2020 Lectures on Urban Economics

Lecture 7: Neighborhoods and Inequality

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23 July 2020

Neighborhoods and Inequality

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Overview

Data:

- over last 40 years large increase in US income inequality
- simultaneous rise in residential income segregation within US metro areas
- micro evidence of neighborhood exposure effects on children's future income

Theory:

- models with neighborhood externalities $\rightarrow$ residential segregation and intergenerational immobility
- feedback effect between residential segregation and inequality $\rightarrow$ quantify effect on inequality rise

Some Literature

- measures of inequality and segregation:
  Katz and Murphy (1992), Jargowsky (1996), Autor et al. (1998), Goldin and Katz (2001), Massey et al. (2009), Watson (2009), Reardon and Bischoff (2011), . . .

- measures of intergenerational mobility and estimates of neighborhood exposure effects:
  Chetty, Hendren and Katz (2016) and Chetty et Hendren (2018a, 2018b), Chetty et al. (2020), . . .

- 90s theoretical work on inequality and local externalities:
  Benabou (1996a,1996b), Durlauf (1996a,1996b), Fernandez and Rogerson (1996,1998),. . .

- general equilibrium model to quantify macro effects:
  Durlauf and Seshadri (2017), Fogli and Guerrieri (2019), Eckert and Kleineberg (2019), Graham and Zheng (2020)

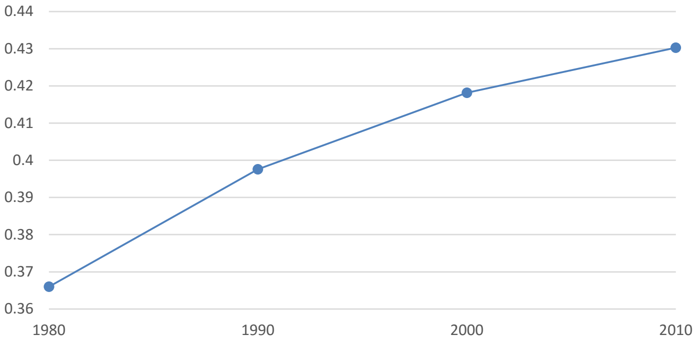
Data Source

- Census tract data on family income 1980 - 2010
- geographic unit and sub-unit: metro area and census tract (according to Census 2000)
- inequality and segregation measures are typically calculated at the metro area level and then aggregated at the national level weighting for population

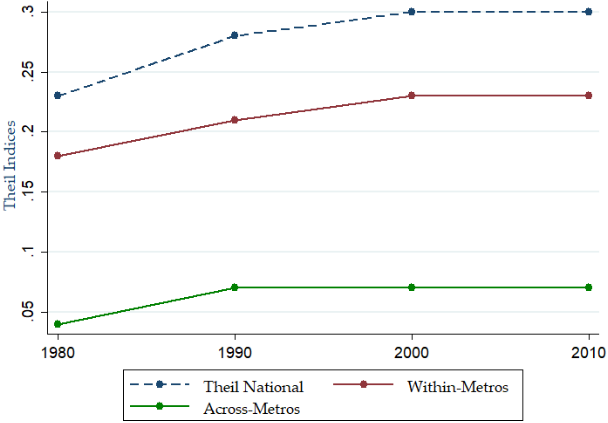
Income Inequality

- increase in US income inequality is a robust finding: Katz and Murphy (1992), Autor et al. (1998), Goldin and Katz (2001), Card and Lemieux (2001), Acemoglu (2002), Card and DiNardo (2002), Piketty and Saez (2003), Autor et al (2008)
- common measures of inequality:
  1. Gini coefficient
  2. Theil index
  3. 90/10, 90/50, 50/10 ratios
- rise in inequality driven by the top of the distribution

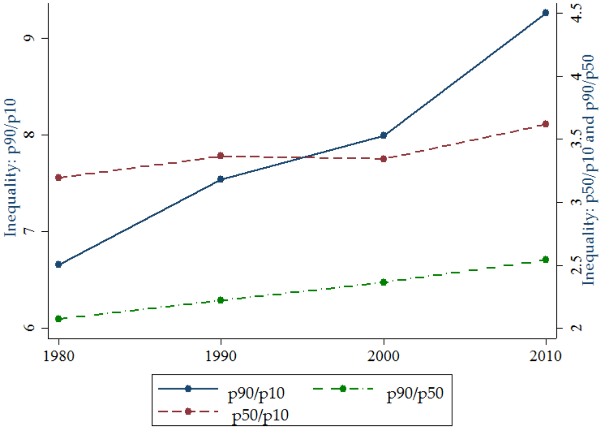
Income Inequality: Gini Coefficient



Inequality Within and Across Metros: Theil Index



Other Measures of Inequality



Residential Segregation by Income

- increase in US residential segregation by income is also a robust finding: Jargowsky (1996), Massey et al. (2009), Watson (2009), Reardon and Bischoff (2011), Reardon et al. (2018)
- common measures of segregation:
  1. dissimilarity index
  2. H index (Reardon and Bischoff)
  3. others: Centile Gap Index, Neighborhood Sorting Index, ...

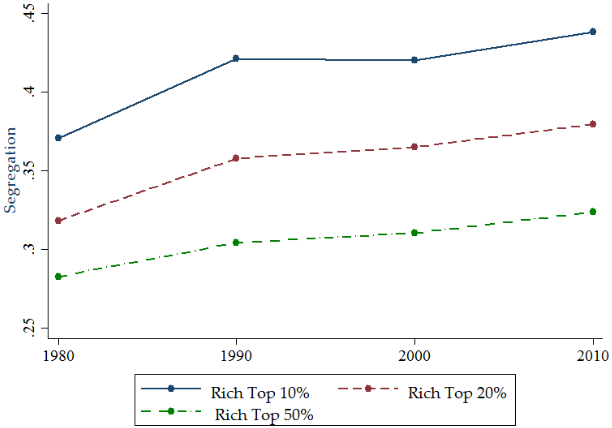
Dissimilarity Index

- it measures how uneven is the distribution of two mutually exclusive groups across geographic subunits
- groups: rich and poor (e.g. above and below the 80th percentile):

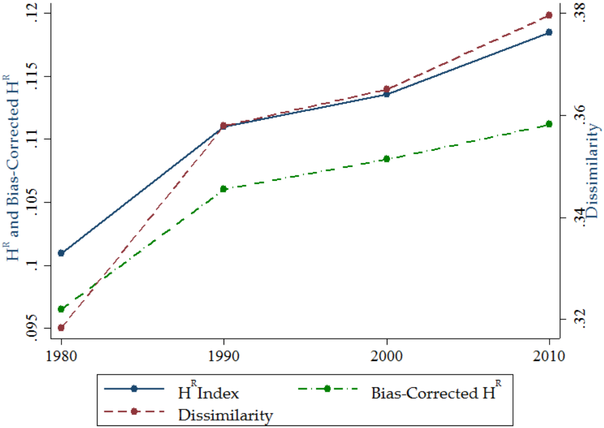
$$D(j) = \frac{1}{2} \sum_i \left| \frac{x_i(j)}{X(j)} - \frac{y_i(j)}{Y(j)} \right| \tag{1}$$

  - $x_i(j)$ = poor in census tract i in metro j
  - $y_i(j)$ = rich in census tract i in metro j
  - $X(j)$ = total poor population in metro j
  - $Y(j)$: total rich population in metro j

Dissimilarity Index with Different Percentiles



Alternative Measures of Segregation

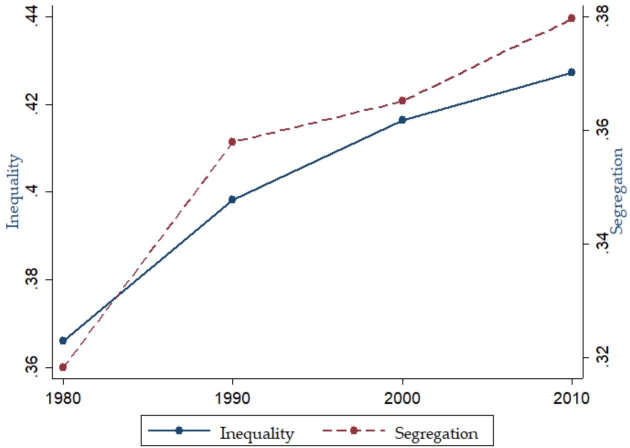


Connection between Inequality and Segregation?

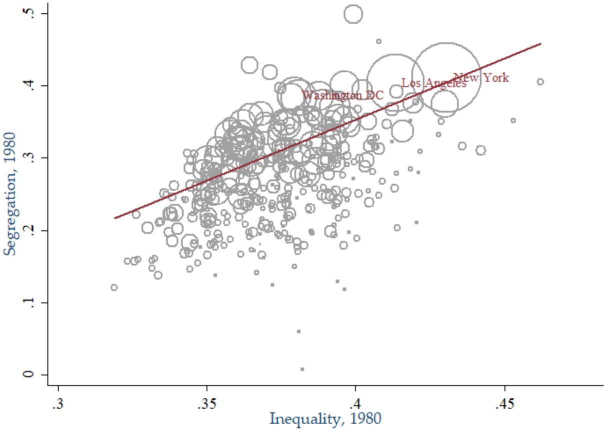
inequality and segregation measures show signs of correlation:

1. at the aggregate level across time
2. at the metro area level across space
3. at the metro area level across space and time

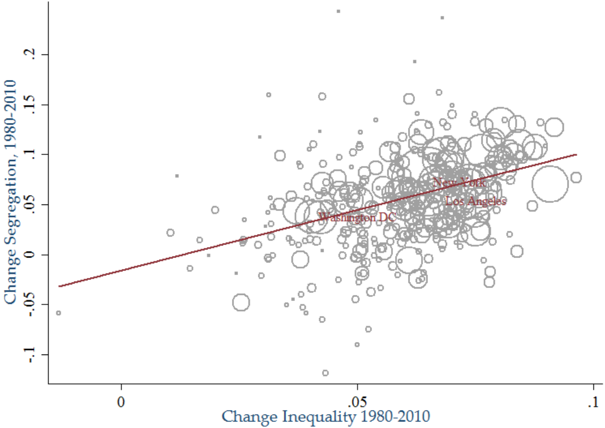
Inequality and Segregation Across Time



Inequality and Segregation Across Space



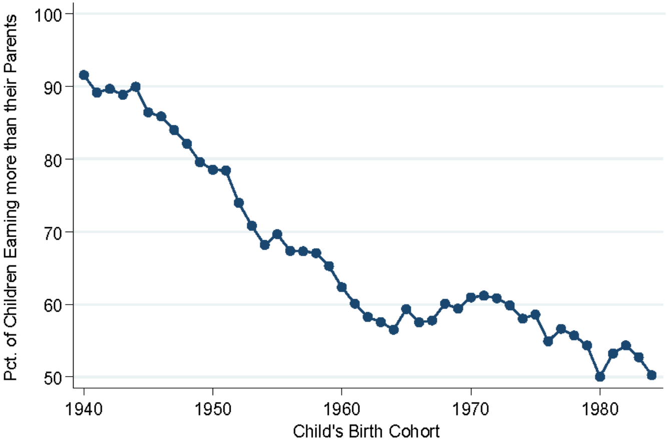
Inequality and Segregation Across Space and Time



Intergenerational Mobility

- Chetty et al. (2016) show that the US has also experienced a "fading of the American dream"
- they show that rates of absolute intergenerational mobility have fallen from approximately 90% for children born in 1940 to 50% for children born in 1980
- Chetty et al. (2014) study the cross-section distribution of intergenerational mobility across different areas in the US
- they find that high mobility areas typically have less income inequality and less residential segregation (both racial and by income)

Mean Rate of Absolute Mobility by Cohort



Source: Chetty et al. (2016)

Intergenerational Mobility Matrix

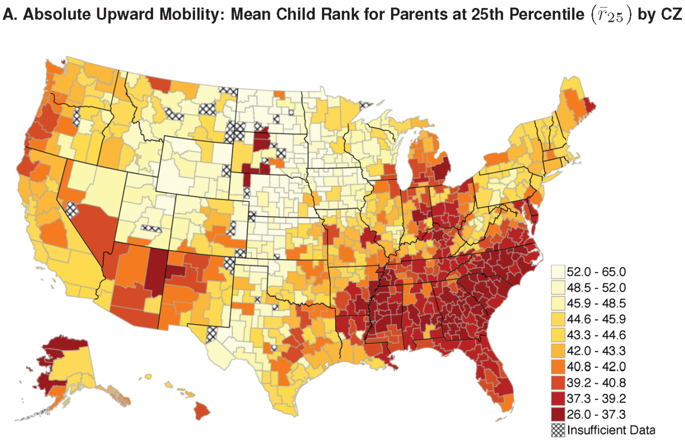
TABLE II
National Quintile Transition Matrix

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

Notes. Each cell reports the percentage of children with family income in the quintile given by the row conditional on having parents with family income in the quintile given by the column for the 9,867,736 children in the core sample (1980-82 birth cohorts). See notes to Table I for income and sample definitions. See Online Appendix Table VI for an analogous transition matrix constructed using the 1980-85 cohorts.

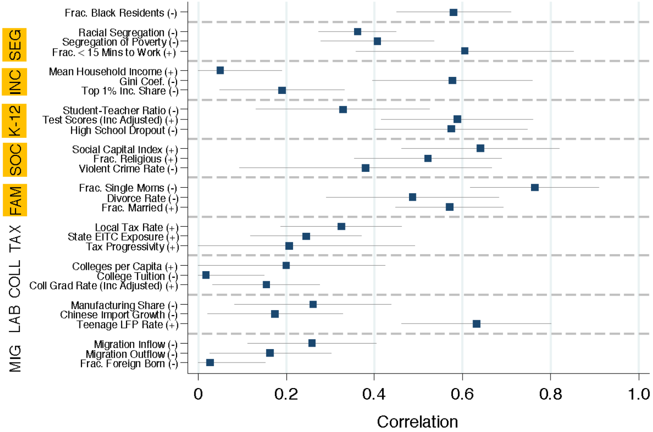
Source: Chetty et al. (2014)

The Geography of International Mobility



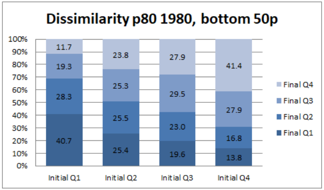
Source: Chetty et al. (2014)

Correlates of Spatial Variation in Upward Mobility

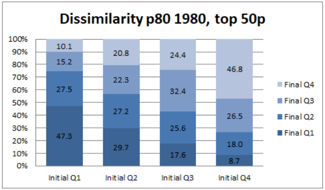


Source: Chetty et al. (2014)

Intergenerational Mobility and Segregation



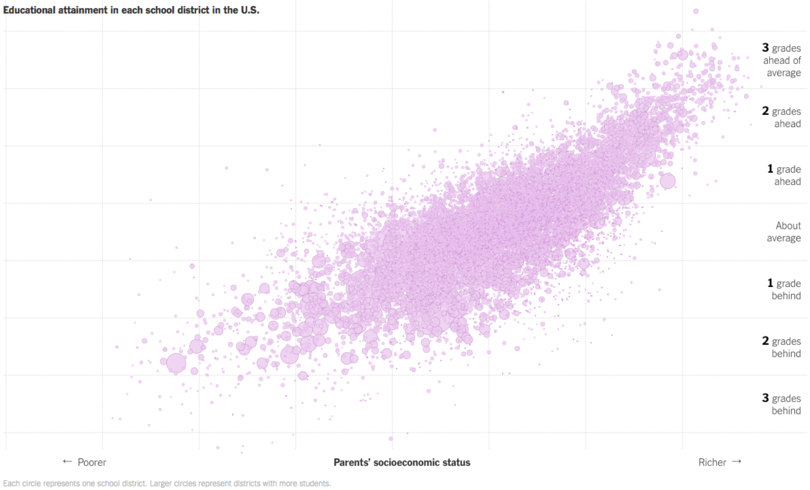
(a) Low Segregation Metros



(b) High Segregation Metros

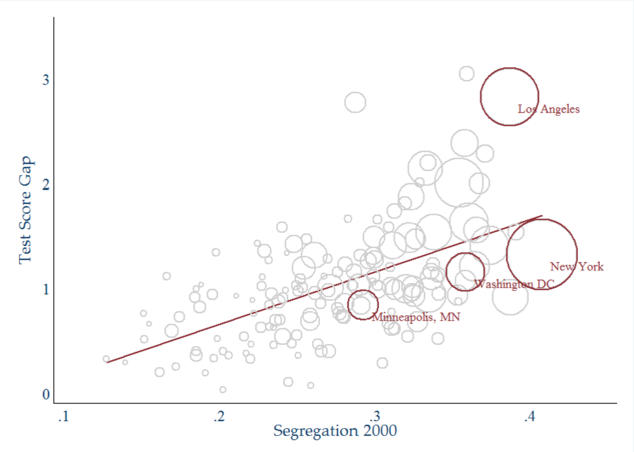
High/low: above/below median Dissimilarity p50 in 1980
Source: restricted-access geocoded version of NLSY79

Educational gap between rich and poor



Source: Stanford Education Data Archive (SEDA)

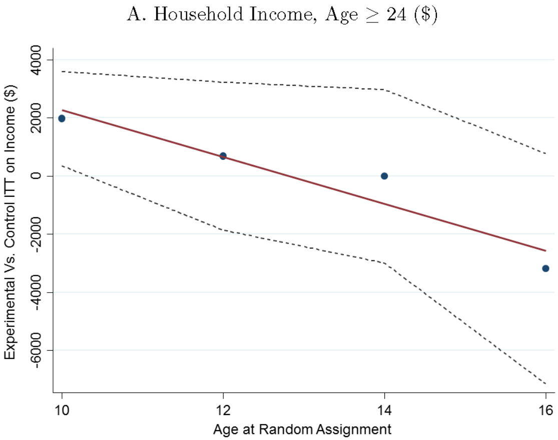
Segregation and Educational Gap



Neighborhood Exposure Effects: Moving to Opportunity

- Chetty, Handren and Katz (2016): use administrative data to study the neighborhood exposure effects on children's income using the MTO program
- MTO program offered randomly selected families living in high-poverty housing projects housing vouchers to move to lower-poverty neighborhoods
- program run between 1994-1998 in 5 cities: Baltimore, Boston, Chicago, Los Angeles, New York
- children whose families participate in the program when thy are less than 13 year old have an annual income 31% higher than control group in their mid-twenties
- possibly negative long-term impact if moving at older age

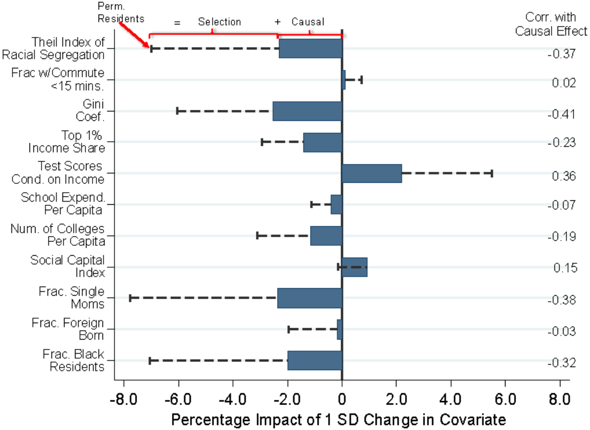
Impact of Experimental Voucher by Age of Random Assignment



County-Level Quasi-Experiment

- Chetty and Hendren (2018) uses administrative data to estimate the causal effect of each county on children's earnings
- quasi-experiment: compare families moving from one county to another with children of different age
- findings:
  1. for children with parents at 25th percentile: 1 SD better county from birth = 10% earning gains
  2. for children with parents at 75th percentile: 1 SD better county from birth = 6% earning gains

Predictors of Place Effects for Poor Children



Moving to Opportunity: Randomized Control Trial

- Chetty et al. (2020) have access to administrative data at the census tract level
- they implement a randomized control trial with housing voucher recipients in Seattle and King County
- they provided services to reduce barriers to moving to high-upward-mobility neighborhoods: customized search assitance, landlord engagement and short-term financial assistance
- the intervention increased the fraction of families moving to high-upward-mobility neighborhoods from 15% to 53%
- $\rightarrow$ redesigning affordable housing policies to provide customized assistance in housing search

2020 Lectures on Urban Economics

Short Break – We are back in a few minutes

Preview

- ’90s theoretical literature on segregation and inequality in GE frameworks: Benabou (1993, 1996), Durlauf (1996a, 1996b), Fernandez and Rogerson (1994, 1996)
- models with three key ingredients
  1. endogenous residential choice
  2. human capital accumulation
  3. local spillovers in human capital accumulation
     - capture public schools, peer effects, role models, social normas, crime, job networks, . . .
- common result: residential segregation/stratification by income arises endogenously
- common theme: residential segregation exacerbates inequality in education and income

Theory Meets New Data

- using new micro data to quantify such models:
  Durlauf and Seshadri (2017), Fogli and Guerrieri (2019), Eckert and Kleineberg (2019), Graham and Zheng (2020)
- **Fogli and Guerrieri (2019)** ask: has residential segregation contributed to amplify inequality response to underlying shocks?
- endogenous response of house prices $\rightarrow$ feedback between inequality and segregation
- calibrate to representative US MSA using the new estimates by Chetty and Hendren
- **main exercise**: MIT shock to skill premium in 1980
- segregation contributes to roughly 28% of the increase in inequality

Set Up

- overlapping generations of agents who live for 2 periods: children and parents
- a parent at time t:
  - earns a wage $w_t \in [\underline{w}, \overline{w}]$
  - has a child with ability $a_t \in [\underline{a}, \overline{a}]$
- assume $log(a)$ follows an AR1 process with correlation ρ
- $F_t(w, a)$ = joint distribution of w and a at time t

Geography and Housing Market

- two neighborhoods: $n \in \{A, B\}$
- each agent live in a house of same size and quality
- R_t^n = rent in neighborhood n at time t
- extreme assumptions on supply:
  - fixed supply H in neighborhood A;
  - fully elastic supply of houses in neighborhood B;
- marginal cost of construction in B = 0 $\Rightarrow R_t^B = 0$ for all t

Education and Wage Dynamics

- parents can directly invest in education $e \in \{e_L, e_H\}$
- cost of $e_L = 0$, cost of $e_H = \tau$
- wage of child with ability a_t, education e, growing up in n:

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

  where ε_t is iid noise and S_t^n is neighborhood n spillover

- S_t^n = average human capital in neighborhood n at time t

$$S_t^n = E[w_{t+1}(w, a, \varepsilon) | n_t(w, a) = n]$$

Parents

- parents' preferences:

$$u(c_t) + E_t[g(w_{t+1})]$$

  u concave, g increasing, both continuously diff

- assumptions:
  - no saving: for simplicity
  - no borrowing: cannot borrow against kids' future wage

- a parent with wage w_t and child ability a_t chooses
  1. consumption $c_t(w_t, a_t)$
  2. neighborhood $n_t(w_t, a_t)$
  3. child's education level $e_t(w_t, a_t)$

Parents' Optimization Problem

parent (w_t, a_t) at time t solves

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

taking as given R_t^k and S_t^k for $k = A, B$

Equilibrium

For given $F_0(w,a)$, an equilibrium is a sequence $\{n_t(w,a), e_t(w,a), R_t^A, S_t^A, S_t^B, F_t(w,a)\}_t$ satisfying

- **agents optimization**: for any t given R_t^A, S_t^A, S_t^B
- **spillover consistency** for any t and $k = A, B$
- **housing market clearing**: for any t

$$H = \int \int_{n_t(w,a)=A} F_t(w,a) dwda$$

- **wage dynamics**: for any t

$$w_{t+1}(w,a,\varepsilon) = \Omega\left(w, a, e_t(w,a), S_t^{n_t(w,a)}, \varepsilon\right)$$

Assumptions

Focus on equilibria with $R_t^A > 0$ for all t $\Rightarrow$ $S_t^A > S_t^B$ for all t

Assumption A1
The function $\Omega(a, e, S, \varepsilon)$ is

- constant in S and a if $e = e_L$
- increasing in S and a if $e = e_H$

Assumption A2
The composite function $g(\Omega(a, e, S, \varepsilon))$ has increasing differences in a and S, a and e, w and S, and w and e

Cut-off Characterization

Proposition

Under A1 and A2, for each t there are two non-increasing cut-off functions $\hat{w}_t(a)$ and $\hat{\hat{w}}_t(a)$ with $\hat{w}_t(a) \leq \hat{\hat{w}}_t(a)$ such that

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

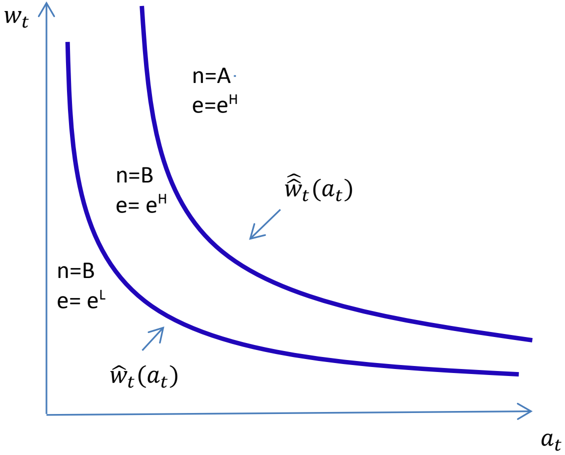
and

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

Corollary

Two cut-off functions coincide when no one in B chooses e_H

Cut-Off Characterization



Functional Forms

- choose $u(c) = log(c)$ and $g(c) = log(c)$
- set $e^L = 0$ and $e^H = 1$
- wage function

$$\Omega(w, a, e, S^n, \varepsilon) = (b + ea\eta(\beta_0 + \beta_1 S^n))w^{\alpha}\varepsilon$$

- ε iid and lognormal
- these functional forms allow us to derive the cut-off functions in closed form

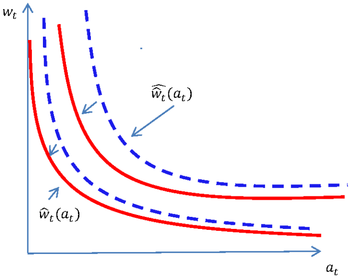
Skill Premium Shock

- what fundamental shock is behind the rise in inequality?
- assume it is skill-biased technical change
- in our model: think about a one-time, unexpected, permanent increase in η

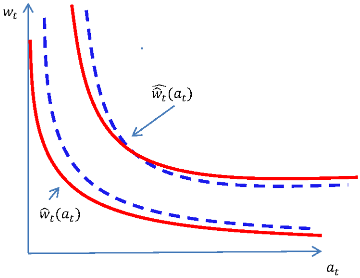
$$\Omega(w,a,e,S^n,\varepsilon) = (b + ea\eta(\beta_0 + \beta_1 S^n))w^{\alpha}\varepsilon$$

- what is the economy's response?

Response to Skill Premium Shock



(c) Partial Equilibrium



(d) General Equilibrium

Extended Model

Two new ingredients:

1. **continuous educational choice**:
   - higher dispersion in investment in human capital
2. **residential preference shock**:
   - this generates more mixing in the initial steady state

Extended Model

- parents' problem

$$
\begin{aligned}
U(w_t, a_t) \quad &= \quad \max_{c_t, e_t, n_t} log[(1 + \theta_t I_{n_t = A})c] + log(w_{t+1}) \\
s.t. \quad & c_t + R_t^{n_t} + \tau e_t \leq w_t \\
& w_{t+1} = (b + e_t a_t \eta_t (\beta_0 + \beta_1 S_t^n)) w_t^{\alpha} \varepsilon_t
\end{aligned}
$$

- educational choice

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

Main Exercise

- calibrate the model steady state to 1980
- one-time, unexpected, permanent shock to η in 1980
- match skill premium increase from .39 (1980) to .54 (1990)
- we interpret 1 period as 10 years (schooling age)
- look at responses of inequality, segregation, mobility
- look at counterfactual exercises to understand the amplifying role of segregation

Calibration Targets

Description	Data	Model	Source
Gini coefficient	0.366	0.365	Census 1980, family income
Dissimilarity index	0.318	0.318	Census 1980, family income
H^R index	0.100	0.094	Census 1980, family income
B/A average income	0.516	0.459	Census 1980
R^A-R^B normalized	0.073	0.074	Census 1980
Rank-rank correlation	0.341	0.330	Chetty et al. (2014)
Return to spillover 25th p	0.104	0.104	Chetty and Hendren (2018b)
Return to spillover 75th p	0.064	0.070	Chetty and Hendren (2018b)
Return to college 1980	0.304	0.306	Valletta (2018)
Return to college 1990	0.449	0.449	Valletta (2018)

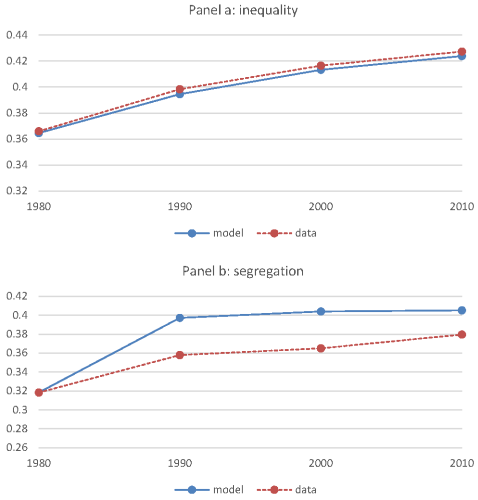
Spillover's effect

- Chetty and Hendren (2018) look at movers across US counties with children of different age
- they focus on children born between 1980 and 1986
- in the model we focus on "moving parents" and look at the neighborhood's effect on their children's income
- these children will be 18 between 1998 and 2004
- $\Rightarrow$ we average this effect between 1980 and 2000

Parameters

Parameter	Value	Description
H	0.08	Size of neighborhood A
α	0.20	Wage function parameter
β_0	2.30	Wage function parameter
β_1	0.26	Wage function parameter
ξ	0.70	Wage function parameter
τ	0.30	Cost of education
b	1.44	Wage fixed component for no-college
ρ	0.38	Autocorrelation of ability
σ	0.48	Standard dev. of log innate ability
μ_a	-3.10	Average of log innate ability
μ_ε	0.42	Average of log wage noise shock
σ_ε	0.65	Standard dev. of log wage noise shock
$\bar{\theta}$	0.05	Preference shock value
π	0.33	Preference shock probability
η	3.13	skill premium shock

Response to Skill Premium Shock



Response to Skill Premium Shock (continued)

	t = 0	t = 1	t= 2	t= 3
Return to college	0.31	0.45	0.52	0.55
Gini coefficient	0.37	0.39	0.41	0.42
Dissimilarity index	0.31	0.38	0.39	0.39
H^R index	0.09	0.12	0.13	0.14
B/A average income	0.47	0.32	0.27	0. 25
R^A-R^B normalized	0.07	0. 18	0.29	0.37
Rank-rank correlation	0.25	0.34	0.40	0.42
A/B spillovers ratio	1.25	1.68	1.98	2.16

Feedback effect of segregation on inequality

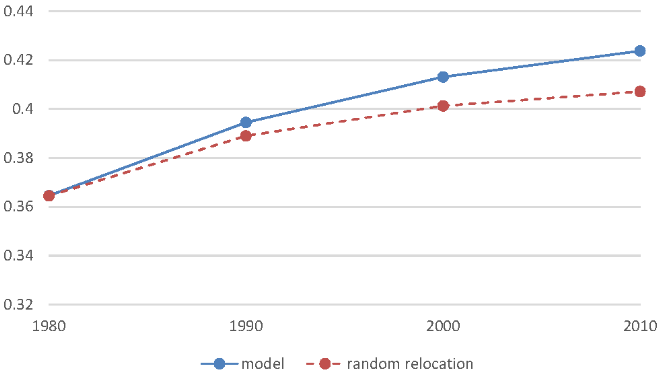
- skill premium shock increases inequality and segregation
- segregation further amplifes the increase in inequality

1. for given spillovers, more rich children will be exposed to better neighborhoods $\rightarrow$ even richer
2. for given spillovers, more poor children will be exposed to worse neighborhoods $\rightarrow$ even poorer
3. higher segregation will increase the gap between the spillovers in the two neighborhoods $\rightarrow$ more inequality

Main Counterfactual: Random Re-Location

- how much does segregation amplify the response of inequality to the skill premium shock?
- main counterfactual: shut down residential choice after the shock
- after the shock families randomly re-located in the two neighborhoods
- spillover equal in two neighborhoods $\rightarrow$ global spillover

Main Counterfactual: Random Re-Location

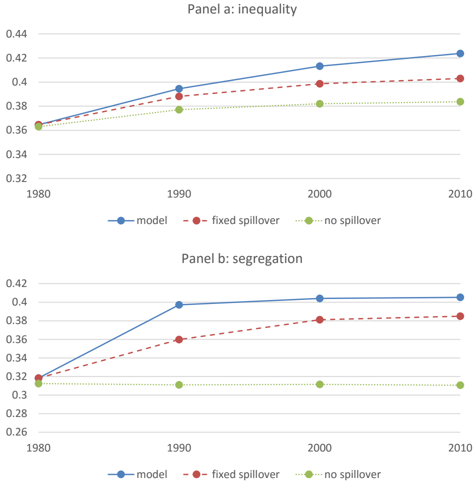


Additional Exercises

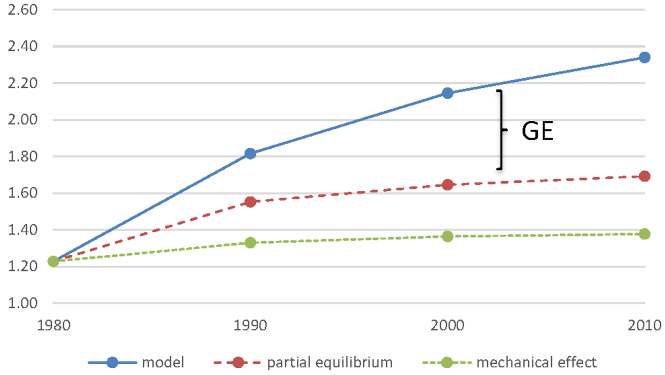
two alternative exercises to quantify the contribution of segregation to inequality

1. no spillover (local or global)
   - wage function not affected by local spillovers: $\beta_1 = 0$
2. fixed local spillover (not responsive to the shock)
   - keep S^A and S^B fixed at the initial steady state levels

No Spillover and No Spillover Feedback

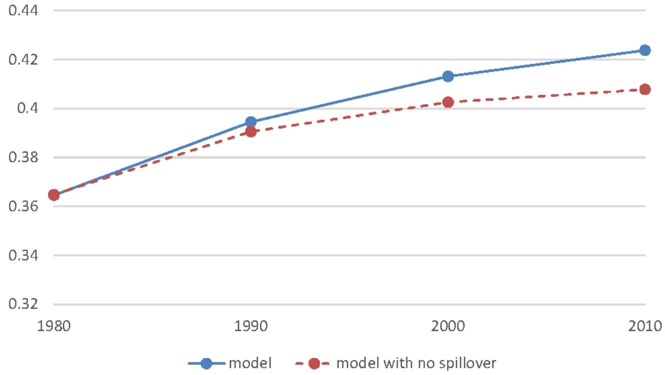


Decomposing the Spillover Feedback



GE effect: as R^A increases, the degree of sorting by income increases

Model with No Spillover



Eckert and Kleineberg (2019)

- estimate a structural spatial equilibrium model to study the effects of different school financing policies
- two local ingredients: human capital accumulation externalities and labor market access
- estimate the model by fitting model predictions to regional data of the US geography
- result: equalization of school funding across all students have some positive effect on education outcomes and intergenerational mobility but small
- general equilibrium responses of local prices and local skill composition significantly dampen the positive effects of such a policy

Final Remarks

- residential segregation has been growing over time
- significant effects on inequality, intergenerational mobility, education, labor market access, ...
- availability of detailed micro data has been booming
- growing opportunity of using these data to quantify spacial models and carefully think about policies
- today I focused on segregation by income, but another important topic is racial segregation ...