ESSAYS ON RESIDENTIAL SORTING, SCHOOL QUALITY, CRIME, AND INCOME MOBILITY

by

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Abstract

This dissertation is composed of three chapters. The first chapter demonstrates that local improvements in school quality and crime are not always beneficial to the households that reside there, once equilibrium effects are taken into account. The model of residential location choice presented here takes into account the endogenous adjustments of neighborhood composition, housing prices, school quality and crime. The estimation uses data from the American Community Survey and detailed data on local school quality and crime in the greater San Francisco area for the years 2009-2013. Results show that household sorting reinforces exogenous improvements in school quality and crime and that the effects of these improvements can be detrimental to the residents. Lower-income, less educated households are particularly likely to be adversely affected.

The second chapter provides estimates of the relationship between school quality and student body composition, taking into account the selection of students into different schools. The model of residential location choice presented in this chapter shows how characteristics of nearby locations can be used to control for household residential location decisions. The two-step estimation procedure uses data from the California Department of Education on the academic performance of California Schools for 2011 and the American Community Survey data on the characteristics of residential locations. The results show significant differences between the effects of student body composition on students of different races, and at worst- and best-performing schools.

The third chapter presents estimates of the distribution of intergenerational income mobility and local characteristics in the United States. The flexible characterization of the distribution takes into account potentially different effects of local characteristics at different locations in the distribution. The data cover most counties in the United States and include demographic, social and economic variables. Results show that while measures of segregation and inequality are highly correlated with income mobility, their effects become negligible when other variables are controlled for. In contrast, economic variables, such as the size of the middle class and the share of workers in manufacturing, have a stronger effect on income mobility, even after other location characteristics are taken into account.

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Chapter 1

School Quality, Crime, and Residential Sorting in an Equilibrium Framework

1.1 Introduction

After decades of declining populations, American cities are growing faster than the suburbs for the first time in half a century. Middle and upper-class neighborhoods are growing in number and size across areas of cities affluent Americans recently avoided. This influx comes with economic benefits and improvements in neighborhood amenities, but also a displacement of less affluent groups, reinforcing residential segregation (Biro (2007)). Cities eager to attract affluent residents have focused on improving schools and reducing crime, hoping for economic benefits. This paper demonstrates that while such improvements may transform city neighborhoods, they can often have adverse effects on the original residents of these neighborhoods.

Racial and ethnic stereotypes, crime, property values, school quality, and other local amenities all influence household choices about where to live and which neighborhoods to avoid. According to the most recent General Social Survey nearly 20% of white Americans would not live in a neighborhood where half of their neighbors were black. And while the relative growth of American city centers is new, residential segregation and its consequences have been a part of American public discourse for a long time, with the discussion of the "culture of poverty" in America's cities and the Coleman report on segregation in America's schools dating from the 1960s. Today, programs seeking to change the patterns of residential sorting are in place across the country, ranging from community-based business initiatives to tax incentives for businesses and households. Despite this, the full effect of even the most basic policy interventions on residential sorting remains poorly understood.

The main difficulty in understanding residential sorting arises from the fact that many neighborhood amenities, such as school quality and crime, are themselves determined in part by the kinds of households that live in a given neighborhood. Econometrically speaking, school quality and crime are determined simultaneously with the residential location of households, thus any study that aims to uncover the causal effects between these factors must confront the endogeneity that results from this simultaneity. To overcome this challenge this paper uses a novel approach based on the urban geography in order to estimate the causal effects of endogenously determined school quality and crime in an equilibrium model of residential sorting where school quality, crime and location decisions of households are made simultaneously. This work provides important insight into the feedback between residential sorting and neighborhood amenities and the role that public policy plays in shaping the outcomes of residential location decisions.

The essential approach is to use the variation in the geographic scale of different amenities to overcome the problem of simultaneous causality. The urban landscape incorporates many amenities over which individuals have preferences, key among them the socio-economic composition, school quality and crime in the individual's neighborhood of choice. The assumption underlying the estimation strategy is that socio-economic composition of a neighborhood only matters in close proximity to the residential location of choice, while crime is determined on a larger scale as it often spills over from neighborhood to neighborhood, and school quality is determined at the school rather than neighborhood level. These assumptions are supported by an examination of the data. The residential sorting model that incorporates these different geographic scales leads naturally to the kinds of exclusion restrictions that are necessary for estimation in the presence of simultaneous causality between variables.

The model in this paper builds on product choice models of Berry, Levinsohn, and Pakes (2004) and a residential sorting model of Bayer, Ferreira, and McMillan (2007) to describe the equilibrium sorting model of the housing market. This model describes a market equilibrium in the housing market where demand is a result of a social interactions equilibrium between households. The social interactions component is crucial because it allows the model to capture feedback between neighborhood composition and neighborhood amenities that produce the social multiplier effect discussed at length in the social interactions literature (Moffitt et al. (2001) and Brock and Durlauf (2001)).

The results presented in this paper show that the social interactions component of the equilibrium is extremely important. Exogenous improvements in school quality and crime are augmented by the equilibrium process as households adjust to the changes. The endogenous response of school quality and crime further reinforce this process. Small initial changes are amplified in the equilibrium framework, much more so than in a model that does not allow for the endogenous changes in school quality and crime. These results align with the theoretical predictions that small policy interventions may be able to "tip" neighborhoods towards significant improvements in crime and school quality.

The second set of results shows that improvements in school quality and crime are not always beneficial for the current residents of a neighborhood. Despite the apparent direct benefit of these improvements, the equilibrium process often leads to households locating in other, less desirable, neighborhoods. Improvements in both school quality and crime have results on the residents that vary significantly across neighborhoods and households, with lower income and less educated households most likely to suffer the largest adverse effects. The relative unpredictability and potential harm from seemingly benign interventions highlight the complexity and the importance of understanding the residential sorting process and all of the factors contributing to it.

1.2 Related literature

There is an extensive theoretical literature in economics dealing with the mechanics of residential sorting and the causes of segregation going back to the work of Tiebout (1956) and Schelling (1969), (1971). Schelling's work emphasizes the role of preferences for neighborhood racial composition in creating racially segregated neighborhoods. In contract Tiebout's model focuses on varying preferences for local public goods, with households sorting across communities that offer different levels of a public good. In both cases follow up work has shown that even minor differences in preferences or in initial endowments in households can lead "neighborhood tipping" from being integrated to being completely segregated (Anas (1980) and Epple, Filimon, and Romer (1984)). The theoretical predictions of these models, combined with casual observation of the worsening patterns of residential segregation in the last three decades have led researchers to focus on empirical studies of the causes and consequences of segregation.

There is mounting evidence about the negative consequences for households that end up in isolated, poor, and unsafe neighborhoods. Many studies find that minority households who live in segregated metropolitan areas have lower educational attainment and lower earnings than their counterparts in more integrated areas. The association between segregated environments and minority disadvantage is driven in part by physical isolation of minority neighborhoods from employment opportunities and in part by harmful social interactions within minority neighborhoods, especially due to concentrated poverty (Boustan (2013)). Ioannides (2002) provides a survey of many neighborhood effects and social interaction effects that have been found to contribute to individual outcomes. Massey and Denton (1993) document how the perpetuation of residential segregation leads to geographic concentration of indigence and the deterioration of social and economic conditions in black communities. This leads to changes in attitudes, behaviors, and practices that further marginalize neighborhoods and drastically reduce the chance of positive individual economic, schooling or labor market outcomes.

There are two strands of literature on residential sorting that aim to explain the patterns of residential segregation, and the framework used in this paper is related to both of them. The literature on hedonic price models focuses on recovering household willingness-to-pay measures for various neighborhood amenities and housing characteristics. Typically households are assumed to be able to buy any level of any amenity or characteristic and the focus is on estimating an equilibrium price function. Early work in this literature includes Rosen (1974) and Epple (1987), while Ekeland, Heckman, and Nesheim (2003) is a more modern example. The second strand of literature is on discrete choice models, starting with the seminal work by McFadden et al. (1973). Developed further by Bresnahan (1987) and Berry, Levinsohn, and Pakes (1995) this literature focuses on how individuals make decisions when presented with a discrete number of alternatives. Importantly, discrete choice models do not assume that the individual may choose any level of a product characteristic, requiring the individuals instead to pick the product with the best "bundle" of characteristics.

Equilibrium sorting models describe a market equilibrium in which demand is a result of a sorting process involving households. These models can be used to develop theoretically consistent predictions for the results of policy interventions without being restricted to marginal effects or a partial equilibrium setting. By incorporating the feedback between the housing market and the social interactions that play a role in household sorting an equilibrium sorting model captures the full market and non-market response of households to exogenous shocks. These feedback effects can have first-order policy implications and can lead to the kinds of results mentioned earlier in which policies aimed at reducing neighborhood segregation achieve the opposite results (Cornes and Hartley (2007)). Given how active policymakers have been in introducing programs to reduce neighborhood segregation and improve the worst neighborhoods it is extremely important to develop an understanding of the feedback effects between the housing market and the sorting process that determines neighborhood composition.

One of the first equilibrium sorting models is that of Epple and Sieg (1998). Their model expands the hedonic price framework to incorporate the household sorting process. Households can still choose any level of amenities, but the choices of other households now enter into their consideration. A model that builds more closely on the discrete choice framework is that of Bayer, Ferreira, and McMillan (2007) where households are required to pick from one of the available houses in a metropolitan area. Bayer and Timmins extend the framework of Berry, Levinsohn, and Pakes (1995) to incorporate the household sorting process. These two equilibrium sorting models have remained the basis for most subsequent work in this area (see Kuminoff, Smith, and Timmins (2013) for a recent survey).

The model used here builds on that of Bayer, Ferreira, and McMillan (2007). This previous work focused on estimating household preferences for different neighborhood amenities and housing characteristics. In these models prices and neighborhood socio-economic composition are endogenously determined as part of the sorting process, but all other neighborhood amenities are exogenously fixed. This means, in particular, that levels of crime and the quality of schools do not change in the process of counterfactual policy evaluation, even when neighborhood composition changes significantly. Bayer, Ferreira, and McMillan (2007) attempt to bound the possible error, but since neighborhood sorting is not a monotonic process, the bounds are not necessarily informative.

The focus of this paper is specifically on being able to evaluate the impact of policies related to neighborhood composition, school quality, and crime on the way households sort across neighborhoods. The strategy is to incorporate endogenous adjustments of key variables in response to the sorting process. It is similar to the use by Epple and Sieg (1998) of two distinct levels of aggregation in their model. More closely it is related to the literature on estimation of social interactions in groups and social networks such as Brock and Durlauf (2001) and Bramoulle, Djebbari, and Fortin (2009). This econometric strategy requires finding characteristics of exogenous groups or neighbors that are sufficiently far removed to not directly influence the endogenous variables but are close enough to have an indirect effect. It is described in detail bellow.

1.3 Model

Traditional product choice models incorporate a market equilibrium between supply and demand in which supply is determined by a Nash equilibrium of a game between different producers. The model presented here incorporates social interactions by making demand a result of a Nash equilibrium between consumers while holding supply fixed. It is one of the very few models to incorporate both a market equilibrium and a social interactions equilibrium, and additionally, includes endogenous adjustment of key variables that determine the equilibrium outcome. The model is an extension of the model studied in Bayer, Ferreira, and McMillan (2007), which itself is based on the product choice model of Berry, Levinsohn, and Pakes (1995).

A metropolitan region is composed of $j = 0, ..., J$ neighborhoods. Each of $i = 1, ..., N$ households must choose one of the neighborhoods to be its residential location. The region is self-contained so that living outside of the region is not an option for the households. Households differ in terms of their socio-economic characteristics described by an r-vector Z_i. Each neighborhood provides a bundle of amenities which are divided into different categories. Exogenous amenities are described by a t-vector X_j. The socio-economic composition of the neighborhood is described by an r-vector $\bar{Z}_j$ containing the average value of Z_i for households that chose to live in the neighborhood. The level of crime in the neighborhood is c_j. The measure of the quality of the schools corresponding to the neighborhood is $s_{s(j)}$. Relative housing prices in a neighborhood are p_j. Unobservable neighborhood quality is ξ_j. The neighborhood that household i chooses as its residential location is denoted Y_i.

Neighborhoods are smaller than school catchment areas, so multiple neighborhoods are assigned to the same schools. Neighborhood j together with the set of neighborhoods that share the same school district is $s(j)$. School quality is determined at the school rather than at the neighborhood level, so all neighborhoods in $s(j)$ contribute to the determination of the common school quality.

Neighborhoods are also smaller than geographic areas relevant for determining crime due to the propensity of crime to spill over from neighborhood to neighborhood (Byrne and Sampson (1986)). Neighborhood j together with the set of neighborhoods that are in close proximity to it is $c(j)$. All neighborhoods in $c(j)$ contribute to the determination of crime in neighborhood j.

The utility of household i from choosing neighborhood j depends on household preferences α_i, all of the amenities of the neighborhood, and an idiosyncratic term $\epsilon_{i,j}$:

$$u_{i,j} = \alpha_{X,i} X_j + \alpha_{p,i} p_j + \alpha_{\bar{Z},i} \bar{Z}_j + \alpha_{c,i} c_j + \alpha_{s,i} s_{s(j)} + \xi_j + \epsilon_{i,j} \tag{1.1}$$

Households are heterogeneous in their preferences which vary with household socio-economic characteristics. The preference of household i for school quality is $\alpha_{s,i} = \alpha_{s,0} + \alpha_s Z_i$ and analogously for other coefficients. Household i chooses neighborhood j if the utility from that neighborhood exceeds the utility from all other neighborhoods: $u_{i,j} > u_{i,k}$ for all $k \neq j$. If $v_{i,j}$ is the non-idiosyncratic part of the utility this implies $\epsilon_{i,j} - \epsilon_{i,k} > v_{i,k} - v_{i,j}$ for all $k \neq j$. Therefore the probability that household i chooses neighborhood j, $P_{i,j}$, depends on household characteristics and the observed and unobserved amenities of all neighborhoods: $P_{i,j} = f(Z_i, X, \bar{Z}, c, s, p, \xi)$. The functional form of $f(.)$ depends on the distribution of ϵ. When ϵ are distributed i.i.d. Extreme Value Type I the expression for choice probabilities takes the closed form:

$$P_{i,j} = \frac{exp(\alpha_{X,i}X_j + \alpha_{p,i}p_j + \alpha_{\bar{Z},i}\bar{Z}_j + \alpha_{c,i}c_j + \alpha_{s,i}s_{s(j)} + \xi_j)}{\sum_{k=1}^{J} exp(\alpha_{X,i}X_k + \alpha_{p,i}p_k + \alpha_{\bar{Z},i}\bar{Z}_k + \alpha_{c,i}c_k + \alpha_{s,i}s_{s(k)} + \xi_k)} \tag{1.2}$$

Crime and school quality depend in part on the socio-economic composition of the neighborhood and are determined by the sorting process. There is little theoretical or empirical work that would justify excluding variables from determining crime and school quality a priori. In the model all amenities of certain neighborhoods can contribute to crime and school quality. In the case of school quality, it is all neighborhoods that share the same schools, and in the case of crime it is all neighborhoods in close proximity to the neighborhood in question:

$$c_j = \beta_X X_{c(j)} + \beta_{\bar{Z}}\bar{Z}_{c(j)} + \eta_j \tag{1.3}$$

$$s_{s(j)} = \gamma_X X_{s(j)} + \gamma_{\bar{Z}}\bar{Z}_{s(j)} + \nu_{s(j)} \tag{1.4}$$

Neighborhood socio-economic composition is also determined by the sorting process. The composition can be written in terms of the probability that households with any given household characteristics chose a given neighborhood. Let $F(Z_i)$ denote the CDF of household characteristics. Equation (2) gives the probability that a household with characteristics Z_i chooses neighborhood j. Together with $F(Z_i)$ this means that average neighborhood socio-economic characteristics can be written as:

$$\bar{Z}_j = \int Z_i P_{i,j} dF(Z_i) \tag{1.5}$$

Prices are set by a market-clearing condition. It is assumed that the number of residences in the neighborhoods is fixed, and neighborhoods cannot accommodate more households than currently reside there. This rules out long-term changes to the types of housing available in the neighborhoods. Let σ_j denote the share of all residences that are in neighborhood j. For the housing market to clear the supply of residences in neighborhood j must equal the demand: $\sigma_j = \int P_{i,j} dF(Z_i)$. This market-clearing condition gives rise to a vector of prices for every neighborhood. Proposition 1 is a direct application of the central result of Berry (1994) and its proof is in the appendix.

Proposition 1: Conditional on X, $\bar{Z}$, s, c, and ξ there exists a unique to scale vector of prices p^* such that $\sigma_j = \int P_{i,j} dF(Z_i)$. This vector is continuous in X, $\bar{Z}$, s, c, and ξ.

The market-clearing prices p^* are functions of all neighborhood amenities of all neighborhoods and of the distribution of household characteristics. These prices adjust to ensure that the fraction of households demanding residences in any neighborhood is equal to the fraction of residences that are in that neighborhood. For any given set of neighborhood amenities and household characteristics, there is only one such set of prices.

The next step is to establish the existence of an equilibrium in the model. Given values for the exogenous amenities, household characteristics, and shares of residences in each neighborhood an equilibrium is a set of choice probabilities and associated values of endogenous amenities that justify the choice probabilities. In equilibrium, each household makes its optimal location decision given the location decisions of all other households.

Definition: An equilibrium in the model is a set of choice probabilities $P^*_{i,j}$ and a set of prices p^* such that the housing market clears according to $\sigma_j = \int P_{i,j} dF(Z_i)$ and $P^*_{i,j}$ are a fixed point of the mapping in equation (2) where c_j is determined according to equation (3), s_j according to equation (4), and $\bar{Z}_j$ according to equation (5).

Proposition 2: If the assumptions of Proposition 1 hold then an equilibrium exists.

The proof of the proposition used Brower's Fixed Point Theorem and is straight forward. It can be found in the appendix.

The existence of an equilibrium guarantees that for any combination of exogenous variables Z, X, ξ, σ there exists an equilibrium of the model. The model will predict self-consistent patterns of location choices for households for any new values of these exogenous variables along with new values of the endogenous variables. This allows for the evaluation of counterfactual scenarios that could not be evaluated without estimating the equilibrium model with endogenous variables.

The uniqueness of equilibrium is not generally a property of models with social interactions. The model could have multiple equilibria, and the number of equilibria depends on the values of parameters of the model. In general, if household preferences for exogenous amenities are strong relative to endogenous ones, then a unique equilibrium will arise, but not otherwise. The number of equilibria of a related model is studied by Brock and Durlauf (2001). As with other models that do not have a unique equilibrium, it is assumed that the equilibrium does not change during the evaluation of counterfactual experiments.

1.4 Estimation

The estimation method is a two-step procedure using detailed data on $F(Z)$, σ, and all neighborhood amenities to estimate the parameters of the model. Although data on the residential location choice of individual households are available, it is not used in the estimation for a number of reasons. As a result of privacy concerns, data that contain residential location choices are much less detailed than data that do not. Additionally, the Census intentionally changes the residential location of some households to some other similar locations. Instead of using location data, this paper uses the method described in Berry, Levinsohn, and Pakes (2004) to combine macro and micro data to estimate the model.

The BLP (2004) method follows work by Petrin (2001) and Imbens and Lancaster (1994) on combining macro and micro data. These methods combine a model of micro decision-making, data on the characteristics of the decision makers, and data on the characteristics and market shares of available choices to estimate preference parameters. For these methods, it is crucial that the market share data are known precisely, which is the case with σ in the Census data described in the next section.

For the purposes of estimation, it is convenient to re-write equation (1) as

$$u_{i,j} = \delta_j + \alpha_X Z_i X_j + \alpha_p Z_i p_j + \alpha_{\bar{Z}} Z_i \bar{Z}_j + \alpha_c Z_i c_j + \alpha_s Z_i s_{s(j)} + \epsilon_{i,j} \tag{1.6}$$

$$\delta_j = \alpha_{X,0} X_j + \alpha_{p,0} p_j + \alpha_{\bar{Z},0} \bar{Z}_j + \alpha_{c,0} c_j + \alpha_{s,0} s_{s(j)} + \xi_j \tag{1.7}$$

The δ_j in equation (7) captures the mean indirect utility that each of the neighborhoods provides to every household, and equation (6) shows how the utility of each neighborhood varies with the characteristics of the household.

Equation (6) is a traditional discrete choice model with choice-specific constants δ_j. It can be estimated from micro data on $F(Z)$ and data on σ given an assumption on the distribution of ϵ, such as in Pakes, Berry, and Levinsohn (1993). Parameters in equation (7) have to be estimated from neighborhood-level data and require an assumption about ξ. Nevo (2000) provides a number of different assumptions on the joint distribution of (X, ξ) that ensure identification of parameters in equation (7). This paper follows Nevo in assuming ξ are continuously distributed with means zero, are independent across j and are independent of X and Z.

1.4.1 First Step

The first step of the estimation procedure is to estimate parameters in equation (6). This is done by matching three sets of moments predicted by the model to the data. The first set of moments follows from equation (6) and is made up of the covariances of the neighborhood characteristics and household characteristics. For example the covariance of the average number of bedrooms in a house in the neighborhood with the average household income in that neighborhood. A separate moment condition for each interaction term in the utility specification is included. The second set of moments are the market shares of the different neighborhoods σ_j.

For any set of parameters (α, δ) the model predicts choice probabilities for each household according to equations (6) and (2). These choice probabilities are used to compute predicted neighborhood socio-economic characteristics for each neighborhood, $\bar{Z}(\alpha, \delta)$ according to equation (5). The first set of sample moments is formed by interacting these socio-economic characteristics with neighborhood characteristics $X, p, \bar{Z}, c, s$ and averaging according to the sample neighborhood market shares:

$$G^1_{x,z}(\alpha, \delta) = \sum_j \sigma_j x_j (\bar{z}_j - \bar{z}_j(\alpha, \delta)) \tag{1.8}$$

In computing $\bar{Z}(\alpha, \delta)$ according to equation (5) the Census-provided estimates of $F(Z)$ are used. Because $\bar{Z}_j$ provided by the Census are themselves functions of the same $F(Z)$ this is unlike other similar estimation procedures which use survey data on $F(Z)$. In this case, the $F(Z)$ that give rise to $\bar{Z}_j$ is known exactly.

Included in X is the commute time for each household. Because the employment location for each member of the household is known, the total commute time will vary from one household to the next even if the two households pick the same location. The moment condition for commute time matches the predicted average commute to the observed average commute for the households, and then averages across neighborhoods using weights σ.

The second set of moments are the market shares of the different neighborhoods. As with the first set of moments, the model predicts neighborhood market shares for any set of parameters (α, δ). These are calculated according to $\sigma_j(\alpha, \delta) = \int P_{i,j} dF(Z_i)$ using $P_{i,j}$ in equation (2). The J moment conditions are:

$$G_j^2(\alpha, \delta) = \sigma_j - \sigma_j(\alpha, \delta) \tag{1.9}$$

The computational burden of searching for J elements of δ makes a direct estimation of these parameters impossible. Typically, the contraction mapping provided by Berry, Levinsohn, and Pakes (1995) is used to estimate δ as a function of α instead. Berry (1994) shows that the mapping between σ and δ is one-to-one for any given α. This makes it possible to choose parameters α and then use the observed market shares σ to solve for δ.

The size of the dataset in this application makes this contraction mapping converge too slowly to make estimation possible. Instead, the SQUAREM squared extrapolation method is used to quickly compute the solution to the fixed point problem (Varadhan (2010)). Specifically, the first step of the estimation procedure is the following:

1. For any guess α use the SQUAREM routine to calculate δ.
2. Use δ from step 1 along with α to calculate G^1 and G^2.
3. Search over the values of α.

The first step of the estimation procedure returns estimates of (α, δ) of equation (6). As mentioned earlier these are not dependent on any assumptions regarding the unobserved neighborhood quality ξ and can be used by themselves to answer some empirical questions. The δ estimated in the first step are used in the second step to estimate the rest of the parameters in the utility, crime, and school quality equations.

1.4.2 Second Step

The second step of the estimation procedure estimates the parameters $(\alpha_0, \beta, \gamma)$ of the following three equations:

$$\delta_j = \alpha_{X,0} X_j + \alpha_{p,0} p_j + \alpha_{\bar{Z},0} \bar{Z}_j + \alpha_{c,0} c_j + \alpha_{s,0} s_{s(j)} + \xi_j \tag{1.10}$$

$$c_j = \beta_X X_{c(j)} + \beta_{\bar{Z}} \bar{Z}_{c(j)} + \eta_j \tag{1.11}$$

$$s_{s(j)} = \gamma_X X_{s(j)} + \gamma_{\bar{Z}} \bar{Z}_{s(j)} + \nu_{s(j)} \tag{1.12}$$

These equations suffer from the problem of simultaneity. Even if the unobserved terms in these equations are distributed independently of each other, the variables in these equations are still endogenous. For example, η_j is a determinant of c_j which, in turn, is a determinant of $P_{i,j}$. This means that η_j is correlated with $\bar{Z}_j$ in the equation for c_j, making $\bar{Z}_j$ endogenous. The typical solution for the simultaneity problem requires exclusion restrictions on what variables enter the equations for different endogenous variables.

Exclusion restrictions take the form of specifying that the amenities of only some neighborhoods enter the equations for each of the endogenous variables. In the case of equation (10) for mean indirect utility only the amenities of neighborhood j enter into the equation. For school quality, the amenities of all neighborhoods that share the same school district enter into the equation (12). The amenities of all neighborhoods that are within close proximity enter in the equation (11) for crime. In this way, exogenous amenities of these neighborhoods are determinants of the endogenous variables, but they do not directly affect the utility that any household receives from choosing neighborhood j.

As mentioned earlier and elaborated in Nevo (2000) in addition to exclusion restrictions an assumption must be made about the distributions of ξ, η, ν. The assumptions and proof of identification are standard for a system of simultaneous equations and can be found in the appendix. The intuition follows from the fact that different sets of neighborhoods are relevant for different equations. Only characteristics of neighborhood j are relevant for its utility, while characteristics of neighborhoods in close proximity are relevant for crime and characteristics of neighborhoods that share the same schools are relevant for school quality.

In equation (10) X_j are exogenous while the rest of the variables are correlated with ξ_j. $X_{c(j)}$ serve as instruments for c_j because exogenous amenities of nearby neighborhoods are correlated with crime in neighborhood j, but are uncorrelated with the unobservable quality of neighborhood j. $X_{s(j)}$ serve as instruments for $s_{s(j)}$ because exogenous amenities of neighborhoods that share schools with neighborhood j are correlated with quality of schools associated with neighborhood j, but are uncorrelated with the unobservable quality of neighborhood j. The sets $c(j)$ and $s(j)$ are distinct for most neighborhoods in the data so different instruments are used for the two different endogenous variables. These exogenous amenities serve as instruments in the first stage of 2SLS estimation of equation (10).

The price p_j is endogenous in equation (10) because price is correlated with unobserved neighborhood quality through the market-clearing mechanism in Proposition 1. From the logic of Proposition 1, the exogenous amenities of all neighborhoods are correlated with price. Therefore exogenous amenities of neighborhoods not otherwise related to neighborhood j serve as instruments for p_j in the first stage of 2SLS estimation of equation (10).

Neighborhood socio-economic composition $\bar{Z}_j$ is endogenous in all three equations (10), (11), and (12). By the equilibrium sorting process described in Proposition 2 $\bar{Z}_j$ depends on the exogenous amenities of all neighborhoods. These exogenous amenities of neighborhoods not otherwise related to neighborhood j are uncorrelated with ξ_j, $\nu_{s(j)}$, and η_j and therefore serve as instruments for $\bar{Z}_j$ in the first stage of 2SLS estimation of equations (10), (11), and (12). The number of instruments is sufficient for estimation as the number of neighborhoods excluded from $\{j, c(j), s(j)\}$ is sufficiently large.

The model falls into a class of models consistency of which is studied by Berry, Linton, and Pakes (2004). Because δ_j used during the 2SLS estimation are themselves estimated from data an additional condition has to be satisfied as in Theorem 1 of Berry, Linton, and Pakes (2004). To guarantee consistency and normality of the estimates in the second stage $\frac{JlogJ}{N} \to 0$ as $J \to \infty$. This condition guarantees that any noise in the estimates of δ_j disappears as the number of neighborhoods grows large.

1.5 Data

Household and neighborhood data come from the American Community Survey. The ACS, which has replaced the long-form Census, contains data on individual households and on the characteristics of Census tracts. Census tracts number approximately 4,000 individuals and are designed to be homogeneous with respect to population characteristics, economic status, and living conditions. The data have household and individual-level information on age, race, education, employment, income, and housing of households. Importantly, the data include information on the number of rooms in the housing unit, the number of units in the structure, the value of the units, the year the structure was built, and other housing-related information for Census tracts. These data provide a clear picture of the types of housing available in every Census tract.

Census tracts are the best available approximation to neighborhoods. Since tracts are designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions they are likely to mimic the choice set actually faced by households when making the residential location decision. The tracts are also small enough that in many cases a school catchment area will encompass a number of Census tracts, meaning that identification of the school quality equation can use these additional tracts within the school district as exclusion restrictions.

Estimation uses data from the six counties of the San Jose-San Francisco-Oakland combined statistical area for the years 2009-2013. This area has been the object of previous studies by Bayer, Ferreira, and McMillan (2007) and so results from the estimation can be directly compared to those from prior work.

The area is self-contained with less than 2% of households commuting into or out of the area for work. The population of the area is racially, socially, and economically diverse. And finally, the area includes urban, suburban, and rural areas with a variety of types of housing and public amenities. In the selected area households have a wide variety of neighborhoods to choose from, making it possible to estimate household preferences for a wide variety of neighborhood amenities.

There are 1,333 neighborhoods in this area. The socio-economic characteristics of these neighborhoods vary widely. Unemployment rate varies from zero to almost 40% and poverty from zero to 52%. The median age of the householder can be as low as 19.8 and as high as 78.1, and rates of marriage and having children range from 7.6% and zero to 92% and 79%. Household size, percentage of individuals with a high school and a bachelor's degree, occupation, median income, race, and foreign origin all differ significantly across the neighborhoods.

The neighborhoods are also very different in terms of their exogenous characteristics. About 16% have access to water and 1% are rural, while density varies between 0.5 people per square mile to almost 90,000 per square mile. The proportion of residences that are detached houses and the proportion of residences that are in apartment buildings with at least 20 units vary from zero to nearly one. The average age of the residences in the neighborhoods varies from 10 years to 77 years and the average number of bedrooms from 0.3 to 4.3. In some neighborhoods, no residences are owned, while in others 98% are. In some neighborhoods, as many as 36% of residences lack full plumbing and

Table 1.1: Summary Statistics: Socio-Economic Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Unemployment	0.095	0.045	0	0.397
Poverty	0.111	0.091	0	0.515
Age	38.80	6.389	19.8	78.100
Married	0.499	0.168	0.076	0.919
Children	0.343	0.133	0	0.792
Household size	2.798	0.643	1.33	6.49
HS	0.871	0.118	0.399	1
BA	0.45	0.218	0.017	0.928
Income	88,224	38,232	12,018	250,000
Commute	28.224	4.661	13.4	53.2
Black	0.069	0.103	0	0.733
Asian	0.255	0.191	0	0.894
Hispanic	0.222	0.18	0	0.895
Foreign	0.312	0.14	0.04	0.837

41% lack a full kitchen. And of course, the median price of a residence in the neighborhood varies from 54 thousand to 3.4 million.

The price variable is self-reported, and so there is reason to doubt its validity. Households may not be very good at estimating the price their residence would sell for if it were on the market. For this reason, average price estimates from Zillow for the years 2009-2013 are also used to make sure the results are robust to misreporting by households. Unfortunately, the Zillow estimates are available only by zip-code, which are larger than Census tracts, so the use of Zillow price estimates entails some loss of information. As results do not differ qualitatively, the self-reported value of the house is used for the analysis presented in this paper.

The ACS also provides data on individual households that live in the six counties. There are 112,635 households in this sample. For every neighborhood

Table 1.2: Summary Statistics: Exogenous Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Water	0.162	0.369	0	1
Density	4,509	6,659	0.535	89,479
Rural	0.01	0.098	0	1
Detached	0.538	0.303	0	1
Apartments	0.133	0.185	0	0.979
Age of residence	48.445	13.316	10.29	77.27
Bedrooms	2.581	0.692	0.324	4.34
Owned	0.562	0.245	0	0.979
No plumbing	0.007	0.022	0	0.367
No kitchen	0.013	0.035	0	0.413
Price	620,473	346,457	54,100	3,419,655

average or median variable, there is a corresponding household variable. Some variables are broken down further, such as whether children in the household are 6 years old and under or 17 years old and under. Other variables are only available at the household level, such as whether the household owns or rents its place of residence. The ACS provides statistical weights for each household to ensure that the sample is representative of the population. Using these weights it is possible to construct average and median characteristics of different sets of the households.

The six counties contain 715 elementary and 142 high schools. California Department of Education maintains an extensive database of school performance data on every school and school district. For the purposes of this paper, school quality is measured by the school district's Academic Performance Index (API) for 2011. The API ranges from 200 to 1,000, with 800 considered by the California Department of Education to be the target for all schools. The API relies primarily on the CST and CAHSEE standardized tests, although it

Table 1.3: Summary Statistics: Household Characteristics

Variable	Mean	Std. Dev.
Own residence	0.611	0.488
Household income	111,229	109,469
Age	52.237	16.622
Married	0.516	0.5
Children 6 and under	0.14	0.347
Children 17 and under	0.237	0.425
HS	0.395	0.489
BA	0.281	0.45
MA or higher	0.234	0.423
Black	0.062	0.241
Asian	0.24	0.427
Hispanic	0.14	0.347
Foreign	0.343	0.475
Unemployed	0.048	0.214
Poverty	0.091	0.288

takes into account attendance and graduation rates. Because it is mandated by law, the API formulas do not change from year to year or from school to school, making it a good indicator of school quality that is readily available to households when they make a choice of residential location.

Table 1.4: Summary Statistics: School Quality

Variable	Mean	Std. Dev.	Min.	Max.	N
Elementary API	844	82.9	605	998	715
High API	770	101.0	422	955	142

Neighborhoods are assigned to elementary and high schools based on the maps provided by the California Department of Education. While school districts almost always follow the same boundaries as Census tracts, some school attendance zones do not. In these cases (which make up 14% of the Census tracts) the Census tracts are broken down into Census blocks, which do always follow school attendance zone boundaries. The Census tracts are then assigned to the school which corresponds to the Census blocks that cover the largest portion of the Census tract population in 2011. In 91% of Census tracts, a single school was assigned to the Census blocks making up more than 85% of the Census tract population.

Not all schools use attendance zones. For example, the San Francisco Unified School District assigns students to high schools based on a number of factors, of which proximity to the school is only one. The Berkeley Elementary School District assigns students to one of three "areas" based on the place of residence, and each area has 2 or 3 elementary schools. Students are then assigned to a specific elementary school based on a number of factors, including proximity.

This paper follows Bayer, Ferreira, and McMillan (2007) to assign Census tracts in districts that do not use attendance zones to specific schools. For each school, the share of the students that school serves in the school district (or "area" in the case of the Berkeley Elementary School District) is calculated. Then the Census tracts closest to the school and that make up that share of children under 18 in the school district are assigned to that school. This procedure affects 11 high schools and 53 elementary schools. The result is the assignment of every Census tract to a single high school and a single elementary school.

For crime, the paper uses data provided by Applied Geographic Solutions for "crime risk" in a given area. This measure uses an analysis of several years of FBI Uniform Crime Reports, which compile data from the vast majority of law enforcement jurisdictions nationwide[1]. Crime risk is divided into two parts - personal and property crime risk. This paper uses personal crime risk, which includes reports of murders, rapes, robberies, and assaults. The resulting variable is an index, with the value 1.00 equal to the national average for the United States.

Table 1.5: Summary Statistics: Crime

Variable	Mean	Std. Dev.	Min.	Max.	N
Crime risk	1.07	0.86	0.04	4.42	1,333

The AGS data use the 2000 Census tract geography, which has to be converted into the 2010 Census tract geography to be congruent with other data. In cases where a single 2000 tract was split into two in the 2010 Census, both of the tracts are assigned the crime risk of the 2000 tract. In cases where two 2000 tracts were combined into a single 2010 tract, the new tract has the average crime risk of the two 2000 tracts, weighted by the 2000 population of the tracts.

1.6 Estimation Results

1.6.1 Interaction Parameters

This section begins with details of the model specification. As in equation (1) utility has interaction terms of the form $\alpha_{X,i} X_j$. For most characteristics $\alpha_{X,i} = \alpha_{X,0} + \alpha_X Z_i$, with exceptions noted bellow. This makes $\alpha_{X,0}$ the part of the utility associated with X that is common to all households, and it is subsumed into δ_j during the first step of the estimation. The specific α_X estimated

[1] A partial methodology is available from AGS on their website

during the first step govern the ways in which household characteristics affect the household's valuation of the different neighborhood characteristics.

The computational burden of the first step of the estimation is significantly larger than for many other applications of this method. One of the largest studies is Berry, Levinsohn, and Pakes (2004), where the number of individuals is 37,000 and the number of choices is 203. In comparison, the data used in this paper cover more than 112,000 households and 1,333 neighborhoods. Even with the SQUAREM routine, which speeds up the fixed-point part of the estimation significantly, the computational complexity restricts the number of parameters in the first step of the estimation.

Descriptive tables and regressions of each X and $\bar{Z}$ guide the choice of the parameters. A number of smaller trial runs helped identify the interaction parameters most important to the model[2]. Some differences in specification provided qualitatively similar results, and estimates from three such specifications are reported. Estimates from the first specification are used in the second step of the estimation and in the counterfactual evaluations.

The commute variable is calculated for each household and each neighborhood. ACS data include the residence Public Use Microdata Area (PUMA) for each household and the place of work PUMA and commute time for each member of the household. Census tracts are assigned to PUMAs and for each pair of PUMAs, the average commute time is calculated from the data. For pairs of PUMAs with fewer than 35 commuters, of which there are 4, commuters from nearby PUMAs were used as well. The commute time for a household for a

[2] The usual caveats to the reported standard errors apply.

given Census tract is the average of the commute times of the adults in the household (provided they work) assuming the place of work remains the same.

Results from trial runs made it clear that the pertinent income variable is the difference between the household income and the mean income in the neighborhood. For every household and each neighborhood the income variable is the absolute value of the difference of log of household income and log of mean neighborhood income. When interacted with price and the fraction of owned residences, the income variable is the log of household income. Price is the log of mean reported value of the residences in the neighborhood. School quality variable is the standard deviations from the mean of the average of elementary school and high school API assigned to the neighborhood.

To ensure that the coefficient on price is always negative for all households, as is required by Proposition 1, it is $-e^W$. This way its log is a decreasing function of $W_i = \alpha_P Z_i$ as in Berry, Levinsohn, and Pakes (2004). Included in Z_i is a constant and the log of household income. Initially household size and education level were included, but these variables proved to be consistently insignificant.

Table (6) provides estimates of three different model specifications. All specifications include the terms found to be the most important, and the coefficients of these terms change only slightly. There are differences between specifications in which interaction terms are included, especially for the types of residences available in different neighborhoods. The estimates are obtained by using the moments G^1 and G^2 described in section (4) and the two-step generalized method of moments estimator of Hansen (1982).

Table 1.6: Estimation Results : Interaction Parameters

Variable	Specification 1	(Std. Err.)	Specification 2	Specification 3
Price:				
Constant	-0.100	(0.016)	-0.100	-0.101
Income	-1.000	(0.118)	-1.00	-1.151
Commute:	-10.308	(0.534)	-10.654	-10.814
Income:	-0.223	(0.049)		-0.263
Owned: Income	1.038	(0.365)	0.579	
Bedrooms:				
Size	0.218	(0.041)	0.244	0.189
Income				0.091
Schools:				
BA × Children	0.388	(0.137)	0.158	0.020
Crime:				
HS	-0.263	(0.140)		
HS × Children			-0.429	
BA				-0.173
Detached:				
Married	0.629	(0.170)		
Children	0.754	(0.123)		
HS			0.127	
BA			-0.037	
Married × Children			0.125	
Apartments:				
Married	-0.642	(0.176)		
Children	-0.763	(0.244)		
Married × Children			-0.160	
Black:	6.991	(0.298)	6.987	7.019
Asian:	5.978	(0.434)	5.953	5.956
Hispanic:	9.993	(0.732)	9.985	10.371

All parameter estimates are significant at the 95% confidence level, with the exception of the interaction between neighborhood crime and the fraction of adults in the households with at least a high school degree, which is borderline significant at that level. The largest coefficients are for the variables for the race of the householder and the fraction of residence in a neighborhood of the same race and on the variable for commute. Households with higher incomes are less sensitive to prices and households dislike living in neighborhoods where the mean household income is significantly different from their own.

Importantly, households with college degrees and children value school quality more than other households, and households with high school degrees dislike crime more. These are the most transparent, but not the only channels for school quality and crime to affect the residential choice of households. As results in the next section show school quality enters the utility of all households positively. This means that all households have a higher preference for neighborhoods with better schools, resulting in higher prices. The higher prices affect neighborhood composition, and, in turn, the residential choice of all households.

1.6.2 Mean Utility, School Quality, and Crime

The first step of the estimation returns estimates of (α, δ) of equation (6). As mentioned earlier, these are not dependent on any assumptions regarding the unobserved neighborhood quality ξ. The second step of the estimation uses the assumptions in section (4.2) to estimate equations:

$$\delta_j = \alpha_{X,0} X_j + \alpha_{p,0} p_j + \alpha_{\bar{Z},0} \bar{Z}_j + \alpha_{c,0} c_j + \alpha_{s,0} s_{s(j)} + \xi_j \tag{1.13}$$

$$c_j = \beta_X X_{c(j)} + \beta_{\bar{Z}} \bar{Z}_{c(j)} + \eta_j \tag{1.14}$$

$$s_{s(j)} = \gamma_X X_{s(j)} + \gamma_{\bar{Z}} \bar{Z}_{s(j)} + \nu_{s(j)} \tag{1.15}$$

Estimation requires exclusion restrictions to deal with the problem of simultaneity as outlined earlier. The exclusion restrictions take the form of specifying that the characteristics of only some neighborhoods enter the equations for each of the endogenous variables. In the case of equation (13) for mean utility only the characteristics of neighborhood j enter into the equation. For school quality the characteristics of all neighborhoods that share the same schools enter into the equation (14). The characteristics of all neighborhoods that are within 120% of the driving time to the closest neighborhood from j enter in the equation (15) for crime. In this way, the exogenous characteristics of these neighborhoods are determinants of the endogenous variables, but do not directly affect the utility that any household receives from neighborhood j.

The estimation of equations (13), (14), and (15) is by 2SLS one equation at a time. The full set of instruments are variables in table (2). Equation (13) uses the values of these variables for neighborhoods that share schools with neighborhood j and that are within close proximity to it. Equation (14) uses neighborhoods that are themselves close to one of the neighborhoods that is in close proximity to neighborhood j to construct instruments. And equation (15) uses neighborhoods that are in close proximity to at least one neighborhood assigned to school $s(j)$ but are not themselves assigned to that school. It is important to emphasize that while the variables in the equations may remain the same, the set of neighborhoods across which the variables are averaged changes both for the variables included in the equations and for the variables used as instruments.

Estimation results for equation (13) are presented in table (7). OLS estimation results are provided as a comparison. For most of the variables, these estimates have to be combined with those from table (6) to interpret the full effect. For example the estimate the coefficient on the fraction of people that are black in the neighborhood is -4.427, but the full term in the utility is $(\alpha_{black,0} + \alpha_{black} Z_{black})\bar{Z}_{black}$. Combining estimates from table (7) and table (6) the coefficient for a black household is 2.564. Similarly for the other variables capturing race.

The estimates suggest that white households are willing to pay prices that are 20.5% higher in order to live in a neighborhood where 10% of the population that was previously black is replaced with whites. This effect is smaller for Hispanics (13.7%) and is statistically zero for Asians. This corresponds to measures of segregation, such as the dissimilarity index, which suggest that the Black population in this area is most segregated from the White population, followed by the Hispanic population, and the Asian population[3].

Households are willing to pay 10.6% for a 10% reduction in personal crime in the neighborhood. As the next section demonstrates, the actual effect of an exogenous change in crime on prices is significantly higher. This is due to the feedback effect between lower crime and other neighborhood characteristics. As crime falls the composition of the neighborhood changes, which reinforces

[3]The index is 0.53 for Black households, 0.51 for Hispanic households, and 0.44 for Asian households.

Table 1.7: Estimation Results : Delta

Variable	2SLS Coefficient	(Std. Err.)	OLS Coefficient	(Std. Err.)
Schools	0.297	(0.097)	0.006	(0.064)
Crime	-0.230	(0.104)	-0.184	(0.059)
Black	-4.427	(0.308)	2.275	(0.514)
Asian	-0.233	(0.834)	-3.311	(0.247)
Hispanic	-2.959	(0.517)	-0.337	(0.321)
Price	-2.157	(0.190)	-0.469	(0.115)
Density	0.277	(0.058)	0.188	(0.053)
Detached	-6.137	(0.221)	-6.215	(0.203)
Apartments	3.378	(0.333)	3.649	(0.307)
Rural	2.050	(0.502)	1.430	(0.462)
Age	0.029	(0.005)	0.017	(0.004)
Intercept	31.821	(2.551)	9.723	(1.552)

the effect on prices. Household willingness to pay for schools is slightly higher than for crime, with households willing to pay 13.8% higher prices for a 10% improvement in the quality of schools.

The only estimate that may be cause for concern in table (7) is the large negative coefficient on the fraction of detached houses in a neighborhood. Even combined with the estimates from table (6) for households that are married and have children it remains large and negative. Part of this may be explained by a lack of other amenities, omitted from the model, that tend to correlate with suburban neighborhoods. These tend to be less walkable and have less immediate access to shopping and dining. Otherwise, it may be the case that households strongly prefer to live in denser, more urban areas, and tend to choose suburbs in order to get access to better schools, lower crime, and neighbors who are similar to themselves.

Results from equation (14) are provided in table (8). Fewer variables are statistically significant, but the set of instruments is the same as described earlier. Consistent with findings in Bayer, Ferreira, and McMillan (2007) the fraction of high school graduates (or higher) has a strong effect on crime, while additional education has no effect. The only race variable that is significant is that for the fraction of population that is black.

Table 1.8: Estimation Results : Crime

Variable	2SLS Coefficient	(Std. Err.)	OLS Coefficient	(Std. Err.)
Poverty	1.725	(0.743)	0.240	(0.563)
HS	-4.112	(1.121)	-2.106	(0.506)
BA	0.411	(0.533)	0.688	(0.274)
Income	0.450	(0.144)	0.121	(0.158)
Black	3.817	(0.429)	5.386	(0.284)
Density	0.422	(0.040)	0.465	(0.031)
Apartments	-1.305	(0.213)	-1.211	(0.173)
Intercept	-3.795	(4.887)	-2.469	(2.022)

The density of a neighborhood increases crime, but the fraction of residences that are in large apartment buildings decreases it strongly. This is consistent with the OLS and summary table findings that the areas with the highest crime rates tend to have many small apartment buildings and duplex homes. In contrast to OLS findings, the causal estimates suggest that the effect of the fraction of the population that is black is lower and the effects of education and income are larger. To some degree, black households appear to tend to live in areas with higher crime for other reasons.

Poverty tends to lead to higher crime, which is a typical finding. Mean incomes in a neighborhood increase crime, but only if the poverty level is held constant. This means that higher incomes cause crime if they go together with inequality in the neighborhood. A 10% increase in income that is accompanied by a 2.6% decline in poverty would lead to a marginal decline in the crime rate. This is consistent with arguments that suggest that inequality in an urban setting can be a cause of crime.

Estimation results for equation (15) are presented in table (9). Separate regressions for high schools and elementary schools showed that there is little difference in the coefficient estimates between the two. High schools and elementary schools are therefore combined into a single school quality equation, with a variable indicating the type of school. In this case, exogenous characteristics of the neighborhoods are excluded from the regression, as they should not be causal in school performance. As a precaution, however, the set of neighborhoods for which the instruments are calculated does not include neighborhoods that are assigned to the school in question.

Table 1.9: Estimation Results : Schools

Variable	2SLS Coefficient	(Std. Err.)	OLS Coefficient	(Std. Err.)
HS	9.149	(11.728)	-56.437	(33.314)
BA	59.561	(29.935)	77.370	(21.970)
Income	92.032	(17.354)	56.522	(9.996)
Black	-124.726	(40.930)	-292.802	(27.064)
Asian	120.148	(62.291)	113.673	(29.454)
Hispanic	-49.591	(30.424)	-104.736	(31.397)
Foreign	-117.462	(49.963)	-139.112	(45.297)
High School	-79.470	(5.052)	-79.607	(5.011)
Intercept	-227.477	(203.026)	257.646	(116.217)

Causal estimates from 2SLS show a greater importance for the average income in the neighborhoods assigned to the school, and less importance for the education and race variables. This is again consistent with the logic of the residential sorting model. All households value good schools, but not all are able to afford to live in areas assigned to one. Since Black and Hispanic households tend to have lower incomes the OLS regression overestimates the causal effect of Black and Hispanic households on school quality. Similarly, more educated households tend to have higher incomes and are able to afford areas with better schools.

It is important to again stress that the 2SLS estimates do not take into account the endogenous adjustment that results from the sorting process that households engage in. For example, new construction may increase the density of a neighborhood and lead to more crime. This effect is captured in the 2SLS estimate. But higher crime makes the neighborhood less desirable and so changes the composition of the neighborhood, which, in turn, feeds into the crime rate and school quality levels. The full effect of exogenous changes to *any* variables requires a simulation of a counterfactual sorting equilibrium.

1.7 Counterfactual Evaluations

The benefit of estimating the full sorting model is to provide credible evaluations of counterfactual experiments. Without estimating the endogenous sorting process of households across neighborhoods and the adjustment of school quality and crime to this sorting it is impossible to predict what effect exogenous changes may have on the distribution of endogenous variables. Reduced-form models of neighborhood composition often do not produce self-consistent distributions of counterfactual neighborhood compositions, and models that do not include endogenous adjustments of school quality and crime do not make fully credible counterfactual predictions.

The counterfactual evaluations in this paper involve an exogenous change in the level of crime or in school quality. These changes may be brought about by a change in police practice or availability of school resources. The object of interest is the full effect, after equilibrium adjustments are taken into account, of an improvement in school quality or crime on neighborhood composition and utility of those households that resided in the neighborhood at the time of the intervention.

The observed data do not form an equilibrium of the model at the estimated values of parameters. The appendix provides charts that compare the actual and model-predicted distributions of race across neighborhoods as an example. Before beginning any counterfactual evaluation the model is set to that equilibrium (which appears to be unique after numerous model evaluations). Effects reported in this section are changes from this initial equilibrium to a new equilibrium predicted by the model. Throughout the counterfactual evaluations, the values of ξ, ν, η are kept constant.

The counterfactual equilibria are calculated according to the following steps:

0. Adjust an exogenous variable that affects the model.

1. Calculate new values of utility for every household for every neighborhood, except the price term.

2. Use the SQUAREM contraction mapping to calculate new prices for every neighborhood such that the market share of every neighborhood matches the observed market share.

3. Calculate choice probabilities and update the values of the endogenous variables, neighborhood composition, school quality, and crime.

4. Return to step 1 and continue until the difference between prices in the current and previous iterations is small.

1.7.1 East Palo Alto Example

A detailed description of an example is useful in understanding the results. This counterfactual example involves a group of 3 Census tracts in East Palo Alto. In 1992 this area had the highest homicide rate in the country and still has one of the highest crime rates in greater San Francisco at more than four times the national average. In is more than 60% Hispanic with only 13% of residents being college graduates. It is notable for being surrounded by extremely affluent areas, with surrounding neighborhoods having more than 80% of adults with college degrees and mean household incomes that are $93,000 higher. The counterfactual intervention is an exogenous reduction of the crime rate in each of these three neighborhoods by one standard deviation, or 0.8575.

Three sets of results are reported in table (10). The first are values of endogenous variables after one iteration of the process described above. The second are new equilibrium values. And the third are values of a new equilibrium where the crime and school quality do not endogenously adjust to neighborhood composition. The first set of results is similar to what a reduced form model that does not capture the full equilibrium sorting process may provide. The third set is what a sorting model without endogenous school quality and crime would predict.

The utility reported in table (10) is the deterministic part of utility of all households, weighted by the probability of living in the three Census tracts before the intervention. This is the best way the model offers to look at households that "initially lived" in East Palo Alto. An increase in utility indicates that under the new equilibrium the households that were the most likely to live in East Palo Alto initially are likely better off, and a decline indicates the reverse.

Table 1.10: Reduction in Crime in East Palo Alto

Variable	Initial Value	1st Iteration	New Equilibrium	Partial Equilibrium
Crime	4.16	2.48	1.19	3.30
Poverty	16.8%	16.2%	12.3%	15.2%
HS	67.7%	68.1%	77.6%	73.0%
BA	14.5%	16.9%	58.9%	26.6%
Income	73,053	79,379	146,040	86,014
Black	16.8%	12.1%	6.2%	11.0%
Asian	3.2%	3.3%	8.7%	4.9%
Hispanic	60.0%	57.6%	29.9%	53.4%
Price	399,521	440,321	773,735	461,220
Schools	-1.35	-1.10	0.48	-1.35
Utility	1.00	1.08	0.89	1.03

The direct effect of the reduction in crime is an increase in the utility the neighborhood provides to everyone, especially to those with high school degrees. The fraction of people with high school degrees rises to 68.1% and prices increase 10.2%. Because black households are much less likely to have a high school degree the fraction of black individuals in the neighborhood goes from 16.8% to 12.1%. The utility of households that initially lived in the area is higher by 8%.

Full equilibrium effects are significantly larger than the direct effects. The change in neighborhood composition causes a further drop in crime and an improvement in school quality. While the full equilibrium effect does not fully close the gap between East Palo Alto and the surrounding areas, it changes the composition of the area drastically. The new equilibrium crime level is just 19% above the national average, compared with 316% initially. The average household income doubles and the fraction of Hispanic households falls by more than half. School quality, which was not exogenously adjusted, goes from -1.35 to 0.48 in response to the changes in neighborhood composition.

There are three main takeaways from this example. First, the equilibrium effects of social interactions are very important in determining the new equilibrium. If these were minor then the full equilibrium outcome would look similar to the first iteration outcome that only takes the direct effect into account. Instead, the feedback process between the endogenous variables of the model accounts for the overwhelming fraction of the total change in neighborhood composition. This leads to the conclusion that even relatively small changes to key variables can have a very significant effect on other endogenous variables.

Second, the partial equilibrium model does a poor job of approximating the full equilibrium outcome. Neighborhood composition is extremely important in determining both crime and school quality, accounting for more than 60% of variations in both cases. Keeping these variables constant despite changes in neighborhood composition eliminates one of the main ways by which changes in neighborhood composition feed back onto themselves. In this example, if crime in East Palo Alto is kept fixed at a very high level after the initial reduction and school quality is kept at a very low level the changes to neighborhood composition are nowhere near as large as in the full equilibrium.

Finally, the households that initially live in East Palo Alto do not benefit from the reduction in crime. The utility of these households is reduced by 11% as a result of the intervention. Under the new equilibrium, these households live in neighborhoods that are significantly less Hispanic (48%), and that have significantly higher prices ($501,769). Additionally, the commute of the individuals in these households is significantly higher (49 minutes vs. 27 minutes before the intervention). Together all of the changes combine to have a large and negative effect on the utility of these households.

As mentioned at the beginning of the section East Palo Alto is unique in being surrounded by neighborhoods that are very different from it. This means that when the option of living in East Palo Alto is taken away the households that initially lived there are forced to move to significantly less attractive neighborhoods from their point of view. The large negative utility from commuting prevents them from moving far away from the area in order to find other neighborhoods that resemble the pre-change East Palo Alto. As a result, these households end up with longer commutes, and in neighborhoods that have higher prices with neighbors who do not resemble them very much.

While the example of East Palo Alto is extreme in the disutility suffered by the residents as a result of an improvement in crime, the next section of the paper demonstrates that this result it is not unique.

1.7.2 Changes in School Quality and Crime

The equilibrium impact of an exogenous change in school quality or crime on the households that reside at that location depends on whether the "menu" of options available to these households is better or worse after the change. Since households already maximize their utility and chose the optimal neighborhood, perhaps it should not be surprising that any large changes to it may result in a loss of utility. But since the direct impact of the exogenous interventions is positive, it must be the case that the negative impact on utility comes from the feedback between the endogenous variables in the model.

In addition to the direct positive effect of an improvement in school quality or crime, there is a feedback effect that operates through prices. The addition of a neighborhood with good schools or low crime makes these amenities more abundant and thus cheaper, especially in the area around the affected neighborhood. This is a positive for all households, but especially those that value good schools and low crime and those with lower household incomes because they are more sensitive to prices. This effect is not contained just to the affected neighborhood, but is present in the area all around it, diminishing with distance.

The negative effect from the feedback between endogenous variables is tied in large part to the commuting variable. Given that there are 1,333 neighborhoods, a household could always choose to find another neighborhood resembling the original one. However, the disutility from commuting is significant, and it is not always beneficial for the households to relocate a large distance away. Of course in this situation some individuals may change jobs, but this possibility is outside of the current model and is left for further research. As a result, the disutility estimates presented here should be understood to be lower bounds that are reached only if the households are unable to change jobs, and are thus forced to trade off longer commutes for otherwise more desirable neighborhoods.

Due to the time required to compute a counterfactual equilibrium, it is impractical to evaluate the results of an intervention in every one of the 1,333 neighborhoods. To get an idea of the effect of an improvement in school quality or crime across different neighborhoods, 100 neighborhoods are selected randomly from those below the average in terms of school quality or crime. Then, for each neighborhood in the set the crime rate or the school quality of the associated elementary school is improved by one standard deviation, 0.8575 for crime and 82.9 for elementary school API. A counterfactual equilibrium is then computed and the results on the counterfactual level of school quality, crime, and utility of the neighborhood residents are reported in table (11) and (12).

As in the example above, the utility is calculated by the average of the deterministic utility of all households weighted by the initial probability of a household living in the affected neighborhood. The 200 neighborhoods are broken down into quartiles by the initial level of school quality or crime and the results are reported for each quartile. These include the average initial levels of the variables as well as the minimum, maximum, and the variance of the counterfactual variables in that quartile of neighborhoods. Graphs of initial and counterfactual school quality and crime can be found in the appendix.

In the case of crime, the new average crime level is lower than a standard deviation bellow the original in all four quartiles, indicating strong social interaction effects from the endogenous variables. In three out of 100 cases, the equilibrium crime level is above the level of the initial intervention. This means that in almost all cases the initial improvement in the crime level is reinforced by the subsequent endogenous adjustment of neighborhood composition and school quality. These effects are a lot more variable in the first two quartiles of the neighborhoods, indicating that the equilibrium results of a reduction in crime are significantly less predictable in high-crime neighborhoods than in moderate-crime neighborhoods.

Table 1.11: Effects of Reduction in Crime on Utility

Variable	Initial Average	New Average	Minimum	Maximum	Variance
Crime:					
1st quartile	3.07	1.32	0.73	2.30	0.18
2nd quartile	2.14	0.86	0.17	1.71	0.16
3rd quartile	1.57	0.40	0.09	0.96	0.06
4th quartile	1.18	0.12	0.00	0.40	0.02
Utility:					
1st quartile	1.00	0.96	0.91	1.01	0.00075
2nd quartile	1.00	0.97	0.94	1.01	0.00035
3rd quartile	1.00	0.99	0.95	1.02	0.00036
4th quartile	1.00	1.01	0.95	1.05	0.00071

The distribution of counterfactual utilities confirms the conclusions from the East Palo Alto example. In three out of four quartiles the average new equilibrium utility of the original residents is lower than before the intervention. On average, *lowering crime rates in neighborhoods with above-average crime rates is detrimental to the households that live there.* The changing composition of the neighborhoods and the rising prices in the area lead to a situation where the original residents are not able to find another neighborhood that is as appealing and prefer the original situation with the higher crime rate.

The disutility from an improvement in crime is not a universal outcome. Even in the lowest quartile, where the decline in utility is most significant, the best possible case features a small increase in utility. This compares with the worst case of a decline of 9%. In the other three quartiles the decline in crime never causes more than a 6% decline in utility, and in the best case increases utility by 5%. So while on average an improvement in the crime rate leads to lower utility for the residents, in some cases it can be beneficial. The variance of the counterfactual utility is higher in the lowest quartile, just like the variance of the counterfactual crime rate, suggesting that the results are most unpredictable when the intervention takes place in neighborhoods with a particularly high initial crime rate.

In the case of school quality improvements, the outcome is a lot more variable. For neighborhoods with the worst school quality, there appears to be little or no social interactions effect and the improvement is roughly equivalent to the initial exogenous change. The variance of the new equilibrium school quality is also highest for the neighborhoods in the lowest quartile of school quality, suggesting that *improvements to the worst schools have the least predictable equilibrium effects*. For schools in the other quartiles the size of the social interactions effect is much more consistent and in all cases positive.

Table 1.12: Effects of Increase in School Quality on Utility

Variable	Initial Average	New Average	Minimum	Maximum	Variance
Schools:					
1st quartile	691	806	688	889	2,929
2nd quartile	755	874	843	905	323
3rd quartile	789	908	883	930	142
4th quartile	816	936	906	953	145
Utility:					
1st quartile	1.00	1.01	0.94	1.06	0.00107
2nd quartile	1.00	0.97	0.93	1.02	0.00054
3rd quartile	1.00	1.03	0.96	1.05	0.00059
4th quartile	1.00	1.02	0.97	1.06	0.00057

The impact of school quality improvements on the utility of the neighborhood residents is a lot more varied than the impact of crime rate improvements. The average utility declines for the residents of the neighborhoods in the second quartile but increases in the other three quartiles. The average new equilibrium utility is higher in the top two quartiles, but the single largest improvement is in a neighborhood in the lowest quartile, an improvement of 6%. In all four quartiles, there are neighborhoods whose residents are better off and neighborhoods whose residents are worse off after the intervention. As previously, the effects are least predictable in neighborhoods with the worst performing schools prior to the intervention.

A possible reason for the difference in the effect of crime and school quality improvements on utility is the difference in their spatial correlation. The school quality of nearby neighborhoods predicts 86% of a neighborhood's school quality, while the crime of nearby neighborhoods predicts only 69% of a neighborhood's crime. This means that if the school quality in a neighborhood changes it is more likely that households are able to find neighborhoods that resemble the original one nearby. Of course, these neighborhoods will also be affected by the feedback between endogenous variables, but a greater initial availability of neighborhoods with a similar school quality may play a role.

1.7.3 Distribution of Utility

Intuition would suggest that since all households dislike crime and like school quality, improvements in these variables should be welfare-improving. In fact, in the East Palo Alto example as well as in all of the 200 simulations described in the previous section, the aggregate utility (*not* weighted by the initial location of households) is higher in the new equilibrium. This suggests that although households which initially resided in the neighborhood where the improvement took place are adversely affected, other households benefit from the change.

Most households live too far away to be seriously affected by a change in crime or school quality in a single neighborhood. For the large majority of households, the change in utility from the initial to the new equilibrium is marginally positive. This reflects the fact that by making lower crime or better schools more abundant, the intervention makes it slightly easier and cheaper for households, even those far away, to find attractive neighborhoods. Large changes in utility affect primarily households that live and work near the neighborhood directly affected by the change.

Table (13) presents a comparison between households that are most positively and negatively affected by the exogenous changes in school quality and crime. For the 200 simulations from the previous section, households are ranked by the change in utility they experience. Socio-economic variables for those in the highest and lowest 10% of the distribution are summarized in the table. Also included for reference are the averages of these variables for the entire urban area. Because the 200 neighborhoods for the counterfactual evaluations are picked from those with below average school quality and crime rates, the household income, education, and other variables even for those households that tend to benefit the most are lower than the averages for the entire area.

It is easy to see the difference between the households that are the most significant gainers and losers from the changes. The average income of the households that lose the most utility is a mere $9,198, and 71.5% of these households are below the poverty line. They are much more likely to include adults that have no high school diploma and also much less likely to be married families. The people in the households that lose the most utility are much more likely to be Black (although Hispanic households are more likely to be in the

Table 1.13: Household Characteristics by Change in Utility

Variable	SF Mean	Top 10%	Bottom 10%
Household income	111,229	72,059	9,198
Married	0.516	0.483	0.159
Children	0.377	0.288	0.175
No HS	0.090	0.086	0.223
HS	0.395	0.455	0.530
BA	0.281	0.275	0.161
MA or higher	0.234	0.185	0.086
Black	0.062	0.059	0.147
Asian	0.240	0.220	0.245
Hispanic	0.140	0.174	0.158
White	0.526	0.516	0.418
Foreign	0.343	0.332	0.376
Poverty	0.091	0.012	0.715
Distance	-	3.71	1.46

group of the largest gainers).

Households that gain the most utility have mean incomes that are below the mean for the entire area. They are also less likely to have advanced degrees and are slightly more likely to be minority households. These results suggest that the largest benefits of improvements in school quality or crime accrue to the households that are moderately well-off at the expense of those households that are the worst off. The changes in utility for the financially best-off households tend to be small, as these households tend to live further away and their probability of living in the affected neighborhood does not change appreciably.

Households that lose the most utility also tend to be those that live in, or near, the neighborhood where the initial change takes place. On average, these households live 1.46 miles away from the neighborhood in question. In contrast, the households that gain the most utility tend to live a little further, on average 3.71 miles, away from the neighborhood in the initial equilibrium. Neither distance is so far that any changes in commuting play a significant role, so the results appear to be due primarily to the changing demographic composition of the neighborhoods and the changes in school quality and crime that accompanied it.

1.8 Conclusion

The most significant finding from the results in this paper is the unpredictability of the new equilibrium outcome following improvements in either crime rate or school quality. While it is true that in most cases the initial improvements in school quality and crime are reinforced by the social interactions equilibrium mechanics, there are exceptions. In addition, when it comes to the evaluation of the impact the improvements have on the residents of the affected neighborhoods, both positive and negative outcomes are possible. On average improvements in crime appear to be detrimental to the original residents, but in some cases the impact is positive. Meanwhile, the effect of improvements in school quality tends to be positive but is more unpredictable. In both cases, extreme care is necessary to account for possible unintended consequences of policy interventions that may initially appear benign.

This variability in outcomes deserves further study. A systematic comparison of neighborhoods whose residents benefit from the changes and those whose residents do not may help explain the unpredictability. Similarly, studying neighborhoods with particularly large or small social interaction equilibrium effects may help to better explain how the equilibrium process operates.

A case-by-case analysis of possible interventions provides an overview of outcomes, but identifying regular patterns is necessary in order to provide concrete policy prescriptions that would mitigate the apparent negative impacts of the interventions considered here.

The results presented in this paper suggest that improvements in school quality and crime lead, in equilibrium, to a reallocation of utility from households that are poor, poorly educated, and more likely to be minority, to households that are better off financially. These results support other evidence that neighborhood "revival" is in many cases synonymous with the displacement of the least well-off households. These effects must be taken into account in consideration of any policies aimed at neighborhood improvement. So far it is not clear what policies would, in equilibrium, lead to utility improvements for the worst-off households, and this is an area where further research is needed.

Of course, there are limitations to the analysis presented in this paper. The free and instant mobility of households and the treatment of all households as renters are issues that have plagued this literature for years (Kuminoff, Smith, and Timmins (2013)). In the consideration of utility, the question of ownership is particularly important. Currently, price increases are a negative for all households, while they may, in fact, be beneficial for households that own their homes. This may mitigate or even reverse the findings in this paper, and it is the first avenue of further research that should be addressed.

Other improvements also need to be considered in future research. The current measure of commute time for households, while being the most comprehensive used in any similar study, does not capture the fact that households may choose to switch jobs. A measure of employment access for a given type of occupation and education level may help mitigate this problem and make the employment location of households endogenous. A similar problem is the static supply of housing in every neighborhood in the model, which is determined by decisions made by builders in response to demand and other variables. If the equilibrium effects presented in this paper are to be considered the long-term effects of a policy intervention, then it is necessary to consider the changes in the supply of housing that would take place over the long-term.

This paper is an example of the importance of considering equilibrium effects in any setting where households or individuals can respond to each other's actions. The social interactions literature emphasizes this fact, but it has not been fully taken into account in many policy evaluations. To achieve credible counterfactual results a model must account for the way key endogenous variables adjust, especially in settings where there is a feedback between individual actions and endogenous variables. A framework that does so allows for a clearer understanding both of individuals' actions and of the equilibrium outcomes of interest.

Chapter 2

Relationship Between School Quality and Composition of the Student Body

2.1 Introduction

There exists significant heterogeneity in school quality, as measured by student achievement, across schools, and this heterogeneity is highly correlated with the characteristics of the schools' student bodies. To the extent that students from lower-income households and minority backgrounds attend worse-performing schools this is an issue of fairness in public policy, and it has received significant public attention. Unfortunately, it is not at all clear how much of the correlation can be attributed to residential sorting by households, and how much is due to the variation in the composition of the schools' student bodies. Different policies may be required to address these two different causes.

This paper uses a new approach to estimate the relationship between school student body composition and school quality, net of the correlation caused by residential sorting by households. The approach in this paper uses instruments that emerge naturally from a model of residential location choice to estimate control variates which can correct the selection bias typically present in studies of school quality. The two step estimation procedure uses data on nearly all of the schools in California from the California Department of Education and data on residential locations from the American Community Survey. The results presented in this paper show what would happen to school quality, as measured by results of standardized tests, if the composition of the school's student body changed exogenously, for reasons unrelated to the school itself.

In many important ways the results of this paper corroborate those of previous studies, while also offering new insights. Economists have been interested in school quality and student achievement for a long time, and there have been many different approaches to studying these topics. Work by Eide and Showalter (1998) looks at the relationship between school quality and student test scores. The authors find significant heterogeneity in effects across the quantiles of school quality, as does this paper. Later work by Todd and Wolpin (2007) focuses on the production function of student achievement, and finds that home inputs and the mother's education can explain about half of the racial gaps in test scores between students. The remainder is attributed to differences in schools and student environments.

There is a sizable literature on the effects students may have on one another. Sacerdote et al. (2011) provide a recent overview of this peer effects literature. One specific finding that the results of this paper confirm is that a greater concentration of black students in a school leads to lower test scores for black students, as found in Hanushek, Kain, and Rivkin (2002). Other findings the results in this paper support include the fact that charter schools may not be beneficial for minority students and students from low-income households (Zimmer and Buddin (2006), Avery and Pathak (2015)), and the fact that class size matters more at good schools and its effect varies by student race (Boozer and Rouse (2001), Levin (2001)).

Because in most cases the location where a student lives determines which school he or she will attend, residential location choice is closely tied to issues of school quality. Galster, Santiago, Stack, and Cutsinger (2016) find that location characteristics matter for student performance, especially the fraction of residents who are black. The effects are different for students of different races, making it clear that such a breakdown is necessary. In light of the fact that many areas in American cities remain highly segregated by race, the results are often discriminatory. Boustan (2013) finds that public schools in majority black neighborhoods receive less funding and other resources and have worse teachers, while Massey and Denton (1993) document other negative outcomes of extreme segregation and isolation of black households. Even when neighborhoods appear to be improving as a result of gentrification, the benefits do not necessarily accrue to the households who live there, as shown in the first chapter of this dissertation and also in Biro (2007).

The study of residential segregation goes back to at least Tiebout (1956) and Schelling (1969). Some authors follow Tiebout (1956) and focus on the differences in amenities across locations. Work by Epple, Filimon, and Romer (1984) and Epple and Sieg (1998) explores the way households sort themselves into jurisdictions so they are then able to vote for their preferred level of a public good. Other models, such as the one in the first chapter of this dissertation and in Anas (1980) and Bayer, Ferreira, and McMillan (2007), follow Schelling (1969) and focus on the role the endogenous socio-economic composition of the location plays in the sorting process. A recent survey by Kuminoff, Smith, and Timmins (2013) provides additional information on the varying approaches to the studies of residential sorting and segregation.

Most (but not all) of the studies cited above use individual student data to estimate the effects of different variables on student performance. This paper uses aggregate data. Because of this limitation, it is not possible to directly address the question of what determines individual student performance. For example, this paper cannot address the issue of peer effects as defined in Manski (1993). Instead, the focus of the paper is on estimating and reporting correlations between average test scores and composition of the student body, net of any selection bias that might arise due to the sorting of students to different schools.

Many studies using individual student data fail to address the possibility of selection bias due to not having data on the specific school students attend. The combination of school-level data from the California Department of Education and the two-step estimation procedure described in this paper makes it possible to address this bias. The question this paper is able to answers is what would happen to the *average* test scores in a school if the composition of the student body of that school were to change exogenously. Some students may do well or poorly at any school. In that case, the results in this paper reflect the correlation between performance of specific groups of students and the groups' characteristics. What the estimation process used in this paper is able to do is control for any correlation between student characteristics and school quality that is due to sorting of students with particular characteristics into good or bad schools.

Typically, studies of school composition have to examine instances of unexpected change in a school's student body. For example, Kane, Riegg, and Staiger (2006) look at schools in a county in North Carolina that are undergoing court-ordered desegregation. This paper, instead, uses variation in school composition that is induced by variation in the characteristics of nearby locations. The intuition is straightforward. Locations that are near a given school, but are assigned to different schools, are possible alternatives for the households that chose to live in the school's location. Depending on whether these alternatives are more or less attractive to the households, the socio-economic composition of the school's location will change, and with it the composition of the school's student body. The use of the characteristics of nearby locations as instruments for a given location's socio-economic composition emerges naturally from a model of residential location choice described in the paper.

The estimation method follows the literature on estimation of triangular simultaneous equations systems. Beginning with Chesher (2003) multiple papers have described the possibility of obtaining structural estimates of the relationship between two variables at different points in their joint distribution using control variates. This paper follows the method described in Imbens and Newey (2009). First, control variates are estimated for all variables describing schools' student body composition using variation in nearby locations. Then, quantile regression is used to estimate the effects of the student body composition on school quality as measured by standardized test scores. Alternative methods that could also be appropriate, but which are not used in this paper, include the instrumental variables method from Chernozhukov and Hansen (2005) and the simultaneous equations estimation method from Blundell, Kristensen, and Matzkin (2013).

The key results confirm findings from earlier studies. Estimates of the effects of student body composition on school quality differ significantly across quantiles of school quality and across student racial background, making it crucial to take these into consideration in any future studies. Any negative effects of the racial composition of the student body are greatest at the worst-performing schools, while positive effects from small class sizes and charter schools are greatest at the best-performing schools. The pattern of the effects of many different variables is different for black students than it is for students of other races. All results are discussed in detail after sections that discuss the model, estimation, and data that are used in this paper.

2.2 Model and Estimation

The object of interest is the function $q_k = f(X_k^S, \bar{Z}_k^S, \epsilon_k)$ that relates school quality q at school k to the exogenous and endogenous variables for that school, X_k^S and $\bar{Z}_k^S$ respectively. The endogenous variables of particular interest are those that capture the socio-economic composition of the student body. The function $f(\cdot)$ should be able to answer the question of what would happen to school quality if the composition of the student body in the school changed for a reason unrelated to the school itself.

Since the socio-economic composition of schools is closely related to the socio-economic composition of the geographic area where they are located, it is necessary to consider how households make location decisions. The literature on urban and regional sorting offers some insight. In particular location choice models, such as Bayer, Ferreira, and McMillan (2007) and the first chapter of this dissertation provide a framework that describes household decisions about location choice, taking into account the endogeneity of many location amenities. This paper uses an adaptation of one of these models.

The indirect utility household i receives from location j is given by $u_{i,j} = u_i(X_j^N, \bar{Z}_j^N, q_j, p_j, \nu_{i,j})$. The first is a vector of exogenous variables X_j^N which may include some of the same variables as X_k^S and location fixed effects. Next is a vector $\bar{Z}_j^N$ of socio-economic characteristics of the location, such as average years of education of residents, average incomes, the fraction of households with children, etc. School quality q_j contains some measure of the quality of the schools associated with the location. The price p_j captures the relative price of this location compared to other ones. Other endogenous location amenities, such as crime rates, may be included as well, as in the first chapter of this dissertation, but they are omitted here for ease of exposition.

The probability that household i chooses location j is given by $P_{i,j} = h_i(X^N, \bar{Z}^N, q, p)$. The functional form of h depends on the distribution of ν. For example, if ν are logistically distributed then $P_{i,j} = exp(u_{i,j})/\sum_j exp(u_{i,j})$. The functional form of $u_{i,j}$ may depend on household-specific characteristics Z_i, as it does, for example, in models with heterogeneous or random coefficients.

The existence of a unique vector of prices and a self-consistent equilibrium in this model are shown in the first chapter of the dissertation.

It is crucial to note that $P_{i,j}$ depends on the full matrices X^N and $\bar{Z}^N$, not just on the vectors X_j^N and $\bar{Z}_j^N$. This is because the alternatives available to household i matter for the probability that the household will choose location j. If an alternative location was to become significantly more attractive, then the probability of choosing location j would decrease. This is likely to be especially true for locations nearby j and is the source of the variation used in the estimation described further down.

The socio-economic composition of location j is a consequence of which households pick location j. Keeping in mind that Z_i are household socio-economic characteristics, the socio-economic characteristics of location j are then the weighted average of the characteristics of the households based on the probability of picking location j: $\bar{Z}_j = \int Z_i P_{i,j} dF(Z)$. Note that since $P_{i,j}$ depends on X^N and $\bar{Z}^N$, so does $\bar{Z}_j^N$. In other words, the socio-economic composition of location j depends on the exogenous and endogenous characteristics of *other* locations.

Since the socio-economc composition of a particular school's student body, $\bar{Z}_k^S$, is related to the socio-economic composition of the location the school is in, it too is related to X^N and $\bar{Z}^N$. Each school is assumed to have a catchment area from which student come, and so the socio-economic composition of this area is directly related to the socio-economic composition of the school's student body. But the exogenous and endogenous characteristics of locations outside of the catchment area do not have any direct effect on the school's student body.

In other words, they can be plausibly excluded from the school quality function $f(\cdot)$.

The intuition for the variables that will serve as instruments during the estimation is straight-forward. Consider a school with a defined catchment area. Now suppose that the exogenous or endogenous characteristics of a nearby location that is outside of the catchment area change, for example new high-rise apartments are built, or more highly educated families with children move in. Because households consider all locations when making their decision, these changes will cause the socio-economic composition of the catchment area, and thus the school student body, to change. In essence, the estimation uses the variation in socio-economic composition that is induced by variation in the characteristics of nearby locations to estimate the impact of the student body composition on school quality.

Direct estimation of $f(X_k^S, \bar{Z}_k^S, \epsilon_k)$ via ordinary least squares is not possible, because $\bar{Z}^S$ is correlated with ϵ if households with different characteristics value school quality differently. Suppose that parents who have more education value the quality of their children's schools more than parents with less education, and thus pay a premium for locations with better schools. A correlation between school quality and parental education can then be a result of this sorting, or of the fact that students with better-educated parents perform better in school. The two-stage estimation method used in this paper makes it possible to separate these two effects.

Write the triangular system of interest as:

$$q_k = f(X_k^S, \bar{Z}_k^S, \epsilon_k) \tag{2.1}$$

$$\bar{Z}_k^S = g_k(X^N, \bar{Z}_{-k}^N, \eta_k) \tag{2.2}$$

The matrix $\bar{Z}_{-k}^N$ denotes the endogenous characteristics of locations not in school k's catchment area. Following Imbens and Newey (2009) and Chesher (2003) I assume that ϵ is distributed independently of $\bar{Z}_{-k}^N$ conditional on η and X^N. Given η and X^N, $\bar{Z}_k^S$ is a function of $\bar{Z}_{-k}^N$. Since, conditional on η and X^N, ϵ is independent of $\bar{Z}_{-k}^N$, it is also independent of $\bar{Z}_k^S$. Blundell, Kristensen, and Matzkin (2013) describe η as a "proxy" for the elements within ϵ that are not independent of $\bar{Z}^N$. Conditioning on η leaves the unobserved part of ϵ independent of $\bar{Z}^N$ and η.

Denote by X_k^I and $\bar{Z}_k^I$ the exogenous and endogenous characteristics of locations close to, but outside of, school k's catchment area. These variables will be the instruments for $\bar{Z}_k^S$ in the estimation as they are likely to be the key components of X^N and $\bar{Z}_{-k}^N$ that go into the function g. Variation in these variables will provide the variation in $\bar{Z}_k^S$ that is used in the estimation of the school quality function $f(\cdot)$.

The first step of the estimation is to recover η that will be used as control variates in the second step. These control variates are acquired by taking the residuals from the R regressions of each element of $\bar{Z}_k^S$ on X_k^S, X_k^I, and $\bar{Z}_k^I$. Call this vector $\hat{\eta}_k$ for a given k. Every endogenous variable in $\bar{Z}_k^S$ has its own different control variate. The second step of the estimation is a quantile regression of school quality q_k on X_k^S, $\bar{Z}_k^S$, and $\hat{\eta}_k$. Quantiles of school quality are assumed to be linear in all of the variables. For comparison, an ordinary least squares regression of q_k on X_k^S, $\bar{Z}_k^S$, and $\hat{\eta}_k$ is also reported.

For both the ordinary and quantile regressions in the second step the inclusion of $\hat{\eta}_k$ corrects for the endogeneity that results from households selecting into different locations. The estimates can be interpreted as changes in school quality associated with exogenous changes in the composition of the school's student body. These reflect both the fact that some students may perform better at *any* school, and the fact that some schools (or school body compositions) may be better for some students in terms of their performance. As such, care should be taken when interpreting the results.

Because of the nature of the two-step procedure, the standard errors in the second step must be corrected for the fact that $\hat{\eta}$ are estimated rather than known. The standard errors reported in the estimation results for structural quantile regressions and the ordinary least squares regression of q_k on X_k^S, $\bar{Z}_k^S$, and $\hat{\eta}_k$ are bootstrapped. The first step $\hat{\eta}$ estimation and the second step estimation are repeated 200 times using data generated by random sampling with replacement from the baseline data set, and the standard errors are computed from the resulting distribution of the coefficients.

2.3 Data

The data used in the estimation come from two sources - the California Department of Education (CDE) and the American Community Survey (ACS). The CDE data are the source of information on school quality and school student body composition. The ACS data provide a breadth of information on the socio-economic composition of different locations across California. The datasets are merged together according to the location of the schools, as described later in the section.

The 1999 California Public Schools Accountability Act established a new academic accountability system for kindergarten through grade twelve public education in California. The cornerstone of this new system is the Academic Performance Index (API) which measures the academic performance and growth of schools on a variety of academic measures. The API is a single number, ranging from a low of 200 to a high of 1,000, which reflects a school's, a school district's, or a student group's performance level, based on the results of statewide assessments.

The API is calculated by converting a student's performance on statewide assessments across multiple content areas into points on the API scale. These points are then averaged across all students and all tests. The result is the API. Currently, the statewide assessments used in API calculations are California Standards Tests (CSTs), the California Modified Assessment (CMA), the California Alternate Performance Assessment (CAPA), and the California High School Exit Examination (CAHSEE). The API is reported for every school, school district, and student group with at least eleven valid scores every year.

This paper uses the 2011 Base API as the measure of school quality. Because the API numbers have such an important role in the evaluation of specific schools and the allocation of funds they tend to be revised for up to two years after initial publication. Additionally, the 2011 Base API falls in the middle

Table 2.1: Summary Statistics: API

Variable	Mean	Std. Dev.	Min.	Max.	Count
Number of API scores	544	422.61	100	3,558	7,633
API	800.7	80.60	389	998	7,633
Hispanic student API	768.0	70.20	407	990	7,550
White student API	845.4	71.59	475	1,000	6,187
Black student API	745.6	87.56	398	996	4,293
Asian student API	891.6	75.56	382	1,000	4,269

of the 2009-2013 ACS 5-year sample used in this paper. The data include an overall API for every school, and an API for student groups in each school based on race, as long as there are enough valid scores within the group. For the purposes of the estimation, I exclude schools and student groups with fewer than one hundred valid scores, as well as any schools that had reporting problems or irregularities during the 2011 API Cycle. The final sample includes 7,633 schools across California.

Additionally, the API data files include information about the school and the school's student body. Relevant school variables include whether the school is a charter school, the school size, and the average class size. Student body variables include the fraction of students that are white, black, Hispanic, and other races, have a disability, or have changed schools during the year. The data also include variables about the programs students participate in, including the free meals program, gifted and talented programs, and English learner programs. Additionally, the data include student-reported parental education level broken down into five categories.

The API data is supposed to include information about teacher qualifications at every school. Unfortunately, due to legal reasons, the 2011 API data do

Table 2.2: Summary Statistics: School Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Black students	0.06	0.10	0.00	0.98
Asian students	0.08	0.02	0.00	0.97
Hispanic students	0.50	0.29	0.00	1.00
White students	0.27	0.25	0.00	0.99
Free meals	0.58	0.30	0.00	1.00
Gifted program	0.08	0.09	0.00	1.00
Migrant education	0.01	0.04	0.00	0.82
English learner	0.25	0.19	0.00	0.98
Disability	0.10	0.04	0.00	0.44
Class size	25.99	4.04	2.15	50.00
Parents' education level:				
No high school	0.20	0.17	0.00	0.89
High school	0.24	0.12	0.00	1.00
Some college	0.23	0.10	0.00	0.82
College	0.18	0.12	0.00	1.00
Graduate school	0.12	0.14	0.00	1.00
Elementary Schools	0.68			
Middle Schools	0.16			
High Schools	0.15			
Charter Schools	0.07			

not include these variables, and, as of yet, no API data sets do, although they may include them in the future. Most of the data in the API data set is related to the school's student body composition rather than to the school's quality of instruction, with the exception of the variables capturing class size and, to some extent, gifted program participation. While this paper examines the effect of student body composition on API across schools of different quality, additional data would be necessary to answer the question of what effect the quality of teachers and instruction has on student performance.

The ACS is an ongoing statistical survey conducted by the U.S. Census

Bureau. It gathers annually information that was previously contained only in the decennial census. Every year the ACS surveys approximately 3.5 million households in the United States with a questionnaire that includes topics covering demographic, economic, housing, and social subject areas. It is the most comprehensive annual survey that provides information on the socio-economic composition of many geographic areas of the United States.

The ACS provides 1-year, 3-year, and 5-year estimates for most of the topics in the questionnaire, although the 3-year estimates are being discontinued. The 1-year estimates are available for larger geographic areas, such as states, congressional districts, and metropolitan areas, while smaller geographic areas, such as school districts, ZIP code areas, and Census tracts, have only 5-year estimates. This paper uses the 2009-2013 5-year estimates for the Census tracts in California. Census tracts are designed to be relatively homogeneous with respect to their characteristics and are relatively small, containing on average 4,000 inhabitants. Because of this, they provide a clear view of the characteristics of the locations around any particular school in California.

For each of the available geographic area and time frame pairs the ACS produces subject tables. These include information about the households living in the geographic area, but not the data on the households themselves. For example, the subject tables will list mean, median and different percentiles of household income in a given Census tract, but will not list the actual incomes of the households living in the area. Therefore these provide a comprehensive snapshot of the economic and demographic characteristics of the households living in the area, but do not provide information on the correlations between these characteristics across the households.

In this paper, the ACS data are used to construct instruments for the first step of the estimation. In general, these are housing, social, and economic variables that are relevant to a household's decision about the location they chose. For every school remaining in the sample, I use driving distance to construct sets of Census tracts that are immediately adjacent to the school, and those that are close, but outside of the school catchment area. In most cases, I use nearby Census tracts that are in a different school district to guarantee they are not assigned to a particular school. In cases of very large school districts, I use Census tracts that are immediately adjacent to somewhat remote schools in the same school district. In all cases I err on the side of caution, making sure to exclude Census tracts that may be part of a school's catchment area based on driving distance.

The first set of instruments used in the paper is the housing characteristics of the Census tracts that are immediately adjacent to the school. These are variables that are excluded from the school quality function q because they should not be directly relevant to students' performance in school. They include the vacancy rate, the fraction of housing units that are detached homes, the fraction that are mobile homes, and the fraction that are in large apartment buildings, the average number of bedrooms, the fraction of housing units that are rented, and the fraction of housing units without full plumbing and kitchen facilities. These are all variables that impact the socio-economic composition of the location, and thus the school's student body, without directly affecting school quality.

Table 2.3: Summary Statistics: Selected School Location Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Vacancy	7.69	6.31	0.00	84.90
Detached homes	62.18	17.76	0.60	100.00
Mobile homes	4.19	5.85	0.00	71.90
Large apartments	9.29	9.97	0.00	88.70
Bedrooms	2.66	0.45	0.57	4.33
Rented	43.17	15.86	2.60	100.00
No plumbing/kitchen	0.50	1.15	0.00	24.20

The second set of instruments are endogenous characteristics of the Census tracts that are close, but outside of the school catchment area. These locations represent the most likely relevant alternatives for the households that chose to live in the school's location. The composition of these locations matters because the households are making a choice between these locations and the school's location, and so the endogenous characteristics of these locations impact the socio-economic composition of the school's location. However, since these locations are outside of the school's catchment area their composition should not have any direct effect on the student body composition of the school and the school quality.

This second set of instruments includes demographic variables such as the racial composition and the median age of residents, the fraction of families that are married and the fraction that have children, and the average household size. Variables that prove to be important as instruments also include the fraction of households that have recently moved, the fraction that were born outside of the united states, the fraction that speak English less than very well, and the fraction that speak Spanish at home. Finally, this set of instruments also

Table 2.4: Summary Statistics: Selected Nearby Location Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Age	36.06	5.67	19.30	67.10
White	62.99	16.79	12.50	100.00
Black	5.98	7.38	0.00	80.00
Asian	12.90	12.22	0.00	70.90
Hispanic	37.68	21.41	0.00	97.01
Married	49.74	9.99	9.60	81.10
Children	34.14	9.09	0.00	70.70
Size	3.53	0.44	2.00	4.87
HS or higher	80.06	12.62	28.31	100.00
BA or higher	28.49	15.89	0.00	85.80
Moved	4.81	3.11	0.00	73.10
Foreign	26.21	11.88	0.00	64.90
Spanish	29.20	19.56	0.00	97.80
LFP	63.18	6.01	13.80	100.00
Unemployment	7.53	2.11	0.00	18.60
Commute	27.10	4.71	5.90	65.20
Income	62,638	22,124	14,401	226,875
SNAP	9.40	6.76	0.00	47.50
Poverty	13.19	8.05	0.00	61.70
Housing prices	352,885	169,723	51,374	965,800

includes economic variables, such as the educational attainment levels of the residents, the labor force participation rate, the unemployment rate, the median commute time, the fraction of residents in each major occupation group, the median household income, the SNAP participation rate, and the poverty rate.

The median household income is the only ACS variable used in the school quality function q. Because the CDE data do not include information on the economic situation of students beyond participation in the free school lunch program, the CDE data are supplemented with the median household income variable from the ACS. For every school, I compute the log of the average of the median household income for the Census tracts immediately adjacent to the school. The variable captures the general income level of the households whose children attend the school in addition to the variable that captures participation in the free school lunch program.

Not all 36 instruments are used in every first step regression. Some instruments are much more relevant to certain variables in $\bar{Z}_k^S$ than they are to others. For each of the endogenous variables, only the 17-28 most relevant instruments are used. There is some judgment involved on whether specific variables should be included in each of the first step regressions. To make sure results are robust they were compared with results from the same estimation procedure with all instruments used in all of the regressions. There were no qualitative differences.

Housing prices should, in theory, be useful as instruments in the same way as other endogenous characteristics of nearby locations are. The prices should affect the attractiveness of the alternatives households have to a given school's location. However, because housing prices may be affected by the housing crisis, and because they are self-reported by the households, their reliability is questionable. One of the two-step regressions presented in this paper uses housing prices in addition to other instruments. The results are not qualitatively different and neither is the precision of the estimates, and so all other regressions do not use housing prices as instruments.

Because the API and all of the other CDE data are averages for a given school or student group, the ordinary least squares and the second step regressions use analytic weights. The variance of the kth observation is assumed to be σ^2/w_k, where w_k is the number of valid API scores for the school or student group. The weights account for the fact that the variables from large schools with thousands of students are much more precisely known than the variables from small schools with only a few dozen students.

Most regressions, including all second step regressions in the two-step procedure, include school district fixed effects. There are 6,303 school districts in the sample, as most elementary schools are classified as belonging to their own school district. All schools belonging to single-school school districts have the same school district fixed effect. Some school districts are much larger than others, with the number of schools ranging from 1 to 754. In the two-step procedure, the school district fixed effects are treated as exogenous variables and are included in the first step regression that is used to estimate the control variates. They are then included again, along with the other exogenous variables, in the second step regression.

Schools that have more than one hundred students of any given race with valid API scores also report average API for students of that race. The number of schools that this includes ranges from 7,550 for Hispanic students to just a few hundred for Native American, Filipino, and Pacific Islander students. The school quality relationship is estimated separately for Hispanic, white, black, and Asian students. The results are used to compare the effect of school student body composition, as well as the effect of different school programs, on students of different racial backgrounds.

2.4 Results

The results include a number of key findings, some of which are general, while some of them relate to students with specific racial backgrounds. Additionally, some of the results come from comparing the ordinary least squares results with the results from the two-step procedure, while others come from using the quantile regressions in the second step. In this section the more general results are presented first, followed by results that are only applicable to specific groups of students or only in specific situations. The full estimation results are included in the appendix.

In general, we would expect ordinary least squares coefficients to be biased upwards in a regression of school performance on student characteristics. The intuition is that good students tend to get sorted to good schools, and so selection reinforces the positive effect the schools may be having. As a result, the actual causal effect of the school on student performance is lower than the ordinary least squares estimate might suggest. This is not what this paper finds. Once the estimates are corrected for selection, using instruments described in the previous section, the effects of charter schools, gifted student programs, and smaller class sizes on API are significantly greater.

The above intuition may be wrong for a number of reasons. First of all, with multiple variables, it is not clear that all should be lower. The effect of some variables may go down while the effect of some others may go up after correcting for selection. More importantly, the presence of equilibrium sorting in the housing market may mean that *all* ordinary least squares coefficients are biased down. Because households face different prices for access to different quality schools it is possible that students who would be most helped by good schools end up unable to attend them.

Consider, for example, the possibility that good schools have more of an impact on students from lower-income households, since students from higher-income households have access to additional resources outside of school. As long as higher-income households still value the additional impact of good schools they will pay the higher prices for locations with good schools and send their children there. Prior work has found that more educated and higher-income households value good schools more than other households[1]. In this situation, the lower-income households may not be able to afford locations with good schools even though students from lower-income households benefit most from good schools.

There is no direct way to test this possibility, but some of the results in this paper do support it. The effect of gifted student programs is most pronounced at lower quantiles of API, especially for Hispanic and black students. In the lower half of the distribution, a 10% increase in the number of students participating in the gifted student programs corresponds to approximately a 20 point increase in API for Hispanic and black students, compared with a negligible effect in the upper half. Students from worse backgrounds and at worse schools may benefit most from gifted student programs, but these programs are more widely available at better schools in locations with higher housing prices.

Additionally, the effect of charter schools changes from 17.62 to 38.41 API

[1]The first chapter in this dissertation and prior work by Bayer, Ferreira, and McMillan (2007) have found this relationship. Conditional on having children, households with higher education levels and higher incomes value good schools significantly more. This is the second largest component contributing to residential segregation, behind only sorting on race.

points once selection is taken into account. Once again, this may be the result of the fact that students who go to charter schools are the students who would do well regardless of what school they go to, while students who would most benefit from a charter school are unable to attend one. Similarly, the effect of a 10% increase in the gifted student enrollment changes from 13.74 to 23.49, and the effect of average class size goes from -2.02 to -8.01. On the other hand, the effect of the fraction of students receiving free meals goes from -2.08 per 10% to a statistically insignificant 0.49. It appears that, as a result of residential sorting, students who may benefit more from specific school programs and smaller class sizes are less likely to attend schools that offer them than students who would do well regardless of the programs and class size.

One of the first results discovered during the estimation process is that there are significant differences in student performance across school districts, in particular when it comes to the performance of Hispanic students. Without school district fixed effects the relationship between the fraction of Hispanic students in a school and the school's API is positive, but once school district fixed effects are taken into account this relationship becomes negative. This suggests that, in general, school districts with higher Hispanic student populations tend to be better overall than school districts with very low Hispanic populations.

Additionally, when school district fixed effects are not accounted for, participation in the migrant education programs appears to have a large negative effect on school API. When the fixed effects are taken into account this relationship becomes insignificant. The conclusion may be that districts with a high fraction of students who are children of migrant workers tend to be significantly worse than other ones. To some extent both of these result may be due in part to the fact that the largest school district in the country, the Los Angeles Unified School District, has 754 schools in the sample and it's student population is more than 70% Hispanic. All other results take school district fixed effects into account.

The effect of charter schools has been extensively debated in the literature. Some recent studies that find both positive and negative effects of charter schools include Zimmer and Buddin (2006), Booker, Gilpatric, Gronberg, and Jansen (2008), and Avery and Pathak (2015). The results from the estimation in this paper suggest that, on balance, charter schools have higher API than traditional schools once selection is accounted for by 38.77 API points. However, the effects are different across quantiles. At the 10th quantile, the effect of charter schools is actually *negative*, lowering the API by −16.78. The effect is positive beginning with the 25th quantile, increasing to a maximum of 53.35 at the 90th quantile. These results strongly suggest that *good* charter schools are significantly better than traditional schools, but that replacing a struggling traditional school with an equally bad charter school may, in fact, hurt the students attending the new school. In as much as oversight over charter schools can focus on identifying the worst performing ones, and either improving or eliminating them, it may help students who are currently attending some of the worst schools in the state.

In general, any negative effects of the racial composition of the school's student body is smaller at better schools. A 10% increase in the fraction of black or Hispanic students at the 10th quantile corresponds to a decrease in API of −14.80 and −2.74 respectively, while at the 90th quantile the effects are

-4.16 and -0.84. For white students, the effect of an additional 10% of black or Hispanic students goes from -9.83 and -0.41 at the 10th quantile to -1.08 and a positive 16.47 at the 90th quantile.

The estimated inter-race effects are somewhat complicated. For white students, the presence of students of any other race is detrimental, except for Asian students at very good schools - white API goes up by 3.57 for every 10% fraction of Asian students at the 90th quantile schools. For Hispanic students, the presence of black students is detrimental, with effects ranging from -0.81 at the 10th quantile to -3.60 at the 90th quantile, but for black students the presence of Hispanic students is beneficial, especially at bad schools, with effects from 12.02 to 2.79 API points. In as much as school administrators take student body racial composition into account when assigning students to schools, they need to be aware of the conflicting effects on different groups.

For groups of students of different racial backgrounds, the effect of the fraction of students of the same race is different across the groups. For white, Asian, and Hispanic students a higher concentration of students of that race at the school leads to higher API, especially at the lower quantile schools. For white students (the omitted group in the regression) the effect of an increase of 10% in the fraction of white students depends on what racial group's membership declined. A change of 10% of the student body from black to white leads to a 9.83 API point gain for white students at the 10th quantile and 1.08 point gain at the 90th quantile. The effects of changes from Asian and Hispanic to white are 9.29 point gain and -3.57 point decline for Asian and 0.41 point gain and -1.64 point decline for Hispanic.

For Hispanic students, an additional 10% of Hispanic students (replacing previously white students) increases API by 11.74 and at the 25th quantile by 4.74 at the 90th quantile. For Asian students, the effects are 7.73 at the 10th quantile and 3.00 at the 90th quantile. These results follow the general pattern of the racial composition of the student body being less important at good schools than at bad schools.

This pattern is reversed in the case of black students. For black students at schools at the lower quantiles, a greater concentration of black students is beneficial. A 10% increase in black students corresponds to API point gains of 4.75 and 1.20 points at the 10th and 25th quantiles. However, at the median schools and above an increase in the concentration of black students corresponds to a *decline* in the black students' API. The effect is largest at the best schools. The decline is −1.79, −7.36, and −8.09 points at the median, the 75th quantile, and the 90th quantile. Counterintuitively, it appears that the presence of their peers at good schools leads to lower scores for black students, while at bad schools it leads to higher scores.

The effect of local household income is very heterogeneous across both API quantiles and student groups based on racial background. In general, higher income has the highest positive effect on API at the lower quantiles, where a 10% increase in median household income corresponds to a 2.20 API point gain. At moderate and high quantiles the effect is much lower at just 0.65 points at the 75th quantile, but it increases to 1.32 points at the 90th quantile. Some of the heterogeneity across quantiles may be due to the fact that the impact of household income seems to be heterogeneous across student body racial composition as well.

For Hispanic students, local household income has a relatively large positive effect across all quantiles, and the effect is especially large at the 90th quantile with 3.49 API point gain per 10% increase in income. For white students, the effect of household income is close to zero and is not statistically significant at any quantiles. For Asian students the effect of income is positive at the lower quantiles, 3.71 and 2.24 point gain at the 10th and 25th quantiles respectively, but is negative at the higher quantiles: −1.08 and −2.45 point loss at the 75th and 90th quantiles.

For black students, the effect is again different from the pattern it follows for other racial groups. Higher local household income is associated with *lower* API scores for black students across all quantiles. The effect is not statistically significant at the upper quantiles, but is strong and negative at the lower quantiles. A 10% increase in local median household income corresponds to a decline of −3.80 points at the 90th quantile and −1.77 points at the 75th quantile for black students. The negative association between household income and some students' performance may be due to stratification of the student body, or increased reliance by students in such areas on resources outside of the school. In these cases, students without access to these additional resources may be at an additional disadvantage.

Already mentioned above is the effect of gifted and talented student programs. Overall, for every 10% student enrollment in the program API scores go up 23.61, making gifted program enrollment the variable with the largest effect on school API. Of course, the effect is not necessarily causal. Even after correcting for selection into the school based on school quality, the estimated coefficient captures some of the heterogeneity among the students. For example, if a group of high-performing students, many of whom are enrolled in the gifted program, are exogenously added to a school the school API score will go up and so will the fraction of students enrolled in the gifted program. In other words, the two-step estimation procedure corrects for selection into the school, but not necessarily into the gifted student program.

With this caveat in place, it is notable that different student group API scores respond differently to the level of enrollment in the gifted programs. These programs appear to be significantly more beneficial to white students, with an API score increase of 38.09 points per 10% enrolled than to students with other racial backgrounds, possibly indicating that white students are more likely to be enrolled in them. In the case of white and Asian students, the benefit of the gifted programs is highest at higher API quantiles, 40.76 and 32.39 points at the 90th quantile vs 32.94 and 25.13 points at the 10th quantile. For Hispanic and black students the pattern is the opposite, with the greatest benefits at the *lowest* quantiles of API, at 22.12 and 22.31 points at the 10th quantile vs 9.67 and a drop of -4.02 at the 90th quantile. This appears to be the first indication in the literature that gifted programs may have different effects on students of different racial backgrounds at different quality schools.

The effects of class size have been extensively studied in the literature, and the results in this paper confirm the general findings. Overall the effect of average class size is -8.11, which is larger than the typical estimates available in the literature, but in line with Boozer and Rouse (2001), implying an increase of 0.4 standard deviation in student performance for a 1 standard deviation reduction in class size. For all groups of students the effect is largest at the higher quantiles, where it ranges between -7.01 for white students and -11.45 for black students. At the lowest quantiles of API, the effect of class size is close to zero and is not statistically significant, echoing the findings in Levin (2001). These results suggest that while overall reducing class size may help with student performance, this effect may not be present at the worst schools, and so such efforts may not actually benefit the students at these schools.

In general, the relationship between parental educational attainment and school and student group API scores is positive. Relative to the omitted category (high-school graduates), a 10% increase in the fraction of parents with no high-school degree is associated with a drop of -8.58 points, while the same increase in parents with a college degree or advanced degree is associated with an increase of 4.16 and 9.47 points respectively. Overall the absolute value of the effect of parental education is smaller at higher quantiles, although this is not always true for every group of students. This relationship may imply that having parents with a greater level of education is beneficial to students who are enrolled in a bad school, while the benefit disappears partially or completely at good schools.

The effect of parental education attainment is significantly smaller across the board for Hispanic students. For white students, there is a big jump in effect of parental educational attainment from the fraction of college graduates to the fraction with advanced degrees, from 4.40 points to 16.78 points per 10%. For black students, the largest jump is between the fraction of parents who are high-school graduates (excluded category) and college graduates, with the effect of 18.25 points per 10%. Additionally, the impact of the fraction of parents without a high-school degree is significantly greater for black students, a decline of −32.23 points, than it is for groups of students with other racial backgrounds, such as Hispanic (0.53 points), white (−11.82), and Asian (−9.39) students.

There are a number of variables for which estimates from the two-step procedure are not available. These include the fraction of Filipino, Native American, and Pacific Islander students, the fraction of students with disabilities, and the enrollment in the migrant education program. For these variables the instruments used in the estimation do not generate enough variation in the variables to allow meaningful estimation of their effects. For example, many students with disabilities attend schools with special programs geared towards them, making the attractiveness of nearby locations largely irrelevant. Additional instruments, perhaps ones specific to each of these variables, are needed in future work to estimate their effects.

2.5 Conclusion

The first, and most important, conclusion of the paper, is that research on school quality must consider the effects of variables at different quantiles. Researchers will never be able to observe all of the relevant information about a given school, and so good and bad schools will continue to differ from one another in important and unobservable ways. As the results in this paper show, the effects of different variables can be drastically different depending on the school's unobservable component of school quality.

One finding that highlights this discrepancy is the effect of charter schools on student test scores. Among low-performing schools, charter schools have worse API scores than comparable traditional schools. Meanwhile, among the median and high-performing schools charter schools perform better than comparable traditional schools. This distinction is crucial to informing public debate on the place charter schools should have in the education system. Proposals to transition low-performing traditional schools into charter schools may not benefit students unless other changes are also made during the transition.

A related, and somewhat discouraging, result is that there are few, if any, ways to improve low-performing schools. Gifted and talented programs may offer the best way, but it is unclear to what degree the estimates in this paper are due to the selection of students into the programs. Free meal programs appear to have no effect on student performance. Reductions in average class size improve student performance on average, but not at the worst-performing schools. These results echo other findings in the literature that show that improving the worst-performing schools is extremely difficult, and the best approach may be to close them and redistribute student to better schools.

It is also important to keep in mind that the effect of school's student body composition differs across student groups with different racial backgrounds. In a number of school districts, administrators take students' demographics into account when making attendance decisions. Understanding that a high degree of racial diversity does not impact high-performing schools, but appears to be detrimental in low-performing schools is important. Counseling or other programs that address the negative effect of racial diversity may be a way to improve some of the low-performing schools where these problems are apparent.

Finally, it is important to keep in mind that the estimates presented in this paper represent data on schools and student groups rather than individual students. This poses challenges for interpretation and limitations for the kinds of conclusions that may be drawn. Future research should use individual student data as they become available. For privacy reasons it is rare to be able to obtain individual student data that also identify the student's school, but if such data become available the approach described in this paper, involving location characteristics instruments, should remain applicable and potentially extremely useful.

Chapter 3

Distribution of Intergenerational Income Mobility and Local Characteristics in the United States

3.1 Introduction

For decades now there has been much concern in the United States about the apparent decline in intergenerational income mobility. It is not unusual to hear that the American Dream is over and children born to poor parents are destined to remain poor. Recent work by Chetty, Hendren, Kline, Saez, and Turner (2014) has shown these claims to be unfounded - intergenerational income mobility in the United States has not declined noticeably since the 1970s. However, in a companion paper, Chetty, Hendren, Kline, and Saez (2014) document substantial variation across locations in children's expected earnings. Intergenerational income mobility in the United States may not have declined, but it is distributed unevenly across the country.

This paper sheds light on the key question posed by Chetty et al.: why do some areas of the United States generally have higher rates of mobility than others? Using a flexible new non-parametric estimator and data on key location characteristics I estimate the full joint distribution of income mobility and local characteristics. This joint distribution allows for the evaluation of the relationship between income mobility and local characteristics while holding the levels of other characteristics constant. Chetty et al. have found income mobility to be correlated with many measures of social, economic, and demographic characteristics of the locations, but many of these measures are heavily correlated amongst themselves. Being able to adequately control for the levels of some local characteristics makes it possible to draw additional conclusions about the way intergenerational income mobility varies across locations in the United States.

The flexible non-parametric specification of the joint distribution used in this paper makes it easy to evaluate the effects of local characteristics on income mobility at any point in the distribution. Importantly, the effects can differ across the quantiles of income mobility and of the local characteristics, and in most cases they do. Locations with particularly high levels of income mobility are affected by a different set of location characteristics than locations with low mobility, and the effect of many location characteristics changes depending on the level of the characteristics. For example, the effect of the share of the workforce working in manufacturing on income mobility is non-monotonic, and the effects are different at low vs high quantiles of income mobility. Being able to identify these differences is crucial to understanding which local characteristics affect income mobility in different situations and locations.

Two different measures of income mobility are used in the analysis in this paper. The first is the expected rank in the national income distribution for children with parents whose income is in the bottom half of the national income distribution. The second measure is the difference between the expected ranks of children with parents in the top and bottom halves of the income distribution. Combined, these two measures show how well children of low-income parents can expect to do, both in absolute terms and relative to children of high-income parents. These measures are constructed from estimates in Chetty, Hendren, Kline, and Saez (2014), which are estimated by the authors from administrative tax data.

Location characteristics used in this paper are county-level variables that describe the economic and social situation of the counties. These include measures of segregation, income inequality, the local labor market, and the health of the community, all of which were found to be strongly correlated with income mobility by Chetty et al. and other prior work. Unfortunately, data on crime and education are not available for the majority of the counties in the sample, and so these variables are omitted from the analysis. Despite this, the local characteristics used in the estimation provide a reasonably comprehensive set of measures of the social, economic, and demographic state of the locations in the sample.

The estimation procedure uses the spline-spline method developed in Spady and Stouli (2016) to estimate the joint distribution of income mobility and local characteristics using maximum likelihood. Unlike local methods for estimating quantile and distribution functions, such as those in Koenker and Bassett Jr

(1978) and Chernozhukov, Fernández-Val, and Melly (2013), this method uses a global characterization of the distribution. The distribution function is flexibly parametrized using splines of the dependent and independent variables. Local derivatives and other objects of interest are then computed from the estimated distribution function.

In addition to the work by Chetty at al. a number of other authors have looked at intergenerational income mobility. Solon (1999) and Black and Devereux (2010) surveys of intergenerational mobility provide an overview of this work. The estimates from Chetty et al. that are used in this paper are broadly consistent with prior results. There have been differences in the literature between estimates that use within-county and cross-county comparisons to estimate income mobility. Chetty et al. use within-county comparisons and a rank-rank specification first presented in Dahl and DeLeire (2008). Their estimates also benefit from the rich administrative tax data used to estimate the measures of income mobility.

There is no consensus within the existing literature on the importance of neighborhood effects in determining income mobility. Observational studies, including Wilson (2012) and Sharkey and Faber (2014), have documented significant variation across neighborhoods in economic outcomes. Experimental studies of families that move, however, have found little evidence that neighborhoods affect economic outcomes Katz, Kling, and Liebman (2000), Oreopoulos (2003), and Ludwig, Duncan, Gennetian, Katz, Kessler, Kling, and Sanbonmatsu (2013). There have also been attempts to quantify not just neighborhood, but also social capital effects, most notably by Putnam (1995). These studies, as well as others in this extensive literature, are reviewed in surveys by Jencks and Mayer (1990) and Sampson, Morenoff, and Gannon-Rowley (2002).

If neighborhood effects do have an impact on economic outcomes, then the ongoing segregation of American communities by race, income, and education presents a potentially serious problem. Boustan (2013) and Massey and Denton (1993) document the racial segregation and isolation of minority communities in the United States, including the low level of public services, such as education, these communities receive. If the cause of low levels of income mobility in these communities is the lack of access to public services, then public policy has a direct role to play in addressing the problem. However, if the cause is the segregation itself, then a public policy solution is not immediately clear. One of the focuses of this paper is to assess whether measures of segregation are still strongly related to income mobility once the effects of other variables are accounted for.

Results suggest that, once other factors are taken into account, measures of racial and income segregation do not have a strong relationship to income mobility. Rather, black children have lower income mobility whether they live in segregated or integrated areas. Additionally, it is economic variables, such as the size of the middle class and the share of workers in manufacturing, that have the most effect on income mobility of children of low-income parents. Social capital appears to have an effect only on income mobility of children with high-income parents.

It is important to keep in mind that the results presented in this paper do not necessarily represent causal relationships. Even when many local characteristics are controlled for, there is still the potential for selection bias in the estimates due to household sorting across locations. The first two chapters of this dissertation show how this selection bias can be controlled for in some situations. The available data on income mobility, however, are not suitable for this approach due to being aggregated to the county level. Future work that looks at income mobility at a more disaggregated level can make use of similar approaches to recover causal estimates.

3.2 Data

All data used in this paper come from the online appendices to Chetty, Hendren, Kline, and Saez (2014) and Chetty, Hendren, and Katz (2016). The first set of data includes the intergenerational income mobility statistics estimates by Chetty et al. by county, and the second set includes covariates by county that Chetty, Hendren, and Katz compiled from numerous sources. Specific sources for individual covariates can be found in the same appendices.

The income mobility statistics estimates by Chetty et al. are divided into absolute and relative mobility measures. In their 2014 paper, the authors show that the child rank in the national income distribution is linear in the parent rank. Therefore the expectation of child rank for any parent rank can be summarized via a slope and intercept. Absolute mobility is the expectation of child rank conditional on parent rank being 25, and relative mobility is the slope of the rank-rank relationship.

In this paper, I characterize the joint distribution between local factors and two different measures of income mobility. The first is the absolute mobility described in Chetty et al., i.e. the expectation of child rank conditional on parent rank being 25. The second is the difference between expected child rank conditional on parent rank being 75 and the first measure. Equivalently, because of the linear nature of the rank-rank relationship, the first measure is the expected rank of children with parents in the bottom half of the income distribution, and the second measure is the difference in expected rank between these children and children with parents in the upper half of the income distribution.

Table 3.1: Summary Statistics: Income Mobility

Variable	Mean	Std. Dev.	Min.	Max.
Child Rank | Parent Rank ≤ 50	43.44	5.41	30.67	63.78
Child Rank | Parent Rank > 50	60.00	4.14	45.45	74.69
Difference in Rank	16.55	3.56	3.43	27.48
Relative Mobility	0.33	0.07	0.06	0.54

The local factors used in the paper include measures of segregation, income inequality, local labor market, and social capital. Some of these measures were computed by Chetty et al. from the administrative tax records available to them, while others come from supplementary materials. The measures of segregation are computed from the 2000 Census data, as is the measure of household income per capita and the share of people working in manufacturing. The Social Capital Index was developed by Rupasingha and Goetz (2008) and combines measures of voter turnout rates, the fraction of people who return their census forms, and measures of participation in community organizations.

For obvious reasons counties for which estimates of income mobility are not available are excluded from the sample. These are counties with fewer than

250 children in the administrative tax data used by Chetty et al. In general, these are counties with extremely small populations, primarily in the mid-west. In as much as they are systematically different from the rest of the sample, some results may not apply. Also excluded are counties for which some measures of local factors are unavailable or are incorrectly coded. The final sample includes 2,741 counties in all 50 states.

The local factors are divided into four different categories - measures of segregation, measures of income inequality, measures of the local labor market, and measures of the health of the community. Measures of segregation include the fraction of individuals who identify as black and indices of racial and income segregation. The measure of racial segregation is the multi-group Theil index calculated at the Census tract level for four groups: white, black, Hispanic, and other. The measure of income segregation is the rank-order index described in Reardon and Bischoff (2011) estimated at the Census tract level. Details are available in appendix D of Chetty et al.

Table 3.2: Summary Statistics: Measures of Segregation

Variable	Mean	Std. Dev.	Min.	Max.
Fraction Identifying as Black	0.094	0.148	0.000	0.859
Racial Segregation	0.082	0.081	0.000	0.538
Income Segregation	0.028	0.030	0.000	0.178

The second category covers measures of income inequality. These include household income per capita (not counting children), the Gini coefficient, and the size of the middle class. The middle class is defined as those individuals whose income falls between the 25th and 75th quantile of the national income distribution. The fraction of middle-class households and the Gini coefficient are computed from the administrative data on the parents of the children in the Chetty et al. sample. Household income per capita is taken from the 2000 Census data.

Table 3.3: Summary Statistics: Measures of Income Inequality

Variable	Mean	Std. Dev.	Min.	Max.
Household Income per Capita	33,061	7,040	15,281	77,942
Gini Coefficient	0.383	0.084	0.161	0.819
Size of Middle Class	0.549	0.089	0.215	0.779

The third category includes variables related to the local labor market. These include the unemployment rate, share of workers in manufacturing, and the teenage labor force participation rate. The teenage LFP is estimated from administrative data by Chetty et al. for children in the birth cohorts 1985-87 for years when they were age 14-16. The other data come from the 2000 Census. The definition of manufacturing follows the NAICS definition, and the variable is self-reported by respondents in the Census.

Table 3.4: Summary Statistics: Measures of the Labor Market

Variable	Mean	Std. Dev.	Min.	Max.
Share in Manufacturing	0.169	0.087	0.007	0.485
Teenage LFP	0.459	0.139	0.125	0.826
Unemployment	0.050	0.017	0.016	0.176

The last category includes measures of the community. First is the measure of social capital using an index developed by Rupasingha and Goetz (2008). It combines measures of voter turnout, the fraction of people who return their Census forms, and measures of participation in community organizations. Additionally, the category includes the poverty rate and the 25th percentile of the housing prices in the county. The housing prices reflect the general affordability of the area, and may capture other local characteristics that are priced into the housing price but are omitted from the analysis.

Table 3.5: Summary Statistics: Measures of the Community

Variable	Mean	Std. Dev.	Min.	Max.
Social Capital Index	-0.119	1.236	-4.258	3.826
Poverty Rate	0.139	0.063	0.021	0.417
Housing Prices	83,150	44,152	13,328	506,673

The data used in Chetty et al. include variables relating to the education and crime in different counties. The education data are from the NCES CCD 1996-1997 Financial and Universe Surveys, and crime data are taken from the FBI Uniform Crime Reports. Unfortunately, crime and education data are not available for all 2,741 counties, and the omissions are clearly non-random. The states of Florida, Illinois, and Wisconsin are missing all crime data. The majority of counties in Iowa, Kentucky, and Minnesota are also missing crime data, while a number of other states have multiple counties missing data as well. New Jersey, Tennessee, Virginia, and the majority of counties in Massachusetts are missing education data, and 23 other states are missing education data for multiple counties.

More than half of the counties that have data on all of the other variables are missing at least some data on education and crime. Because the pattern of missing data is non-random, and because so many observations are missing the data, these variables are not used in the analysis in this paper. The correlations between income mobility and education and crime variables, for the counties where they are available, can be found in Chetty, Hendren, Kline, and Saez (2014).

3.3 Estimation

The estimation is using the spline-spline method of Spady and Stouli (2016). The procedure uses splines to flexibly parametrize the conditional density $f(Y|X)$ and then estimates it using maximum likelihood. Because of the large number of parameters involved, I make use of a stability selection procedure via a penalized MLE described in Shah and Samworth (2013). The resulting estimates of the density are more flexible than location-scale specifications, and avoid the problems that sometimes result in density estimation, such as crossing quantiles, by imposing monotonicity of $F(Y|X)$ in Y.

The method makes use of the change of variables formula to express the joint distribution in terms of the residual e. Write $e = e(Y, X)$ as an arbitrary representation of the joint distribution of Y and X. The conditional density of Y given X is given by $f(Y = y|X = x) = f_e(e(y, x))\frac{\partial e(y,x)}{\partial y}$, and the corresponding log-likelihood is:

$$ln(f(Y = y|X = x)) = ln(f_e(e(y, x))) + ln(\frac{\partial e(y, x)}{\partial y}) \tag{3.1}$$

Spady and Stuoli show that different assumptions on the distribution of e lead to very similar estimates of the density. I assume $e \sim N(0, 1)$. Give this assumption the log-likelihood becomes:

$$ln(f(Y = y|X = x)) = -\frac{ln(2\pi)}{2} - \frac{e^2}{2} + ln(\frac{\partial e(y, x)}{\partial y}) \tag{3.2}$$

The function $e(y, x)$ is flexibly parametrized using I-splines. In this representation $e(y, x)$ is a linear combination of I-spline functions of Y, and the coefficients on the splines depend on the values of X. Specifically:

$$e = \sum_{j=1}^{J} \beta_j(X) S_j(Y) \tag{3.3}$$

where $S_j(Y)$ are the I-spline functions and $\beta_j(X)$ are the coefficients. In the estimates presented in this paper $J = 5$, so there are five basis functions including an intercept.

The I-spline basis functions are everywhere non-negative, as are their derivatives. Write $s_j(Y) = S'(Y)$. Then the derivative of the residual function $e(y, x)$ can be written as:

$$\frac{\partial e(y, x)}{\partial y} = \sum_{j=1}^{J} \beta_j(X) s_j(Y) \tag{3.4}$$

The coefficients $\beta_j(X)$ are parametrized using b-spline functions. Each variable in X is expanded as a spline of fourth order polynomials with five knots: $\beta_j(X) = b_j W(X)$, where $W(X)$ is a vector of the spline basis functions of all variables in X. For the model in this paper with 12 local factors, this setup means there are 73 coefficients of the X spline basis, and a total of 365 parameters.

A more compact notation uses the Kronecker product to represent the function $e(y, x) = b[W(X) \otimes S(Y)]$. The derivative of $e(y, x)$ is then $\frac{\partial e(y,x)}{\partial y} = b[W(X) \otimes s(Y)]$. Re-stating the log-likelihood, and its derivatives gives:

$$L(b) = -\frac{ln(2\pi)}{2} - \frac{(b[W(X) \otimes S(Y)])^2}{2} + ln(b[W(X) \otimes s(Y)]) \tag{3.5}$$

$$\frac{\partial L}{\partial b} = [-[W(X) \otimes S(Y)](b[W(X) \otimes S(Y)]) + \frac{[W(X) \otimes s(Y)]}{b[W(X) \otimes s(Y)]}] \quad (3.6)$$

$$\frac{\partial^2 L}{\partial b^2} = -([[W(X) \otimes S(Y)][W(X) \otimes S(Y)]^T] + [\frac{[W(X) \otimes s(Y)][W(X) \otimes s(Y)]^T}{(b[W(X) \otimes s(Y)])^2}]) \quad (3.7)$$

The use of I-splines and b-splines guarantees that $S(Y)$, $s(Y)$, and $W(X)$ are non-negative. Under these conditions, Spady and Stuoli show that there exists a unique solution b^* to the MLE problem.

Because of the large number of parameters involved, the likelihood is penalized by a term $\lambda \sum |b|$, following the complementary pairs stability selection procedure of Shah and Samworth (2013). This procedure divides the data into two equal and non-overlapping subsamples, and then computes the coefficients via penalized MLE. This sample-splitting procedure is repeated, and after sufficient repetitions, only those coefficients that prove to be consistently significant are retained. In this paper I use values of $\lambda = (0.5, 1, 2)$ and repeat the sample-splitting procedure 25 times, creating 50 subsamples for each value of λ. I retain the coefficients that remain significant in at least 60% to 67% of the total subsample estimations.

3.4 Results

All results are available for two measures of income mobility. The first is the expected rank in the national income distribution of children with parents whose income is in the bottom half of the national income distribution. Graphs and tables of results for this measure are labeled "Income Mobility" and "P=25." The second is the difference between the expected rank of these children and those with parents in the upper half of the national income distribution. These results are labeled "Difference in Income Mobility" and "P=75 vs P=25." The results are grouped into three categories, with all graphs and tables in the appendix.

The first set of results in section 4.1 shows the distribution of both income mobility measures conditional on one local factor. These are a more complete representation of the relationships shown in Chetty et al. by correlations between income mobility and local factors. Because in some cases the relationships are non-linear, and in many cases, the relationships are different at different quantiles of income mobility, the conditional distribution functions provide information not available from the correlations.

The second set of results in section 4.2 describes the multivariate distribution of expected income rank for children with low-income parents and all of the local factors. Conditional distribution functions in this set of results show the relationship between income mobility and a given local factor, conditional on the median value of all other local factors. These should be interpreted as changes in income mobility associated with changes in a given local factor, holding the values of all other local factors constant.

The third set of results in section 4.3 shows the multivariate distribution of the difference in expected income rank for children with low- and high-income parents. Whereas the second set of results shows what local factors contribute to absolute income mobility of children with low-income parents, the third set of results identifies factors that contribute to the relative mobility of children of low- vs high-income parents. By looking at the effects of variables in the second vs the third set of results it is also possible to see the effect of the variables on income mobility of children with high-income parents as well.

Results include graphs of the conditional distribution functions and tables summarizing information about the conditional distributions. Each graph shows the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution function $F(Y|X)$ that are calculated from the estimated density $f(y|x) = \phi(e(y,x))\frac{\partial e(y,x)}{\partial y}$. The parametrization of the function $e(\cdot)$ is given in equation (3) and its derivative in equation (4), and the estimated spline coefficients in appendix C.5. For graphs in the first set of results, actual data are plotted in red along with the estimated quantiles.

For the second and third sets of results, a table is included to help summarize each conditional distribution function. The tables shows the conditional quantiles $Q_{Y|X}(q|x)$ for $q \in (0.25, 0.5, 0.75)$ at different values of x. The value of one local factor in x changes between the 0.15, 0.33, 0.5, 0.67, and 0.85 quantiles of that factor in the data, while the values of all other factors are kept constant at their medians. The tables are meant to give a snapshot of the distributions of income mobility at a number of different values of local factors.

The tables also include the slopes of the quantiles $Q_{Y|X}(q|x)$ for $q \in$

$(0.25, 0.5, 0.75)$ between different values of x, providing a measure of the impact of the changing factor on income mobility at different points in the distribution. For two given quantiles of the local factor, the table shows the change in $Q_{Y|X}(q|x)$ divided by the change in the local factor between those quantiles. These slopes are provided instead of the instantaneous rates of change $\partial y/\partial x$ since the slopes between fixed quantiles of x are less volatile, and likely to be more informative, than estimates of $\partial y/\partial x$ at specific values of x.

Heteroskedasticity-robust standard errors are reported for the spline coefficients in appendix C.6. It is important to note that the stability selection process is not taken into account when calculating these standard errors. Standard errors for the quantiles of the conditional distributions of income mobility and for the average slopes are computed using a bootstrap that also omits the stability selection procedure. The bootstrap uses 500 iterations of the maximum likelihood estimation on different samples from the data while setting the coefficients not retained by the stability selection process to zero. As a result, some caution should be taken when drawing conclusions from the standard errors.

Appendix C.7 contains results from multivariate OLS regressions of income rank of children with low-income parents and the difference in income rank between children of low- and high-income parents on all local factors. The results provide a basis for comparison of the main results presented in this paper. In general, OLS results appear to overstate the effects of local factors, since in many cases local factors appear to be important at some values but much less important at other values of the local factor. Extrapolating the effects of the local factors estimated via OLS outside of the region where the data are most concentrated could lead to very misleading conclusions.

3.4.1 Distributions of Income Mobility and Local Factors

The first set of results expands on the findings in Chetty, Hendren, Kline, and Saez (2014). These results show the distributions of income mobility and the difference in income mobility conditional on different local factors, with one figure for each local factor for each of the two measures of income mobility (figures C.1.1:24). The figures showing income mobility of children with low-income parents are labeled "Income Mobility" and "P=25," and the figures showing the difference in income mobility between children with low- vs high-income parents are labeled "Difference in Income Mobility" and "P=75 vs P=25." These figures show the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution function $F(Y|X)$, calculated using the estimated spline coefficients in appendix C.5. In addition to the estimated quantiles, actual data are plotted in red. The results are grouped into four categories based on the local factors that measure segregation, income inequality, the local labor market, and health of the community.

All measures of segregation are closely related to the distribution of income mobility. Income mobility of children with low-income parents decreases with the fraction of black households in the county, and measures of racial and income segregation (figures C.1.1, C.1.3, and C.1.5). Figure C.1.1 shows that the median income rank of children with low-income parents who grow up in a county that is twenty percent black is at the 40th percentile of the national income distribution, and the 25th and 75th quantiles of these children's income ranks are at the 38th and 42nd percentiles of the national income distribution, respectively. The median income rank of children with low-income parents who grow up in a county that is sixty percent black is at the 36th percentile of the national income distribution, and the 25th and 75th quantiles are at the 35th and 37th percentiles. The relationship between all three measures of segregation and income mobility is strongest at low values of the measures of segregation, especially in the case of income segregation. For both measures of segregation, the upper quantiles of income mobility decline faster than the lower quantiles, indicating that these measures of segregation correlate to rapid declines in income mobility of children who would otherwise do particularly well.

The difference in income mobility of children with low- vs high-income parents is increasing with all measures of segregation (figures C.1.2, C.1.4, and C.1.6). The relationship is strongest with the fraction of black households in the county. In the case of income segregation, the effect is present only at levels below 0.025 income segregation, with minimal relationship above that point. Taken together, these results show that counties with high fractions of black households and high levels of segregation are those where income mobility is lowest, and the difference in outcomes between children of low- and high-income parents are highest. The fact that the relationship is strongest at lower values of segregation measures suggests that the difference between counties with low measures of segregation and moderate measures of segregation is higher than between counties with moderate and high levels of segregation.

Higher incomes and a higher fraction of middle-class households are associated with higher income mobility (figures C.1.7 and C.1.11), while greater inequality (as measured by the Gini coefficient) is associated with lower income mobility (figure C.1.9). The relationship between income and income mobility is in part non-linear: higher incomes are associated with greater mobility up until incomes of $\$34,000$ per capita and with incomes of $\$40,000$ and above, but between $\$34,000$ and $\$40,000$ higher incomes appear to be associated with lower income mobility, especially at the higher quantiles. The peak in income mobility (especially at the highest quantiles) between $\$30,000$ and $\$40,000$ per capita corroborates the finding that a higher fraction of middle-class households is associated with higher income mobility.

The relationships between income mobility and inequality and the size of the middle class, are strong and monotone. At lower levels of the size of the middle class the distribution of income mobility is bimodal. This is likely due to the fact that a small middle class may be indicative either of a large upper class or a large lower class, and since income plays a role in income mobility, the counties with a large lower class are those with lower income mobility and those with a large upper class are those with higher income mobility. It is worth noting that a high fraction of middle-class households (> 0.65) correlates to higher income mobility for children with low-income parents than a high fraction of upper-class households.

Higher household incomes and a larger size of the middle class are associated with a smaller difference in income mobility between children of low- and high-income parents (figures C.1.8 and C.1.12), while greater income inequality is associated with a larger difference (figure C.1.10). The effect of income is strongest between $\$25,000$ and $\$30,000$ per capita, but the negative association continues throughout. Just like above, the distribution of the difference in income mobility is bimodal at low values of the size of the middle class, depending on whether remaining households are largely upper or lower class. All three effects are strongest at upper quantiles of the difference in income mobility, suggesting that these variables exacerbate or attenuate differences in income mobility that are unusually large more so than differences that are unusually small.

Measures of employment are strongly associated with income mobility (figures C.1.13, C.1.15, and C.1.17). Higher unemployment is associated with lower income mobility, and higher teenage LFP is associated with higher income mobility, with the effect increasing at LFP above 0.6. The relationship between income mobility and manufacturing is not as strong, but it is negative throughout. The higher the fraction of workers working in manufacturing the lower the income mobility in the county. The effect is very small for moderate levels of manufacturing (0.1 to 0.2) and is stronger at lower and higher levels.

All three of these measures are also strongly associated with the difference in income mobility (figures C.1.14, C.1.16, and C.1.18). Higher unemployment is associated with larger differences, and higher teenage LFP is associated with smaller differences. The share of workers in manufacturing is more strongly related to the difference in income mobility than to the income mobility of children with low-income parents. A higher share of workers in manufacturing is associated with a larger difference between income mobility of children of low- and high-income parents. This suggests that while a higher share of workers in manufacturing correlates to lower income mobility for children with low-income parents, it correlates to higher income mobility for children with high-income parents.

Social capital is strongly associated with increased income mobility, as is poverty (figures C.1.19 and C.1.21). Counties with higher values of the social capital index and lower values of poverty have higher income mobility. The peak in income mobility at the 10% poverty rate is likely to be related to the positive effect of the middle class. It again suggests that counties with primarily upper-class households, extremely low poverty, and very high incomes per capita have lower measures of income mobility than counties with somewhat lower measures of these local factors. Counties that produce the greatest income mobility for children with low-income parents have incomes per capita slightly above the national median, moderately low poverty rates, and very high fractions of middle-class households.

The relationship between income mobility and housing prices is more complicated (figure C.1.23). At low levels of housing prices, higher housing prices are associated with lower mobility, up until $60,000 to $100,000, depending on the quantile of mobility. After this point, higher housing prices are associated with higher levels of income mobility. Housing prices appear to be one of the few local factors that affect the lower quantiles of income mobility more than the higher quantiles. It is likely that this result is due to the fact that the measure of the housing prices used in this paper is the 25th percentile of all of the housing prices in the county. The lower percentile of the housing prices is then correlated more strongly with the lower quantiles of income mobility.

Higher social capital is also associated with a smaller difference in income mobility between children of low- and high-income parents, except at very low levels of social capital (< -1.25) where the relationship is positive (figure C.1.20). Higher poverty is associated with a larger difference in income mobility, with the effect being greater at the higher quantiles of difference in income mobility (figure C.1.22). At low poverty rates the distribution of the difference in income mobility is significantly tighter than at higher poverty rates, indicating that higher poverty is correlated with a greater spread of potential outcomes. At low levels, housing prices are associated with a larger difference in income mobility, but after $\$35,000$ to $\$55,000$, depending on quantile, the association is negative - counties with higher housing prices have a smaller difference in income mobility (figure C.1.24).

The estimates of conditional distributions of income mobility presented above give a clearer picture of the relationship between income mobility and local factors than simple correlations that were previously available. It is possible to see non-linearities and relationships that are different depending on the level of income mobility and the local factor. In general, most local factors are more closely correlated with the higher quantiles of income mobility measures than with the lower quantiles, suggesting that places with abnormally low levels of income mobility are less affected by the changes in local factors. However, the distributions presented in this section do not hold other factors constant, and many of the local factors are likely to be correlated with one another. The next set of results presents the distribution of income mobility conditional on all local factors.

3.4.2 Effect of Local Factors on Income Rank

Because local factors are sometimes highly correlated amongst themselves, the information from the bivariate distributions of income mobility and a given local factor presented in the previous section can give an incomplete picture of the relationship between income mobility and the local factors. It is desirable to see the association between income mobility and a given local factor while holding the values of all other local factors constant. The results presented in this section do just that, showing the relationship between income mobility and specific local factors while holding the values of other local factors at their medians. Unlike the prior section, the results in this section cover only the relationship between expected rank of children with low-income parents and local factors. The relationship between the difference in expected ranks and local factors is covered in the next section.

This set of results presents the multivariate distribution of expected income rank for children with low-income parents and all of the local factors. Figures C.2.1:24 show the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution function $F(Y|X)$ when the value of one local factor changes while the values of all of the other local factors are kept constant at their medians in the data. The figures showing income mobility of children with low-income parents are labeled "Income Mobility" and "P=25." Tables C.3.1:12 summarize the values of the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution functions at specific quantiles of income mobility and local factors. The tables also include the slope of the quantiles of income mobility $\Delta Q_{Y|X}(q|x)/\Delta Q_X$ between the quantiles of the local factors. These results make it easier to see both the incremental and the total effect of a local factor on income mobility. The results are again grouped into four categories covering measures segregation, income inequality, the local labor market, and health of the community.

Of the measures of segregation, only the fraction of black households remains strongly predictive of income rank when all other local factors are held constant (figures C.2.1, C.2.3, and C.2.5). The conditional distribution of income mobility and the fraction of black households is summarized in table C.3.1. The median income rank of children with low-income parents is 44.08 in counties that are at the 15th quantile of the fraction of black households and 39.12 in counties that are at the 85th quantile. The effects are largest at low values of the fraction of black households. The slope of the median of income mobility is -2.69 ranks per one percent of black households between the 15th and 33rd quantiles of the fraction of black households. The slope of the 0.75 quantile between the 15th and 33rd quantiles of black households is even larger in absolute value at -5.77, meaning for every one percent increase in the fraction of black households the expected 0.75 quantile of income rank falls by nearly six.

Once other local factors are controlled for, racial segregation has only a marginal positive effect on income mobility (the effect was strongly negative when not controlling for other factors) (table C.3.2). At different parts of the distribution, the effect ranges from 0.26 to zero increase in income rank per one percent increase in racial segregation. The median of income mobility increases from 41.60 at the 15th quantile of racial segregation to 42.43 at the 85th quantile. The effect of income segregation is large, but only at lower levels (table C.3.3). From the 15th to the 33rd quantile of income segregation the effect of a one percent increase in segregation is a -1.10 decline in income rank. At higher levels the effect becomes small in absolute value, ranging between -0.2 and 0.1 income rank per one percent increase in income segregation. It is worth noting that because variation in income segregation is much lower than variation in racial segregation across the country, even when the effect per one percent change is large , the effect of going from the 15th to the 33rd quantile represents a change of only -0.49 in terms of income rank.

Household income and the Gini coefficient have only marginal effects on income mobility (figures C.2.7 and C.2.9, and tables C.3.4 and C.3.5). The effect of household income is non-linear, with median income rank increasing by 0.48 per $\$10,000$ of income between the 15th and 33rd quantiles of income, but decreasing by -0.75 per $\$10,000$ between the 50th and 85th quantiles. The overall effect is very small, as median income rank varies only between 42.26 and 41.77, but the marginal effects are significant between the 50th and 85th quantiles. The effect of the Gini coefficient is negative and close to zero at all levels of income inequality. The estimates of the effects are not statistically significant, and the estimated cumulative effect on the median is only -0.66 rank between the 15th and 85th quantiles of the Gini coefficient.

The effect of the size of the middle class is relatively large, especially if the middle class itself is large (figure C.2.11 and table C.3.6). The effect on the median income rank is close to zero (0.00 to 0.08) between the 15th and 50th quantile of the size of the middle class, but between the 66th and 85th quantile it is between 0.27 and 0.33 per one percent, making the difference between expected income rank at the 67th and 85th quantiles between 1.82 and 1.49, depending on the quantile of income rank. The median income rank increases from 41.93 to only 42.26 as the size of the middle class increases from the 15th to the 50th quantile but then increases rapidly to 44.41 at the 85th quantile.

Unemployment and the share of workers in manufacturing both have a pronounced negative effect on income mobility (figures C.2.13 and C.2.17, and tables C.3.7 and C.3.9). The effect of an extra one percent of workers in manufacturing is about -0.15 rank in the income distribution for children of low-income parents. The effect is largest at very low and very high shares of workers in manufacturing - between the 15th and the 33rd quantiles the slope is -0.18 and between the 50th and 85th quantiles it is -0.16. For unemployment, the overall slope is -0.32, and between the 33rd and 50th quantiles of unemployment, it is as large as -0.58. It is especially large at the top quantiles of income mobility (-0.45 vs -0.22 at the median), indicating that high unemployment disproportionately affects those children who would otherwise do particularly well.

Teenage labor force participation has a non-monotonic effect on income mobility (figure C.2.15 and table C.3.8). Between the 15th and 33rd quantiles, the effect is negative, with an extra percent of teen LFP correlating to -0.12 rank in the income distribution. The effect between the 33rd and 67th quantile is between 0.02 and 0.04 increase in rank per one percent and is not statistically significant. At higher levels of teen LFP, between the 67th and 85th quantiles, the effect is between 0.06 and 0.10 rank per one percent of teen LFP, depending on the quantile of income rank.

The effect of the social capital index on income mobility is relatively small and positive (figure C.2.19 and table C.3.10). The index varies from -4 to 4, although most of the data fall between -1.5 and 1.5. A one unit increase in the index correlates to an increase of about 0.25 rank in the income distribution. The effect is largest at low values of the index, with a slope of 0.51 between the 15th and 33rd quantiles. The overall effect is modest because the span of the index is small compared to some of the other variables, with an increase of just 0.66 rank (from 41.93 to 42.59) between the 15th to the 85th quantile of the index.

Poverty has a large negative effect on income mobility, but only at low values of poverty (figure C.2.21 and table C.3.11). Between the 15th and 33rd quantiles of poverty a one percent increase in the poverty rate reduces the median income rank by -0.34. However, after the 33rd quantile of poverty, the effect is zero all the way until the 67th quantile when it again becomes negative, but small (-0.1). Almost all of the decline in income mobility associated with poverty happens between the 15th and 33rd quantiles of poverty where the median income rank falls from 43.09 to 42.26. Between the 33rd and 85th quantiles of poverty, the median income rank declines only slightly, from 42.26 to 41.77. An increase or decrease in poverty, in other words, is likely to matter only if the current level of poverty is quite low.

Higher housing prices also adversely affect income mobility (figure C.2.23 and table C.3.12). Similarly to poverty, the effect is greatest when housing prices are low. Between the 15th and 33rd quantiles, a $\$10,000$ increase in the housing price correlates to a decrease of -0.80 in the median income rank. The effect becomes smaller as housing prices rise, with a slope of -0.67 between the

33rd and 50th quantiles and −0.44 between the 50th and 67th quantiles, until it becomes effectively zero between the 67th and 85th quantiles. Overall the impact of the housing prices is significant, with a change from the 15th to the 67th quantile corresponding to a decline from 44.41 to 41.77 median income rank.

3.4.3 Effect of Local Factors on Difference in Income Mobility

The difference in income mobility is the difference between expected rank of children with parents who have incomes in the top half of the national income distribution and children with parents who have incomes in the bottom half. A large difference in income mobility indicates that children from high-income households tend to do significantly better than children from low-income households. Factors that contribute to the difference can be thought of as factors that are related to the persistence of income inequality over time. As in the previous section, the results show the relationship between the difference in income mobility and different local factors, while holding the values of other local factors constant.

The estimates presented in this section describe the multivariate distribution of the difference in income mobility and all of the local factors discussed earlier. Figures C.2.1:24 show the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution function $F(Y|X)$ when the value of one local factor changes while the values of all of the other local factors are kept constant at their medians in the data. The figures showing the difference in income mobility between children with low- vs high-income parents are labeled "Difference in Income Mobility" and "P=75 vs P=25." Tables C.4.1:12 summarize the values of the quantiles $Q_{Y|X}(q|x)$ of the conditional distribution functions at specific quantiles of difference in income mobility and local factors. The tables also include the slope of the quantiles of difference in income mobility $\Delta Q_{Y|X}(q|x)/\Delta Q_X$ between the quantiles of the local factors. Results are again grouped by local factors that cover measures of segregation, income inequality, the local labor market, and health of the community.

The fraction of black households remains the most important measure of segregation that is related to the difference in income mobility (figure C.2.2 and table C.4.1). Particularly at low levels of the fraction of black households, the relationship is strong and positive. Between the 15th and 33rd quantiles a one percent increase in the fraction of black households increases the median difference in income mobility by 0.55 and between the 33rd and 50th quantiles the effect is 0.48. Going from the 15th to the 85th quantile of the fraction of black households corresponds to an increase from 15.94 to 19.55 median difference in rank, for a total increase of 3.61.

Racial and income segregation have a much smaller effect on the difference in income mobility (figures C.2.4 and C.2.6, and tables C.4.2 and C.4.3). The effect of racial segregation is small and negative. It is largest in absolute value between the 15th and 33rd quantiles, at -0.12. The effect of income segregation is positive and slightly larger in absolute terms. Between the 15th and 33rd quantiles, it is 0.26 difference in income rank per one percent of income segregation. Overall the effects are small, as the variation in segregation accounts for, at most, 0.48 difference in rank in the case of racial segregation and 0.12

difference in rank in the case of income segregation.

None of the measures of income inequality are closely related to the difference in income mobility. Income per capita has a small positive effect (0.19) between the 15th and 33rd quantiles of income, but it is not large enough to make a difference greater than 0.36 rank and is not statistically significant (figure C.2.8 and table C.4.4). The Gini coefficient and the size of the middle class have even less of an effect, with none of the estimated slopes significantly different from zero despite relatively small standard errors between 0.03 and 0.06 for the median difference in rank (figures C.2.6 and C.2.10, and tables C.4.5 and C.4.6). What is notable is the fact that the size of the middle class is very strongly related to the income rank of children with low-income parents. This result means that while a large middle class has a positive effect on income rank, its effect on children with low- and high-income parents is very similar.

The share of workers in manufacturing has a large effect on the difference in income mobility (figure C.2.14 and table C.4.7). As discussed above, a high share of workers in manufacturing reduces the expected income rank of children with low-income parents. The figure and table show that, additionally, a high share of workers in manufacturing also increases significantly the difference in income mobility between children with low- and high-income parents, especially at lower values. Between the 15th and 33rd quantile a one percent increase in the share of workers in manufacturing correlates to a 0.15 increase in the median difference in income mobility. The total difference between the 15th and 85th quantiles of the share of workers in manufacturing corresponds to an increase in the median difference in income mobility from 15.94 to 17.50.

The other two measures of the labor market have very little effect on the difference in income mobility (figures C.2.16 and C.2.18, and tables C.4.8 and C.4.9). Teenage LFP has a negligible effect with none of the estimated slopes statistically significantly different from zero, and unemployment has a small positive effect of 0.42 ranks per one percent between the 33rd and 50th quantiles only. It is important to note that teenage LFP does have a large effect on the income rank of children with low-income parents, so it's lack of effect on the difference in rank means that it has a similarly large effect on the income rank of children with high-income parents.

The measure of social capital is one of the strongest predictors of the difference in income mobility, despite having little effect on the income rank of children with low-income parents, as discussed earlier (figure C.2.20 and table C.4.10). The effect ranges from 0.55 to 0.44 difference in income rank per one unit of the social capital index between the 15th and 33rd and the 67th and 85th quantiles of the index respectively. The overall change in going from the 15th to the 85th quantile of the index corresponds to a change from 16.3 to 17.62 for mean difference in income ranks. This means that social capital is strongly related to the income rank of children with high-income parents, but not of those with low-income parents. It may be that the measure of social capital is primarily picking up the social capital accumulated by the wealthier families, or it may be that only children from wealthier families are able to leverage the social capital available to them into better-paying jobs.

Poverty has very little to no effect on the difference in income mobility at all points in the distribution, and none of the estimated slopes are statistically significant (figure C.2.22 and table C.4.11). Housing prices, however, have a persistent negative effect (figure C.2.24 and table C.4.12). The effect is larger at higher values of housing prices, up to -0.28 difference in rank per $\$10,000$ between the 67th and 85th quantiles. It is notable that high housing prices lower income mobility of children with low-income parents, but they also lower the difference in income mobility. It means that high housing prices negatively affect children with high-income parents *more* than children with low-income parents. Going from the 15th to the 85th quantile of housing prices is associated with a 2.69 drop in the expected income rank of children with low-income parents, but a 4.01 drop in income rank for children with high-income parents.

3.5 Conclusion

The relationship between income mobility and local factors can differ greatly depending on whether other local factors are controlled for or not. Compared to raw correlations in Chetty, Hendren, Kline, and Saez (2014) the conditional distributions in this paper show the effect on income mobility that can be attributed to local factors while holding the values of other factors constant. This gives a much clearer picture of what factors actually correlate with intergenerational income mobility, providing useful information to public and policy discussion.

Some of the factors that correlate with income mobility when other factors are not accounted for become largely unimportant when other factors are held constant. Measures of racial and income segregation appear to have very little effect, as do the level of income and the Gini coefficient. These findings suggest that alarm over the effects of segregation and inequality on income mobility may be overblown. The difference in income mobility, when it is present, appears to be very marginal between counties with very low and very high levels of segregation and inequality, as does the difference between income mobility of children with low-income and high-income parents.

The fraction of black households is the single most important factor in predicting income mobility. This finding is consistent with other work that shows black children falling behind their peers in educational attainment and labor income, and black families falling behind white families in wealth accumulation Black and Devereux (2010). Additionally, a larger fraction of black households correlates to a much greater difference in income mobility between children with low- and high-income parents. The fact that this penalty does not correlate to racial segregation suggests that black children face a harder time in climbing the income ladder whether they live in largely black or highly-integrated areas.

The measure of social capital used in the analysis appears to have little effect on income mobility of children with low-income parents, but a large effect on the difference in income mobility between children with low- and high-income parents. Some authors have argued that social capital and community ties are essential to future success, and have blamed the deterioration of social support systems for economic hardship in poor urban and rural areas Putnam (1995). At least in as much as social capital is captured by the measure used in this paper this does not appear to be the case. It seems more likely that children with high-income parents are better able to use social capital to obtain high-wage jobs.

The size of the middle class is the second most important determinant of income mobility. A large middle class correlates to much higher expected rank for children of low-income parents, although it does not seem to matter for the difference in income mobility between children with low- and high-income parents. It appears that for children of low-income parents, living in an area with a large middle class is preferable to living in an area with mostly upper-class households. Therefore, in as much as growing income inequality diminishes the size of the middle class, it may have an adverse effect on income mobility.

The share of the workforce in manufacturing also correlates strongly with income mobility, even after controlling for other local factors. Areas with large manufacturing workforces also have much lower income mobility and a larger gap in income rank between children with low- and high-income parents. This means children of manufacturing workers have lower incomes than their peers, while their parents have had to deal with the effects of declining manufacturing in the United States. This combination of factors may provide an additional explanation for the economic anxiety that continues to be felt across parts of the United States that were dominated by manufacturing in past decades.

These results confirm the finding in Chetty, Hendren, Kline, and Saez (2014) that income mobility is a local problem. Local economic factors appear to be the ones most closely related to income mobility, and to some degree, these could be addressed using place-based policies Kline and Moretti (2013). Future research will focus on the impact of possible policies, as well as on estimating the causal effects of local characteristics on income mobility, as in Chetty, Hendren, and Katz (2016). Understanding whether the relationships described in this paper are due to neighborhood effects or sorting by households will be crucial in determining what policies may be effective in addressing the inequality in intergenerational income mobility across locations in the United States.

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Appendix A

Appendix for Chapter 1

A.1 Proofs of Propositions

Proposition 1

Assumptions:

1. Choice probabilities $P_{i,j}$ follow equation (2).
2. Coefficients $\alpha_{p,i}$ are negative for all Z_i.

Proposition: Conditional on X, $\bar{Z}$, s, c, and ξ there exists a unique to scale vector of prices p^* such that $\sigma_j = \int P_{i,j} dF(Z_i)$. This vector is continuous in X, $\bar{Z}$, s, c, and ξ.

Proof: $P_{i,j}$ given in equation (2) is continuous and differentiable in p. Given assumption 2 the derivatives follow $\partial P_{i,j}/\partial p_j < 0$ and $\partial P_{i,j}/\partial p_k > 0$ for $k \neq j$. The share of households choosing neighborhood j, $\sigma_j = \int P_{i,j} dF_{Z_i}$, is also continuous and differentiable in p and derivatives follow $\partial \sigma_j / \partial p_j < 0$ and $\partial \sigma_j / \partial p_k > 0$ for $k \neq j$. The result then follows from the appendix in Berry (1994). The second part of the claim follows from the Lemma in the same appendix.

Proposition 2

Definition: An equilibrium in the model is a set of choice probabilities $P^*_{i,j}$ and a set of prices p^* such that the housing market clears according to $\sigma_j = \int P_{i,j} dF(Z_i)$ and $P^*_{i,j}$ are a fixed point of the mapping in equation (2) where c_j is determined according to equation (3), s_j according to equation (4), and $\bar{Z}_j$ according to equation (5).

Proposition: If the assumptions of Proposition 1 hold then an equilibrium exists.

Proof: $\bar{Z}_j = \int Z_i * P_{i,j} dF_{Z_i} = \int Z_i * \frac{exp(\alpha_{X,i}X_j - \alpha_{p,i}p_j + \alpha_{\bar{Z},i}\bar{Z}_j + \alpha_{C,i}C_j + \alpha_{S,i}S_j + \xi_j)}{\sum_k exp(\alpha_{X,i}X_k - \alpha_{p,i}p_k + \alpha_{\bar{Z},i}\bar{Z}_k + \alpha_{C,i}C_k + \alpha_{S,i}S_k + \xi_k)} dF_{Z_i}$.

This equation defines a mapping from $\bar{Z}$ to itself on a closed set that is bounded by the maximum and minimum values of Z_i. This mapping is continuous in $\bar{Z}$ since all arguments of $P_{i,j}$ are continuous in $\bar{Z}$ by equations (3) and (4) and Proposition 1. By the Brower's fixed-point theorem there exists $\bar{Z}^*$ that is a fixed point of this mapping. Associated with this $\bar{Z}^*$ is a unique set of market-clearing prices p^* and a set of choice probabilities $P^*_{i,j}$ that together satisfy the definition of the equilibrium.

Proposition 3

Assumptions:

3. The matrix $(X, p, \bar{Z}, c, s)$ has full rank.

4. ξ, η, ν are continuously distributed with means zero, are independent across j, and are independent of X and Z.

5. There exists at least one j s.t. $s(j) \neq c(j)$.

6. $||\{k|k \notin \{j, s(j), c(j)\}\}|| \geq (r+1)/t$.

Proposition: Given a distribution of $(\delta, X, p, \bar{Z}, c, s)$ and assumptions 3-6 there exist unique values of α_0, β, γ corresponding to equations (10), (11), (12).

Proof: Define X_{-j} to be the exogenous amenities of the neighborhoods other than those included in $\{j, s(j), c(j)\}$. By equations (2) and (5) and Proposition 1 X_{-j} is correlated with p_j and $\bar{Z}_j$ and by Assumption 4 is uncorrelated with ξ_j. $X_{s(j)}$ is correlated with s_j and by Assumption 4 is uncorrelated with ξ_j. $X_{c(j)}$ is correlated with c_j and by Assumption 4 is uncorrelated with ξ_j. By Assumptions 5 and 6 the number of available instruments is greater than or equal to the number of endogenous variables in equation (10).

By equations (2) and (5) X_{-j} is correlated with $\bar{Z}_{s(j)}$ and $\bar{Z}_{c(j)}$ and by Assumption 4 is uncorrelated with $\nu_{s(j)}$ and η_j. By Assumption 6 the number of available instruments is greater than the number of endogenous variables in equations (7) and (8).

All coefficient restrictions in the linear system of simultaneous equations take the form of exclusion restrictions. The existence of the required number of instruments together with Assumptions 3 and 4 satisfy conditions for identification given in Hsiao (1983). Each equation of the model is identified by Corollary 3.3.2 therein.

A.2 Equilibrium Distributions of Race

Distribution of Black, Asian, and Hispanic individuals across neighborhoods. Solid green line is the model equilibrium and the blue line plots the actual data.

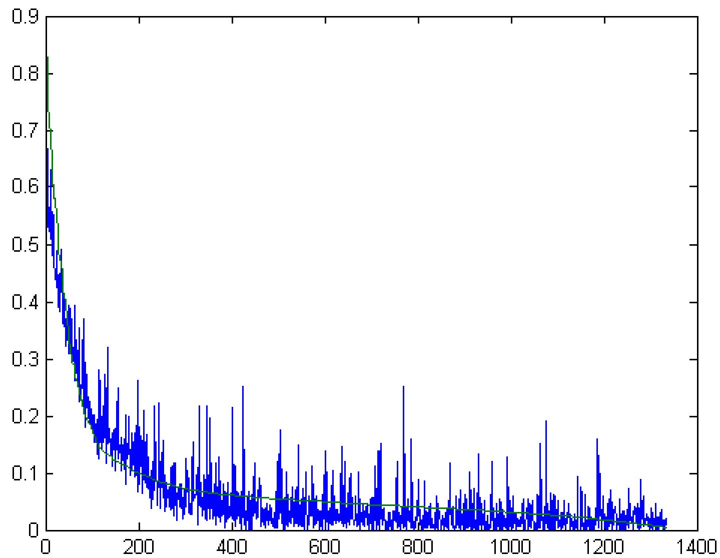


Figure A.1: Proportion Black

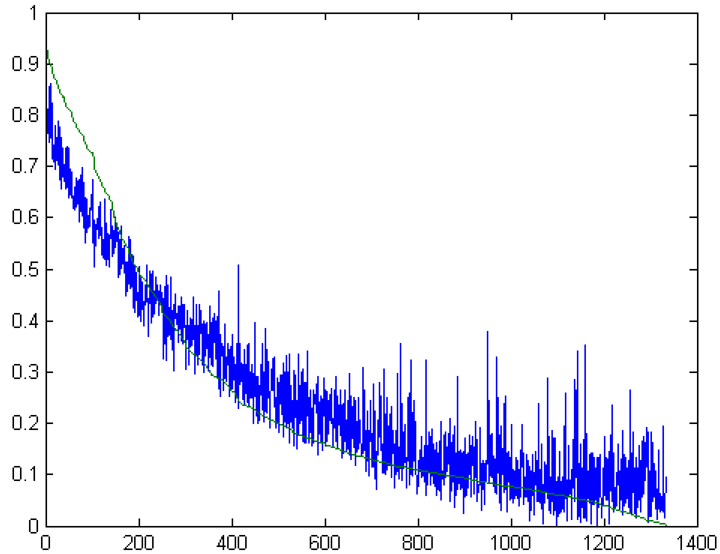


Figure A.2: Proportion Asian

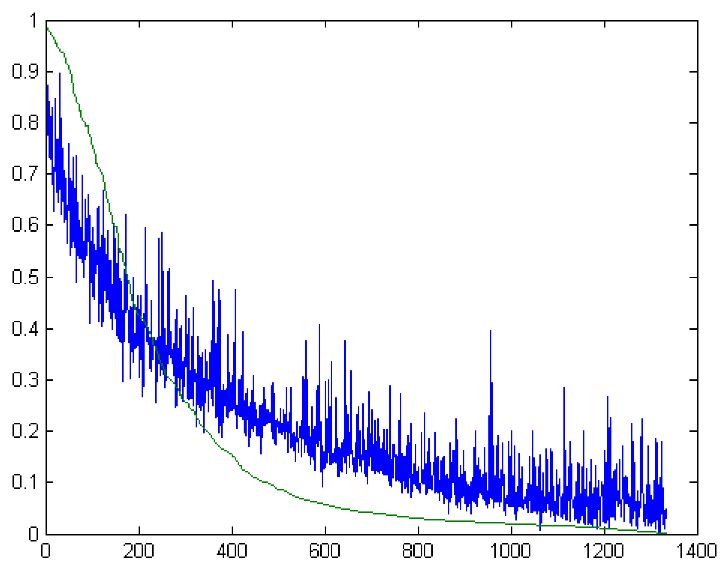


Figure A.3: Proportion Hispanic

A.3 Counterfactual School Quality and Crime

Distribution of initial school quality or crime in 100 neighborhoods chosen from neighborhoods bellow average in that variable is in blue. In red is the exogenous improvement of one standard deviation. In yellow is the new equilibrium level of school quality or crime after all endogenous variables have adjusted.

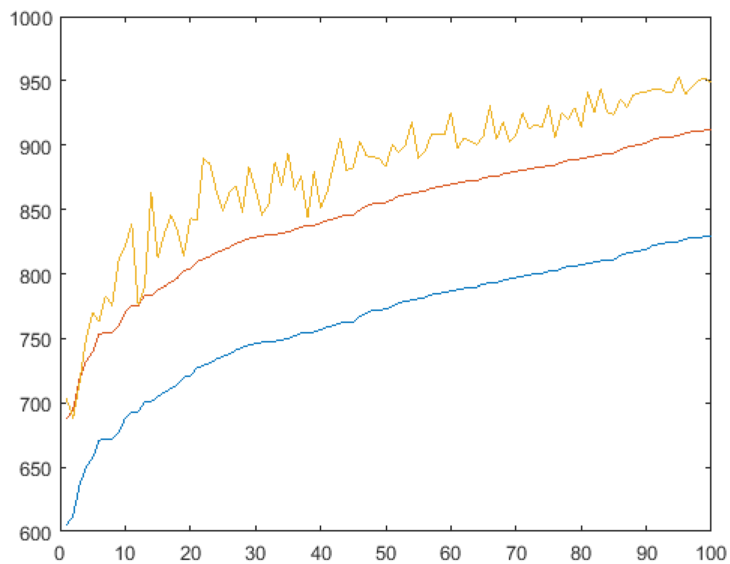


Figure A.4: School Quality

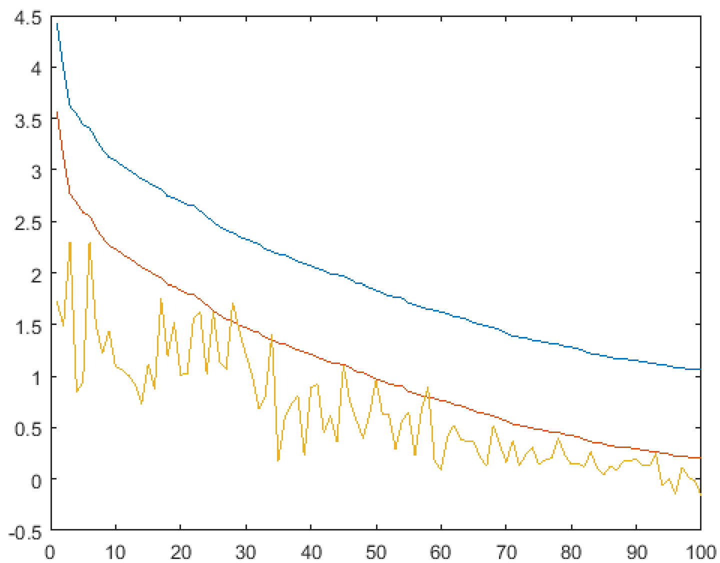


Figure A.5: Crime

Appendix B

Appendix for Chapter 2

B.1 Estimation Results

Table B.1: API OLS

Variable	**Coefficient** (Std. Err.)			
middle	-38.40	-39.37	-38.01	-37.93
	(1.58)	(1.59)	(1.37)	(1.37)
high	-68.99	-66.26	-64.19	-64.01
	(1.95)	(2.08)	(1.80)	(1.80)
charter	5.04	14.19	17.60	17.62
	(1.99)	(2.08)	(2.13)	(2.13)
size	-0.01	-.02	-.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)
black	-97.06	-130.50	-131.16	-130.70
	(5.24)	(7.29)	(7.48)	(7.47)
asian	87.26	77.23	79.15	79.04
	(5.14)	(7.16)	(6.61)	(6.59)
hispanic	22.37	-33.43	-30.29	-30.70
	(4.14)	(6.81)	(6.44)	(6.44)
other	-44.47	-30.42	-22.79	-24.00
	(7.50)	(10.04)	(9.58)	(9.59)
free meals	-51.66	-15.86	-22.07	-20.80
	(4.02)	(5.61)	(5.44)	(5.46)
median income				4.79
				(1.87)
gifted	84.17	133.60	138.23	137.40
	(5.44)	(7.03)	(6.17)	(6.17)
migrant ed	-100.56	35.76	15.14	
	(11.72)	(22.07)	(22.66)	
esl	-63.10	-55.79	-55.64	-54.11
	(5.17)	(7.04)	(6.85)	(6.82)
former esl	-20.71	-1.38	-23.49	-22.79
	(7.36)	(8.94)	(7.95)	(7.94)
disability	-154.96	-208.48	-245.61	-249.55
	(12.15)	(12.66)	(13.27)	(13.36)
transfer	-334.28	-346.93	-346.41	-347.69
	(12.28)	(12.58)	(13.55)	(13.54)
class size	0.62	-2.43	-2.18	-2.09
	(0.13)	(0.17)	(0.18)	(0.18)
no hs	-60.53	-57.85	-61.05	-59.05
	(7.06)	(8.30)	(7.82)	(7.74)
some college	-17.08	31.09	32.12	32.26
	(7.55)	(9.74)	(9.30)	(9.30)
college grad	77.80	48.80	37.28	36.94
	(7.36)	(9.32)	(7.61)	(7.60)
grad school	79.85	68.96	69.04	68.31
	(6.73)	(10.22)	(9.87)	(9.87)
district FE	NO	YES	YES	YES
weighted	NO	NO	YES	YES
N	7,633	7,633	7,633	7,633
R^2	0.75	0.82	0.86	0.86
F	1169.7	783.8	1034.0	1035.3

Table B.2: API Two Stage Estimates

Variable	Coefficient (Std. Err.)			
	2SE	2SE	2SE (with prices)	OLS
middle	-39.82	-49.81	-53.44	-37.93
	(6.32)	(4.97)	(4.92)	(1.37)
high	-63.11	-79.20	-81.87	-64.01
	(6.60)	(5.57)	(5.51)	(1.80)
charter	36.76	38.41	43.74	17.62
	(4.15)	(6.35)	(6.25)	(2.13)
size	-0.00			-0.02
	(0.92)			(0.00)
black	-150.08	-142.90	-147.20	-130.70
	(19.02)	(18.13)	(17.21)	(7.47)
asian	55.13	76.70	69.61	79.04
	(22.45)	(15.27)	(18.64)	(6.59)
hispanic	-43.58	-26.57	-32.24	-30.70
	(18.41)	(18.71)	(18.25)	(6.44)
other	-91.04			-24.00
	(61.60)			(9.59)
free meals	9.33	4.92	-0.22	-20.80
	(15.48)	(16.17)	(13.22)	(5.46)
median income	8.95	14.43	13.34	4.79
	(4.05)	(3.64)	(3.73)	(1.87)
gifted	166.01	234.98	278.60	137.40
	(21.53)	(21.47)	(23.79)	(6.17)
esl	-34.99	-31.82	-33.84	-54.11
	(12.82)	(9.72)	(9.42)	(6.82)
former esl	-62.58			-22.79
	(37.99)			(7.94)
disability	-19.26			-249.55
	(121.87)			(13.36)
transfer	-324.48			-347.69
	(130.48)			(13.54)
class size	-6.95	-8.01	-9.05	-2.02
	(1.91)	(1.48)	(1.37)	(0.17)
no hs	-72.16	-93.01	-85.31	-59.05
	(24.10)	(23.73)	(18.34)	(7.74)
some college	-42.26	11.42	-19.75	32.26
	(31.17)	(29.33)	(24.29)	(9.30)
college grad	24.95	40.09	37.30	36.94
	(20.73)	(21.44)	(21.55)	(7.60)
grad school	81.39	98.79	86.48	68.31
	(24.06)	(23.09)	(17.59)	(9.87)
district FE	YES	YES	YES	YES
weighted	YES	YES	YES	YES
N	7,633	7,633	7,369	7,633
R^2	0.86	0.84	0.83	0.86
F	562.8	618.8	578.5	1035.3

Table B.3: API Structural Quantile Regression

Variable	**Coefficient** (Std. Err.)					
	2SE	q10	q25	q50	q75	q90
middle	-49.83	-57.41	-49.14	-50.47	-49.60	-45.78
	(4.98)	(4.85)	(5.18)	(4.04)	(4.86)	(6.07)
high	-79.18	-93.36	-81.80	-81.43	-80.21	-74.63
	(5.56)	(5.24)	(6.59)	(5.87)	(5.84)	(6.06)
charter	38.77	-16.78	3.11	17.72	35.91	53.35
	(6.35)	(11.23)	(6.05)	(7.06)	(6.09)	(8.88)
black	-142.48	-148.00	-145.03	-108.30	-80.32	-41.62
	(17.48)	(29.80)	(15.21)	(15.80)	(19.09)	(24.91)
asian	78.01	24.86	28.90	61.18	81.04	80.34
	(14.69)	(16.32)	(12.43)	(10.28)	(13.58)	(12.45)
hispanic	-28.99	-27.49	-17.87	-37.21	-19.09	-8.46
	(18.35)	(26.77)	(13.23)	(14.59)	(12.61)	(12.47)
free meals	7.47	8.82	3.47	5.29	3.72	2.48
	(15.95)	(18.47)	(13.05)	(16.97)	(11.81)	(15.70)
median income	14.69	22.04	12.84	7.12	6.53	13.21
	(3.64)	(5.54)	(2.67)	(3.23)	(4.01)	(4.24)
gifted	236.10	271.72	187.24	174.90	190.38	206.78
	(21.06)	(29.43)	(23.58)	(17.56)	(22.35)	(28.63)
esl	-31.70	-26.60	-30.49	-43.93	-45.66	-41.83
	(9.41)	(9.61)	(8.97)	(6.77)	(10.11)	(9.69)
class size	-8.11	-5.24	-13.92	-12.01	-8.47	-9.28
	(1.48)	(2.32)	(1.21)	(1.43)	(1.05)	(1.50)
no hs	-85.87	-90.85	-80.12	-60.57	-40.33	-9.20
	(15.34)	(21.79)	(16.15)	(16.96)	(14.93)	(8.43)
college grad	41.60	-26.63	65.67	65.76	53.56	61.23
	(20.43)	(21.90)	(16.39)	(14.34)	(13.49)	(15.32)
grad school	94.75	56.65	122.28	108.27	101.25	91.76
	(14.62)	(18.00)	(14.62)	(16.08)	(11.47)	(17.31)
district FE	YES	YES	YES	YES	YES	YES
weighted	YES	NO	NO	NO	NO	NO
N	7,633	7,633	7,633	7,633	7,633	7,633
R^2	0.84					
F	665.6					

Table B.4: Hispanic API Structural Quantile Regression

Variable	Coefficient (Std. Err.)					
	2SE	q10	q25	q50	q75	q90
middle	-61.50	-76.32	-72.32	-68.13	-67.85	-56.23
	(5.89)	(10.38)	(6.12)	(7.13)	(7.30)	(6.35)
high	-91.35	-113.69	-106.28	-96.97	-96.63	-81.00
	(6.57)	(11.59)	(6.70)	(7.84)	(9.26)	(6.72)
charter	39.08	-6.90	8.50	23.30	38.03	47.16
	(7.57)	(14.28)	(9.54)	(9.03)	(9.61)	(7.23)
black	-23.05	-8.13	-20.49	-22.25	-35.10	-36.06
	(10.33)	(17.31)	(10.29)	(9.53)	(11.26)	(12.14)
asian	2.79	-24.91	-12.11	-0.58	3.82	3.56
	(8.72)	(14.07)	(8.51)	(7.00)	(12.74)	(7.44)
hispanic	85.51	64.69	117.46	102.66	74.57	47.43
	(10.85)	(15.10)	(10.40)	(8.77)	(10.55)	(11.22)
free meals	-15.21	-59.95	-34.78	-13.47	-16.86	-0.72
	(18.91)	(29.61)	(21.57)	(19.27)	(23.93)	(18.96)
median income	23.35	23.61	19.14	21.52	22.61	34.92
	(4.31)	(7.03)	(4.48)	(4.53)	(4.73)	(5.74)
gifted	198.46	221.26	186.43	175.44	136.91	96.70
	(24.92)	(45.68)	(26.43)	(32.25)	(38.14)	(23.53)
esl	-69.67	-123.16	-105.14	-106.12	-102.11	-76.17
	(11.13)	(16.75)	(8.64)	(9.74)	(13.63)	(12.82)
class size	-3.63	-0.25	-2.30	-4.31	-6.45	-8.49
	(1.76)	(2.56)	(1.72)	(1.32)	(2.02)	(1.92)
no hs	0.53	-53.39	-31.03	-40.25	6.07	0.87
	(18.13)	(26.79)	(14.93)	(18.99)	(19.67)	(19.20)
college grad	22.09	9.74	23.89	61.68	50.12	14.83
	(24.30)	(26.80)	(25.04)	(30.08)	(24.74)	(34.27)
grad school	48.73	10.23	69.25	104.06	102.59	127.33
	(17.37)	(19.90)	(20.33)	(17.23)	(23.82)	(20.97)
district FE	YES	YES	YES	YES	YES	YES
weighted	YES	NO	NO	NO	NO	NO
N	7,550	7,550	7,550	7,550	7,550	7,550
R^2	0.69					
F	338.7					

Table B.5: White API Structural Quantile Regression

Variable	Coefficient (Std. Err.)					
	2SE	q10	q25	q50	q75	q90
middle	-40.25	-37.24	-36.57	-34.94	-34.66	-40.43
	(7.26)	(9.26)	(7.98)	(5.81)	(4.24)	(7.20)
high	-67.35	-73.68	-69.90	-67.20	-67.60	-69.69
	(8.18)	(10.52)	(9.90)	(6.83)	(4.97)	(10.53)
charter	20.94	-40.38	-14.86	2.26	12.75	24.65
	(8.84)	(13.02)	(8.60)	(7.69)	(5.08)	(9.39)
black	-37.83	-98.38	-59.33	-54.48	-27.89	-10.85
	(15.04)	(19.05)	(12.22)	(12.45)	(11.56)	(19.95)
asian	15.55	-92.90	-71.42	-23.27	-12.89	35.79
	(10.49)	(11.26)	(5.76)	(6.47)	(6.88)	(10.41)
hispanic	3.60	-4.17	-5.48	-7.50	11.01	16.47
	(12.67)	(9.94)	(6.95)	(7.51)	(6.49)	(14.17)
free meals	-28.20	-72.28	-60.79	-21.55	-29.58	-21.95
	(22.20)	(26.56)	(16.60)	(15.55)	(15.67)	(22.83)
median income	-4.86	7.17	0.04	5.12	5.52	-11.75
	(5.07)	(5.56)	(3.54)	(3.61)	(3.05)	(7.95)
gifted	380.92	329.44	364.62	378.80	393.00	407.63
	(30.33)	(49.31)	(38.02)	(25.34)	(18.02)	(29.86)
esl	-0.54	7.17	4.75	2.37	11.10	-21.64
	(14.56)	(15.70)	(15.32)	(14.75)	(10.28)	(8.38)
class size	-4.50	-2.03	-3.16	-4.16	-6.12	-7.01
	(2.05)	(2.30)	(1.23)	(1.15)	(1.56)	(2.51)
no hs	-118.24	-173.77	-137.37	-98.35	-93.29	-20.54
	(24.04)	(28.10)	(29.99)	(27.45)	(14.14)	(23.83)
college grad	44.00	32.77	30.68	40.07	62.35	80.73
	(27.49)	(26.51)	(19.00)	(21.70)	(20.31)	(32.65)
grad school	167.82	198.29	182.43	182.17	177.47	172.04
	(20.02)	(21.36)	(18.83)	(13.35)	(15.17)	(20.61)
district FE	YES	YES	YES	YES	YES	YES
weighted	YES	NO	NO	NO	NO	NO
N	6,187	6,187	6,187	6,187	6,187	6,187
R^2	0.69					
F	245.5					

Table B.6: Black API Structural Quantile Regression

Variable	**Coefficient** (Std. Err.)					
	2SE	q10	q25	q50	q75	q90
middle	-47.28	-56.89	-46.94	-44.27	-59.07	-37.15
	(10.86)	(13.16)	(10.80)	(14.98)	(11.59)	(16.40)
high	-75.10	-81.99	-65.58	-72.19	-89.51	-70.57
	(12.12)	(14.26)	(12.04)	(15.84)	(14.20)	(18.92)
charter	36.46	-7.25	14.53	18.14	43.43	39.44
	(13.82)	(26.29)	(15.39)	(16.17)	(12.54)	(17.47)
black	-72.88	47.56	12.07	-17.99	-73.69	-80.94
	(17.79)	(26.23)	(20.72)	(20.03)	(17.05)	(20.73)
asian	32.05	3.96	16.91	32.84	64.34	66.30
	(16.09)	(24.01)	(14.99)	(14.18)	(11.79)	(17.09)
hispanic	59.40	120.28	85.69	91.51	63.48	27.96
	(19.84)	(25.18)	(17.81)	(15.91)	(12.97)	(16.43)
free meals	32.00	52.36	43.02	-26.82	-36.84	-31.90
	(33.85)	(29.36)	(28.86)	(30.89)	(37.05)	(48.70)
median income	-7.07	-38.06	-17.73	-2.35	-12.63	-8.19
	(7.82)	(11.18)	(9.47)	(9.19)	(6.67)	(10.27)
gifted	204.93	223.13	245.03	45.22	-16.72	-40.27
	(44.54)	(59.90)	(54.40)	(51.86)	(56.14)	(83.65)
esl	-7.75	-5.17	3.09	2.70	-8.96	3.74
	(20.76)	(19.12)	(13.74)	(26.89)	(21.73)	(23.20)
class size	-10.82	-4.82	-1.90	-8.28	-10.25	-11.45
	(1.48)	(4.68)	(3.53)	(3.18)	(2.41)	(3.58)
no hs	-322.35	-388.06	-330.78	-249.12	-165.99	-152.04
	(33.89)	(44.76)	(38.87)	(45.86)	(38.16)	(40.08)
college grad	182.50	132.25	233.32	215.10	171.57	195.13
	(44.80)	(35.42)	(41.52)	(39.74)	(43.54)	(83.39)
grad school	234.04	155.16	250.20	261.37	165.10	208.22
	(31.46)	(35.64)	(31.34)	(28.89)	(33.64)	(43.15)
district FE	YES	YES	YES	YES	YES	YES
weighted	YES	NO	NO	NO	NO	NO
N	4,293	4,293	4,293	4,293	4,293	4,293
R^2	0.62					
F	135.6					

Table B.7: Asian API Structural Quantile Regression

Variable	Coefficient (Std. Err.)					
	2SE	q10	q25	q50	q75	q90
middle	-24.73	-26.09	-30.97	-25.05	-16.97	-26.17
	(8.55)	(17.43)	(9.51)	(11.51)	(9.25)	(10.15)
high	-65.92	-60.42	-68.18	-59.46	-57.43	-68.18
	(9.67)	(17.18)	(11.35)	(12.04)	(11.40)	(14.23)
charter	29.36	49.41	57.68	52.67	36.21	49.46
	(10.46)	(17.78)	(8.34)	(11.12)	(8.55)	(11.20)
black	-149.19	-153.59	-160.44	-163.63	-102.88	-117.60
	(17.43)	(22.20)	(13.34)	(12.84)	(12.44)	(14.40)
asian	55.90	77.39	67.88	49.45	40.23	30.06
	(11.32)	(14.07)	(10.78)	(10.43)	(8.27)	(8.20)
hispanic	-5.00	-36.69	4.18	0.19	21.34	-7.39
	(15.16)	(17.68)	(11.32)	(10.81)	(10.77)	(13.04)
free meals	-36.46	53.82	-28.19	-29.55	-83.51	-135.85
	(27.01)	(27.04)	(26.56)	(20.66)	(16.99)	(30.76)
median income	6.88	37.11	22.44	2.04	-10.88	-24.56
	(5.88)	(7.90)	(6.74)	(4.22)	(4.28)	(6.28)
gifted	223.83	251.37	261.45	284.19	243.21	323.93
	(35.07)	(69.26)	(39.51)	(36.94)	(26.74)	(48.90)
esl	-47.37	-43.76	-67.94	-49.92	-40.77	-71.58
	(17.27)	(17.41)	(15.20)	(16.58)	(17.78)	(17.39)
class size	-2.49	0.47	-0.38	-4.26	-7.48	-9.07
	(2.41)	(2.91)	(2.28)	(2.71)	(2.15)	(2.61)
no hs	-93.97	-79.03	-53.04	-88.13	-137.92	-109.78
	(27.91)	(46.89)	(33.80)	(30.69)	(35.98)	(30.84)
college grad	45.53	134.53	64.82	50.59	14.82	-7.89
	(32.60)	(28.64)	(26.31)	(16.59)	(17.27)	(25.04)
grad school	69.51	184.21	148.51	127.18	67.08	-16.98
	(24.11)	(30.46)	(24.17)	(21.66)	(20.40)	(34.07)
district FE	YES	YES	YES	YES	YES	YES
weighted	YES	NO	NO	NO	NO	NO
N	4,269	4,269	4,269	4,269	4,269	4,269
R^2	0.73					
F	151.8					

Appendix C

Appendix for Chapter 3

C.1 Bivariate Income Mobility Conditional Distributions

Figure C.1.1: Distribution of Income Mobility vs Fraction Black

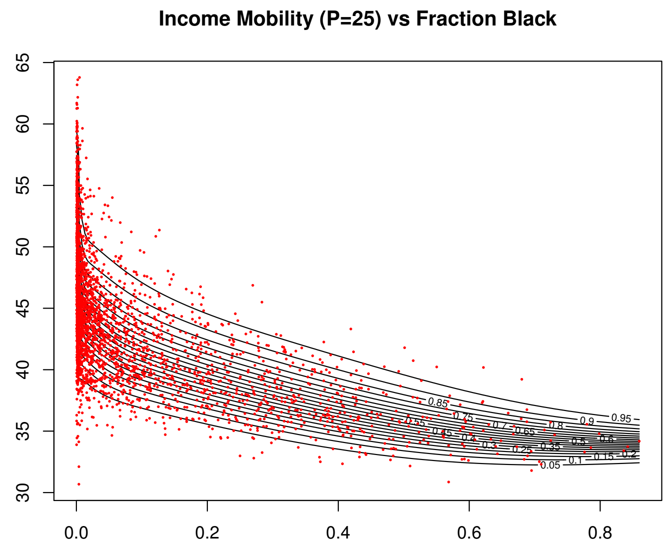


Figure C.1.2: Distribution of Difference in Income Mobility vs Fraction Black

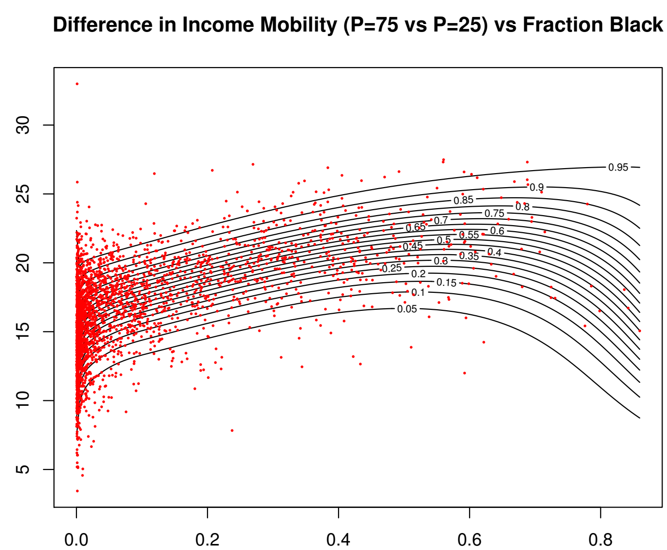


Figure C.1.3: Distribution of Income Mobility vs Racial Segregation

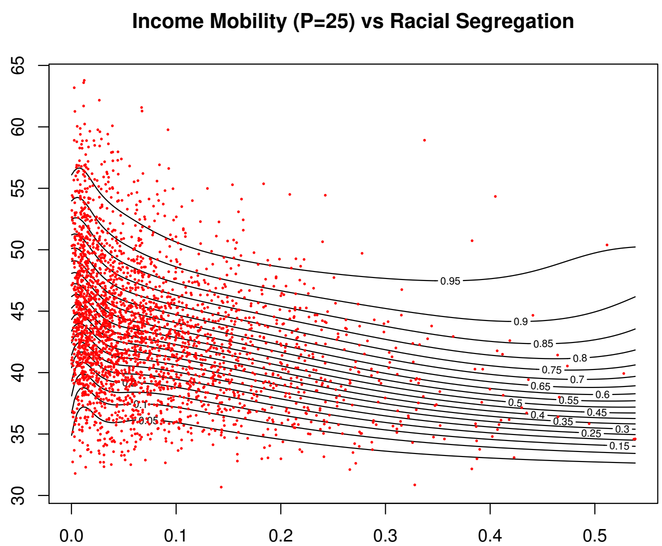


Figure C.1.4: Distribution of Difference in Income Mobility vs Racial Segregation

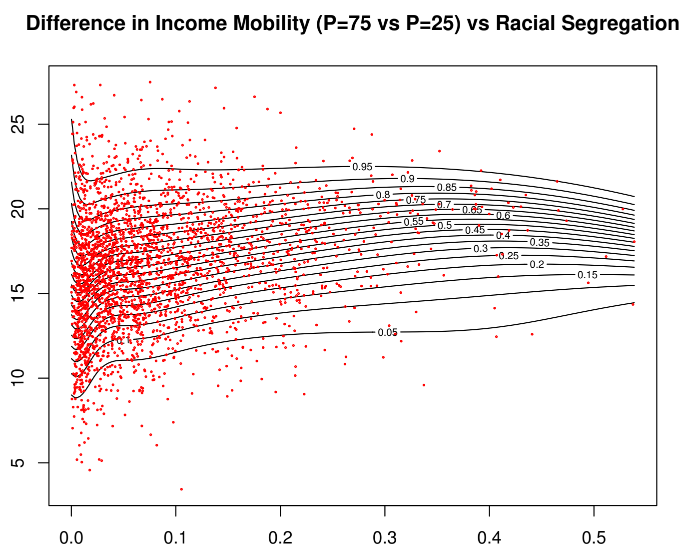


Figure C.1.5: Distribution of Income Mobility vs Income Segregation

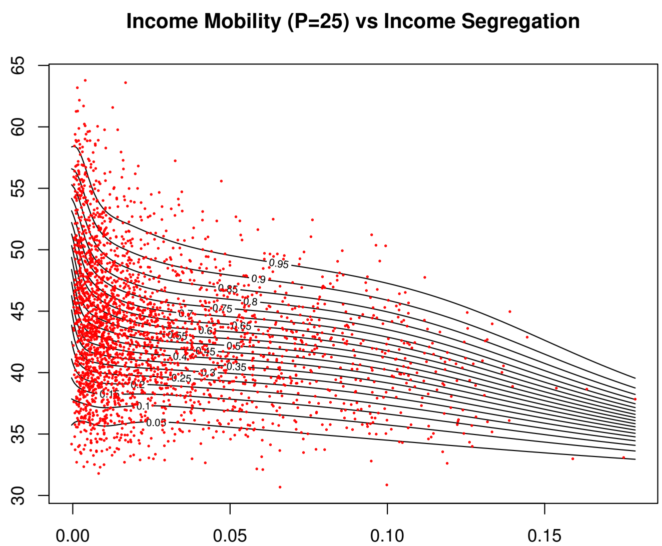


Figure C.1.6: Distribution of Difference in Income Mobility vs Income Segregation

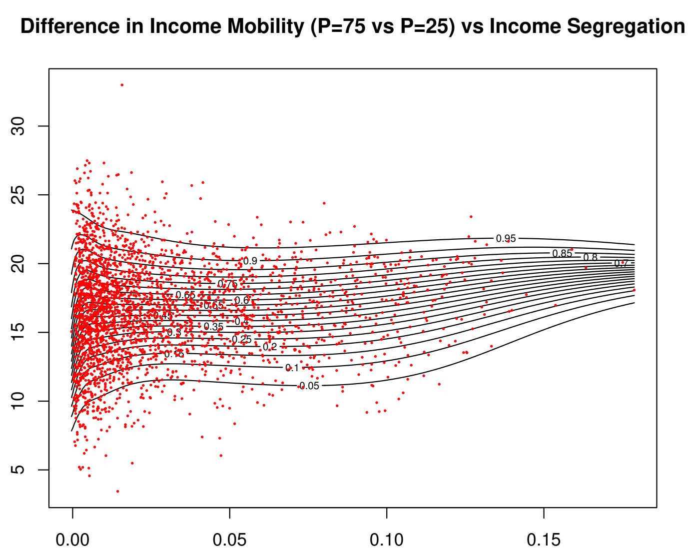


Figure C.1.7: Distribution of Income Mobility vs Income (per capita)

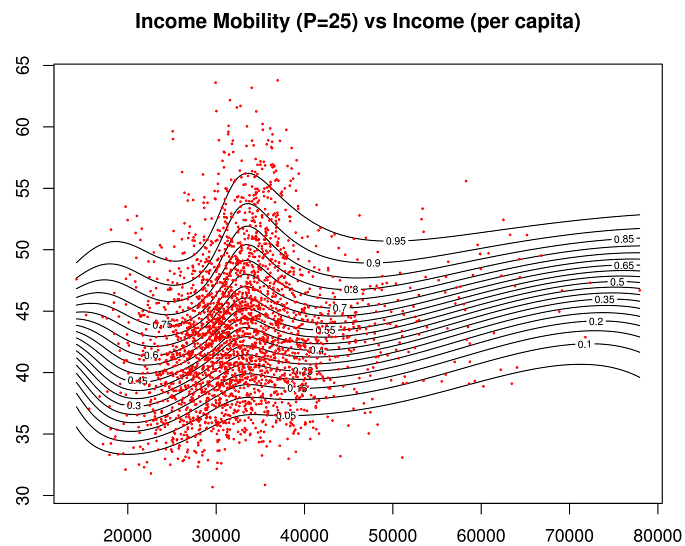


Figure C.1.8: Distribution of Difference in Income Mobility vs Income (per capita)

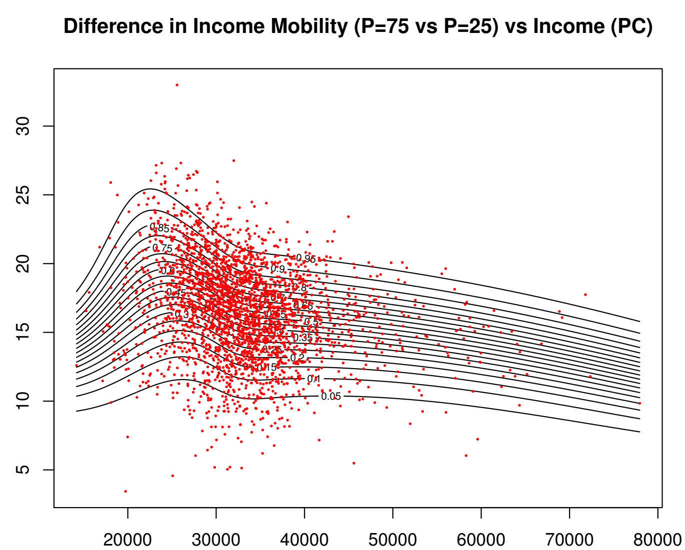


Figure C.1.9: Distribution of Income Mobility vs Gini Coefficient

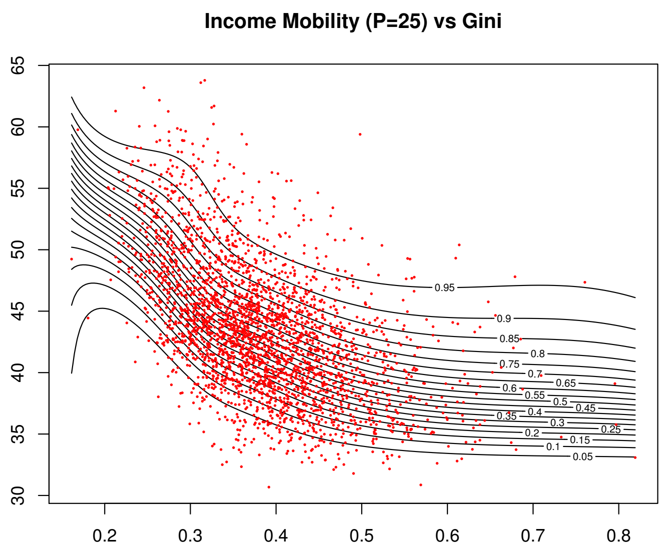


Figure C.1.10: Distribution of Difference in Income Mobility vs Gini Coefficient

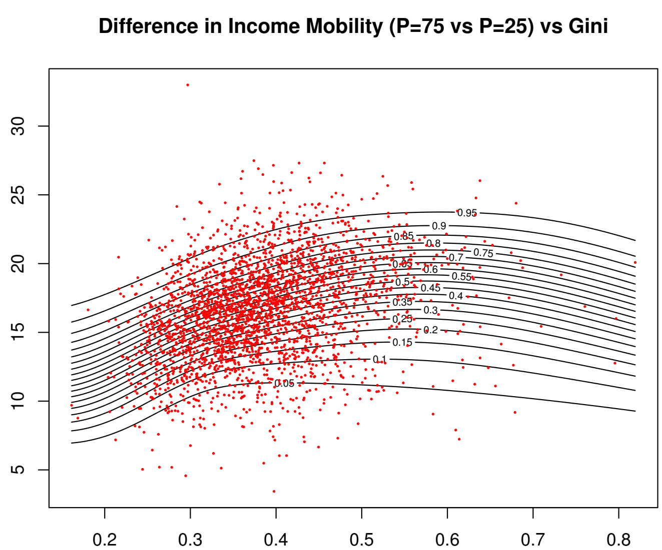


Figure C.1.11: Distribution of Income Mobility vs Size of Middle Class

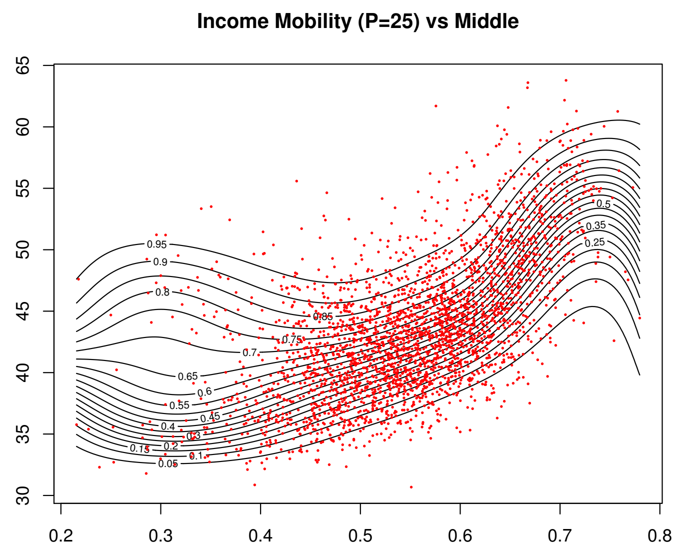


Figure C.1.12: Distribution of Difference in Income Mobility vs Size of Middle Class

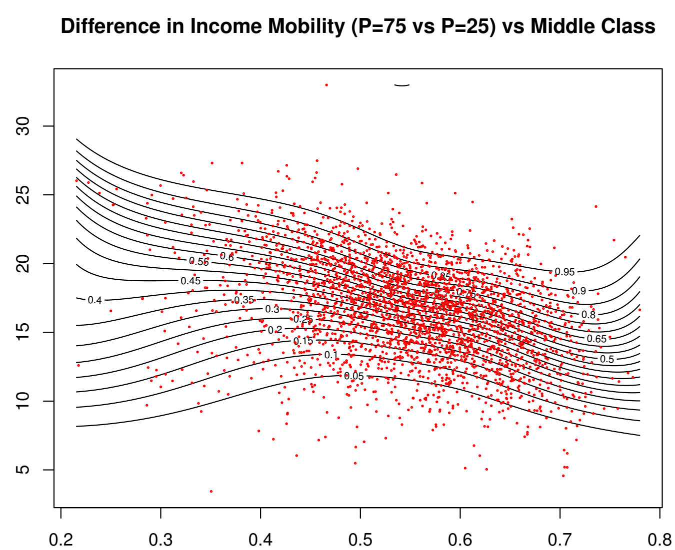


Figure C.1.13: Distribution of Income Mobility vs Share of Workers in Manufacturing

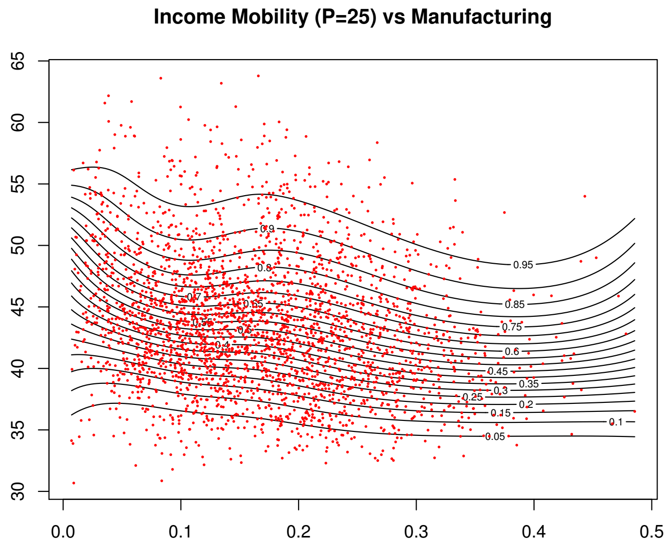


Figure C.1.14: Distribution of Difference in Income Mobility vs Share of Workers in Manufacturing

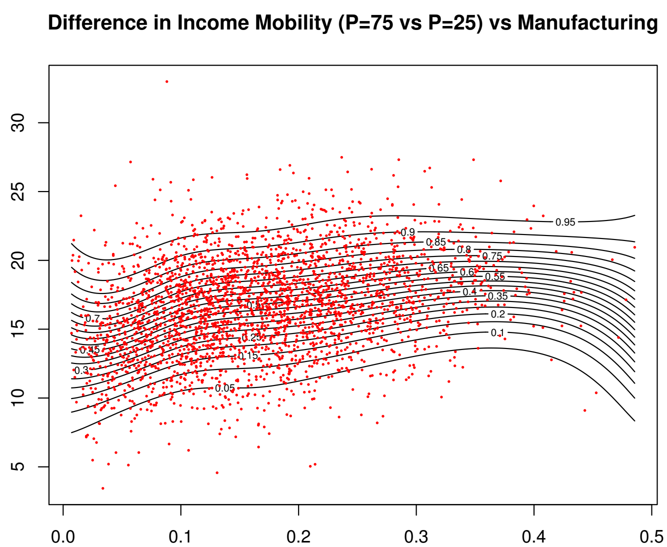


Figure C.1.15: Distribution of Income Mobility vs Teenage Labor Force Participation

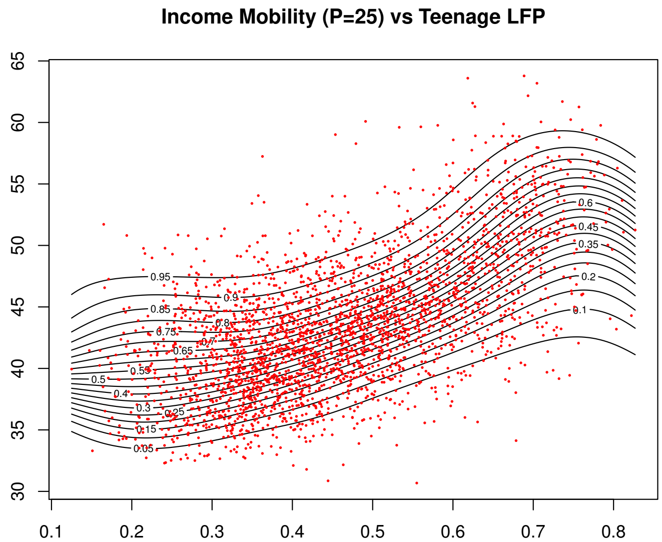


Figure C.1.16: Distribution of Difference in Income Mobility vs Teenage Labor Force Participation

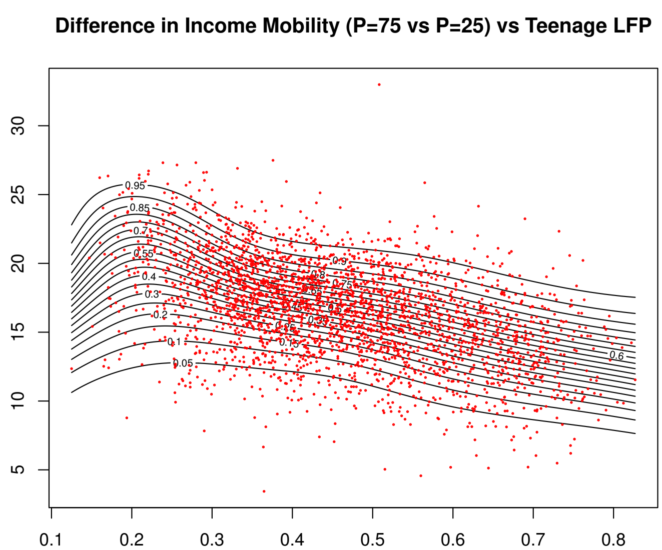


Figure C.1.17: Distribution of Income Mobility vs Unemployment Rate

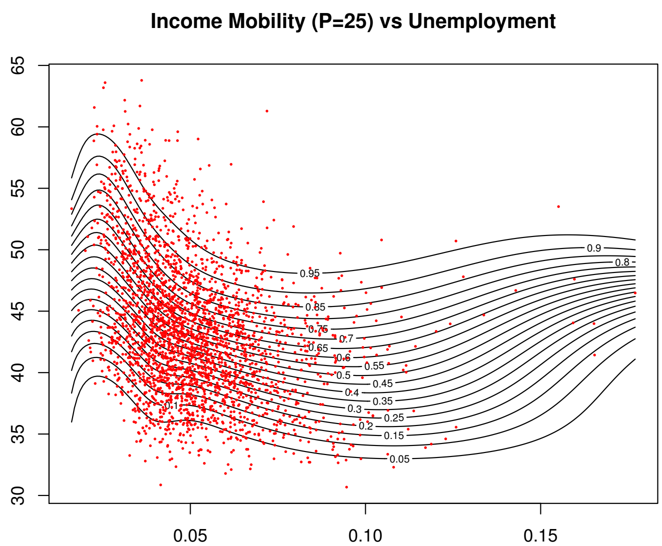


Figure C.1.18: Distribution of Difference in Income Mobility vs Unemployment Rate

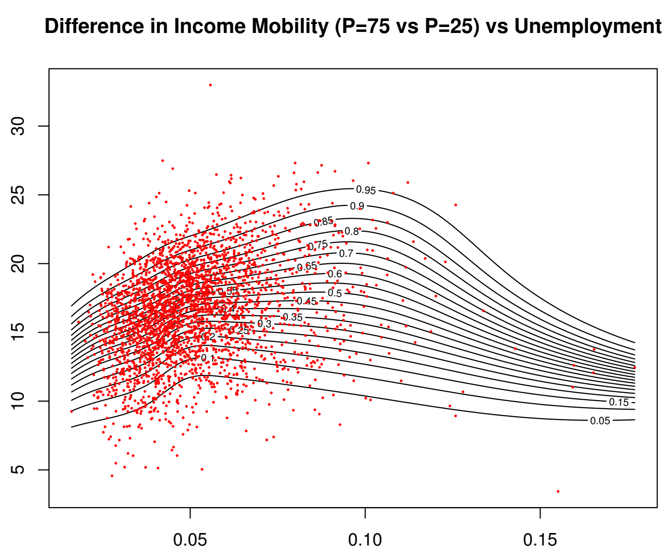


Figure C.1.19: Distribution of Income Mobility vs Social Capital Index

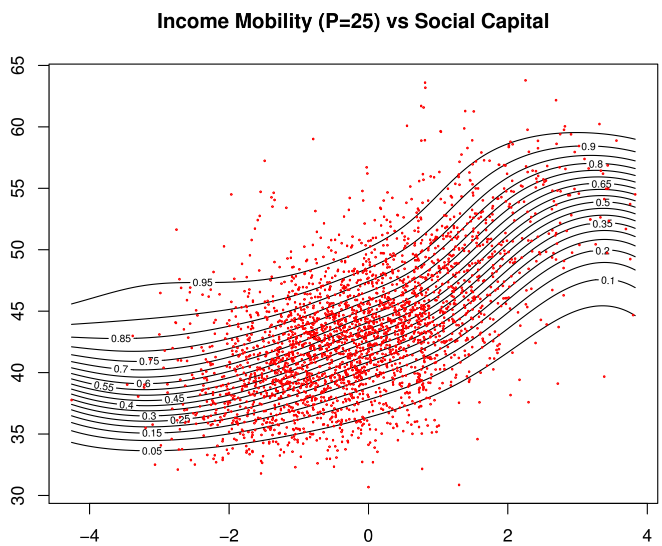


Figure C.1.20: Distribution of Difference in Income Mobility vs Social Capital Index

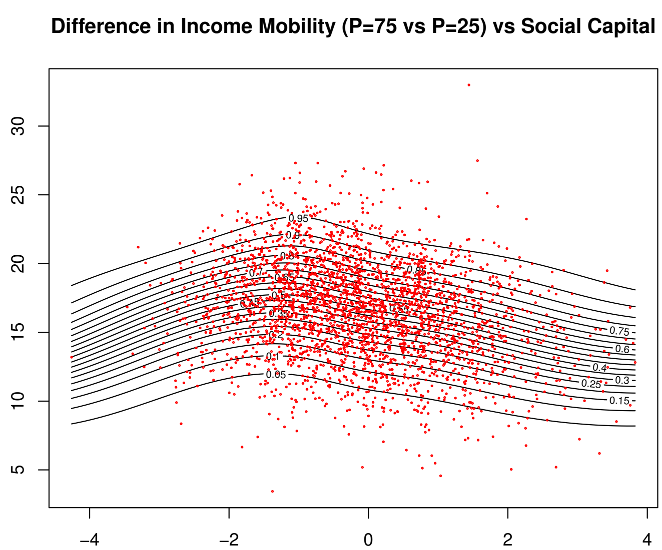


Figure C.1.21: Distribution of Income Mobility vs Poverty Rate

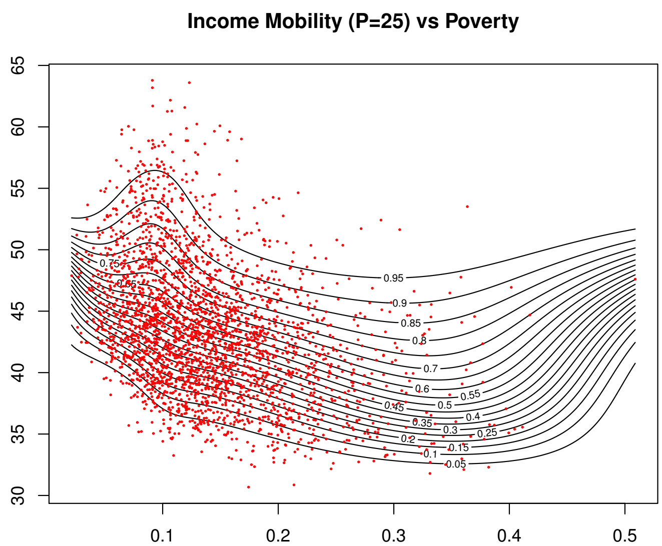


Figure C.1.22: Distribution of Difference in Income Mobility vs Poverty Rate

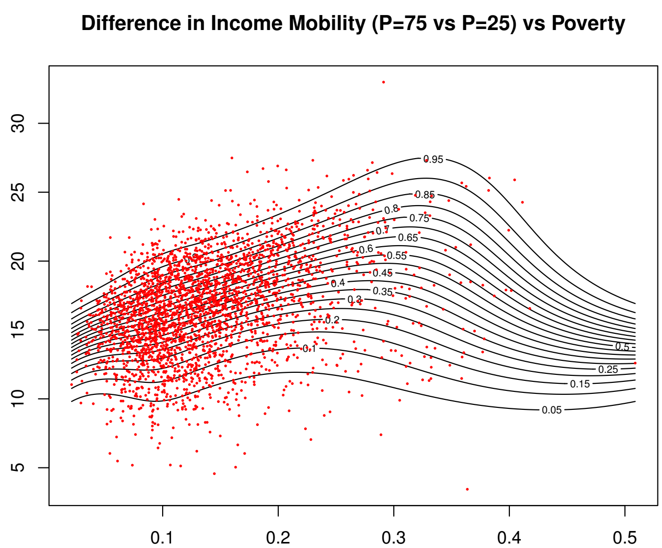


Figure C.1.23: Distribution of Income Mobility vs Housing Prices

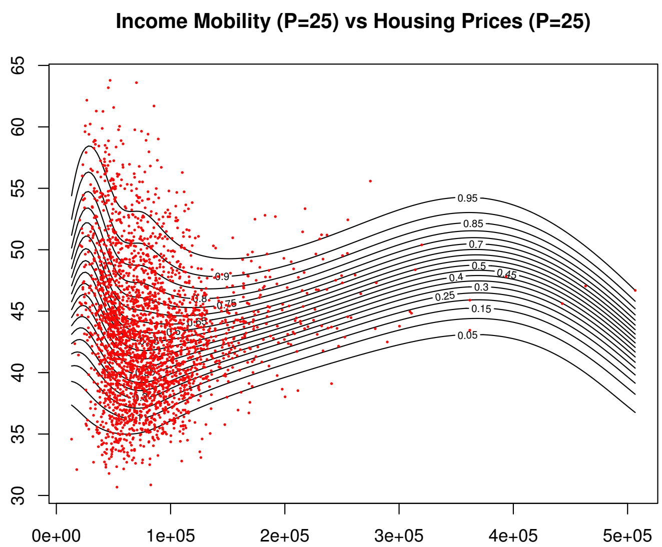
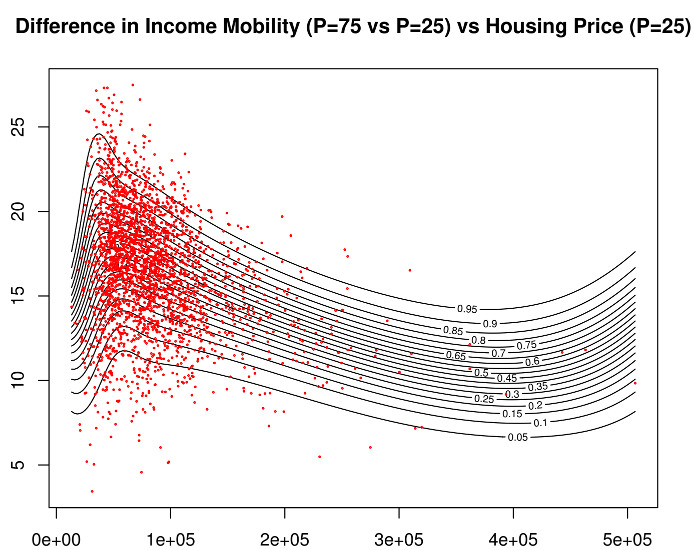


Figure C.1.24: Distribution of Difference in Income Mobility vs Housing Prices



C.2 Multivariate Income Mobility Conditional Distributions

Figure C.2.1: Distribution of Income Mobility vs Fraction Black

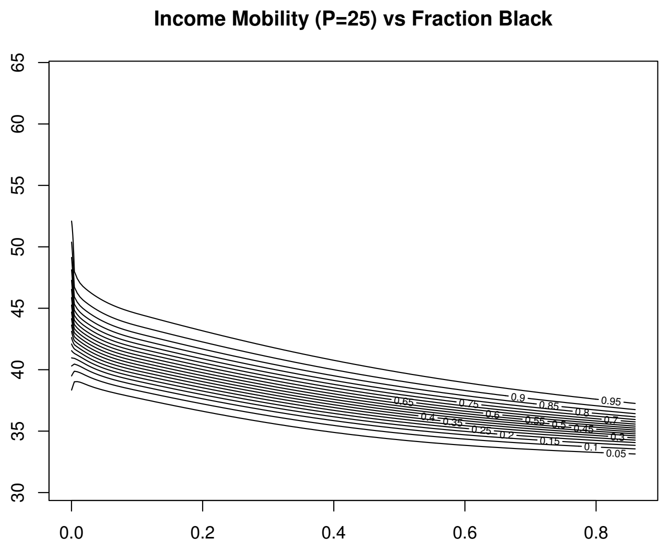


Figure C.2.2: Distribution of Difference in Income Mobility vs Fraction Black

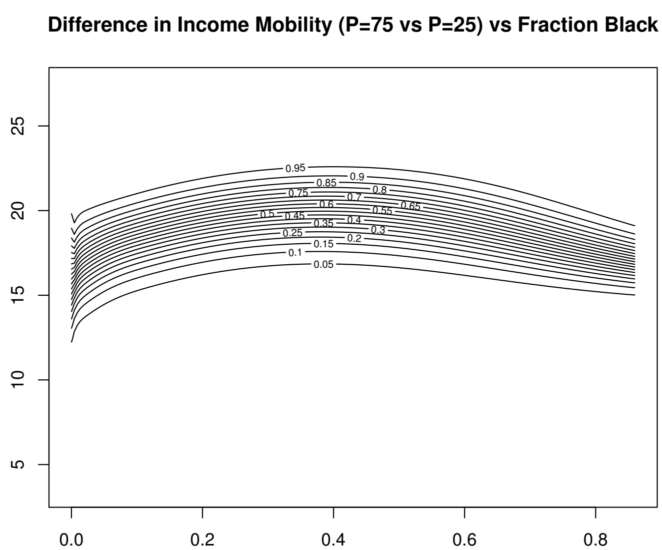


Figure C.2.3: Distribution of Income Mobility vs Racial Segregation

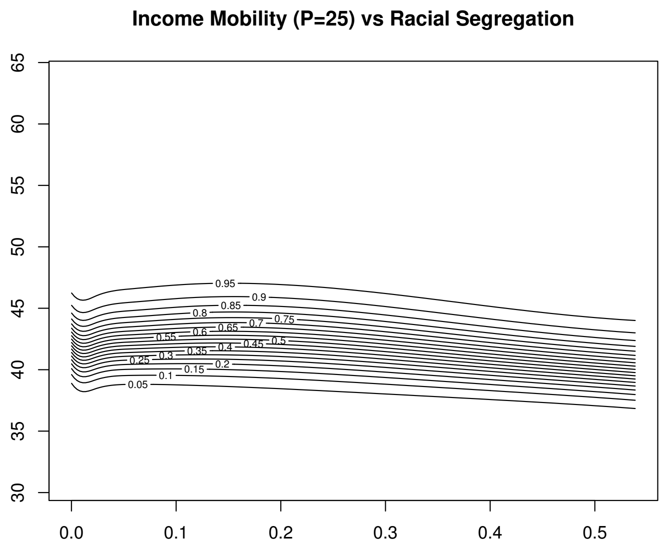


Figure C.2.4: Distribution of Difference in Income Mobility vs Racial Segregation

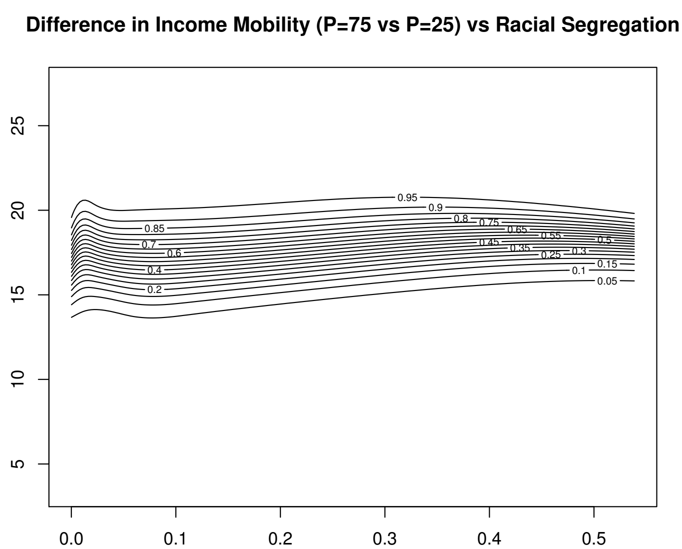


Figure C.2.5: Distribution of Income Mobility vs Income Segregation

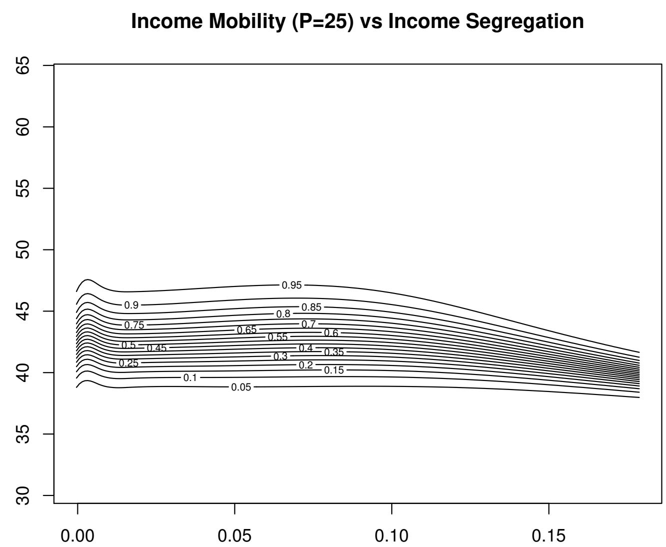


Figure C.2.6: Distribution of Difference in Income Mobility vs Income Segregation

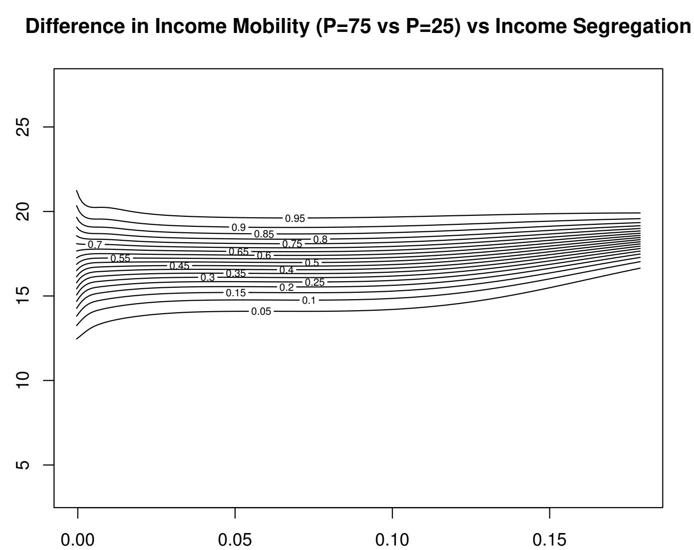


Figure C.2.7: Distribution of Income Mobility vs Income (per capita)

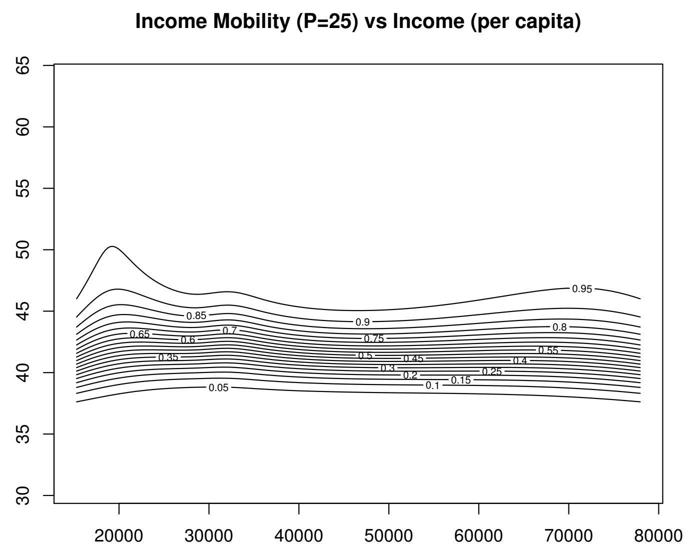


Figure C.2.8: Distribution of Difference in Income Mobility vs Income (per capita)

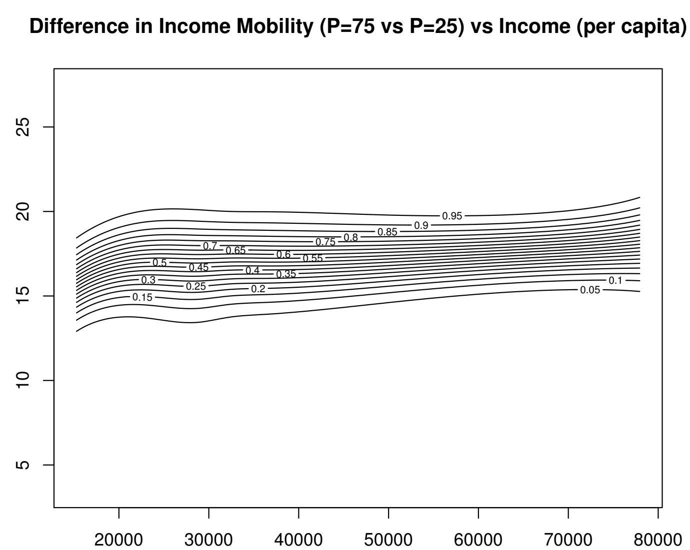


Figure C.2.9: Distribution of Income Mobility vs Gini Coefficient

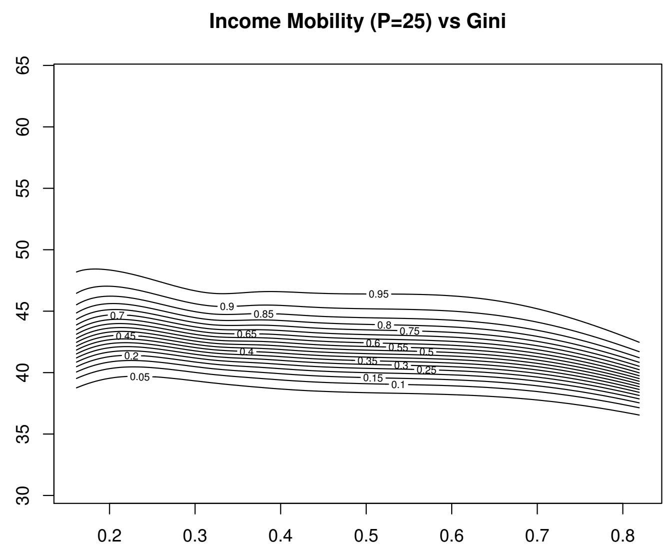


Figure C.2.10: Distribution of Difference in Income Mobility vs Gini Coefficient

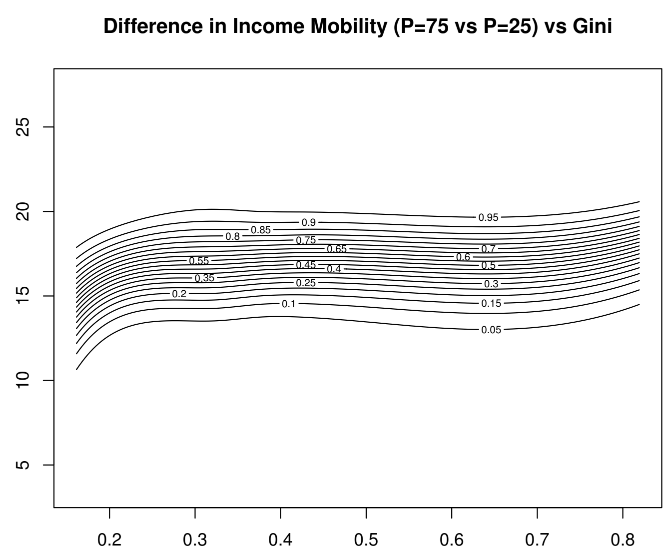


Figure C.2.11: Distribution of Income Mobility vs Size of Middle Class

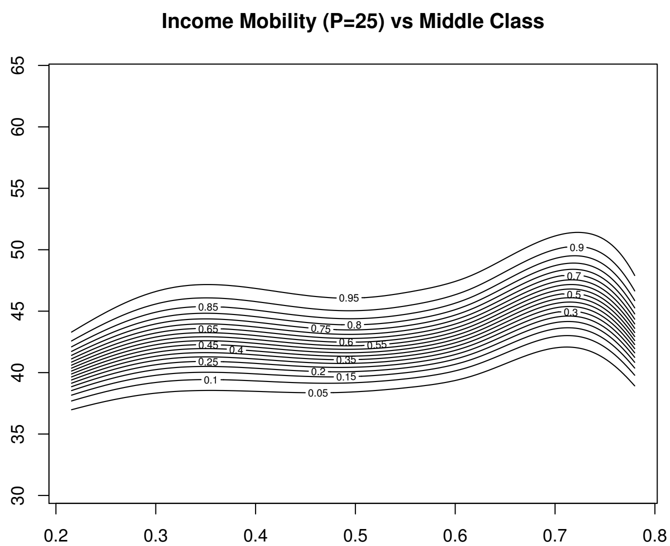


Figure C.2.12: Distribution of Difference in Income Mobility vs Size of Middle Class

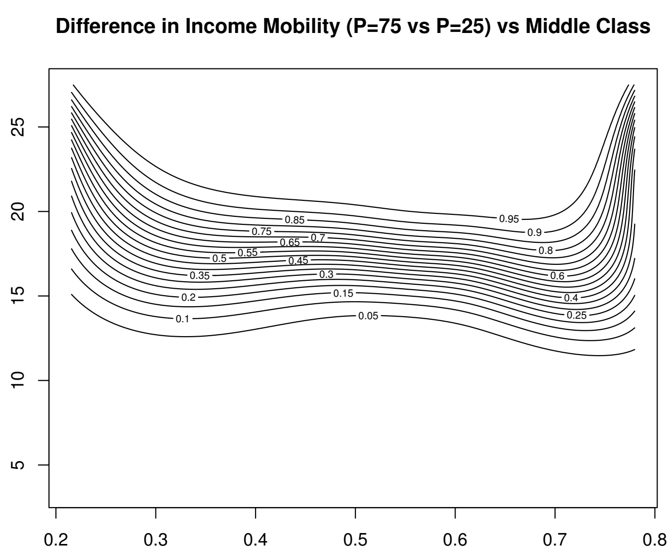


Figure C.2.13: Distribution of Income Mobility vs Share of Workers in Manufacturing

Figure C.2.14: Distribution of Difference in Income Mobility vs Share of Workers in Manufacturing

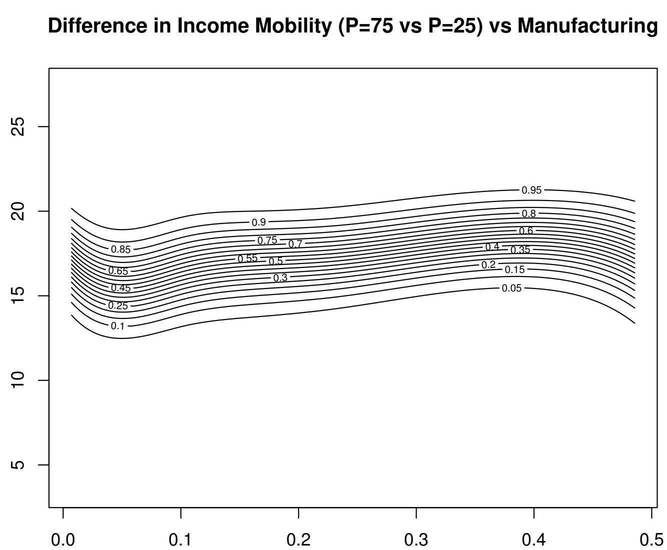


Figure C.2.15: Distribution of Income Mobility vs Teenage Labor Force Participation

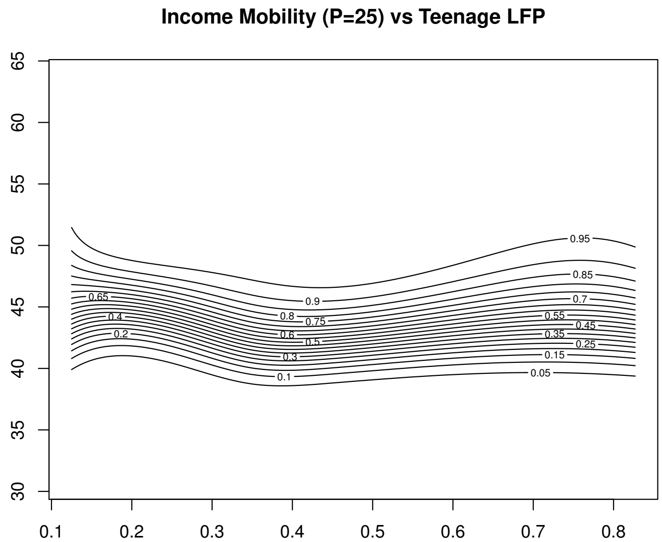


Figure C.2.16: Distribution of Difference in Income Mobility vs Teenage Labor Force Participation

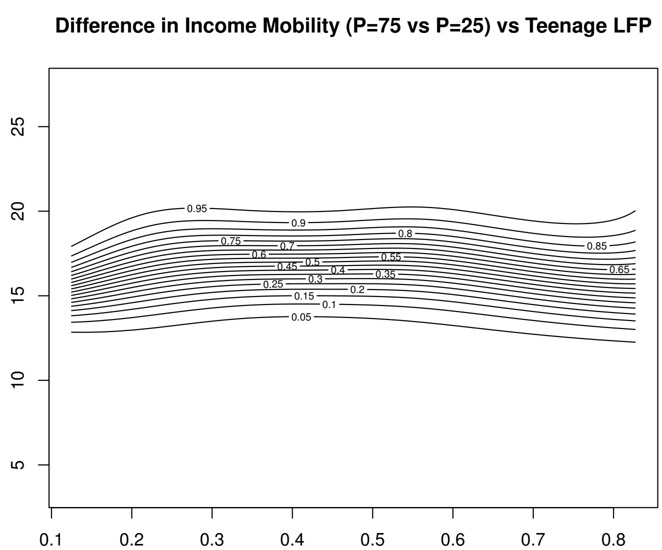


Figure C.2.17: Distribution of Income Mobility vs Unemployment Rate

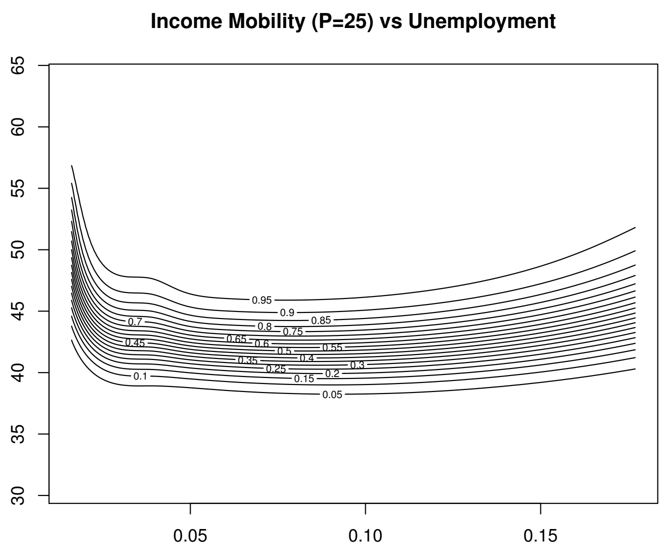


Figure C.2.18: Distribution of Difference in Income Mobility vs Unemployment Rate

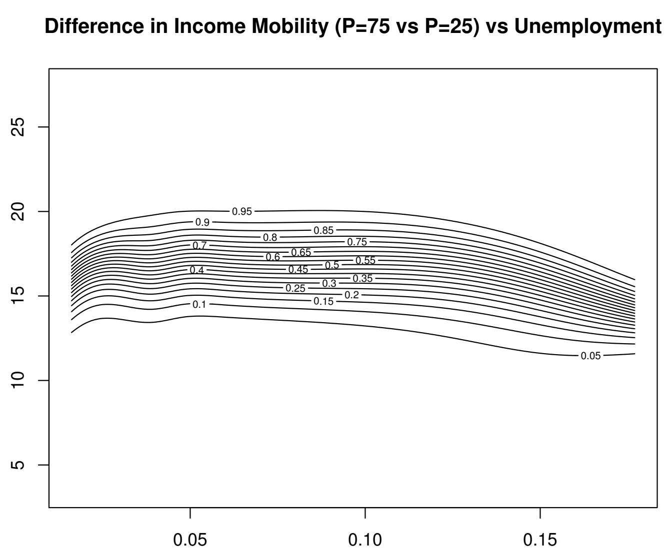


Figure C.2.19: Distribution of Income Mobility vs Social Capital Index

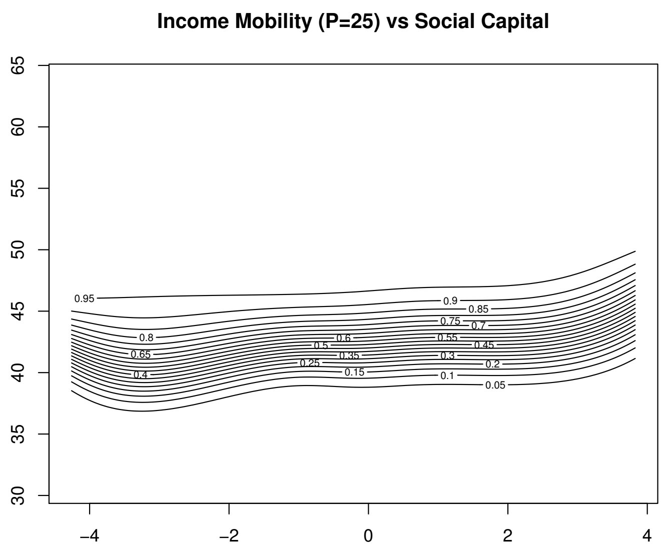


Figure C.2.20: Distribution of Difference in Income Mobility vs Social Capital Index

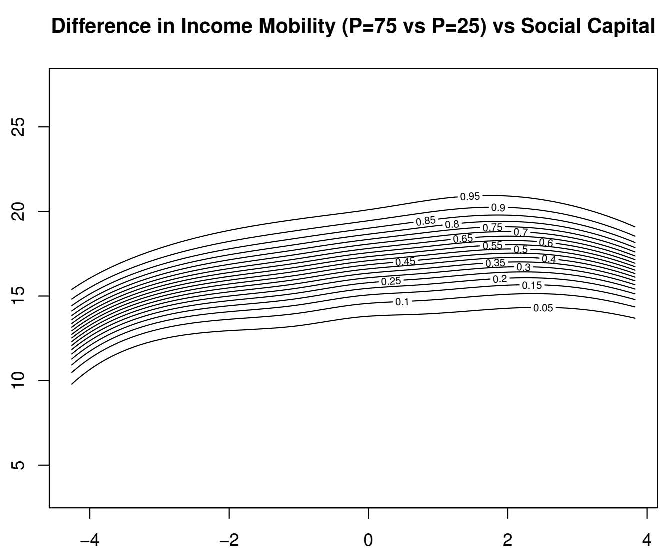


Figure C.2.21: Distribution of Income Mobility vs Poverty Rate

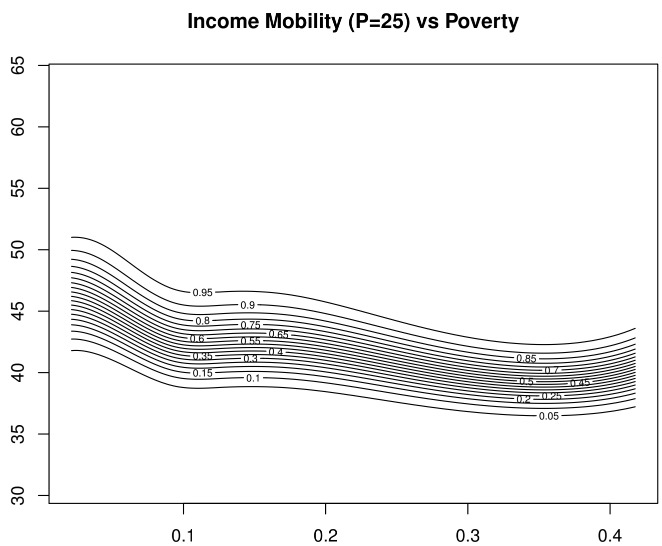


Figure C.2.22: Distribution of Difference in Income Mobility vs Poverty Rate

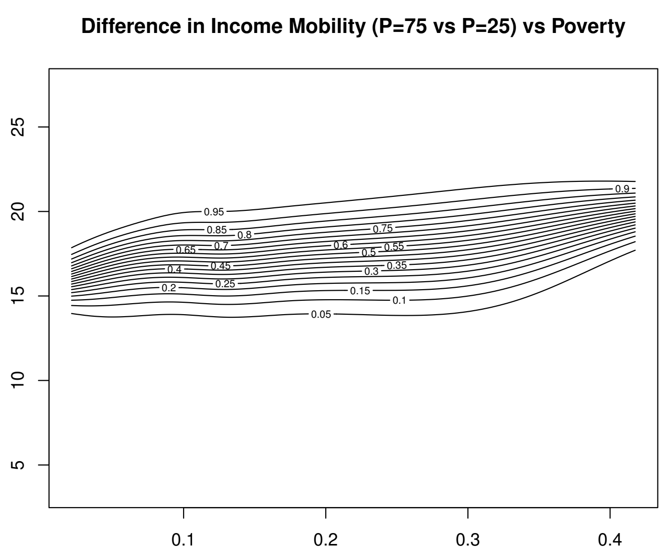


Figure C.2.23: Distribution of Income Mobility vs Housing Prices

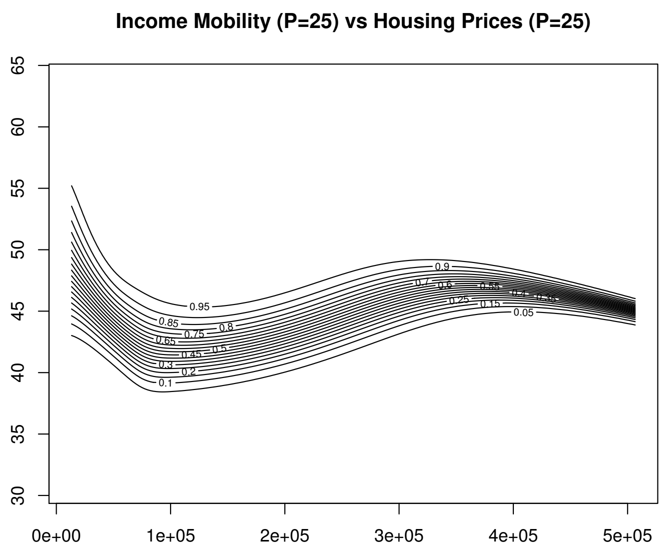
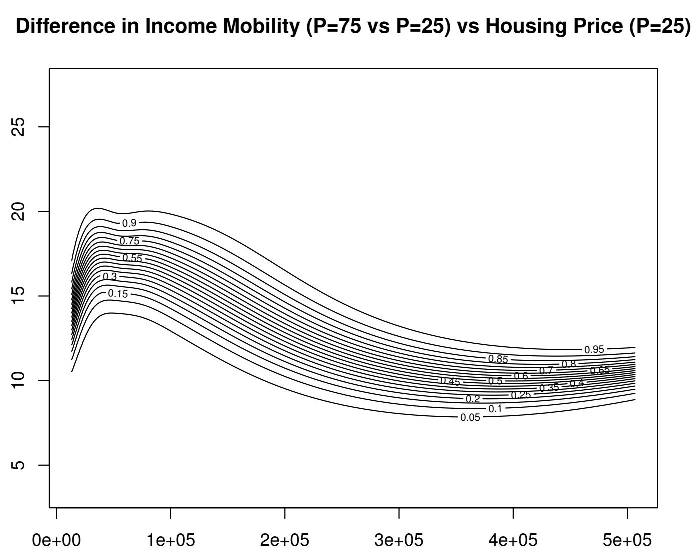


Figure C.2.24: Distribution of Difference in Income Mobility vs Housing Prices



C.3 Income Mobility Conditional Distribution Tables

Table C.3.1: Distribution of Income Mobility vs Fraction Black

Quantiles of Fraction Black	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.60	44.08	47.23
	(1.47)	(1.85)	(1.89)
$Q_X(0.33)$	41.27	42.92	44.74
	(1.44)	(1.82)	(1.83)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.49)	(0.56)	(0.62)
$Q_X(0.67)$	39.78	41.10	42.59
	(0.42)	(0.47)	(0.56)
$Q_X(0.85)$	37.96	39.12	40.44
	(0.44)	(0.45)	(0.49)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.77	-2.69	-5.77
	(0.81)	(0.99)	(1.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.5-0.33}}$	-0.28	-0.38	-0.48
	(0.17)	(0.25)	(0.28)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.23	-0.26	-0.30
	(0.08)	(0.09)	(0.09)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.10	-0.11	-0.12
	(0.02)	(0.02)	(0.03)

Note: slope given in rank per 1%.

Table C.3.2: Distribution of Income Mobility vs Racial Segregation

Quantiles of Racial Segregation	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	40.11	41.60	43.09
	(0.61)	(0.66)	(0.80)
$Q_X(0.33)$	40.61	41.93	43.59
	(0.51)	(0.53)	(0.65)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.39)	(0.42)	(0.50)
$Q_X(0.67)$	40.77	42.43	44.08
	(0.36)	(0.37)	(0.47)
$Q_X(0.85)$	40.77	42.43	44.25
	(0.44)	(0.48)	(0.55)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.26	0.17	0.26
	(0.12)	(0.12)	(0.14)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.06	0.12	0.12
	(0.11)	(0.11)	(0.12)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.05	0.05
	(0.08)	(0.08)	(0.09)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.00	0.00	0.02
	(0.06)	(0.06)	(0.06)

Note: slope given in rank per 1%.

Table C.3.3: Distribution of Income Mobility vs Income Segregation

Quantiles of Income Segregation	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.43	42.92	44.58
	(0.44)	(0.43)	(0.49)
$Q_X(0.33)$	40.94	42.43	44.08
	(0.40)	(0.43)	(0.54)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.43)	(0.44)	(0.53)
$Q_X(0.67)$	40.77	42.26	43.92
	(0.40)	(0.51)	(0.61)
$Q_X(0.85)$	40.94	42.59	44.25
	(0.47)	(0.51)	(0.62)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-1.10	-1.10	-1.10
	(0.20)	(0.19)	(0.19)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.20	-0.20	-0.20
	(0.09)	(0.10)	(0.11)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.07)	(0.06)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.05	0.10	0.10
	(0.04)	(0.04)	(0.04)

Note: slope given in rank per 1%.

Table C.3.4: Distribution of Income Mobility vs Income (per capita)

Quantiles of Income (per capita)	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	40.61	42.10	43.75
	(0.52)	(0.52)	(0.61)
$Q_X(0.33)$	40.77	42.26	43.75
	(0.51)	(0.52)	(0.55)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.44)	(0.49)	(0.48)
$Q_X(0.67)$	40.61	42.10	43.59
	(0.41)	(0.43)	(0.48)
$Q_X(0.85)$	40.44	41.77	43.09
	(0.48)	(0.53)	(0.58)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.48	0.48	0.00
	(0.61)	(0.62)	(0.81)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.00	0.00	0.75
	(0.29)	(0.26)	(0.27)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.75	-0.75	-1.50
	(0.17)	(0.16)	(0.21)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.37	-0.75	-1.13
	(0.10)	(0.11)	(0.10)

Note: slope given in rank per $\$10,000$.

Table C.3.5: Distribution of Income Mobility vs Gini Coefficient

Quantiles of Gini Coefficient	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.27	42.59	44.08
	(0.51)	(0.50)	(0.59)
$Q_X(0.33)$	40.94	42.26	43.75
	(0.42)	(0.40)	(0.440
$Q_X(0.5)$	40.77	42.26	43.92
	(0.42)	(0.41)	(0.49)
$Q_X(0.67)$	40.61	42.10	43.75
	(0.42)	(0.40)	(0.48)
$Q_X(0.85)$	40.44	41.93	43.59
	(0.46)	(0.47)	(0.50)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.07	-0.07	-0.07
	(0.05)	(0.05)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.04	0.00	0.04
	(0.01)	(0.03)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.05	-0.05	-0.05
	(0.04)	(0.04)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.02	-0.02	-0.02
	(0.04)	(0.02)	(0.02)

Note: slope given in rank per 1%.

Table C.3.6: Distribution of Income Mobility vs Size of Middle Class

Quantiles of Size of Middle Class	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	40.44	41.93	43.59
	(0.45)	(0.45)	(0.55)
$Q_X(0.33)$	40.44	41.93	43.42
	(0.39)	(0.41)	(0.48)
$Q_X(0.5)$	40.77	42.26	43.75
	(0.41)	(0.44)	(0.48)
$Q_X(0.67)$	41.27	42.76	44.41
	(0.39)	(0.43)	(0.48)
$Q_X(0.85)$	42.76	44.41	46.23
	(0.42)	(0.45)	(0.51)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.00	0.00	-0.02
	(0.06)	(0.06)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.08	0.08	0.08
	(0.06)	(0.07)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.13	0.13	0.18
	(0.04)	(0.04)	(0.08)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.27	0.30	0.33
	(0.03)	(0.04)	(0.05)

Note: slope given in rank per 1%.

Table C.3.7: Distribution of Income Mobility vs Share of Workers in Manufacturing

Quantiles of Share in Manufacturing	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.93	43.42	45.08
	(0.53)	(0.52)	(0.60)
$Q_X(0.33)$	41.27	42.59	44.08
	(0.38)	(0.43)	(0.47)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.42)	(0.41)	(0.48)
$Q_X(0.67)$	40.28	41.60	43.26
	(0.42)	(0.45)	(0.48)
$Q_X(0.85)$	39.28	40.61	42.10
	(0.53)	(0.54)	(0.57)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.14	-0.18	-0.21
	(0.05)	(0.05)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.11	-0.07	-0.03
	(0.05)	(0.05)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.12	-0.16	-0.16
	(0.07)	(0.06)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.16	-0.16	-0.19
	(0.06)	(0.06)	(0.07)

Note: slope given in rank per 1%.

Table C.3.8: Distribution of Income Mobility vs Teenage Labor Force Participation

Quantiles of Teenage LFP	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.43	42.92	44.74
	(0.49)	(0.52)	(0.57)
$Q_X(0.33)$	40.61	42.10	43.92
	(0.37)	(0.38)	(0.43)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.44)	(0.46)	(0.49)
$Q_X(0.67)$	41.10	42.59	44.25
	(0.42)	(0.43)	(0.52)
$Q_X(0.85)$	41.77	43.42	45.41
	(0.35)	(0.38)	(0.46)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.12	-0.12	-0.12
	(0.06)	(0.07)	(0.08)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.02	0.02	0.00
	(0.06)	(0.06)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.04	0.04	0.04
	(0.04)	(0.05)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.06	0.07	0.10
	(0.04)	(0.03)	(0.04)

Note: slope given in rank per 1%.

Table C.3.9: Distribution of Income Mobility vs Unemployment Rate

Quantiles of Unemployment	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.10	42.76	44.58
	(0.48)	(0.54)	(0.69)
$Q_X(0.33)$	40.94	42.59	44.25
	(0.43)	(0.42)	(0.52)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.44)	(0.48)	(0.51)
$Q_X(0.67)$	40.61	42.10	43.59
	(0.44)	(0.48)	(0.53)
$Q_X(0.85)$	40.44	41.93	43.42
	(0.62)	(0.64)	(0.79)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.22	-0.22	-0.45
	(0.04)	(0.04)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.29	-0.58	-0.58
	(0.04)	(0.04)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.22	-0.22	-0.45
	(0.03)	(0.04)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.14	-0.14	-0.14
	(0.03)	(0.03)	(0.04)

Note: slope given in rank per 1%.

Table C.3.10: Distribution of Income Mobility vs Social Capital Index

Quantiles of Social Capital Index	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	40.61	41.93	43.59
	(0.39)	(0.37)	(0.43)
$Q_X(0.33)$	40.77	42.26	43.75
	(0.32)	(0.33)	(0.41)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.39)	(0.38)	(0.46)
$Q_X(0.67)$	40.94	42.43	44.08
	(0.37)	(0.41)	(0.50)
$Q_X(0.85)$	41.10	42.59	44.25
	(0.37)	(0.43)	(0.57)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.25	0.51	0.25
	(0.15)	(0.15)	(0.16)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.00	0.00	0.29
	(0.18)	(0.14)	(0.18)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.29	0.29	0.29
	(0.17)	(0.13)	(0.24)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.20	0.20	0.20
	(0.12)	(0.15)	(0.18)

Note: slope given in rank per index unit.

Table C.3.11: Distribution of Income Mobility vs Poverty Rate

Quantiles of Poverty	Quantiles of Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	41.60	43.09	44.74
	(0.41)	(0.48)	(0.61)
$Q_X(0.33)$	40.77	42.26	43.75
	(0.38)	(0.38)	(0.48)
$Q_X(0.5)$	40.77	42.26	43.92
	(0.40)	(0.39)	(0.43)
$Q_X(0.67)$	40.77	42.26	43.92
	(0.40)	(0.40)	(0.41)
$Q_X(0.85)$	40.44	41.77	43.26
	(0.41)	(0.39)	(0.41)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.34	-0.34	-0.41
	(0.05)	(0.07)	(0.11)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.00	0.00	0.06
	(0.18)	(0.17)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.16)	(0.15)	(0.09)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.06	-0.10	-0.13
	(0.03)	(0.03)	(0.04)

Note: slope given in rank per 1%.

Table C.3.12: Distribution of Income Mobility vs Housing Prices

Quantiles of Housing Prices	Quantiles of Income Mobility		
	$Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	42.92	44.41	46.07
	(0.49)	(0.51)	(0.61)
$Q_X(0.33)$	41.93	43.42	44.91
	(0.41)	(0.41)	(0.50)
$Q_X(0.5)$	40.94	42.43	43.92
	(0.42)	(0.41)	(0.49)
$Q_X(0.67)$	40.44	41.77	43.42
	(0.39)	(0.39)	(0.44)
$Q_X(0.85)$	40.44	41.77	43.09
	(0.47)	(0.41)	(0.43)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.80	-0.80	-0.93
	(0.31)	(0.39)	(0.39)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.67	-0.67	-0.67
	(0.37)	(0.31)	(0.44)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.33	-0.44	-0.33
	(0.24)	(0.17)	(0.27)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.00	0.00	-0.11
	(0.18)	(0.18)	(0.20)

Note: slope given in rank per $10,000.

C.4 Difference in Income Mobility Conditional Distribution Tables

Table C.4.1: Distribution of Difference in Income Mobility vs Fraction Black

Quantiles of Fraction Black	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	14.38	15.94	17.50
	(0.76)	(0.81)	(0.90)
$Q_X(0.33)$	14.86	16.18	17.38
	(0.75)	(0.80)	(0.90)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.31)	(0.32)	(0.34)
$Q_X(0.67)$	16.66	17.86	19.06
	(0.36)	(0.36)	(0.31)
$Q_X(0.85)$	18.34	19.55	20.63
	(0.37)	(0.40)	(0.44)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	1.11	0.55	-0.27
	(0.40)	(0.44)	(0.50)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.48	0.48	0.48
	(0.19)	(0.20)	(0.23)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.22	0.19	0.19
	(0.06)	(0.06)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.10	0.10	0.09
	(0.02)	(0.02)	(0.02)

Note: slope given in rank per 1%.

Table C.4.2: Distribution of Difference in Income Mobility vs Racial Segregation

Quantiles of Racial Segregation	Quantiles of Difference in Income Mobility		
	$Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	16.18	17.50	18.82
	(0.53)	(0.50)	(0.50)
$Q_X(0.33)$	16.06	17.26	18.46
	(0.45)	(0.47)	(0.51)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.38)	(0.36)	(0.33)
$Q_X(0.67)$	15.70	17.02	18.22
	(0.38)	(0.35)	(0.36)
$Q_X(0.85)$	15.94	17.26	18.46
	(0.48)	(0.48)	(0.45)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.06	-0.12	-0.19
	(0.09)	(0.10)	(0.11)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.13	-0.08	-0.08
	(0.11)	(0.11)	(0.12)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.08)	(0.08)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.03	0.03	0.03
	(0.06)	(0.06)	(0.06)

Note: slope given in rank per 1%.

Table C.4.3: Distribution of Difference in Income Mobility vs Income Segregation

Quantiles of Income Segregation	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.46	16.90	18.34
	(0.37)	(0.37)	(0.40)
$Q_X(0.33)$	15.58	17.02	18.34
	(0.30)	(0.28)	(0.31)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.34)	(0.32)	(0.30)
$Q_X(0.67)$	15.82	17.02	18.10
	(0.37)	(0.33)	(0.35)
$Q_X(0.85)$	15.82	17.02	18.10
	(0.35)	(0.33)	(0.36)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.26	0.26	0.00
	(0.13)	(0.12)	(0.15)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.14	0.00	-0.14
	(0.07)	(0.07)	(0.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.09	0.00	-0.09
	(0.05)	(0.04)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.00	0.00	0.00
	(0.03)	(0.03)	(0.03)

Note: slope given in rank per 1%.

Table C.4.4: Distribution of Difference in Income Mobility vs Income (per capita)

Quantiles of Income (per capita)	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.46	16.66	17.86
	(0.43)	(0.39)	(0.43)
$Q_X(0.33)$	15.70	16.90	18.10
	(0.34)	(0.30)	(0.35)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.29)	(0.30)	(0.33)
$Q_X(0.67)$	15.70	17.02	18.34
	(1.77)	(0.30)	(0.32)
$Q_X(0.85)$	15.58	16.90	18.22
	(1.78)	(0.29)	(0.31)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.19	0.19	0.19
	(0.65)	(0.51)	(1.07)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.00	0.08	0.08
	(0.22)	(0.20)	(0.52)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.08
	(0.14)	(0.13)	(0.13)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.04	-0.04	-0.04
	(0.07)	(0.07)	(0.07)

Note: slope given in rank per $10,000.

Table C.4.5: Distribution of Difference in Income Mobility vs Gini Coefficient

Quantiles of Gini Coefficient	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.46	16.78	18.10
	(0.46)	(0.41)	(0.41)
$Q_X(0.33)$	15.46	16.90	18.22
	(0.34)	(0.31)	(0.33)
$Q_X(0.5)$	15.58	16.90	18.22
	(0.29)	(0.31)	(0.33)
$Q_X(0.67)$	15.70	16.90	18.22
	(0.29)	(0.30)	(0.37)
$Q_X(0.85)$	15.82	17.02	18.34
	(0.65)	(0.37)	(0.54)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.00	0.03	0.03
	(0.01)	(0.02)	(0.02)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.04	0.00	0.00
	(0.02)	(0.02)	(0.02)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.04	0.00	0.00
	(0.02)	(0.02)	(0.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.02	0.02	0.02
	(0.03)	(0.04)	(0.03)

Note: slope given in rank per 1%.

Table C.4.6: Distribution of Difference in Income Mobility vs Size of Middle Class

Quantiles of Size of Middle Class	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.58	17.26	18.82
	(0.42)	(0.48)	(0.56)
$Q_X(0.33)$	15.82	17.38	18.82
	(0.68)	(0.36)	(0.39)
$Q_X(0.5)$	15.94	17.38	18.70
	(0.69)	(0.31)	(0.33)
$Q_X(0.67)$	15.94	17.38	18.70
	(0.36)	(0.30)	(0.27)
$Q_X(0.85)$	15.82	17.14	18.46
	(0.39)	(0.36)	(0.34)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.06	0.03	0.00
	(0.07)	(0.05)	(0.08)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.03	0.00	-0.03
	(0.05)	(0.06)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.04)	(0.04)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.03	-0.06	-0.06
	(0.03)	(0.03)	(0.03)

Note: slope given in rank per 1%.

Table C.4.7: Distribution of Difference in Income Mobility vs Manufacturing

Quantiles of Share in Manufacturing	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	14.62	15.94	17.14
	(0.43)	(0.43)	(0.59)
$Q_X(0.33)$	15.34	16.66	17.98
	(0.37)	(0.35)	(0.48)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.40)	(0.38)	(0.36)
$Q_X(0.67)$	15.94	17.14	18.34
	(0.36)	(0.36)	(0.32)
$Q_X(0.85)$	16.30	17.50	18.70
	(0.47)	(0.39)	(0.33)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.15	0.15	0.18
	(0.05)	(0.04)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.08	0.08	0.05
	(0.04)	(0.04)	(0.06)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.05	0.02	0.02
	(0.05)	(0.05)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.06	0.06	0.06
	(0.05)	(0.05)	(0.04)

Note: slope given in rank per 1%.

Table C.4.8: Distribution of Difference in Income Mobility vs Teenage LFP

Quantiles of Teenage LFP	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.46	16.90	18.22
	(0.39)	(0.39)	(0.39)
$Q_X(0.33)$	15.70	17.02	18.22
	(0.32)	(0.32)	(0.34)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.42)	(0.30)	(0.33)
$Q_X(0.67)$	15.70	17.02	18.22
	(0.30)	(0.29)	(0.33)
$Q_X(0.85)$	15.70	17.02	18.34
	(0.30)	(0.32)	(0.38)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.04	0.02	0.00
	(0.04)	(0.02)	(0.05)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.00	0.00	0.00
	(0.29)	(0.29)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.33)	(0.03)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.00	0.00	0.01
	(0.21)	(0.02)	(0.02)

Note: slope given in rank per 1%.

Table C.4.9: Distribution of Difference in Income Mobility vs Unemployment Rate

Quantiles of Unemployment	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.46	16.78	17.98
	(2.03)	(0.36)	(0.38)
$Q_X(0.33)$	15.46	16.78	17.98
	(1.50)	(0.27)	(0.29)
$Q_X(0.5)$	15.70	17.02	18.22
	(1.49)	(0.32)	(0.31)
$Q_X(0.67)$	15.70	17.02	18.22
	(1.50)	(0.35)	(0.33)
$Q_X(0.85)$	15.58	16.90	18.10
	(0.49)	(1.26)	(1.32)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.00	0.00	0.00
	(0.20)	(0.03)	(0.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.42	0.42	0.42
	(0.03)	(0.03)	(0.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.00	0.00	0.00
	(0.03)	(0.03)	(0.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.10	-0.10	-0.10
	(0.14)	(0.10)	(0.12)

Note: slope given in rank per 1%.

Table C.4.10: Distribution of Difference in Income Mobility vs Social Capital Index

Quantiles of Social Capital Index	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	14.98	16.30	17.50
	(0.40)	(0.38)	(0.41)
$Q_X(0.33)$	15.34	16.66	17.86
	(0.36)	(0.35)	(0.35)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.35)	(0.33)	(0.32)
$Q_X(0.67)$	15.94	17.26	18.58
	(0.35)	(0.32)	(0.35)
$Q_X(0.85)$	16.18	17.62	18.94
	(0.41)	(0.40)	(0.46)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.55	0.55	0.55
	(0.16)	(0.13)	(0.13)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	0.63	0.63	0.63
	(0.15)	(0.14)	(0.14)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.42	0.42	0.63
	(0.15)	(0.15)	(0.17)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.29	0.44	0.44
	(0.11)	(0.12)	(0.16)

Note: slope given in rank per index unit.

Table C.4.11: Distribution of Difference in Income Mobility vs Poverty Rate

Quantiles of Poverty	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.82	17.02	18.10
	(0.34)	(0.30)	(0.28)
$Q_X(0.33)$	15.82	17.02	18.22
	(0.38)	(0.34)	(0.36)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.35)	(0.31)	(0.37)
$Q_X(0.67)$	15.82	17.14	18.34
	(0.36)	(0.32)	(0.37)
$Q_X(0.85)$	16.06	17.38	18.70
	(0.50)	(0.43)	(0.44)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	0.00	0.00	0.05
	(0.09)	(0.08)	(0.04)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.05	0.00	0.00
	(0.03)	(0.03)	(0.02)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	0.05	0.05	0.05
	(0.02)	(0.03)	(0.03)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	0.05	0.05	0.07
	(0.07)	(0.05)	(0.03)

Note: slope given in rank per 1%.

Table C.4.12: Distribution of Difference in Income Mobility vs Housing Prices

Quantiles of Housing Prices	Quantiles of Difference in Income Mobility $Q_{Y\|X}(0.25)$	$Q_{Y\|X}(0.5)$	$Q_{Y\|X}(0.75)$
$Q_X(0.15)$	15.94	17.26	18.34
	(0.33)	(0.34)	(0.37)
$Q_X(0.33)$	15.82	17.14	18.22
	(0.35)	(0.36)	(0.39)
$Q_X(0.5)$	15.70	17.02	18.22
	(0.38)	(0.38)	(0.39)
$Q_X(0.67)$	15.46	16.78	18.10
	(0.38)	(0.40)	(0.40)
$Q_X(0.85)$	14.38	15.94	17.38
	(0.41)	(0.40)	(0.46)
Slopes of Quantiles of Income Mobility			
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.33-0.15}}$	-0.09	-0.09	-0.09
	(0.24)	(0.23)	(0.21)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.50-0.33}}$	-0.08	-0.08	0.00
	(0.30)	(0.27)	(0.25)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.67-0.5}}$	-0.16	-0.16	-0.08
	(0.20)	(0.18)	(0.17)
$\Delta Q_{Y\|X}/\Delta Q_{X_{0.85-0.67}}$	-0.36	-0.28	-0.24
	(0.17)	(0.15)	(0.16)

Note: slope given in rank per $10,000.

C.5 Estimated Spline Coefficients

Table C.5.1: Coefficients for Distribution of Income Mobility

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W1(X)	-1.527	-0.355	0.000	0.000	0.226
W2(X)	0.000	-0.180	0.384	0.000	-0.321
W3(X)	0.000	-0.326	0.798	-0.366	-0.149
W4(X)	-3.419	0.644	-0.033	0.072	0.000
W5(X)	0.000	0.376	0.000	0.000	0.000
W6(X)	0.000	0.545	0.000	0.000	0.000
W7(X)	0.000	0.749	0.000	0.000	0.000
W8(X)	0.000	-0.255	0.620	-0.553	0.000
W9(X)	0.000	0.217	0.128	-0.233	-0.290
W10(X)	0.000	0.114	0.323	-0.494	0.000
W11(X)	0.000	0.205	0.000	0.000	0.000
W12(X)	0.000	0.618	0.000	0.000	0.000
W13(X)	0.000	0.364	0.000	0.000	0.000
W14(X)	0.000	0.188	-0.309	0.284	-0.264
W15(X)	0.000	0.017	0.017	-0.190	0.400
W16(X)	-0.245	0.096	-0.135	0.045	0.011
W17(X)	0.000	0.381	-1.144	1.160	0.000
W18(X)	0.000	0.149	-0.106	0.000	0.000
W19(X)	0.000	0.317	-0.328	0.000	0.000
W20(X)	0.000	-0.114	0.098	0.000	-0.333
W21(X)	0.000	0.027	-0.036	0.000	0.000
W22(X)	0.000	-0.103	0.320	-0.398	0.000
W23(X)	0.000	0.142	-0.355	0.000	1.211
W24(X)	0.000	-0.058	0.000	0.000	0.000
W25(X)	0.000	-0.368	1.314	0.000	0.000
W26(X)	0.000	0.000	-0.207	0.000	0.000
W27(X)	0.000	-0.270	0.425	0.000	0.000
W28(X)	0.000	-0.113	-0.097	0.504	0.000
W29(X)	0.000	-0.261	0.609	0.000	0.000
W30(X)	0.000	-0.095	0.000	0.000	0.000
W31(X)	0.000	0.000	0.000	0.000	0.000
W32(X)	0.000	-0.141	0.000	0.000	1.307
W33(X)	0.000	-0.260	0.587	-0.226	-0.238
W34(X)	0.000	-0.005	0.000	0.000	0.744
W35(X)	0.000	0.070	0.000	0.000	0.000

Table C.5.2: Coefficients for Distribution of Income Mobility, cont.

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W36(X)	0.000	0.004	0.000	0.000	0.000
W37(X)	0.000	0.240	0.000	0.000	0.000
W38(X)	0.000	-0.104	-0.370	0.000	0.000
W39(X)	0.000	-0.024	-0.155	0.000	0.000
W40(X)	-1.370	0.111	0.000	-0.426	0.000
W41(X)	0.000	-0.242	-0.033	0.000	0.000
W42(X)	0.000	-0.556	0.000	0.000	0.000
W43(X)	0.000	-0.155	0.000	-0.314	0.000
W44(X)	0.000	-0.465	0.339	0.000	0.000
W45(X)	0.000	-0.483	0.660	0.000	-0.236
W46(X)	-0.675	-0.167	0.265	0.000	0.000
W47(X)	-1.373	0.316	-0.190	0.000	0.499
W48(X)	0.000	-0.003	0.320	0.000	0.000
W49(X)	0.000	0.079	0.000	0.000	0.000
W50(X)	0.000	-0.304	0.000	0.985	0.000
W51(X)	0.000	0.186	-0.084	-0.061	0.000
W52(X)	0.000	0.003	0.204	0.000	0.000
W53(X)	0.000	-0.056	0.168	0.000	0.000
W54(X)	0.000	0.027	-0.048	0.000	0.000
W55(X)	0.000	0.038	0.000	0.000	0.000
W56(X)	0.000	0.740	-1.079	0.000	0.000
W57(X)	-1.152	0.000	0.318	-0.268	0.000
W58(X)	0.000	0.004	-0.036	0.000	0.000
W59(X)	0.000	-0.096	0.009	0.106	0.000
W60(X)	0.000	0.030	0.000	-0.141	0.000
W61(X)	0.000	-0.207	0.000	0.000	0.589
W62(X)	0.000	-0.060	0.148	0.000	0.000
W63(X)	0.000	0.024	0.243	0.000	0.000
W64(X)	0.000	0.459	-0.293	0.028	0.191
W65(X)	0.000	0.095	0.619	0.000	0.000
W66(X)	0.000	-0.497	0.000	0.000	0.000
W67(X)	0.000	0.000	-2.451	6.979	0.000
W68(X)	0.000	0.214	0.106	0.000	0.000
W69(X)	0.000	0.232	0.000	-0.243	0.665
W70(X)	-0.443	0.266	0.158	-0.123	0.171
W71(X)	0.000	0.402	-0.244	0.363	0.000
W72(X)	0.000	0.255	0.000	0.000	0.000
W73(X)	0.000	0.130	0.000	0.000	0.000

Table C.5.3: Coefficients for Distribution of Difference in Income Mobility

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W1(X)	-1.968	0.084	2.041	0.000	0.794
W2(X)	0.000	-0.001	-0.153	0.349	0.000
W3(X)	0.000	-0.140	-0.036	0.323	-0.105
W4(X)	0.000	0.053	-0.699	0.840	-0.024
W5(X)	0.000	-0.481	-0.074	0.000	0.505
W6(X)	0.000	-0.351	0.000	0.000	0.315
W7(X)	0.000	-1.311	1.533	0.000	0.000
W8(X)	0.000	0.454	0.000	-2.242	3.667
W9(X)	0.000	0.202	0.000	-0.873	0.000
W10(X)	0.000	0.426	-0.392	-0.490	-0.378
W11(X)	0.000	0.546	-0.735	-0.477	0.000
W12(X)	0.000	0.536	0.000	-1.556	0.000
W13(X)	0.000	0.060	-0.718	0.000	0.000
W14(X)	0.000	0.061	0.071	-0.645	0.648
W15(X)	-0.493	-0.078	0.263	-0.291	0.320
W16(X)	0.000	-0.193	0.706	-1.171	1.089
W17(X)	0.000	-0.446	0.570	0.000	-0.616
W18(X)	0.000	-0.213	0.000	-0.010	0.000
W19(X)	0.000	-0.029	0.000	-1.194	3.457
W20(X)	0.000	0.551	-1.554	1.791	-0.881
W21(X)	0.000	0.270	-1.100	1.664	-1.204
W22(X)	0.000	0.231	-1.201	1.902	-1.060
W23(X)	0.000	-0.099	-0.693	1.623	-0.652
W24(X)	0.000	-0.081	0.000	0.000	0.771
W25(X)	0.000	-0.983	0.000	1.695	0.000
W26(X)	0.000	-0.153	0.000	-0.042	0.000
W27(X)	0.000	0.370	-0.601	0.000	0.000
W28(X)	-1.393	0.440	-0.431	-0.020	0.193
W29(X)	0.000	-0.455	0.735	-0.599	0.000
W30(X)	0.000	-0.550	0.000	0.772	0.000
W31(X)	0.000	-0.242	0.000	0.000	0.000
W32(X)	0.000	-0.504	0.360	0.000	0.000
W33(X)	0.000	-0.778	1.343	-1.109	0.000
W34(X)	0.000	-0.414	0.188	0.346	-0.868
W35(X)	0.000	-0.002	-0.485	0.448	-0.293

Table C.5.4: Coefficients for Distribution of Difference in Income Mobility, cont.

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W36(X)	0.000	-0.112	0.000	0.000	0.000
W37(X)	0.000	-0.289	0.000	0.000	0.000
W38(X)	0.000	0.240	0.000	0.000	0.548
W39(X)	0.000	0.526	-1.288	1.465	0.000
W40(X)	-1.570	0.460	-0.623	1.257	-0.150
W41(X)	0.000	0.136	-0.109	-0.004	1.688
W42(X)	0.000	0.033	0.440	0.084	0.000
W43(X)	0.000	0.236	0.000	-0.289	0.000
W44(X)	0.000	0.027	0.471	-0.483	0.139
W45(X)	-1.047	0.169	0.175	-0.174	-0.098
W46(X)	0.000	0.106	-0.190	0.097	0.104
W47(X)	0.000	-0.340	0.455	0.001	-0.402
W48(X)	0.000	-0.367	0.000	0.271	-0.003
W49(X)	0.000	0.206	-0.264	0.000	0.000
W50(X)	0.000	0.178	0.000	-0.977	0.782
W51(X)	0.000	0.149	-0.291	-0.414	0.772
W52(X)	0.000	0.060	-0.056	-0.734	1.151
W53(X)	0.000	0.491	-0.895	0.000	0.237
W54(X)	0.000	0.365	-0.650	0.247	0.000
W55(X)	0.000	0.171	0.000	-0.592	0.000
W56(X)	0.000	-0.792	0.835	-0.498	0.000
W57(X)	0.000	-0.365	0.294	-0.541	0.000
W58(X)	0.000	-0.381	0.000	-0.212	0.000
W59(X)	0.000	-0.233	-0.266	-0.017	-0.574
W60(X)	0.000	-0.221	-0.452	0.000	0.000
W61(X)	0.000	-0.415	0.000	0.000	0.000
W62(X)	0.000	0.001	-0.702	0.502	0.000
W63(X)	0.000	-0.075	-0.745	0.926	0.009
W64(X)	0.267	-0.376	-0.009	0.000	0.486
W65(X)	0.000	0.317	0.000	-0.602	0.000
W66(X)	0.000	0.645	0.000	0.000	0.000
W67(X)	0.000	-0.347	1.606	0.000	0.000
W68(X)	0.000	0.195	-0.536	0.000	0.347
W69(X)	0.000	-0.165	0.340	0.000	-1.810
W70(X)	0.517	-0.576	1.050	-1.215	0.000
W71(X)	0.000	-1.096	2.522	-2.333	0.000
W72(X)	0.000	1.069	-1.757	0.000	0.518
W73(X)	0.000	-0.237	0.668	0.000	0.000

C.6 Spline Coefficient Standard Errors

Table C.6.1: Standard Errors for Income Mobility Coefficients

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W1(X)	0.530	0.277	0.000	0.000	0.343
W2(X)	0.000	0.100	0.140	0.000	0.154
W3(X)	0.000	0.109	0.274	0.371	0.332
W4(X)	0.914	0.278	0.356	0.285	0.000
W5(X)	0.000	0.056	0.000	0.000	0.000
W6(X)	0.000	0.119	0.000	0.000	0.000
W7(X)	0.000	0.130	0.000	0.000	0.000
W8(X)	0.000	0.260	0.558	0.496	0.000
W9(X)	0.000	0.159	0.365	0.427	0.348
W10(X)	0.000	0.148	0.325	0.324	0.000
W11(X)	0.000	0.071	0.000	0.000	0.000
W12(X)	0.000	0.104	0.000	0.000	0.000
W13(X)	0.000	0.106	0.000	0.000	0.000
W14(X)	0.000	0.195	0.439	0.474	0.395
W15(X)	0.000	0.147	0.360	0.436	0.360
W16(X)	0.607	0.228	0.382	0.397	0.357
W17(X)	0.000	0.194	0.454	0.421	0.000
W18(X)	0.000	0.229	0.390	0.000	0.000
W19(X)	0.000	0.206	0.300	0.000	0.000
W20(X)	0.000	0.151	0.211	0.000	0.204
W21(X)	0.000	0.107	0.138	0.000	0.000
W22(X)	0.000	0.134	0.242	0.192	0.000
W23(X)	0.000	0.170	0.274	0.000	0.589
W24(X)	0.000	0.091	0.000	0.000	0.000
W25(X)	0.000	0.375	0.741	0.000	0.000
W26(X)	0.000	0.000	0.154	0.000	0.000
W27(X)	0.000	0.118	0.189	0.000	0.000
W28(X)	0.000	0.103	0.240	0.233	0.000
W29(X)	0.000	0.169	0.267	0.000	0.000
W30(X)	0.000	0.121	0.000	0.000	0.000
W31(X)	0.000	0.000	0.000	0.000	0.000
W32(X)	0.000	0.155	0.000	0.000	0.347
W33(X)	0.000	0.183	0.380	0.503	0.438
W34(X)	0.000	0.121	0.000	0.000	0.229
W35(X)	0.000	0.116	0.000	0.000	0.000

Table C.6.2: Standard Errors for Income Mobility Coefficients, cont.

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W36(X)	0.000	0.173	0.000	0.000	0.000
W37(X)	0.000	0.264	0.000	0.000	0.000
W38(X)	0.000	0.243	0.309	0.000	0.000
W39(X)	0.000	0.168	0.203	0.000	0.000
W40(X)	0.620	0.177	0.000	0.125	0.000
W41(X)	0.000	0.182	0.209	0.000	0.000
W42(X)	0.000	0.159	0.000	0.000	0.000
W43(X)	0.000	0.176	0.000	0.213	0.000
W44(X)	0.000	0.179	0.239	0.000	0.000
W45(X)	0.000	0.121	0.178	0.000	0.198
W46(X)	0.536	0.160	0.172	0.000	0.000
W47(X)	0.750	0.214	0.236	0.000	0.348
W48(X)	0.000	0.203	0.307	0.000	0.000
W49(X)	0.000	0.072	0.000	0.000	0.000
W50(X)	0.000	0.150	0.000	0.365	0.000
W51(X)	0.000	0.160	0.339	0.322	0.000
W52(X)	0.000	0.158	0.212	0.000	0.000
W53(X)	0.000	0.140	0.184	0.000	0.000
W54(X)	0.000	0.233	0.304	0.000	0.000
W55(X)	0.000	0.116	0.000	0.000	0.000
W56(X)	0.000	0.203	0.353	0.000	0.000
W57(X)	0.505	0.000	0.257	0.295	0.000
W58(X)	0.000	0.132	0.217	0.000	0.000
W59(X)	0.000	0.179	0.405	0.313	0.000
W60(X)	0.000	0.132	0.000	0.211	0.000
W61(X)	0.000	0.156	0.000	0.000	0.231
W62(X)	0.000	0.255	0.343	0.000	0.000
W63(X)	0.000	0.189	0.241	0.000	0.000
W64(X)	0.000	0.216	0.355	0.298	0.235
W65(X)	0.000	0.262	0.361	0.000	0.000
W66(X)	0.000	0.166	0.000	0.000	0.000
W67(X)	0.000	0.000	1.442	3.215	0.000
W68(X)	0.000	0.202	0.236	0.000	0.000
W69(X)	0.000	0.096	0.000	0.244	0.333
W70(X)	0.702	0.244	0.326	0.341	0.255
W71(X)	0.000	0.193	0.407	0.468	0.000
W72(X)	0.000	0.132	0.000	0.000	0.000
W73(X)	0.000	0.085	0.000	0.000	0.000

Table C.6.3: Standard Errors for Difference in Income Mobility Coefficients

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W1(X)	1.071	0.854	1.027	0.000	0.840
W2(X)	0.000	0.191	0.400	0.335	0.000
W3(X)	0.000	0.212	0.501	0.599	0.554
W4(X)	0.000	0.235	0.508	0.511	0.411
W5(X)	0.000	0.369	0.476	0.000	0.362
W6(X)	0.000	0.119	0.000	0.000	0.417
W7(X)	0.000	0.462	0.583	0.000	0.000
W8(X)	0.000	0.222	0.000	0.908	1.581
W9(X)	0.000	0.139	0.000	0.392	0.000
W10(X)	0.000	0.281	0.536	0.721	0.576
W11(X)	0.000	0.387	0.669	0.567	0.000
W12(X)	0.000	0.232	0.000	0.497	0.000
W13(X)	0.000	0.627	0.808	0.000	0.000
W14(X)	0.000	0.308	0.701	0.794	0.616
W15(X)	1.347	0.496	0.599	0.531	0.346
W16(X)	0.000	0.246	0.550	0.596	0.416
W17(X)	0.000	0.263	0.361	0.000	0.354
W18(X)	0.000	0.190	0.000	0.367	0.000
W19(X)	0.000	0.253	0.000	1.150	2.032
W20(X)	0.000	0.364	0.869	1.012	0.793
W21(X)	0.000	0.241	0.579	0.673	0.519
W22(X)	0.000	0.288	0.691	0.813	0.654
W23(X)	0.000	0.493	1.197	1.417	1.227
W24(X)	0.000	0.135	0.000	0.000	0.644
W25(X)	0.000	0.321	0.000	0.576	0.000
W26(X)	0.000	0.237	0.000	0.490	0.000
W27(X)	0.000	0.343	0.471	0.000	0.000
W28(X)	1.091	0.470	0.610	0.634	0.444
W29(X)	0.000	0.482	0.886	0.666	0.000
W30(X)	0.000	0.302	0.000	0.760	0.000
W31(X)	0.000	0.200	0.000	0.000	0.000
W32(X)	0.000	0.330	0.442	0.000	0.000
W33(X)	0.000	0.330	0.728	0.570	0.000
W34(X)	0.000	0.275	0.590	0.566	0.466
W35(X)	0.000	0.414	0.920	0.887	0.658

Table C.6.4: Standard Errors for Difference in Income Mobility Coefficients, cont.

Spline Coefficeints	S1(Y)	S2(Y)	S3(Y)	S4(Y)	S5(Y)
W36(X)	0.000	0.179	0.000	0.000	0.000
W37(X)	0.000	0.203	0.000	0.000	0.000
W38(X)	0.000	0.230	0.000	0.000	0.502
W39(X)	0.000	0.404	0.761	0.564	0.000
W40(X)	1.143	0.567	0.807	0.723	0.540
W41(X)	0.000	0.369	0.761	0.894	0.781
W42(X)	0.000	0.466	0.975	0.826	0.000
W43(X)	0.000	0.233	0.000	0.419	0.000
W44(X)	0.000	0.355	0.887	1.211	1.174
W45(X)	1.368	0.550	0.803	0.907	0.772
W46(X)	0.000	0.215	0.529	0.784	0.834
W47(X)	0.000	0.376	0.873	1.024	0.840
W48(X)	0.000	0.236	0.000	0.763	1.114
W49(X)	0.000	0.390	0.489	0.000	0.000
W50(X)	0.000	0.230	0.000	0.617	0.825
W51(X)	0.000	0.442	0.847	0.712	0.462
W52(X)	0.000	0.337	0.625	0.646	0.604
W53(X)	0.000	0.322	0.426	0.000	0.431
W54(X)	0.000	0.486	0.991	0.811	0.000
W55(X)	0.000	0.197	0.000	0.441	0.000
W56(X)	0.000	0.516	0.877	0.629	0.000
W57(X)	0.000	0.323	0.590	0.483	0.000
W58(X)	0.000	0.155	0.000	0.243	0.000
W59(X)	0.000	0.307	0.616	0.677	0.498
W60(X)	0.000	0.322	0.449	0.000	0.000
W61(X)	0.000	0.169	0.000	0.000	0.000
W62(X)	0.000	0.477	0.826	0.645	0.000
W63(X)	0.000	0.313	0.579	0.631	0.635
W64(X)	0.759	0.384	0.418	0.000	0.409
W65(X)	0.000	0.201	0.000	0.441	0.000
W66(X)	0.000	0.238	0.000	0.000	0.000
W67(X)	0.000	0.837	1.526	0.000	0.000
W68(X)	0.000	0.452	0.668	0.000	0.855
W69(X)	0.000	0.277	0.401	0.000	0.366
W70(X)	0.857	0.481	0.697	0.503	0.000
W71(X)	0.000	0.442	0.824	0.599	0.000
W72(X)	0.000	0.696	0.960	0.000	0.730
W73(X)	0.000	0.631	1.002	0.000	0.000

C.7 OLS Multivariate Regression Results

Table C.7.1: OLS Results: Income Mobility

Variable	Coefficient	(Std. Err.)
black	-8.42	(0.596)
race seg	-4.28	(0.997)
income seg	-20.90	(3.176)
hh income	1.34	(0.212)
gini	-11.59	(1.088)
middle class	11.09	(1.463)
manufacturing	-13.96	(0.840)
teen lfp	4.91	(0.754)
unemployment	-28.28	(4.601)
social capital	0.94	(0.074)
poverty	15.14	(2.503)
housing price	-0.10	(0.023)
Intercept	39.49	(1.664)

Table C.7.2: OLS Results: Difference in Income Mobility

Variable	Coefficient	(Std. Err.)
black	6.59	(0.475)
race seg	5.00	(0.795)
income seg	4.54	(2.533)
hh income	-0.27	(0.169)
gini	2.60	(0.868)
middle class	-8.84	(1.167)
manufacturing	9.58	(0.670)
teen lfp	-5.28	(0.601)
unemployment	-7.04	(3.669)
social capital	0.26	(0.059)
poverty	-8.71	(1.996)
housing price	-0.23	(0.018)
Intercept	24.48	(1.327)

Curriculum Vitae

Mikhail Smirnov (born 30 November 1987 in Yaroslavl, Russia) received his BS/BA in Economics and International Studies from the University of Washington in 2009. Between 2010 and 2016 he completed his Ph.D. at the Johns Hopkins University. During this time, he taught courses and engaged in research in the areas of urban and labor economics, social and economic networks, and applied econometrics. In August 2016 he joined the Center for Naval Analysis in Arlington, Virginia as a Research Analyst, working in the area of defense workforce analysis.