Understanding the Great Gatsby Curve

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Abstract

The Great Gatsby Curve, the observation that for OECD countries, greater cross-sectional income inequality is associated with lower mobility, has become a prominent part of scholarly and policy discussions because of its implications for the relationship between inequality of outcomes and inequality of opportunities. We explore this relationship by focusing on evidence and interpretation of an intertemporal Gatsby Curve for the United States. We consider inequality/mobility relationships that are derived from nonlinearities in the transmission process of income from parents to children and the relationship that is derived from the effects of inequality of socioeconomic segregation, which then affects children. Empirical evidence for the mechanisms we identify is strong. We find modest reduced form evidence and structural evidence of an intertemporal Gatsby Curve for the US as mediated by social influences.

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1. Introduction

This paper is designed to provide insights into the relationship between cross-sectional inequality in the United States and the associated level of intergenerational mobility. Miles Corak's (2013) finding that there exists a positive correlation across OECD economies between inequality and mobility, dubbed The Great Gatsby Curve by Krueger (2012) (based on Corak's data), has not only received much scholarly attention, it has entered the realm of political discussions. The Great Gatsby Curve has had political traction in the US, because it has been interpreted as suggesting that high inequality of outcomes is not, in the American experience, offset by higher equality of opportunity or, following Bénabou and Ok (2001), upward mobility. The curve suggests that beliefs in the evitability of this tradeoff are illusory.

Substantive interpretation of the international Gatsby Curve is naturally problematic because of the heterogeneity of the countries described, even given their common OECD membership. Cross country comparisons suffer from the well understood limits to their ability to identify causal mechanisms in light of the heterogeneity of individual country experiences and the high dimensionality of factors that induce this heterogeneity.[1] A focus on a particular country, in principle, allows for understanding of the mechanisms that can produce a Gatsby Curve and hence allows for the assessment of possible government policies. Such a focus, though, changes the nature of the concept of a Gatsby Curve to an intertemporal one: a Gatsby Curve exists if an increase in cross-section inequality during one period in time is associated with an increase in the persistence in socioeconomic status between parents whose inequality is measured and their children.

This paper is designed to develop the argument that that an intertemporal Gatsby Curve is a salient feature of inequality in the US and that this relationship is causal. We claim that inequality within one generation determines the level of mobility of its children, and so argue that the Gatsby curve phenomenon is an equilibrium feature where mechanisms run from inequality to mobility. Our analysis proceeds at both theoretical and empirical levels.

[1] Durlauf, Johnson, Temple (2005) discuss specification econometric problems to cross country comparisons that justify this general skepticism.

The basic ideas underlying this paper are intuitive. Increases in cross-sectional inequality increase the magnitude of the differences in the characteristics of social contexts in which children and adolescents develop. This is so both because increased cross sectional inequality implies greater differences in the quality of social context experienced by the relatively rich and the relatively poor, conditional on to an initial income distribution, and because the degree of segregation of rich and poor into disparate social contexts is itself an increasing function of the level of cross sectional inequality and so can increase. We make these ideas concrete in the consensus of neighborhoods, so increased income inequality is linked to greater income segregation of neighborhoods which in in turn increases the intergenerational persistence of socioeconomic status.

Within economics, theoretical models of social determinants of persistent inequality emerged in the middle 1990's (Bénabou (1996a,b), Durlauf (1996a,b), Fernandez and Rogerson (1996,1997)). These models focused on the role of communities in forming human capital and determining member productivity.[2] This work, among other things, represented a good faith effort to couple substantive sociological idea with the formal economic reasoning[3]. In addition to continuing theoretical work, a substantial body of empirical studies has emerged in the last two decades which has uncovered a plethora of dimensions along which neighborhoods affect socioeconomic outcomes (see Durlauf (2004) and Topa and Zenou (2015) for surveys of the state of empirical findings). Somewhat separately, the last two decades have seen the emergence of a new "social economics" that explores a broad set of contexts in which sociological, social psychological, and cultural mechanisms have been integrated into economic analyses; Benhabib, Bisin, and Jackson (2011) provides a comprehensive overview of the field. Particularly relevant for this paper, much research in social economics has documented the presence of different types of peer influences in education (Epple and Romano (2011) survey the state of the literature).

[2]Of course, the idea that there are social determinants of behavior had appeared many times previously; see Becker (1974) for a seminal early contribution as well as discussion of social factors in the history of economic thought. Loury (1977) is particularly closely related to the work in the 1990's.

[3]The renaissance of neighborhoods research in sociology, for example Wilson (1987), was very influential in economics.

Our analysis is strongly motivated by and related to these literatures. More generally, the model we develop constitutes an example of what Durlauf (1996c, 2006) titled the “memberships theory on inequality”: a perspective that identifies segregation as an essential determinant of inequality within and across generations. We regard this perspective as a potentially important complement to the important developments over the last decade involving the study of cognitive and socioemotional skill formation in childhood and adolescence; see Heckman and Mosso (2014) for a synthesis which focuses on the skills formation/mobility relationship and Lee and Seshadri (2015) for a recent analysis.

Our theoretical model and stylized facts derive from a specific vision of the nexus between inequality and mobility, one in which segregation represents the fundamental causal mechanism linking inequality and mobility. In our conception, increases in cross-sectional inequality increase the magnitude of the differences in the characteristics of neighborhoods in which children and adolescents develop. This occurs for two reasons. First, increased cross-sectional inequality alters mobility because of interactions between parental input and neighborhood quality relative to an initial income distribution. Second, the degree of income segregation is itself a function of the level of cross-sectional income inequality and so can increase. Greater neighborhood disparities, because of their association with parental income, in turn increase the intergenerational persistence of socioeconomic status.

While we focus on education, the causal chain between greater cross-sectional inequality, greater segregation, and slower mobility may apply to a host of contexts. For example, there is some evidence of increasing assortative matching of workers by skill, which is a prediction of increasing skill heterogeneity or of technical change which increases complementarity between skills types. There is also evidence of increasing assortative matching by ability in colleges. Gary Becker’s (1973) demonstration of the efficiency of assortative matching in the presence of complementarity provides an argument for how increasing incentives for segregation are derived from inequality. Separate incentives for segregation exist when agents do not differentially benefit from shared activities. This occurs when more able students do not receive scholarships from schools that match them with less able ones.[4] On the other hand, incentives also exist for diversity, be it through larger groups or intrinsic benefits to differences. For neighborhoods, schools, and firms, there are good reasons to believe that greater inequality of income, of academic ability, of workplace skills increases segregation of types. For example, in their paper Reardon and Bischoff (2011) show that income inequality affects income segregation primarily through its effect on the large-scale spatial segregation of affluence. Once this happens, individuals are decoupled and the mobility of their descendants can take distinct paths.

Section 2 describes the environment that we study. Section 3 characterizes income dynamics for the environment. We then turn to empirical evidence that supports our perspective. Section 4 describes some broad stylized facts from the empirical literature. Section 5 presents a set of exercises that complement the broad stylized facts. Section 6 presents a calibrated model that links our general theory to some of the empirical patterns we have identified. Section 7 provides summary and conclusions.

2. Neighborhood formation and intergenerational income dynamics: model description

This section outlines an environment in which incomes evolve across generations in response to the social production of education. The purpose of this theoretical exercise is to demonstrate how an intertemporal Gatsby Curve can emerge, as an equilibrium property, from the level of socioeconomic segregation produced by the decentralized choices of individuals. As such, the model captures our general claim that segregation represents a causal explanation for the curve.

One way to understand our argument is to start with a linear model relating parental income Y_{ip} and offspring income Y_{io}

[4] Our point is that, regardless of whether there is complementarity or substitutability between individuals, equal division rules imply that more productive agents will wish to segregate themselves. See Gall, Legros and Newman (2007) for analysis of environments where inefficient segregation occurs.

$$Y_{io} = \alpha + \beta Y_{ip} + \varepsilon_{io} \tag{1}$$

As shown by Solon (2004), this linear relationship can describe the equilibrium of the Becker-Tomes model of intergenerational mobility, under suitable functional form assumptions. Note that ε_{io} is an MA (1) process. In this model, changes in the variance of income will not change β, of course, whereas changes in β will change the variance of income. As a statistical object, (1) can produce a Gatsby curve, but only one where causality runs from mobility to inequality.

In contrast, if the equilibrium model mapping of parent to offspring income is

$$Y_{io} = \alpha + \beta\left(X_i\right)Y_{ip} + \varepsilon_{io} \tag{2}$$

for some set of variables X_i, a causal mapping from changes in the variance of income to the measure of mobility β, i.e. the coefficient produced by estimating (1) when (2) is the correct intergenerational relationship, can exist. If $X_i = Y_{ip}$ $\beta\left(Y_{ip}\right)Y_{ip} = f\left(Y_{ip}\right)$, then (2) becomes a nonlinear family investment income transmission model.

Our theoretical model is based on Durlauf (1996a,b) which developed a social analogue to the class of family investment models of intergenerational mobility developed by Becker and Tomes (1979) and Loury (1981). By social analogue, we mean a model in which education and human capital are socially determined and thereby mediate the mapping of parental income into offspring economic attainment. Relative to (2), we thus implicitly consider X_i variables that are determined at a community level.

Our model's structure and equilibrium properties can be summarized simply with four propositions.

1. Labor market outcomes for adults are determined by the human capital that they accumulate earlier in life.

2. Human capital accumulation is, along important dimensions, socially determined. Local public finance of education creates dependence between the income distribution of a school district and the per capita expenditure on each student in the community. Social interactions, ranging from peer effects to role models to formation of personal identity, create a distinct relationship between the communities in which children develop and the skills they bring to the labor market.

3. In making a choice of a neighborhood, incentives exist for parents to prefer more affluent neighbors. Other incentives exist to prefer larger communities. These incentives interact to determine the extent to which communities are segregated by income in equilibrium. Permanent segregation of descendants of the most and least affluent families is possible even though there are no poverty traps or affluence traps, as conventionally defined.

4. Greater cross-sectional inequality of income increases the degree of segregation of neighborhoods. The greater the segregation the greater are the disparities in human capital between children from more and less affluent families, which creates the Great Gatsby Curve.

The model assumptions and properties thus create a causal relationship between cross-sectional (within generation) inequality, levels of segregation, and rates of intergenerational mobility.

Before proceeding, it is important to recognize that our social determination of education approach is only one route to generating equilibrium mobility dynamics of the form (2). Mulligan (1999) showed how credit market constraints, by inducing differing degrees in constraints for families of different incomes, could produce (2). In this case, X_i can be thought of as family income. While he did not consider the Gatsby Curve, it clearly could be produced in his model. Becker, Kominers, Murphy, and Spenkuch (2015) show how the Gatsby Curve behavior can emerge in a family investment model in which the productivity of human capital investment in a child is increasing in the level of parental human capital, which is another choice of X_i in (2). Both models, in essence, move beyond the conditions that map the Becker-Tomes model from a constant coefficient autoregressive structure to one in which the autoregressive coefficient varies across families. We will present empirical evidence that is supportive of the way we induce parameter heterogeneity in (2), but regard these other approaches as complementary to ours.

a. demography

The population possesses a standard overlapping generations structure. There is a countable population of family types, indexed by i, which we refer to as dynasties. Each family type consists of many identical "small" families. This is a technical "cheat" to avoid adults considering the effect of their presence in a neighborhood on the income distribution. It can be relaxed without affecting any qualitative results.

Each agent lives for two periods. Agent it is the adult member of dynasty i and so is born at time $t-1$.[5] In period 1 of life, an agent is born and receives human capital investment from the neighborhood in which she grows up. In period 2, adulthood, the agent receives income, becomes a member of a neighborhood, has one child, consumes and pays taxes.

b. preferences

The utility of adult it is determined in adulthood and depends on consumption C_{it} and income of her offspring, Y_{it+1}. Offspring income is not known at t, so each agent is assumed to maximize expected utility that has a Cobb-Douglas specification.

$$EU_{it} = \pi_1 \log(C_{it}) + \pi_2 E\left(\log(Y_{it+1}) \middle| F_t\right) \tag{3}$$

where F_t denotes parent's information set.

[5]For variables, the time index t refers to the period in which a variable is realized.

The assumption that parental utility is a function of the income of their offspring differs from the formulations such as Becker and Tomes (1979), which makes offspring human capital the argument in parental utility, as well as those which follow Loury (1981) in assuming that parents are affected by the lifetime utility of offspring. Our formulation retains the analytical convenience of Becker and Tomes, by ruling out the need for a parent to form beliefs about dynasty income beyond $t+1$, i.e. their immediate offspring. We prefer to directly focus on income as it captures our intuition that parents have preferences over the opportunity sets of their children as opposed to education per se, so in this sense our assumption is more in the spirit of Loury. This all said, we do not believe that there is a principled basis for distinguishing the different preference formulations.

Cobb-Douglas utility plays an important role in our analysis. By eliminating heterogeneity in the desired fraction of income that is spent on consumption, the political economy of the model becomes trivial. More general formulations could be pursued following Durlauf (1996a). The potential problem with more general specifications of preferences is the identification of general conditions that are sufficient for the existence of equilibrium neighborhood configurations. The Cobb-Douglas form is not unique in terms of ensuring existence, but is very convenient.

c. income and human capital

Adult it 's income is determined by two factors. First, each adult possesses a level of human capital that is determined in childhood, H_{it-1}. Income is also affected by a shock experienced in adulthood ξ_{it}. These shocks may be regarded as the labor market luck, but their interpretation is inessential conditional on whatever is assumed with respect to their dependence on variables known to the parents. We model the shocks as independent of any parental information, independent and identically distributed across individuals and time with finite variance.

We assume a multiplicative functional form for the income generation process.

$$Y_{it} = \phi H_{it-1} \xi_{it} \tag{4}$$

This functional form matters as it will allow the model to generate endogenous long term growth in dynasty-specific income. Equation (4) is an example of the AK technology studied in the growth literature.[6] We employ this technology in order to understand inequality dynamics between dynasties in growing economies.

d. family expenditures

A parent's income decomposes between consumption and taxes.

$$Y_{it} = C_{it} + T_{it} \tag{5}$$

The introduction of family-level parental investments, separate from the public provision of education, will be done in the next version of the model. This generalization will be interesting because of the interaction between private investments and neighborhood characteristics. Wodtke, Elwert, and Harding (2016) find complementarity between neighborhood quality and parental investment, suggesting that this extension will exacerbate the potential for segregation to reduce intergenerational mobility, although this intuition does not account for the effects of the complementarity on equilibrium sorting.

e. educational expenditure and educational investment in children

Taxes are linear in income and are neighborhood- and time-specific

$$\forall i \in nt,\ T_{it} = \tau_{nt} Y_{it} \ . \tag{6}$$

[6] See Jones and Manuelli (1992) for infinite horizon growth models and Jones and Manuelli (1990) for overlapping generations models with AK-type structures.

The total expenditure available for education in neighborhood n at t is

$$TE_{nt} = \sum_{j \in nt} T_{jt} \tag{7}$$

and so constitutes the resources available for educational investment. Figure 12 taken from the NCES shows that there is a lot of spatial variation in per capita public school expenditure. This is due to the fact that spending on public education, the major public program funded by local governments, is funded by local spending. Local spending in turn depends on local property tax rates. As shown in the report by the National Association of Home Builders from April 1, 2016 property tax rates differ substantially across the United States. That's why we allow for taxes to be neighborhood- and time-specific and for educational spending to depend on taxes.

The translation of these resources into per capita educational investment (which will constitute a school's direct contribution to human capital) will depend on the size of the population of children who are educated. Angrist and Krueger (1999) and Card and Krueger (1992) find evidence of small non-convexities in education in the US. Thus, we also assume that the education process exhibits non-convexities with respect to population size, i.e. there exists a type of returns to scale (with respect to student population size) in the educational process. Let p_{nt} denotes the population size of n at time t. The educational investment provided by the neighborhood to each child, ED_{nt} (equivalent to educational quality), requires total expenditures

$$ED_{nt} = \frac{TE_{nt}}{\nu(p_{nt})} \tag{8}$$

where $\nu(p_{nt})$ is increasing such that that for some positive parameters λ_1 and λ_2,

$$0 < \lambda_1 < \frac{\nu(p_{nt})}{p_{nt}} < \lambda_2 < 1$$

One interpretation of this functional form is that there are fixed and variable costs to education quality. For example, Andrews et. al. (2002) find evidence of economies of scale at the district level, and weaker evidence at the school level. Another is that there are educational benefits to larger communities. The reason for making this assumption is that it allows the number of neighborhoods and their sizes to be endogenously determined without any a priori restrictions on either. Standard models of neighborhood formation and neighborhood effects usually fix the number and size of neighborhoods. These limits, while empirically perfectly reasonable, implicitly build in exogenous constraints on the levels of segregation or integration. Since the core logic of the model is so closely tied to the consequences of inequality for segregation, we do not want any level of integration or segregation to be imposed a priori. In other words, we want the possibilities to exist that all families are combined in a common neighborhood or are completely segregated in separate neighborhoods.

f. human capital

The human capital of a child is determined by two factors: the child's skill level s_{it} and the educational investment level ED_{nt}

$$H_{it} = \theta(s_{it}) ED_{nt}, \tag{9}$$

where $\theta(\cdot)$ is positive and increasing. The term "skills" is used as a catch-all to capture the class of personality traits, preferences, and beliefs that transform a given level of educational investment into human capital. This formulation is a black box in the sense that the particular mechanisms are not delineated and for our purposes, modelling them is inessential. The linear structure of (9) is extremely important as it will allow dynasty income to grow over time. Together, equations (4), (8), and (9) produce an AK-type growth structure relating educational investment and human capital, which can lead family dynasties to exhibit income growth because of increasing investment over time.

Entry level skills are determined by an interplay of family and neighborhood characteristics

$$s_{it} = \zeta\left(Y_i, \bar{Y}_{-i}\right) \tag{10}$$

where ζ is increasing and exhibits complementarities. Dependence on Y_i is a placeholder for the role of families in skill formation. Dependence on $\bar{Y}_{-i}$ is readily motivated by a range of social interactions models. By this we mean the following. There is a plethora of nonmarket influences that map the characteristics of adults in a community into the process of educational attainment of children. The importance of neighborhood effects on children's test scores was emphasized in Burdick-Will et. al. (2011). Some other papers that support the claim that neighborhoods affect child outcomes are Chetty et. al. (2016) and Davis et. al. (2017). One example of how neighborhoods affect child outcomes is the role model effects. The aspirations of children and adolescence are influenced by the adults with whom they interact. One form of this is psychological, i.e. a basic desire to imitate. Another form is social learning: perceptions of benefits of education are determined by the information that is locally available to the young. For example, Jensen (2010) documents low perceived returns to education, among boys in the Dominican republic, and finds that their subsequent education choices respond to information on actual returns. Equations (9) and (10) express the fact that the income distribution in a neighborhood generates distinct political economy and social interaction effects. These dual channels by which neighborhood income affect children combine to determine the properties of the dynastic income processes and hence differences between them, i.e. intergenerational inequality dynamics.

g. neighborhood formation

Neighborhoods reform every period, i.e. there is no housing stock. As such, neighborhoods are like clubs. Neighborhoods are groupings of families, i.e. all families who wish to form a common neighborhood and set a minimum income threshold for membership. This is a strong assumption. That said, we would emphasize that zoning restrictions matter in neighborhood stratification, so the core assumption should not be regarded as obviously inferior to a neighborhood formation rule based on prices.[7]

h. political economy

The equilibrium tax rate in a neighborhood is one such that there does not exist an alternative one preferred by a majority of adults in the neighborhood. The Cobb-Douglas preference assumption renders existence of a unique majority voting equilibrium trivial because, under these preferences, there is no disagreement on the preferred tax rate. The reason for this is that conditional on neighborhood composition, tax rates determine budget shares, which under private consumption and Cobb-Douglas preferences are, of course, fixed. Families differ in the implicit prices by which offspring income trades off against consumption, because of different influences as embodied in $\phi(\cdot)$, but this is irrelevant with respect to desired budget share allocation.

i. borrowing constraints

Neither families nor neighborhoods can borrow. This extends the standard borrowing constraints in models of this type. With respect to families, we adopt Loury (1981) idea that parents cannot borrow against future offspring income. Unlike his case, the borrowing constraint matters for neighborhood membership, not because of direct family investment. In addition, in our analysis, communities cannot entail children who grow up as members to pay off debts accrued for their education. Both assumptions follow legal standards, and so are not controversial.

[7] In the next version of the paper we explore whether prices can support the equilibrium neighborhood configurations produced by the minimum income level rule. Benabou (1996) and Becker and Murphy (2000) illustrate how social interactions are not sufficient to generate equilibrium neighborhood segregation; intuitively willingness to pay needs to be increasing in family income. Previous work and initial calculations suggest that this is the case for this framework, but we have not yet proven it at this point.

3. Neighborhood formation and intergenerational income dynamics: model properties

a. neighborhood equilibria

What neighborhood equilibria emerge in this environment? Observe that the expected utility of adult it given membership in neighborhood can be rewritten in terms of neighborhood characteristics as

$$\begin{gathered} EU_{it} = \pi_1 \log\left(\left(1-\tau\right)Y_{it}\right) + \pi_2 E\left(\log\left(\phi H_{nt}\left(\tau\right)\xi_{it}\right)\middle| F_t\right) = \\ \pi_1 \log\left(\left(1-\tau\right)Y_{it}\right) + \pi_2 \log\left(\tau\phi\xi_{it}\theta\left(\bar{Y}_{nt}\right)\nu\left(p_{nt}\right)\bar{Y}_{nt}\right) \end{gathered} \tag{11}$$

Taxes therefore determine budget shares for families. The first proposition is immediate from the Cobb-Douglas formulation. A family's preferred tax rate is thus the fraction of income it wishes to spend on education. Under our preference assumption, equilibrium tax rates are unanimously preferred and constant in all neighborhoods at all times $\forall n,t$

$\tau_{nt} = \dfrac{\pi_1}{\pi_1 + \pi_2}$.

While constant tax rates are empirically unappealing, they simplify the model in useful ways. In particular, Proposition 1 immediately implies a monotonicity property that links the utility of a parent to the income distribution in a neighborhood. Conditional on a given neighborhood population size p_{nt}, the expected utility of a parent it is increasing in monotonic rightward shifts of the empirical income distribution over other families in his neighborhood. This follows from the positive effects of more affluent neighbors on the revenues available for education as well as the social interactions effects that are built into the model.

The monotonic preference for more affluent neighbors, in turn, allows for a simple construction of equilibrium neighborhoods as well as a characterization of their structure. To see this, consider the highest income adult at time t. This adult will have the most preferred neighborhood composition. This most preferred neighborhood will consist of all families with incomes above some threshold, since higher income neighbors are always preferred to lower income neighbors. All neighbors in that neighborhood will agree on the income threshold since the educational quality of the neighborhood is constant across families[8]. Repeat this procedure until all families are allocated to neighborhoods. This will lead to a stable configuration of neighborhoods.

Proposition 1. **Equilibrium neighborhood structure**

i. At each t for every cross-sectional income distribution, there is at least one equilibrium configuration of families across neighborhoods.

ii. In any equilibrium, neighborhoods are segregated.

Proposition 1 does not establish that income segregation will occur. Clearly it is possible that all families are members of a common neighborhood. If all families have the same income, complete integration into a single neighborhood will occur because of the nonconvexity in the education investment process. Income inequality is needed for segregation. Proposition 2 follows immediately from the form of the education production function nonconvexity we have assumed.

Proposition 2. Segregation and inequality

There exist income levels $\bar{Y}^{high}$ and $\bar{Y}^{low}$ such that families with $Y_{it} > \bar{Y}^{high}$ will not form neighborhoods with families with incomes $\bar{Y}^{low} > Y_{it}$.

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[8]Another way to understand the result is to consider the variable $\frac{g(p_{nt})\Theta(\bar{Y}_{nt})}{\bar{Y}_{nt}}$ which is the implicit price, in consumption terms, of an additional unit of offspring human capital in a neighborhood. The most affluent family seeks to minimize this price, given the fixed budget share that is implicitly paid for human capital of offspring. The maximization for one family applies to all.

Intuitively, if family incomes are sufficiently different, then more affluent families do not want neighbors whose tax base and social interactions effects are substantially lower than their own. Benefits to agglomeration for the affluent can be reversed when families are sufficiently poorer.

b. Income dynamics

Along an equilibrium path for neighborhoods, dynasty income dynamics follow the transition process

$$\Pr\left(Y_{it+1} \middle| F_t\right) = \Pr\left(Y_{it+1} \middle| \bar{Y}_{nt}, p_{nt}\right) \tag{12}$$

This equation illustrates the primary difficulty in analyzing income dynamics in this framework: one has to forecast the neighborhood composition. This leads us to focus on the behavior of families in the tails of the income distribution, in particular the highest and lowest income families at a given point in time.

We first observe that there is a deep relationship between the equilibrium neighborhood configurations in the model and persistent income inequality.

Proposition 3. Equilibrium income segregation and its effect on the highest and lowest income families

i. Conditional on the income distribution at t, the expected offspring income for the highest family in the population is maximized relative to any other configuration of families across neighborhoods.

ii. Conditional on the income distribution at t, the expected offspring income of the lowest income family in the population is minimized relative to any other configuration of families across neighborhoods that does not reduce the size of that family's neighborhood.

The maximization of inequality along an equilibrium path of matches occurs in other contexts. For example, Becker's (1973) marriage model, in which complementarities between partners induce assortative matching of types which maximizes differences in the output of marriages. Unlike the Becker case, our equilibria are not necessarily efficient, i.e. they do not necessarily lie on the Pareto frontier, because borrowing is ruled out.

The maximization of offspring differences by equilibrium neighborhood configurations interacts with the technology structure we have assumed. Higher income neighborhoods can produce higher expected average growth in offspring income than poorer ones. Formally,

Proposition 4. Expected average growth rate for children in higher income neighborhoods than for children in lower income neighborhoods

Let g_{nt+1} denote the average expected income growth between parents and offspring in neighborhood n,t. For any two neighborhoods n and n' if $\bar{Y}_{nt} < \bar{Y}_{n't}$ $p_{nt} \geq p_{nt'}$, then $g_{nt+1} - g_{n't+1} > 0$.

Intuitively, neighbors have three distinct effects on a family. The more neighbors are present in a community (high income or not), the greater is the set of taxpayers to defray fixed costs to educational investment. Higher is the income of a set of neighbors, the greater is the tax base and the more favorable are social interaction effects. The Proposition, by ordering neighborhood sizes, formalizes these factors.

Proposition 4 does not speak to the sign of g_{nt}. Under the linear assumptions of this model, there exists a formulation of $\Theta(\cdot)$ and $\xi(\cdot,\cdot,\cdot)$ such that neighborhoods exhibit positive expected growth in all time periods, i.e. $\forall nt \;\; g_{nt} > g_{\min} > 0$. In essence, this will hold when educational investment is sufficiently productive relative to the preference-determined equilibrium tax rates so that investment levels grow (this is the AK growth model requirement as modified by the presence of social interactions). We assume positive growth in what follows.

c. inequality dynamics

This model is consistent with extreme forms of income persistence. Our model admits the possibility that the upper and lower tails can decouple from the rest of the population. This possibility is formalized in Proposition 6.

Proposition 6. Decoupling of upper and lower tails from the rest of the population of family dynasties

i. If $\forall nt \;\; g_{nt} > 0$, then there exists a set of time t income distributions such that the top α% of families in the distribution never experience a reduction in the ratios their incomes compared to any dynasty outside this group

ii. If $\forall nt \;\; g_{nt} > 0$, then there exists a set of time t income distributions such that the bottom β% of families in the distribution never experience an increase in the ratios their incomes compared to any dynasty outside this group

The mathematical intuition for this proposition is the following. Differences in the logarithm of income behave in a fashion that is qualitatively equivalent to random walk with drift. Taking the initial income difference between two adults as an absorbing barrier, a future reduction of the initial income ratio among descendants is equivalent to asking whether the process ever hits the absorbing barrier. For this environment, the probability is less than one. In our model, disparities between the neighborhoods experienced by the descendants of the highest and lowest income families can grow and thereby induce disparities in growth rates across generations. This drift away from the absorbing barrier defined by the initial income difference may be overcome by the shocks to human capital and income experienced by individual members of a dynasty. However, because in/ absence of shocks, disparities would grow, there is no guarantee that the sample path of shocks will lead the income disparity to decrease. Local public finance and social interactions can therefore be combined to produce permanent differences between dynasties.

This proposition does not imply that dynastic income differences can ever become fixed, i.e. that contemporary inequality becomes irreversible. There is no literal poverty or affluence trap, in which a dynasty is permanently consigned to absolute or relative income levels. Permanent differences occur with probabilities bounded between 0 and 1. How can this occur? The key to our results is that the economy is growing, and so is nonstationary. Specifically, the range of incomes over which an income takes a probability $1-\varepsilon$ value changes, for any $\varepsilon > 0$[9]. A growing economy admits forms of intergenerational persistence that are ruled out in stationary environments. Moreover, the possible (nonzero probability) patterns for dynastic income differences are qualitatively different. Growth, in fact, facilitates the emergence of permanent inequality.[10][11]

Our final proposition formalizes one exact sense in which the Gatsby Curve can be produced by the model.

Proposition 7. Intergenerational Great Gatsby curve

> There are skill formation technologies such that there exists a set of time *t* income distributions such that the intergenerational elasticity of parent/offspring income will be increased by a mean preserving increase in the variance of logarithm of initial income.

[9]This is a technical detail that accounts for the fact that the densities for shocks are not required to have bounded supports.
[10]The distinction between the types of persistent inequality found in stationary versus growing environments suggest limitations of conventional forms of inequality measurement such as the intergenerational correlation of income or the Markov transition matrix for relative rankings. Durlauf (2011) discusses some metrics for mobility for environments with growth.
[11]If there is a minimum positive average income requirement for the expected growth of income of offspring in a neighborhood, then it is possible for the model to exhibit a conventional poverty trap in the sense that some family dynasties follow a stationary income process, i.e. one without growth.

Underlying the theorem, there are two routes by which Gatsby Curves can be generated. First, mean-preserving spreads alter the family-specific IGEs, which in this model take the form $\beta\left(Y_i, \bar{Y}_i\right)$. Hence once can construct cases where the linear approximation, i.e regression coefficient, increases with a mean-preserving spread. Second, increased inequality can alter segregation. The existence of at least one such income distribution, where inequality increases segregation and so decreases mobility is trivially proved by an example. Starting with an initial income distribution, in which all families are members of a common neighborhood, an increase in income dispersion which generates multiple neighborhoods will necessarily raise the parent/child income correlation.

Proposition 7 does not logically entail that increases in variance of income increase the intergenerational elasticity of income. The reason is that the model we have set up is nonlinear and effects of changes in parental income inequality into a scalar measure of mobility such as the IGE will typically not be independent of the shape of the income density, conditional on the variance. Put differently, the construction of a Great Gatsby Curve from our model involves two moments of a nonlinear, multidimensional stochastic process of family dynasties, and so the most one can expect is logical compatibility. The subtleties of producing Gatsby-like behavior in nonlinear models of course is not unique to our framework; see discussion in Becker, Kominers, Murphy and Spenkuch (2015).

4. Empirical claims about the inequality/segregation/mobility nexus

In this section, we present four broad empirical facts that, collectively, suggest that the generative mechanisms in our theoretical model have empirical salience.

a. direct estimates of Gatsby-like phenomena

Our first claim is that there is direct evidence of an intertemporal Gatsby Curve: inequality and mobility are negatively associated. This claim might appear to be a nonstarter for the United States, since it is commonly argued the intergenerational elasticity of income (IGE) between parents and children has not changed much over the last 40 years[12], despite substantial increases in conventional cross-sectional inequality measures. The invariance of the standard measure may reflect its relative lack of insensitivity to changes in mobility for the offspring of very advantaged and very disadvantaged parents, Kearney and Levine (2016) make this argument. We believe the argument is powerful and observe that an exact parallel to it previously appeared in the economic growth literature, where evidence of convergence (which is equivalent to 1 minus the IGE) was misinterpreted to argue that there are no nation-level poverty traps (see Bernard and Durlauf (1996) for elaboration). The intuitive point is that if the generative mechanism for the Gatsby curve involves parameter heterogeneity or nonlinearity, then the empirical Gatsby relationship may not appear in a linear analysis.

There are a number of studies that find a Gatsby relationship once one focuses on the tails of the income distribution. Aaronson and Mazumder (2008), for example, identify covariation between the IGE and two measures of the tail(s) of the income distribution: the 90/10 income ratio and the share of income accrued by the top 10% (see Figure 1). In each case, there is a positive relationship between inequality and mobility. Aaronson and Mazumder (2008) also find evidence of a positive relationship between the college wage premium and the IGE (shown in Figure 1). This evidence is indirect, but given what is known about the roles of levels of education and inequality, the relationship between the premium and the IGE implicitly links mobility to inequality. This finding is also suggestive of a possible mechanism: the role of inequality in producing educational inequalities that matter in labor force outcomes. Kearney and Levine (2016) also document correlations between different percentile ratios and mobility (shown in Figure 2).

b. location/mobility nexus

Second, there exists a location/mobility nexus. In one interesting recent study, Kearney and Levine (2016) document how, at the state level increasing inequality affects mobility related outcomes at the state level. Figure 3 illustrates how variance of state

[12]See Davis and Mazumder (2017) for a recent important challenge to the conventional claim.

income is positively associated with the high school dropout rate. Note that the dropout rate speaks to the economic prospects of children from less affluent families. It also implies a statistical relationship between income inequality, educational inequality, and implicitly mobility, all consistent with the theoretical framework.

Any discussion of location and inequality must be deeply informed by the seminal work of Chetty, Hendren, Kline, and Saez (2014). Figure 4 reproduces their classic visual depiction of spatial variation in relative income rankings of parents and children. This study also finds that high school dropout rates exhibit similar spatial heterogeneity, leading the authors to conclude that “much of the difference in intergenerational mobility across areas emerges when children are teenagers, well before they enter the labor market as adults” (p. 1602). These authors also find a negative relationship between income segregation and mobility as well as between Gini coefficients and upward mobility. Both of these findings are consistent with our theoretical model.

c. location and segregation

Our third empirical claim is that there is much evidence of pervasive segregation across locations with respect to factors that matter, at a collective level, education and economic success. The empirical importance of social factors to individual outcomes will not entail anything about mobility unless the social factors lead to differences in community characteristics. We make this claim both with respect to income and to social interactions, the two mechanisms highlighted in our theoretical model.

a. Income

Evidence of economic segregation is straightforward to compile. One dimension of income segregation is the spatial concentration of poverty, which is illustrated in Figure 5 at the country-level. Similar segregation exists at lower levels of aggregation. Figure 6 reproduces poverty rates across Chicago neighborhoods. Another facet of this stylized fact is the increasing stratification of neighborhoods by income, with some attendant reduction in racial segregation. Reardon and Bischoff (2011) and Reardon, Fox, and

Townsend (2014) provide evidence of this phenomenon. Some of these findings are summarized in Figure 7.

Changes in the distribution of average income and variance of income across census tracts and states, respectively, across decades are depicted in Figures 8-11. The distribution of census tract incomes exhibits some increase in dispersion, while the analogous state measures exhibit a substantial increase. In parallel, the upper tail of the variance of census tract income exhibits a modest increase, while the upper tail of state income exhibits a substantial increase.

These changes matter because of the findings of how the mean and variance of income interact with the IGE coefficient. Leaving aside the variance of census tract income (which did not prove to have a robust influence on the IGE), all these shifts, via the logic of equation (2), produce the Great Gatsby Curve.

b. Education-related mechanisms

Beyond spatial segregation by income, there is substantial spatial variation in factors that matter for education, which represents our fourth stylized fact. One mechanism which produces locational disparity is local public finance in education. Figure 12 illustrates these differences while Figure 13 illustrates these differences in the context of Texas. Of course, differences in per capita student expenditures do not necessarily entail differences in human capital formation, which is the natural object of interest. Many studies of financial resources and cognitive outcomes have failed to identify significant positive covariation (Hanushek (2006)). That said, there is a general consensus that certain consequences of expenditures, for example classroom size, have nontrivial influences (see e.g. Dustmann, Rajah, and van Soest (2003) and Krueger (2003)). We therefore conclude that this mechanism is important with the obvious caveat that the impact of expenditures depends on what educational inputs are purchased. We also note that the evidence of the effects of expenditures on future outcomes is stronger than it is for cognitive skills. Despite the evidence that the effect of small class size on test scores fades out by eighth grade (Krueger and Whitmore (2001)), for example, Chetty et al (2011) find that kindergarten classroom quality affects adult earnings.

A distinct mechanism involves social interactions. Conceptually, these can range from primitive psychological tendencies to conform to others, to information-based influences of observed patterns of behaviors and consequences on individual cost-benefit calculations, to more complex notions of culture. There are complex identification problems in the formal identification of social interaction effects because of the endogeneity of social structures such as neighborhoods, inducing self-selection issues, as well as social structures inducing correlations in unobservables such as the one that occurs when a teacher influences a classroom (see Blume, Brock, Durlauf and Ioannides (2011) for a discussion of identification problems and Durlauf (2004) and Topa and Zenou (2015) for surveys of the evidence on neighborhood effects).

Figure 14 gives one example of a location-determined social interaction effect: exposure to violent crime across the US. Figure 15 gives a related figure for homicides in Chicago. Exposure to violence has been linked to stress among children and lower educational attainment (e.g. Burdick-Will (2013)). One of the robust findings from the Moving to Opportunity Demonstration was the positive effect on stress-levels among individuals who moved to lower poverty neighborhoods (e.g. Katz, Kling and Liebman (2007) and Gennetian et al (2012)).

What conclusions do we take from these broad stylized facts? First, there are reasons to believe that the intertemporal Gatsby Curve exists. Second, segregation patterns and associated disparities in social interactions explain its existence. These constitute the logic and implications of our theoretical framework.

5. Empirical properties of the intergenerational elasticity of income

In this section, we provide some additional stylized facts on patterns that relate intergenerational mobility to cross-sectional inequality by focusing on some of the statistical properties of the relationship between parent and offspring income. The results in this section both complement those provided in Section 4 and illustrate the statistical relationships that produce the Great Gatsby Curve.

a. data

We use the parent-child pairs from the Panel Study of Income Dynamics (PSID) with Census data on various state, county, and school district characteristics from Geolytics' Neighborhood Change Database (NCDB). We use the PSID because it includes many birth cohorts, allowing for exploration of how mobility varies along with changes in inequality across time and space. While the PSID's core sample is composed both of the Survey Research Center (SRC) national sample and the Survey of Economic Opportunity (SEO) low-income oversample, given serious sampling irregularities in the SEO sample (Brown (1996)) our analysis focuses only on the SRC sample.

In order to compare our results with the results obtained in other papers on the topic, we apply the same set of restrictions that were used in Bloome (2015). To be more specific, we focus on survey years between 1968 and 2007. Given the data, for each parent-child pair we examine permanent family income, defined as a five-year average of total family income. Permanent family income includes income from labor earnings, assets, and transfers such as AFDC accruing to heads, spouses, and other family members. We want to abstract from endogenous family formation decisions. Thus, our family income measure is not adjusted for family size. We adjust for inflation using the CPI-U-RS. Given the intertemporal nature of our exercise we focus on permanent family income when the child was 15 and 32 years old as our measures of parental income when the child was growing up and the child's adult income, respectively.

Inequality at the census tract and state level when children were 15 years old is taken from the Decennial Census via Geolytics' NCDB. The NCDB only provides categorical income data (e.g. the number of families in a certain tract with incomes in the range $5,000-$9,999); therefore we linearly interpolate the cumulative density function of income. As no maximum income is given for the top category, we assign the remainder of aggregate income (after following the assumption of a piecewise-linear CDF) to this category. When there is no remainder we assume that all households in the highest category make the lower bound of that category. Inequality measures for inter-census years were linearly interpolated by state. At the family level, for some of the regressions estimated below we included other control variables such as mother's education and race. To match tracts between Census years, we used the tract crosswalk developed by the US2010 Project (see Logan, Xu, and Stults (2014)).

Given these restrictions, at the end we have 1,725 parent-child pairs with the average parent income being \$22,844 and the child's adulthood income averaging at \$19,929 in 1977 dollars. When we include mother's education level, the number of observations drops to 1,462. On average 27% of the mothers in the sample were high school dropouts with almost 89% of the sample being white.

b. nonlinearity in the parent/offspring income relationship

Our first exercise considers nonlinearities in the intergenerational mobility process. One explanation of the Gatsby curve linking the variance of income to mobility is that the linear transmission process is misspecified, i.e.

$$y_{io} = f\left(y_{ip}\right) + \varepsilon_{io} \tag{13}$$

It is obvious that, depending on the shape of $f(\ )$, increases in the variance of y_{ip} can increase the variance of y_{io}.

To explore this possibility, we first construct a nonparametric estimate of $f(\ )$. Figure 16 presents the nonparametric function. Figure 17 presents two ways of measuring local IGE values: $\frac{f\left(Y_{ip}\right)}{Y_{ip}}$ and $f'\left(y_{ip}\right)$ respectively. As the point estimates and associated standard errors indicate, there is some evidence of nonlinearity, particularly in the tails of the income distribution. The decreasing $\frac{f\left(Y_{ip}\right)}{Y_{ip}}$ values are consistent with Chetty, Hendren, Kline and Saez (2014). The derivatives of the transmission function $f'\left(y_{ip}\right)$, while roughly consistent with the first measure, are too erratic to interpret. Together, we conclude that there is some, but not extremely strong evidence of nonlinearity in the sense of (2).

We complement these nonparametric results with some simple regressions which allow for differences in the linear IGE coefficients for parents in the tails of the income distribution as opposed to the middle. Table 1 splits the sample according to whether a family was in the bottom 10%, the middle 80%, or the top 10% of the national income distribution. Table 2 repeats this exercise when income distribution location is calculated at the state level while Table 3 performs the same exercise at the census tract level. For each split, we both consider the case where all heterogeneity is consigned to the IGE as well as the case where heterogeneity is allowed in the intercept. The latter heterogeneity is of interest since it speaks to differential growth rates.

The national, state, and census tract level results are similar. In each case, there is relatively little heterogeneity in the IGE coefficients, while there is heterogeneity in the intercepts, with the bottom and top 10% growing more rapidly than the middle 80%. While the precision of the intercept estimates does not allow for very strong statements, these results are suggestive of decoupling of the upper tail of the type that is consistent with the admittedly extreme case of complete immobility that appears as a theoretical possibility. Note that the relatively higher growth of the lower 10% than the middle 80% is evidence of a convergence mechanism that lies outside the linear structure of (1), but nevertheless can generate the Gatsby Curve like behavior.

c. neighborhood income and the IGE levels

Our second exercise considers how the IGE may depend on the mean and variance of neighborhood income. We focus on parametric models that are variations of

$$y_{io} = \alpha + \beta y_{ip} + \gamma_1 \bar{y}_{ig(p)} + \gamma_2 y_{ip} \bar{y}_{ig(p)} + \gamma_3 ineq\left(y_{ig(p)}\right) + \gamma_4 y_{ip} ineq\left(y_{ig(p)}\right) + \varepsilon_{io} \tag{14}$$

The parameters γ_1 and γ_2 capture average group income effects while γ_3 and γ_4 capture inequality effects. Table 4 presents results where parental income is interacted with census tract income. Table 5 conducts the same exercise at the state level. Bloome (2015) estimates analogous models for variance at the state level. Table 6 combines census tract and state variables. We report results using the variance of log income. Models using the Gini coefficient to measure inequality produce extremely similar results.

Table 4, while revealing some fragility in coefficient estimates across specifications, does allow some conclusions to be discerned. There is evidence that census tract income increases expected offspring income additively (column 2) and via interaction with parental income (column 3). Column 4 fails to identify statistically significant effects when both types of average income effects are included, presumably due to collinearity. In contrast, statistically significant evidence is found that census tract inequality affects offspring income. With respect to our model, we expected the coefficient on the interaction of family income and variance log income to be negative. This is consistent with the negative signs on family income × log income in columns 5 and 6. But large standard errors make results of these specifications disappointing in terms of corroboration of our ideas. But the positive effect on census tract income means is supportive of the claim that census tract membership matters.

The state level results in Table 5 provide clearer evidence that average state income helps predict offspring income. Again, the results for the variance of log income and the Gini coefficient are very similar. Columns 2, 4, 6 all contain positive and statistically significant estimates of an additive state mean effect. Interactions of family income with average state income, which appear in specifications for columns 3, 4, and 6, are statistically significant but exhibit fragile signs as the coefficient in 2 is positive while negative for the others. Income variance is positive and significant in 5 while negative and insignificant in specification 6. This fragility can be understood as a derivative of collinearity. Finally, income variance, when interacted with family income, affects the IGE positively. This finding is consistent with the logic of our theoretical ideas, which suggest that states with higher income variance will exhibit greater segregation at lower levels.

We complete this discussion by considering regressions which allow for both census tract and state effects. These appear in Table 6. Column 1, which considers census tract and state income averages, finds relatively stronger evidence that average census tract income matters as compared to state income. Column 2 focuses on census tract and state variances. No variables are statistically significant in isolation and there is a substantial reduction in goodness of fit relative to the model with average incomes.

Column 4 focuses on interactions of means and variances with parental income. Here, average census tract and state income interactions are positive and statistically significant as is state variance interaction. The insignificance of the interactions of census tract variance and income echoes earlier results. When all variables are combined, average state income survives as being statistically significant.

In summary, with respect to the general ideas of our theoretical framework, we would expect census tract and state means to enhance offspring income as well as interact positively with family income. We would predict census tract income to reduce the family IGE because of increased local integration and state variance to increase the IGE because of the potential for increased segregation, and census tract variance to reduce it. Thus these reduced form findings are qualitatively consistent with our priors, although the lack of robustness to census tract variance/mobility link is disappointing, at least with reference to our theoretical model.

d. reduced form Great Gatsby Curves

Our final exercises construct some Gatsby Curves from our statistical models. Figure 18 reports the Great Gatsby Curves that are implied by equation (13). To generate them, we construct counterfactual values of y_{io} given changes in the variance of y_{io} as produced by scaling the historical y_{io} values. For each counterfactual parental income series, we calculate the implied value of β if (1) is the linear model used to analyze the parent-offspring income relationship.

As indicated by Figure 18, the nonparametric family income model does not generate a relationship between inequality and mobility. This is not consistent with the Gatsby Curve idea: greater variance in parental income is associated with higher mobility. Some insight into the reasons for this may be seen in Figures 17a-b The nonlinearities in our sample suggest high means and lower local IGE coefficients for families in the tails of the income distribution than in the middle. Hence increased spread of parental incomes pushes more families into the lower IGE regions.

Figure 19 reports the implied Gatsby Curve associated with our parametric nonlinear model that is reported in Table 1. The unusual shape reflects the fact that spreading income distribution moves families away from the middle linear IGE model towards the models for the upper and lower tails.

For our purposes, there is one important message from Figures 18 and 19: nonlinearities in family income dynamics do not provide good reasons to think an intemporal Great Gatsby Curve exists for the US.

Our second set of reduced form Gatsby Curves is generated by parametric models we constructed that included census tract and state income distribution characteristics. In each case, we scale the log parental income, census tract, and state incomes proportionately. Figures 20-21 present Gatsby Curves for census tract variables, 22-23 for state level variables, while 24 and 25 combine both census tract and state variables. We consider cases where the results are based on means as well as the ones where results are based both on means and variances.

A consistent picture emerges from these calculations. At the census tract level, a Gatsby curve is implied by our parametric regressions, but the slope is small. For state-level variables, a large negative slope occurs. Hence the state level interactions produce the opposite phenomena from the Gatsby Curve property per se. When census tract and state variables are combined, a gently sloped positive relationship between income inequality and mobility reemerges.

We conclude from these exercises that there is some weak evidence of the Gatsby Curve like phenomena from the parametric IGE regressions with neighborhood effects. Perhaps unsurprisingly, a necessary condition for stronger evidence is a greater attention to the mechanisms underlying the social interactions/Gatsby relationship. And as argued in Section 4, there is evidence to think the mechanisms that underlie our theoretical model matter in ways that create Gatsby-like outcomes. We thus move from these reduced for exercises to see whether a calibrated structural model can provide additional insights.

6. Linking theory and empirics: a calibrated model

In this section, we integrate the theoretical ideas of Sections 2 and 3 with the various facts highlighted in Sections 4 and 5 via a model calibration exercise. The model is a version of Kotera and Seshadri (2017) extended to incorporate heterogeneity at the school district level.

environment

Households live for four periods, one as an offspring and three as an adult. The first period is 18 years and the next three periods are 6 years each. We keep track of each offspring from birth until the age of 36. Each household *i* in a school district *j* maximizes utility given by

$$u\left(c_{j1}^{i}\right)+\theta V\left(a_{j}^{i},h_{j2}^{i},g_{j}^{i}\right) \tag{15}$$

where $u\left(c_{j1}^{i}\right)$ is the utility from consumption c_{j}^{i}, $V\left(a_{j}^{i},h_{j2}^{i},g_{j}^{i}\right)$ is the lifetime utility of the offspring at the beginning of the second period, and θ is a measure of parental altruism. g_{j}^{i} is a transfer from a parent to his offspring who can use these resources in the second period. Assume that $g_{j}^{i}\geq 0$ so that an offspring cannot be responsible for debts undertaken by his parents on his behalf.

A central feature of the model is the human capital production function – an offspring's human capital depends on his own ability, public and private inputs, parent's human capital and the average human capital in the neighborhood. Thus, the offspring's human capital varies at the school district level. Specifically, for household *i*'s offspring in school district *j*, the stock of offspring human capital at the beginning of the second period, h_{j2}^{i}, is given by

$$h_{j2}^{i}=a_{j}^{i}\left(x_{j1}^{i}+\bar{x}_{j}\right)^{\alpha_1}\left(h_{j0}^{i}\right)^{\alpha_2}\left(h_{j}^{i}\right)^{\alpha_3} \tag{16}$$

where a_{j}^{i} is the learning ability, $\bar{x}_{j}$ represents public inputs, h_{j0}^{i} is parent's human capital, and h_{j} is the average parental human capital in a school district, i.e. $h_{j}=\frac{1}{n}\sum_{i}h_{j0}^{i}$. We assume that $\alpha_1 < 1$, $\alpha_2 < 1$ and $\alpha_3 < 1$. Additionally, $\overline{x}_j$ is collected using local tax rates on income, so $\bar{x}_j = \frac{1}{n}\sum_i y_j^i$. We take these rates as given.

An offspring becomes independent at the beginning of the second period. He makes decisions on human capital accumulation and consumption in the second, third, and fourth periods ($\left\{c_{j2}^i, c_{j3}^i\right\}$) to maximize his utility

$$V\left(a_j^i, h_{j2}^i, g_j^i\right) = \max_{\{c_{j2}^i, c_{j3}^i, c_{j4}^i, n_{j2}^i, n_{j3}^i, x_{j1}^i\}} u\left(c_{j2}^i\right) + \beta u\left(c_{j3}^i\right) + \beta^2 u\left(c_{j4}^i\right) \tag{17}$$

subject to the budget constraint

$$c_{j2}^i + \frac{c_{j3}^i}{1+r} + \frac{c_{j4}^i}{\left(1+r\right)^2} = wh_{j2}^i\left(1-n_{j2}^i\right) + \frac{wh_{j3}^i\left(1-n_{j3}^i\right)}{1+r} + \frac{wh_{j4}^i}{\left(1+r\right)^2} + g_j^i \tag{18}$$

and the human capital production functions (19)

$$h_{j3}^i = a_j^i\left(n_{j2}^i h_{j2}^i\right)^{\eta_1} + h_{j2}^i$$

$$h_{j4}^i = a_j^i\left(n_{j3}^i h_{j3}^i\right)^{\eta_1} + h_{j3}^i$$

where β is the discount factor, r is the interest rate, w is the rental rate of human capital, n_{j2}^i and n_{j3}^i are the time spent on human capital accumulation in the second period. Equation (19) is a standard Ben–Porath human capital accumulation model. It allows individuals to accumulate human capital in the second period in case if they received too little education in the first period - either due to the state of birth or by virtue of having poor parents. This extra margin of adjustment leads to a more flexible relationship between first-period investments and earnings at later ages, which we believe is important in understanding the data. With the last three periods, we can relate n_{j2}^i to college education, and wh^i_{j3} and wh^i_{j4} to earnings at ages 24-30 and 30-36, respectively. There are no borrowing constraints in the last three periods.

For simplicity, we assume there is a common wage rate w for all school districts in all states. This will be the case if there is no moving cost so that any spatial difference in the wage rate will be eliminated by migration. Given the large fraction of workers who do not live in their state of birth, we consider this simplification a useful benchmark.

model solution

The solution to the model in the last three periods is straightforward. In particular, individuals invest to maximize lifetime income and then allocate consumption across the two periods to maximize discounted utility. Next, the maximization problem in the first period can be written as

$$\max_{c^i_{j1},x^i_{j1},g^i_j} u\left(c^i_{j1}\right) + \theta V\left(a^i_j, h^i_{j2}, g^i_j\right) \tag{20}$$

subject to (15), the budget constraint

$$c^i_{j1} + x^i_{j1} + g^i_j = \left(1-\tau\right) y^i_j \tag{21}$$

and a non-negativity condition $g^i_j \geq 0$.

The first-order conditions for x^i_{j1} and g^i_j are given by

$$\theta V_{h^i_{j2}}\left(a^i_j, h^i_{j2}, g^i_j\right) a^i_j \alpha_1 \left(x^i_{j1} + \bar{x}_j\right)^{\alpha_1 - 1} \left(h^i_j\right)^{\alpha_2} \left(h_j\right)^{\alpha_3} = u\left(c^i_{ji}\right) \tag{22}$$

and

$$\theta V_{g^i_j}\left(a^i_j, h^i_{j2}, g^i_j\right) \leq u\left(c^i_{ji}\right) \tag{23}$$

where $V_{h_{j3}^i}\left(a_j^i,h_{j2}^i,g_j^i\right)$ and $V_{g_j^i}\left(a_j^i,h_{j2}^i,g_j^i\right)$ are the derivatives of $V\left(a_j^i,h_{j2}^i,g_j^i\right)$ with respect to h_{j2}^i and g_j^i, respectively, and $u'\left(c_{j1}^i\right)$ denotes the derivative of $u\left(c_{j1}^i\right)$ with respect to c_{j1}^i. The first condition implies that private investment would equate the marginal benefits for offspring in the last two periods with the marginal costs incurred by parents in the first period. The second condition holds with equality if $g_j^i > 0$. In this case, the value of a dollar to the parent is the same regardless of whether it's consumed or left to the offspring. Otherwise, if the value of a dollar to the parent is larger when it's consumed even if $g_j^i = 0$, the inequality in the third condition would be strict.

calibration

fixed parameters

We assume a standard CRRA utility function over consumption, $u(c) = \dfrac{c^{1-\alpha}}{1-\alpha}$, so that

$$V\left(a_{j1}^i,h_{j2}^i,g_j^i\right) = \frac{\left(c_{j2}^i\right)^{1-\alpha}}{1-\alpha} + \beta\frac{\left(c_{j3}^i\right)^{1-\alpha}}{1-\alpha} + \beta^2\frac{\left(c_{j4}^i\right)^{1-\alpha}}{1-\alpha}$$

We set $\alpha = 2$, $\beta = 0.96$, and $r = \left(1.04\right)^6 - 1$, where 6 is the number of years in each of the last three periods of our model.

To calibrate the wage rate w, we assume that parental income in school district j is given by $y_j = w_j \exp\left(\phi \times school_j\right)$. In this equation, parental income y_j is decomposed into two components: wage rate w_j and human capital h_{j0}^i. Since data on y_j and $school_j$ at the school district level are available, we can pin down w_j if we had knowledge of h_{j0}^i. Since we do not model parental human capital accumulation, we assume h_{j0}^i is a function of parental schooling $school_j$ with a coefficient ϕ, where $school_j$ is parent's schooling level. We set the return to schooling $\phi = 0.1$. We calibrate w_j to match y_j. Then, we average them to obtain w appeared in the last three periods. The value of w obtained is 0.1707. Last, we calibrate τ_j to match public school spending per pupil in a school district. This data is available from the U.S. Census Bureau. Due to the data limitations, we use public school spending per pupil and average income in 1990 to calibrate τ_j. Table 7 summarizes the fixed parameters of our model.

parameters to be estimated

We assume that parental human capital h_{j0}^i and an offspring's learning ability a_j^i follow a joint log normal distribution at the national level:

$$\begin{pmatrix} \log h_{j0}^i \\ \log a_j \end{pmatrix} \sim N\begin{pmatrix} \mu_{h_{j0}^i} & \sigma_{h_{j0}^i}^2 & \rho\sigma_{h_{j0}^i}\sigma_{a_j} \\ \mu_{a_j} & \rho\sigma_{h_{j0}^i}\sigma_{a_j} & \sigma_{a_j}^2 \end{pmatrix} \tag{24}$$

Given $school_j^i$ and ϕ, parental human capital $h_{j0}^i = \exp\left(\phi \times school_j^i\right)$ is available for each school district j. Additionally, the mean $\mu_{h_{j0}}$ and standard deviation $\sigma_{h_{j0}}$ of initial human capital at the national level can be calculated. This allows us to focus on the conditional distribution of a_j^i, namely

$$\log a_j^i \mid \log h_{j0}^i \sim N(\mu_{h_{j0}^i} + \rho_{h_{j0}^i a_j^i} \frac{\sigma_{a_j^i}}{\sigma_{h_{j0}^i}} (\log h_{j0}^i - \mu_{h_{j0}^i}), \sigma_{a_j^i}^2 (1 - \rho_{h_j^i a_j^i}^2)) \tag{25}$$

In addition to state-specific parameters $\{\mu_{a_j}, \sigma_{a_j}, \rho_{h_{j0}, a_j}\}$ that allow the model to match the variation in public school spending and income across states, we also need to estimate five parameters $\{\alpha^1, \alpha^2, \alpha^3, \eta^1, \theta\}$ that are common to all states. θ is the degree of parental altruism and the rest are parameters governing human capital accumulation in the last three periods. The novel part is the estimation of returns to the neighborhood effects, α^3.

estimation strategy

We estimate the parameters using the Method of Simulated Moments. Let Θ_s be the set of parameters to be estimated. Using data moments M_s, we obtain the estimated

$$\hat{\Theta}_s = \underset{\Theta_s}{\arg\min}[M_s(\Theta_s) - M_s]' W_s [M_s(\Theta_s) - M_s]'$$

where $M_s(\Theta_s)$ is the simulated model moments and W_s is a weighting matrix. In practice, we use the variance-covariance matrix of M_s as the weighting matrix W_s.

The moments we target are primarily related to offspring income. This data is available from the PSID. The nice feature of this data is that we use average offspring income both between 24-28 (corresponding to the third period) and between 30-34 (corresponding to the fourth period). We exploit them to identify the parameters of the model. The corresponding model moments are $E\left(wh_{j3}^i\right)$ and $E\left(wh_{j4}^i\right)$. These moments can identify θ and μ_{a_j}. In particular, μ_{a_j} is sensitive to changes in income from the third period to the fourth period because a_j predominantly determines h_{j4}^i given h_{j3}^i in our model. Next, we employ offspring income conditional on parent's schooling level in each period. Here, we construct two groups of school districts categorized by parent's schooling level: Group 1 and Group 2 where categories include school districts with parent's schooling level between 11 and 12 and between 12 and 13, respectively. The corresponding model moments are $E\left(wh_{j3}^i \middle| Group1\right)$, $E\left(wh_{j3}^i \middle| Group2\right)$, $E\left(wh_{j4}^i \middle| Group1\right)$, and $E\left(wh_{j4}^i \middle| Group2\right)$. These four moments allow us to mainly identify the returns to parental human capital, namely a_2 and $\{\sigma_{a_j}, \rho_{h_{j0}a_j}\}$. Furthermore, we use offspring income conditional on parental schooling level and average schooling level in a school district. Specifically, the moments for offspring income with average schooling level between 11 and 12 and between 12 and 13 within Group 1 (denoted by Group 11, Group 12) in the third period are used. The corresponding model moments are $E\left(wh_{j3}^{i} \middle| Group11\right)$ and $E\left(wh_{j3}^{i} \middle| Group12\right)$. These moments allow for identification of the return to average human capital in a school district, α_3, and the return to inputs, α_1. Finally, the return to time for human capital accumulation, η_1, can be identified by average school years in college. This data can be obtained from the 1990 Census. The corresponding moment is $E\left(6 \times n_{j2}^{i}\right)$ because the second period consists of 6 years in our model. In total, there are 9 moments. Table 8 summarizes the moments.

baseline results

targeted moments

Tables 9 and 10 provide values of the estimated parameters and the targeted moments, respectively. It is worth noting that, with regards to the targeted moments, we do a fine job matching moments for all variables except for average school years in college. One possible reason is that since the level of offspring's human capital in the second period is small, children need to spend time on accumulating human capital to match moments for their income in the following periods.

non-targeted moments

First, we turn to the relationship between parental income and offspring income (in logs) which is illustrated in Figure 26. As for offspring income, we use offspring income in the fourth period, wh_{j4}^{i}. Notably, there is a positive correlation between parental income and offspring income. However, the coefficient is smaller than the one implied by the data. In the previous section, the range of the correlation is between 0.36 and 0.44. By contrast, the correlation in the model is 0.23. The reason for this difference might be because the sample size used in the calibration is smaller. In this exercise, we use only 193 individual data due to data limitations. This underestimates the magnitude of the correlation coefficient.

We then turn our attention to the local IGE estimates for income dislayed in Figure 27. As in the previous section, the local IGE estimates are defined as the ratio of offspring income to parental income level. Figure 27 points out that the local IGE estimates fall as parental income rises. Both qualitatively and quantitatively, this exhibits the same tendency as the one observed in the data. Unlike the data, however, the local IGE estimates fall to 0 in the calibration. Again, this gap is, in part, due to our smaller sample size.

counterfactual results

To improve our understanding of the forces at work in our model that help explain the positive correlation between parental income and offspring income, we use the estimated model to conduct two counterfactual simulations. The first counterfactual simulation examines what would happen if there was no return to some factors that are important in forming offspring's human capital in the second period. In our model, offspring's human capital contains three elements: inputs including both public and private ones, parent's human capital, and average human capital in a school district. In this simulation, we study how important each element is in forming offspring's human capital. The second counterfactual simulation examines the importance of parental income distribution. This exercise allows us to quantify the contribution of parental income distribution to intergenerational mobility.

return to elements for offspring's human capital in the second period

Figure 28 summarizes intergenerational mobility in the following five cases: i) baseline, ii) no return to all elements: $\alpha_1 = \alpha_2 = \alpha_3 = 0$, iii) no return to inputs: $\alpha_1 = 0$, iv) no return to parent's human capital: $\alpha_2 = 0$, and v) no return to average human capital in a school district: $\alpha_3 = 0$. If all three elements were eliminated, the correlation coefficient would fall to 0.16. Thus, these forces play a key role in driving intergenerational mobility. Additionally, when we decompose this effect, we find that the contribution of inputs is the largest. On the other hand, parent's human capital and average human capital have a smaller effect on intergenerational mobility.

impact of parental income distribution

How much the distribution of parental income affects intergenerational mobility is also an interesting question. Since the distribution of parental income is given in our model, we conduct a counterfactual simulation in which we make this distribution more disperse. Specifically, we raise its standard deviation by 10% and 20% holding its mean fixed. School district variables are fixed. Figure 29 presents the results, suggesting that intergenerational mobility decreases if the distribution of parental income spreads out. But the effect is rather modest —the 20% increase in dispersion of parental income increases the IGE by 2%. Attanasio, Hurst, and Pistaferri (2015) argue that the standard deviation of income increased by about 20% between 1980 and 2008. Consider the difference between an IGE of .3 and .4. If our theory explained 2% of a 33% increase, that would represent over 5% of the overall change. Not a large fraction, but still a meaningful piece of the overall story.

7. Conclusions

In this paper, we have explored some theoretical and empirical aspects of the Great Gatsby Curve. We have argued that the curve may be understood as a causal relationship in which segregation is the mediating variable that converts inequality into lower mobility. We have provided a theoretical model and a set of broad empirical facts that support this view. Our reduced form and structural empirical analyses are consistent with our qualitative claims, but the magnitude of the implied Gatsby slopes is quite modest. This is so despite the reduced form evidence that social effects matter for intergenerational mobility and the presence of this property in the structural model we calibrate. We take it as a challenge to better map our theoretical framework into empirical exercises so that the Gatsby-type aspects of inequality and mobility can be better identified.

We conclude this paper with a few comments about policy. There are straightforward routes to justify government interventions in the environment we describe. First, the environment does not correspond to an idealized market economy in which equilibrium outcomes are efficient. The interdependences between individuals created by local public finance and social interactions are classic examples of spillover effects. Markets do not efficiently adjudicate these effects. In particular, in this environment, there is no equalization of the marginal benefits to educational expenditure or of neighborhood quality across individuals. It is possible that Pareto-improving redistribution policies can be implemented. The intuition is simple. The placement of high ability, low income children in better educational environments may produce sufficiently higher returns that low ability, high income children can be compensated in ways that leave everyone better off. However, it is not clear whether such Pareto-efficient redistributive schemes are empirically meaningful. Other justifications can be derived from the normative argument that motivates equality of opportunity as a social objective.

But what sort of interventions? Here we wish to draw attention to policies that engage in "associational redistribution" (Durlauf (1996c)), i.e. policies that alter the associations that individuals experience. This form of redistribution is qualitatively different from conventional redistribution policies which are based on taxes and transfers. While the idea of associational redistribution can abstractly raise unique questions of personal autonomy (obvious for contexts such as the marriage market), here we will note that many policies are in fact chosen in order to engage in associational redistribution: affirmative action is a salient case.

In the context of residential neighborhoods, there are ready mechanisms to alter the degree of socioeconomic segregation. One example of a policy that promotes economic integration of communities is the requirement that a new residential construction should include mixed income housing. The court ordered implementation of mixed housing construction in Mt. Laurel, New Jersey is a famous example (see Massey et al. (2013) for a discussion of its positive effects on disadvantaged families). Mixed income housing is closely linked to zoning laws. The common requirement, in affluent communities, that all housing consists of single family dwellings, is another example of how laws can determine neighborhood composition.

Alternatively, policies can attempt to obviate the effects of neighborhood inequality. In the context of our theoretical model, equalization of school funding across districts is an obvious policy possibility. Another is the redrawing of school district boundaries. Further, once one incorporates distinctions between social influences that occur at the school district and school levels, the rules by which students are assigned to schools become a policy tool.

A key question in thinking about policies of this type is the ability of private choices to cause effects of the policy to unravel. A useful analogy is school busing for racial integration. Court order school busing was always done within school districts, never across them. As a result, some school districts experienced white flight and became even more segregated than they were previously.

There is an immediate analogy to the school busing case if the policy objective is economic integration of communities: movements from the public school system to private schools. Note that there is an analogous danger with respect to a policy being counterproductive. Self-interested parents who transfer children to private schools will presumably support lower financial support for public schools than when their children are enrolled in public schools. Hence, in addition to exacerbating economic segregation, as more affluent children are completely isolated, resources could become even scarcer for poor children.

Nothing we have said should be construed as advocating any particular policy. Further, there are complex normative questions involved when one shifts the focus on distribution from income to group memberships. What we do believe is that environments with social influences of the type we have described require consideration of policies that directly focus on how groups, such as neighborhoods, are formed.

Technical Appendix

To be completed

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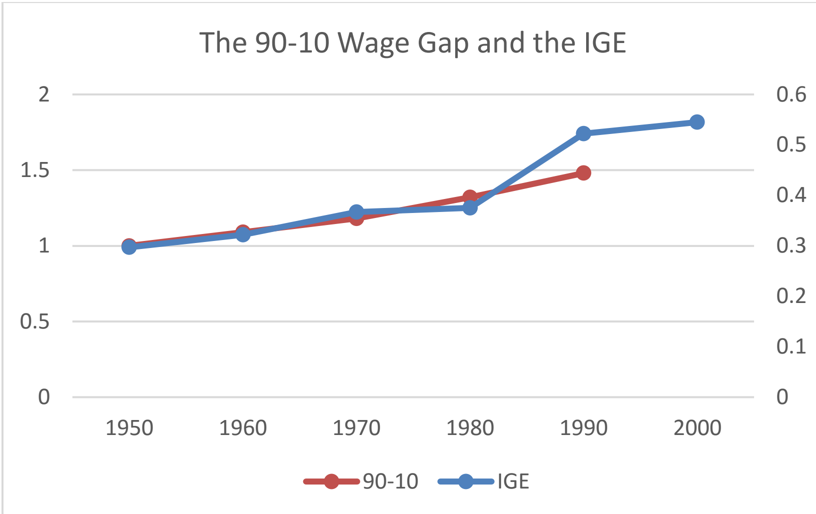
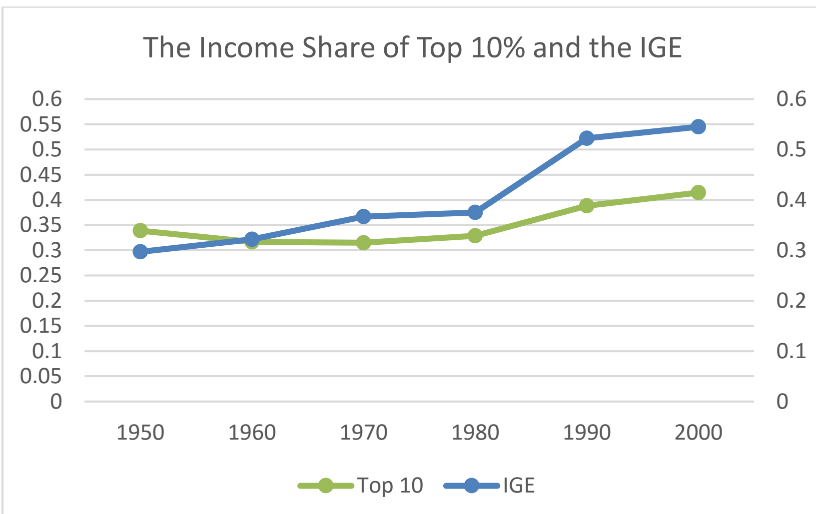
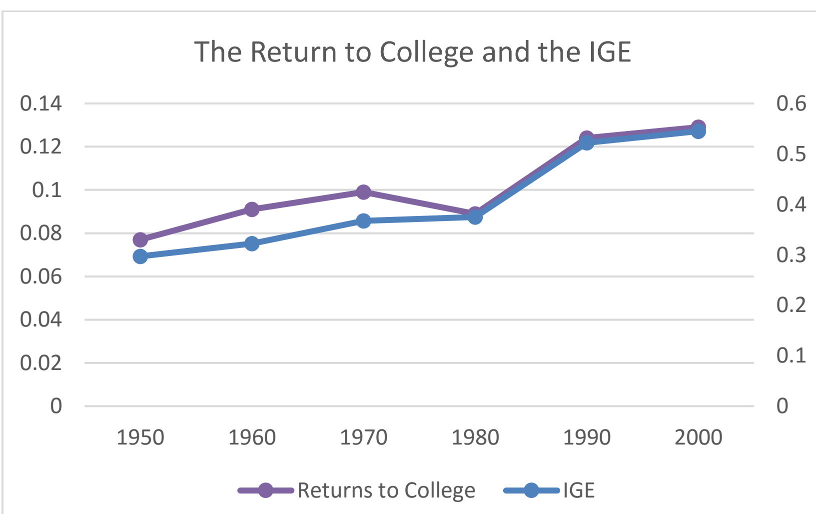
Figure 1. Rising intergenerational elasticities

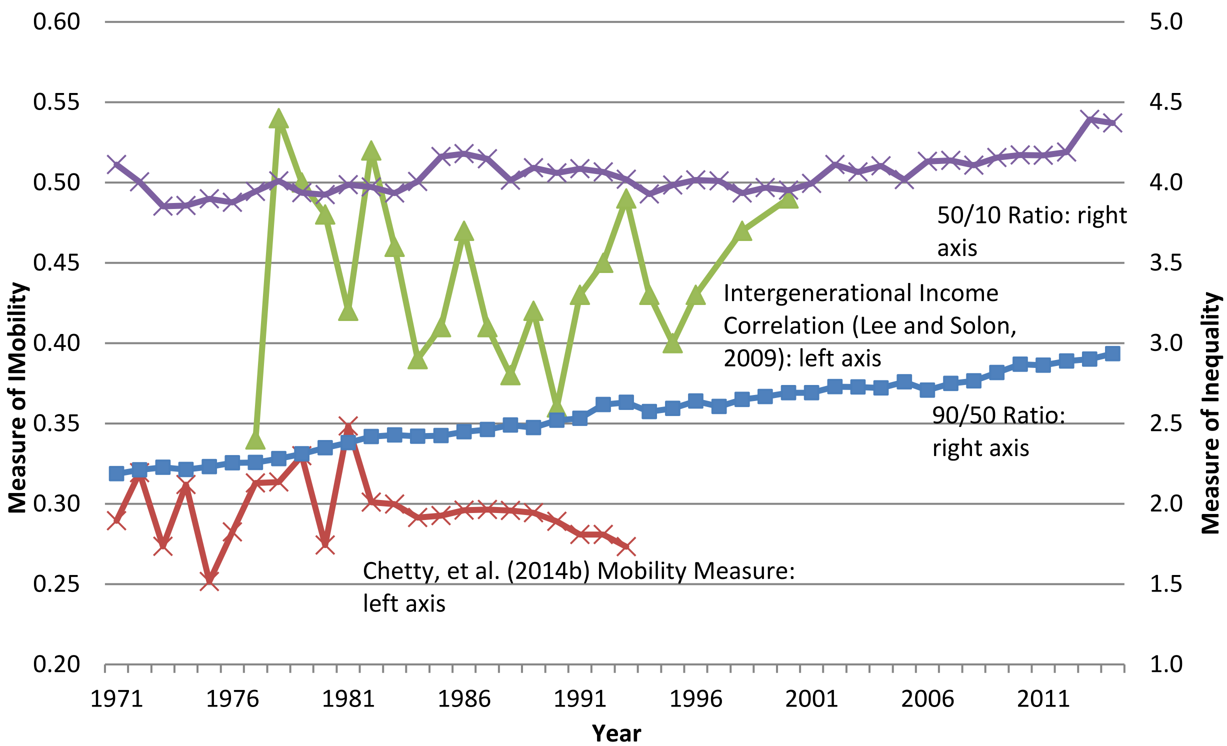






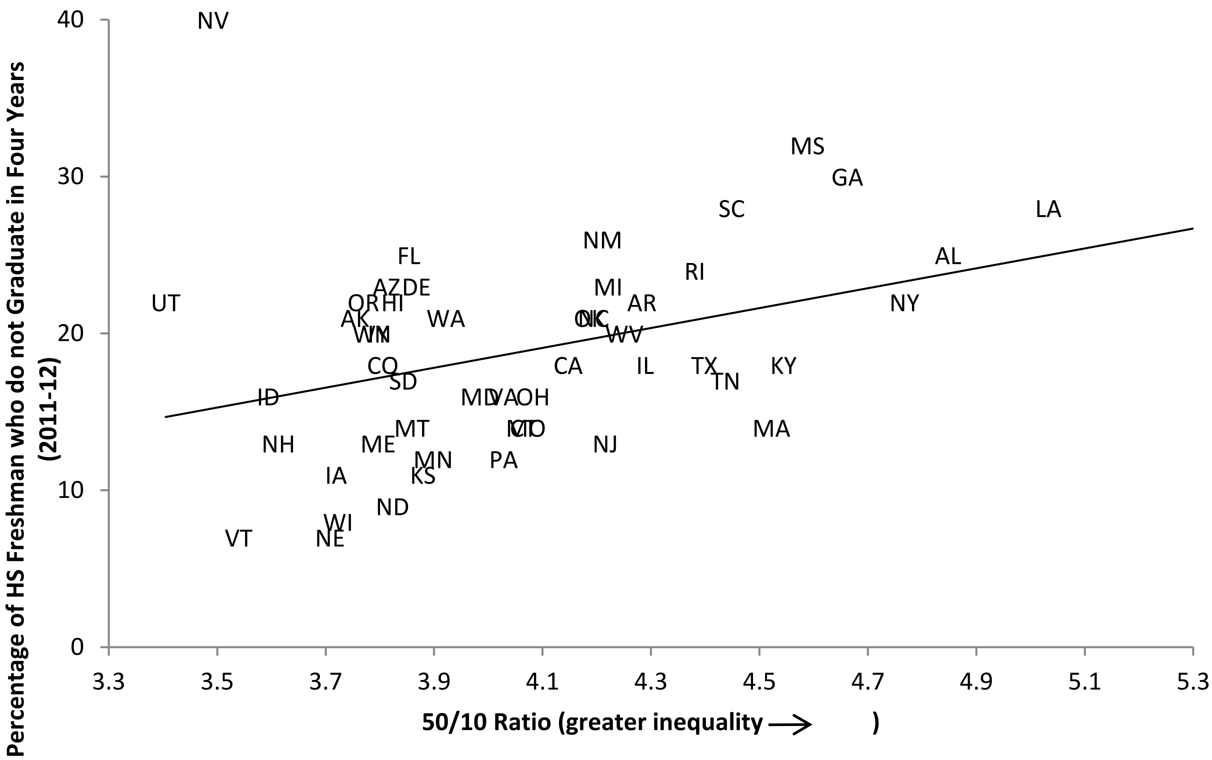
Source: Aaronson and Mazumder (2008)

Figure 2. Kearney and Levine 90/10 and other ratios



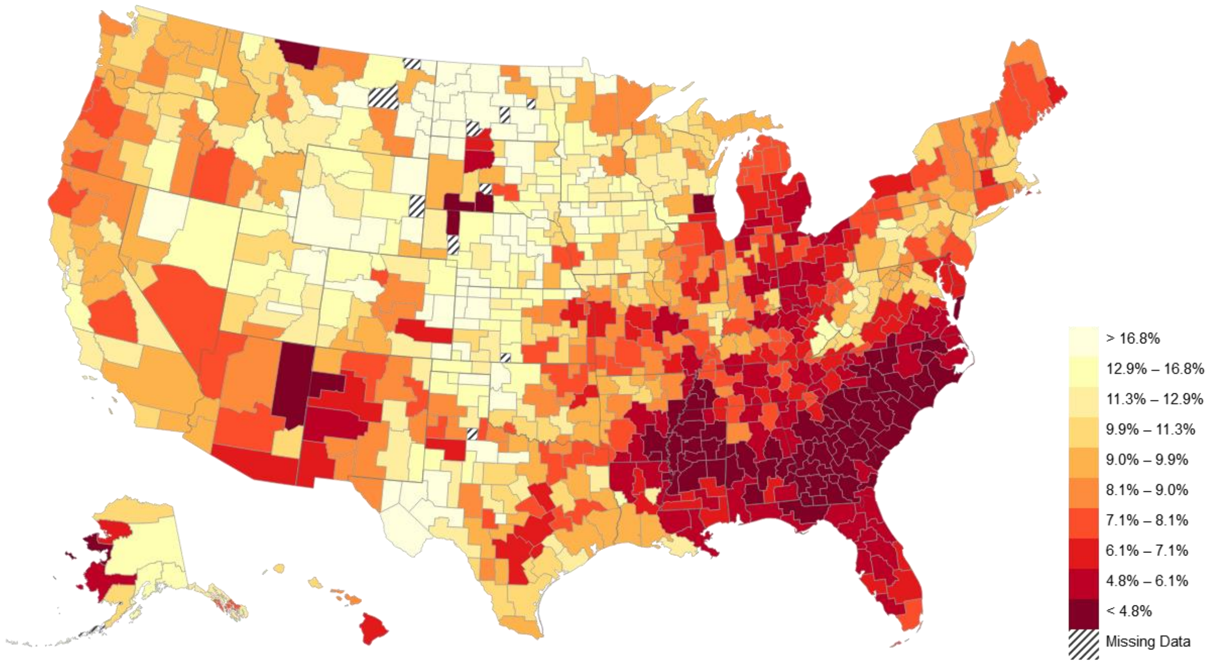
Source: Kearney and Levine (2016). Notes: The x-axis reflects the year in which income is measured for the 90/50 and 50/10 ratios. For the mobility measure in Chetty, et al. (2014b), year reflects birth cohort. For the mobility measure in Lee and Solon (2009), year reflects the year in which the son's income was recorded.

Figure 3. Relationship between inequality and the rate of high school non-completion



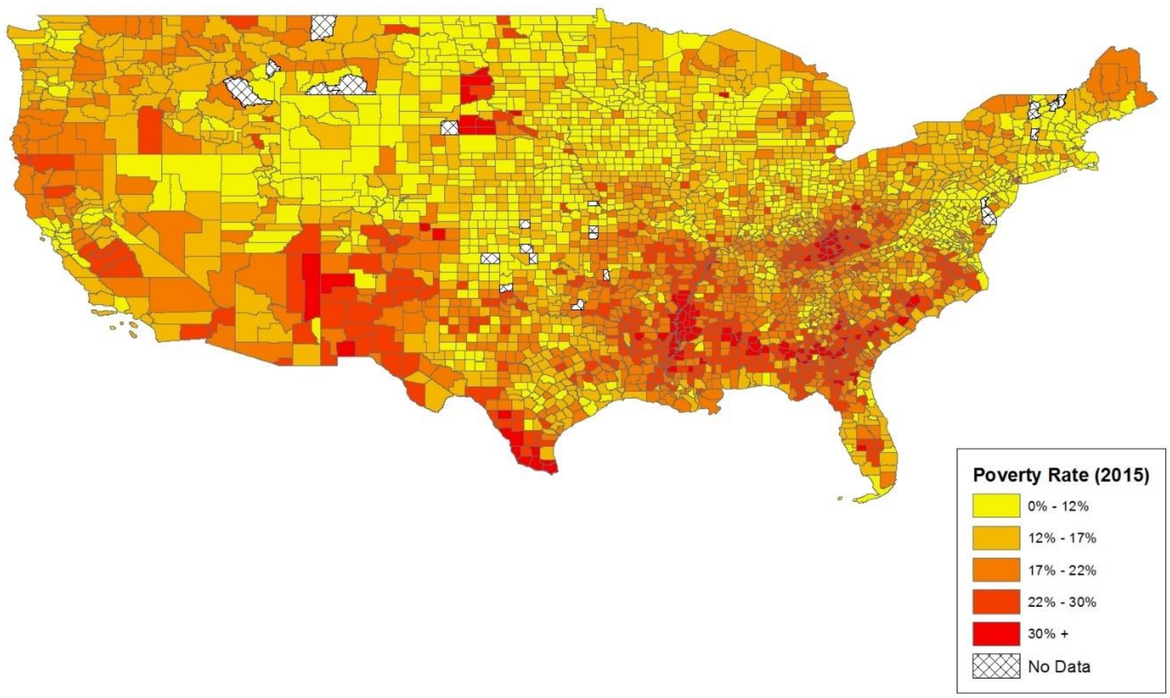
Source: Kearney and Levine (2016). Notes: The graduation data is from Stetser and Stillwell (2014). The 50/10 ratios are calculated by the authors. The District of Columbia is omitted from this figure because it is an extreme outlier on the X axis (50/10 ratio = 5.66).

Figure 4. Chetty, Hendren, Kline, and Saez (2014): Spatial heterogeneity in rates of relative mobility



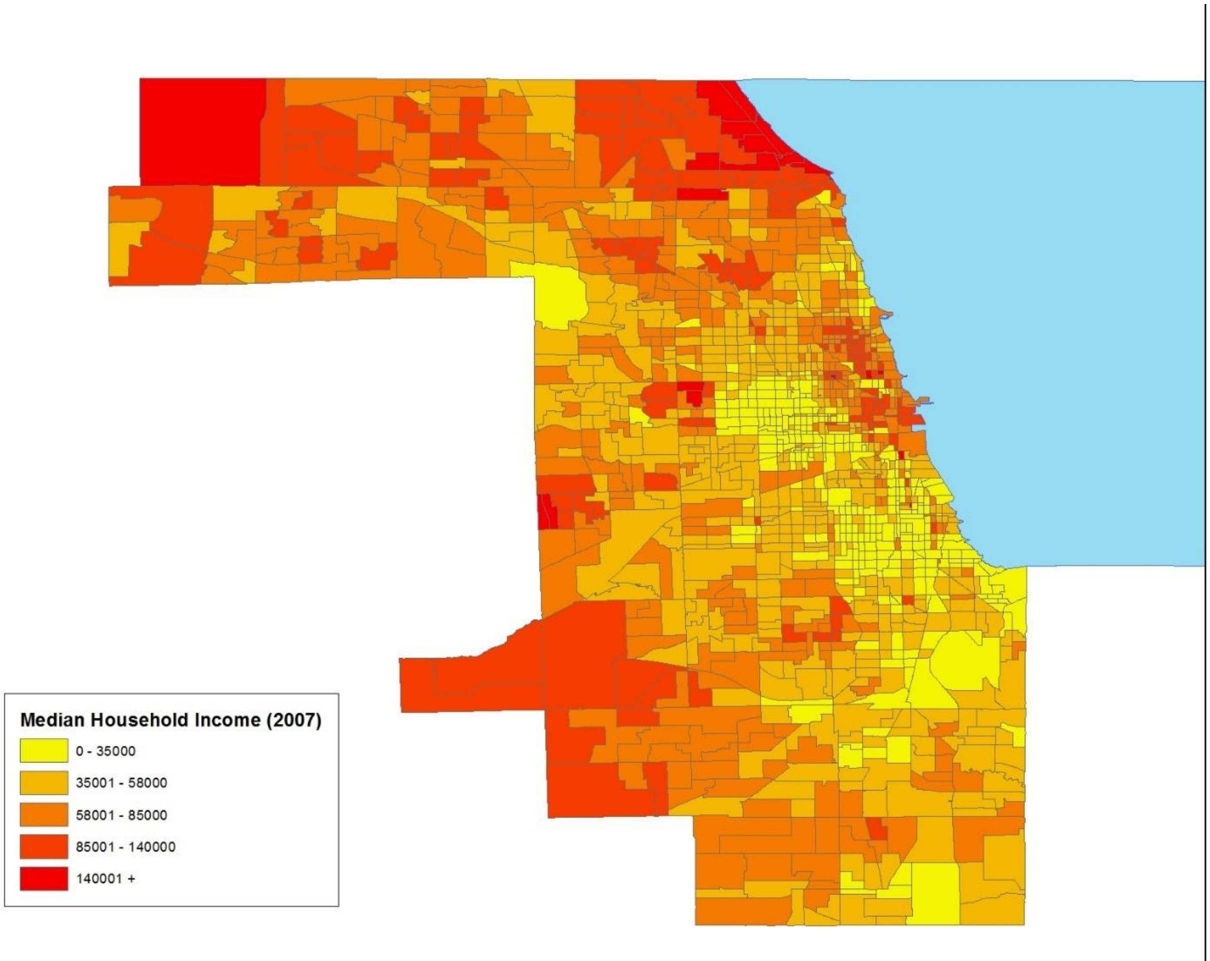
This map shows rates of upward mobility for children born in the 1980s for 741 metro and rural areas ("commuting zones") in the U.S. Upward mobility is measured by the fraction of children who reach the top fifth of the national income distribution, conditional on having parents in the bottom fifth. Lighter colors represent areas with higher levels of upward mobility.

Figure 5. Spatial distribution of poverty rates



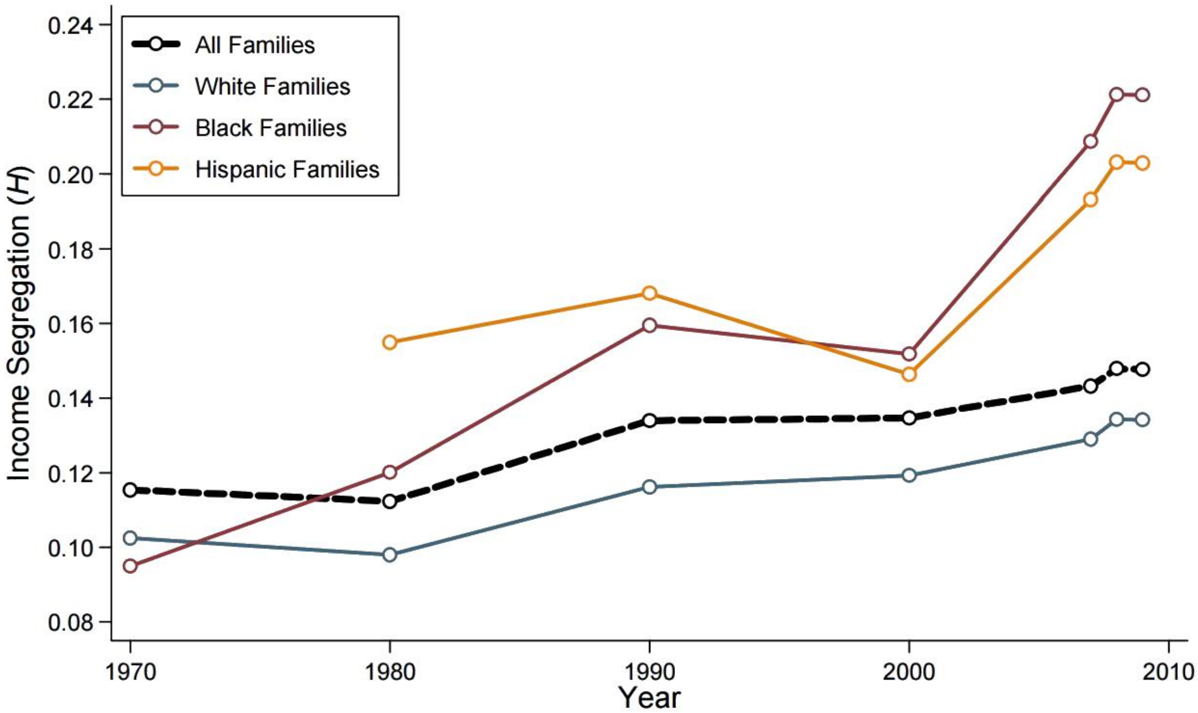
Source: US Census Bureau

Figure 6. Income segregation in Chicago



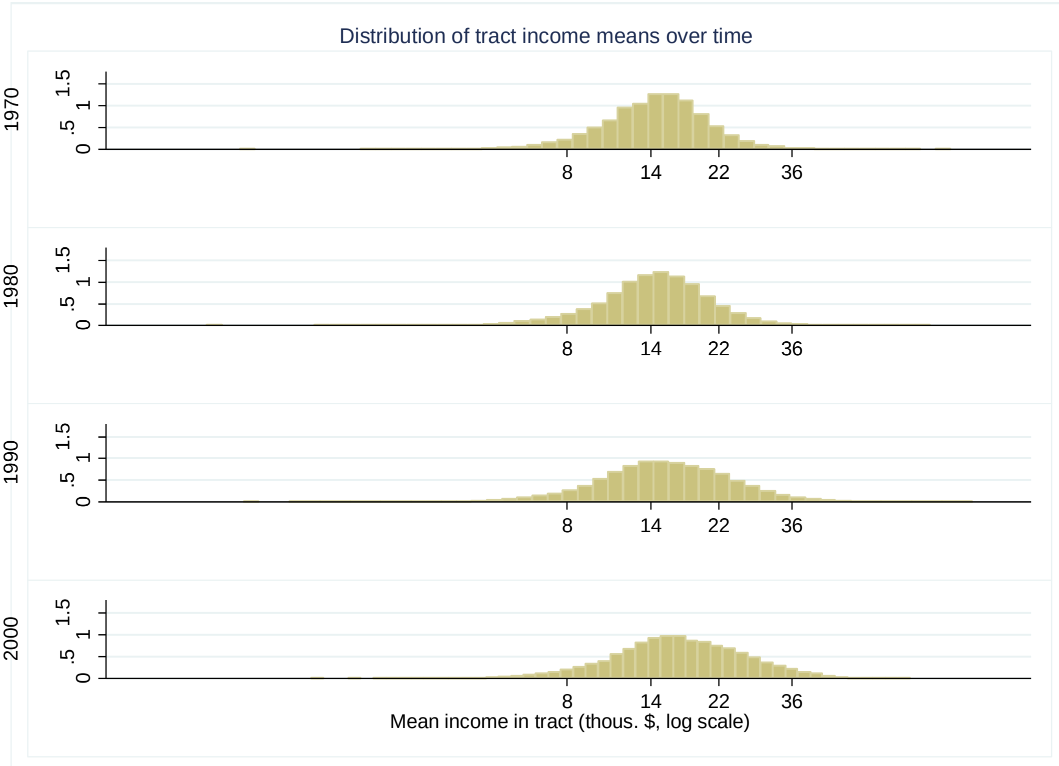
Source: US Census Bureau

Figure 7. Trends in family income segregation, by race



Source: Bischoff and Reardon (2013); authors' tabulations of data from U.S. Census (1970-2000) and American Community Survey (2005- 2011). Averages include all metropolitan areas with at least 500,000 residents in 2007 and at least 10,000 families of a given race in each year 1970-2009 (or each year 1980-2009 for Hispanics). This includes 116 metropolitan areas for the trends in total and white income segregation, 65 metropolitan areas for the trends in income segregation among black families, and 37 metropolitan areas for the trends in income segregation among Hispanic families. Note: the averages presented here are unweighted. The trends are very similar if metropolitan areas are weighted by the population of the group of interest.

Figure 8. Changes in census tract income averages over time



Notes for Figures 8–11: All income deflated using CPI-U-RS and expressed in logs.

Figure 9. Evolution of state income averages over time

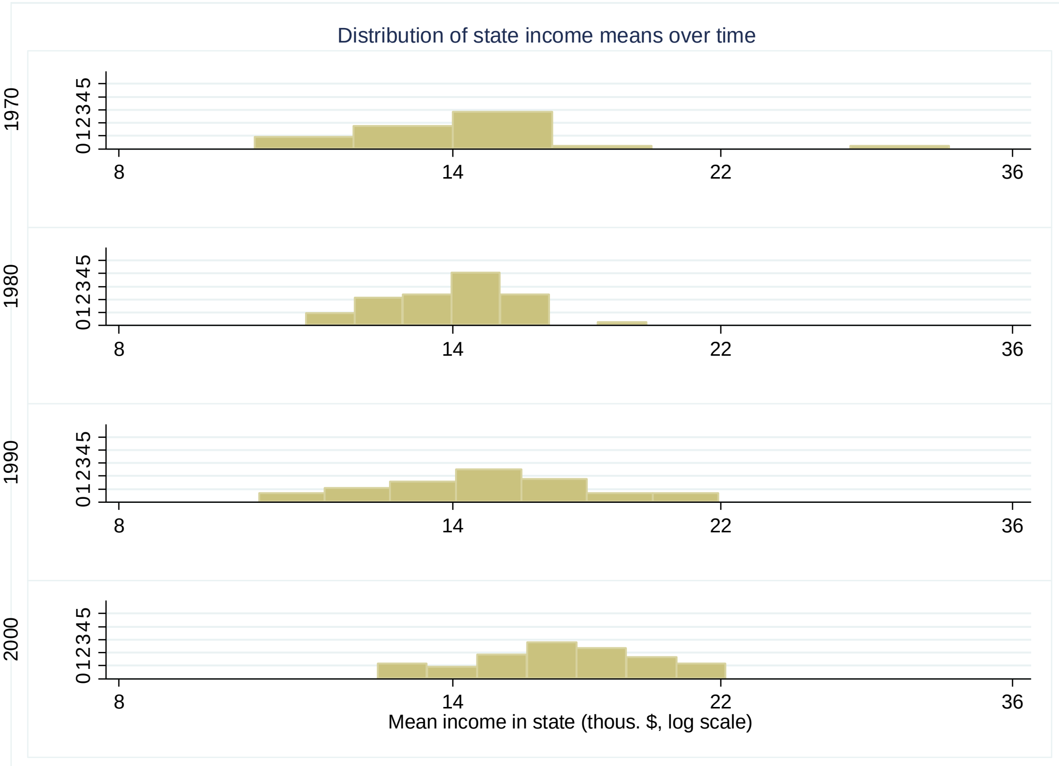


Figure 10. Evolution of census tract income variances over time

Figure 11. Evolution of state income variances over time

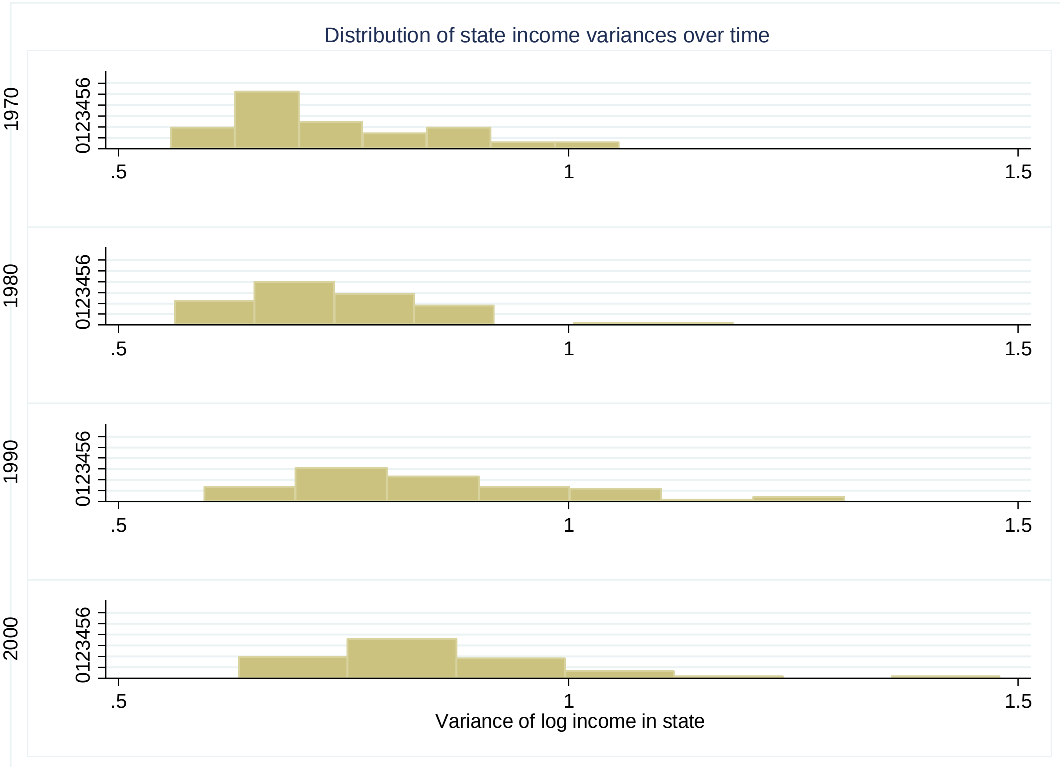
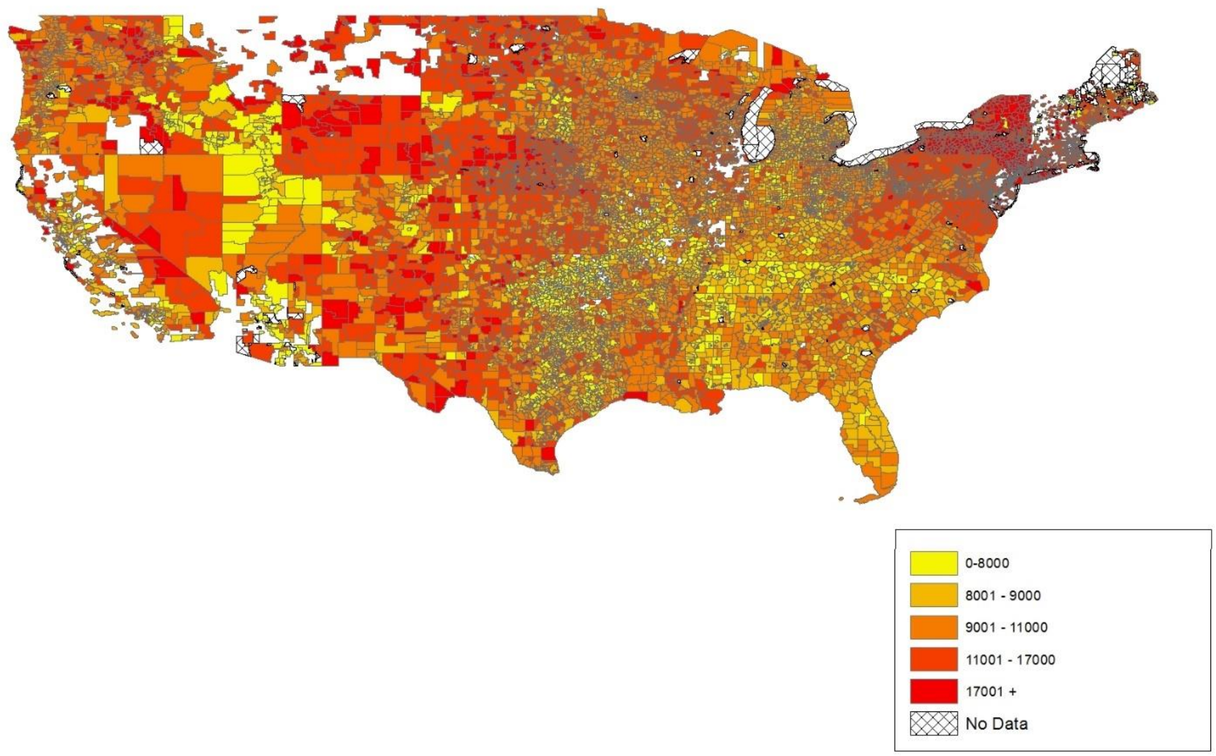
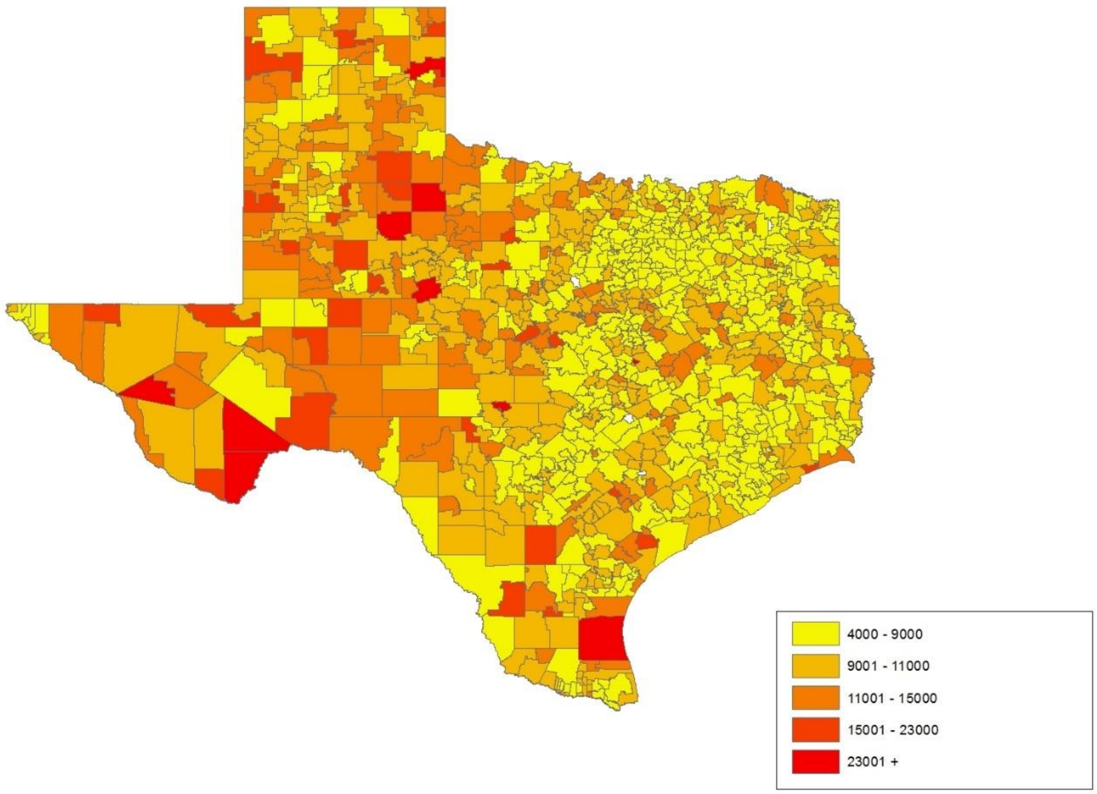


Figure 12. Spatial variation in per capita public school expenditure



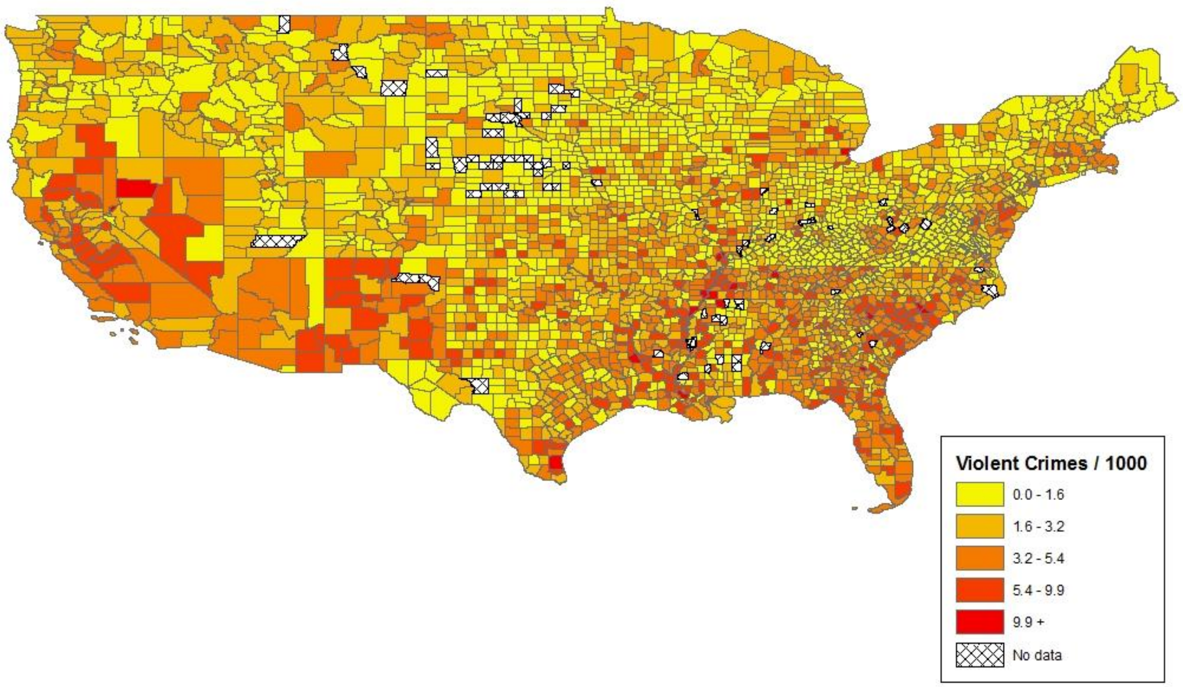
Note: 2014 per pupil expenditure, in dollars. Source: NCES.

Figure 13. Spending per student, by school district, Texas



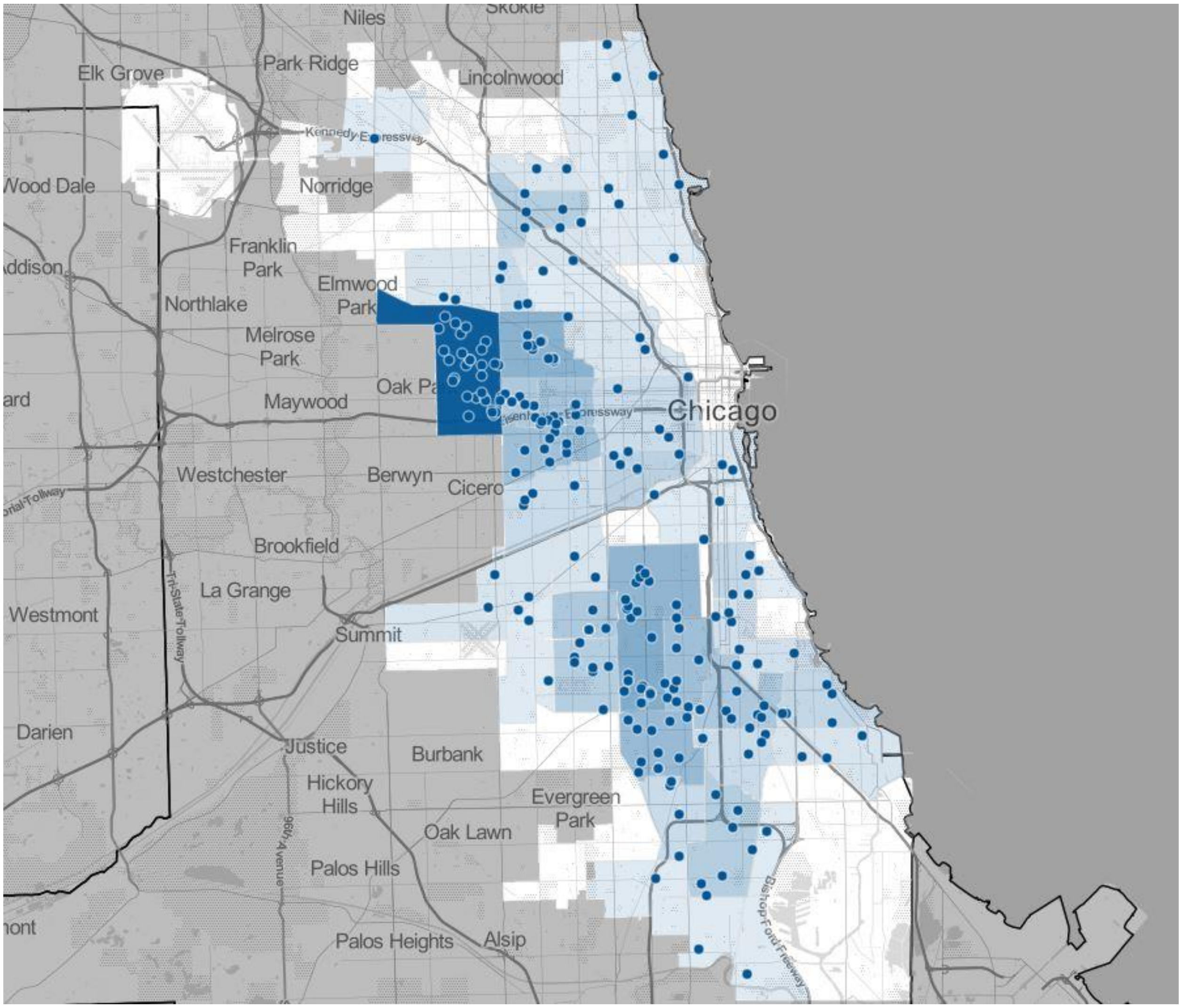
Note: 2014 per pupil expenditure, in dollars. Source: NCES.

Figure 14. Exposure to violent crime



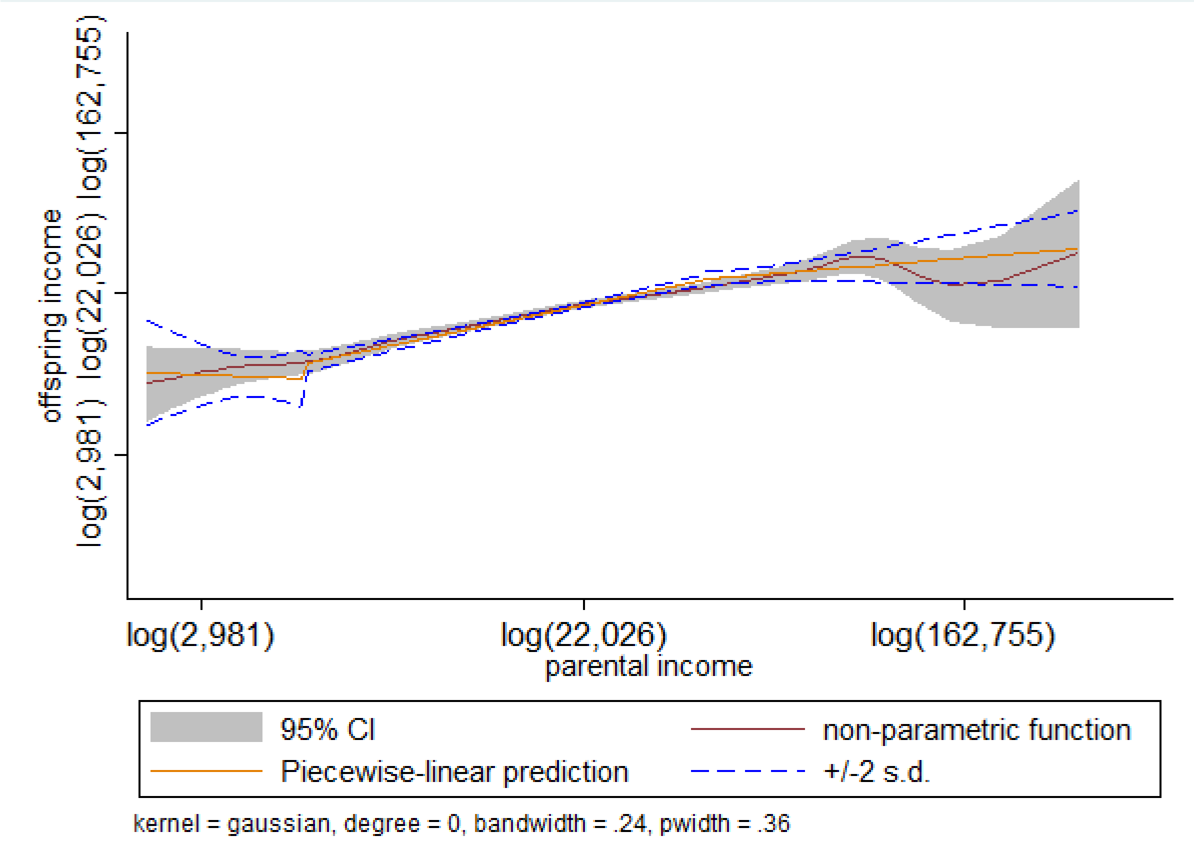
Note: Violent crimes per thousand people, 2012. Source: Uniform Crime Reporting Program.

Figure 15. Distribution of homicides in Chicago



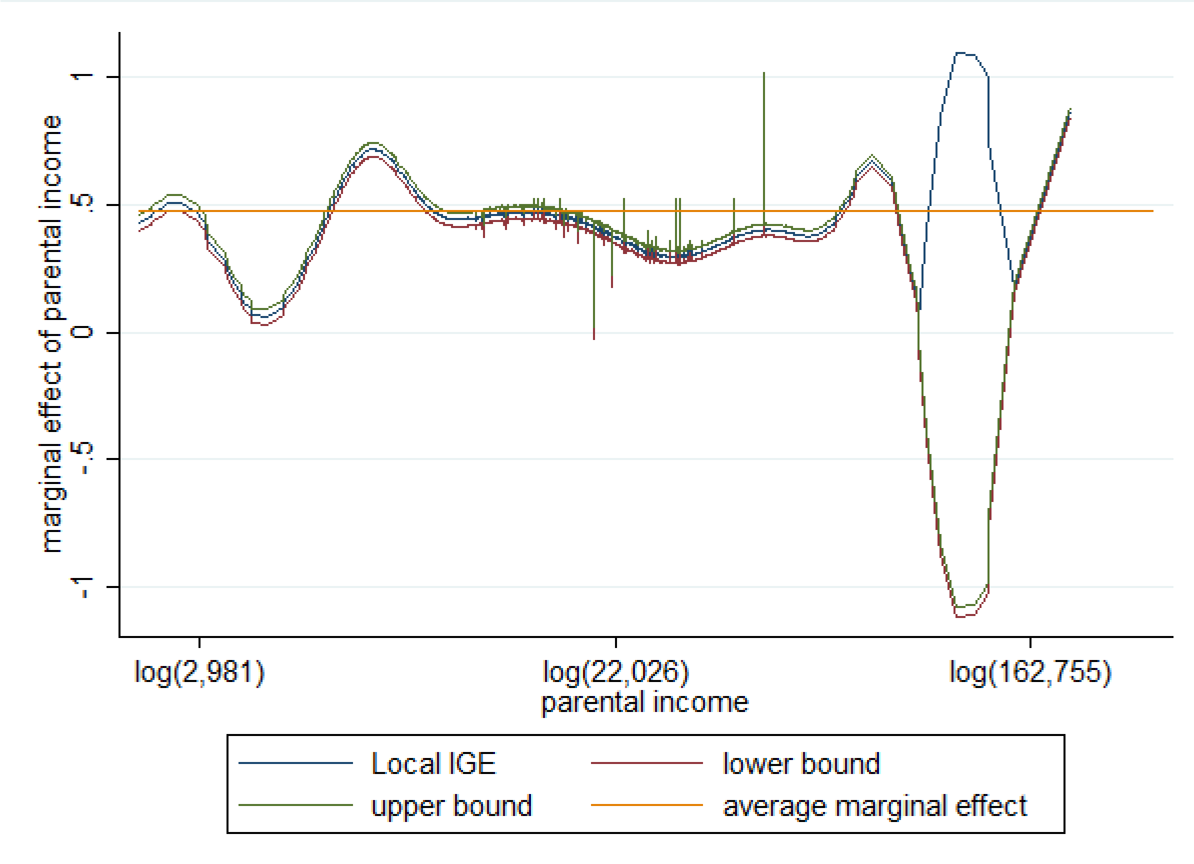
Source: Chicago Tribune. Accessed May 21, 2016.

Figure 16. Non-parametric estimation of offspring's income given parental income



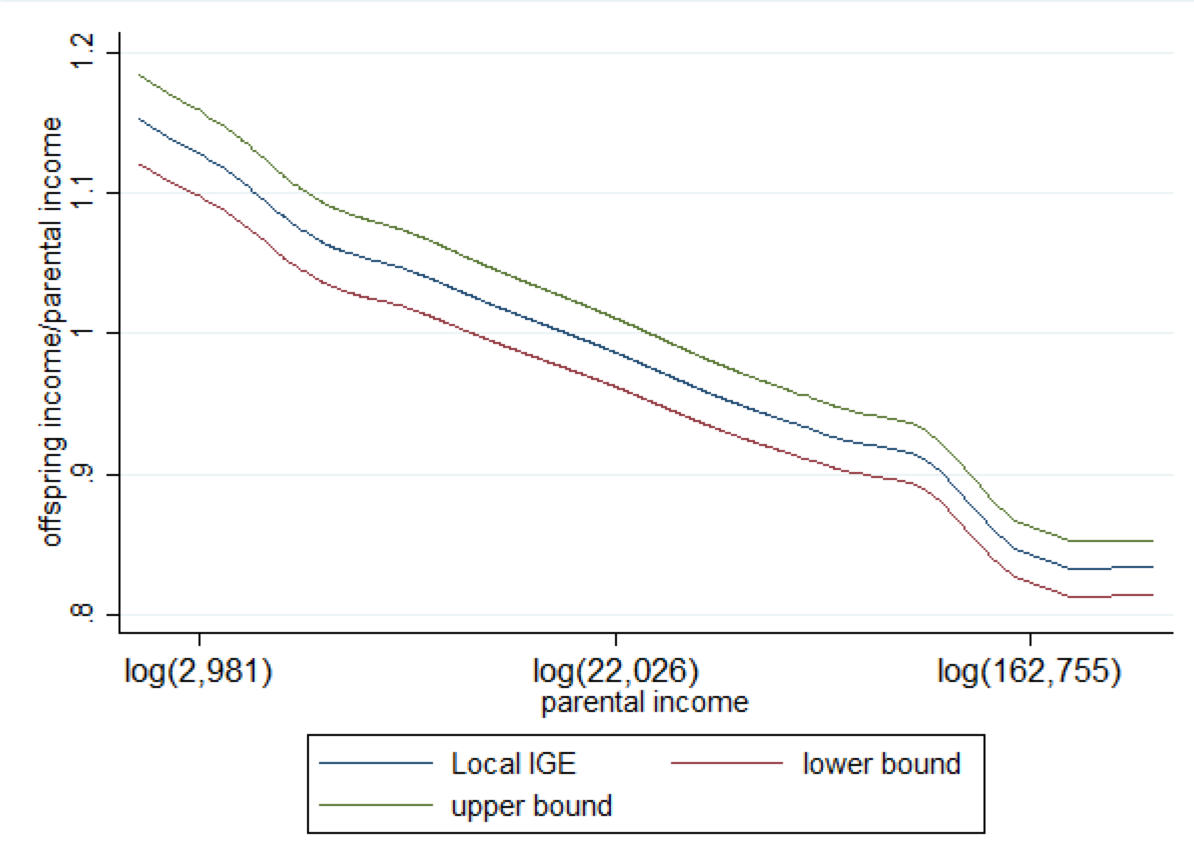
The figure shows that expected offspring income is non-linearly dependent on parental income. Offspring income conditional on parental income (red line) was non-parametrically calculated using a kernel density estimator with a normal density weighting function. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30—34. Parental income is individual's family income in adolescence (averaged over ages 13-17). The orange line represents the piece-wise linear prediction of offspring's income given parental income.

Figure 17a. Local IGE estimates for income



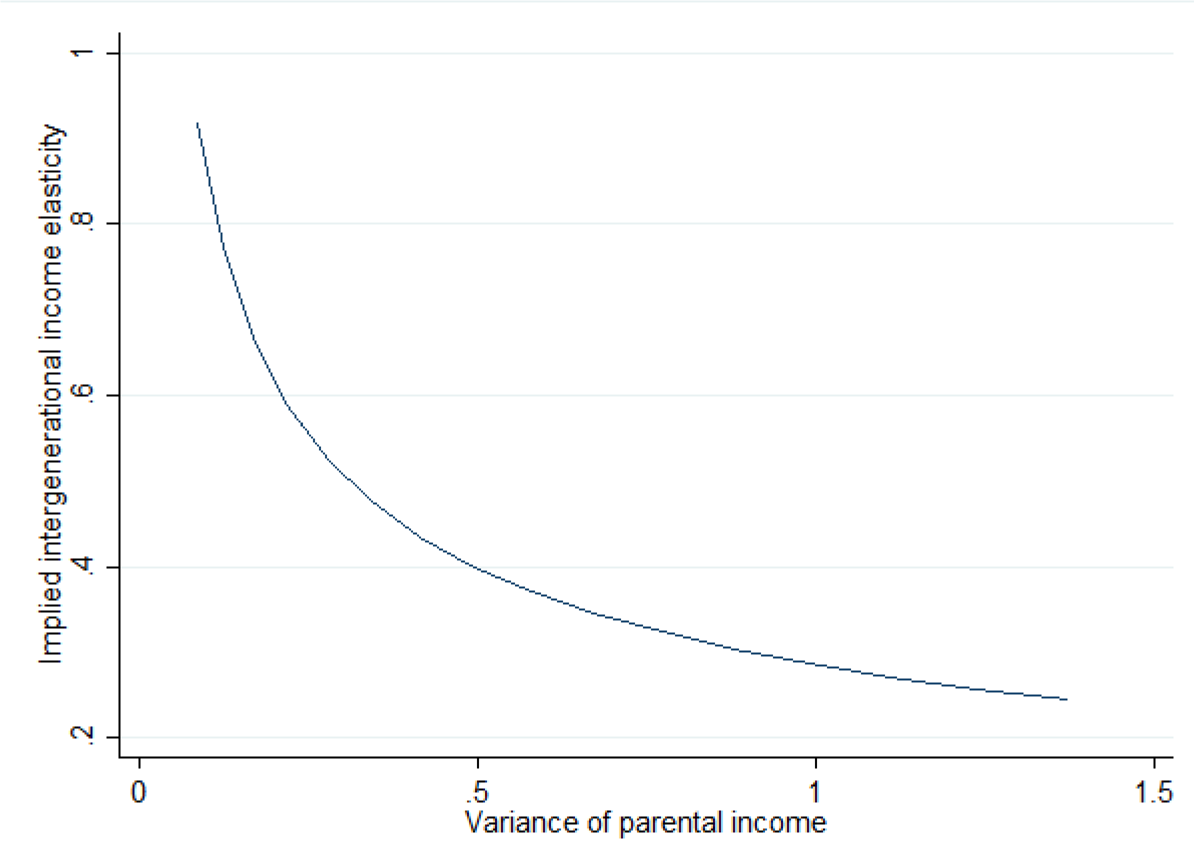
The graph displays local IGE estimates - defined as the marginal effect of parental income at each income level - obtained from non-parametric estimation of offspring's income conditional on parental income. The dependent variable is the marginal effect of parental income. Lower and upper bounds represent 1 standard deviation from the local IGE. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30—34. Parental income is individual's family income in adolescence (averaged over ages 13-17).

Figure 17b. Local IGE estimates for income



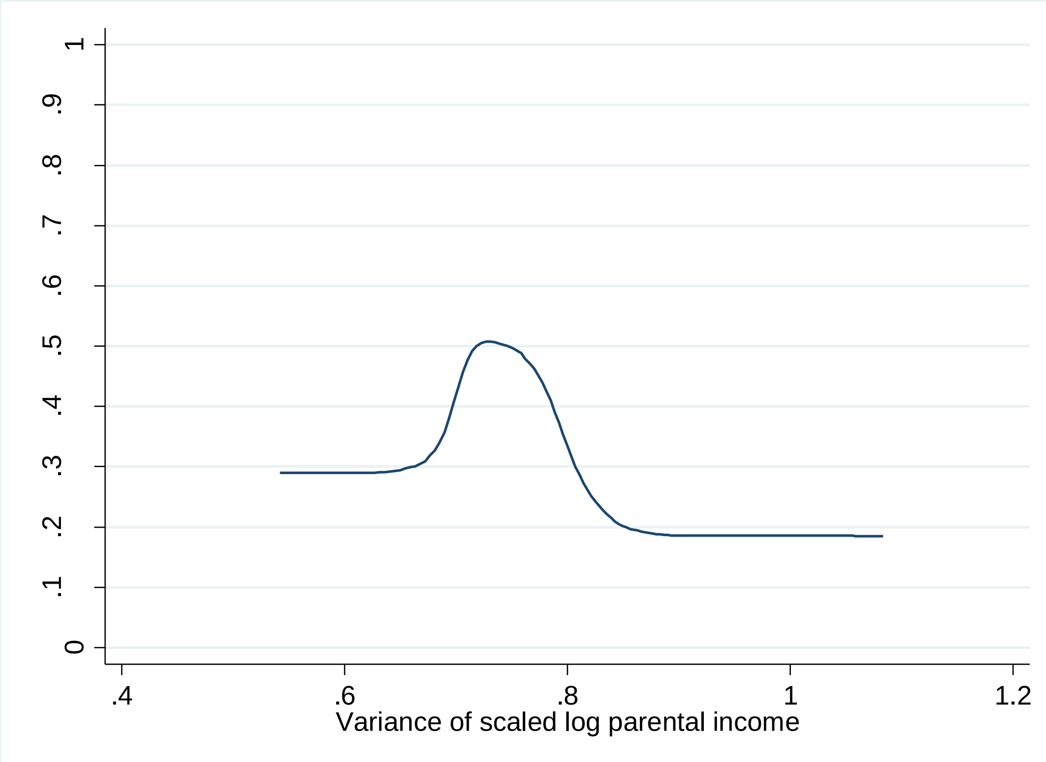
The graph displays local IGE estimates - defined as the ratio of offspring income to parental income level - obtained from non-parametric estimation of offspring's income conditional on parental income. The dependent variable is the ratio of offspring income to parental income. Lower and upper bounds represent 1 standard deviation from the local IGE. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30—34. Parental income is individual's family income in adolescence (averaged over ages 13-17).

Figure 18. Great Gatsby Curve implied by nonparametric specification under scaling of parental income



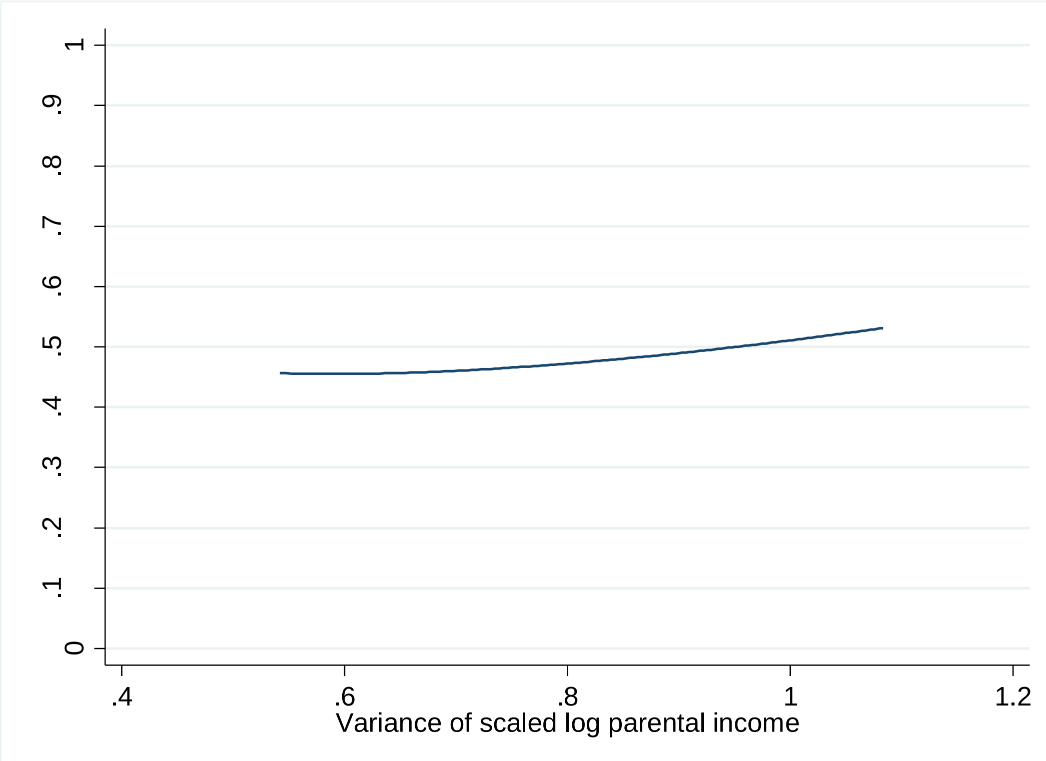
The graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. The initial parental income distribution corresponds to the parental income in the PSID sample. The graph was constructed as follows. We, first, non-parametrically estimated offspring's income given parental income and saved residuals from the estimation. Then for each scaling of log of parental income - that also scaled variance of parental income (horizontal axis) - offspring income is predicted using the non-parametric estimation and residuals from the first step. Afterwards, predicted offspring income is regressed on scaled parental income; the regression coefficients - the implied IGEs - are plotted. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 19. Great Gatsby curve implied by parametric specification including parents' percentile in nation



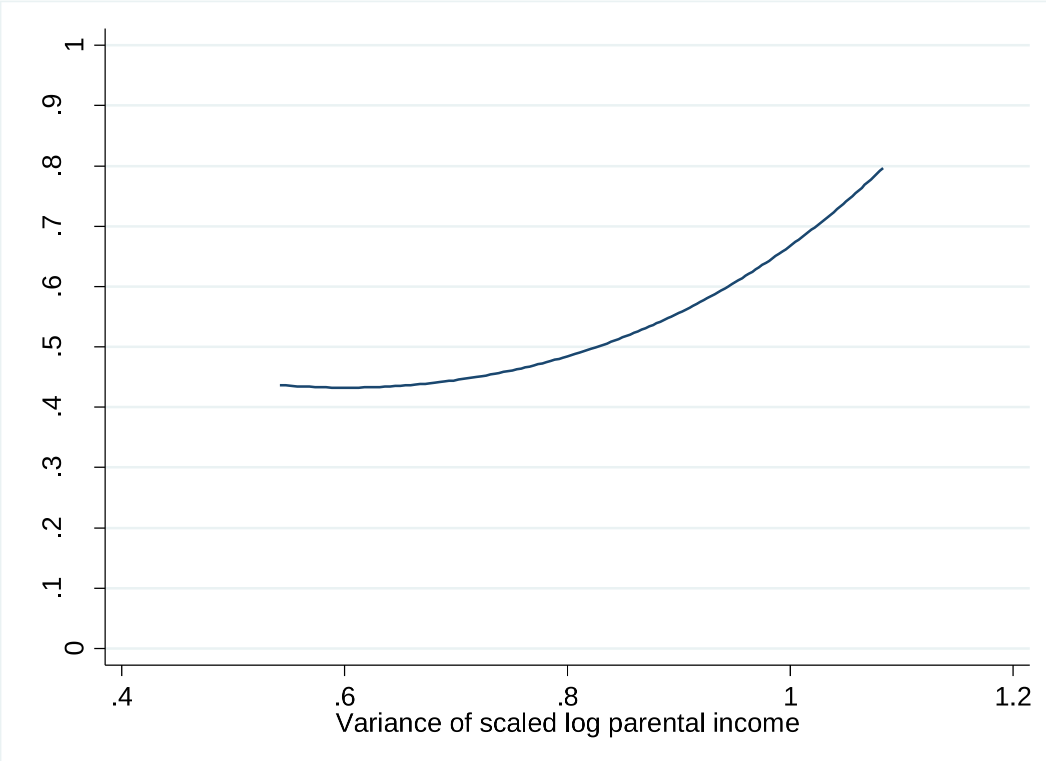
This graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. For each scaling of log parental income (from -50% to +100%), offspring incomes are predicted using the estimated coefficients from Table 1, specification 2. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 20. Great Gatsby curve implied by parametric specification including tract average, under scaling of parental income



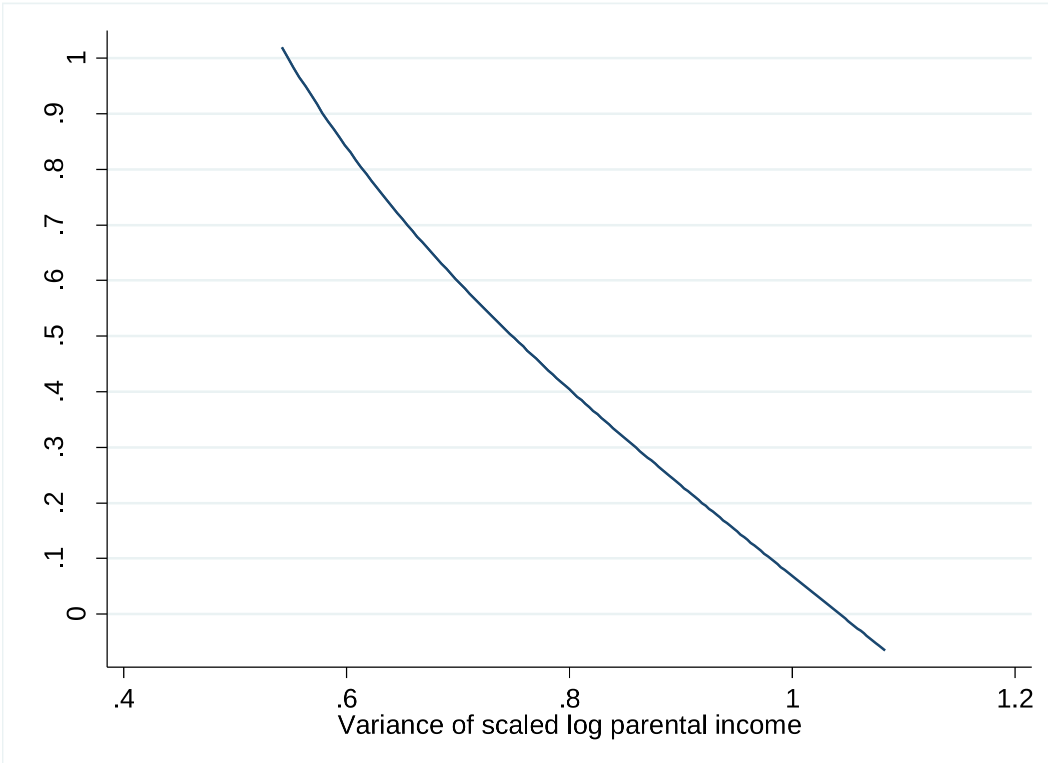
This graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. For each scaling of log parental income (from -50% to +100%), which is also applied to tract averages, offspring incomes are predicted using the estimated coefficients from Table 4a, specification 4. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 21. Great Gatsby curve implied by parametric specification including tract average and variance, under scaling of parental income



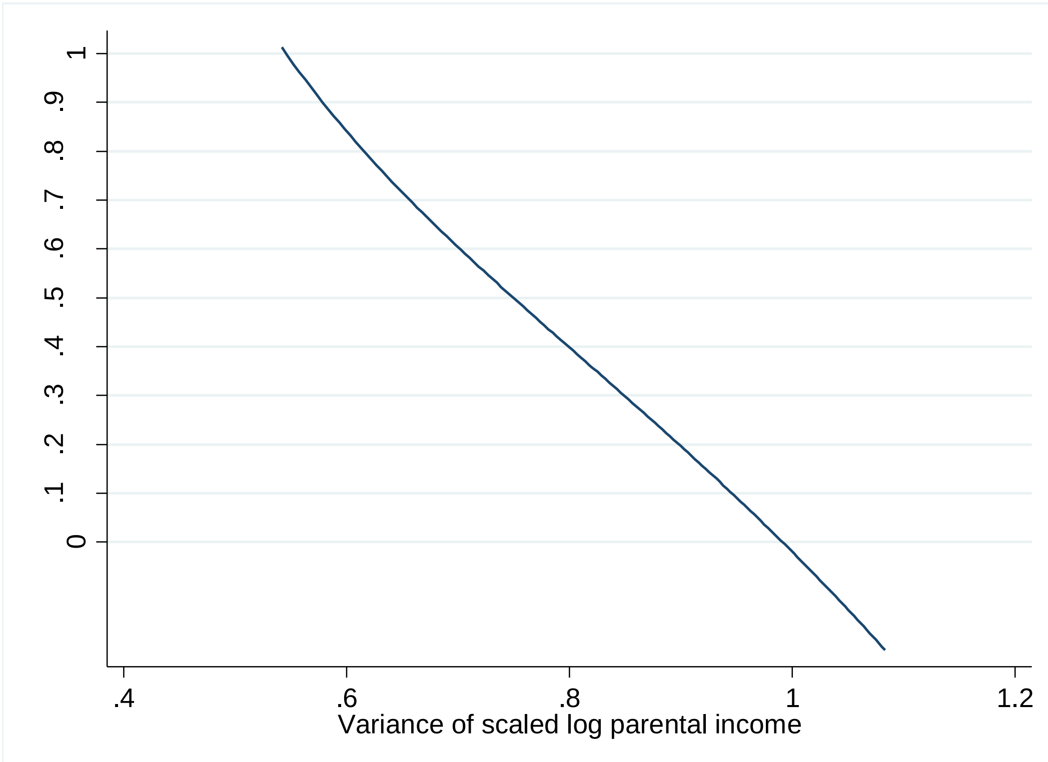
This graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. For each scaling of log parental income (from -50% to +100%), which is also applied to tract averages and variances, offspring incomes are predicted using the estimated coefficients from Table 4, specification 6. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 22. Great Gatsby curve implied by parametric specification including state average, under scaling of parental income



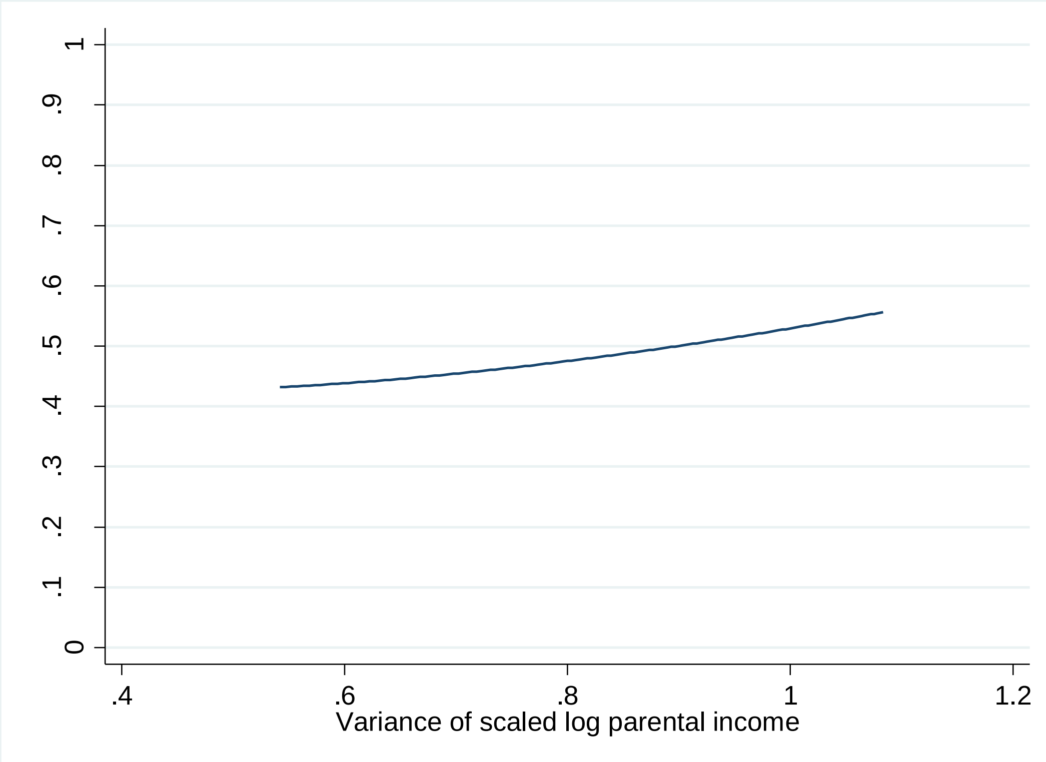
This graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. For each scaling of log parental income (from -50% to +100%), which is also applied to state averages, offspring incomes are predicted using the estimated coefficients from Table 5, specification 4. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 23. Great Gatsby curve implied by parametric specification including state average and variance, under scaling of parental income



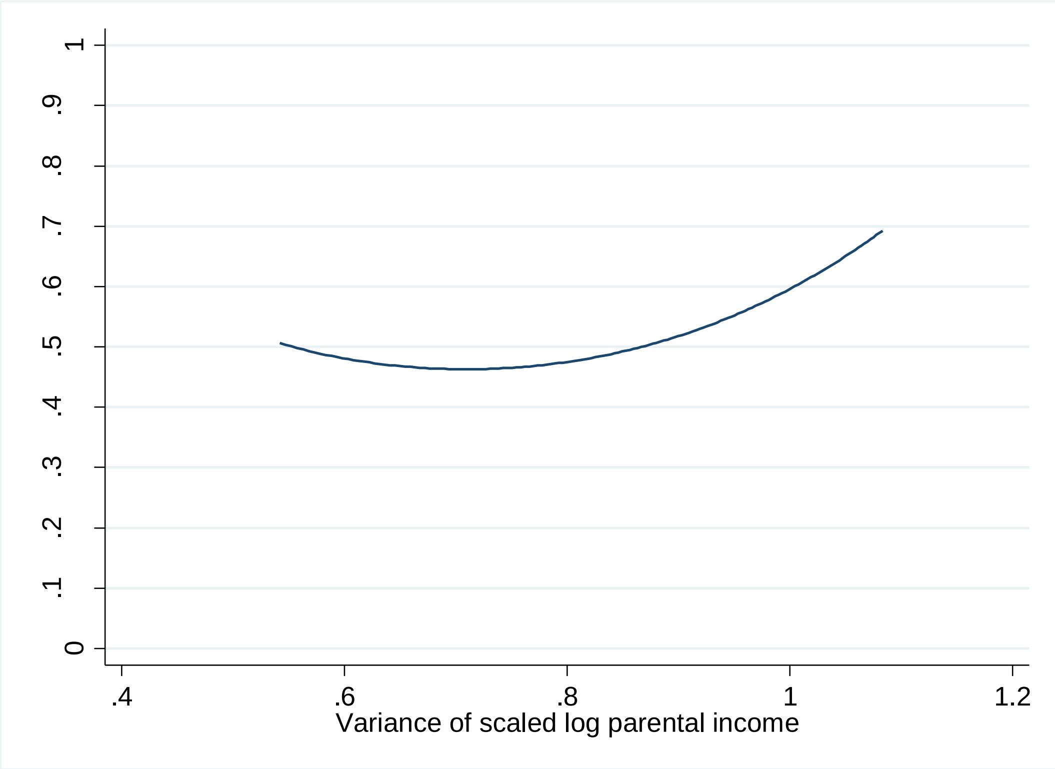
This graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. For each scaling of log parental income (from -50% to +100%), which is also applied to state averages and variances, offspring incomes are predicted using the estimated coefficients from Table 5, specification 6. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 24. Great Gatsby curve implied by parametric specification including tract and state average, under scaling of parental income



The graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. This figure assumes that offspring income depends linearly on parental income, average tract and state income, and the interaction of parental income with these variables. For each scaling of log parental income (from -50% to +100%), which is also applied to tract and state averages, offspring incomes are predicted using the estimated coefficients from Table 6, specification 1. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 25. Great Gatsby curve implied by parametric specification including tract and state average and variance, under scaling of parental income



The graph depicts how the IGE—the marginal effect of parental income on offspring's income—responds to scaling of parental income. This figure assumes that offspring income depends linearly on parental income, average and variance of tract and state income, and the interaction of parental income with these variables. For each scaling of log parental income (from -50% to +100%), which is also applied to tract and state averages and variances, offspring incomes are predicted using the estimated coefficients from Table 6, specification 4. Then predicted offspring income is regressed on scaled parental income; the regression coefficients are plotted. The horizontal axis displays the variance of the scaled log parental incomes. All income measures are deflated using CPI-U-RS and expressed in logs. Offspring income is an individual's family income averaged over ages 30–34. Parental income is individual's family income in adolescence (averaged over ages 13–17).

Figure 26. Relationship between parental income and offspring income in the model

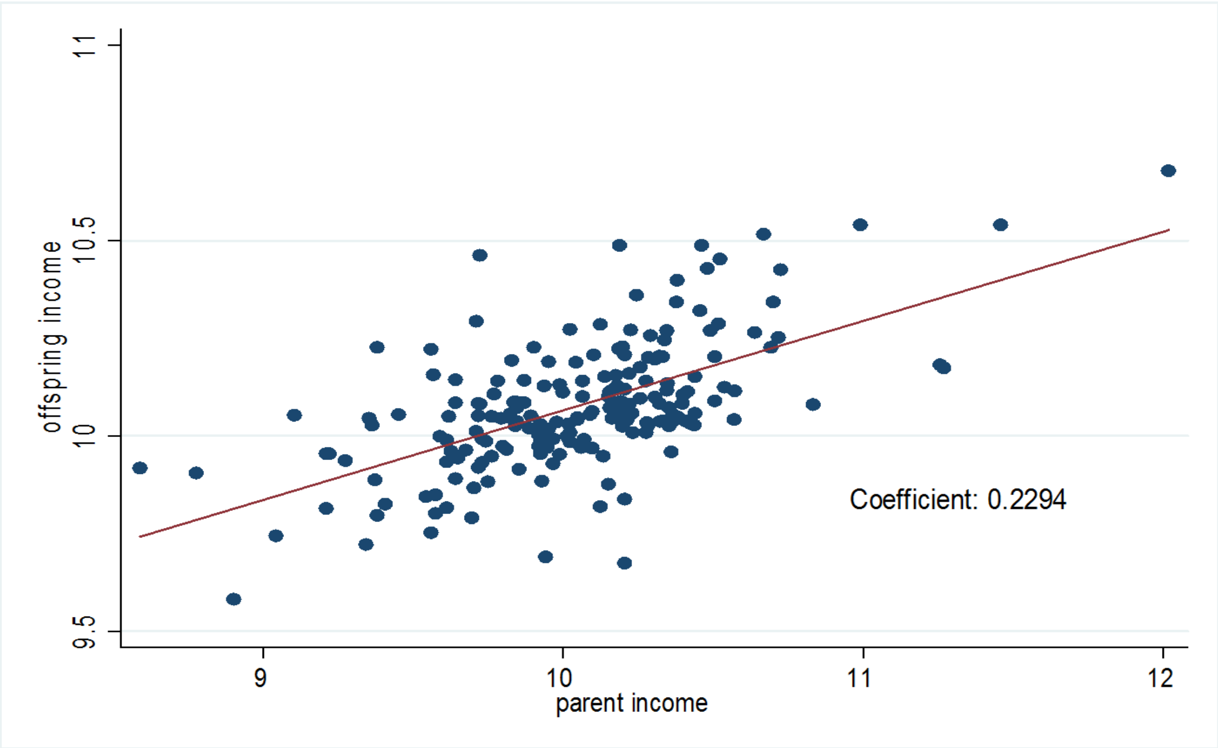


Figure 27. Relationship between ratio of offspring income to parental income and offspring income

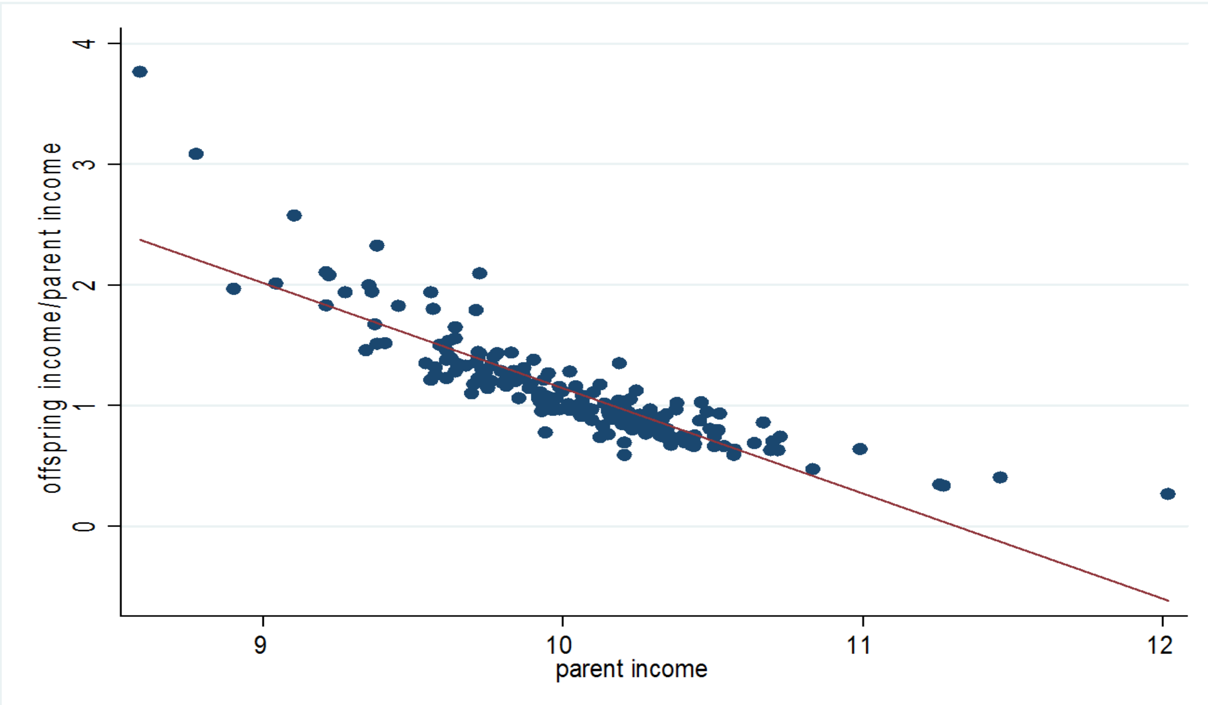


Figure 28. Counterfactual simulation: contribution of various elements to intergenerational mobility

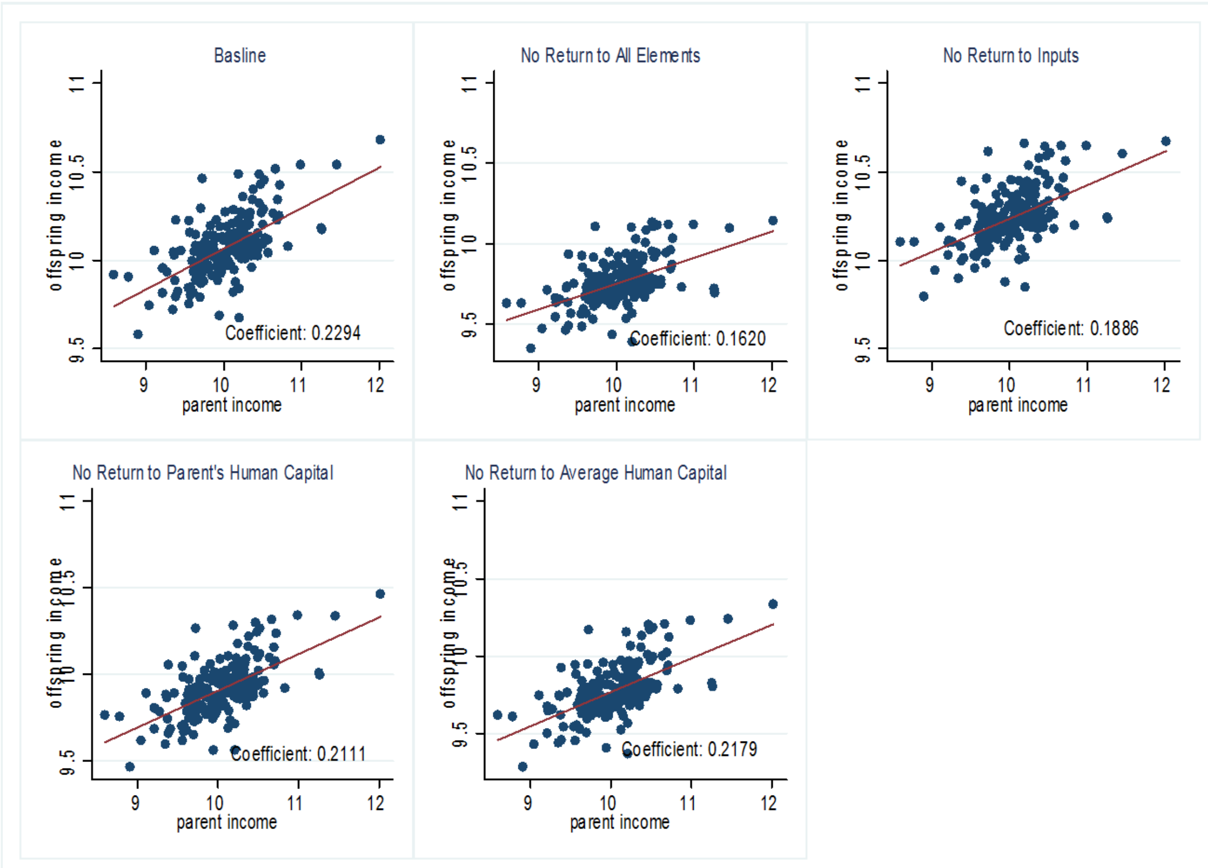


Figure 29. Counterfactual simulation: effect of changing parental inequality on intergenerational mobility

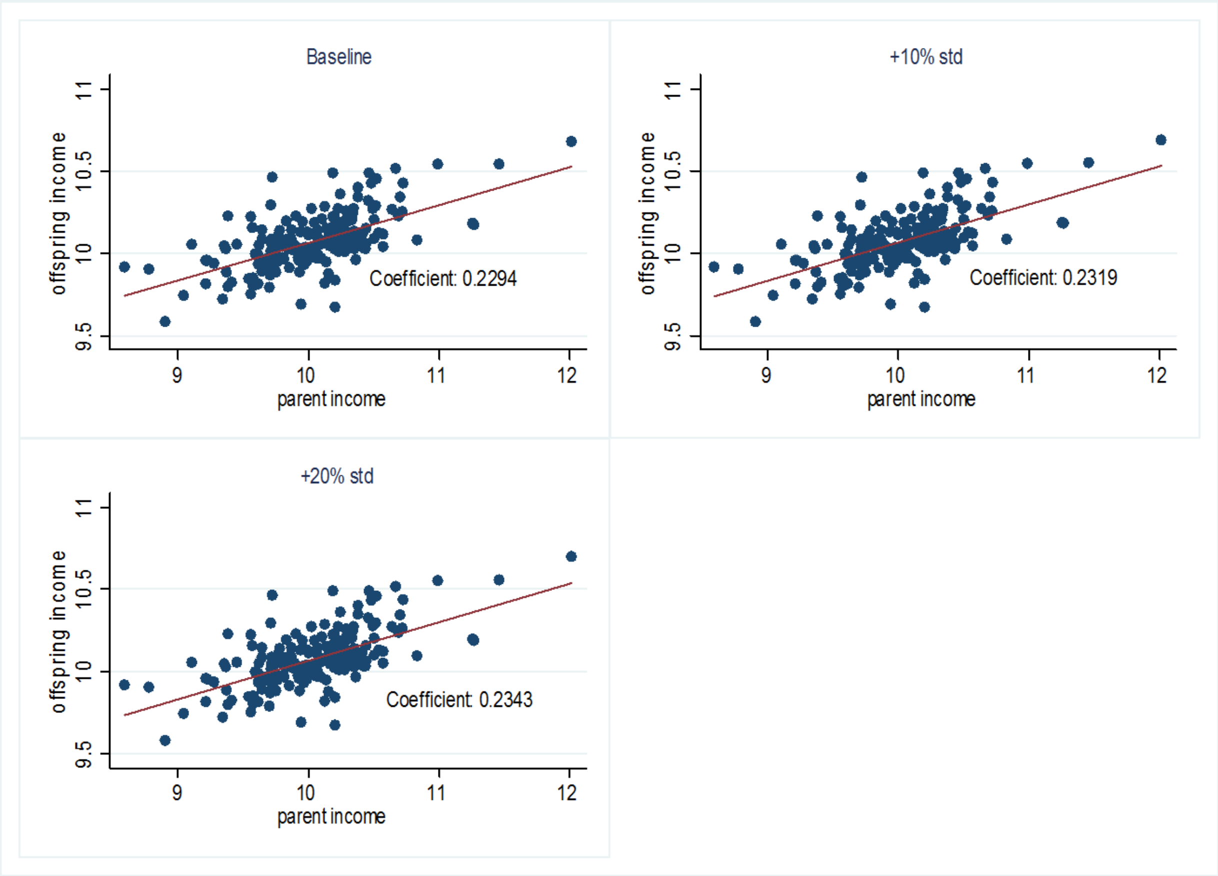


Table 1. IGE regressions for bottom 10%, middle 80% and top 10% relative to nation

Family income
ages 30-34

VARIABLES	(1)	(2)
Low (parents' income below 10th percentile in country)		6.527***
		(1.976)
Mid (parents' income between 10th and 90th percentiles in country)		4.991***
		(0.395)
High (parents' income above 90th percentile in country)		8.215***
		(1.450)
Low*parents' income	0.438***	0.290
	(0.0471)	(0.234)
Mid*parents' income	0.458***	0.487***
	(0.0384)	(0.0399)
High*parents' income	0.456***	0.185
	(0.0353)	(0.134)
Constant	5.271***	
	(0.379)	
Observations	1,617	1,617
R-squared	0.172	0.996

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All income in logs.

Table 2. IGE regressions for bottom 10%, middle 80% and top 10% relative to state

Family income ages 30-34		
VARIABLES	(1)	(2)
Low (parents' income below 10th percentile in state)		6.358***
		(1.831)
Mid (parents' income between 10th and 90th percentiles in state)		4.528***
		(0.395)
High (parents' income above 90th percentile in state)		6.674***
		(1.629)
Low*parents' income	0.518***	0.332
	(0.0474)	(0.217)
Mid*parents' income	0.509***	0.534***
	(0.0384)	(0.0400)
High*parents' income	0.499***	0.323**
	(0.0353)	(0.150)
Constant	4.772***	
	(0.380)	
Observations	1,617	1,617
R-squared	0.172	0.996

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All income in logs.

Table 3. IGE regressions for bottom 10%, middle 80% and top 10% relative to census tract

Family income ages 30-34		
VARIABLES	(1)	(2)
Low (parents' income below 10th percentile in tract)		5.587***
		(0.532)
Mid (parents' income between 10th and 90th percentiles in tract)		4.826***
		(0.422)
High (parents' income above 90th percentile in tract)		6.067***
		(1.144)
Low*parents' income	0.455***	0.417***
	(0.0334)	(0.0546)
Mid*parents' income	0.467***	0.507***
	(0.0327)	(0.0423)
High*parents' income	0.459***	0.380***
	(0.0307)	(0.106)
Constant	5.216***	
	(0.326)	
Observations	1,617	1,617
R-squared	0.177	0.996

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All income in logs.

Table 4. IGE and interactions with census tract income distribution

Family income ages 30-34						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Family income, ages 13-17	0.471***	0.361***	0.363***	0.363***	0.450***	0.370***
	(0.0294)	(0.0389)	(0.0387)	(0.0390)	(0.0354)	(0.0404)
Average income in tract		0.330***		0.0817		0.571
		(0.0672)		(0.731)		(0.968)
Income variance in tract		0.0438			1.081	1.296
		(0.0950)			(1.176)	(1.504)
Family income*tract avg.			0.0326***	0.0235		-0.0244
			(0.00658)	(0.0729)		(0.0953)
Family income*tract var.			0.00266		-0.134	-0.128
			(0.00959)		(0.121)	(0.152)
Constant	5.136***	6.261***	6.240***	6.248***	5.374***	6.173***
	(0.293)	(0.389)	(0.388)	(0.391)	(0.356)	(0.405)
Observations	1,617	1,153	1,153	1,153	1,153	1,153
R-squared	0.170	0.179	0.179	0.179	0.163	0.180

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes for tables 4–6: All income deflated using CPI-U-RS. Tract measures are normalized to have zero mean. The dependent variable in the linear regression results of Tables 4–6 is an individual's family income averaged over ages 30–34; individual's family income in adolescence is averaged over ages 13–17.

Table 5. IGEs and interaction with state income distribution

Family income ages 30-34						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Family income, ages 13-17	0.471***	0.434***	0.436***	0.426***	0.449***	0.414***
	(0.0294)	(0.0294)	(0.0294)	(0.0287)	(0.0283)	(0.0284)
Average income in state		0.788***		6.962***		4.871**
		(0.145)		(2.132)		(2.462)
Income variance in state		0.644***			-9.647***	-5.772
		(0.177)			(3.189)	(3.625)
Family income*state avg.			0.0773***	-0.654***		-0.416*
			(0.0146)	(0.215)		(0.248)
Family income*state var.			0.0675***		1.002***	0.656*
			(0.0177)		(0.320)	(0.364)
Constant	5.136***	5.502***	5.483***	5.602***	5.363***	5.717***
	(0.293)	(0.292)	(0.293)	(0.285)	(0.282)	(0.282)
Observations	1,617	1,611	1,611	1,611	1,611	1,611
R-squared	0.170	0.184	0.183	0.183	0.178	0.193

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All income in logs; state measures normalized to have zero mean.

Table 6. IGE's and census tract and state income distributions

Family income ages 30-34				
VARIABLES	(1)	(2)	(3)	(4)
Family income, ages 13-17	0.361***	0.442***	0.362***	0.366***
	(0.0391)	(0.0355)	(0.0384)	(0.0407)
Family income*tract average	0.0942		0.0282***	0.0334
	(0.0824)		(0.00604)	(0.104)
Family income*state average	-0.519*		0.0492***	-0.504
	(0.270)		(0.0186)	(0.313)
Average income in tract	-0.633			-0.0627
	(0.826)			(1.050)
Average income in state	5.329**			5.507*
	(2.697)			(3.130)
Family income*tract variance		-0.197		-0.116
		(0.129)		(0.158)
Family income*state variance		0.493	0.0768***	0.0664
		(0.315)	(0.0198)	(0.377)
Income variance in tract		1.638		1.073
		(1.264)		(1.564)
Income variance in state		-4.357		0.143
		(3.155)		(3.777)
Constant	6.257***	5.455***	6.238***	6.208***
	(0.392)	(0.358)	(0.385)	(0.409)
Observations	1,153	1,153	1,153	1,153
R-squared	0.183	0.171	0.190	0.193

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All income in logs; measures normalized to have zero mean.

Table 7: Fixed parameters in the calibration exercise

Description	Parameter	Value
CRRA coefficient	α	2.0
Discount factor	β	0.96^6
Return to schooling	ϕ	0.1
Average wage rate in the U.S	w	0.1707
Interest Rate	r	$(1+0.04)^6-1$

Table 8: Data moments used in the calibration exercise

Moments	Value
Average offspring income between 24 and 28	$18,313
Average offspring income between 30 and 34	$23,737
Average offspring income between 24 and 28 in Group 1	$16,418
Average offspring income between 24 and 28 in Group 2	$18,409
Average offspring income between 30 and 34 in Group 1	$21,059
Average offspring income between 30 and 34 in Group 2	$24,248
Average offspring income between 24 and 28 in Group 11	$17,583
Average offspring income between 24 and 28 in Group 12	$18,470
Average school years in college	1.6016

Table 9: Estimated parameters for the calibration exercise

Parameters	Value
θ	0.5657 (0.0172)
α_1	0.1283 (0.001)
α_2	0.2642 (0.1202)
α_3	0.5314 (0.1302)
η_1	0.5263 (0.003)
μ_{a_j}	0.3634 (0.0048)
σ_{a_j}	0.1691 (0.0053)
$\rho_{h_{j0}a_j}$	0.2531 (0.1112)

Table 10: Targeted moments used in the calibration exercise

Moments	Data	Model
Average child income between 24 and 28	$18,313	$18,590
Average child income between 30 and 34	$23,737	$24,101
Average child income between 24 and 28 in Group 1	$16,418	$16,439
Average child income between 24 and 28 in Group 2	$18,409	$18,237
Average child income between 30 and 34 in Group 1	$21,059	$21,298
Average child income between 30 and 34 in Group 2	$24,248	$23,582
Average child income between 24 and 28 in Group 11	$17,583	$17,526
Average child income between 24 and 28 in Group 12	$18,470	$18,232
Average school years in college	1.6016	2.3469