Online Appendix for
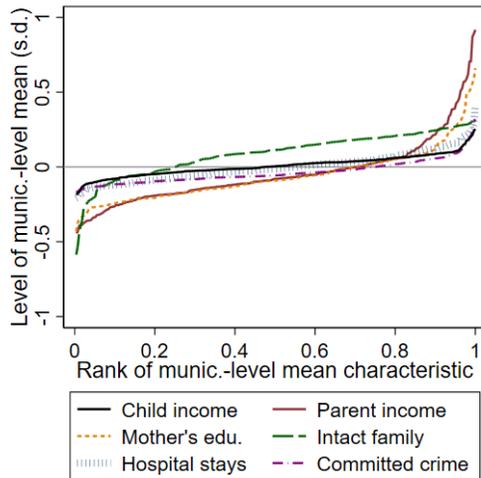# "Understanding the Heterogeneity of Intergenerational Mobility across Neighborhoods"

Neil A. Cholli, Steven N. Durlauf, Rasmus Landersø, and Salvador Navarro
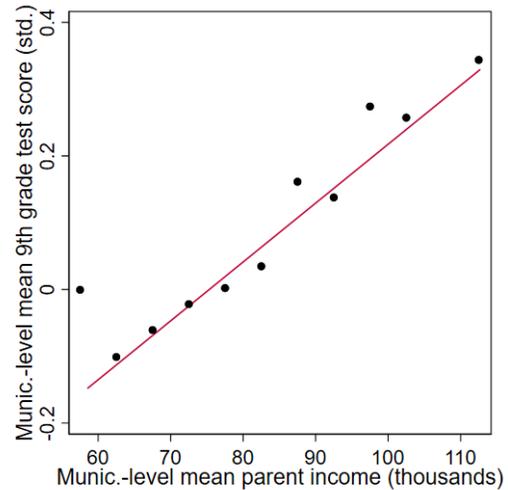
September 27, 2024

A   Supplemental Figures and Tables

Figure A.1: Inequality in family and location characteristics (municipalities)

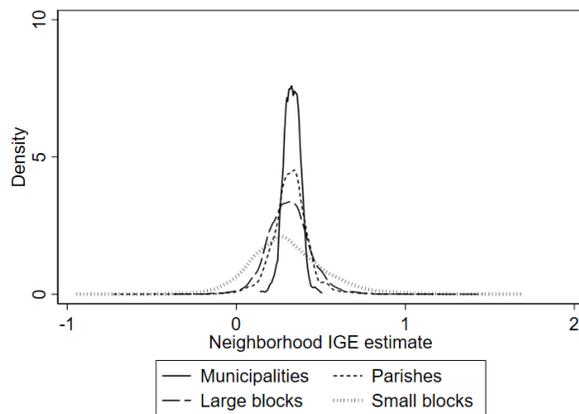(a) Inequality in family characteristics across municipalities

(b) Association between mean 9th grade test scores and parental income across municipalities
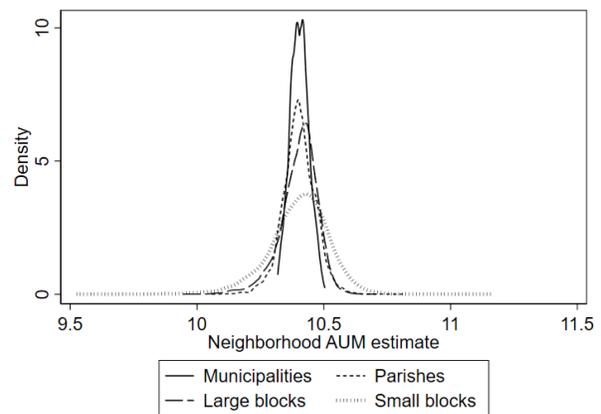

Notes: See notes of Figure 1.

Figure A.2: Neighborhood-level mobility estimates, by neighborhood unit
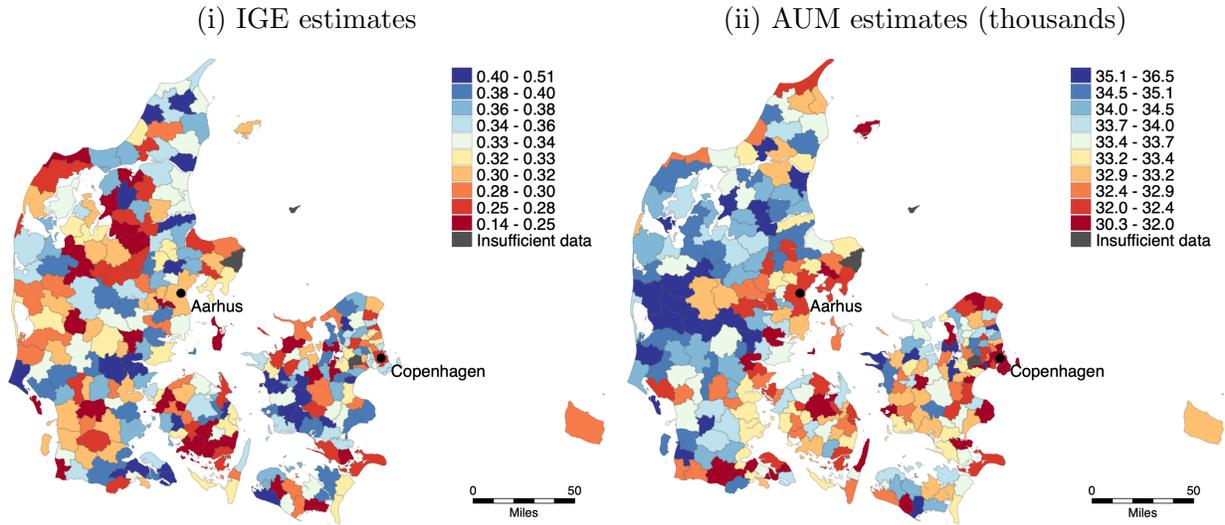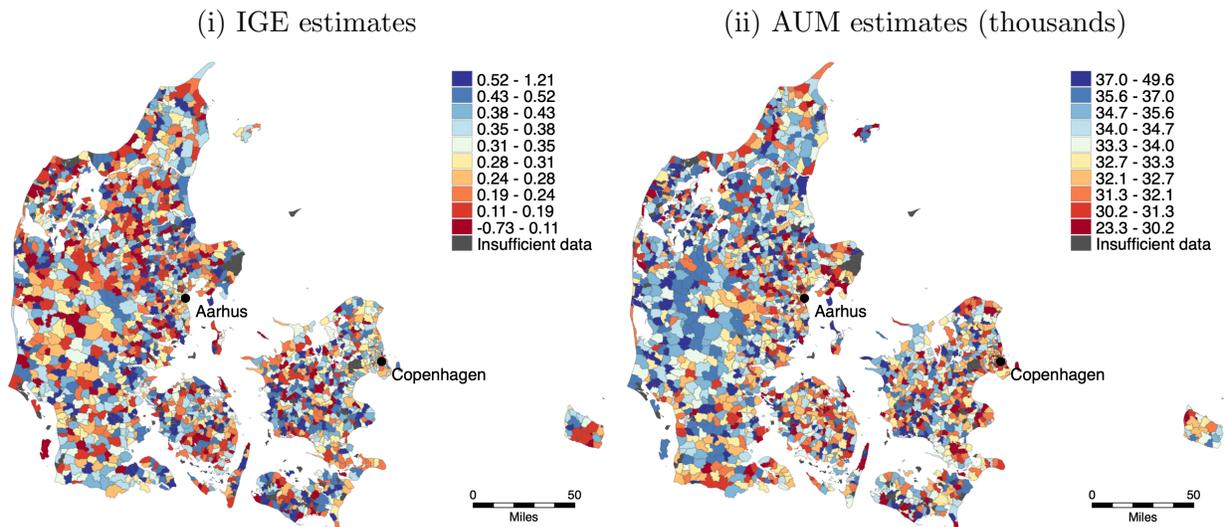
(a) IGE estimates

(b) AUM estimates

Notes: All estimates based on regressions restricted to neighborhood units with at least 25 families.

Figure A.3: Heat maps of baseline intergenerational mobility estimates across neighborhoods

(a) Municipalities

(i) IGE estimates

■	0.40 - 0.51
■	0.38 - 0.40
■	0.36 - 0.38
■	0.34 - 0.36
■	0.33 - 0.34
■	0.32 - 0.33
■	0.30 - 0.32
■	0.28 - 0.30
■	0.25 - 0.28
■	0.14 - 0.25
■	Insufficient data

(ii) AUM estimates (thousands)

■	35.1 - 36.5
■	34.5 - 35.1
■	34.0 - 34.5
■	33.7 - 34.0
■	33.4 - 33.7
■	33.2 - 33.4
■	32.9 - 33.2
■	32.4 - 32.9
■	32.0 - 32.4
■	30.3 - 32.0
■	Insufficient data

(b) Parishes

(i) IGE estimates

■	0.52 - 1.21
■	0.43 - 0.52
■	0.38 - 0.43
■	0.35 - 0.38
■	0.31 - 0.35
■	0.28 - 0.31
■	0.24 - 0.28
■	0.19 - 0.24
■	0.11 - 0.19
■	-0.73 - 0.11
■	Insufficient data

(ii) AUM estimates (thousands)

|	
■	37.0 - 49.6
■	35.6 - 37.0
■	34.7 - 35.6
■	34.0 - 34.7
■	33.3 - 34.0
■	32.7 - 33.3
■	32.1 - 32.7
■	31.3 - 32.1
■	30.2 - 31.3
■	23.3 - 30.2
■	Insufficient data

Notes: Heat maps of estimates of the neighborhood-level IGE β_n and exponentiated AUM $\bar{y}_{25n}^c$ from Equation (1).

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Figure A.4: Second-stage correlations between location characteristics and neighborhood IGE estimates, without vs. with select controls
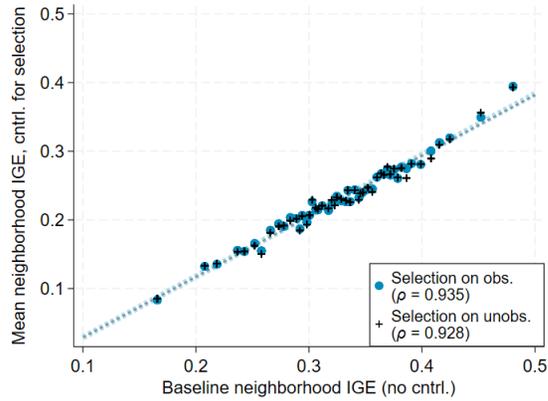
(a) Municipalities
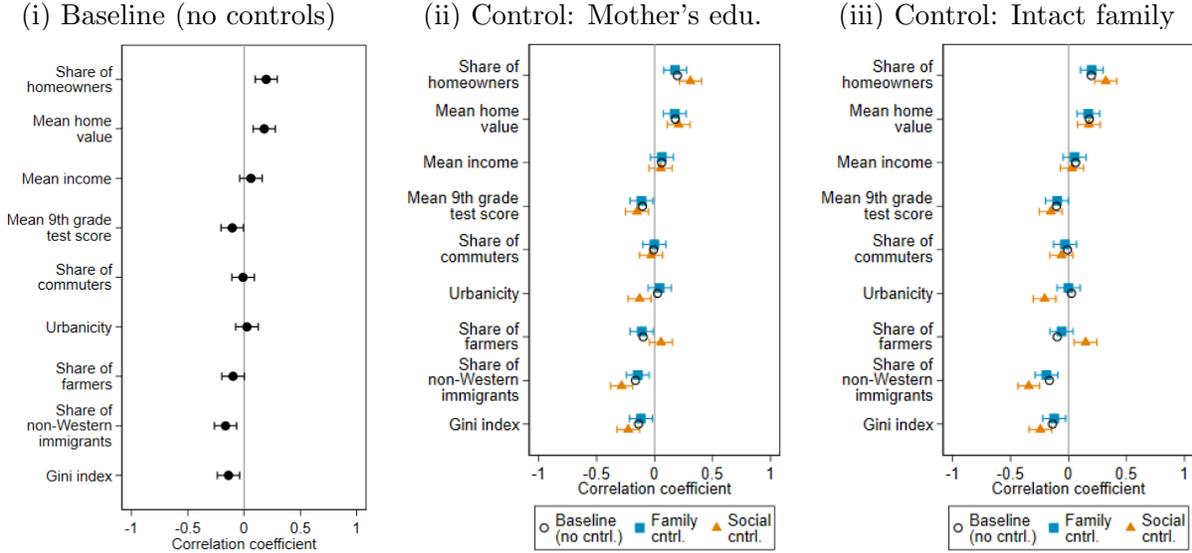
(b) Parishes
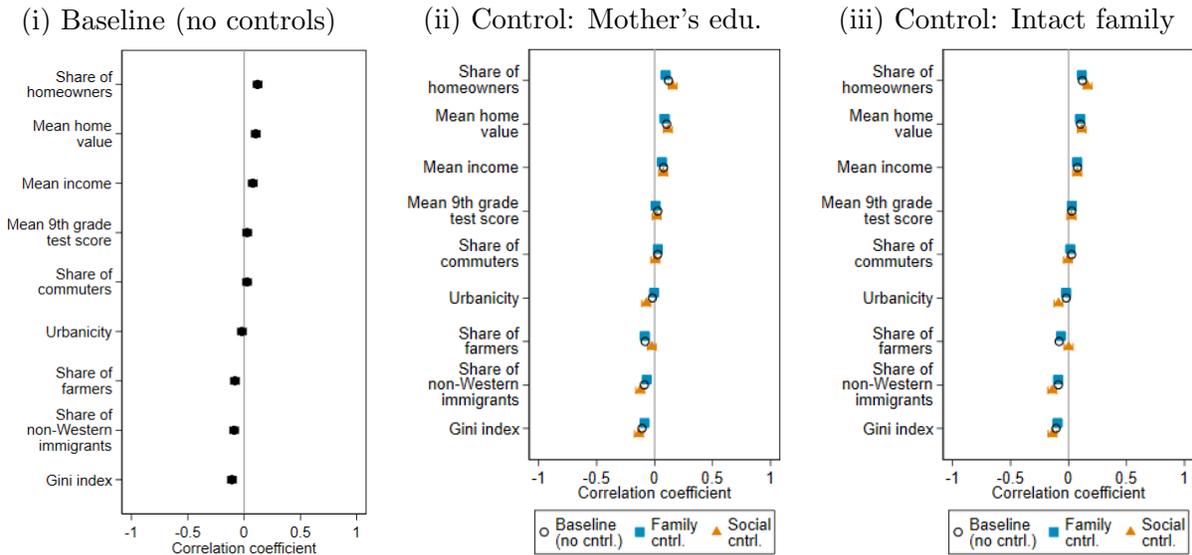
Notes: This figure plots correlation coefficients between neighborhood-level IGE estimates and location characteristics. See notes of Figure 2 for details.

Figure A.5: IGE estimates from the generalized mobility model

(a) Municipalities

(i) Comparison with baseline estimates | (ii) PDFs of indiv.-level AUM components | (iii) PDFs of location effects, by model
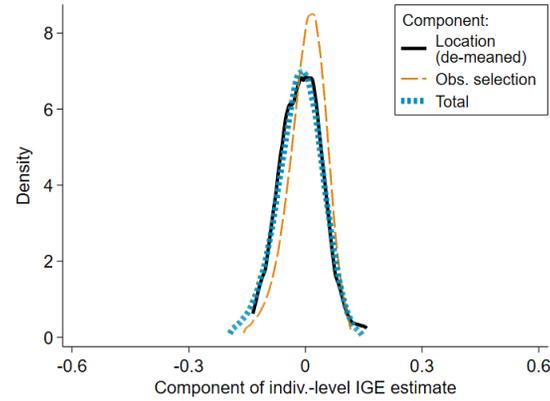
(b) Parishes
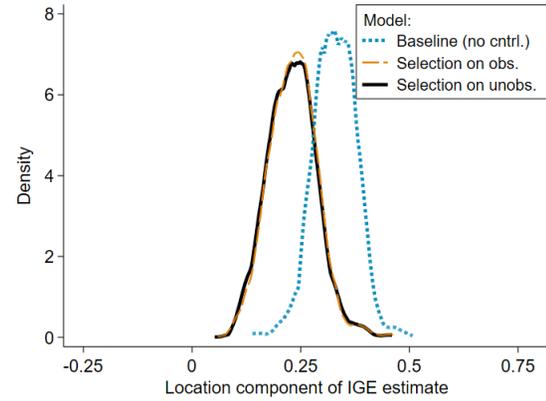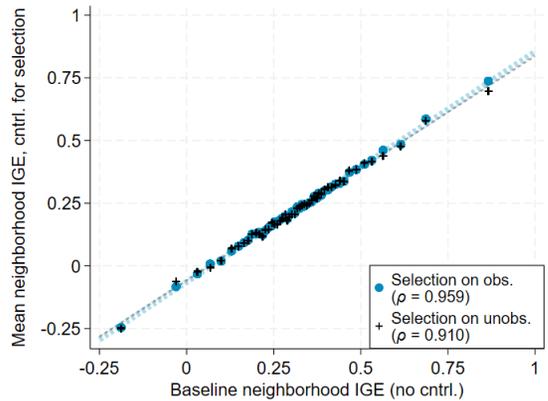
(i) Comparison with baseline estimates | (ii) PDFs of indiv.-level IGE components | (iii) PDFs of location effects, by model
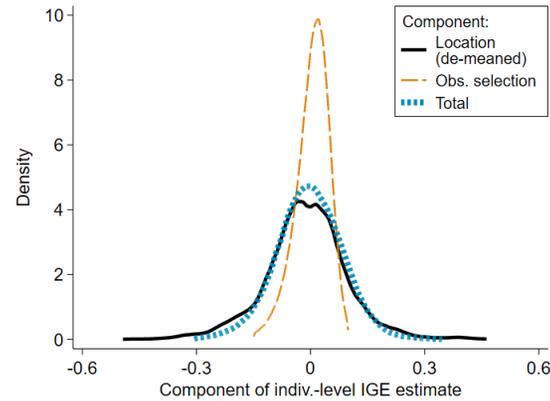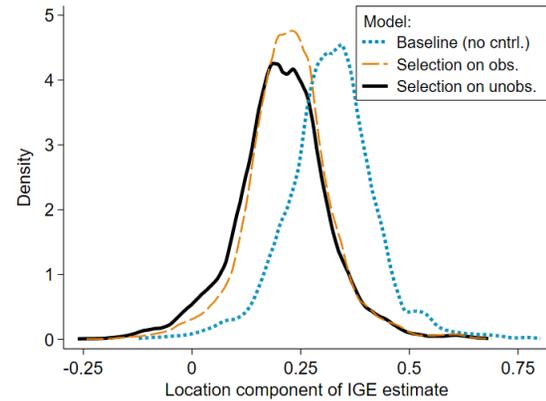
Notes: This figure plots estimates of the mean neighborhood IGE, individual-level IGE, and individual-level IGE components from Equation (5). See notes of Figure 3 for details.

Figure A.6: Second-stage correlations between location characteristics
and IGE location effect estimates

(a) Municipalities

(b) Parishes
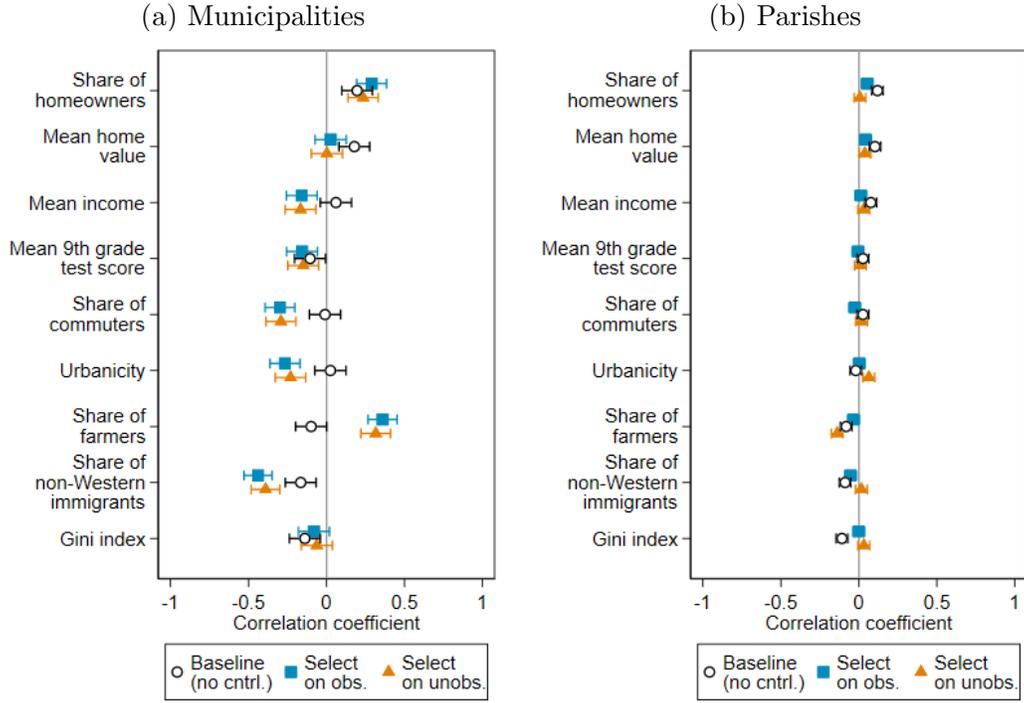
Notes: This figure plots estimates of the correlation coefficients between various location characteristics of neighborhoods and the residual location IGE effect estimates from Equation (5). See notes of Figure 6 for details.

Figure A.7: Scree plots for *k*-means cluster analysis of irreducible location estimates

(a) Municipalities

(i) Within-sum of squares

(ii) Proportional reduction of error
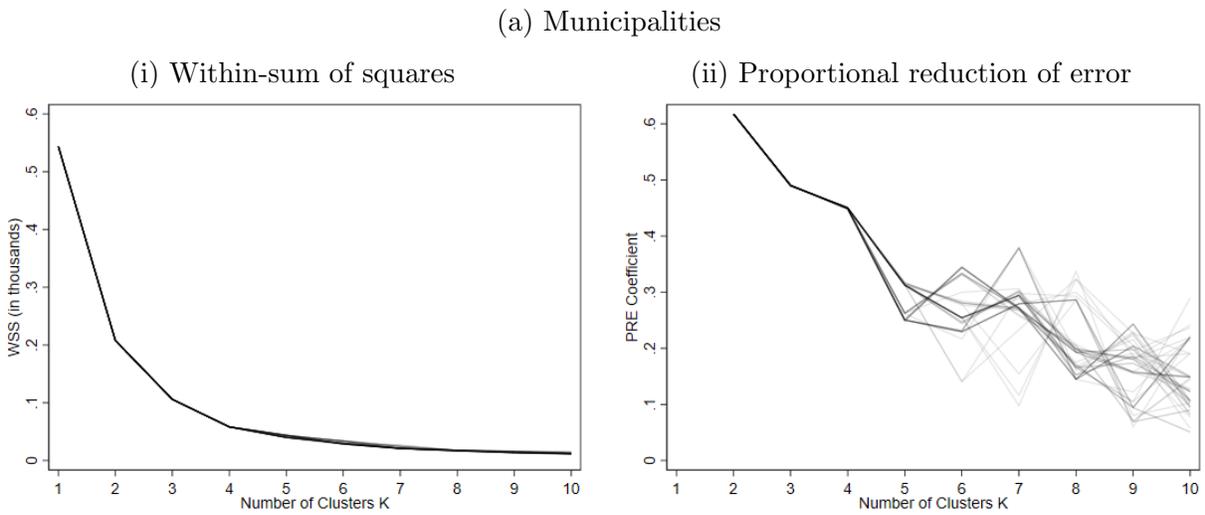
Notes: (see next page)

Figure A.7: *(cont'd)*

(b) Parishes

(i) Within-cluster sum of squares

(ii) Proportional reduction of error
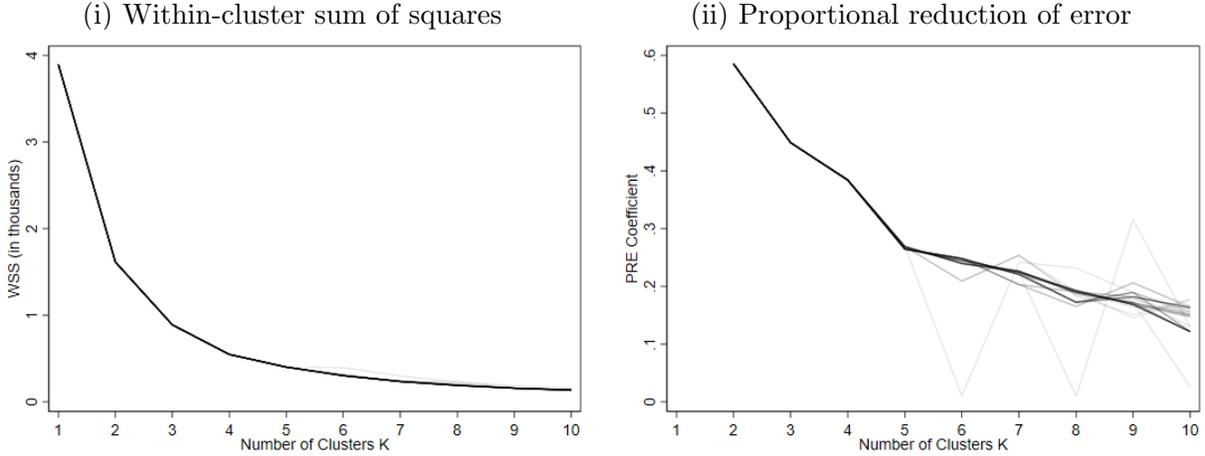
Notes: This figure plots the within-cluster sum of squares (WSS) and proportional reduction of error (PRE) coefficient against different choices of the number of clusters k for fifty random starting values of the k-means clustering algorithm.

Table A.1: Variance decomp. of parish mobility estimates within/between municipalities

	(1) Weighted	(2) Total	(3) Within-Munic.	(4) Between-Munic.
$\hat{\beta}_n$		0.0320 (100.0)	0.0274 (85.5)	0.0046 (14.5)
$\hat{\beta}_n$	✓	0.0130 (100.0)	0.0105 (80.6)	0.0025 (19.4)
$\hat{\bar{y}}^c_{25n}$ (thousands)		8.16 (100.0)	6.39 (78.3)	1.77 (21.7)
$\hat{\bar{y}}^c_{25n}$ (thousands)	✓	4.44 (100.0)	3.03 (68.3)	1.41 (31.7)

Notes: This table reports variance decompositions of parish-level mobility estimates from Equation (1) into components explained within and between municipalities. Column (1) indicates if this decomposition is weighted by neighborhood sample size. Percent contribution of each component toward total variance is reported in parentheses. All AUM estimates $\hat{\bar{y}}^c_{25n}$ are exponentiated and expressed in thousands of dollars.

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Table A.2: Variance decomposition of individual-level IGE estimates

	Assump.	(1) Total (%)	(2) Obs. Selection (%)	(3) Location (%)	(4) Sorting (%)
A. Municipalities					
Total	O	100.0	67.5	69.5	−37.0
	U	100.0	67.1	70.0	−37.1
1. Between-neighborhood	O	41.3	13.2	44.1	−30.3
	U	20.9	13.7	34.2	−27.0
2. Within-neighborhood	O	58.7	54.3	25.3	−6.7
	U	79.1	53.4	35.8	−10.1
2.1. Signal	O	45.9	45.9	—	—
	U	40.3	40.3	—	—
2.2. Noise	O	12.8	8.3	25.3	−6.7
	U	38.8	13.1	35.8	−10.1
Total variance	O		0.005		
	U		0.005		
B. Parishes					
Total	O	100.0	19.0	81.7	−0.7
	U	100.0	17.6	83.2	−0.8
1. Between-neighborhood	O	23.4	1.0	22.1	0.4
	U	17.6	1.0	15.9	0.7
2. Within-neighborhood	O	76.6	18.0	59.6	−1.1
	U	82.4	16.5	67.4	−1.5
2.1. Signal	O	15.8	15.8	—	—
	U	13.3	13.3	—	—
2.2. Noise	O	60.8	2.2	59.6	−1.1
	U	69.1	3.2	67.4	−1.5
Total variance	O		0.014		
	U		0.015		

Notes: This table reports fractions (expressed as percentages) of the total variance of individual-level IGE estimates (from Equation (5)). See notes of Table 2 for details.

Table A.3: Differences between neighborhood types under $K = 3$

	Municipalities			Parishes		
	Type 1 Mean	Type 2 Diff.	Type 3 Diff.	Type 1 Mean	Type 2 Diff.	Type 3 Diff.
A. Mobility estimates						
Irreducible location IGE	0.050	−0.045***	−0.097***	0.117	−0.115***	−0.222***
		(0.004)	(0.005)		(0.004)	(0.005)
E.B. irreducible location IGE	0.016	−0.015***	−0.034***	0.034	−0.035***	−0.073***
		(0.001)	(0.001)		(0.001)	(0.001)
Irreducible location AUM	−0.019	0.018**	0.044***	−0.045	0.038***	0.085***
		(0.009)	(0.009)		(0.011)	(0.012)
E.B. irreducible location AUM	−0.006	0.006***	0.009***	−0.003	0.003***	0.007***
		(0.002)	(0.002)		(0.000)	(0.000)
Location component of IGE	0.279	−0.045***	−0.106***	0.329	−0.118***	−0.221***
		(0.006)	(0.006)		(0.004)	(0.005)
Location component of AUM	10.434	0.033***	0.043***	10.421	0.041***	0.085***
		(0.010)	(0.010)		(0.011)	(0.012)
Population component of IGE	−0.007	0.003	0.019***	−0.001	0.001**	0.001*
		(0.004)	(0.004)		(0.001)	(0.001)
Population component of AUM	0.000	0.013**	−0.017***	−0.001	0.001	0.003
		(0.006)	(0.006)		(0.002)	(0.003)
Control function estimate	−0.023	−0.026***	−0.023**	−0.021	−0.019*	−0.031**
		(0.009)	(0.010)		(0.010)	(0.012)
B. Population characteristics						
Mean mother age	26.735	0.162**	0.002	26.796	−0.006	0.043
		(0.079)	(0.084)		(0.041)	(0.048)
Mean parent income (thousands)	69.348	4.161***	1.042	71.385	−0.498	1.030
		(1.267)	(1.345)		(0.572)	(0.675)
Mean parent assets (thousands)	23.107	5.344***	−1.182	24.711	−0.309	1.642
		(1.939)	(2.060)		(0.929)	(1.096)
Share of mothers not employed	0.419	−0.017**	−0.008	0.417	−0.009*	−0.015***
		(0.009)	(0.009)		(0.005)	(0.005)
Mean mother years of education	12.746	0.160**	0.217**	12.852	0.028	0.070
		(0.079)	(0.084)		(0.037)	(0.044)
Mean father years of education	13.063	0.120	0.201**	13.188	−0.046	0.036
		(0.095)	(0.101)		(0.044)	(0.052)
Share of intact families	0.684	0.004	−0.055***	0.669	0.001	−0.001
		(0.013)	(0.013)		(0.006)	(0.007)
Mean household size	4.142	−0.002	−0.135***	4.105	0.001	−0.028*
		(0.032)	(0.034)		(0.014)	(0.016)
Share of divorced families	0.207	−0.004	0.030***	0.216	−0.004	−0.001
		(0.009)	(0.009)		(0.004)	(0.005)
Share of never married families	0.142	−0.000	0.026***	0.145	0.006***	0.006**
		(0.004)	(0.004)		(0.002)	(0.003)
Share of parents hospitalized	0.736	−0.013***	−0.011**	0.730	−0.003	−0.006**
		(0.004)	(0.005)		(0.002)	(0.003)
Share of parents committed crime	0.142	−0.007	0.018***	0.145	−0.001	0.001
		(0.005)	(0.005)		(0.003)	(0.003)
Share of parents incarcerated	0.057	−0.004*	0.003	0.057	−0.001	−0.001
		(0.002)	(0.003)		(0.001)	(0.002)
Number of neighborhoods	56	150	67	357	1,158	434

Notes: See notes of Table 3 for details.

B Data Appendix

B.1 Sample Construction

We use full population administrative registers provided by Statistics Denmark. Our base sample consists of 710,329 children born between 1973–1983 that possess key, non-missing data in the Household and Family registers (*Husstande og Familier*, FAIN) before age 17.

We link each child to their birth/adoptive parents' individual identification numbers defined by birth records.[1] We consider a parental birth date to be missing if the recorded year of birth of either parent implies that the parent was below age 14 when their child was born. Next, the base sample is matched to immigrant status, provided by the Population register (*Befolkningen*, BEF). We exclude children who are either first- or second-generation immigrants of Denmark. These steps leaves about 90% of the original sample: 640,434 native Danish child–parent dyads.

To proxy for emigration, account for deaths of children and parents during key age ranges of the child (ages 0–17 and 30–45), and to remove frequent non-tax filers, we merge the sample to the 1980–2018 Income registers (*Indkomst*, IND) and remove observations with missing income data during the final 3 years of the windows used in the long-run mean income used in the analysis (see Section B.2.1 for more details).[2] To reduce the noise in our measures of mean income, we also remove the very few cases with fewer than three years of available parent income between child ages 0–17 or of available child income between ages 30–45. We then construct our measures of long-run mean gross market income excluding transfers for children and parents and remove cases with negative values.[3]

Finally, we link children and parents to a comprehensive set of geographic identifiers and family characteristics, described in depth in Sections B.2.2 and B.2.3. Since we require these data for our richer empirical models, we restrict our main sample to have no missing values in any of these variables.

Since IGE estimates are highly sensitive to the inclusion of values near $0, the sample used in the main analysis excludes families where either the child or parents have less than $1,000 in market income (excluding transfers). We further remove parishes with fewer than 25 families to maintain statistical power. This reduces the number of parishes from our

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1. It is extremely rare (< 1% of observations) for the parents' identifiers to change over time. To resolve these cases, we use the modal parental identifiers between 1986 to 2007.

2. Note that an income of $0 is not considered missing. In particular, we remove observations where (a) both parents have missing income when the child is between ages [15, 17] or (b) the child has missing income between ages [$2016 - y$, $2018 - y$], where y is the child's year of birth.

3. It is possible for annual market income to be negative due to business losses. Averaging market income over several years reduces the number of observations that need to be removed. Once these observations are excluded, we replace the rare cases of negative earnings, gross income, and net income with $0.

Table B.1: Overview of sample construction

Step	Description	Sample size		Number of parishes	
1	Find 1973–1983 cohorts observed before age 17	710,329	100.0%	2,102	100.0%
2	Remove missing parent identifiers or birth dates	681,236	95.9%	2,083	99.1%
3	Remove immigrant families	640,434	90.2%	2,083	99.1%
4	Remove missing income data	617,747	87.0%	2,083	99.1%
5	Remove negative mean market income	615,278	86.6%	2,083	99.1%
6	Remove any missing family characteristics	586,612	82.6%	2,082	99.0%
7	Remove parishes with < 25 observations	584,563	82.3%	1,958	93.1%
8	Remove families with < $1,000$ (and parishes < 25)	560,926	79.0%	1,949	92.7%

analysis by around 7% and reduces the number of municipalities in our sample from 276 to 273. We examine the ramifications of including observations near $0 as robustness checks in Appendix A. This process leaves us with a sample size of 560,926 families used in the main analysis. Table B.1 summarizes our strategy.

B.2 Variables

B.2.1 Income

We follow Landersø and Heckman (2017) to construct different types of income. *Earnings* are given by taxable wage earnings and fringes, severance pay, paid sickness and maternity leave, and the value of share options after deductions toward employer-managed pension programs. *Market income (excluding transfers)* is all taxable income excluding public transfers, including earnings, capital income, business profits, property income, and foreign income. *Gross income (including transfers)* is gross market income including all taxable and non-taxable public transfers. Public transfers include (but are not limited to) social assistance benefits, activation and rehabilitation benefits, unemployment insurance benefits, sickness benefits, public pensions including early retirement pay, housing allowance, child allowance, and state educational (SU) grants. *Net-of-tax (disposable) income* is the remaining income after deducting all taxes (including on foreign income) from gross income.

Our primary income measure of interest is gross market income excluding transfers (also called "market income" for short). All incomes are deflated to 2010 Danish kroners using the Danish consumer price index and converted to 2010 U.S. dollars using a purchasing power parity exchange rate of $100 to 776 Danish kroner.

For each of type of income, we compute long-run averages of parental income when the child is between ages 0–17 and of child income when the child is between ages 30–45, whenever they are available. To mitigate the influence of outlier observations, we winsorize the top 0.5% tails of the child and parent income distributions.

Figure B.1: Distribution of birth cohorts by neighborhood

(a) Parishes

(b) Municipalities
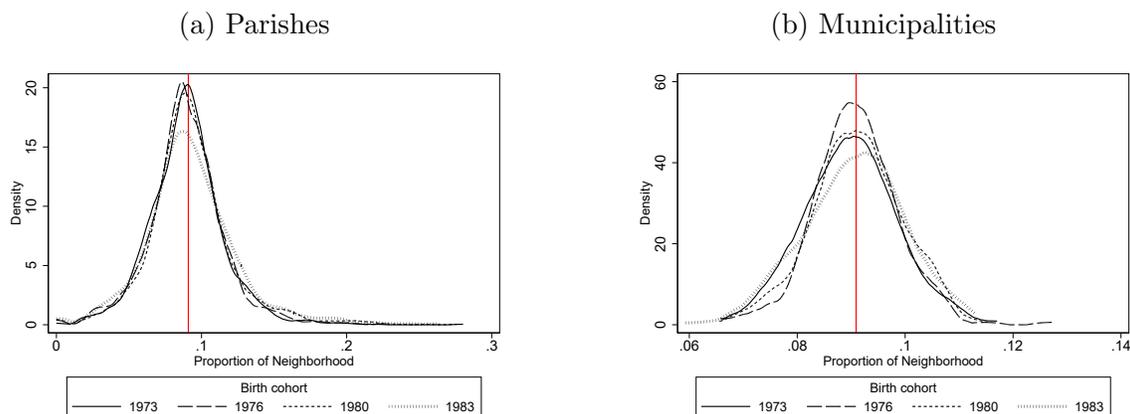
Notes: This figure plots densities of neighborhood shares of the 1973, 1976, 1980, and 1983 birth cohorts. Neighborhood birth cohort shares are weighted by the inverse probability of the cohort's share in the entire sample normalized to 1/11 (the vertical red line), since there are 11 birth cohorts in our sample. All densities use Epanechnikov kernels with cohort-specific rule-of-thumb bandwidths.

Since the income registers (IND) are only available between 1980–2018, this means that parent income is only available between child ages 7–17 for the 1973 cohort and child income is available only between ages 30–35 for the 1983 cohort. We prefer to use all available data when the child is between ages 0–17 and 30–45 to eliminate measurement error and develop better proxies of permanent income. Truncating income above the earliest ages of childhood and above later ages of adulthood may generate varying degrees of life-cycle bias in intergenerational mobility estimates across particular birth cohorts. Nonetheless, since we estimate mobility pooled over birth cohorts by neighborhood, the life-cycle bias will only affect our comparisons of mobility across neighborhoods to the extent that certain birth cohorts are disproportionately concentrated in certain neighborhoods. Figure B.1 finds that this is not the case for most neighborhoods. When we limit parent income to be averaged between child ages 7–17 and child income to be averaged between ages 30–35, and reweight observations within neighborhoods so that the conditional distribution of birth cohorts within neighborhoods matches the national distribution of birth cohorts, our core findings still hold.

B.2.2 Geographic units

There are five main types of administrative geographic units in Denmark: regions, municipalities, parishes, large blocks (approximately 600 household units), and small blocks (approximately 150 household units). We use municipality codes in place before the 2007 Municipal Reform. We also use parish codes from 1985 since some codes change during the childhoods of the birth cohorts we study. We construct regions by slightly modifying

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groupings of municipalities based on postal codes to improve geospatial clustering. Finally, the dataset of Damm and Schultz-Nielsen (2008) provides the large and small block units.

Geographic codes over time. Residential addresses and municipalities are available beginning in 1980 through FAIN. However, parish codes are matched with addresses beginning in 1982 through the Housing Census registers (*boligtælling*, BOL), while large and small blocks are matched beginning in 1985 through Neighborhood Cluster register (KOMK-LYNG). In an effort to identify as many addresses to parish and block codes, we compile the universe of addresses from the 1980 FAIN, 1981–1984 BOL, and 1985–2004 KOMKLYNG and retroactively match missing geographic codes to common addresses. Addresses with missing municipalities are removed. Through this process, 98.3% of our universe of over 3 million addresses have matched parish codes, while 88.6% have matched block codes.

Assigning geographic units to children. Children are assigned to the parish they lived in for the longest duration during childhood (ages 0–17).[4] Since data is available starting in 1980, this means we do not observe the family's residence during the earliest ages of childhood for children born between 1973–1979. We are less concerned by the missing residential data for two main reasons. First, social influences of neighborhoods are likely most salient after children enter school; in Denmark, most children begin school at age 7. Second, Figure B.2 demonstrates that among the 1980–83 cohorts (for whom we observe residential data starting at age 0), many families move across parishes and municipalities during early childhood and that residence within the child's assigned parish stabilizes by age 7. This gives us greater confidence that we are not missing much by assigning children to their longest-lived parish with the years of data at our disposal. Indeed, the incomplete panels among the 1973-1979 cohorts trace the patterns found among the 1980–83 cohorts.

We use parish assignment as a basis for the assignment of the other geographic units. There are very few cases of parishes that lie in two municipalities. In these cases, we assign the parish to the municipality with the largest population share. Assigning municipalities to children is thus immediately determined by their parish assignment.

Damm and Schultz-Nielsen (2008) describe the construction of small and large block units which are comprised of roughly 150 and 600 households, respectively, available between 1985 and 2004. Their methodology produces 9,404 units that are smaller than the 2,103 parishes in both population size and geographic area in the vast majority of cases. Large and small neighborhood blocks are not always enclosed within parish boundaries since they are produced based on a hectare grid algorithm. We do not attempt to partition small or

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4. We break ties by randomly assigning a child to one of the tied neighborhoods.
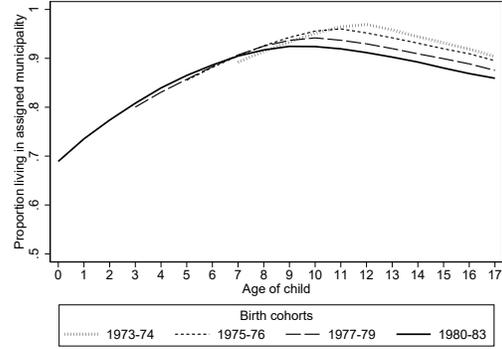
Figure B.2: Sorting patterns over child's life cycle

(a) Municipalities

(i) Moving to new neighborhood

(ii) Living in assigned neighborhood

(b) Parishes

(i) Moving to new neighborhood
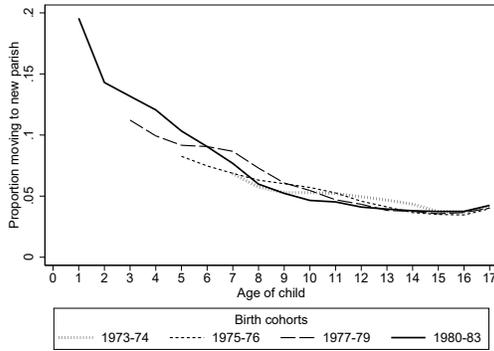
(ii) Living in assigned neighborhood
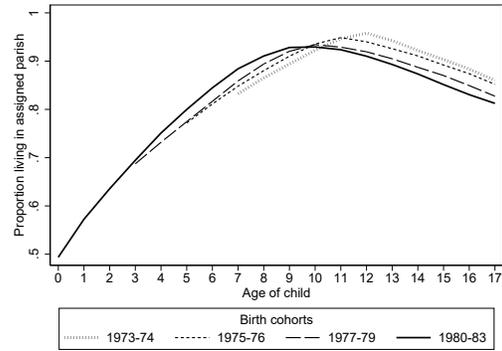
Notes: This figure plots (i) the proportion of families how move to a new neighborhood over the course of childhood and (ii) the proportion of families who live in the neighborhood that they were assigned to (based on the longest duration of time between child ages 0–17), by groups of birth cohorts. The 1980–83 cohorts' neighborhood of residence at age 0 is imputed using the neighborhood of residence of their birth mothers. Data is limited to the oldest child of each birth mother in the sample.

large blocks by parish boundaries in order to retain statistical power and capture localized social effects that are not necessarily restricted within parish boundaries (see Section B.2.4 for further discussion). We assign families to the small and large block that they lived in for the longest duration during childhood *within* their assigned parish.

Table B.2 presents summary statistics of sizes of each of these four types of geographic units in both the main sample (using our revised geographic codes, including the refined partition of neighborhood blocks) and, for comparative purposes, the entire population of Denmark in 1985 (using the original geographic codes).

Table B.2: Summary statistics of geographic unit sample sizes

	N	Mean	SD	Min	p10	p25	p50	p75	p90	Max
A. Municipalities										
Population	276	18,519	36,351	119	5,400	6,878	9,681	17,779	36,356	478,615
Sample	273	2,055	2,689	313	678	930	1,276	2,193	4,047	25,418
B. Parishes										
Population	2,102	2,432	3,176	16	275	503	1,075	2,902	6,904	28,164
Sample	1,949	288	344	25	43	74	155	363	720	3,117
C. Large blocks										
Population	2,277	2,198	901	752	1,267	1,583	1,994	2,607	3,327	7,434
Sample	2,253	285	185	1	68	134	264	397	528	1,270
D. Small blocks										
Population	9,325	537	181	70	327	407	506	637	794	1,535
Sample	9,169	70	45	1	15	34	65	98	131	309

Notes: This table presents various summary statistics of the sample sizes of municipalities, parishes, large neighborhood blocks, and small neighborhood blocks. The column "N" refers to the number of geographic units. The "Population" rows provide statistics of population sizes for the entire population of Denmark in the year 1985, while the "Sample" rows provide statistics of sample sizes from our main sample.

B.2.3 Family characteristics

This section defines all individual-level family characteristics used in the analysis. Most of the variables are defined as summary statistics of family characteristics between ages 0–17 of the child. Almost all variables are constructed using administrative registers that are available from 1980 onward;[5] thus, different child birth cohorts will have different years of data available between ages 0–17. We use whatever data is available between ages 0–17 in constructing these variables for all children. For variables representing years or duration, we define "years" or "duration" as the proportion of childhood that meet the criteria of the family characteristic out of the number of non-missing years available between ages 0–17. We standardize each continuous variable to have zero mean and unit variance and demean each dummy variable within each birth cohort to account for systematic differences in the number of non-missing years available across cohorts. We also construct analogous measures for between ages 7–17 so that there are no differences between cohorts; these measures are used as part of different robustness checks.

1. Demographics (from FAIN) *Age and age squared of mother and father* are the age of each parent in the year of child's birth. *Female* is a dummy indicating child sex at birth.

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5. The Hospital Use registers (*Sygehusbenyttelse*, SYHB) are only available beginning in 1991.

2. Household Assets   *Assets* is the average sum of father and mother net assets between ages 0–17 of the child (from IND).

3. Labor Supply (from IND)   *Stay-at-home mother* is a dummy indicating whether the mother ever earned \$0 in earnings and business profits or did not submit tax returns between ages 0–17 of the child. *Stay-at-home mother (years)* is the number of years that the mother earned \$0 in earnings and business profits between ages 0–17 of the child.

4. Education   *Years of education and years of education squared of mother and father* are constructed from the number of years of highest completed education attained by each parent between 1980–2014 from the Education registers (from *Uddannelse*, variable UDDANY). *College educated mother and father* is a dummy indicating attainment of at least 15 years of education (see definition above) for each parent. See Landersø and Heckman (2017) and Karlson and Landersø (2024). *College educated parents (both)* is a dummy indicating whether both the mother and father are college educated.

5. Household Structure (from FAIN)   *Household size* is the modal number of members of the mother's household between ages 0–17. *Number of siblings* is the modal number of children below age 18 who reside in the mother's household between ages 0–17 of the child. *Number of parental figures* is the total number of distinct birth or adoptive parents, step-parents, or cohabiting partners who reside with the child between ages 0–17. *Intact family* is a dummy indicating that both birth or adoptive parents reside with child between ages 0–17. *Intact family (years)* is the number of years that both birth or adoptive parents reside with child between ages 0–17.

6. Marital Status (from FAIN)   *Divorced* is adummy indicating whether the parental figures (see definition above) residing with the child ever divorced between ages 0–17 of the child. *Divorced (years)* is the number of years that a child resides with a parental figure (see definition above) between the year of a divorce and the year before another parental figure joins household between ages 0–17 of the child. *Never married* is a dummy indicating whether the parental figures (see definition above) residing with the child never married between ages 0–17 of the child. *Never married (years)* is the number of years that a child resides with parental figure(s) (see definition above) before the year of the first occurrence of marriage between the parental figures ages 0–17 of the child.

7. Hospitalizations   *Hospital stay* is a dummy indicating whether either the mother or father stayed overnight at a hospital between ages 8–25 of the child from the Hospital Use

registers (SYHB). SYHB is available starting in 1991; hence, age 8 is the first available year of data that we observe (for the 1983 cohort only). *Hospital stay (years)* is the number of years in which either the mother or father ever stayed overnight at a hospital between ages 8–25 of the child. *Hospital stay (duration)* is the duration of time (expressed in years) that either the mother or father stayed at hospital between ages 8–25 of the child.

8. Crime *Commit crime* is a dummy indicating whether either the mother or father committed any crime (excluding road/traffic crimes) between ages 0–17 of the child from the Crime Charge Statistics registers (*Kriminalstatistik sigtelser*, KRSI). *Commit crime (years)* is the number of years that either the mother or father committed any crime (excluding road/traffic crimes) between ages 0–17 of the child. *Incarcerated* is a dummy indicating whether either the mother or father were ever sentenced for incarceration between ages 0–17 of the child from the Crime Sentence Statistics registers (*Kriminalstatistik afgørelser*, KRAF). *Incarcerated (duration)* is the number of years that either the mother or father were sentenced to incarceration between ages 0–17 of the child.

B.2.4 Social characteristics

Using parent income discussed in Section B.2.1, geographic assignments described in Section B.2.2, and family characteristics defined in Section B.2.3, we possess neighborhood-specific distributions of parent income and family characteristics. Following the literature, we assume that social influences faced by family i may be proxied by the mean characteristics of *other families* within i's social group associated with neighborhood n, denoted n_g. In other words, $\bar{C}_{-in_g} = \frac{1}{I_{n_g}-1} \sum_{j \in n_g, j \neq i} C_j$, where C_i is a component of $(\boldsymbol{X}_i, Y_i^p)$ and $I_{n_g} \equiv |\{i \in n_g\}|$.

We avoid multicollinearity issues by defining n_g as well-defined subsets of families within n. Our chosen subsets not only provide greater within-neighborhood variation in social characteristics, but are also appealing from a theoretical perspective since they better proxy the family's social network based on geographic proximity (neighbors) and peers in school.

When neighborhoods are defined as parishes, our preferred social groups n_g are small blocks and parish school cohorts; when they are municipalities, our preferred social groups are small blocks and municipality school cohorts.[6] Whenever $I_{n_g} = 1$, we replace $\bar{C}_{-in_g}$ with $\bar{C}_{-in}$ for each characteristic C.

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6. We follow Landersø et al. (2017) by using the age at entering 8th grade to proxy for school cohorts.

B.2.5 Location characteristics

We construct a number of *location* characteristics, generally constructed using characteristics of the neighborhood's entire adult population. Unlike the social characteristics, the location characteristics are computed using *population* data (rather than the *sample*).

Whenever possible, each characteristic is constructed as a long-run average of person-year observations of the adult population (ages 18–60) between 1980–2000 for each neighborhood unit.[7] Since parishes are only available in the Housing Census beginning in 1982, we focus on addresses in 1980 and 1981 that were successfully matched with parish codes from the universe of addresses between 1982–2004 (see Section B.2.2 for more details).

Mean income (from IND) — the mean market income (before taxes and transfers) of the population aged 18–60 averaged between 1980–2000. *Gini index* — the annual Gini index of market income (before taxes and transfers) of the population aged 18–60, averaged between 1980–2000 weighted by annual population size. *Housing value (from IND)* — the mean housing value, defined as the publicly-assessed cash value of properties, of the population aged 30–60 between 1983–2000. The population is restricted to ages 30–60 since there is very low home ownership rates before age 30 and it begins to decrease around age 60. The upper tail of each year's distribution of positive housing values are winsorized to the 99.5th percentile ($1.07 million in 2000). *Home ownership rate* — the fraction of individuals aged 30–60 with positive housing values in their income records (IND) between 1983–2000. *Urbanicity* — the fraction of addresses from BOL that belong to a city of at least 20,000 residents in the year 2000.[8] *Commuting* — the fraction of employed individuals aged 18–60 from registers on labor force statistics (*registerbaserede arbejdsstyrkestatistik*, RAS) between 1980–2000 who travel outside of their own municipality and surrounding contiguous municipalities to their workplace. *Farmers* — the fraction of the taxable population aged 18–60 working in the farming/agriculture sectors, based on occupational codes from the Employment Classification Module (*arbejdsklassifikationsmodulet*, AKM), between 1982–1999. The AKM's occupational codes used during this time period is available up to 1999.) *Non-Western immigrants (from FAIN)* — the fraction of the population (all ages) who originate from outside of Europe, North America, Australia, and New Zealand. *9th grade test scores* — mean standardized 9th grade exam scores in 2002. For small neighborhoods, we use subsequent years of data until the sample size is at least 20 students. See discussion below.

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7. The year 1980 is typically the first year that administrative records are available, while the year 2000 is the 1983 birth cohort's final year of childhood. Different time or age ranges are used for certain characteristics due to data availability or to preserve the definition or quality of the characteristic's measurement.

8. City size is defined in the year 2000 to account for boundary changes of the greater Copenhagen area.

Robustness of the 9th Grade Test Scores over Time. One concern is that neighborhood-level mean test scores are constructed using data that is only available starting in 2002. This may not be representative of the features captured by mean test scores, like school quality, experienced by children in our sample since the vast majority attend schools between 1980–2000. To check this, we exploit the fact that higher-income neighborhoods tend to have higher mean test scores. If the correlations between (i) mean test scores in (approximately) 2002 and mean income in earlier years and (ii) mean income in 2002 and mean income in earlier years are both stable over time, this suggests that mean test scores in 2002 may successfully proxy mean test scores in earlier years. Figure B.3 plots these correlation coefficients over time. We find largely stable relationships between the location characteristics over time, providing greater confidence in our use of mean test scores measured in 2002.

Figure B.3: Correlating neighborhood mean 9th grade test scores and mean income by year

(a) Municipalities

(i) Mean test scores

(ii) Mean income in 2002

(b) Parishes

(i) Mean test score

(ii) Mean income in 2002

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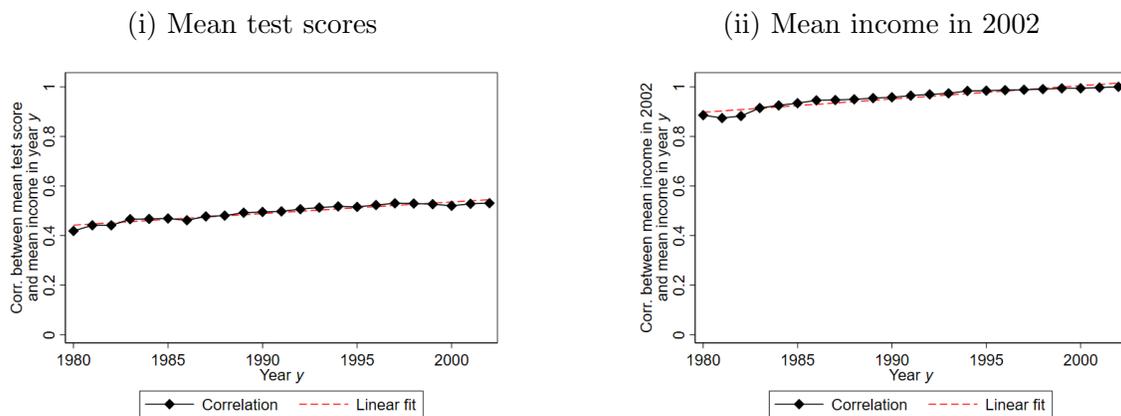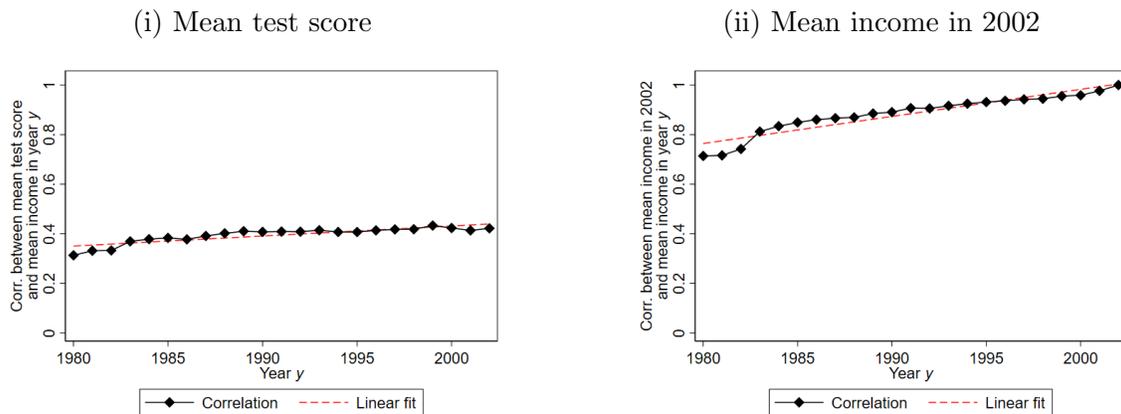
C Descriptive Statistics

C.1 Summary Statistics

Table C.1: Child outcomes, parent income, and family characteristics

	Mean	S.D.	Min.	Max.
A. Child outcomes				
Earnings (thousands)	39.316	20.736	0.00	123.94
Market income, excl. transfers (thousands)	41.943	21.742	1.00	145.03
Gross income, incl. transfers (thousands)	46.260	18.964	1.02	145.42
Net-of-tax income (thousands)	34.356	12.092	0.00	94.54
Years of schooling	14.882	2.324	7.00	21.00
B. Parent income				
Earnings (thousands)	58.704	27.677	0.00	151.62
Market income, excl. transfers (thousands)	71.400	30.393	1.00	213.97
Gross income, incl. transfers (thousands)	78.509	26.887	1.52	216.69
Net-of-tax income (thousands)	55.305	17.733	0.00	152.47
C. Family characteristics				
Female	0.490	0.500	0.00	1.00
Year of birth	1977.626	3.136	1973.00	1983.00
Age, father	29.515	5.304	13.00	75.00
Age, mother	26.803	4.623	13.00	49.00
Assets (thousands)	24.952	84.594	-252.84	524.21
Mother out of labor force	0.410	0.492	0.00	1.00
Mother out of labor force (years)	0.123	0.225	0.00	1.00
Years of schooling, father	13.175	3.160	0.00	22.00
Years of schooling, mother	12.880	2.922	6.00	21.00
College, father	0.238	0.426	0.00	1.00
College, mother	0.232	0.422	0.00	1.00
College, both parents	0.122	0.327	0.00	1.00
Household size	4.099	0.930	1.00	17.00
Number of siblings	1.129	0.795	0.00	12.00
Number of parental figures	1.969	0.655	0.00	9.00
Intact family	0.669	0.471	0.00	1.00
Intact family (years)	0.801	0.340	0.00	1.00
Divorced	0.214	0.410	0.00	1.00
Divorced (years)	0.096	0.229	0.00	1.00
Never married	0.150	0.357	0.00	1.00
Never married (years)	0.097	0.260	0.00	1.00
Hospital stay	0.727	0.446	0.00	1.00
Hospital stay (years)	0.103	0.109	0.00	1.00
Hospital stay (duration)	0.002	0.005	0.00	0.28
Commit crime	0.145	0.352	0.00	1.00
Commit crime (years)	0.018	0.062	0.00	1.00
Incarcerated	0.056	0.230	0.00	1.00
Incarcerated (years)	0.007	0.035	0.00	1.00
Observations	560,926			

Table C.2: Social characteristics

	Munic. school cohort				Parish school cohort				Small block			
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Female	0.490	0.040	0.00	1.00	0.491	0.102	0.00	1.00	0.490	0.066	0.00	1.00
Parent income	71.400	8.914	7.74	125.52	71.406	12.238	1.21	213.97	71.406	14.709	8.24	190.12
Age, father	29.515	0.766	22.00	52.00	29.515	1.373	18.00	59.00	29.511	1.238	17.00	49.00
Age, mother	26.803	0.723	17.00	35.00	26.804	1.257	16.50	43.00	26.801	1.227	17.00	41.50
Assets	24.952	16.702	-145.81	127.45	24.981	25.853	-252.84	524.21	24.942	26.460	-194.23	506.98
Mother out of labor force	0.410	0.081	0.00	1.00	0.410	0.137	0.00	1.00	0.410	0.139	0.00	1.00
Mother out of labor force (years)	0.123	0.029	-0.00	1.00	0.123	0.059	-0.00	1.00	0.123	0.066	-0.00	1.00
Years of schooling, father	13.175	0.717	7.00	18.00	13.175	1.064	7.00	21.00	13.177	1.101	7.00	20.00
Years of schooling, mother	12.880	0.652	8.00	17.00	12.880	0.952	7.00	21.00	12.881	0.963	7.33	20.00
College, father	0.238	0.092	-0.00	1.00	0.238	0.133	-0.00	1.00	0.238	0.143	-0.00	1.00
College, mother	0.232	0.078	0.00	1.00	0.232	0.123	-0.00	1.00	0.232	0.124	-0.00	1.00
College, both parents	0.122	0.066	-0.00	1.00	0.122	0.098	-0.00	1.00	0.122	0.105	-0.00	1.00
Household size	4.099	0.234	2.75	8.00	4.099	0.318	1.00	9.00	4.099	0.321	1.50	7.00
Number of siblings	1.129	0.169	0.00	3.50	1.129	0.243	0.00	8.00	1.129	0.226	0.00	4.00
Number of parental figures	1.969	0.080	0.00	3.00	1.969	0.152	0.00	6.00	1.970	0.135	0.00	5.00
Intact family	0.669	0.099	0.00	1.00	0.669	0.149	0.00	1.00	0.669	0.173	-0.00	1.00
Intact family (years)	0.801	0.073	0.00	1.00	0.801	0.112	0.00	1.00	0.801	0.141	-0.00	1.00
Divorced	0.214	0.069	-0.00	1.00	0.214	0.112	-0.00	1.00	0.214	0.126	0.00	1.00
Divorced (years)	0.096	0.038	-0.00	0.88	0.096	0.062	-0.00	1.00	0.096	0.075	-0.00	1.00
Never married	0.150	0.081	-0.00	1.00	0.149	0.110	-0.00	1.00	0.150	0.075	-0.00	1.00
Never married (years)	0.097	0.055	-0.00	1.00	0.097	0.079	-0.00	1.00	0.097	0.070	-0.00	1.00
Hospital stay	0.727	0.074	0.00	1.00	0.727	0.112	0.00	1.00	0.727	0.079	0.00	1.00
Hospital stay (years)	0.103	0.025	0.00	0.78	0.103	0.034	-0.00	0.83	0.103	0.023	0.00	0.50
Hospital stay (duration)	0.002	0.001	-0.00	0.03	0.002	0.001	-0.00	0.09	0.002	0.001	-0.00	0.04
Commit crime	0.145	0.048	-0.00	1.00	0.145	0.090	-0.00	1.00	0.145	0.094	-0.00	1.00
Commit crime (years)	0.018	0.008	-0.00	0.22	0.018	0.015	-0.00	0.94	0.018	0.017	-0.00	0.75
Incarcerated	0.056	0.024	-0.00	1.00	0.056	0.052	-0.00	1.00	0.056	0.054	-0.00	1.00
Incarcerated (years)	0.007	0.003	-0.00	0.08	0.007	0.008	-0.00	0.50	0.007	0.008	-0.00	0.50
Observations	560,926				560,926				560,926			

Table C.3: Location characteristics

| | *Municipalities* | | | | *Parishes* | | | |
	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Mean income (thousands)	30.011	3.745	24.247	49.901	29.446	4.156	15.109	65.847
Gini index	0.416	0.029	0.336	0.515	0.420	0.040	0.329	0.620
Mean home value (thousands)	47.645	9.451	21.074	91.387	46.505	11.761	2.667	115.755
Share of homeowners	0.492	0.046	0.247	0.628	0.482	0.082	0.057	0.669
Mean 9th grade test score (s.d.)	-0.052	0.130	-0.426	0.360	-0.052	0.197	-0.737	0.600
Urbanicity	0.135	0.316	0.000	1.000	0.162	0.360	0.000	1.000
Share of commuters	0.191	0.133	0.033	0.619	0.159	0.109	0.030	0.631
Share of farmers	0.072	0.047	0.002	0.211	0.100	0.078	0.001	0.421
Share of non-Western immigrants	0.011	0.015	0.001	0.140	0.010	0.022	0.000	0.304
Observations	1,949				273			

C.2 Income

Figure C.1: Population income distributions, by income type
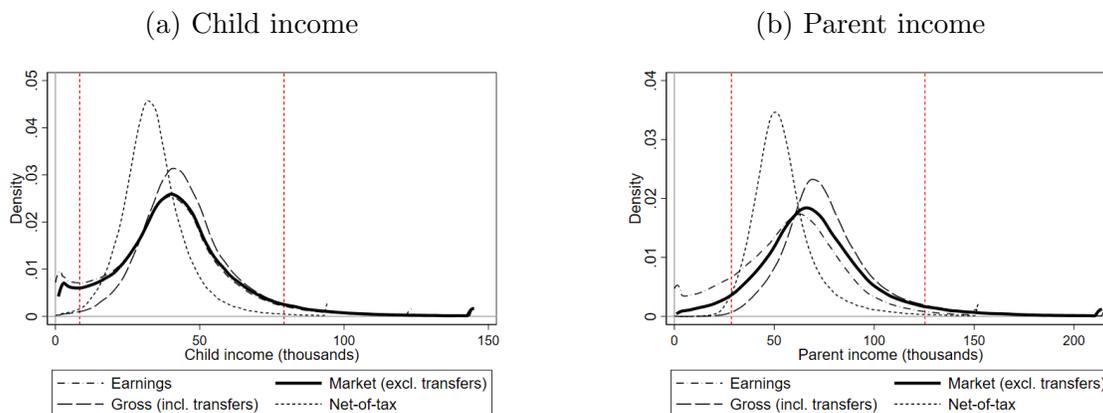
(a) Child income

(b) Parent income

Notes: This figure presents densities of child and parent income in the sample. Dashed red lines represent the 5th and 95th percentiles of the market income distribution. All densities are smoothed by Epanechnikov kernels with their respective rule-of-thumb bandwidths.

C.3 Spatial Segregation

To assess the extent that neighborhoods are segregated from one another, we decompose different measures of inequality in family characteristics into within- and between-neighborhood components. We focus on variance and Theil indices, as these are well-documented measures of inequality that are additively decomposable, and report results for parishes.

Let i index families in the set $\mathcal{I}$ and n index neighborhoods in the set $\mathcal{N}$. Family i's membership in neighborhood n is denoted $i \in n$. Population size is $I = |\mathcal{I}|$ and neighborhood

Figure C.2: Neighborhood-level mean income distributions, by income type

(a) Municipalities

(i) Child income

(ii) Parent income

(b) Parishes

(i) Child income
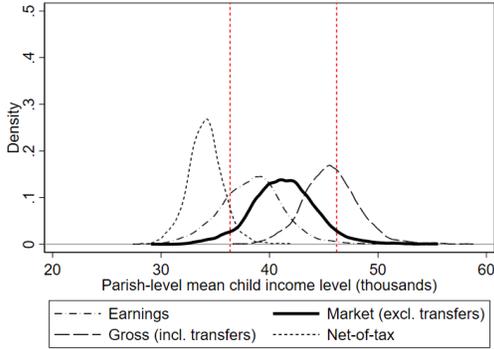
(ii) Parent income
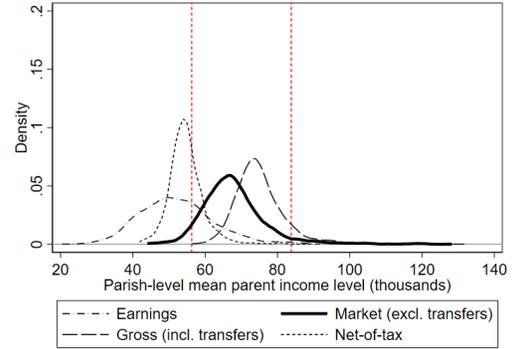
Notes: This figure presents densities of child and parent income in the sample. Dashed red lines represent the 5th and 95th percentiles of the market income distribution. All densities are smoothed by Epanechnikov kernels with their respective rule-of-thumb bandwidths.
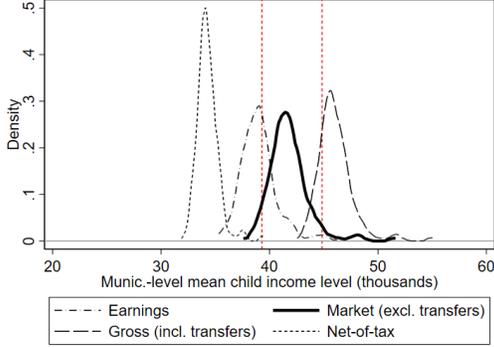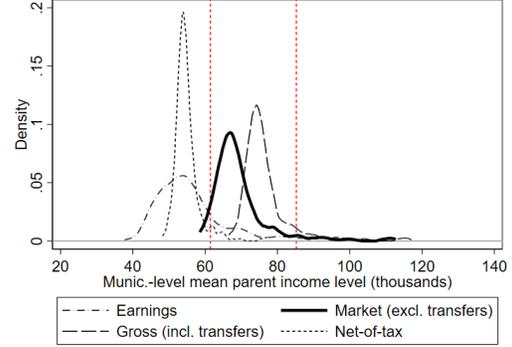
population size is $I_n = |n|$. For any characteristic X_i, we decompose the variance of C_i as

$$\text{Var}(C_i) = \underbrace{\mathbb{E}_n \left[\text{Var} \left(C_i \,|\, n(i) = n \right) \right]}_{\text{within-neighborhood}} + \underbrace{\text{Var}_n \left(\bar{C}_n \right)}_{\text{between-neighborhood}} \tag{C.1}$$

where $\bar{C}_n = \mathbb{E}[C_i \,|\, n(i) = n]$. A larger between-neighborhood variance component indicates greater degree of segregation across neighborhoods. See Table C.4, Columns 1 and 2. Figures 1(a) and A.1(a) plot inverse cumulative distribution functions of neighborhood-level mean family characteristics underlying the between-neighborhood variance component.

We use different Theil indices depending on whether the family characteristic is contin-

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Figure C.3: Mean income over the life cycle

(a) Own life cycle

(b) Child life cycle
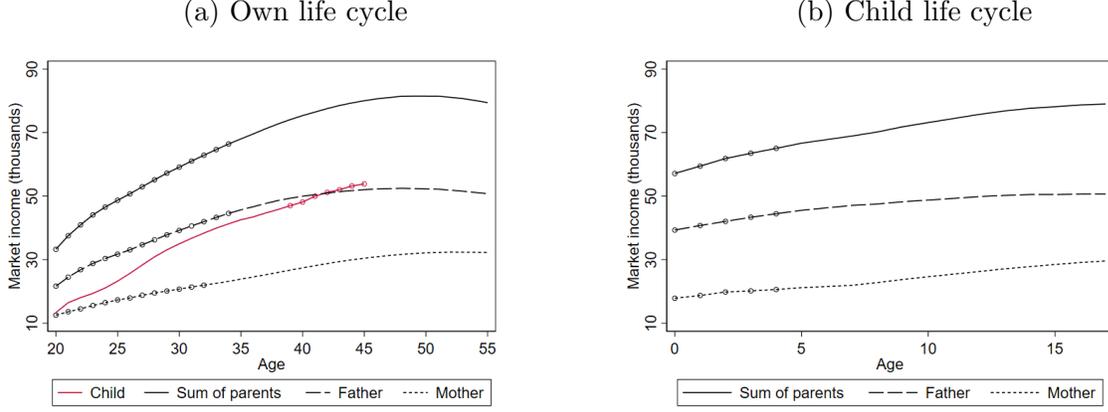
Notes: Panel (a) plots each family member's income against their respective age; sum of parents' income is plotted against age of father. Panel (b) plots each family member's income against the child's age. Lines with hollow markers indicate ages where income is observed for less than 75% of the sample.

uous or categorical. For continuous characteristic C_i, we decompose Theil's T index as

$$T \equiv \frac{1}{I} \sum_{i \in \mathcal{I}} \frac{C_i}{\bar{C}} \ln\left(\frac{C_i}{\bar{C}}\right) = \underbrace{\sum_{n \in \mathcal{N}} \frac{I_n \bar{C}_n}{I \bar{C}} \cdot T_n}_{\text{within-neighborhood}} + \underbrace{T_{\mathcal{N}}}_{\text{between-neighborhood}} \quad (C.2)$$

where $\bar{C} = \mathbb{E}[C_i]$; $T_n \equiv \frac{1}{I_n} \sum_{i \in n} \frac{C_i}{\bar{C}_n} \ln\left(\frac{C_i}{\bar{C}_n}\right)$, Theil's T index in neighborhood n; and $T_{\mathcal{N}} \equiv \sum_{n \in \mathcal{N}} \frac{I_n \bar{X}_n}{I \bar{C}} \cdot \log\left(\frac{\bar{C}_n}{\bar{C}}\right)$, Theil's T index among the set of neighborhoods $\mathcal{N}$. For categorical (non-ordinal) family characteristics such as household structure and marital status, we use Theil's H index.[9] We use a refined partition of small blocks along parish boundaries so that they are proper sub-geographic units of parishes. Let b index the set of small blocks $\mathcal{B}$; each parish n is a collection of blocks such that $n \subset \mathcal{B}$, $\forall n \in \mathcal{B}$, and $n_1 \cap n_2 = \emptyset$, $\forall n_1 \neq n_2$, $n_1, n_2 \in \mathcal{N}$. For categorical characteristic C_i, we decompose Theil's H index as

$$H \equiv \sum_{c \in \text{supp}(C)} \sum_{b \in \mathcal{B}} \frac{I_b}{IE} \cdot \pi_{cb} \ln\left(\frac{\pi_{cb}}{\pi_b}\right) = \underbrace{\sum_{n \in \mathcal{N}} \frac{I_n E_n}{IE} H_n}_{\text{within-neighborhood}} + \underbrace{H_{\mathcal{N}}}_{\text{between-neighborhood}} \quad (C.3)$$

where $\pi_c \equiv \frac{\sum_{i \in \mathcal{I}} \mathbb{1}\{C_i = c\}}{I}$, the population share of group $C_i = c$; $\pi_{cg} \equiv \frac{\sum_{i \in n} \mathbb{1}\{C_i = c\}}{I_g}$, the population share of group $C = c$ in geographic unit g; $E \equiv \sum_{c \in \text{supp}(C)} \pi_x \cdot \ln\left(\frac{1}{\pi_c}\right)$, Shannon's entropy score; H_n is Theil's H index among neighborhoods within neighborhood n; and $H_{\mathcal{N}}$

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9. Reardon and Firebaugh (2002) find this is one of the only known multigroup inequality indices that is additively decomposable by mutually-exclusive groups of units.

is the Theil's H index among the set of parishes $\mathcal{N}$. Larger between-neighborhood components $T_{\mathcal{N}}$ and $H_{\mathcal{N}}$ indicates a greater degree of segregation explained by neighborhoods, respectively. These are reported in Table C.4, Columns 3 and 4.

Table C.4: Segregation of family characteristics across neighborhoods

	(1)	(2)	(3)	(4)
	Variance decomposition		*Theil decomposition*	
	Total	% Between	Total	% Between
Parent income (thousands)	923.70	12.94	0.09	12.73
Age, father	28.14	2.15	0.02	2.20
Age, mother	21.37	2.87	0.01	2.89
Assets	7156.18	4.40	0.50	7.53
Mother out of labor force	0.24	3.23	0.07	33.47
Mother out of labor force (years)	0.05	3.16	0.35	3.42
Years of schooling, father	9.99	7.12	0.03	6.66
Years of schooling, mother	8.54	5.91	0.03	5.65
College, father	0.18	6.58	0.11	51.90
College, mother	0.18	4.50	0.09	43.78
College, both parents	0.11	5.67	0.14	48.94
Household size	0.87	7.84	0.03	7.62
Number of parental figures	0.43	1.43	0.03	0.67
Number of siblings	0.63	5.39	0.09	5.77
Intact family	0.22	6.32	0.12	42.49
Intact family (years)	0.12	7.65	0.07	4.09
Divorced	0.17	3.93	0.10	38.66
Divorced (years)	0.05	4.35	0.22	5.00
Never married	0.13	1.64	0.06	30.03
Never married (years)	0.07	2.94	0.34	4.00
Hospital stay	0.20	1.05	0.04	23.01
Hospital stay (years)	0.01	1.57	0.22	1.75
Hospital stay (duration)	0.00	0.84	0.83	1.96
Commit crime	0.12	2.53	0.09	31.62
Commit crime (years)	0.00	2.59	0.29	7.12
Incarcerated	0.05	1.55	0.12	27.96
Incarcerated (years)	0.00	1.37	0.24	10.66

Notes: Decompositions based on parish assignments. Theil's T index used for continuous variables; Theil's H index used for binary variables. See text for details.

D Alternative Neighborhood Mobility Estimates

This appendix considers alternatives to our main estimates of the baseline model, Equation (1). We first summarize alternative neighborhood mobility models considered in our analysis. We then report their correlations with our main estimates.

In what follows, Y_i^j is defined as log income of family member j of family i. The "slope" is defined as the coefficient on the main regressor measuring parent socioeconomic status (SES) (if the regressor is log income, then the slope is the IGE). The AUM is analogously defined as the predicted measure of child SES conditional on parent SES at the 25th percentile.

Alternative mobility models.

1. *Conditional expectation of income model*: Following Mitnik and Grusky (2020), we estimate $\exp(Y_i^c) = \alpha_n^E + \beta_n^E Y_i^p + \varepsilon_i$ via Poisson pseudo-maximum likelihood estimation.

2. *Rank–rank model*: Let R_i^j be the percentile rank of family member j in the child's birth cohort-specific national income distribution. We estimate $R_i^c = \alpha_n^R + \beta_n^R R_i^p + \varepsilon_i$.

3. *Level–level income model*: $\exp(Y_i^c) = \alpha_n^L + \beta_n^L \exp(Y_i^p) + \varepsilon_i$

4. *Transition probability of upward mobility*: We estimate the share of children in each neighborhood whose incomes are above the bottom quartile conditional on parent income lying below the bottom quartile (among each respective birth cohort-specific child and parent income distributions). That is, $\Pr(R_i^c > 25 \,|\, R_i^p \leq 25, n(i) = n)$. There is no well defined slope parameter in this model. It closely resembles the AUM; hence we only correlate this parameter estimate with our main AUM estimate.

Alternative measures of socioeconomic status.

1. *Income*: We consider earnings; gross income (with transfers); and net-of-tax income.

2. *Life-cycle measures of income*: Our data employs the 1980–2018 income registers. In our main measures of income, parent income for the 1973 birth cohort can be observed starting when the child is age 7 and child income for the 1983 birth cohort can be observed up to when the child is age 35. Hence we also estimate our baseline mobility model where income in each generation is averaged over age ranges observed for all birth cohorts: child income between 30–35; parent income between 7–17.

3. *Education*: We consider replacing log income with years of schooling in our regression.

Alternative family units.

1. *Child gender*: Instead of including both sons and daughters, we consider estimating our baseline mobility model using subsamples of sons only and daughters only.

2. *Father income only*: Instead of sum of parent income, we use father income only.

Alternative weighting schemes.

1. *Neighborhood exposure model*: Instead of assigning each family to a single neighborhood, we consider the share of childhood that child i spent in neighborhood n, S_{in} to run: $Y_i^c = \sum_{n \in \mathcal{N}} \alpha_n^{exp} S_{in} + \sum_{n \in \mathcal{N}} \beta_n^{exp} S_{in} Y_i^p + \varepsilon_i$.

2. *Birth cohort weights*: We re-estimate Equation (1) by weighting observations by the share of birth cohorts in each neighborhood.

Table D.1: Correlations between alternative and main neighborhood mobility estimates

	Municipality		Parish	
	IGE	AUM	IGE	AUM
A. Alternative models				
Cond'l. expectation of income model, sample $\geq \$1,000$	0.846	0.881	0.845	0.876
Cond'l. expectation of income model, sample $\geq \$0$	0.721	0.861	0.758	0.835
Rank-rank model, sample $\geq \$1,000$	0.608	0.849	0.662	0.797
Rank-rank model, sample $\geq \$0$	0.542	0.826	0.626	0.773
Level-level model, sample $\geq \$1,000$	0.630	0.817	0.674	0.835
Level-level model, sample $\geq \$0$	0.556	0.805	0.631	0.799
Transition probability model, sample $\geq \$1,000$	—	0.696	—	0.585
Transition probability model, sample $\geq \$0$	—	0.658	—	0.570
B. Alternative measures of SES				
Earnings	0.294	0.669	0.251	0.611
Gross income (incl. transfers)	0.679	0.819	0.703	0.751
Net-of-tax income	0.635	0.748	0.625	0.733
Child income b/w ages 30-45; Parent income b/w child ages 7-17	0.860	0.958	0.942	0.986
Child income b/w ages 30-35; Parent income b/w child ages 7-17	0.730	0.870	0.764	0.812
Child income b/w ages 30-35; Parent income b/w ages 38-55	0.544	0.805	0.657	0.772
Education	0.171	0.463	0.128	0.377
C. Alternative measures of SES				
Subsample of sons; Sum of parents' income	0.784	0.804	0.662	0.758
Subsample of daughters; Sum of parents' income	0.698	0.609	0.656	0.697
Sons and daughters; Father income	0.742	0.714	0.767	0.713
Subsample of sons; Father income	0.630	0.700	0.516	0.589
Subsample of daughters; Father income	0.465	0.429	0.522	0.515
D. Alternative weighting schemes				
Neighborhood exposure model	0.929	0.963	0.862	0.921
Birth cohort weights	0.995	0.997	0.994	0.995

E Assessing Existence and Magnitude of Heterogeneity in Neighborhood Mobility Parameters

This appendix reports statistical exercises that evaluate the extent of heterogeneity in location mobility parameters from the baseline model (Equation 1) and different specifications of the generalized model (Equation 5 under Assumptions O and U).

E.1 Hypothesis Tests

Fraction of Neighborhoods with Same Mobility. We rank neighborhoods from smallest to largest by the difference between their mobility estimate and the mean mobility estimate pooled across neighborhoods, normalized by their standard error, and sequentially conduct Wald tests among the highest ranked estimates.[10] First, we test the null that the first and second highest ranked neighborhood estimates are equal. If we fail to reject the null, we add the next highest ranked neighborhood and conduct the joint Wald test among the three neighborhood parameters, and continue iterating this process until we reject the null. This procedure thus identifies a lower bound of the number of neighborhoods with statistically indistinguishable measures of mobility.[11] Panel A of Tables E.1–E.3 summarizes results of the largest share of neighborhoods where we fail to reject the null of joint equality. For example, Column (3) of Table E.1 reports at least 71% of municipalities and 88% of parishes have statistically indistinguishable estimates of the AUM $\bar{y}_{25n}$.

Multiple Hypothesis Test Procedure. A multiple hypothesis test procedure (MHTP) allows us to conduct separate hypothesis tests for each neighborhood-level parameter controlling for the probability of "false discoveries" or incorrect rejections of the null. We employ the Benjamini and Hochberg (1995) step-up MHTP to control for the false discovery rate of $q < 0.05$ among our raw IGE and AUM estimates. Panel B of Tables E.1–E.3 reports the percent of neighborhoods that fail to reject the null that their mobility measures equal the population-level counterpart measures, β and $\bar{y}_{25}^c \equiv \alpha + \beta y_{25}^p$, estimated from the pooled mobility regression $Y_i^c = \alpha + \beta Y_i^p + \varepsilon_i$.

E.2 Magnitude of Neighborhood Heterogeneity

We quantify how much sampling error drives the neighborhood heterogeneity of our IGE and AUM estimates. For example we may express each neighborhood's IGE estimate as $\hat{\beta}_n = \beta_n + u_n$, where $u_n \sim N(0, \hat{\sigma}_{\hat{\beta}_n}^2)$ is noise due to estimation error and $\hat{\sigma}_{\hat{\beta}_n}$ denotes the standard error of $\hat{\beta}_n$. The total variance of $\hat{\beta}_n$ across $n \in \mathcal{N}$ may be expressed as

$$\text{Var}(\hat{\beta}_n) = \underbrace{\text{Var}(\beta_n)}_{\text{signal}} + \underbrace{\mathbb{E}\left[\hat{\sigma}_{\hat{\beta}_n}^2\right]}_{\text{noise}}. \tag{E.1}$$

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10. The pooled mean is inversely weighted by the squared standard errors of the AUM estimators.

11. We interpret these percentages as lower bounds since we recognize there may be a more optimal procedure for identifying the largest set of neighborhoods that fail to reject joint tests of equality.

Table E.1: Share of neighborhoods with statistically-indistinguishable neighborhood mobility estimates from baseline model (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IGE β_n	\multicolumn{5}{c}{AUM $\bar{y}_{qn}^c$ conditional on $Y_i^p = y_q^p$}	N
		$q = 10$	$q = 25$	$q = 50$	$q = 75$	$q = 90$	
A. Joint tests: Equality of neighborhood mobility with each other							
Municipalities	84.2	73.3	71.4	72.2	77.7	80.6	273
		[100.0]	[100.0]	[100.0]	[100.0]	[100.0]	
Parishes	91.8	88.1	88.6	90.1	91.6	92.5	1,949
		[99.3]	[99.9]	[100.0]	[99.5]	[96.8]	
B. Multiple hypothesis tests: Equality of neighborhood mobility with population mobility							
Municipalities	95.2	89.0	85.0	83.5	85.0	90.5	273
		[100.0]	[100.0]	[100.0]	[100.0]	[100.0]	
Parishes	99.9	97.3	96.9	96.8	96.9	98.1	1,949
		[99.3]	[99.9]	[100.0]	[99.5]	[96.8]	

Notes: Panel A reports results on the size of the largest subset of neighborhoods (as a percent of the total number of neighborhoods) with IGE or AUM estimates from Equation (1) where we fail to reject joint equality at the 0.05 level. See main text on the procedure used to identify the size of these neighborhood subsets. Panel B reports the share of neighborhoods that fail to reject the null hypothesis that their neighborhood mobility measure equals its population mobility counterpart at the false discovery rate of $q < 0.05$ using the Benjamini-Hochberg step-up procedure. Columns (2)–(6) report results for AUM measures that set log parent income to the qth percentile of the parent income distribution. The percent of neighborhoods where y_q^p lies within the neighborhood's range of parent income are reported in brackets.

By estimating the noise with the mean squared standard error of the estimates, we can recover an estimate of the signal variance, which measures the magnitude of heterogeneity among the underlying neighborhood mobility parameters. We can also assess the contribution of noise toward the overall variance; in the case of the IGEs, this is $\frac{\mathbb{E}[\hat{\sigma}^2(\hat{\beta}_n)]}{\text{Var}(\hat{\beta}_n)} \times 100\%$.

Tables E.4–E.5 report variance decompositions that are unweighted or weighted by the sample size of neighborhoods. In general, a significant proportion of variance is due to sampling error. Note that for Equation (5) under Assumption U, weighing estimates by sample size implies the noise component *exceeds* 100% of the variance of AUM location estimates; not weighing by sample size lowers this share to 93.7%. This is indicated in Row 2.2 of Table 2. As robustness checks, Table E.6 reports unweighted decomposition results for the alternative baseline estimates described in Appendix D.

Large contributions of noise are not exclusive to the Danish context. Table G.3 shows the vast majority of variation in U.S. Census tract slope estimates from Chetty et al. (2018) is due to sampling error, while AUM estimates have similar precision to Danish municipalities.

Table E.2: Share of neighborhoods with baseline mobility statistically-indistinguishable from population mobility, based on robust empirical Bayes confidence intervals

	Neighborhood parameter	IGE β_n^{EB}	AUM $\bar{y}_{25n}^{c,EB}$
Municipalities	β_n^{EB}	93.4	78.0
Parishes	β_n^{EB}	97.9	93.4

Notes: See notes of Table E.1 on Panel B. Robust empirical Bayes confidence intervals are constructed à la Armstrong et al. (2022).

Table E.3: Share of neighborhoods with statistically indistinguishable location effect estimates after controlling for selection (%)

	Assump.	(1) IGE β_n	(2) $q=10$	(3) $q=25$	(4) $q=50$	(5) $q=75$	(6) $q=90$	(7) N
			AUM $\bar{y}_{qn}^c$ conditional on $Y_i^p = y_q^p$					
A. Joint tests: Equality of location effects with each other								
Municipalities	O	84.2	78.0	76.2	83.2	84.2	82.8	273
	U	58.6	60.8	61.5	60.8	58.2	59.0	273
			[100.0]	[100.0]	[100.0]	[100.0]	[100.0]	
Parishes	O	93.6	91.8	94.5	97.3	98.1	97.8	1,949
	U	95.8	74.9	93.2	90.1	93.5	93.3	1,949
			[99.3]	[99.9]	[100.0]	[99.5]	[96.8]	
B. Multiple hypothesis tests: Equality of location effects with population effect								
Municipalities	O	99.9	99.6	99.9	99.7	99.7	99.9	273
	U	99.9	100.0	99.9	100.0	100.0	100.0	273
			[100.0]	[100.0]	[100.0]	[100.0]	[100.0]	
Parishes	O	93.8	87.5	94.9	91.9	97.1	98.9	1,949
	U	99.6	100.0	94.9	100.0	100.0	100.0	1,949
			[99.3]	[99.9]	[100.0]	[99.5]	[96.8]	

Notes: Location effect estimates are based on β_n and $\bar{y}_{qn}^c \equiv \alpha_n + \beta_n y_q$ estimated from Equation (5) under Assumption O or U. See notes of Appendix Table E.1 for details.

Table E.4: Signal-noise decomp. of neighborhood mobility estimates from baseline model

	Weighted	(1) Total S.D.	(2) Signal S.D.	(3) Noise (%)
A. Municipalities				
$\hat{\beta}_n$		0.062	0.043	51.4
$\hat{\beta}_n$	✓	0.050	0.038	44.6
$\hat{\bar{y}}^c_{25n}$		0.035	0.027	38.2
$\hat{\bar{y}}^c_{25n}$	✓	0.036	0.032	21.8
B. Parishes				
$\hat{\beta}_n$		0.179	0.084	78.0
$\hat{\beta}_n$	✓	0.114	0.063	69.3
$\hat{\bar{y}}^c_{25n}$		0.086	0.046	71.7
$\hat{\bar{y}}^c_{25n}$	✓	0.064	0.045	49.6

Notes: This table reports results from the signal-noise decomposition described in Equation (E.1) applied to mobility estimates from Equation (1). The "Weighted" column indicates if the estimates are weighted by neighborhood sample size. Column (1) reports the total standard deviation (S.D.) of the point estimates. Column (2) reports the signal standard deviation (S.D.), estimated by the square root of the difference between the total variance of the point estimates and the mean squared standard error. Column (3) reports the contributions of signal variance toward total variance as percentages.

Table E.5: Signal-noise decomposition of location effect estimates from generalized model

	Assump.	Weighted	(1) Total S.D.	(2) Signal S.D.	(3) Noise (%)
A. Municipalities					
$\hat{\beta}_n$	O		0.064	0.045	49.8
$\hat{\beta}_n$	O	✓	0.058	0.046	36.5
$\hat{\beta}_n$	U		0.064	0.037	66.1
$\hat{\beta}_n$	U	✓	0.058	0.040	51.4
$\hat{\bar{y}}^c_{25n}$	O		0.033	0.025	43.1
$\hat{\bar{y}}^c_{25n}$	O	✓	0.030	0.024	34.7
$\hat{\bar{y}}^c_{25n}$	U		0.076	0.047	61.6
$\hat{\bar{y}}^c_{25n}$	U	✓	0.067	0.038	67.6
B. Parishes					
$\hat{\beta}_n$	O		0.171	0.076	80.6
$\hat{\beta}_n$	O	✓	0.108	0.056	73.0
$\hat{\beta}_n$	U		0.176	0.077	81.0
$\hat{\beta}_n$	U	✓	0.111	0.048	81.3
$\hat{\bar{y}}^c_{25n}$	O		0.079	0.035	80.2
$\hat{\bar{y}}^c_{25n}$	O	✓	0.055	0.032	64.6
$\hat{\bar{y}}^c_{25n}$	U		0.321	0.081	93.7
$\hat{\bar{y}}^c_{25n}$	U	✓	0.204	—	101.5

Notes: This table reports results from the signal-noise decomposition applied to location effect estimates from Equation (5) under Assumptions O and U. See notes of Table E.4 for details.

Table E.6: Robustness of signal-noise decomposition of neighborhood mobility estimates to alternative baseline models

| | Municipalities | | | | Parishes | | | |
| | $\hat{\beta}_n$ | | $\hat{\bar{y}}^c_{25n}$ | | $\hat{\beta}_n$ | | $\hat{\bar{y}}^c_{25n}$ | |
	Total S.D.	Noise %	Total S.D.	Noise %	Total S.D.	Noise %	Total S.D.	Noise %
Main model	0.062	51.4	0.035	38.2	0.179	78.0	0.086	71.7
A. Alternative mobility models								
Cond'l. expectation of income model, sample $\geq$ \$1,000	0.048	66.1	0.025	44.1	0.132	84.1	0.061	75.7
Cond'l. expectation of income model, sample $\geq$ \$0	0.052	71.4	0.029	38.1	0.145	78.6	0.069	68.5
Rank-rank model, sample $\geq$ \$1,000	0.038	59.1	1.676	38.1	0.103	93.3	3.789	79.0
Rank-rank model, sample $\geq$ \$0	0.041	51.3	1.890	30.0	0.107	88.6	4.021	70.2
Level-level model, sample $\geq$ \$1,000	0.035	43.1	1.140	38.2	0.095	73.6	2.492	87.7
Level-level model, sample $\geq$ \$0	0.038	38.3	1.304	29.8	0.099	70.0	2.698	76.5
Transition probability model, sample $\geq$ \$1,000	—	—	0.034	64.8	—	—	0.097	80.0
Transition probability model, sample $\geq$ \$0	—	—	0.040	46.8	—	—	0.101	72.8
B. Alternative measures of SES								
Earnings	0.064	22.2	0.044	38.7	0.159	46.8	0.118	67.9
Gross income (incl. transfers)	0.053	58.6	0.027	40.1	0.153	79.7	0.062	78.8
Net-of-tax income	0.052	56.1	0.018	36.0	0.145	76.2	0.044	72.3
Child income b/w ages 30-45; Parent income b/w child ages 7-17	0.063	39.2	0.034	38.7	0.168	75.7	0.086	70.8
Child income b/w ages 30-35; Parent income b/w child ages 7-17	0.074	51.0	0.042	45.7	0.223	77.1	0.114	72.7
Child income b/w ages 30-35; Parent income b/w ages 38-55	0.069	48.0	0.041	50.7	0.230	66.6	0.121	69.2
Education	0.048	27.5	0.175	13.4	0.106	60.1	0.332	43.6
C. Alternative measures of SES								
Subsample of sons; Sum of parents' income	0.085	51.2	0.052	31.9	0.214	79.1	0.104	67.8
Subsample of daughters; Sum of parents' income	0.078	64.4	0.042	50.0	0.218	76.8	0.098	77.7
Sons and daughters; Father income	0.050	43.4	0.039	32.9	0.141	78.3	0.093	72.7
Subsample of sons; Father income	0.069	44.7	0.048	41.9	0.173	77.9	0.107	74.8
Subsample of daughters; Father income	0.063	54.6	0.050	39.4	0.171	80.1	0.106	76.3
D. Alternative weighting schemes								
Neighborhood exposure model	0.068	54.1	0.037	40.4	0.208	78.3	0.095	76.2
Birth cohort weights	0.062	50.3	0.035	37.3	0.179	77.6	0.085	71.8

Notes: This table reports results from the signal-noise decomposition described in Equation (E.1) applied to the alternative mobility estimates described in Appendix D. All variance decompositions are unweighted by neighborhood sample size. The transition probability model has missing results for β_n since this parameter is not well defined in the model. RES

F   Variance Decomposition of Generalized Mobility

If $\boldsymbol{W}_{in}$ and $\boldsymbol{\beta_w}$ have K elements and W_{in}^k and $\beta_{\boldsymbol{w}}^k$ are their kth elements and if $\sigma_{\hat{\theta}}^2$ and $\sigma_{\hat{\theta},\hat{\theta}'}$ denote the variance and covariance terms of parameter estimates $\hat{\theta}$ and $(\hat{\theta},\hat{\theta}')$, respectively, then Equation (7) can be further decomposed as follows:

$$
\begin{aligned}
&\mathrm{Var}\left(\beta(\widehat{\boldsymbol{W}_{in}},n)\right)\\
&= \underbrace{\sum_{j=1}^K \sum_{k=1}^K \left(\mathrm{Cov}\left(\hat{\beta}_{\boldsymbol{w}}^j W_{in}^j, \hat{\beta}_{\boldsymbol{w}}^k W_{in}^k\right) - \mathbb{E}_n\left[\mathrm{Cov}\left(\hat{\beta}_{\boldsymbol{w}}^j W_{in}^j, \hat{\beta}_{\boldsymbol{w}}^k W_{in}^k \,|\, n(i)=n\right)\right]\right)}_{\substack{\text{Observed selection effect:}\\\text{Between-neighborhood}}} \quad \text{(F.1)}\\
&+ \underbrace{\sum_{j=1}^K \sum_{k=1}^K \left(\mathbb{E}_n\left[\mathrm{Cov}\left(\hat{\beta}_{\boldsymbol{w}}^j W_{in}^j, \hat{\beta}_{\boldsymbol{w}}^k W_{in}^k \,|\, n(i)=n\right)\right] - \sigma_{\hat{\beta}_{\boldsymbol{w}}^j,\hat{\beta}_{\boldsymbol{w}}^k} \cdot \mathbb{E}[W_{in}^j W_{in}^k]\right)}_{\substack{\text{Observed selection effect:}\\\text{Within-neighborhood (signal)}}}\\
&+ \underbrace{\sum_{j=1}^K \sum_{k=1}^K \sigma_{\hat{\beta}_{\boldsymbol{w}}^j,\hat{\beta}_{\boldsymbol{w}}^k} \cdot \mathbb{E}[W_{in}^j W_{in}^k]}_{\substack{\text{Observed selection effect:}\\\text{Within-neighborhood (noise)}}} + \underbrace{\mathrm{Var}\left(\hat{\beta}_n\right) - \mathbb{E}_n\left[\sigma_{\hat{\beta}_n}^2\right]}_{\substack{\text{Location effect:}\\\text{Between-neighborhood}}} + \underbrace{\mathbb{E}_n[\sigma_{\hat{\beta}_n}^2]}_{\substack{\text{Location effect:}\\\text{Within-neighborhood (noise)}}}\\
&+ \underbrace{2\sum_{k=1}^K \left[\mathrm{Cov}\left(\hat{\beta}_{\boldsymbol{w}}^k W_{in}^k, \hat{\beta}_n\right) - \mathbb{E}_n\left[\sigma_{\hat{\beta}_{\boldsymbol{w}}^k,\hat{\beta}_n} \cdot \mathbb{E}[W_{in}^k \,|\, n(i)=n]\right]\right]}_{\substack{\text{Sorting effect:}\\\text{Between-neighborhood}}}\\
&+ \underbrace{2\sum_{k=1}^K \mathbb{E}_n\left[\sigma_{\hat{\beta}_{\boldsymbol{w}}^k,\hat{\beta}_n} \cdot \mathbb{E}[W_{in}^k \,|\, n(i)=n]\right]}_{\substack{\text{Sorting effect:}\\\text{Within-neighborhood (noise)}}}
\end{aligned}
$$

A similar decomposition can be conducted for $\hat{\bar{y}}_{25n}^c$.

G   Comparisons with U.S.

We develop analogous mobility estimates using our Danish sample to those publicly available from the Opportunity Atlas (OA) developed by Chetty et al. (2018). We compare the OA's mobility estimates on their white sample over U.S. Census tracts against our Danish municipality and parish estimates on our native Danish sample, since Census tracts roughly

fall in between the population size of parishes and municipalities.[12]

Section G.1 summarizes differences in the sample and characterizes income inequality across neighborhoods in both countries. Section G.2 describes Chetty et al.'s methodology and compares estimates of upward mobility in Denmark and the U.S. Section G.2 approximates the underlying locational mobility parameters from the OA and compares them with estimates from Denmark. Section G.3 reports variance decomposition exercises.

G.1 Comparison with OA Sample

The OA includes families with \$0 parent and child income since it focuses on percentile rank-based measures of socioeconomic status. We therefore employ a larger data sample ($N = 584{,}563$) than what was used in our main analysis to include observations where parent and child income fall below \$1,000 to make our estimates more comparable. This results in a slightly larger number of parishes included in our analysis ($N = 1{,}958$). Table G.1 compares summary statistics of the distributions of neighborhood sample sizes between both samples.

G.2 Methodology

Estimating Neighborhood Mobility. The OA estimates neighborhood mobility with the following three steps. First, child and parental income data are converted to national percentile ranks of the child's birth cohort, denoted R_i^c, R_i^p. Second, the OA estimates a nonlinear population-level mobility model using conditional means of child rank $\bar{R}_r^c \equiv \mathbb{E}[R_i^c \mid R_i^p = r]$ by parental rank r:

$$\bar{R}_r^c = f(r) + \varepsilon_r. \tag{G.1}$$

The OA employs a lowess function with bandwidth 0.3. Third, the OA estimates neighborhood-level linear regressions[13]:

$$R_{in}^c = \alpha_n^R + \beta_n^R \cdot \hat{f}(R_i^p) + \varepsilon_{in}, \ \ n \in \mathcal{N}. \tag{G.2}$$

Note that (G.2) departs from the baseline neighborhood-level mobility regression that employs a linearized measures of parental income.

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12. The U.S. Census Bureau defines census tracts to contain populations ranging 1,200–8,000, with an optimum size of 4,000. Danish parishes and municipalities are more heterogeneous in their population size, with a median of 1,075 and 9,681 in 1985, respectively (see Table B.2).

13. Chetty et al. weigh observations based on the fraction of time that children spend in each neighborhood during childhood. Our analysis assigns children to the neighborhood where children spend the largest fraction of time during childhood. Since Chetty et al. ignore estimation error of $\hat{f}$, we also do.

Table G.1: Summary statistics of neighborhood sample sizes in OA vs. Danish sample

	N	Mean	S.D.	Min.	p10	p25	p50	p75	p90	Max.
U.S. Census tracts (OA)	67,965	544	282	22	216	337	505	706	918	5,401
Danish munic. (this paper)	273	2,148.69	2,838	322	737	963	1,342	2,262	4,177	26,809
Danish parishes (this paper)	1,958	298.55	359	25	44	75	160	378	752	3,272

The neighborhood-specific parameter estimates $(\hat{\alpha}_n^R, \hat{\beta}_n^R)$ are used to construct two AUM statistics that are publicly available in the OA: forecasts of child rank conditional on parental rank at the 25th percentile (denoted $\hat{R}_{25n}^c$) and at the 75th percentile (denoted $\hat{R}_{75n}^c$):

$$\hat{\bar{R}}_{25n}^c = \hat{\alpha}_n^R + \hat{\beta}_n^R \cdot \hat{f}(25) \tag{G.3}$$
$$\hat{\bar{R}}_{75n}^c = \hat{\alpha}_n^R + \hat{\beta}_n^R \cdot \hat{f}(75).$$

We follow this procedure using our Danish sample for municipalities and parishes.

Recovering Neighborhood-level Slope Estimates We study heterogeneity in AUM and on neighborhood slope estimates. The OA does not report slope estimates, so we employ an imputation method to recover slope estimates and standard errors in the OA.

Let $\hat{\alpha}_n^R$, $\hat{\beta}_n^R$ denote the parameter estimates from Equation (G.2) and $\hat{\sigma}(\hat{\alpha}_n^R)$, $\hat{\sigma}(\hat{\beta}_n^R)$ denote their standard errors. The OA provides the following statistics for each Census tract: (1) mean parent rank income, $\bar{R}_n^p$, (2) predicted child rank conditional on parent rank at 25th and 75th percentiles, $\hat{\bar{R}}_{25n}^c$ and $\hat{\bar{R}}_{75n}^c$, and (3) the standard errors of predicted child ranks at 25th and 75th percentiles, $\hat{\sigma}(\hat{\bar{R}}_{25n}^c)$ and $\hat{\sigma}(\hat{\bar{R}}_{75n}^c)$. With these statistics, we can approximate the point estimates $\hat{\beta}_n^R$ and their standard errors $\hat{\sigma}(\beta_n^R)$.

In principle, we could retrieve the neighborhood slope estimates from the system of equations (G.3) and their standard errors by solving the systems of equations

$$\hat{\sigma}(\hat{\bar{R}}_{25n}^c)^2 = \hat{\sigma}(\hat{\alpha}_n^R)^2 + \hat{f}(25)^2 \cdot \hat{\sigma}(\hat{\beta}_n^R)^2 + 2\hat{f}(25) \cdot \hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R)$$
$$\hat{\sigma}(\hat{\bar{R}}_{75n}^c)^2 = \hat{\sigma}(\hat{\alpha}_n^R)^2 + \hat{f}(75)^2 \cdot \hat{\sigma}(\hat{\beta}_n^R)^2 + 2\hat{f}(75) \cdot \hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R)$$
$$\hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R) = -\overline{(\hat{f}(R^p))}_n \cdot \hat{\sigma}^2(\hat{\beta}_n^R),$$

where $\hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R)$ is the sample covariance between $\hat{\alpha}_n^R$, $\hat{\beta}_n^R$ for a given neighborhood n, and $\overline{(\hat{f}(R^p))}_n \equiv \frac{1}{|\{i \,|\, n(i)=n\}|} \sum_{n(i)\in n} \hat{f}(R_{in}^p)$.

Two complications prevent us from perfectly solving these systems of equations. First, the OA does not provide $\overline{(\hat{f}(R^p))}_n$ but rather $\bar{R}_n^p$; we therefore approximate $\overline{(\hat{f}(R^p))}_n$ with $\hat{f}(\bar{R}_n^p)$.[14] Second, the OA's point estimates $\hat{\bar{R}}_{25n}^c$, $\hat{\bar{R}}_{75n}^c$ and the standard error estimates

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14. Since the middle 90% of neighborhood-level mean ranks lie between the 37th and 81st percentiles—a region where $\hat{f}$ is highly linear—$\hat{f}(\bar{R}_n^p)$ should provide a reasonable approximation for most neighborhoods.

$\hat{\sigma}(\hat{\alpha}_n^R)$, $\hat{\sigma}(\hat{\beta}_n^R)$ are infused with some random noise to protect privacy with a "standard deviation...typically less than one-tenth of the standard error due to sampling variation" (Chetty et al. 2018, Figure 2 notes). Given these complications, we instead solve

$$\frac{81}{100} \cdot \hat{\sigma}(\hat{R}_{25n}^c)^2 = \hat{\sigma}^2(\hat{\alpha}_n^R) + \hat{f}(25)^2 \cdot \hat{\sigma}(\hat{\beta}_n^R)^2 + 2\hat{f}(25) \cdot \hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R) \qquad (G.4)$$
$$\frac{81}{100} \cdot \hat{\sigma}(\hat{R}_{75n}^c)^2 = \hat{\sigma}^2(\hat{\alpha}_n^R) + \hat{f}(75)^2 \cdot \hat{\sigma}(\hat{\beta}_n^R)^2 + 2\hat{f}(75) \cdot \hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R)$$
$$\hat{\sigma}(\hat{\alpha}_n^R, \hat{\beta}_n^R) = -\hat{f}(\bar{R}_n^p) \cdot \hat{\sigma}(\hat{\beta}_n^R)^2.$$

Whenever any estimates of the standard errors are below zero, we set them equal to 10^{-4}.

We estimate the point estimates of β_n^R via Equation (G.3) since the infused noise in $\hat{R}_{25n}, \hat{R}_{75n}$ is independent across neighborhoods, but also develop upper and lower bounds by adding and subtracting two times the standard error implied by the added noise, which amounts to one-fifth of the standard error $\hat{\sigma}(\hat{\beta}_n^R)$ estimated via Equation (G.3). The "upper" and "lower estimates" are respectively denoted $\hat{\beta}_n^{Ru}$ and $\hat{\beta}_n^{R\ell}$. We analogously construct upper and lower estimates of the AUM measure, $\hat{\bar{R}}_{25n}^{c,u}$ and $\hat{\bar{R}}_{25n}^{c,\ell}$.

Figure G.1 compares the distributions of neighborhood mobility estimates between Denmark and the U.S. The slope estimates $\hat{\beta}_n^R$ are remarkably similar between both countries, with slightly more variance in the U.S., while the AUM estimates $\hat{R}_{25n}^c$ have significantly more spread in the U.S. than Denmark.

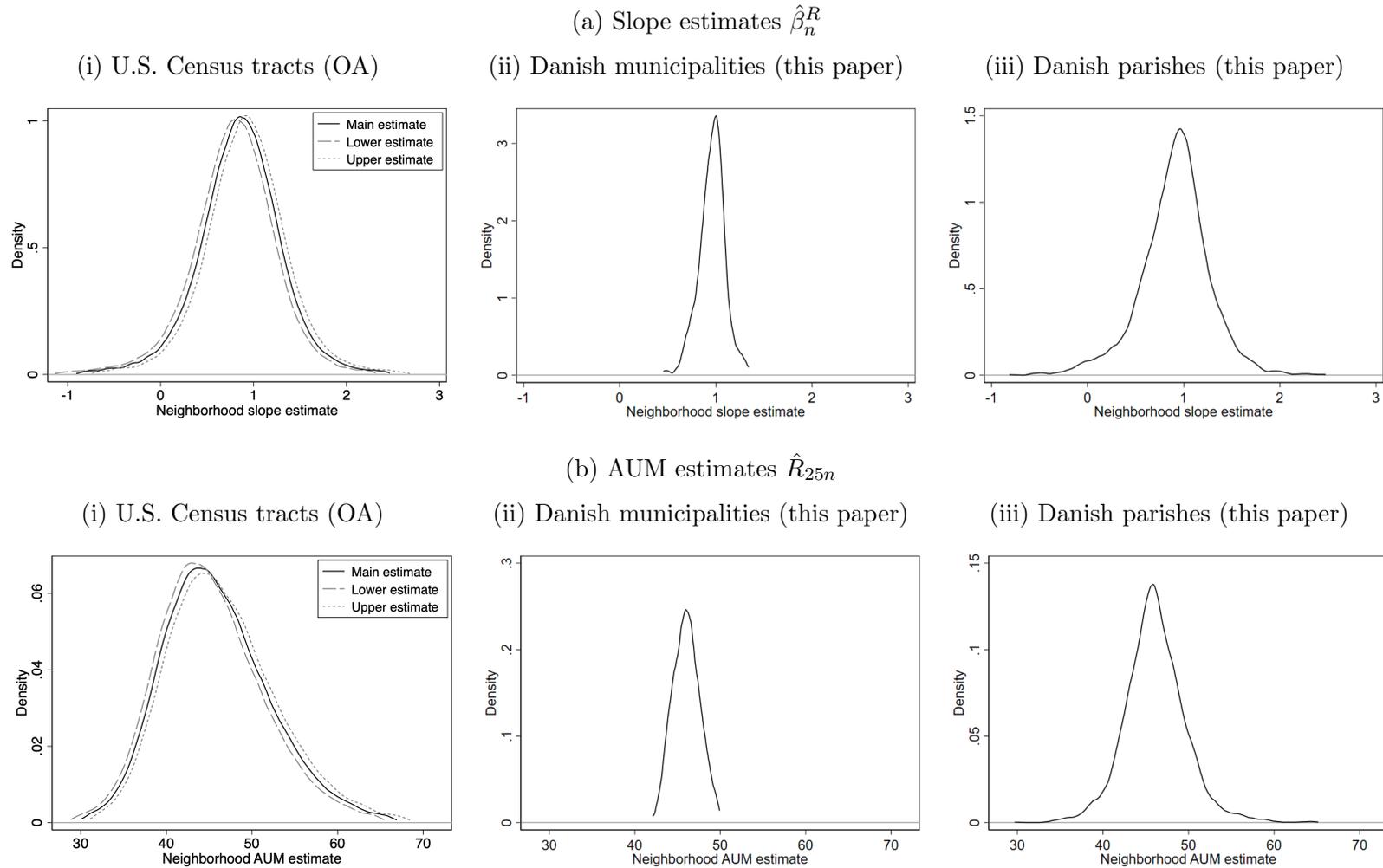## G.3 Assessing Magnitude of Heterogeneity in Neighborhood Mobility Estimates

This section repeats select exercises from Appendix E to assess the extent that neighborhood mobility estimates measured à la Chetty et al. (2018) vary in the OA and in our sample.

Multiple Hypothesis Test Procedure. Table G.2 reports the share of neighborhoods with mobility measures β_n^R and $\bar{R}_{25n}^c$ that are statistically indistinguishable from their population counterparts based on the Benjamini-Hochberg step-up procedure with a false discovery rate of 0.05.[15] For the OA estimates, we also conduct tests on their lower and upper estimates. The vast majority of the neighborhood slope and AUM estimates cannot be distinguished from their population-level counterparts. For example, 88% of U.S. neighborhoods and 97% of Danish neighborhoods have AUMs that cannot be distinguished from the national predicted child income rank conditional on parental income at the 25th percentile.

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15. The population slope measure is 1 since when $(\alpha_n^R, \beta_n^R) = (0, 1)$, Equation (G.2) collapses to Equation (G.1). The population AUM measure is $\bar{R}_{25}^c$ defined in Equation (G.1).

Figure G.1: Distributions of neighborhood mobility estimates in OA vs. Danish sample

(a) Slope estimates $\hat{\beta}_n^R$

(i) U.S. Census tracts (OA) (ii) Danish municipalities (this paper) (iii) Danish parishes (this paper)

(b) AUM estimates $\hat{R}_{25n}$

(i) U.S. Census tracts (OA) (ii) Danish municipalities (this paper) (iii) Danish parishes (this paper)

Notes: This figure plots densities of neighborhood mobility estimates from Equation (G.2) across neighborhoods in Denmark and the U.S. The dashed gray lines in the left panels are the lower and upper estimates defined in the main text. The U.S. plots exclude the extreme 0.5% tails of the point estimates to retain a reasonable scale. All densities are smoothed by the Epanechnikov kernel with rule-of-thumb bandwidths.

Signal-Noise Decomposition. Table G.3 reports results from decomposing the variance of the neighborhood mobility estimates into "signal"and "noise" components via Equation (E.1). We find the OA possesses larger total variance in both slope and AUM estimates than our Danish sample. We find that in both the U.S. and Denmark, noise explains the vast majoirty of the variation in neighborhood slope estimates $\hat{\beta}_n^R$. In contrast, variation in AUM estimates $\hat{R}_{25n}^c$ is primarily explained by signal in the U.S. but not in Denmark.

Table G.2: Share of neighborhoods with neighborhood mobility estimates that fail to reject equality with population mobility estimate in OA vs. Danish sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Slope			AUM		
	US Census tracts (OA)	DK munic. (this paper)	DK parishes (this paper)	US Census tracts (OA)	DK munic. (this paper)	DK parishes (this paper)
Main	89.0	91.2	99.9	82.9	70.0	95.3
Lower	87.9	—	—	83.1	—	—
Upper	89.7	—	—	82.2	—	—

Notes: This table reports the percentage of neighborhood mobility measures estimated à la Chetty et al. (2018) that fail to reject equality with their counterpart population measure at the false discovery rate of $q < 0.05$ using the Benjamini-Hochberg step-up procedure. Columns (1) and (4) include upper and lower estimates based on the noise infusion added to the OA mobility estimates. Column (1) uses approximations of the slope estimates as described in Section G.2.

Table G.3: Signal-noise decomposition of neighborhood mobility estimates in OA vs. Danish sample

		(1)	(2)	(3)	(4)	(5)	(6)
		US Census tracts (OA)		DK munic. (this paper)		DK parishes (this paper)	
	Weighted	Total S.D.	% Noise	Total S.D.	% Noise	Total S.D.	% Noise
$\hat{\beta}_n^R$		0.502	115.3	0.135	58.7	0.371	89.8
$\hat{\beta}_n^R$	✓	0.369	92.1	0.114	47.8	0.238	80.6
$\hat{R}_{25n}^c$		6.615	33.5	1.546	35.6	3.590	72.4
$\hat{R}_{25n}^c$	✓	5.786	25.6	1.549	22.2	2.625	54.6

Notes: This table reports results from signal-noise decompositions of neighborhood mobility measures estimated à la Chetty et al. (2018). The "Weighted" column indicates if variances are weighted by neighborhood sample size. Columns (1) and (2) use approximations of the slope estimates and standard errors as described in Section G.2.

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