Understanding the Great Gatsby Curve

By **Steven N. Durlauf,** *University of Chicago and NBER*
Ananth Seshadri, *University of Wisconsin*

James J. Heckman

THE UNIVERSITY OF CHICAGO

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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
- Our analysis is strongly motivated by and related to these literatures
- Our theoretical model and stylized facts are derived from a specific vision of the nexus between inequality and mobility, one in which segregation represents the fundamental causal mechanism linking inequality and mobility
- 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

We proceed as follows:

- **Section 2** describes the environment that we study
- **Section 3** characterizes income dynamics for the environment
- **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

- One way to understand our argument is to start with a linear model relating parental income *Yip* and offspring income *Yio*

$$Y_{io} = \alpha + \beta Y_{ip} + \varepsilon_{io}. \qquad (1)$$

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

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

- 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)

A. Demography

- The population possesses a standard overlapping generations structure

- Each agent lives for two periods
  - 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 *Cit* and income of her offspring, *Yit*+1. Offspring income is not known at *t*, so each agent is assumed to maximize expected utility that has a Cobb-Douglas specification

$$EU_{it} = \pi_1 \log(C_{it}) + \pi_2 E(\log(Y_{it+1}) \mid F_t) \quad (3)$$

- Cobb-Douglas utility plays an important role in our analysis

C. Income and Human Capital

- Adult *it*'s income is determined by two factors
- 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

D. Family Expenditures

- Parental 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

E. Educational Expenditure and Educational Investment in Children

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

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

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

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

- The educational investment provided by the neighborhood to each child, ED_{nt} (equivalent to educational quality), requires total expenditures

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

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}

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

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

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

G. Neighborhood Formation

- Neighborhoods reform every period, that is, there is no housing stock

- As such, neighborhoods are like clubs. Neighborhoods are groupings of families, that is, all families who wish to form a common neighborhood and set a minimum income threshold for membership

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 Understanding the Great Gatsby Curve 343 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

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 from Loury (1981) the 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

3. Neighborhood Formation and Intergenerational Income Dynamics: Model Properties

A. Neighborhood Equilibria

- Observe that the expected utility of adult *it* given membership in a neighborhood can be rewritten in terms of neighborhood characteristics as

$$\begin{aligned} EU_{it} &= \pi_1 \log((1-\tau)Y_{it}) + \pi_2 E(\log(\phi H_{nt}(\tau)\xi_{it}) \mid F_t) \\ &= \pi_1 \log((1-\tau)Y_{it}) + \pi_2 \log(\tau\phi\xi_{it}\theta(\bar{Y}_{nt})\nu(p_{nt})\bar{Y}_{nt}). \end{aligned} \tag{11}$$

- **Proposition 1.** *Equilibrium neighborhood structure*

- **Proposition 2.** *Segregation and inequality*

B. Income Dynamics

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

$$\Pr(Y_{it+1} | F_t) = \Pr(Y_{it+1} | \overline{Y}_{nt}, p_{nt}). \qquad (12)$$

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

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

C. Inequality Dynamics

- **Proposition 5.** *Decoupling of upper and lower tails from the rest of the population of family dynasties*
- **Proposition 6.** *Intergenerational Great Gatsby Curve*
- Underlying the theorem, there are two routes by which Gatsby Curves can be generated

4. Empirical Claims about the Inequality/Segregation/ Mobility Nexus

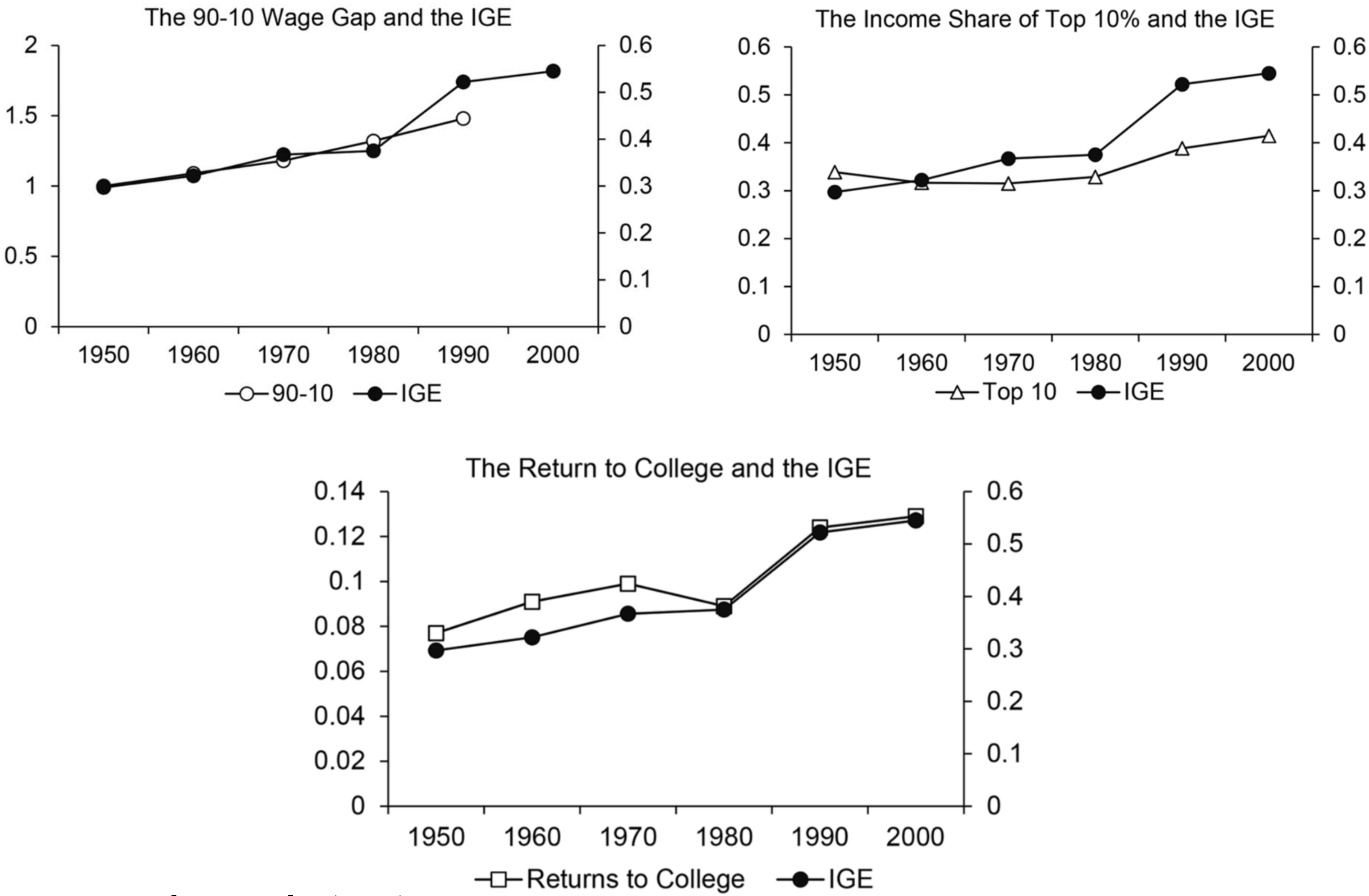
A. Direct Estimates of Gatsby-Like Phenomena

- Our first claim is that there is direct evidence of an intertemporal Gatsby Curve: inequality and mobility are negatively associated

- 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) also find evidence of a positive relationship between the college wage premium and the IGE (shown in **Figure 1**)

Figure 1: Rising intergenerational elasticities



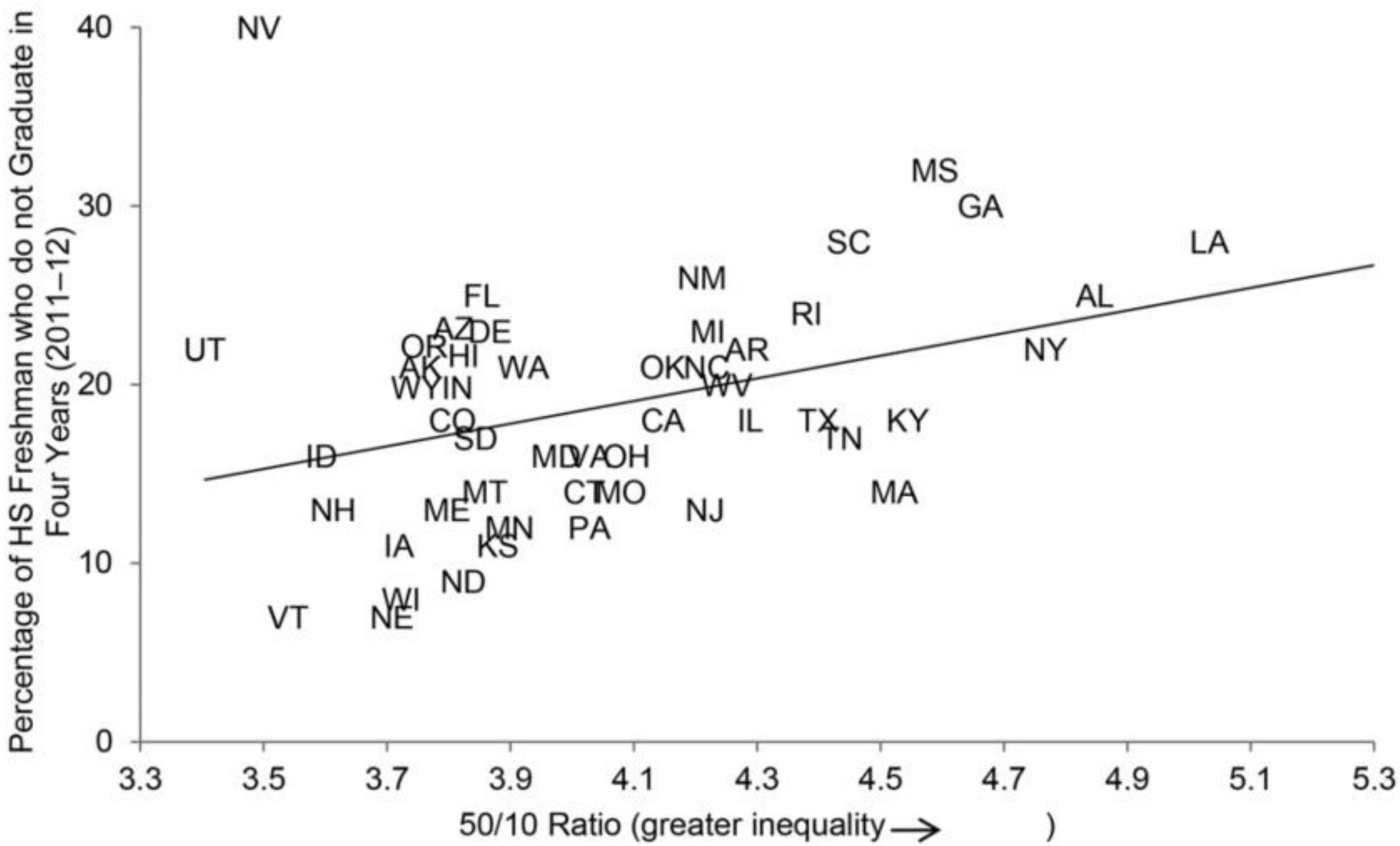
Source: Aaronson and Mazumder (2008)

B. Location/Mobility Nexus

- **Figure 2** illustrates how variance of state income is positively associated with the high school dropout rate

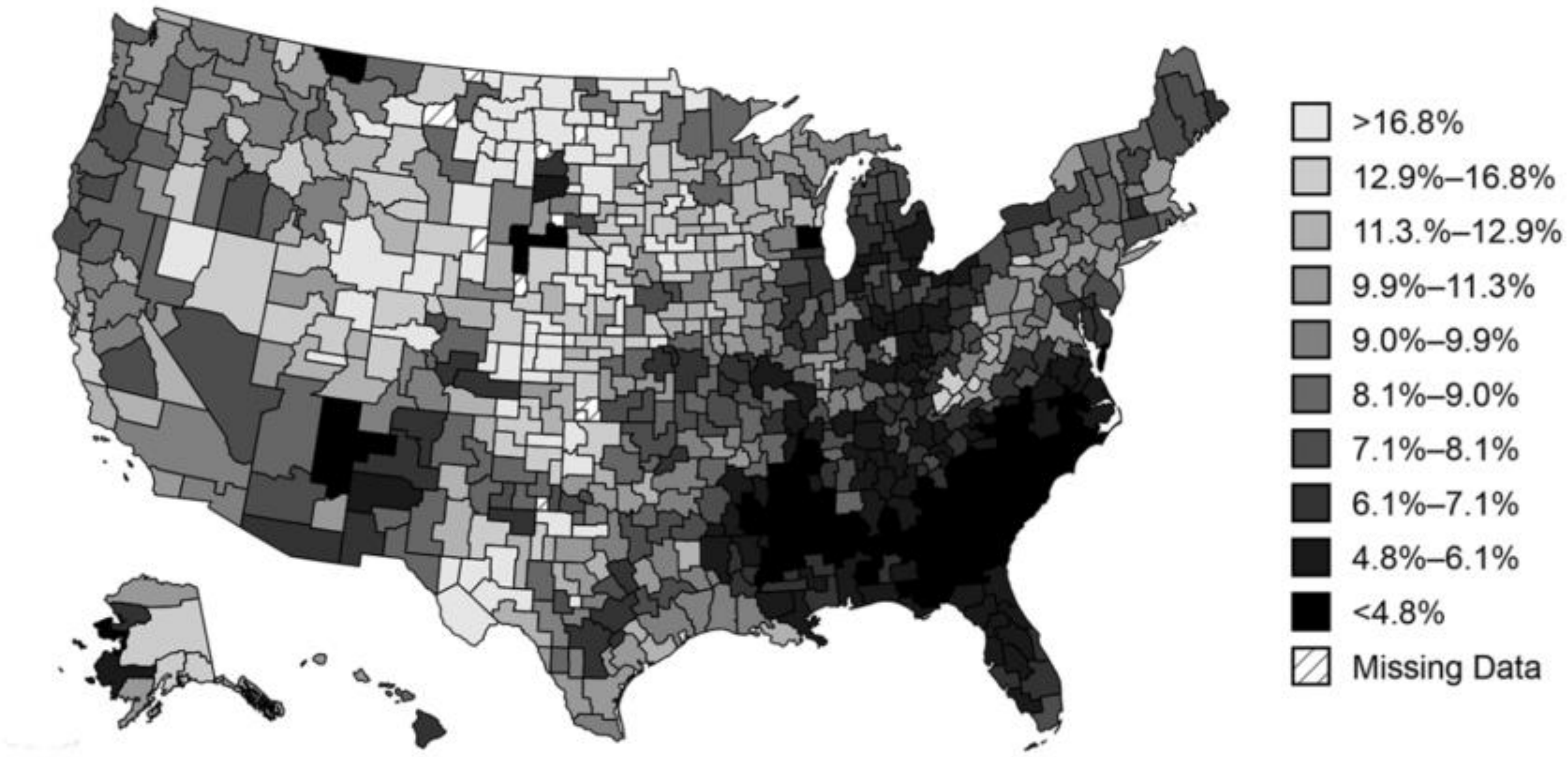
- Any discussion of location and inequality must be deeply informed by the seminal work of Chetty, Hendren, Kline, and Saez (2014). These authors also find a negative relationship between income segregation and mobility as well as between Gini coefficients and upward mobility. Both of these findings are consistent with our theoretical model. (See **Figure 3**.)

Figure 2: Relationship between inequality and the rate of high school noncompletion



Source: Kearney and Levine (2016). The graduation data is from Stetser and Stillwell (2014).
Note: 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 3: Chetty, Hendren, Kline, and Saez (2014): Spatial heterogeneity in rates of relative mobility



Notes: This map shows rates of upward mobility for children born in the 1980s for 741 metro and rural areas ("commuting zones") in the United States. 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

C. Location and Segregation

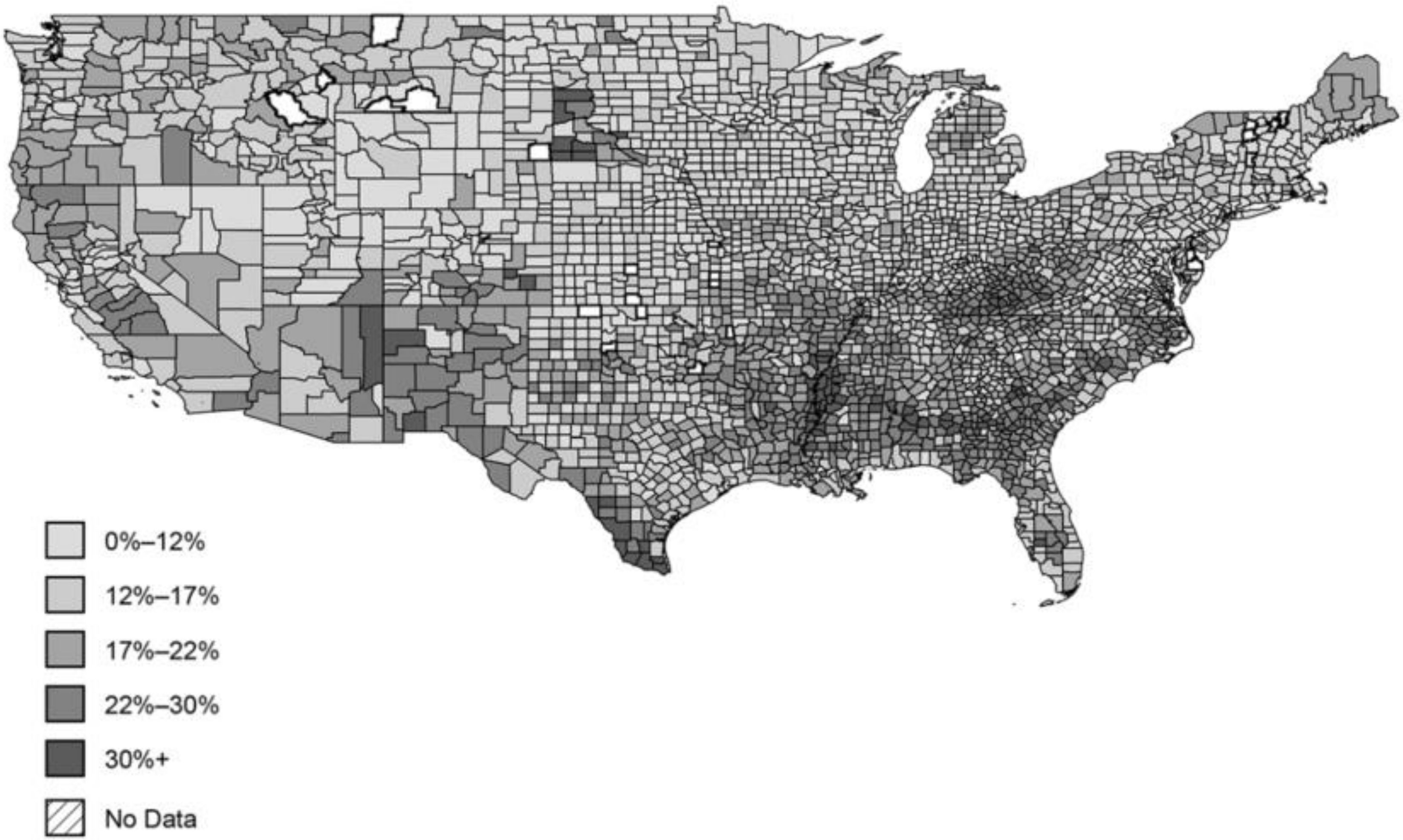
- Our third empirical claim is that there is much evidence of pervasive segregation across locations with respect to factors that matter, at a collective level, education and economic success

- 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

D. Income

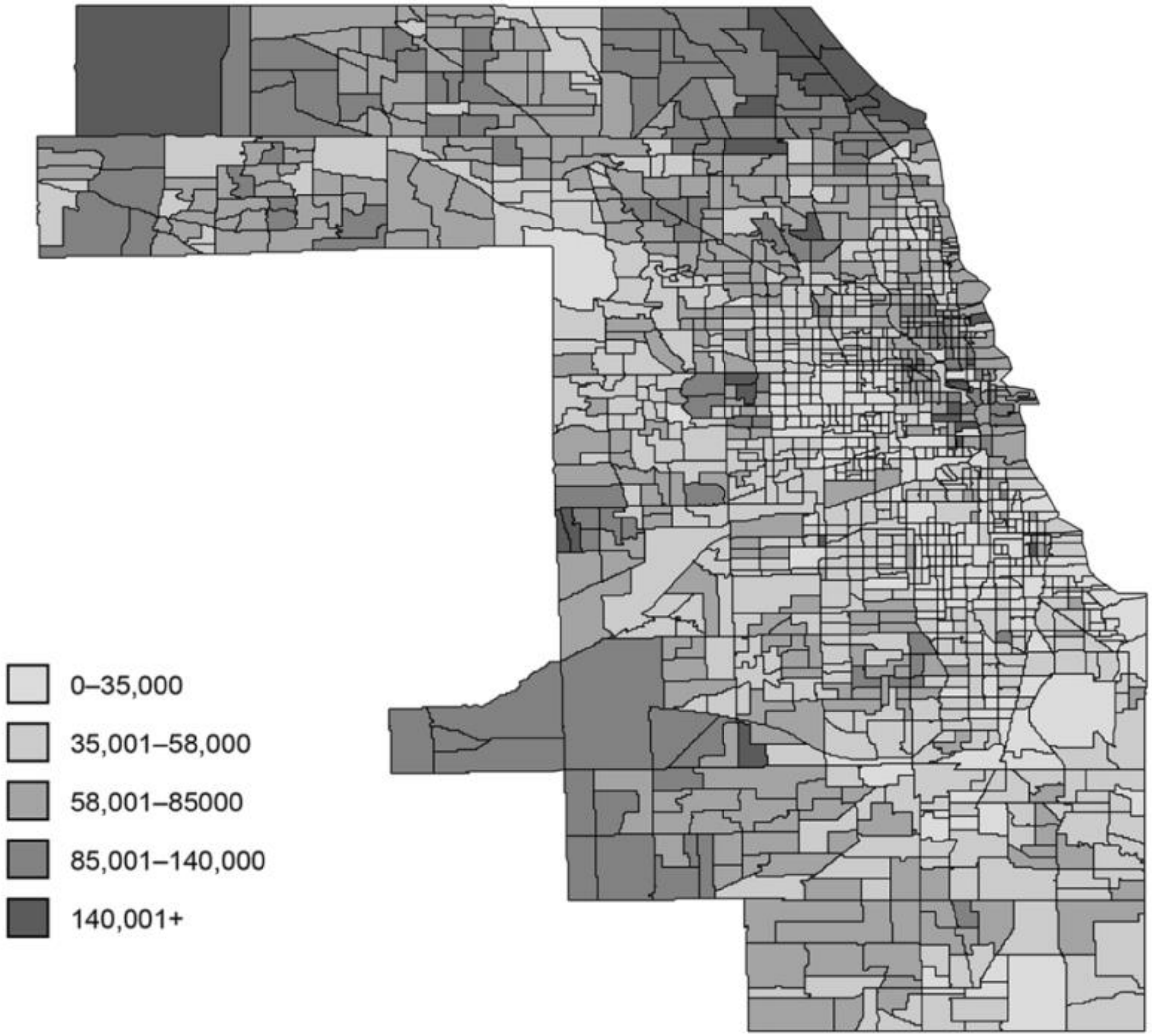
- One dimension of income segregation is the spatial concentration of poverty, which is illustrated in **Figure 4** at the country level
- **Figure 5** reproduces poverty rates across Chicago neighborhoods
- Reardon and Bischoff (2011) and Reardon, Townsend, and Fox (2015) provide evidence of this phenomenon. Some of these findings are summarized in **Figure 6** and **Table 7**

Figure 4: Spatial distribution of poverty rates (2015)



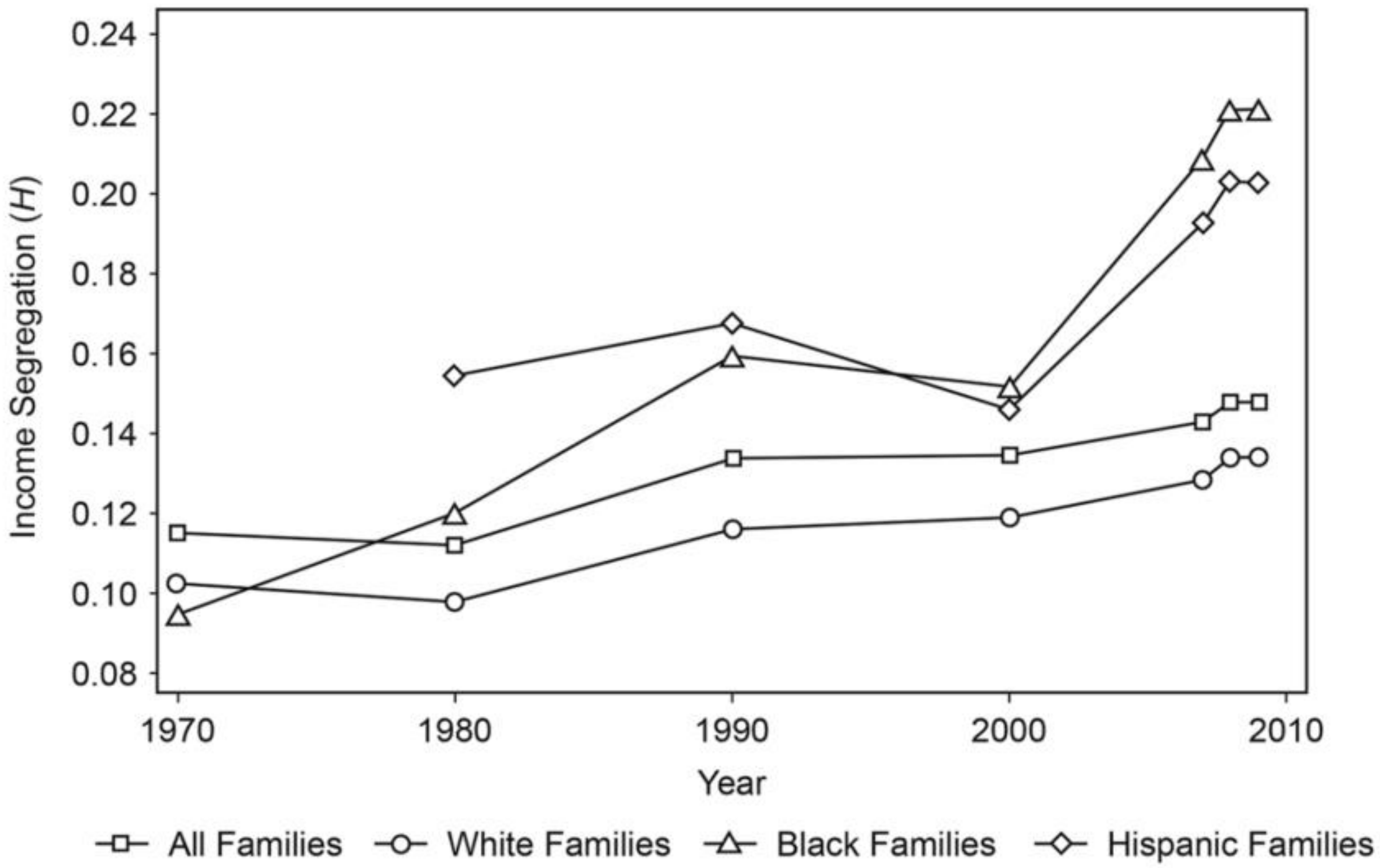
Source: US Census Bureau

Figure 5: Income segregation in Chicago (median household income 2007)



Source: US Census Bureau

Figure 6: Trends in family income segregation by race



Source: Bischoff and Reardon (2014); authors' tabulations of data from the US Census (1970–2000) and American Community Survey (2005–2011)

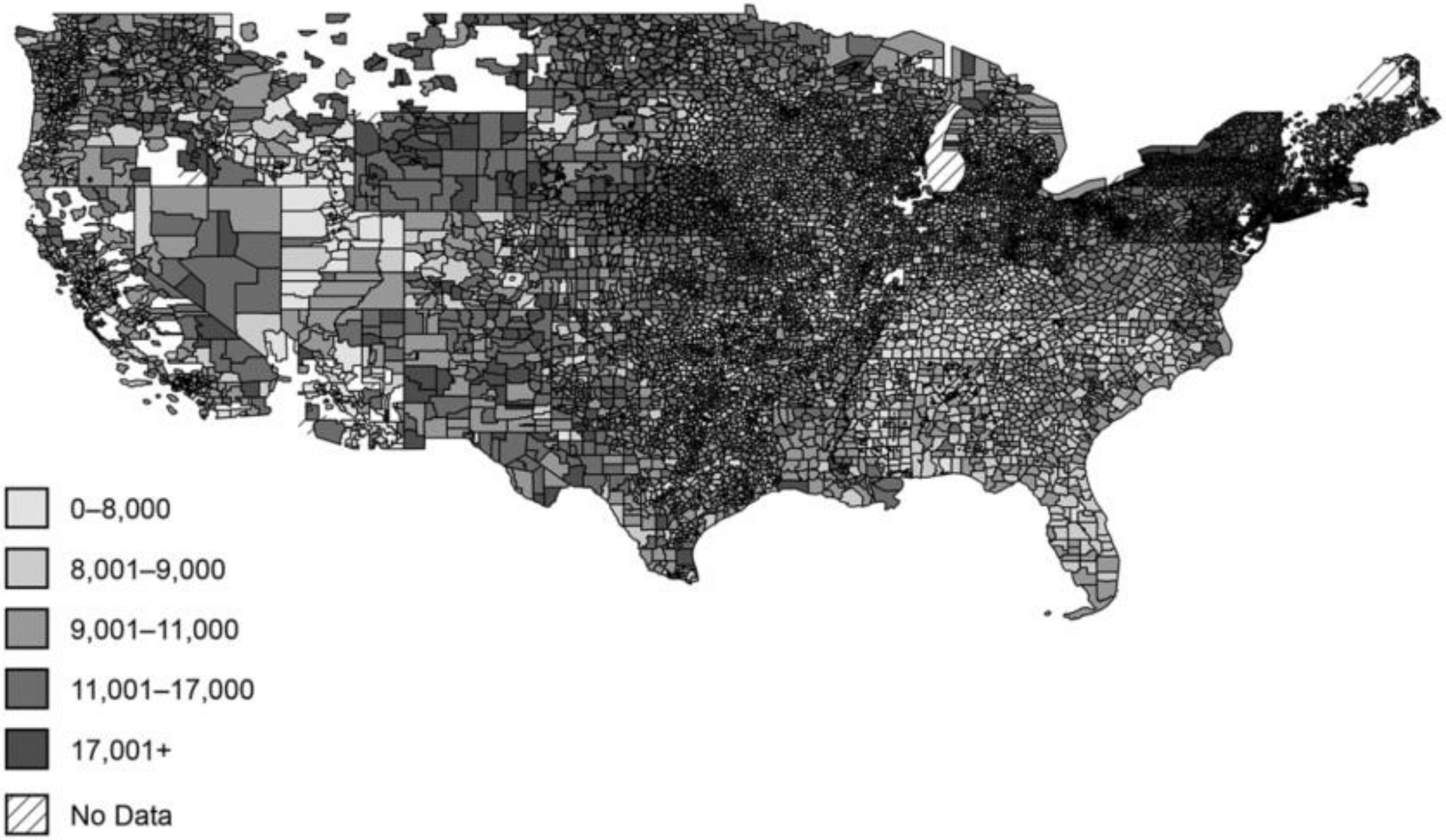
Table 7
Increasing Segregation over Time

	1970	1980	1990	2000
Variance of real family income	1.42E8	3.46E8	1.37E9	1.67E9
Variance of log real family income	0.769	0.783	0.907	0.903
Neighborhood sorting index (tract, $ income)	0.378	0.481	0.569	0.756
Neighborhood sorting index (state, $ income)	0.093	0.097	0.173	0.190
Neighborhood sorting index (tract, log income)	0.417	0.429	0.471	0.444
Neighborhood sorting index (state, log income)	0.135	0.101	0.163	0.127
Reardon's H	0.115	0.112	0.134	0.135

E. Education-Related Mechanisms

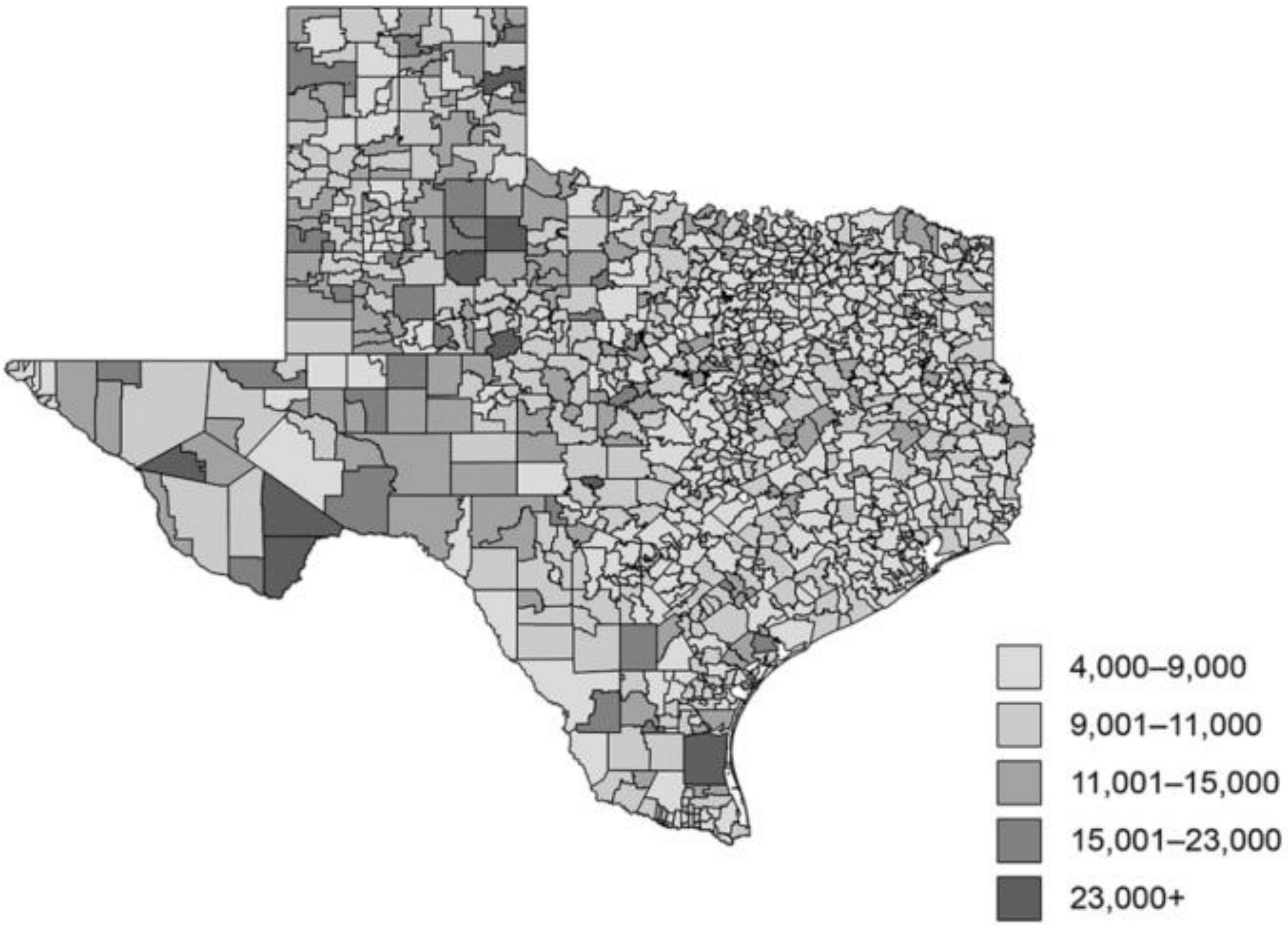
- **Figure 7** illustrates these differences, while **Figure 8** illustrates these differences in the context of Texas
- **Figure 9** gives one example of a location-determined social interaction effect: exposure to violent crime across the United States
- **Figure 10** gives a related figure for homicides in Chicago

Figure 7: Spatial variation in per capita public-school expenditure



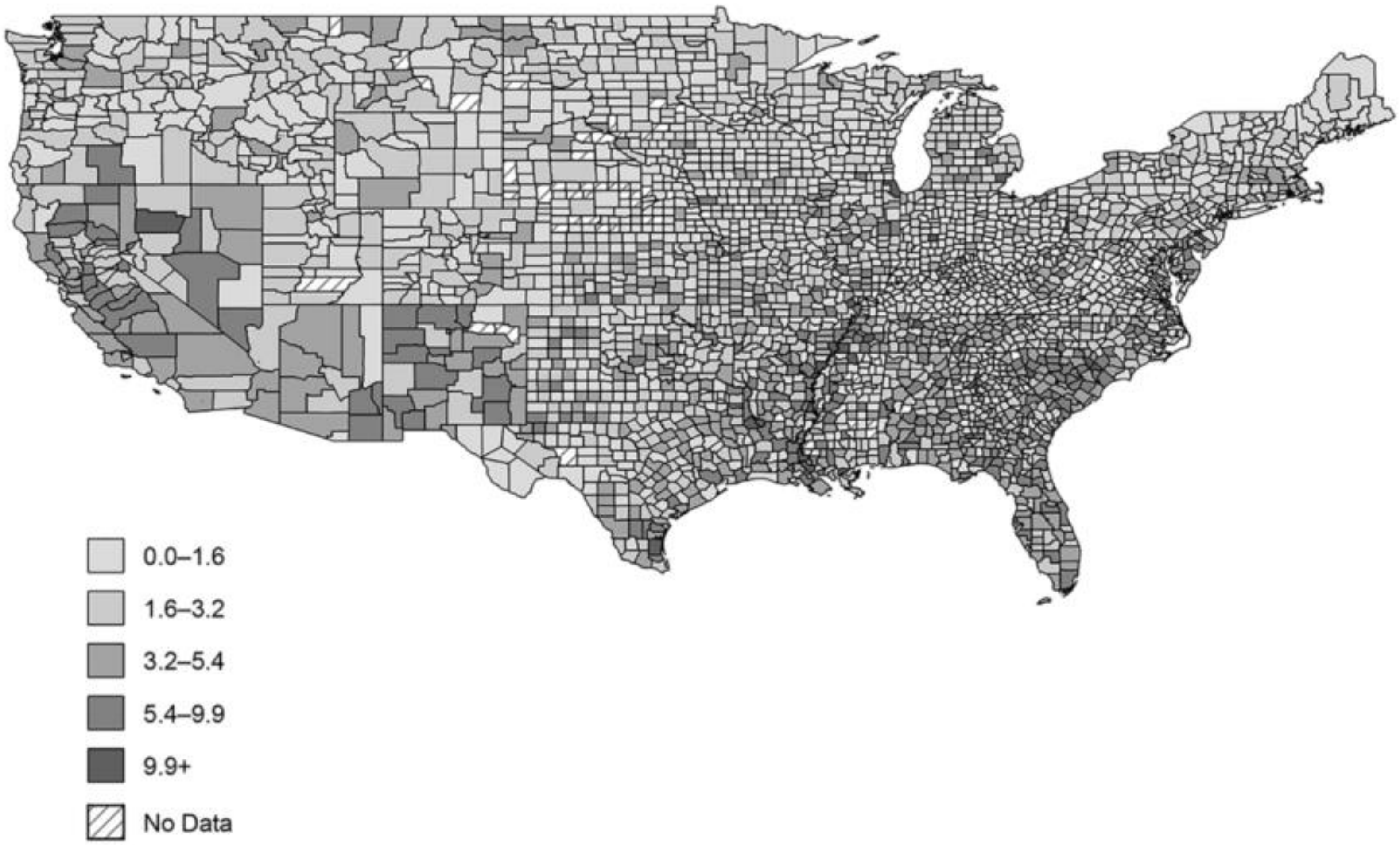
Source: NCES
Note: Per pupil expenditure in dollars (2014)

Figure 8: Spending per student, by school district, Texas



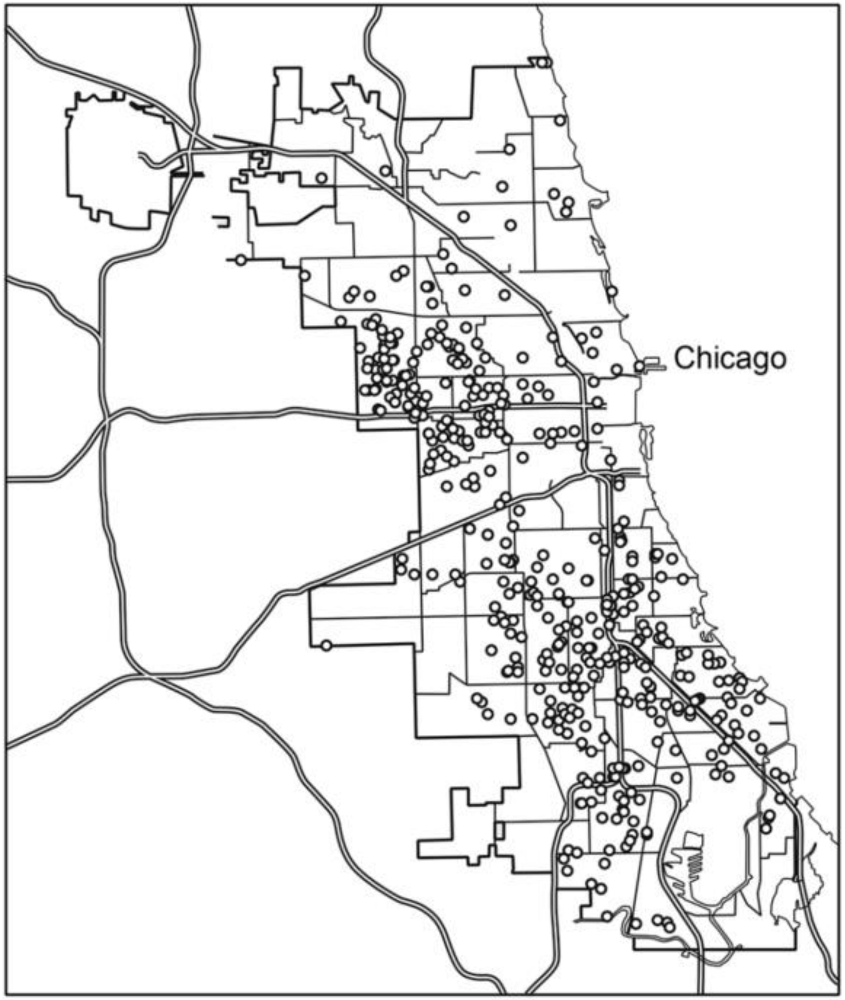
Source: NCES
Note: Per pupil expenditure in dollars (2014)

Figure 9: Exposure to violent crime (violent crimes/1,000)



Source: Uniform Crime Reporting Program
Note: Violent crimes per thousand people (2012)

Figure 10: Distribution of homicides in Chicago



Source: *Chicago Tribune* (accessed May 21, 2016)

5. Empirical Properties of the Intergenerational Elasticity of Income

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)

- Inequality at the census tract and state level when children were 15 years old is taken from the Decennial Census via GeoLytics' NCDB

B. Nonlinearity in the Parent/Offspring Income Relationship

- One explanation of the Gatsby Curve linking the variance of income to mobility is that the linear transmission process is mis-specified, that is,

$$y_{io} = f(y_{ip}) + \varepsilon_{io}. \qquad (13)$$

- **Figure 11** presents the nonparametric function

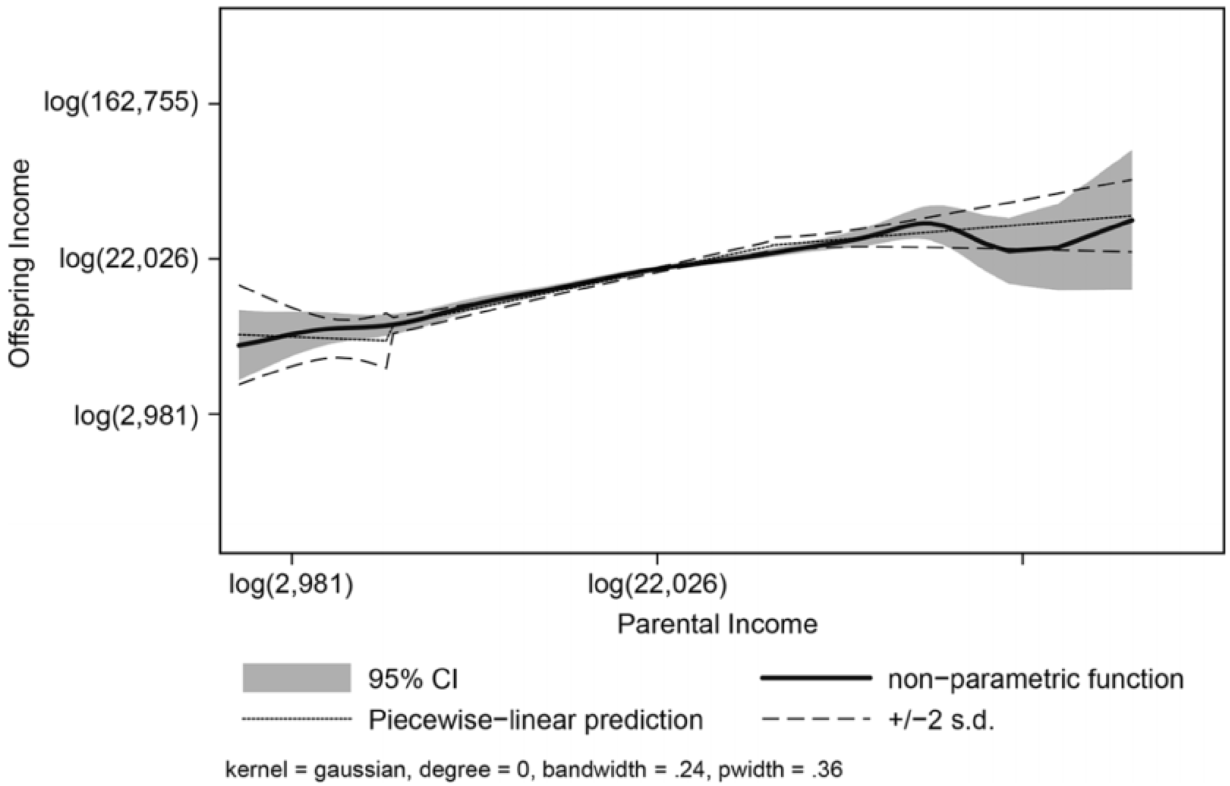
- **Figure 12** (panels A and B) presents two ways of measuring local IGE values

Cont.

B. Nonlinearity in the Parent/Offspring Income Relationship

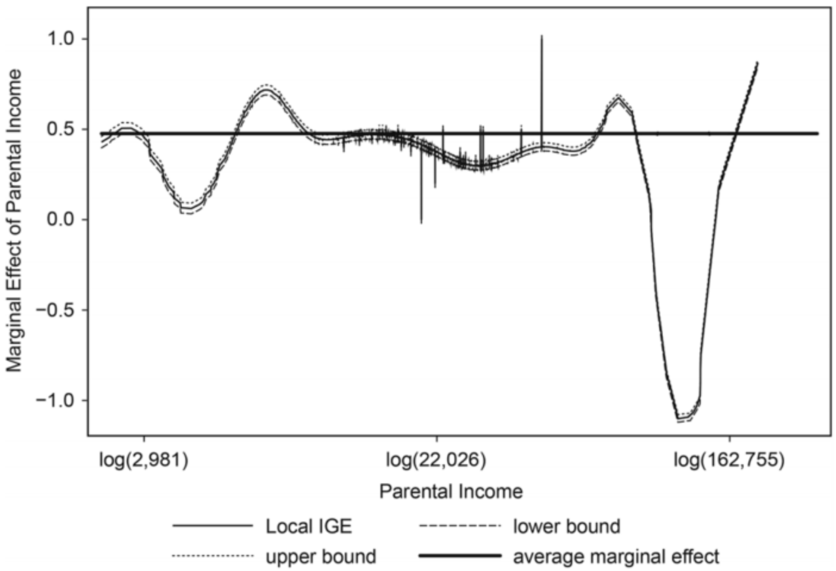
- **Table 1** splits the sample according to whether a family was in the bottom 10%, the middle 80%, or the top 10% of the national income distribution
- **Table 2** repeats this exercise when income-distribution location is calculated at the state level.
- **Table 3** performs the same exercise at the census-tract level

Figure 11: Nonparametric estimation of offspring's income given parental income



Note: The figure shows that expected offspring income is nonlinearly dependent on parental income. Offspring income conditional on parental income (solid line) was nonparametrically 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 dotted line represents the piece-wise linear prediction of offspring's income given parental income

Figure 12: Local IGE estimates for income



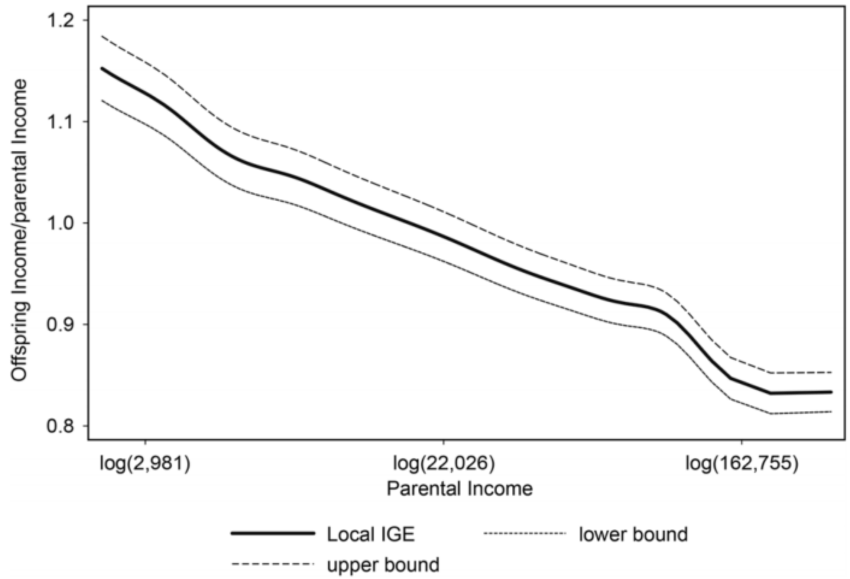


Table 1
IGE Regressions for Bottom 10%, Middle 80%, and Top 10% Relative to Nation (Family Income, Ages 30–34)

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

Note: Robust standard errors in parentheses. All income in logs.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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

Note: Robust standard errors in parentheses. All income in logs.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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

Note: Robust standard errors in parentheses. All income in logs.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

C. Neighborhood Income and the IGE Levels

- **Table 4** presents results where parental income is interacted with census-tract income
- **Table 5** conducts the same exercise at the state level
- **Table 6** combines census-tract and state variables. We report results using the variance of log income

Table 4

IGE and Interactions with Census-Tract Income Distribution (Family Income, Ages 30–34)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Family income,	0.471***	0.361***	0.363***	0.363***	0.450***	0.370***
ages 13–17	(0.0294)	(0.0389)	(0.0387)	(0.0390)	(0.0354)	(0.0404)
Average income		0.330***		0.0817		0.571
in tract		(0.0672)		(0.731)		(0.968)
Income variance		0.0438			1.081	1.296
in tract		(0.0950)			(1.176)	(1.504)
Family income *			0.0326***	0.0235		–0.0244
tract avg.			(0.00658)	(0.0729)		(0.0953)
Family income *			0.00266		–0.134	–0.128
tract var.			(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

Notes: For tables 4, 5, and 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. Robust standard errors in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 5
IGEs and Interaction with State Income Distribution (Family Income, Ages 30–34)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Family income,	0.471***	0.434***	0.436***	0.426***	0.449***	0.414***
ages 13–17	(0.0294)	(0.0294)	(0.0294)	(0.0287)	(0.0283)	(0.0284)
Average income		0.788***		6.962***		4.871**
in state		(0.145)		(2.132)		(2.462)
Income variance		0.644***			–9.647***	–5.772
in state		(0.177)			(3.189)	(3.625)
Family income *			0.0773***	–0.654***		–0.416*
state avg.			(0.0146)	(0.215)		(0.248)
Family income *			0.0675***		1.002***	0.656*
state var.			(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

Note: Robust standard errors in parentheses. All income in logs; state measures normalized to have zero mean.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6
IGEs and Census-Tract and State Income Distributions (Family Income, Ages 30–34)

Variables	(1)	(2)	(3)	(4)
Family income,	0.361***	0.442***	0.362***	0.366***
ages 13–17	(0.0391)	(0.0355)	(0.0384)	(0.0407)
Family income *	0.0942		0.0282***	0.0334
tract average	(0.0824)		(0.00604)	(0.104)
Family income *	–0.519*		0.0492***	–0.504
state average	(0.270)		(0.0186)	(0.313)
Average income	–0.633			–0.0627
in tract	(0.826)			(1.050)
Average income	5.329**			5.507*
in state	(2.697)			(3.130)
Family income *		–0.197		–0.116
tract variance		(0.129)		(0.158)
Family income *		0.493	0.0768***	0.0664
state variance		(0.315)	(0.0198)	(0.377)
Income variance		1.638		1.073
in tract		(1.264)		(1.564)
Income variance		–4.357		0.143
in state		(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

Notes: Robust standard errors in parentheses. All income in logs; measures normalized to have zero mean.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

D. Reduced-Form Great Gatsby Curves

- **Figure 13** reports the Great Gatsby Curves that are implied by equation (13)
- **Figure 14** reports the implied Gatsby Curve associated with our parametric nonlinear model that is reported in table 1
- **Figures 15–16** present the Gatsby Curves for census-tract variables
- **Figures 17–18** for state-level variables
- **Figures 19** and **20** combine both census-tract and state variables

Figure 13: Great Gatsby Curve implied by nonparametric specification under scaling of parental income

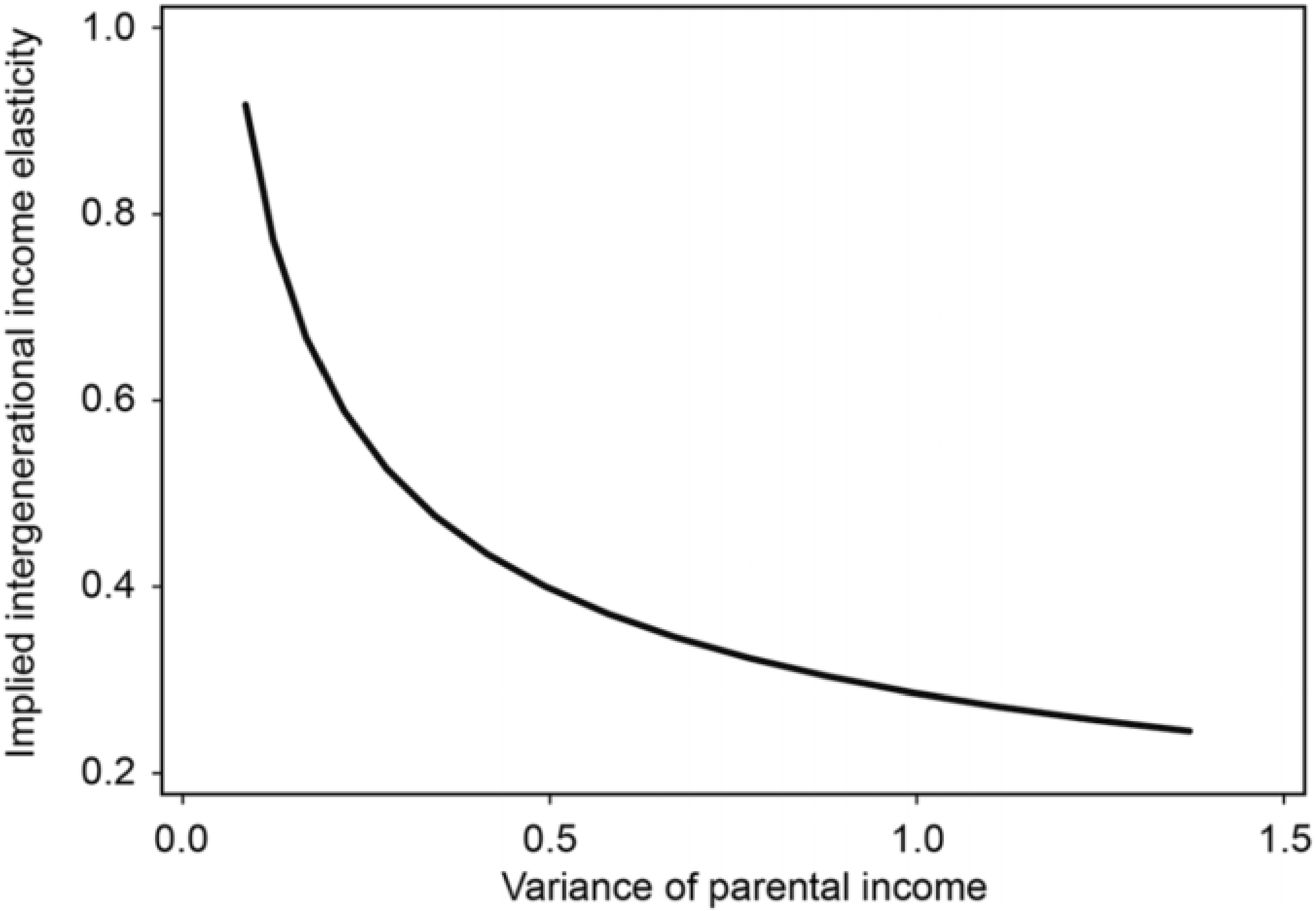


Figure 14: Great Gatsby Curve implied by parametric specification including parents' percentile in nation

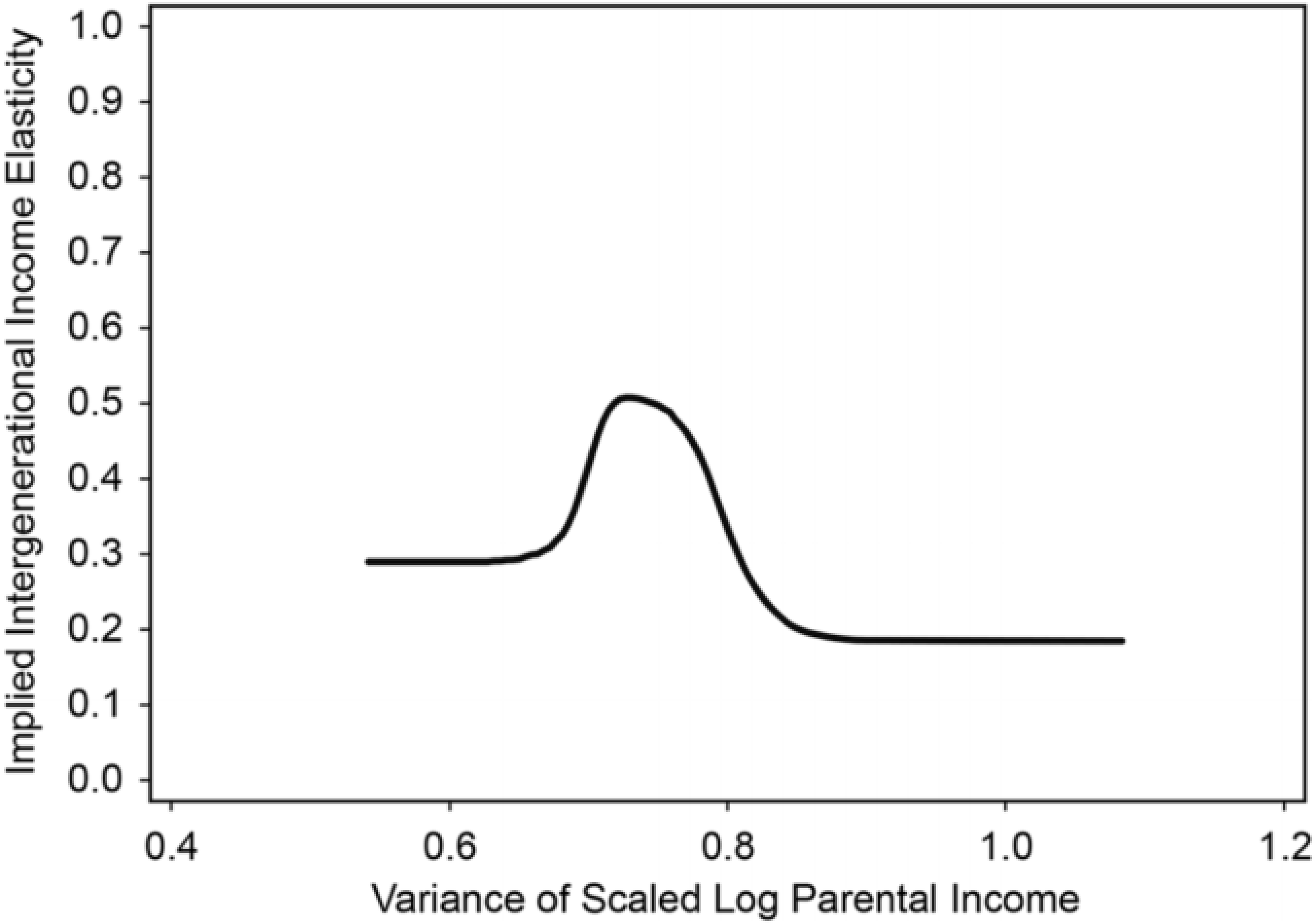
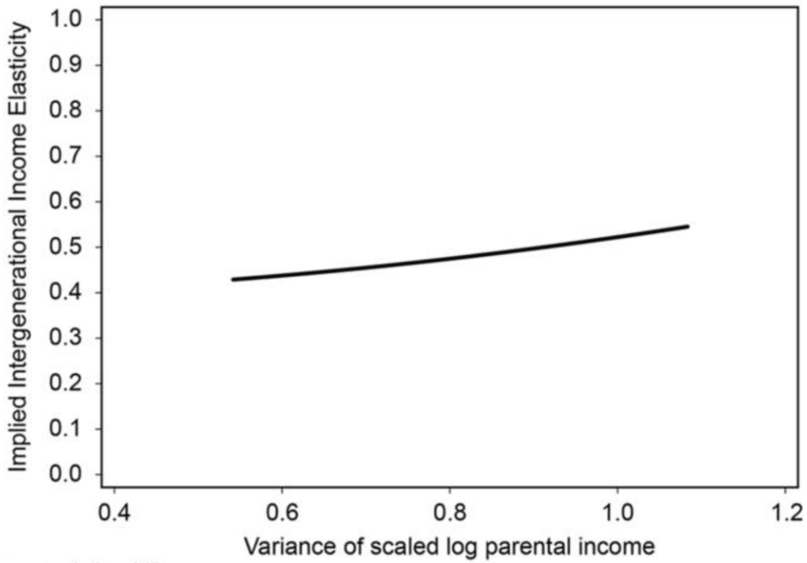
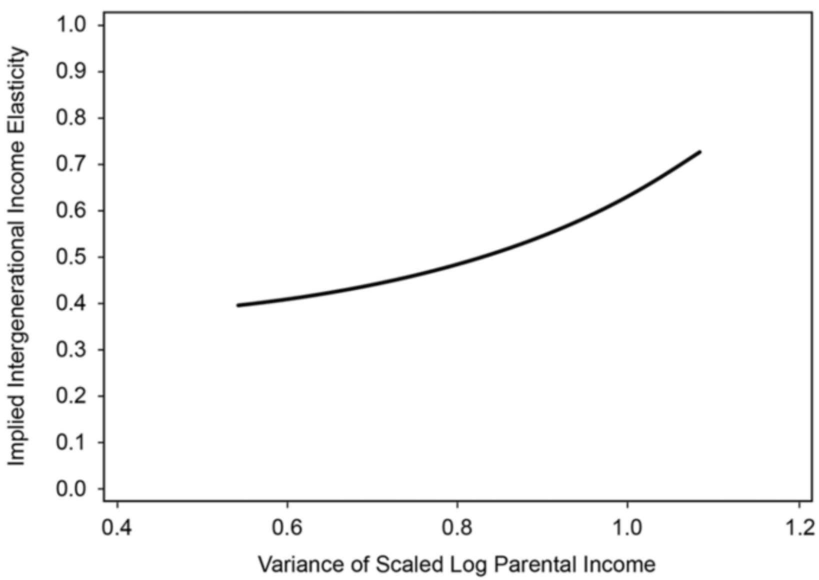


Figure 15: Great Gatsby Curve implied by parametric specification including tract average, under scaling of parental income

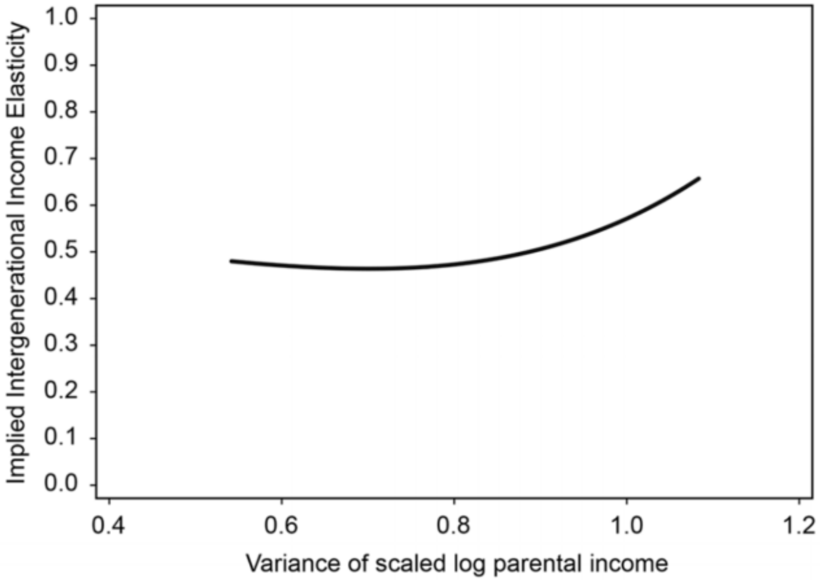


All incomes scaled up k%

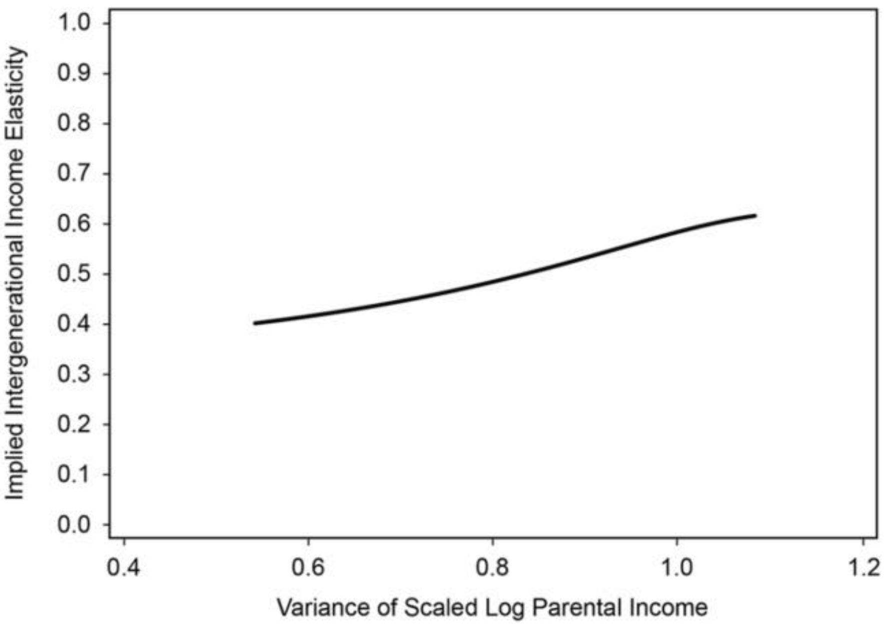


Incomes scaled up k%, NSI linear in k

Figure 16: Great Gatsby Curve implied by parametric specification including tract average and variance, under scaling of parental income

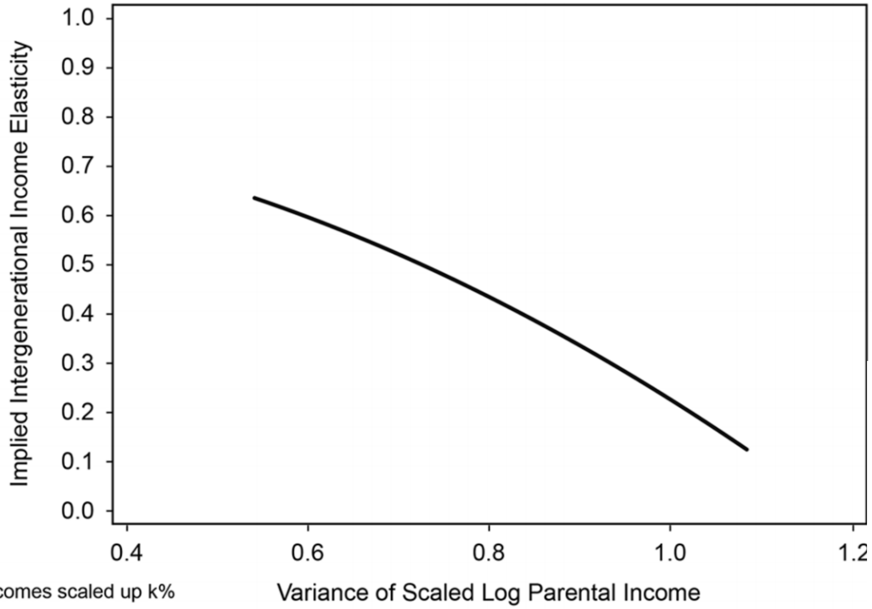


All incomes scaled up k%

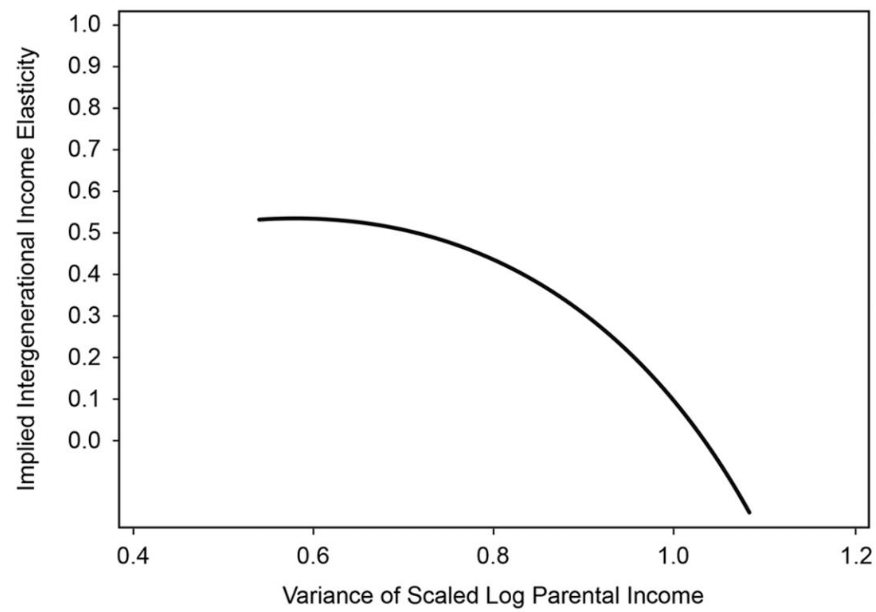


Incomes scaled up k%, NSI linear in k

Figure 17: Great Gatsby Curve implied by parametric specification including state average, under scaling of parental income

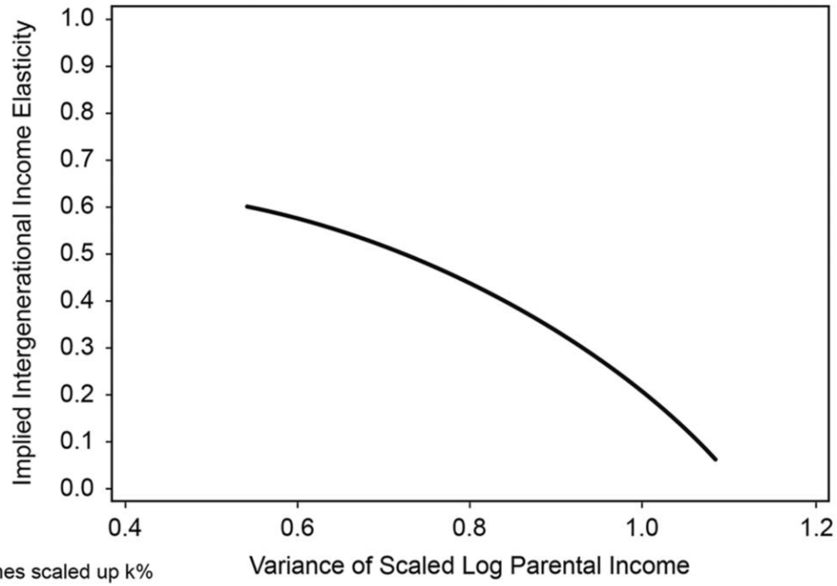


All incomes scaled up k%

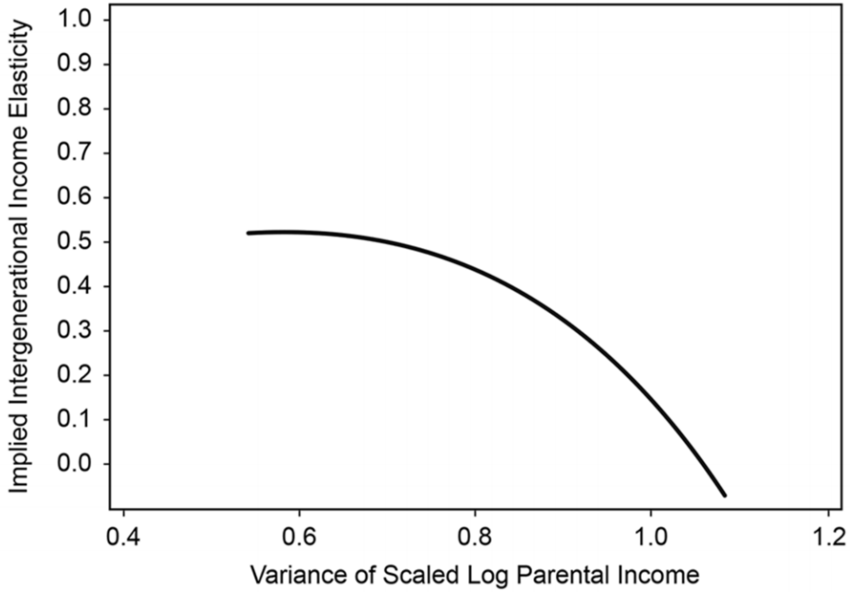


Incomes scaled up k%, NSI linear in k

Figure 18: Great Gatsby Curve implied by parametric specification including state average and variance, under scaling of parental income

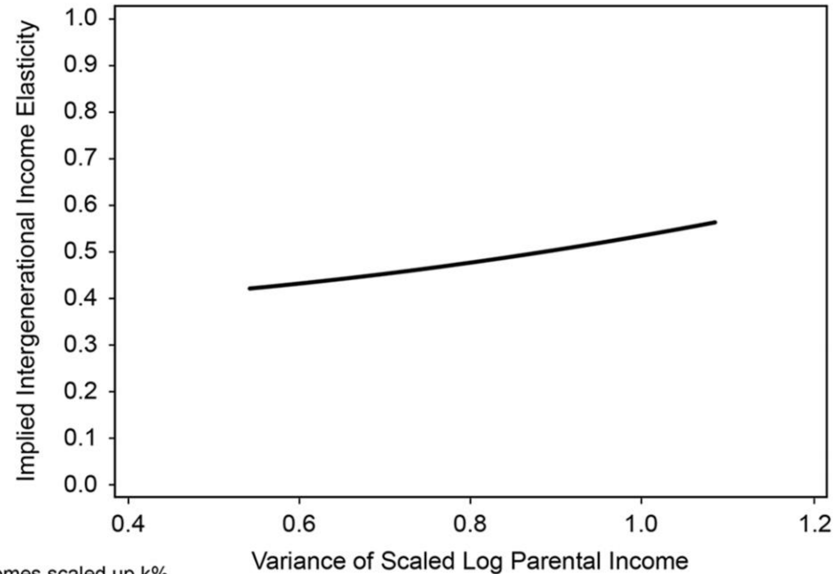


All incomes scaled up k%

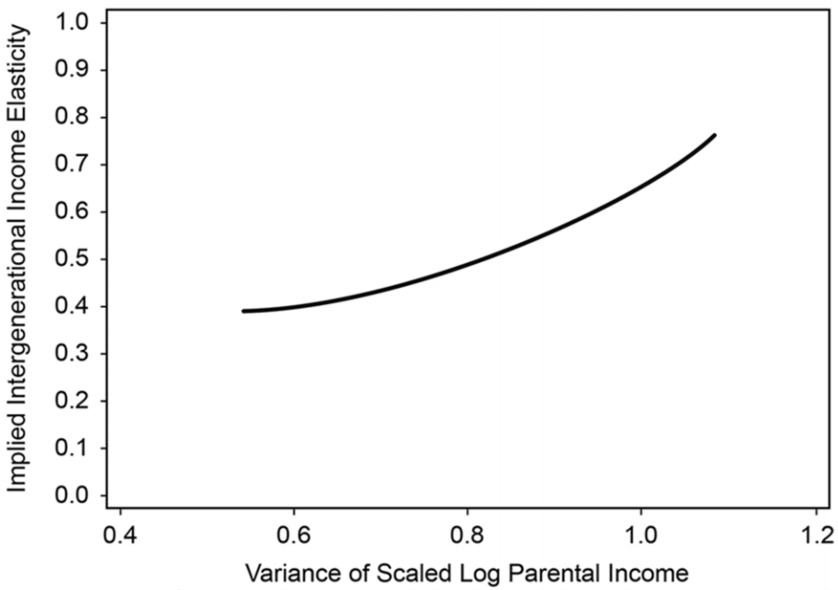


Incomes scaled up k%, NSI linear in k

Figure 19: Great Gatsby Curve implied by parametric specification including tract and state average, under scaling of parental income

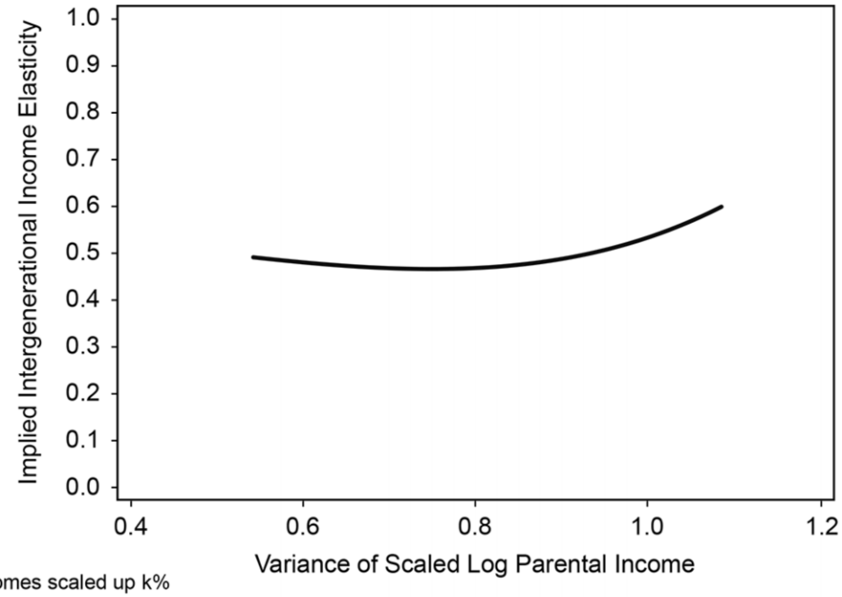


All incomes scaled up k%

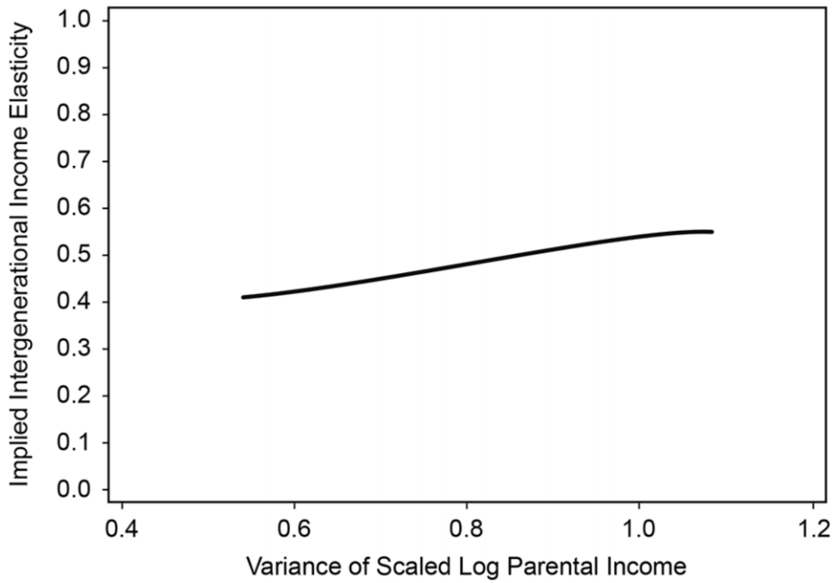


Incomes scaled up k%, NSI linear in k

Figure 20: Great Gatsby Curve implied by parametric specification including tract and state average and variance, under scaling of parental income



All incomes scaled up k%



Incomes scaled up k%, NSI linear in k

6. Linking Theory and Empirics: A Calibrated Model

A. Environment

- Each household *i* in a school district *j* maximizes utility given by

$$u(c^i_{j1}) + \theta V(a^i_j, h^i_{j2}, g^i_j) \qquad (15)$$

- Specifically, for household *i*'s offspring in school district *j*, the stock of offspring's human capital at the beginning of the second period, *hij*2, is given by

$$h^i_{j2} = a^i_j(x^i_{j1} + \bar{x}_j)^{\alpha_1}(h^i_{j0})^{\alpha_2}(h^i_j)^{\alpha_3} \qquad (16)$$

Cont.

A. Environment

- He makes decisions on human capital accumulation and consumption in the second, third, and fourth periods ({*cij*2, *cij*3, *cij*4}) to maximize his utility

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

subject to the budget constraint

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

and the human capital production functions (19)

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

$$h_{j4}^i = a_j^i(n_{j3}^i h_{j3}^i)^{\eta_1} + h_{j3}^i \quad (19)$$

B. Model Solution

- Next, the maximization problem in the first period can be written as

$$\max_{c_{j1}^i, x_{j1}^i, g_j^i} u(c_{j1}^i) + \theta V(a_j^i, h_{j2}^i, g_j^i) \quad (20)$$

subject to equation (15), the budget constraint

$$c_{j1}^i + x_{j1}^i + g_j^i = (1 - \tau)y_j^i \quad (21)$$

- The first-order conditions for x_{j1}^i and g_j^i are given by

$$\theta V_{h_{j2}^i}(a_j^i, h_{j2}^i, g_j^i)a_j^i\alpha_1(x_{j1}^i + \bar{x}_j)^{\alpha_1 - 1}(h_j^i)^{\alpha_2}(h_j)^{\alpha_3} = u(c_{ji}^i) \quad (22)$$

$$\theta V_{g_j^i}(a_j^i, h_{j2}^i, g_j^i) \leq u(c_{ji}^i) \quad (23)$$

C. Calibration

- **Table 8** summarizes the fixed parameters of our model
- 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:

$$\begin{pmatrix} \log h_{j0}^{i} \\ \log a_j \end{pmatrix} \sim N\left(\begin{matrix} \mu_{h_{j0}^{i}} \\ \mu_{a_j} \end{matrix}, \begin{matrix} \sigma_{h_{j0}^{i}}^{2} & \rho\sigma_{h_{j0}^{i}}\sigma_{a_j} \\ \rho\sigma_{h_{j0}^{i}}\sigma_{a_j} & \sigma_{a_j}^{2} \end{matrix} \right). \quad (24)$$

- This allows us to focus on the conditional distribution of a_j^i, namely

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

- **Table 9** summarizes the moments

Table 8
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 United States	w	0.1707
Interest rate	r	$(1 + 0.04)^6 - 1$

Table 9
Data Moments Used in the Calibration Exercise

Moments	Value
Average child income between 24 and 28	$18,788
Average child income between 30 and 34	$24,029
Change in average child income in group 1	1.2744
Change in average child income in group 2	1.3467
Coefficient of variation between 30 and 34	0.4639
Coefficient of variation between 30 and 34 in group 1	0.3807
Coefficient of variation between 30 and 34 in group 2	0.4459
Average school years in college	1.6016

D. Baseline Results

- **Table 10** and **Table 11** describe the results of the estimated parameters and the targeted moments
- First, let us look at relationship between parent income and child income illustrated in **Figure 21**
- **Figure 22** shows that the local IGE estimates fall as parent income rises

Table 10
Estimated Parameters for the Calibration Exercise

Parameters	Value
θ	0.3145
	(0.019)
α_1	0.0725
	(0.031)
α_2	0.2912
	(0.1369)
α_3	0.4230
	(0.1174)
η_1	0.4321
	(0.001)
μ_{a_j}	0.3225
	(0.004)
σ_{a_j}	0.3789
	(0.002)
$\rho_{h_{j0}a_j}$	0.1789
	(0.016)

Table 11
Targeted Moments Used in the Calibration Exercise

Moments	Data	Model
Average child income between 24 and 28	$18,788	$18,499
Average child income between 30 and 34	$24,029	$24,295
Change in average child income in group 1	1.2744	1.3068
Change in average child income in group 2	1.3467	1.3099
Coefficient of variation between 30 and 34	0.4639	0.4684
Coefficient of variation between 30 and 34 in group 1	0.3807	0.4089
Coefficient of variation between 30 and 34 in group 2	0.4459	0.4139
Average school years in college	1.6016	1.5952

Figure 21: Relationship between parental income and offspring income in the model

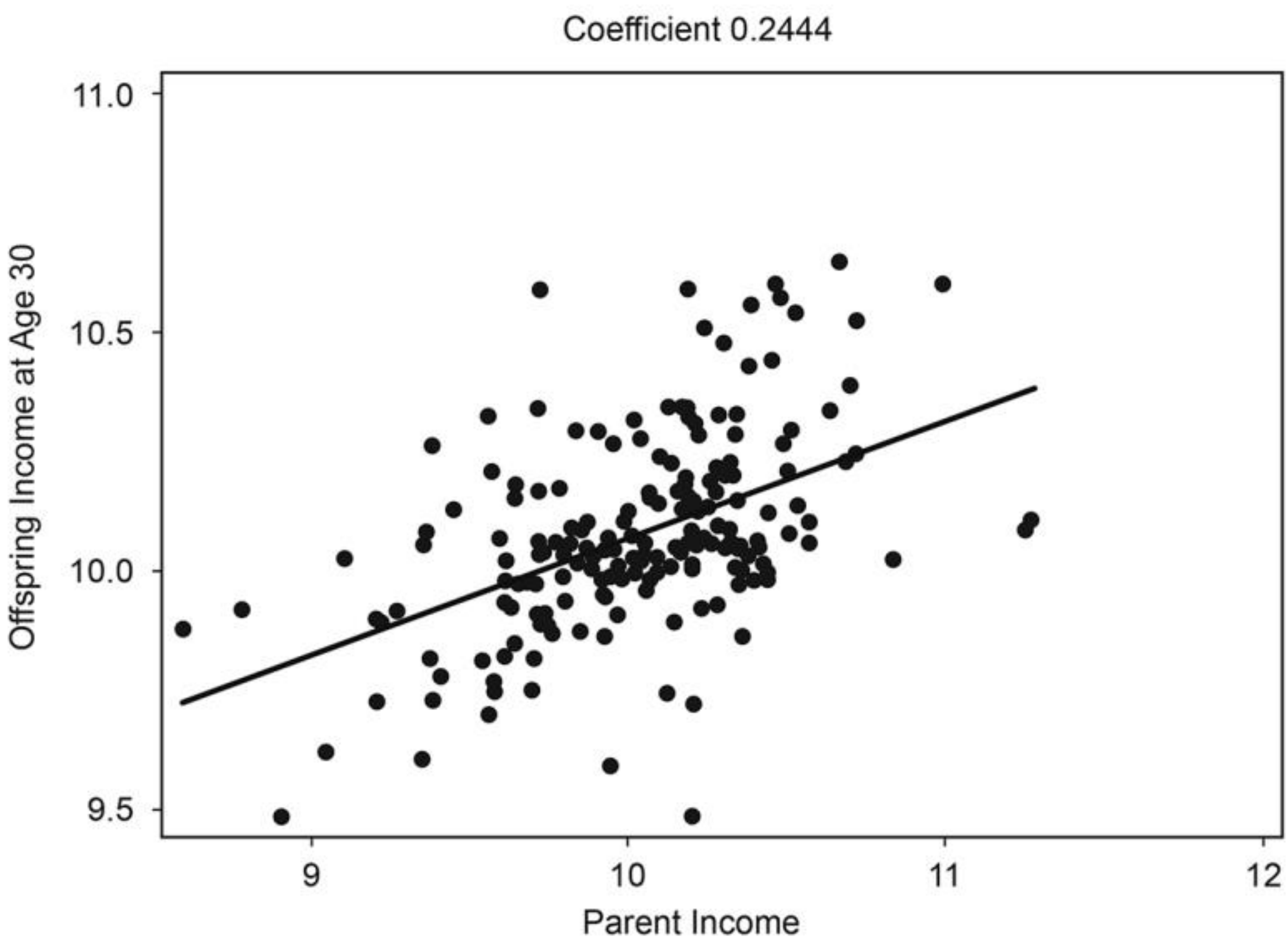
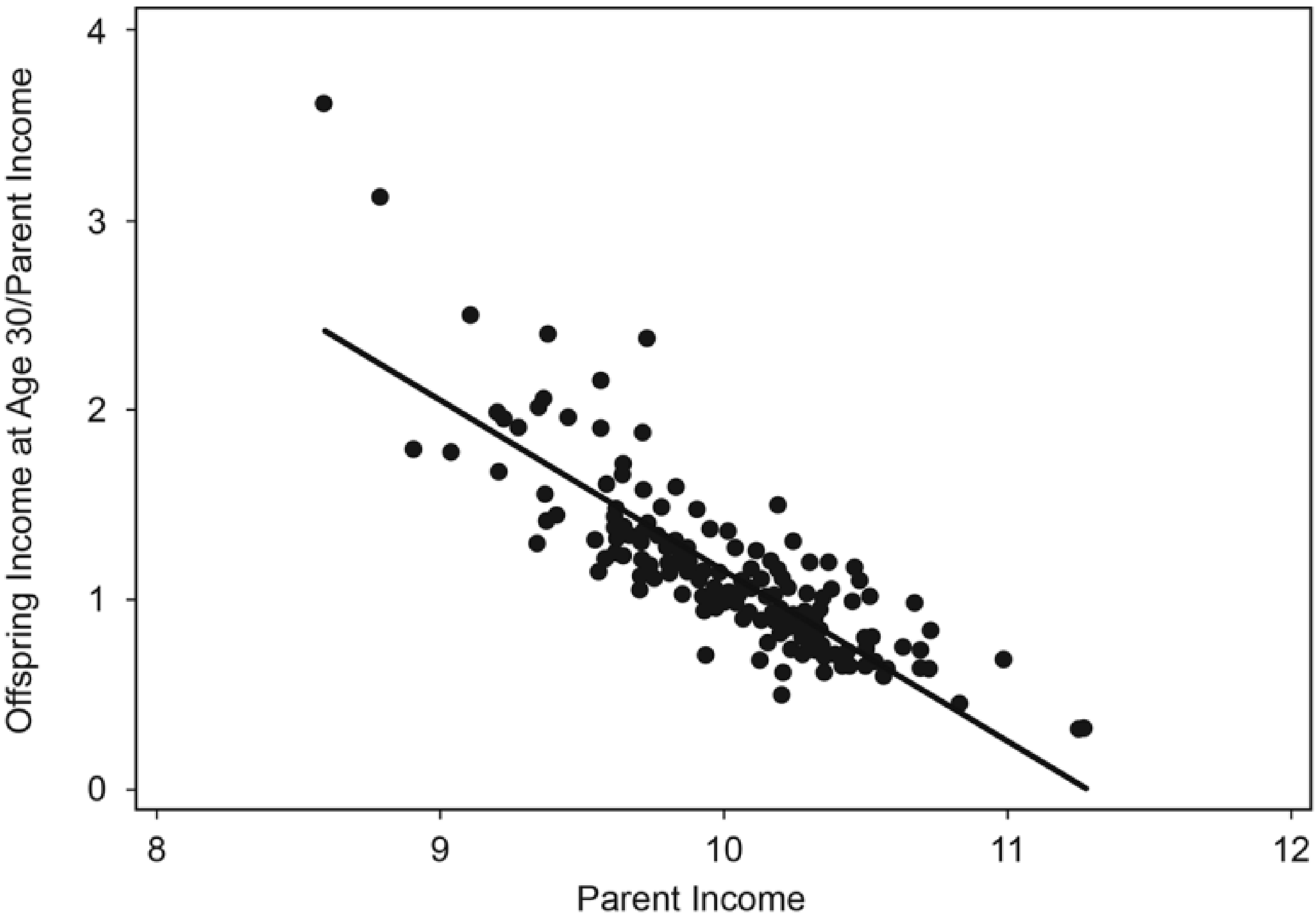


Figure 22: Relationship between ratio of offspring income to parental income and offspring income



E. Counterfactual Results

- The first counterfactual simulation examines what would happen if there were no return to the elements for formulating child human capital in the second period

- The second counterfactual simulation examines the importance of exogenous variables

F. Return to Elements for Child Human Capital in the Second Period

- **Figure 23** summarizes intergenerational mobility in the five cases
- Specifically, we raise their standard deviations by 20%, holding other variables fixed. **Figure 24** presents the result

Figure 23: Counterfactual simulation: Contribution of various elements to intergenerational mobility

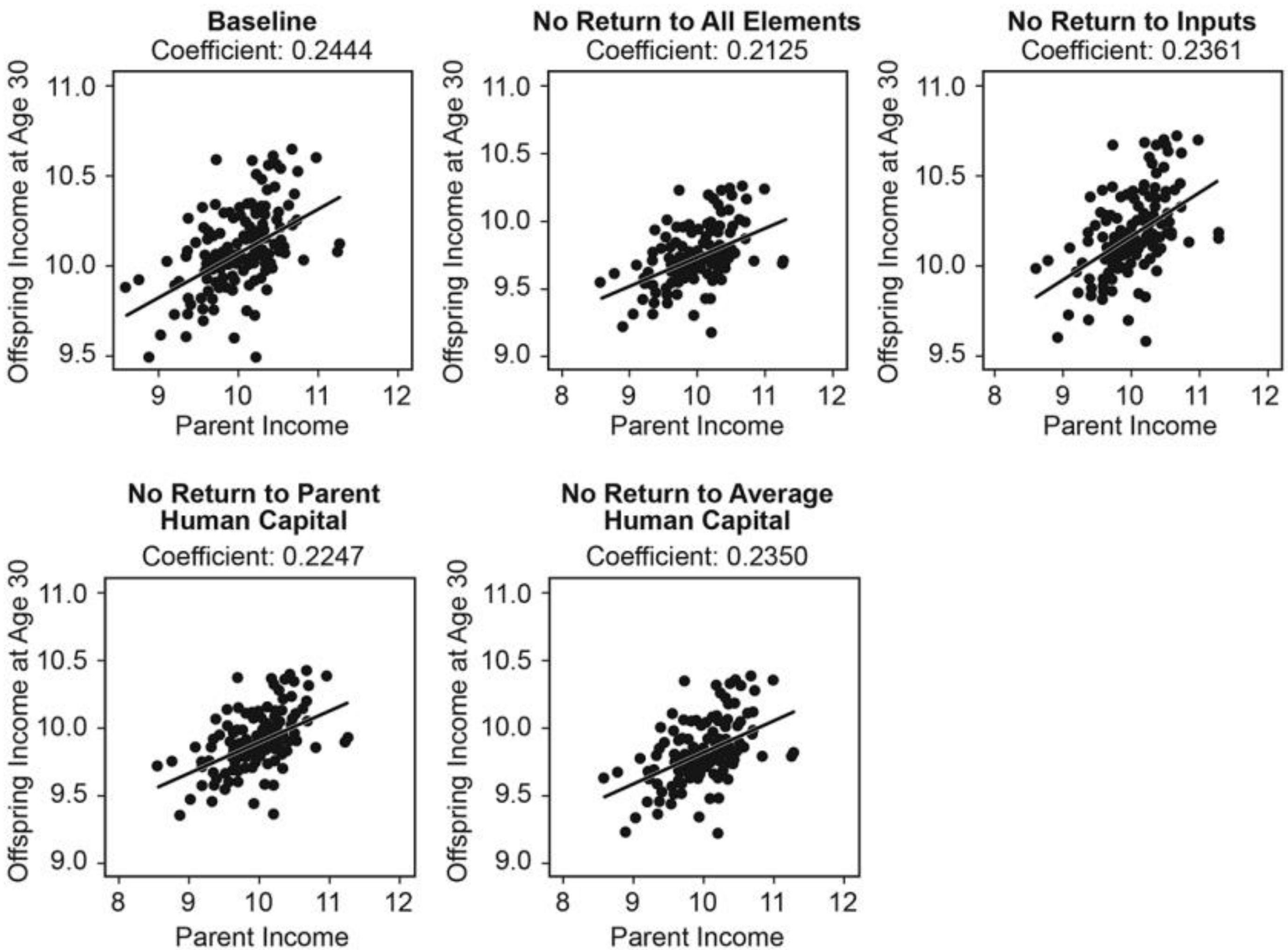
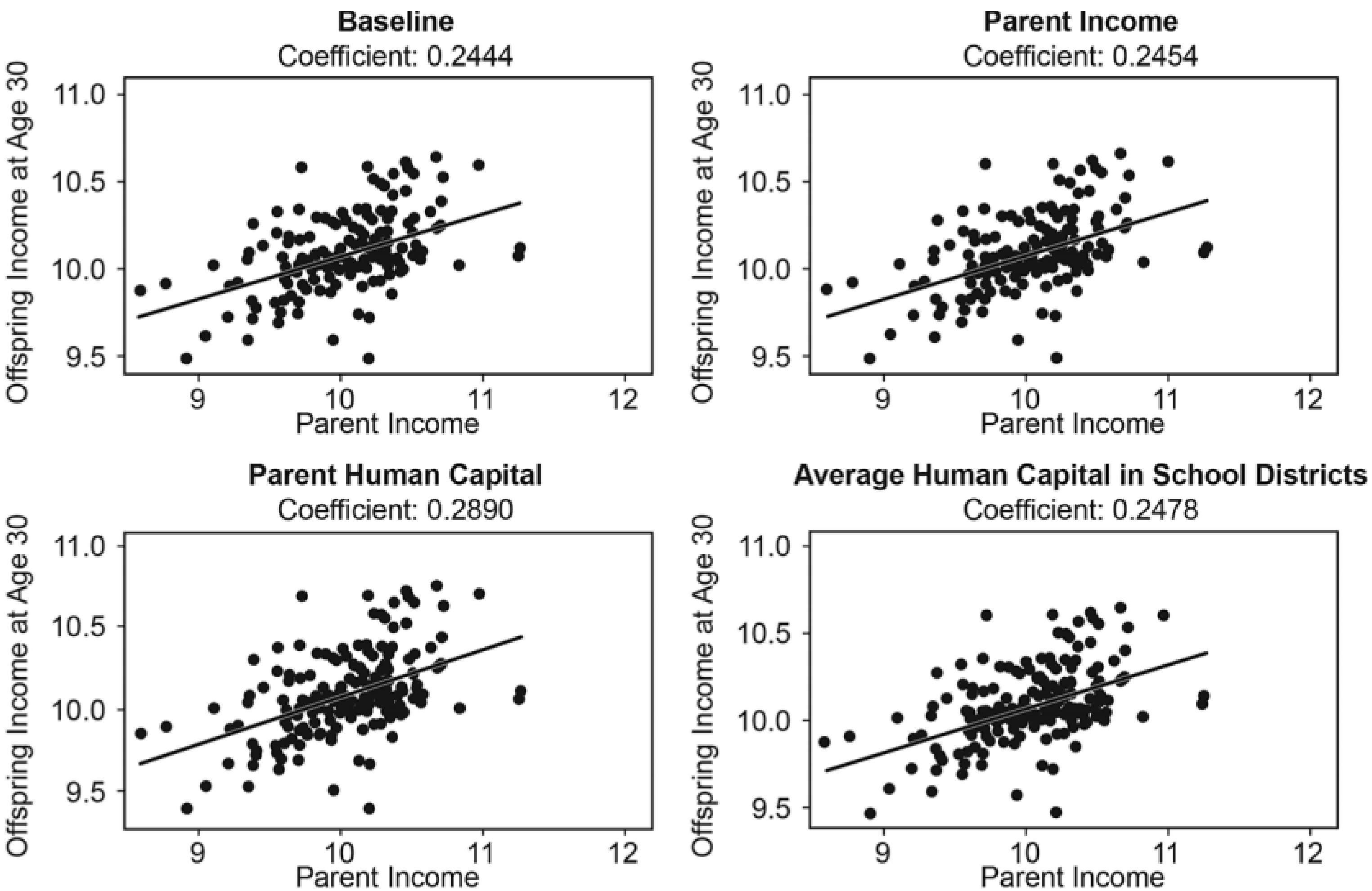


Figure 24: Counterfactual simulation: Effect of changing dispersion of exogenous variables on offspring income



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 conclude this paper with a few comments about policy

- In the context of residential neighborhoods, there are ready mechanisms to alter the degree of socioeconomic segregation

- A key question in thinking about policies of this type is the ability of private choices to cause effects of the policy to unravel

- Nothing we have said should be construed as advocating any particular policy