity is discussed in greater detail in my conclusion in Section 5.

By "strong" and "weak," I am considering the value of β_1 when X = eviction rate, i.e. I am not considering the eviction filing rate in this section. I'm considering the "stronger" relationships to be those where β_1 is greater, and "weaker" relationships to be those where β_1 is lesser. Additionally, in this section I'm only using a regular OLS regression with no controls similar to the models I used in columns (1) and (2) from Table 2 in Section 4.1. Moreover, as in Section 4.1, my dependent variable is still the absolute upward mobility rates for males of all races born at the 25th percentile of the household income distribution. An analysis of racial heterogeneity follows in Section 4.3.

Table 4 below shows the top 10 cities with the weakest relationship between eviction rates and absolute upward mobility, whereas Table 5 shows the top 10 cities with the strongest relationship. For the purposes of this analysis, I define "city" here as those commuting zones with populations of at least 1,000,000 people.

Table 4: Weakest Values of β_1

	City	Estimated Value of β_1
1	Chicago, IL	0.50
2	Atlanta, GA	-0.09
3	Washington DC	-0.25
4	Las Vegas, NV	-0.29
5	Jackson, MS	-0.32
6	Phoenix, AZ	-0.37
7	Denver, CO	-0.38
8	Tucson, AZ	-0.53
9	Indianapolis, IN	-0.56
10	Jacksonville, FL	-0.71

Table 5: Strongest Values of β_1

	City	Estimated Value of β_1
1	San Francisco, CA	-2.83
2	Birmingham, AL	-2.49
3	Sacramento, CA	-1.97
4	Fresno, CA	-1.89
5	San Diego, CA	-1.79
6	Bridgeport, CT	-1.77
7	Springfield, MA	-1.69
8	Columbus, OH	-1.44
9	St. Louis, MO	-1.34
10	Port St. Lucie, FL	-1.27

4.3 Racial Group Analysis

This section of my paper focuses on the heterogeneity of the relationship between eviction rates and intergenerational mobility as it relates to race.

Perhaps the first methodological quirk to consider in this analysis is to think about the fact that some census tracts have very few representations of certain racial groups, and therefore conducting an analysis of the relationship between eviction rates and absolute upward mobility might be somewhat difficult. However, Chetty's dataset from Opportunity Insights simply omits any values of upward mobility for certain races if they are not represented well-enough in the census block. Therefore, the way I analyze the heterogeneity for, say, Black males across America, is simply by omitting values in the dataset for which the value of absolute upward mobility for Black males is classified as NA.

The regression model I take on in this section is similar to Equation (6), though I have four different dependent variables indicating absolute upward mobility for White, Black, and Hispanic males. Tables 6-8 display these results accordingly, with heteroskedastic-robust standard errors as in Section 4.1. Moreover, I've removed the race controls while keeping controls for household incomes, property values, and rent burden. In addition, the control for incarceration rates in this section is still the pooled incarceration rates per census tract for males of all races. I made this decision on the basis that it is more valuable to consider, say, the average outcome of White males if they live in a place with high incarceration rates, even if the probability of being incarcerated disproportionately falls on minorities.

Table 6: Outcomes for White Males

	Dependent variable: kfr_white_male_p25			
	(1)	(2)	(3)	(4)
eviction.rate	−0.641***		−0.390***	
	(0.012)		(0.010)	
eviction.filing.rate		−0.203***		−0.118***
		(0.005)		(0.004)
median.household.income			0.00000***	0.00000***
			(0.00000)	(0.00000)
median.property.value			0.00000***	0.00000***
			(0.000)	(0.000)
rent.burden			−0.068***	−0.079***
			(0.007)	(0.007)
jail_pooled_male_p25			−0.294***	−0.313***
			(0.012)	(0.012)
Constant	0.467***	0.460***	0.436***	0.434***
	(0.0005)	(0.0004)	(0.002)	(0.002)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6 shows that, for every 10 percentage point increase in the eviction rate, the expected decrease in the percentile rank for white males on a census-tract level is about 3.9 percentiles on the income distribution when controls are included. This is the strongest negative relationship among the three races included in this analysis. For Black males (Table 7), the associated expected decrease for a 10 percentage point increase in eviction rates is only about 1 percentile, and for Hispanic males (Table 8) the decrease is about 2.7 percentiles. A deeper analysis of this heterogeneity is outlined in my conclusion in Section 5.

Table 7: Outcomes for Black Males

	Dependent variable: kfr_black_male_p25			
	(1)	(2)	(3)	(4)
eviction.rate	-0.256^{***}		-0.099^{***}	
	(0.011)		(0.009)	
eviction.filing.rate		-0.064^{***}		-0.015^{***}
		(0.003)		(0.003)
median.household.income			0.00000^{***}	0.00000^{***}
			(0.00000)	(0.00000)
median.property.value			0.000^{**}	0.00000^{***}
			(0.000)	(0.000)
rent.burden			-0.043^{***}	-0.051^{***}
			(0.009)	(0.009)
jail_pooled_male_p25			-0.310^{***}	-0.317^{***}
			(0.009)	(0.009)
Constant	0.320^{***}	0.316^{***}	0.308^{***}	0.307^{***}
	(0.001)	(0.001)	(0.003)	(0.004)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Outcomes for Hispanic Males

	Dependent variable: kfr_hisp_male_p25			
	(1)	(2)	(3)	(4)
eviction.rate	−0.461***		−0.274***	
	(0.016)		(0.015)	
eviction.filing.rate		−0.149***		−0.074***
		(0.006)		(0.006)
median.household.income			0.00000***	0.00000***
			(0.00000)	(0.00000)
median.property.value			−0.00000***	−0.000*
			(0.000)	(0.000)
rent.burden			−0.071***	−0.086***
			(0.012)	(0.012)
jail_pooled_male_p25			−0.289***	−0.308***
			(0.015)	(0.015)
Constant	0.439***	0.434***	0.429***	0.430***
	(0.001)	(0.001)	(0.004)	(0.004)
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Conclusion

Chetty et al. (2014) discuss five key factors that are most highly correlated with absolute upward mobility: segregation, inequality, school quality, social capital, and family structure. All of these variables seem to be related to one another (family structure and school quality, for example), and the researchers argue that there may be a causal link to establish between these factors and intergenerational mobility. Nowhere in the paper, however, is there any mention of broader urban trends such as urban displacement, gentrification, and evictions.

My hope in sharing this research is that evictions in America are considered as yet another key correlate with intergenerational mobility. In that sense, this ought to serve as an extension to Chetty et al.'s (2014) original analysis of "the Land of Opportunity." I believe that this insight should shed a new moral light on how one thinks about these broader urban trends, as it should force one to think more carefully the impact evictions and urban displacement may have on future outcomes. I also believe that this is a very timely discussion, given the housing crisis that affects many of America's wealthiest cities (albeit disproportionately), including Boston. Moreover, my hope is that I've given enough proof that there is a significant link between eviction rates and upward mobility on a census-tract level.

Perhaps the most interesting part of this research was the heterogeneous estimates of β_1 when considering different commuting zones, as well as different races. The cities with the strongest values of β_1 might have been expected from the beginning of this paper. San Francisco, CA, had the strongest relationship: For every 10 percentage point increase in eviction rates, the associated drop in income percentile rank was about 28 percentiles. Additionally, four out of the top five cities in this ranking were in California, where housing is known to be very expensive. Meanwhile, the places with the smallest relationship were cities including Chicago, IL; Atlanta, GA; Jackson, MS; and Jacksonville, FL. A particular irony with this finding, in my opinion, is that places on Chetty's map where upward mobility is lower, such as Jackson and Atlanta, have smaller values of β_1 than places on Chetty's map where mobility is higher, like San Diego and San Francisco. This may be indicative of the fact that in some places, those other correlates mentioned in Chetty et al. (2014), such as segregation or income inequality, have a stronger predictive power of upward economic mobility than eviction rates alone.

To make sense of the heterogeneity in races, there are a variety of paths one might take. The regression output might suggest that there is a stronger negative impact on eviction rates for White males than for Black or Hispanic males. I question this result for two reasons. First, in my analysis of the relationship between eviction rates and upward mobility, we omit any analysis of the uneven distribution of evictions in America. A future study might aim to weigh eviction rates appropriately. Second, in my analysis, though Chetty's dataset provides variables for economic outcomes on a racial level, Desmond's dataset only provides census-tract level evictions, further making it difficult to establish the true relationship on a race-by-race basis. A future project might aim to get this data and/or make it publicly available for the benefit of social scientists everywhere.

Finally, I would also want to make clear that I have been very careful to exclude any discussion of a causal relationship. I did the best I could do with the publicly available data: I established a simple relationship using census-tract level data. I believe that, with a finer dataset on an individual level, establishing a causal link could be more easily completed with something like a regression discontinuity design. This would surely be a more exciting, more provocative study for someone to take on in the future.

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