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

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Abstract

Since the 1980s both income inequality and residential segregation in the United States have substantially increased. We develop a general equilibrium model where parents make residential and educational choices, affecting intergenerational mobility. Segregation and inequality amplify each other because of local spillovers that affect educational returns. We calibrate the model using US data and the estimates of neighborhood exposure effects by Chetty and Hendren (2018b). We explore the response of the model to an unexpected permanent skill premium shock and find that residential segregation has contributed roughly one fourth to the increase in income inequality between 1980 and 2010.

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1 Introduction

It is a well documented fact that the US has experienced a steady increase in income inequality over the last 40 years. At the same time, there has been a substantial increase in residential segregation by income. What is the link between inequality and residential segregation? In particular, has residential segregation amplified the response of income inequality to underlying shocks, such as skill-biased technical change? How do these patterns in inequality and segregation affect intergenerational mobility? In this paper, we build a model of educational investment and residential choice with local spillovers that can be used to address these questions.

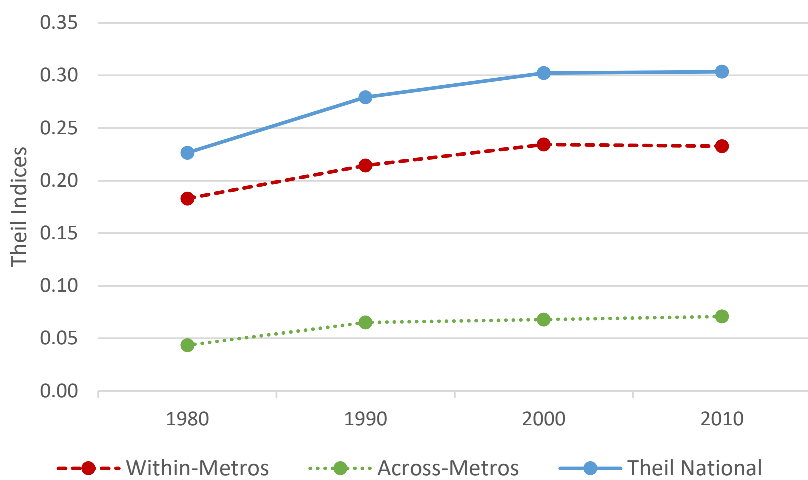
There has been a large theoretical literature in the 1990s focusing on the relation between inequality and local externalities, starting from the seminal work by Benabou (1996a,b), Durlauf (1996a,b), and Fernandez and Rogerson (1996, 1997, 1998). More recently, administrative data have been used to obtain direct estimates of neighborhood spillover effects. In particular, Chetty et al. (2016) and Chetty and Hendren (2018a,b) have shown that children's exposure to different neighborhoods has substantial effects on their future income. We bridge these two strands of literature, by proposing a general equilibrium model calibrated using the micro estimates from Chetty and Hendren (2018b) to understand the contribution of local externalities to segregation, inequality, and intergenerational mobility patters.

In order to do so, our model focuses on inequality across neighborhoods within cities. A recent vibrant literature has focused on the increase in inequality across metro areas.[1] However, this literature has largely abstracted from the significant contribution of rising inequality within cities to the overall increase in US income inequality over the past decade. In Figure 1 we use the Theil index to decompose the increase in income inequality at the national level (blue solid line) into the increase in income inequality within metro areas (red dashed line) and the increase in income inequality across metro areas (green dotted line).[2] The figure shows that both types of income inequality have increased steadily since the '80s and have substantially contributed to the overall rise in US income inequality. We then document that the increase in inequality within cities is correlated with a simultaneous increase in segregation by income across neighborhoods.

[1] See for example Moretti (2004), Shapiro (2006), Moretti (2012), Eeckhout et al. (2014), Hsieh and Moretti (2015), Diamond (2016), Giannnone (2018), Diamond and Gaubert (2022).

[2] For this figure, we use the Theil index because it is well suited for this type of decomposition. We use the same Census tract data on family income between 1980 and 2010 that we describe in Section 2.

Figure 1: Inequality Within and Across Metros: Theil Index 1980-2000



In the first part of the paper, we document a positive correlation between income inequality and residential segregation by income at the MSA level, both across time and across space. To measure inequality and segregation, we use US Census tract data on family income between 1980 and 2010 at the MSA level.[3] Using these measures, we show that 1) average inequality and residential segregation have increased steadily since 1980; 2) levels of inequality and residential segregation in 1980 are correlated across MSAs; and 3) changes in inequality and residential segregation between 1980 and 2010 are correlated across MSAs.

We then build a general equilibrium overlapping generation model with educational and residential choices that features local externalities. The model generates a feedback effect between income inequality and residential segregation that amplifies the response of inequality to underlying shocks. In Section 3 we use a simple version of the model to explain the mechanism. Agents live for two periods: first they are young and go to school, and then they are old and become parents. There are two neighborhoods and parents choose both the neighborhood where they raise their children and the level of their children's education. The key ingredient of the model

[3]To measure inequality, we use the Gini coefficient as baseline indicator. To measure segregation, we use the dissimilarity index, which is a measure of how uneven is the distribution of two exclusive groups across geographical areas. In particular, we divide the population in two income groups, rich and poor, using the 80th income percentile, and compute the dissimilarity index across census tracts belonging to the same MSA.

is a local spillover: investment in education yields higher returns in neighborhoods with higher expected future income of children, that is, neighborhoods with higher parents' income and children's ability. Such a spillover can capture a variety of mechanisms: differences in the quality of public schools, peer effects, social norms, learning from neighbors' experience, networks, and so forth.[4] We assume that the local spillover is complementary to the children's innate ability and to their level of education. The model generates sorting in equilibrium: richer parents and parents with more talented children choose to pay higher rents to live in the neighborhood with the higher local spillover. It follows that one neighborhood endogenously becomes the "good" one and hence the one where houses are more expensive. This means that in the model, residential choice is a form of investment in children's education, implying that talented children who grow up in poorer families may be stuck in worse neighborhoods. This hurts intergenerational mobility even more, because educational choices are endogenous and the return to education is endogenously lower in the worse neighborhood.

We use this simple version of the model to qualitatively understand the feedback effect between inequality and segregation and to explore how the model responds to an unexpected permanent skill premium shock. When a skill premium shock hits the economy, inequality increases mechanically, because the wage gap between educated and non-educated workers increases. Moreover, given the complementarity between neighborhood spillover and education, when the skill premium is higher, more parents would like to live in the neighborhood with the stronger spillover. However, given the inelastic housing supply, this translates into higher rental rates, and hence into higher degree of segregation by income. The endogenous change in neighborhood composition, in turn, drives up the spillover differential between the two neighborhoods and translates into even higher inequality. In particular, poor families with talented children may be pushed into worse neighborhoods, where the incentive to invest in education is lower. This further increases the gap between spillovers and worsens intergenerational mobility over time.

In order to bring the model to the data, in Section 4 we generalize the model in a number of directions. First, we introduce an additional neighborhood to capture richer spatial dynamics. Second, we make the educational choice continuous, so as to not restrict the investment choice set. Third, we introduce two types of preference shocks: one that stands for local amenities

[4] Among the most recent contributions, Agostinelli (2018) shows that peer effects account for more than half of the neighborhood effects in Chetty and Hendren (2018a), while Rothstein (2019) argues that job networks and the structure of local and marriage market play a more important role.

and captures an additional force for residential segregation, the other that captures idiosyncratic determinants of the residential choice. We then calibrate the steady state of the model to the average US metro area in 1980. To discipline the calibration, we target a number of features of the US economy in 1980, and to discipline the strength of the local spillover, we use the micro estimates for neighborhood exposure effects obtained in the quasi-experiment in Chetty and Hendren (2018b).

We then perform our main quantitative exercise. Assuming that the original increase in inequality comes purely from skill-biased technical change, we study the effects of an unexpected, one-time shock to the skill premium on inequality, segregation, and intergenerational mobility over time. Despite the parsimony of the model, the exercise generates patterns for inequality and segregation that resemble the data. We also validate the model with a number of other statistics at the city and neighborhood level. In particular, we use dynamics of house prices in different neighborhoods, dynamics of neighborhoods sizes, and intergenerational mobility matrices across family income quartiles. We then use our model to ask our main quantitative question: how much does segregation by income contribute to the rise in inequality? To answer this question, in Section 5, we run two main counterfactual exercises where we look at the response of the economy to the same shock, but mute the sorting. In the first exercise, we assume that, after the shock, families are randomly re-located between the two neighborhoods, which implies that all the neighborhoods have the same distribution of income and ability and there is no residential segregation. In the second one, we assume that, after the shock, families cannot re-optimize their residential choice. These exercises show that segregation by income contributes significantly, respectively by 27% and 25%, to the total increase in inequality between 1980 and 2010. We then perform a number of different exercises to decompose the effect of the shock into different channels.

Finally, in Section 6, we explore a battery of alternative versions of the model both to confirm some our modeling choices and to check the robustness of our results. First, we study a version of the model where the spillover is global and the only source of residential segregation is the presence local amenities. Second, we study the response of our baseline model to a shock that increases the volatility of the wage process rather than a skill premium shock. In both cases, we re-calibrate the model and show that these versions are not able to generate some important features of the data which our model is able to capture. We also study versions of the model to show that our results are neither driven by the complementarity assumption between spillover and ability nor by the specific definition of the spillover.

Related Literature.

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 fundamental 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.[5] 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.[6] 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 it 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, with no growth, where residential stratification is purely driven by locally financed public education.[7] 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. 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 shows that disentangling between financial and social local spillover is important for assessing different types of policies.

[5] 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)).

[6] 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.

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

Similarly to this class of paper, our model builds on the idea 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 direction, we enrich the model to obtain 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 we address in this 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 several dimensions, although the calibration strategy and the main exercise are different and complement each other.[8]

In contemporaneous work, Eckert and Kleineberg (2021) study a related model of residential and educational choice where local spillovers generate residential sorting, but use it to study the effects of school financing policies. To this end, they structurally estimate the model using regional data of the US geography to match model cross-sectional predictions. In a related paper, Zheng and Graham (2022), calibrate a similar model to study the effects of different public school allocation mechanisms.

More recently, there has been a growing body of literature focusing on related models with neighborhood effects.[9] Among the others, Fogli et al. (2022) analyze the dynamic effects of scaled up moving to opportunity and placed-based policies using a model similar to the one developed in this paper that allows for general equilibrium effects and endogenous response of the

[8]See Durlauf et al. (2022) for a survey on the Gatsby Curve.

[9]Another interesting literature has focused on the role of parenting style choices on educational outcomes. See Doepke et al. (2019) for a survey.

neighborhood composition to the policy. In a similar spirit, Chyn and Daruich (2022) uses a neighborhood-based model also to study the long-run and large scale effects of vouchers and place-based subsidies. Their model has only two neighborhoods, but has a more general production function including capital income and has a different notion of neighborhood spillover. Another recent paper building on a model where segregation is driven by neighborhood effects is Gregory et al. (2022), who introduce the racial dimension of segregation to explore the effects of segregation on racial wage gaps.

Another interesting policy is analyzed in Agostinelli et al. (2020), who focus on the effects of busing poor children to rich neighborhoods. In their framework, the neighborhood effect is mainly driven by peer effects, which are shaped by parenting choices. Differently from our model, in this paper residential choice is muted, given that the focus is on the endogeneity of the parenting style. The paper shows that busing poorer children to richer neighborhoods becomes less effective if implemented in larger scale. Using a related framework, Agostinelli et al. (2022) study the effect on inequality of switching to e-learning during the pandemic.

Our paper is also related to a broad literature on urban development economics.[10] In particular, Ferreira et al. (2017) is a recent paper that uses 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.

Another related strand of the literature focuses on spatial sorting generated by local amenities. The early work by Brueckner et al. (1999) and Glaeser et al. (2001) emphasizes the role of urban amenities and spurred a vibrant literature on gentrification. Among the others, Guerrieri et al. (2013) have focused on the endogenous nature of amenities, by introducing a consumption externality that comes from the average income of the neighbors. In contemporaneous work, Couture et al. (2019) study a spatial model with locations with different endogenous amenities and non-homotetic preferences. The paper focuses on the growth and welfare effects of spatial

[10] See Bryan et al. (2020) for a survey.

resorting within urban areas after the '90s. Another related paper is Bilal and Rossi-Hansberg (2021) who emphasize that the location choice of individuals is a form of asset investment.

Our work is also related to the literature investigating the evolution of race-based segregation in US cities and its consequences on individual outcomes. The seminal paper of Cutler and Glaeser (1997) shows that blacks living in more segregated metros have significantly worse outcomes than blacks living in less segregated cities. Given the correlation between income and race, these findings are relevant for our analysis. Interestingly, however, Cutler et al. (1999) show that the American ghetto, rapidly expanding between 1890 and 1970 as blacks migrated to the cities, eventually started declining. Income-based segregation has progressively replaced race-based segregation in US cities.

Besides the vast literature on city segregation, there are also papers that investigate the consequences of high levels of segregation in a cross section of countries. Alesina and Zhuravskaya (2011), using a measure of segregation similar to ours, show that countries where different linguistic and ethnic groups are more segregated across regions are characterized by significantly lower government quality.

The paper is organized as follows. In Section 2, we document the positive correlation between inequality and segregation across space and time. Section 3 describes the baseline model and shows how the model responds to a skill premium shock. In Section 4 we extend the model, describe our calibration strategy, and show the response of the economy to a skill premium change as in the data. Section 5 shows our main counterfactual exercises to quantify how much segregation has contributed to the increase in inequality. Section 6 explores a number of different versions of the model. Section 7 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 et al. (2009), this is a new phenomenon in US cities, which historically were predominantly segregated on the basis of race.[11] During the last third of the twentieth

[11] Massey et al. (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

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 steady increase in income inequality.

In this section we document the magnitude of these phenomena and explore the correlation between segregation and inequality across time and space.

2.1 Segregation and Inequality over Time

To measure residential segregation by income we use the dissimilarity index, which is the most common measure of evenness. In our main analysis, we define as rich families with income above the 80th percentile, within a given metro, and all other families as poor. The dissimilarity index for metro j is 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.[12]

We use tract level family income data from Decennial Censuses (1980 to 2000) and from the American Community Surveys (2008-2012). Our sample includes 380 metropolitan areas using the 2003 OMB definition.[13] We calculate the dissimilarity index for all metro areas in each decade and average at the national level using metro level population weights. Figure 2 plots the resulting measure of segregation at the national level. The graph shows that the distribution of income has become progressively more uneven across census tracts over time.[14] If in 1980, roughly 32% of families in the average US metro had to change residence to achieve an even distribution across census tracts, in 2010 the population that needed to change residence increased to roughly 38%. The increase was especially large between 1980 and 1990 and again between 2000 and 2010.[15]

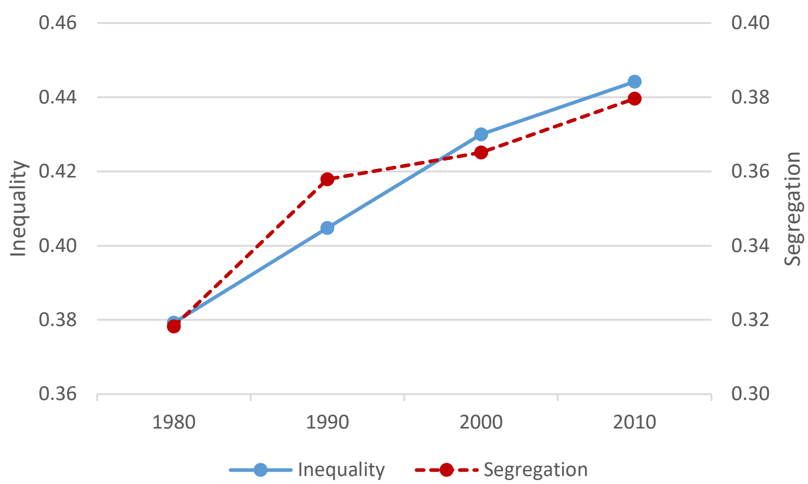
micro level (municipalities and neighborhoods).

[12]The dissimilarity index varies from 0 to 1, with the former value indicating perfect evenness and the latter maximum separation.

[13]For summary statistics of our sample see Appendix A.1.

[14]In Appendix A.1 we use the metro area of Chicago as an example to visualize the change in segregation across

Figure 2: Inequality and Segregation over Time



Using the same data on family income at the tract level that we use to calculate the dissimilarity index, we also compute the Gini coefficient at the metro level and similarly average at the national level using metro population weights. Income data at the census tract level are reported in bins and are top coded. Top-coded income data are a significant concern when calculating inequality measures. We follow a recent methodology proposed by von Hippel et al. (2017) who estimate the CDF of the income distribution non-parametrically and then use the empirical mean to fit the top-coded distribution.[16] We plot the resulting estimate of the Gini coefficient in Figure 2

census tracts.

[15]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 et al. (2018) document this fact using the information theory index.

[16]Some papers dealing with individual level income data, such as Armour et al. (2016), have addressed the issue of top-coded data by estimating a Pareto distribution for the top income bracket. However, this methodology is not feasible when dealing with binned, rather than continuous, income data. The methodology mostly used for binned data has been the one proposed by Nielsen and Alderson (1997), who use the Pareto coefficient from the last full income bracket to estimate the conditional mean of the top-coded bracket, as, for example, in Reardon and Bischoff (2011). However, such procedure does not exploit the fact that the Census reports the precise empirical average income by census tract. Our method uses this information to improve the estimation of the top-coded distribution. For details, see Appendix A.1.

together with the dissimilarity index. Both measures show a significant increase over time, with the Gini coefficient rising from roughly .38 to roughly .44 over the entire period. The figure shows that the increase in spatial segregation by income across neighborhoods happened at the same time of the increase in income inequality.

We now check the robustness of these patterns, using alternative measures of income segregation and income inequality.

Figure 3: Dissimilarity Index: different cutoffs

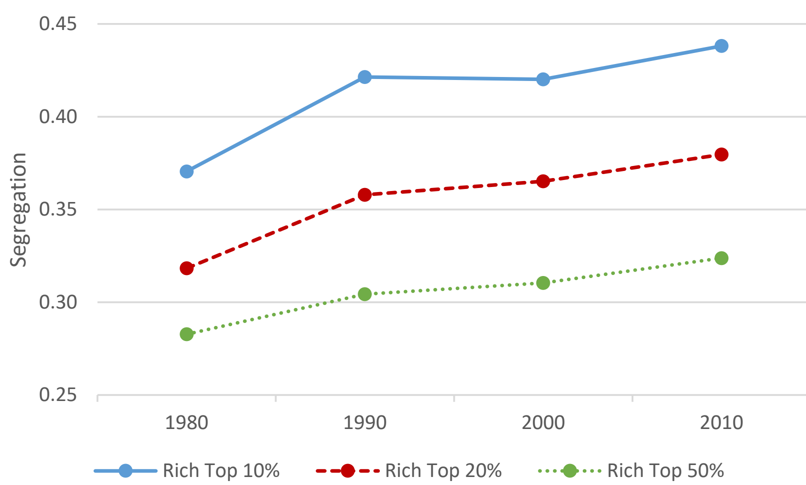


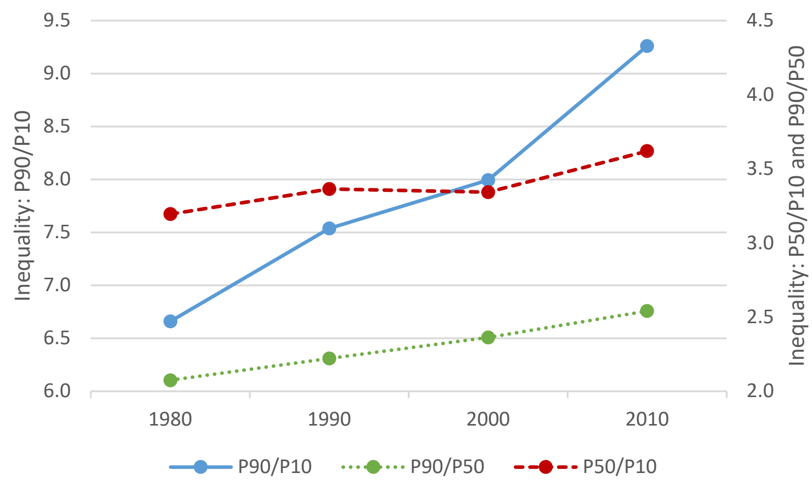
Figure 3 plots the dissimilarity index calculated using different percentiles to define the income groups. The red dashed line shows our benchmark dissimilarity index, while the solid blue line and the dotted green line show the dissimilarity index constructed using the $10th$ and the $50th$ percentiles respectively. The figure shows that the dissimilarity index shifts up as the cut-off percentile decreases, suggesting that as groups become progressively more homogeneous according to income they are also characterized by higher levels of segregation. However, regardless of the level, all measures show an increasing trend over time. From now on, when we refer to the dissimilarity index, we refer to the average, population-weighted, of the dissimilarity indexes calculated at the metro level, using the 80th percentile as cut-off to define the rich and the poor.

The increase in inequality is also a robust finding.[17] Figure 4 plots three other measures of income

[17] See, for example, Katz and Murphy (1992); Autor et al. (1998); Goldin and Katz (2001); Card and Lemieux

inequality that have been widely used in the literature: the 90/10 ratio that measures the ratio of the family income in the top 90th percentile of the population relative to the income in the bottom 10th percentile, and, similarly, the 50/10 ratio, and the 90/50 ratio.[18] Figure 4 shows that both the 90/10 and the 90/50 ratios have increased steadily since 1980, while the 50/10 ratio is flat or even slightly decreasing after 1990. This confirms that the rise in income inequality has been driven by the top of the distribution, as already shown by Autor et al. (2008) for individual wage inequality.

Figure 4: Inequality: different measures



It is interesting to notice that if we restrict the sample to families with children, not only is the level of segregation higher, but the increase over time is more pronounced. Figure 5 shows separately the pattern of segregation for families with children and for families without children.[19] The figure shows that in 1980 the dissimilarity index for families with children is 0.35, compared to 0.31 for families without children. By 2010, the dissimilarity index for families with children increases to 0.46, while the dissimilarity index for the other families only reaches 0.35.

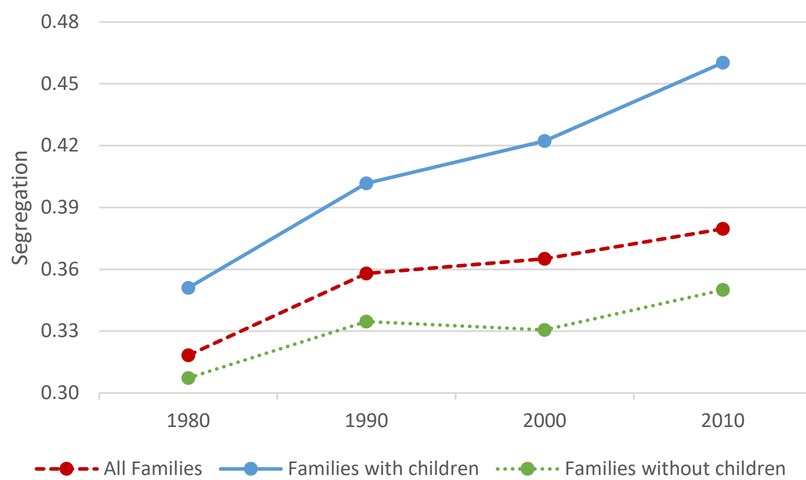
(2001); Acemoglu (2002); Autor et al. (2008).

[18] The procedure implemented to calculate these ratios from binned data at the census tract level is described in Appendix A.1.

[19] See Appendix A.1 for details on how we construct the sample of families with kids not readily available for 1980 at the census tract level.

This finding suggests that children are an important factor in residential decisions and is one of the reasons why we focus on the role of local spillovers on children's future income as a key mechanism behind the correlation between segregation and inequality.

Figure 5: Segregation: different samples

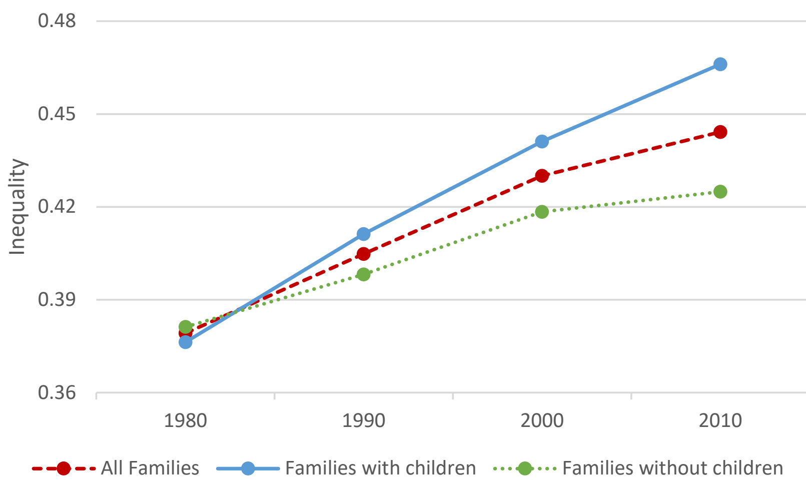


The increase in inequality is also stronger if we restrict the sample to families with children. Figure 6 shows that, while the level of inequality in 1980 is similar if we look at families with children and families without children, both equal roughly to 0.38, inequality for families with children rises to 0.47 in 2010, while inequality for families without children only reaches 0.42 in the same year. These findings point to the presence of children as an important driver of both residential segregation and income inequality.

2.2 Segregation and Inequality Across US Metros

Next, we document that residential segregation and inequality are also correlated across space. Figure 7 shows the relationship between the Gini coefficient and the dissimilarity index across metro areas in 1980, where the bubbles are proportional to the population of the metro area. The figure shows a positive correlation between segregation and inequality in 1980. We estimate a regression coefficient of 0.25, with a standard error of 0.015. The significance of this relationship

Figure 6: Inequality: different samples



is robust to the inclusion of controls for demographic and industry composition.[20] It also holds for the other decades in the sample and using the dissimilarity index constructed with other cut-off to define rich and poor families. If we restrict the sample to families with children the regression coefficient becomes 0.33 with a standard error of 0.017.

The significance of the relationship between inequality and segregation is robust not just in levels but also in differences. Figure 8 plots the change at the metro level in the Gini coefficient between 1980 and 2010 against the change at the metro level in the dissimilarity index over the same time period. Again, the size of the bubble is proportional to the population of the metro area. The figure shows that the metro areas that experienced a larger increase in inequality between 1980 and 2010 are also those that experienced a larger increase in residential segregation over the same time period. The regression coefficient is 0.18 with a standard error of 0.017. If we restrict the sample to families with children, the coefficient becomes 0.24 with a standard error of 0.022. In Appendix A.2, we show that these results are robust to the inclusion of controls for changes in racial and industrial composition.[21]

[20]The results of the regression of inequality on segregation across US metros in 1980 with and without controls are reported in Table 13, Appendix A.2.

[21]The results of the regression of changes in inequality on changes in segregation across US metros between 1980 and 2010 with and without controls are reported in Table 14, Appendix A.2.

Figure 7: Inequality and Segregation across US Metros

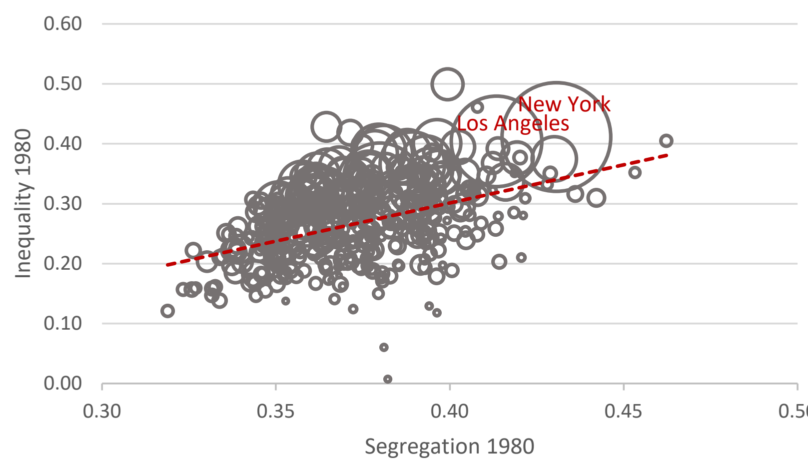
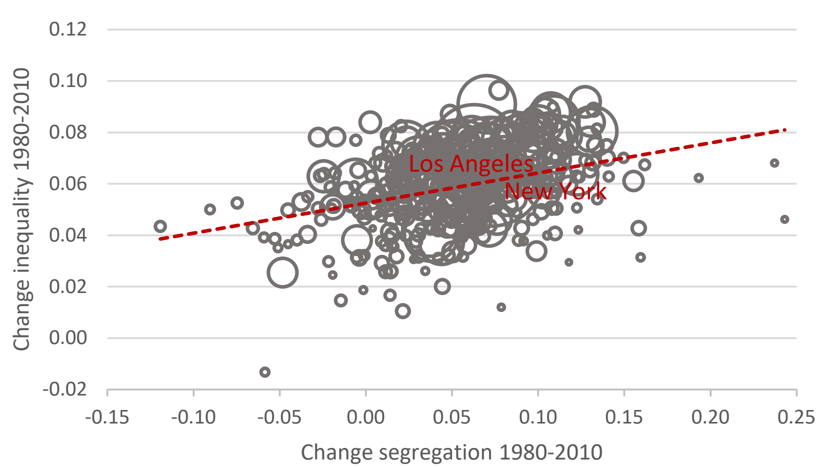


Figure 8: Change in Inequality and Segregation 1980-2010



Our analysis suggests a positive correlation between inequality and segregation especially for families with children, both across time and across space. US cities have become increasingly segregated over time reflecting an increased tendency of families to sort in different neighborhoods according to income.[22]

Prompted by this empirical evidence, we next develop a model with local externalities and endogenous residential choice, that is able to endogenously generate a feedback effect between inequality and residential segregation. We will then use the data to calibrate it and quantitatively assess the role of this feedback effect for the increase in inequality.

3 Simple Model

We first propose a simple model of a metro area where families choose the neighborhood where to live taking into consideration that there are local spillovers affecting their children's future income. We make a number of stark assumptions, as the purpose of the simple model is to explain the mechanism behind the feedback effect between inequality and residential segregation. In section 4 we generalize the model in a number of directions to make it more realistic and useful for the quantitative exercises.

3.1 Set up

The economy is populated by overlapping generations of agents who live for two periods. In the first period the agent is a child and in the second period she is a parent. A parent 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 a child is correlated with the ability of the parent. In particular, $log(a_t)$ follows an AR1 process

$$log(a_t) = x + \rho log(a_{t-1}) + \nu_t,$$

where ν_t is normally distributed with mean zero and variance σ_ν, $\rho \in [0,1]$ is the autocorrelation coefficient, and x is a constant normalized so that the mean of a_t is equal to 1. The joint distribution of parents' wages and children's abilities evolves endogenously and is denoted by $F_t(w_t, a_t)$, with $F_0(w_0, a_0)$ taken as given.

[22] One of the important drivers of sorting is the quality of public school. The relevant subunit of analysis for public school driven type of segregation is the school district. We analyze the evolution of segregation across US school districts in Appendix A.3. We find a similar pattern of increase over time slightly mitigated in the last part of the period by the rise of private schools. We think that the census tract is a preferable unit of analysis in our context since better reflects our flexible notion of neighborhood spillover, is less affected by potential small sample bias, and can be more directly linked to metros.

There are two neighborhoods, denoted by $n \in \{A, B\}$. All houses are of the same dimension and quality and the rent in neighborhood n at time t is denoted by R_{nt}. For simplicity, in the simple model we make the extreme assumption that the housing supply is fixed and equal to M in neighborhood A and fully elastic in neighborhood B. We normalize the marginal cost of construction in neighborhood B to 0, so that $R_{Bt} = 0$ for all t. The rental price in neighborhood A, R_{At}, is a key endogenous equilibrium object.[23]

In the simple model we also assume that there are only two educational levels, $e \in \{e^L, e^H\}$. There is no cost to obtain the low level of education, while $\tau > 0$ is the cost of investing in high education.[24] We can interpret $e = e^H$ as college education and $e = e^L$ as no college education.

Parents care both about their own consumption and about their children's future wage.[25] 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. A parent with wage w_t and with a child of ability a_t chooses 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 the child's education, $e_t(w_t, a_t) \in \{e^L, e^H\}$. These choices affect the child's future wage, as explained below.

A key ingredient of the model is the presence of local spillovers that affect the children's return to education, and hence their future income. Children's wages are affected by their ability, by their education, by the neighborhood where they grow up because of the local spillover effect, and also directly by their parents' wage. Formally, the child of an agent (w_t, a_t) who grows up in neighborhood n and gets education level e is going to earn a wage

$$w_{t+1} = \Omega(w_t, a_t, e, S_{nt}, \varepsilon_t), \tag{1}$$

where ε_t is an iid noise with cdf Ψ, S_{nt} is the size of the local spillover in neighborhood n at time t, and Ω is non-decreasing in all its arguments. We assume that Ψ is a normal distribution with mean one and standard deviation σ_ε. Children with higher ability and higher education, who grow

[23]In the general model in section 4, we allow for three neighborhoods and assume that all three neighborhoods feature an increasing housing supply function. The only necessary assumption for our mechanism to work is that there is at least one neighborhood where housing supply is not fully elastic.

[24]The general model in section 4 allows for a continuous choice of education.

[25]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. An alternative specification could have parents getting utility directly from their children's consumption, but with the introduction of a borrowing constraint.

up in neighborhoods with larger spillover and have richer parents will have higher future income. Due to the fact that the residential and the educational choice are functions of parents' wage and children's ability (w_t, a_t), with a slight abuse of notation, we can write $w_{t+1} = w_{t+1}(w_t, a_t, \varepsilon_t)$. We will show that in equilibrium parents with a higher wage, for given children's ability, are more likely to choose higher education and the neighborhood with higher spillover. This implies that children's wages will be increasing in parents' wages, both because of the direct effect in (1) and because of indirect effects operating through education and neighborhood choices.

Let us now turn to the spillover. We assume that the size of the spillover effect in neighborhood n at time t is equal to the expected future income of the children growing up in that neighborhood:

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

Given that wages are increasing in ability and in parents' wage, neighborhoods with a higher spillover are neighborhoods with both richer parents and children with higher ability. The presence of this externality implies that the rental rate in neighborhood A, R_{At}, also depends on the size of the spillover in that neighborhood, S_{At}, which is endogenous.

We chose this broad specification for S_{nt} because it can capture different sources of pecuniary and social externalities. On the one hand, the fact that neighborhoods with higher spillovers are neighborhoods with richer parents allows us to interpret the spillover as linked to better public schools that are typically locally financed and hence tend to improve with the average taxpayers' income. On the other hand, the fact that neighborhoods with higher spillovers are neighborhoods with more talented children allows us to interpret the spillover as peer effects. Both richer parents and more talented kids may also be the source of stronger networks on the labor market, social norms more conducive to educational investment, and so forth. An alternative specification could 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 innate ability and the second would underplay the role of parental income. We use the more general specification in equation (2) because it is a better mapping to the empirical estimates from Chetty and Hendren (2018b) that we use in our calibration, which capture the total effect of growing up in a given neighborhood on future income.

In our analysis, we make two assumptions. First, for simplicity, we assume that ability and spillover's size affect children's future wages only if they get the high level of education.

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

The assumption that the wage of children with low education does not depend on ability stands for the fact that abilities that are relevant in high-skill jobs (which typically require college) may be different and more heterogenous than abilities that are relevant for low-skill jobs. The assumption that the spillover's size does not affect the wage of children with low education is extreme, but can be interpreted as stating that the quality of k-12th schooling is more important in determining future wages of college graduates than of no-college graduates. This second assumption simplifies the analysis because 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. We will relax Assumption 1 in the extended model in Section 4 where we will have a continuous educational choice.

Second, we make the following assumption.

Assumption 2 *The composite function $g(\Omega(w,a,e,S,\varepsilon))$ has increasing differences in a and S, in a and e, in w and S, and in w and e.*

These complementarities assumptions play a crucial role for our mechanism, as we will describe in the next subsections. One of the key assumption is the complementarity between innate ability and education and between innate ability and neighborhood's spillover. Although it is hard to get direct estimates of innate ability, these assumptions reflect some of the findings of the recent empirical literature. [26]

To sum up, a parent with wage w_t who has a child with ability a_t at time t solves the following

[26] Our assumptions of complementarity between innate ability and education and between innate ability and neighborhood's spillover are consistent with the latest research on technology of skill formation. Cunha et al. (2010) show that the higher the initial conditions for cognitive and non-cognitive skills of children, the higher the return to parental investment in children at later stages in life. As they highlight "family environments and genetic factors may influence these initial conditions." In our model, parental investment in children's future outcome takes place both through educational investment and through residential choice. Moreover, the recent human capital literature, reviewed in Sacerdote (2011), also highlights the presence of non-linearity in peer effects, which are one of the forces behind our spillover effects. In particular, Sacerdote (2001), Imberman et al. (2012), and Lavy et al. (2012) find that high ability students are the ones who benefit the most from peer effects of other high ability students. Another paper that speaks more specifically to the complementarity between ability and spillover effects is Card and Giuliano (2016), who show that high achievers from minority and disadvantaged groups show high returns when included in school tracking programs.

problem:

$$U(w_t,a_t) = \max_{c_t,e_t,n_t} u(c_t) + E[g(w_{t+1})] \tag{P1}$$
$$s.t.\ \ c_t + R_{n_t t} + \tau e_t \leq w_t$$
$$w_{t+1} = \Omega(w_t,a_t,e_t,S_{n_t t},\varepsilon_t),$$

taking as given spillovers and rental rates in the two neighborhoods, $S_{n_t t}$ and $R_{n_t t}$ for $n_t = A,B$.

3.2 Equilibrium

We are now ready to define an equilibrium.

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 and spillover's sizes in neighborhoods A and B, $\{R_{nt}\}_t$ and $\{S_{nt}\}_t$ for $n = A,B$, and a sequence of distributions $\{F_t(w_t,a_t)\}_t$ that satisfy:*

1. *agents' optimization: for each t, the policy functions e_t and n_t solve problem (P1), for given R_{nt} and S_{nt} for $n = A,B$;*
2. *spillovers' consistency: for each t, equation (2) is satisfied for both $n = A,B$;*
3. *market clearing: for each t, $R_{Bt} = 0$ and R_{At} ensures housing market clearing in neighborhood A*
$$M = \int\int_{n_t(w_t,a_t)=A} F_t(w_t,a_t)dw_t da_t; \tag{3}$$
4. *wage dynamics: for each t,*
$$w_{t+1} = \Omega(w_t,a_t,e_t(w_t,a_t),S_{n_t(w_t,a_t)t},\varepsilon_t). \tag{4}$$

From now on, we focus on equilibria where the housing market in neighborhood A clears with positive rental rate, that is, $R_{At} > 0$ for all t, which requires also $S_{At} > S_{Bt}$ for all t.[27]

Assumptions 1 and 2 allow us to characterize the equilibrium in a fairly simple way, as shown in the following proposition.

[27] If $S_{At} \leq S_{Bt}$, 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*

$$e_t(w_t, a_t) = \begin{cases} e^L \text{ if } w_t < \hat{w}_t(a_t) \\ e^H \text{ if } w_t \geq \hat{w}_t(a_t) \end{cases}, \tag{5}$$

and

$$n_t(w_t, a_t) = \begin{cases} B \text{ if } w_t < \hat{\hat{w}}_t(a_t) \\ A \text{ if } w_t \geq \hat{\hat{w}}_t(a_t) \end{cases}. \tag{6}$$

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

Figure 9: Equilibrium Characterization

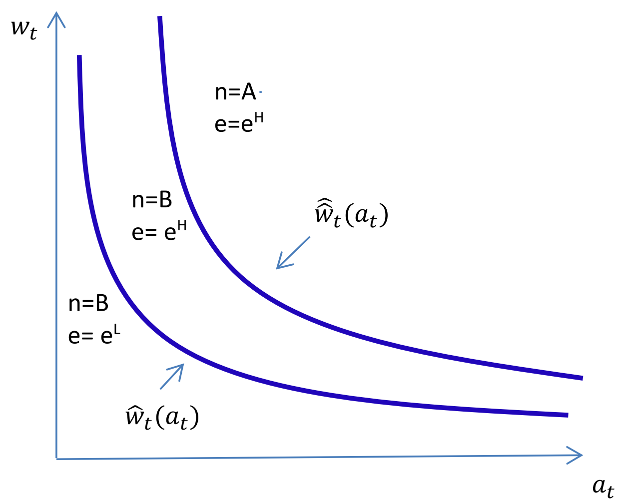


Figure 9 shows a graphical characterization of the equilibrium, for given spillovers and rental rates, with $R_{At} > 0$. The x-axis shows the children's ability level a_t and the y-axis the parents' wage w_t. For any given level of children's ability a_t, there are two thresholds for the parents' wage $\hat{w}_t(a_t)$ 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 invest in high-level education, parents with wage $\hat{w}_t(a_t) \leq w_t < \hat{\hat{w}}_t(a_t)$ choose to live in B and to invest in high-level education, and parents with wage $w_t \geq \hat{w}_t(a_t)$ choose to live in A and to invest in high-level education. The figure shows that children with richer parents and higher ability tend to be more educated and to live in neighborhood A. On the one hand, for given children's ability, richer parents are more willing to pay the cost of high-level education (τ) and the cost of a higher local externality (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 high-level education and for a higher local externality because of the complementarity between ability and education and between ability and local spillovers, respectively, implied by Assumption 2. For a given ability, a random child who grows up in B rather than A has lower probability of getting a high-level education, both because parents living in B are poorer on average and because the size of the local spillover is smaller, reducing the incentive to pay for education even further.

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 $\hat{\hat{w}}_t(a_t)$ 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 in ability 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 simple model, given the binary choice of education, neighborhood A will always be fully segregated, in the sense that all children will get high-level education. However, neighborhood B will generically feature a mix of children with the high- and the low-level of education. In particular, the degree of segregation by education is driven by the distance between the two cut-off functions $\hat{w}_t(a_t)$ and $\hat{\hat{w}}_t(a_t)$. For some parameter configurations, these two functions can coincide, in which case there is perfect segregation by education, as all children living in A will get high-level education and all children in B will not.

3.3 Skill Premium Shock

In this section we show the model's response to a skill premium shock, which is going to be at the core of the main quantitative exercise in the next section.

To simplify the analysis we set $e^L = 0$, $e^H = 1$, and make the following functional form assumptions: $u(c) = g(c) = log(c)$, and

$$\Omega(w, a, e, S_n, \varepsilon) = (b + ae\eta(\beta_0 + \beta_1 S_n)^{\xi})w^{\alpha}\varepsilon. \tag{7}$$

On the one hand, this implies that the wage of a child with low education ($e_t = 0$) is simply equal to $bw^{\alpha}\varepsilon_t$ and does not depend on either the child's ability or the size of the neighborhood spillover, satisfying Assumption 1. On the other hand, the wage of a child with high education ($e_t = 1$) is a function of the child's ability as well as of the spillover's size. Notice that β_1 and ξ are the key parameters affecting the strength of the spillover's effect. The specific functional form in (7) also satisfies Assumption 2. In particular, ability is complementary both to education and to the size of the local spillover.

With these assumptions, the cut-off functions that characterize the optimal education and residential choices can be characterized in closed form. Assume that for each ability level a, there is a positive measure of children with high education in neighborhood B.[28] In this case, the two cut-offs are:

$$\hat{w}_t(a) = \tau \left[1 + \frac{b}{a\eta(\beta_0 + \beta_1 S_{Bt})^{\xi}}\right], \tag{8}$$

and

$$\hat{\hat{w}}_t(a) = \tau + R_{At} \left\{ \frac{b + a\eta(\beta_0 + \beta_1 S_{At})^{\xi}}{a\eta[(\beta_0 + \beta_1 S_{At})^{\xi} - (\beta_0 + \beta_1 S_{At})^{\xi}]} \right\}. \tag{9}$$

Equation (8) shows that the education cut-off $\hat{w}_t(a)$ is decreasing in ability, as established in Proposition 1, given that the return to education is higher the higher is the ability level. Moreover, for given ability, the cut-off is decreasing in the local spillover effect in neighborhood B, that is, the higher is the spillover effect in B, the higher is the return to education in that neighborhood, and the higher is the willingness of parents living there to pay for their children's education. It also shows that, as expected, for given ability, the willingness of parents living in B to pay for education is higher when the parameters affecting the strength of the return to education and to the spillover, η, β_0, and β_1 are higher, and when the cost of education τ and/or the fixed component of the income of low-educated children b are lower. Equation (9) shows that also the residential cut-off $\hat{\hat{w}}_t(a)$ is decreasing in a, again in line with Proposition 1, as the return to the

[28]This case arises when the RHS of equation (8) is weakly smaller than the RHS of equation (9) for all ability levels. When instead this is not the case for some ability a, there is perfect segregation by education, that is, all children with that ability level who grow up in B get the low education level, and the residential and educational cutoff functions coincide and are equal to $\hat{w}_t(a) = \hat{\hat{w}}_t(a) = (\tau + R_{At})[1 + b/a\eta(\beta_0 + \beta_1 S_{At})]$.

larger spillover in neighborhood A is higher the higher is the level of ability. The equation shows that the location decision also depends on the trade-off between the spillover advantage relative to the cost of living in neighborhood A.

We are now ready to study the response of the economy to an unexpected permanent increase in the skill premium. Under the lens of the model, we can think of an increase in the skill premium as an increase in the parameter η in equation (7), where we interpret high education as college and low education as no college. How is the economy going to respond to such a shock?

First, there is a direct effect of the increase in the skill premium. Keeping the spillovers' size, the house rental price, and the educational and residential choices as given, inequality mechanically increases for two reasons. First, the income gap between college and non-college educated workers mechanically increases, that is, $\partial^2\Omega/\partial e\partial\eta > 0$, which is why we interpret a shock to η as a skill premium shock. Second, the return to the local spillover effect, which is complementary to education, is also higher, that is, $\partial^2\Omega/\partial S_n\partial\eta > 0$. This direct effect generates per se an increase in inequality because richer kids have a higher probability both to be college-educated and to live in neighborhood A where the spillover effect is larger.

The second effect comes from the change in the educational and residential choices, keeping the spillover levels fixed at their pre-shock values. Using equations (8) and (9), we can derive the response of the cut-off functions to an increase in η as follows:

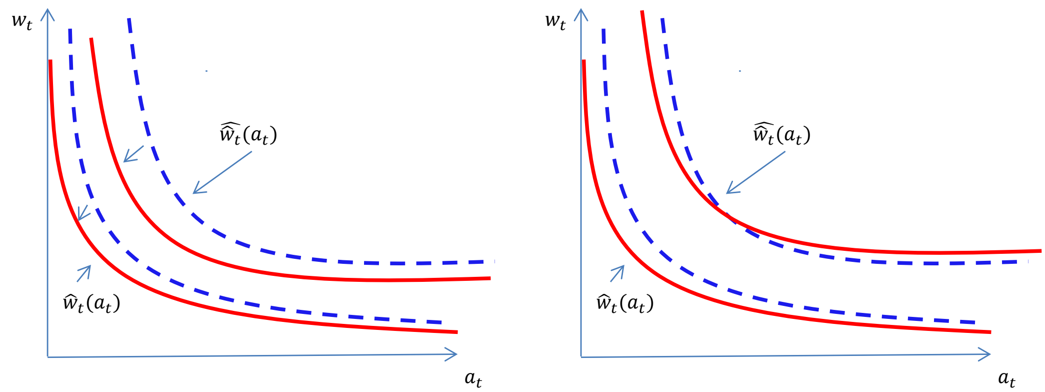
$$\left.\frac{d\hat{w}_t(a_t)}{d\eta}\right|_{S_{At},S_{Bt}} = -\frac{1}{\eta^2}\frac{\tau b}{a_t(\beta_0+\beta_1 S_{Bt})^{\xi}}, \tag{10}$$

and

$$\left.\frac{d\hat{\hat{w}}_t(a_t)}{d\eta}\right|_{S_{At},S_{Bt}} = -\frac{R_{At}b}{\eta^2 a_t[(\beta_0+\beta_1 S_{At})^{\xi}-(\beta_0+\beta_1 S_{At})^{\xi}]} + \left\{\frac{b+a\eta(\beta_0+\beta_1 S_{At})^{\xi}}{a\eta[(\beta_0+\beta_1 S_{At})^{\xi}-(\beta_0+\beta_1 S_{At})^{\xi}]}\right\}\frac{dR_{At}}{d\eta}. \tag{11}$$

These derivations show that in partial equilibrium, that is, when the rental rate is kept fixed ($dR_{At}/d\eta = 0$), both cut-off functions shift to the left, so that more children of any ability get higher education and live in neighborhood A. The change in the educational choice is intuitive: the higher the skill premium, the higher the return to college, conditional on any level of ability. Moreover, given that the local spillover is complementary to education, the higher the skill

Figure 10: Cut-off Response to Skill Premium Shock



(a) Partial Equilibrium (b) General Equilibrium

premium, the higher is the return to the spillover, and hence the higher is the demand to live in neighborhood A, conditional on any level of ability. Panel (a) in Figure 10 shows qualitatively the partial equilibrium response of the educational and residential cut-off functions to the skill premium shock, when spillovers in both A and B and rental rate in A are kept fixed at the pre-shock levels. The figure shows that both cut-off functions also become flatter after the shock, as it is easy to derive that $d^2\hat{w}_t(a_t)/da_t d\eta|_{S_{At},S_{Bt}} > 0$ and $d^2\hat{\hat{w}}_t(a_t)/da_t d\eta|_{S_{At},S_{Bt}} > 0$ if $dR_{At}/d\eta = 0$. This means that, with our functional form, the marginal impact of ability on the return to education is smaller when the skill premium is larger.

Next, we analyze the general equilibrium effect, coming from the response of the rental rate in neighborhood A to clear the housing market. Panel (b) in Figure 10 shows that, when we consider the general equilibrium, the residential cut-off function shifts back to the right but in a tilted fashion. As we explained above, 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 the spillover and education, shifting the residential cut-off to the left. Given that the housing supply in neighborhood A is fixed, this pushes up rental rates in that neighborhood, shifting the housing demand back to the right. In particular, the figure shows that the shift back is more pronounced for the poorer parents, who won't be able to afford the higher cost of living in the rich neighborhood, irrespective of their children's ability. On net, this generates the tilting that we see in panel (b) in Figure 10, which leads to a higher degree of income segregation: after the shock, some richer families will move to neighborhood A even if their children do not have high ability at the expense of some talented children from poorer families who will be induced to move to neighborhood B. This implies that more children from rich families will be exposed to stronger spillover effects and will have even higher future income, while more poor children will grow up in neighborhoods with weaker externalities and will have worse prospects for their future. This, in turn, will amplify the increase in inequality and reduce intergenerational mobility.

The analysis so far kept the spillover size in the two neighborhoods as given and showed that if a skill premium shock hits a segregated economy, the degree of segregation by income increases and the response of inequality is amplified because of that. However, in our model the spillover sizes in the two neighborhoods respond endogenously to the shock. The increase in η increases the future wage of all the educated children, increasing the spillover size in both neighborhoods, S^A and S^B. The shift in the educational cut-off implies that more children get high education in neighborhood B, increasing even further the spillover in that neighborhood. Moreover, the tilting of the residential cutoff implies that neighborhood A will be populated by richer but less talented children. This has two effects. First, it tends to increase the spillover gap between the two neighborhoods: for given ability, children with richer parents who live in A have higher future income and children of poorer parents who live in B have lower future income (not only because of the direct effect of their parents' wage but also because they will have higher chance to get educated). Second, it tends to decrease the same gap, given that more talented children move from A into B, pushing in the opposite direction. The quantitative exercise in Section 4 will show that the sorting effect by income dominates, so that the spillovers' size in both neighborhoods will increase, but the one in neighborhood A will increase relatively more, generating an additional source of inequality amplification.

4 Quantitative Exercise

As the data show, the US experienced a steady increase in labor income inequality starting in 1980. Many factors have contributed to this increase, but in this paper we focus on skill-biased technical change, which is widely recognized to be a crucial source of inequality (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 section, we generalize the simple model to explore the quantitative response of the economy to an unexpected, one-time, permanent shock to the skill premium, as described in subsection 3.3. We show that the model is able to replicate well the dynamics of inequality and segregation and the patterns of the intergenerational mobility across income groups. We also validate the model using data on the dynamics of housing prices and neighborhood sizes.

4.1 General Model

For the quantitative analysis, we generalize the model in a number of dimensions to make it more suitable to capture important features of the data.

First, we extend the analysis to a city with three neighborhoods instead of two to allow for richer sorting dynamics. Neighborhood n is now $\in \{A,B,C\}$. Having an intermediate neighborhood makes the geographic decisions of the agents less extreme, allowing for more realistic sorting dynamics. We focus on equilibria where $R_{At} > R_{Bt} > R_{Ct}$ and $S_{At} > S_{Bt} > S_{Ct}$ for all t, so that kids who grow up in neighborhood A are the ones with highest expected income and the ones who grow up in C the ones with the lowest.

Second, we generalize the formalization of the housing market, allowing for a general upward-sloping housing supply curve in each neighborhood. In particular, the housing supply curve in neighborhood n at time t is given by

$$H_{nt} = \lambda_n \left(\frac{R_{nt}}{\bar{w}_t} \right)^{\phi_n},$$

where ϕ_n represents the housing elasticity in neighborhood n, λ_n is a shift parameter in the same neighborhood, and $\bar{w}$ is the average parental wage in the city at time t.[29] This implies that neighborhoods sizes become endogenous and the model generates dynamic patterns that we can compare with the data.

Third, we introduce two different forms of preference shocks. The first type of preference shock is meant to capture that all agents prefer the richer neighborhoods to the poorer ones for reasons other than the education spillover, that is, fixed amenities, such as parks, water access, restaurants,

[29] We normalize the housing rental rates by average wages so that if all prices increase proportionally to wages, there are no real effects on the neighborhood sizes.

or even status considerations. In particular, we assume that utility from current consumption for an agent who chooses neighborhood n is given by $log[(1+\theta_n)c]$, where $\theta_A > \theta_B = 1 > \theta_C$ with probability π and $\theta_A = \theta_B = \theta_C = 1$ with probability $1-\pi$.[30]

The second type of preference shock is an idiosyncratic component that is iid across neighborhoods and agents. In particular, the utility of an agent is now given by

$$log[(1+\theta_n)c] + log[\Omega(w,a,e,S_n,\varepsilon)] + \sigma_\zeta \zeta_n,$$

where Ω satisfies condition 7 and ζ_n follows a Type-I Extreme Value distribution with scale parameter σ_ζ. This shock introduces some additional randomness that is not systematically related to some particular ranking of the neighborhoods and helps making the model analytically tractable.

Both these types of preference shocks help obtaining 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 simple 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. By missing this feature of reality, the simple model might generate a distribution of children growing up in neighborhood A biased towards too high ability and biased towards too high levels of education investments.

Fourth, we make the educational choice continuous to allow for richer investment decisions in education, which we believe are particularly important given the nature of our mechanism. In the simple model with binary educational choice, rich parents are constrained in how much they can invest in their children's education, given that the best they can do is to pay for their college. This means that the binary choice would arbitrarily bound the possible increase in the spillover in response to a skill premium shock. To overcome these limitations, we now assume that the educational choice is continuous, with $e \in R_+$ and that the cost of education is τe^γ.[31] The optimal educational level turns out to be increasing in the parents' wage, innate ability, and, more importantly, in the size of the local spillover because of the complementarity assumption. This

[30] This shock alone would generate residential segregation, even in the absence of local spillovers. In Section 6.1 we will explore a model where this is the only driver of residential segregation and spillovers are global.

[31] If one calibrates the baseline model would obtain too much intergenerational mobility. The continuous educational choice is more appealing also in light of the evidence in Duncan and Murnane (2016) that there has been an increasing polarization between educational investment in rich and poor families.

generates an amplification channel for the feedback between inequality and segregation. When the gap in local spillovers increases, parents living in neighborhoods with stronger spillovers invest more in their children's education, which in turns, increase further the gap in local spillovers.

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

$$U(w,a) = \max_{e,n} log((1+\theta_n)(w - R_{nt} - \tau e^{\alpha})) + log((b + ae(\beta_0 + \beta_1 S_{nt})^{\xi})w^{\alpha}\varepsilon) + \sigma_{\zeta}\zeta_n. \quad \text{(P3)}$$

The equilibrium definition is a natural extension of Definition 1 in Section 3.2, where the agents' optimization problem is given by P3, there are three neighborhood, and the housing market clearing conditions for the three neighborhoods are given by equation (4.1).

4.2 Calibration

We now describe our calibration strategy. As the rise in labor income inequality started in 1980, we assume that in 1980 the economy is in steady state and is hit by an unexpected, one-time, permanent shock to the skill premium. In particular, we change η to match the increase in the skill premium in the data between 1980 and 1990.

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 to the schooling period. Given our focus on the educational investment, we choose to interpret one period as 10 years.[32] 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 the economy and η increases to $\eta' > \eta$, so that the skill premium goes from 0.39 in 1980 ($t = 0$) to 0.55 in 1990 ($t = 1$).

We choose parameters so that the steady state equilibrium of the model matches salient features of the US economy mostly in 1980.[33] Table 1 shows the targets of our baseline calibration, which we are now going to discuss.

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

[33]Below we explain that the data available for the rank-rank correlation and the neighborhood exposure effect give us only one data point that we interpret as an average between 1980 and 2000.

Table 1: *Calibration Targets*

Description	Data	Model	Source
Return to college 1980	0.391	0.391	Goldin and Katz (2009)
Return to college 1990	0.549	0.553	Goldin and Katz (2009)
Gini coefficient	0.376	0.376	Census 1980
Dissimilarity index by income	0.334	0.334	Census 1980
Income 25th/75th p	0.667	0.694	Chetty and Hendren (2018b)
Rank-rank correlation	0.341	0.336	Chetty et al. (2014)
Return to spillover 25th p	0.062	0.062	Chetty and Hendren (2018b)
Return to spillover 75th p	0.046	0.046	Chetty and Hendren (2018b)
Neighborhood A size 1980	0.194	0.193	Census 1980
Neighborhood A size 1990	0.217	0.215	Census 1990
Neighborhood B size 1980	0.301	0.301	Census 1980
Neighborhood B size 1990	0.250	0.278	Census 1990
Average population growth rate	1.089	1.089	Census 1980-2010
Share of rich in A 1980	0.437	0.459	Census 1980
Share of rich in B 1980	0.225	0.212	Census 1980
R_A/R_B	1.253	1.252	Census 1980
R_B/R_C	1.277	1.279	Census 1980
College share A	0.340	0.351	Census 1980
College share B	0.178	0.200	Census 1980
Dissimilarity index by education	0.243	0.266	Census 1980

The first two targets in Table 1 are the US college premia in 1980 and 1990 from Goldin and Katz (2009). In the model, we map the skill premium in 1980 to the steady state difference between the average log wage of college-educated individuals and the average log wage of the others. Given that the educational choice is continuous, 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, 17.8% of the population is college educated, as in the Census data.[34] Finally, we map the skill premium in 1990 to the same difference between the average log wage of college-educated individuals and the average log wage of the others one period after the shock, keeping the college cut-off $\hat{e}$ constant.

Next target is the 1980 value of the Gini coefficient that we have described in Section 2, as baseline measure of inequality by income for the average metro area. For the calibration, we restrict the sample to families with children because our mechanism emphasizes the parental

[34]To calculate this number, we look at the number of people above 25 year old who completed college at the census tract level.

decision of investment in the children' future. Another measure of inequality at the metro area that we target is the ratio of the average income for families in the top 25th percentile of the income distribution to the average income for families in the bottom 25th percentile.

Next, we target the 1980 value of the dissimilarity index by income. In order to calculate the dissimilarity index, we first map the three neighborhoods in the model, A, B, and C, to the data. For each MSA, we group the census tracts according to the share of rich families who live there, where we define as rich the families in the top 20th percentile of the income distribution of that MSA. In particular, for each MSA, we define neighborhood A the group of census tracts with more than 30% rich families, neighborhood C the group of tracts with less than 17% rich, and neighborhood B the group of residual tracts. Given that, as we have shown in Section 2, the rise in inequality and segregation have been driven by the top of the distribution, we choose the cut-offs of 17% and 30% to focus on that by having roughly 50% of the population in neighborhood C and splitting the rest between A and B. Once we have grouped the census tracts in three neighborhoods for each MSA, we calculate the dissimilarity indexes for all the MSAs and then average them, weighting by population. Once again, we restrict the sample to families with children.

Another feature of the US data we 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 et al. (2014).[35] In particular, they use children born between 1980 and 1982, calculate parent income as mean family income between 1996 and 2000 and child income as mean family income between 2011 and 2012, when the children are approximately 30 years old. Given that this correlation is calculated over several decades, we map it in the model to the average rank-rank correlation across 1980, 1990, and 2000, where the 1980 value corresponds to the steady state and the 1990 and 2000 values are calculated after the skill premium shock hits the economy.

A key target for our exercise is what we call the "return to spillover", that is, the effect of the neighborhood exposure on children's income in adulthood. This effect is difficult to measure in the data. Fortunately, there has been a recent growing literature that uses micro data to estimate it. In particular, we use the results from the quasi-experiment in Chetty and Hendren (2018b).

[35]The rank-rank correlation is the relationship between the rank based on income of children relative to others in the same birth cohort and the rank based on parents' income relative to others in the same birth cohort. We choose this statistic instead than the log-log correlation or other measures because, as emphasized by Chetty et al. (2014), it provides a more robust summary of intergenerational mobility.

Using tax returns data for all children born between 1980 and 1986, Chetty and Hendren (2018b) estimate the effect of local spillovers on children's future income, by looking at movers across US counties.[36] We focus on their estimations for families moving across counties within the same commuting zone, given that we use the metro area as our geographic unit of analysis. Their estimation implies that for a child with parents at the 25th percentile of the national income distribution, growing up in a 1 standard deviation better county from birth would increase household income in adulthood by approximately 6.2%. This number becomes 4.6% for a child with parents at the 75th percentile of the income distribution.[37] These are the values that we target in our calibration. Let us explain how we map these targets to our model. First, we map the "movers" in Chetty and Hendren (2018b) to the parents who decide to live in a neighborhood different from the one where they grew up, that is, the one chose by their own parents. Then, we calculate the standard deviation of the expected future wage of the children of "movers" at the 25th percentile and at the 75th percentile of the income distribution and divide that by the average wage of the parents.[38] Given that these children are born between 1980 and 1986, they will be in pre-Kindergarten to 12th grade, and hence exposed to the local spillover, in 1984-1998 and 1990-2004. Hence, as we do for the rank-rank correlation, we map these numbers to the average "spillover effects" in the model across 1980, 1990, and 2000, where again the values of 1990 and 2000 are calculated after the shock.[39]

Our model is able to match a higher spillover return for the lower percentile of the distribution. Given that innate ability is positively correlated with parents' income, one would expect

[36] Chetty and Hendren (2018b) control for selection effects by looking at families who move from one county to another with kids of different age, so that they were exposed for different fractions of their childhood to the new county. Building on this logic, they effectively use a sample of cross-county movers to regress children's income ranks at age 26 on the interaction of fixed effects for each county and the fraction of childhood spent in that county. The identification assumption is that children's future income is orthogonal to the age they move to a new county.

[37] See table II in Chetty and Hendren (2018b). The table also shows estimates for families moving across counties not necessarily within the same commuting zone. In Section 5.1, we explore how these alternative estimates would change our main results.

[38] The exposure effect is equal to $\frac{1}{\bar{w}}\sqrt{\frac{1}{2}\sum_{n\in\{A,B,C\}}(E(w'|n,m)-E(w'|m))^2}$, where $E(w'|n,m)$ is the expected income of children of movers (m) from neighborhood n, and $E(w'|m)$ is the average expected income of all movers (m).

[39] The fact that we match the rank-rank correlation and the spillover effects to averages in the model over the period 1980-2000 is the reason why we simultaneously calibrate the parameters of the model and the size of the shock. An alternative calibration strategy would be to calibrate all the parameters of the model so that the steady state matches only the targets for 1980, and using the rank-rank correlation from Chetty et al. (2014) and the spillover effects from Chetty and Hendren (2018b) as if they were numbers for 1980. This alternative calibration would generate a larger increase in the implied spillover effect after the shock, so our choice is conservative.

that the assumption of complementarity between ability and spillover would make the neighborhood effect stronger for richer families. However, this is true for the population, but not for the selected sample of movers that we use to map the Chetty statistics. Let us use the simple two-neighborhood model in Section 3 to explain the mechanism. As we have shown in Figure 9, the cut-off function that represents the residential decision is non-increasing in the space ability/parent's wage. This implies that families who tend to live in A are both richer and have children with higher ability. This also implies that in equilibrium rich families who decide to live in B instead of A have children with lower ability than a random rich family in the population. Moreover, a poor that moves from neighborhood B to neighborhood A will tend to have a child with higher ability than a richer one, also because she will have a higher ability cut-off to be willing to pay the higher housing cost. So, on average, poor movers from B to A will tend to have children with higher ability than rich movers from B to A, and hence higher return from the spillover.

In the model, the size of the neighborhoods are endogenously determined and evolve over time in response to the shock. We use micro data on the evolution of the share of population across census tracts to calculate the size of the three neighborhoods in terms of population for the average MSA. We target the population growth in the average metro area and the size of neighborhoods A and B both in 1980 and 1990.[40] We also target the share of rich families in the different neighborhoods in 1980.

Another important object in our model is the relative cost of housing in the different neighborhoods. We use housing values in 1980 at the census tract level from the Census data and convert them into rental rates.[41] Using the same methodology described above to aggregate census tracts, we calculate the ratio of rental rates in neighborhood A to neighborhood B and of neighborhood B to neighborhood C. We then average these ratios across MSAs weighting by population.

Finally, we use Census tract data to calculate the number of people above 25 years old who completed college residing in neighborhood A, B, and C for the average MSA. We then target the share of college educated individuals in neighborhood A and the share of college educated individuals in neighborhood B. Moreover, we can use these data to calculate the dissimilarity index by education for the average MSA, where the two exclusive categories are college educated

[40]The size of neighborhood C can be calculated as a residual.

[41]We use a standard coefficient of 0.05 for the conversion.

and non-college educated.[42]

Table 2: *Parameters*

Parameter	Value	Description
ρ	0.44	Autocorrelation of log ability
σ_v	1.06	St. dev. of log ability
σ_ε	0.65	St. dev. of log wage noise shock
α	0.25	Wage function parameter
β_0	0.14	Wage function parameter
β_1	0.07	Wage function parameter
ξ	1.07	Wage function parameter
b	1.90	Wage fixed component for no-college
γ	4.78	Education cost parameter
θ_A	1.20	Preference shock for neighborhood A
θ_C	0.46	Preference shock for neighborhood C
π	0.53	Preference shock probability
σ_ζ	0.15	St. dev. of idiosyncratic preference shock
λ_A	0.13	Shift parameter of housing supply in A
λ_B	0.30	Shift parameter of housing supply in B
ϕ_A	2.37	Elasticity of housing supply in A
ϕ_B	0.11	Elasticity of housing supply in B
ϕ_C	13.62	Elasticity of housing supply in C
η'	2.78	Skill premium shock
n	1.09	Average population growth

Table 2 shows the parameters that we are using to calibrate the model, their calibrated value, and their description. We normalized the value of η, τ, the mean of the ability process a_t, the mean of the noise shock to the wage process ε to be all equal to 1 in steady state. Moreover, λ_C is pinned down by normalizing the average wage to be equal to 2.44, which is its empirical counterpart in 1980.[43] Notice that we have 20 parameters to match 20 targets.

4.3 Skill Premium Shock

We are now ready to show the response of the economy to a skill premium shock. As we explained above, we assume that in 1980 the economy is in steady state and that, at the end of the period, is hit by an unexpected, one-time, permanent increase in η.

[42]The share of college educated individuals in neighborhood C can be backed out by the combination of these statistics, using the formula for the dissimilarity index.

[43]For details about the normalizations see Appendix C.

Table 3 shows the response of the economy to such a shock, one, two, and three periods ahead.

Table 3: *Response to a Skill Premium Shock*

	t = 0	t = 1	t= 2	t= 3
Return to college	0.391	0.553	0.591	0.610
Gini coefficient	0.376	0.402	0.431	0.447
Dissimilarity index	0.334	0.382	0.418	0.438
A/B spillover ratio	1.112	1.540	1.787	1.920
B/C spillover ratio	1.126	1.181	1.166	1.162
R_A/R_B	1.135	1.495	1.703	1.824
R_B/R_C	1.162	1.234	1.228	1.229
SizeA	0.193	0.215	0.230	0.235
SizeB	0.301	0.278	0.256	0.237
SizeC	0.506	0.507	0.514	0.528

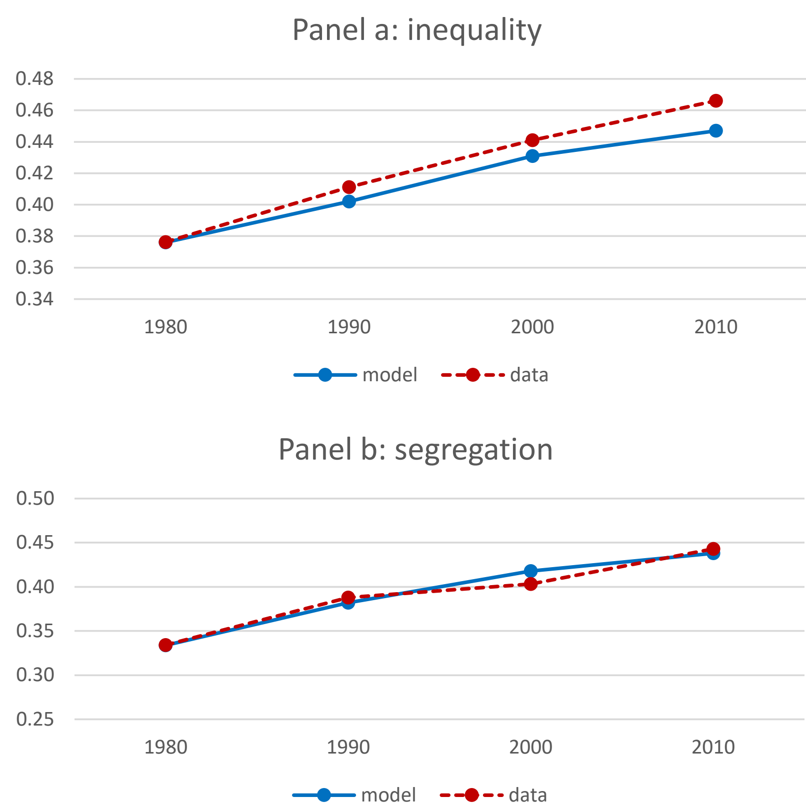
The first row shows the dynamics of the return to college. Remember that we choose the shock to match the increase in the return to college between 1980 and 1990 in the data. What is interesting is that the one-time unexpected permanent shock generates persistence in the return to college that keeps increasing after 1990, similarly to the data. In particular, the return to college is equal to 0.61 and 0.68 respectively in 2000 and 2010 (from Autor et al. (2020)), which is close to the predicted path in our model.

The second and third rows show the response of inequality and segregation, captured by the Gini coefficient and the dissimilarity index. To visualize these results, Figure 11 shows the model response (solid lines) of inequality and segregation to the shock together with their pattern in the data (dashed lines). While the values of inequality and segregation in 1980 are targets of the calibration, their path over time after 1980 is an outcome of the model and can be compared to the data as a form of validation.

Panel a shows that the dynamics of inequality in response to the skill premium shock in the model are close to the data. However, the model generates a bit less inequality growth, which is to be expected given that there are other sources of inequality increase that are outside the model. Panel b shows that the model generates a response of segregation to the skill premium shock that also well replicates the pattern in the data.

Table 3 also shows that in response to the shock, both the spillover in A relative to B and in B relative to C increase and so the respective rental rate ratios. At the same time, the size of

Figure 11: Responses to a skill premium shock



neighborhood A and C increase, while the size of neighborhood C shrinks. Moreover, these effects are persistent but declining over time.

As we have discussed in subsection 3.3 there is a rich feedback effect between inequality and segregation at the heart of our model. First, as the skill premium increases, inequality mechanically increases because college educated workers earn even more than the ones with no college. Given that educated workers are more likely to grow up in neighborhood A relative to B and in B relative to C, segregation by income also mechanically increases. Second, as the return to education increases and given the complementarity between the neighborhood spillover and education, the return to live in neighborhood A relative to B and in B relative to C increases. Given that housing supply is somewhat elastic, this shows up in part in a response of the housing supply and in part in a response of the rental rates. In particular, neighborhood A becomes more attractive relative to the others, so that its size increases but also its rental rate increases more than the others. This implies that some households move to A because it is more attractive, but at the same time some poorer households who previously lived in A may be pushed out into neighborhood B or C because of the higher rental rate. On net, the size of A increases. At the same time, neighborhood B becomes more attractive than neighborhood C, which implies that the rental rate in B increases relative to rental rate in C. This again implies that more talented kids would be attracted to neighborhood B, but the increase in rental rate may actually force poorer kids, even talented, to move out from B to C. On net, the table shows that the size of B declines. These sorting patterns imply that segregation by income increases, and this will increase the spillover gaps between A and B and B and C, as shown in the table. Such an increase in spillover differentials feeds back into even higher future inequality.

The dynamics of the rental rate ratios and of the neighborhood sizes can also be compared to the data for further validation. Table 4 shows the dynamics of the rental rate in neighborhood A relative to B and in B relative to C and the sizes of the three neighborhoods. Comparing them with the correspondent model dynamics in Table 3 shows that the model, although stylized, is able to replicate these interesting patterns. In particular, the increase in inequality and segregation happened at the same time with an increase in concentration of the population in the more extreme neighborhoods. The population living in neighborhoods characterized by a percentage of rich between 17% and 30% went from 30% to 22%, while neighborhoods with an extreme concentration of either rich or poor households have expanded.

Table 4: *Neighborhood sizes and rental rates: data*

	1980	1990	2000	2010
R_A/R_B	1.253	1.282	1.326	(1.265)
R_B/R_C	1.277	1.318	1.343	(1.291)
SizeA	0.193	0.217	0.228	0.251
SizeB	0.301	0.250	0.229	0.215
SizeC	0.506	0.533	0.543	0.534

NOTE: The rental rate ratios in 2010 are in parenthesis because the definition of house prices in the Census changed in 2010 from single family housing units to a broader category including also condos and mobile homes.

4.4 Intergenerational Mobility

An important implication of the model is that the same mechanism behind the feedback between segregation and inequality also generates low intergenerational mobility. As living in neighborhoods with higher spillover is expensive, richer families can afford to expose their children to strong local spillover effects, while poorer families are forced to live in less attractive but more affordable neighborhoods. This inevitably makes it difficult for poor children to climb up the social ladder and easier for the richer children to perpetuate their status. One summary statistic that captures the degree of intergenerational mobility is the rank-rank correlation that we target in our calibration. A richer picture of the degree of intergenerational mobility is given by the intergenerational mobility matrix that reports the probability for a child to be in a given income quintile conditional on the parents income quintile. In Table 5 we show the intergenerational mobility matrix generated by the model. The table shows averages across the period 1980-2000 to make it comparable to the data. Table 6 shows the same matrix, as calculated using administrative data by Chetty et al. (2014).

Table 5: *Intergenerational Mobility Matrix: Model*

	Children's Quintile				
Parents' Quintile	1	2	3	4	5
1	34.0%	24.7%	19.3%	14.4%	7.6%
2	23.3%	22.9%	21.5%	19.1%	13.3%
3	18.2%	20.8%	21.6%	21.5%	18.0%
4	13.8%	18.2%	20.9%	23.2%	24.0%
5	8.3%	13.4%	17.9%	23.7%	36.6%

Table 6: *Intergenerational Mobility Matrix: Data*

	Children's Quintile				
Parents' Quintile	1	2	3	4	5
1	33.7%	28.0%	18.4%	12.3%	7.5%
2	24.2%	24.2%	21.7%	17.6%	12.3%
3	17.8%	19.8%	22.1%	22.0%	18.3%
4	13.4%	16.0%	20.9%	24.4%	25.4%
5	10.9%	11.9%	17.0%	23.6%	36.5%

Without targeting it, our model is able to replicate quite well the intergenerational mobility matrix, which is a good validation of the model. The main feature of the data, well matched by the model, is that the highest probabilities are in the diagonal and, in particular, in the two extreme quintiles. That is, children tend to stay with higher probability in the same income quintile of their parents and this is especially true for the highest and, even more, for the lowest quintile. The data shows that the probability for a child born from parents in the lowest quintile of the distribution to stay in the same income quintile (Q5-Q5 probability) is 36.5%, and the model implies 36.6%. This is an important number to take into consideration for policy prescriptions and in future work we will think how it is affected by alternative policies. Another important statistic is the probability for a child born from parents in the highest quintile of the distribution to stay in the same income quintile (Q1-Q1 probability), which is 33.7% in the data and 34% in the model.

Another implication of the model is that in response to the skill premium shock, intergenerational mobility declines over time. For example, the rank-rank correlation goes from 0.34 in 1980 to roughly 0.35 in 2010, while the Q5-Q5 probability goes from 29.2 in 1980 to 42.8 in 2010. Unfortunately, given the limited availability of data, it is hard to calculate a reliable time-series for the rank-rank correlation or for the intergenerational mobility matrix. 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. Moreover, Kulkarni and Malmendier (2022) use cross sectional variation to show that cities with higher homeownership segregation have lower intergenerational mobility.

5 Segregation's Contribution to Inequality

We now use the model to perform a number of exercises in order to answer our main question: how important is segregation in amplifying the effects of a skill premium shock to income inequality? We also explore the role of segregation in affecting intergenerational mobility. In the next subsection, we propose two main exercises that help us answer this question. Next, we explore a number of exercises to better understand the quantitative role of different channels in the model.

5.1 Main Counterfactual Exercises

In this section, we show the main counterfactual exercises that quantify the role of segregation in amplifying inequality. In the model, the presence of local spillovers generates sorting of richer parents into the better neighborhoods, generating residential segregation by income. As explained in detail in Section 4.3, segregation amplifies the response of inequality to a skill premium shock because of two main effects. First, even keeping fixed the strength of the spillover effects in the two neighborhoods, the increase in income segregation implies that more of the rich children will benefit from the exposure to the better neighborhood and will become even richer, while more of the poor children will be forced to grow up in worse neighborhoods, which will worsen their income prospects. Second, the higher degree of income segregation will, in turn, endogenously translate into a larger gap between the spillover effect in the different neighborhoods, further increasing inequality.

One natural way to assess the contribution of segregation to inequality is to shut down the residential choice of the households in response to the shock, which is going to mute the sorting process. We can do that either by randomly relocate households across neighborhoods or by not allowing agents to move away from the neighborhood where they grew up. We construct two counterfactual exercises corresponding to these two alternatives.

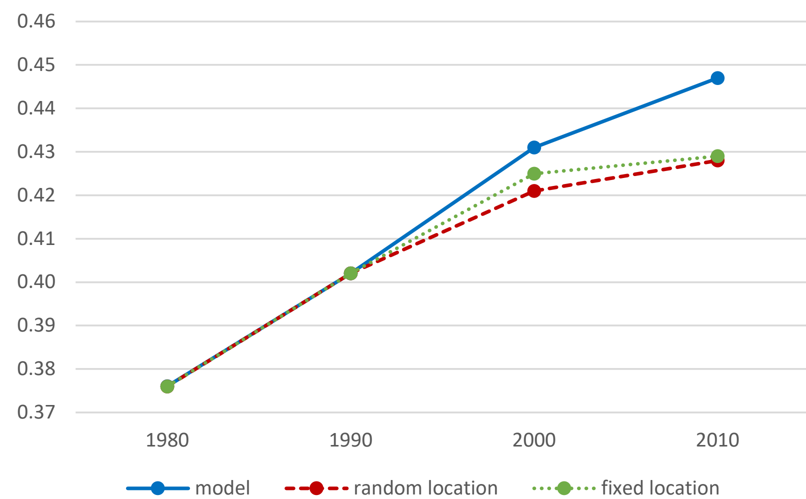
First, we consider a counterfactual exercise where at the moment of the shock and at any time after that, families are forced to be randomly re-located to the three neighborhoods.[44] This implies that the sizes of the local spillover effects in the three neighborhoods are equalized, given that the distribution of families is identical, and so is the expected income of the children growing up there. We impose that the rental rate in the three neighborhoods is the same and is equal to the rental rate that clears a single metro-wide housing market.

In this exercise, children are still exposed to a positive externality that evolves over time, but the strength of the spillover is the same for any location, so this becomes a global instead of local spillover. Parents' income still affects children's wages through the direct effect on the wage function Ω and through the educational choice, but the location is not relevant for their future earnings. This mitigates the effect of intergenerational linkages on income and hence mitigates

[44] We use the same parameters calibrated in Section 4.2, given that we assume that the economy is in the same steady state in 1980.

the response of income inequality to a skill premium shock.

Figure 12: Counterfactuals: Inequality



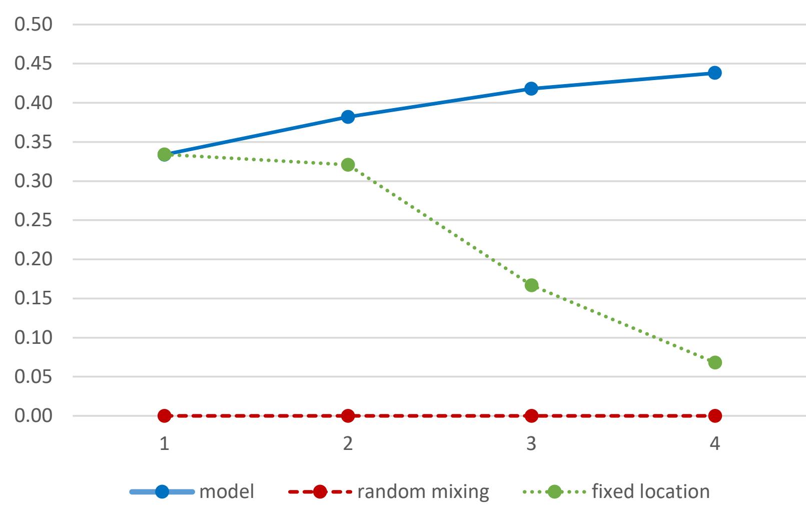
In in Figure 12 we compare the response of inequality to the skill premium shock in the baseline model (blue solid line) with the response of the economy when families are randomly re-located across the neighborhoods every period after the shock (red dashed line). The figure shows that segregation contributes to 27% of the increase in inequality over the whole period between 1980 and 2010 (long run from now on). The same exercise implies that segregation also amplifies the decrease in intergenerational mobility in response to the shock. In particular, it contributes to 32% of the increase in the rank-rank correlation between 1980 and 2010.

Second, we consider a counterfactual exercise where, after the shock, parents are not allowed to move to a neighborhood different from the one where they grew up, that is, locations are fixed. This implies that there is not housing market clearing and therefore we have to decide how to determine the rental rates dynamics. We choose to keep the rental rates in the three neighborhoods fixed to their steady state levels.[45] The green dotted line in Figure 12 represents the response of inequality in this exercise and shows that according to this counterfactual exercise, segregation contributes to 25% of the inequality increase between 1980 and 2010. Morevoer, we

[45]In Appendix D, we also explore the alternative exercise where we keep the neighborhoods' sizes constant at their steady state levels and choose the rental rates that clear the markets. Figure 24 shows that the contribution of segregation to inequality calculated with this alternative exercise is very similar.

calculated that segregation contributes to 33% of the increase in the rank-rank correclation in the same period. It is reassuring to notice that the two exercises generate similar results.

Figure 13: Counterfactuals: Segregation



Although the two counterfactual exercises deliver a similar pattern for the dynamics of inequality, the patterns of segregation are very different. Figure 13 compares the dynamics of the dissimilarity index in the baseline model and in the two counterfactuals. In the first exercise, where we randomly re-allocate households at every time after the shock, all neighborhoods end up having the same distribution of households and the dissimilarity index is constant and equal to zero (dashed red line). To be more conservative, we considered the second exercise, where we keep the location of households fixed and the level of the dissimilarity index at the time of the shock does not change. However, in this exercise, even if location is fixed, the dissimilarity index does not stay constant, but declines over time after the shock (dotted green line). This decline reduces the contribution to inequality.

The main reason why the dissimilarity index declines in the counterfactual with fixed location is the evolution of the distribution of ability across neighborhoods. In particular, in our model, given the complementarity between spillover and ability, the neighborhoods with higher spillover tend to attract families with children with higher ability. Once we shut down the sorting process, the average ability in the neighborhoods tend to converge over time, given mean reversion in the ability process.[46] One may think that endogenous education might be another reason behind the decline in segregation, but in Appendix D we show that quantitatively this is not the case.

A key moment behind these results is the estimate of the strength of the neighborhood spillover that we take from Chetty and Hendren (2018b). They find that growing up in a 1 standard deviation better county within the same commuting zone would increase adulthood's income by 6.2% for child in the lowest 25th percentile of the income distribution and by 4.6% for a child in the top 25th percentile. We also explore how these results change if we recalibrate the model targeting 10.4% and 6.4%, respectively for the lowest and the highest 25th percentile, which are the estimates that Chetty and Hendren (2018b) calculate by looking at families moving across counties, but not necessarily within the same commuting zone. In this case, the contribution of segregation to inequality is, as expected, even higher, and equal to 54% according to the first counterfactual exercise and to 53% according to the second.[47]

5.2 Understanding the Mechanism

We now show two alternative counterfactual exercises that complement the previous ones to better understand how local spillover amplify the effect of inequality on segregation. First, we explore what would happen to inequality if there were no local spillovers at all, and, second, if there were local spillovers, but they were not responsive to the shock. The first exercise is extreme, as it shuts down any form of externality, and the second one keeps the spillovers constant, only focusing on the endogenous response of the spillovers' strength.

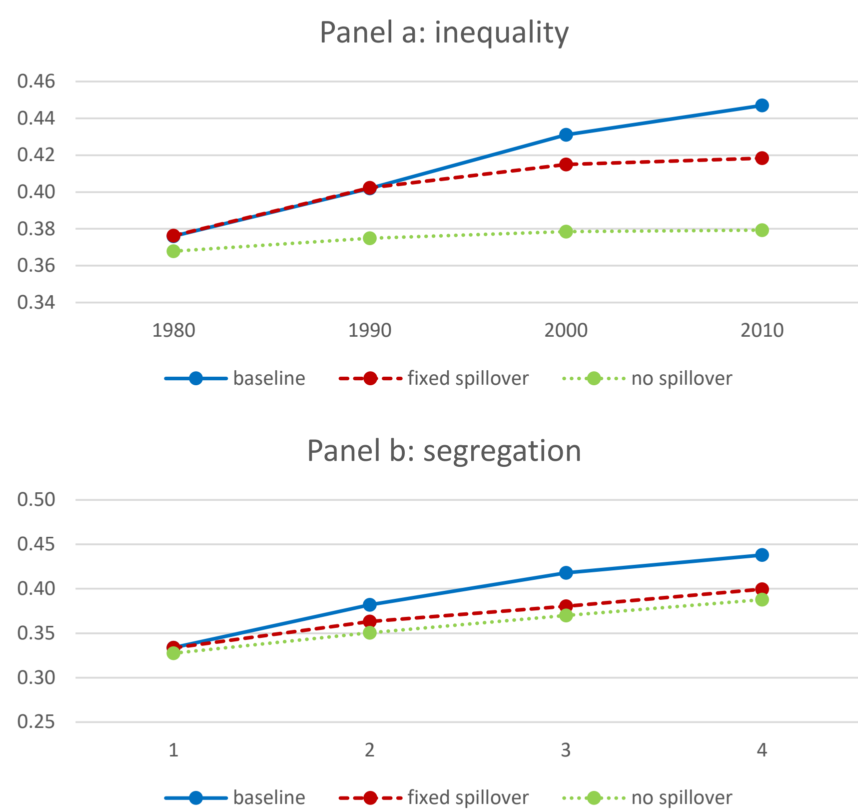
The first additional exercise is to consider an economy where there are no spillover effects at all, that is, where the wage function Ω is not affected by the spillover, or $\beta_1 = 0$. In this case, the only difference between the three neighborhoods is the existence of different "fixed amenities", which in our model are captured by the fact that a random fraction of the households always prefer to live in neighborhood A relative to B and in B relative to C. This generates some degree of segregation in the initial steady state that is purely driven by income: richer families would be the only ones willing to pay to live in the better neighborhoods. The blue solid lines in figure 14 report the response of the baseline model to the skill premium shock as in subsection 4.3, while the dotted

[46] See Figure 22 in Appendix D.

[47] For robustness, we also recalibrate the model using smaller values, respectively 5% and 3% for the lowest and the highest 25th percentile. In this case, the contribution of segregation to inequality are equal to 15% and 13% respectively with the two counterfactual exercises.

green lines show the response to the same shock of the economy with $\beta_1 = 0$ and all the other parameters unchanged. The figure shows that both inequality and segregation increase much less when there are no local spillover effects. In particular, we interpret the distance between the blue solid lines and the green dotted lines as the contribution of the existence of local spillovers to the increase in inequality. The figure shows that the existence of local spillover effects contribute for most of the increase in inequality in the model. This exercise is quite extreme as it rules out not only local spillovers, but any type of externality in education returns.[48]

Figure 14: Counterfactuals with no spillover and no spillover feedback



The second exercise that we consider aims to assess the contribution to the rise in inequality coming from the feedback effect due to the endogeneity of the local spillovers. To this end, we

[48]Figure 14 is realized without re-calibrating the parameters to focus on the decomposition of the response in the model. In the next subsection, we will consider a different exercise where we re-calibrate a model where the difference among neighborhoods is driven purely by amenities and the spillover effects to education returns are global.

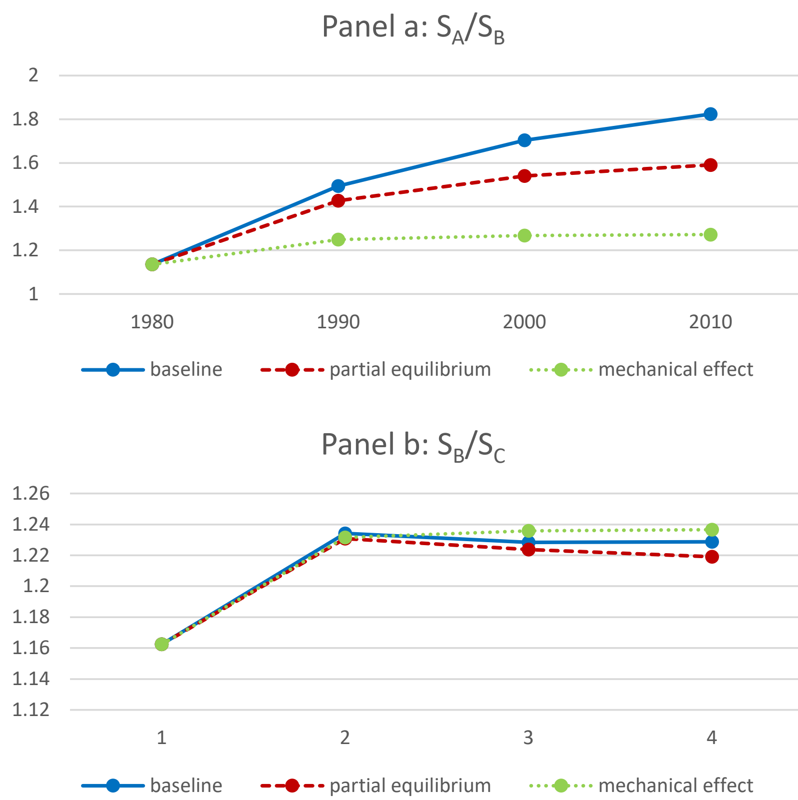
explore the response of the economy to the same skill premium shock if local spillovers were present but not changing endogenously, that is, if S^A, S^B, and S^C were fixed at their initial steady state levels. The red dashed lines in panel a and b of Figure 14 show the responses of inequality and segregation respectively in this exercise. When we compare them to the baseline model, we can interpret the differential response as the amplification due to the feedback effect coming from the endogeneity of the local externality. The figure shows that the spillover feedback effect contributes to 40% of the increase in inequality. Moreover, the contribution to the increase in segregation is 37%.

Why does the endogenous change in the spillover effects further amplify inequality? The local spillover effects in the three neighborhoods, S_t^A, S_t^B, and S_t^C, increase in response to the skill premium shock, given that all college educated workers have higher wages and, moreover, everybody invests more in education. However, the strength of the local spillover in neighborhood A increases relatively more than in neighborhood B and in B relative to C.[49] Table 3 reports the increase in the spillover ratios in response to the shock, which is illustrated by the solid blue lines in Figure 15.

We can decompose the response of S_t^A/S_t^B and S_t^B/S_t^C to the skill-premium shock in three effects. First, there is a mechanical effect: children in richer neighborhoods benefit more from the increase in the skill premium because they are more highly educated and are exposed to stronger spillover effects. This mechanically increases their expected income, and hence the strength of the spillover in the richer neighborhoods. The green dotted lines in the figure show the increase in the spillover ratios due to this mechanical effect, that is, fixing the rental rate and the optimal choices of the parents, but letting the spillover adjust. Second, there is an effect coming from the endogenous response of the optimal educational and residential choice of the parents. As the return to education increases, all parents increase their investment in education, but the richer parents, who are more concentrated in richer neighborhoods, do it even more, increasing the gap in returns. Moreover, parents will tend to move to neighborhoods with higher returns, so families will move from B to A and from C to B. This implies that the ratio S_A/S_B will increase even further, while the ratio S_B/S_C could go in either direction. The dashed red lines in Figure 15 show the increase in the spillover ratios due the sum of the mechanical effect and the effect

[49]The ratio S_t^B/S_t^C increases on impact in response to the shock and overall between 1980 and 2010, although is not always monotone.

Figure 15: Decomposing the increase in the spillover ratio



coming from the endogenous change in educational and residential choices, what we call partial equilibrium effect, and shows that the increase in S_A/S_B is amplified, while the ratio S_B/S_C starts declining after the first period. Finally, there is a general equilibrium effect coming from the increase in the rental rate in the richer neighborhoods, which increases the degree of sorting by income. Although the more talented children will benefit more from the increase in skill premium, only richer families will be able to pay the higher cost of living in richer neighborhoods, irrespective of their children's ability. This further raises the gap between the spillovers' strengths in the different neighborhoods. We can interpret the difference between the blue solid lines and the red dashed line as the contributions of the general equilibrium effect to the increase in the spillover ratio. The figure shows that the endogenous reallocation of households across neighborhoods due to the general equilibrium effect plays a crucial role in producing a large increase in the spillover ratio, contributing to 34% of the increase in S_t^A/S_t^B and to 15% of the increase in S_t^B/S_t^C between 1980 and 2010.

6 Alternative model specifications and robustness

In this section, we explore alternative versions of our main model to understand the role of some of our modeling choices. In particular, we explore a version of the model where segregation is driven purely by local amenities and a version of the exercise where we use our main model but we consider a shock to wage dispersion instead of a skill premium shock. For both cases, we show that our main exercise is able to better replicate important features of the data. Next, we investigate a version of the model where we mute the complementarity between ability and local spillovers, and a version of the model where we define the local spillover as the average income of parents living in the neighborhoods instead of the average expected income of the children growing up there. We find that our main results are broadly robust to both these alternative specifications.

6.1 Model with global spillovers and local amenities

In our model, spatial segregation is driven not only by the presence of local spillovers, but also by the presence of local amenities. In this section, we try to disentangle between the two by studying a version of the model where spillovers are global and not local and local amenities are the only source of segregation.

In particular, we consider a version of the model where the spillover is the same in all three neighborhoods and equal to the expected wage of the children in the city, $S_t = E_t(w_{t+1})$, so that future wages do not depend on the neighborhood where children grow up. Rental rates in different neighborhoods are still different but just to reflect the presence of different local amenities that make a random fraction π of the agents prefer neighborhood A to B and neighborhood B to C, given that $\theta_A > \theta_B > \theta_C$. This generates segregation by income, given that richer families can afford to pay higher rents to live in neighborhoods with better amenities. However, such a spatial segregation does not translate in differential returns to education. This implies that a skill premium shock does not affect directly the marginal advantage of living in a neighborhood relative to another. When the skill premium shock hits the economy, inequality increases making richer people even richer and willing to pay higher rental rates for better amenities. This, in turns, increases residential segregation. However, such an increase in segregation does not feedback in higher inequality because residential choices do not affect expected wages in this version of the model.

Figure 16: Local spillover vs local amenities

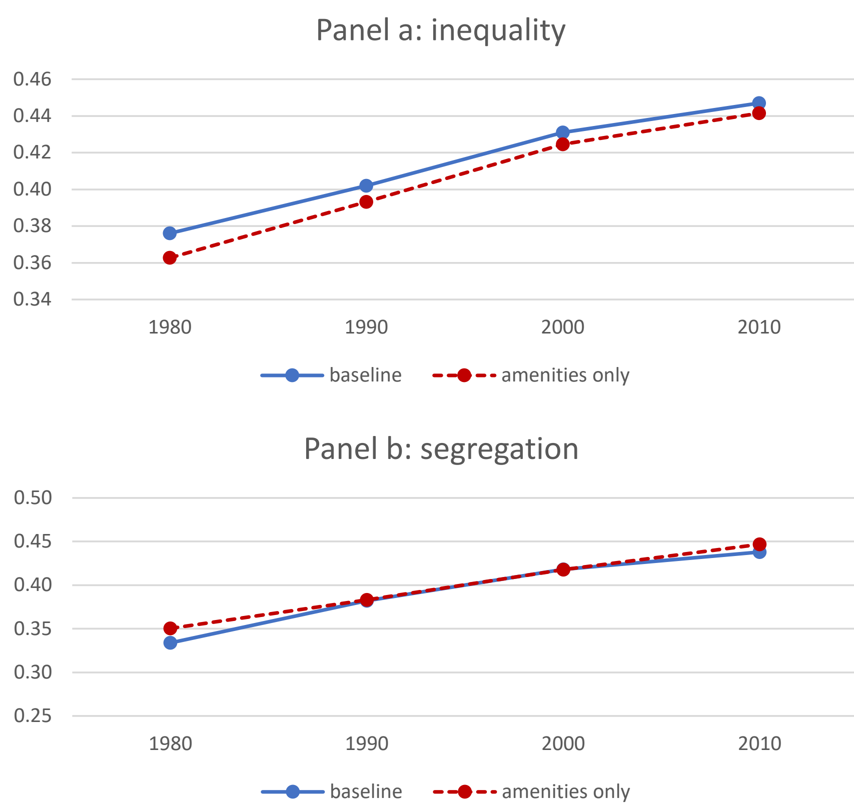


Figure 16 compares the pattern of inequality and segregation after the skill premium shock in the baseline model (blue solid lines) with the same patterns in the version of the model just described (red dashed lines). The figure shows that, after re-calibrating the model to hit the same moments as in the baseline exercise, inequality and segregation behave quite similarly in the two models. However, such a model would miss important features of the data that our baseline model with local spillover can generate. In particular, Table 7 shows that this model would not be able to replicate two salient patterns in the data: the increase over time in the size of neighborhood A and the increase over time of the ratio of rental rates in neighborhood A relative to B, that are documented in Table 4. As we have shown in Table 3 in Section 4.3, our baseline model can match both these dynamics. The reason is that when the skill premium increases, everybody wants to invest more in education. This implies that when educational spillover are equalized across neighborhoods, relatively poorer households may find more attractive to live in neighborhoods with worse amenities but cheaper housing, where they can afford to invest more in education, hence reducing the demand to live in neighborhood A. On the contrary, in our baseline model with local spillover, neighborhood A becomes relatively more attractive because of the complementarities between spillover and education, then being able to match the increase in demand to live in neighborhood A that is a feature of the data. In the next section, we will explore an alternative shock that does not affect directly the return to education.

Table 7: *Neighborhood sizes and rental rates*

	1980	1990	2000	2010
R_A/R_B	1.421	1.398	1.384	1.367
R_B/R_C	1.412	1.581	1.805	1.980
SizeA	0.193	0.183	0.174	0.163
SizeB	0.301	0.277	0.255	0.234
SizeC	0.506	0.541	0.573	0.602

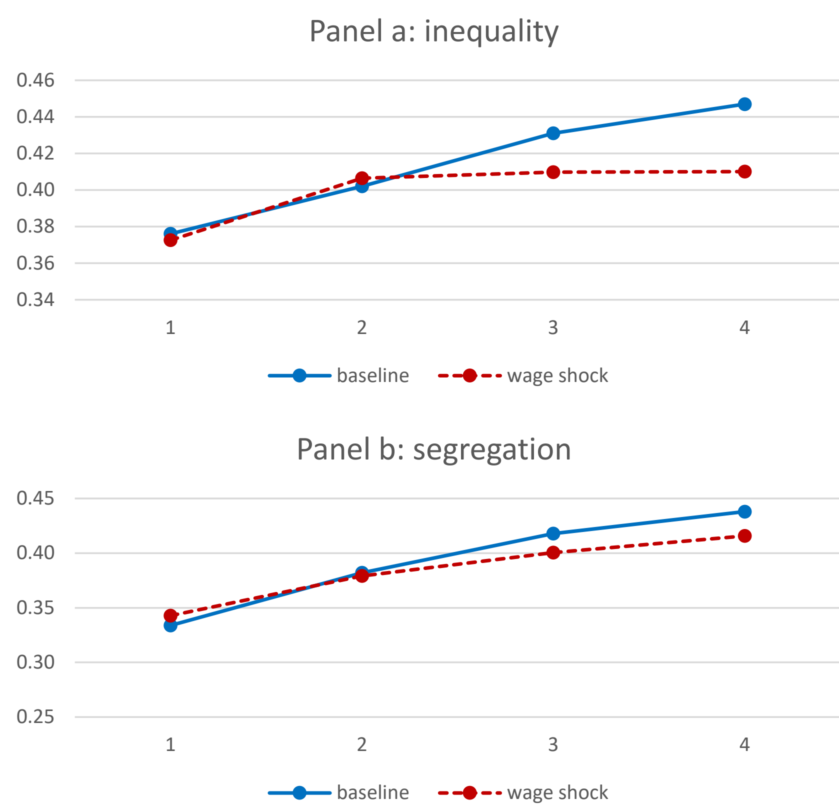
6.2 Different shock to inequality

Another important choice that we make in our baseline exercise is about the nature of the shock. One natural question is if the implied dynamics of the model would be similar if we considered a different type of inequality shock, for example a simple increase in the volatility of the noise of the wage process. It is interesting to notice that given the nature of our mechanism that is centered around the effect of local spillover on returns to education, such a shock has some different implications relative to a skill premium shock that affects directly the return to education.

Figure 17 shows the dynamics of inequality and segregation implied by our baseline model in response to an increase in the volatility of the wage noise σ_ε. The figure shows that both inequality and segregation increase less over time in response to such a shock relative to a skill premium shock, and this difference is quantitatively larger for inequality. This is due to the fact that a skill premium shock has a more persistent effect on educational investment, which increases the gap between rich and poor.

Another important difference with our baseline exercise is that, after a wage volatility shock, the model is not able to replicate the relative rental rates dynamics. Table 8 shows that after a

Figure 17: Shock to volatility of wage process



wage volatility shock both the rental rate ratio of neighborhood A versus B and of B versus C are decreasing over time in contrast with the data. This happens because there is no change in the return to education, so the pool of families that select into the better neighborhoods is mainly determined by income and not by ability. In contrast, in response to a skill premium shock, richer families with more talented kids tend to move to better neighborhoods, ending up investing more in education and increasing the spillover gaps between neighborhoods. This, in turns, feeds back into more future segregation and inequality, generating a persistent effect over time.

6.3 Role of complementarities

In the baseline model, we assume complementarity between the spillover and innate ability in the wage process. Although we believe this assumption is consistent with some recent empirical literature on skill formation (see papers cited in Section 3), we also find it interesting to relax it

Table 8: *Neighborhood sizes and rental rates*

	1980	1990	2000	2010
R_A/R_B	1.286	1.260	1.222	1.186
R_B/R_C	1.306	1.284	1.249	1.226
SizeA	0.193	0.207	0.205	0.210
SizeB	0.301	0.285	0.272	0.259
SizeC	0.506	0.507	0.523	0.531

and explore the case where spillover and ability enter linearly in the wage process. In particular, we assume that

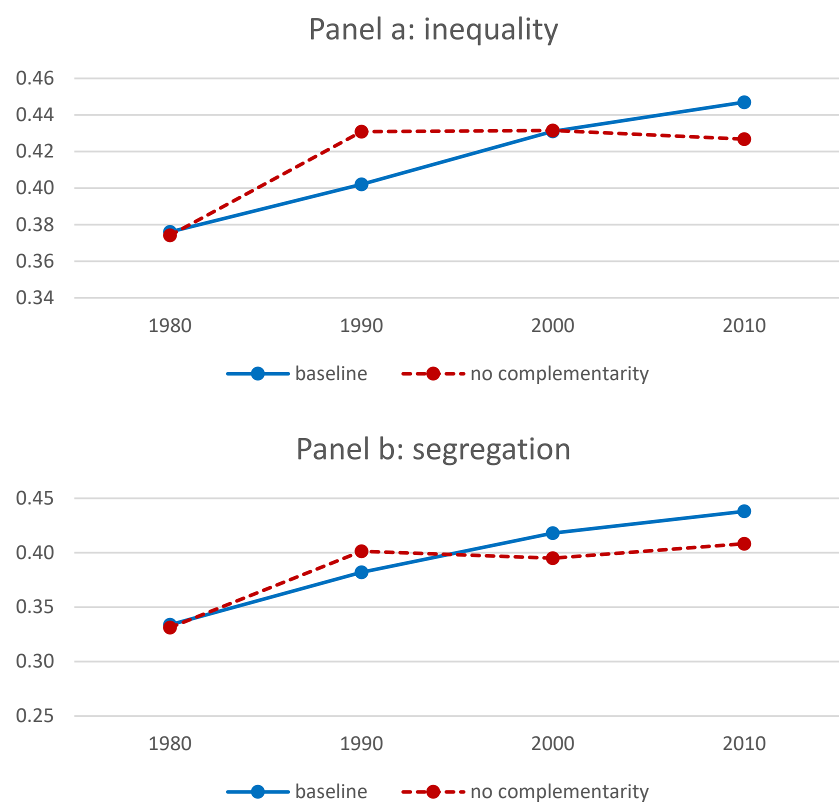
$$w_{t+1} = (b + e_t(a_t + (\beta_0 + \beta_1 S_{nt})^{\xi})w^{\alpha}\varepsilon$$

Figure 18 compares our baseline model with a re-calibrated version of the model with the above wage process. The figure shows that this assumption is not particularly crucial for the qualitative properties of the model because both inequality and segregation increase in response to the shock. However, the persistency of both inequality and segregation decrease substantially relative to our baseline. When ability and spillover are complementary, in response to the skill premium shock, families with more talented kids tend to move to the better neighborhood to exploit the higher spillover where the return to education is higher. This, in turns, increase the spillover gap and makes the effect persistent. However, when spillover and ability enter linearly the wage process, there is no particular incentive for families with more talented kids to move and so this effect is muted.

6.4 Alternative Spillover Specification

Our choice of spillover definition is motivated by the desire not to take a stand on the specific source of the local spillover, to better replicate the quasi-experiment studied in Chetty and Hendren (2018b). In particular, we define the spillover as average expected wage of the children growing up in a neighborhood. Future wages are affected both by the parental income, through a direct effect and an indirect effect on the residential and educational choice, and by the children's ability, that affect the returns to education and to spillover. This means that in our formulation both average ability and average parental income affect the size of the spillover, making it possible to capture a variety of mechanisms: peer effects, public school quality, networks,

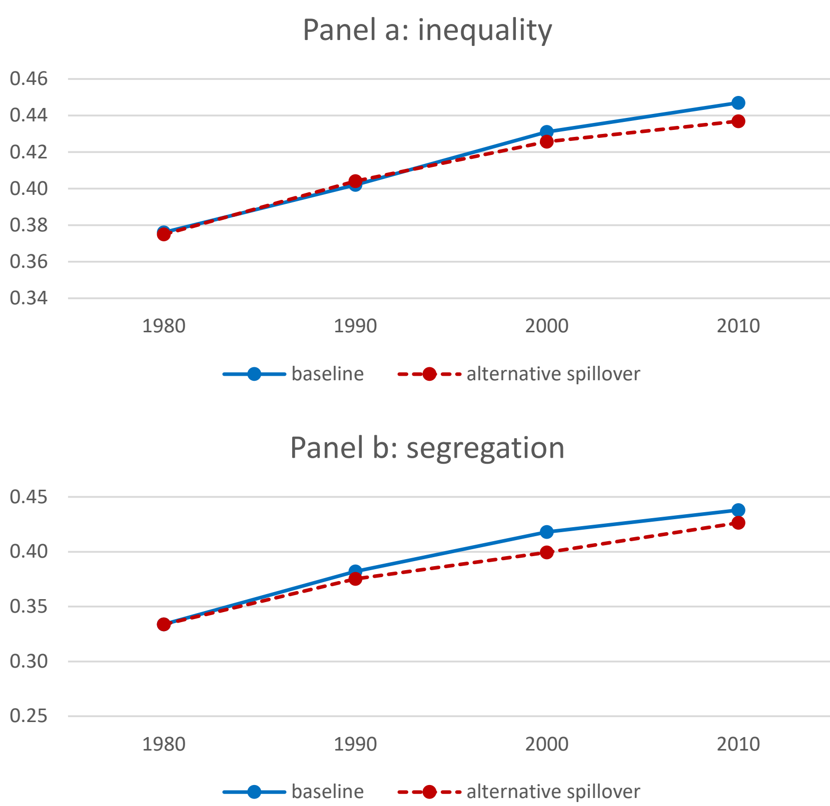
Figure 18: Role of complementarity in wage process



social norms, ... However, the past literature on local spillovers (e.g. Benabou (1996a), Benabou (1996b), Fernandez and Rogerson (1996), Fernandez and Rogerson (1997), Fernandez and Rogerson (1998), Eckert and Kleineberg (2021)) has focused on the effect of the quality of public schools. Given that public schools are locally financed, these papers define the spillover as the average parents' income in the neighborhood. In this section, we explore this alternative spillover specification and compare the implied dynamics of inequality and segregation in response to a skill premium shock to our main results.

Figure 19 compares the dynamics of inequality and segregation in the baseline model (blue solid lines) with the same dynamics in the model where the neighborhood spillover is defined as the average income of the parents living in the neighborhood (red dashed lines). The figure shows that in the baseline model there is more propagation of the skill premium shock both for inequality and segregation. This is expected, given that in the baseline model the spillover does not depends only

Figure 19: Spillover equal to parents' average income



on parents income but also on children's ability, which allows additional mechanisms to affect local spillover, such as, for example, peer effects. However, the figure shows that quantitatively the difference is not large, which could be interpreted as the fact that parents income is the most important factor in local spillover effects, for example by affecting the quality of public schools. For future research, it would be interesting to use micro data to better disentangle better these different effects.

If we run the same counterfactual exercises that we have performed for the baseline model in Subsection 5.1, we obtain that the contribution of segregation to the increase in inequality between 1980 and 2010 with this spillover specification is equal to 22% and to 16% relative to 27% and 25% respectively with the two exercise performed.

Overall, this exercise also shows that the relevance of our mechanism to explain the increase in inequality due to segregation is sizeable, irrespective of the specific definition of the local spillover.

7 Concluding Remarks

In this paper, we propose a model where segregation and inequality amplify each other because of a local spillover that affects the returns to education. We calibrate the model using US data in 1980, and using the micro estimates for neighborhood exposure effects in Chetty and Hendren (2018b). We then hit the economy with an unexpected permanent shock to the skill premium and look at the responses over time of inequality, residential segregation, and intergenerational mobility. We use a number of counterfactual exercises to show the role of local spillovers and of the resulting segregation in amplifying inequality. Our main exercises show that segregation contributes between 25% and 27% of the increase in inequality between 1980 and 2010, in response to a skill-biased technical change shock. We also consider a battery of alternative specifications of the model to check the robustness of our results.

There are multiple interesting directions for future research. One interesting dimension to extend the model would be to endogenize the cost of education, that has also increased over time, and think about possible feedback effects. Another interesting avenue for future work would be to push the normative implications of the model and think about alternative policy experiments that exploit the spatial nature of the model.

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Appendix (For Online Publication)

A Data Methodology

A.1 Segregation and Inequality over Time

Data sources and sample selection. We use tract level income data from Decennial Censuses (1980 to 2000) and from the American Community Surveys (ACS) for the 5 year period spanning 2008-2012. Our sample includes metropolitan areas using the 2003 OMB definition. Table 9 reports the sample size, in terms of number of MSAs, census tracts, and all families. Census tracts are small, relatively permanent statistical subdivisions of a county, and are designed to have an optimum size of 4,000 people. Census tracts are merged or added over time to keep population size constant. The number of census tracts has increased over time reflecting the increase in the population.

Table 9: All Families: Summary Statistics

Year	MSAs	Census Tracts	All Families
1980	379	42,406	46,154,644
1990	380	48,412	52,853,972
2000	380	53,033	59,087,771
2010	380	59,842	63,325,283

In our calibration, we restrict the sample to families with children. The data on families with and without children at the census tract level is available only for 2000 and 2010, but not for 1980 and 1990. The data in 2000 and 2010 are available for six groups at each income bracket level: 1) married couple family with own children under 18 years; 2) male householder (no wife present) with own children under 18 years; 3) female householder (no husband present) with own children under 18 years; 4) married couple family without own children under 18 years; 5) male householder (no wife present) without own children under 18 years; and 6) female householder (no husband present) without own children under 18 years. We calculate the number of families with children at the census tract - income bracket level as the sum of (1), (2), and (3). Families without children at the census tract - income bracket level are calculated as the sum of (4), (5) and (6).

Table 10: Families with children: Summary Statistics

Year	**MSAs**	**Census Tracts**	**Families with Kids**
1980	347	41,246	23,325,537
1990	373	47,184	24,922,747
2000	380	53,033	29,209,867
2010	380	59,842	29,155,384

For 1980 and 1990, this data is not directly available at the census tract level. However, the data is available for those years at a compound geographic level. In particular, from IPUMS NHGIS we use "Census Tract/Block Numbering Area (by State–Standard Metropolitan Statistical Area - County–Place)" for 1980 and "Census Tract/Block Numbering Area (by State–County–Metropolitan Statistical Area/Consolidated Metropolitan Statistical Area/Remainder–Primary Metropolitan Statistical Area/Remainder)"for 1990.

The data is available for 9 groups at each income bracket level as follows:1) married couple family with own children under 6 years old; 2)married couple family with own children between 6 and 17 years old; 3) male householder (no wife present) with own children under 6 years old; 4) male householder (no wife present) with own children between 6 and 17 years old; 5) female householder (no husband present) with own children under 6 years old; 6) female householder (no husband present) with own children between 6 and 17 years old, 7) married couple family without own children,; 8) male householder (no wife present) without own children; and 9) female householder (no husband present) without own children.

We extract the state, county, and census tract codes from the unique GISJOIN identifier. The unique GISJOIN identifier has information on state, county, census tract, and block code. Since we use compound geographic levels, there are multiple observations for census tracts that lie along multiple county subdivisions. For 1980, we have 47,974 observations with 41,246 unique census tracts. For 1990, we have 47,271 observations with 47,184 unique census tracts. We aggregate the counts of (1) - (9) at the census tract level using the extracted census tract codes. The data for families with children at the census tract - income bracket level is calculated by summing up (1) - (6). Families without children at the census tract - income bracket level is calculated by summing up (7) - (9).

The data on non-family households and all households is available at the census tract level for

1990. This means that we do not have to use the compound geographic level information for the two series and allows us to check if we have the correct numbers for families with and without children at the census tract level using the census tract codes extracted from the unique GIS identifier. We find that the sum of families with children, families without children, and non-family households is equal to the number of total households at the census tract level as shown in Table 11 below.

Table 11: Sample Size in 1990

Year	Metro	Counties	Census Tracts	Families		Non-Family Households	All Households
				with children	without children		
1990	373	870	47,184	24,922,747	26,684,647	22,122,914	73,730,308

Computing the Dissimilarity Index. The dissimilarity index uses the following formula

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

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. To use this formula, we must define poor and rich families within an MSA. To this end, we rank family income buckets from lowest to highest, and calculate the cumulative population across buckets. We then find the bucket with a cumulative share closest to our cut-off percentile (we calculated the dissimilarity index using the 50th, 80th, and 90th percentiles). All families with an income greater than the cut-off bucket are labeled "rich" and all families with a lower income are labeled "poor". This definition is then applied to all census tracts within the relevant MSA. The dissimilarity index is then calculated for each MSA and the results are aggregated to the national level using metro level population weights.

Computing the Gini The Gini coefficients in this paper are calculated following the method of von Hippel et al. (2017). First, a non-parametric estimation of the income CDF is calculated for each metropolitan area. The non-parameteric CDF is calculated using the function binsmooth, provided by von Hippel et al. (2017). This function linearly interpolates between the upper bounds of each income bracket to calculate the CDF, preserving the empirical cumulative distribution for each bin. It then uses the empirical mean income to calculate the implied upper bound for the support of the PDF, choosing the upper bound and the scale parameter so that the mean of the estimated CDF matches the empirical mean. Three methods are proposed to characterize the distribution of the top bracket: linear, Pareto, and exponential. The default method is linear and is what is used here. The binsmooth function returns a non-parameteric CDF function, which can be used to calculate the Gini coefficient (and the conditional mean income of the top-coded bracket). Define:

$$\mu = \int x f(x) dx$$

Then the Gini coefficient is calculated as:

$$G = 1 - \frac{1}{\mu} \int_0^E (1 - F(x))^2 dx$$

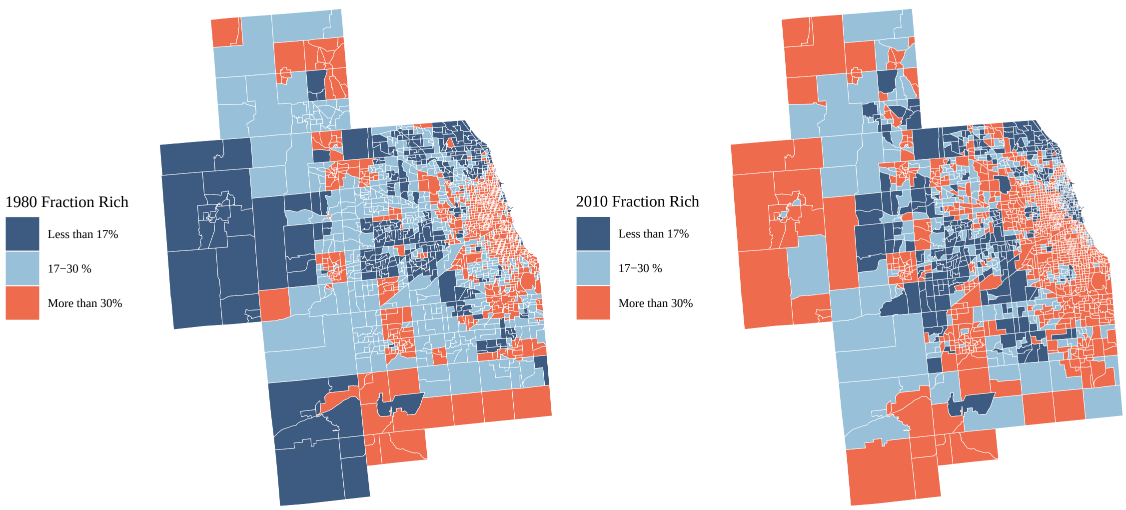
These integrals must be calculated numerically, however because the CDF is piecewise linear, the approximation error is small. Importantly, the μ from the non-parametric CDF matches the empirical mean. We calculate the Gini coefficient for each MSA, and then take the weighted average using metro level population weights to aggregate at the national level.

Example: Segregation in Chicago over time. The dissimilarity index captures the deviation from an even distribution of rich and poor families. Given that we define rich the families in the top 20th percent of the metro distribution, the index is equivalent, up to a constant, to a weighted sum of the deviations of the share of rich in all census tracts from 20%, with weights given by the census tract population relative to the metro population. Figure 20 plots the share of rich families in each census tract of Chicago in 1980 and 2010.[50] If there were no segregation, each census tract would have the same share of rich families equal to 20%. To visualize how segregation has changed over the period we use a heat map. We use orange to identify census tracts with a share of rich families higher than 30% (which correspond to neighborhood A in our calibrated model), dark blue for the census tracts with a share of rich families below 17% (which correspond to neighborhood C), and light blue for census tracts with a share of rich between 17% and 30% (which correspond to neighborhood B). We observe that over time the number of tracts with either high or low concentration of rich increases at the expenses of tracts with an intermediate

[50]To construct this figure we use the sample of all families.

fraction of rich. To do these figures, we keep the geography constant over time and map the 2010 distribution using the 1980 geographic borders. As we explained above, the census tracts are comparable in terms of population but not necessarily in terms of geographic area (larger in suburban and less densely populated areas). This is why for clarity we also report in Table 12 the number of tracts that corresponds to the three neighborhoods in 1980 and 2010.[51]

Figure 20: Share of Rich Families in Chicago



(a) 1980 (b) 2010

Table 12: *Number of Census Tracts by Fraction of Rich*

	A	B	C	Total
1980	360	607	894	1861
2010	421	380	1060	1861

A.2 Regression Analysis

To explore the relationship between segregation and inequality, we run several regressions. First, we regress the Gini coefficient on the dissimilarity index at the MSA level.[52] Table 13 shows

[51]Note that this measure is different from the one proposed by Reardon and Bischoff (2011) since it is not affected by changes in inequality. Their measure defines the rich in terms of distance from the median income in the metro. With the recent large increase in inequality, the share of people at the tails of the income distribution has increased even without changes in segregation. The measure we propose is not affected by this issue as it keeps constant the percentile to define the rich group.

[52]For this analysis, we define the cut-off between rich and poor as the 80th percentile. We use population weighting in the regressions, although the results do not change significantly if the observations are unweighted.

the results both without and with controls for racial and industrial composition. Racial shares are reported at the MSA level and are from the Decennial Census and the American Community Survey. Industry employment shares are from the Quarterly Census of Employment and Wages, provided by the Bureau of Labor Statistics. The results are largely similar to the regressions without controls.

Table 13: *Regression analysis: levels*

	Dependent variable: Gini_{1980}			
	(1)	(2)	(3)	(4)
$\text{Dissimilarity}_{1980}$	0.250^{***}	0.107^{***}	0.171^{***}	0.077^{***}
	(0.015)	(0.016)	(0.017)	(0.017)
Constant	0.300^{***}	0.562^{***}	0.151^{**}	0.346^{***}
	(0.005)	(0.023)	(0.063)	(0.059)
Race_{1980}	No	Yes	No	Yes
Industry_{1980}	No	No	Yes	Yes
Observations	379	379	379	379
R^2	0.421	0.632	0.607	0.724
Adjusted R^2	0.420	0.627	0.596	0.713
Residual Std. Error	9.637 (df = 377)	7.725 (df = 373)	8.044 (df = 367)	6.781 (df = 363)
F Statistic	274.303^{***} (df = 1; 377)	128.136^{***} (df = 5; 373)	51.629^{***} (df = 11; 367)	63.505^{***} (df = 15; 363)

Note: *p<0.1; **p<0.05; ***p<0.01 — Regressions use population weights

Table 14 shows the results of regressing changes in Gini coefficient between 1980 and 2010 on changes in dissimilarity index in the same period at the MSA level. We report the results both without and with controls for changes in the racial and industrial composition in the same period. Table 17 shows the crosswalk we used to construct consistent time series for the industrial composition for the MSAs. We also run regressions controlling for the initial level of racial and industrial composition and the results are robust to this change. Tables 15 and 16 report the summary statistics for the different variables in both regressions.

We also run the same regressions restricting the sample to families with kids and find larger coefficients. In particular, the coefficient for the level regression is 0.33 (0.12 with both conrols) and the coefficient for the regression in changes is 0.24 (0.20 with both controls).

A.3 School District Analysis

In our model, local spillovers are broadly defined to include many channels. However, school quality is an important one, which makes it interesting to explore the evolution of residential segregation by income at the school district level.

Table 14: *Regression analysis: changes*

	Dependent variable: $\Delta \text{Gini}_{2010-1980}$			
	(1)	(2)	(3)	(4)
$\Delta \text{Dissimilarity}_{2010-1980}$	0.176***	0.170***	0.158***	0.154***
	(0.017)	(0.018)	(0.016)	(0.016)
Constant	0.054***	0.054***	0.031***	0.031***
	(0.001)	(0.002)	(0.003)	(0.004)
$\Delta \text{Race}_{2010-1980}$	No	Yes	No	Yes
$\Delta \text{Industry}_{2010-1980}$	No	No	Yes	Yes
Observations	379	379	379	379
R^2	0.212	0.231	0.402	0.420
Adjusted R^2	0.209	0.221	0.384	0.396
Residual Std. Error	6.183 (df = 377)	6.139 (df = 373)	5.458 (df = 367)	5.407 (df = 363)
F Statistic	101.158*** (df = 1; 377)	22.431*** (df = 5; 373)	22.424*** (df = 11; 367)	17.493*** (df = 15; 363)

Note: *p<0.1; **p<0.05; ***p<0.01 — Regressions use population weights

Table 15: *Regression in levels: Summary Statistics*

Variable	Mean	Min	Max	Std
$\text{Dissimilarity}_{1980}$	0.27	0.01	0.50	0.07
Gini_{1980}	0.37	0.32	0.46	0.02
Pct. White_{1980}	0.86	0.33	0.99	0.11
Pct. Black_{1980}	0.10	0.00	0.44	0.10
Pct. Indian_{1980}	0.01	0.00	0.33	0.02
Pct. Asian_{1980}	0.01	0.00	0.60	0.03
Pct. Other_{1980}	0.03	0.00	0.38	0.05
Pct. Agriculture, Forestry, and Fishing_{1980}	0.02	0.00	0.41	0.05
Pct. $\text{Construction}_{1980}$	0.05	0.02	0.17	0.02
Pct. Finance, Insurance, and Real Estate_{1980}	0.05	0.02	0.19	0.02
Pct. $\text{Manufacturing}_{1980}$	0.24	0.00	0.60	0.12
Pct. Mining_{1980}	0.01	0.00	0.25	0.03
Pct. Nonclassifiable $\text{Establishments}_{1980}$	0.00	0.00	0.01	0.00
Pct. Public $\text{Administration}_{1980}$	0.06	0.00	0.49	0.06
Pct. Retail Trade_{1980}	0.19	0.11	0.35	0.03
Pct. Services_{1980}	0.27	0.11	0.53	0.06
Pct. Transportation and Public Utilities_{1980}	0.06	0.03	0.16	0.02
Pct. Wholesale Trade_{1980}	0.05	0.00	0.12	0.02

Dissimilarity Index at the School District Level. The National Center for Education Statistic (NCES) collaborates with the U.S. Census Bureau to provide demographic data for school districts. The data are provided from the 1990 and 2000 Decennial Census, as well as the 2008-2012

Table 16: *Regression in changes: Summary Statistics*

Variable	Mean	Min	Max	Std
ΔDissimilarity$_{2010-1980}$	0.05	-0.12	0.24	0.05
ΔGini$_{2010-1980}$	0.06	-0.01	0.10	0.02
ΔPct. White$_{2010-1980}$	-0.07	-0.27	0.22	0.05
ΔPct. Black$_{2010-1980}$	0.01	-0.10	0.16	0.02
ΔPct. Indian$_{2010-1980}$	0.00	-0.02	0.04	0.00
ΔPct. Asian$_{2010-1980}$	0.02	-0.06	0.24	0.02
ΔPct. Other$_{2010-1980}$	0.03	-0.22	0.19	0.03
ΔPct. Agriculture, Forestry, and Fishing$_{2010-1980}$	-0.01	-0.41	0.07	0.04
ΔPct. Construction$_{2010-1980}$	-0.01	-0.12	0.04	0.02
ΔPct. Finance, Insurance, and Real Estate$_{2010-1980}$	0.01	-0.11	0.08	0.02
ΔPct. Manufacturing$_{2010-1980}$	-0.12	-0.34	0.11	0.07
ΔPct. Mining$_{2010-1980}$	-0.01	-0.11	0.03	0.01
ΔPct. Nonclassifiable Establishments$_{2010-1980}$	0.00	0.00	0.00	0.00
ΔPct. Public Administration$_{2010-1980}$	0.00	-0.31	0.26	0.04
ΔPct. Retail Trade$_{2010-1980}$	-0.05	-0.17	0.06	0.03
ΔPct. Services$_{2010-1980}$	0.22	0.00	0.38	0.06
ΔPct. Transportation and Public Utilities$_{2010-1980}$	-0.02	-0.10	0.05	0.02
ΔPct. Wholesale Trade$_{2010-1980}$	-0.01	-0.07	0.05	0.02

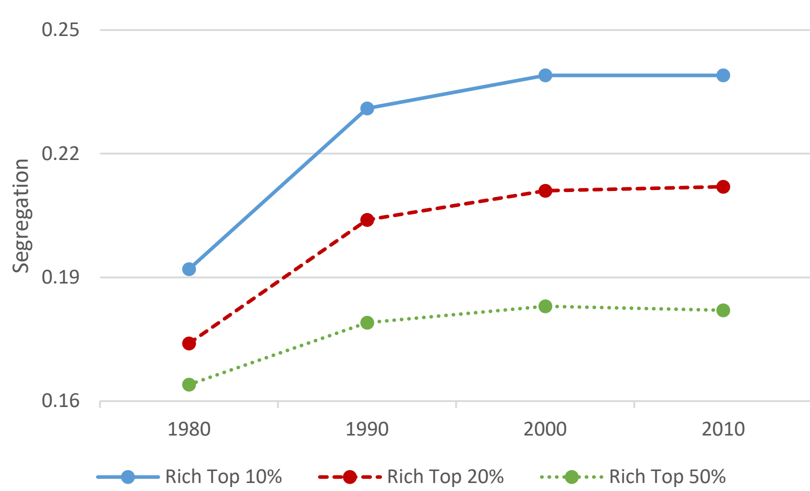
American Community Survey. The data for 1980 are taken from the Census of Population and Housing, Summary Tape 3F and are provided by ICPSR. After combining these files, we calculate the dissimilarity index for all families using school districts as the relevant sub-unit.[53] Figure 21 shows the results of these calculations. The first thing to note is that the overall trend is almost identical to what we get with census tracts. The main difference is that there is a greater increase in dissimilarity from 1990 to 2000 at the school district level and less of an increase from 2000 to 2010. One possible explanation for this trend is the increase in the attendance of private school which has taken place precisely in the last twenty years and mostly on the East Coast where there are some of the most populated metros in the US (which have larger weight in our estimates). The increase in the share of children attending private schools weakens the incentive to segregate across school districts lines.

[53] Income data for families with children are not available.

Table 17: Industry Crosswalk

NAICS Industry Classification	SIC Industry Classification
Real estate and rental and leasing Finance and insurance	Finance, Insurance, and Real Estate Division
Transportation and warehousing Utilities	Transportation and Public Utilities Division
Educational services Accommodation and food services Administrative and waste services Other services, except public administration Arts, entertainment, and recreation Professional and technical services Management of companies and enterprises Information Health care and social assistance	Services Division
Agriculture, forestry, fishing and hunting	Agriculture, Forestry, and Fishing Division
Construction	Construction Division
Manufacturing	Manufacturing Division
Mining, quarrying, and oil and gas extraction	Mining Division
Unclassified	Nonclassifiable Establishments
Public administration	Public Administration Division
Retail trade	Retail Trade Division
Wholesale trade	Wholesale Trade Division

Figure 21: Inequality and Segregation over Time



Census Tracts vs School Districts. Census tracts have several advantages over school districts as our unit of analysis. Census tracts are determined by the Census Bureau and are largely fixed over time. When initially determined, the Census aims to include roughly 4,000 people per tract and attempts to define the tract over a homogeneous population. Further, boundaries for census tracts generally follow local government boundaries, such as state, MSA, and county borders, allowing for a clean mapping between sub-units and metros.

In contrast, school districts are locally administered and their geographic structure can vary by region. Like census tracts, the definitions are relatively stable over time. However, many states have seen a significant consolidation in school districts over time. School districts follow state boundaries but not necessarily MSA lines, complicating our ability to cleanly map sub-units to metros. The degree to which school districts coincide with government boundaries differs across the nation. For instance, on the east coast, school districts tend to coincide with counties, townships, or city boundaries while in the Midwest they are almost entirely independent of municipal boundaries. Finally, the dissimilarity index can be misleading when there are not enough sub-units available. For example, consider an MSA that has a single school district. The dissimilarity index would necessarily be 0 in this case, since the population at the district level necessarily coincides with the population at the metro level. This result may potentially hide significant income segregation within the MSA. The literature has noted that over the past three decades segregation has increased both between school districts as well as between schools. Using census tracts will reflect these changes, whereas using school districts would mask the latter trend.

Table 18 reports summary statistics at the district level. The average number of districts in a metro is much smaller that the number of census tracts. This also explains why the sample size is not the same when using different geographic sub-units as districts may span across multiple counties, where only some of them may belong to a metro area, while the others do not. Several metros only have one school district and the dissimilarity index is necessarily equal to zero in such cases since the income distribution at the district level coincides with the income distribution of the metro.

Table 18: School Districts: Summary Statistics

Year	**MSAs**	**School Districts**	**All Families**
1980	379	6611	75,233,974
1990	379	6669	63,218,899
2000	379	6849	70,998,529
2010	380	6838	76,071,068

B Proof of Proposition 1

Given that we focus on equilibria with $R_t^A > R_t^B = 0$, we require $S_t^A > S_t^B$ for all t. Also, this together with Assumption 1 implies that agents who choose 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 notation, let us drop ε, given that it is iid, so does not play any role for the optimal policies. Consider an agent with wealth w and ability a who chooses *HA*. It must be that he prefers that to *HB* or *LB*, that is,

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

and

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

Take any $w' > w$. By concavity of u and $R^A > 0$, we have

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

and

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

Combining these conditions with the assumption that the composite function $g(\Omega)$ has increasing differences in w and S and in w and e (from Assumption 2), we obtain

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

and

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

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 (12) and (13) 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 non-increasing functions, and hence that $\hat{w}(a)$ is a non-increasing function as well.

Next, consider an agent with wealth w and ability a who chooses *LB*. By revealed preferences, he must prefer that to *HA* or *HB*, that is,

$$u(w-R^B)+g(\Omega(w,a,e^L,S^B)) \geq u(w-R^A-\tau)+g(\Omega(w,a,e^H,S^A)) \tag{14}$$

and

$$u(w-R^B)+g(\Omega(w,a,e^L,S^B)) \geq u(w-R^B-\tau)+g(\Omega(w,a,e^H,S^B)). \tag{15}$$

Following analogous steps to before, we can show that, for given a, all agents with $w' < w$ prefer *LB* to both *HA* and *HB*. Notice that the value w that makes equation (14) 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 (15) 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 non-increasing function, and hence that $\hat{\hat{w}}(a)$ is a non-increasing function as well. Given that both $\hat{w}(a)$ and $\hat{\hat{w}}(a)$ are non-increasing 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 non-increasing functions $\hat{w}(a)$ 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 $w > \hat{w}(a)$ choose $e = e^H$ and $n = A$ and all agents with (w,a) such that $w < \hat{\hat{w}}(a)$ choose $e = e^L$ and $n = B$.

C Normalizations

For convenience, let us report the optimization problem for a household with wage w and a child with ability a

$$u(w,a) = max_{e,n} \ln(w - R_n - \tau e^{\gamma}) + \ln\left(b + ae(\beta_0 + \beta_1 S_n)^{\xi}\right) + \alpha \ln w + \ln \varepsilon + \sigma_{\zeta} \zeta_n, \tag{16}$$

and her future wage

$$w'(w,a) = \left(b + ae(\beta_0 + \beta_1 S_n)^{\xi}\right) w^{\alpha} \varepsilon. \tag{17}$$

First note that average ability is not independent of β_0 and β_1, as we can scale a by a constant c_a and scale both β_0 and β_1 by $c_a^{-\frac{1}{\xi}}$ while leaving the optimization problem and the wage expression unchanged. Specifically, we can set $c_a = \frac{1}{\mu_a}$ so that the adjusted average ability is equal to 1.

Moreover, we can scale ε by a constant c_ε, and at the same time scaling b by c_ε^{-1} and both β_0 and β_1 by $c_\varepsilon^{-\frac{1}{\xi}}$, leaving again the problem unchanged. We can normalize the mean of ε to 1 by setting $c_\varepsilon = \frac{1}{\mu_\varepsilon}$.

Next, notice that we can multiply w by a constant c_w and scale b by $c_w^{-(1-\alpha)}$, β_0 and β_1 by $c_w^{\frac{-(1-\alpha)}{\xi}}$. This leaves the wage dynamics unchanged. Moreover, from the housing market condition, R_n is going to be automatically scaled up by the same constant and we can multiply τ by c_w, so that the optimization problem is unchanged as well. This means that we can choose $c_w > 0$ so that the average wage in the economy is equal to 2.44, the average income for a family with children in 1980, in $\$10,000s$.

Finally, we show that we can normalize $\tau = 1$. In particular, we can make the transformation $\tilde{e} = \tau^{\frac{1}{\gamma}} e$ and scale β_0 and β_1 by $\tau^{\frac{1}{\gamma\xi}}$. This leaves the optimization problem (where we now optimize over n and $\tilde{e}$ instead of n and e) and the wage equation unchanged.

D More on counterfactual exercise II

In Section 5.1, we show that in the second counterfactual exercise where we keep location fixed, segregation is not constant but declines over time. This is mainly driven by the endogenous dynamics of the ability distribution in the different neighborhoods. In particular, in our model, given the complementarity between spillover and ability, the neighborhoods with higher spillover tend to attract families with children with higher ability. This is even more true in response to the skill premium shock. Once we shut down the sorting process by fixing the families' location, the average ability in the neighborhoods tend to converge over time, given mean reversion in the ability process. Panel a in Figure 22 shows that average ability in the three neighborhoods in our baseline model in response to the skill premium shock tend to diverge, while panel b in the same figure shows that, once we keep fixed the family residential choice, average ability in the three neighborhoods tend to converge. The speed of this convergence is affected by the persistence of the ability process that we calibrated in Section 4.2.

Figure 22: Evolution of average ability in the neighborhoods

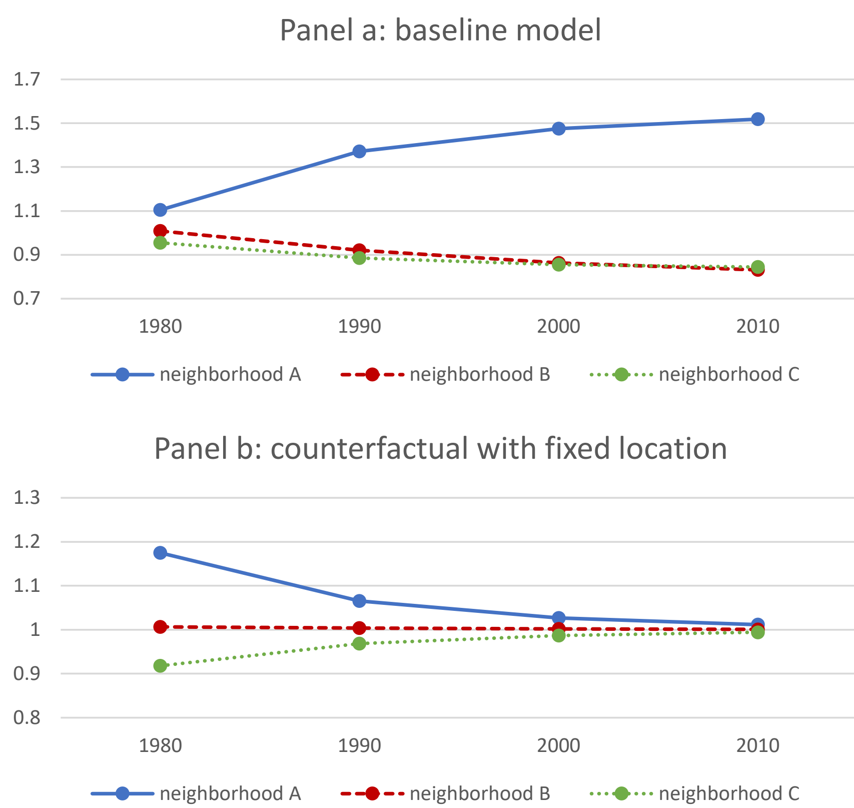
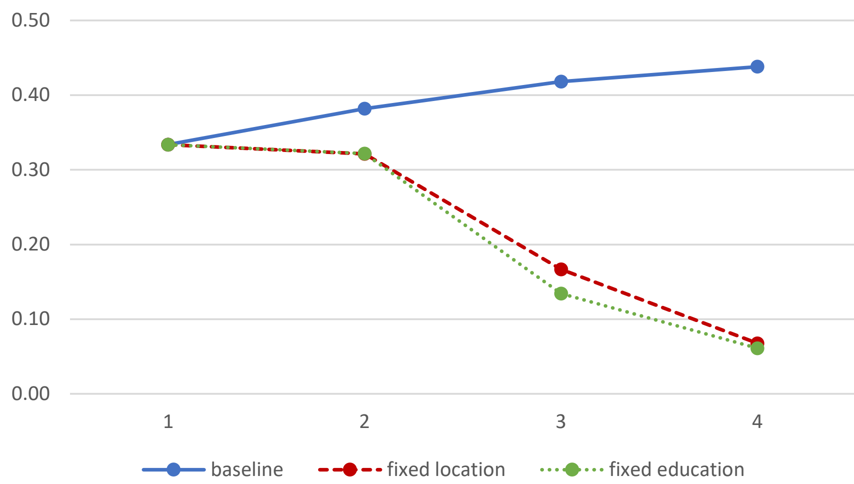


Figure 23 compare the dynamics of segregation in the baseline model and in the counterfactual with fixed location with an alternative counterfactual where keep fixed not only the families' location but also their investment in education. This figure shows that the pattern of segregation does not change much when we keep education fixed and, if anything, decreases even further. This implies that the endogenous choice of education cannot be behind the decline in segregation.

Figure 23: Segregation: fixed location and education



In the counterfactual with fixed location that we explore in section 5.1, we keep the rental rates in the three neighborhoods constant at their steady state values. In Figure 24 we explore an alternative version of the counterfactual, where we keep fixed the housing supply in the three neighborhoods at their steady state values and let the rental rates adjust to clear the housing markets. The figure shows that this choice does not quantitatively affect the results.

Figure 24: Segregation: fixed location and housing supply