Intergenerational Mobility and Housing Wealth in the United States

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Motivation: Housing, wealth and inequality in the U.S.

- Housing is the most important asset (along w/ pensions) for the vast majority of the wealth distribution in the U.S.
  - Considered stepping stone to wealth building and financial security
- Wealth distributed highly unequally in the U.S.
- A lot of research on intergenerational mobility (IGM) of income in the U.S., but with no administrative wealth data, much less is known about IGM of wealth
  - Wealth is likely a better proxy for a concept of total resources or utility
  - Housing generally not reflected in income flows
- Large persistent racial wealth gaps between Black and White households in the U.S.
  - Long legacy of financial exclusion and segregation, particularly in housing
  - persistence in gap suggests differential IGM is important

This paper

Data: New linked data on housing assets, census and tax records

- Intergenerational links
- Measurement of housing assets

IGM of Housing Assets in the U.S.

- Rank-Rank relationships of IGM of housing wealth
- Racial differences in IGM of housing wealth

Relationships between parent and child wealth and income

- Measurement: Wealth v. income
- Mechanisms: transmission of parent resources (static IG capital accumulation model)
- Implications for racial differences

Mechanisms: Cross area variation in IGM and racial IG gaps

- Great recession, housing supply, segregation

Key findings

1. Larger intergenerational persistence of housing wealth than income in the U.S.
2. Large gaps in absolute and relative mobility in housing between Black and White families
   - Contrast to income, where there is no relative mobility gap.
   - Extensive margin of home ownership important for racial mobility gaps
3. Housing has an important role, independent of income, for understanding IGM of resources in the U.S.
   - Income-Income IGM estimates understate IG persistence of resources
   - Persistence partly from parent resources affecting child earnings, but also a large independent role of parent wealth conditional on child earnings
   - True for housing and for capitalized total wealth
4. Housing IGM varies systematically with local housing supply elasticities
   - B-W IG gaps substantially larger (smaller) with inelastic (elastic) housing supply.

Contribution to literature

- IGM with focus on income, wealth, and race.
  - Income IGM: Bhattacharya and Mazumder (2011), Davis and Mazumder (2018), Chetty et al. (2020), Collins and Wanamaker (2022), Derenoncourt (2022).
  - Wealth IGM: Pfeffer and Killewald (2018, 2019), Killewald and Bryan (2018).
  - Income and the racial wealth gap: Barsky et al. (2002), Derenoncourt et al. (2022), Sabelhaus and Thompson (2022).
  - Income versus transfers: Charles and Hurst (2003), Feiveson and Sabelhaus (2018), Black et al. (2020, 2022), Gilraine et al. (2023).
- Administrative housing data to study IGM **or** racial disparities.
  - Housing IGM: Daysal et al. (2022, 2023), Benetton et al. (2022), Wold et al. (2023)
  - Cross-sectional racial disparities: Avenancio-Leon and Howard (2024), Kermani and Wong (2024), Box-Couillard and Christensen (2024).
- Capitalizing income flows to estimate cross-sectional wealth distribution.
  - Piketty and Zucman (2014), Saez and Zucman (2016), Smith et al. (2023).
  - We are the first to study IGM in this context.

Data and Empirical Strategy

Data overview

- Sample of children (g) and their parents ($g-1$).
  - 2000 Census Long Form (LF): all householders' children aged 14-16.
  - Opportunity Insights Databank (DB): all dependents aged 14-16 claimed on a 1994 or 1998 tax return
    - whose claimer was also a LF householder.
- Administrative housing records.
  - 2019-2021 property assessment, deed, and valuation files from Black Knight, Inc (BK).
  - Census linkage branch assigned Protected Identification Keys (PIKs) to these records.
  - Ownership determined by (PIK) of owner on assessment file or PIK of buyer on deed file.
  - Valuation imputed from assessed / sold values where missing. Details
- Contemporary income information.
  - 2018, 2019, 2021 tax records available in the DB.

Final sample characteristics

- 3.4 million parent-child pairs.
- Race-ethnicity, geography, birth year, homeownership and assets, family income, capitalized wealth.
- Incomes averaged across 3 years of data.
- Children born in 1978-86, aged 34-42 in 2020.
- Parent mean (SD) age in 2000: 46.3 (7.2).
- Sample requires:
  - Valid PIK for parent and child,
  - Parent being in filing population at least once,
  - Parent being a householder in 2000.

Housing measurement details / limitations

- Child wealth concept comes from Black Knight.
  - Business ownership cannot be PIK'd without info on business structure.
  - Focus on "personal" wealth holdings.
  - Property versus housing.
  - No debt data.
- Parent wealth concept comes from 2000 LF.
  - Tenure question gives us ownership info. Follow-up question about home value.
  - 25 different bins of home value.
  - Cannot learn about remote / multiple ownership.
  - Assume household reference person is homeowner.

Housing measurement details / limitations

- Assigning ranks.
  - Let $x =$ ownership rate.
  - Assign non-owners rank of $(1 - x)/2$.
  - Owners ranked $1 - x + 1/N$ up to 1 by asset values.
- Imperfect assignment of PIKs to property records.
  - Assignment algorithm works best when we have SSN and/or {DOB, full name, location}.
  - Only observe {full name, location}.
  - Merge of ACS housing info onto our sample reveals slight under-count of owners:

2021		BK owner		*2020*		BK owner	
		No	Yes			No	Yes
ACS	No	0.353	0.058	ACS	No	0.330	0.069
owner	Yes	0.112	0.477	owner	Yes	0.113	0.488

Source: American Community Survey linked to Black Knight property records.

Weighting estimator: simple example

- Ignore intensive margin for now.
- Start with ownership rate estimate from survey data.
  - Children sampled by 2018-2021 ACS.
  - Some individuals may not own their ACS address but remotely own property.
  - Estimate this population in 2018 SIPP, get $a_{SIPP} = \frac{x_{SIPP}+r_{SIPP}}{x_{SIPP}}$.
  - Construct $x_{ACS^*} = x_{ACS} \cdot a_{SIPP}$.
- "Final" weight, fw_i, $=$
  - $bw_i \cdot \frac{1-x_{ACS^*}}{1-x_{BK}}$ if kid i is not a BK owner
  - $bw_i \cdot \frac{x_{ACS^*}}{x_{BK}}$ if kid i is a BK owner
  - where bw_i is a base weight.

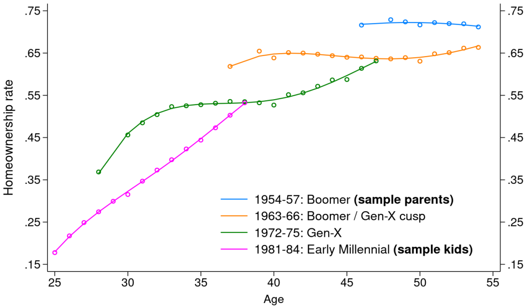
Weighting estimator: adding detail

- Wish to estimate ownership cdf $H_{g-1}(x) = H(x|g-1)$.
- Iterate the reweighting procedure within 550 bins defined by $\{$ White, Black, Hispanic, Asian, Other $\} \cdot \{$ nonowner, 10 deciles of parental housing wealth $\} \cdot \{$ 10 deciles of parental income $\}$.
- To estimate valuation cdf $F(v|g-1, x)$, implement intensive margin adjustment as well.
  - Compare ACS owners' home values across owners who differ in BK ownership status.
  - If most "unlinked" owners are relatively poor, up-weight observed poorer BK owners and down-weight observed richer BK owners.

▸ Intensive margin details

Weighting estimator: life-cycle adjustment

Figure: Age-Ownership Profile for Selected Cohorts

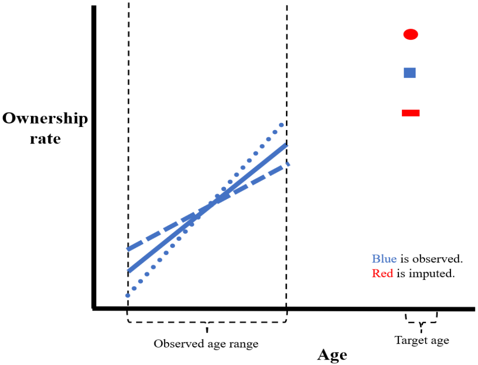


Source: public-use 2000 LF and 2005-2022 ACS files.
Sample restricted to those born in the U.S.

- Major re-ranking when purchase first house that likely scales with parental wealth.
- Adjust the extensive margin weights to "target" age 45-49 ownership rates in ACS.

Weighting estimator: life-cycle adjustment

- Challenge: individuals are too old to observe target ownership rate by $g-1$ status.
- Solution: extrapolate based on differential observed age-ownership profiles. ▸ Details
- If $x_a^{1978} - x_a^{1986} > \overline{x}^{1978} - \overline{x}^{1986}$, add a larger-than-average constant to a's observed rate x_a.



Weighting estimator: life-cycle adjustment

- Challenge: no parental housing info $(g-1)$ for those of the target age
- Leverage differential cohort variation across $g-1$ statuses in our data to understand which subgroups are further from eventual ownership rates.
  - Let t_{ACS^*} = target ownership rate.
  - Define $\Delta_{ACS*} = t_{ACS^*} - x_{ACS^*}$ and $\delta^c_{ACS^*} = x^{oldest}_{ACS^*} - x^{youngest}_{ACS^*}$.
  - By construction, $t_{ACS^*} = x_{ACS^*} + \Delta_{ACS^*} \cdot \frac{\delta^c_{ACS^*}}{\delta^c_{ACS^*}}$.
  - Assumption: for given subgroup $g-1$, $t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS*} \cdot \frac{\delta^{c,g-1}_{ACS^*}}{\delta^c_{ACS^*}}$.
  - I.e., a subgroup whose ownership rate grew faster than the sample average is assigned a higher than average Δ to add to its base ownership rate.
- In implementation, allow t_{ACS^*}, Δ_{ACS^*}, and $\delta^c_{ACS^*}$ to vary by race.
- $lcaw_{i(g-1)} = fw_i \cdot \frac{1-t^{g-1}_{ACS^*}}{1-x^{g-1}_{ACS^*}}$ if kid i of background $g-1$ is not a BK owner.
- $lcaw_{i(g-1)} = fw_i \cdot \frac{t^{g-1}_{ACS^*}}{x^{g-1}_{ACS^*}}$ if kid i of background $g-1$ is a BK owner.

Back

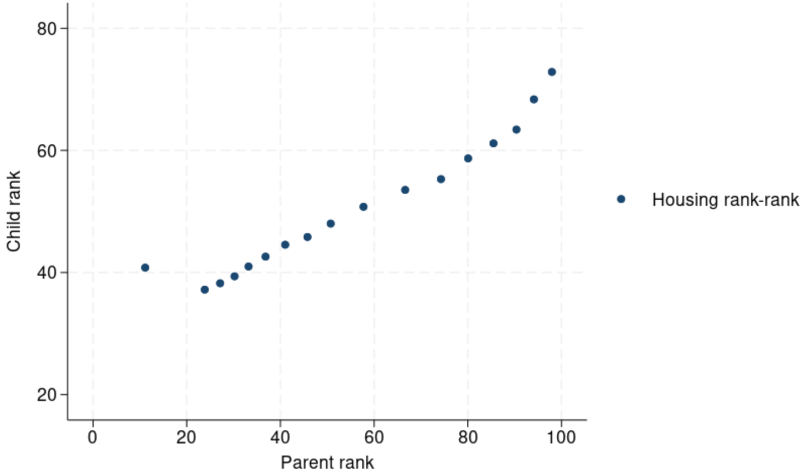
Empirical design: Rank-rank intergenerational mobility

$$Y_g = \alpha + \beta Y_{g-1} + u_g \tag{1}$$

- Absolute Mobility (α): average rank of children with worst-off parents.
- Relative Mobility (β): gain in child rank associated with a one-rank gain in parent rank.
- Consider various measures of Y including housing assets, income, and wealth.
- Ranks always defined at the full population level.

Intergenerational Mobility of Housing Wealth in the U.S.

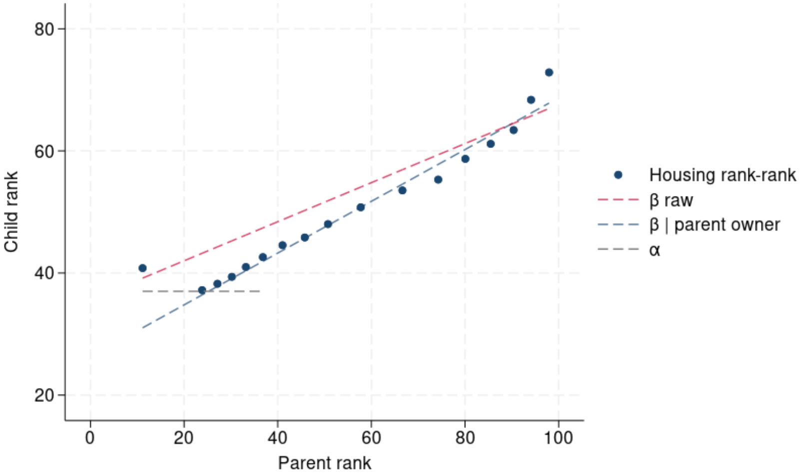
Extensive margin, absolute mobility (α), and relative mobility (β)



Source: IRS federal income tax records linked to 2000 LF and BK property records.

▸ Parent Income by Housing Rank

Extensive margin, absolute mobility (α), and relative mobility (β)

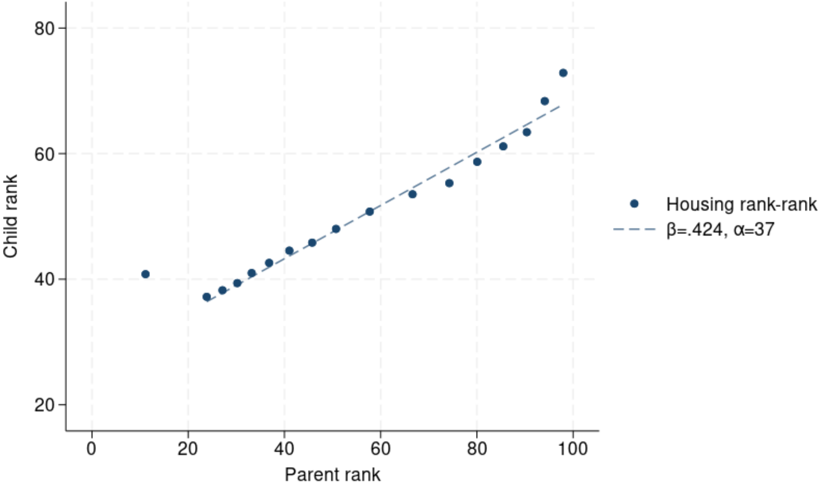


Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Add a "parent renter" fixed effect to equation (1).

▸ Parent Income by Housing Rank

Rank-Rank estimates of housing IGM

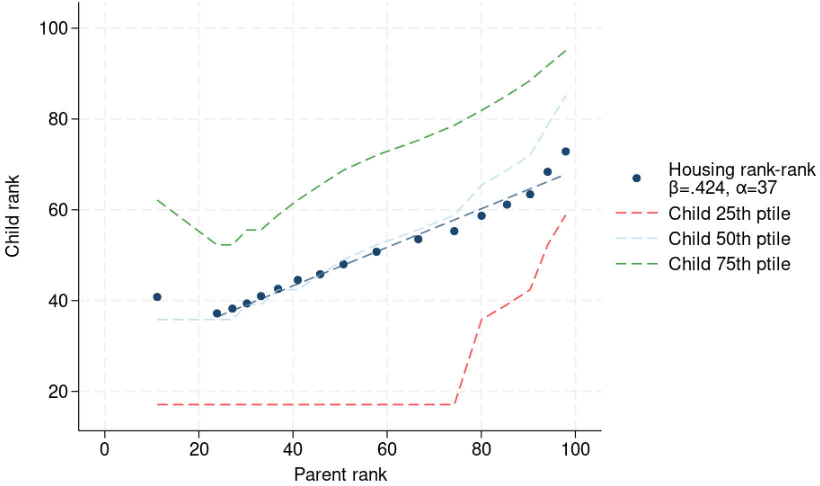


Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Compare Chetty et al. (2020) Income rank-rank β=0.35, α=32.5 (our data: β=0.36, α= 32.2)

▸ Life cycle ▸ Table ▸ Income

Rank-Rank estimates of housing IGM

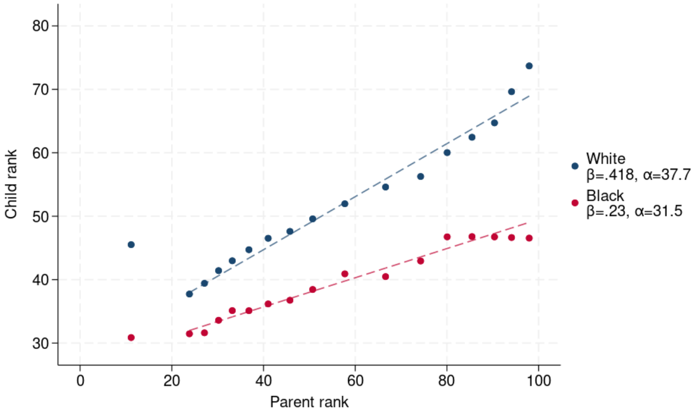


Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Compare Chetty et al. (2020) Income rank-rank β=0.35, α=32.5 (our data: β=0.36, α= 32.2)

▸ Table ▸ Income

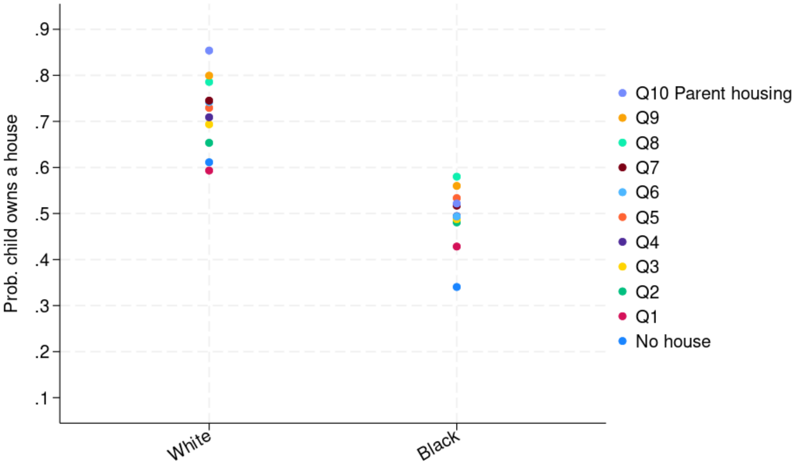
Racial gaps in IGM of housing



Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Income comparisons:
  - Chetty et al. (2020): White β=0.32, α=36.8; Black β=0.28, α=25.4.
  - Our data: White β=0.322, α=36; Black β=0.274, α=22. ▸ Figure

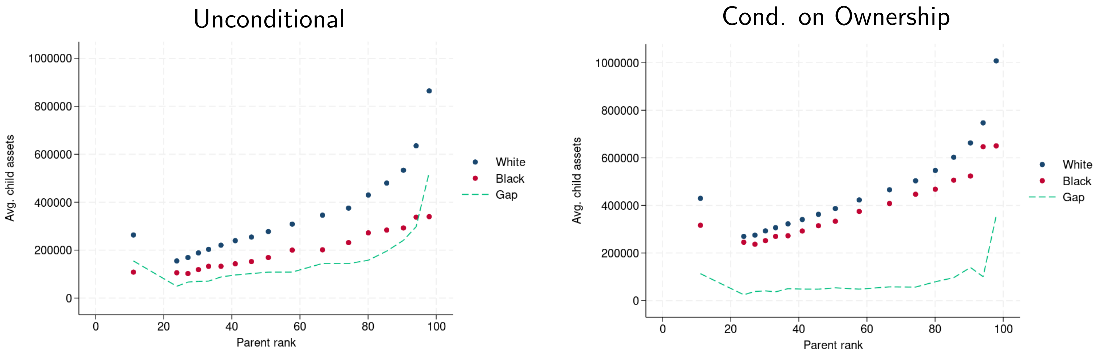
Racial gaps in the probability of child home ownership



Source: IRS federal income tax records linked to 2000 LF and BK property records.

▸ Robust-no LCA ▸ Robust-Income

Average child housing assets by parent rank and race

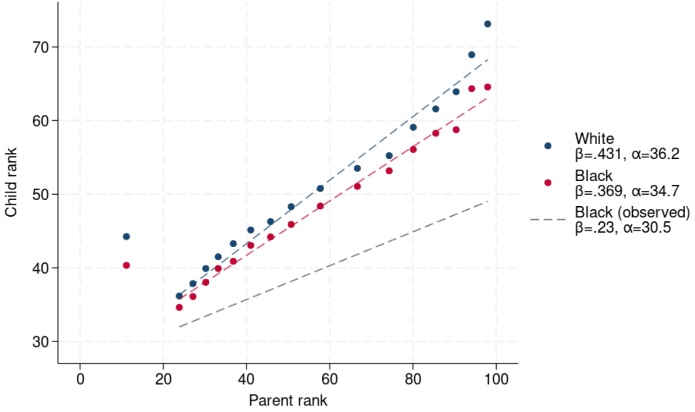


Source: IRS federal income tax records linked to 2000 LF and BK property records.

▸ Gap shares

How important is extensive margin for observed differences in IGM?

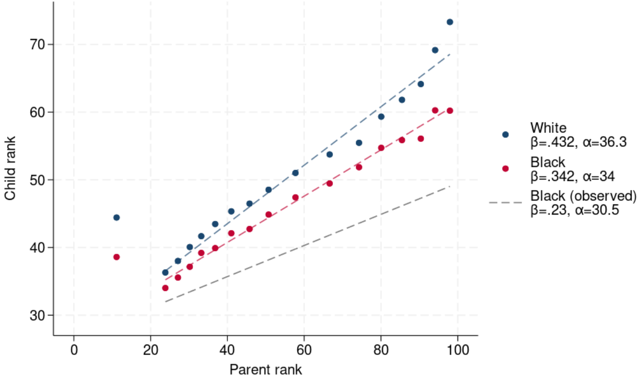
- Equalize Black and White child ownership rates | parent housing rank.
- CF1: assign new Black home owners average home value of observed Black homeowners.



Source: IRS federal income tax records linked to 2000 LF and BK property records.

How important is extensive margin for observed differences in IGM?

- CF2: capitalize rents paid by Black renters.



Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Reduces conditional gap ≈66% through most of the distribution, ≈55% in top 10%.

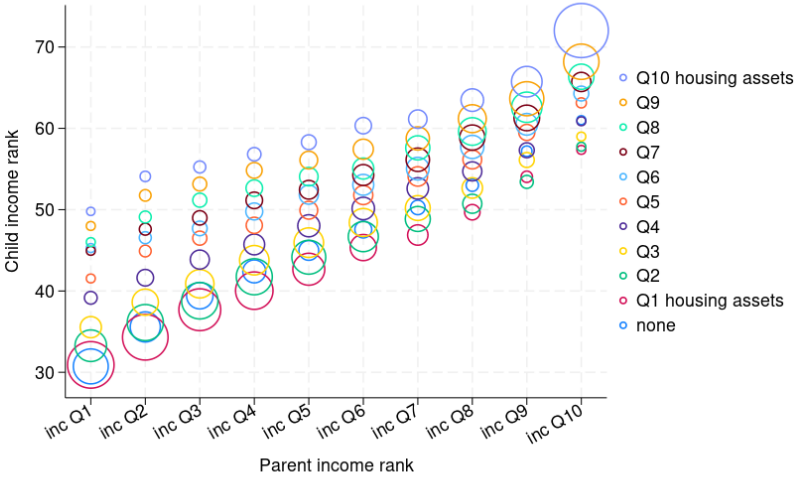
‣ CF3 ‣ CF4 ‣ Details

Intergenerational Relationships between Income and Wealth

What can we learn about IGM of total resources in the U.S.

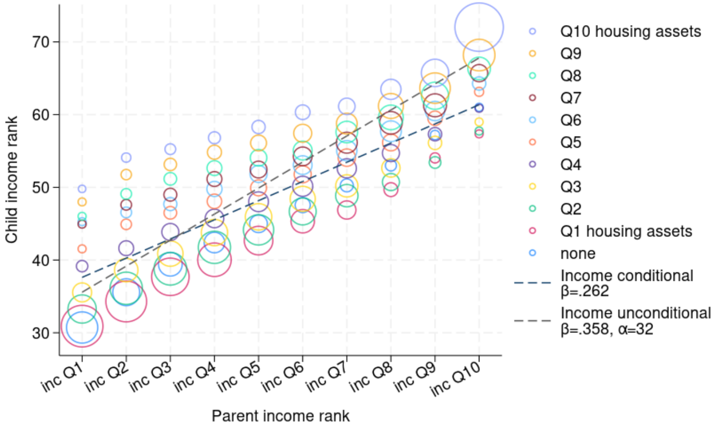
1. Does accounting for housing give context for IGM in the U.S. (relative to what we know from IGM relationships of income alone)?
    - Housing is the most important asset in the U.S. at all but the very top of the wealth distribution (SZZ, 2022)
    - Housing is not accounted for in income flows in the U.S.
    - Simple statistical model shows that the income-income relationship will understate IG persistence of total resources ▸ model
        - Income is a noisy proxy for underlying assets w/ heterogeneous realized returns
        - Housing assets have no realized income flows, so income flows understate total resources
2. Do the joint relationships of parent income and wealth inform mechanisms behind the qualitative differences in Black-White IGM?

Joint relationship of parent housing and parent income on child income



Source: IRS federal income tax records linked to 2000 LF and BK property records.

Joint relationship of parent housing and parent income on child income



Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Income-Income unconditional β=.36; conditional on housing β=.26. Table

Joint relationship of parent housing and parent income on child housing

Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Conditional Coefficients, Income: 0.181*** (0.001); Housing: 0.290*** (0.001) Table

Simple model of child asset accumulation

Take generation g's lifetime budget constraint as:

$$c_g + b_g = s_g Y_g (1 + r) + (1 - s_g) Y_g + b_{g-1}$$

- c_g: Lifetime consumption
- b_g: Wealth bequest to next generation
- Y_g: Lifetime earnings, saved at rate s_g
- r: rate of return on savings
- b_{g-1}: Inherited wealth from previous generation

Parent influences on child resources

1) Children imperfectly inherit labor market productivity from parents.

$$Y_g = f(W_{g-1}) + u_g = \rho_y W_{g-1} + u_g$$

Children use their earnings to accumulate wealth, but may obtain additional wealth, from:

2) A direct transfer from parents:

$$b_{g-1} = f(W_{g-1}) = \rho_b W_{g-1}$$

3) Parental-wealth-induced saving behavior, i.e.

$$s_g = f(W_{g-1}) + \nu_g = \rho_s W_{g-1} + \nu_g$$

Simultaneous equation model

Child earnings are a function of parent wealth:

$$Y_g = \rho_y W_{g-1} + u_g. \tag{2}$$

Simultaneous equation model

Child earnings are a function of parent wealth:

$$Y_g = \rho_y W_{g-1} + u_g. \tag{2}$$

Child wealth is a function of child earnings and parent wealth:

$$\begin{aligned} W_g = f(Y_g, W_{g-1}) &= (1+r)s_g Y_g + b_{g-1} \\ &= (1+r)(\rho_s W_{g-1} + \nu_g)Y_g + \rho_b W_{g-1} \\ &= (1+r)\bar{s} Y_g + \rho_b W_{g-1} + (1+r)\rho_s (Y_g \times W_{g-1}) \end{aligned}$$

Simultaneous equation model

Child earnings are a function of parent wealth:

$$Y_g = \rho_y W_{g-1} + u_g. \tag{2}$$

Child wealth is a function of child earnings and parent wealth:

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Which gives the following regression:

$$Y_g = \beta W_{g-1} + u_g$$

$$W_g = \gamma_y Y_g + \rho_b W_{g-1} + \gamma_s (Y_g \times W_{g-1}) + \epsilon_g. \tag{3}$$

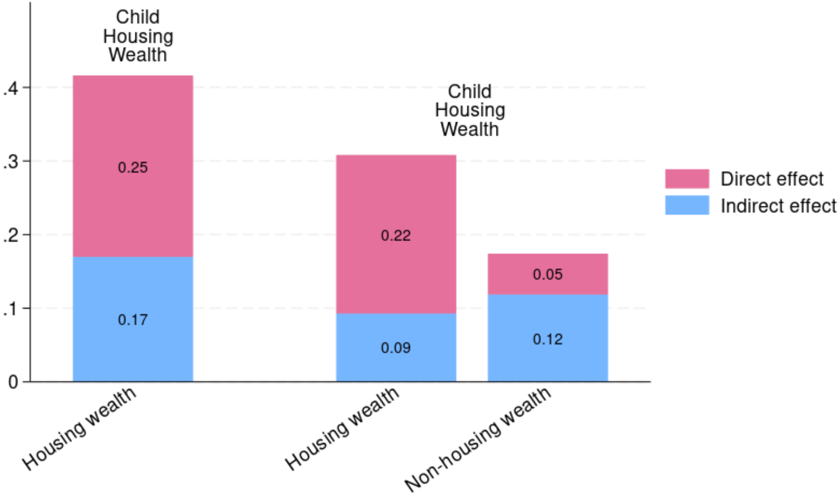
Simultaneous equation model: direct and indirect effects

$$Y_g = \rho_y W_{g-1} + u_g$$

$$W_g = \gamma_y Y_g + \rho_b W_{g-1} + \gamma_s (Y_g \times W_{g-1}) + \epsilon_g$$

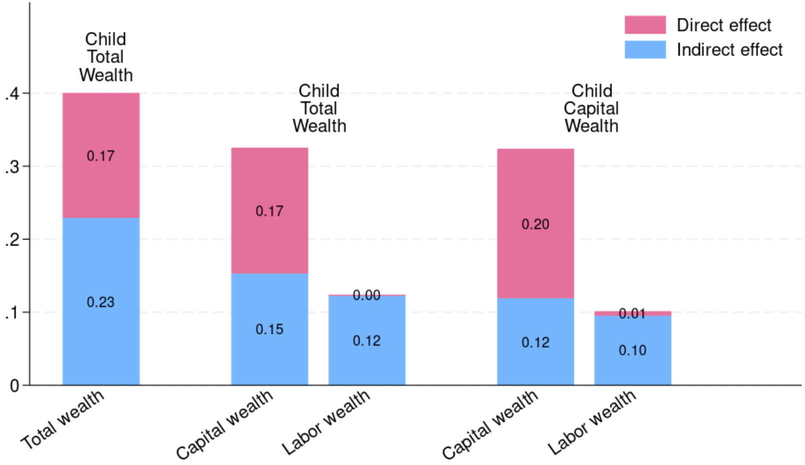
- "Direct Effect": Impact of parent wealth on child wealth, independent of child income (ρ_b).
- "Indirect Effect": Impact of parent wealth on child wealth through child earnings ($\rho_y * \gamma_y$).
  - Parent wealth increases child earnings (ρ_y).
  - Child earnings purchase wealth (γ_y).
- These effects decompose the relative mobility coefficient β from equation (1): $W_g = \alpha + \beta W_{g-1} + e_g$.

Direct and indirect effects of parent resources on child housing



Source: IRS federal income tax records linked to 2000 LF and BK property records.

Direct and indirect effects of parent resources on child total wealth



Source: IRS federal income tax records linked to 2000 LF and BK property records.

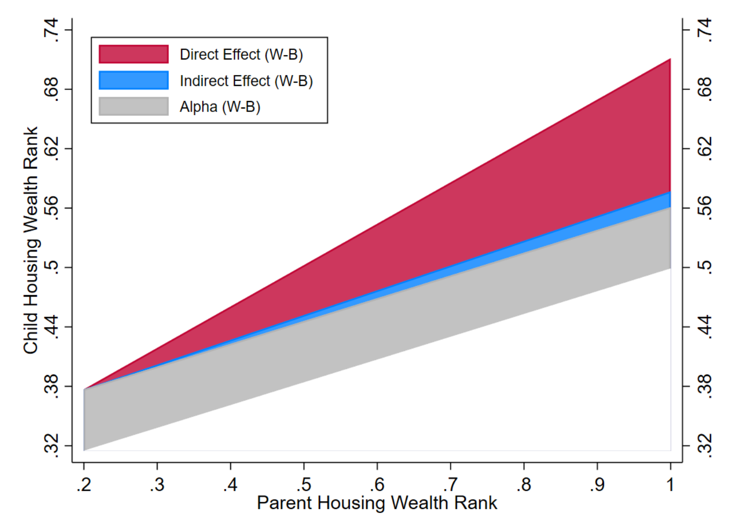
▸ Capitalization details ▸ Table ▸ Full IGM plot

Direct and indirect effects of parent resources on child housing, by race

Source: IRS federal income tax records linked to 2000 LF and BK property records.

▸ Table ▸ Total wealth

Decomposing racial IGM gaps in housing assets



Source: IRS federal income tax records linked to 2000 LF and BK property records.

▸ Total wealth

Exploring Cross-County Variation

Constructing a cross-area dataset

- Estimate IGM equations (1), (2), and (3) separately by county.
- Require at least 30 unweighted observations. Weight by $\sqrt{N_c}$.
- Yields cross-county distributions of ρ, β, ρ_y, γ_y, ρ_b.
- Merge on county-level exposures:
  - Great Recession unemployment shock: p.p. change in UR, Jan 2007-Dec 2009.
  - Housing unit supply elasticity: aggregated to counties from tract-level estimates in Baum-Snow and Han (2024).
  - Racial segregation: county-level dissimilarity index across tracts (Binder et al. 2024).

Cross-Area analyses

$$\beta_c = \phi + \theta_\beta E_c + \xi_c. \tag{4}$$

- θ_β: **association** between 1-unit change in given exposure and change in relative (im)mobility.
- θ_{ρ_b}: change in direct effect. $\theta_\beta - \theta_{\rho_b} = \theta_\iota$: change in indirect effect.
- Indirect effect composed of "income levels" (ρ_y) and "income returns" (γ_y) channels.
  - Exposure may influence each channel.
  - With a technical assumption, a simple decomposition results:

$$\theta_\beta = \theta_{\rho_b} + \frac{\theta_\iota + \theta_{\rho_y}\overline{\gamma_y} - \theta_{\gamma_y}\overline{\rho_y}}{2} + \frac{\theta_\iota + \theta_{\gamma_y}\overline{\rho_y} - \theta_{\rho_y}\overline{\gamma_y}}{2}. \tag{5}$$

▸ Details

- Estimate (4) and (5) separately for Whites and Blacks. Compute effect of exposure on
  - Racial mobility gap at bottom and at top
  - And decomposition of top gap.

Full-Population results

Table: Associations between County-Level Exposures and Housing Wealth Mobility

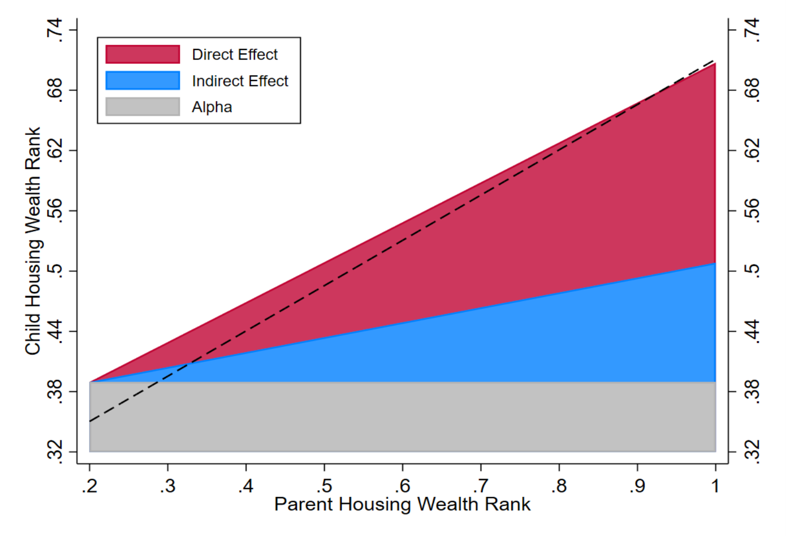
Exposure	α	β and its decomposition			
		Total	Direct effect	Income returns	Income levels
GR unemployment shock (p.p. increase / 100)	-.697*** (.044)	0.945*** (.093)	0.181*** (.069)	.259*** (.028)	.505*** (.032)
Exposure mean, SD, N: .046, .022, 3100					
Housing supply elasticity (dlog units / dlog price)	-.036* (.021)	-.305*** (.031)	-.142*** (.022)	-.071*** (.013)	-.092** (.025)
Exposure mean, SD, N: .310, .123, 800					
Racial segregation (W / nW dissimilarity index)	-.109*** (.006)	0.294*** (.015)	0.115*** (.010)	0.033*** (.005)	0.146*** (.009)
Exposure mean, SD, N: .426, .173, 3100					

Mobility data source: IRS federal income tax returns linked to 2000 Census Long Form and Black Knight property records.
Great Recession shock data source: BLS Local Area Unemployment Statistics
Housing supply data source: Baum-Snow and Han (2024)
Racial segregation data source: Binder et al. (2024), who use IRS federal income tax returns linked to Census race and ethnicity files.

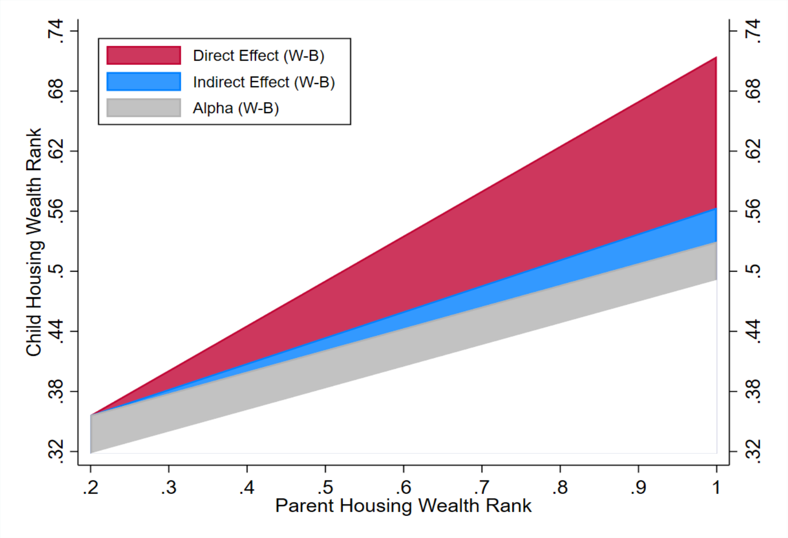
▸ Results by racial group

Full population: High GR exposure

Full population: Low GR exposure

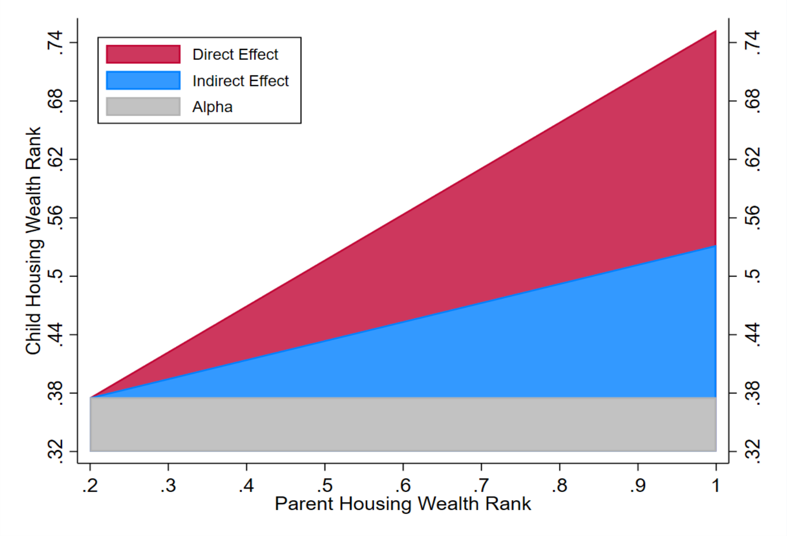


Racial disparity: High GR exposure

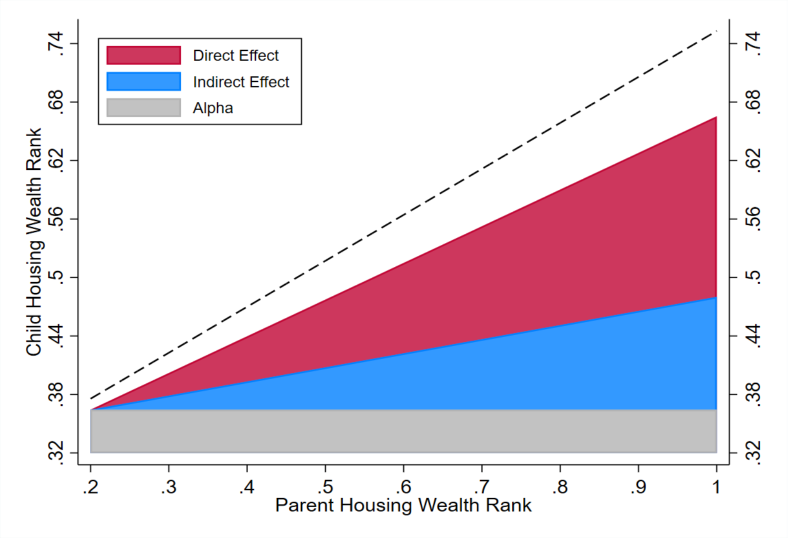


Racial disparity: Low GR exposure

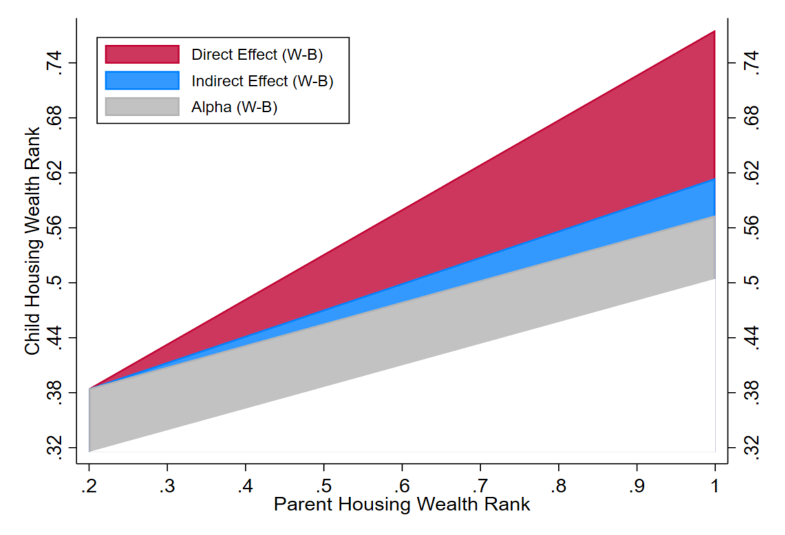
Full population: Inelastic housing supply



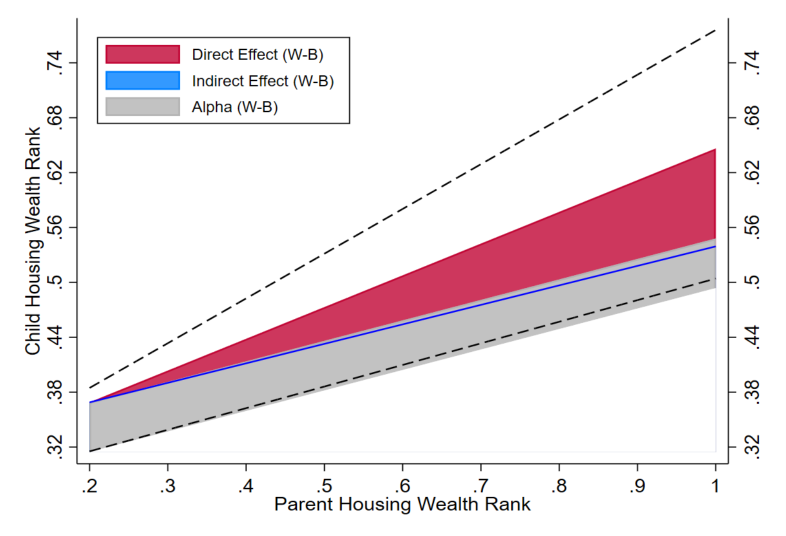
Full population: Elastic housing supply



Racial disparity: Inelastic housing supply



Racial disparity: Elastic housing supply



Conclusion / Next Steps

Conclusion and ongoing work

- Housing and other capital wealth plays an important role, independent of income flows, in generating IG persistence in economic resources among U.S families.
- Implications for racial disparities, spatial variation, and housing and macro stabilization policies.
  - Inequality in opportunities in access to capital markets matters, in addition to opportunities in labor markets
- Ongoing work:
  - Maps of IGM of housing assets across U.S. counties to be posted publicly
  - Relax the (α, β) framework to allow non-linearity; interact our indirect / direct approach with quantile decomposition methods.
  - Augmenting IG capital accumulation model to account for racial gaps in indirect and direct effects.
  - Mechanisms: Further analysis from variation in housing supply - augment the model to include location, housing supply, and human capital investment.
    - extensive v. intensive margin
  - Implications for (wealth/capital) tax policy

Appendix

Imputing property valuations

- Valuation file contains most recent automated valuation model (AVM) estimate of market value. Virtually always corresponds to vintage year.
- AVM estimate is based on recent transaction of similar properties, weighted by recency of sale and similarity to given property.
- Small but non-negligible share of properties in assessment and deed files have missing valuations.
- Assessment (deed) file contains virtually always nonmissing information on last assessed (sold) value, and date of assessment (sale).
- Imputation procedure. For each county c:
  - Within each county c:
  - Estimate $\ln(v_{pcy}) = \lambda_{0c} + \lambda_{1c}\ln(a_{pcy}) + \lambda_{2c} ta_{pcy} + \boldsymbol{\lambda_{3c}}' Y + \epsilon_{pcy}$
  - Estimate $\ln(v_{pcy}) = \nu_{0c} + \nu_{1c}\ln(s_{pcy}) + \nu_{2c} ts_{pcy} + \boldsymbol{\nu_{3c}}' Y + e_{pcy}$
  - Where p is property, y is vintage year, a (s) is last assessed (sold) value, ta_{pcy} (ts_{pcy}) is y minus the year of the last assessment (sale), as recorded in vintage y, and Y is a set of vintage year fixed effects.
  - Impute missing valuations as the assessment prediction, sale prediction, or a simple average of the two, depending on whether a, s, or both are non-missing.

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Intensive margin weighting adjustment

- Consider ACS owned home value distribution function $A(v)$.
- Consider two conditional distribution functions, $A_1(v) = A(v|\text{ACS owner is a BK owner})$ and $A_0(v) = A(v|\text{ACS owner is not a BK owner})$.
  - Consider a sequence of $Q+1$ uniformly-spaced quantiles $q_0, q_1, \ldots, q_Q$. That is, $A_1(q_n) - A_1(q_{n-1}) = 1/Q$.
  - It follows that $A(q_n) - A(q_{n-1}) = \frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0}$ where N_1 and N_0 are respective sample sizes.
- **Assumption:** Consider a sequence of $Q+1$ quantiles $p_0, p_1, \ldots, p_Q$ of the observed BK valuation distribution. $\frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0}$ is an unbiased estimate of $F(p_n) - F(p_{n-1})$.
- This assumption dictates setting $fw_i = bw_i \cdot \frac{x_{ACS*}}{x_{BK}} \cdot \frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0}$ if kid i is a BK owner with housing assets in the $[n-1, n)$ quantile range.
- As for the extensive margin, perform the intensive margin adjustment within each of 550 $g-1$ subgroups.
- Set $Q = \lfloor N_{g-1}/15 \rfloor$ where N_{g-1} is the number of BK owners with characteristics $g-1$.
- Set intensive margin weight to 1 if $N_{g-1} < 30$.

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Life-Cycle weighting adjustment

- Let t_{ACS^*} = target ownership rate.
- Define $\Delta_{ACS*} = t_{ACS^*} - x_{ACS^*}$ and $\delta^c_{ACS*} = x^{oldest}_{ACS*} - x^{youngest}_{ACS*}$.
- By construction, $t_{ACS^*} = x_{ACS^*} + \Delta_{ACS^*} \cdot \frac{\delta^c_{ACS*}}{\delta^c_{ACS*}}$.
- Assumption: for given subgroup $g-1$, $t^{g-1}_{ACS^*} = x^{g-1}_{ACS*} + \Delta_{ACS*} \cdot \frac{\delta^{c,g-1}_{ACS*}}{\delta^c_{ACS*}}$.
- I.e., a subgroup whose ownership rate grew faster than the sample average is assigned a higher than average Δ to add to its base ownership rate.
- In implementation, allow t_{ACS^*}, Δ_{ACS^*}, and δ^c_{ACS*} to vary by race.
- This yields the following life-cycle-adjusted weights:
  - $lcaw_{i(g-1)} = fw_i \cdot \frac{1-t^{g-1}_{ACS*}}{1-x^{g-1}_{ACS*}}$ if kid i of background $g-1$ is not a BK owner.
  - $lcaw_{i(g-1)} = fw_i \cdot \frac{t^{g-1}_{ACS*}}{x^{g-1}_{ACS*}}$ if kid i of background $g-1$ is a BK owner.

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Parent income by housing rank

Table: Parent average net income by housing asset rank

	None	2	3	4	5	6	7	8	9	10	11
mean	40,470	32,270	37,070	40,910	43,830	46,660	50,140	53,570	70,760	87,110	272,800
SD	64760	25,380	27,280	26,920	28,720	25,840	36,810	38,500	51,730	112,000	677,000

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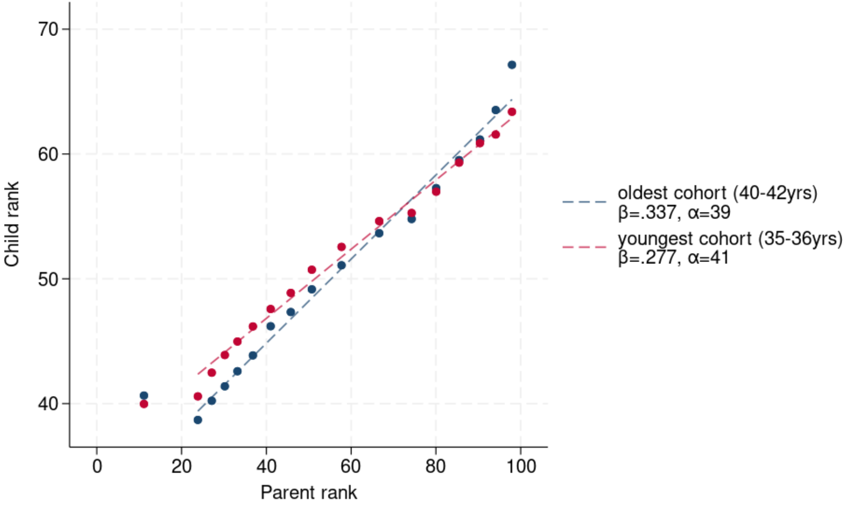
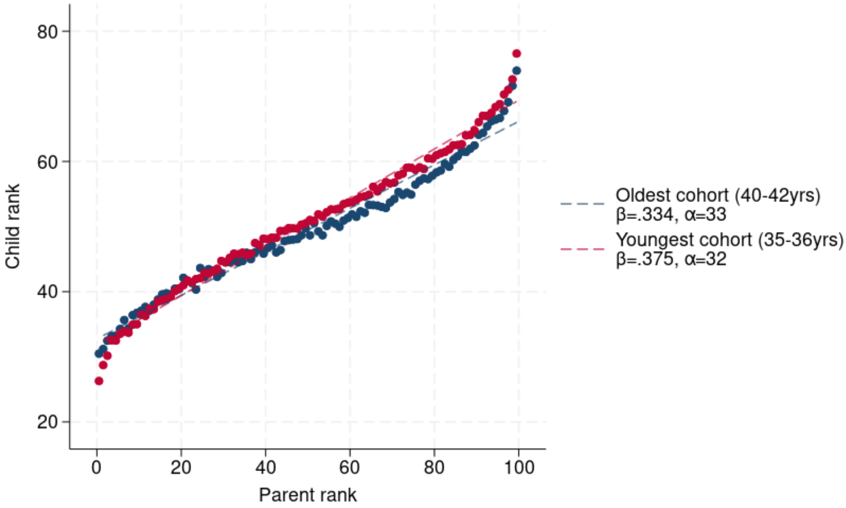
Life-Cycle accumulation of housing assets



Source: IRS federal income tax records linked to 2000 LF and BK property records.

- Use "Life Cycle Adjusted" (LCA) weights to account for this ▸ Table ▸ Income ▸ Main

Life-Cycle rank-rank relationships for income



▸ Housing Cohorts ▸ Income All

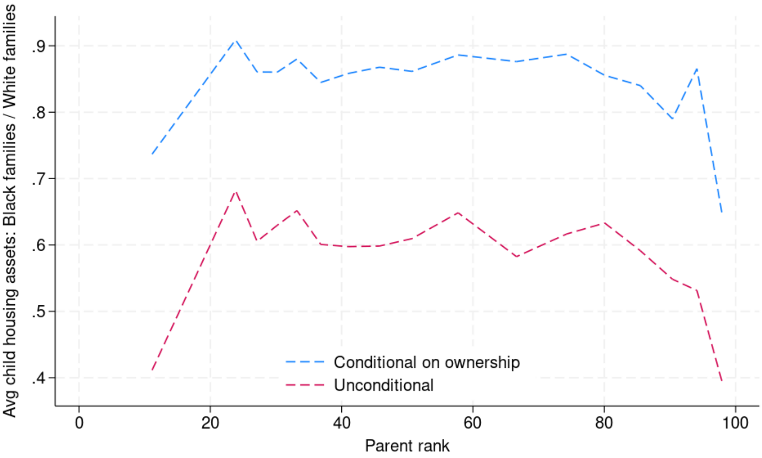
Rank-Rank relationships in housing wealth over life cycle

Table: α and β estimates across kid cohorts and weighting

	All Cohorts	Ages 35-36	Ages 38-39	Ages 41-42	LCA weights
β	0.305***	0.277***	0.303***	0.337***	0.424***
α	40	41	40	39	37

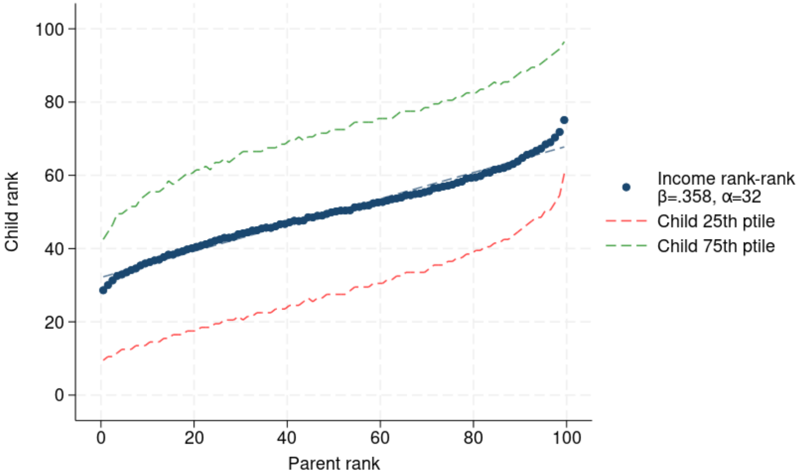
Fig Cohorts Fig LCA

Housing assets of children of Black families as a share of White assets



▸ B-W housing gaps ▸ Fig: CF 1

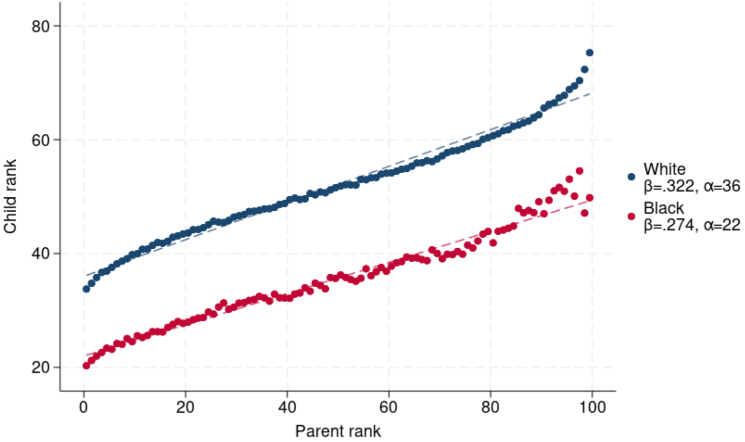
Rank-Rank estimates of income



- Compare Chetty et al. (2020) Income rank-rank β=0.35, α=32.5

Housing Wealth Figure
Income Cohorts

Racial gaps in IGM of income

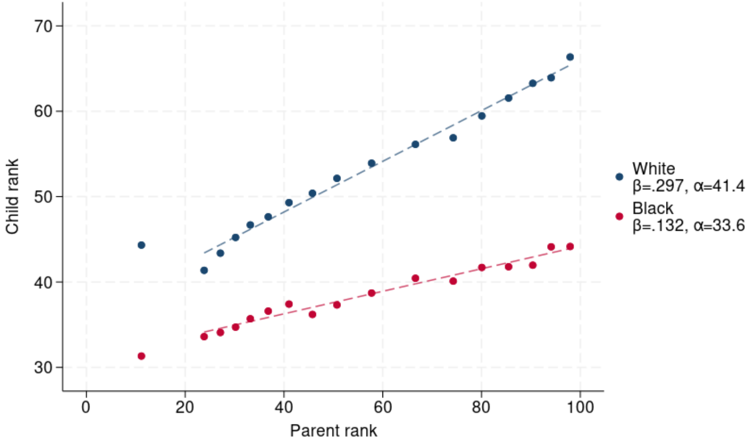


Compare Chetty et al. (2020) for Income:

- White β=0.32, α=36.8; Black β=0.28, α=25.4

▸ Housing Wealth

Racial gaps in IGM of housing (no LCA weights)

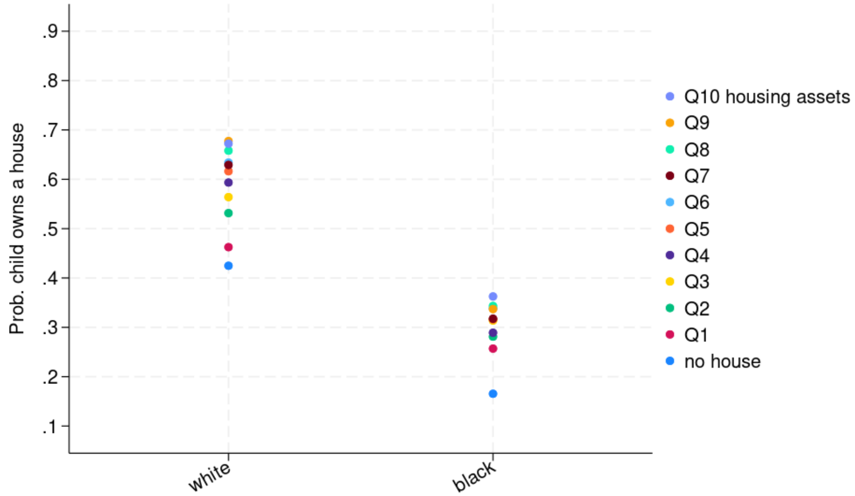


Compare Chetty et al. (2020) for Income:

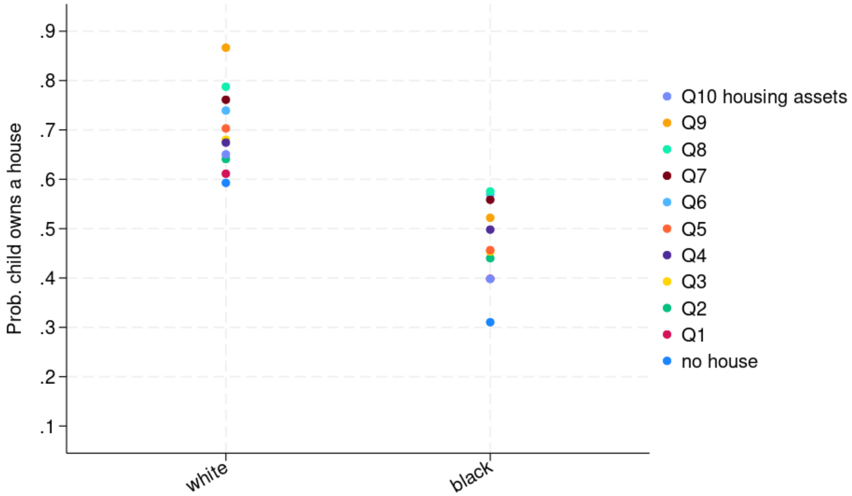
- White β=0.32, α=36.8; Black β=0.28, α=25.4

▸ Housing Wealth

Racial gaps in probability of home ownership (no LCA)



Racial gaps in probability of home ownership, by income



▸ Main ▸ Robust-no LCA

Assigning counterfactual housing wealth ranks to Black renters

- Merge 2016-2021 ACS data on monthly rental payment to main dataset.
- Approach 1: Capitalize observed monthly rental payments R (for years 2018-2021).
  - What price P would make a risk-neutral investor indifferent about purchasing the unit.
  - Assume alternative rate of return $a = .08$ and housing rate of return $h = .03$.
  - User cost of capital implies $P = \frac{12 \cdot R}{a - h} = 240 \cdot R$.
  - Investor impatience would raise P while maintenance costs would lower P.
- Approach 2: Predict "starter" home values from observed renter-to-owner. Consider folks who were renting in 2016-2019 and also showed up as BK owners.
  - Regress log BK housing wealth on quadratic in log rent and parental background variables.
  - Predict BK housing wealth for observed Black renters in 2018-2021.
- Compute the $(5^{th}, 20^{th}, 50^{th}, 80^{th}, 95^{th})$ pctile values, within each parental wealth vigintile, for each counterfactual.
- Randomly draw one of these numbers with probabilities $(.10, .20, .40, .20, .10)$ in the simulation.
- Compute counterfactual ranks after assigning these counterfactual values.

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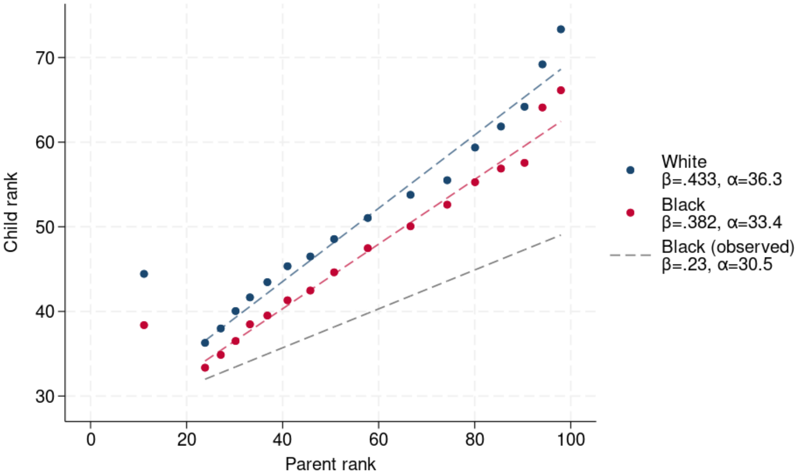
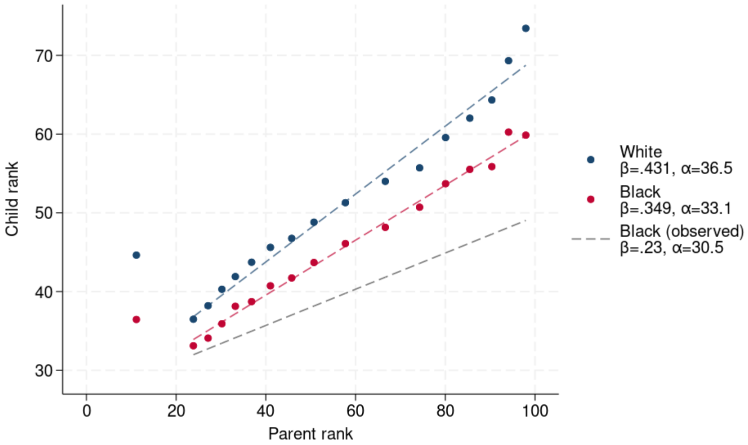
Counterfactual: Estimated from observed transitions



- Reduces conditional gap ≈60% in the bottom half and ≈72% in the top half of the distribution

▸ CF rent ▸ Calc. details

Counterfactual: 25th pctile of observed owners



- Reduces conditional gap ≈45% in the bottom quartile and ≈55% in the top 3/4 of the distribution

▸ CF mean ▸ CF rent

Recovering β for total resources

Want to recover β from reduced form IG model of total resources (W):

$$W_g = \beta W_{g-1} + u_g$$

Aggregate income flows represent returns to various sources of underlying wealth:

$$Y_i = \sum_j r_j w_{ij} = W_i \sum_j \alpha_{ij} r_j$$

- r_j=realized rate of return on source j and α_j=share of wealth in source j.

Represent as:

$$Y_i = rW_i + \eta_i$$

- r=avg realized rate of return on wealth and η_i=degree to which income overstates wealth
- Ex. if most of wealth is in housing (h), r_h=0 so η_i will be low (income will understate wealth)
- Ex. If all income is wages (l), $r_l \approx$1 so η_i will be high (income will overstate wealth)

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Income-Income regressions lead to biased estimates of β

Want to recover β from reduced form IG model of total resources (W):

$$(Y_g - \eta_g)/r = \beta(Y_{g-1} - \eta_{g-1})/r + u_g \implies$$

$$Y_g = \beta(Y_{g-1} - \eta_{g-1}) + \eta_g + ru_g$$

Therefore, an income-income regression of Y_g on Y_{g-1} gives a biased estimate of the true β

- omitted η_{g-1} is directly positively related to $Y_{g-1} \implies$ *understated*
- omitted η_g is positively related to Y_g and likely negatively related to $Y_{g-1} \implies$ *understated*

Implication: when income represents heterogeneous returns to underlying assets and composition of assets varies across individuals, income-income relationships understate IG persistance of total wealth.

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Joint relationship of parent housing and parent income

Table: Joint relationship of parent income and housing on child resources

	Child Net Inc.	Child Housing
Income	0.271***	0.181***
	(0.0013)	(0.0011)
Housing	0.175***	0.290***
	(0.0013)	(0.0013)
Interaction	-0.0003***	-0.0004***
	(0.0000)	(0.0000)
constant	28.31***	32.72***
	(0.0564)	(0.0705)

▸ Figure: IxIxHW ▸ Figure: HWxIxHW

Direct and indirect effects of parent resources on child housing

Child:	Housing Wealth		Housing Wealth
Parent:	Housing Wealth		Housing Wealth
			Non-Housing Wealth
Eq. 1: Child Earnings (Y_c)			
Parent Housing	0.325***	Parent Housing	0.182***
	(0.0008)		(0.0008)
		Parent Non-housing	0.232***
			(0.0006)
Eq. 2: Child Resources			
Child Labor	0.549***	Child Labor	0.522***
	(0.0009)		(0.0010)
Parent Housing	0.266***	Parent Housing	0.241***
	(0.0011)		(0.0013)
		Parent Non-housing	0.039***
			(0.0011)
Interaction $Y_c \times H_p$	-0.0003***	Interaction $Y_c \times H_p$	-0.0005***
	(0.0000)		(0.0000)
		Interaction $Y_c \times Wnh_p$	0.0003***
			(0.0000)

▸ Figure

Estimating total wealth: Capitalization approach

Capitalize observed income flows to estimate wealth stocks, by source (j)

- $y_j = r_j * W_j \implies W_j = (1/r_j)y_j$
- use capitalization factors from PSZ for: fixed income assets (interest income), corporate assets (dividends and capital gains)
- use observed housing assets in our data
- capitalization factors for pension wealth using labor earnings and age profile from SZZ
- $\sum_j W_j$ and rank by total W

Key issues / assumptions:

- Don't need to get wealth right, just need to get ranks right at point in time
- Average over 3 years to reduce noise
- For the large majority of the distribution, Housing and Pensions are effectively the only assets. (i.e. robustness of capitalization factors only matters at the top)

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Direct and indirect effects of parent resources on child resources

Child:	Wealth		Wealth	Capital Wealth
Parent:	Wealth		Capital Wealth Labor Wealth	Capital Wealth Labor Wealth
Eq. 1: Child Earnings (Y_c)				
Parent Wealth	0.331***	Parent Wealth	0.220***	0.220***
	(0.0006)		(0.0006)	(0.0006)
		Parent Labor	0.176***	0.176***
			(0.0006)	(0.0006)
Eq. 2: Child Resources				
Child Labor	0.725***	Child Labor	0.725***	0.523***
	(0.0007)		(0.0008)	(0.0010)
Parent Wealth	0.203***	Parent Wealth	0.220***	0.217***
	(0.0008)		(0.0000)	(0.0010)
		Parent Labor	-0.020***	-0.028***
			(0.0009)	(0.0011)
Interaction $Y_c \times W_p$	-0.0006***	Interaction $Y_c \times CW_p$	-0.0009***	-0.0002***
	(0.0000)		(0.0000)	(0.0000)
		Interaction $Y_c \times Y_p$	0.0004***	0.0006***
			(0.0000)	(0.0000)

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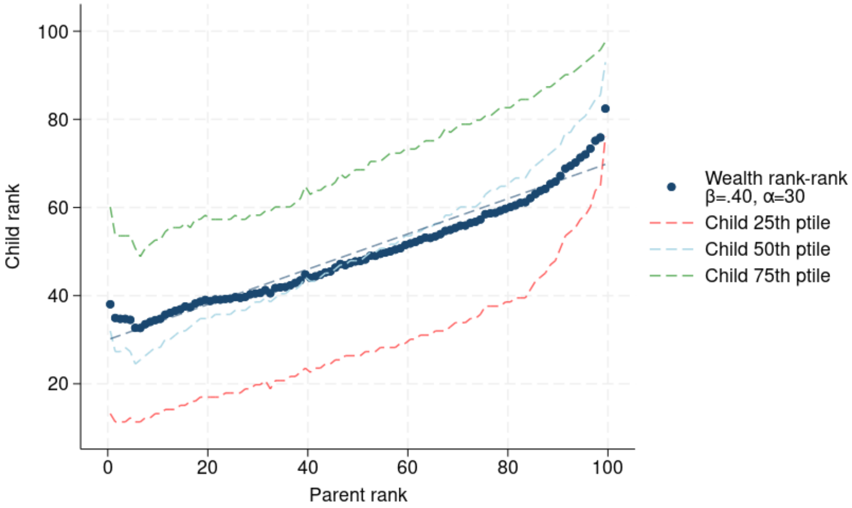
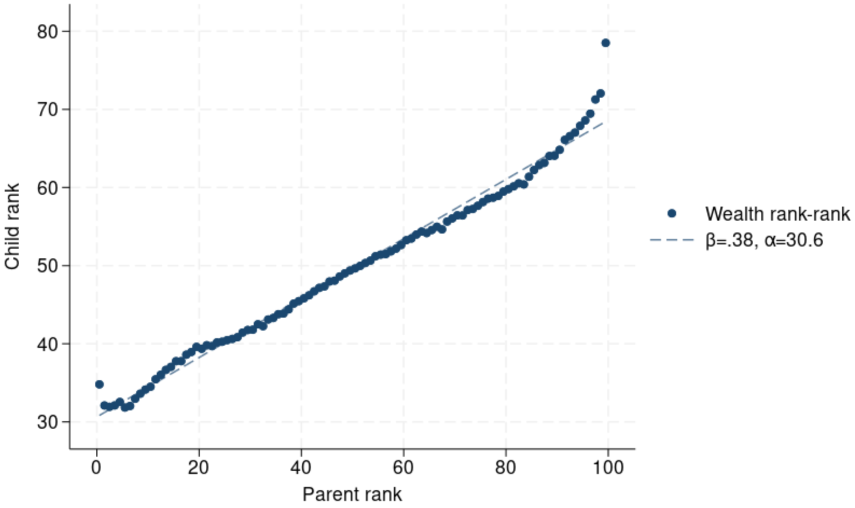
IGM of total wealth



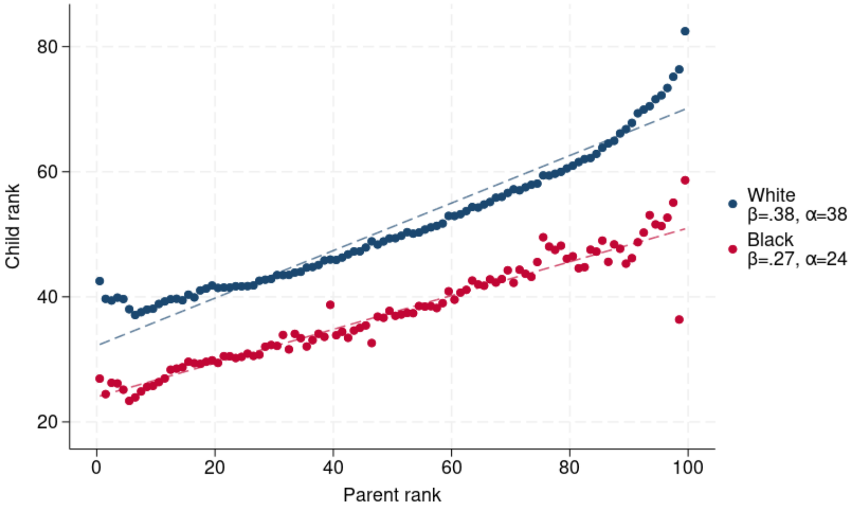
▸ Back ▸ by race ▸ Robust: no LCA

IGM of total wealth (no LCA)



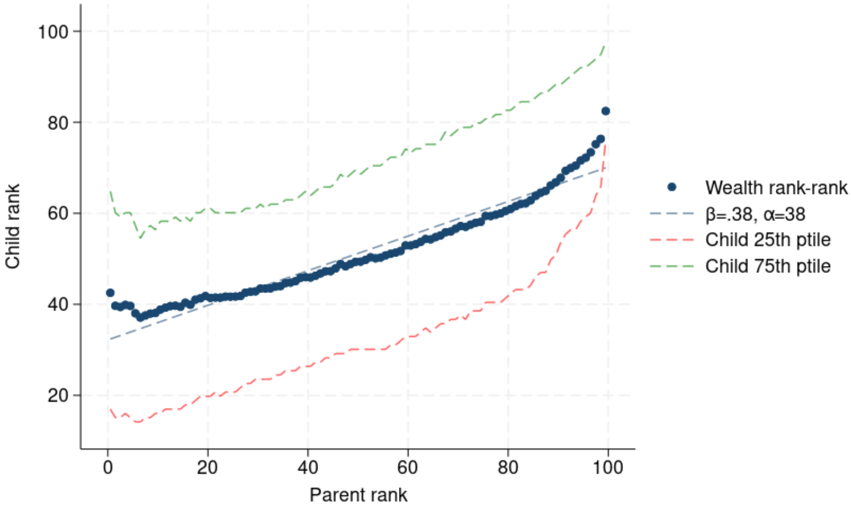
▸ Back

IGM of total wealth by race



▸ Full ▸ Quantiles

IGM of total wealth: White families



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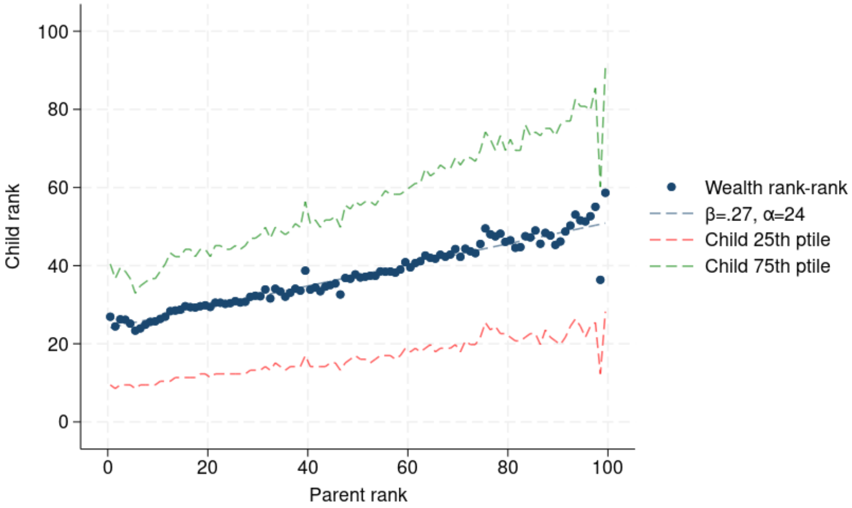
IGM of total wealth: Black families



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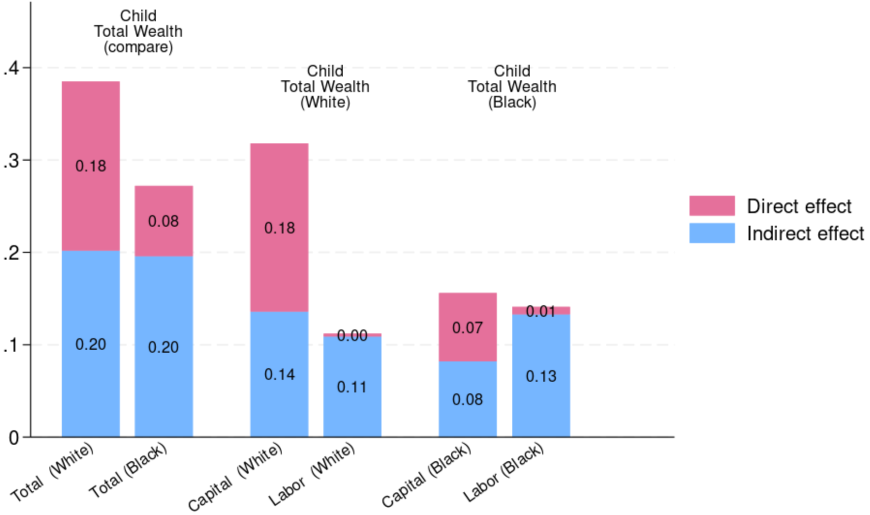
Direct and indirect effects: Parent resources on child housing, by race

Parent:	Housing Wealth			Housing Wealth Non-Housing Wealth	
	White	Black		White	Black
Eq. 1: Child Earnings (Y_c)					
Parent Housing	0.294***	0.251***	Parent Housing	0.171***	0.129***
	(0.0009)	(0.0026)		(0.0010)	(0.0028)
			Parent Non-housing	0.206***	0.209***
				(0.0007)	(0.0019)
Eq. 2: Child Resources					
Child Labor	0.529***	0.490***	Child Labor	0.510***	0.481***
	(0.0011)	(0.0023)		(0.0013)	(0.0025)
Parent Housing	0.286***	0.0722***	Parent Housing	0.265***	0.062***
	(0.0013)	(0.0034)		(0.0015)	(0.0036)
			Parent Non-housing	0.0322***	0.0194***
				(0.0013)	(0.0030)
Interaction $Y_c \times H_p$	-0.0004***	0.0005***	Interaction $Y_c \times H_p$	-0.0005***	0.0003***
	(0.0000)	(0.0001)		(0.0000)	(0.0001)
			Interaction $Y_c \times Wnh_p$	0.0003***	0.0003***
				(0.0000)	(0.0001)

Figure

Direct and indirect effects: Parent resources on child wealth, by race



Direct and indirect effects: Parent resources on child wealth, by race

Parent:	Total Wealth			Capital Wealth Labor Wealth	
	White	Black		White	Black
Eq. 1: Child Earnings (Y_c)					
Parent Wealth	0.301***	0.247***	Parent Cap Wealth	0.202***	0.112***
	(0.0006)	(0.0016)		(0.0007)	(0.0019)
			Parent Labor	0.162***	0.182***
				(0.0007)	(0.0018)
Eq. 2: Child Resources					
Child Labor	0.707***	0.736***	Child Labor	0.702***	0.741***
	(0.0010)	(0.0018)		(0.0011)	(0.0021)
Parent Wealth	0.218***	0.0839***	Parent Cap Wealth	0.243***	0.0764***
	(0.0009)	(0.0021)		(0.0011)	(0.0025)
			Parent Labor	-0.0337***	0.0117***
				(0.0010)	(0.0024)
Interaction $Y_c \times W_p$	-0.0006***	-0.0002***	Interaction $Y_c \times CW_p$	-0.0010***	-0.0000
	(0.0000)	(0.0000)		(0.0000)	(0.0000)
			Interaction $Y_c \times Y_p$	0.0006***	-0.0002***
				(0.0000)	(0.0001)

▸ Figure

Decomposition of indirect effect into income levels and income returns

- Given a set of initial (ρ_y, γ_y) values, the change in the indirect effect from a given exposure is $(\rho_y + \theta_\rho)(\gamma_y + \theta_\gamma) - \rho_y\gamma_y$.
- Splitting the cross term yields "income levels" channel of $\theta_\rho(\gamma_y + \theta_\gamma/2)$ and "income returns" channel of $\theta_\gamma(\rho_y + \theta_\rho/2)$.
- Recall that we have already estimated the total change in the indirect effect θ_ι.
- Assumption: the initial values implicit in the comparison are given by the population means modified by the exposure coefficients times a common unknown scalar σ. (i.e. "proportional scaling")
- This yields the following equation: $\theta_\iota = \theta_\rho(\overline{\gamma_y} - \theta_\gamma\sigma + \theta_\gamma/2) + \theta_\gamma(\overline{\rho_y} - \theta_\rho\sigma + \theta_\rho/2)$
- Solving yields $\sigma = \frac{\theta_\rho\overline{\gamma_y} + \theta_\gamma\overline{\rho_y} + \theta_\gamma\theta_\rho - \theta_\iota}{2\theta_\gamma\theta_\rho}$
- Substituting this value back into the above expression and canceling terms yields decomposition equation (5).

▸ Back

Results for White families

Table: Associations between County-Level Exposures and Housing Wealth Mobility

Exposure	α	β and its decomposition			
		Total	Direct effect	Income returns	Income levels
GR unemployment shock	-.731***	1.062***	0.365***	.214***	.483***
(p.p. increase / 100)	(.042)	(.099)	(.076)	(.026)	(.030)
Exposure mean, SD, N: .046, .022, 3100					
Housing supply elasticity	-.045***	-.380***	-.226**	-.067***	-.087***
(dlog units / dlog price)	(.011)	(.029)	(.023)	(.010)	(.019)
Exposure mean, SD, N: .310, .120, 800					

Mobility data source: IRS federal income tax returns linked to 2000 Census Long Form and Black Knight property records.
Great Recession shock data source: BLS Local Area Unemployment Statistics
Housing supply data source: Baum-Snow and Han (2024)

Results for Black families

Table: Associations between County-Level Exposures and Housing Wealth Mobility

Exposure	α	β and its decomposition			
		Total	Direct effect	Income returns	Income levels
GR unemployment shock	0.117^{*}	-.502	-.396	0.201^{**}	$-.307^{***}$
(p.p. increase / 100)	(.066)	(.360)	(.296)	(.098)	(.096)
Exposure mean, SD, N: .049, .021, 1000					
Housing supply elasticity	-.002	-.037	0.005	-.029	-.013
(dlog units / dlog price)	(.018)	(.061)	(.047)	(.040)	(.040)
Exposure mean, SD, N: .294, .129, 500					

Mobility data source: IRS federal income tax returns linked to 2000 Census Long Form and Black Knight property records.
Great Recession shock data source: BLS Local Area Unemployment Statistics
Housing supply data source: Baum-Snow and Han (2024)

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