The End of the American Dream? Inequality and Segregation in US cities *

Alessandra Fogli
Minneapolis Fed

Veronica Guerrieri
University of Chicago

March 2018
(Preliminary - First draft: March 2017)

Abstract

Over the last 40 years, the US has experienced a large increase in inequality. At the same time there has been a substantial increase in residential segregation by income and education. What is the link between inequality and residential and educational choices? We first document a strong correlation between inequality and residential segregation in the US between 1980 and 2010, both across time and across space, at the MSA level. Next, we develop a general equilibrium overlapping generations model where parents choose both the neighborhood where they live and their children's education level. In the model, segregation and inequality amplify each other because of a local spillover that affects the returns to education. The spillover captures quality of public schools, peer effect, social norms, learning from neighbors' experience and so forth. We calibrate the model to 1980 using Census data and the micro estimates of the local spillover effect derived in the notable work by Chetty and Hendren (2017b). We then hit the economy with a skill premium shock and show that roughly one third of the increase in inequality and segregation and roughly one fourth of the decrease in intergenerational mobility can be attributed to the local spillover.

1 Introduction

Over the last 40 years, the US has experienced a large increase in inequality. At the same time there has been a substantial increase in residential segregation by income and education. What is

*Email addresses: afogli00@gmail.com; vguerrie@chicagobooth.edu. For helpful comments, we are grateful to Roland Benabou, Jarda Borovicka, Steven Durlauf, Luigi Guiso, Erik Hurst, Francesco Lippi, Guido Lorenzoni, Alexander Monge-Naranjo, Fabrizio Perri, Richard Rogerson and numerous seminar participants. For outstanding research assistance, we thank Gustavo Gonzalez, Hyunju Lee, Qi Li, Emily Moschini, Luis Simon, and, in particular, Yu-Ting Chiang.

the link between inequality and residential segregation? We propose a model where segregation and inequality amplify each other because of a local spillover that affects the returns to education.

There has been a large theoretical literature in the '90s focusing on the relation between inequality and local externalities, starting from the seminal work by Benabou (1996a,b), Durlauf (1996a,b), Fernandez and Rogerson (1996, 1997, 1998). More recently, administrative data have been used to propose direct estimates of neighborhood spillover effects. In particular Chetty, Hendren and Katz (2016), and Chetty and Hendren (2017a,b) have shown that there are substantial income effects coming from the childhood exposure to better neighborhood. We bridge these two strands of literature, by proposing a general equilibrium model calibrated using the micro estimates from Chetty and Hendren (2017b) to understand the role of these types of externalities to explain the recent dramatic rise in inequality.

We first document a strong correlation between inequality and residential segregation at the MSA level, both across time and across space, especially in MSA with higher percentage of families with children. We use Census tract data on family income between 1970 and 2010 to construct measures of inequality and residential segregation at the MSA level. To measure inequality, we use the Gini coefficient at the MSA level. To measure segregation, we use the dissimilarity index, which is a measure of how uneven is the distribution of two groups across geographical areas. In particular, we divide the population in two income groups, rich and poor, using the 80th income percentile. We then compute the dissimilarity index across census tracts belonging to the same MSA.[1] Using these data, we show that 1) average inequality and residential segregation have increased steadily since 1980; 2) inequality and residential segregation in 1980 are correlated across MSA; 3) the change in inequality and residential segregation between 1980 and 2000 are correlated across MSA.

We also look at intergenerational mobility, by using a restricted-access geocoded version of the National Longitudinal Survey of Youth (NLSY79). We show that intergenerational mobility is lower in metro areas that display higher levels of residential segregation. In particular, we split the metro areas in two groups: above and below the median dissimilarity index in 1980. We then show the share of people who stay in the lowest quartile of the wage distribution conditional on their parents being in the same quartile goes from 41.5% in the less segregated metros to 50.3%

[1] Our results are robust to using alternative measures of inequality and different cutoffs for rich and poor.

in the more segregated ones, testifying a lower degree of intergenerational mobility in the more segregated metro areas. Similarly, the share of people who stay in the highest quartile of the wage distribution conditional on their parents being in the same quartile goes from 39.1% to 48.7%.

We then interpret the facts just described through the lens of a general equilibrium overlapping generation model with education and residential choice. Agents live for two periods: first they are young and go to school and then they are old and become parents. Agents have some innate ability that is persistent across generations. There are two neighborhoods: one has a fixed supply of houses and the other has a fully elastic supply of houses. Parents choose both the neighborhood where they raise their children and their children's education level. The key ingredient of the model is a local spillover: conditional on innate ability and educational level, income is higher for children who grew up in a neighborhood where parents are richer and other children have higher ability. The spillover generates sorting in equilibrium: the inelastic neighborhood has higher rents and a higher spillover. This implies that parents face a trade-off: the high rent neighborhood is more expensive but leads to better outcomes for the children. Due to an income effect and to complementarity between ability and the local spillover, the high rent neighborhood tends to attract parents that are richer and/or have children with higher ability. The spillover effect in the model is meant to capture a variety of mechanisms: differences in the quality of public schools, peer effect, social norms, learning from neighbors' experience and so forth. For our purposes here, it does not matter which of these effects are causing the spillover.

Next, we calibrate the steady state of the model to the US economy in 1980, before the sharp increase in inequality. In particular, we target the average level of inequality and residential segregation, using the Census data just described. We also target the skill premium, the share of collage graduates a the ratio of collage graduates in the two neighborhoods, and the rank-rank correlation between children's and parents' income. An important target of our calibration is the effect of the local spillover. This is where we use the micro estimates obtained with the quasi-experiment in Chetty and Hendren (2017b).

We then perform our main exercise. Assuming that the original shock to inequality comes from biased technical change, we want to understand the role of the local spillover in amplifying the increase in inequality over time. In particular, we study the effects of an unexpected, one-time shock to the skill premium on inequality, segregation, and intergenerational mobility over time and then run a counterfactual where we keep the level of the spillover in the two neighborhoods

as given. The exercise shows that the spillover effect can contribute to roughly one third of the increase in inequality and segregation, and to roughly one fourth of the decrease in intergenerational mobility.

We finally explore an extended version of the model where we embed a preference shock that also affect the residential choice, and where the educational choice is continuous. The extended version of the model improves in terms of matching the intergenerational mobility, but it is still far from the level in the data. We are still working on improving the calibration. The analogous exercise performed with the baseline model, shows that, in this version of the model, the spillover effect can contribute to roughly one fourth of the increase in inequality and of the decrease in intergenerational mobility, and roughly three fourth of the increase increase in residential segregation.

Our model builds on a large class of models with multiple communities, local spillovers, and endogenous residential choice, studying the effects of stratification (residential segregation in our language) on income distribution, going back to the seminal work by Becker and Tomes (1979) and Loury (1981). Among the seminal papers in this literature, Benabou (1993) explores a steady state model where local complementarities in human capital investment, or peer effects, generate occupational segregation and studies its efficiency properties.[2] Durlauf (1996b) proposes a related dynamic model with multiple communities, where segregation is driven by both locally financed public schools and local social spillovers. The paper shows that economic stratification together with strong neighborhood feedback effects generate persistent inequality.[3] Benabou (1996a) embeds growth with complementary skills in production in a similar model, where local spillovers are due both to social externalities (as peer effects) and locally financed public school. The paper analyzes the trade-off coming from the fact that stratification helps growth in the short run due to the complementarities in skills, while integration helps growth in the longer run, as generates less inequality, and hence heterogeneity in skills, over time. It also studies how alternative systems of education financing affect the economy. Fernandez and Rogerson (1996) also study the impact of a number of reforms on public education financing using a related model,

[2]De Bartolome (1990) also studies efficiency properties of a similar type of model where communities stratification is driven by peer effects in education. In similar papers, the local social externalities take the form of role models (Streufert (2000)), or referrals by neighborhoods (see Montgomery (1991a,b))

[3]Durlauf (1996a) uses a related model to study how it can generate permanent relative income inequality (opposed to absolute low-income or poverty traps) in an economy where everybody's income is growing.

with no growth, where residential stratification is purely driven by locally financed public education.[4] Fernandez and Rogerson (1998) calibrate to US data a dynamic version of a similar model to analyze the static and dynamic effects of public school financing reforms. This paper is, to the best of our knowledge, the first to calibrate a model in this literature. Benabou (1996b) also studies the effects of public-school financing reforms in a similar model, but he allows for non-fiscal channels of local spillovers, like peers, role models, norms, networks, and so forth and show that disentangling between financial and social local spillover is important for assessing these type of policies.

Our model builds on the same idea of this class of papers that stratification, due to a local spillover, generates more inequality over time. We focus on a model that can be calibrated and brought to the data, while, most of the papers discussed, with the notable exception of Fernandez and Rogerson (1998), focus on the qualitative implications of the models. In that spirit, most of them analyze the two extreme scenarios of full stratification and full integration. Given our quantitative ambition, we need to make the model more special under some dimensions in order to handle a continuous measure of segregation. In order to discipline the model with data on education, we also introduce an endogenous educational choice, that is absent in the previous papers. Moreover, differently from the literature, we model the local spillover as a black box, that can be interpreted as driven either by a financial or a social channel. While for normative questions that have been explored in the literature the specification of the spillover is clearly important, for positive questions like the ones analyzed in our paper, it is less so. This is why we prefer to leave the framework more flexible to possibly incorporate different types of local spillover effects.

The most related paper to our work is the contemporaneous work of Durlauf and Seshadri (2017). They also build on this class of models to explore the idea that larger income inequality is associated to lower intergenerational mobility, the "Gatsby curve". The model in the paper is close to our model in many dimensions, although the calibration strategy and the main exercise are different and complement well each other.

More recently, Zheng (2017) also studies a model similar to ours where local spillover generates residential sorting and calibrate it to the US data. Relative to us, she models the local spillover explicitely in terms of public school quality and peer effect, but she does not have endogenous

[4] In a similar framework, Fernandez and Rogerson (1997) study the effect of community zoning regulation on allocations and welfare.

educational choice. Moreover, the main objective of her paper is to study the effects of different public school allocation mechanisms, while we foucs on quantifying the role of the local spillover in amplifying the changes in inequality over time.

Another recent related paper is Ferreira, Monge-Naranjo and Torres de Mello Pereira (2017), who use a model close to ours to think about the emergence and persistence of urban slums and calibrate it to Brazilian data. They propose a model with overlapping generation of individuals with different skills, where local spillovers take the form of human capital externalities. They embed growth in the model to think about structural transformation together with urban evolution. They use the model to ask what are the effects of slums on human capital accumulation, structural transformation, urban development and mobility.

The paper is organized as follows. In Section 2, we document the strong correlation between inequality and segregation across space and time and the correlation between intergenerational mobility and segregation. Section 3 describes the model. In Section 4 we describe our calibration strategy and we present our main quantitative results. Section 5 proposes an extended version of the model and describes its quantitative implications. Section 6 concludes.

2 Empirical Evidence

Over the last forty years US cities have experienced a profound transformation in their socio-economic structure: poor and rich families have become increasingly spatially separated over time. As noted by Massey, Rothwell and Domina (2009), this is a new phenomenon in US cities, historically predominantly segregated on the basis of race.[5] During the last third of the twentieth century, the United States moved toward a new regime of residential segregation characterized by decreasing racial-ethnic segregation and rising income segregation. Such a shift took place at the same time of a dramatic increase in income inequality. In this section we document the magnitude of the phenomenon. These measures will be used for our calibration exercise in the next section.

[5]Massey, Rothwell and Domina (2009) documents that from 1900 to 1970s what changed over time was the level at which racial segregation occurred, with the locus of racial separation shifting from the macro level (states and counties) to the micro level (municipalities and neighborhoods).

2.1 Segregation and Inequality over Time

The term segregation refers to the spatial distribution of different groups of the population of a geographic unit across geographic subunits. The groups can be defined according to different categories, such as race, education and income and segregation can be measured at different geographic levels, such as state, county or metro. We are interested in measuring the residential segregation by income within US cities. To this end, we divide the populations in two groups, rich and poor, and we use the metro area as our geographic unit and the census tract (according to the definition of the Census 2000) as our subunit. We use census tract tabulations of family income and define rich all families above the 80th percentile of the metro income distribution.[6]

In general, segregation is a multidimensional concept, capturing different aspects of the spatial distribution of the population.[7] In this paper we follow Massey, Rothwell and Domina (2009) and focus on the dimension known as evenness, that is the degree to which two or more groups are distributed evenly over a set of geographic units. Evenness is most commonly measured by the index of dissimilarity, which varies from 0 to 1, with the former value indicating perfect evenness and the latter maximum separation. A group is evenly distributed when each geographic subunit has the same percentage of group members as the population in the geographic unit. In our case, the dissimilarity index measures the percentage of rich and poor that would have to change residence for each census tract to have the same percentage of that group as the whole metro area.[8]

The dissimilarity index for metro j is then calculated as follows:

$$D(j) = \frac{1}{2}\sum_i \left| \frac{x_i(j)}{X(j)} - \frac{y_i(j)}{Y(j)} \right|,$$

where $X(j)$ and $Y(j)$ denote the total number of, respectively, poor and rich families in metro j, while $x_i(j)$ and $y_i(j)$ denote the number of, respectively, poor and rich families in census tract i in metro j.

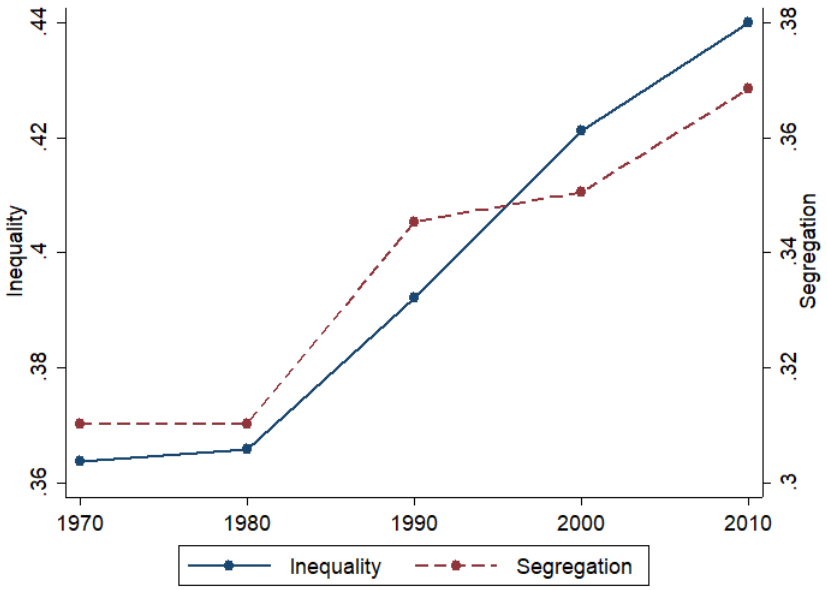
We calculate the dissimilarity index for a sample of approximately 279 metros over the period

[6] We also explore other cutoffs with similar findings.

[7] Massey and Denton (1988) grouped the measures into 5 key dimensions:evenness, exposure, concentration, centralization, and clustering.

[8] US Census Bureau, Appendix B: Measures of Residential Segregation". This is also the measure followed by Domina (2006). The two measures are equivalent when the two groups span the whole population, which is our case.

Figure 1: Inequality and Segregation over Time

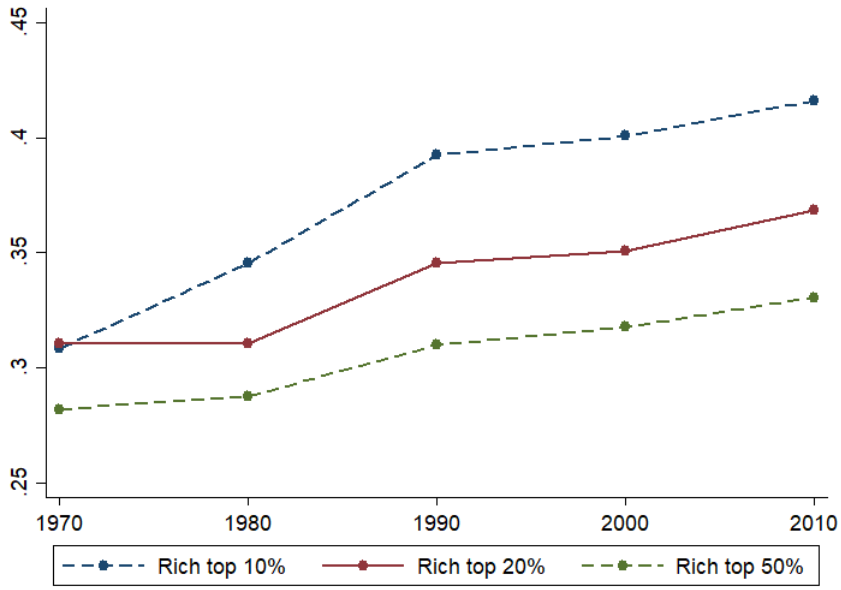


1970-2010. We then aggregate the metro level dissimilarity indexes into a national one using metro level population weights. We plot the resulting measure of segregation at the national level in Figure 1. The graph shows that the distribution of income has become progressively more uneven across census tracts over time. If in 1970, 30% of the population had to change residence to achieve an even distribution across census tracts in the average US city, in 2010 the population that needed to change residence increased to 37%. The increase was especially large between 1980 and 1990 and again between 2000 and 2010.

Using the same data on family income that we used to calculate the dissimilarity index, we also compute the gini coefficient at the metro level and similarly aggregate the metro level statistics at the national level using metro population weights. The tendency of the population to spatially separate across neighborhoods along income lines happened at the same time of a dramatic increase in income inequality.

In Figure 2 and 3 we show that the increase in residential segregation and inequality over time is robust to different measures. Figure 2 plot the dissimilarity index calculated using different

Figure 2: Different Measures Segregation

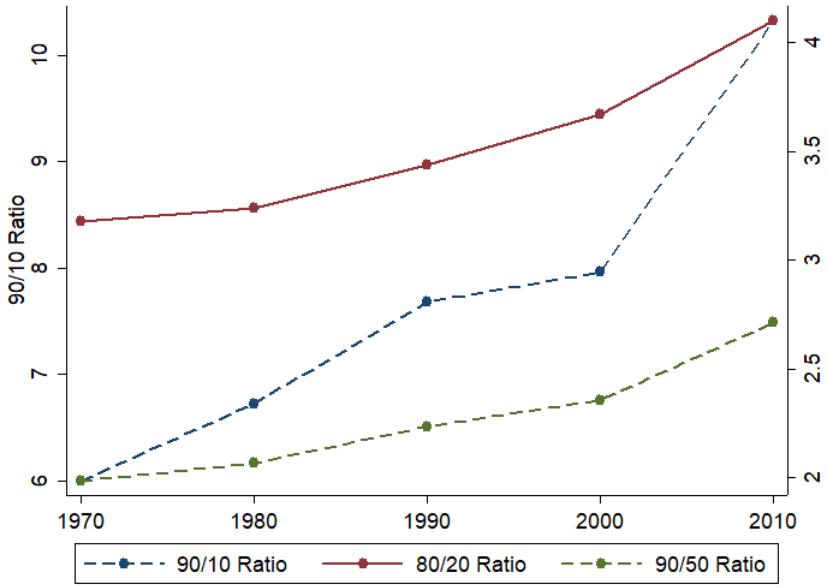


cutoffs to define the income groups. The graph shows the average across metros in each year for the dissimilarity index that used different definitions of the rich: the top 50% of the metro by family income, the top 10%, or the top 20%.[9] Figure 3 plots three measures of inequality, other than the gini coefficient, that have been widely used in the literature: the 90/10 ratio that measures the ratio of the labor income of the 90th percentile of the population relative to the income of the 10th percentile, and, similarly, the 80/20 ratio, and the 90/50 ratio. All these measures show that inequality has increased steadily at least since 1980.[10]

[9]The increase in residential income segregation over time is a robust finding. Several sociologists have documented this fact using different measures of segregation. In particular, Jargowsky (1996) documents an increase in economic segregation for US metros between 1970 and 1990 using the Neighborhood Sorting Index, Watson (2009) finds an increase in residential segregation by income between 1970 and 2000 using the Centile Gap Index and, most recently, Reardon and Bischoff (2011) and Reardon, Bischoff, Owens and Townsend (2018) document this fact using the information theory index. Similar conclusions have also been reached by Owens (2018) who analyses segregation within US cities using school districts instead of census tracts as subunits of analysis.

[10]See also Autor, Katz and Kearney (2008).

Figure 3: Different Measures Inequality



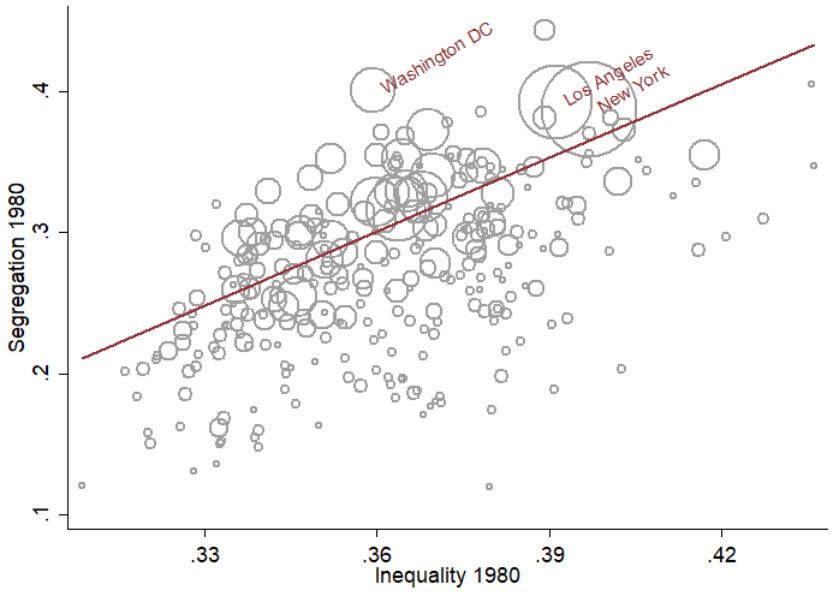
2.2 Segregation and Inequality Across US Metros

We now show that residential segregation and inequality are also correlated across space. In particular, Figure 4 shows the relationship between the gini coefficient and the dissimilarity index across metro areas in 1980, again defining the rich as the population in the 80th percentile of the income distribution. The graph shows population-weighted data-points (with bubbles proportional to population weights) using 1980's metro-level population weights (based on population counts within each metro in our sample from the U.S. census for that decade). The correlation between segregation (as captured by the dissimilarity index) and inequality (as captured by the gini coefficient) is large and statistically significant.[11]

Next, we show that a significant positive association between segregation and inequality also holds for changes over time. Figure 5 documents the correlation between the change at the metro level in the gini coefficient between 1980 and 2000 and the change at the metro level in the

[11]The results of a regression of segregation on inequality across US metros in 1980 are reported in Table 8, Appendix B.

Figure 4: Inequality and Segregation across US Metros



dissimilarity index over the same time period. Interestingly, the metro areas that experienced a larger increase in inequality between 1980 and 2000 are also those that experienced a larger increase in residential segregation over the same time period.[12]

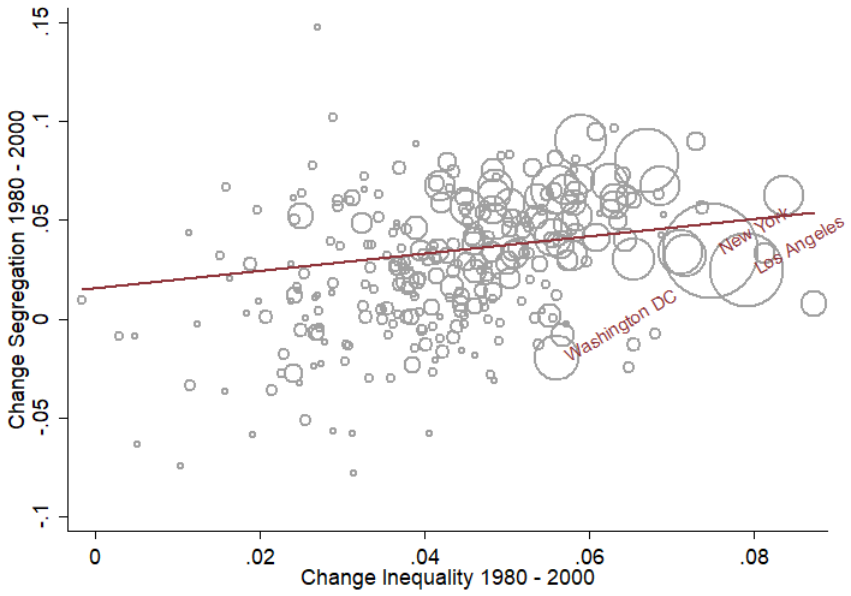
2.3 Intergenerational Mobility and Segregation Across US Metros

Finally, we show that residential segregation across metros is also correlated with intergenerational mobility.[13] To this end, we use a restricted-access geocoded version of the National Longitudinal Survey of Youth (NLSY79). The NlSY is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are currently interviewed on a biennial basis. We use this survey to construct intergenerational transition matrices for family income,

[12]The results of a regression of change in segregation on change in inequality over the period 1980-2000 across US metros are reported in Table 8, Appendix B.

[13]This is consistent with the findings in Chetty, Hendren, Kline and Saez (2014).

Figure 5: Change in Inequality and Segregation 1980-2000



calculated separately for observations in high-segregation locations and low-segregation areas.[14] Using the geocoded version of the NLSY we are bale to associate individual-level observations with their geographical location.[15]

Combining the cross-sectional and supplemental samples, we create two variables: initial income and final income. Initial income is the average of the family income observed in the first 3 survey years. Final income is the average in the last 5 survey years. Each observation is assigned to a quartile in the initial income distribution and in the final income distribution separately.

Using the restricted-access geocoded NLSY data, we associate each observation of the NLSY79 subsample we constructed with a metro area where each individual grew up when young (1979-1981). Next we rank the metros from the main dataset by level of segregation in 1980, using the dissimilarity index with rich being the families in the 80th percentile, and we create two groups: high-segregation metros are the one above the 50th percentile and low-segregation metros are the

[14] In constructing the matrices we follow closely Mazumder (2005) that shows significant differences in the mobility matrices for white and black individuals.

[15] Summary statistics of the final dataset used to produce the transition matrices are included in Table 9, AppendixB

others. We can then construct two transitional matrices, as described above, one for each group.

Figure 6: Mobility Matrix in Low Segregation Metros

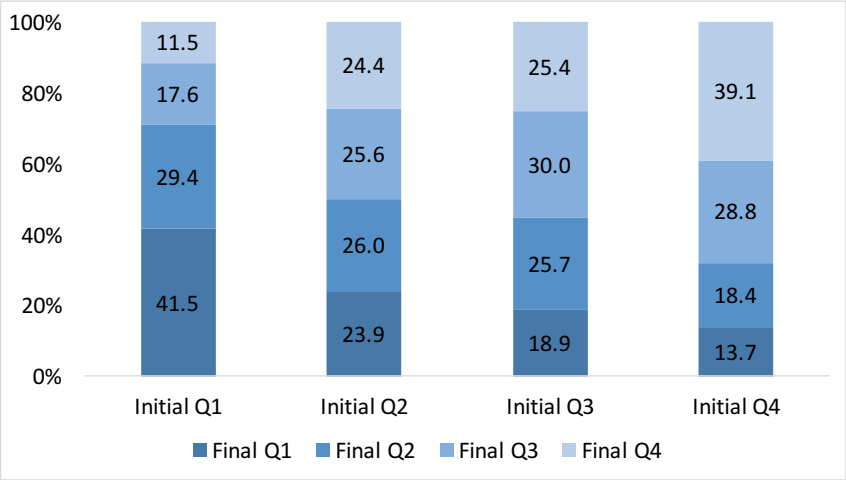
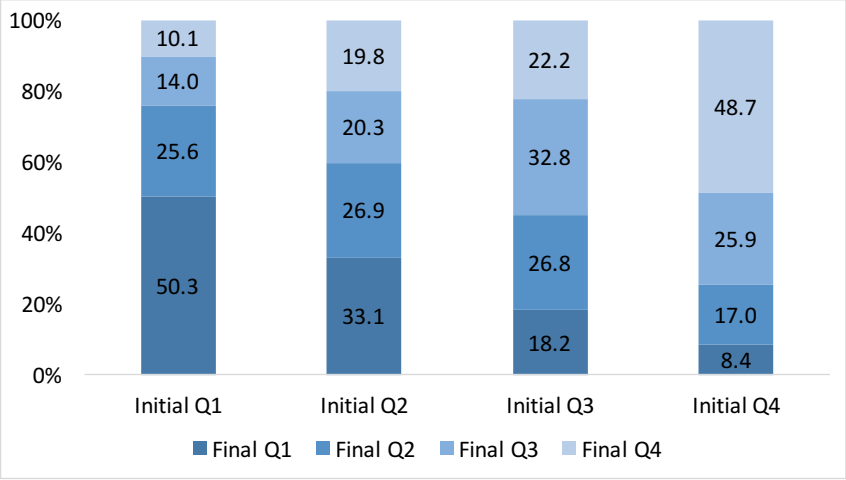


Figure 7: Mobility Matrix in High Segregation Metros



Figures 6 and 7 show the transitional matrices constructed for the low-segregation metros and for the high-segregation metros, respectively. The figures show that intergenerational mobility is in general stronger in areas that experience lower levels of residential segregation. In particular, we can focus on the two quadrants on the bottom left and top right, which tell us something about

upward and downward mobility, respectively. The bottom left quadrant of the matrix captures the persistence of poverty: the probability of ending up in the lowest quartile when one's parents were in the lowest quartile. This probability is roughly 42% in the low-segregation metros while it is roughly 50% in the high-segregation metros.[16] Similar differences characterize the persistence of wealth: the top right quadrant of the matrix represents the probability of ending up in the top quartile of the income distribution when one's parents were in the same quartile. This probability is roughly 39% in the low-segregation areas, while it is roughly 49% in the high-segregation areas.

3 Model

We now propose a model of a metro area where families choose the neighborhood where to reside taking into consideration that there are local spillover affecting their children's future income. The model will generate a feedback effect between inequality and residential segregation.

3.1 Set up

The economy is populated by overlapping generations of agents who live for two periods: young and old, or children and parents. An old agent at time t earns a wage $w_t \in [\underline{w}, \overline{w}]$ and has one child with ability $a_t \in [\underline{a}, \overline{a}]$. The ability of the child is correlated with the ability of the parent according to an AR1 process

$$a_t = \rho a_{t-1} + \nu,$$

where ν is normally distributed with mean zero and variance σ_ν, and $\rho \in [0,1]$ is the correlation coefficient. The parents' wages and the children's abilities evolve over time accordingly to an endogenous joint distribution, denoted by $F_t(w_t, a_t)$, with $F_0(w_0, a_0)$ taken as given.

There are two neighborhoods, denoted by $n \in \{A, B\}$. Houses have all the same dimension and quality and the rent in neighborhood n at time t is denoted by R_t^n. For simplicity we make the extreme assumption that the housing supply is fixed and equal to H in neighborhood A and fully

[16] This difference is statistically significant at the 1% level. We present results of our hypothesis testing in Table10, AppendixB. These results are robust to different combinations of groupings and different cutoffs for the dissimilarity index.

elastic in neighborhood B.[17] In particular, we assume that the marginal cost of construction in neighborhood B is equal to 0 so that, by assumption, $R_t^B = 0$ for all t. The rental price in neighborhood A, R_t^A, is going to be an endogenous equilibrium object.

In the baseline model we assume that there are two educational levels, that is, $e \in \{e^L, e^H\}$, where e^H stands for college education and e^L for less than college education.[18] Also, let τ be the cost of investing in college education.

We assume that parents care both about their own consumption and about their children's future wage.[19] In particular, their preferences are given by $u(c_t) + g(w_{t+1})$, where u is a concave and continuously differentiable utility function, and g is increasing and continuously differentiable. An old agent with wage w_t and with a child of ability a_t is going to choose 1) how much to consume, $c_t(w_t, a_t) \in R_+$; 2) where to live, $n_t(w_t, a_t) \in \{A, B\}$; and 3) how much to invest in his child's education, $e_t(w_t, a_t) \in \{e^L, e^H\}$. These choices are going to impact his child's future wage, as explained below.

A key ingredient of the model is the presence of a local spillover that affects the children's returns to education, and hence future income. Children's wages are affected by their ability shock, their education, and the neighborhood where they grow up because of the local spillover effect. This means that they are also indirectly affected by their parents' wages through the educational and neighborhood choices. Formally, the child of an agent (w_t, a_t) who chooses to live in neighborhood n and education level e is going to earn a wage

$$w_{t+1} = \Omega(a_t, e, S_t^n, \varepsilon_t), \tag{1}$$

where ε_t is an iid normally distributed noise with cdf $H(\varepsilon)$, and S_t^n is the local spillover effect in neighborhood n at time t. Children with higher ability, higher education, and who live in neighborhoods with higher spillover will earn higher wages. We will show that in equilibrium parents with higher wage, for given ability, will choose higher education and the neighborhood with higher spillover. This implies that wages will end up being increasing in parents' wages.

[17] We make this assumption for simplicity, but we could relax it and introduce an elastic housing supply in both neighborhoods.

[18] In Section 5 we explore a version of the model with a continuous choice of education.

[19] This assumption is common in this class of models. The assumption that agents cannot save (if not by investing in housing or kids'education) is for simplicity. The assumption that agents cannot borrow is for realism, given that typically people cannot borrow against children's future income.

We assume that the spillover in neighborhood n at time t is equal to the average expected wage of children growing up in that neighborhood, that is,

$$S_t^n = \frac{\int\int\int_{n_t(w_t,a_t)=n} w_{t+1}(w_t,a_t,\varepsilon_t)F_t(w_t,a_t)H_t(\varepsilon_t)dw_t da_t d\varepsilon_t}{\int\int_{n_t(w_t,a_t)=n} F_t(w_t,a_t)dw_t da_t}. \tag{2}$$

Given that wages are increasing in ability and, as we will show, in parents' wage, neighborhoods with higher expected income tend to be neighborhoods with higher ability children and richer parents. The idea is that children growing up in these neighborhoods will earn higher wages, for the same level of education and ability, because of pecuniary and social local externalities.[20] This formalization of the spillover can capture different sources of local externalities: neighborhoods with richer families have better public schools that are locally financed, children who grow up there have better peers, parents who live there may invest more in education because they learn more successful stories, social norms are more conducive to educational investment, and so forth. In this paper we model this spillover effect in reduced form, but in future work it would be interesting to try to disentangle different mechanisms behind it. The presence of the spillover effect implies that rents in neighborhood A, R_t^A, will also depend on the strength of the externality S_t^A, which is going to be endogenous.

To sum up, an old agent with wage w_t and a kid with ability a_t at time t solves the following problem

$$\begin{aligned} U(w_t,a_t) = \max_{c_t,e_t,n_t} & \; u(c_t) + E[g(w_{t+1})] \\ s.t. \;\; & c_t + R_t^n + \tau e_t \leq w_t \\ & w_{t+1} = \Omega(a_t,e_t,S_t^n,\varepsilon_t) \end{aligned} \tag{P1}$$

taking as given spillover effects and rental rates in the two neighborhoods, S_t^n and R_t^n for $n = A,B$.

3.2 Equilibrium

We are now ready to define an equilibrium.

[20] A alternative specifications would have the spillover equal to the average wage of the parents or to the average level of education of the children in the neighborhood. However, the first would miss the role of the innate ability and the second the role of parents' income. Also, in the baseline model, the second specification would not be particularly appealing because of the binary nature of the education level. We will explore this alternative in the continuous education version of the model.

Definition 1 *For a given initial wage distribution $F_0(w_0,a_0)$, an equilibrium is characterized by a sequence of educational and residential choices, $\{e_t(w_t,a_t)\}_t$ and $\{n_t(w_t,a_t)\}_t$, a sequence of rents in neighborhood A, $\{R_t^A\}_t$, a sequence of spillover effects in neighborhoods A and B, $\{S_t^A\}_t$ and $\{S_t^B\}_t$, and a sequence of distributions $\{F_t(w_t,a_t)\}_t$ subject to*

1. *agents optimization: for each t, the policy e_t and n_t solve problem (P1), for given R_t^n and S_t^n for $n=A,B$;*
2. *consistency of the spillover effect: for each t, equation (2) is satisfied for both $n=A,B$;*
3. *market clearing: for each t, $R_t^B=0$ and R_t^A satisfies the market clearing condition:*
$$H=\int\int_{n_t(w_t,a_t)=A} F_t(w_t,a_t)dw_t da_t; \tag{3}$$
4. *wage dynamics: for each t condition (1) is satisfied.*

From now on, we focus on equilibria where the housing market in neighborhood A clears with positive rents, that is, $R_t^A>0$ for all t, which requires also $S_t^A>S_t^B$ for all t.[21]

We now impose two assumptions to simplify the characterization of the equilibrium. First, in the baseline model we assume that the spillover effect is relevant only if one invests in college education. This simplifies the analysis because implies that all parents living in the rich neighborhood also pay for their children's college, given that there would be no other reason to pay a higher rent in the first place.

Assumption 1 *The function $\Omega(a,e,S,\varepsilon)$ is constant in S and a if $e=e^L$, and is increasing in S and a if $e=e^H$.*

Second, we assume that there are complementarities between the spillover and the children's innate ability. In particular, we will make the following assumption.

Assumption 2 *The composite function $g(\Omega(a,e,S,\varepsilon))$ has increasing differences in a and S, that is, for $a'>a$ and $S'>S$,*

$$g(\Omega(a',e,S',\varepsilon))-g(\Omega(a',e,S,\varepsilon))\geq g(\Omega(a,e,S',\varepsilon))-g(\Omega(a,e,S,\varepsilon)) \text{ for any } e.$$

These assumptions allow us to characterize the equilibrium in a fairly simple way, as shown in the following proposition.

[21] If $S_t^A\leq S_t^B$, nobody would like to live in A and the rental rate in A would be zero.

Proposition 1 *Under assumptions 1 and 2, for each time t there are two non-increasing cut-off functions* $\hat{w}_t(a_t)$ *and* $\hat{\hat{w}}_t(a_t)$*, with* $\hat{w}_t(a_t) \leq \hat{\hat{w}}_t(a_t)$ *such that*

$$e_t(w_t, a_t) = \begin{cases} 0 \text{ if } w_t < \hat{w}_t(a_t) \\ 1 \text{ if } w_t \geq \hat{w}_t(a_t) \end{cases}, \tag{4}$$

and

$$n_t(w_t, a_t) = \begin{cases} B \text{ if } w_t < \hat{\hat{w}}_t(a_t) \\ A \text{ if } w_t \geq \hat{\hat{w}}_t(a_t) \end{cases}. \tag{5}$$

This proposition shows that in equilibrium the residential and the educational choices can be simply characterized by two monotonic cut-off functions.[22]

Figure 8: Equilibrium Characterization

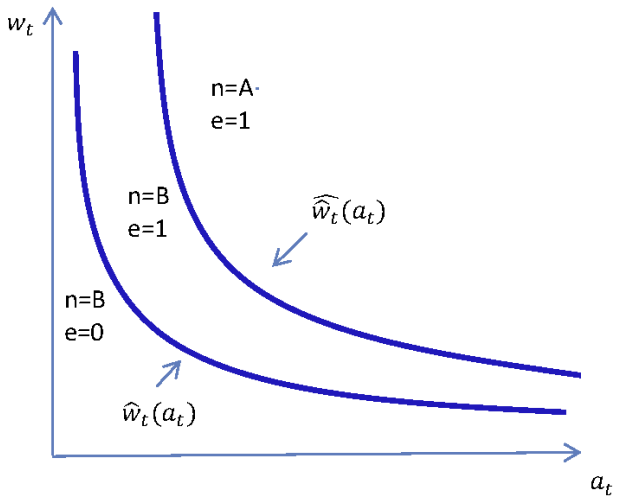


Figure 8 shows a graphical characterization of the equilibrium, for given spillover and rental rates, with $R_t^A > 0$. On the x-axis there is the children's ability level a_t and on the y-axis there is the parents' wage w_t. For any given level of children's ability a_t, there are two thresholds for the parents' wage $\hat{w}_t(a_t)$ and $\hat{\hat{w}}_t(a_t)$, with $\hat{w}_t(a_t) \leq \hat{\hat{w}}_t(a_t)$, such that parents with wage $w_t < \hat{w}_t(a_t)$ choose to live in B and not to educate their children, parents with wage $\hat{w}_t(a_t) \leq w_t < \hat{\hat{w}}_t(a_t)$ choose to live in B and educate their children, and parents with wage $w_t \geq \hat{\hat{w}}_t(a_t)$ choose to live in A and educate their children. The figure shows that children with richer parents and higher

[22] Assumptions 1 and 2 are needed to obtain the monotonicity result.

ability will tend to be more educated and to live in neighborhood A. On the one hand, for given children's ability, richer parents will be more willing to pay the cost of higher education (college tuition) and the cost of higher local externalities (higher rental rate). On the other hand, for given wage, the higher the ability of a child, the more willing the parent is to pay for college education and for higher local externality because of the complementarities between ability and education and between ability and local spillover, respectively. For a given ability, a child will have much lower probability of going to college if he/she grows up in B rather than A, both because parents living in B are poorer on average and because the local spillover is weaker, hence making the incentive to pay for college education even smaller.

The classic papers in this literature, building on Benabou (1996b) and Durlauf (1996b), typically focus on two extreme cases of segregation by income: either the two neighborhoods are equal to each other and have a representative distribution of income, or they are perfectly segregated, with all the richest agents residing in one and all the poorest in the other. Our model is richer in this dimension, as it allows us to obtain an intensive measure of segregation which we can match to the data. This is due to the presence of heterogeneity in ability: if all agents had the same ability level, the cut-off function $\hat{\hat{w}}_t(a_t)$ in figure 8 would be horizontal and the two neighborhoods would feature full segregation by income. However, thanks to the heterogeneity in ability, the two cut-off functions are monotonically non-increasing and some poorer parents with high ability children choose to live in A to exploit the complementarity with the higher spillover.

Our model also allows us to think about segregation by education. In our baseline model, given the binary choice of education, neighborhood A will always be fully segregated, in the sense that all children will have college education. However, neighborhood B will generically feature a mix of college and non-college educated children. In particular, the degree of segregation by education is driven by the cut-off functions $\hat{w}_t(a_t)$. If this function coincides with $\hat{\hat{w}}_t(a_t)$, then there would be perfect segregation by education, as all children living in A will go to college and all children in B will not. However, as long as the two functions do not coincide, there will be some children in B with college education.

3.3 Special Case

To make the analysis more tractable, we now make some functional form assumptions. In particular, assume that $e^L = 0$, $e^H = 1$, $u(c) = g(c) = log(c)$, and that the law of motion for the wages takes the form

$$\Omega(a_t, e_t, S_t^n, \varepsilon_t) = (b + a_t e_t(\beta_0 + \beta_1 S_t^n))\varepsilon_t. \tag{6}$$

On the one hand, this expression shows that the wage of children with no college education ($e_t = 0$) is simply equal to $b\varepsilon_t$, and does not depend on either the children's ability or the neighborhood spillover. The assumption that the wage of no-college graduates does not depend on their ability stands for the fact that abilities that are relvant in high-skill jobs may be different and more heterogenous than abilities that are relevant for low-skill jobs. The assumption that the spillover does not affect the wage of no-college graduates is extreme, but can be interpreted with the idea that the quality of schooling k-12th turns out to be important in determining future wages of college graduate more than no-college graduates.

On the other hand, the wage of children who go to college ($e_t = 1$) is a function of their ability as well as of the spillover. In particular, β_1 is the key parameter that determines the strength of the spillover. We assume that ability and spillover are complementary, so that higher ability children will take more advantage of the local externality.[23]

With these functional forms, the household's problem reduces to

$$U(w_t, a_t) = \max_{e,n} log(w_t - R_t^n - \tau e) + log(b + a_t e(\beta_0 + \beta_1 S_t^n))\varepsilon_t, \tag{P2}$$

where $R_t^B = 0$, R_t^A is determined implicitly by $H = \int [1 - F_t(\hat{\hat{w}}_t)] dG(a)$, and the spillover effects are given by

$$S_t^A = \frac{\int_{\underline{\varepsilon}}^{\overline{\varepsilon}} \int_{\underline{a}}^{\overline{a}} \int_{\hat{\hat{w}}_t(a)}^{\overline{w}} w_{t+1} dF(w_t) dG(a_t) dH(\varepsilon_t)}{\int_{\underline{a}}^{\overline{a}} \int_{\hat{\hat{w}}_t(a)}^{\overline{w}} dF(w_t) dG(a_t)}, \text{ and } S_t^B = \frac{\int_{\underline{\varepsilon}}^{\overline{\varepsilon}} \int_{\underline{a}}^{\overline{a}} \int_{\underline{w}}^{\hat{\hat{w}}_t(a)} w_{t+1} dF(w_t) dG(a_t) dH(\varepsilon_t)}{\int_{\underline{a}}^{\overline{a}} \int_{\underline{w}}^{\hat{\hat{w}}_t(a)} dF(w_t) dG(a_t)}. \tag{7}$$

With the simple functional forms assumed, the cut-off functions that characterize the optimal education and residential choices can be characterized in closed form as I describe below.

[23] This is probably the more tricky assumption that would require some further investigation.

For every ability level a, two cases are possible. In the first case, there is a positive measure of children who get high education in neighborhood B, and the two cut-offs are:

$$\hat{w}_t(a_t) = \tau \left[1 + \frac{b}{a_t(\beta_0 + \beta_1 S_t^B)} \right], \tag{8}$$

and

$$\hat{\hat{w}}_t(a_t) = \tau + R_t^A \left[1 - \frac{b + a_t(\beta_0 + \beta_1 S_t^B)}{b + a_t(\beta_0 + \beta_1 S_t^A)} \right]^{-1}. \tag{9}$$

This case arises when the RHS of equation (8) is smaller than the RHS of equation (9). Equation (8) shows that the education cut-off $\hat{w}_t$ is decreasing in the spillover in neighborhood B, that is, the higher is the spillover in B, the higher is the return to go to college, the higher is the willingness of parents living in B to pay for their children' college. Moreover, it shows that, for a given ability, the willingness of parents leaving in B to pay for college is higher when the parameters affecting the strength of the return to education (β_0) and to spillover (β_1) are higher, and when the cost of college τ and/or the average wage of non-educated workers b are lower. Equation (9) shows that the location decision depends on the trade-off between the spillover advantage relative to the cost of leaving in neighborhood A.

In the second case, there is perfect segregation by education, that is, all children in B get the low education level. In this case, the cutoff functions coincide and are equal to

$$\hat{w}_t(a_t) = \hat{\hat{w}}_t(a_t) = (\tau + R_t^A) \left[1 + \frac{b}{a_t(\beta_0 + \beta_1 S_t^A)} \right].$$

The higher is the cost of education τ or the lower is the return from education, which, for a given ability, depends on parameters β_0 and β_1, and on the local spillover in A, the higher is the cutoff and the more the parents who decide to live in B. Moreover, more parents decide to live in B, the higher is the rental rate to live in A, R_t^A, and the higher is the wage for non-educated workers.

4 Numerical Analysis

In this section we perform the main exercise of the paper. First, we calibrate the steady state of the model to the US economy in 1980. Then, we look at the effects of an unexpected, one-time, permanent shock to the skill premium on inequality, segregation, and intergenerational mobility over time and we quantify the contribution of the local spillover effect to these dynamics.

4.1 Calibration

We now discuss how we choose the parameters so that the steady state equilibrium of the model matches important features of the US economy in 1980. We choose 1980 as the starting point of our exercise, because after that date inequality starts to increase more sharply. For the calibration we use the specific functional forms for the utility and the wage dynamics function that we have described in subsection 3.3, that is, $e^L = 0$, $e^H = 1$, $u(c) = g(c) = log(c)$, and Ω satisfying equation (6). Table 1 shows the targets of our baseline calibration, which we are now going to discuss.

Table 1: *Calibration Targets*

Description	Value	Source
Return to spillover	0.10	Chetty and Hendren (2017b)
Return to college	0.39	Goldin and Katz (2009), Census 1980
Gini coefficient	0.37	Census 1980, family income
Dissimilarity index	0.31	Census 1980, family income
Labor income volatility	0.77	Census 1980, family income
Rank-rank correlation	0.34	Chetty, Hendren, Kline and Saez (2014)
Share of college grads	0.24	IPUMS 1980, head of household
Poor/rich college share	0.19	IPUMS 1980, head of household

A crucial target for our calibration is what we call the "return to the spillover", that is, the effect of the local spillover on future wages. This is a difficult effect to measure in the data. Fortunately, there has been a wave of recent research that uses micro data to estimate it. In particular, we use the results of Chetty and Hendren (2017b). Using tax returns data for all children born between 1980 and 1986, they estimate the causal effect of local spillovers on children's future income, by looking at movers across US counties. Their baseline estimation implies that growing up in a 1 standard deviation better county from birth would increase a child's household income in adulthood by approximately 10%. This is the number that we target in our calibration. Let us explain how we do that. Given that nobody literally moves in our model, we map the "movers" in Chetty and Hendren (2017b) to the parents who decide to live in a neighborhood different from the one where they grew up, that is, the one chosen by their own parents. Then, we calculate the difference between the expected future income of the children of "movers" if they grew up in the rich neighborhood (A) and the expected future income of the same children if they grew up in the poor neighborhood (B). Finally, we divide this by the standard deviation of the spillover S^n

across the two neighborhoods.[24]

Another important target is the US skill premium in 1980s that is calculated using Census data, following Goldin and Katz (2009). In the model, we map the skill premium to the difference between the average log wage of educated agents and the average log wage of non educated agents in steady state.

We then target the average gini coefficient and average dissimilarity index for all metro area in 1980. As described in Section 2, we use Census data to calculate both the gini coefficient and the dissimilarity index at the metro level and then we aggregate them, weighting by population. For the baseline calibration we target the dissimilarity index constructed defining the rich as the households in the top 20th percentile, and the poor as the others.[25] We also target the labor income volatility from 1980, calculated again using Census data.

Another important feature of the US data we want to target is the level of intergenerational mobility. To this end, we target the rank-rank correlation between log wages of parents and children estimated using administrative records by Chetty, Hendren, Kline and Saez (2014).[26] We chose this statistic instead than the log-log correlation because Chetty, Hendren, Kline and Saez (2014) argue that it provides a more robust summary of intergenerational mobility.[27]

Finally, we target the share of college graduates in 1980 and the ratio of the share of college graduates in the poor relative to the rich neighborhoods that we obtain using IPUMS data. In particular, to match these data to the model, we need to divide the census tracts in each metro area in two groups that correspond to neighborhood A and B. We do so, by ranking the cencus tracts by average income and defining neighorhood A as the ones that are above the 10th percentile (given that the calibrated value for H is 0.08).

Table 2 shows the results of our calibration, in terms of how we match our targets for the steady state equilibrium of the model. The table shows that we are able to match well the return to

[24] This is simply equal to $\sqrt{H(1-H)}(S^A - S^B)$, where H is the housing supply in the rich neighborhood and S^A and S^B the spillover effects in steady state.

[25] We also do some robustness using different cut-off for rich and poor.

[26] The rank-rank correlation is the relationship between the rank based on income of children relative to others in their birth cohort and the rank of parents based on income relative to others in the same birth cohort.

[27] In alterative calibrations, we have also looked at the probability that a child ends up in the lowest quartile of the distribution when his parents are in the lowest quartile of the distribution and at the probability that a child ends up in the highest quartile of the distribution when his parents are in the same quartile. However, these statistics rely more heavily on the shape of the wage distribution which we do not target, given the stylized nature of the model.

Table 2: *Calibration Results*

Target	Data	Model
Return to spillover	0.10	0.10
Return to college	0.39	0.39
Gini coefficient	0.37	0.37
Dissimilarity index	0.31	0.31
Labor income volatility	0.77	0.66
Rank-rank correlation	0.34	0.12
Share of college grads	0.24	0.25
Poor/rich college share	0.19	0.19

spillover, the return to college, the Gini coefficient, the dissimilarity index, the share of college graduates, and the relative share of college graduates in the two neighborhoods. We do less well on matching labor income volatility and the rank-rank correlation. Clearly the fact that we cannot match well all the moments comes from the stylized nature of our model. In particular, we overestimate intergenerational mobility (underestimate the rank-rank correlation). We believe that the more problematic assumption in this regard is the binary choice of education. The model imposes that the rich parents can at best pay for their children's college, but they cannot invest more than that in education. This means that in order to match better intergenerational wage persistence, the model would require the poor to underinvest in college education, explaining that it is hard for our baseline model to match both these moments. In Section 5 we are going to explore an extended version of the model where we allow for a continuous educational choice. We will show that this will help us matching better the level of intergenerational mobility, as the rich parents will be able to invest disproportionally more in their children's education, increasing the persistence in their income. An additional extension that could help us in obtaining an even lower degree of intergenerational mobility would be to assume that parents' wage can directly affect their children's wage on top that through the residential and educational choice, for example because of social networks. This is often assumed in theoretical models in the related literature and would create an additional motive for low mobility.

Table 3 shows the parameters that we are using to calibrate the model, their calibrated value, and their description.

Table 3: *Parameters*

Parameter	Value	Description
H	0.09	Size of neighborhood A
β_0	1.21	Wage function parameter
β_1	0.18	Wage function parameter
τ	0.27	Cost of education
b	1.35	Wage fixed component for no-college
ρ	0.90	Correlation of log innate ability
σ	0.62	Standard dev. of log innate ability
μ_a	-2.2	Average of log innate ability
μ_ε	0.42	Average of log wage noise shock
σ_ε	0.61	Standard dev. of log wage noise shock

4.2 Skill Premium Shock

The data show a sharp increase in labor income inequality starting in 1980. While, there are different driving forces behind this increase, here we focus on skill-biased technical change, which is widely recognized to be a crucial part of the story (see, for example, Katz and Murphy, 1992; Autor, Katz and Krueger, 1998; Goldin and Katz, 2001; Card and Lemieux, 2001; Acemoglu, 2002; Autor, Katz and Kearney, 2008).

In this spirit, our main exercise it to explore the response of the economy to an unexpected, one-time, permanent shock to the skill premium. In particular, we change β_0 and β_1 proportionally so as to match the increase in the skill premium in the data. According to Census data, the skill premium in the US increased from .39 in 1980 to .54 in 1990 and up to .57 in 2000. In the model, individuals live for two periods: in the first period, they are young and go to school, and in the second period, they are old and work. As noted by Fernandez and Rogerson (1998), in this class of models, individuals spend the same time in period 1 and 2, so we could target the length of a period to the working period or of the schooling period. Given our focus on educational spillover, we choose to interpret one period as 10 years.[28] We interpret period $t = 0$ as 1980, when the economy is in steady state. Then, we assume that at that time an unexpected, permanent shock hits proportionally β_0 and β_1 so that the skill premium goes from 0.39 in 1980 ($t = 0$) to 0.54 in 1990 ($t = 1$).

[28]The schooling age could be interpreted as 10 or 15 years depending on which level of education one targets. We ended up choosing 10 years also considering that Census data are available every 10 years.

Table 4: *Response to a Skill Premium Shock*

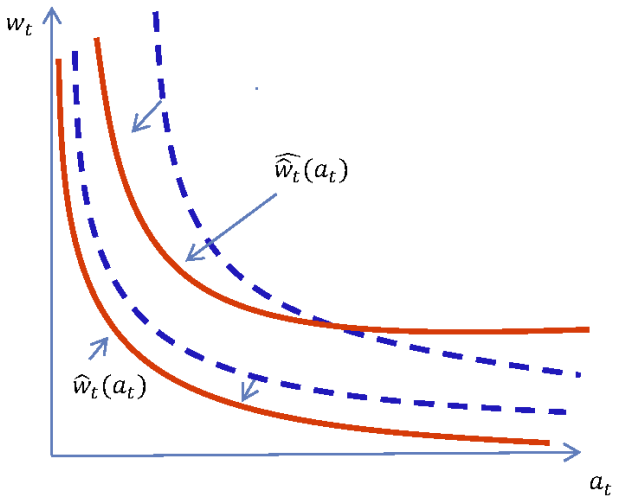
	t = 1980	t = 1990	t= 2000
Return to college	0.3939	0.5357	0.5266
Gini coefficient	0.3652	0.4252	0.4292
Dissimilarity index	0.3070	0.3430	0.3734
Rank-rank correlation	0.1147	0.1702	0.2252
Rent in neighborhood A	0.2397	0.7583	1.1871
Counterfactual with no spillover feedback			
Return to college	0.3939	0.4944	0.4824
Gini coefficient	0.3652	0.4047	0.4048
Dissimilarity index	0.3070	0.3311	0.3635
Rank-rank correlation	0.1147	0.1557	0.2003
Rent in neighborhood A	0.2397	0.3564	0.4823

The first part of table 4 shows the response of the economy to such a shock, one and two periods ahead. In particular, we focus on the return to college, the gini coefficient, the dissimilarity index, the rank-to-rank correlation, and the rent in the rich neighborhood. In response to our shock, both inequality and segregation increase and intergenerational mobility reduces. Although the model is stylized in many dimensions, these responses are not too far from what happened in reality. In particular, the gini coefficient increased from roughly 0.37 in 1980 to roughly 0.43 in one period, while in the data it rose to roughly 0.39 in 1990 and to .42 in 2000. The dissimilarity index increased from roughly 0.31 to roughly .0.34 in one period and rank-to-rank correlation increased from roughly 0.12 to roughly 0.17. In the data the dissimilarity indexed achieved .345 in 1990, which is roughly what happened in our simulation. Unfortunately, given the limited availability of data, it is hard to calculate a reliable time-series for the rank-to-rank correlation. However, Aaronson and Mazumder (2008) show some indirect evidence of a positive relationship between the skill premium and the IGE (intergenerational elasticity) that is consistent with our findings.

It is interesting to notice that in response to the skill premium shock, the rental rate in the rich neighborhood increases substantially. We next explain the mechanism behind these responses.

The skill premium shock has a standard direct effect of increasing inequality, for given distribution of college and no-college graduates. We now want to explain the additional effect coming from the mechanism in our model. Figure 9 shows qualitatively the response of the educational

Figure 9: Cut-off Response to Skill Premium Shock



and residential cut-off functions, respectively $\hat{w}_t(a)$ and $\hat{\hat{w}}_t(a)$, to the skill premium shock. First, the figure shows that the educational cut-off function shifts to the left, so that more children of any ability will go to college. This is quite intuitive: the higher the skill premium, the higher the demand for skill, conditional on any level of innate ability. This effect actually dampens the increase in inequality because more children will go to college. Second, the figure shows that the residential cut-off function gets tilted so that richer children will end up living in neighborhood A, even if their innate ability is lower, at the expense of more able children with poorer parents. Let us first explain the partial equilibrium effect. Taking as given the rental rate and the spillover effects, the demand to live in neighborhood A will increase because of the differential spillover and the complementarity between spillover and education, shifting also the residential cut-off to the left. Given that the housing supply is fixed, this will push up rental rates in neighborhood A, shifting the housing demand back to the right. However, the shift will be more pronounced for the poor people who won't be able to afford higher rental rates.[29] On net, this will generate the tilting that we see in figure 9, which will generate more segregation: neighborhood A will become richer disproportionally more than neighborhood B. This will feedback in even more

[29]Given the complementarity of education and ability, the partial equilibrium shift to the left would be more pronounced for the more able children. However, the other effect dominates.

inequality.

From the description of the mechanism, it emerges that the general equilibrium effect through rental rates is key to generate the amplification of inequality through the increase in segregation we want to focus on. To highlight the strength of the mechanism, the second part in table 4 also shows the results of a counterfactual exercise where we keep the spillover effects at the initial steady state levels. We interpret the differential response to the skill premium shock when we keep the spillover fixed, as the amplification effect due to the local externality. In particular, the table shows that the gini coefficient increased by 0.06 in period 1, while it would have increased only by 0.04 if the spillover was held constant. This gives us our first main result that in our baseline model the local externality accounts for roughly 34% of the increase in inequality in the first period. If we look at the second period, inequality increased by 0.064 and only by 0.0396 if the spillover was constant, implying a contribution of roughly 38% in the longer run. The table also shows that in the first period the dissimilarity index increased by 0.036 and only by 0.0241 without taking into consideration the response of the spillover effect. This implies that the local externality also contributed to roughly 33% of the increase in segregation in the first period. In the same period, the rank-rank correlation between parents and kids increased by 0.0555 and only by 0.041 if we kept the spillover constant, so that the local externality contributed to roughly 26% of the decrease in intergenerational mobility in the first period. In the second period, the contribution of the local externality to the increase in segregation and the decrease in intergenerational mobility in the longer run, that is, over two periods, is instead reduced to roughly 15% and 23% respectively.

5 Extended Model

In this section, we extend the model in two main dimensions: first, we introduce a residential preference shock and, second, we make the educational choice continuous. The introduction of the preference shock is important to obtain a more realistic setting where not all parents who live in the more expensive neighborhood choose high levels of education for their children. In our baseline model, the only reason to pay a higher rent to live in neighborhood A is to exploit the higher externality that affects the returns to education. In reality, residential choices are not purely driven by educational considerations. Families may prefer more expensive neighborhoods

for a number of different reasons, such as better amenities, or higher status. By missing this feature of reality, the baseline model might generate a distribution of children growing up in neighborhood A biased towards too high innate ability. We then introduce a preference shock $\theta \in \{0, \bar{\theta}\}$ where $\bar{\theta} \geq 0$ and $\pi = Prob(\theta = \bar{\theta})$, so that families with $\theta = \bar{\theta}$ will enjoy their consumption more if they live in neighborhood A, that is, utility from current consumption becomes $log((1 + \theta I_{n=A})c)$.

The introduction of a continuous educational choice is particularly important for our quantitative exercise. The binary educational choice is enough to qualitatively obtain the feedback mechanism between inequality and segregation we want to focus on. However, it has the disadvantage that constraints rich parents on how much they can invest in their children' education, given that the best they can do is to pay for their college. As we mentioned in the previous section, this means that the baseline model generates too much intergenerational mobility, given that the only way parents have to invest in their children's education is to pay for college, but the data discipline the skill premium and hence bound how much rich parents can pay to increase their children expected income. This means that the binary choice also naturally bounds the possible increase in the spillover in response to an increase in inequality. Finally, this is consistent with the fact that there has been an increasing polarization between educational investment in the rich and poor neighborhoods. We then assume that the educational choice is continuous, that is, $e \in R_+$ and that the cost of education is linear τe.

With these two modifications, the problem of a household (w, a) becomes

$$U(w,a) = \max_{e,n} log((1 + \theta I_{n=A})(w - R_t^n - \tau e)) + log(b + ae(\beta_0 + \beta_1 S_t^n))\varepsilon. \qquad \text{(P3)}$$

In order to understand better the role of the educational choice, let us, for a moment, shut down the preference shock, that is, set $\hat{\theta} = 0$. In this case, the first order condition for the educational choice gives

$$e(w,a|n) = \frac{w - R_t^n}{2\tau} - \frac{b}{2a(\beta_0 + \beta_1 S_t^n)},$$

where $e(w,a|n)$ is the educational choice of a parent with wage w and a child with innate ability a conditional on living in neighborhood n and on $e(w,a|n)$ being positive. The expression shows that, as expected, education is increasing in income w, innate ability a, and in the spillover of the neighborhood S_t^n. It is also increasing in β_0 and β_1, which determine the return to education.

Moreover, it is decreasing in the cost of education τ and in b, which is the average wage of non-college educated workers.

The equilibrium definition is a natural extension of Definition 1 in Section 3.2, except that the agents' policy functions now also depend on the preference shock and the educational choice is now a continuous choice. Also, given the continuous choice of education, we need to bound the spillover effect to avoid that the wage distribution explodes. In this version of the model, we choose $\tilde{S}_t^n = log(1 + S_t^n)$, where S_t^n is the natural extension of the definition in equation 2. We are still exploring other variants of this specification.

We now calibrate the model according to the same strategy described in Section 4. The only difference is that, given that now education level is a continuous variable, we define a cut-off $\hat{e}$ such that individuals with an education level above $\hat{e}$ are college educated, and the ones with education below are not. We choose $\hat{e}$ so that, in 1980, 24% of the population is college educated, as in the data. When we look at the evolution of the ratio of college graduates in the two neighborhoods, we keep $\hat{e}$ fixed to that level to define college and no-college graduates in the model.

Table 5: *Calibration Results*

Target	Data	Model
Return to spillover	0.10	0.10
Return to college	0.39	0.39
Gini coefficient	0.37	0.37
Dissimilarity index	0.31	0.31
Labor income volatility	0.77	0.65
Rank-rank correlation	0.34	0.18
Poor/rich college share	0.35	0.37

Table 5 shows how we match the targets with our calibration. It is worthwile to notice that we improved in matching the degree of intergenerational mobility that we observe in the data (using the rank-rank coefficient), although our model still generates too much intergenerational mobility. [30]

We then perform the same exercise that we have conducted in section 4 and hit the steady state economy with an unexpected and permanent shock that proportionally increases β_0 and β_1 in

[30] We are now considering other extensions of the model to improve in this dimension. Following the theoretical literature, we want to introduce a direct effect of parents' wage on children's wage on top of the one that goes through the residential and educational choice. This could capture things like social networks.

order to increase the skill premium from 0.39 in 1980 to 0.54 in 1990.

Table 6: *Response to a Skill Premium Shock*

	t = 1980	t = 1990	t= 2000
Return to college	0.3936	0.5405	0.6826
Gini coefficient	0.365	0.4138	0.4664
Dissimilarity index	0.3093	0.7312	0.8283
Rank-rank correlation	0.1746	0.3402	0.4505
Rent in neighborhood A	0.0732	0.115	0.1929
Counterfactual with no spillover feedback			
Return to college	0.3935	0.4897	0.5689
Gini coefficient	0.365	0.4013	0.4325
Dissimilarity index	0.3093	0.4044	0.4894
Rank-rank correlation	0.1746	0.3103	0.3871
Rent in neighborhood A	0.0732	0.0786	0.0926

Table 6 shows the responses of the economy to such a shock. The results are qualitatively similar to the benchmark: in response to an increase in the skill premium, inequality and residential segregation increase, while intergenerational mobility decreases. Relative to the benchmark, the increase in inequality is closer to the data, while the increase in residential segregation is much larger. We then perform the same counterfactual exercise, keeping the spillover levels in the two neighborhoods at their 1980 values. This shows that 26% of the increase in inequality and 78% of the increase in residential segregation can be attributed to the spillover effects. Clearly in this calibrated version of the model, the local externality has an effect that is too large on residential segregation. We are working on exploring other alternative versions of the model or calibrations to improve in all dimensions.

6 Concluding Remarks

We proposed a model where segregation and inequality amplify each other because of a local spillover that affects returns to education. We calibrated the model using US data in 1980, and using the micro estimates of neighborhood externalities that Chetty and Hendren (2017b) proposed using administrative data. We then hit the economy with an unexpected permanent shock to the skill premium and looked at the responses over time of inequality, residential segregation,

and intergenerational mobility. We used the model to show that neighborhood spillover effects contributed to roughly one third of the increase in inequality and residential segregation, and to roughly one fourth of the decrease in intergenerational mobility.

There are many directions to extend the model in future work. It would be interesting to have a larger number of neighborhoods to use the full richness of the data to discipline the model. Another interesting extension would be to endogenize the cost of education, that has also increased over time, and think about possible feedback effects. Also, it would be interesting to explore the normative implications of our results.

Another interesting direction that we are planning to explore in the future is to use the model to think about the correlation of inequality, segregation, and intergenerational mobility across metro areas, also to understand their differential responses to a common skill premium shock.

References

Aaronson, Daniel and Bhashkar Mazumder, "Intergenerational economic mobility in the United States, 1940 to 2000," *Journal of Human Resources*, 2008, *43* (1), 139–172.

Acemoglu, Daron, "Technical change, inequality, and the labor market," *Journal of economic literature*, 2002, *40* (1), 7–72.

Armour, Philip, Richard V. Burkhauser, and Jeff Larrimore, "Using the pareto distribution to improve estimates of topcoded earnings," *NBER Working Paper No. 19846*, 2014.

Autor, David H, Lawrence F Katz, and Alan B Krueger, "Computing inequality: have computers changed the labor market?," *The Quarterly Journal of Economics*, 1998, *113* (4), 1169–1213.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, "Trends in US Wage Inequality: Revising the Revisionists," *The Review of Economics and Statistics*, 2008, *90* (2), 300–323.

Bartolome, Charles AM De, "Equilibrium and inefficiency in a community model with peer group effects," *Journal of Political Economy*, 1990, *98* (1), 110–133.

Becker, Gary S and Nigel Tomes, "An equilibrium theory of the distribution of income and intergenerational mobility," *Journal of political Economy*, 1979, *87* (6), 1153–1189.

Benabou, Roland, "Workings of a city: location, education, and production," *The Quarterly Journal of Economics*, 1993, *108* (3), 619–652.

_ , "Equity and efficiency in human capital investment: the local connection," *The Review of Economic Studies*, 1996, *63* (2), 237–264.

_ , "Heterogeneity, stratification, and growth: macroeconomic implications of community structure and school finance," *The American Economic Review*, 1996, pp. 584–609.

Card, David and Thomas Lemieux, "Can falling supply explain the rising return to college for younger men? A cohort-based analysis," *The Quarterly Journal of Economics*, 2001, *116* (2), 705–746.

Chetty, Raj and Nathaniel Hendren, "The Effects of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects," *Quarterly Journal of Economics*, 2017, *forthcoming.*

_ **and** _ , "The Effects of Neighborhoods on Intergenerational Mobility I: County Level Estimates," *Quarterly Journal of Economics*, 2017, *forthcoming.*

_ **,** _ **, and Lawrence F Katz**, "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment," *American Economic Review*, 2016, *106* (4), 855–902.

_ **,** _ **, Patrick Kline, and Emmanuel Saez**, "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *The Quarterly Journal of Economics*, 2014, *129* (4), 1553–1623.

Domina, Thurston, "Brain Drain and Brain Gain: Rising Educational Segregation in the United States, 1940-2000," *City and Community*, 2006, *5* (4), 387–407.

Durlauf, Steven N, "Neighborhood feedbacks, endogenous stratification, and income inequality," *in Dynamic Disequilibrium Modelling: Proceedings of the Ninth International Symposium on Economic Theory and Econometrics, W. Barnett, G. Gandolfo, and C. Hillinger, eds.*, 1996.

_ , "A theory of persistent income inequality," *Journal of Economic growth*, 1996, *1* (1), 75–93.

_ **and Ananth Seshadri**, "Understanding the Great Gatsby Curve," in "NBER Macroeconomics Annual 2017, volume 32," University of Chicago Press, 2017.

Fernandez, Raquel and Richard Rogerson, "Income distribution, communities, and the quality of public education," *The Quarterly Journal of Economics*, 1996, *111* (1), 135–164.

_ **and** _ , "Keeping People Out: Income Distribution, Zoning, and the Quality of Public Education," *International Economic Review*, 1997, *38* (1), 23–42.

_ **and** _ , "Public education and income distribution: A dynamic quantitative evaluation of education-finance reform," *American Economic Review*, 1998, pp. 813–833.

Ferreira, Pedro C, Alexander Monge-Naranjo, and Luciene Torres de Mello Pereira, "Of Cities and Slums," 2017.

Goldin, Claudia and Lawrence F Katz, "Decreasing (and then increasing) inequality in America: a tale of two half-centuries," *The causes and consequences of increasing inequality*, 2001, pp. 37–82.

Goldin, Claudia Dale and Lawrence F Katz, *The race between education and technology*, Harvard University Press, 2009.

Jargowsky, Paul A., "Take the Money and Run: Economic Segregation in U.S. Metropolitan Areas," *American Sociological Review*, 1996, *61* (6), 984–998.

Katz, Lawrence F and Kevin M Murphy, "Changes in relative wages, 1963–1987: supply and demand factors," *The quarterly journal of economics*, 1992, *107* (1), 35–78.

Loury, Glenn C, "Intergenerational transfers and the distribution of earnings," *Econometrica: Journal of the Econometric Society*, 1981, pp. 843–867.

Massey, Douglas S and Nancy A Denton, "The dimensions of residential segregation," *Social forces*, 1988, *67* (2), 281–315.

_ , **Jonathan Rothwell, and Thurston Domina**, "The changing bases of segregation in the United States," *The Annals of the American Academy of Political and Social Science*, 2009, *626* (1), 74–90.

Mazumder, Bhashkar, "Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data," *Review of Economics and Statistics*, 2005, *87* (2), 235–255.

Montgomery, James D, "Social networks and labor-market outcomes: Toward an economic analysis," *The American economic review*, 1991, *81* (5), 1408–1418.

_ , *Social networks and persistent inequality in the labor market*, Center for Urban Affairs and Policy Research Evanston, 1991.

Owens, Ann, "Income Segregation between School Districts and Inequality in Students' Achievement," *Sociology of Education*, 2018, *91* (1), 1–27.

Reardon, Sean F and Kendra Bischoff, "Income inequality and income segregation," *American Journal of Sociology*, 2011, *116* (4), 1092–1153.

Reardon, Sean F., Kendra Bischoff, Ann Owens, and Joseph B. Townsend, "Has Segregation Really Increased? Bias and Bias Correction in Sample-Based Estimates," *CEPA Working Paper*, 2018, (No. 18-02).

Streufert, Peter, "The effect of underclass social isolation on schooling choice," *Journal of Public Economic Theory*, 2000, *2* (4), 461–482.

Watson, Tara, "Inequality and the Measurement of Residential SEgregation by Income in American Neighborhoods," *NBER Working Paper No. 14908*, 2009.

Zheng, Angela, "Public Education Inequality and Intergenerational Mobility in an Overlapping Generations Model," 2017.

Appendix

A Proof of Proposition 1

Given that we focus on equilibria with $R^A > R^B = 0$, we require $S^A > S^B$. Also, this together with assumption 1 implies that agents who chooses low education strictly prefer neighborhood B to neighborhood A, so nobody chooses $e = e^L$ and $n = A$. Hence, agents choose among three options: 1) high education and neighborhood A, for short HA; 2) high education and neighborhood B, HB; 3) low education and neighborhood B, LB.

Let us consider a given time t and drop the time subscript to simplify notation. Also, to simplify the notation, let us drop ε, given that it is iid, so does not play any role for the cut-off functions. Consider an agent with wealth w and ability a who chooses HA. It must be that he prefers that to choosing HB or LB, that is,

$$u(w - R^A - \tau) + g(\Omega(a, e^H, S^A)) \geq u(w - R^B - \tau) + g(\Omega(a, e^H, S^B)) \tag{10}$$

and

$$u(w - R^A - \tau) + g(\Omega(a, e^H, S^A)) \geq u(w - R^B) + g(\Omega(a, e^L, S^B)). \tag{11}$$

Take any $w' > w$. By concavity of u and $R^A + \tau > R^B + \tau > R^B$, we have

$$u(w' - R^A - \tau) - u(w' - R^B - \tau) \geq u(w - R^A - \tau) - u(w - R^B - \tau)$$

and

$$u(w' - R^A - \tau) - u(w' - R^B) \geq u(w - R^A - \tau) - u(w - R^B).$$

Therefore

$$u(w' - R^A - \tau) + g(\Omega(a, e^H, S^A)) \geq u(w' - R^B - \tau) + g(\Omega(a, e^H, S^B))$$

and

$$u(w' - R^A - \tau) + g(\Omega(a, e^H, S^A)) \geq u(w' - R^B) + g(\Omega(a, e^L, S^B))$$

for all $w' > w$ and given a. Let us call $w_1(a)$ and $w_2(a)$ the values of w that make respectively conditions (10) and (11) hold with equality for given a. We can then define the cutoff function

$$\hat{w}(a) = \max\{w_1(a), w_2(a)\}.$$

This proves that all agents with $w \geq \hat{w}(a)$ choose the option *HA* for given a. Using assumption 1 and 2 and the implicit function theorem, it is straightforward to show that both $w_1(a)$ and $w_2(a)$ are decreasing functions, and hence that $\hat{w}(a)$ is a decreasing function as well.

Next, consider an agent with wealth w and ability a who chooses *LB*. It must be that he prefers that to choosing *HA* or *HB*, that is,

$$u(w-R^B)+g(\Omega(a,e^L,S^B)) \geq u(w-R^A-\tau)+g(\Omega(a,e^H,S^A)) \tag{12}$$

and

$$u(w-R^B)+g(\Omega(a,e^L,S^B)) \geq u(w-R^B-\tau)+g(\Omega(a,e^H,S^B)). \tag{13}$$

Following analogous steps to before, we can show that, for given a, all agents with $w' < w$ will prefer *LB* to both *HA* and *HB*. Notice that the value w that makes equation (12) hold with equality is the cut-off value $w_2(a)$ defined above. Moreover, let us call $w_3(a)$ the value of w that makes condition (13) hold with equality for given a. We can then define the cutoff function

$$\hat{\hat{w}}(a) = \min\{w_2(a), w_3(a)\}.$$

This proves that all agents with $w \leq \hat{\hat{w}}(a)$ choose the option *LB* for given a. Using assumption 2 and the implicit function theorem, it is straightforward to show that $w_3(a)$ is also a decreasing function, and hence that $\hat{\hat{w}}(a)$ is a decreasing function as well. Given that both $\hat{w}(a)$ and $\hat{\hat{w}}(a)$ are decreasing functions, it must be that $\hat{w}(a) \geq \hat{\hat{w}}(a)$ for all a. If there was an a' such that $\hat{w}(a) < \hat{\hat{w}}(a)$, then all agents with $w \in (\hat{w}(a), \hat{\hat{w}}(a))$ would find strictly optimal both HA and LB, which is a contradiction. This proves that an equilibrium is characterized by two decreasing function $\hat{w}(a)$ and $\hat{\hat{w}}(a)$ with $\hat{w}(a) \geq \hat{\hat{w}}(a)$ for all a, such that all agents with (w,a) such that $w > \hat{w}(a)$ will choose $e = e^H$ and $n = A$ and all agents with (w,a) such that $w < \hat{\hat{w}}(a)$ will choose $e = e^L$ and $n = B$.

B Data Methodology

B.1 Segregation and Inequality over Time

Data sources and sample selection We use tract level income data from Decennial Censuses (1970 to 2000) and from the American Community Surveys. Our sample includes metropolitan areas using the 2000 OMB definition. We construct a crosswalk to match tract level data at the metro level with individual data at the metro level in IPUMS (IPUMS does not have census tract information and IPUMS does not contain individual level information). Starting with 283 metro areas in IPUMS 2000 (variable metarea) we match each metro to counties, using the 2000 OMB definition of metros. We then use the information about county composition of metros to match our data with the tract level data set. Since a few counties appear in the definition of more than one metro and a few metro are missing in the OMB definition, our sample includes 279 metros in 2000. This number of metros corresponds to a total of 50509 census tracts. Table 7 reports our summary statistics at the metro and census tract level. Two things to notice: the size of our sample is smaller in 1970 since not all metros were tracted at that time and the number of census tracts has been increasing over time.

Table 7: Census tract summary statistics

year	No. Metro Areas	No. Census Tracts	Average No. Census Tracts
1970	231	28853	124.9
1980	278	40798	146.8
1990	279	45963	164.7
2000	279	50509	181.0
2010	279	57121	204.7

B.2 Computing the Gini

There are two ways we can aggregate family income tabulations to the metro level, either using tract-level family income tabulations or using county-level tabulations. The difference between methods only arises in years where some parts of the counties assigned to metros were not tracted: in those years we have more observations in county-level tabulations than in tract-level tabulations. We experiment using both ways and find no significant difference in the trend over time.

Family income tabulations report counts of families by income brackets and the data is topcoded. When calculating our index, we assume that families are uniformally distributed within each bracket, except for the top one. We follow Armour, Burkhauser and Larrimore (2014) to assign values for the topcode in each decade.

B.3 Segregation and Inequality Across US Metros

In Table 8 we report the results of a regression of segregation on inequality at the metro level, first in levels and then in first differences. The results show a strong correlation between the two variables: metros with higher level of inequality are also those that display higher level of segregation. This finding is robust to different definitions of the two variables and it holds for all decades in our sample. The relationship between the change in inequality and the change in segregation between 1980 and 2000 is not as strong but still statistically significant, meaning that the metros where inequality has grown the most are also those where segregation has increased the most.

Table 8: Correlation between Segregation and Inequality Across US Metros

	(1)	(2)
VARIABLES	dissimilarity 80	dissimilarity 80_00
gini1980	1.749	
	(0.124)	
gini80_00		0.440
		(0.106)
Constant	-0.329	0.0155
	(0.0455)	(0.00610)
Observations	278	278
R-squared	0.418	0.059
F-test	198.5	17.25

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B.4 Intergenerational Mobility and Segregation Across US Metros

Computing initial and final income We keep only observations with observed family income for any of the 3 years 1978, 1979, 1980 and also for any of the 5 years 1997, 1999, 2001, 2003, 2005. Income recorded in year y refers to income in year $y-1$, so these are for survey years 1979-1981 and 1998-2006 respectively. We deflate all income observations to 1978 dollars using the CPI series for all consumers (U.S. city average) downloaded from the BLS. Zeros are included in the averages. Since we include only individuals with at least one positive income observation in the survey years 1979-1981 and 1997-2005, there is no case where an observation has all missing income values.

Summary Statistics NLSY sample In Table 9 we report the number of observations as well as the number of metros and counties in each segregation quartile.

Table 9: Geographic Units and Population per Segregation Quartile (p80)

Segregation Index	Quartile	No. Metro Areas	No. Counties	Pop.
Dissimilarity of Income (p80) in 2000	1	141	271	1,348
	2	82	240	1,351
	3	28	150	1,326
	4	28	123	1,289
Dissimilarity of Income (p80) in 1980	1	140	257	1,336
	2	68	199	1,366
	3	48	201	1,330
	4	22	126	1,281

Hypothesis Testing The transition matrices in Figures 6 and 7 compare intergenerational mobility across metros grouped by the dissimilarity index where the cutoffs is the top 20 percent of the income distribution. Mobility is consistently lower in highly segregated metros compared to low segregated ones.

Table 10: Hypothesis Testing

Low Segregation	High Segregation	Significance p50	Significance p80
Bottom 50 %	Top 25 %	0.008	0.002
Bottom 50 %	Top 50 %	0.002	0.003

Table 10 reports the significance levels for a Wald test, adjusted for survey weights. Each row of the table reports the significance level of the test for the null hypothesis that the low segregation group has the same persistence of the first quartile of family income as the high segregation group. We define the low segregation group of metros as those in the bottom 50 percent according to the dissimilarity index. The first row shows results for the case in which we compare this group with the high segregation group defined as the top 25 percent and the second row shows results for the case in which we compare the same low segregation group with the high segregation group defined as the top 50 percent. Since the measured levels of persistence for the first quartile are always higher in the high segregation metro group, rejecting the null hypothesis means accepting the alternative hypothesis that the high segregation metros have a higher persistence of the first quartile of family income. We run the test for these two different definitions of "high" segregation metros and for two different cutoffs of the dissimilarity index. In all these instances we can reject the hypothesis that mobility is the same in the two group of metros at the 1 percent level.